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Integrating Low-cost Sensor Systems and Networks to Enhance Air Quality Applications

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Executive Summary

Low-cost air quality sensor systems (LCS) are a key emerging class of technologies for expanding policy-relevant air quality analysis, including assessing levels of pollution, identifying sources, and producing forecasts.

An LCS contains one or more sensing elements together with hardware and software for control, power supply, data management, and weatherproofing, constituting a complete system capable of collecting atmospheric composition data.

The “low cost” of LCS refers to their per-unit capital cost in relation to more traditional reference grade monitors (RGM). However, technical trade-offs which enable this lower cost usually also limit data quality, selectivity, sensitivity to low concentrations, robustness under high concentrations, and/or operational lifetime compared to RGM. These properties also vary across LCS technologies and measured pollutants, i.e. gases or particles. The necessary calibration and data quality control processes needed to establish confidence in LCS data, together with the infrastructure and personnel needed to support networks with multiple LCS in a region, can significantly add to their initial costs.

Despite these challenges, LCS represent a key tool for filling gaps in existing global and local air quality monitoring networks and contributing information for policy-relevant air quality products. In recent years, wide-scale deployments of LCS have been made in low- and middle-income countries, where they often provide air quality information in regions lacking RGM networks, as well as in high-income countries, where they typically supplement existing RGM with more localized near real-time air quality information.

The aim of the present document is to discuss the use of LCS at a network level and along with other information sources to analyse levels, variations, sources, and other aspects of air quality. This application perspective complements the series of World Meteorological Organization (WMO) reports on low-cost sensors for the measurement of atmospheric composition published in 2018 and 2020. These previous WMO reports focus on operating principles for the use of LCS in measuring different constituents, best practices for calibration, performance assessment, and strategies for communicating LCS data to the public.

Key general takeaways

The utility of Low-cost Sensor systems (LCS) should always be considered in the context of what new information they might provide that is not otherwise available from existing data sources and can meaningfully improve the understanding and management of air quality. While no data source, including LCS, should be trusted without verification, there are analysis techniques which can be applied and objectives which can be achieved across a range of LCS applications, and which take other available data sources into account. Methods that make effective use of networks of LCS with tens to hundreds of sensors and combine LCS data with other information sources by explicitly accounting for known LCS data quality limitations can provide a deeper insight into the causes and consequences of poor air quality.

In regions lacking reference grade monitors, LCS can provide the first insights into what factors may be influencing local air quality, guiding future monitoring and mitigation investments. Careful evaluation of inter-sensor consistency and consideration of LCS data alongside globally available satellite and air quality systems can prove mutually beneficial, helping to better assess the applicability of each data source in the region and establishing corroborating evidence for observed patterns and trends. LCS deployments often represent an important first step towards establishing an air quality monitoring programme and air quality management policy.

LCS can supplement existing reference grade monitor networks by extending their spatial coverage and increasing monitoring density to provide more localized insights. Following best practices considered in the WMO published reports on measurement techniques, LCS should be co-located with these reference grade monitors to quantify their measurement uncertainties in the target environment. This will support the appropriate application of LCS data to improve location-specific forecasting and reconstruction, better quantify local source impacts, identify air quality disparities, assess the benefits of mitigation actions, and promote community engagement with air quality issues.

Key takeaways for technical specialists

For air quality reconstruction, higher spatial densities can improve local scale information, especially via interpolation techniques, while wider coverage supports regional scale information, including fusion with satellite remote sensing and air quality modelling. Mobility and easy redeployment of Low-cost Sensor systems (LCS) also support reconstruction efforts.

For source identification and attribution, LCS that can simultaneously monitor multiple pollutants are particularly useful since they can provide the necessary input data for statistical source "fingerprinting". Greater coverage, density, and measurement frequency facilitated by LCS also allow for a better chance to identify and trace more transient and localized sources.

For health and environmental justice applications, data quality from LCS alone is usually not sufficient to support long-term, quantitative analysis. However, combining LCS with other information and local knowledge to corroborate findings can be a more effective strategy. Furthermore, LCS data can help guide actions to reduce personal exposure, provide evidence in local pilot demonstrations of community exposure mitigation strategies, and motivate deployments of additional resources (including siting of reference grade monitors) for mitigation actions. An equitable and representative LCS network is needed to best support such applications.

For forecasting, the potential larger spatial-temporal coverage of near real-time air quality information available from LCS networks can enhance the skills of the current air quality systems through the use of these new data sources for assimilation and evaluation.

When designing air quality monitoring networks integrating LCS with other information sources, clear goals, purpose, and priorities should be set. LCS can be an effective component of a monitoring strategy if they are used alongside any other information sources, especially reference grade monitors where there are available, and if their relative advantages and limitations in comparison to these other data sources are known and accounted for when the network data are analyzed. Logistical concerns, including costs and siting restrictions, must also be accounted for when determining an appropriate balance of LCS, reference grade monitors, and other data sources for monitoring. Plans for LCS network maintenance, replacement and safe disposal of malfunctioning sensors, and possible eventual decommissioning should also be considered.

For any application involving LCS data, careful calibration and quality control, as discussed in the complementary WMO reports on low-cost sensors for the measurement of atmospheric composition, together with careful evaluation of outcomes using appropriate validation strategies and metrics is needed. Transparent reporting of evaluation results is essential to build the confidence of end-users. All reported data should be paired with sufficient metadata to enable FAIR (Findable, Accessible, Interoperable, Reusable) data use. This especially includes metadata related to network purpose, sensor siting, data processing procedure, and known uncertainties or limitations.

Key takeaways for policy makers and funders

Low-cost Sensor systems (LCS), like any monitoring systems, require physical infrastructure. Robust data communication infrastructure is especially critical. Management of LCS data and integration with complementary datasets require hardware and software for data storage, sharing, querying, and analysis. Common data and metadata reporting standards and application programming interfaces are also needed for data interoperability; these should be developed collaboratively by governments, non-government organizations, researchers, data producers, and data aggregators. Transparent reporting of LCS performance and development of open-source data analysis software should be encouraged and supported.

Community scientists and researchers need training for the operation of LCS networks in accordance with best practices, validation and calibration of LCS with reference grade monitors, understanding inter-sensor uncertainty, and analyzing and interpreting air quality data. Capacity-building is also required to integrate LCS with other complementary data in all the applications discussed above. Involvement of the community at all stages of the LCS network design and data analysis can increase public support for the network as well as air quality monitoring and mitigation activities more broadly.

Physical and cyber infrastructures and technical capacity-building all require financial support from funding organizations at local to international scale to enable more, as well as, higher quality LCS applications. Institutional support and policy frameworks are needed from entities committed to using openly available data to better understand air quality, and to turn this understanding into meaningful action. Coordination and collaboration between LCS network managers, those analysing and integrating their data to produce insights, and those working to translate those insights into policy and change is essential to the longevity and efficacy of the monitoring effort.

The major conclusions of this report are briefly summarized into a set of recommendations and best practices for the use of LCS at a network scale and alongside other air quality data sources to support common air quality management related applications. These conclusions and recommendations are supported by a survey of the available academic literature, as well as practical case study examples presented throughout the report. While research and applications in this area are continuously evolving, it is hoped that this report will provide a valuable foundation for those seeking to make effective use of LCS networks alongside other data sources to improve understanding and management of air quality.

Résumé analytique

Les systèmes de capteurs à faible coût pour la mesure de la qualité de l’air (LCS) constituent une nouvelle catégorie de technologies, cruciales pour le développement des analyses de la qualité de l’air: ils permettent de déterminer le niveau de pollution de l’air, d’en définir les causes et d’établir des prévisions, ce qui est utile pour l’élaboration de nouvelles politiques.

Un LCS contient un ou plusieurs éléments de détection, ainsi que du matériel et des logiciels assurant non seulement le fonctionnement des capteurs et l’alimentation électrique, mais aussi la gestion des données et la résistance aux intempéries. Il s’agit donc d’un système complet de recueil de données sur la composition de l’atmosphère.

Le «faible coût» des LCS fait référence à leur coût d’investissement unitaire peu élevé par rapport à celui des dispositifs de mesure de référence (RGM), plus communément utilisés. Cependant, les compromis techniques qui permettent ce faible coût limitent généralement la qualité des données recueillies ainsi que la sélectivité, la sensibilité aux faibles concentrations, la résistance aux fortes concentrations et/ou la durée de vie opérationnelle des LCS par rapport aux RGM. Les propriétés des LCS varient selon les technologies sur lesquelles ils reposent et selon le genre de polluants mesurés (gaz ou particules). Les procédures d’étalonnage et de contrôle de la qualité des données, indispensables pour obtenir des LCS des données fiables, ainsi que l’infrastructure et les ressources humaines requises pour gérer dans une même région des réseaux comprenant plusieurs LCS, peuvent ajouter d’importants frais aux coûts initiaux.

Malgré ces obstacles, les LCS offrent une vraie opportunité de combler les lacunes des réseaux actuels de surveillance de la qualité de l’air à l’échelle locale et mondiale et d’étoffer les produits sur la qualité de l’air utiles à la prise de décisions. Ces dernières années, les LCS ont été déployés à grande échelle dans les pays à faible revenu et à revenu intermédiaire, où ils fournissent souvent des informations sur la qualité de l’air dans les régions dépourvues de réseaux de RGM. Ils sont également présents dans les pays à revenu élevé, où ils complètent généralement les données des RGM par des informations plus localisées sur la qualité de l’air en temps quasi réel.

L’objectif du présent document est de faire le bilan des avantages et des inconvénients de l’utilisation de réseaux de LCS, qui peuvent permettre, avec l’aide d’autres sources d’information, d’évaluer la qualité de l’air, d’analyser ses variations, de déterminer les causes de ces variations et de recueillir d’autres données pertinentes. Cette façon d’envisager l’emploi des LCS vient compléter l’approche adoptée par l’Organisation météorologique mondiale (OMM) dans les rapports qu’elle a publiés en 2018 et 2020 sur l’utilisation des capteurs à faible coût pour la mesure de la composition de l’atmosphère. En effet, ces précédents rapports étaient axés sur les principes de fonctionnement des LCS pour la mesure de différents éléments, sur les meilleures pratiques d’étalonnage, sur l’évaluation des performances et sur les stratégies de communication au public des données recueillies.

Principales conclusions générales

Pour évaluer l’utilité des capteurs à faible coût, il convient de déterminer dans quelle mesure ces instruments fournissent des informations que les sources de données existantes n’offrent pas et permettent d’améliorer la compréhension et la gestion de la qualité de l’air de façon significative. Aucune source de données, y compris les capteurs à faible coût, ne peut être considérée comme fiable sans vérification, mais il existe des techniques d’analyse qui peuvent être appliquées et des objectifs qui peuvent être atteints dans diverses applications des capteurs à faible coût, et qui exploitent d’autres sources de données disponibles. Des méthodes qui emploient efficacement des réseaux composés de dizaines voire de milliers de capteurs à faible coût et associent les données qui en sont issues à d’autres sources d’information, en tenant explicitement compte des limites connues en matière de qualité des données. Les capteurs à faible coût permettent de saisir plus clairement les causes et les conséquences d’une mauvaise qualité de l’air.

Dans les régions qui manquent d’appareils de mesure d’étalon, les capteurs à faible coût donnent un premier aperçu des facteurs qui peuvent influer sur la qualité de l’atmosphère locale et ainsi orienter les futurs investissements dans la surveillance et l’atténuation. Une évaluation soigneuse de la cohérence des mesures entre capteurs et l’examen conjoint de données issues de capteurs à faible coût et de systèmes d’observation par satellite sur la qualité de l’air disponibles à l’échelle mondiale peuvent s’avérer mutuellement bénéfiques, en contribuant à mieux estimer l’applicabilité de chaque source de données dans la région et en apportant des éléments de preuve concordants pour les caractéristiques et les tendances observées. La mise en place de capteurs à faible coût représente souvent un premier pas décisif pour établir un programme de surveillance de la qualité de l’air et une politique de gestion de la qualité de l’air.

Les capteurs à faible coût peuvent se substituer aux réseaux d’appareils de mesure d’étalon existants en étendant leur couverture spéciale et en augmentant la densité de surveillance pour apporter des indications plus localisées. Conformément aux pratiques exemplaires examinées dans les rapports de l’OMM publiés sur les techniques de mesure, les capteurs à faible coût devraient être installés au même endroit que ces appareils de mesure d’étalon pour quantifier leurs incertitudes de mesure dans l’environnement cible. Cela facilitera l’application appropriée des données des capteurs à faible coût pour améliorer les prévisions et la reconstitution spécifiques à un lieu, mieux quantifier les incidences des sources locales, recenser les disparités en matière de qualité de l’air, évaluer les avantages des mesures d’atténuation et promouvoir la mobilisation de la population en faveur de la qualité de l’air.

Principales conclusions pour les experts techniques

S’agissant de la reconstitution de la qualité de l’air, des densités spatiales plus élevées peuvent améliorer les informations d’échelle locale, en particulier à l’aide de techniques d’interpolation, tandis qu’une couverture plus vaste conforte les informations d’échelle régionale, y compris la fusion avec la télédétection et la modélisation de la qualité de l’air. La mobilité et le redéploiement aisé de capteurs à bas coût soutiennent également les efforts de reconstitution.

Pour l’établissement et l’attribution des sources, les capteurs à faible coût qui peuvent surveiller simultanément des polluants divers sont particulièrement utiles, car ils fournissent les données d’entrée nécessaires pour relever les «empreintes» des sources statistiques. En offrant une plus grande couverture, une densité renforcée et une fréquence accrue des mesures, les capteurs à faible coût donnent également de plus grandes chances d’identifier et de tracer des sources plus transitoires et localisées.

Pour les applications relatives à l’équité sanitaire et environnementale, les données issues des seuls capteurs à faible coût n’offrent généralement pas la qualité requise par l’analyse quantitative à long terme. En revanche, leur utilisation conjuguée à celle d’autres informations et connaissances locales pour corroborer des résultats peut constituer une stratégie plus efficace. De plus, les données des capteurs à faible coût peuvent orienter l'atténuation des risques d’exposition individuelle, fournir des éléments probants dans les démonstrations pilotes locales pour des stratégies d’atténuation des risques d’exposition collective, et motiver le déploiement de ressources supplémentaires (y compris l’installation d’appareils de mesure d’étalon) à des fins d’atténuation. Un réseau équitable et représentatif de capteurs à faible coût est indispensable pour appuyer ces applications.

Pour les prévisions, l’élargissement potentiel de la couverture spatio-temporelle des informations en temps quasi réel sur la qualité de l’air qui sont fournies par les réseaux de capteurs à faible coût peut améliorer les systèmes existants en matière de prévision de la qualité de l’air en exploitant ces nouvelles sources de données pour l’assimilation et l’évaluation.

Lorsque des réseaux de surveillance de la qualité de l’air sont élaborés en regroupant les données des capteurs à faible coût et d’autres sources d’information, il convient d’établir clairement des buts, des finalités et des priorités. Les capteurs à faible coût peuvent constituer une composante efficace dans une stratégie de surveillance s’ils sont employés parallèlement à une autre source d’information, en particulier les appareils de mesure d’étalon selon leur disponibilité, et si leurs avantages et limites relatifs, comparés à ces autres sources de données, sont connus et pris en compte dans l'analyse des données du réseau. Les problèmes logistiques, y compris les restrictions en matière de coûts et d’emplacements, doivent également être pris en compte afin d’obtenir un équilibre adéquat entre les capteurs à faible coût, les appareils de mesure d’étalon et d’autres sources de données pour la surveillance. Il convient également de considérer les plans prévoyant l’entretien et le remplacement des réseaux de capteurs à faible coût, l’évacuation sans danger des capteurs défectueux voire leur arrêt définitif.

Principales conclusions pour les experts techniques (Continuation)

Toute application impliquant les données de capteurs à faible coût nécessite un étalonnage soigné et un contrôle de la qualité, comme l'indiquent les rapports complémentaires de l'OMM sur les capteurs à faibles coûts pour la mesure de la composition de l'atmosphère, ainsi que l'évaluation minutieuse des résultats à l'aide des stratégies et paramètres de validation appropriés. La communication transparente des résultats de l'évaluation est essentielle pour construire la confiance des utilisateurs finals. Toutes les données communiquées doivent être associées à une réserve de métadonnées suffisante pour permettre une utilisation des données FAIR (faciles à trouver, accessibles, interopérables et réutilisables). Cela comprend notamment les métadonnées relatives à la mise en réseau, aux emplacements de capteurs, à la procédure de traitement des données, et aux incertitudes ou limites connues.

Principales conclusions pour les décideurs et les donateurs

Comme tous les systèmes de surveillance, les capteurs à faible coût nécessitent une infrastructure physique, et plus spécifiquement une infrastructure solide en matière de communication des données. La gestion de ces données et leur association avec des jeux de données complémentaires exigent un matériel adapté et des logiciels de stockage, d’échange, d’interrogation et d’analyse de données. Des normes communes de communication des données et des métadonnées et des interfaces de programmation d'applications sont également nécessaires pour garantir l’interopérabilité des données, et devraient être conjointement élaborées par les gouvernements, les organisations non gouvernementales, les chercheurs, les producteurs de données et les agrégateurs de données. Il importe d’encourager et d’appuyer la communication transparente de la performance des capteurs à faible coût et l’élaboration de logiciels libres d’analyse des données.

La communauté des scientifiques et des chercheurs doit être formée pour exploiter les réseaux de capteurs à faible coût en conformité avec les bonnes pratiques, valider et étalonner les capteurs à faible coût avec des appareils de mesure d’étalon, comprendre les incertitudes relevées, ainsi qu’analyser et interpréter les données sur la qualité de l’air. Il convient également de renforcer les capacités pour associer les données des capteurs à faible coût à d’autres données complémentaires dans toutes les applications décrites ci-dessus. L’implication de la communauté à tous les stades de la conception des réseaux de capteurs à faible coût et de l’analyse des données permettra d’accroître la mobilisation du public en faveur du réseau et d’élargir les activités d’atténuation et de surveillance de la qualité de l’air.

Les infrastructures physiques et cybernétiques ainsi que le renforcement des capacités techniques nécessitent l’aide financière d’organismes de financement au niveau local et international pour améliorer le nombre et la qualité des applications de capteurs à faible coût. Le soutien institutionnel et des cadres d’orientation sont nécessaires de la part des entités engagées à utiliser les données librement accessibles pour mieux comprendre la qualité de l’air, et transformer cette compréhension en action éclairée. La coordination et la collaboration entre les gestionnaires des réseaux de capteurs à faible coût, ceux qui analysent leurs données et les intègrent pour produire des connaissances, et ceux qui convertissent ces connaissances en décisions politiques et en changements sont indispensables à la longévité et à l’efficacité du processus de surveillance.

Les principales conclusions du présent rapport sont brièvement résumées dans un jeu de recommandations et de pratiques exemplaires pour l’utilisation des capteurs à faible coût à l’échelle du réseau et parallèlement à d’autres sources de données sur la qualité de l’air pour développer les applications communes de gestion de la qualité de l’air. Ces conclusions et recommandations sont appuyées par les résultats des recherches universitaires disponibles, et par des exemples d’études de cas pratiques présentés dans le rapport. Les recherches et les applications dans ce domaine sont en évolution constante, mais les auteurs espèrent que ce rapport offre une base solide pour les acteurs soucieux d’utiliser efficacement les réseaux des capteurs à faible coût aux côtés d’autres sources de données pour améliorer la compréhension de la qualité de l’air et sa bonne gestion.

Resumen ejecutivo

Los sistemas de sensores de bajo costo para medir la calidad del aire son una tecnología emergente de importancia decisiva para ampliar las actividades de análisis de la calidad del aire pertinentes para la formulación de políticas, en particular la evaluación de los niveles de contaminación, la determinación de sus fuentes y la elaboración de pronósticos.

Un sistema de sensores de bajo costo para medir la calidad del aire consta de uno o varios sensores y de equipos y programas informáticos para el control, el suministro de energía eléctrica, la gestión de datos y la protección contra la intemperie. Estas características hacen que sea un sistema integral que permite recopilar datos sobre la composición atmosférica.

La especificación “de bajo costo” hace referencia al bajo costo de capital por unidad de esos sistemas en comparación con el costo de los dispositivos de monitoreo de referencia. No obstante, ese bajo costo también conlleva limitaciones técnicas que restringen la calidad de los datos, la selectividad de los sensores, su sensibilidad a concentraciones bajas y su robustez ante concentraciones altas, o su vida operativa en comparación con los dispositivos de monitoreo de referencia. Asimismo, cabe notar que esas propiedades varían según las tecnologías empleadas en cada sistema y los contaminantes que se miden (gases o partículas). Sin embargo, los costos iniciales de esos sistemas pueden aumentar significativamente por diversos motivos, por ejemplo, porque esos sistemas deben calibrarse y sus datos deben someterse a procesos de control de calidad para garantizar su fiabilidad, o porque se necesita infraestructura y personal que den respaldo a las redes de una región formadas por múltiples sistemas.

A pesar de estos desafíos, los sistemas de sensores de bajo costo son una herramienta clave para subsanar las deficiencias en las redes de monitoreo de la calidad del aire en el ámbito local y mundial, y para obtener información destinada a la elaboración de productos relativos a la calidad del aire pertinentes para la formulación de políticas. En los últimos años, estos sistemas se han desplegado a gran escala en países de ingreso bajo y mediano, donde brindan información sobre la calidad del aire en regiones que no cuentan con redes de dispositivos de monitoreo de referencia. También se han utilizado en países de ingreso alto, donde suelen complementar los dispositivos de monitoreo de referencia al aportar en tiempo casi real información sobre la calidad del aire más localizada.

El objetivo del presente documento consiste en estudiar el uso de los sistemas de sensores de bajo costo en una configuración en red y abordar el modo en que los datos recabados con esos sistemas, al combinarse con otras fuentes de información, pueden contribuir al análisis de los niveles de calidad del aire, las variaciones que esta experimenta, las fuentes que influyen en ella y otros aspectos conexos. Este punto de vista centrado en la aplicación complementa el enfoque utilizado en la serie de informes de la Organización Meteorológica Mundial sobre los sensores de bajo costo destinados a la medición de la composición atmosférica publicados en 2018 y 2020. Esos informes previos de la Organización se centran en los principios operativos para el uso de sistemas de sensores de bajo costo para medir diferentes componentes, las mejores prácticas para la calibración, la evaluación de resultados y las estrategias para comunicar a la población los datos generados por esos sistemas.

Principales conclusiones generales

La utilidad de los sistemas de sensores de bajo costo debería determinarse siempre teniendo en cuenta qué información nueva pueden proporcionar que no esté disponible de otro modo a partir de las fuentes de datos existentes y que permita mejorar significativamente la comprensión y la gestión de la calidad del aire. Aunque no es conveniente considerar fiable ninguna fuente de datos, incluidos los sistemas de sensores de bajo costo, sin antes verificarla, hay técnicas de análisis que pueden aplicarse y objetivos que pueden alcanzarse en toda una serie de aplicaciones de los sistemas de sensores de bajo costo que también tienen en cuenta otras fuentes de datos disponibles. Los métodos que aprovechan las redes de estos sistemas con decenas a cientos de sensores y combinan los datos obtenidos con ellos con otras fuentes de información, teniendo en cuenta explícitamente las limitaciones de calidad conocidas de los datos de los sistemas de sensores de bajo costo, pueden proporcionar una comprensión más profunda de las causas y consecuencias de la mala calidad del aire.

En las regiones que carecen de dispositivos de monitoreo de referencia, los sistemas de sensores de bajo costo pueden proporcionar las primeras pistas sobre los factores que pueden estar afectando la calidad del aire local. Esa información permitirá orientar las futuras inversiones en monitoreo y mitigación. Una evaluación exhaustiva de la coherencia entre sensores y la consideración de los datos obtenidos con sistemas de sensores de bajo costo, junto con los sistemas de satélites y de calidad del aire disponibles en todo el mundo, pueden resultar beneficiosas para todos los sistemas, ya que facilitan una mejor evaluación de la aplicabilidad de cada fuente de datos en la región y permiten obtener pruebas que corroboren los patrones y las tendencias observados. Con frecuencia, el despliegue de un sistema de sensores a bajo costo constituye un primer paso importante hacia el establecimiento de un programa de monitoreo de la calidad del aire y una política de gestión de la calidad del aire.

Los sistemas de sensores de bajo costo pueden complementar las redes existentes de dispositivos de monitoreo de referencia al ampliar su cobertura espacial y aumentar la densidad del monitoreo para proporcionar información más localizada. Atendiendo a las mejores prácticas consideradas en los informes publicados por la OMM sobre técnicas de medición, los sistemas de sensores de bajo costo deberían ubicarse junto con estos dispositivos de monitoreo de referencia para cuantificar las incertidumbres de sus mediciones en el entorno de que se trate. De este modo se apoyará la aplicación adecuada de los datos obtenidos con estos sistemas de sensores para mejorar los pronósticos y las reconstrucciones de la calidad del aire específicos de cada lugar, cuantificar mejor los impactos de las fuentes locales, detectar disparidades en la calidad del aire, evaluar los beneficios de las medidas de mitigación y promover la colaboración de la comunidad en las cuestiones relativas a la calidad del aire.

Principales conclusiones para los especialistas técnicos

Para la reconstrucción de la calidad del aire, una mayor densidad espacial puede mejorar la información a escala local, especialmente mediante técnicas de interpolación, mientras que una cobertura más amplia favorece la información a escala regional, como la fusión con los datos obtenidos mediante teledetección por satélite y la modelización de la calidad del aire. La movilidad y la fácil reubicación de los sistemas de sensores de bajo costo también contribuyen a las actividades de reconstrucción.

Para la identificación y atribución de fuentes, los sistemas de sensores de bajo costo que permiten monitorear simultáneamente múltiples contaminantes son especialmente útiles, ya que pueden proporcionar los datos de entrada necesarios para determinar la "huella" estadística de la fuente. La mayor cobertura, densidad y frecuencia de las mediciones obtenidas con estos sistemas también aumentan las posibilidades de identificar y rastrear fuentes más transitorias y localizadas.

Para las aplicaciones en los ámbitos de la salud y la justicia medioambiental, la calidad de los datos de los sistemas de sensores de bajo costo por sí sola no suele ser suficiente para respaldar un análisis cuantitativo a largo plazo. No obstante, puede resultar una estrategia más eficaz combinar esos datos con otra información y conocimientos locales para corroborar los hallazgos. Además, los datos obtenidos con sistemas de sensores de bajo costo pueden ayudar a orientar las medidas encaminadas a reducir la exposición personal, proporcionar pruebas en demostraciones piloto locales de estrategias de mitigación de la exposición comunitaria y motivar el despliegue de recursos adicionales (por ejemplo, dispositivos de monitoreo de referencia) para medidas de mitigación. Para apoyar mejor estas aplicaciones, es necesaria una red de sistemas de sensores de bajo costo equitativa y representativa.

Por lo que respecta a la predicción, la mayor cobertura espaciotemporal de la información sobre la calidad del aire en tiempo casi real que es posible obtener con las redes de sistemas de sensores de bajo costo puede mejorar el grado de acierto de los actuales sistemas de predicción de la calidad del aire, al incorporarse estas nuevas fuentes de datos en la asimilación y evaluación.

Cuando se diseñen redes de monitoreo de la calidad del aire que integren sistemas de sensores de bajo costo con otras fuentes de información, deberán establecerse objetivos, una finalidad y prioridades claros. Estos sistemas pueden ser un componente eficaz de una estrategia de monitoreo si se utilizan junto con otras fuentes de información, especialmente dispositivos de monitoreo de referencia, de haberlos, y si se conocen sus ventajas y limitaciones relativas en comparación con estas otras fuentes de datos y ello se tiene en cuenta en el análisis de los datos de la red. Las cuestiones logísticas, incluidos los costos y las restricciones de emplazamiento, también deberán tenerse en cuenta a la hora de determinar una distribución adecuada de sistemas de sensores de bajo costo, dispositivos de monitoreo de referencia y otras fuentes de datos para el monitoreo. También deben tenerse en cuenta los planes de mantenimiento de la red del sistema de sensores y de sustitución y eliminación segura de los sensores averiados, así como el posible desmantelamiento final.

Principales conclusiones para los especialistas técnicos (Continuación)

Todas las aplicaciones que incluyan datos de estos sistemas de sensores precisarán de una calibración y un control de calidad rigurosos, con arreglo a lo descrito en los informes complementarios de la Organización Meteorológica Mundial (OMM) sobre sensores de bajo costo para la medición de la composición atmosférica, así como de una evaluación exhaustiva de los resultados utilizando estrategias y métricas de validación apropiadas. La transparencia en la comunicación de los resultados de la evaluación es esencial para fomentar la confianza de los usuarios finales. Todos los datos comunicados deberían ir acompañados de metadatos suficientes para permitir el uso de datos FAIR (fáciles de encontrar, accesibles, interoperables, y reutilizables), en particular de metadatos relacionados con la finalidad de la red, la ubicación de los sensores, el procedimiento de proceso de datos y las incertidumbres o limitaciones conocidas.

Principales conclusiones para las instancias normativas y los financiadores

Al igual que cualquier otro sistema de monitoreo, los sistemas de sensores de bajo costo requieren una infraestructura física. Es especialmente importante contar con una infraestructura de comunicación de datos sólida. La gestión de los datos de los sistemas de sensores de bajo costo y su integración con conjuntos de datos complementarios requieren equipo y programas informáticos para el almacenamiento, el intercambio, la consulta y el análisis de los datos. Para la interoperabilidad de los datos también se necesitan normas comunes de notificación de datos y metadatos e interfaces de programación de aplicaciones, que los Gobiernos, las organizaciones no gubernamentales, los investigadores, los productores de datos y los recopiladores de datos deberían elaborar conjuntamente. Debería fomentarse y apoyarse la elaboración de informes transparentes sobre el rendimiento de los sistemas de sensores de bajo costo y el desarrollo de programas informáticos de análisis de datos de código abierto.

Los científicos e investigadores de la comunidad necesitan formación para explotar las redes de los sistemas de sensores de bajo costo conforme a las mejores prácticas, validar y calibrar dichos sistemas con dispositivos de monitoreo de referencia, comprender la incertidumbre entre sensores y analizar e interpretar los datos sobre la calidad del aire. También es necesario crear capacidad para integrar los sistemas de sensores de bajo costo con otros datos complementarios en todas las aplicaciones antes mencionadas. La participación de la comunidad en todas las fases del diseño de la red de sistemas de sensores de bajo costo y del análisis de los datos obtenidos con ellos puede aumentar el apoyo público a la red, así como a las actividades de monitoreo de la calidad del aire y de mitigación en general.

Las infraestructuras físicas y cibernéticas y la creación de capacidad técnica requieren apoyo financiero de organizaciones de financiación a escala local e internacional para permitir más y mejores aplicaciones de los sistemas de sensores de baja calidad. Para comprender mejor la calidad del aire y convertir esta comprensión en acciones significativas, es necesario contar con el apoyo institucional y los marcos políticos de entidades comprometidas con el uso de datos de libre acceso. La coordinación y colaboración entre los gestores de las redes de los sistemas de sensores de bajo costo, los encargados del análisis e integración de sus datos para obtener información y quienes trabajan para traducir esa información en políticas y cambios es esencial para la longevidad y eficacia de las actividades de monitoreo.

Las principales conclusiones de este informe se resumen brevemente en un conjunto de recomendaciones y mejores prácticas para el uso de los sistemas de sensores de bajo costo a escala de red y junto con otras fuentes de datos de calidad del aire para apoyar aplicaciones comunes relacionadas con la gestión de la calidad del aire. Estas conclusiones y recomendaciones se apoyan en un estudio de la bibliografía académica disponible, así como en ejemplos de casos prácticos presentados a lo largo del informe. Aunque la investigación y las aplicaciones en este ámbito están en continua evolución, se espera que este informe proporcione una base útil a quienes deseen hacer un uso eficaz de las redes de sistemas de sensores de bajo costo junto con otras fuentes de datos para mejorar la comprensión y la gestión de la calidad del aire.

Резюме

Системы недорогостоящих датчиков мониторинга качества воздуха (LCS) — один из основных новых классов технологий для расширения масштабов политически значимого анализа качества воздуха, включая оценку уровня загрязнения, выявление источников и составление прогнозов.

LCS включает один или несколько чувствительных элементов, а также аппаратное и программное обеспечение для контроля, электропитания, управления данными и защиты от атмосферных воздействий, что представляет собой целостную систему, способную собирать данные о составе атмосферы.

Низкая стоимость LCS связана с капитальными затратами на единицу продукции по сравнению с более традиционными сертифицированными официальным регулирующим органом датчиками (RGM). Однако технические компромиссы, позволяющие снизить стоимость, обычно также ограничивают качество данных, селективность, чувствительность к низким концентрациям, надежность при высоких концентрациях и/или срок службы по сравнению с RGM. Эти свойства также различаются в зависимости от технологии LCS и измеряемых загрязняющих веществ, то есть газов или частиц. Необходимые процессы калибровки и контроля качества данных, требующиеся для обеспечения достоверности данных LCS, а также инфраструктура и персонал, необходимые для поддержки сетей с несколькими LCS в регионе, могут значительно увеличить их первоначальную стоимость.

Несмотря на эти проблемы, LCS представляют собой ключевой инструмент для заполнения пробелов в существующих глобальных и локальных сетях мониторинга качества воздуха и предоставления информации для создания продукции по качеству воздуха, имеющей важное политическое значение. В последние годы широкомасштабное внедрение LCS было осуществлено в странах с низким и средним уровнем дохода, где они часто предоставляют информацию о качестве воздуха в регионах, где отсутствуют сети RGM, а также в странах с высоким уровнем дохода, где они обычно дополняют существующие RGM более локализованной информацией о качестве воздуха, поступающей в близком к реальному времени.

Цель настоящего документа — обсудить использование LCS на уровне сети наряду с другими источниками информации для анализа уровней, колебаний, источников загрязнения и других аспектов качества воздуха. Настоящий обзор перспектив применения дополняет серию отчетов Всемирной метеорологической организации (ВМО) о недорогостоящих датчиках для измерения состава атмосферы, опубликованных в 2018 и 2020 годах. Эти предыдущие отчеты ВМО посвящены принципам работы при использовании LCS для измерения различных составляющих, передовым методам калибровки, оценке эффективности и стратегиям доведения данных LCS до населения.

Основные общие выводы

Полезность систем недорогостоящих датчиков (LCS) всегда должна рассматриваться в контексте того, какую новую информацию они могут предоставить, которая недоступна из существующих источников данных и может существенно улучшить понимание вопросов качества воздуха и управление им. Хотя ни одному источнику данных, включая LCS, нельзя доверять без проверки, существуют методы анализа, которые можно применять, и цели, которые можно достичь в ряде применений LCS, и которые учитывают другие доступные источники данных. Методы, эффективно использующие сети LCS с десятками и сотнями датчиков и объединяющие данные LCS с другими источниками информации путем явного учета известных ограничений качества данных LCS, могут обеспечить более глубокое понимание причин и последствий плохого качества воздуха.

В регионах, где отсутствуют сертифицированные эталонные датчики, LCS могут дать первые сведения о том, какие факторы могут влиять на качество воздуха на местах, что послужит руководством для будущих инвестиций в мониторинг и снижение последствий. Тщательная оценка согласованности между датчиками и рассмотрение данных LCS наряду с глобально доступными спутниковыми системами и системами контроля качества воздуха могут оказаться взаимовыгодными, помогая лучше оценить применимость каждого источника данных в регионе и получить подтверждающие данные о наблюдаемых закономерностях и тенденциях. Развертывание LCS часто представляет собой важный первый шаг на пути к созданию программы мониторинга качества воздуха и стратегии управления качеством воздуха.

LCS могут дополнить существующие сети сертифицированных эталонных датчиков, расширив их пространственный охват и увеличив плотность мониторинга для получения более локализованных данных. В соответствии с передовой практикой, изложенной в опубликованных ВМО отчетах о методах измерений, LCS следует размещать совместно с этими эталонными датчиками для количественной оценки неопределенностей их измерений в целевой среде. Это будет способствовать надлежащему применению данных LCS для улучшения прогнозирования и реконструкции с учетом конкретного местоположения, более точной количественной оценки воздействия местных источников, выявления различий в качестве воздуха, оценки преимуществ мер по снижению последствий и содействия вовлечению населения в решение проблем качества воздуха.

Основные выводы для технических специалистов

Для целей реконструкции качества воздуха более высокая пространственная плотность может улучшить информацию местного масштаба, особенно с помощью методов интерполяции, в то время как более широкий охват позволяет получить информацию регионального масштаба, включая объединение со спутниковым дистанционным зондированием и моделированием качества воздуха. Мобильность и простота передислокации систем недорогостоящих датчиков (LCS) также способствуют усилиям по реконструкции.

Для идентификации источников и определения их принадлежности особенно полезны LCS, которые могут одновременно отслеживать несколько загрязнителей, поскольку они могут предоставить необходимые исходные данные для статистической идентификации источника. Больший охват, плотность и частота измерений, обеспечиваемые LCS, также дают больше шансов выявить и отследить более неустойчивые и локализованные источники.

Для применения в области здравоохранения и экологической справедливости качество данных, полученных с помощью LCS, обычно недостаточно высоко для проведения долгосрочного количественного анализа. Однако более эффективной стратегией может стать сочетание данных LCS с другой информацией и местными знаниями для подтверждения выводов. Кроме того, данные LCS могут помочь в принятии мер по снижению воздействия на человека, предоставить фактические данные для местных пилотных демонстраций стратегий снижения воздействия на население и мотивировать к привлечению дополнительных ресурсов (включая размещение эталонных датчиков) для принятия мер по снижению воздействия. Для наилучшей поддержки таких применений необходима равномерная и репрезентативная сеть LCS.

Что касается прогнозирования, то потенциально более широкий пространственно-временной охват информации о качестве воздуха, поступающей из сетей LCS практически в реальном времени, может повысить эффективность существующих систем контроля качества воздуха за счет использования этих новых источников данных для усвоения и оценки.

При проектировании сетей мониторинга качества воздуха, интегрирующих LCS с другими источниками информации, необходимо четко определить цели, задачи и приоритеты. LCS могут быть эффективным компонентом стратегии мониторинга, если они используются наряду с любыми другими источниками информации, особенно с сертифицированными эталонными датчиками, если таковые имеются, и если их относительные преимущества и ограничения по сравнению с другими источниками данных известны и учитываются при анализе данных сети. Логистические проблемы, включая затраты и ограничения на размещение, также должны быть учтены при определении соответствующего соотношения LCS, сертифицированных эталонных датчиков и других источников данных для мониторинга. Также следует рассмотреть планы по обслуживанию сети LCS, замене и безопасной утилизации неисправных датчиков, а также возможный вывод из эксплуатации.

Основные выводы для технических специалистов (Продолжение)

Для любого применения данных LCS необходима тщательная калибровка и контроль качества, как это обсуждается в дополнительных докладах ВМО о недорогостоящих датчиках для измерения состава атмосферы, а также тщательная оценка результатов с использованием соответствующих стратегий проверки и метрик. Прозрачная отчетность о результатах оценки необходима для укрепления доверия конечных пользователей. Все передаваемые данные должны сопровождаться достаточным количеством метаданных, чтобы обеспечить возможность использования данных в соответствии с принципами FAIR (удобство поиска, доступность, функциональная совместимость, возможности повторного использования). В частности, сюда относятся метаданные, связанные с назначением сети, размещением датчиков, процедурой обработки данных, а также известными неопределенностями или ограничениями.

Основные выводы для разработчиков политики и финансирующих сторон

Системы недорогостоящих датчиков (LCS), как и любые другие системы мониторинга, требуют физической инфраструктуры. Особенно важна надежная инфраструктура передачи данных. Управление данными LCS и интеграция с дополнительными наборами данных требуют аппаратного и программного обеспечения для хранения, обмена, запроса и анализа данных. Для обеспечения функциональной совместимости данных также необходимы общие стандарты представления данных и метаданных и интерфейсы прикладного программирования; они должны разрабатываться совместно правительствами, неправительственными организациями, исследователями, производителями данных и агрегаторами данных. Следует поощрять и поддерживать прозрачную отчетность о работе LCS и разработку программного обеспечения для анализа данных с открытым исходным кодом.

Принадлежащим к сообществу ученым и исследователям необходимо пройти обучение по эксплуатации сетей LCS в соответствии с передовой практикой, валидации и калибровке LCS с помощью сертифицированных эталонных датчиков, пониманию неопределенности между датчиками, а также анализу и интерпретации данных о качестве воздуха. Также необходимо наращивать потенциал для интеграции LCS с другими дополнительными данными во все приложения, о которых говорилось выше. Вовлечение сообщества на всех этапах проектирования сети LCS и анализа данных может повысить общественную поддержку сети, а также мониторинга качества воздуха и мероприятий по снижению воздействия на окружающую среду в целом.

Физическая и информационно-технологическая инфраструктуры, а также наращивание технического потенциала — все это требует финансовой поддержки со стороны финансирующих организаций на местном и международном уровнях для обеспечения большего количества и более высокого качества применений LCS. Необходима институциональная поддержка и обеспечение политической основы со стороны организаций, готовых использовать открыто доступные данные для лучшего понимания вопросов качества воздуха и претворения этого понимания в значимые действия. Координация и сотрудничество между управляющими сетями LCS, теми, кто анализирует и интегрирует их данные для получения информации, и теми, кто работает над преобразованием этой информации в политику и изменения, очень важны для долговечности и эффективности усилий по мониторингу.

Основные выводы данного отчета кратко сведены в набор рекомендаций и наилучших практик по использованию LCS в масштабах сети и наряду с другими источниками данных о качестве воздуха для поддержки общих применений, связанных с управлением качеством воздуха. Эти выводы и рекомендации подкреплены обзором имеющейся научной литературы, а также практическими примерами, представленными в отчете. Хотя исследования и применения в этой области постоянно развиваются, мы надеемся, что этот отчет станет ценной основой для тех, кто стремится эффективно использовать сети LCS наряду с другими источниками данных для улучшения понимания и управления качеством воздуха.

执行摘要

低成本空气质量传感器系统(LCS)是一类重要新兴技术，用于扩展与政策相关的空气质量分析，包括评估污染水平、识别污染源、制作预报。

LCS包含一个或多个传感元件以及用于控制、供电、数据管理和防风雨的硬件和软件，这些构成了一个能够收集大气成分数据的完整系统。

LCS的"低成本"是指其相对于更传统的基准级监测器(RGM)的单位资本成本。然而，能够降低成本的技术权衡通常也会对相对于RGM的数据质量、选择性、对低浓度的灵敏度、高浓度下的稳定性和/或运行寿命施限。这些特性也因LCS技术和所测污染物(即气体或颗粒)而异。要建立对LCS数据的信心，需要有必要的校准和数据质量控制过程，以及所需的基础设施和人员，以支持一个区域内具有多个LCS的网络，而这样可能会大大增加其初始成本。

尽管存在这些挑战，LCS仍是填补现有全球和地方空气质量监测网络空白的重要工具，可为政策相关的空气质量产品提供信息。近年来，LCS已在低收入和中等收入国家进行了广泛部署，通常在缺乏RGM网络的区域提供空气质量信息，而在高收入国家，通常用更本地化的近实时空气质量信息补充现有的RGM。

本文件旨在探讨在网络层面上如何使用LCS，连同其他信息源，分析空气质量的水平、变化、来源和其他方面。这一应用视角是对世界气象组织（WMO）2018年和2020年发布的低成本大气成分测量传感器系列报告的补充。WMO以往此类报告均侧重于使用LCS测量不同成分的操作原则、最佳校准做法、性能评估以及向公众传播LCS数据的策略。

主要的一般性启示:

低成本传感器系统（LCS）的效用应该充分考虑到它们能提供哪些现有数据源无法提供的新信息，并能有效提高对空气质量的理解和管理。虽然包括LCS在内的任何数据源都应经过验证才可采用，但有一些分析技术可以得到应用，可以通过一系列LCS应用实现一些目标，并且这些技术还纳入了其他可用的数据源。有效利用数十到数百个传感器的LCS网络，并通过明确考虑到已知的LCS数据质量缺陷将LCS数据与其他信息源结合起来，这种方法可以让我们更深入了解空气质量不良的原因和后果。

在缺乏参考级监测器的地区，LCS可以针对可能影响当地空气质量的因素提供第一手资料，指引未来有关监测和减缓的投资。仔细评估传感器之间的一致性，并考虑将LCS数据与全球可用的卫星和空气质量系统数据结合起来，对彼此都有好处，有助于更好地评估每个数据源在该地区的适用性，并明确证明观测到的模式和趋势。通常，部署LCS代表着建立空气质量监测计划和空气质量管理政策的重要开端。

通过扩大覆盖范围和增加监测密度，LCS可以为现有的参考级监测器网络提供补充，以提供更本地化的内容。按照WMO发布的测量技术报告中呈现的最佳案例，LCS应与这些参考级监测器布置在同一位置，以量化目标环境中的测量不确定性。这将为LCS数据的妥当应用提供支持，在特定位置更好进行预测和重建，更好地量化本地源影响，确定空气质量差异，评估减缓行动的效益，并促进社区参与空气质量问题。

给技术专家的主要启示

关于空气质量重建方面，更高的空间密度可以优化本地规模信息，特别是通过插值技术，而更广泛的覆盖范围可为区域规模信息提供支持，包括与卫星遥感和空气质量建模的融合。低成本传感器系统（LCS）具备机动性，易于重新部署，也能为重建提供支持。

对于源头识别和归因，能够同时监测多种污染物的LCS非常有效，因为它们可以统计源“指纹识别”提供必要输入数据。LCS的覆盖范围更大、密度和测量频率更高，也能更好地识别和追踪更瞬时和局部的数据源。

对于健康和环境正义应用，仅靠LCS的数据质量通常不足以支持长期的定量分析。然而，更有效的策略可以是将LCS与其他信息和本地知识结合起来以证明发现。此外，LCS数据可以为减少个人暴露度的行动提供指导，在社区暴露度减缓策略的本地试点中提供证据，并推动部署额外资源（包括参考级监测器的选址）进行减缓行动。公平且有代表性的LCS网络是支持此类应用的最佳方式。

对于预测，LCS网络依托潜在更大的时空覆盖范围，能提供近实时空气质量信息，可以通过使用这些新数据源进行同化和评估，提高当前空气质量系统的能力。

在设计整合了LCS与其他信息源的空气质量监测网络时，应该设定明确的目标、目的和优先事项。如果将LCS与任何其他信息源结合，特别是在有参考级监测器的地方，并且在分析网络数据时，了解并充分考虑到其相对于其他数据源的优势和局限性，那么LCS就能成为监测策略的有效组成部分。在确定用于监测的LCS、参考级监测器和其他数据源达到适当平衡时，还必须考虑后勤问题，包括成本和选址限制。还应考虑到以下问题：LCS网络的维护、故障的传感器的更换和安全处置、最终可能的报废计划等。

对于涉及LCS数据的任何应用，都需要仔细的校准和质量控制，WMO关于低成本传感器测量大气成分的补充报告中有所论述，也需要使用适当的验证策略和指标对结果进行仔细评估。透明地报告评估结果对于建立终端用户的信心至关重要。所有报告的数据都应该配有足够的元数据，以在数据使用上实现可发现、可访问、可互操作、可复用（FAIR）。其中尤其包括与网络目的、传感器选址、数据处理程序以及已知的不确定性或局限性相关的元数据。

给政策制定者和资方的主要启示：

和其他任何监测系统一样，低成本传感器系统（LCS）也需要实体基础设施。健全的数据通信基础设施尤为重要。LCS数据的管理和与补充数据集的整合都需要软硬件来进行数据存储、共享、查询和分析。还需要通用的数据和元数据报告标准以及应用程序编程接口来实现数据互操作性；这些应由政府、非政府组织、研究人员、数据生产者和数据收集者共同制定。应当鼓励和支持以透明的方式报告LCS性能，以及开发开源数据分析软件。

社区科学家和研究人员需要接受培训，以便根据最佳实践做法操作LCS网络、利用参考级检测器验证和校准LCS、了解传感器间的不确定性、分析和释用空气质量数据。也应开展能力建设，以将LCS与上述所有应用中的其他补充数据整合在一起。在LCS网络设计和数据分析的所有阶段，社区的参与可以增加公众支持该网络，同时支持更广泛开展空气质量监测和减缓活动。

实体和网络基础设施以及技术能力建设都需要从地方到国际规模的资助组织提供财政支持，以实现LCS应用数量和质量的提升。也需要一些实体提供机构支持和政策框架，这些实体应致力于使用公开可用数据以更好地了解空气质量，并将其转化为有意义行动。长期有效开展监测工作，亟需LCS网络管理者、分析和整合数据以产生监测结论的人员，以及努力将这些结论转化为政策和变革的人员之间充分开展协调和合作。

本报告的主要结论简要归纳为一套建议和最佳实践做法，用于在网络规模上使用LCS以及结合其他空气质量数据源，以支持常见的空气质量管理相关应用。现有学术文献的研究以及报告中呈现的实际案例研究为这些结论和建议提供了支撑。虽然这一领域的研究和应用还在不断发展，但希望本报告能为相关人士就有效利用LCS网络、结合其他数据源以深化对空气质量的了解和管理提供宝贵的基础。

ملخص تنفيذي

تُعَد أنظمة استشعار جودة الهواء المنخفضة التكلفة (LCS) فئةً جديدة وبالغة الأهمية من التكنولوجيات المستخدمة في توسيع نطاق أنشطة تحليل جودة الهواء ذات الصلة بالسياسات، وكذلك في تقييم مستويات التلوث وتحديد مصادره ووضع التنبؤات بشأنه.

ويتكون نظام استشعار جودة الهواء المنخفض التكلفة من عنصر واحد أو أكثر من عناصر الاستشعار، بالإضافة إلى المعدات والبرمجيات الخاصة بالتحكم، وإمدادات الطاقة، وإدارة البيانات، ومقاومة العوامل الجوية، الأمر الذي يجعله نظاماً كاملاً قادراً على جمع البيانات عن تكوين الغلاف الجوي.

