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Full length article



Wastewater-based epidemiology in hazard forecasting and early-warning systems for global health risks

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ABSTRACT

With the advent of the SARS-CoV-2 pandemic, Wastewater-Based Epidemiology (WBE) has been applied to track community infection in cities worldwide and has proven successful as an early warning system for identification of hotspots and changing prevalence of infections (both symptomatic and asymptomatic) at a city or sub-city level. Wastewater is only one of environmental compartments that requires consideration. In this manuscript, we have critically evaluated the knowledge-base and preparedness for building early warning systems in a rapidly urbanising world, with particular attention to Africa, which experiences rapid population growth and urbanisation. We have proposed a Digital Urban Environment Fingerprinting Platform (DUEF) – a new approach in hazard forecasting and early-warning systems for global health risks and an extension to the existing concept of smart cities. The urban environment (especially wastewater) contains a complex mixture of substances including toxic chemicals, infectious biological agents and human excretion products. DUEF assumes that these specific endo- and exogenous residues, anonymously pooled by communities' wastewater, are indicative of community-wide exposure and the resulting effects. DUEF postulates that the measurement of the substances

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continuously and anonymously pooled by the receiving environment (sewage, surface water, soils and air), can provide near real-time dynamic information about the quantity and type of physical, biological or chemical stressors to which the surveyed systems are exposed, and can create a risk profile on the potential effects of these exposures. Successful development and utilisation of a DUEF globally requires a tiered approach including: Stage I: network building, capacity building, stakeholder engagement as well as a conceptual model, followed by Stage II: DUEF development, Stage III: implementation, and Stage IV: management and utilization. We have identified four key pillars required for the establishment of a DUEF framework: (1) Environmental fingerprints, (2) Socioeconomic fingerprints, (3) Statistics and modelling and (4) Information systems. This manuscript critically evaluates the current knowledge base within each pillar and provides recommendations for further developments with an aim of laying grounds for successful development of global DUEF platforms.

1. Introduction

1.1. The global challenge of maintaining public and environmental health in the face of rapid urbanization

The coming decades will bring profound changes to the size and spatial distribution of the global population. It is projected that 66% of the world's population will live in urban areas by 2050, with ~90% of this concentrated in Asia and Africa (United and Nations). This unprecedented rate of urbanization constitutes substantial risks to the resilience of cities, with public and ecosystem health and welfare being of critical concern. This includes the emergence of non-communicable diseases (NCDs). NCDs are the leading cause of death globally, with 71% of the world's 56.9 M deaths recorded in 2016, including diabetes and cardiovascular/respiratory diseases (WHO and diseases 2014).

Urbanization is a powerful driver of population mobility which results in increased risks in contracting and spread of communicable disease, e.g. SARS (2003), H1N1 (2009), Ebola (2014), Zika (2015) and SARS-CoV-2 (2019). The most densely populated regions present the highest risk, particularly in low- to middle income countries (LMICs). Africa is experiencing the fastest rate of urbanisation and population growth globally, leading to exponential urban densification within regions where service delivery and healthcare do not meet the demands of such rapid growth. The recent SARS-CoV-2 (Covid-19) pandemic has clearly illustrated the need for improved risk prediction in low resource settings, including urbanised regions in LMIC settings where less physical distancing, rapid clinical testing and limited case isolation pose challenges to mitigate disease spread in densely populated communities (Wells et al., 2020). Reports throughout Africa have shown an underestimation of the true mortality rate caused by Covid-19, for example a case where post-mortem investigations at an African hospital have shown a high rate of confirmed infection with the virus without prior knowledge of their infection before their death (Mwananyanda et al. 2021). Apart from the health challenges posed by population density in urban settings, many LMIC (peri)urban communities rely on communal waste discharge facilities (solid- and excretion waste) and potable water supplies for their day-to-day activities and may discharge anthropogenic waste into the environment on which they depend for freshwater. Urban settings in Africa, and LMICs in general, thus present additional challenges compared to higher-income countries (HICs) to safeguard both public- and ecological health.

