Data-driven sensor network development for continuous monitoring in low-resourced African cities

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About AirQo (www.airqo.africa)

Founded in 2015 at Makerere University, to close the gaps in air quality management across Africa through leveraging technology innovation to influence action through contextual evidence

Vision

Clean air in all African Cities

Strategic mission: advance Africa's participation in the development and use of a robust, scalable open data infrastructure that serves as a foundation for advancing clean air actions in Africa.

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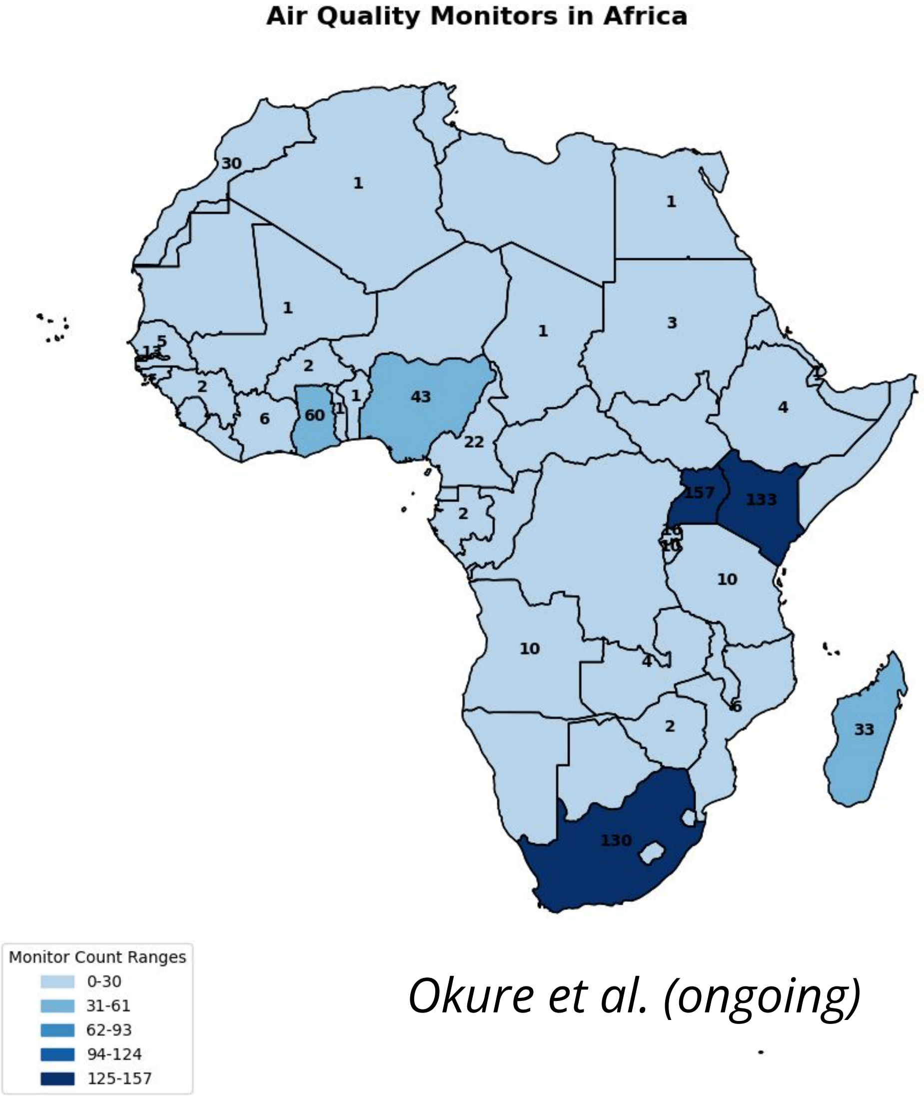
Air pollution in African cities