وعبارة "المنخفضة التكلفة" التي تصف "أنظمة استشعار جودة الهواء" تشير إلى انخفاض التكلفة الرأسمالية لكل وحدة من هذه الأنظمة مقارنةً بأجهزة المراقبة المرجعية التقليدية والأكثر استخداماً (RGM). ومع ذلك، فإن هذه التكلفة المنخفضة تقابلها قيود فنية عادةً ما تحدّ أيضاً من جودة البيانات، وتؤثر على انتقائية هذه الأنظمة، وحساسيتها للتركيزات المنخفضة، وقدرتها على مقاومة التركيزات العالية، و/ أو عمرها التشغيلي مقارنةً بأجهزة المراقبة المرجعية. وتختلف هذه الخصائص كذلك باختلاف التكنولوجيات المستخدمة في أنظمة استشعار جودة الهواء المنخفضة التكلفة والملوثات المراد قياسها، أي الغازات أو الجسيمات. ومن الممكن أن ترتفع التكاليف الأولية لأنظمة استشعار جودة الهواء المنخفضة التكلفة ارتفاعاً كبيراً، ويرجع السبب في ذلك إلى عمليات المعايرة ومراقبة جودة البيانات اللازمة لضمان الحصول على بيانات موثوقة من هذه الأنظمة، وإلى البنية التحتية والموارد البشرية الضرورية لدعم الشبكات التي تضم العديد من أنظمة استشعار جودة الهواء المنخفضة التكلفة في منطقة معينة.

وعلى الرغم من هذه التحديات، فإن أنظمة استشعار جودة الهواء المنخفضة التكلفة تمثل إحدى الأدوات الرئيسية التي تسدّ الفجوة في شبكات مراقبة جودة الهواء العالمية والمحلية القائمة، وتقدم معلومات تساعد على إعداد نواتج تتفق مع السياسات بشأن جودة الهواء. وقد شهدت السنوات الأخيرة انتشاراً واسع النطاق لأنظمة استشعار جودة الهواء المنخفضة التكلفة في البلدان المنخفضة والمتوسطة الدخل، حيث تُوفّر هذه الأنظمة في كثير من الأحيان معلومات عن جودة الهواء في المناطق التي تفتقر إلى شبكات من أجهزة المراقبة المرجعية. وتُستخدَم هذه الأنظمة كذلك في البلدان المرتفعة الدخل حيث تدعم في العادة أجهزة المراقبة المرجعية القائمة من خلال تقديم معلومات ذات طابع محلي أكبر وشبه آنية حول جودة الهواء.

وتسعى هذه الوثيقة إلى مناقشة استخدام أنظمة استشعار جودة الهواء المنخفضة التكلفة على مستوى الشبكة وإلى جانب مصادر المعلومات الأخرى بهدف تحليل مستويات جودة الهواء والتغيرات فيها والمصادر التي تؤثر عليها والجوانب الأخرى المتصلة بها. ويأتي هذا المنظور التطبيقي استكمالاً لسلسلة تقارير أصدرتها المنظمة العالمية للأرصاد الجوية في عامي 2018 و2020 حول أجهزة الاستشعار المنخفضة التكلفة لقياس تكوين الغلاف الجوي. وركز هذان التقريران السابقان على المبادئ التشغيلية لاستخدام أنظمة استشعار جودة الهواء المنخفضة التكلفة في قياس المكونات المختلفة، وعلى أفضل الممارسات للمعايرة وتقييم الأداء، واستراتيجيات توصيل البيانات المستمدة من هذه الأنظمة إلى الجمهور.

النقاط الرئيسية للجمهور

ينبغي النظر دائماً في فائدة أنظمة استشعار جودة الهواء المنخفضة التكلفة في سياق ما قد توفره هذه الأنظمة من معلومات جديدة لا توفرها بطريقة أخرى مصادر البيانات الحالية، وما يمكن أن تؤدي إليه من تحسُّن مفيد في فهم جودة الهواء وإدارتها. وعلى الرغم من أنه لا ينبغي الوثوق في أي مصدر من مصادر البيانات، ومنها أنظمة الاستشعار المنخفضة التكلفة، دون التحقق منه، هناك تقنيات تحليل يمكن تطبيقها وأهداف يمكن تحقيقها باستخدام مجموعة من تطبيقات أنظمة الاستشعار المنخفضة التكلفة، إذ تأخذ هذه التقنيات والأهداف في اعتبارها مصادر البيانات الأخرى المتاحة. ويمكن الوقوف على نظرة أعمق في أسباب وعواقب جودة الهواء السيئة من خلال الطرق التي تستخدم بفعالية شبكات أنظمة الاستشعار المنخفضة التكلفة، التي تضم العشرات إلى المئات من أجهزة الاستشعار، وتجمع البيانات المستمدة من هذه الأنظمة ومصادر المعلومات الأخرى من خلال مراعاتها الواضحة للقيود المعروفة على جودة بيانات هذه الأنظمة.

وفي المناطق التي تفتقر إلى أجهزة المراقبة المرجعية التقليدية، يمكن أن توفر أنظمة الاستشعار المنخفضة التكلفة أفكاراً أولى عن العوامل التي قد تؤثر على جودة الهواء المحلي، على النحو الذي يفيد في توجيه الاستثمارات المستقبلية في مجالي المراقبة والتخفيف. ومن شأن التقييم الدقيق للاتساق بين أجهزة الاستشعار ودراسة بيانات أنظمة الاستشعار المنخفضة التكلفة، إلى جانب الأنظمة الساتلية وأنظمة جودة الهواء المتاحة عالمياً، أن يعودا بمنافع متبادلة، وهو ما يساعد على تقييم أفضل لإمكانية تطبيق كل مصدر من مصادر البيانات في المنطقة ووضع أدلة داعمة للأنماط والاتجاهات المرصودة. وغالباً ما تمثل عمليات نشر أنظمة الاستشعار المنخفضة التكلفة خطوة أولى مهمة نحو إرساء برنامج لمراقبة جودة الهواء ووضع سياسة لإدارة جودة الهواء.

وتستطيع أنظمة الاستشعار المنخفضة التكلفة أن تُكمِّل شبكات أجهزة المراقبة المرجعية التقليدية الحالية من خلال توسيع نطاق تغطيتها المكانية وزيادة كثافة المراقبة لتوفير رؤى أكثر تركيزاً على مناطق بعينها. وعملاً بأفضل الممارسات التي نظرت فيها التقارير المنشورة للمنظمة العالمية للأرصاد الجوية بشأن تقنيات القياس، ينبغي أن توضَع أنظمة الاستشعار المنخفضة التكلفة في نفس الموقع مع أجهزة المراقبة المرجعية التقليدية من أجل تحديد أوجه عدم اليقين التي تعتري قياساتها في البيئة المستهدفة تحديداً كمياً. وهو ما سيدعم الاستفادة المناسبة من بيانات أنظمة الاستشعار المنخفضة التكلفة لتحسين التنبؤات الخاصة بمواقع معينة وأنشطة إعادة البناء، وتحسين القياس الكمي لتأثيرات المصادر المحلية، وتحديد أوجه التفاوت في جودة الهواء، وتقييم فوائد إجراءات التخفيف، وتعزيز تفاعل المجتمعات المحلية مع قضايا جودة الهواء.

النقاط الرئيسية للمتخصصين التقنيين

فيما يتعلق بإعادة بناء جودة الهواء، يمكن أن تؤدي الكثافات المكانية الأعلى إلى تحسين المعلومات على النطاق المحلي، ولا سيما من خلال تقنيات الاستكمال، في حين تدعم التغطية الأوسع نطاقاً المعلومات على النطاق الإقليمي، بما في ذلك الاندماج مع الاستشعار عن بعد بواسطة السواتل ونمذجة جودة الهواء. والقدرة على نقل أنظمة الاستشعار المنخفضة التكلفة والسهولة في إعادة نشرها تدعمان أيضاً جهود إعادة البناء.

وفيما يتعلق بتحديد المصادر والعزو إليها، فإن أنظمة الاستشعار المنخفضة التكلفة التي يمكنها مراقبة ملوثات متعددة في وقت واحد مفيدة جداً؛ إذ يمكنها أن توفر مدخلات البيانات اللازمة من أجل "تحديد خصائص" المصادر الإحصائية. وتتيح كذلك زيادة التغطية والكثافة وتواتر القياس، التي توفرها أنظمة الاستشعار المنخفضة التكلفة، فرصة أفضل لتحديد المزيد من المصادر المؤقتة والمحلية وتتبُّعها.

وبالنسبة لتطبيقات العدالة الصحية والبيئية، لا تكفي في العادة جودة بيانات أنظمة الاستشعار المنخفضة التكلفة وحدها لدعم إجراء تحليل كمي على المدى الطويل. ومع ذلك، فإن الجمع بين البيانات المأخوذة من هذه الأنظمة والمعلومات الأخرى والمعارف المحلية لتأكيد النتائج يمكن أن يمثل استراتيجية أكثر فعالية. أضف إلى ذلك أن البيانات المأخوذة من هذه الأنظمة يمكن أن تساعد في توجيه الإجراءات الرامية إلى الحد من تعرض الأشخاص للتلوث، وتوفير الأدلة التي تستند إليها العروض التوضيحية التجريبية على المستوى المحلي لاستراتيجيات التخفيف من التعرض المجتمعي، وفي تحفيز نشر موارد إضافية (منها تحديد مواقع أجهزة المراقبة المرجعية التقليدية) من أجل تنفيذ إجراءات التخفيف. ولا بد من شبكة عادلة وتمثيلية من أنظمة الاستشعار المنخفضة التكلفة لدعم هذه التطبيقات على أفضل وجه.

وبالنسبة للتنبؤ، فإن التغطية المكانية والزمانية الأكبر المحتملة للمعلومات شبه الآنية عن جودة الهواء التي توفرها شبكات أنظمة الاستشعار المنخفضة التكلفة يمكن أن تعزز مهارات الأنظمة الحالية لجودة الهواء من خلال استخدام هذه المصادر الجديدة للبيانات لأغراض تصفيف البيانات وتقييمها.

وينبغي وضع أهداف وأغراض وأولويات واضحة عند تصميم شبكات مراقبة جودة الهواء التي تجمع بين أنظمة الاستشعار المنخفضة التكلفة ومصادر المعلومات الأخرى. فأنظمة الاستشعار هذه قد تكون عنصراً فعالاً من عناصر استراتيجية المراقبة إذا استُخدِمت جنباً إلى جنب مع أي مصادر أخرى للمعلومات، وخاصة أجهزة المراقبة المرجعية التقليدية حيثما توافرت، وعند معرفة المزايا النسبية لهذه الأنظمة والقيود المفروضة عليها، مقارنةً بمصادر البيانات الأخرى، ومراعاة هذه المزايا والقيود عند تحليل البيانات المستمدة من شبكة مراقبة جودة الهواء. ويجب أيضاً مراعاة الشواغل اللوجستية، التي تشمل التكاليف والقيود المفروضة على تحديد المواقع، عند تحديد التوازن المناسب بين أنظمة الاستشعار المنخفضة التكلفة وأجهزة المراقبة المرجعية التقليدية ومصادر البيانات الأخرى المستخدمة لأغراض المراقبة. كذلك، ينبغي النظر في الخطط الموضوعة لصيانة شبكة أنظمة الاستشعار المنخفضة التكلفة واستبدالها، والتخلص الآمن من أجهزة الاستشعار المعطلة، وإمكانية إخراجها من الخدمة في نهاية المطاف.

النقاط الرئيسية للمتخصصين التقنيين

ولا بد من معايرة أي تطبيق يستخدم البيانات المستمدة من أنظمة الاستشعار المنخفضة التكلفة معايرة دقيقة ومراقبة جودته، على نحو ما ناقشته تقارير المنظمة التكميلية بشأن أجهزة الاستشعار المنخفضة التكلفة لقياس تكوين الغلاف الجوي، إلى جانب إجراء تقييم دقيق للنتائج باستخدام استراتيجيات ومقاييس التحقق المناسبة. ومن الضروري الإبلاغ بشفافية عن نتائج التقييم لبناء ثقة المستخدمين النهائيين. وينبغي أن تقترن جميع البيانات المبلغ عنها ببيانات وصفية كافية تساعد في استخدام بيانات توصف اختصاراً بالكلمة الإنكليزية FAIR التي تشير إلى أن هذه البيانات (يمكن العثور عليها، ويسهل الوصول إليها، وقابلة للتشغيل البيني، ويمكن إعادة استخدامها). ويتضمن ذلك على وجه الخصوص البيانات الوصفية المتعلقة بالغرض من الشبكة، وتحديد مواقع أجهزة الاستشعار، وإجراءات معالجة البيانات، وأوجه عدم اليقين أو القيود المعروفة.

النقاط الرئيسية لواضعي السياسات والممولين

تتطلب أنظمة الاستشعار المنخفضة التكلفة بنية تحتية مادية، مثلها في ذلك مثل أي أنظمة للمراقبة. وتكتسي البنية التحتية القوية لنقل البيانات أهمية كبيرة. فإدارة بيانات أنظمة الاستشعار المنخفضة التكلفة والتكامل مع مجموعات البيانات التكميلية يتطلبان أجهزة وبرمجيات لتخزين البيانات ومشاركتها والاستعلام عنها وتحليلها. وهناك حاجة أيضاً إلى معايير مشتركة للإبلاغ عن البيانات والبيانات الوصفية ولواجهات برمجة التطبيقات بما يضمن التبادلية التشغيلية للبيانات؛ وهذه المعايير ينبغي أن تتعاون على وضعها الحكومات والمنظمات غير الحكومية والباحثون ومنتجو البيانات ومُجمِّعو البيانات. والإبلاغ بشفافية عن أداء أنظمة الاستشعار المنخفضة التكلفة وكذلك تطوير برمجيات لتحليل البيانات المفتوحة المصدر أمران ينبغي دعمهما والتشجيع عليهما.

ويحتاج علماء وباحثو المجتمع إلى التدريب على تشغيل شبكات أنظمة الاستشعار المنخفضة التكلفة وفقاً لأفضل الممارسات، والتحقق منها ومعايرتها مع أجهزة المراقبة المرجعية التقليدية، وإلى فهم أوجه عدم اليقين بين أجهزة الاستشعار، وتحليل بيانات جودة الهواء وتفسيرها. ويلزم أيضاً بناء القدرات اللازمة لإدماج أنظمة الاستشعار المنخفضة التكلفة مع البيانات التكميلية الأخرى في جميع التطبيقات التي نوقشت أعلاه. ومن شأن مشاركة المجتمع في جميع مراحل تصميم شبكة أنظمة الاستشعار المنخفضة التكلفة وتحليل البيانات أن تزيد من الدعم العام للشبكة ولأنشطة مراقبة جودة الهواء وأنشطة التخفيف على نطاق أوسع.

وتتطلب البنى التحتية المادية والسيبرانية وبناء القدرات التقنية دعماً مالياً من منظمات التمويل على المستويين المحلي والدولي على حد سواءٍ لتمكين المزيد من تطبيقات أنظمة الاستشعار المنخفضة التكلفة ذات الجودة العالية. وعلى الكيانات الملتزمة باستخدام البيانات المتاحة للجمهور أن تقدم الدعم المؤسسي وأن توفر أطر السياسات من أجل تعزيز فهم جودة الهواء، وتحويل هذا الفهم إلى عمل هادف. ومن الضروري أن يتعاون مديرو شبكات أنظمة الاستشعار المنخفضة التكلفة، والقائمون على تحليل وإدماج البيانات المستمدة من هذه الشبكات لوضع أفكار، والمعنيون بترجمة هذه الأفكار إلى سياسة وتغيير على أرض الواقع، وأن ينسِّقوا فيما بينهم بهدف إطالة مدة جهود المراقبة وضمان فعاليتها.

ويُوجِز هذا التقرير ما خلص إليه من استنتاجات رئيسية في مجموعة من التوصيات وأفضل الممارسات بشأن استخدام أنظمة الاستشعار المنخفضة التكلفة على نطاق الشبكة، جنباً إلى جنب مع مصادر بيانات جودة الهواء لدعم التطبيقات الشائعة المتعلقة بإدارة جودة الهواء. وهذه الاستنتاجات والتوصيات تدعمها دراسة استقصائية للمؤلفات الأكاديمية المتاحة، وأمثلة من دراسات الحالات العملية المعروضة في ثنايا التقرير. ومع ما تشهده البحوث والتطبيقات في هذا المجال من تطور مستمر، من المأمول أن يُرسي هذا التقرير أساساً قيماً لأولئك الذين يسعون إلى الاستفادة الفعالة من شبكات أنظمة الاستشعار المنخفضة التكلفة، إلى جانب مصادر البيانات الأخرى، من أجل تحسين فهم جودة الهواء وتعزيز إدارتها.

1. Objectives of this document

This document serves as a resource for those who wish to effectively use data collected by networks of low-cost sensor systems (LCS) for air quality applications, especially for the management of air pollution, tracking of air pollutant and greenhouse gas emissions, and investigation of the associated health, economic, and environmental impacts.

The intended audience for this document includes:

(1) Members of the atmospheric science community engaged in operational air pollution monitoring, modelling, and management;

(2) World Meteorological Organization (WMO) Members and other United Nations (UN) agencies with direct interests in air pollution and greenhouse gas emissions (e.g. World Health Organization (WHO), United Nations Environment Programme (UNEP), Climate & Clean Air Coalition (CCAC), etc.);

(3) Public and private organizations engaged in the development of LCS networks and/or data analysis incorporating LCS information;

(4) Governmental, intergovernmental, and non-governmental organizations, as well as community groups engaged in the use of LCS data for applications relevant to outdoor air quality, including for educational and/or awareness purposes.

The recommendations of this document (especially those outlined in Section 10) are also relevant to funding organizations and philanthropies seeking to effectively support those engaged in using LCS for air quality applications. This report covers applications relevant both in nations and regions with existing reference grade monitor (RGM) networks for air quality, as well as in nations and regions with few or no operational RGM.

WMO has published two reports on the use of LCS for atmospheric composition measurements *An update on low-cost sensors for the measurement of atmospheric composition* (WMO, 2020) To complement these series of reports, the current report searches to synthesize best practices for using LCS as a supporting tool in air quality analysis and decision-making applications, including reconstruction of local and regional air quality, source attribution, design of air quality monitoring networks, investigation of environmental justice via LCS, use of LCS to support health impact studies, air quality forecasting, and integration of LCS into larger air quality monitoring services, including associated infrastructure needs. The key difference between this and the previous reports is that, in this report, LCS observations will be treated within a context of other available sources of air quality information. Furthermore, this report will focus on LCS networks, with multiple LCS covering a region of interest, rather than on single LCS. The task of this report is to articulate the role which LCS can, and should play, within a larger effort to understand and manage air quality.

Throughout this report, we adopt an application-focused view for LCS and other data, seeking to assess the usefulness of data for specific purposes. The concept of "useful data" is related to but distinct from data quality in terms of accuracy or bias. According to the *WMO Global Air Quality Forecasting and Information System (GAFIS) Implementation Plan* (GAW Report 277) (WMO, 2022, p. 27), "useful data are data which are suited for particular use cases by being sufficiently timely, at the right temporal and spatial scale for the question being asked, well enough labelled that uncertainty can be factored into their use, readily and reliably retrievable, among other characteristics". Consequently, this report is structured according to use cases, and describes the usefulness of LCS data together with other data sources in the context of these use cases.

While a complete review of research and operational activities involving LCS is beyond the scope of this report, an international group convened by WMO have worked to distil key insights from scientific literature and other public materials published prior to October 2023. It is hoped that these insights will allow stakeholders to make informed decisions about the use of LCS networks in air quality monitoring and management.

Definition of low-cost sensor systems

Both LCS and RGM perform in situ atmospheric constituent measurements. Colloquially, LCS are distinguished by their relatively lower (often by an order of magnitude or more) per-unit purchase cost as compared to RGM providing measurements of the same nominal quantities (i.e. measuring the same pollutants). However, we do not specify a cost limit to distinguish LCS from RGM. Further, we distinguish LCS from RGM in terms of the existence (for RGM) or lack (for LCS) of a certification from an official regulating body establishing the data quality and traceability of the measurements to an accepted standard and allowing for data from certified instruments to be used in support of regulatory enforcement activities. Furthermore, for RGM, established techniques and approaches can be applied to analyse their data and draw conclusions with a high degree of confidence based on the proven reliability of RGM, while for LCS, due to their shorter use history and known data quality limitations, such well-established and accepted methods do not currently exist.

This report considers LCS measuring reactive gaseous air pollutants, particulate matter (PM), and greenhouse gases (GHG). The reactive gaseous air pollutants commonly measured by LCS are nitrogen oxides (NO_x), sulfur dioxide (SO_2), carbon monoxide (CO), and ozone (O_3). Several LCS also measure volatile organic compounds (VOC), although here they often lack species specificity (Spinelle et al., 2017). LCS measure PM size fractions, most commonly $PM_{2.5}$, followed by PM_{10} and PM_1. Some LCS measure GHG, most commonly carbon dioxide (CO_2) and methane (CH_4).

LCS in this report refers to a complete functional sensor system, i.e. a self-contained apparatus with one or more sensing elements, commonly referred to as low-cost detectors or as original equipment manufacturer (OEM) sensors, combined with necessary hardware and software for control, power supply, and data management, and packaged into an enclosure. In other words, a LCS is a ready-to-use system, without the need for additional hardware (besides for mounting) or software to make it operable in-field deployments (Karagulian et al., 2019). Passive samplers are not considered, and outdoor air quality is the focus.

The reader should note that the "low-cost" aspect of LCS can potentially be misleading. While the initial purchase cost of an LCS may be orders of magnitude less than a RGM nominally providing the same measurements, once the additional effort needed to deploy, maintain, replace, collect data, and ensure sufficient data quality from a network of many LCS over an extended period are accounted for, the overall costs may be more comparable with an RGM (*An update on low-cost sensors for the measurement of atmospheric composition, Annex 3*, WMO, 2020). Stated another way, the costs for operating an RGM or LCS network to support a given application may be comparable, but differently allocated between initial setup costs, ongoing maintenance costs, and costs for data management and analysis. For the RGM, the initial capital cost to establish the network and the ongoing costs to calibrate the instruments will likely be largest. For the LCS, the same or even smaller costs may allow for more sites to be established and maintained, but additional costs will be incurred for analysing the data and ensuring data quality at the network level. Furthermore, even a "low-cost" system may be prohibitively expensive for certain users. While the technical requirements and skills needed to operate LCS are less extensive than for RGM, some basic technical proficiencies are still needed. Furthermore, robust data analytic skills are necessary to assess the quality of LCS data for meeting application needs.

1.1. Structure of this report

- Section 2 of this report summarizes the findings of the WMO series of reports on low-cost sensors measurements for atmospheric composition on the advantages and limitations of LCS for air quality monitoring and introduces other important air quality information sources.
- Section 3 discusses the role of LCS in supporting air quality reconstruction, i.e. using knowledge at certain locations to estimate its status at unmonitored locations.
- Section 4 examines the role of LCS providing inputs to source apportionment techniques, which identify and track the factors contributing to air quality.
- A more outcome-oriented view of air quality monitoring is taken in Section 5, which discusses the use of LCS in concert with other information sources and alongside socioeconomic information to support applications in environmental justice.
- Section 6 then discusses the use of LCS information to support epidemiological studies and personal exposure monitoring for health applications.
- Section 7 discusses the role of LCS in supporting air quality forecasting, i.e. predicting future air quality based on knowledge of present and past conditions.
- Data quality assessment methods for evaluating and disclosing methods using LCS in air quality applications are discussed in Section 8.
- The design of networks for monitoring outdoor air quality, the potential for LCS to support such designs, and considerations for including LCS as a part of designs alongside RGM and other information sources, is the concern of Section 9.
- Section 10 discusses the infrastructure and investments needed to support integration of LCS into air quality systems (i.e. operations).
- Finally, Section 11 gives overall best practices and recommendations for currently achievable applications using LCS together with other air quality data, as well as promising directions for future work.

1.2. Recommendations for readers on how to best use this report

For those new to LCS, and for those looking for guidance in how to evaluate LCS performance, it is recommended to first review the updated prior report published by the WMO (WMO, 2020). Although key results from that report are summarized in Section 2.1, there are many technical details and recommendations which are not included in the summary. There are also many nuances regarding specific LCS technologies and their capabilities and limitations, including for measuring specific gases or PM classifications, which are covered in that report but omitted here for brevity. This report is instead intended for those who have some familiarity with the operation of individual LCS or small LCS networks, and are seeking guidance in how to effectively use LCS data in applications and/or how best to expand their existing network with these applications in mind.

Throughout this report, **key takeaways relevant to all readers** will be summarized in text blue boxes like this. Usually, each new section will include such a summary at the beginning.

Key takeaways for technical specialists will be presented in text yellow boxes like this. The technical "skim reader" is directed to Section 11.1 for the most concise summary of best practices for integrating LCS with other data sources to support different applications related to air quality forecasting, reconstruction, and analysis.

Key takeaways for policymakers and funders will be presented in text green boxes like this. The "skim reader" focused on policy and funding to support LCS applications is directed to Section 10, which outlines the physical, cyber, training, and financial infrastructure needs of successful applications of LCS networks alongside other data sources.

2. Introduction

LCS are a key emerging air quality monitoring tool. When their technical limitations are adequately accounted for, they can expand and improve our understanding of air quality and its drivers from hyper-local to global scales, especially when used in large networks and alongside other information from reference-ground-monitors, satellites, numerical models and local knowledge. Communicating the uncertainty associated with LCS observations is essential if LCS data are to be used appropriately.

Atmospheric composition and its impacts on air quality have important implications for human health, ecosystem health, economic activity, and climate change. Air quality monitoring is relevant across spatial scales from local communities to the entire globe, and across temporal scales from short-term changes triggering immediate impacts to multidecade changes with relevance to global climate (Brasseur et al., 2003). Stakeholders in air quality monitoring are similarly diverse, ranging from government policymakers and regulators, to non-governmental organizations (NGO) and advocacy groups, to researchers, to philanthropies, to private sector technology and data providers, to international agencies, and of course to the communities impacted by outdoor air quality.

The understanding of outdoor air quality likewise takes many forms. Broadly speaking, we would like to know the current air quality and the factors impacting, along with the history and likely future trajectory of air quality changes. We would also like to understand the past, present, and potential future impacts of air quality on human health, the environment, and economic activity, as well as the impact of human actions and natural processes on air quality. These questions underpin most operational air quality monitoring and forecasting, including early warning systems which contribute to the UN initiative to provide Early Warnings for All.

To answer these questions requires making regular, systematic measurements of ambient concentrations of various atmospheric constituents, including trace gases, aerosols, and greenhouse gases (GHG), and integrating these measurements with atmospheric models. International programmes, for example, the WMO Global Atmosphere Watch (GAW) programme, are fundamental to coordinate such monitoring networks via standard quality assurance and quality control (QA/QC) requirements. Most of these efforts focus on RGM systems providing accurate, traceable measurements used in authoritative networks. However, the infrastructure and financial resources needed to establish and maintain RGM networks has historically limited their spatial coverage, leaving many parts of the world, primarily in low- and middle-income countries (LMIC), without routine or even any air quality monitoring at all. In 2023, of the settlements reporting RGM data to WHO, only 8% were in LMIC (WHO, 2023; Shairsingh et al., 2023). To alleviate this information gap, the use of alternative LCS to supplement and expand air quality measurements has been a topic of increased interest and activity in recent years.

Furthermore, other direct and indirect air quality information sources exist to support and supplement RGM and LCS data. Satellite remote sensing data provide routine information about global aerosol and trace gas column concentrations and their horizontal spatial extents. However, spaceborne sensors are limited in their ability to quantify concentrations near the surface, which are directly measured by RGM and LCS. Numerical modelling can produce spatially and temporally complete air quality estimates even in the absence of measurements, and can produce forecasts in support of early warnings. Nevertheless, accurate inputs and observational constraints are essential to minimize uncertainty in the model outputs.

Building on previous work, this report discusses how LCS can be used on a network scale and in conjunction with other information sources to gain practical insights into air quality. To introduce these concepts, Section 2.1 summarizes LCS and their capabilities and limitations, while Section 2.2 introduces the other sources of air quality information considered in this report.

2.1. Background on LCS for air quality monitoring

A series of WMO reports have examined the state of LCS technology and best practices for using LCS to measure atmospheric composition (*An update on low-cost sensors for the measurement of atmospheric* composition; WMO, 2020). Their main findings are briefly summarized here to provide a general background on LCS.

There has been a rapid expansion in the number of LCS manufacturers since 2020, including many adopting a "sensing as a service" business model which combines LCS hardware with calibration activities, data management, analysis, and visualization. The worldwide deployment of LCS has similarly grown, driven by a combination of individual and community organization deployments, academic research efforts, and some deployments by government agencies at local to national levels. These efforts have been supported through private means as well as via grants and philanthropic funding. The vastly expanded availability of LCS and their use in new settings have consequently led to the expanded application of LCS to address different questions regarding air quality, which is what this report will be highlighting. In terms of LCS technologies and operational methods, there has been mainly incremental as opposed to revolutionary progress; salient developments will be noted below where appropriate.

Besides their relative costs compared with RGM, as discussed in Section 1.1, other common traits of LCS which make them attractive are: their low weight; small size; minimal power requirements (sometimes being satisfiable using integrated solar panels); minimal maintenance needs; ease of deployment and operation; and communications connectivity using integrated wireless internet or cellular communications; which non-technical users are often already familiar with.

LCS are not without limitations. In general, LCS provide lower accuracy (i.e. including both trueness and precision), sensitivity, and specificity in their data and typically have a shorter operational lifetime compared with a RGM providing the same nominal measurements. These characteristics are highly dependent on the measurement principle and technical design of the LCS. However, in general, the measurement techniques used by LCS are indirect; for example, many LCS for infer PM mass from the light scattering of particles. Calibration algorithms attempt to relate these indirect measurements to the desired physical quantities obtained by the corresponding RGM, but inherent physical and chemical limitations and cross-sensitivities complicate these calibrations. For example, relative humidity affects the accuracy of LCS measuring PM, with higher relative humidities being associated with overestimation of PM by the LCS (e.g. Jayaratne et al., 2018, 2020b; Pawar and Sinha, 2020; Patel et al., 2023). Temperature variations have also adversely affected LCS performance (e.g. X. Liu et al., 2020; Wei et al., 2020). These cross-sensitivities are typically complicated, non-linear, may be poorly characterized under actual field conditions, and may vary under different atmospheric conditions and for different pollutant mixtures (deSouza et al., 2022). Furthermore, LCS sensitivity and cross-sensitivity can vary over time; many LCS technologies feature sensing elements which are more or less consumable during their operational lifetimes. This phenomenon, generally referred to as "aging", typically leads to decreased performance during deployment, which is again not well characterized and can vary considerably for different LCS types and under different environmental conditions (Tryner et al., 2020; J. Li et al., 2021; deSouza et al., 2023a; X. Liu et al., 2020). Overall, the different measurement techniques used by LCS and RGM limit the comparability of their data, and so LCS are not yet widely accepted for use in legal applications, in which measurements that are traceable to established standards are needed for the enforcement of air quality regulations. The effort required to ensure robust operation of LCS networks and sufficient data quality to meet performance targets, and the need to re-calibrate or replace LCS as their performance degrades, can greatly increase the long-term operational costs of LCS networks.

Despite this, the benefits of LCS may outweigh these limitations under certain conditions and for certain applications. LCS have been found to be useful, and are widely used in practice, for qualitative assessments and exploratory studies of air quality, identification of pollution hotspots or areas where concentrations are increasing rapidly, and to support public education and engagement with air quality issues. LCS have given non-technical users access to air quality monitoring equipment which they can deploy according to their own priorities. In many regions of the world, as well as in understudied areas of otherwise extensively monitored regions, LCS are often the most accessible and cost-effective means of air quality monitoring. The potential for LCS to enable de-centralized data collection and empower individuals and communities to take an active role in assessing air quality should not be dismissed.

Current common practice is to first deploy LCS near to a RGM in an environment which as closely as possible resembles the target deployment environment. Such a co-location experiment enables quantitative verification of the LCS performance under a range of environmental conditions. An appropriate calibration can then be developed (or an existing calibration applied) which brings the LCS data into better agreement with the corresponding RGM observations. While there is no universally applicable co-location protocol nor approach to calibration, there have been recent efforts to codify and standardize testing protocols and performance targets for LCS, e.g. performance targets for O_3 and $PM_{2.5}$ LCS from the USA EPA (Duvall et al., 2021a, 2021b), a technical specification for the evaluation of LCS gas sensors from Working Group 42 of Technical Committee 264 on Air Quality of the European Committee for Standardization, and the British Standards Institution's PAS 4023 code of practice. Following these or similar protocols, LCS data are assessed on a case-by-case basis, depending on the availability of RGM to provide reference data for comparison, and accounting for the intended application of the LCS data and associated data quality objectives. This report will illustrate how, by incorporating LCS into a larger air quality monitoring system, the utility of the LCS data for particular applications can be assessed.

Communicating the uncertainty associated with LCS observations is difficult, but essential if LCS data are to be used appropriately. Prior work and experience indicate that the public tend to view information from LCS as comparable to that obtained from RGM. In cases of disagreement, they may even trust LCS data more, particularly in cases where individuals and organizations deploying LCS are perceived as being more invested in the well-being of the community than regulatory bodies operating RGM. Unfortunately, some of the ways in which LCS data are commonly reported can be misleading, such as applying air quality index scales calibrated for long-term averages to short-term concentrations. This can exacerbate the problem of perceived under-reporting of poor air quality by regulatory agencies, undermining public trust. Appropriate use of LCS information requires they be placed within a proper context, accounting for necessary calibrations and known data quality limitations, while acknowledging the real benefits which LCS provide for situational awareness of air quality, e.g. that denser networks of LCS may pick up local pollutant signals which could be missed otherwise (Mead et al., 2013). This report outlines ways in which combining LCS with other information sources can provide this context.

Table 1. Summary of the proposed processing levels for LCS data. *Adapted from (WMO, 2020), with additional levels relevant to the present report.*

Level	Name	Definition/Example	Example
0	Raw measurements	Original measurand produced by a sensing element aboard the LCS.	Detector voltage
1	Intermediate geophysical quantities	Estimate based on the sensing element measurand using basic physical principles or simple (e.g. linear) calibration equations, and no compensation schemes.	Detector voltage multiplied by a scaling factor, with a constant offset added
2	Standard geophysical quantities	Estimate made using the sensing element plus other detectors on board the LCS demonstrated as appropriate for artifact correction and directly related to the measurement principles. May also include external data (e.g. meteorological information from nearby weather stations) which are directly related to the measurement principles.	Multiple linear regression equation involving the detector voltage, temperature, and relative humidity as inputs
Measurement/Prediction Boundary			
3	Advanced geophysical quantities	Estimate using data from multiple sensing elements on board the LCS (potentially supplemented with external inputs) not explicitly related to the measurement principles.	Estimate of $PM_{2.5}$ made using input from NO_2 and SO_2 detectors also aboard the LCS
4	Network geophysical quantities	Air quality information derived from a network of LCS, possibly supplemented by other data sources (e.g. RGM, satellite remote sensing, models).	A spatially continuous map of pollutants across a city
5	Network geophysical insights	Air quality analysis and predictions derived from a network of LCS supplemented by other data sources (e.g. RGM, satellite remote sensing, models, health data, inverse modelling methods).	Estimated emissions from a known source; a forecast of tomorrow's air quality

A useful taxonomy, presented in Table 1 of the WMO report (2020) on LCS and reproduced with modifications here in Table 1, classifies data derived from LCS via processing levels. This is analogous to the processing levels used to describe NASA satellite data products or the ACTRIS classification scheme. The previous reports focused on Levels 0 through 2, where data collected by an individual LCS, potentially supported by other information directly relevant to the measurement principle, are used to estimate air quality at the measurement location and time. This report focuses instead on levels beyond the "measurement/prediction boundary" identified in that table. This includes methods informed by data sources external to the LCS and not explicitly related to its measurement principle

(Level 3), as well as methods involving networks of LCS, potentially combined with external data sources (Level 4). We also propose an additional level (Level 5), where LCS and other data sources are analysed together to synthesize insights which would not be achievable using only one type of technology or source of information.

2.2. LCS as part of a larger information system

An important goal of this report is to situate LCS within a larger context of air quality data sources. These include RGM (Section 2.2.1), satellite remote sensing (Section 2.2.2), and air quality systems (Section 2.2.3). By understanding the capabilities, strengths, and weaknesses of these systems, together with those of LCS, the best use can be made of each system in contributing to a broader understanding of air quality. We also briefly introduce additional information, such as health and environmental data, needed to contextualize the impacts of air quality (Section 2.2.4).

2.2.1. Reference Grade Monitor Networks

RGM, together with their associated operational procedures, are the nationally and internationally accepted systems for directly measuring ambient concentrations of atmospheric constituents at specific locations and regular time intervals. Different terms are used to refer to RGM in different countries and regions, corresponding to different applicable standards for classifying these instruments within a regulatory framework. For example, in the United States of America (USA), Federal Reference Method (FRM) and Federal Equivalent Method (FEM) instruments would be considered as RGM in this report. The key strength of RGM is their measurement accuracy and traceability to established standards, which is ensured through rigorous adherence to prescribed operation, calibration, and maintenance practices. This provides a high level of trustworthiness in RGM data, making it appropriate for almost any application, and especially essential for legally-binding regulatory purposes. This also extends to the use of RGM for LCS calibration.

The downside of RGM compared with LCS is their higher per-unit purchase and operational costs, and greater technical requirements for operation. RGM require a secure location and physical infrastructure, including shelters to maintain required operational conditions, consistent power supply, and access to spare parts and consumables, e.g. calibration gases. RGM operation also requires staff with specialized skills, incurring corresponding costs. These costs and infrastructure requirements have historically limited the deployment of RGM, and therefore the spatial representativity of their data. While the number of RGM deployed worldwide has significantly increased, with a more than 600% increase between 2011 and 2022 in the number of human settlements worldwide with RGM data reported by WHO, several deficiencies in RGM networks for air quality monitoring exist globally, with major disparities noted in terms of spatial and temporal coverage (WHO, 2023). As of 2020, only 57 countries (30%) continuously operated RGM networks with multiple sites (UNEP, 2021). Filling such gaps in RGM networks has been a key motivator for the development and deployment of LCS.

Figure 1 illustrates the regional deployment of RGM and LCS, compared to estimated annual average $PM_{2.5}$ concentrations. Although this analysis is limited to openly available monitoring data shared through the OpenAQ Platform, and is therefore incomplete and may exhibit regional biases (especially in regions with relatively few monitors), some general trends can be observed. Firstly, regions with higher annual average concentrations tend to have fewer monitors per capita. This is due to a variety of historical and socioeconomic factors, and may to some degree be an artifact of the implementation of national air quality regulations leading to both more RGM deployment and ambient concentration reductions.

Secondly, the impact of LCS on increasing per capita monitor density is apparent. Similar relative increases are visible in both well monitored regions and high-income countries (HIC), e.g. North America, as well as poorly-monitored regions and LMIC, e.g. West Africa. While not yet addressing global disparities in air quality monitoring, this nonetheless indicates the potential of LCS to contribute to a solution. Thirdly, even well monitored areas rarely have more than ten $PM_{2.5}$ RGM per million people, and even including LCS does not bring many regions past this threshold. Considering the observed spatiotemporal differences in $PM_{2.5}$, it is doubtful whether this level of monitoring is sufficient to fully characterize the exposures of the population within the regions in question, let alone at a global scale.

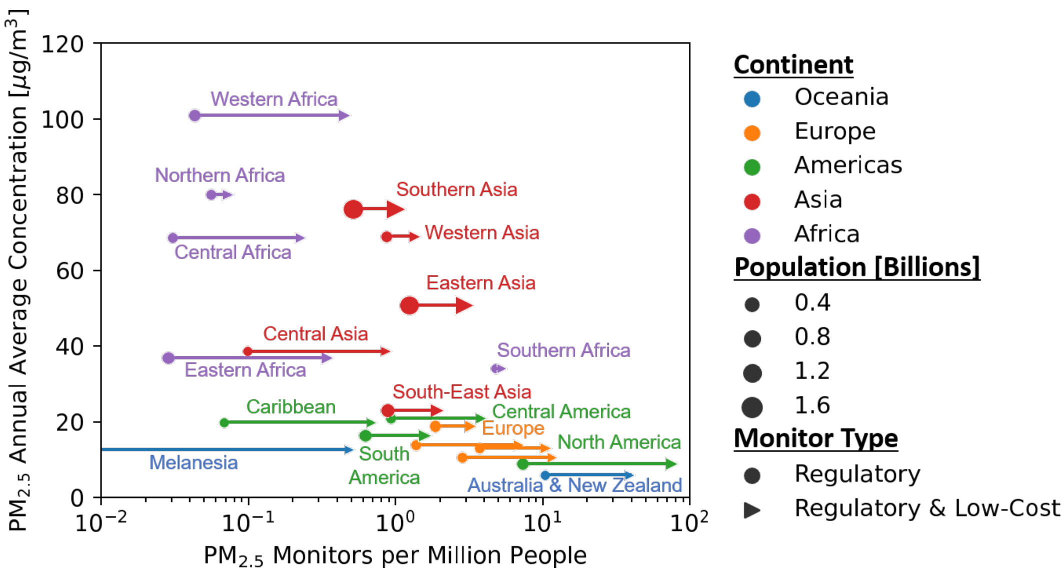

Figure 1. Comparative per capita densities of surface $PM_{2.5}$ monitoring regionally around the world, considering both RGM and LCS. *Underlying data on monitor deployments were obtained from the OpenAQ platform. Figure reproduced from 2022 International Conference on Air Quality in Africa Proceedings.*

2.2.2. Satellite Remote Sensing

Satellite remote sensing is another important source of atmospheric composition data on regional to global scales. Satellite remote sensing has great potential to augment air quality management by providing situational awareness, especially of transported pollutants, and tracking long-term and large-scale changes in air quality, including as a result of pollution control policies (Duncan et al., 2021; Potts et al., 2021). Capabilities of active and passive satellite remote sensing have been increasing in recent years, with current missions able to distinguish emissions from major transportation corridors, port facilities, and large power plants from background levels (Goldberg et al., 2021). While satellite missions are expensive to launch and operate, many agencies which do so make the resulting data freely available, and improvements in computational resources are enabling more widespread use of satellite remote sensing data for a variety of applications.

However, there are limitations to the direct application of satellite remote sensing for air quality monitoring. Active remote sensing is limited in spatial coverage, while passive remote sensing is typically limited to daytime monitoring under clear sky conditions. Polar-orbiting satellites provide global coverage, but typically with one overpass per day of a given location. Geostationary satellites, while providing multiple observation opportunities per day, provide a fixed field of view covering only part of the Earth. Thus, a constellation of multiple satellites is needed for frequent global coverage, and even so, atmospheric conditions cause data gaps. Finally, passive remote sensing typically provides information about the full atmospheric column, which may not be representative of surface air quality. Other data sources, especially in situ measurements, are required to relate these column quantities to surface air quality; lack of such data in LMIC has limited the performance of satellite-derived air quality datasets (World Bank, 2022a). Additional background on satellite remote sensing for air quality is provided in Appendix C.1.

LCS and satellite remote sensing data can be complementary, with LCS providing necessary ground measurements in regions lacking RGM, and satellites providing regional-scale and long-term trend information which is more difficult to obtain with LCS networks. Section 3.3 will discuss specific applications combining LCS and satellite data for air quality reconstruction.

2.2.3. Global and regional Air Quality Modelling systems

Air quality modelling systems (AQM) are important tools supporting a comprehensive understanding of air quality and its drivers. AQM are the basis of forecasting for the provision of early warnings), reanalysis of past air quality for assessment studies, inverse modelling to understand the drivers of air quality, and simulation of potential pollution mitigation strategies. As with satellite data, agencies with the resources to routinely operate regional or global AQM typically make their outputs freely available as a global public good. Finally, many AQM are combined with in situ and remote sensing data via data assimilation or data fusion techniques, enhancing the accuracy and local relevance of AQM products (e.g. Van Donkelaar et al., 2021; Wei et al., 2023).

To function effectively, AQM require accurate inputs, especially inventories of emitted pollutants. These inventories can be missing, incomplete, and/or outdated in many areas, often due to a dearth of in situ data. AQM also require suitable parameterizations of atmospheric processes; calibration of these parameterizations can likewise be hindered by a lack of locally relevant observational data. Finally, in the absence of other data sources, it is difficult to validate AQM results. This is especially concerning given the relative sparsity of RGM on a global scale noted earlier, and is another area where the additional information provided by LCS can be valuable. Applications involving the use of AQM along with LCS data are discussed in Sections 3.4, 4.3, 7.1, and 7.2.

Figure 2 illustrates how the data sources discussed here compare in terms of their typical spatial and temporal scales of applicability. RGM and LCS provide complementary point measurements, with LCS typically being focused on shorter timescales, while the reliability of RGM make them better suited for longer timescales. Satellite data and AQM are suited for expanding spatial coverage to regional and global scales. The overlapping capabilities of different data sources allow for intercomparison and redundancy. A comprehensive understanding of air quality, spanning across spatial and temporal scales, would require contributions from all these data sources.

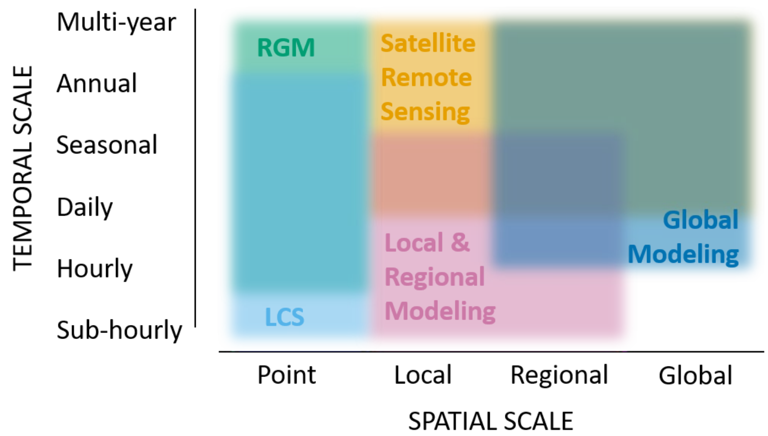

Figure 2. Typical spatial and temporal applicability scales of outdoor air quality monitoring and modelling systems. *Figure adapted from Cromar et al. (2019). Shaded regions denote the typical realms of current practical applications for each system, with different systems distinguished by colour. Note that these regions are not meant to convey absolute limitations of the different data sources, hence the fuzzy boundaries.Note also that mobile monitoring via RGM or LCS is not considered here, but would be most applicable to local spatial scales and sub-hourly to daily or seasonal temporal scales, depending on the monitoring plan.*

2.2.4. Information on Air Quality Drivers and impacts

Besides direct information about air quality, contextual information on sources and drivers as well as information about the impacts of air quality serve to motivate further air quality monitoring and mitigation actions. Socioeconomic factors like age, gender, education, race/ethnicity, and economic status have been found to be linked with air quality exposure and health impacts around the world (Clark et al., 2014; Fecht et al., 2015; Hajat et al., 2015; Chellakan et al., 2022; deSouza et al., 2023b). For 2019, WHO estimated that 6.7 million premature deaths were attributed to ambient and household air pollution from $PM_{2.5}$. This study, as well as related work at national and international levels (Babatola, 2018; Yang et al., 2019; Hammer et al., 2020; Zhang et al., 2020; McDuffie et al., 2021; Southerland et al., 2022), helps to quantify the health impacts of poor air quality, motivating action to monitor air quality globally. When considering future climate and projected emissions changes, despite uncertainties, the projected near-term benefits of emission reduction for reducing mortality are clear (Parsons et al., 2023).

Poor air quality also has negative economic impacts. A study by the World Bank estimated the economic impact of poor air quality at more than 8 trillion United Stated Dollars (US$) in 2019, or 6% of global gross domestic product (World Bank, 2022b). Air quality also impacts agricultural productivity (Agrawal et al., 2003; Li et al., 2022), damages infrastructure and cultural heritage sites (Zhang et al., 2023), and reduces water and soil quality (Singh and Agrawal, 2008).

Many of the United Nations Sustainable Development Goals (SDG) also impact, and are impacted by air quality. Several indicators directly assess air quality and its impacts, such as SDG 11.6.2 Concentrations of fine PM (i.e. $PM_{2.5}$), the population-weighted annual average $PM_{2.5}$ concentration, and SDG 3.9.1: Mortality rate attributed to household and ambient air pollution (Ezzati et al., 2003; Brauer et al., 2012; Lim et al., 2012; Burnett et al., 2014; Shaddick et al., 2018a, 2018b, 2020). Several SDGs provide information on processes affecting air quality. SDG 7: Ensure access to affordable, reliable, sustainable and modern energy for all, includes indicators for access to electricity (SDG 7.1.1) and to clean cooking fuels and technologies (SDG 7.1.2), both of which impact the degree and types of locally versus regionally generated air pollution. Air quality improvement co-benefits are noted as a driver behind efforts to achieve SDG 7 (IEA et al., 2023).

Additionally, air quality and its impacts can also influence several of the SDGs (Mudu et al., 2023), such as:

- SDG 11.7: Provide access to safe and inclusive green and public spaces;
- SDG 12: Ensure sustainable consumption and production patterns; and
- SDG 9: Build resilient infrastructure, promote sustainable industrialization and foster innovation.

Finally, community knowledge and subjective experience of air quality, pollution sources, and impacts should be considered. This is especially relevant on a local level and in regions with limited prior systematic air quality monitoring. Here, local knowledge can fill in critical gaps in understanding, especially during the initial planning phases of air quality monitoring (Wong et al., 2018a). Co-development of monitoring and mitigation strategies with communities will increase their longevity and effectiveness in responding to local needs. Involving community members in leadership roles and establishing long-term partnerships supported by multiple funding mechanisms are identified as key factors in making substantive improvements to local air quality (Davis and Ramírez-Andreotta, 2021; Y. Zhang et al., 2021; Ward et al., 2022).

3. Air Quality Reconstruction

Greater spatial and land use type coverage are typical advantages of LCS. Calibrated LCS networks can be used together with RGM, satellite products and numerical models for air quality reconstruction.

This section discusses the problem of estimating air quality at unobserved locations based on data from observed locations, referred to as air quality reconstruction. Reconstruction can imply the application of spatial estimation simultaneously to an entire domain, either on a uniform grid or at discrete locations meant to represent the domain (e.g. centroids of administrative districts). Reconstruction is typically a Level 4 technique according to the taxonomy of Table 1, since data from multiple sites in a network are included, potentially alongside other inputs.