To increase the sustainability of cities, there is a critical need for Early Warning Systems (EWSs) for public and environmental health diagnostics that operate on a large scale and in real time. The requirements for an EWS might differ between cities, countries and continents. For example, HICs are well-equipped for digital innovation and have established infrastructure, although this is often outdated. In contrast, there has been an unprecedented uptake of new technology among the young, rapidly expanding and increasingly urbanized African population (Millington 2017, Carbone 2018). This trend presents a unique opportunity for the development of a comprehensive and real time EWS that is codesigned with multi-sector stakeholders and attuned to public and environmental health risk intervention.

This manuscript aims to explore opportunities for an innovative

hazard forecasting platform for global public and environmental health diagnostics, with particular attention to Africa and the challenges presented by LMICs (Fig. 1).

1.2. Digital urban environment fingerprinting (DUEF) - a new approach in hazard forecasting and early-warning systems

The urban environment consists of various components amenable to measurement and monitoring: water, air, and soil, but also less commonly recognized biological entities such as invertebrates. These components contain a complex mixture of substances including toxic chemicals, infectious biological agents and human excretion products that are indicative of community-wide exposure and the resulting effects. The urban environment can thus be considered as a community-wide diagnostic medium for the health status of a city, with communities' wastewater representing a particularly accessible and rich source of anonymously collected data. DUEF postulates that the measurement of endo- and exogenous environments and human-derived residues, provides qualitative and quantitative information on the physical, biological or chemical stressors to which the surveyed systems are exposed.

The approach of extracting epidemiological information from one environmental compartment - wastewater emerged as Wastewater-Based Epidemiology (WBE) that currently informs worldwide illicit drug use trends (Thomas et al. 2012, Ort et al. 2014, González-Mariño et al. 2020) and has been further applied to estimate public exposure to alcohol (Castiglioni et al. 2014, Baz-Lomba et al. 2016), tobacco (Castiglioni et al. 2014) and viruses (Lodder et al. 2012, Lodder et al. 2013). There is also a growing number of reports focusing on public exposure to toxic chemicals including pesticides (Rousis et al. 2017) and industrial chemicals (Lopardo et al. 2019; Been et al. 2018, Kasprzyk-Hordern et al. 2021). Further information on WBE can be found elsewhere (Gracia-Lor et al. 2017, Choi et al. 2018, Choi et al. 2020, Daughton 2020) Moreover, with the advent of the SARS-CoV-2 coronavirus pandemic since the end of 2019 (COVID-19), WBE has been successfully applied globally to track community infection (Bivins et al. 2020, Lundy et al. 2021). Although WBE shows promise as an EWS for profiling of (non)communicable disease and chemical substance use/exposure, several research gaps still need to be addressed to ensure a successful global implementation of EWS, including:

- (1) the application of the principles of WBE to develop digital, autonomous EWS,
- (2) the development of new sensing and systems integration methodologies amenable to widespread deployment through Internet-of-Things, citizen science, or a combined approach,
- (3) the development of models that will integrate both biological and chemical stressors for pattern recognition to enable reliable cause-effect identification,
- (4) the development of EWS and stable biomarkers for infectious diseases with rapid onset of action requiring immediate response versus EWS for NCDs requiring multilevel longitudinal data collection,
- (5) integration of community and expert knowledge in the development of EWS to ensure technology uptake

(6) approaches for rapid community wide knowledge dissemination through effective data integration, visualisation and curation.

In response to these requirements for successful EWS development on a global scale, this manuscript explores different dimensions of possible implementation of an EWS in contrasting locations worldwide.