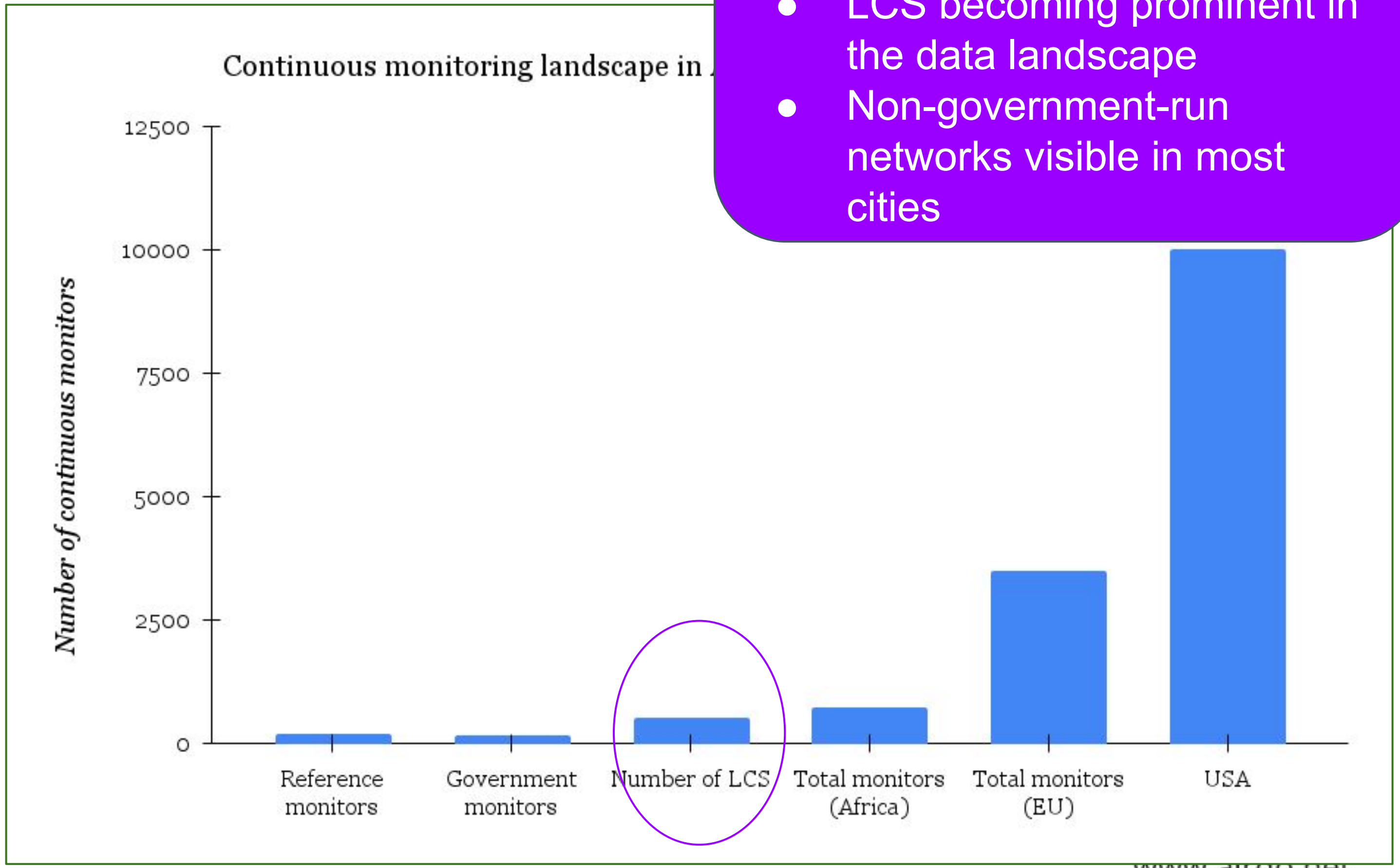
1. 1.2 million people die every year from exposure to air pollution in Africa
2. Heavily influenced by localised pollution sources from transportation, and domestic sources such as waste and biomass burning
3. Shared air quality challenges across the region:
   a. Limited access to ground monitoring data
   b. Enabling mechanisms for collaborations
   c. Growing, but limited awareness and evidence-driven policy development