There are a variety of reconstruction approaches applicable with LCS data, such as statistical interpolation (Section 3.1), land use regression (Section 3.2), fusion with satellite remote sensing data (Section 3.3), and use along with AQM via post-processing or reanalysis (Section 3.4). Hybrid approaches combining multiple techniques are also common (Jerrett et al., 2005). LCS data can also support situational awareness without explicit reconstruction (Section 3.5). A more detailed technical description on the different approaches described in this Section and Table 2 summarizes the required and optional input data to each reconstruction technique; details are provided in the corresponding subsections.

Table 2. Summary of the input data sources (both required and optional) utilized by different air quality reconstruction techniques discussed in Section 3. *These include in situ data (with LCS being the data source of interest here), land use information (considered to be static in time), satellite remote sensing information (which may be dynamic, considering the application timescale), and AQM outputs.*

Technique	In situ (LCS) data	Land use data (static)	Satellite data (dynamic)	AQM data
Statistical Interpolation (3.1)	required			
Land Use Regression (3.2)	required	required		
Data Fusion (satellite data) (3.3)	required	optional	required	
AQM Post-Processing (3.4)	required	optional	optional	required
Data Assimilation (3.4)	required			required*
Informational Use (3.5)	optional		optional	optional

* Near real-time operation of the AQM is required, not simply access to its output data.

The higher spatial densities achievable with LCS as compared with RGM make LCS networks generally more amenable to high spatial resolution reconstruction, especially via statistical interpolation. However, drifts in calibration between LCS across the network and systematic calibration biases affecting all LCS would tend to degrade their performance for reconstruction. Conversely, independent calibration errors (noise) between LCS would tend to average out via reconstruction. Quantitative air quality reconstruction thus relies on a thorough characterization of LCS measurement uncertainty, especially the relative contributions of noise and bias.

The relative value of LCS data and other input information for reconstruction is context dependent, given that there is a considerable variety in the factors determining pollution in different places. For example, if local air quality is dominated by traffic emissions, traffic data will be an informative predictor. Conversely, if concentrations are dominated by long-range transport, satellite data are likely to be more informative than correlates of local emissions.

Network design will also play a role in the performance of reconstruction methods (see Section 8). Independent observations are needed to robustly evaluate reconstruction performance, with spatial cross-validation being the suggested approach.

3.1. Statistical interpolation techniques

LCS data are generally suited for using in statistical interpolation due to the relatively higher spatial density and coverage achievable with LCS compared to RGM. Kriging, though more difficult to implement, has several advantages over other interpolation techniques, including explicit handling of the higher uncertainty in LCS data compared to RGM.

Statistical interpolation uses data collected at discrete points in a domain and generalizes these to other locations. Typically, statistical interpolation depends only on the distances between each point of interest (where concentrations are to be estimated) and the locations of the measurements.

A more detailed statistical interpolations technique is presented in Appendix C.3. Overall, statistical interpolation techniques commonly applied with LCS include nearest neighbour methods, bilinear interpolation, inverse distance weighting (Chu et al., 2020; Esie et al., 2022), and kriging. Kriging in particular has the advantage of explicitly using information on LCS measurement uncertainty to inform the interpolation, and producing estimates of posterior uncertainty alongside the interpolations, which can help in communicating these uncertainties to end-users (Kelly et al., 2021). While ordinary kriging is most common, and interpolates based on spatial distance alone, more sophisticated kriging approaches can take into account factors such as wind speed and direction (H. Zhang et al., 2021). Machine learning (ML) approaches have also been applied to interpolation with LCS data (Veiga et al., 2021); however, there is a risk of overfitting the ML model to a specific configuration of the LCS network.

In general, the performance of any statistical interpolation technique will be sensitive to the design and density of the observation network. The greater spatial densities and coverage achievable with LCS compared to RGM make them amenable for such techniques. When using both RGM and LCS data together for interpolation, kriging approaches can explicitly account for the different observational uncertainties of RGM and LCS based on previously assessed performance.

Figure 3 provides a simple visual comparison of some common interpolation techniques as follows:

- Figure 3a depicts the nearest neighbour approach, with characteristically sharp delineations between the regions of influence of each observation.
- Figure 3b depicts an inverse distance weighted approach, with smooth transitions between the observations. Note that the reconstructed value exactly matches the observed value at each monitor site, and the reconstructed values tend toward the average of all observations as one moves farther from the sites.
- Figure 3c depicts ordinary kriging. Note that the reconstructed values do not necessarily match the observation values at their sites; kriging allows for uncertainties in observations to be reflected in the reconstruction, which is not necessarily forced to exactly match the uncertain observations.
- Figure 3d depicts a non-isotropic kriging approach which takes into account a prevailing wind direction. Despite using the same inputs, these reconstruction approaches produce quite different outputs.

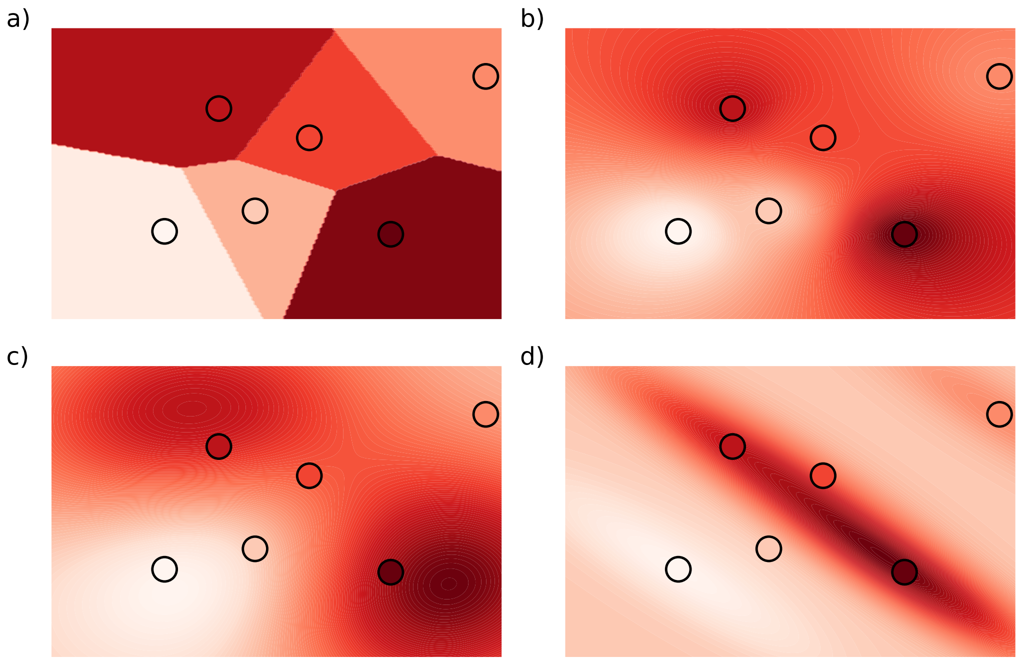

Figure 3. A comparison of statistical interpolation techniques: a) nearest neighbour technique; b) inverse distance weighting; c) kriging, with a longer and isotropic length scale; d) kriging, with a shorter and anisotropic length scale.
Observation values are depicted by circles and are the same across all examples; the shaded backgrounds indicate the reconstructed values.

3.2. Land Use Regression

LCS networks often give better coverage of different land use categories. Establishing relationships between a few discrete measurement locations (using LCS alone or a combination of LCS and RGM) and certain land use characteristic (i.e. land use regression techniques) has shown robust performance reconstructions, especially in urban areas. LCS also provide opportunities to calibrate or validate these reconstructions in rural or otherwise previously unmonitored areas.

Land use regression (LUR) involves reconstruction from a few discrete measurement locations by establishing relationships between the measured quantity and certain land use characteristics of these locations which might affect the local air quality. LUR has a long standing history of use for air quality reconstruction with RGM data (Ryan and LeMasters, 2007; Hoek et al., 2008), generally allowing for high spatial resolution reconstruction over large domains, even in regions with sparse ground measurements. Unfortunately, LUR developed in specific regions have often generalized poorly when applied to new regions (Allen et al., 2011; Patton et al., 2015; Z. Li et al., 2021).

Various studies have applied LUR techniques with LCS data. A more detailed review of LUR techniques is presented in Appendix C.4. Specific LUR approaches, in terms of the land use parameter inputs and the regression approaches, can vary in efficacy depending on the particular characteristics of the region in question and the pollutant being reconstructed (Lu et al., 2021; Coker et al., 2021). However, most studies note that dense LCS networks are especially beneficial in supporting robust high spatial resolution LUR in urban areas, where land use variability is high (Weissert et al., 2019, 2020; Lu et al., 2022a). Furthermore, while most LUR approaches focus on annual- or monthly-average reconstruction, LUR incorporating LCS has been found to support daily average reconstruction, likely due to better representation of local sources achieved using dense LCS networks (Zimmerman et al., 2020; Jain et al., 2021, 2023). In regions with limited to no RGM data, especially LMIC and rural regions in HIC, LCS can be used to assess the generalizability of existing LUR models (Hankey et al., 2019; Abera et al., 2020; Coker et al., 2021; Tang et al., n.d.) or update parameters of LUR models developed with older datasets (Alli et al., 2023). Where both LCS and RGM are available, many studies have found advantages to incorporating both when developing LUR models (Masiol et al., 2019, 2018; Lu et al., 2022a; Bi et al., 2022a). However, it is generally advised to treat the data differently, e.g. by applying lesser weight to LCS data relative to RGM data when calibrating the LUR model to account for the higher relative uncertainty in the LCS data (Bi et al., 2022c).

3.3. Reconstruction with Satellite Remote Sensing Data

Large spatially distributed LCS networks can support reconstruction of surface level air quality from satellite remote sensing data, especially at regional scales. Calibrated LCS can also provide independent data for verifying satellite derived air quality in otherwise unmonitored areas.

As discussed in Section 2.2.2, satellite remote sensing data provide a source for dynamic air quality information over a wide spatial domain and with relatively low latency, compared to the functionally static land use parameters typically used in LUR. However, ground-based data are needed to relate the atmospheric column information, typically available from satellites, to near-surface air quality. Gaps in satellite information, e.g. due to cloud cover, must also be filled.

A more detailed review of atmospheric composition reconstruction based on satellite data is presented in Appendix C.1.2. The utility of including both satellite aerosol optical depth (AOD) and LCS data for high-resolution spatial reconstruction of $PM_{2.5}$ within cities is not clear, and may be dependent on local conditions, LCS network density, and the specific objectives of the application (Huang et al., 2019; Malings et al., 2020; Chao et al., 2021; Atuhaire et al., 2022; Liang et al., 2023; Regmi et al., 2023). In contrast, at regional and national scales, combining satellite AOD data with RGM and LCS network information, has been shown to improve reconstruction accuracy compared with methods not incorporating the satellite information. In particular, inclusion of LCS data in such regional-scale applications was found to enhance detailed spatial features (Li et al., 2020; Bi et al., 2020a) and improve performance under atypical conditions, e.g. during wildfires (Gupta et al., 2018; Bi et al., 2020b). LCS data have been combined with geostationary satellite AOD and other data to improve hourly $PM_{2.5}$ reconstruction during wildfire events (Vu et al., 2022). Furthermore, component-specific AOD available from certain satellite data products has been combined with LCS data to better constrain fine and ultrafine PM concentration (deSouza et al., 2020b). For trace gases (such as NO_2), use of data satellite (e.g. TROPOMI) combined with in situ RGM and LCS data has been shown to improve hourly, 1 km spatial resolution NO_2 reconstruction for Tangshan, China, compared with the use of any of the input datasets independently (Fu et al., 2023). Overall, LCS networks have been shown to meaningfully improve regional-scale efforts to reconstruct air quality from satellite remote sensing data by expanding the spatial coverage and density of in situ monitoring over what is typically possible using RGM alone (Zhu et al., 2023).

In areas without RGM, calibrated LCS can be used in the evaluation of satellite-derived data products (Kondragunta, 2022). In the absence of RGM data for LCS calibration, however, only qualitative comparisons between these datasets might be possible. Globally-distributed LCS calibration centres can support the expansion of calibrated LCS networks for satellite data product verification. They might also serve as capacity-building hubs to enhance local access to relevant satellite remote sensing data products.

3.4. Model post-processing and reanalysis

Combining available observational from LCS networks and model information using data fusion and assimilation techniques improves reconstruction at city to national scales. Understanding LCS measurement error characteristics is important for the performance of these techniques. Furthermore, LCS can also be used to verify modelling reconstructed fields qualitatively or quantitatively.

AQM can be combined with LCS observations via data fusion (post-processing) or data assimilation (reanalysis) to bring model outputs into better agreement with observations and/or increase the spatial resolution of the reconstruction. A more detailed description of AQM types is presented in Appendixes C.2.1 and C.2.2 and an extended discussion on air quality reconstructions based on AQM in Appendix C.2.3.

Data fusion approaches for combining AQM outputs with LCS data, typically focus on urban applications and make use of residual kriging techniques to enhance the spatial resolution of AQM outputs (Schneider et al., 2017; Gressent et al., 2020; Munir et al., 2021). These techniques have been shown to reduce biases and improve the representation of diurnal cycles and concentration peaks in the reconstruction compared to the AQM output alone (Gressent et al., 2020; Huang et al., 2021). Similar post-processing of AQM using both RGM and LCS data has been used to improve real-time, locally-specific public air quality information in the Netherlands (Wesseling et al., 2019), and Southern California, USA (Schulte et al., 2020). Understanding the relative uncertainty of LCS data, as assessed during calibration, is important to incorporating LCS data correctly via this approach. Low data latency of the LCS is also important if post-processing is to be applied in near real-time.

Assimilation of LCS data can also improve reanalysis products (i.e. a consistent and harmonized long-term modelling product of past periods which provides spatially and temporally complete distributions) at urban (Mijling, 2020; Schneider et al., 2023; Hassani et al., 2023b) and regional scales (Lopez-Restrepo et al., 2021). Assimilating LCS data has improved the representation of localized and transient pollution events, such as alternative traffic routes or wood burning, in the high-resolution AQM in these examples. Again, prior characterization of LCS measurement uncertainty through a calibration process, and in some cases, assessment of their performance through comparisons with nearby RGM, were essential for proper application of the data assimilation in these examples.

Finally, LCS can provide data for AQM evaluation, especially for high spatial resolution AQM needing dense in situ data (e.g. Zhang, 2023a). Quantitative evaluation requires that LCS be well calibrated using RGM; more qualitative comparison of AQM outputs (e.g. comparing relative positions of "hotspots" between AQM outputs and LCS data) are simpler to achieve.

3.5. Informational use alongside other data sources

LCS can be displayed alongside other data to enhance the local relevance of public air quality awareness communications, even without explicit reconstruction.

Explicit reconstruction combining LCS data with other information to produce a complete map is not always necessary. Simply plotting multiple data sources over the same domain, possibly with additional informational overlays, can allow users to mentally judge air quality based on nearby data sources, or determine that insufficient data exist. Of course, this relies on some expertise from the end-users, and there is no guarantee that any mental estimate of this kind will be reasonable. Still, this is often sufficient to provide a general air quality situational awareness to the public.

By displaying all these information sources together, even without explicit reconstruction, visitors to the website can infer whether their local air quality is likely being impacted by a wildfire. Gaps in the available data are also apparent.

The USA EPA Fire and Smoke Map is an example of overlaying multiple distinct data sources, including RGM and LCS in situ monitors, reported fire locations, and fire detections and smoke plume extents estimated from satellite remote sensing data, as illustrated in Figure 4. Guidance is provided on the website on best practices for interpreting the map, such as under what conditions one might reasonably assume that their local situation is reflected by a nearby monitor. A discussion of the abilities and limitations of LCS and the role played by LCS data in the tool is provided. It is also important to note that the tool is provided for public awareness purposes and does not provide the basis for regulatory or compliance information.

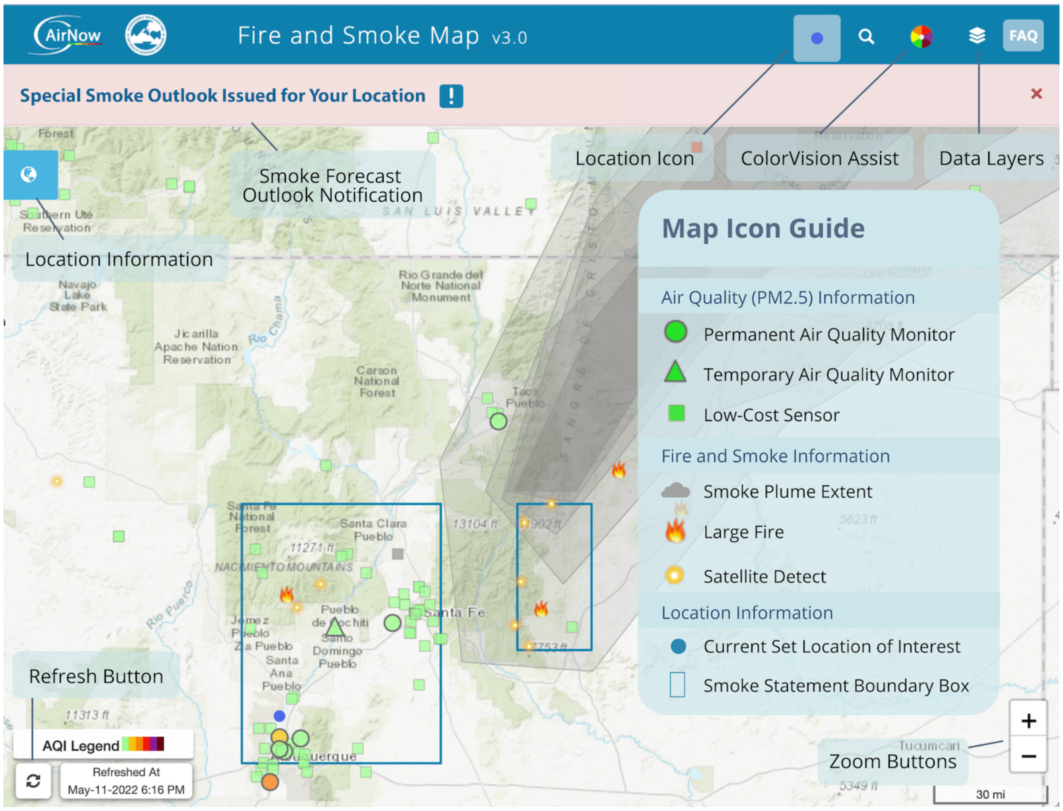

Figure 4. Interface example from the online user guide for the USA EPA Fire and Smoke Map (version 3.0). *The map displays multiple information sources relevant to air quality during wildfires, including air quality index (AQI) values from permanent RGM (circles), temporarily deployed RGM (triangles), and LCS (squares). Also included are satellite remote sensing information about fire detections (yellow points) and smoke plume extent (grey shaded areas), alongside reports of fire activity (fire symbols) and advisory regions (blue rectangles).*

4. Source Identification and Attribution

Higher spatial densities achievable by LCS networks can improve the detection of local emission sources, particularly in otherwise under-monitored areas. High temporal resolution multi-pollutant data from LCS can support the identification and quantification of emissions from specific sources and sectors using signal decomposition techniques. Some techniques can be applied even to factory calibrated LCS, with additional data normalization and analysis.

The use of collected data to identify the sources of pollutants and quantify their emissions is a key step which bridges the collection of air quality data and the enaction of policies to influence air quality. This is broadly referred to as source identification, source attribution, or source apportionment. LCS can offer a cost-effective method for identifying and tracking emissions, especially in regions without existing emissions monitoring systems in place. The high spatial density possible with LCS relative to RGM allows for more chances to detect local sources, with potentially greater source signals due to closer proximity of the LCS to the source. Analysis of high temporal frequency data available from LCS can also identify short-duration source signals (minutes or even seconds), provided that calibrated LCS noise levels are established to be low relative to the signals of interest. Greater spatial coverage possible with LCS networks improves background subtraction approaches for source increment identification. Finally, the multipollutant capabilities of many LCS can be used to detect co-occurring pollutant mixtures associated with certain sources or sectors.

Techniques for source identification and attribution with LCS can be grouped into observational techniques (Section 4.1), statistical techniques (Section 4.2), and model-based techniques (Section 4.3). Observational techniques use circumstantial evidence to connect concentration changes to potential sources. Statistical techniques use more robust statistical analyses to make these connections. Model-based techniques use AQM, especially in an inverse modelling configuration, in order to support these connections. These techniques would typically fall under Level 5 of the taxonomy from Table 1, since they provide insight into the factors contributing to observed ambient concentrations. Additional details on these techniques are provided in Appendix C.5.

4.1. Observational techniques

Simple observational techniques can connect LCS data to specific pollution sources or sectors, identifying their relative contributions. LCS can also cost-effectively track the impacts of specific activities or certain mitigation strategies on ambient air quality. These capabilities can also contribute to environmental justice efforts.

Observational techniques often use diurnal or other temporal patterns to match spikes in concentrations of certain pollutants to observed or assumed activities taking place nearby, as a form of circumstantial source apportionment. Data from LCS networks, especially multipollutant data, can be combined with meteorological information and community knowledge to identify likely sources of the observed pollutant concentration patterns (Collier-Oxandale et al., 2020). With more extensive LCS networks, gradient and transect studies can determine regions of influence for sources; sparser RGM networks may not capture the spatial heterogeneity of concentrations with sufficient fidelity for such a study (Caubel et al., 2019). LCS can also be deployed to cost-effectively assess the impacts of specific events or activities on local air quality (Kuhn et al., 2021) or for early detection of intermittent sources (e.g. wildfires) in remote areas (Dampage et al., 2022), supporting a more rapid mitigation response.

Integration of LCS data with wind speed and direction information, typically via the use of "wind rose" plots, is a common approach to identifying the directions of and possible distances to sources (Carslaw et al., 2006; Carslaw and Ropkins, 2012). Several LCS include integrated anemometers to support this. Application of these techniques in more extensive LCS networks can allow for the triangulation of sources (Rose Eilenberg et al., 2020). The collection of LCS data with basic wind information is often a more readily deployable solution in areas with limited infrastructure. Techniques incorporating LCS with wind speed data have facilitated a first systematic analysis of local pollution sources in several LMIC (Owoade et al., 2021; Hodoli et al., 2023).

For known emission sources such as industrial facilities, seaports (Jayaratne et al., 2020a), and airports (Popoola et al., 2018), LCS can be used in fence line monitoring along the facility perimeter to quantify its impact on local air quality. In such applications, desirable characteristics for the LCS include (1) multipollutant capabilities, especially for CO, CO_2 and NO_2, for identifying the emission factors associated with different activities, (2) high temporal resolution to detect intermittent emissions and better separate background concentrations, and (3) extensive coverage around the source to compare upwind and downwind concentrations and determine the source increment irrespective of the wind direction (Popoola et al., 2018). Deployment of LCS on drones may also be useful for monitoring specific emission sources in certain applications, e.g. monitoring emissions of individual ships offshore (Anand et al., 2020).

Major roadways also represent distributed sources impacting local air quality. Again, multipollutant LCS are useful for determining vehicle emission factors. LCS networks covering both roadside sites and background locations can help identify the relative contribution of traffic to local air pollution. Such applications require high inter-unit precision of the LCS (Pope et al., 2018; Alli et al., 2021; Hofman et al., 2022c). Analysis of roadside LCS data together with traffic patterns (Chu et al., 2022), vehicle counts (Wang et al., 2020a), and/or meteorological information (Jayaratne et al., 2021) can associate concentration increments with specific vehicle types and operating conditions, providing useful information to help target traffic emission control strategies. LCS can also be used to cost-effectively track the impacts of certain human activity changes and vehicle use restrictions on local air quality, supporting evidence-based traffic emission mitigation policies (Subramanian et al., 2020; Liu et al., 2021; Hofman et al., 2022c), especially in areas without the infrastructure to support routine monitoring with RGM.

4.2. Statistical techniques

Positive or non-negative matrix factorization and spectral analysis techniques are readily applicable to LCS data. In some cases, meaningful results have been obtained using these techniques on multi-pollutant LCS data even without localized calibration of the LCS.

Statistical techniques for source apportionment seek to identify common patterns, trends, and groupings in data via statistical analysis and to associate these with a source or sector. Despite limitations on LCS calibration, many studies have found comparable results when applying these techniques using LCS versus using RGM data in the same environment. Characteristics of certain LCS such as higher temporal resolution and simultaneous multipollutant measurements make them more suitable for these techniques than lower temporal resolution and single-pollutant RGM.

While many LCS for PM lack sensitivity for different size fractions (e.g. Tryner et al., 2020), clustering based on size fractions to which the detectors are sensitive has been used to distinguish key contributing source sectors (deSouza et al., 2020a). Clustering approaches applied to LCS particle size data have identified sources similar to those identified using RGM particle size data, although it was noted that the LCS were more applicable to background sites, where larger particles sizes and longer temporal variations are of greater importance (Bousiotis et al., 2021).

Positive or non-negative matrix factorization techniques have been applied to multipollutant LCS data incorporating both gas and particle detectors. Analysing the co-variation of different pollutants with this LCS data allowed the identification of source profiles similar to those identified with RGM data in several cases (Hagan et al., 2019; Yang et al., 2022; Bousiotis et al., 2022, 2023, Westervelt et al., 2023). In particular, these studies noted the applicability of these techniques even to uncalibrated LCS data (e.g. to raw signals from the detectors), provided data cleaning and normalization are applied. The applicability of such techniques in regions lacking RGM for calibration is especially important for supporting source apportionment in many LMIC.

Spectral analysis techniques have also been applied to LCS data to separate high-frequency signals, typically representing local sources, from low-frequency signals, typically representing background sources (Frederickson et al., 2022; Qin et al., 2023). In these applications, high temporal resolution (minutes or even seconds) of the LCS data is important.

4.3. Model-based techniques

Inverse modeling methods can be applied to verify or update emissions inventories, especially in urban areas with dense LCS networks. Expanding the use of these techniques with LCS data for air pollutant and GHG emissions is a major opportunity to enhance our understanding of contributors to air pollution.

Emissions inventories can be updated with measurement data, including LCS data, via inverse modelling (e.g. Ahangar et al., 2019). Dense LCS networks in urban areas can be especially useful here. For example, the BEACO$_2$N network of LCS in the region of San Francisco, California, USA, has been extensively used to determine emissions, including identifying local emissions enhancements, determining vehicle fleet emission factors, and verifying the impacts of policy changes on emissions (Shusterman et al., 2018; Turner et al., 2020; J. Kim et al., 2022; Fitzmaurice et al., 2022). Noted success factors for this network include the multipollutant capabilities (CO_2 and NO_x) of the LCS, the typical inter-node spacing of 2 km, and high temporal resolution (10 seconds) allowing for the separation of background signals.

The use of LCS for emissions quantification has the potential to cost-effectively track policy impacts to reduce urban pollutant as well as GHG emissions, including CO_2 (Turner et al., 2020; Carruthers et al., 2023) and CH_4 (Sasakawa et al., 2010; Collier-Oxandale et al., 2018; Jørgensen et al., 2020; Sieczko et al., 2020). Use of data assimilation (i.e. combining observational data and numerical model information), and inverse modelling with LCS CO_2 data can verify or update existing GHG emissions inventories, e.g. in a case study in Glasgow, UK, where it was found that some local updates to the existing inventory were needed (Carruthers et al., 2023).

5. Air Quality Patterns & Trends for Environmental Justice

LCS can be used to identify disparities in air pollutant exposure within and between communities, enabling environmental justice advocacy, provided that high inter-unit consistency of the LCS has been demonstrated. Data from multiple sources can be combined to corroborate exposure disparities identified by LCS.

Despite overall reductions in pollution in HIC, internal disparities in pollution exposure persist, disproportionately impacting economically disadvantaged and racial or ethnic minority communities (Clark et al., 2014; Fecht et al., 2015; Y. Zhang et al., 2021). Similar disparities have been identified in LMIC (Hajat et al., 2015; Chellakan et al., 2022; deSouza et al., 2023b). Given that such groups may not be well represented by RGM networks, and that LCS are more readily accessible to these communities than other sources of air quality information, LCS are a valuable tool to identify issues of environmental injustice. LCS can be used, along with other information sources, to examine such disparities in exposures based on various social, economic, and demographic factors, provided that technical issues of their calibration and data integration, along with other issues of data privacy, accessibility, and sampling or interpretation bias, are addressed. Environmental justice analysis would be a Level 5 application under the taxonomy from Table 1.

5.1. Robust pattern and trend analysis with LCS

When air quality patterns and trends are analysed alongside social, economic, and demographic factors, insights into exposure disparities within and between communities can emerge. Careful consideration of sources of error and statistical significance in uncertain data is needed when performing quantitative analysis for air quality trends and patterns. Concerns about inter-unit precision and long-term stability of LCS data thus complicate the assessment of patterns and trends using LCS data, especially where average concentrations are low. The relatively shorter operational lifetimes of LCS compared to RGM also hinder their use for long-term trend analysis.

Despite these difficulties, appropriate characterization of LCS uncertainties and the selection of statistical techniques which take these uncertainties into account can offset some of the limitations on LCS data quality, enabling effective environmental justice research with LCS (Tanzer et al., 2019; Do et al., 2021; Lu et al., 2022b); additional details on these case studies are provided in Appendix C.6. In general, establishing high inter-unit precision between LCS using pre- and post-deployment co-location studies is recommended to give robust performance metrics against which any disparities identified using LCS can be compared to establish statistical significance.

Dense LCS network data can support environmental justice studies at finer spatial and temporal scales than available with many other air quality information sources. LCS have been used to investigate exposure disparities under specific conditions, such as atmospheric inversions (Mullen et al., 2020) or fireworks displays (Esie et al., 2022), which might be masked when looking at more spatially aggregated and temporally averaged exposure data available from other information sources. The ability of LCS to support local air quality reconstruction (discussed in Section 3) and source identification (discussed in Section 4) also support their utility in identifying and investigating air quality issues at community scale. Finally, the availability of LCS to community scientists and their relative ease of deployment and redeployment make them accessible and flexible tools to enable investigations centring the needs and concerns of the community, including changes to those concerns as conditions change over time and new situations arise.

5.2. Other Considerations to Support Environmental Justice Analysis

Combining insights from multiple datasets, especially including remote sensing data, can corroborate the patterns and trends observed by LCS and offset the relatively higher uncertainty in LCS data. While an analysis based on LCS data alone may be inconclusive, it may contribute to a larger meta-analysis of an issue, which may find broad agreement across multiple studies in support of a common conclusion or outcome. Satellite data and model outputs have been used to identify pollution exposure disparities on global to local scales (Demetillo et al., 2020, 2021; Kerr et al., 2021; Castillo et al., 2021; Anenberg et al., 2022). Comparisons with LCS data can help to corroborate and localize such remote sensing estimates. For example, data from LCS networks showed improved air quality in cities during COVID-19 lockdowns (Tanzer-Gruener et al., 2020; Chadwick et al., 2021; Puttaswamy et al., 2022). These matched anecdotal observations of citizens, as well as satellite remote sensing data and global air quality forecasts. LCS can also provide more detailed information about spatial and especially temporal variabilities in disparities, since satellite data may be biased by limitations on spatial resolution, daylight observation, and overpass times. Combining insights from LCS and satellite data is especially valuable in LMIC where few other data resources are available (McFarlane et al., 2021; Bittner et al., 2022).

To support environmental justice analysis, careful consideration must be taken to ensure LCS network distributions are sufficiently representative of the communities in question. This requires close collaboration with and participation of those communities and careful network design (see Section 9). Studies on the spatial distribution of voluntary or ad-hoc LCS networks, i.e. networks deployed by private individuals purchasing and deploying LCS of their own volition, have identified social and economic disparities in densities of LCS. Relatively more affluent and less socially vulnerable communities within HIC often feature more LCS per capita (deSouza and Kinney, 2021; Mullen et al., 2022; Yi Sun et al., 2022). Thus, while ad-hoc LCS deployments are useful for raising community awareness of air quality issues and exposure disparities, differences in socioeconomic status can limit the utility of such networks for unbiased analysis. Community members must be able to afford the upfront cost of purchasing the LCS as well as the ongoing costs of power and data connectivity. Provision of targeted financial support and incentives, e.g. by the organization conducting the analysis, can help to offset these potential monitoring disparities to support more equitable data collection.

Integrating LCS into large-scale community-led air quality monitoring has demonstrated a positive interplay between advances in exposure assessment and policy development through collective action (Perelló et al., 2021). Participatory research, which sees researchers and communities involved in all aspects of a study, can improve study outcomes and foster greater data accessibility by community end-users. Participatory research also increases the transparency of the study methods to the public, promoting acceptance of the findings and garnering support for identified solutions. LCS have a key role to play in participatory research as a readily accessible tool for environmental data collection (English et al., 2018). Engaging with community science using LCS can build technical capacity and scientific literacy to resolve disparities in data access and create stronger networks to inform policies to promote environmental justice.

> Programs that build community capacity in LCS development, deployment, and data analysis should be supported. Increased community involvement in data collection can also support designing and implementing mitigation strategies.

6. Health Studies and Personal Exposure Monitoring

LCS may support more spatially and temporally focused health studies. LCS are particularly valuable for these purposes in LMIC where ground monitoring is limited, exposure mixtures tend to be complex, and concentration differences can be great. LCS can also help promote behaviors reducing personal exposure. Actions to ensure the privacy of personally identifiable health data are needed in these applications.

Due to the negative impacts of air pollution on human health, as discussed in Section 2.2.4, exposure and epidemiological analysis is a key application for air quality information. The increased availability of locally and even personally specific air quality information enabled by LCS has led to their increased use to investigate such health questions. Health studies would typically be considered a Level 5 application under the taxonomy from Table 1, since network level data are being combined with health information to study air quality impacts.

Information on current best practices for leveraging LCS data for health effect studies are introduced in Section 6.1. The high spatial densities possible using LCS allow for the assessment of time-varying exposures from different microenvironments. This is particularly true for LMIC, where ground monitoring is limited and exposure from a complex mixture of sources tends to be high. LCS further provide opportunities to more widely investigate the health effects of transient and short-term exposure.

Use of wearable LCS to assess personal exposure has been found to be a viable approach, as discussed in Section 6.2. However, calibration of wearable LCS against RGM in diverse monitoring microenvironments is even more difficult than calibration of stationary LCS, and requires careful consideration of techniques and robust testing to ensure necessary data quality. More qualitative, indicative measurements which can guide individuals to lower their exposure to potentially hazardous pollutants is a more readily achievable goal with current technology.

6.1. Use of LCS to support health studies

Increased spatial data density facilitated by LCS can allow more focused health studies. LCS when combined with other data sources may support epidemiological studies, particularly short-term assessments. Lack of in-situ data to support local epidemiological studies is a critical issue for low- and middle-income countries which LCS can begin to address.

Section 3 has established that LCS can be used, along with other information sources, to reconstruct air quality information at fine spatial and temporal scales. For health studies, these air quality reconstructions will then need to be combined with health data, which is subject to its own uncertainties and potentially limited availability. Careful consideration needs to be made of these, especially confounding factors which can lead to non-independent errors, e.g. biases in sampling of both air quality and health information due to demographic factors and systemic disparities. The timescales of analysis are also important to consider. Health studies typically rely on unbiased and continuous data records over long periods of time. Due to calibration drift, LCS are not as well suited to this as are some other data sources, such as RGM or long-term satellite-derived data products. However, LCS can still supplement these data sources via the techniques outlined in Section 3. For example, Bi et al. (2022a) noted that, once LCS were calibrated to available RGM, including LCS data when reconstructing exposures (via a LUR approach) resulted in a better representation of the epidemiological study cohort participants' exposures in residential and commercial areas. Further details on this case study and others are presented in Appendix C.7.

A range of data analytic and modelling methods have been applied in past studies of air pollution health impacts. A guidance framework for selecting between these approaches given the purpose of analysis, users, and available resources has been proposed by Gardner-Frolick et al. (2022); this scheme is presented in Figure 5 for reference. This framework is readily applicable to LCS, considering their advantages or limitations in terms of accuracy, interpretability, spatiotemporal resolution, and usability.

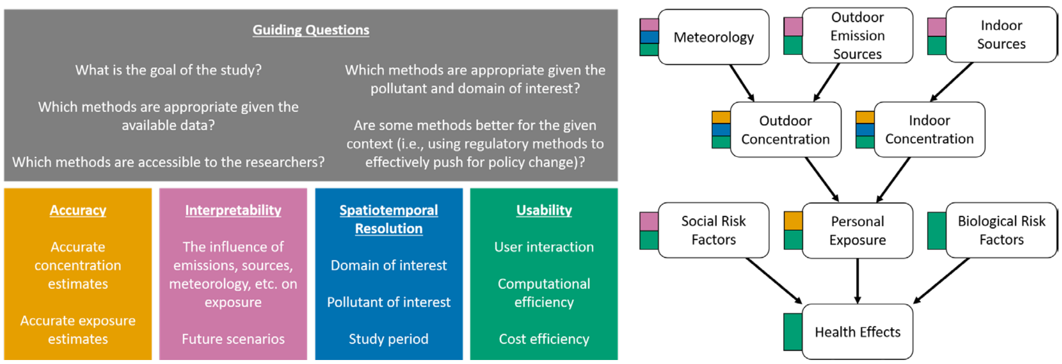

Figure 5: A guidance framework for selecting between approaches for environmental justice and health effect studies. *The framework is adapted from Gardner-Frolick et al. (2022), Figures 2 and 3. The overall guiding questions for the study are presented on the left, along with questions related to the accuracy, interpretability, spatiotemporal resolution, and usability of the methodologies or study approaches being considered. The flow chart at right shows (using coloured tabs) how each of these relate to aspects of a generic health effect study.*

LMIC have been inadequately represented in air pollution epidemiological studies, largely due to the lack of local monitoring network data (Pozzer et al., 2023). This has raised concerns that estimates using global models may underestimate the disease burden attributable to air pollution in several LMIC (Coker and Kizito, 2018). LCS represent an opportunity to remedy this situation, despite data quality concerns (Amegah, 2018; Awokola et al., 2020; Wernecke and Wright, 2021). LCS data have been used to support epidemiological studies in LMIC lacking prior health studies or RGM data, and have established statistically significant relationships between exposure and health impacts, even in cases where locally-specific LCS calibrations were not available and more generic calibrations needed to be used instead (Amegah et al., 2022; Coker et al., 2022). However, a lack of RGM data for LCS calibration and logistical challenges with running the LCS network have also hindered similar efforts (Abera et al., 2020).

The high temporal frequency of LCS data might also support short-term exposure and health impact studies, which have been less extensively studied than the impacts of chronic exposure (Mannshardt et al., 2017). The fact that many LCS report ambient air quality information using health indices related to longer exposures has led to misinterpretation; assessment of short-term health impacts and development of relevant indices may help to remedy this situation. Increased spatial densities achievable with LCS might offset the need for averaging over large regions and populations to achieve statistical power in studies based on sparser monitor networks. This might facilitate more localized, community-specific health studies. LCS can also be quickly deployed to regions following disasters and can operate in environments with limited infrastructure, allowing for exposure studies in otherwise inaccessible areas.

6.2. LCS for personal exposure monitoring

Providing qualitative insights into air quality to help individuals manage their exposure is a viable use case for current portable and wearable LCS technologies.

The potential to use wearable or otherwise portable LCS to assess personal exposure has long been recognized (Snyder et al., 2013). While difficulties in ensuring stable calibration of portable LCS have generally prevented quantitative use of their data, good qualitative agreement is often noted between the portable LCS and RGM when assessing variability in exposure between microenvironments and throughout the course of the day (Jerrett et al., 2017; Kim et al., 2021; Zong et al., 2021). Thus, the use of portable LCS for more qualitative, indicative, or comparative applications has proven more tractable. These include evaluating qualitatively how different mitigation activities, personal routines and behaviors, travel mode choices, and building characteristics increase or decrease relative personal exposure (Mazaheri et al., 2018; Nyarku et al., 2018; Bertrand et al., 2020). More details are provided in Appendix C.7. LCS can also be integrated with air quality forecasts, behavioral, and medical information to provide personalized symptom forecasts, as well as individualized feedback and guidance to help manage individual health and reduce exposure, provided that personal medical data privacy is adequately addressed in the system design (Che et al., 2020).

7. Air Quality Forecasting

Well-characterized and calibrated LCS networks can improve short-term, localized forecasting from regional or global AQM to support advisories and warnings. LCS can also provide data for evaluating other forecast methods where RGM networks lack coverage.

Air quality forecasting involving LCS is an increasingly important field due to its potential to support widespread monitoring and early warning systems, particularly in areas lacking RGM. Air quality forecasting is important to support effective decision-making to manage air quality impacts, especially in terms of human health. Studies have indicated the potential for air quality forecast alerts to promote changes in people's behaviors to avoid excessive exposure and resultant negative health impacts, especially in those with health conditions which make them more susceptible to poor air quality (Wen et al., 2009; Neidell and Kinney, 2010; Saberian et al., 2017). Forecasting can also support broader societal decision-making, e.g. restricting certain activities such as agricultural burning or industrial processes when unfavorable atmospheric conditions might lead to excessive air quality impacts resulting from these activities. Forecasting is typically a Level 5 technique according to the taxonomy of Table 1, since additional information beyond that of the LCS is typically needed to inform the forecasts.

In this report, we consider two types of air quality forecasting models. **Statistical** models such as pattern repetition, autoregressive models, and ML techniques, are trained using historical air quality measurements and potentially other data. The models learn the complex relationships between input features and air quality parameters. These trained models are evaluated using validation datasets to assess their performance in predicting air quality. Once trained and evaluated, the models can make future air quality forecasts based on real-time LCS data, potentially augmented with meteorological or AQM forecasts. Appendix C.2.1 provides details on these statistical forecasting techniques. **Deterministic** models are computational tools that can simulate and predict air pollutant concentrations based on the physical and chemical processes governing atmospheric dispersion and transformation. Validating deterministic models against observed data, including LCS data, is crucial to ensure their accuracy and reliability and identify areas for improvement. Furthermore, data assimilation techniques can incorporate observational data from a variety of sources, bringing the deterministic model into better agreement with the latest observations and thereby improving its near-term forecasts. Appendix C.2 provides a more complete description of AQM, in addition to more details their use together with observational data for air quality forecasting.

Overall, the differences between statistical and deterministic forecasting approaches in terms of computational resources or areas of application, LCS data can support both by providing locally relevant calibration data (Section 7.1) and by supplementing RGM for forecast validation (Section 7.2). By calibrating model outputs with observational data, errors and uncertainties in model predictions are reduced, leading to more accurate forecasts. Evaluating model performance is fundamental to conducting sensitivity analyses to assess the impact of input parameters on model predictions and/or to ensure the reliability and accuracy of model predictions. For applications, an important aspect of forecast model evaluation focuses on the predictive capacity to forecast high pollution events or exceedances of short-term air quality regulation thresholds.

Implementing LCS networks to support air quality forecasting at a global, regional, or urban scale requires careful planning, coordination, and integration of various technologies and approaches. Here, the design of the sensor network layout is fundamental to ensure adequate spatial coverage across the target area, but also the data quality assurance and timely provision of data required considering the forecasting system needs (see Section 9).

7.1. Providing Forecast Calibration Data

LCS can provide data to drive statistical forecasting or to improve deterministic forecast localization. Particularly, for data assimilation, it is fundamental to known the uncertainty of the LCS data.

Statistical forecasting requires historical data for calibration. Real-time observational data can also be integrated into forecasting models to improve their accuracy and reliability in providing timely warnings of poor air quality events. Observational data for forecast calibration can come from various sources including RGM, LCS, satellites, remote sensors, and mobile monitors. This data provides information on key air quality parameters such as pollutant concentrations, meteorological conditions, and emissions, offering comprehensive coverage across different spatial and temporal scales. Before use, observational data undergoes preprocessing to correct errors, remove biases, and standardize formats. Quality control procedures ensure data consistency and reliability, facilitating seamless integration with air quality models (see Section 10.2.3).

Calibration techniques such as data fusion, data assimilation, statistical downscaling, and other methods to reconcile differences between observed and simulated data have different requirements in terms of data quantity, quality, and latency. In general, thorough characterization of LCS measurement uncertainties under different conditions are needed. This can be achieved following best practices outlined in the WMO report (WMO, 2020). Categorical forecasts (e.g. using air quality index levels) can be more robust to the relatively higher uncertainty of LCS data. LCS forecast calibration data may thus be better suited to support more qualitative use cases, e.g. the issuing of alerts or advisories based upon overall prevailing conditions. Many techniques, especially assimilation, require low data latency, i.e. within three to six hours. Here, most LCS have the advantage of providing their data in near-real-time. Automated calibration of LCS data and provision of these data via web-based interfaces using interoperable data standards (see Section 10.2.3) can facilitate this low latency and use of LCS data for assimilation.

Data fusion is the combination of data from multiple sources to produce an output distinct from the initial sources; in the context of air quality forecasting, it refers to the synthesis of model forecasts together with recent observational data (and potentially with additional ancillary inputs) to produce the fused forecast. A data fusion approach is more flexible than a bias correction approach since it can take into account recent measurement data as well as air quality forecasts, rather than being entirely dependent on measurements collected during an historical calibration period. A wide variety of statistical techniques are applicable to data fusion (Appendix C.3). ML methods are often sufficiently flexible to handle a variety of potential input information, including air quality forecasts, and so are popular in data fusion approaches. Statistical approaches like Kalman Filtering are also popular, but require better characterization of uncertainties in both model forecasts and in situ measurements. In most data fusion approaches, especially ML methods, missing observational data may invalidate the chosen approach, as a certain number of inputs will be expected by the algorithm. In such cases, it may be necessary to fall back upon an alternative forecasting approach, e.g. a bias correction method not relying on recent observational data. Data fusion techniques like Kalman Filtering are more robust to missing data, e.g. the Kalman Filter will default to the air quality forecast in the absence of any recent measurements to use for the fusion. As an example of this, a ML technique (gradient-boosted decision trees) was applied to outputs of the Goddard Earth Observing System Composition Forecast (GEOS-CF) system (Keller et al., 2021a). Multiple meteorological and chemical variables from the GEOS-CF forecast for a grid cell corresponding to the location of an RGM or LCS are used as inputs, with the output being a location-specific forecast. This approach to bias correction greatly improved the skill of the forecast at these specific locations, effectively eliminating bias and improving correlation and accuracy for the bias-corrected forecasts for O_3 and NO_2 up to five days in advance. This method required a year or more of surface monitor data to be calibrated effectively, and these location-specific bias-corrected forecasts were found to not necessarily generalize well, even to nearby locations. However, the method is relatively straightforward and equally applicable to RGM and well calibrated LCS datasets. To that end, CanAIRy Alert is a partnership that supports air quality managers to develop air pollution forecasting tools and better understand pollutant sources. The programme translates and packages globally available datasets such as the GEOS-CF forecast, local air quality monitoring data from calibrated LCS & RGM, emissions inventories and others into decision-relevant and locally accessible tools. Following a successful pilot in Latin America, the tool was piloted in four African cities (Accra, Ghana; Kampala, Uganda; Kigali, Rwanda and Nairobi, Kenya) to enable air quality managers and policymakers to identify key pollution sources and forecast pollution episodes. The ML forecast bias correction technique described above is being adapted and operationalized through CanAIRy Alert, such that local LCS operators can have their data ingested to support creating location-specific bias-corrected forecasts using the same technique.

Data assimilation provides an opportunity to use LCS data to improve air quality forecasting while accounting for known accuracy limitations. In an experiment by Lopez-Restrepo et al. (2021) focusing on $PM_{2.5}$ forecasting in Aburrá Valley, Colombia, LCS data assimilation improved the performance of the air quality forecasts (based on the LOTOS-EUROS model) from one to three days in advance. A similar improvement was seen when assimilating RGM data from a smaller number of sites. Thus, the denser network of LCS, with relatively lower accuracy, provided similar value to sparser but more accurate RGM network data when assimilated into this AQM. This suggests an effective trade-off for using more numerous LCS with well characterized uncertainty to fill gaps where RGM are lacking to support data assimilation, although more studies in different regions and for different pollutants are needed to better understand this trade-off. While data assimilation is potentially a highly effective method of utilizing LCS data to support air quality forecasting, it is also probably the most technically involved method discussed here, as it also requires operation of the forecasting AQM. For this reason, it may be beyond the means of organizations without the specific expertise and computational resources needed to operate an air quality forecasting system. Also, data assimilation still produces forecasts at the spatial and temporal resolution of the AQM; if a finer resolution is required, a data fusion approach may be more appropriate.

7.2. Forecast evaluation

LCS networks can facilitate forecast evaluation at fine spatial scales and in remote areas without RGM. Latency, quality (i.e. accuracy and uncertainty) and spatial representativity of the LCS data are key factors for considering a long-term performance forecast evaluations or a near-real time validation.

The evaluation of AQM air quality forecasts is a key procedure to further improve the development of the air quality forecasting system. Well calibrated and characterized LCS can provide valuable information in verifying forecasts produced by an AQM, especially in remote and understudied areas where no other in situ data sources exist. One example is the case of the Warning Advisory System (WAS) for airborne dust of the WMO Barcelona Dust Regional Center. This WAS uses a multimodel forecast product providing daily dust WAS forecasts for seven West African countries (Terradellas et al., 2018). To evaluate the performance of the WAS in each country, information from two different types of LCS were utilized. These LCS measured surface PM concentration (as PM_{10} and $PM_{2.5}$) and AOD via a hand-held Calitoo sunphotometer, and included a meteorological station. The LCS were specially designed to be robust and self-sustaining in terms of electricity supply, connectivity, and maintenance. The deployment of these LCS is especially important in this region, since field measurements of dust there are scarce. Validation of WAS forecasts across their region of applicability would be extremely difficult if not impossible without such LCS deployments.

Spatially dense LCS networks can also be a cost-effective solution to verify outputs from fine spatial resolution AQM in urban areas. For example, LCS data were used for verifying a specific implementation of the Weather Research and Forecasting Community Multiscale Air Quality (WRF-CMAQ) model for Ho Chi Minh City, Viet Nam (Phung et al., 2020). Strong correlations between LCS and RGM data were used as evidence that similarly strong correlations between modelled $PM_{2.5}$ concentrations and LCS measurements indicated sufficient performance of the forecasting model. When using LCS to verify air quality forecasts, even qualitative verification (e.g. matching the peaks in diurnal cycles) can provide valuable insight into the performance of the AQM. LCS data can also be used to identify sources and emissions, providing improved input information needed by AQM for accurate forecasting; this will be discussed in Section 4. However, in order to provide data for quantitative forecast validation, a very high level of quality control and calibration are necessary for the LCS, which is not typically achievable in the absence of local RGM. In such a case, the RGM would be used for validation anyway. The comparison of AQM concentration output fields and LCS observations, often representing a much finer spatial scale than represented in the AQM, requires the development of upscaling methods, which are applied not only for model evaluation but also for data assimilation.