2. Development and utilisation of a digital urban environment fingerprinting platform

A comprehensive DUEF platform for EWS requires interdisciplinary bioanalytical, socio-economic and citizen science approaches, as well as geospatial and statistical modelling tools that could transform global cities if the technologies are focused on key areas of critical importance for public or ecological health. This holds especially true for rapidly growing cities worldwide, particularly those in Africa, to address key challenges, including: (1) sanitation and the importance of water in managing infectious disease and antimicrobial resistance (AMR), and (2) mitigating the impact of urbanisation and pollution on environmental degradation and non-communicable disease risks. Such a platform would add a much-needed pathway to predict the cascade of consequences resulting from natural and anthropogenic hazards (e.g. floods, droughts, infectious diseases and toxic chemical exposure) in the context of sustained urbanisation. For example, flooding can lead to a power-cut that disables communal amenities, which may in turn trigger the spread of pathogenic organisms and toxins via contaminated water, resulting in affected communities starting to excrete elevated levels of disease biomarkers (Brown and Murray 2013, Boyce et al. 2016, Chad-suthi et al. 2018). There will be immediate environmental and socio-economic impacts (e.g. lost livelihoods and an increased strain on health-care systems) and, if unchecked, yet wider ripple effects through withdrawal of investment from, and stigmatisation of the region. Applying systems thinking to these causal networks, could help identify the feedback mechanisms that lock the system into a certain state, as well as indicating intervention points to increase the resilience of the system.

Successful development and utilisation of a DUEF requires a tiered approach including: Stage I: network building, capacity building, stakeholder engagement as well as a conceptual model followed by Stage II: DUEF development, STAGE III: implementation and STAGE IV: management (Fig. 2).

The rapid evolution of the Internet of Things (IoT) has greatly enhanced the utility of sensors and cloud computing to capture a wide range of environmental measures (Fig. 3) (Malche et al. 2019). Case studies have demonstrated the value of such distributed systems in identifying correlations between environmental factors, such as trends

of increased fluctuation in air temperature and precipitation, with ecological indicators such as gross primary production (Fang et al. 2014). The collaborative IoT (C-IoT) is an emerging paradigm that involves multiple stakeholders cooperating in data gathering and service sharing. Applications, such as smart cities and environmental monitoring, use the concept of crowdsensing to produce the quantity and quality of data that such IoT scenarios need in order to be pervasive. Architectures have been developed that are able to handle the complex features associated with these systems such as: heterogeneous data sources, information representation and unification, IoT device management and deployment and mobile crowdsensing management (Montori et al. 2018). Beyond the C-IoT paradigm, the Internet of Everything (IoE) concept recognises the four (4) interconnected pillars of people, data, process, and things, extending the role of stakeholders and communities beyond data gathering by applying the C-IoT to aid automated and people-based processes (Miraz et al. 2015).

The input variables for the development of an EWS include data on bio-physicochemical markers, and information from geospatial mapping and autonomous sampling and sensing platforms. An advantage of the C-IoT approach is the integration of multiple datasets gathered by a variety of stakeholders. Citizen science and citizen sensing not only increase capacity for generation of input data, but also facilitate the direct inclusion of specific citizen interests into the EWS (Jollymore et al. 2017). In addition to these technological advances, there is a clear need for further stakeholder engagement and community input to generate related socio-economic indicators for incorporation into EWS platforms, and to ensure EWS outputs are integrated with automated and human response processes (IoE). Forecasting and projection with statistical modelling tools, hydrological models, and pattern recognition are essential variables for the development of an EWS. These requirements can be met by integration of the C-IoT paradigm with a cloud-based computing service that offers scalable, highly available, secure and cost-effective compute resources that are not reliant on local hardware or infrastructure. Such cloud platforms have already been demonstrated to provide a scalable and extremely reliable EWS for earthquake sensing in New Zealand’s GeoNet system. DUEF proposes a distributed sensor architecture (Fig. 4), based on the concept of IoT enabled sensor platforms, with a scalable set of individual sensors that are tailored both for the local environment, and provide a useful set of data for large scale data analysis with associated conceptual data.