Air quality monitoring in Africa: Gaps in continuous data and emergence of LCS

Continuous monitoring in Africa is evolving ↑

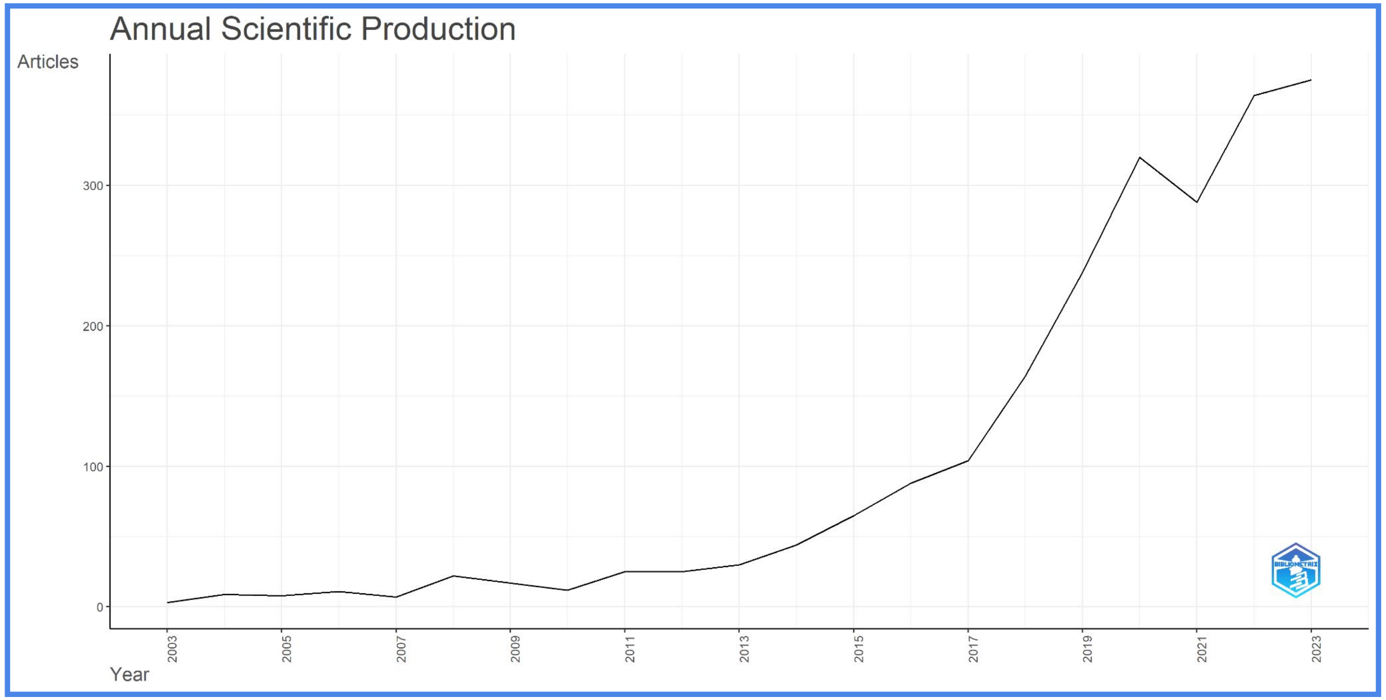


Okure et al. (ongoing)



- A number of countries have no access to continuous monitoring
- LCS becoming prominent in the data landscape
- Non-government-run networks visible in most cities