Evaluation of an air quality forecasting system not only guides its development but is also a prerequisite for the acceptance of the system by users. Only air quality forecasting systems with a proven track record of good performance in predicting air quality events may lead to mitigating action by users. Near real-time evaluation of the forecast and its display to users is a feature of many advanced air quality forecasting systems. Including LCS in these evaluation chains may help to enhance the societal impact of the air quality forecasts.

A key consideration when using LCS data to evaluate air quality forecasts is the representativeness of the LCS observations for the spatial scales, which is determined by the model resolution. The deployment of LCS networks often does not aim to maximize the spatial representativeness of the LCS observations for the surrounding area, which is an important consideration for many RGM networks (see Section 9). Hence, spatial processing of the LCS observations to average their data over an appropriate spatial domain is required before LCS can be applied for the evaluation of air quality forecasts. The reconstruction techniques discussed in Section 3 represent possible approaches to spatial smoothing of LCS network data.

Since the LCS will typically represent a totally independent data source to an air quality forecast, there is relatively low risk of common factors impacting accuracy of both the model and LCS simultaneously (although this possibility should not be ruled out). Having a thorough understanding of LCS accuracy and uncertainty and relating these to potential accuracies and uncertainties in air quality forecasts will help understand when one source or the other (or neither) is most applicable, and how best these data can be used for evaluation. Data latency is typically less of a concern for evaluation, unless rapid validation of forecasts is a priority. Instead, it is often more important to have a long-term data record with stable performance. As noted in Section 2.1, long-term performance evaluations of LCS are often lacking, so the suitability of LCS to support long-term forecasting evaluation may be limited.

8. Data quality and Disclosure

Data producers and users must understand their objectives for using LCS data in terms of how these data are expected to contribute to air quality management decision-making. Products incorporating LCS data can then be evaluated according to those objectives, ensuring that the results are relevant and useful for the intended needs. Data quality should be conducted using well defined, commonly accepted, and repeatable methods and metrics. The results of these evaluations, as well as pertinent details of the methodology used to create the data, should be disclosed in accessible, transparent ways.

Air quality data products are fundamental for assessing and managing the environmental and public health impacts associated with air pollution (Shaddick et al., 2018b). These data products are used to inform policies, risk assessment, regulations compliance, and for strategic decisions (Pinder et al., 2019). The development of different data products using a variety of data generating processes (DGP) has been discussed throughout this report. Any resulting data product requires a rigorous evaluation of its quality based on its ability to meet the pre-established objectives for which it was implemented, as discussed in Section 8.1. The data quality (i.e. accuracy and uncertainty to meet reference objectives) should be reported using common metrics, discussed in Section 8.2, each of which has advantages and limitations. Systematic disclosure and reporting of the DGP and evaluation process, as discussed in Section 8.3, is critical for users to assess the suitability of the data product for its intended application.

The air quality information ecosystem is the community of air quality data producers and users, the stakeholders who rely on them to provide insights into air quality to support action, and the ways in which these groups interact. A healthy air quality information ecosystem requires incentives for maintaining and improving the quality of data and its use. Effective communication of user needs and requirements allows data producers to hone their DGP. Disclosure of DGP methods and performance allows users to make informed decisions and provide feedback to producers. Infrastructure for storing, accessing, and analysing data facilitate interactions between all parts of this ecosystem. User scrutiny is an important incentive and force for innovation in this ecosystem, and is best facilitated by objective evaluations following standard methods and metrics which are clearly and transparently disclosed.

In this section, we focus on the data quality and disclosure of applications incorporating LCS data. This is distinct from the data quality and disclosure of LCS performance itself, which was discussed in the WMO report 2020 (WMO, 2020). However, many of the same data quality methodologies (including performance metrics), and disclosure practices can and should be applied in both cases.

8.1. Data quality Assessment Methods

Data quality assessment methods should mimic the intended use case as closely as possible. Assessment should use datasets which are representative of the intended application but independent from data used to develop or calibrate the data generating process being evaluated.

A DGP is a set of methods and procedures encompassing statistical, mathematical, and computational techniques used for processing input data to produce quantitative or qualitative outputs in service of a specific objective. For example, this might be an estimate of concentrations at a location other than those being monitored by the LCS, as discussed in Section 3, or a forecast of future concentrations based on LCS measurements of past concentrations, as discussed in Section 7. Evaluate the quality of a DGP incorporating LCS data should be guided by answering the questions, "What objectives do I intend to accomplish using this DGP? How can I measure the effectiveness of the DGP in achieving these objectives? What alternatives are available to complete these objectives without the DGP in question and its LCS inputs, and how do these compare in terms of cost-effectiveness?" While theoretical evaluations offer valuable information, evaluation approaches and associated metrics should mimic the intended use case of the DGP as closely as is feasible, using datasets which are representative of the intended application but independent of the data used for DGP development. Cross-validation, data denial experiments, and comparisons with well-established baseline approaches are the recommended techniques for evaluation of the quality of a DGP incorporating LCS data.

Here, we differentiate between two DGP assessment processes: **Internal validation** is carried out during the development phase of the DGP, and aims to (1) identify and correct errors or deficiencies at an early stage; and (2) ensure that the product is suitable for the intended use by the data producer. **Performance evaluation** is an activity usually conducted independently of the data producer (i.e. carried out by third parties and data users) and after DGP development. It aims to (1) provide an objective perspective on the utility and applicability of the DGP in real-world contexts and (2) verify that the data are fit for their intended purpose according to the needs of the stakeholders. Both internal validation and performance evaluation provide feedback for product improvement. Moreover, they help ensure that the data meet the specific needs and expectations of all members of the air quality information ecosystem. All data quality assessment activities should be transparent and reproducible, generating confidence in the results.

8.1.1. Internal validation

During internal validation, both the individual components of the DGP and its overall operation are inspected. This involves verifying the accuracy, robustness, and stability of the DGP for anticipated inputs, as well as identifying and evaluating potential limitations. This phase ensures that the DGP will function as intended before its implementation in real-world applications. It is also a useful process for:

- Understanding the advantages and disadvantages of the DGP in relation to its intended use;
- Recognizing the inherent limitations and implicit assumptions on which it is based;
- Optimizing the architecture or operational structure of the DGP;
- Selecting inputs that promote the best outputs from the DGP;
- Detecting and correcting errors to prevent biases and reduce uncertainties in outputs.

This is a continuous process throughout the development of the DGP, allowing for iterative adjustments as needed to meet user requirements. A recent example of this process can be found in Adong et al. (2022). During internal validation of a DGP incorporating LCS data, it is also necessary to consider the assessed performance of the LCS, and how this performance impacts the performance of the DGP overall. Internal validation may inform the choice of appropriate LCS technology, calibration approach, or network design to supply input data to the DGP.

8.1.2. Performance evaluation

Performance evaluation is an independent activity in which the DGP is subjected to a series of tests to assess whether it meets required performance characteristics (e.g. accuracy, sensitivity, etc.). These characteristics are determined by DGP end-users based upon the clearly defined needs and questions which stakeholders intend to answer using the outputs from the DGP (Diez et al., 2022). This performance evaluation should also consider operational constraints such as budget, spatial coverage, and project duration, as well as how stakeholder needs might alternatively be met in the absence of the DGP and associated LCS input data.

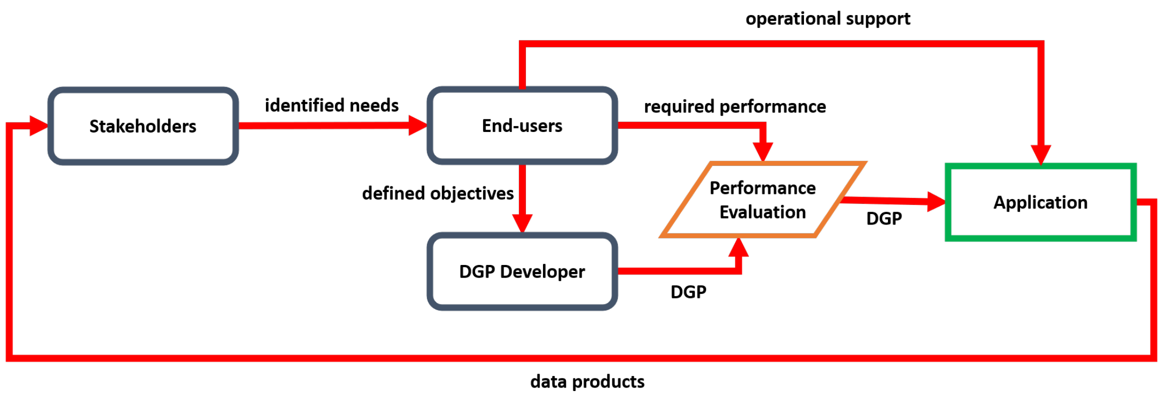

Figure 6. Schematic representation of performance evaluation. *Stakeholders can include LCS manufacturers, researchers, government, non-governmental organizations, community organizations, and other interested parties. Note that, in this diagram, the stakeholders, end-users, and DGP developers are distinct groups, but in reality there may be significant overlap or one group may take on multiple roles at different stages of the process.*

Figure 6 illustrates how performance evaluation fits into the development and deployment of a DGP. First, stakeholders identify and articulate the specific knowledge and decision-making needs that the new DGP should address. These needs may be informed by previously available DGP and input data. End-users, the technical experts who will implement the DGP, work with the stakeholders to formulate specific objectives and associated performance requirements for the DGP, including requirements for stability in performance over time or robustness under different atmospheric conditions. Next, the stakeholders or end-users contact a DGP developer or seek out an existing DGP which meets the defined objectives; in the latter case, the DGP developer would not necessarily be involved. Following any necessary DGP development and associated internal validation, the DGP is subjected to a performance evaluation. If it meets its requirements, it can be deployed by the end-users to generate data products which will be provided to the stakeholders, meeting their need. If it fails to meet these requirements, it may be improved upon through iteration, or a new DGP might be identified for performance evaluation.

Throughout this process, the stakeholders, end-users, and DGP developers must communicate and iterate with each other. Performance evaluation serves to organize, clarify, and guide refinement of the DGP to ultimately aid in the decision-making of the stakeholders. This iterative nature is fundamental for the refinement of the questions posed, the information generated, and the evaluation process itself. For end-users, a key aspect of this process is assessing the capability of the DGP to yield information pertinent to specific applications. For stakeholders, a key aspect is how well these applications and resulting data and decision support information meet their needs. For DGP developers, performance evaluation offers essential feedback, not only for fine-tuning their products and methods but also for calibrating expectations, strengthening user confidence, and potentially engaging new stakeholders with similar needs.

8.2. Global performance metrics

Global performance metrics provide valuable information when estimated accurately and conscientiously. However, the practice of condensing multidimensional characteristics into single-value statistics has limitations that are crucial to realize. This is especially relevant given that the robustness of LCS and applications involving their data is a work in progress.

In the internal validation and performance evaluation of DGP, the aim is to accurately estimate the uncertainty of the results and determine whether an intended application's objective can be achieved given these uncertainties (Diez et al., 2022). Uncertainty denotes an interval or range within which the true value of a quantity of interest is likely to be found (*Quantifying Uncertainty in Analytical Measurement, Third Edition*, 2012); this is in contrast to "error", which specifies the difference between a measurement or DGP output and this true value when it is known. DGP data quality assessment uses past assessments of error, typically summarized through a variety of performance metrics, to extrapolate the DGP uncertainty to a future application scenario.

The coefficient of determination (R^2), root mean square error (RMSE), mean absolute error (MAE), bias, slope, and intercept of linear regression are typical metrics used to describe error for many applications involving LCS data (Karagulian et al., 2019). Categorical metrics such a precision and recall are also applicable to certain DGP with discrete outputs, including many qualitative applications of LCS data. Extended details of these metrics and guidance on their use are provided in Appendix C.8.

Global performance metrics provide valuable insights and allow for easily communicating and comparing results. However, the practice of condensing multidimensional error characteristics into single-value statistics has its limitations, emphasizing certain aspects of the error while neglecting others (Chai and Draxler, 2014). Furthermore, it is often not clear how many metrics are needed to adequately characterize the error for a given application. Conversely, there is the danger that many of the reported metrics will be redundant, or that very different outputs will result in the same metric values (Tian et al., 2016). Graphical presentations such as Target Plots and Bland-Altman Plots can combine multidimensional metrics and present error patterns which might be obscured with single-value metrics, as illustrated in Figure 7.

Additional contextual information is also needed to comprehensively evaluate DGP involving LCS data. This includes details on the intended application, the inputs available to the DGP, the environment in which the evaluation was conducted, and the methodology and datasets used for the quality assessment. Such considerations are essential for DGP incorporating LCS data, since applications involving LCS data are constantly evolving and the performance of LCS themselves are often sensitive to environmental conditions.

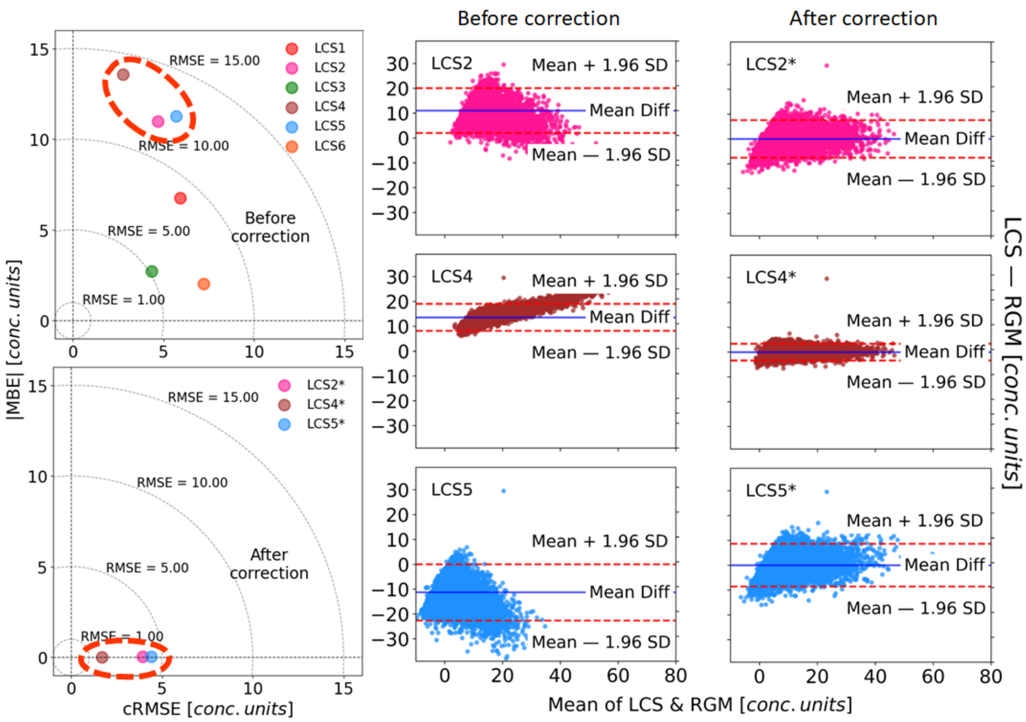

Figure 7. Example comparing various graphical approaches to presenting performance, illustrated using examples of LCS calibration. *A Target Plot for 6 LCS before a bias correction is presented in the top left and a subgroup of 3 LCS after correction is presented in the bottom left. Plots in the centre and on the right are Bland-Altman plots for these LCS before and after correction, respectively.*

It is also important to consider global performance metrics in the context of alternate approaches to addressing the need for which the DGP was created. This is especially relevant when considering DGP incorporating LCS data, since the LCS data are likely being considered to address a deficiency in an existing DGP which uses other available data sources. It must be acknowledged that no DGP or measurement, including RGM, is free from error, and so performance of the data quality assessment must be conducted in the context of known limitations so that performance metric expectations can be realistic. Finally, any metrics should be considered as indicators of potential DGP performance and not a guarantee for performance under any possible application scenario.

8.3. Disclosure, transparency, and availability of LCS-derived data products

> Providing open access to data, metadata, methods, performance, and known limitations for applications incorporating LCS data brings multiple benefits. Making this information publicly available in a transparent, standardized, and reproducible manner allows researchers and policymakers to better interpret findings, provide valuable feedback to improve performance, and update guidelines and regulations.

Throughout this report, many DGP have been presented for utilizing LCS data in combination with other air quality information to generate data products and insights relevant to public and environmental health. However, the details of these DGP or the ways in which their data products are presented (e.g. through websites, dashboards, mobile applications, etc.) can lack context, clarity, and transparency, increasing the risk of misinterpretation and confusion. Data product users should be able to find answers to questions, such as: "What methods were used to produce the data? Have these been evaluated and peer-reviewed?" And perhaps most importantly: "What are the limitations and uncertainties associated with this data product?"

Transparently providing information on the DGP – including input data sources, methodology, evaluation approach, and evaluation outcomes – promotes greater confidence and comparability of results. Detailed documentation and transparency not only facilitate third-party validation of results, but also promote collaboration and innovation in the field of air quality monitoring and analysis. In addition, this can help to answer societally relevant questions about who collects, stores, and accesses our data, and how this impacts our privacy. Active involvement of the public and impacted communities in air quality data analysis can be facilitated by data product developers, decision makers, and scientists through transparent and accessible reporting.

The following sections highlight a few challenges related to air quality data products derived from LCS data and other information, along with actions or good practices that could mitigate their effects. Understanding that air quality research is a dynamic field, new challenges and opportunities continually arise. Those making use of LCS data for air quality applications should strive for a comprehensive consideration all stakeholder concerns when addressing these challenges.

8.3.1. Navigating an ocean of information

LCS data, alongside the other air quality information sources discussed in this report, can present a dauntingly vast ocean of information, accessible in a myriad of ways, which is overwhelming and sometimes confusing for users to interpret. The effectiveness of these data depends on how they are organized, presented, and used. Data producers should specify and explicitly communicate **clear objectives** for which their data were created and published. This includes identifying the target audience and explaining how users are expected to employ these data, including specific use case examples. Clear messaging should be provided about the applicable **spatial and temporal domains and scales** of the data (e.g. do these represent annual, monthly, daily, or hourly concentrations?).

Each data product or analysis tool should be accompanied by accessible, easy-to-understand **instructions and guidance** on how to interpret and understand the information presented. Additionally, it is important to include explicit statements about limitations, such as any significant uncertainties or inherent assumptions in the models or measurement processes. This includes proscriptions for common use cases which the data product is not intended to support.

8.3.2. Illuminating "black box" data generating processes

Air quality data providers vary considerably in their approach to disclosing their DGP methods. It is common, especially among for-profit entities, for data processing to be conducted under a "black box" approach, particularly when using ML. While these methods can be beneficial for improving data quality and protecting intellectual property, they can also limit the traceability of the data. This impacts the ability of users to reproduce these methods to verify the data, undermining trust. Such lack of transparency is particularly problematic when dealing with air quality information that directly impacts public health and well-being.

The **processing levels** for LCS data, as detailed in Table 1, are designed to allow data providers to offer a measure of transparency in their methods while maintaining control over their proprietary algorithms. For DGP incorporating other external data sources, the types of input data used should be specified, and the **original sources for external input data** should be given. Describing DGP methods and performance results via **open access publication** facilitates peer review and validation of the methods used. Although open access presents its own challenges, such as the need to ensure data confidentiality, it could be a significant step towards improving transparency and trust in the data. Users should also seek out and **prioritize open providers** of air quality information which offer a greater degree of transparency in their system design and performance and in the data handling and quality assurance approaches they employ. Scientific funding entities, public organizations, non-profits, and the scientific community at large should **support open data practices** through grants, preferential collaborations, and public recognition of entities adhering to these principles. Encouraging and rewarding transparency can motivate more entities to follow these practices. **Balance** should be sought between protecting intellectual property rights and promoting transparency and reproducibility of air quality data.

When employing ML techniques in processing air quality data, use of **explainable ML** approaches to investigate the input factors contributing to specific outputs is an encouraged best practice (Adadi and Berrada, 2018). This is especially important given that the inherent complexity of ML techniques can make the results difficult to interpret. The application of ML must be accompanied by detailed documentation that explains in a clear and accessible way how these methods work and any limitations in the training data which might impact generalizability.

8.3.3. Quantifying and communicating uncertainty

As discussed throughout this report, the concept of uncertainty plays a crucial role in appropriately making use of LCS data in many applications. However, we often encounter data that are presented without a statement of uncertainty, either qualitative or quantitative. This is problematic when discrepancies arise between different data products, such as when making comparisons between AQM outputs and RGM or LCS measurements, leading to confusion among users about which data source is most appropriate for their use case. Such confusion can also lead to erroneous decisions in public policy, eroding public trust in air quality data and the decisions based on them.

Data providers should make **quantifying uncertainty** a goal for all their products, using the data quality assessment methods and performance metrics discussed in Sections 8.1 and 8.2 as a starting point. Data providers should clearly and transparently communicate this uncertainty to data users. This will allow users to adjust their expectations and make better informed decisions on appropriate applications of the data. Data providers, educational and research institutions, and governments should work together to develop standardized, plain-language methods of **communicating uncertainty** in air quality information to the public. Akin to a basic understanding of weather forecasting uncertainty, some level of uncertainty in any air quality information should be expected by end-users; methods by which weather forecast uncertainty is communicated can serve as a starting point for this effort. Clear communication of uncertainty can improve the public's capacity for response and decision-making based on uncertain air quality data, facilitating better outcomes.

8.3.4. Communication and open data

Prompt and transparent communication of air quality data is fundamental to maintaining public trust. Furthermore, discrepancies between official information (e.g. from RGM) and unofficial sources (e.g. forecast applications, data provided by aggregators, real-time air quality maps, etc.) undermine trust when the reasons for these discrepancies are not effectively communicated by the data providers. This situation has sometimes motivated the development of community LCS networks as a response to a perceived lack of transparency by government entities (e.g. Labzovskii et al., 2023). If data communication is not carried out properly, any measurement or data product, even those from RGM, can be perceived as unreliable or simply as "noise" without significant value. This can further confuse the air quality situation and lead to disillusionment among those with genuine concerns for their community health and well-being.

Official air quality agencies should **proactively develop effective communication strategies**, creating clear guides on the inclusion of LCS data in public air quality information, its limitations, and the expected use of the information. NGO and universities could contribute significantly to the development and supervision of these guides, helping to ensure that the information provided is accessible and understandable to the public. Air quality data communication can also be improved through **active local community involvement** in the development and maintenance of monitoring networks, and especially LCS networks. Here, scientists and local educational institutions can offer technical support and training to community members, increasing their technical capacity and fostering greater accountability for air quality decision-making; see also the discussion in Section 10.3.3. Mechanisms should be established to ensure traceability of the final data product (e.g. an air quality mobile application) to the **original data sources** used (e.g. RGM and/or LCS networks) that may have been initially collected by data aggregators.

8.3.5. Balancing data privacy with public benefit

LCS networks, especially those involved with epidemiological studies or using wearable sensors as discussed in Section 6, carry a risk that their geolocated data could be traced to specific individuals or population subgroups. Such information might be used for targeted marketing without consent, or identifying people based on their health. Additionally, there could be discrimination against those living in areas with higher levels of pollution, affecting their access to insurance and employment due to perceived health risks. Systems involving such data need to be designed to help marginalized communities take charge of understanding and mitigating their local air quality situation while guarding against further disempowerment and exploitation of these communities (Zhang et al., 2021). Those deploying LCS networks or developing data products using their information should **involve the communities** where these data are being collected and who will most likely use the outputs. These communities can provide guidance for how their interests can be protected and how negative outcomes might be avoided. Principles of **minimization** should be followed, where only strictly necessary personal data are collected. **Anonymization** should be implemented in any public data product, and **rigorous controls** should be put in place to prevent unauthorized access to non-anonymized data. Finally, participants should be clearly informed about the nature of the personal information being collected, how their data will be used, and the measures taken to protect their privacy. This is achieved through an **informed consent** process, where participants voluntarily agree to participate in the study, knowing all relevant aspects related to their personal data.

9. Air Quality Monitoring Network Design

> Air quality monitoring network design should be guided by a clear goal and priorities for the monitoring, including the role played by LCS in relation to other available data sources. Where possible, LCS should supplement existing data sources, filling identified gaps.

Air quality monitoring network design includes selecting appropriate measurement device types, identifying sites, and creating a data management and quality assurance plan. When designing a monitoring network, or planning to expand an existing network, design decisions should be guided by specific objectives or use cases to be addressed. This section begins with some common objectives and use cases in Section 9.1, followed by typical considerations for network design in Section 9.2 (as such as the availability of supplementary data sources related to air quality and logistical considerations, limitations or siting selection); and a discussion of in situ network calibration in Section 9.3. While the emphasis of this section is on the design of networks incorporating fixed monitoring sites, some additional considerations for mobile monitoring are discussed in Section 9.4. The overall approach to network design and several of the considerations discussed in this section are summarized in Figure 8.

Network design is often imperfect due to limitations on siting access, power supply, data connectivity, and safety considerations. Advanced planning, written agreements, discussions on liability, and jurisdictional considerations are all essential to successful network deployment. A robust monitoring network incorporating LCS with other information sources requires significant infrastructure to sustain it, including not just physical and data infrastructure, but also local expertise and institutions for long-term support. These considerations are discussed in the next Section 10.

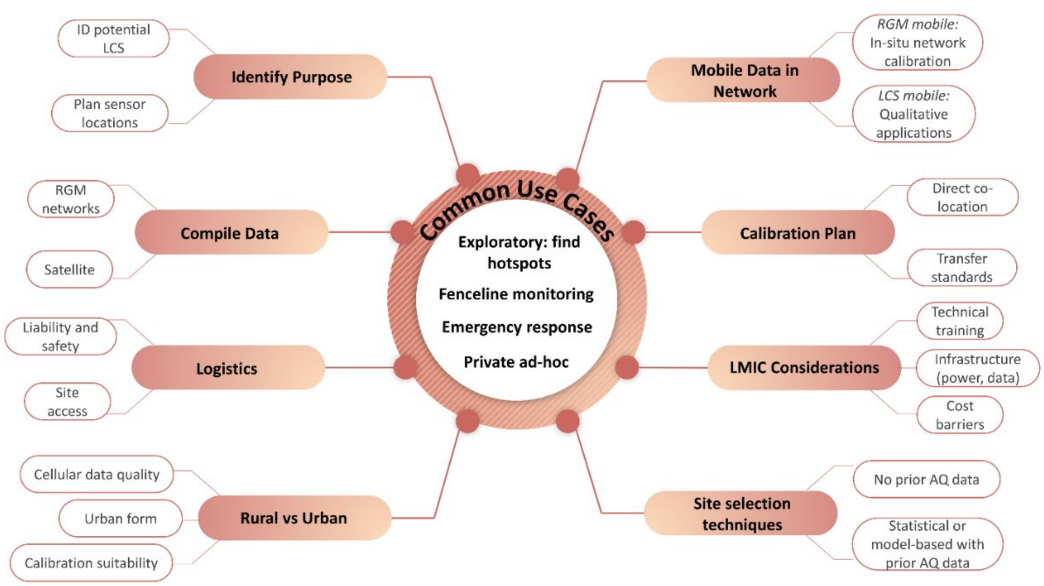

Figure 8. A summary of the sensor network design considerations addressed in this section. *Central to the network design is identifying an intended use case (see Section 9.1) which is define the purpose of the network.*

9.1. Common use cases for LCS network design

This section presents some common use cases for which a network of LCS might be deployed. In general, network design should be guided by the intended primary use case. If no use case has been explicitly identified, an exploratory analysis use case is often implicitly assumed. Note that these do not represent all the potential use cases for which a LCS network might be deployed. Further examples are provided in Appendix C.9.1.

9.1.1. Pilot deployments for exploratory analysis

LCS, along with satellites and mobile monitoring, can help identify potential hotspots for increased monitoring or verify the representativeness of existing or proposed networks. Prior information, including any reference grade monitor data, should be integrated in such an exploratory analysis. It is best to focus pilot deployments in a specific area, allowing intercomparison of nearby LCS for localized insight.

Limited prior information on expected air quality in a region may necessitate a pilot deployment for exploratory analysis prior to the establishment of a more permanent monitoring network. A temporary network can also help to assess the operational feasibility of a proposed network design and provide preliminary data while a more permanent network of LCS and/or RGM is being established. The relatively low capital cost and smaller logistical footprint of LCS compared to RGM make them attractive for exploratory monitoring. However, there can still be significant costs even for temporary deployments. Mobile monitoring and/or the use of satellite remote sensing data should also be considered during such an exploratory phase.

Analysis of data from exploratory LCS networks is generally focused on identifying hotspots for further investigation and monitoring. This requires, first of all, a definition of what constitutes a “hotspot”, which will guide the analysis of the data to be collected. This includes developing an appropriate LCS calibration strategy to ensure sufficient data quality to robustly detect the defined hotspots (deSouza et al., 2022). LCS networks can also assess if the current monitoring strategy is adequately characterizing the hotspots within the given region (e.g. Caubel et al., 2019; Okure et al., 2022). Typically, data analysis from exploratory LCS networks will involve applying the reconstruction and source identification techniques discussed in Sections 3 and 4.

Hotspot identifications can be influenced by the LCS calibration strategy and the definition of hotspots.

Satellite remote sensing data can also provide guidance in identifying pollution hotspots and designing new networks. However, it is necessary to verify whether the pollution hotspots identified by remote sensing align with the spatial and temporal patterns at ground-level. For instance, ground-level CO hotspots measured by LCS rarely match those observed by satellites, necessitating further analysis to better relate the column and surface CO concentrations (Bi et al., 2022c). In contrast, local NO_2 hotspots tend to be well captured by satellite remote sensing data (Novotny et al., 2011; Kerr et al., 2021). Section 3.3 provides additional guidelines on integrating LCS and satellite data for air quality reconstruction. Mobile RGM have also been used in tandem with LCS networks to help identify hotspots (Zhang, 2023b); Section 9.4 will discuss mobile monitoring.

Effective collaboration with local government and community groups, especially in resource-constrained settings and LMIC, can help use local knowledge to prioritize resources for exploratory LCS monitoring. The design of a spatially-focused monitoring campaign, using both mobile and stationary instruments with sufficient support for a sustained campaign across several months, can help ensure relevant exploratory data are collected. While the temptation might exist to divide LCS deployments between different cities or regions for maximum spatial coverage, a spatially-constrained intensive effort is more likely to yield actionable data, which will strengthen the case for future expanded campaigns (Okure et al., 2022).

> Collaboration with local government and community groups, especially in resource-constrained settings and low- and medium-incoming countries, is important for prioritizing resources for exploratory monitoring.

9.1.2. Supplemental local and fenceline monitoring

> LCS can be used for cost-effective “fenceline monitoring” around known sources.

LCS can provide supplemental information in environments already equipped with RGM networks. This information can improve the identification and quantification of local sources, using methods discussed in Section 4. It can also support localized health impact or environmental justice studies, as discussed in Sections 5 and 6. The inherent advantage of LCS here is their ease of deployment and low capital cost, together with the fact that precision usually outweighs absolute accuracy in these applications. For example, LCS used for fenceline monitoring of known sources may only need to detect unusually high concentrations; these detections can then trigger warning systems, response actions, or the deployment of more sophisticated instrumentation to investigate the detected anomalies (MacDonald et al., 2022; Riddick et al., 2022; Roy et al., 2023).

9.1.3. Networks for emergency response or time-sensitive applications

> LCS can be deployed temporarily in response to transitory or emergency situations.

Because of their portability and low power demand (often capable of solar-powered operation), LCS can be temporarily deployed in response to transitory or emergency situations such as hurricanes (Subramanian et al., 2018), volcanic eruptions (Crawford et al., 2021), wildfires (Melo et al., 2020; Nguyen et al., 2021), or industrial accidents (Liu et al., 2022). Such LCS networks can characterize emissions and estimate population exposure during and in the immediate aftermath of extreme events, as they can be deployed relatively quickly and in regions with limited or damaged infrastructure.

9.1.4. Ad-hoc networks deployed by private individuals

> Incentives can be used to guide and coordinate LCS deployments by individuals and community groups, promoting coherent networks that ultimately provide the most socially beneficial data.

Since LCS systems are widely available for purchase by private individuals, many individuals deploy LCS for their own purposes, leading to the development of ad-hoc LCS networks. Analysis of product reviews has indicated that private LCS purchasers are typically interested in applications such as tracking wildfire smoke, managing their own health conditions (including allergies), evaluating known or suspected sources in their community, and raising awareness about air quality (deSouza, 2022). Ad-hoc networks which have achieved extensive spatial coverage and a relatively high density will be attractive to researchers seeking to answer questions with already existing datasets. However, when analysed objectively, such an ad-hoc network may feature redundant deployments and be sub-optimal, from the point of view of a user with a specific application in mind, e.g. for environmental justice investigations, as discussed in Section 5.2. For example, a study of $PM_{2.5}$ LCS deployments in California, USA, found an inverse relationship between annual average $PM_{2.5}$ concentrations and LCS deployment density; thus, an analysis using this dataset would tend to underestimate the regional average $PM_{2.5}$ concentration (deSouza and Kinney, 2021). Furthermore, if data from ad-hoc networks are not publicly accessible, or if inaccurate or inadequate metadata about the LCS are available (e.g. a site labelled as being outdoors when the sensor is in fact deployed indoors), the data may not be usable by others.

If ad-hoc LCS network data are accessible and usable, they can support specific applications. For example, a more representative subset of the network may need to be selected for analysis (Geng et al., 2018; Bi et al., 2022a; Kim et al., 2023). Ad-hoc networks can also act as exploratory networks and provide a real-world test case for alternative network design strategies. If ad-hoc networks are to be "crowdsourced" to support specific air quality monitoring objectives, educational campaigns and/or financial incentives may be useful mechanisms to encourage the expansion of the ad-hoc LCS networks to meet the desired goal. These educational activities and incentives should also include support for accurate metadata reporting, since this is critical to the usability of the data. Mechanisms for verifying user-supplied metadata should also be considered.

9.2. Considerations and methods for LCS network design

There are three key considerations for LCS network design, summarized in Section 9.2.1: (1) establishing the purpose of the network including the required degree of accuracy; (2) surveying complementary data sources and prior knowledge to inform the network design; and (3) identifying and addressing logistical considerations. Generally applicable network design approaches not requiring prior air quality information are presented in Section 9.2.2, and statistical and model-based approaches incorporating prior air quality information are presented in Section 9.2.3. Additional locally relevant considerations are discussed in Section 9.2.4. Case studies for how these considerations have been addressed in practice are presented in Section 9.2.5.

9.2.1. Key considerations

> Understanding the purpose of the LCS network is critical to guiding the design. Compilation of prior available air quality data sources should inform the design. Logistical challenges should be identified and addressed in the design phase.

9.2.1.1 Purpose of the network

Before beginning LCS network design, local pollutants of concern should be identified and a review of available LCS technologies should be conducted. This review should assess the performance characteristics of the candidate LCS technologies (e.g. accuracy, precision, selectivity) relative to the network goals. This assessment should initially be based on published results from prior applications, as assessed by independent organizations (i.e. not the manufacturers themselves). When candidate LCS have been selected, testing should be done in an environment which as closely as possible mimics the intended deployment. Applicable testing methods are discussed at length in prior WMO LCS publications (WMO, 2020).

The purpose of the network, along with the technical capabilities of the chosen monitoring technology, will guide the choice of data analysis techniques alongside the network design. For example, when using LCS to support interpolation techniques (Section 3.1), the network design will require a specific spatial coverage and density, i.e. inversely proportional to the representative length scale of the pollutant of interest. If an LUR approach (Section 3.2) will better support the intended application, the network must cover different land use and socioeconomic characteristics to improve statistical power. If the network will support an environmental justice investigation (Section 5), it is important to adopt an intentional network design strategy which can offset the tendency for over-representation of ad-hoc LCS deployments in wealthier and urban areas (deSouza and Kinney, 2021; Mullen et al., 2022; Yi Sun et al., 2022). Finally, the ability of LCS to be readily re-deployed makes them attractive for temporary objectives, e.g. evaluating the impact of a planned mitigation measure by comparing pre- and post-mitigation monitoring data.

9.2.1.2 Compilation of data sources

Air quality network design should consider existing information, both from previous or ongoing monitoring efforts, as well as from external information sources (e.g. satellite remote sensing data) which will be available to supplement the LCS network. The role of RGM data in particular should be emphasized due to its unique ability to provide localized calibration and verification information for the LCS. Determining an appropriate mixture between RGM and LCS within the network will depend on the purpose of the network and the resources available. Plans for how the RGM will be used for calibration and/or verification of LCS data should also be created as part of this network design. Such calibration approaches are further discussed in Section 9.3.

Existing air quality data can support LCS network design as discussed in Section 9.2.3. Well established characteristic length scales of atmospheric mixing and atmospheric lifetimes of constituents can help guide decisions about appropriate spacing and data collection frequency.

9.2.1.3 Logistics

Practical considerations are always a factor in LCS network design. While often having a smaller "footprint" than RGM, host sites must still be obtained for LCS. In many cases, LCS site hosting is performed on a voluntary basis. This may lead to self-selection and unintentional bias in LCS network representativity, which must be guarded against especially for exposure studies and environmental justice applications. Additionally, there are often barriers to deployment based on property ownership, jurisdiction, and safety or liability concerns. This might also bias the LCS network towards areas where these concerns are more easily addressed (Ismagilova et al., 2022).

Network design should also include a data management and quality assurance plan tailored to the intended application, detailing how LCS performance will be verified during deployment; techniques for achieving this are discussed in Section 9.3. Furthermore, there must be a plan for how malfunctioning LCS will be identified and repaired or replaced, and how defective LCS will be safely disposed of, as these can become a source of electronic waste. Consideration must also be made of the computing requirements for any calibration algorithms to be applied in near real-time (Motlagh et al., 2020). Additional concerns related to power requirements, data connectivity, and other infrastructure needed to support LCS networks are discussed in the next Section 10.

9.2.2. Approaches not requiring prior air quality information

LCS locations should be representative of the attributes of their region. In the absence of prior air quality information in an area, population distribution or land use information might be considered as proxies to guide network design.

In the absence of prior air quality information, attributes of the region in question and its population can be used to develop an initial LCS monitoring network design. These attributes might include population density, socioeconomic characteristics of the population, roadway density and traffic patterns, known industrial sources, or locations of hospitals, schools, and nurseries where vulnerable populations might congregate; these might be the same attributes considered when developing a LUR model (see Section 3.2). A strategy can then be employed to allocate LCS to locations which best represent the range of these attributes across the domain and meet the monitoring network objectives (Lerner et al., 2019; Sun et al., 2019; Bi et al., 2022a; Kim et al., 2023). Examples of applicable strategies are provided in Appendix C.9.2.

LCS networks have the advantage of facilitating more deployments compared to RGM networks, increasing the likelihood of a LCS being near to a location of interest. However, without careful network design, even a dense LCS network may over- or underrepresent certain areas, which can lead to systematic biases in interpretation of data form the network (Considine et al., 2023).

9.2.3. Approaches utilizing prior air quality information

Prior knowledge of air quality, especially its variability, can guide network design. Such prior knowledge may come from existing networks, AQM, or satellite data. Statistical techniques (coverage maximization, LUR, ML) or inverse modeling can use this prior knowledge to support network design.

Most LCS network design approaches in situations where prior air quality data are available rely on statistical techniques and/or inverse atmospheric modelling; details of these techniques are provided in Appendix C.9.3. These approaches might require a pre-existing LUR model (Kanaroglou et al., 2005; Hsieh et al., 2015), analysis of data from an existing or exploratory network deployment (Herrera, 2022; Jain et al., 2024), or high-resolution modelling simulations and/or satellite-derived estimates (Araki et al., 2015; Kelp et al., 2022, 2023). Inverse modelling (see Section 4.3) or reconstruction approaches such as kriging (see Section 3.1) also provide posterior uncertainty information which can support improving network design. Many of these techniques allow for explicit trade-offs between network density and measurement accuracy to be analysed and compared; this can help to determine a suitable strategy for integrating both RGM and LCS into the network design if costs are also taken into account (Turner et al., 2016).

9.2.4. Local and regional considerations for LCS network design

Certain environments impose additional stress on LCS technologies, such as low relative humidity for electrochemical detectors and high particulate loading for PM detectors. More frequent recalibration and additional redundant LCS may be required due to faster LCS aging in these environments. In many LMIC, limited power and data communications infrastructure, import restrictions on LCS technology and lack of technical instruction and support for LCS network managers present barriers to effective LCS network deployment as it is discussed in the next Section 10. Furthermore, despite their relatively low cost compared to RGM, certain LCS may still be too expensive to allow for extensive deployments in LMIC.

Urban street canyon profiles and uncertainty in the boundary layer conditions near buildings should inform LCS network design in dense urban areas (Frederickson et al., 2023; Schmitz et al., 2023). Finally, while LCS present an opportunity to cost-effectively expand air quality monitoring in rural areas, existing LCS calibrations developed for urban areas may not generalize due to the different sources and pollutant mixes.

9.2.5. Case studies in LCS network design

Here we present several practical examples of how the considerations discussed in this section have led to specific decisions in real-world LCS network designs.

9.2.5.1 Europe: United Kingdom

In London, United Kingdom, the Breathe London pilot programme involved the deployment of a network of over 100 NO_2 LCS over 2 years. This exploratory network helped to characterize inter-annual, diurnal, and weekday/weekend variability, as well as identify intermittent pollution events. Results of this exploratory network emphasized the importance of repeated and long-term co-locations with available RGM to assess the impact of environmental factors on long-term LCS performance and data quality (Peters et al., 2022). The Breathe London LCS network has since expanded to over 420 LCS measuring $PM_{2.5}$ and NO_2, including 60 LCS placed in response to community requests through the Breathe London Community Programme. The network also includes 19 continuous LCS co-locations with RGM at 17 sites supporting continuous calibration, as recommended by the pilot deployment results. This illustrates the benefits of combining existing RGM networks with LCS to vastly expand near real-time local monitoring using well calibrated and characterized LCS (Mead, n.d.).

9.2.5.2 Africa: Nigeria and Uganda

The World Bank in conjunction with the Lagos State Environmental Protection Agency and with funding support from the Pollution Management and Environmental Health Multi-Donor Trust Fund used an LCS network for long-term observations of air quality in Lagos, Nigeria (Akpokodje et al., 2022). Observations from LCS and RGM at six sites across the city provided data for initial health and economic impact assessments of air quality, as well as for evaluation of air quality models. The study recommended expanding the network by 8 to 12 sites, with a focus on assessing the impacts of ports, traffic, and industrial activity by using paired upwind and downwind sites.

The AirQo network in Uganda has been locally designed specifically for operation in resource-constrained environments, taking limitations on power and communications infrastructure as well as environmental stressors on the sensing technology into account. This local development has provided opportunities for technical capacity-building, and facilitated sensor deployment to other parts of Sub-Saharan Africa with similar constraints. The AirQo network combines fixed and mobile LCS with a locally developed data management and analysis platform. LCS deployments are optimized using clustering of parish-level characteristics such as population density, household density, waste management practices, vegetation cover, roadway length, and dominant fuel types to allocate sensors and maintain network representativity within the deployment area (Bainomugisha et al., 2023).

9.2.5.3 Asia: Kazakhstan, Kyrgyzstan, Uzbekistan and Tajikistan

At a recent meeting of the Air Quality Central Asia Dialogue Platform discussing air quality monitoring activities in central Asian countries (Kazakhstan, Kyrgyzstan, Uzbekistan, Tajikistan), recommendations were developed regarding a mechanism whereby LCS data might be included within official air quality monitoring databases and analysis activities, provided the LCS deployments meet with recommended requirements. These requirements include having at least one site representing background conditions to allow local emissions to be more easily distinguished, achieving a minimum network density based on population size, and a combination of deployments near roadways, major industrial facilities, and government buildings (to help motivate air quality awareness). Further developments in Bishkek, Kyrgyzstan aim to augment existing fixed-location LCS and RGM with mobile LCS to better understand local air pollution.

9.2.5.4 Americas: Mexico

In Mexico, the objective of the VER-PM2.5 (Variación Espacial Regional de $PM_{2.5}$) network is to provide information on the regional spatial variations of $PM_{2.5}$ and the exchange of plumes between different urban centres, and to evaluate the spatial representativeness of the existing RGM network to support siting new RGM in critical areas. The network currently has 50 sites and will expand to 150 sites across states surrounding Mexico City, covering not only the main urban centres but also non-urbanized areas. This involves installation of LCS at all regional RGM sites and the use of portable RGM to calibrate LCS in rural areas. LCS sites are selected following the same criteria established for RGM sites to allow better interoperability of the datasets.

9.3. Opportunities for in situ calibration of LCS

> In-situ calibration in networks combining LCS with reference grade monitors is a promising approach to maintain data quality, but often requires assumptions on spatial similarities in atmospheric composition under certain conditions which can be difficult to verify.

Although best practices call for LCS performance to be verified via co-location with RGM, there is also interest in assessing the performance of LCS in situ as they are deployed in the field, to reduce the logistical burdens and network down-time associated with co-location. Furthermore, in situ calibration might also be carried out to compensate for LCS aging over time.

Assumptions of spatially homogenous pollutant concentrations under specific conditions, e.g. at night, can allow in-field calibration of LCS networks by assuming that all LCS (and any RGM) in the region are measuring the same background conditions at the same time (Broday and the Citi-Sense Project Collaborators, 2017; Maag et al., 2018; Wang et al., 2020b; Hofman et al., 2022b). However, these homogeneity assumptions may be difficult to verify. Multipollutant LCS can similarly be calibrated using assumptions of homogeneity in vehicle emission factors and concentrations of pollutants with typically low spatial variability, but again, these are difficult to verify in practice (Kim et al., 2018).

Permanent co-location involves one or more LCS being continuously co-located with RGM, while other LCS of the same type are deployed. Readings of the co-located LCS can be continuously re-calibrated to match the RGM, and these same calibrations can be extended to the rest of the LCS network (Maag et al., 2018; Daepp et al., 2022; Montgomery et al., 2023). With multiple co-location sites, a spatially varying calibration can be created either based on distance to the co-location site (Zheng et al., 2018; Chu et al., 2020; Bi et al., 2020b) or on similarity of land use characteristics (Miskell et al., 2018; Considine et al., 2021). This is a promising approach where RGM are present but might suffer if the environmental conditions and/or pollutant mixtures at the RGM sites are not representative of the rest of the network. While this is a concern for all calibrations based on data collected at limited co-location sites, it is especially acute if one relies on a single continuous co-location site to develop and update the calibrations. Combining available RGM data with modelling and satellite remote sensing information to establish a prior estimate to which LCS can be calibrated on a regional basis is also a possible approach (Malings et al., 2021). Additional details and case studies of in situ calibration are presented in Appendix C.9.4.

9.4. Special considerations for mobile networks

LCS deployments on fleet vehicles can vastly expand the coverage of mobile monitoring. However, verifying calibrations of mobile LCS is especially challenging.

Here we mention a few special considerations for using LCS as part of mobile monitoring networks. If appropriate equipment exists, mobile RGM can support in situ LCS data quality verification or calibration (Cui et al., 2021); however, access to RGM capable of both mobility and reliable operation is even more rare on a global scale than access to stationary RGM.

Compared to RGM, LCS can more readily be deployed on existing vehicles, especially fleet vehicles such as buses or taxis. Mobile monitoring using fixed routes, such as with buses, can support consistently repeated measurements allowing for robust statistics (Wei et al., 2021; deSouza et al., 2023c). Monitoring with vehicles using random routes, such as taxis, can increase spatial coverage (Van Den Bossche et al., 2016; Yuxi Sun et al., 2022; Hofman et al., 2023). Deploying LCS on airborne platforms is also a promising direction for mobile monitoring, including the capability for obtaining vertical air quality gradient profiles (Sun et al., 2023).

Calibration performance of mobile LCS is typically lower than for stationary LCS, making mobile LCS typically better suited for qualitative assessments of relative air quality (deSouza et al., 2023c). More quantitative analysis requires strict LCS calibration and validation strategies and robust data analysis combining many passes of the same locations (Hofman et al., 2023). Mobile LCS can be re-calibrated using opportunistic or scheduled close passes of stationary RGM (Fu et al., 2017; Hassani et al., 2023a), or passes with other mobile LCS which have been more recently calibrated (Kizel et al., 2018).

A recent report of the European RI-URBANS project provides an overview of fixed and mobile sampling strategies for an improved understanding of the spatial and temporal variability of air quality, with mobile sampling providing more complete spatial information and fixed sites conveying more complete temporal information. With proper calibration, LCS can play a role in increasing the spatial density of fixed site monitoring while also providing high temporal resolution and coverage. Such a strategy also allows for more coincident measurements from the fixed and mobile networks, resulting in a more extensive dataset for intercomparison and mutual calibration. Additional details and case studies for mobile monitoring are presented in Appendix C.9.5.

10. Air Quality Monitoring Network Operations: Infrastructure Needs

Setting up an LCS network requires not only procuring and deploying LCS hardware, but also the physical and cyber infrastructure and the technical personnel required to keep it running. Turning monitoring data into action also requires dedicated personnel and funding, as well as public and institutional support. Coordination with existing organizations and institutions on the ground is key to establishing this support. Access to sustained funding is necessary to support all these aspects and ensure the longevity and effectiveness of LCS networks.

All the forms of LCS data application and associated monitoring networks mentioned in this document demand supporting infrastructure of one kind or another to establish and sustain them for operational purposes. **Physical infrastructure** is needed to support the deployment of LCS or other monitoring systems. **Cyber infrastructure** is needed to support the collection, transmission, storage, analysis, and dissemination of data and insights from multiple information sources. Both physical and cyber infrastructure require trained and motivated personnel with appropriate technical capacities, who must be supplied by appropriate systems for **capacity-building** and be enabled to share best practices among the worldwide community of their peer practitioners. Finally, the above types of infrastructure require **financial and institutional support** to ensure their longevity and appropriate integration into larger environmental management approaches, such that the data and insights gathered can be translated into management plans, legislation, or policy implementations (Bartonova et al., 2019).