Previous work on environmental sensing demonstrated the importance of appropriate visualisations of data, tailored to stakeholder needs (Kanjo et al. 2008, Chamberlain et al. 2014). This may include providing contextual data for readings, real time maps or graphs. Heterogeneous data sources (from both IoT and community sources) can be aggregated and presented across a broad range of platforms such as web and mobile

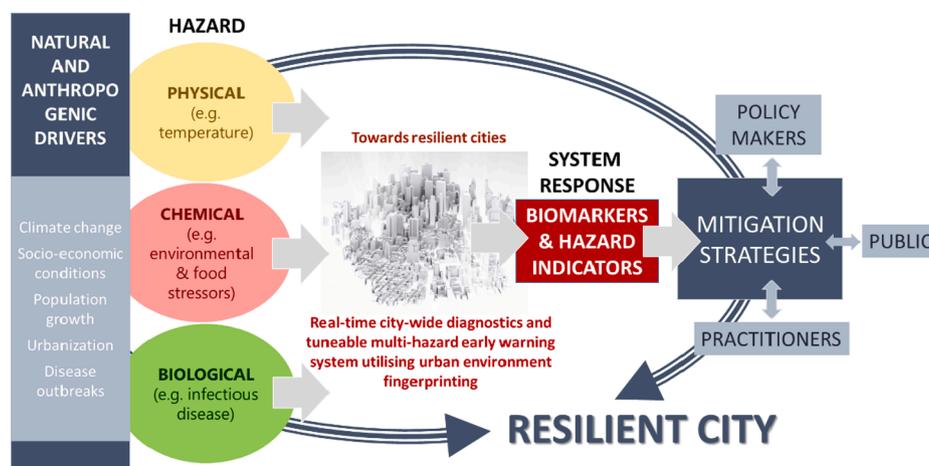


Fig. 1. Multi-hazard early warning system utilising urban water.

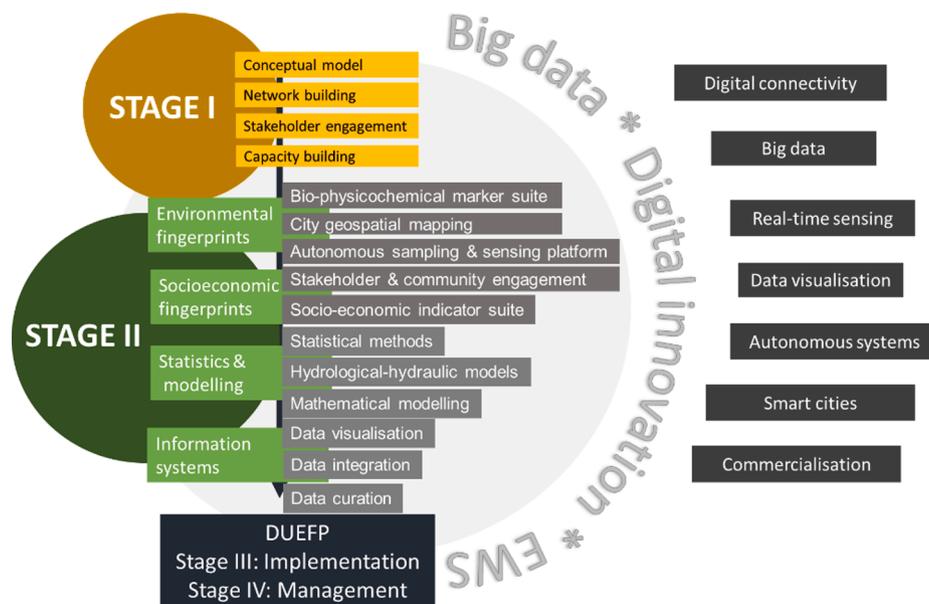


Fig. 2. Hazard forecasting and early-warning system for health risks, a four-stage approach.