Emergence of LCS



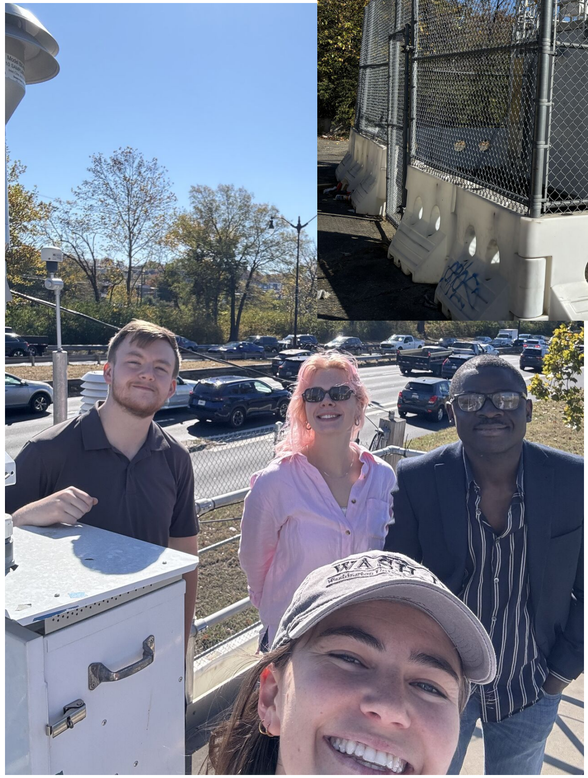
Growth in scientific publications with key words low cost OR low-cost AND sensors AND air quality (Author generated)

Low-cost sensor platforms have gained traction over the years due to their robustness (~26% annual growth over 20-year period)

- Affordability
- enhanced computational capabilities
- wireless communication and high data relay frequency

There are significant barriers to adoption in resource-limited settings but real-life case studies offer opportunities for scalability

Transition from ‘elaborate’ to portable (Summarised in Okure et al. 2022)