This section outlines the infrastructure needs for the maintenance of LCS networks and for integrating them within an air quality monitoring and management system. Many of the advantages of LCS are realized through large network deployments. However, even a small number of LCS may be placed in locations that are data-poor and so can provide important information about air quality that would otherwise not be known. In some regions of the world, infrastructure needed to support LCS applications might already be well established. Unfortunately, in many regions, significant infrastructure deficiencies still exist.

10.1. Physical Infrastructure

Physical infrastructure includes physical security structures at the LCS placement site, communication systems, and power supply. Coordination with existing organizations and institutions on the ground can help ensure the availability of this infrastructure.

Physical infrastructure consists of the measurement devices themselves, e.g. the LCS, as well as their siting locations. Some themes will be outlined here; the reader is also referred to Chapter 3.5 of the USA EPA's Enhanced Air Sensor Guidebook (Clements et al., 2022) and Part 4 of the Guidebook for Developing a Community Air Monitoring Network (Wong et al., 2018b).

10.1.1. Physical accessibility

LCS and RGM need to be physically accessible to allow for servicing and maintenance once deployed. Stable and secure structures are needed: stable enough to withstand environmental conditions and secure enough to allow the systems to be deployed and operated with a minimal threat of damage or vandalism. Because of their size, LCS typically offer the ease of placement on existing vertical structures like lamp posts, traffic lights, or utility poles. The loss associated with damage or destruction of an individual LCS is also relatively low compared to a RGM, making it less risky to deploy LCS in many situations. Climate-controlled shelters are typically required for RGM, while many LCS may be compact and robust enough to not warrant additional shelters. These shelters, the physical mounting of the monitor, and its immediate surroundings should not obstruct or interfere with measurements. Permission and access requirements for any physical location should be determined early in the planning stage; see also Section 10.1.3.

10.1.2. External Infrastructure

LCS may also require external infrastructure to supply power continuously, i.e. an electricity grid, as well as the physical infrastructure needed to support communication and data transmission, i.e. an existing cellular or wireless internet network (Thibault et al., 2023). Wireless network connectivity is often difficult to predict in advance and might be unreliable, requiring scouting of intended deployment areas and possibly an investment in backup communication strategies. LCS are often better able to operate independently of external power sources compared to RGM, i.e. some LCS are solar powered, but available sunlight might still be limited. Data storage also has physical aspects. When setting up an LCS network, consider the hardware required for data storage, which in turn might need its own climate control and security in a separate location. Data storage will be discussed further in Section 10.2.

10.1.3. Working with anchor points

Where local resources are limited, external groups such as international organizations, NGO, diplomatic offices, or the private sector can supply LCS or RGM to serve as “anchor points” of networks. RGM deployed at US Embassies and Consulates sometimes serve this function in various LMIC. This offloads some of the infrastructure requirements onto the external group maintaining the physical site. However, this situation might pose problems because of restrictions on physical access, e.g. stricter access rules in diplomatic facilities. This may be an additional complication for planning the siting of the devices, which may require significant efforts to reconcile, especially when formal agreements need to be in place. In the case of collaboratively operated RGM or LCS networks, divergent operational priorities between the parties must also be considered, e.g. supporting the health and safety of personnel on the premises versus those wishing to make use of the data for more public applications.

10.1.4. Procurement

Customs regulations in each country should be considered when planning the importation of LCS and/or RGM. Import regulations might incur additional time and cost. In some cases, it might be more prudent to assemble a LCS in-country, but this comes with its own risks, technical challenges, and infrastructure and supply chain needs. These will be highly dependent on local conditions, and so no general guidance can be given on how to approach procurement.

10.2. Cyber Infrastructure

> *Cyber infrastructure* includes hardware and software for data transmission, storage, management, engineering, analysis, visualization, and dissemination. Ideal cyber infrastructure should enable frictionless interoperability of air quality data from multiple sources. This can be facilitated with freely accessible archives for LCS and other relevant data which use interoperable standards for data and metadata and feed into accessible, modular, adaptable tools for analysis and visualization.

Cyber infrastructure includes the computational processing, storage, and software needed to manage and analyse air quality data from multiple sources, including LCS. The concept of a digitally enabled environment, which couples physical sensors with digital infrastructure for data reporting, management, and analysis, all supporting the management of the environment, is inherently applicable to air quality monitoring broadly and monitoring with LCS specifically (Mead et al., 2022). Indeed, several LCS manufacturers now include data management and analysis platforms alongside their sensors as product offerings in a "sensing as a service" business model. Some cyber infrastructure themes will be discussed here; for further discussion, the reader is also referred to Part 5 of the Guidebook for Developing a Community Air Monitoring Network.

10.2.1. Data transmission, and storage

The measurements taken by LCS must first be transferred to a data repository in order to be useful. Some LCS do not have the capability to remotely transmit data from the device, thus requiring data to periodically be downloaded in a USB memory stick, SD card, or similar offline storage device. This entails labor time and continued physical accessibility of the device. Other LCS can transmit their data via cellular or wireless networks. Remotely deployed sensors may require remote data transmission when constant human access is not feasible. The choice of LCS may then depend on ease of accessibility for data download and/or the presence of existing cellular or wireless internet (Wi-Fi) connectivity (see Section 10.1.2).

LCS tend to report measurements at higher frequencies than other systems (e.g. filter-based PM sampling or canister sampling for gases). For supporting a network with many LCS for the duration of a project, or in perpetuity, the scalability of the data storage and associated costs (both monetary and environmental) must be considered. Storage requirements for LCS data collected from a modestly sized network (tens of sensors) can usually be managed by personal computers. However, storage needs will increase as network size and deployment duration increase. This might entail large-scale data storage hardware and servers which might require their own physical location, climate control and security facilities. For good data storage practice, regular back-ups and redundancies should be employed, also requiring additional data storage.

Cloud storage services may be convenient and cost-effective for storing LCS network data by offloading some processing and storage requirements. However, these require paying storage and service fees, which will grow as the network expands and are difficult to plan for in advance, as they are subject to change by the cloud service providers. Offloading data to an external server might also present privacy and data ownership concerns.

10.2.2. Data engineering and management

Data management systems are necessary to systematically organize data collected by LCS and from other relevant data sources and allow them to be efficiently queried and integrated. Data management and engineering, including aggregation and harmonization of data, is separate from and can be just as time- and resource-intensive as data analysis (see Section 10.2.4). Data management and engineering should be treated as an integral part of an LCS network design (see Section 9), and either carried out internally by the network manager or contracted out. Several LCS manufacturers now include data management and analysis services alongside their sensors as product offerings. A network of LCS from different manufacturers, measuring different pollutants, and with different technical requirements may require a customized solution supported by software developers and computer scientists. Data aggregators like OpenAQ or the UNEP GEMS/Air and ODMS portals can also facilitate data management and integration with other data sources.

LCS data management requires accurate and detailed metadata, i.e. information about key properties of the data. This includes information about site locations, purpose, and characteristics (e.g. street-level, ambient air, indoors, proximity to pollution sources, placement height). Metadata also includes information about the measurement technique, sampling frequency, LCS calibration and quality control processes, firmware or version information associated with the data collection and processing, and the estimated quality of the resulting data. Metadata should also point to reports and publications describing the calibration process and any prior assessments of accuracy. These metadata should be preserved when data are collected by data aggregators or incorporated into national data repositories. Adequate metadata supports FAIR (Findable, Accessible, Interoperable, and Reusable) data principles, contributing to a more open and accessible data ecosystem. Conversely, inadequate metadata can lead to misinterpretations or the underutilization of LCS data. The integration of LCS data with other datasets and systems can also be promoted through harmonization and standardization of metadata formats.

10.2.3. Data accessibility, interoperability, and standards

Use of widely accepted formats for archiving and presenting data are necessary to support FAIR data principles. Several open-source data standards are available for continuous monitoring information, such as is provided by LCS. Common standards can support typical use cases including enabling data access, facilitating querying of datasets, establishing origins and ownership of the data, and providing for robust long-term archiving of data (Dickerson et al., 2018). However, common data and metadata standards are not currently well established for air quality data. For example, data are often reported in different units and with local as opposed to universal time codes (it is much easier to convert from universal time to local time on the front-end than to do the reverse). An Air Quality Data exchange (AQDx) format is being developed based on the USA EPA Air Quality System (AQS) data format. Similar standards might be developed for other regions, e.g. for Europe based on the European Environment Agency Air Quality e-Reporting standards. Eventually, these efforts should be coordinated into an international standard which can be accepted by governments, NGO, data aggregators, data providers, and data users. This ongoing standardization effort should be supported and encouraged, and (when ready) adopted by national repositories, data producers, and data aggregators.

It is also important to note the primary access point for users of the data, such as desktop software, mobile apps, web portals, and other digital platforms. This will dictate the cyber infrastructure that will be required to develop data interfaces. All of these might require different lengths of development time and special expertise. Similarly, bulk data access may require a different cyber architecture and results stream compared with real-time small batch data access, e.g. via Application Programming Interfaces (API). API provide ways to interact with online databases, allowing the easy sharing of data via automated database queries. Many large LCS manufacturers and data aggregators provide their own API. Development and standardization of API for air quality information in various forms should be encouraged and supported, and can be a parallel effort alongside the data and metadata standard which the API will use.

Adopting standards for data and metadata storage and access will make LCS data more accessible and amenable to integration with other air quality information sources via the methods discussed throughout this report. Data licensing, governing its availability for use and reuse by third parties, should also be considered when planning for data availability and deciding what platform to use for data dissemination.

10.2.4. Data analysis and visualization

Data analysis tools and platforms interface with data management systems to provide a programming or graphical user interface to perform queries and analysis of data and present results in readily interpretable forms (e.g. plots, maps, and tables). These tools are essential for making effective use of the large volumes of data which can be collected by LCS networks.

Performing LCS data analyses on national or global scales and incorporating additional datasets such as satellite remote sensing or air quality forecasts will likely require access to a high-performance computing cluster. Geographic Information Systems (GIS) are designed for manipulating and displaying spatiotemporal datasets. Algorithms for integrating multiple spatiotemporal datasets can also commonly be implemented in GIS. Freely accessible online GIS platforms, e.g. Google Earth Engine, can help lower barriers to accessing and processing large quantities of data. Novel methods of encoding big datasets, especially satellite remote sensing data, can also increase their accessibility and usability in resource-constrained settings (Rolf et al., 2021).

An issue which has been noted with many currently available LCS data management and analysis solutions is that they are expensive and overwrought for many groups who are seeking to support an exploratory LCS network project. Open-source, modular, transparent, and reproducible tools are a key resource which should be used, promoted, and supported. Open-source licensing allows generic and community-supported tools, e.g. the AirSensor R package (Collier-Oxandale et al., 2022), to be used for certain common tasks and be customized to perform better within a local context or fulfil specific user needs. It should be noted, however, that such software packages may be fast-evolving, and some packages may become obsolete as technical improvements happen.

Finally, platforms for disseminating analysis outputs and results, e.g. web tools and interactive maps, are needed to help bridge the gap from data to action, especially for presentations of data that are customizable to local language and context. One example of this is the Quantification of Utility of Atmospheric Network Technologies (QUANT) platform (Diez et al., 2023). For more discussion of data analysis platforms, the reader is referred to Part 5, Chapter 15: Disseminating the air monitoring data in the Guidebook for Developing a Community Air Monitoring Network*.*

10.3. Technical capacity and training

Developing and maintaining the physical and cyber infrastructure supporting LCS networks and related applications requires significant personnel time and specific technical expertise. Regional LCS calibration centers with reference grade monitors can serve as hubs for technical capacity building in air quality data collection and analysis. Regional and international communities of practice should also be developed and supported.

A key challenge in the actionability of air quality data is the current disparity in technical capacities among different regions, especially between HIC and LMIC. Limited technical capacities can restrict the ability to collect, analyse, and effectively use the gathered data. Particularly, researchers in LMIC may face significant obstacles in terms of publishing their data and results. This situation not only limits scientific and technological development in these regions but also has a direct impact on "brain drain"; researchers trained in these countries often decide to migrate to places where they can find better financial opportunities and the possibility of applying their technical knowledge more effectively. This migration of talent can further exacerbate gaps in technical capacities between different regions, creating a vicious cycle.

Expanded efforts in **technical training and capacity-building** can help address these problems. These may take many forms, from formal courses in universities to networks of users sharing best practices. Funding organizations and international bodies should encourage knowledge sharing and fair and equitable collaboration between researchers and communities with relatively higher and lower technical capacities. For example, exchange programmes where researchers at institutions in HIC and LMIC conduct part of their research in each other's countries can promote better connections between those with technical expertise and those with local knowledge, enable more research focusing on specific local and regional needs, and foster long-term collaborations. Furthermore, international funding institutions can prioritize direct investments in LMIC to help develop and expand technical capacity and infrastructure.

10.3.1. For implementers

Training for network implementers may include how to select appropriate LCS systems for different applications, how to site units and design networks, how to operate LCS hardware, and how to manage and interpret LCS data. Examples of best practices for LCS calibration and use can be collected and disseminated by training centres, national and international organizations, and communities of practice. Regionally based organizations can help to share locally relevant knowledge, especially in regions sharing a common language. Connections between regionally based organizations, especially those focused on particular technologies or applications, can help to disseminate knowledge and resources between regions and break down interregional disparities. These collaborations can be facilitated through an online presence including discussion forums, scheduled virtual meetings and teleconferences, and code exchange repositories.

Some examples of platforms or organizations to share experiences, best practices, and provide expertise and technical assistance to institutional and community implementers are:

- The Air Quality Sensor Performance Evaluation Centre, AQ-SPEC (USA). AQ-SPEC performs verification of LCS systems in laboratory and field conditions. Similar regional verifications centres can be established globally, and can serve as "centres of excellence" for technical capacity-building in the use of LCS. The Air Quality Sensor Evaluation and Training Centre for West Africa (Afri-SET) is an example of such a regional centre.

- The Clean Air Monitoring and Solutions Network, CAMS-Net (Global). CAMS-Net is an international network of networks for obtaining useful, actionable data from LCS with an emphasis on LMIC. The network has been operating since 2020, holding free-to-attend capacity-building events and providing seed funding to researchers working on LCS in LIMC.

- The Bay Air Center (San Francisco, USA). This centre offers free technical training and other resources to support community air monitoring. Universities often serve this role in many areas but are subject to funding uncertainty and high turnover of personnel (students). Establishment of dedicated centres with sustained funding can alleviate some of these problems.

- Allin-Wayra (Global). This initiative by the International Global Atmospheric Chemistry (IGAC) project aims at capacity-building, knowledge democratization, and enhancement of atmospheric chemistry science, especially in regions lacking in situ air quality measurements.

- The Knowledge and climate services from an African observation and Data research Infrastructure (KADI) project (Europe/Africa). The KADI project is a European Union Horizon Infrastructures project, coordinated by the Integrated Carbon Observation System European Research Infrastructure Consortium. The general goal of KADI is to advance pan-African research infrastructure for atmospheric and climate services, developing the best available science and science-based climate services in Africa. This includes the development of data and research-driven infrastructure to integrate RGM, LCS, and citizen science approaches into both new and pre-existing climate services, with the expectation that they are able to operate over the long-term. The project commenced in September 2022.

- Conferences like the Air Sensors International Conference (ASIC) bring together researchers, practitioners, and community scientists to share new approaches to and best practices for LCS applications, including the use of LCS alongside other data sources.

- Several LCS manufacturers, aggregators, and research institutions provide training in their specific technologies and support general training in data access, management, and analysis.

Beyond LCS, training and capacity-building must be available for the other data sources to be integrated alongside LCS data in support of various applications. Some examples include:

- The NASA Applied Remote Sensing Training (ARSET) programme provides free online trainings in the use of satellite remote sensing data to support various applications, including health and air quality. The NASA Health and Air Quality Applied Science Team (HAQAST) further represents a community of practice bringing together remote sensing experts with air quality managers and other stakeholders to solve challenges;

- The United Nations Institute for Training and Research (UNITAR) offers courses in many topics, including air pollution;

- WMO, via the WMO Training and Education Department and the GAW programme, also has several capacity development activities, including online training courses, webinars, and hands-on training workshops for monitoring (ground-based and satellite), emissions inventory development, air quality modelling and forecasting;

- Partnering with university computer science departments or sponsoring "hackathons" can help to attract those with data analysis and processing expertise and provide real-world case studies on which they can hone their skills.

10.3.2. For policymakers

Air quality monitoring is one of the most important management tools for decision makers. It is essential to strengthen institutional capacity, including how to use observational data from multiple sources for policy design. This might include broad dissemination of examples of policies, regulations, and/or enforcement actions informed by combinations of LCS and other air quality data. This might also lead to the development, for different regions and governments, of specific reporting mechanisms whereby LCS data, potentially in concert with other data, can support specific policy decisions. In this context, facilitating exchanges of information and experiences between those working in LMIC, or "South-South" exchanges, can be especially helpful since LMIC are often grappling with similar resource and skill challenges. Such capacity-building efforts will require significant input from those with legal and political expertise. According to the U.S. Government Accountability Office (GAO), seven policy options to address challenges in developing and using air sensors for policy include:

- Maintaining status quo.
- Enhancing the transparency of sensor performance.
- Supporting innovation in sensor technologies.
- Facilitating access to expertise, including universities.
- Improving access to guidance.
- Improving data management and sharing.
- Clarifying the level of quality assurance needed to spur action, including co-developing guidelines on the level of quality assurance required for various applications.

For further reading, see *Technology Assessment: Air Quality Sensors (Policy Options to Help Address Implementation Challenges),* GAO-24–106393.

10.3.3. For the general public

A broader form of capacity-building involves educating the public in air quality data literacy and the importance of air quality to health, livelihood, and the environment. LCS can support this effort by facilitating firsthand experiences with air quality data, e.g. by loaning out LCS at libraries, schools, or other community centres and helping people to interpret and act on the data.

Examples of programmes that incorporate LCS deployments in their educational strategy include:

- Love My Air. This programme combines LCS deployment with educational materials to provide diverse communities in Denver, USA, with visible, accessible, and actionable air quality information. The Love My Air information allowed school employees to make informed decisions on outdoor activities on bad air quality days and empowered students to take preventive asthma medication or find alternative activities to protect their own health.

- EducAIR. This programme in the metropolitan region of Manaus, Brazil is an effort aimed at educating students and their families about the importance of forest conservation and clean air.

- Cityzens4CleanAir. This campaign involves urban runners with air quality data collection using wearable LCS, leading to analysis, advocacy, and awareness-raising activities.

- sensors.AFRICA. This programme of the Code for Africa non-profit organization provides do-it-yourself (DIY) kits available through the open-source Luftdaten project (also known as Sensor.Community) allowing individuals to construct and operate LCS. The programme also offers instruction in data collection and analysis and guidance about how to communicate findings. This increases awareness of air quality issues, technical capacity for air quality measurement, and ability to advocate for air quality policies more effectively.

- Clean Air Catalyst. A five-year programme funded by the USA Agency for International Development to build capacity in three pilot cities: Indore, India; Jakarta, Indonesia; and Nairobi, Kenya. RGM are installed in the pilot cities and stakeholders are trained to educate, implement and incorporate air quality in their local governance.

- MoveGreen. An environmental non-profit based in Kyrgyzstan which supports and promotes general environmental awareness and has deployed LCS to various locations in Central Asia.

- Aire Ciudadano. Based in Colombia, Aire Ciudadano utilizes citizen science to learn about air quality. They have deployed DIY $PM_{2.5}$ LCS in Colombia and neighbouring countries.

- Ciudadanos Científicos. A local science, education and technology programme developed by the Aburrá Valley Early Warning System (SIATA) and funded by the Aburrá Valley Metropolitan Area (AMVA), Colombia. The programme began in 2015 and currently has 250 LCS distributed throughout the metropolitan area. Each citizen scientist hosts a $PM_{2.5}$ LCS in their home. SIATA also operates the RGM network in the Aburrá Valley.

- Pakistan Air Quality Initiative. Launched by a citizen in 2016, the initiative has deployed LCS across cities in Pakistan, and has led advocacy and engagement on air quality.

10.4. Financial and institutional resources

There is great opportunity for government and private funders to invest in air quality monitoring. Funders and funding recipients alike should be cognizant of financial considerations and budgets not only for the LCS hardware and its supporting physical and cyber infrastructure, but also the personnel time required for setup and maintenance, as well as administrative and financial reporting overhead. To be most effective, funding must be sustained and should support development of local infrastructure and technical capacity. Funding to support freely accessible air quality databases and analysis tools should also be considered.

Financial resources are necessary to support any operational activity including physical and cyber infrastructures along with technical capacity development and maintenance. For example, subscription models for LCS require sustained funding or the subscribers will lose access to their data. On the other hand, the creation of custom LCS and data platforms requires technical expertise which also translates to equivalent working person-hours. In addition, when accepting grants, grantees must be aware of the reporting requirements of the funder. The administrative overhead (e.g. accounting) required for managing a grant is nontrivial and should be accounted for in budget proposals. The coordination of procurement, calibration, maintenance, and additional technical work required to deploy, maintain, and if necessary, dismantle the LCS network operations also require financial capital that should be accounted for during planning and grant-writing.

When considering the effort needed to deploy, operate, maintain, and analyse data from LCS networks, workable models to enable the financing of LCS and associated infrastructure are needed, along with appropriate incentives to activate and sustain community engagement. To this end, socially driven financing of LCS – despite their nominally low cost – may not be sufficient in the long term. This can be expanded by engaging local corporate actors to invest in LCS in exchange for branding opportunities like being "air quality champions". Working with communities to invest in these LCS through their structures – such as communal cooperatives – can also enable sustainable financing of sensors. Communities can be incentivized to assist in LCS calibration and network maintenance activities in exchange for promotion of the solutions they generate to address the air quality risks they monitor. For example, communities engaged in PM monitoring of indoor air can be engaged to promote clean cooking solutions they can produce at the local levels – e.g. waste recovery to biogas, a clean cooking fuel.

Whatever the source, financial and institutional resources must be committed for extended periods of time, with clear pathways to securing ongoing support. A consistent source of frustration for those seeking to develop air quality monitoring networks using LCS is that "funders get disinterested after a year or two" (Hasenkopf et al., 2023). Without long-term support, LCS networks risk becoming another source of electronic waste. Sustained institutional resources and support are needed to ensure stable and sufficient financial resources, as well as to support the translation of air quality data into meaningful action.

Targeted funding opportunities for LMIC and under-resourced communities within HIC are needed to build capacity and support collection and analysis of locally relevant air quality data, especially from LCS. From 2015 to 2021, only 1% of international development funding and 2% of international public climate finance supported clean air projects. Only in 2021 did international development funding for clean air projects exceed that of fossil fuel projects for the first time. Globally, funding is unevenly distributed, with Africa receiving only 5% of air quality funding between 2017 and 2021, and Latin America and the Caribbean receiving only 1%. A much greater volume of funding (especially as grants and concessional financing) is needed to support improvements in air quality, including more funding for air quality monitoring and modelling, which can build public and political support and help target mitigation strategies. With an increase in global action towards climate change and heightened sensibility of corporate social responsibility, the co-benefits of air quality improvement and GHG emission reductions may also be emphasized to leverage internal support, e.g. from large corporate stakeholders. This funding must be targeted to where it can make a more decisive impact (Clean Air Fund, 2023).

Provision of publicly accessible and verifiable information on air quality is often a prerequisite for public pressure and political action to improve the air quality situation (Greenstone and Hasenkopf, 2023). However, conversely, there needs to be some pre-existing political and public (and financial) support for the establishment of air quality monitoring systems such as LCS and RGM.

Institutional resources are also needed to support the use of LCS data. Policy mechanisms should be in place whereby LCS data can contribute to decision-making to prompt mitigation actions. At minimum, there must be a willingness by those responsible for undertaking such activities to consider LCS data in their decision-making. Following the best practices outlined in this and previous reports for LCS calibration, data quality verification, analysis of LCS data at network scale and in conjunction with other available air quality information sources, and evaluation and reporting of data products based on such analysis can establish the confidence necessary for such an acceptance of LCS data in decision-making.

In comparison to the cost of the air pollution problem, currently valued at 8.1 trillion USD annually (World Bank, 2022b), it is relatively inexpensive to support the underlying air quality data infrastructure needed to build clean air action locally. This reduction in cost can be further expanded by utilizing LCS and integrating efforts with already existing infrastructure or collaborating with other local sectors. For example, if one were to invest 15 million USD in developing global air quality data infrastructure and supporting local entities to set up $PM_{2.5}$ monitoring where data are not yet available and/or openly accessible, and if as a result one relatively small country (e.g. Guatemala) was able to avoid 10% of its current estimated costs due to $PM_{2.5}$ pollution, this cost reduction would equate to about ten times more than that global 15 million USD investment (World Bank, 2020; Hasenkopf et al., 2023).

An important supporting role can be played by international organizations and NGO to reduce some of the burdens currently facing local practitioners. This can include the establishment of data-sharing protocols and platforms, development and maintenance of open-source data management and analysis software, creation, and operation of regional QA/QC hubs for LCS calibration and verification, provision of technical training and capacity-building, and fostering of international communities of practice. Supporting free access to LCS data is also a key role which national and international funding organizations can play. Analogous to the NASA Commerical Smallsat Data Acquisition Program, which purchases relevant satellite remote sensing data from commercial providers so that they are available to the scientific community, a similar programme might be established to support the open availability of LCS data as a public good.

11. Best Practices for Integrating Low-cost Sensor Systems

> LCS are useful tools for acquiring air quality pattern and trend information. In regions lacking of air quality monitoring networks, LCS can provide the first insight into local air quality, guiding further investigations and prioritizing mitigation strategies. Assessing LCS performance in the target environment via reference grade monitors co-location is recommended wherever possible to better support quantitative applications of LCS data. When this performance is appropriately accounted for, LCS networks have tremendous potential to enhance air quality reconstruction, forecasting, source identification, and health and environmental justice applications.

This report has summarized the current status and potential to use LCS at a network level and alongside other data sources in a broad range of applications. These include air quality reconstruction, identifying and quantifying source contributions, and tracking patterns and trends in air quality and their impacts on human health and the environment as well as to improve air quality forecasts. The relatively broader and denser spatial coverage of monitoring possible with LCS are often a key advantage in these applications. Other commonly cited advantages are low data latency, capacity of sensors to be deployed by non-expert users and in areas with limited infrastructure, and the ability of certain LCS to simultaneously measure multiple pollutants. Conversely, the common limitations of LCS relate to their uncertain and potentially unstable performance, including undesirable cross-sensitivities with other pollutants or environmental factors, and performance degradation over time. It is important to remember, however, that all measurements are subject to uncertainty. If uncertainties can be understood, characterized, and communicated, then the measurement can be used appropriately. The rapid development of LCS technologies and their expanding deployments worldwide are providing an ever-growing wealth of experiments and case studies which can be used to establish this necessary understanding, thus enhancing the utility of LCS into the future.

LCS must be integrated with other data sources in a comprehensive air quality management system. This is also stressed in the series of WMO report on low-cost sensor measurement of atmospheric composition (WMO, 2018, 2020). First, the necessary level of data quality will depend on the intended application. Broadly qualitative assessments of air quality derived from multiple sources may be sufficient for providing information to the public in near real-time. Meanwhile, retrospective assessments used to inform public health and to understand environmental inequities will require more rigorous treatment of uncertainties and higher data quality. Second, the need for transparency in the data handling methodology is paramount. Understanding exactly how different data sources were combined, and how peculiarities of each data source may be reflected in the final synthesis, is critical to determining how reliable the resulting estimates are, and under what circumstances and for what applications they are appropriate. Finally, as with LCS technology, the integration of LCS with other data sources to support a comprehensive understanding of air quality is a rapidly evolving field of research and practice.

Many air quality applications require only qualitative or comparative analysis, relying on high inter-unit consistency, which is an achievable objective for many existing LCS technologies with some basic data quality assurance and control. Demonstrating such consistency can support the use of LCS for non-regulatory advisories of poor air quality to protect vulnerable populations or populations whose air quality is declining quickly. LCS can also support targeted strategies to reduce controllable emission sources, such as "no-burn" advisories or traffic reduction measures. In these applications, false negative and false positive rates remain a concern and appropriate trade-offs should be carefully considered when calibrating these approaches. Finally, LCS are a valuable tool for increasing societal awareness about air quality and air pollution sources.

For more quantitative use cases, many data analysis methods applicable to RGM (e.g. reconstruction, source identification, forecasting) can and have also been applied to LCS with positive results. Difficulties lie in the appropriate handling of errors and uncertainties when using these approaches. Careful statistical consideration and establishing data quality thresholds based on intended use cases can inform the suitability of LCS to particular applications. This is done via analysis of LCS performance in the target environment, in comparison to each other and to any available RGM. Bringing in external data sources, such as air quality modelling products (i.e. reanalysis or forecasts) and satellite remote sensing data, also has potential benefits here. LCS with well understood performance can provide useful data for evaluating AQM results or connecting satellite retrievals to near-surface air quality. Data assimilation and inverse modelling with well characterized LCS network data can refine high-resolution air quality reconstruction and improve localized source apportionment.

In areas lacking RGM, especially in LMIC and under-resourced and rural areas of HIC, LCS can provide the first insights into local air quality. Local experiences corroborated with LCS data can be used to advocate for policies to mitigate poor air quality and to expand monitoring and emissions control activities. The main prerequisites here are that inter-sensor uncertainty be smaller than the concentration differences being measured, that the network design is appropriate to the intended analysis (e.g. it should include some sites to measure "background" conditions), and that appropriate technologies are chosen for measuring the key pollutants and atmospheric parameters. To do this requires technical capacity and physical and data infrastructure for the effective use of LCS at network scale and alongside other data sources. Where possible, peer-to-peer sharing of best practices should be supported and encouraged, as this helps to build and retain local capacity. This will promote the longevity of the monitoring effort, especially for tracking the effectiveness of mitigation actions. Common data reporting standards and metadata formats are also needed for LCS, along with open-source data management, integration, and analysis tools.

11.1. Summary of best practices for several common use cases

11.1.1. Informational use alongside other data sources

In the simplest case, LCS data can be displayed alongside RGM, satellite, and/or AQM output. Such informational use provides an awareness of current air quality without additional analysis or interpretation. This has the benefit of putting LCS and other data into context and presenting a variety of data sources in a straightforward and relatively transparent way. However, this risks confusion or misinterpretation when different sources present seemingly contradictory data.

When designing such a system, it is important to clearly identify the intended use case and audience. Considering the use case will help inform what kinds of data should be displayed (or not displayed), as well as the appropriate spatial and temporal resolutions. It can also inform the appropriate level of abstraction for the information (e.g. presenting data as quantitative concentration values or qualitative indices) as well as the data quality objectives and quality control measures which best match the use case. The audience's level of knowledge of air quality in general and LCS in particular must be accounted for. Based on this, preliminary assessments of what mistakes they are likely to make in interpreting data can guide the system design to help avoid such misunderstandings. User testing and feedback prior to deployment is also needed.

The following basic practices should apply to all cases where LCS data are displayed alongside other data sources for informational purposes and on platforms intended for broad public use:

- Provide straightforward plain-language guidance to help users interpret the data, and especially to explain disparities between data sources. This can take the form of, for example, a short tutorial for new users of an air quality app, or a message on a public display board indicating the source of the data being displayed, and noting what agency is the authoritative source for public air quality information in that region (if applicable).

- Identify the purpose for which the data are being displayed, and emphasize what the data should not be used for. Feedback from users during a trial period can be used to identify common misconceptions or misuses of the data, which can be highlighted here.

- Indicate the original sources of all data being displayed, with references or links as appropriate. Also, direct users to the authoritative source for air quality information in their region.

- Apply basic quality control steps before displaying any data. Data of unknown quality or outdated information should be clearly indicated with warnings, or should not be displayed at all. Explain these quality control steps in accessible documentation. Regulatory agencies should establish quality control practices and data quality objectives for LCS data being used for public display purposes; data providers can then show that their data meet these objectives.

- Allow easy access to measurement metadata and data quality information for each measurement displayed, either from an internal database or by referencing the original source.

- Ensure that information is displayed with a consistent temporal basis (e.g. hourly average quantities) and in consistent units. Further, ensure that the temporal basis and units being displayed are appropriate to the intended purpose; e.g. do not present hourly concentration data using a health-based index calibrated for annual average exposures.

Any tool for presenting multiple data sources together will require a robust data management system, and associated technical personnel and funding to maintain it. Harmonizing diverse air quality data and managing the flow of that data remains an important (and costly) challenge, as discussed in Section 10.2. Data harmonization efforts, including metadata standardization, is an active area of development which should be supported and encouraged.

11.1.2. Reconstructing near real-time concentration across a domain

When using LCS to support air quality reconstruction, the increased density and expanded coverage possible with LCS compared to RGM are their key advantages. High temporal frequencies and low data latency are also important to support near real-time reconstruction applications. Care should be taken to quantify and to minimize inter-sensor measurement differences and biases, as these will have negative impacts on the reconstruction accuracy.

Simple statistical interpolation is readily applicable to LCS data, and its performance is improved through the higher spatial densities achievable with LCS compared to RGM. LUR is likewise facilitated by better coverage of different land use categories, which can be supported through more LCS deployment. These techniques require quality control, as even single inaccurate datapoints can severely bias many interpolation approaches. Kriging tends to be most robust here, although not immune. Statistical interpolation and LUR also risk reinforcing systematic sources of error which impact all LCS across the network. Including a few RGM sites as inputs may help alleviate this. In fact, many reconstruction approaches can weight LCS and RGM differently to account for relative uncertainty. Thus, LCS can supplement existing RGM networks to improve reconstruction and/or extend it to areas (e.g. rural areas) without adequate RGM coverage.

Using satellite remote sensing combined with LCS for time-varying air quality reconstruction is a promising approach, garnering much recent attention. Currently, satellite-informed reconstruction approaches are more applicable to regional-scale reconstruction than urban-scale reconstruction, as limitations in satellite data resolution and in developing robust relationships with LCS data remain challenging. Further work is needed in this area, including tools facilitating satellite data access and taking advantage of new and upcoming atmospheric composition satellite missions. LCS can also update and improve the local relevance of global satellite-derived air quality data products or air quality forecasts. For this purpose, AQM, LCS, RGM, and/or satellite data can be combined through data fusion or data assimilation.

Optimal design of an LCS network to support reconstruction can be informed by the scale of spatial variability of the constituents of interest. These scales might be estimated from other data sources (e.g. AQM) or determined during a pilot network deployment. Mobile LCS support reconstruction by expanding spatial coverage with fewer sensors, but careful handling of mobile data is needed to ensure consistent performance and reduce biases due to the routes followed by the mobile sensors. Combining mobile LCS with stationary RGM is a recommended approach here.

The utility of LCS data in supporting reconstruction should be evaluated using spatial cross-validation as well as by comparing sophisticated methods against simple baselines (e.g. nearest neighbour interpolation). An appropriate spatial resolution should be associated with any reconstructed product. Finally, appropriate data visualizations and interactive tools should be designed based on the intended audience and the key messages to be conveyed.

11.1.3. Identifying the contribution of a source to local concentrations

When used for source identification and apportionment, the key attributes of LCS are their ability to provide high temporal resolution data, to achieve a high spatial density and broad coverage, and the multipollutant capabilities of many LCS. High temporal resolution, on the order of minutes, is helpful to identify short-lived or intermittent pollution events, to separate these from more persistent background concentrations, and to apply statistical techniques identifying temporal patterns connected to specific sources. High spatial density and broad coverage is important for distinguishing sources spatially through comparison of different deployment sites (e.g. roadside versus urban background), for triangulation of unknown sources, and for surrounding of known sources to distinguish, e.g. upwind versus downwind concentrations. Multipollutant capabilities are important since different emissions sources will have different signatures, in terms of the mixture of pollutants produced, and thus can be more easily distinguished by exploiting prior knowledge of these mixtures and ratios of pollutants. The most relevant pollutants to measure will depend on the local context, but in general multipollutant LCS incorporating $PM_{2.5}$, NO_x, CO, and/or CO_2 have been effective for distinguishing pollution sources. It is important to note that even factory calibrated (i.e. not locally calibrated) LCS have been used for such analysis. Ratios of raw LCS signals, with appropriate normalization and statistical analysis, have identified similar pollutant source contributions as achieved through analysis of RGM. This has important implications for source apportionment in regions lacking RGM.

The choice of LCS technology to support source identification and apportionment will depend on the sources of interest. A multipollutant LCS combining gas-phase and particle detectors can support detecting a range of emissions sources. Establishing inter-sensor precision between LCS is important to support source triangulation and fenceline monitoring of known sources with LCS networks. Ancillary information needed for source apportionment, especially wind speed and direction information, might be collected by the LCS themselves or via a separate meteorological network or model, if these are available. It is important to consider at an early stage how these data will be collected and integrated to support source identification and apportionment.

At a network level, extensive deployment of LCS can facilitate more comprehensive fenceline monitoring of known sources and better identification of local sources by taking advantage of higher signal-to-noise ratios of pollutants near their sources. Such deployments should also always include one or more background sites which are not likely to be impacted by the sources of interest, to allow for more effective assessment of the source impacts. In all cases, characterization of inter-sensor precision of the LCS is critical, as this will inform the appropriate analysis techniques and the ability of the data to support inverse modelling. Short-term LCS network deployments can facilitate exploratory studies to identify new sources or assess if pre-existing emissions inventories and/or air quality modelling products (i.e. reanalysis or forecasts) are reasonable or if they might be missing key sources. Long-term LCS networks can better characterize emission changes over time, including for assessing the impact of mitigation activities; such deployments require sustained funding. Finally, mechanisms must exist whereby source and emission identifications via LCS can be used for targeting mitigation policies, and where LCS might subsequently be used for tracking the impacts of these policies.

11.1.4. Understanding air quality disparities

The ability of communities to deploy their own LCS or access pre-existing LCS data has led to their use in investigating air quality disparities and their environmental justice implications. Using LCS data for such applications requires thorough characterization of sensor-to-sensor variability in the target environment. Local conditions will play a role; areas with higher concentrations and/or higher variability of pollutants will have more favourable signal-to-noise characteristics, allowing easier identification of patterns using LCS. For long-term trend analysis, stable performance over time and across different meteorological conditions is needed; establishing such stability often requires repeated co-locations with available RGM. In the short-term, sub-daily temporal frequency can elucidate time-dependent exposure disparities. Multipollutant measurements can establish if disparities are unique to specific pollutants or more generalized. High spatial density enables locally-specific analyses. All these are achievable through appropriate use of LCS.

LCS networks supporting environmental justice investigations must be representative of the areas under consideration; over- or under-representation of certain environments or communities can undermine the statistical analysis. This is especially a concern for privately deployed LCS networks, since underlying socioeconomic factors have been found to influence the private purchasing and deployment of LCS. External data sources, especially satellite remote sensing data, can provide corroboration for air quality exposure disparities identified by LCS, or vice-versa. Integrating these datasets often requires technical capacity beyond what might be available to the community; free data analysis and technical capacity-building resources are needed to address such needs. Finally, mechanisms to use disparities identified by LCS and/or other data sources to advocate for mitigation actions are needed. Mitigation actions also might be informed by evidence from LCS data suggesting factors such as vegetation or street layouts correlating with lower concentrations.

11.1.5. Use of LCS to support health impact studies

This report has established how LCS data can be used and integrated with other sources of information to improve the local assessment of air quality. To assess the impacts of air quality on human and environmental health, air quality data need to be further combined with health data, which are subject to their own uncertainties and limitations. Health impact studies usually require long-term continuous data records, which LCS are typically not as suitable for as other information sources. However, in areas otherwise lacking data, especially in rural areas and in LMIC, LCS can and should be utilized together with satellite- and model-derived products to begin addressing the inadequate representation of these areas in existing air quality epidemiological studies. LCS with well characterized performance and rigorous quality control can also cost-effectively support short-term health impact studies, including with deployments following natural disasters or major pollutant releases. In any study, confounding factors such as the impact of socioeconomic status on both LCS deployment and health impacts must be considered.

Data quality assurance of wearable LCS for personal exposure monitoring remains a challenge. However, wearable LCS and/or dense stationary LCS networks, potentially integrated with other data sources, can assess relative differences in exposure across microenvironments. This can enable personalized guidance to reduce exposures based on these qualitative differences.

11.1.6. Forecasting tomorrow's concentrations

Forecasting methods and products should be aligned with the actions which the forecast will inform, e.g. personal activity changes or reductions in pollution-producing activities. This will inform the required latency and data quality of input information, including LCS data. Key attributes of LCS which support their use in forecasting are their ability to provide good spatial coverage and near real-time data with low latency. Good coverage allows the resulting forecasts to be more locally relevant, as compared to forecasts from regional or global AQM. Low latency allows LCS data to support near-term forecasts of conditions hours to days in advance. Relatively lower data quality of LCS compared with RGM, however, may make them less suitable for more quantitative forecasting in the absence of other data sources. The impacts of prevailing environmental conditions or pollutant mixes with cyclical characteristics on LCS performance can also introduce time of day or seasonal biases to forecasts incorporating LCS data.

LCS data can support qualitative and even some quantitative evaluation of air quality forecasts, especially in regions lacking other in situ data. Appropriate quantification of LCS uncertainties can support the improvement of air quality forecasts through data assimilation or statistical data fusion. This has the potential to create more locally relevant forecasts.

When using LCS for forecasting to support public risk communication, it is recommended to consider categorical, action-oriented forecasts with associated uncertainty, similar to weather forecasting norms; e.g. "tomorrow there is a 70% chance that the air quality will be unhealthy for sensitive groups in the morning; consider avoiding strenuous outdoor activities". In this way, relevant actionable information can be simply and effectively conveyed, alongside inherent uncertainties associated with the forecast. This will also need to consider the relevant air quality indices and associated recommended actions for the country or region in question.

11.1.7. Encouraging community involvement

The relative accessibility of LCS technology and data have made them a valuable tool in focused air quality investigations in specific communities, such as discussed in Section 11.1.4. However, there is a potential for misuse and enabling extractive scientific practices. In particular, "helicopter science" refers to a research practice where data or resources are collected from a community but no connections with the community are made and no tangible benefits are provided. This extractive approach results in research lacking local relevance and harms the communities' perception of science (Ivey et al., 2022). Another potential problem is the use of open data by established researchers to pre-empt publication by the local community scientists who established the LCS network. There is also the risk of misinterpretation of data by those lacking local knowledge, and privacy concerns related to sharing geolocated LCS data. Negative impacts for the community also include lacking access to technical expertise needed to effectively operate LCS and interpret their data, making it more difficult for community findings to be accepted by policymakers.

At the same time, the availability and accessibility of LCS offer many opportunities to increase community involvement and engagement, which should be explored and encouraged. The local knowledge and experience of community members can provide valuable contextual information for interpreting air quality data. By actively including local communities at all stages of the research process, i.e. engaging in community-based participatory research, air quality monitoring strategies can be designed in a way that reflects and respects the customs and values of local communities and integrates their knowledge and experiences. To facilitate this, community contributions should be recognized, e.g. through co-authorship of research results and by funding community members' time. Also, involvement in monitoring activities should yield tangible benefits for the community, e.g. strengthening of local capacities, creating employment opportunities, and/or supporting community projects with targeted funding opportunities.

11.1.8. Translating LCS data into mitigation action

The ultimate value of LCS lie in the extent to which their data can catalyse and support actions enhancing air quality and environmental sustainability. In order to do this, first, their data must be made available to researchers, policymakers, and the affected communities. Availability also requires that the data have sufficient and appropriate metadata and documentation, as well as be available in interoperable data formats and findable by those seeking them out, e.g. appearing in environmental data aggregation systems. Second, their data must be useful, in the sense of being of sufficient quality to provide meaningful answers to policy-relevant questions about air quality. Finally, there must be the community engagement, political will, institutional mechanisms, and financial resources to use the data to identify and implement the most promising solutions.

LCS deployments with appropriate network design and data quality control can be used to evaluate potential mitigation activities. For example, LCS can be deployed to cost-effectively evaluate the efficacy of a small pilot mitigation project, or to quickly identify opportunities where existing projects can be expanded. The increased network densities achievable via LCS, as well as their potential to catalyse community involvement, provide opportunities to explore locally tailored mitigation strategies as well as to develop community support for strategies which are found to be effective. However, financial and policy support must be in place to enable such activities.

11.2. Future directions

Examining the uses of network level LCS data with other information sources in air quality applications, several areas of promising work and potential for advancement can be discerned. Firstly, despite much progress and continuing efforts, more research is needed to characterize the performance of LCS in different environments and conditions, and to systematically report this performance in standardized ways which will help users make informed decisions about how different LCS technologies and products might meet their needs. Lack of access to RGM data globally have hindered these efforts. Of the research surveyed in drafting this report, about 41% represents North America, 24% represents Asia, and less than 15% represents South America and Africa combined. Increased funding and support are needed for establishing regional LCS calibration centres with RGM. These centres should also serve as hubs for technical capacity-building in air quality monitoring using both RGM and LCS.

In situ LCS performance verification and recalibration is a promising approach for data quality assurance. However, many current methods require extensive RGM networks, or rely on assumptions about air quality which might be difficult to verify. More research and development are still needed, including leveraging satellite and AQM data to assess in situ LCS performance.

Even so, LCS calibrations are limited in their ability to compensate for inherent limitations of the sensing technology and hardware design. Thus, more research and innovation are also needed to improve the quality, reliability, and durability of LCS and their constituent components. Better understanding the physical and chemical processes that govern the detector response can support developing new materials and methods to overcome the challenges of selectivity, sensitivity, and stability. This can enhance the application of LCS for long-term monitoring.

Use of artificial intelligence and ML techniques is becoming increasingly common in many fields, including the use of LCS. The flexibility and efficiency of these techniques are highly promising, both when applied to the calibration of individual LCS as well as in facilitating the integration of LCS with other information sources. However, without a thorough understanding of the limitations of these techniques and careful testing to avoid common pitfalls (e.g. overfitting to training datasets), application of these techniques can exacerbate data quality concerns. In particular, regions with sparse in situ air quality monitoring likely lack sufficient data for robust training of ML algorithms. Increased use of explainable ML techniques to interrogate the advantages and limitations of ML approaches for different applications should be considered a best practice.

Using LCS in combination with other data sources to support air quality exposure and health studies is an important emerging area of research which should be supported and expanded. Globally, there is a lack of detailed large-scale air quality health impact studies in regions lacking comprehensive RGM networks. Making effective use of LCS alongside other data sources for these applications would be extremely beneficial in addressing this critical deficiency. Better understanding health impacts can also support improved air quality management and policy development. Initially, health studies using LCS information supplemented by other globally available data sources might be conducted in areas where the health impacts of different pollutants have already been well documented, allowing for the most effective analysis methods to be identified. These methods could then be extended to understudied regions with expanding LCS networks. Overall, the use of LCS to support air quality exposure and health studies, especially in the context of LMIC where exposures and infrastructures can differ substantially from the well-studied contexts of HIC, remains a critical yet challenging problem.

Recent progress has also been made in the application of LCS to GHG monitoring. As calibration and long-term stability improve, LCS can support efforts such as the WMO Global Greenhouse Gas Watch (G3W) are also suited to local validation of emissions inventories and tracking of changes, especially as an independent data source to verify claimed reductions. Multipollutant LCS capable of co-located air quality and GHG monitoring can quantify and emphasize the air quality co-benefits of GHG emissions reductions. As with all applications of LCS, calibration and data quality verification must be conducted according to established best practices.

For any application of LCS data, a decision-oriented understanding of its information content should be encouraged. Such a framework focuses on a defined end goal, e.g. reducing population exposure to specific air pollutants, considers the potential actions to reach this goal, and determines how different sources of data or combinations of these sources can best inform these actions. Statistical decision theory concepts such as Value of Information consider data which are most likely to affect the outcome of a decision-making process to be of the highest value (Raiffa and Schlaifer, 1961). Despite acknowledged limitations on precision and accuracy, LCS data are already sufficient to support a wide range of decision-making activities. Increased application of decision theory to understanding the value of different air quality data sources should be explored.

Systematic and explicit handling of uncertainties is needed to make the best use of LCS data, and indeed any source of air quality information. Reporting uncertainties in measurements in a common and usable format would allow for easier comparability and integration of these data sources. For example, whenever correction factors and performance statistics for LCS are documented in reports and scientific literature, these should be intrinsically linked with and included alongside LCS data wherever it is disseminated. Communicating uncertainties in different data sources to decision makers and to the public is a difficult task, but is important in ensuring that these sources, including LCS, are treated appropriately. More research is needed into public and political perceptions of air quality information and associated uncertainties, connected with specific programmes to test how air quality information can support decision-making. For example, recent work examining decision-focused strategies in interpreting probabilistic ozone forecasts for air quality applications could provide some guidance for how to effectively make use of and communicate uncertainties in air quality information (Balashov et al., 2023).

With the increasing amount and variety of air quality information being gathered, there is a major need to effectively store, organize, combine, and analyse this information, alongside appropriate metadata. More research & investment are needed to develop globally applicable data management systems and analysis tools to facilitate storage, dissemination, and integration of multiple data sources. This will be facilitated by the establishment of common data and metadata reporting standards, including data quality reporting, applicable to a range of air quality datatypes. International communities must be encouraged and supported to share best practices for using LCS data for different applications and in concert with other information sources.

Sustained and attainable funding is needed to support all aspects of LCS network design, deployment, management, data storage and analysis, and translating data into insight and action. This should especially include the development and expansion of regional centers for LCS calibration and verification, including funding reference grade monitor deployments to regions lacking these. It should also include support for maintaining freely accessible data archives for LCS and other data relevant to air quality as a public good, along with the software tools and technical guidance needed to make effective use of these data.