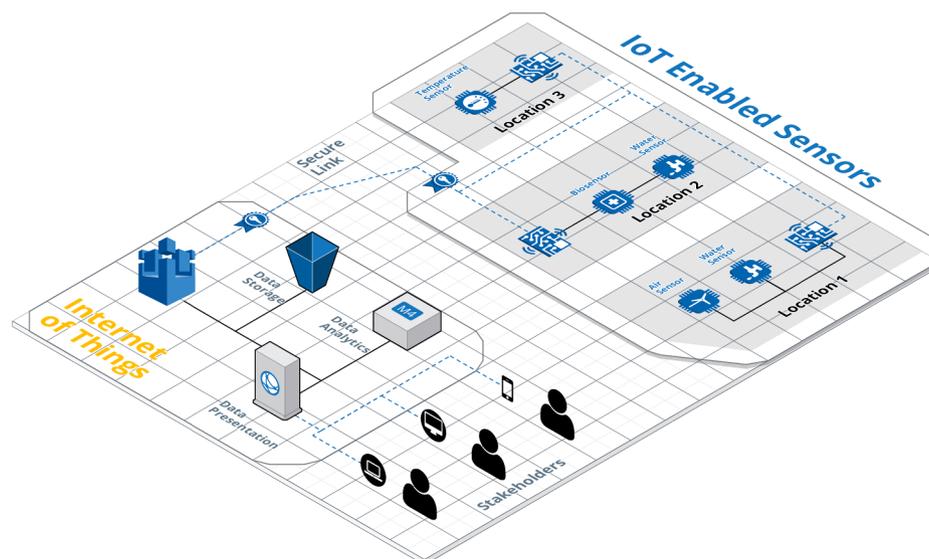


Fig. 3. Environment fingerprinting platform for public, environmental health diagnostics and hazard forecasting based on Internet of Things sensors and utilising the cloud for distributed data storage and analytics.

applications. While participatory sensing and collaborative analysis can be deployed as part of a data collection process, a user centred approach in the design of the system including an awareness of the motivations of the stakeholders, helps to tailor the process and develop engagement in the use of the system (Aoki et al. 2017) and can aid in the eventual technology uptake. Fig. 4(a) shows the potential architecture of an IoT sensor-based system that uses a cloud and edge-based processing paradigm, with a configurable array of water sensors such as the Atlas Scientific (Long Island City, NY) sensor array shown in Fig. 4(b), that can be tailored to the local environmental context. For example, these could include a typical water quality sensor array that measures temperature, pH, dissolved oxygen, but could be extended with additional custom sensors for specific characteristics including but not limited to heavy metals, nitrates, or pathogens. The sensor nodes can be deployed in static locations or on autonomous surface platforms such as the PRIME platform shown in Fig. 4(c) (Metcalfe et al., 2016, 2018) which has been used for remote sensor deployment in rivers, lakes and canals, and

integration with GIS data as shown in Fig. 4(d).

3. Understanding and characterising cause-effect associations in hazard forecasting via environment fingerprinting – Conceptual framework

We have identified four (4) key pillars required for the establishment of a DUEF framework: (1) Environmental fingerprints, (2) Socioeconomic fingerprints, (3) Statistics and modelling and (4) Information platforms, as described below. We consider that these four pillars need to be equally addressed upon the development of an EWS and should be tailored according to the unique challenges within each test location. A summary of the four key pillars are described below:

3.1. Environmental fingerprints

Several factors require consideration when establishing

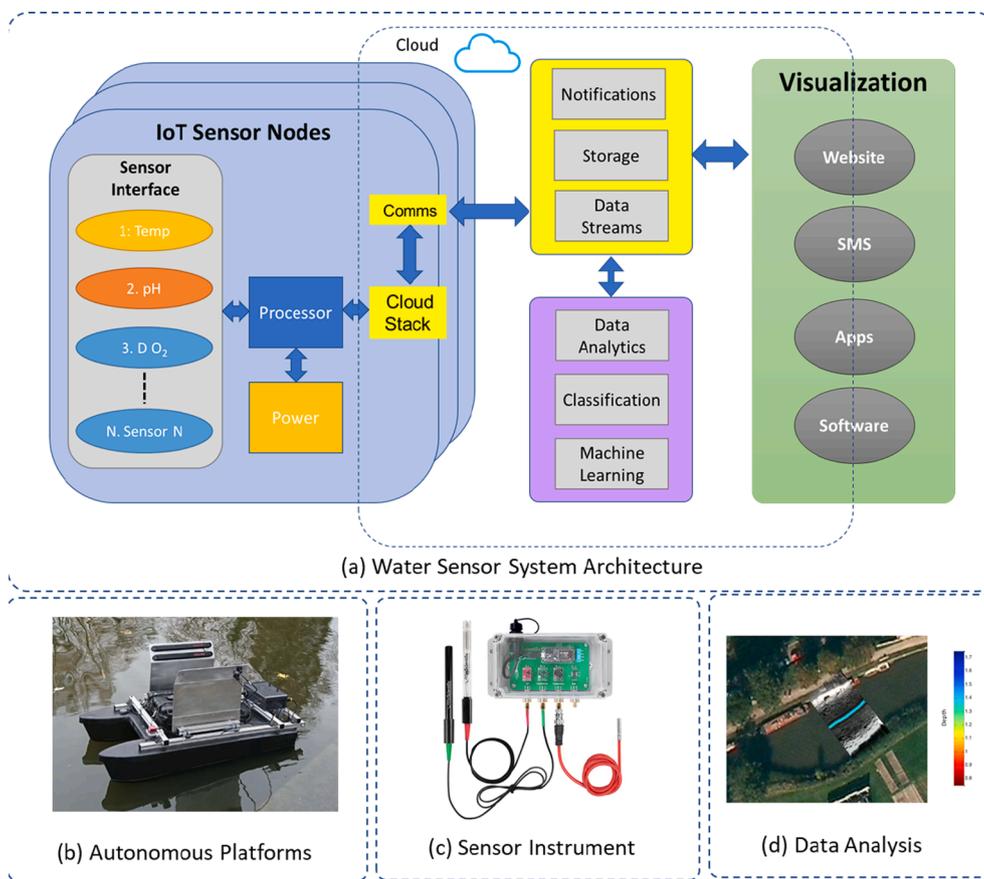


Fig. 4. a-d. Environment fingerprinting platform using multiple IoT sensor platforms, edge computation and distributed visualization tools.

environmental fingerprints, namely: (1) selection of bio-physico-chemical marker suite, (2) city-geospatial mapping, and (3) design of autonomous sampling and sensing platforms.

3.1.1. Biophysicochemical marker suite

Carefully informed selection of the bio-physico-chemical marker suite required for the study of cause-effect associations is key to successful implementation. Examples of potential marker groups that characterise hazard, stressors, and their resulting effects (focusing on the measurement in water) are listed in Table 1. These include: (1) biological/biochemical markers (such as pathogens: bacterial infections – cholera, typhoid; viral infections – norovirus, rotavirus and hepatitis; and fungal infections); (2) climate (physical) markers (e.g. rainfall, ambient air temperature) and basic indicators of ambient water quality (pH, DO, conductivity, etc); (3) chemical markers (e.g. metals, nutrients, legacy and emerging organic contaminants) of cause - health effect associations (e.g. oxidative stress, inflammation) (Rice and Kasprzyk-Hordern 2019, Sims and Kasprzyk-Hordern 2020).

3.1.2. City-geospatial mapping

Geospatial information-based city profiling and mapping based on physical, social, economic, health and governance structure variabilities provides a good entry-point to DUEF development including selection of sampling sites for deployment of autonomous sensing and sampling devices, as well as identification of the communities for engagement and citizen science. The need for city profiling and mapping is premised on the underlying relationship between location and health (Pigott et al. 2015, Murad and Khashoggi 2020) and the fact that spatial mapping could provide insights into the dynamics of disease outbreaks (Gao et al. 2008). Spatial aspects are also relevant to the relationships between pathological factors and their environments (Cromley 2003), diseases prioritization (Pigott et al. 2015), and disease surveillance (Kumar et al.

2017, Franch-Pardo et al. 2020, Quan et al. 2020). Spatio-temporal visualisation of the bio-physico-chemical markers is critical for EWS and disease management.