Network management team in DC: Conventional stations requires a high technical expertise with a full-time on-site personnel

What makes it low-cost?

- Purchase cost threshold
  - $100-$2,500 (Jiao et al, 2016; Borrego et al., 2018; Karagulian, 2019; US-EPA, 2020, etc.) vs $30,000 for a single pollutant
  - Limits resolution
- Installation and maintenance
- Data retrieval/access
- Logistics of security and site access

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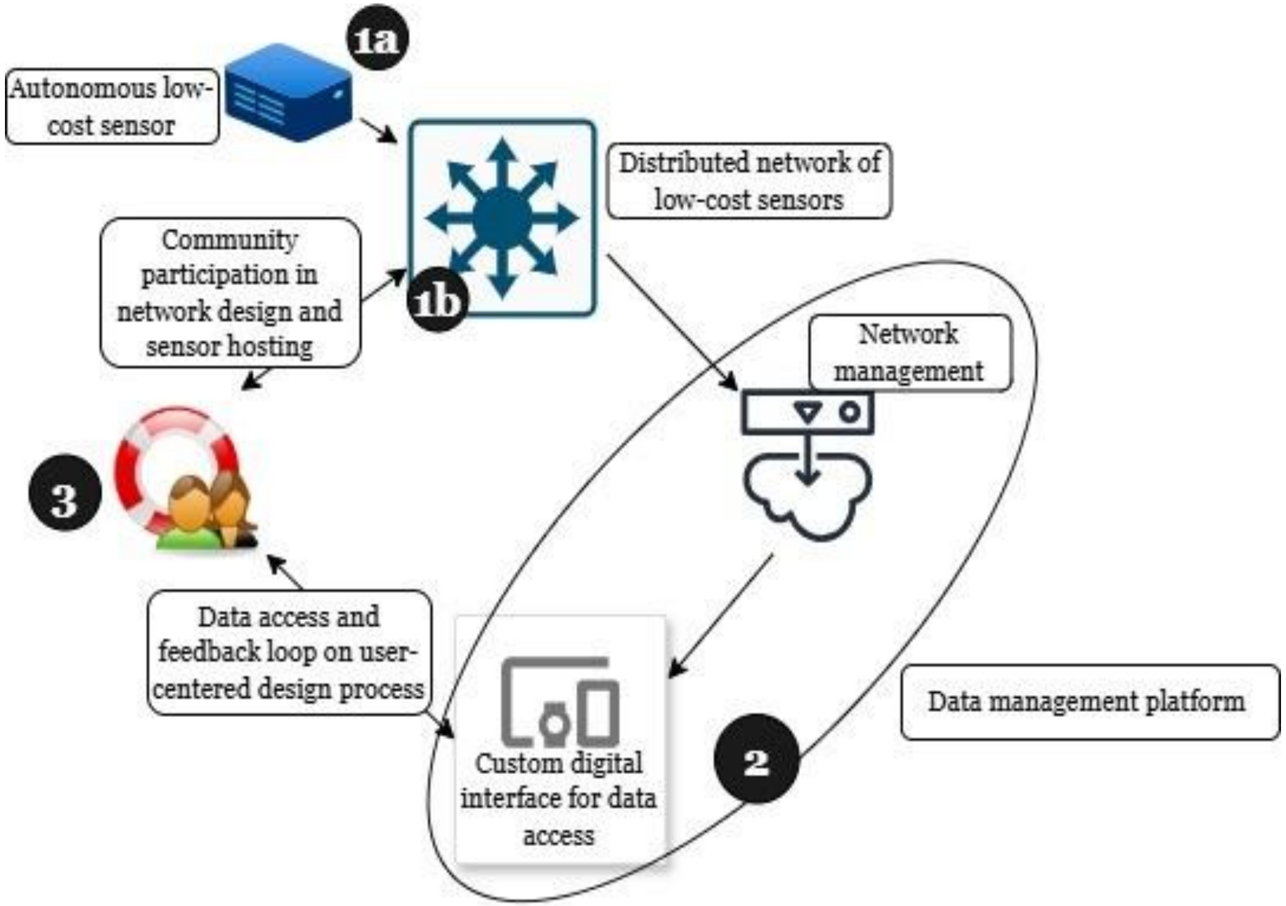
What is the optimal framework for continuous data generation using LCS?