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Appendix A. Abbreviations

ACTRIS	Aerosol, Clouds and Trace Gases Research Infrastructure
Afri-SET	African Sensor Evaluation and Training centre
AOD	Aerosol Optical Depth
API	Application Programming Interface(s)
AQDx	Air Quality Data exchange
AQI	Air Quality Index (or Indices)
AQM	Air Quality Model(s)
AQS	Air Quality System
AQ-SPEC	Air Quality Sensor Performance Evaluation Centre
ARIMA	Autoregressive Integrated Moving Average
ARMA	Autoregressive Moving Average
ARSET	Applied Remote Sensing Training
ASIC	Air Sensors International Conference
CAMS	Copernicus Atmosphere Monitoring Service
CAMS-Net	Clean Air Monitoring and Solution Network
CCAC	Climate & Clean Air Coalition
CEDS	Community Emissions Data System
COVID-19	Coronavirus Disease 2019
CTM	Chemical Transport Model(s)
DGP	Data Generating Process(es)
DIY	Do-It-Yourself
ECCAD	Emissions of atmospheric Compounds and Compilation of Ancillary Data
ECMWF	European Centre for Medium-Range Weather Forecasts
EDGAR	Emissions Database for Global Atmospheric Research
EPA	Environmental Protection Agency
EPIC	Energy Policy Institute at the university of Chicago
ESA	European Space Agency
FAIR	Findable, Accessible, Interoperable, and Reusable
FEM	Federal Equivalent Method(s) (United States of America)
FRM	Federal Reference Method(s) (United States of America)
GAFIS	Global Air Quality Forecasting and Information System
GAW	Global Atmosphere Watch
GEIA	Global Emissions InitiAtive
GEMS	Geostationary Environmental Monitoring Spectrometer

GEOS-CF	Goddard Earth Observing System Composition Forecast
GHG	GreenHouse Gas(es)
GIS	Geographic Information System(s)
HAQAST	Health and Air Quality Applied Science Team
HIC	High-Income Country (Countries)
HTAP	Hemispheric Transport of Air Pollution
IEA	International Energy Agency
IGAC	International Global Atmospheric Chemistry
LCS	Low-Cost (air quality) Sensor System(s)
LIDAR	Light Detection and Ranging
LMIC	Low- and Middle-Income Country (or Countries)
LSTM	Long-Short Term Memory
LUR	Land Use Regression
MAE	Mean Absolute Error(s)
MAIAC	Multi-angle Implementation of Atmospheric Correction
MBE	Mean Bias Error(s)
MISR	Multiangle Imaging SpectroRadiometer
ML	Machine Learning
MODIS	MODerate resolution Imaging Spectroradiometer
NAAPS	Navy Aerosol Analysis and Prediction System
NASA	National Aeronautics and Space Administration (United States of America)
NGO	Non-Governmental Organization(s)
NOAA	National Oceanic and Atmospheric Administration (United States of America)
OEM	Original Equipment Manufacturer(s)
OPC	Optical Particle Counter(s)
PM	Particulate Matter
PMF	Positive Matrix Factorization
QA/QC	Quality Assurance and Quality Control
REU	Relative Expanded Uncertainty
RGM	Reference Grade (air quality) Monitor(s)
RMSE	Root Mean Square Error
SDG	Sustainable Development Goal(s)
SEDAC	SocioEconomic Data and Applications Centre
TEMPO	Tropospheric Missions: Monitoring of POllution
TROPOMI	TROPOspheric Monitoring Instrument
UK	United Kingdom (of Great Britain and Northern Ireland)

UN	United Nations
UNEP	United Nations Environment Programme
UNITAR	United Nation Institute for Training and Research
USA	United States of America
USD	United States Dollar(s)
VOC	Volatile Organic Compound(s)
WAS	Warning Advisory System
WHO	World Health Organization
WMO	World Meteorological Organization
WRF-CMAQ	Weather Research and Forecasting Community Multiscale Air Quality

Appendix B. Glossary

This glossary provides definitions for some commonly used terms and phrases in this report. The provided definition refers to the usage of the term in this report, and is not a universal definition applicable in all contexts.

Ad-hoc network: a network which develops emergently, not according to a plan or programme of a single organization. Typically, this is the result of multiple individuals and organizations deploying LCS and/or reference grade monitors within the same geographic reason, each for their own purposes, with minimal or no coordination.

Aging: the tendency for the sensitivity of an LCS to vary over time. While this typically denotes a decrease in sensitivity, it might also represent an increase in certain cases. Nevertheless, any change in sensitivity will impact the performance of the LCS calibration.

Air quality model system (AQM): a comprehensive framework designated to simulate and predict the distribution, dispersion, and transformation of air pollutants in the atmosphere. These systems incorporate various components such as meteorological data, emission sources, chemical reactions, atmospheric transport processes, and deposition mechanisms to estimate the concentrations of pollutants at different locations and times, as well as, calibration (including data fusion or data assimilation) or procedures to assess the model's performance. A wide range of potential model forms are considered; despite the name, these need not explicitly include representations of chemical mechanisms to qualify as an AQM for the purposes of this report.

Calibration: a mathematical function whereby measurements from one instrument are transformed to better match corresponding measurements from another instrument. Calibration will typically refer to the process of adjusting raw LCS measurements (i.e. outputs from the onboard detectors) to better match reference grade monitors measurements, using data collected during co-location.

Co-location: the practice of placing multiple measurement instruments in close spatial proximity for a certain time period. Data gathered by the instruments during this time can be compared to establish the inter-unit precision of their measurements, or (especially in the case of co-location of LCS with reference grade monitors) to establish a calibration to relate the measurements of the instruments.

Community science: scientific research carried out by members of the public. Typically involves individuals without formal training in the relevant scientific discipline. Also typically conducted outside of traditional academic and governmental research mechanisms. May be supported by funding, but most typically involves unpaid voluntary efforts.

Coverage: the domain encompassed by a network. While this often refers to physical space, coverage in terms of representation across land use characteristics is also considered in the context of land use regression (LUR) techniques.

Data generating process (DGP): A procedure and a mathematical algorithm whereby one or more input datasets are used to produce an output dataset distinct from the inputs. Calibration, reconstruction, forecasting, and source attribution are examples of DGP.

Data quality: a description of how closely a dataset matches with the true physical property it is meant to represent. Includes concepts of accuracy, bias, and uncertainty.

Many metrics are used to assess and communicate aspects of data quality, although no combination of metrics is necessarily a complete description of data quality.

Data usefulness: an assessment of the suitability of data to fulfil a specific purpose, i.e. to answer a specific question. Encompasses not only data quality, but also timeliness, spatial and temporal resolution, availability for use, and interoperability with other data and with analysis methods.

Density: proximity between instruments in a network. While this often refers to physical proximity, density in terms of similarity in land use characteristics is also considered in the context of land use regression (LUR) techniques. The terms “dense” and “sparse” are used to qualitatively describe density; these are relative and context dependent.

Environmental justice: Equitable distribution of environmental risks across a population, regardless of their social, demographic, and economic characteristics. Also includes the involvement of those affected by the impacts of environmental hazards in decision-making regarding how those hazards are managed.

Fenceline monitoring: an air quality monitoring effort supported by a network with instruments placed along a perimeter surrounding a known or suspected source. This allows for identifying the impact of the source by comparing upwind and downwind readings.

Forecasting: estimation of future air quality based on measurements of the present and past air quality, together with knowledge of mechanisms impacting the change in air quality over time.

Hyperlocal: pertaining to a very fine spatial scale. While no strict definition exists, it may be considered for the purposes of this report that the spatial scale is on the order of one square kilometer. For impact studies, it may also pertain to a population group on the order of 100 people or fewer.

Low-cost sensor system (LCS): an instrument for in situ air quality measurement. An LCS contains one or more sensing elements measuring atmospheric pollutants and environmental parameters. And LCS also includes hardware and software for control, power supply, data management, and weatherproofing, making it a complete functional system. LCS are distinguished from reference grade monitors by (1) a lower per-unit purchase cost and (2) lack of certification by a regulatory body establishing traceability to a standard and utility in regulatory enforcement.

Metadata: information about properties and attributes of data. This includes information about the measurement device used to collect the data and its operation, the applicable spatial extent and sampling frequency which the data represent, the techniques used to process the data (i.e. the data generating process, DGP), and the quality or uncertainty of the data.

Mobile network: a network whose instruments are placed on mobile platforms, e.g. motor vehicles or drones.

Network: multiple measurement instruments distributed over a geographic region, together with associated personnel and infrastructure to collect and analyse their data and ensure their continued operation. While no specific number of instruments is implied, a network will typically have more than ten instruments (considering low-cost sensors, reference grade monitors or a combination of both), and many as many as hundreds or (in rare cases) thousands of instruments.

Participatory research: active inclusion of and engagement with the local communities within a research study area at all stages of a research process.

Pattern: the spatial distribution and variation of air quality in a determined area or region.

Reconstruction: estimation of air quality over a defined spatial domain and/or for a certain past time period, using measurements of air quality at specific locations and times within the domain and period, together with assumptions or air quality modelling systems (i.e. reanalysis) of how these relate to unobserved locations and times.

Reference grade monitor (RGM): an instrument for in situ air quality measurement. In contrast to LCS, RGM have well established traceability to standard methods by a recognized national or international monitoring organization (e.g. the WMO Global Atmosphere Watch, GAW). Where applicable, RGM will have certification from an official regulatory body for use in legal enforcement. Otherwise, an instrument with well established, rigorously tested, peer-reviewed methods for operation and data quality assurance can be considered as RGM. RGM consist not only of instrumentation but of associated operational protocols to ensure data quality and traceability.

Source apportionment: quantifying the relative contribution of multiple sources or source sectors to ambient air quality.

Source attribution: connecting an observed change in air quality to a specific source or source sector.

Source identification: qualitatively specifying and/or geographically locating one or more sources or source sectors (groups of sources with common attributes) which are contributing to ambient air quality.

Trend: temporal changes in air quality.

Uncertainty: the interval or range within which the true value of a quantity of interest is likely to be found.

Appendix C. Supporting Materials

C.1. Satellite atmospheric composition

C.1.1. Satellite remote sensing data

Remote sensing instruments on board of satellites are another important source of atmospheric composition information, especially on a global scale. Capabilities for routine, systematic assessment of the composition of the atmosphere from space have only truly become possible in the 21st century, with the launch of USA National Aeronautics and Space Administration (NASA) Earth Observing System satellite fleet, the GOES-R missions of the USA National Oceanic and Atmospheric Administration (NOAA), and the European Space Agency (ESA) and European Organisation for the Exploitation of Meteorological Satellites (EUMETSAT) Copernicus Programme missions. The most common basic principle by which this remote sensing is conducted is to use sunlight reflected by the Earth's surface and passing through the atmosphere to infer atmospheric properties, including trace gas and aerosol constituents, based on the signal's attenuation; this is referred to as passive remote sensing. There is also active remote sensing, such as using Light Detection and Ranging (LIDAR) to send signals and measure returns. Although active instruments are typically more limited in their spatial coverage compared to passive instruments, they provide certain key capabilities which passive instruments lack, e.g. the ability to detect aerosols in the planetary boundary layer. This can make active remote sensing especially relevant when used in conjunction with ground-based data, including from LCS. Several important limitations of using remote sensing data for air quality monitoring must also be acknowledged. Since passive techniques rely on reflected sunlight for their measurement principle, in the absence of sunlight, measurement becomes difficult or impossible. Practically, this means that remote sensing instruments typically cannot retrieve data at night, or through dense cloud or smoke cover which blocks the signal. These missing data are not necessarily random in nature, as there can be systematic differences in daytime and nighttime concentrations, as well as systematic differences in cloud cover or smoke density in different regions.

Satellite remote sensing data require ground-based information for validation; in the case of near-surface air quality, RGM provide these data, and where these are unavailable, LCS may fill this need. Remote sensing instruments (on board of satellites or deployed in ground networks) typically provide information about the entire atmospheric column, which may or may not be well related to air quality at the surface level where RGM and LCS operate. Converting between atmospheric column information and surface concentrations is non-trivial. Most passive instruments do not provide extensive information about the vertical distribution of atmospheric constituents. Furthermore, many retrieval algorithms have additional difficulties and uncertainties associated with the planetary boundary layer. Thus, for example, a relatively thin but high concentration band of pollutants near the Earth's surface might register as a relatively low average concentration throughout the atmospheric column, and thus be misinterpreted as "clean air". For all these reasons, efforts to estimate surface air quality from satellite remote sensing data, particularly for PM, have met with varying success, often with poorer performance precisely in sparsely monitored regions and in LMIC where such remote sensing data would be most beneficial (World Bank, 2022a). Active remote sensing instruments and/or AQM can provide additional data to alleviate these difficulties, but in situ measurements are still necessary to adequately represent the surface conditions. There are also ground-based remote sensing networks (e.g. AERONET), which provide atmospheric composition data relevant to air quality, including for validation of satellite remote sensing data. Complementary ground-based networks such as SPARTAN are also aiding the utilization of satellite remote sensing data for the purposes of understanding chemical composition and variability around the world (Weagle et al., 2018).

Generally speaking, satellite remote sensing has the advantage of providing routine, systematic measurements of key atmospheric parameters on wide regional and global scales. Depending on the orbital characteristics of different satellites, satellite-based instruments usually have the opportunity to observe the entire Earth's surface once per day (for polar-orbiting missions), or continuously observe the same hemisphere throughout the day (for geostationary missions). Spatial resolution of remote sensing data depends on the characteristics of the instrument, and can differ among various atmospheric constituents, but can generally be said to be improving as remote sensing hardware and processing algorithms improve. For example, currently operating missions have the ability to distinguish emissions from major transportation corridors, port facilities, and large power plants from background levels. The fact that these same instruments operate for years or even decades in some cases, with minimal baseline drift, has made them very useful for long-term trend analyses, including quantifying the large-scale impacts of emission control policies.

The capabilities of satellite remote sensing remain limited in certain key areas, especially for applications requiring sub-daily temporal frequency. Polar-orbiting satellites are typically synchronized with the rotation of the Earth such that they will pass over a given location at roughly the same local time each day. While this allows for comparability of measurements between passes, polar-orbiting instruments cannot provide information about diurnal variability, which might be quite large compared to day-to-day variability for certain constituents and regions. Geostationary instruments orbit above fixed points, and so are able to provide some information on diurnal variability, but only within their field of regard, limiting their spatial coverage. For example, the recent constellation of GEMS, TEMPO, and Sentinel-4 geostationary missions with an atmospheric composition and air quality observing focus almost exclusively covers the Northern Hemisphere, although there are proposals to further expand this constellation. Satellite remote sensing missions are also technically sophisticated and expensive, and not all nations have the ability to launch and operate them. While many of the agencies operating such missions make their data freely available worldwide, technical and infrastructural barriers exist to the use of satellite remote sensing data for more routine regional applications.

In spite of these limitations, satellite data have tremendous potential to augment the standard operations of air quality management (Duncan et al., 2021; Potts et al., 2021). Considering the evident gaps in existing RGM networks, even as supplemented by LCS deployments, satellite information has a key role to play in providing a high-level overview of spatial patterns and long-term temporal trends of air quality. This is particularly relevant for regional transport, where satellite data products can inform the horizontal spatial extent and air mass transport information for plumes, sometimes in near real-time (for certain geostationary instruments). Satellites also represent the only source of routine air quality information over the global oceans, as well as over many sparsely populated areas (deserts, tundra, dense forests) which lack the infrastructure to support surface-based monitoring. This sort of "big picture" information from satellites tends to well complement and provide context for "nose level" data sources such as LCS.

Analogous to LCS, smaller and less expensive satellites which can be launched in greater numbers, referred to as SmallSats or CubeSats, are also becoming more commonly used in remote sensing (Love et al., 2021; Maasakkers et al., 2022). As new satellite missions with increased technical capabilities are launched, and as these missions are supported with new data infrastructure for more effectively disseminating relevant information in readily accessible formats, the utility of satellites for assessment of air quality is likely to increase.

C.1.2. Air quality reconstruction with satellite remote sensing data

Typically, satellite instruments provide information on the presence and concentrations of different atmospheric constituents throughout all or a significant portion of the atmospheric column. To increase their relevance for near-surface applications, they are often paired with surface-based measurements, and relationships are established (using techniques similar to LUR discussed in Section 3.2) between the remotely sensed atmospheric parameters from the satellite and the surface air quality measured at monitoring sites. These relationships are then applied to satellite remote sensing information as an approach to reconstruct air quality on a wider spatial domain, i.e. all or part of what the satellite can observe.

For particular matter (PM), AOD retrievals are commonly used as the relevant satellite dataset. For certain regions and time periods, AOD has been shown to correlate reasonably well with near-surface PM, including $PM_{2.5}$ (Wang and Christopher, 2003; Engel-Cox et al., 2004; Zhang et al., 2009). In other applications, however, large uncertainties have been noted when translating AOD to surface $PM_{2.5}$ (World Bank, 2022a). Thus, remote sensing data and associated relationships between AOD and $PM_{2.5}$ should be used cautiously, considering their varying applicability at regional and local scales and for different time periods (Rudke et al., 2023). This is due to many factors, including the vertical distribution of aerosols in the atmospheric column, the composition and size distribution of the aerosols, and hygroscopic effects. Spatial resolution of satellite AOD datasets varies according to instrument. MODIS MAIAC is a commonly used data product in air quality applications with a 1 km spatial resolution.

For atmospheric trace gases, column concentration retrievals from satellites for the corresponding gases can be used. This is most relevant for NO_2, as remotely sensed column concentrations tend to correlate well with surface concentrations, due to the tendency for NO_2 to be most prevalent in the lower troposphere. This allows, for example, identifying pollution exposure disparities at urban scales (Demetillo et al., 2020, 2021). Satellite retrievals for other atmospheric trace gases of interest, such as CO_2, SO_2, CO, methane (i.e. CH_4), and formaldehyde are also available from orbiting instruments. Satellite retrievals of ozone concentrations tend to be much more sensitive to the upper atmosphere, and so are not directly relevant to near-surface air quality. Spatial resolutions of trace gas data products also vary; the current state-of-the-art TROPOMI instrument provides NO_2 tropospheric vertical column data products with 3.5 km by 5.5 km nominal resolution, for example. TROPOMI NO_2 data are used on an operational basis jointly with RGM observations and other auxiliary datasets for reconstructing continental-scale annual average air quality for Europe by the European Environment Agency (Horálek et al., 2022, 2023).

Satellite spatial coverage and temporal frequency are largely governed by their orbital characteristics. Polar-orbiting satellites allow for full global coverage, and typically provide about one overpass per day of a given location, usually at similar local times each day. Thus, reliance on these data can provide spatial distribution information only relevant for specific times of day. Geostationary satellites maintain a fixed position over the Earth's surface, allowing for more frequent observations (limited by atmospheric and light conditions, the capabilities of the instrument, and data communication bandwidth), but limiting these to a fixed field of regard of the instrument. Several applications have combined geostationary satellite AOD with surface RGM $PM_{2.5}$ data to produce hourly regional surface $PM_{2.5}$ products (Zeng et al., 2018; Zhang et al., 2022). Geostationary observations of atmospheric trace gases are a relatively new capability of the GEMS and TEMPO instruments launched in 2020 and 2023 respectively, and will likely provide similar capability of such "nowcasting" of near-surface trace gas concentrations, although only for certain parts of the world.

Clouds, Sun glint from reflective surfaces, and dense smoke can interfere with satellite remote sensing of aerosols and trace gases. Averaging satellite remote sensing data over time can reduce the impact of this interference, improving spatial coverage at the expense of temporal resolution. This approach is especially favorable when working with geostationary satellite data, due to their more frequent observations, and therefore a lesser sacrifice of temporal resolution. Even so, for some regions, persistent cloud cover may prevent any relevant satellite retrievals, or resulting reconstructions may be heavily biased to represent a relatively small number of cloud-free days.

Ground-based information is essential for both developing and validating air quality data products derived from satellite remote sensing data. For the near-surface composition which is most directly relevant to air quality, RGM have typically provided these data as noted in several of the examples above. LCS can also contribute to these efforts. For example, a recent white paper on satellite monitoring for surface PM specifically highlights the need for calibrated LCS data for $PM_{2.5}$ to validate satellite-derived data products (Kondragunta, 2022). Data provided by well calibrated LCS are amenable to combination with satellite data via regression approaches, similar to those applied with RGM data. Furthermore, the large spatial coverage achievable via LCS can be beneficial to establishing robust relationships between remotely sensed quantities from satellites and air quality near the surface.

Most current applications combining satellite remote sensing and LCS data for reconstruction have focused on $PM_{2.5}$ estimation, and have used AOD as the corresponding remotely sensed parameter. Despite difficulties, these applications demonstrate that standard techniques can relate satellite AOD with surface $PM_{2.5}$ using LCS data, especially when larger networks of LCS can provide better spatial coverage within the satellite's field of view. For example, a network of $PM_{2.5}$ LCS data across California, USA, was used to calibrate satellite AOD to reconstruct surface $PM_{2.5}$ during a wildfire event. It was found that, while measurements of $PM_{2.5}$ by each individual LCS correlated poorly with coincident satellite AOD, collecting LCS data from many sensors across a large domain (the state of California) produced a more robust regression relationship, such that the reconstructed surface $PM_{2.5}$ derived from the satellite AOD information agreed well with $PM_{2.5}$ measured at the sparser network of RGM sites across the state (Gupta et al., 2018). This illustrates the value of regional coverage from both LCS networks and satellite remote sensing data when used together. For an application in Kampala, Uganda, Atuhaire et al. (2022) combined LCS with satellite AOD information from Landsat-8 and Sentinel-2 to generate high-resolution $PM_{2.5}$ using a geographically weighted regression approach with additional meteorological information. Here, it was found that the relationship between satellite AOD and surface $PM_{2.5}$ was highly variable, requiring separate calibrations for each satellite pass rather than, e.g. seasonal calibrations. Nevertheless, the satellite-derived $PM_{2.5}$ was highly correlated with held-out ground measurement data (R^2 between 0.69 and 0.89), with the higher spatial resolution Sentinel-2 product resulting in better agreement. Cloud cover and limited numbers of ground-based $PM_{2.5}$ measurements for validation were identified as key challenges in this application. It has also been found that correcting for the influence of relative humidity can improve agreement between satellite AOD and LCS $PM_{2.5}$ (Regmi et al., 2023).

When high-density ground networks are available, incorporating satellite AOD may be less beneficial to reconstruction than simpler statistical interpolation approaches. Incorporating satellite AOD information was found not to improve surface $PM_{2.5}$ reconstruction relative to statistical interpolation from a dense network of LCS (over 40, for roughly one LCS per 5 km^2) in Pittsburgh, Pennsylvania, USA. However, AOD information was found to be useful in Kigali, Rwanda, where far fewer LCS (less than 5, for roughly one LCS per 150 km^2) were present (Malings et al., 2020). Similarly, Chao et al. (2021) found that including AOD-derived $PM_{2.5}$ tended to decrease cross-validation performance for Xinxiang, China, compared to inverse distance weighted regression using dense networks of RGM (48 sites, for roughly one RGM per 170 km^2) and/or LCS (144 sites, for roughly one LCS per 60 km^2).

In an example of daily high spatial resolution (100 m) surface $PM_{2.5}$ reconstruction in New York City, USA, better performance was achieved when using satellite AOD and RGM data together than when LCS data were also included, indicating that the existing RGM network alone was sufficient for establishing a local relationship between AOD and surface $PM_{2.5}$ (Huang et al., 2019). This is consistent with the findings of Malings et al. (2020) for Pittsburgh, USA. Nevertheless, Huang et al. also found that integrating LCS data yielded estimates that were about 15% higher alongside major highways and in densely populated urban areas. These systematic differences highlight the potential benefits of considering LCS information when producing such reconstructions, as other data sources might systematically underrepresent certain areas. In an approach which also incorporated land use information (land cover categories, tree and building heights, distance to and length of roadways) for very high spatial resolution (30 m) daily average $PM_{2.5}$ reconstruction via convolutional neural networks across several counties in Texas, USA, LCS data were found to be more informative than AOD information, but less informative than land cover or roadway information (Liang et al., 2023). This indicates that remote sensing information may be of less relevance in high spatial resolution reconstruction where dense LCS networks are already available to provide nearby ground-truth data. The utility of including both satellite AOD and LCS data for high-resolution spatial reconstruction, especially within cities, is thus not clear, and may be dependent on local conditions, LCS network density, and the specific objectives of the application.

In contrast to these city-scale examples, incorporating satellite AOD and LCS data have clearer benefits in regional-scale applications. Satellite AOD information was combined with both RGM and LCS information to create spatially continuous $PM_{2.5}$ reconstructions across the island of Taiwan by Li et al. (2020). When compared with other methods, including the use of kriging with either RGM or LCS data, the combination of all available information was shown to provide the best reconstruction of surface $PM_{2.5}$ during cross-validation. Furthermore, inclusion of LCS data was noted to provide greater detail and enhanced spatial distribution while maintaining desirable characteristics of reconstruction generated from the RGM and AOD information alone. Satellite AOD information, meteorological data, and land use data were combined via a random forest ML approach to reconstruct daily $PM_{2.5}$ at 1 km resolution for Imperial Valley, California, USA (Bi et al., 2020a). In cross-validation testing, incorporating LCS data alongside the RGM for model training resulted in improved accuracy compared to using the RGM data alone. Even after calibration of the LCS to reduce bias, noise in the LCS data contributed to residual uncertainties in the resulting reconstruction. However, it was noted that incorporation of LCS data did result in more reasonable spatial patterns in the final product. In a similar approach, scaled up to the entire state of California, USA, LCS were first regionally calibrated using a geographically weighted regression approach, and then both RGM and LCS data were used for training, with the LCS data being assigned a lesser weight, which was determined as a by-product of the regional calibration step (Bi et al., 2020b). Cross-validation testing indicated that, when LCS data were incorporated in this weighted manner, the output better captured the impacts of wildfires on local air quality. These results illustrate that, through a combination of multiple data sources, performance of LCS networks can be better characterized regionally, and furthermore that this characterization allows for their appropriate use (considering relatively higher uncertainties) in combination with satellites and other data sources to improve regional air quality reconstruction efforts.

For sub-daily reconstruction, geostationary AOD information have been combined with surface RGM and LCS data, as well as meteorological information from models and land use information, to estimate surface $PM_{2.5}$ concentrations on an hourly basis during the 2018

Camp Fire event in California, USA (Vu et al., 2022). Regression to surface $PM_{2.5}$ was carried out using a random forest ML method, with a synthetic minority over-sampling technique to improve estimation performance for rare extreme concentrations due to the fire. LCS data were given a relatively lower weight (15%) in this method compared to RGM measurements. Nonetheless, incorporating LCS data was found to improve the accuracy of the reconstruction versus using RGM data only, especially in terms of reducing underestimation of extremes during the wildfire event.

In addition to PM mass concentrations, certain types of satellites and LCS also provide information relevant to aerosol size distributions, which can be used together synergistically. In deSouza et al. (2020b), raw aerosol size distributions from multiple, surface-based low-cost Optical Particle Counters (OPC) are used to constrain the Multiangle Imaging SpectroRadiometer (MISR) component-specific AOD data, which contains some particle-size-resolved information. This technique allows for deriving surface aerosol concentrations for particles as small as about 0.1 μm in diameter, which MISR detects but are below the OPC detection limit of about 0.5 μm. As such, the technique allows for better constraints on the near-surface fine and ultrafine PM concentration. This technique was tested using data from a network of OPC in Nairobi, Kenya (deSouza, 2017).

Although less common, applications combining LCS and satellite information for trace gases have also been attempted. Data from LCS and RGM were combined via a ML approach with TROPOMI satellite data and local meteorological and land use information to produce hourly, 1 km spatial resolution NO_2 reconstruction for Tangshan, China (Fu et al., 2023). In this technique, multiple gradient-boosted decision tree models were calibrated to iteratively impute missing data for each grid cell, with different trees used depending on which data sources (LCS, RGM, and/or satellite data) were available in each grid cell at each timestep. Within this method, the dependence of LCS performance on meteorological factors such as relative humidity was implicitly accounted for by including meteorological predictors as inputs to the ML approach, rather than explicitly accounting for these through prior LCS calibration to nearby RGM. In this study, it was noted that the inclusion of both satellite and LCS data improved reconstruction performance compared to the use of either dataset on its own. The incorporation of LCS data provided important benefits outside of satellite overpass times as well as in the identification of fine-scale pollution gradients below the resolution of the satellite information. Although this study was conducted in an area with dense networks of both RGM (over 200 sites, or about one site per 60 km^2) and LCS (over 600 sites, or about one site per 20 km^2), a sensitivity study found reasonably good performance even using only 10% of sites (randomly selected), indicating that the method could still be applicable in more sparsely monitored regions.

Overall, despite some limitations of different satellite instruments for retrieving useful information for certain atmospheric constituents, at certain times of day, and for certain regions subject to interference such as persistent dense cloud cover, satellites provide a useful source of near real-time information on air quality and its spatial characteristics over relatively board areas. Combining this information with ground-truth data, especially considering the increased spatial coverage and high temporal resolution achievable with LCS networks, can provide an attractive approach to air quality reconstruction (Zhu et al., 2023). Unfortunately, a lack of technical expertise in the relevant techniques discussed here, along with difficulties in accessing and manipulating large quantities of satellite remote sensing data, can pose barriers to the effective use of these data.

C.2. Air Quality Modelling systems

C.2.1. Statistical forecasting

The simplest and most straightforward methods of forecasting, statistical techniques rely on the assumption that future conditions will be similar to measured past conditions. By analysing data records for past conditions, representative examples can be found or extrapolations made which are then used to represent a forecast of future conditions. Provided that data from LCS are well calibrated and have adequately characterized errors, almost any statistical forecast technique which can be applied to another data source, e.g. a RGM, can be applied equally to a LCS. The most important caveat to this would be the presence of confounding factors, such as meteorological conditions, impacting the performance of a LCS calibration. For example, if a LCS for $PM_{2.5}$ was heavily impacted by relative humidity, and these impacts were not sufficiently accounted for in its calibration, a statistical technique for forecasting $PM_{2.5}$ from data collected by this LCS would tend to confound humidity with $PM_{2.5}$, predicting (for example) co-occurrence of high relative humidity with high $PM_{2.5}$, effectively encoding this potentially spurious relationship into its forecasts. Long data records representing a diversity of air quality and meteorological conditions, together with an appropriate statistical methodology capable of disentangling such effects where they exist, are generally the best approach to avoiding such problems. This closely mirrors guidance for calibrating LCS, as most LCS calibrations are statistical techniques, many of which have direct analogs in forecasting as well. Finally, also analogous to LCS calibrations, continuous testing and validation of statistical forecasts, and recalibration of these forecasts to account for changes in underlying conditions (i.e. when the future is no longer being well represented by the past) are recommended. Best practices for calibrating LCS, discussed in the WMO report (WMO, 2020), should be followed to allow characterization of LCS performance under different conditions and thus the identification of confounding factors which could influence the performance of a statistical forecasting method.

The **persistence forecast** is a simple yet powerful forecasting technique. This forecast assumes that future conditions will be the same as the most recently measured conditions. Despite this simplicity, these forecasts can be highly accurate in the short term, especially in cases and for constituents where conditions do not change rapidly, e.g. for regional pollutants with long atmospheric lifetimes. Persistence forecasts tend to become increasingly inaccurate as the most recent measurements are increasingly outdated, although periodically the accuracy may improve due to cyclic patterns in constituent concentration, e.g. diurnal cycles. LCS data are directly applicable to persistence forecasting. In fact, the technique is unintentionally used by many LCS data visualization tools, where the most recent measurement taken by each device is often displayed as the assumed current value. This is potentially subject to removal after the measurement becomes sufficiently outdated, e.g. beyond one day old. Many users of data will also implicitly employ this method when assuming that near-future conditions will match what is currently being displayed on the dashboard of their air quality app of choice. For this reason, it can be important to verify the accuracy of persistence forecasts during network setup and user interface design, and to choose appropriate data age thresholds (which should vary by atmospheric constituent) beyond which old data are removed to ensure reasonably accurate implicit persistence forecasting by users. Persistence forecasts can also be explicitly used when their performance is sufficient. Due to their simplicity, they can be very attractive for certain applications where the most straightforward methods are preferred. The methods are likely to be best applied to short-term forecasts, on the order of minutes or hours, with performance depending on the rate of change in the air quality parameter being forecast. Pattern-persistence forecasts use identified repeating patterns in past data to forecast future conditions. A typical pattern-persistence forecast involves stratifying a past in situ data record by hour-of-day, day-of-week, and month-of-year (or perhaps season-of-year), and reporting a forecast for a specific day and time as the average of past data collected at that same time of day, day-of-week, and month-of-year or season. Such stratification attempts to capture common diurnal and seasonal trends in atmospheric conditions, as well as weekly trends in human activity which impact air quality. Pattern-persistence forecasts depend on stationarity in these cycles; cycle changes can invalidate a pattern-persistence forecast, necessitating a new period of data collection to capture the new conditions. To counteract this, a "rolling window" for pattern identification can be used, e.g. using only the past week of data.

Where sufficient data are available to robustly describe general cycles, a pattern-persistence forecast can be a very simple and effective method. However, pattern-persistence forecasts must be developed for each environment in which they are to be applied, and usually generalize poorly to new locations and environmental conditions. Furthermore, pattern-persistence forecasts are unable to anticipate unique events, e.g. a specific wildfire, although they may capture the generalized impacts of multiple such events, e.g. a wildfire season. Pattern-persistence forecasts can be readily applied to LCS data, provided that the LCS calibration is not affected by the same cycles which the pattern-persistence forecast is attempting to capture (e.g. diurnal cycles of humidity). The issue of the same factors impacting both pattern-persistence forecasts and LCS calibrations may not be apparent if both meteorological conditions and air quality follow similar periodic patterns; however, a shift or disconnection of these patterns can invalidate the forecasting approach. Furthermore, it may be difficult to detect such a change using LCS data, as both the forecasting method and the measurements taken by the LCS will be similarly impacted, especially if both the LCS calibration and the pattern-persistence forecast are based on the same historical dataset. Thus, successful application of a pattern-persistence forecast to LCS data would require an LCS with proven stability in performance over a relatively long time period, with minimal drift and little to no diurnal or seasonal variations in performance. This is especially relevant since long-term performance evaluations of LCS are often lacking (WMO, 2020). It is worth noting that persistence forecasts and pattern-persistence forecasts represent complementary simple techniques. For example, persistence forecasts may be more suitable to forecasts of several hours in advance or less, when the impacts of unique events are most acute, while pattern-persistence forecasts might outperform these over periods of several hours to days, due to their ability to account for typical recurring patterns. Combinations of persistence and pattern-persistence forecasts can therefore be attractive for use cases where simple, robust methods are sought.

A rules-based forecast can be considered as a generalization of a pattern-persistence forecast, where factors besides time are used to stratify the historical data for statistical forecasting. Although in principle any additional factors can be considered, in practice, prevailing weather conditions are often used for stratification. Air quality can be quite different during and immediately following rain, for example, as compared to dry conditions. After stratifying historical data based on relevant meteorological factors, e.g. total rainfall in the last 24 hours, a new average can be calculated which better represents those specific conditions. The forecast can then reflect this as well by considering additional meteorological forecast information from a different source, e.g. the predicted rainfall for the next day.

The overall rules-based forecasting approach is often described using a series of "if-then" statements, which might be formally organized into a decision tree, where the forecaster follows "branches" of the tree based on the various ancillary information considered until a "leaf" is reached, describing the forecast under those specific conditions. Determining which additional factors could be relevant to a rules-based forecast will depend on local conditions, and rules-based forecasts are unlikely to be transferable to new environments. Rules-based forecasts are especially amenable to the incorporation of local knowledge and expert opinion solicitation. This would result in an "expert forecast" based on implicitly connecting predicted future conditions with extensive experience to develop the relevant forecast, and considering local phenomena (prevailing wind direction, atmospheric inversions, festivals, etc.) which are known to coincide with pollution episodes. For example, in the absence of emissions data to support air quality modelling systems (AQM), a classification technique based on synoptic patterns was used to forecast PM_{10} concentrations in Northwestern Thailand a day in advance, which was over 90% accurate in forecasting periods with concentrations above 120 µg/m^3 (Kim Oanh and Leelasakultum, 2011). The process of determining the important ancillary factors to be considered for data stratification and the creation of decision trees using these factors can also be automated using software, including clustering and ML techniques.

Generally, the same considerations for using LCS to support pattern-persistence forecasting discussed above are also applicable to any rules-based forecast method. Namely, there should be sufficient data to cover the range of conditions under which the forecasts are to be made, and the calibration performance of the LCS should not be influenced by the same factors which are being used as ancillary factors in the rules-based forecast.

Regression based forecasts use a pre-determined (often linear) function of specified inputs to make their predictions. In regression forecasts, the inputs often include current and past in situ data at some specific time interval (e.g. hourly measurements covering the previous day), expanding on the basic idea of the persistence forecast. Additionally, as with rules-based forecasting, different ancillary factors (e.g. time of day, day-of-week, forecasted humidity, etc.) might also be included as inputs to the regression. Alternatively, different coefficients of the regression or different regression equations might be calibrated under these different conditions.

Typical regression forecasting techniques involve autoregressive linear functions, especially the autoregressive moving average (ARMA) and autoregressive integrated moving average (ARIMA) techniques. These regression approaches are straightforward to apply to LCS, since many LCS calibration approaches already use regression (especially linear regression) techniques. These methods are also simple enough to be implemented directly into LCS architectures. An exponential smoothing with drift mode, essentially a moving weighted average of recent historical data, was applied to forecast hourly $PM_{2.5}$ concentrations up to 3 hours in advance using data from an extensive LCS network in Taiwan (Mahajan et al., 2018). This method performed well in comparison to other techniques such as ARIMA and autoregressive neural networks. ARMA and ARIMA were both used successfully to forecast air pollutant concentrations up to four hours in advance using data from a multipollutant LCS (Mani et al., 2021). A simple autoregressive linear model was employed for hourly $PM_{2.5}$ and PM_{10} forecasting using LCS data inputs in Battipagli, Italy; in this case, it was found that allowing regression coefficients to vary seasonally and with meteorological conditions led to improved performance (Lotrecchiano et al., 2019). Certain statistical techniques, notably the Kalman Filter, can also be considered as applications of regression forecasting once their parameters have been established. A Kalman Filtering approach was applied to multipollutant LCS data for one-hour-ahead prediction, and was found to outperform an ARIMA approach on the same dataset (Lai et al., 2019). The variety of regression techniques available, as well as potential choices about the number and types of input parameters and combinations of parameters which can be used, allow for a great deal of flexibility, but also the possibility of unnecessary model complexity leading to overfitting. Robust performance evaluation methods (as discussed in Section 8.1) should be used to balance trade-offs between model complexity, robustness, accuracy, and explainability. Depending on the regression approach used, a certain number of past measurements may be required as inputs. If there are gaps in the data series, e.g. due to the malfunctioning of an LCS, the method may not be able to be applied, or some fill value may need to be used to impute the missing data. This may seriously degrade forecast performance.

Finally, as with all statistical forecasting techniques, regression forecasts encode assumptions about the representation of future conditions by the historical datasets used to calibrate the regression. When underlying conditions change, the forecasting method may no longer be valid. It may be difficult to ascertain when this has occurred without comparing forecasts to an independent dataset.

ML techniques are a general description of approaches to automatically identify relevant patterns in data which can be used for a variety of applications, including forecasting. While regression techniques could also be considered as a class of ML methods, ML more typically refers to non-parametric approaches without a fixed functional form. Compared to regression techniques, especially linear regression, ML techniques are typically better suited to handling non-linear relationships between data, which is often an important ability for air quality applications. ML techniques, like regression approaches, are frequently employed in the calibration of LCS, and so their application for forecasting has been a natural extension of some existing LCS calibration efforts. Common ML techniques for forecasting include decision trees, random forest models, and long-short term memory (LSTM) neural networks. Decision tree methods are an automated system for creating the types of rules-based forecasts. Random forests involve ensembles of decision trees, where an average or consensus forecast among the trees is used to improve performance and generalization. LSTM is a category of neural network model suitable for handling sequential data and making predictions about the next values in a sequence, making them applicable for forecasting.

All these techniques, as well as numerous variations, can be applied to forecasting. A combination of LSTM and wavelet transformation was applied to provide daily next day multipollutant forecasts using RGM data in several regions of China, providing good performance (Liu et al., 2020). A number of different ML forecasting techniques were tested and compared for the forecasting of hourly $PM_{2.5}$ using the previous day's $PM_{2.5}$ measurements, together with wind speed and rainfall information (Moursi et al., 2021). The algorithms were also evaluated on their ability to be deployed on a small edge computing device, such as might be part of a LCS package. The study concluded that a hybrid of Nonlinear AutoRegression with Exogenous Input and Extreme Gradient-Boosted Random Forest architecture provided the best balance between performance and efficiency.

ML forecasting techniques involving LCS data can suffer from all the drawbacks of the previously discussed statistical forecasting methods, especially in failing to generalize beyond the range of conditions represented in the historical dataset used to calibrate them. Furthermore, unlike rules-based or regression methods, the mechanisms involved in ML forecasting are especially opaque, even to experts. ML methods are often perceived to be "black boxes" by users, undermining trust. Explainable ML techniques, for example the calculation of Shapley Values to describe how the different inputs to the ML algorithm influenced the value of a specific forecast output, can be an important tool to gain insight into the internal mechanisms and key features of different ML techniques and build confidence in their applicability (Adadi and Berrada, 2018). However, such techniques require additional effort to implement are still not common practice in ML applications.

Parsimony is recommended when applying ML techniques. ML approaches should be compared with simpler techniques, especially persistence and pattern-persistence forecasts, to determine whether their application is justified with sufficiently improved performance. Wherever possible, gains in forecasting accuracy due to the use of more sophisticated forecasting approaches should be compared to the uncertainties in the input LCS data, e.g.

due to known calibration limitations. It would be unlikely, for example, that an air quality forecast using only LCS data as inputs would be more accurate than the data obtained from the LCS itself, and such results should be treated with some skepticism until robustly verified with independent data sources.

A modified persistence forecasting approach was used for predicting $PM_{2.5}$ concentrations during the burning season on Thailand (Kanabkaew et al., 2019). High temporal frequency (15 minute average) data from a small LCS network were combined with wind speed and direction information, with concentrations measured at upwind locations being used to predict downwind concentration, with the wind speed and direction determining the lag time used to make the prediction. This demonstrates that, even with basic meteorological information and a simple forecasting technique, a network of LCS covering upwind directions can provide useful information. Various ML approaches, especially deep learning approaches, can also be applied and have the ability to capture highly nonlinear spatiotemporal relationships in large datasets (e.g. H. Wang et al., 2023). Using a network of 28 LCS in Delhi, India, a reconstruction and forecasting approach was developed using a combination of spatiotemporal hierarchical models, message-passing neural networks, and cubic splines (Iyer et al., 2022). Hsieh et al. (2015) use an affinity graph structure, where unmonitored locations and times are connected with monitored locations and times, with the weights of connections being determined by physical distance, similarities in land use, temporal closeness, and similarity in meteorological conditions (which vary over time). This approach was found to outperform several others for reconstruction and forecasting, even with sparse observations. Furthermore, the approach produced probabilistic rather than deterministic estimates. However, this approach requires a new graph structure with new weights to be constructed for each new timestep considered, as well as whenever the monitoring network configuration changes.

C.2.2. Deterministic models

Air quality modelling systems (AQM), while not a direct source of atmospheric composition or air quality measurements themselves, are an important tool for putting measurements in context and building understanding of air quality and the processes and trends governing it. AQM play a critical role in air quality management, policy development, and public health protection by providing valuable insights into the factors influencing air quality and informing decision-making processes. AQM require input data on emissions, meteorological conditions, land use, and atmospheric chemistry.

They simulate processes such as advection, diffusion, chemical reactions, and deposition to predict pollutant concentrations at various locations and times. These models are essential for understanding the impacts of emission sources, meteorological events, and control measures on air quality.

AQM vary greatly in terms of their framework (Eulerian, Lagrangian, Hybrid, Receptor, Statistical), complexity and dimensionality (0-D or box model, 1-D dispersion or column model, 2-D model, and 3-D offline and online-coupled meteorology with chemistry and transport models, or CTM), parameterization (assumptions and mathematical simplifications built into the model), scale (local, regional, global), resolution (spatial, temporal, and number of tracked parameters), application (regulatory, research, or operational), and connections with other models and/or data sources (Zhang, 2008; Zhang et al., 2012a, 2012b; Baklanov et al., 2014; Bocquet et al., 2014).

AQM provide an important tool for understanding air quality beyond what is possible via measurement alone. At a basic level, AQM outputs are complete, providing the desired information over their entire application domain, with no missing data, as is a risk for any measurement system. AQM can also capture uncertainty or sensitivity, e.g. through an ensemble of models. Finally, AQM are not necessarily constrained to present reality; they can be run forward to provide forecasts 3–5 days in advance (Zhang et al., 2012a, 2012b), as well as backward to examine historical circumstances (i.e. as reanalysis). By adjusting model inputs, counterfactual simulations can also be run, allowing quantitative assessment of what the impacts of certain changes to the system might be. This is useful for helping understand the basic processes governing air quality, as well as the potential effects of proposed regulations and policies. Many AQM can also be run in an inverse mode, in which they can correct a priori pollutant emission inventories based on observations (e.g. from RGM, satellite data, or potentially LCS; see Section 4.3).

The relationship between AQM output and reality is limited both by the capabilities of the AQM, e.g. its treatment and/or parameterization of different chemical and physical processes, as well as by the availability and quality of data input into the model. For the case of air quality, the emissions inventories needed to inform AQM of what is being put into the atmosphere are often unavailable, incomplete, and/or outdated, and will vary in terms of completeness and accuracy across geographical regions and economic sectors. Although global inventories are available (e.g. EDGAR, CEDS, HTAP, ECCAD) and initiatives exist to support global inventory development and improvement through the Global Emissions InitiAtive (GEIA), these rely on assumptions and extrapolations, and many nations lack domestically developed and/or verified inventories which are necessary for more locally relevant analysis. The process of developing or updating local emissions inventories is also time-consuming, and such inventories do not capture near real-time emissions changes. Additionally, the technical expertise and computational resources needed to run AQM are extensive, and computational complexity tends to increase rapidly as model formulation, resolution, and sophistication expand. As with satellite data, countries and organizations with the capability to routinely operate regional or global AQM often make relevant outputs freely available to users. Furthermore, new data science approaches, especially in ML, are reducing the computational resources needed to operate AQM. Even so, the technical and computational resources needed even to analyse AQM output sometimes remain a barrier to their use. Finally, in the absence of other data sources, it is difficult to validate AQM results. This is especially concerning given the relative sparsity of RGM on a global scale noted earlier, and is another area where the additional information provided by LCS can be valuable.

It is also important to note, especially in the context of this report, the methods whereby AQM are commonly combined with measurements to provided air quality reconstruction (such as reanalysis) or enhanced air quality forecasts. Techniques of data assimilation and data fusion are all applicable in such cases.

Data assimilation refers to the process of using observational data to adjust the state of a model, to bring it into better agreement with reality while simultaneously preserving the internal self-consistency of the model (Bocquet et al., 2014). That is, data assimilation does not merely change the model outputs to match observations but brings the model into a new state which is both internally consistent with other modelled quantities and externally consistent with observations (considering that the observations are also subject to uncertainty). Typically, especially in global AQM, remote sensing data provide the majority of observations used in current data assimilation systems, due to their (generally) global coverage and comparable spatial resolution to the model itself. In a coupled chemistry and meteorology model of the atmosphere, data assimilation can involve meteorological observations, which can in turn impact air quality through the mechanisms of the coupled model. Data fusion refers to the process of blending model outputs (i.e. post-processing) with other information sources, including observational data, to produce a new representation of reality. Unlike data assimilation, data fusion does not update the model state, and does not necessarily produce a self-consistent estimate. Data fusion is commonly employed in AQM "downscaling", i.e. taking the outputs of an AQM at a coarse resolution and producing similar outputs at a finer spatial and/or temporal resolution, through a form of interpolation or regression model informed by other information sources (e.g. Goldberg et al., 2019). Data fusion is also useful in correcting for biases between AQM and observations without resorting to the computational complexities of a full data assimilation approach. An example of large-scale data fusion is provided by Van Donkelaar et al. (2021), where global AQM outputs are combined with satellite information on AOD and surface-level RGM data to estimate monthly-average global surface $PM_{2.5}$ concentrations, together with associated uncertainty; more recently, similar techniques have been applied to produce daily average global surface $PM_{2.5}$ estimates (Wei et al., 2023). Global AQM forecasts from the GEOS-CF system, relevant data from the TROPOMI satellite instrument, and surface-based RGM data for NO_2 were combined via a data fusion approach to support NO_2 forecasting up to 24 hours in advance and reconstruction to unmonitored locations in a cross-validation experiment across RGM locations in several cities in the USA (Malings et al., 2021). The combination of AQM, satellite, and RGM data improved forecasting performance with respect to either the AQM forecasts alone or simple persistence and pattern-persistence forecasts and nearest neighbour interpolations applied to the RGM data. A similar approach could also be used to integrate LCS data, with the caveat that the additional uncertainties of LCS data with respect to RGM data would need to be properly accounted for. In another example of data fusion, a random forest ML method was applied to a combination of output from GEOS-CF, which provided the forecasting, and land use information, which was used to produce a higher spatial resolution reconstruction (Bi et al., 2022b). In this case, RGM data were also used for calibrating the ML approach, but LCS data could again be applied instead. The data assimilation study of Lopez-Restrepo et al. (2021) discussed earlier also considers both forecasting and reconstruction applications.

National agencies, especially those concerned with meteorological forecasting and/or air quality management, often operate national- or regional-scale AQM. Examples of this include the National Air Quality Forecasting Capability (AQFC) of the USA via NOAA (Campbell et al., 2022), the China Meteorological Administration Unified Atmospheric Chemistry Environment (CUACE) (L. Zhang et al., 2021), the United Kingdom Chemistry and Aerosols (UKCA) Model within the UK Met Office Unified Model (Archibald et al., 2020), the MOdèle de Chimie Atmosphérique à Grande Echelle (MOCAGE) of Météo-France (Martet and Peuch, 2009), the Air Quality Early Warning System for Delhi, India (Ghude et al., 2020), and the System for Integrated Modeling of Atmospheric Composition (SILAM) of the Finnish Meteorological Institute (Sofiev et al., 2006). At a global scale, routine atmospheric composition forecasting systems include the Copernicus Atmosphere Monitoring Service (CAMS) Integrated Forecasts system (IFS) developed by the European Centre for Medium-Range Weather Forecasts (ECMWF) (Inness et al., 2019), the NASA Goddard Earth Observing System Composition Forecast (GEOS-CF) (Keller et al., 2021b), and the Navy Aerosol Analysis and Prediction System (NAAPS) (Rubin et al., 2016). These AQM are moving towards the use of data assimilation, especially of satellite data products, to improve their accuracy and performance. There are also global atmospheric composition **reanalysis** data products, where AQM simulations are run retrospectively for past conditions, including assimilating relevant measurements. See more details in Section C.2.3. Examples of such global reanalysis products include the ECMWF CAMS Reanalysis (Inness et al., 2019) and the NASA Modern-Era Retrospective Analysis for Research and Applications, Version 2 (MERRA-2) (Gelaro et al., 2017).