Tackling the common challenges associated with sensor network development

1. *How many sensors are enough?*
2. *How best can we deploy sensors to achieve the best possible outcome(s)?*
3. *What are the most cost effective approaches to manage sensor networks?*

Making LCS work: integrated framework for continuous monitoring

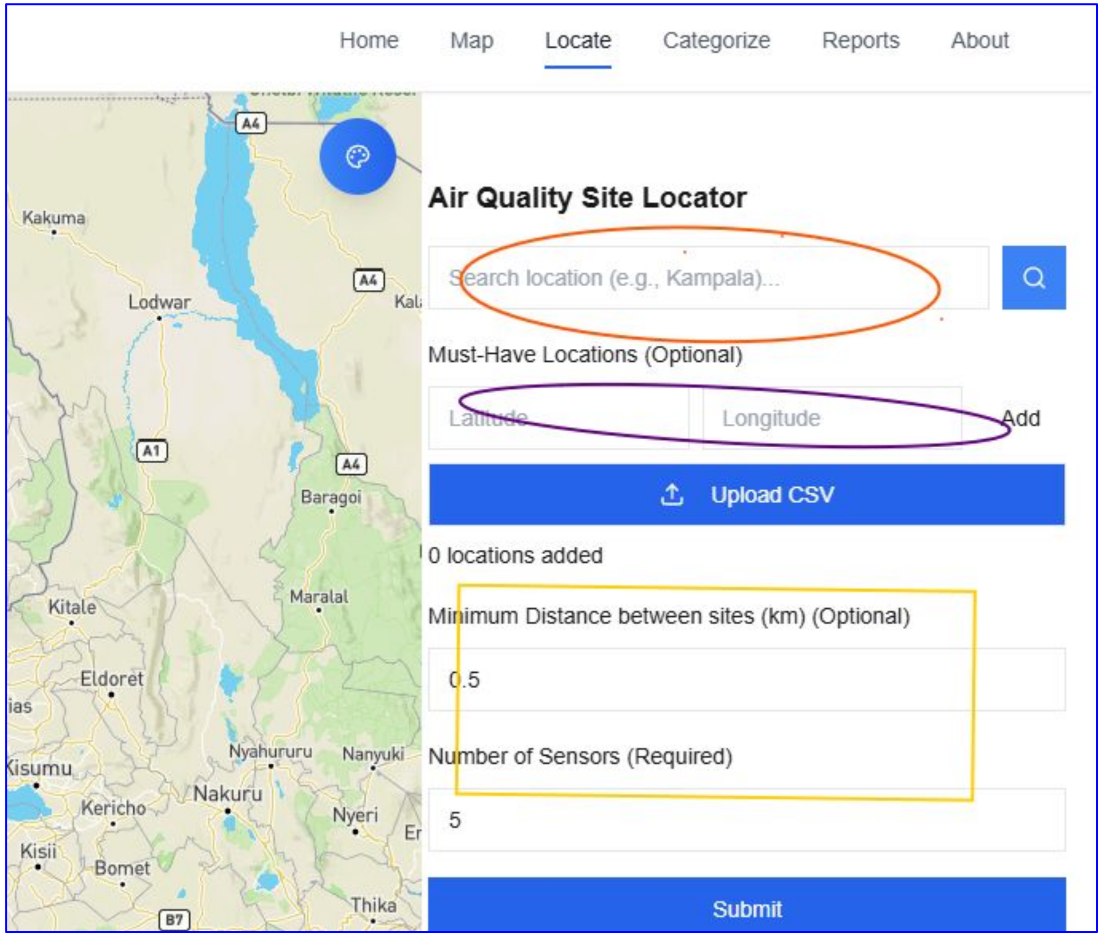


1. Network development
   a. Custom technology interface for sensors
   b. Autonomous distributed network
2. Network management infrastructure
   a. Data credibility
   b. Automated network development and performance management
3. Community ownership/participation
   a. Data access
   b. Enhancing API applications and interoperability
   c. Data governance

Sensor placement optimisation: Machine Learning approach (link)

Checklist and trade-offs

1. Boundaries (city/geographical boundaries)/an airshed
2. Sensors (resources) available
3. Polygon - area of interest
   a. Distance between sites
4. Candidate sites - (co-developed)
   a. Exposure, activities, sources, etc.
5. Must have locations - regulatory/planning regimes
6. Network periodic evaluation



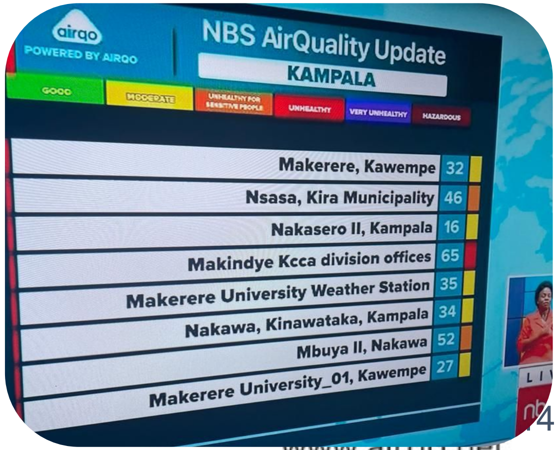
Network Management - QA/QC

- Without robust methodologies and maintenance protocols, accuracy of LCS can degrade overtime including resulting in overestimation of pollution concentration by up to 5 times for $PM_{2.5}$
- Sensor measurement uncertainty often provided by sensor manufacturers - only useful as a decision metric for initial choice of sensors
- Local independent sensor evaluation at the point of use is necessary to correct for contextual environmental factors, such as high concentrations, and local meteorological factors
- Access to local reference monitors should be an important consideration for new networks - regional test centres have been useful in African region.
- Important key performance metrics
    - *intra-sensor correlation, (ii) inter-sensor correlation, (iii) correlation with reference monitors, and (iv) data completion.*

Scalable end-end monitoring infrastructure

- Portable sensors for decentralised monitoring networks
- Open-source cloud-native/platform for network management
  - Cloud-based calibration
  - Tools for network managers to analyse sensor network performance
- Community-aware digital platforms to enable access (Mobile App, web platform, API)

https://analytics.airqo.net/user/home



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