In terms of non-operational activities (such as reanalyisis), many universities and research institutions develop national or global estimates of near-surface atmospheric composition relevant for air quality applications for a variety of purposes. These efforts often involve sophisticated data fusion techniques, combining model and satellite data, and occasionally also RGM information, to derive their estimates. The results of these research efforts are often archived for use by other researchers and policymakers. For example, the NASA

Socio-Economic Data and Applications Center (SEDAC) archives global and national air quality datasets for health-related applications. Due to the level of effort involved in developing these datasets, as well as the different goals they are intended to fulfil, the spatial and temporal coverage and resolutions of these datasets can vary greatly, and the latency of these datasets are often measured in years, making them unsuitable for real-time applications and forecasting. Instead, they are most often used to support long-term health impact assessment, such as the Global Burden of Disease project. Finally, due to the specific focus and scope of the organizations generating these datasets, they may be more or less suitable for different applications or in different regions. For example, an annual average estimate of global surface $PM_{2.5}$ from one of these datasets (e.g. CIESIN, 2022), while reasonably accurate at those spatial and temporal scales, is unsuitable for examining the day-to-day exposures of inhabitants in a specific urban area, for which more locally-specific estimates would be required.

There is an inherent mismatch between the operational scale of a global or even regional model and location-specific information, which is often the desired goal of a forecast. In other words, while an AQM may accurately forecast the average air quality over an area represented by a grid cell in the model, the value at a specific point within that grid cell may differ substantially from the grid cell average depending on a variety of factors. Local information, including that provided by LCS, may be useful for understanding disparities between the AQM's grid-cell-level estimates and local conditions, especially when local topography and/or local sources cause major air quality variability at a scale below that represented in the AQM. At a basic level, comparisons with local data can evaluate the AQM performance, potentially leading to improvements in the AQM. Furthermore, this local information can be used to adjust AQM outputs to bring them into better agreement with these local conditions (i.e. through assimilation or data fusion). Since the AQM will typically represent a totally independent data source to the LCS, there is relatively low risk of common factors impacting accuracy of both the model and LCS simultaneously (although this possibility should not be ruled out). Having a thorough understanding of LCS accuracy and uncertainty and relating these to potential accuracies and uncertainties in AQM forecasts will help understand when one source or the other (or neither) is most applicable, and how best these data can be used together.

C.2.3. Air Quality reconstructions

AQM are often used to generate air quality reconstructions. For reconstruction applications, AQM can be combined with observations via data fusion (post-processing) or data assimilation (reanalysis) to bring model outputs into better agreement with observations and/or increase the spatial resolution of model outputs. Both RGM and LCS data can support these applications, as long as LCS are well calibrated and their uncertainties have been characterized.

Data fusion approaches for combining AQM outputs with LCS data typically focus on city-scale applications. These often make use of a residual kriging approach, where AQM outputs form a prior estimate, which is updated with local measurements from a combination of LCS and RGM. This approach can explicitly consider the relative uncertainties in the AQM outputs compared to the RGM or LCS datasets. In an example from Schneider et al. (2017), outputs from a high-resolution pollution dispersion model for Oslo, Norway, were used as a static annual average of NO_2 for the city which was updated via regression and kriging from LCS data. The resulting estimates were highly correlated (R^2 of 0.89) with independent RGM data, with high accuracy (about 15 $\mu g/m^3$ RMSE, compared with typical concentrations ranging from 30 to 100 $\mu g/m^3$ of NO_2). A similar approach was applied for hourly PM_{10} reconstruction in Nantes, France, where data fusion reconstructions including LCS data were found to reduce bias compared to using dispersion model outputs directly, as assessed using independent RGM data (Gressent et al., 2020). This study also highlighted the tendency of the method to dampen observed peaks, and emphasized the need for appropriate characterization of LCS measurement uncertainty to minimize this issue. When comparing universal kriging approaches to data fusion using either an LUR or dispersion model as a prior estimate for reconstructing NO_2 in Sheffield, UK, Munir et al. (2021) found that fused reconstructions produced more realistic concentration estimates than either using ordinary kriging with observational data alone or using the LUR or dispersion model approaches without data fusion. It was noted that using monitors of the same type (e.g. LCS from a single manufacturer) led to better results, compared with using a larger number of monitors of different types. In the southeastern USA, fusing $PM_{2.5}$ concentrations from the CMAQ AQM and LCS for $PM_{2.5}$ to generate hourly spatiotemporal reconstructions improved the detection of prescribed burning impacts. Adding observations from LCS also reduced the underestimation of nighttime $PM_{2.5}$ concentrations and reproduced peaks that were missed by AQM simulations (Huang et al., 2021). These examples illustrate that data fusion of AQM outputs with LCS data can have major benefits, especially for better representing spatial patterns which might not be well captured by the AQM outputs alone. Understanding the relative uncertainty of LCS data, is, however, important to incorporating them correctly via this approach. Data fusion of AQM with available RGM and LCS has also been used effectively to support public air quality communications. For example, a Netherlands National Institute for Public Health and the Environment data portal includes the option to display national real-time $PM_{2.5}$ and PM_{10} reconstructions produced from the data fusion of model, RGM, and LCS data. Development of a centralized data platform for collecting all these air quality data sources (together with appropriate metadata) was identified as key, allowing standardized calibration approaches to be applied across the entire network (e.g. comparing groups of LCS to nearby RGM to verify their accuracy). It was also noted that, while LCS data did not meet local regulatory requirements, they provided significant added value when used alongside RGM data in this way, especially in enhancing the experience of public data portal users when seeking local air quality information (Wesseling et al., 2019). Furthermore, both RGM and LCS data were fused via residual kriging with AQM outputs for $PM_{2.5}$ and O_3 to produce hourly, 5 km resolution spatial reconstructions over Southern California, USA, which were further post-processed to generate real-time air quality index maps for the public (Schulte et al., 2020). Inclusion of LCS data significantly improved the reconstruction performance during wildfire periods versus other reconstruction methods tested.

Data assimilation techniques are applicable to city-scale and regional reconstruction efforts as well. Assimilation of LCS NO_2 data into a high spatial resolution (125 m) urban air quality model for Amsterdam, The Netherlands, showed that by including LCS in addition to RGM data, more detailed patterns of concentrations were apparent in areas and during time periods which were poorly represented by the a priori model and by the RGM network, e.g. during rerouting of typical traffic patterns onto alternate routes (Mijling, 2020). It is noted that careful calibration of LCS and correction for known cross-sensitivities was needed, but that the Bayesian data assimilation approach used was able to appropriately include measurements with different uncertainties. Offline data assimilation into a high-resolution AQM has recently been used to incorporate data from LCS networks measuring NO_2 (Schneider et al., 2023) and $PM_{2.5}$ (Hassani et al., 2023b). In the latter, the joint use of a LCS network with AQM data for reconstructing residential wood combustion found an improvement in RMSE of 40–50% when using LCS data assimilation compared to using the AQM without assimilation. The regional example of data assimilation by Lopez-Restrepo et al. (2021) found that assimilation of a dense network of LCS in the region (145 sites) improved the AQM performance, and also outperformed assimilation of data from a sparser RGM network (14 sites). However, the best performance was achieved by assimilating a subset of the LCS network (115 sites) which were best correlated with nearby RGM. This illustrates how combining the advantages of LCS (high spatial density) with RGM (high accuracy) can lead to an overall improvement in concentration reconstruction when integrated via data assimilation in a suitable high-resolution AQM, and how proper characterization of LCS performance using available RGM data can support data assimilation efforts.

AQM can also support the integration of other sources of information as LCS data, e.g. by providing information to relate near-surface concentration, which is measured by LCS and is typically the goal of the air quality reconstruction. Satellite remote sensing data typically considers atmospheric column concentration (such as AOD). Data fusion using a ML approach incorporating satellite AOD, reanalysis, meteorology, and land characteristic information (land use, population, elevation, vegetation cover) was conducted for South Korea (Tang et al., 2024). A sensitivity test for this approach found that using a high-resolution regional reconstruction only slightly improved performance compared to using a coarser resolution global reanalysis, indicating the applicability of the data fusion method with globally available. In terms of ground-based data, ML performance dropped significantly once fewer than 150 ground measurement sites were available in the South Korea domain, or roughly three sites per million people (one site per 670 km^2); this number could include both LCS and RGM. For the satellite data inputs, little difference was observed in the monthly performance considering the lower temporal frequency polar-orbiting satellite data product (i.e. MODIS MAIAC AOD) versus more frequent geostationary satellite data (from GEMS). For daily reconstruction, it is recommended to use the geostationary satellite data due to improved coverage. The same methodology is being adapted for applications in the USA, Thailand, and Viet Nam, with satisfying preliminary results.

Overall, methods of data fusion and data assimilation are both applicable to support air quality reconstruction by incorporating AQM with LCS data. Proper characterization of the LCS measurement error characteristics and uncertainties are important in these applications. High spatial densities and low latency of LCS data compared to other data sources support their applicability to bias-correct and downscale air quality reconstructions at local scales.

C.3. Statistical interpolation techniques

Statistical interpolation uses data collected at several discrete points in a domain and generalizes these to other locations, either on a site-specific basis or to build a complete reconstruction of the domain. Typically, these techniques depend only on the distances between each point of interest (where concentrations are to be estimated) and the locations of the measurements. Statistical interpolation techniques commonly applied with LCS include nearest neighbour methods, bilinear interpolation, inverse distance weighting, and kriging.

The simplest statistical interpolation technique is a **nearest neighbour** approach, where the value at an unobserved location is assumed to be the same as the value at the nearest observed location. This technique is implicitly being applied when people seek out data from the nearest monitoring station to determine their local air quality. This is a simple approach to interpolation, but results in rapid changes in value along the "boundaries" between regions which are closer to one observation location or another.

Inverse distance weighting approaches estimate concentrations at an unobserved location as a weighted average of concentrations at observed locations, where the weight factors are inversely proportional to the distance from the unobserved to each observed location. Inverse distance weighting approaches produce smoother spatial outputs than nearest neighbour methods. Inverse distance weighting also has the property that, far from the locations of any observations, the predicted value will tend towards the average of all observations across the domain. Examples of inverse distance weighting applied to a network of LCS data are provided by Chu et al. (2020) and Esie et al. (2022). Various definitions of the weights for inverse distance weighting can be chosen; use of the inverse of the squared distance is common. Bilinear interpolation can also be considered as a particular case of inverse distance weighting. However, bilinear interpolation is only applicable within the convex domain bounded by the available observation sites, limiting its utility for complete reconstruction over arbitrary domains.

Kriging, a specific application of the more general technique known as Gaussian process regression, is a probabilistic technique for reconstruction which is common in many geostatistical applications. The technique relies upon a prior assumption about the quantity to be reconstructed. Generally, a uniform prior assumption is adopted, based on an assumed average or typical value of the quantity of interest. Measurements are then used to update this prior assumption, taking the relative uncertainties of the measurements together with the assumed uncertainty in the prior assumption into account to determine the "kriging weights" given to different sources of information. Beyond the locations of measurements, information is propagated using the covariance between the modelled quantity at its measured locations and at the locations of interest. This covariance is parameterized using certain specified functions, called kernel functions, which describe the covariance between points in the domain. Typically, these are only functions of the distances between points; common examples include exponential, square exponential, and spherical kernels. However, more complicated functional forms can also account for more sophisticated covariance relationships (Rasmussen and Williams, 2006). In contrast to bilinear interpolation and inverse distance weighting, kriging explicitly accounts for the spatial autocorrelation in the observations and can provide estimates of spatial prediction uncertainty.

Various kriging techniques have been extensively applied to air quality reconstruction using LCS data. Ordinary kriging, using only distance information, was found to be a suitable approach for generating spatially contiguous estimates from LCS ozone data, as well as informing the appropriate spatial and temporal sampling approaches to best support this reconstruction (Alvear et al., 2016). More general Gaussian process regression was used to reconstruct $PM_{2.5}$ data from LCS during fireworks, wildfire, and persistent cold air pool events in Salt Lake City, USA (Kelly et al., 2021). The LCS-derived estimates agreed well with RGM data during leave-one-out cross-validation, with mean-normalized RMSE ranging from about 15–25%. Furthermore, the Gaussian regression process produced estimates of residual uncertainty which helped to communicate results to end-users.

An example of a more sophisticated approach involved the incorporation of wind data into the kriging kernel function, capturing the fact that locations which are up/downwind of each other will tend to have more similar concentrations. Tests of such an approach using RGM $PM_{2.5}$ data in an urban area in China showed that this approach outperformed other interpolation methods including nearest neighbour approaches, inverse distance weighting, and ordinary kriging (Zhang et al., 2021). An analogous technique could easily be applied with LCS data.

ML approaches can be applied to interpolation as well. For example, a random forest regression algorithm using data collected by other LCS in a network was able to infer $PM_{2.5}$ and PM_{10} concentrations at a target location more accurately than using just the nearest LCS, or the average of the nearest three LCS (Veiga et al., 2021). However, there is a risk of "overfitting" the ML model to a specific configuration of monitoring network. In the example of Veiga et al. (2021), each ML model was trained specifically for the point it was reconstructing to, and it was unclear how well the method could generalize to other locations. To avoid overfitting to a specific configuration of an LCS network, and thus rendering the algorithm useless if that configuration changes or an LCS goes offline, it is recommended that ML techniques for interpolation include more general spatiotemporal information as input features. For example, data from a few nearby active LCS sites, paired with information about the distances of those sites to the target location, can be used as inputs. This would be more robust than using features specific to a given configuration of the network, e.g. including data from every other LCS site in the network.

In general, the performance of any statistical interpolation technique will be sensitive to the design and density of the observation network. If few observed locations are available, such that the spacing between observations is large compared to the characteristic length scales of variability of the quantity being reconstructed, the performance of the approach is likely to be poor. The spatial variability of the constituent of interest will thus be a factor in the appropriateness of interpolation techniques. Constituents with long atmospheric lifetimes that tend to be more spatially uniform tend to be amenable to interpolation techniques, whereas other constituents with more variability and complex interactions are less amenable to interpolation.

Statistical interpolation approaches do not generally consider factors beyond the distances of observations to the location being reconstructed. However, certain kriging approaches do make use of other information, such as wind speed and direction, to define distance metrics which do not directly correspond to the physical distance between locations. Similar approaches can be used to account for factors beyond spatial distance which are likely to affect the similarity of air quality. However, for many applications, especially where relatively dense LCS networks are available, the additional complexity of defining and validating such an alternative metric may not provide sufficient advantages over simple distance-based approaches to justify the additional effort.

In practice, both available RGM and LCS observations can be incorporated into any of the interpolation approaches discussed here. Observations by RGM or LCS can either be treated equally, or some additional weight might be placed on RGM observations to reflect their greater accuracy. In particular, kriging approaches can include explicit quantification of different observation uncertainties for different observation types (e.g. RGM vs. LCS) based on previously assessed performance.

Overall, kriging is more difficult to appropriately apply than other interpolation techniques discussed here, requiring explicit quantification of input uncertainties, selection of an appropriate prior mean and variance, and an appropriate choice of kernel function to capture spatial covariance. However, as noted above, it provides additional flexibility, and the explicit handling of uncertainties, both in the quantity of interest to be reconstructed and in the measurements of this quantity from LCS and/or RGM. This can be beneficial for air quality reconstruction, since it allows for prior physical knowledge and assessments of measurement accuracy to be considered. Furthermore, the additional spatial density of observations possible using LCS could also support kriging by helping to create and validate semi-variograms. Semi-variograms are plots of concentration auto-covariance as a function of distance which are used to help determine an appropriate form for the kriging kernel function. With more measurement locations, more inter-location distance pairs can be analysed, providing more data with which to generate the semi-variogram, and thus a more robust result from this type of analysis.

C.4. Land Use Regression

Land use regression (LUR) involves reconstruction from a few discrete measurement locations by establishing relationships between the measured quantity and the characteristics of locations relevant to the land use which would affect the local air quality. Parameters commonly used in LUR include population density, restaurant or cooking activity density, density of nearby roadways and traffic flows, distances to known pollution sources (e.g. ports, power plants, industries), elevation, and information about prominent vegetation types and land cover (e.g. fraction impervious surfaces or typical street canyon depth). LUR has a longstanding history of use for air quality reconstruction (Ryan and LeMasters, 2007; Hoek et al., 2008).

A key advantage of LUR over other reconstruction approaches is that the land use information may be available or obtainable at high spatial resolution over large spatial domains. The resulting products can thus have similarly wide coverage at high resolution, even where air quality measurements are sparse. For example, multiple satellite products can provide global land use information (e.g. MODIS Land Cover Type Version 6.1) at a high spatial resolution (500 m). Note that in this section we consider satellite information regarding land use and land cover, but not satellite remote sensing information about atmospheric composition directly; this is the focus of Section 3.3. LUR can be superior to interpolation techniques when there are few measurement locations, since reconstruction via LUR does not rely on the physical distances to the nearest observations.

While LUR is less sensitive to the spatial density of observations than statistical interpolation techniques, enough measurements are still needed to adequately "span the space" of different land use characteristics used as inputs to the regression. Otherwise, the resulting regression will not be robust and may reflect spurious relationships between land use and air quality. Unfortunately, it is difficult to determine a priori when sufficient data have been collected to enable a robust regression. Furthermore, as more land use characteristics are considered, more measurements are typically needed. For these reasons, LUR relationships developed for certain regions have often generalized poorly to other regions (Allen et al., 2011; Patton et al., 2015; Z. Li et al., 2021). Caution must also be taken when applying LUR reconstruction in certain applications. For example, certain land use patterns may be related with both air quality and demographic factors, and so using a LUR approach to estimate air pollutant exposure to be compared with demographic information may over-emphasize certain relationships if appropriate statistical analysis is not performed.

LUR is a reconstruction technique well suited to application with LCS data, and even with a combination of RGM and LCS data where available, given the caveats that LCS data must be reliable and well characterized within the application domain. LCS provide advantages towards addressing spatial sampling issues with LUR calibration by enabling more measurement locations, and thus a greater coverage for different land use types. For this reason, LUR incorporating LCS data can be a promising method for developing robust, high-resolution air quality products, especially in urban areas with dense LCS networks and high variability in land use (Weissert et al., 2019, 2020). A variety of regression techniques have been used for LUR. While linear regression techniques have been more commonly applied, recent approaches have seen benefits in using ML techniques, due to their ability to readily capture non-linear relationships between land use and air quality. Various ML models were found to outperform a linear model for a LUR model calibrated in Uganda (Coker et al., 2021). A LUR approach using ML (random forest algorithm) has been conducted in Hanoi, Viet Nam, by the University of Iowa for supporting tuberculosis studies (Tang and Carmichael, n.d.). Despite limited surface observations (10 LCS and 1 RGM at the USA embassy), evaluations using tenfold cross-validation yielded strong performance (a Pearson correlation coefficient of 0.86 and RMSE of 7.81 $\mu g/m^3$).

In LUR, it is typically assumed that the land use characteristics are static. The resulting reconstruction of air quality will therefore also be static. Some LUR approaches involve either time-varying land use information where available (e.g. nearby traffic densities at different times of day) or additional time-varying parameters (e.g. hour-of-day, day-of-week, month-of-year) to allow the regression approach to capture varying patterns at greater temporal frequency, allowing for more insightful analysis. A daily average LUR model for $PM_{2.5}$ in Pittsburgh, USA, calibrated using data from 47 LCS, was used to generate more accurate exposure estimates for the population which considered dynamic movement patterns of people, e.g. on weekends versus weekdays, compared to estimates assuming a static population distribution (Jain et al., 2023). The ability of LCS to provide higher temporal resolution data than some RGM was found to support higher temporal resolution LUR, particularly since short-term changes in air quality, likely the result of local sources, were better related to certain land use parameters, and thus more suitable to reconstruction using LUR (Zimmerman et al., 2020; Jain et al., 2021).

Various studies have identified different parameters useful for different LUR applications and regions. There are certain parameters which are generally applicable to many urban areas. Meteorological, traffic, topographical, and primary land use (e.g. residential, commercial, industrial, open space, etc.) variables were integrated into an LUR calibrated with LCS $PM_{2.5}$ data to produce hourly maps of surface $PM_{2.5}$ on a 500 meter grid for Los Angeles, USA (Lu et al., 2021). Certain land use characteristics are more particularly applicable for certain pollutants. For example, including restaurant or cooking activity information is especially relevant when ultrafine particles are considered; however, LCS data for ultrafine particles may not be readily available. Relevant land use characteristics can also be regionally dependent. For example, monthly precipitation, solid fuel use, green space, and proximity to Lake Victoria were found to be the most important predictors for calibrating a LUR model for monthly $PM_{2.5}$ concentrations using data from a network of 23 LCS in eastern & central Uganda (Coker et al., 2021). The good performance of the model was attributed to the use of atypical but locally relevant land use features in the LUR model. The significant within-region variability in PM2.5 and good coverage by the LCS network of different explanatory spatial features used in the regression were also noted as important factors.

Where both RGM and LCS data are available, there are advantages to using both to support LUR reconstruction. LCS networks in New York State, USA, were used to calibrate hourly LUR models for PM (Masiol et al., 2018) and ozone (Masiol et al., 2019). Measurements of an RGM within the region were used as an additional predictor in the LUR, contributing to the temporal variability while spatial variability was informed by LCS data. This represents a way in which the strengths of RGM (better accuracy) and LCS (better spatial coverage) can be combined to support time-varying reconstruction. A combination of RGM and LCS data, together with land use information (e.g. population density, impervious surfaces, distance to railroads, distance to airports), was used to develop a high spatial resolution daily LUR model for CO in Baltimore, USA (Bi et al., 2022c). In this method, dense deployments of LCS enabled good characterization of CO concentrations, which would not have been possible relying solely on the sparse RGM in the region. However, RGM data were instrumental to calibrate the LCS, and RGM and LCS data were treated differently in the statistical model, with higher relative uncertainties associated with LCS data. In this case, similar reconstruction techniques which also incorporated meteorological, satellite, and multipollutant data did not meaningfully improve the reconstruction performance. In a study in Puget Sound, USA, calibrated $PM_{2.5}$ LCS were used alongside RGM to support LUR reconstruction in two different ways (Bi et al., 2022a). First, LCS data were used alongside RGM as dependent variables for the fitting of the LUR. Second, statistically interpolated $PM_{2.5}$ from the LCS data (developed via a kriging approach; see Section 3.1) were used as a potential covariate in the LUR, with only RGM measurements as the dependent variables. Both models improved $PM_{2.5}$ estimates over a baseline (a LUR model considering only the RGM data) evaluated at independent sites, with the former approach showing a larger improvement. This indicates that using calibrated LCS data alongside available RGM information as dependent variables in the development of LUR models is a suitable approach. Finally, it has been found that local LUR models for $PM_{2.5}$ using only LCS provided comparable performance to national models using RGM, and hybrid models using both RGM and LCS were better capable of capturing variability within urban areas (Lu et al., 2022a).

Overall, when both RGM and LCS data are available, it is suggested to consider both RGM and LCS data as dependent variables for calibrating the LUR, and to use a regression approach which allows for proportionally larger weight to be assigned to the RGM data to reflect its better accuracy compared to LCS data, with this accuracy determined through co-location studies with the RGM. When developing a time-varying LUR, it is recommended to use the RGM rather than LCS data as the independent variable.

In regions without established RGM networks, LCS alone may provide a basis on which LUR can be performed, or can be used to assess the generalizability of existing LUR models. This is an important consideration for LMIC (Abera et al., 2020; Coker et al., 2021), as well as in less well monitored rural areas in all countries, which have generally been understudied with respect to LUR development and verification (Hankey et al., 2019; Tang et al., 2024). It should be noted that accurate and up-to-date land use information may be similarly lacking in such regions, but crowd-sourcing approaches, use of satellite remote sensing information, and emphasizing the co-benefits of collecting such information to other efforts (e.g. development planning, resource management, public health) can help to address the need for land use information. LUR can be directly calibrated using LCS network data, as in the example of Uganda by Coker et al. (2021) noted earlier. In some cases, LUR models are developed based on data collected from an intensive measurement campaign, but then cannot be updated with new measurements as conditions change. For example, high spatial resolution LUR models for $PM_{2.5}$ and black carbon were developed for the Greater Accra Metropolitan Area, Ghana, using data from more than 100 filter samplers deployed at various locations throughout the region over the course of a year (Alli et al., 2023). A relatively modest network of LCS could be used to verify the performance of such an LUR derived from a past measurement campaign data and to identify when and if the estimates from the LUR became sufficiently outdated to warrant a new campaign.

LUR techniques are also applicable to mobile LCS data. A random forest regression model using various land use inputs (e.g. population density, roadway length, poverty index) was used to reconstruct $PM_{2.5}$ data collected by LCS deployed on motor bikes in Nairobi, Kenya, before and during the COVID-19 lockdown. The reconstructed data were used to evaluate granular changes in $PM_{2.5}$ concentrations during the lockdown (deSouza et al., 2021). The results were compared to those obtained using a universal kriging statistical interpolation approach; both methods identified similar intraurban trends, e.g. higher concentrations in poorer neighbourhoods than wealthier ones. A methodology for using ML techniques to perform reconstruction using both fixed and mobile LCS measurements for $PM_{2.5}$, NO_2, and black carbon, as well as meteorological and land use information (points of interest, road network, traffic data, street canyon type, etc.) is presented by Hofman et al. (2022a), building on previous related work (Do et al., 2019, 2020; Qin et al., 2020, 2021). The methodology was tested in Antwerp, Belgium; Utrecht, The Netherlands; and Oakland, USA, and outperformed several other reconstruction techniques, including kriging and inverse distance weighting. Performance approached that of a state-of-the-art dispersion model, while being less computationally intensive. Overall, it was concluded that good model performance still depended on the spatial representativity and coverage of the mobile monitors, the performance and calibration of the LCS, and the size and representativeness of the training dataset.

LUR can also be hybridized with other reconstruction techniques. For example, a LUR approach can provide a prior estimate of air quality, which can serve as the starting point for a kriging approach, allowing near real-time observation data to also be incorporated. Furthermore, traditional LUR is suitable for reconstructing average or typical situations, but cannot represent atypical or transient conditions, e.g. wildfire smoke or sand and dust storms. To do so, other temporally varying input data would need to be included, such as from satellite remote sensing, discussed in Section 3.3, or AQM, discussed in Section 3.4.

C.5. Source identification and attribution

C.5.1. Observational techniques

A very dense network of over 100 LCS was used, together with knowledge of potential emissions sources and transportation patterns in the community, to investigate black carbon concentrations in Oakland, California, USA (Caubel et al., 2019). The study identified highly variable spatial and temporal pollutant patterns throughout the domain and linked this variability to local sources and phenomena. It was found that the single RGM present in the study domain greatly underestimated the heterogeneity in observed concentrations, although it was found that the long-term average concentration from the LCS network was fairly consistent with that of the RGM. This is an example of the use of LCS for validation of RGM siting choices (see Section 8). Compared with a mobile monitoring study of the same domain, this LCS deployment was able to provide for continuous data, as opposed to weekday- and daytime-only data obtained during the mobile campaign. The authors noted that the deployment and maintenance of more than 100 LCS for this study was extremely labor-intensive, and that even a shorter-term deployment of this dense network would likely have been able to identify many of the same patterns, at least within that season. They also noted that close collaboration with the local community, both for LCS deployment and maintenance and for "surveillance" of pollution-generating activities, was key to project success.

Observational techniques can also be applied to qualitatively identify changes in emissions due to changes in activity or other intermittent events. Kuhn et al. (2021) describe a citizen science project which was conducted during the Commonwealth Games held at the Gold Coast, Australia, in April 2018. In this case, the network of LCS measuring $PM_{2.5}$ and CO showed that the Games did not result in significant deterioration of local air quality. It was noted that the involvement of stakeholders including the local authorities, the community and a high school resulted in an increased awareness of the importance of air quality monitoring, and elevated interest of the students in environmental science. LCS were also used to help identify wildfires in remote areas of Thailand during their initial stages (Dampage et al., 2022). This indicates the capacity for qualitative information from LCS to be useful for early identification of intermittent sources (such as wildfires), allowing for appropriate interventions to be made.

Integration of wind speed and direction data, typically via the use of "wind rose" plots, is a common approach to identifying the directions and possible distances of sources with respect to observations (Carslaw et al., 2006). Although not universal, many LCS manufacturers provide integrated or add-on anemometers to facilitate such analysis. The OpenAir package supports making wind rose plots with various observational data, including from LCS (Carslaw and Ropkins, 2012). Together with data from extensive LCS networks, such techniques can be useful for triangulating sources and identifying the environmental conditions under which their influence is greatest. For example, $PM_{2.5}$ data from a network of 64 LCS across Pittsburgh, USA, were sorted according to land use characteristics, wind direction, and time of day (Rose Eilenberg et al., 2020). Using these grouped data, the effect of activities at a specific industrial facility on air quality could be quantified based on times of day the facility was known to operate and prominent wind directions. Careful assessment of LCS error characteristics and statistical analysis of measurement uncertainties was necessary to arrive at this quantitative assessment and establish confidence in the result.

These techniques are also highly useful in areas without existing monitoring infrastructures, where the collection of data using LCS alongside basic wind speed and direction information is a more readily deployable solution. LCS were used for source apportionment via wind rose plots in Ghana (Hodoli et al., 2023). This study indicated the potential of LCS to be used for source identification in regions lacking RGM infrastructure. Furthermore, Owoade et al. (2021) utilized LCS to assess gaseous pollutants (CO, NO, NO_2, O_3 and CO_2) and particulates ($PM_{2.5}$ and PM_{10}) in a semi-urban area of Nigeria for 8 weeks. Using a conditional bivariate probability function (CBPF), an analysis technique for pollutant concentrations based on wind speed and direction, the pollutant variations over time and space were identified, as well as the likely origins of these pollutants. These included local heating, cooking, and traffic pollution, as well as a scrap processing facility. These studies represented some of the first systematic analyses of local pollution sources in their respective regions, which were made possible with LCS data.

Major transportation nexuses, especially seaports and airports, are often primary locations of interest for source monitoring, with multiple related pollutant producing activities co-located in close proximity, and with activities being carried out on specific schedules and timetables. Various techniques for monitoring such activities, especially fenceline monitoring along the facility perimeter (see Section 9.1.2), can be facilitated by LCS. LCS incorporating detectors for multiple pollutants which are known or suspected to be emitted by the sources at these port facilities are especially useful for extracting useful signals and disentangling the often-complex mixtures of pollutants observed.

As an example, a network of multipollutant LCS with integrated anemometers were positioned in and around London Heathrow Airport, UK, allowing emissions from the airport to be distinguished from background or transported pollution (Popoola et al., 2018). This approach relied on the fact that the single source under investigation (the airport) was well covered by a group of 17 LCS; the tenth percentile of CO and NO_x values across the network at any given time established the background concentrations, from which the local contribution from the airport can be established. Nevertheless, this simple technique can be applied readily in cases of fenceline monitoring where there is a known emission source of concern (e.g. an industrial facility) and a relatively dense network of LCS can be established around it. The multipollutant capabilities (including measurement of CO_2) and integrated anemometers of the LCS system used were beneficial in gaining additional insights into emission ratios and specific activities contributing to emitted pollution, but the basic technique for identifying the relative contribution of the source relative to the background can be applied for single-pollutant LCS without wind information. High temporal resolution also allowed for the effective separation of background conditions. Finally, in this case, the information gleaned from the LCS network was used to validate and refine a local dispersion model, which was further used to investigate possible changes in airport emissions under different operating scenarios, illustrating synergistic use of LCS with atmospheric models.

Another such application is the use of a network of LCS to assess the impact of ship emissions on a residential community (Jayaratne et al., 2020a). Seven KOALA LCS were installed in a small network near the premier cruise ship terminal in Melbourne, Australia over a continuous period of 98 days during the peak cruise ship season to monitor the dispersion of particle and CO emissions among a residential community. The time profiles showed numerous spikes in the $PM_{2.5}$ concentration, some of which exceeded 200 μg/m^3 for periods of 5–10 minutes, coinciding with ship movements. On average, the spikes were about 4 to 5 times above the normal background value (about 10 μg/m^3). The results were instrumental in the subsequent decision to relocate the cruise ship terminal to another location.

Anand et al. (2020) describe a novel approach to quantify ship emissions using LCS deployed on drones. The study highlights the potential of LCS in monitoring and assessing emissions from ships. By utilizing drones equipped with these sensors, the research team was able to capture temporal variations in pollutant concentrations, providing a detailed understanding of emission patterns. This method offers a cost-effective, flexible, and comprehensive way to monitor emissions from marine sources, which are often challenging to quantify due to their mobile nature and the complexity of the marine environment.

Major roadways also represent more distributed sources of interest to local air quality. While full fenceline monitoring along roadways is usually infeasible, analysing data alongside different types of roads and under different traffic conditions can yield insights into the degree and spatial extent of their impacts on air quality, along with potential mitigation strategies. Again, use of multipollutant LCS, especially those incorporating detectors for CO_2, is useful for determining emission factors for vehicles.

Chu et al. (2022) conducted an in-depth investigation using LCS to quantify on-road emissions, focusing specifically on NO_2 and $PM_{2.5}$. The study deployed LCS at roadside locations to monitor these pollutants, revealing significant temporal variations in emission levels that correlated with traffic patterns. Additional data might help connect these patterns with specific classes of vehicle. By using observations from $PM_{2.5}$ LCS installed at two roadside locations with vehicle counts from traffic cameras, Wang et al. (2020a) estimated roadside $PM_{2.5}$ concentration increments due to different types of vehicles. Meteorological data can also provide insight into different engine operating regimes. Multipollutant LCS measuring both $PM_{2.5}$ and CO were used to identify anomalous diurnal variations in Brisbane, Australia, related to the difference in vehicle emissions resulting from cold- or warm-starts, as well as localize this pattern to city car parks and the central business district (Jayaratne et al., 2021). Such information could be helpful in targeting emissions control strategies.

LCS networks covering both roadside sites and background locations can help identify the relative contributions of traffic to local air pollution. LCS data on PM from three locations were used to identify the urban and roadside increments in Nairobi, Kenya, pointing to traffic as being responsible for about half the observed concentrations (Pope et al., 2018). In Accra, Ghana, weekly gravimetric filters and LCS were combined to monitor air pollution at 146 unique locations over a period of a year (Alli et al., 2021). The increased spatial resolution highlighted that high-density residential areas which were mostly influenced by traffic and biomass use tended to have 35–50% more pollution that peri-urban areas that were predominantly influenced by commercial and industrial activities and had less traffic. The higher temporal resolution available from LCS data, as compared to the gravimetric filters, elucidated diurnal patterns, with peaks in pollution at dusk and dawn which coincided with rush-hour traffic and increased biomass burning.

LCS can also help to track the impacts of human activity changes and policy interventions on traffic-related pollution. Liu et al. (2021) conducted on-road CO_2 observations in Beijing, China using mobile platforms with both RGM and LCS before, during and after the implementation of COVID-19 restrictions. Both RGM and LCS showed a clear CO_2 concentration decrease during COVID-19 restrictions, which is consistent with the CO_2 emissions reductions due to the pandemic. Furthermore, Hofman et al. (2022c) demonstrated that LCS can accurately quantify air quality impacts from local traffic control measures and contribute to evidence-based policy making under the conditions of a proper methodological setup, including background normalization and data quality assurance via recurrent calibration. Three multipollutant LCS were used to evaluate the impact of traffic restrictions on local pollution in two communities in Belgium. By focusing on traffic-related pollutants such as NO and using data from multiple sites to separate local traffic impacts from background pollution levels, the impacts of traffic reduction policies on local air quality could be quantified. High inter-LCS precision enabling direct comparisons between multiple nearby LCS was cited as an important factor in supporting the conclusions of the study. Finally, LCS $PM_{2.5}$ measurements in Kigali, Rwanda, were used to evaluate the impacts of a "car-free Sunday" policy on local air pollution (Subramanian et al., 2020). High temporal frequency of these data, in contrast to filter-based measurements, indicated that the policy had the largest impact on concentrations during the morning hours. This highlights the utility of LCS for analysing policy impacts in LMIC, where existing monitoring networks might not be available.

C.5.2. Statistical techniques

Clustering implies grouping together of data based on a predefined measure of similarity, with the intention of associating these clusters of similar measurements with an emission source or sector. A clustering approach, specifically k-means clustering, was used on data from a single LCS (an OPC) to differentiate periods of differing pollution, atmospheric conditions, and particle sizes, likely corresponding to different sources (Bousiotis et al., 2021). Results in terms of identified potential sources were similar to those achieved with an RGM (a scanning mobility particle sizer), although the RGM was better able to distinguish direct emission sources, and was more responsive to diurnal variability, whereas the LCS responded better to daily and weekly variations. The study notes that the technique using LCS is likely more applicable to background sites, where larger particles sizes and longer temporal variations are of greater importance.

The size distribution measurements from several low-cost OPC deployed on trash trucks, within the diameter range that the OPC could detect particles, were similarly clustered in a different study by deSouza et al. (2020a). The properties of each cluster, i.e. vehicle speed, local $PM_{2.5}$ concentrations, and background $PM_{2.5}$ concentrations, were used to qualitatively assess key sources that likely contributed to each cluster.

It should be noted that many LCS for PM typically lack selectivity for different size fractions, and so might not be suitable for distinguishing sources based on different particle size categories (e.g. Tryner et al., 2020). In several of the cases mentioned above, different size bins associated with low-cost OPC were used as inputs to a statistical source apportionment technique, rather than the aggregate size fraction estimates like $PM_{2.5}$ or PM_{10}. However, sensitivity of LCS to ultrafine particles remains a limitation.

Positive or non-negative matrix factorization implies the disaggregation of a measured pollutant signal as the sum of multiple contributing factors, each of which is constrained to have a positive or non-negative contribution to the total signal. Each signal component can then be associated with a putative source. Measurement of multiple pollutants and/or different particle sizes by LCS can be useful for source identification or apportionment, even if the target of the study is only a single pollutant (e.g. PM). For example, CO and NO can indicate combustion sources, whereas NO_2 or O_3 may indicate photochemical sources.

Non-negative matrix factorization was applied on data from a multipollutant (CO, NO_2, O_3, SO_2) LCS in Delhi, India (Hagan et al., 2019). Three factors were identified, corresponding to one combustion factor and two particle factors. These aligned well with factors identified by the same technique applied to RGM data. This indicated the utility of LCS for this application, despite acknowledged limitations on calibration and the ability of LCS to measure ultrafine particles. This work demonstrates the utility of multipollutant LCS, as the co-variation of different pollutants provided information on source profiles. For example, in this environment CO measurements were shown to correlate very strongly with primary combustion particles, which were not measured directly by the LCS.

Expanding on the results of a previously mentioned clustering analysis, positive matrix factorization (PMF) was applied as well to multipollutant (gas and particle) data collected by several co-located LCS and RGM, together with meteorological information (Bousiotis et al., 2022). Comparing results obtained from PMF of LCS data to PMF of RGM data, three of four factors were substantially the same between the two analyses, although slight differences in the temporal variation of the factors were observed between the LCS and RGM analyses. The results were also generally consistent with the previous study in terms of the sources identified, although PMF allowed for apportionment of concentrations among these sources. Overall, it is noted that both the clustering and PMF approaches are applicable to LCS data alone, and that including both RGM and LCS data in the analysis can lead to additional insights into the relative effects of different sources. A similar technique using size-resolved PM data was applied to quantify and pinpoint sources of indoor air pollution, with PMF used to distinguish between outdoor and indoor sources (Bousiotis et al., 2023).

Furthermore, non-negative matrix factorization was applied to multipollutant (CO, NO, NO_2, O_3, PM) LCS data for source apportionment in Atlanta, USA (Yang et al., 2022). The analysis was applied to the raw data supplied by the LCS, e.g. voltage or current from the electrochemical sensing elements. Normalization of these raw data prior to source apportionment allowed for discerning primary and secondary organic aerosol factors. This study notes the potential for using this technique in areas without access to RGM, where LCS calibration will be more limited.

Different spectral analysis techniques, such as wavelet decomposition, have also been applied with LCS data, with promising results. A network of 18 multipollutant LCS deployed in Staffordshire, UK, measuring NO_2 and PM, provided data for a spectral analysis to evaluate periodicities of pollutant patterns at different sites and across the network (Frederickson et al., 2022). High-frequency spectral components were typically associated with local sources, while low-frequency components could be associated with regional and long-range sources or with periodic emissions from local sources. Significant differences in low-frequency components between measured pollutants allowed for apportionment of the measured pollution between local, urban, and regional source categories. Furthermore, Qin et al. (2023) utilized multichannel PM sensors monitoring varying PM sizes in the vicinity of construction sites. The iterative discrete wavelet transform method enabled the decomposition of pollutant concentration time series into distinct frequency-based components. Again, the low-frequency component represented the regional background concentration with slight daily fluctuations, while a high-frequency component reflects the emissions surge from local sources.

C.5.3. Model-based techniques

Updating emissions inventories using LCS data requires an existing model and existing assumed emissions for known sources. It is unclear how effective such techniques might be at identifying and quantifying new sources not included in the initial inventory, or in the absence of any pre-existing inventory. Nevertheless, dense LCS networks, especially in urban areas, can be useful in providing specificity for different sources under such methods.

In a study in the Imperial Valley, California, USA, data collected by a network of LCS were compared with outputs from a pollutant dispersion model using known and estimated emission sources (Ahangar et al., 2019). Based on this comparison, the emissions were adjusted to bring the modelled concentrations into better agreement with the LCS measurements. In this case, the quantification of emissions with a known source (wind-blown dust) was improved using LCS networks deployed in this otherwise under-monitored area.

The BEACO$_2$N network of LCS in the region of San Francisco, California, USA, has been extensively used to determine emissions, including identifying local emissions enhancements, determining vehicle fleet emission factors, and verifying the impacts of policy changes on emissions (Shusterman et al., 2018; J. Kim et al., 2022; Fitzmaurice et al., 2022). For example, data from the network were used to quantify the impacts of vehicle speeds and fleet composition on highway emissions, producing estimates within 3% of state-of-the-art emissions estimation methods in use in California (Fitzmaurice et al., 2022). The ability of the LCS network to simultaneously measure multiple emitted gaseous species, especially CO_2 and NO_x, was essential here. The density of this network is also an important factor, with over 50 nodes having a typical inter-node spacing of 2 km. Finally, high temporal resolution (10 seconds) of the data allowed for more easily separating background and local source signals. Altogether, the ability of the network to identify and quantify vehicular and other urban emissions supports the use of LCS data, either in conjunction with RGM where possible or on their own in resource-limited settings, to support the tracking of policy impacts to reduce urban pollutant and GHG emissions.

In reference to GHG emissions, there are several new studies showing that measurements of CO_2 using LCS can be used to verify and update GHG emissions inventories using model-based techniques. Data assimilation of observations from a network of LCS for CO_2 in Glasgow, UK, suggested that CO_2 emission inventories for the city were up to date, with small regions requiring potential updates (Carruthers et al., 2023). Turner et al. (2020) utilized the BEACO_2N network of LCS discussed above together with a local AQM to quantify changes in urban CO_2 emissions in response to COVID-19 mobility regulations. They observed a 30% decrease in anthropogenic CO_2 emissions during the "shelter-in-place" order and showed that this decrease is primarily due to changes in traffic (–48%) with pronounced changes to daily and weekly cycles. Non-traffic emissions showed smaller changes (–8%). They suggest such findings provide a glimpse into a future with reduced CO_2 emissions through electrification of vehicles. Verification of emissions reductions due to vehicle electrification efforts is thus another potential use case for LCS.

For methane (CH_4), Sasakawa et al. (2010) conducted continuous measurements of CH_4 concentration from a network of towers in Siberia (JR-STATION) using CH_4 semiconductor sensors based on a tin dioxide natural gas leak detector developed by Suto and Inoue (2010). Regular in situ calibration was performed using three standard gases. They also performed AQM simulations supported by the LCS data which suggested that the major contributor to the observed CH_4 concentrations switched from wetlands during summer to fossil fuel use during winter. Eugster et al. (2020) presented an empirical function to correct the Figaro TGS 2600 (a solid-state LCS that responds to ambient levels of CH_4) for temperature and humidity effects and addressed the long-term reliability of the sensors in the Arctic over 7 years. Due to cross-sensitivities, they found the TGS 2600 was only suitable in an environment where levels and variations of other hydrocarbon gases are rather stable compared to those of CH_4. Despite such limitations, the TGS-series CH_4 sensors have been widely used in-field measurements (e.g. complex rural/urban areas, the Arctic region), enabling high-resolution spatiotemporal measurements and monitoring for CH_4 emissions (Collier-Oxandale et al., 2018; Jørgensen et al., 2020; Sieczko et al., 2020).

C.6. Air quality patterns and trends for environmental justice

In the absence of local RGM data, LCS information, remote sensing data, and AQM estimates of surface CO concentrations at several locations in rural and urban areas of Malawi were compared to identify temporal trends and spatial disparities (Bittner et al., 2022). While there were quantitative disagreements between these diverse data sources due to several factors, all data sources qualitatively agreed that CO concentrations increased notably during the local agricultural burning season (September and October), and that concentrations were higher in the urban than in rural areas, although this disparity was reduced during the burning season. In another study, satellite remote sensing and local LCS data provided corroboratory evidence of reduced $PM_{2.5}$ concentrations in Brazzaville, Republic of Congo, and Kinshasa, Democratic Republic of Congo, from 2019 to 2020, likely due to the impacts of COVID-19 and associated containment measures on human activities (McFarlane et al., 2021). These provided complimentary information, with the satellite data illustrating the spatial extent of the changes, while the LCS data provided information on its diurnal aspects, highlighting a larger decrease in peak evening concentrations. All these examples show the utility of combining multiple lines of evidence to support pattern and trend analysis, especially in LMIC where trusted in situ data sources may be lacking.

Leveraging LCS in combination with engagement of community residents was used to develop a community-based monitoring programme across disadvantaged groups with high proportions of low-income and racial/ethnic minority populations in Southern California, USA (Lu et al., 2022b). Southern California communities with a higher percentage of Hispanic and Black American population and higher rates of unemployment, poverty, and housing burden were found to be exposed to higher $PM_{2.5}$ concentrations in that study. In a related study, a streamlined, robust, and accessible $PM_{2.5}$ exposure assessment approach was developed to support environmental justice analyses and characterize individual $PM_{2.5}$ exposure over multiple 24-hour periods in the inland Southern California region, USA (Do et al., 2021). Aggregated ratios indicated that participants from the lowest socioeconomic status communities in the region experienced higher home exposures compared to participants of other communities over consecutive 24-hour monitoring periods, despite high participant mobility and relatively low variability in ambient $PM_{2.5}$ during the study period. Overall, the approach was found to be promising for larger-scale, community-focused personal exposure campaigns for direct and precise environmental justice analyses. Integrating LCS into a community science-based air monitoring programme therefore holds promise to resolve monitoring disparity and capture hotspots to inform emission control and urban planning policies and as a result helping to promote environmental justice.

Statistical methods which account for previously established LCS performance are important to ensure a robust analysis of LCS network data. As an example, a network of over 40 multipollutant LCS was used to examine spatiotemporal concentration disparities and relate these to socioeconomic characteristics in Pittsburgh, USA (Tanzer et al., 2019). Statistical analysis, taking into account the previously characterized uncertainty in these LCS measurements as well as the distribution of various social and demographic factors across the LCS network sites, found no significant relationships between ambient concentrations and either minority population or poverty levels in this study. However, significant differences were found either upwind or downwind of a known major pollution source in the region. The study also noted differences in concentrations within site groupings with similar land use characteristics, highlighting the utility of a dense LCS network in allowing for better specificity to local conditions.

Mullen et al. (2020) studied Salt Lake City, USA public school students’ $PM_{2.5}$ exposure under three pollution conditions (relatively clean air, and moderate and major atmospheric inversions) using data from an LCS network established through a community-university collaboration. These data showed that disadvantaged students faced higher exposure in cleaner and moderate pollution scenarios. In contrast, such disparities decreased during major atmospheric inversions. Schools with a higher percentage of racial/ethnic minority students consistently faced exposure disparities across all scenarios. Esie et al. (2022) used a network of LCS to study $PM_{2.5}$ exposure in Chicago, USA to evaluate the relationship between pollutant concentrations and neighbourhood demographic composition across multiple timescales. Ambient exposure levels were notably higher in neighbourhoods with larger compositions of Hispanic residents across the entire study period, and notably higher in neighbourhoods with larger Black populations during a pollutant episode resulting from the 4th of July national holiday fireworks, as compared to levels in neighbourhoods with larger non-Hispanic White populations. The use of LCS to complement existing RGM in this study allowed for identification of these short-term, neighbourhood-level exposure inequities.

C.7. Health studies and personal exposure monitoring

An overview by Larkin and Hystad (2017) found that combining LCS data with personalized monitoring leveraging mobile phones and AQM has the potential to improve long-term personal exposure assessment at the scales needed for population-level research. However, they note that logistical and data science challenges exist for handling such extensive datasets, along with privacy and ethical concerns associated with collecting and analysing health-relevant data at scale. Another review by Morawska et al. (2018) found that, in spite of the lack of standardized performance metrics for LCS, under certain application conditions, in certain monitoring environments, and for some study goals, fixed site LCS networks may be fit for use in exposure assessments.

A study incorporating both LCS and RGM to assess exposures in the conduct of an epidemiological cohort study found that incorporating LCS data alongside RGM data for reconstructing exposures (via a LUR approach) was beneficial. This is because LCS deployed in residential and commercial areas better represented the exposure of cohort participants than RGM deployed to more source-oriented or regional background locations. However, the need to calibrate LCS on a regional basis before including their data in the analysis has been emphasized, as including uncalibrated LCS data tended to reduce exposure assessment accuracy (Bi et al., 2022a).

A study using a LCS for $PM_{2.5}$ in Rio Branco, Brazil, established a relationship between ambient $PM_{2.5}$ and daily all-cause respiratory hospitalization using generalized additive models and distributed lag non-linear models (Coker et al., 2022). Statistically significant associations between increased $PM_{2.5}$ and increased daily hospitalization were found using both raw LCS data and LCS data corrected using a calibration developed for the USA which was applied to the Brazil LCS data; see Barkjohn et al. (2021) for details on that calibration. The effects found using corrected data agreed well with those determined using AQM, despite the fact that a non-regionally-specific LCS calibration was used in this case. These effects were attenuated, however, when the uncorrected data were used, supporting the possibility that any calibration, even if not regionally specific, is an improvement on the uncalibrated data.

Ten $PM_{2.5}$ LCS deployed along six traffic routes in Accra, Ghana, were used to undertake a cross-sectional health study of street traders and office workers (Amegah et al., 2022). This study found evidence linking street traders' $PM_{2.5}$ exposure with respiratory and cardiovascular symptoms. For this understudied region and population group, LCS data were critical due to the lack of local RGM information or suitable exposure models. In another instance, in Ethiopia, an attempt was made to develop an LUR model using RGM and LCS data (Abera et al., 2020). However, the model was found to be not reliable for epidemiological analysis; this was due to the lack of availability of reliable RGM data for calibration and testing and logistical challenges with running the LCS network. The study offers interesting insights into common challenges that researchers may encounter when attempting to use LCS data for health applications.

Using portable gas LCS for personal exposure monitoring, it was found that LCS data correlated highly with measurements from research-grade instruments typically used in such studies (Jerrett et al., 2017). In that work, performance was found to vary across gases, with correlations for primary pollutants (e.g. CO, NO) being higher than for secondary pollutants (e.g. NO_2). There were also notable biases in the measurements of certain gases. Thus, while quite well suited to capturing the variability in exposures across different microenvironments and throughout the day, LCS were found to be less suitable for establishing quantitative average exposure values (at least, without calibration to a reference). Similar conclusions were drawn in a study on personal $PM_{2.5}$ exposure by Kim et al. (2021); temporal patterns were found to be substantially the same whether determined from personal LCS or RGM data, but discrepancies were noted in the average values from the different data sources.

A dynamic baseline tracking method and a range of calibration protocols to address LCS performance were explored under practical scenarios to assess the performance of a compact diffusion-based Personal Exposure Kit (PEK) in reducing the impact of rapid changes in the ambient environment in personal exposure assessment applications. The device was found to be suitable even in heterogeneous environments without the need for mathematical algorithms for processing the data and highlights the potential for its use in personal exposure monitoring which has been difficult in the past, and for reporting more accurate and reliable data in real-time to support personal exposure assessment and portable air quality monitoring applications (Zong et al., 2021).

A mobile phone equipped with air pollution sensors ($PM_{2.5}$ and VOC) was evaluated to establish whether it is a viable option to reduce the burden of disease attributable to air pollution (Nyarku et al., 2018). This evaluation found that, in spite of the numerous limitations that hinder its use for personal exposure and continuous monitoring, mobile phones may be used for comparative assessments, for example when comparing outcomes of intervention measures or local impacts of different air pollution sources. LCS have also been found to be suitable for evaluating how everyday routines and building characteristics affect relative personal exposures to air pollution (Mazaheri et al., 2018).

LCS for CO mounted on bicycles were used to estimate the inhaled dosage of cyclists during trips and provide an estimate of how the health benefits of cycling might be partially offset by increased pollutant exposure, depending on route and time of day (Bertrand et al., 2020). This kind of individualized feedback could be valuable to support personal health and activity decisions, provided personal medical data privacy is adequately addressed.

The PRAISE-HK system, developed by Che et al. (2020), integrates LCS in various microenvironments such as homes, schools, offices, and vehicles with forecasts from local and regional AQM and with crowdsourced health symptom data. The system delivers personalized symptom forecasts through a mobile app or a web portal. PRAISE-HK is an example of collective intelligence that integrates technologies and knowledge from different areas to empower the public to reduce their exposure and improve their health. Such action-oriented applications of personal exposure monitoring are achievable using current LCS technologies integrated with other information sources on personal health.

C.8. Data Quality Assessment Methods: Metrics

A common evaluation practice is to create and calibrate a Data Generating Process (DGP) using a portion of the available input dataset (e.g. 70%) along with the corresponding target data (i.e. the values for the intended result against which the DGP outputs will be compared), while holding the rest of the available data aside to test whether the DGP is meeting the objective. However, this partitioning could inadequately capture the distribution of the data, leading to a biased result. Furthermore, the results may vary significantly depending on the specific partition of the data affecting its representativeness (Liang, 2021). For this reason, it is recommended to use techniques such as cross-validation to limit these effects (Johnson et al., 2016). The k-fold cross-validation technique has become the recommended standard in ML. This method involves splitting the dataset into k folds, training the model on $k-1$ of these folds and testing it with the remaining of the data. This process is then repeated k times, with typical values for k between 5 and 10 (Giordano et al., 2021). Splitting data for cross-validation can be done at random, but in specific applications, more systematic splits may be more meaningful. For example, in a forecasting application (as discussed in Section 7), data may be divided temporally, with data from certain seasons being used as inputs, with validation being conducted on data from another season; such an evaluation would provide a fair assessment of the ability of the forecasting method in question to generalize across seasons. Similarly, in a reconstruction application (as discussed in Section 3), data collected at one subset of locations might be used as inputs to a method which is then evaluated using data collected at another distinct set of locations; this provides for a fair assessment of the ability of the method to generalize to new locations from which it did not have input data. For hybrid networks consisting of both RGM and LCS, a useful validation approach can be to compare the values at RGM locations reconstructed from LCS data to the RGM observations themselves.

Sensitivity analyses should be used to test the robustness of assumptions made or the analysis approaches adopted in any DGP. Methodologies, definitions, and assumptions should be tested to ensure that they are reasonable and that they are necessary and useful to the task at hand. For an example investigating LCS calibration transferability using a variety of cross-validation approaches, see deSouza et al. (2022). This provides a good example of conducting sensitivity tests which are appropriate to the intended applications of the data. In this case, the sensitivity tests aimed to identify how robust the detection of pollution "hotspots" was to different LCS calibration methods and different definitions of what constituted a "hotspot".

One form of sensitivity analysis, a data denial experiment, can be used to identify the utility of different information sources as inputs to a DGP. In the case of LCS specifically, when evaluating the utility of LCS information to the intended application, it is important to consider how the task might have been done in the absence of the LCS information. The outcomes achieved with and without the LCS information included can then be compared to evaluate the impact which the LCS data have had. For example, in source identification, such as discussed in Section 4, it would be useful to compare the sources identified using LCS data to sources identified using an independent dataset (e.g. an existing but sparse RGM network). The differences in identified sources will allow an assessment of the additional utility provided by the LCS data, i.e. the sensitivity of the method to the availability of the LCS data.

Similarly, any proposed DGP should be compared with simple existing standard or baseline methods to establish what additional benefits they might have. For example, in the case of a new reconstruction approach, it is important to compare it to a simple statistical interpolation approach (see Section 3.1) to determine what improvement it provides. When evaluating the DGP, it is important to question how the intended task might be accomplished without it.

When characterizing the error between a dependent variable y and independent variable x, a linear additive model is typically assumed, as follows:

$$y = b_1 x + b_0 + \epsilon \qquad \text{(Equation 1)}$$

In this equation, b_1 is the slope of the regression line, b_0 is the intercept (ordinate at the origin), and ϵ is the random error, typically assumed to have a mean of zero and a standard deviation of σ_ϵ. The random error represents the portion of y which cannot be explained by x. In the ideal case where b_1 is equal to one, and b_0 and ϵ are null, this makes y equal to x, implying that the dependent variables are in perfect alignment with the independent variables, i.e. that the DGP is performing perfectly.

These parameters — b_0, b_1 and ϵ — capture the error characteristics of y. In fact, Tian et al. (2016) shows how commonly used metrics can be derived from these three parameters. These are also useful for classifying the types of errors:

- If $b_0 \neq 0$, b_0 represents the constant bias or displacement error
- If $b_1 \neq 1$, $(b_1 - 1)$ represents the proportional bias or scale error
- If $\sigma_\epsilon \neq 0$, σ_ϵ represents the random error.

The Pearson correlation coefficient (r) is a dimensionless measure that assesses the strength and direction of a linear relationship between two variables:

$$r = \frac{\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \bar{x})^2}\sqrt{\sum_{i=1}^{n}(y_i - \bar{y})^2}} = \frac{\mathrm{cov}(x,y)}{s_x s_y} \qquad \text{(Equation 2)}$$

Here, $\bar{x}$ denotes the mean of all x_i, and $\bar{y}$ denotes the mean of all y_i. The Pearson coefficient ranges from −1 to 1, with values closer to zero indicating a weaker linear relationship between x and y.

The coefficient of determination, R^2, represents the proportion of the total variation in y (i.e. the output of the DGP) that is attributable to its linear relationship with x (i.e. the target values, typically RGM data). It can be expressed as:

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(x_i - y_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2} = 1 - \frac{Un\exp lained\,Variation}{Total\,Variation} \qquad \text{(Equation3)}$$

R^2 is more intuitive than r, as it explicitly quantifies the extent of variation in y explained by x. Unlike r, R^2 is less than one ($R^2 \leq 1$); R^2 is also typically greater than zero, but can be negative in cases of particularly poor performance, when the unexplained variance of the DGP output exceeds the total variance of the target quantity. Under most circumstances, the coefficient of determination is equivalent to the square of the Person correlation coefficient; in other words, it is typically redundant to report both r and R^2. A detailed discussion can be found in Legates and McCabe (1999).

R^2 is perhaps the single most popular metric used in evaluating LCS applications (Karagulian et al., 2019). However, it has a few limitations that need to be acknowledged. R^2 is insensitive to both proportional and constant bias. This means that if the regression line between x and y moves away from the one-to-one line, this is not reflected in the value that this metric takes. Another important limitation is that R^2 is sensitive to dynamic range. Simply expanding the range over which an application is evaluated tends to improve correlation by increasing the total variation term in the calculation of R^2. Thus, making decisions solely based on R^2 can be misleading. For these reasons, it is recommended to always report R^2 accompanied by other metrics.

For particular applications, the correlations between differently sub-divided sets of data might be more meaningful to assess. For example, in a forecasting application as in Section 7, the temporal correlation between a time series of forecasts and a time series of observations would be meaningful. For a reconstruction application, as in Section 3, the spatial correlation between estimates from the method under evaluation and independent observations would be more meaningful to examine. There is also the concept of anomaly correlation, where typical patterns and trends, e.g. seasonal and diurnal fluctuations, are subtracted out from the datasets before their correlation is calculated. This can help to avoid a situation where the correlation between datasets is high only because well known periodic variability is reflected in both datasets, while the differences from these well known patterns which are the actual subject of investigation, i.e. the anomalies, remain poorly characterized.

In the field of atmospheric sciences, the MAE and the RMSE are widely used to evaluate the accuracy of models, as emphasized by Chai and Draxler (2014). These metrics, expressed in the same units as the variable of interest, provide a more comprehensive perspective than R^2 alone. However, it is important to recognize that both MAE and RMSE are measures of average error. While MAE calculates the average magnitude of errors without considering their direction (it is based on the absolute differences), RMSE represents the standard deviation of the squared differences between the output and target values. These metrics are calculated as follows:

$$MAE = \frac{1}{\mathrm{n}} \sum_{i=1}^{n} |y_i - x_i| \qquad \text{(Equation 4)}$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (y_i - x_i)^2} \qquad \text{(Equation 5)}$$

Both MAE and RMSE are single-value accuracy measures frequently utilized in LCS applications, although they exhibit distinct practical differences. MAE assigns equal weight to all errors, meaning each error contributes proportionally to the total amount. In contrast, RMSE significantly penalizes outliers, as it emphasizes larger errors more heavily due to its squaring of the differences (Willmott and Matsuura, 2005).

Despite their usefulness, MAE and RMSE are unable to differentiate systematic errors — such as constant and proportional bias — from random errors. This limitation may be relevant in situations where understanding the nature of the error is necessary for corrective action. If systematic errors are more prevalent than random errors, correcting them can significantly enhance the accuracy of a DGP. Therefore, a metric that can describe both types of errors would provide valuable insights into the effectiveness of such corrections.

In the case of RMSE, it can be mathematically manipulated through the square root of the Mean Square Error (RMSE) to derive metrics which better distinguish the systematic and random errors:

$$RMSE = \sqrt{MSE} = \sqrt{bias^2 + variance} = \sqrt{MBE^2 + cRMSE^2} \qquad \text{(Equation 6)}$$

where:

$$MBE = \frac{1}{\mathrm{n}} \sum_{i=1}^{n} (y_i - x_i) \qquad \text{(Equation 7)}$$

$$cRMSE = \sqrt{\frac{1}{n} \sum_{i=1}^{n} \big((x_i - \bar{x}) - (y_i - \bar{y})\big)^2} \qquad \text{(Equation 8)}$$

While the MBE is the Mean Bias Error, a measure of accuracy or systematic error, the cRMSE is the centred Root Mean Squared Error, a measure of precision or random error (Kim et al., 2022). In some texts the cRMSE is also called unbiased Root Mean Squared Error, uRMSE (Guimarães et al., 2018). This approach allows for a more nuanced understanding of the error characteristics, facilitating targeted corrective measures for performance improvement.

In the literature, there are frequent examples in which authors compare the metrics of a DGP with those of other alternative DGP. However, evaluations of these different DGP were often conducted in different environments with distinct emission regimes or climatological conditions, and they may cover varying time periods (for example, only during one season) or durations (for example, days or years). Therefore, making direct comparisons between performance metrics obtained under different contexts can potentially lead users to incorrect conclusions.

One approach to mitigate this issue is to present and communicate metrics in a normalized manner. Ideally, when normalizing a metric, results from different studies become comparable. This is particularly relevant in cases where measurement scales differ (e.g. NO_2 concentrations in ppb versus μg/m³) or when concentration ranges vary. For instance, consider the task of comparing the performance of a DGP for O_3 concentrations during summer, when concentrations are typically highest, to its performance in winter, with generally lower concentrations. Normalization in this context allows for a more meaningful comparison by adjusting for seasonal concentration differences. However, caution is advised because normalization focuses solely on the variable being measured (for example, O_3 in the previous scenario). This approach overlooks the influence of other variables that also affect the quality of information provided by a DGP. Therefore, although normalization is undoubtedly a valuable tool, it should be employed cautiously and within the context of its inherent limitations.

Of the several existing alternatives for the normalization of metrics, some of the most common methods applied use either the standard deviation (e.g. Topalović et al., 2019; Kim et al., 2022):

$$NRMSE = \frac{\sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - x_i)^2}}{\sqrt{\frac{1}{n}\sum_{i=1}^{n}(x_i - \bar{x})^2}} \qquad \text{(Equation 9)}$$

or the mean of the measurements (e.g. Aix et al., 2023; Margaritis et al., 2021):

$$NRMSE = \frac{\sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - x_i)^2}}{\bar{x}} \qquad \text{(Equation 10)}$$

While the metric name remains the same in both cases, the method of calculation differs. Therefore, it is advised that any user looking to compare their normalized metrics with those from other studies should first verify the normalization method of the metric in question, in addition to being mindful of the other limitations previously discussed.

According to the International Vocabulary of Metrology (VIM, 2012), uncertainty is defined as a "non-negative parameter that characterizes the dispersion of the quantitative values attributed to a measurand, based on the information used". Any measurement is incomplete unless it is accompanied by a statement of its uncertainty (Grégis, 2019). Characterizing measurement uncertainty is crucial in determining whether a measurement is suitable for a specific purpose or meets the required level of performance as defined by its data quality objectives (Brown et al., 2008).

Relative Expanded Uncertainty (REU) has been utilized in several performance indicator studies (Castell et al., 2017; Bigi et al., 2018; Cordero et al., 2018; Bagkis et al., 2021). However, evaluating this metric is often perceived as arduous and cumbersome, and it is not commonly included in most sensor studies (Karagulian et al., 2019). The mathematical definition of measurement uncertainty, as indicated in the "*Guidance for the Demonstration of Equivalence of Ambient Air Monitoring Methods*" (GDE, 2010) and in alignment with the data quality objectives of the European Air Quality Directive (2008/50/EC), is:

$$U(y_i) = \sqrt{\frac{RSS}{n-2} - u(x_i)^2 + (y_i - b_0 - b_1 x_i)^2} \qquad \text{(Equation 11)}$$

$$REU(y_i) = \frac{kU(y_i)}{\bar{x}} \qquad \text{(Equation 12)}$$

$$RSS = \sum_{i=1}^{n}(y_i - b_0 - b_1 x_i)^2 \qquad \text{(Equation 13)}$$

where $U(y_i)$ is the measurement uncertainty in target units (e.g. concentration), $REU(y_i)$ is the dimensionless relative expended uncertainty, $u(x_i)$ is the uncertainty in the target value, e.g. the measurement uncertainty of the RGM, n is the number of datapoints considered, RSS is the residual sum of squares, and k is the coverage factor corresponding to the interval to be determined, e.g. $k = 2$ for the 95% confidence interval.

Unlike single-value metrics such as R^2, RMSE, and MAE, which aim to evaluate the entirety of a dataset, the uncertainty $U(y_i)$ is evaluated "point by point", allowing for its graphical representation (e.g. as a time series or in the concentration space). This metric, unlike the others mentioned, also takes into account the uncertainty in the target value, denoted as $u(x_i)$. This is an important aspect, as every measurement carries an associated uncertainty, and the RGM data commonly used as target values are no exception. For example, if adequate QA/QC measures are not followed for the RGM, $u(x_i)$ might be a significant contribution to the overall uncertainty. Furthermore, with the continual advancements in LCS technology and data analysis methods, the assumption that all errors originate solely from the LCS or the DGP incorporating LCS data might become excessively stringent. Recognizing the uncertainties inherent in both the DGP and RGM provides a more balanced and accurate assessment of DGP performance and data reliability. Although somewhat laborious, another interesting advantage of these metrics is their ability to be decomposed into systematic and random errors. For guidance on how to do this, the work of Yatkin et al. (2022) is recommended, as it provides an excellent description of the process.

Like any other tool, these metrics have certain limitations that should be considered. Estimating Uncertainty or REU is a more complex process than conventional metrics, requiring more time, additional input information (such as the uncertainty of the RGM), and a certain level of expertise to fully utilize the information they offer. However, the trade-off is that they provide more detailed information in return. On the other hand, it is important to remember that these are still metrics like the ones previously mentioned, which incorporate assumptions and considerations that must be acknowledged when drawing conclusions. For example, they assume that the errors follow an additive linear model (presented in Equation 1). While we as users might expect this assumption to be suitable for most application, there can be non-linear behaviors that diverge from this foundational assumption. Ultimately, it is the user's responsibility to verify this working hypothesis and ensure its applicability to their specific context.

Some DGP might yield qualitative or categorical outcomes, as opposed to quantitative data. This includes, for instance, categorizing air quality under the descriptive labels like "good" or "bad", or assessing if particular thresholds have been surpassed. In such scenarios, categorical metrics become particularly relevant and useful. Some commonly used categorical performance metrics are:

- ***False Positive Rate***: the fraction of estimates falling within a specific category when the true value does not fall within that category;
- ***False Negative Rate***: the fraction of estimates not falling withing a specific category when the true value does fall within that category;
- ***Precision***: the fraction of instances, when an estimate fell in a specific category, that the true value was in that same category;
- ***Recall***: the fraction of instances, when the true value fell in a specific category, that the estimate was in that same category.

In situations with multiple potential categories (e.g. air quality classification as "good", "fair", "poor", etc.), it is also common to report what is called the confusion matrix, i.e. the fraction of estimates falling into each category across all categories of the true value. Additionally, the harmonic mean of precision and recall, known as the F1 score, can be used. For more details on these metrics see Grandini et al. (2020). Malings et al. (2019) employed classification metrics to evaluate the frequency with which LCS matched RGM in determining exceedance of a legal threshold. On the other hand, Russell et al. (2022) used these metrics to estimate accuracy in microenvironment classification, utilizing LCS measurements combined with ML techniques. Similarly, Mohammadshirazi et al. (2022) implemented LCS data as inputs for ML models, aiming to predict high concentration events in indoor environments. Given the relatively low accuracy of LCS compared to RGM, categorical quantifications of air quality such as these be might appropriate, particularly in the absence of local co-location studies.

Data coverage or completeness should also be reported. Limitations on different methodologies, especially in terms of required input data from multiple sources, means that in certain cases it may not be possible to apply a given method. Although this should not be treated in the same way as an incorrect or inaccurate output, assessing how often and under what circumstances these null outputs are produced is also important to assessing a method's applicability. Considerations of temporal resolution, and the trade-offs between this resolution and data coverage, are also important in assessing coverage, e.g. coverage may be improved by averaging results over longer time periods. Limitations in data availability can also impact the calculation or robustness of other performance metrics.

In addition to the performance metrics presented above, it is possible to use various graphical methods and standard plots to present performance information. One of the simplest and most commonly used graphical methods is the Target Plot (Jolliff et al., 2009), which provides a clear visualization of the decomposition of the RMSE. In this type of plot, the horizontal axis represents the MBE, while the vertical axis shows the error variance (Entekhabi et al., 2010). It is important to note, however, that like any single-value metric, this form of visualization represents the average characteristics of the entire set of measurements under evaluation as a single point in space.

Bland-Altman plots, introduced by Altman and Bland (1983), provide another valuable graphical method for understanding performance. In these plots, the average of the DGP output and target value (e.g. RGM measurement) is depicted on the horizontal axis, while the difference between these is displayed on the vertical axis. Bland-Altman plots are particularly useful for quickly visualizing the discrepancies between two sets of data. For examples of specific LCS applications utilizing Bland-Altman plots, one can refer to the work of Diez et al. (2022).

Figure 7 in Section 8.2 presents a hypothetical example demonstrating the combined use of these analytical tools, for a case study of LCS calibration. A Target Plot (top left) displays the performance of six sensors, three of which (LCS2, LCS4, and LCS5, indicated by the red circle) show an RMSE greater than 10 concentration units. A notable feature of these devices is that their bias, as indicated by the MBE, is more prominent than the cRMSE, suggesting that a correction of the zero and span would be beneficial. The bottom part of the figure illustrates these three sensors (now labelled LCS2*, LCS4*, and LCS5*) after undergoing such corrections. The Bland-Altman plots in the middle and on the right side of Figure 7 depict these same three sensors before (middle panels) and after (right panels) the corrections. Initially, LCS4 exhibited the largest error of the group, but the corrective measures led to a marked improvement in data quality, even more so than in the other two sensors (LCS2 and LCS5). This improvement can be attributed to the fact that the impact of noise is lower compared to the bias in this sensor, as reflected by the width of the limits of agreement in the Bland-Altman plot.

Summary and Best Practices for Using Performance Metrics

Global performance metrics such as R^2, RMSE, and MAE, among others, provide valuable insights when estimated accurately and conscientiously. They are also beneficial for communicating and comparing their magnitudes with pre-established standards and objectives. However, the practice of condensing multidimensional characteristics into single-value statistics has its limitations, which is crucial to acknowledge:

- Single-value performance metrics are not necessarily independent of each other and may even be correlated as shown by Tian et al. (2016). Furthermore, they do not necessarily describe unique error characteristics, since different combinations of errors can result in the same metric values.

- These metrics assume that errors come exclusively from the DGP. However, we must recognize that no measurement is perfect, including RGM, which means that the "true values" against which the DGP is being evaluated are also subject to error. Therefore, if reference measurements are not properly maintained and subjected to QA/QC, conclusions derived from the evaluation of DGP could be biased.

- The results obtained for any metric are significantly influenced by the context in which they are gathered, such as the domain, period, and environmental conditions. Therefore, any change in this context will result in different metrics. This limitation is especially relevant for DGP involving LCS, given that their measurement methods are often sensitive to environmental variables (e.g. sensitivity to cross interference). Therefore, while benchmarking DGP using metrics derived under varying conditions can offer valuable insights, it can also be misleading and should be approached with caution.

A strategy focused on alleviating this last point is the use of normalized metrics. However, it is important to note that the normalization process focuses on a single variable, such as the target concentration, whether through mean, standard deviation, or range. This can be limiting, as it does not consider the multiple variables that can affect the distribution of results. Therefore, any comparisons between results from different studies should be approached with caution.

Although estimating multiple metrics might provide overlapping information and doesn't guarantee a granular view of an DGP performance, it can be beneficial, particularly for less experienced users. Above all, it will result in a better understanding of the advantages and limitations of each metric. A good practice is to complement these metrics with multidimensional visualizations of errors, such as regression plots, Bland-Altman plots, and Target Plots. These graphical tools can be valuable additions, revealing details and patterns that might go unnoticed in single-value metrics. Furthermore, including more comprehensive statistics like uncertainty, which provides deeper insights and can also be visualized, can enhance the analysis. Ultimately, the combined use of multiple tools, while not guaranteeing absolute success, will facilitate a better understanding of whether DGP performance is adequate for specific applications.

Performance metrics have a limited capacity to communicate the numerous aspects that underlie their estimation: the specific objectives of the study, the user experience, and the ranges of the inputs, among others. These factors directly impact the accuracy and relevance of the metrics. Therefore, if they are documented and accessible, users should review them carefully. Focusing solely on the numerical values of metrics without considering the underlying context and complexity can be misleading. Metrics represent just a fraction of the information needed to evaluate DGP performance. In evaluating these metrics, it is essential to understand the limitations and potential biases of each data source to reach the most reasonable conclusion. Metrics should always be contextualized. Comparing metric values against pre-established performance goals, or comparing metrics from different methodologies addressing the same issue, is more meaningful than considering metrics in isolation. Such a comparative approach not only highlights the value added by the DGP but also helps in setting realistic expectations regarding its performance. Understanding the context in which the data will be used, and how it compares to other data sources or methods, is key to ensuring an effective application which best meets the intended objectives.

An aspect that frequently causes confusion among users is the interpretation of metrics published by commercial LCS manufacturers and data analytics companies. In any case, information from these entities should be taken with caution, due to potential conflicts of interest. Users should look for supporting documentation that the LCS manufacturer or DGP developer should transparently provide, demonstrating how performance was evaluated. Such documentation should answer questions like: "Are the published metrics based on theoretical evaluations or field tests? Are they referring to the entire system or are they reproducing the metrics provided for particular inputs? What is the temporal resolution of the data that provided these performance metrics? For how long and under what season or climatic regime (e.g. temperature and humidity ranges) was the evaluation conducted? Were multiple alternative DGP tested under the same circumstances? Does the DGP evaluated belong to a specific version? What reference data were used as a standard for comparison? Was this evaluation carried out by the data developer itself or by an independent group?" Additionally, it is important to recognize that any published metrics are only an indicator of potential system performance and do not guarantee that the system is suitable for the user's specific purpose. To use a metric as a reliable indicator of future performance, the conditions under which the metrics were obtained must reflect the intended use of the DGP as closely as possible.

C.9. Air Quality Monitoring Network Design

C.9.1. Common use cases for LCS network design

There are important study design considerations when conducting a pilot scale or exploratory analysis to identify hotspots. A study conducted in Denver, USA showed that hotspot identification with LCS is sensitive to factors such as the calibration approach and data averaging period (deSouza et al., 2022). As such, to ensure robust hotspot detection, it is recommended that the consistency of a location being identified as a hotspot is assessed for different scenarios, including varying averaging times, sampling strategies, LCS calibration approaches, and diverse definitions of what constitutes a "hotspot". For example, hotspot classification may be based on high average concentration, prolonged periods of elevated concentrations, or atypical diurnal pollution profiles compared to other monitored locations. These different potential dimensions of what defines a hotspot emphasize the need for both spatial and temporal analysis of LCS network data.

In Boston, USA, networks consisting of stationary LCS and roving RGM within a mobile van were used to identify air pollution hotspots and understand their drivers and health impacts in order to inform city decision-making and address environmental justice (Zhang, 2023b).

In Okure et al. (2022), a multipollutant LCS deployment across various regions and urban areas in Uganda for a six-month period highlighted inconsistent temporal patterns across different cities and regions, indicating an inadequate, sparse dataset. More sensor deployments, including a combination of mobile and stationary sampling, was indicated as a possible solution. Additionally, increased monitoring of gaseous pollutants was recommended to better characterize traffic-related emissions. The study emphasized the importance of long-term monitoring campaigns to account for the influence of seasonal changes. Furthermore, the utility of engaging volunteers for opportunistic sampling (further discussed in Section 9.1.4) was underscored.

There are several examples of LCS use for fenceline monitoring, particularly for VOC and CH_4. In one study, LCS were able to detect CH_4 leaks above a certain threshold with high accuracy and were even able to quantify leak rates to within 25% given more than roughly two days of data (Riddick et al., 2022). LCS used in this way may help constrain the potential climate effects of fugitive CH_4 from natural gas production. Others have used fenceline LCS systems for VOC to trigger the collection of canister samplers for later analysis using laboratory equipment (MacDonald et al., 2022), enhancing the overall efficacy of environmental monitoring. Fenceline sampling can also be used to attribute the fractional contribution to total pollutant concentrations at receptor sites. For example, they have been used to attribute how much of the $PM_{2.5}$ and PM_{10} at a high school was from a nearby asphalt facility by combining fenceline sampling with dispersion modelling (Roy et al., 2023).

Following Hurricane Maria in Puerto Rico, a deployment of multipollutant LCS effectively detected a significant surge in SO_2 concentrations, which was attributed to the use of lower-quality fuels in emergency generators (Subramanian et al., 2018).

In 2018, Kīlauea Lower East Rift Zone eruption (May to August 2018) blanketed much of Hawai Island in "vog" (volcanic smog), a mixture of primary volcanic SO_2 and secondary PM. This episode was captured by several monitoring platforms, including a LCS network consisting of 30 nodes designed and deployed specifically to monitor PM and SO_2 during the event (Crawford et al., 2021).

In the aftermath of a fire at an industrial facility in Houston, USA, a network of LCS for PM were used to assess the impact on potential exposures. The identified concentration increases during and immediately after the fire were comparable to those observed by the local RGM network (Liu et al., 2022).

The USA Forest Service uses temporary LCS deployments to supplement other technologies, including deployable RGM, to provide temporary monitoring of smoke from wildfires or prescribed burning. LCS networks paired with fire hotspots and deforestation data have also been implemented by local municipalities in Acre State, Brazil to increase understanding of the air quality impacts during critical periods of air pollution such as annual biomass burning in the Amazon region (Melo et al., 2020). Building-scale LCS networks have also been used in a paired indoor-outdoor context to assess real-time wildfire smoke infiltration rates and adjust building ventilation practices accordingly in vulnerable settings such as hospitals (Nguyen et al., 2021).

If an ad-hoc network represents a wide array of demographic and geographic characteristics, it can be used to develop LUR models or study air quality disparities. In doing so, it may be necessary to select a subset of the network for analysis, rather than using all LCS available within the region (Bi et al., 2022a; Kim et al., 2023). For example, in an epidemiological analysis focusing on a cohort residing in urban areas, sensors located in regions characterized by high population density, socioeconomic status, and impervious surfaces were found to be good candidate sensors for inclusion in the study (Geng et al., 2018).

C.9.2. Approaches not requiring prior air quality information

The problem of LCS network design using citizen-centric objectives and in the absence of prior air quality information is considered by Sun et al. (2019). Proposed objectives here included the proximity of LCS to population groups, the proximity of LCS to locations where vulnerable populations congregate (e.g. nurseries or hospitals), and the proximity of LCS to major roadways. It is suggested not to optimize some combination of these objectives, since the resulting placements would not necessarily be optimal for any single objective. Instead, the available LCS should be allocated among these objectives, and then optimally sited according to each objective, with suggested sites for different objectives that are reasonably nearby being combined. This ensures that sites which are most crucial to solving each objective become part of the optimized network design.

Lerner et al. (2019) propose a methodology to design a multipollutant LCS network considering only land use characteristics of the region of interest and the accuracy of the LCS. In this approach, different types of LCS are assigned a suitability for deployment near different pollutant sources (e.g. roadways or industrial sources) that are present near potential deployment locations. Networks were then optimized by maximizing the total suitability weighted by spatial coverage. While this approach requires a subjective determination of LCS suitability, it is straightforward to implement in the absence of sufficient quantitative information about the region of interest (e.g. concentration estimates or information about vulnerable populations). Principal component analysis on a variety of land use features (predictors to be used in an LUR model) was also used to identify different locations or types of locations for monitors which would best support the LUR model development (Bi et al., 2022a). This was done by defining a distance metric based on differences between principal component values across sites, and then selecting sites which would minimize this distance metric to a set of points of interest in the domain to be monitored. It was also noted that the large number of LCS capable of being deployed in an area (in contrast to RGM) increases the likelihood of their proximity (both geographically and in terms of principal component distance) to a point of interest.

For the goal of near real-time reporting with combined LCS and RGM networks, it was found that the utility of the LCS network depended on (1) the degree and type of measurement errors, e.g. errors independent of versus errors proportional to the measured value as discussed at the beginning of this section, and (2) the method of reporting, i.e. as concentration values or as categorical classifications such as air quality index values (Considine et al., 2023). In particular, without careful design of the LCS network, reporting air quality based on a dense LCS network under realistic assumptions of LCS measurement accuracy was found to produce poorer information than relying on a sparser but more accurate and more strategically placed RGM network. It was also found that placing LCS at schools resulted in the most accurate and equitable distribution of air quality information among the strategies considered; in this case, schools in the study area (California, USA) were most representative of estimated $PM_{2.5}$ exposure in their surrounding communities. It was also noted that a few strategic deployments near major roadways could be beneficial, especially in less densely populated areas. While focusing LCS deployments in areas with higher relative pollutant exposure is beneficial to populations living in those areas, over-representation of these areas may skew reporting for people living outside such areas. Therefore, special considerations might be needed when incorporating data from such areas and reporting these data as part of more regional analyses. It should be noted that this study was conducted based on previously obtained air quality estimates, and that results will not necessarily generalize universally, e.g. schools may not always be sufficiently representative of their surrounding communities.

For the purpose of public health analysis, strategically determining the locations of potential target populations or epidemiological cohorts is a critical factor for sensor deployment (Kim et al., 2023). The LCS network should be designed to represent the target population’s demographic features, including socioeconomic status, age structures, and race/ethnicity, as well as geographical features such as differing land use and land cover characteristics. A representative LCS deployment is crucial for the accuracy of air pollution exposure modelling for the underlying populations. In cases where sensor deployment does not target specific populations, it is imperative to position the sensors to capture a wide spectrum of demographic and geographic characteristics for exposure modelling.

C.9.3. Approaches utilizing prior air quality information

A theoretical framework for air quality monitoring network design based on maximization of coverage was first presented by Liu et al. (1986), and demonstrated by McElroy et al. (1986). This methodology involved the use of models to assess the probabilities of occurrence of different pollutant conditions in different areas. Monitors would then be placed to maximize coverage of the most potentially problematic areas. Local variability of a LUR model output can also serve as an estimate of the variability of pollutant concentrations and be used to guide network design (Kanaroglou et al., 2005). This approach requires some pre-existing monitors to calibrate an appropriate LUR model for the region of interest. In Hsieh et al. (2015), a ML model using meteorological and land use features as inputs (see Section 3.2) was first created to infer air quality at unobserved locations, including uncertainties in the local air quality. Then, a network was designed to reduce these uncertainties across unmonitored locations. This approach also relies on some existing monitoring stations to calibrate the ML approach, but it was found to perform well even with a small number of initial stations.

In a reconstruction context where concentration surfaces will be estimated in between sampling locations using tools such as LUR or kriging, the relative importance of a given sampling location can also be assessed using a Monte Carlo simulation, i.e. the creation of many possible concentration surfaces. If concentration estimates or other network level statistics in an unsampled location change by a statistically significant margin across these simulations after removal of a given LCS, then that sensor could be flagged as required, and non-essential sensors could be relocated (Jain et al., 2024).

Statistical analysis of historical air quality information using techniques such as multiresolution dynamic mode decomposition has helped identify monitoring locations that best support detection of pollution events significantly above background concentrations (Kelp et al., 2022). Such a technique requires long-term, high-resolution air quality data, which may be available for some domains. Existing AQM simulations and/or satellite remote sensing estimates may be useful as a starting point to employ such a technique; sensor placements can then be re-optimized after more data have been collected. A cost-constrained multiresolution dynamic mode decomposition algorithm has also been used to optimize the deployment of $PM_{2.5}$ monitor locations to both accurately measure concentrations and their spatial variability and to create an equitable network across a variety of socioeconomic factors (Kelp et al., 2023). This method required historical high resolution (1 km, daily) $PM_{2.5}$ concentration estimates from a combined model and satellite dataset. These were decomposed into dynamic modes by the proposed algorithm, and then monitor sites were iteratively selected based on the variability of different modes at different locations. A constraint was applied to the optimization to ensure coverage of low-income and non-white population groups. While this method relies on pre-existing high-resolution air quality estimates which may not be available, and tends to suggest redundant placements, it illustrates a potential approach to LCS network design to balance air quality measurement and environmental justice needs.

Inverse modelling (see Section 4.3) has also been used to investigate trade-offs of monitoring density and precision (Turner et al., 2016). That study concluded that a dense monitoring network comprised of systems with a moderate precision (1 ppm CO_2 in this case) is preferable from the perspective of accuracy of the inferred emissions (being able to characterize these with less than 5% error overall) as well as network setup cost. In general, the study found that networks may either fall within "noise-limited" or "site-limited" regimes from the point of view of emissions quantification, where, respectively, reductions in measurement error or the deployment of new sites will most improve the performance of the network for its intended purpose of emission quantification. Investigating an appropriate trade-off of measurement error and number of deployed sites, while also taking costs into account, can help to determine an optimal strategy for network design (including how to grow existing networks) to meet a given need.

Statistical forecasting or reconstruction approaches like kriging (see Section 3.1), Gaussian process models (Herrera, 2022), or data assimilation techniques (see Sections 3.4 and 7.1) can support posterior uncertainty quantification and analysis. In other words, the reduction in uncertainty due to the inclusion of a new observation with known characteristics (i.e. with a pre-determined measurement accuracy) can be quantified. This requires, however, both a thorough understanding of prior uncertainty (e.g. an ensemble of models representing the range of possible situations which could occur in a given domain) and of measurement uncertainty (e.g. good characterization of potential errors in LCS measurements). For example, a study in Japan used a kriging variance reduction approach, where AQM simulations generated synthetic datasets which were then used to calculate the semi-variograms of the constituents to be monitored (Araki et al., 2015). Using these, a hybrid genetic algorithm and simulated annealing approach was used to find a network design which minimized the average kriging posterior variance over the domain to be monitored. This approach required high spatial resolution AQM simulations of the domain (4 km in this example), which may be unavailable or computationally intensive to obtain. This also illustrates how an optimization approach can be linked to a reconstruction approach (kriging). In this case, an optimal monitoring network design for assessing annual averages of one pollutant was also found to perform well for daily and hourly averages of the same pollutant and for other pollutants; however, this may be a limitation of the simulation approach used to estimate the pollutant concentrations, and might not be replicated in real-world conditions.

C.9.4. In situ calibration case studies

In situ calibrations strategies for LCS can be categorized as reference-based, where there are at least some trusted RGM present to which LCS can be calibrated, or blind, where no local RGM exists (Delaine et al., 2019). In networks including both LCS and RGM, various strategies might be employed for calibrating or validating LCS data, including (1) routine co-locations where LCS are periodically moved to be co-located at RGM sites, (2) permanent co-location where several LCS are kept permanently co-located with RGM, (3) mobile co-location where RGM are moved to the locations of LCS for co-location, or (4) the creation of transfer standards where one or more LCS are co-located with RGM, and then additional LCS are co-located with those "standardized" LCS (Yatkin et al., 2022).

In situations with multiple RGM and LCS spanning a domain, a spatially varying in situ calibration approach can be employed. An example is provided by Chu et al. (2020), where a weighted regression based on multiple co-located RGM and LCS and the distance of each co-located pair were used to inform location-specific calibration factors for deployed LCS. A similar geographically weighted regression approach for calibration parameters between sets of relatively nearby (within 0.5 km) paired LCS and RGM was used by Bi et al. (2020b). In-field calibration of LCS networks can also be carried out iteratively by calibrating each LCS to its nearest RGM, interpolating concentrations from the RGM and all but one LCS (see Section 3 for methods whereby this might be done), re-calibrating the left-out LCS to the estimated concentration from the interpolated product, and iterating this procedure across all LCS until their calibrations converge (Zheng et al., 2018). That study notes that this technique is only suitable where concentrations are expected to be relatively homogenous; any hyperlocal sources which might be detected by the LCS will tend to be masked out during the iterative recalibration.

Assumptions of homogenous concentrations, at least under certain conditions, can also support in-field calibration of LCS networks. Such a calibration was conducted using ML techniques which combined the LCS data, data from a nearby RGM, and information about the distance between the LCS and the RGM (Wang et al., 2020b). That study found better performance when calibration was conducted based on nighttime-only data, to minimize the influence of hyperlocal sources which are typically present during the daytime. However, this technique still required a fairly dense network of RGM for calibration. Use of nighttime-only data has also been used to calibrate O_3 LCS (Broday and the Citi-Sense Project

Collaborators, 2017) as well as NO_2 and PM LCS (Hofman et al., 2022b). When an LCS device measures multiple gaseous pollutants (NO, NO_2, O_3, CO), in situ calibration can be done using only a relatively small number of RGM together with information on regional atmospheric chemistry conditions and emission factors (Kim et al., 2018). However, some of the assumptions necessary for this approach, such as knowledge of vehicle fleet emission factors and assumptions about spatial uniformity in O_3 and background CO concentrations, may not be available in the types of environments where LCS are intended to be used.

Land use characteristics can also play a role in in situ calibration. An investigation in Denver, USA, noted that a linear correction model developed using LCS data from the prior eight weeks at co-location sites, together with temperature and humidity data and a near-highway indicator, provided the best performance for an "on-the-fly" week-by-week $PM_{2.5}$ calibration when assessed via site-based cross-validation (Considine et al., 2021). In another study, by assuming that LCS respond linearly to their measurands, several O_3 LCS were paired with proxy RGM sites not by proximity but by similar land use. Linear regression was performed to match basic statistics (mean, variance) between LCS and proxy RGM data on a rolling 72-hour basis (Miskell et al., 2018). It was noted that, despite this method forcing distributions of LCS and RGM to match, important additional information about the times of occurrence of different pollutant levels obtained by the LCS were preserved, resulting in good agreement with co-located RGMs during testing. This method may be most suited for regions where there is good coverage of different land use types by RGM and/or little variability in land use, and thus the assumption of sites having similar distributions of concentrations would be reasonable. In areas with heavy influence of local sources, this assumption might be invalidated. Also, the methodology might be more suitable for regional pollutants such as O_3, although the work proposes some solutions for more spatially variable pollutants.

When considering co-location time, one calibration approach involving a network of LCS was developed under the assumption that while many previous LCS deployments may have been co-located with an RGM, a new LCS added to a network may have very limited co-location time. Thus, data from this limited co-location may be combined with the ensemble of previous calibration models for other LCS in the network to derive a calibration model for the new LCS leveraging information from the previously calibrations, while still being specific to the new LCS (Villanueva et al., 2023). Others have conducted continuous calibration of LCS by applying statistical or ML-based correction models based on LCS collocated at RGM sites, which significantly increase the accuracy of the LCS network for measuring NO_2 and $PM_{2.5}$ (Daepp et al., 2022; Montgomery et al., 2023).

A possible future direction is to use multisource air quality estimates from a combination of any available RGM, AQM, and satellites to provide a first basis against which groups of similar LCS can be calibrated. The calibrated LCS can then provide locally relevant information (Malings et al., 2021). This approach risks passing any biases in the combined AQM, satellite, and RGM estimates onto the LCS calibrations.

C.9.5. Mobile monitoring case studies

The increased spatial coverage afforded with mobile monitoring makes it attractive to support air quality reconstruction (Brantley et al., 2013; Van Den Bossche et al., 2015; Apte et al., 2017; deSouza et al., 2020a; Hassani et al., 2023a; Hofman et al., 2023). Use of LCS mounted to personal or official vehicles for mobile monitoring can reduce mobile monitoring costs, i.e. by not requiring a dedicated vehicle and driver to transport the monitor as is often needed with mobile RGM. Less heavily trafficked rural areas may be less suitable for extensive mobile monitoring in this form, but could potentially benefit from alternative mobile monitoring solutions. To date, high spatiotemporal resolution mobile air quality measurements have been conducted in collaboration with Google Street View cars in

Houston (USA), the San Francisco Bay Area (USA), Amsterdam (The Netherlands), Copenhagen (Denmark), and London (UK). Recently, mobile LCS platforms have been used to measure hyperlocal PM, NO_2, temperature, and relative humidity in Boston (USA), New York City (USA), and Beirut (Lebanon) (A. Wang et al., 2023).

When calibrating $PM_{2.5}$ LCS for mobile deployments, it was found that simpler calibration approaches (e.g. linear regression incorporating raw measurement as well as humidity and dewpoint terms) outperformed more complicated approaches (e.g. ML methods) when transferring calibrations developed during stationary co-locations with RGM to mobile monitoring. Also, calibrations developed using high temporal frequency data (i.e. minute averages) generalized better to mobile applications. However, performance of the LCS in mobile applications was still lower than assessed during stationary monitoring. For these reasons, use of mobile LCS may currently only be suitable for qualitative analysis, e.g. determining areas of generally higher concentrations relative to other areas; LCS performed well for that purpose during testing (deSouza et al., 2023c).

In terms of mobile LCS network design, one design decision may be the choice of random or fixed routes. One of the main differences between random routes and fixed routes in mobile monitoring is the degree of spatial coverage and temporal representativeness of the data. The random route design, e.g. using taxis as in Sun et al. (2022), postal vans as in Hofman et al. (2023) or city wardens as in Van Den Bossche et al. (2016), can cover a wider network of roads and capture the spatial variability of traffic-related air pollution in urban areas. However, a random route design also introduces uncertainty and potential bias in the data quality and analysis, as for example the taxis may not follow the same routes or visit the same locations every day. A fixed route design, e.g. using buses as in Wei et al. (2021) or garbage collection vehicles as in deSouza et al. (2020a), can ensure a consistent and repeated measurement of on-road air pollution along certain routes, which can reflect the temporal patterns and trends. However, a fixed route design may not be able to capture the spatial heterogeneity of traffic-related air pollution across different road types and environments, as sampling is limited to predefined routes. Therefore, both designs have their advantages and disadvantages for mobile network monitoring, and the choice of design depends on the research objectives, data availability, associated costs, and availability and access to different types of mobile platforms.

In general, the same techniques can be applied to mobile monitor data as to stationary data for reconstruction, but several additional important considerations must be made when dealing with mobile monitor data. First, while spatial coverage is greatly improved via mobile monitoring, it is still incomplete, and may be increasingly incomplete in less populated and/or less accessible areas. In particular, measurements will be confined to roadways, which introduces a sampling bias. Second, as monitors move in space, they are also moving through time, and changes in concentration due to movement in these multiple dimensions can be difficult to disentangle. Multiple passes along the same routes, deliberately made at different times of day, are necessary to reduce such potential biases (Apte et al., 2017). Representativity analyses (e.g. subsampling) are crucial in order to determine how many passes are required in order to obtain representative long-term results (Van Den Bossche et al., 2015; Apte et al., 2017; Hofman et al., 2023). Opportunistic data collection using LCS on service fleet vehicles was showcased in Antwerp, Belgium, as an efficient approach to (1) cover a wide spatial area (59% of the city roads were covered by 17 LCS after one month) and (2) collect many repeated runs (about 200 measurements per segment per month), resulting in more accurate pollution exposure assessments (Hofman et al., 2023). Nevertheless, this was only achieved under the condition of a strict LCS validation and calibration strategy. Monthly maps showed recurring pollution gradients greatly exceeding the observed inter-sensor uncertainty. Moreover, sufficient monitoring passages (31 after post-processing) were required in order to obtain representative long-term NO_2 averages (Hofman et al., 2023). Analysis and interpolation approaches must also be careful to consider natural autocorrelations in mobile monitor data; data collected in close spatial and temporal proximity will tend to be similar, and if they are treated as independent (as is an assumption in many analysis techniques), the results may show unwarranted and excessive statistical confidence. Grouping nearby or otherwise similar data into "super-observations" can help minimize the impact of this autocorrelation.

Ordinary kriging, using only distance information, was found to be a suitable approach for generating spatially contiguous estimates from mobile LCS ozone data, as well as informing the appropriate spatial and temporal sampling approaches to best support this reconstruction (Alvear et al., 2016). LUR techniques are also applicable to mobile LCS data. A random forest regression model using various land use inputs (e.g. population density, roadway length, poverty index) was used to reconstruct $PM_{2.5}$ data collected by LCS deployed on motor bikes in Nairobi, Kenya, before and during the COVID-19 lockdown. The reconstructed data were used to evaluate granular changes in $PM_{2.5}$ concentrations during the lockdown (deSouza et al., 2021). The results were compared to those obtained using a universal kriging statistical interpolation approach; both methods identified similar intraurban trends, e.g. higher concentrations in poorer neighbourhoods than wealthier ones. A methodology for using ML techniques to perform reconstruction using both fixed and mobile LCS measurements for $PM_{2.5}$, NO_2, and black carbon, as well as meteorological and land use information (points of interest, road network, traffic data, street canyon type, etc.) is presented by Hofman et al. (2022a), building on previous related work (Do et al., 2019, 2020; Qin et al., 2020, 2021). The methodology was tested in Antwerp, Belgium; Utrecht, The Netherlands; and Oakland, USA, and outperformed several other reconstruction techniques, including kriging and inverse distance weighting. Performance approached that of a state-of-the-art dispersion model, while being less computationally intensive. Overall, it was concluded that good model performance still depended on the spatial representativity and coverage of the mobile monitors, the performance and calibration of the LCS, and the size and representativeness of the training dataset.

Sun et al. (2023) introduced innovative methods for pollution reconstruction using LCS deployed on various airborne platforms, including helicopters. The study highlights the potential of LCS in capturing vertical as well as horizontal spatial dimensions of air pollution, a crucial aspect often overlooked in traditional ground-based measurements. By using helicopters equipped with LCS, the researchers were able to gather comprehensive data on pollutant distribution across different altitudes and locations. This approach not only provides a more detailed understanding of pollution patterns but also enables the identification of emission sources that might be missed by ground-level sensors alone. The flexibility and cost-effectiveness of LCS, combined with the mobility and extensive reach of airborne platforms, offer a novel and efficient way to support pollution reconstruction, paving the way for more targeted and effective air quality management strategies.