3.1.3. Autonomous spatiotemporal sensing and sampling platform

Effective environmental fingerprinting necessarily requires the development of innovative integrated systems able to monitor in situ the range of bio-physico-chemical markers listed in Table 1. Such systems would also require an embedded wireless communication platform for real-time data transfer and control into the cloud. Several sensors are already available for some of the markers of interest (Yang et al. 2016, Bernalte et al. 2020). However, current sensing technologies cannot achieve the required limits of detection for most biological markers. Also, real time monitoring of biological biomarkers and emerging pollutants remains an issue. The key difficulty is associated with the need for sample pre-treatment (e.g. DNA extraction for genetic markers, pre-concentration of protein markers) that challenges real-time operations. It is therefore important to develop new technologies capable of effectively integrating detection with sample pre-treatment, while maintaining key features such as portability, simplicity of use and affordability. PCR on a chip or single-molecule sequencing based on nanopores are possible solutions for point of need sequencing (Saettone et al. 2019). Along with the development of innovative sensors, autonomous spatiotemporal sampling based on custom built Internet of Things platforms must be developed. The resulting devices should be geographically distributed in the target area to be monitored to form a mesh-network of devices that provides responsive spatiotemporal sampling.

Table 1

List of bio-physico-chemical markers of interest to DUEF and required innovation needed for global implementation.

Biophysicochemical marker group	Specific markers/indices	Current development stage and innovation needed
Biological/biochemical markers	Genetic, cellular, microbial, behavioural responses	Genetic and microbial markers: analysis largely laboratory based using PCR, sequencing more affordable with an option of field measurements. Real time PCR analysis by citizen scientists is increasingly common in ecology (eDNA), but not for microbiology (Biggs et al. 2015). Direct citizen science monitoring of disease markers has both positive and negative social implications. Information can become directly available; however, citizen science methods should not be taken as public health information due to potential data quality issues as well as political and ethical issues. Endogenous biomarkers linked with physiological response (e.g. oxidation and inflammation). At early stages of method development. Requirement for sophisticated laboratory tools (mass spectrometry) due to very low concentrations (ppq-ppt levels). Step change needed in biomarker analysis. Behavioural responses in relation to environmental stressors are being increasingly studied and applied (ex. using acoustic telemetry) (Taylor et al. 2018), <i>Daphnia</i> toximeter (Green et al. 2003). However, improved sensing and real-time data logging and output are needed.
Climate (physical) markers	Rainfall, temperature, river hydrology parameters including river discharge and velocity	Global datasets available for direct inclusion in EWS, including citizen science datasets. Citizen science monitoring of rainfall, river-level and flood observations can provide more accurate information about highly localised patterns and therefore improve accuracy of flood modelling (Starkey et al. 2017). Low cost weather stations to improve granularity of the data.
Chemical Markers	pH, DO, EC, COD, BOD, nutrients, Metals, Organic contaminants, including emerging pollutants (pharmaceuticals, pesticides and their metabolites)	Sensors available for general water quality determinants (pH, DO, conductivity, nutrients, metals, turbidity) that could be used as proxies for environmental burden. Citizen science methods for water quality monitoring (e.g. FreshWater Watch) are also readily available and low-cost. Xenobiotic chemicals require the development of smart sampling approaches that will account for diurnal and seasonal variabilities. Analyses are laboratory based and focused entirely on mass spectrometry techniques due to trace concentration levels and complex matrix requiring highly sophisticated tools. Sensitive and selective sensor arrays are required for multiresidue measurements in longitudinal studies.

3.2. Socioeconomic fingerprints

3.2.1. Stakeholder and community engagement

The involvement of stakeholders and communities in environmental quality monitoring is gaining attention globally with the growth of citizen science for biodiversity evaluations, environmental advocacies, and monitoring wildlife threats, among others (Bernalte et al. 2020). Digital technology using smart phones, social media, IoT, big data analytics, cloud computing (Paul et al. 2019) and KoBo Toolbox, which is a suite of tools for field data collection in use in challenging environment can be adopted. These devices and strategies could make engagement of the broader population in environmental monitoring easier. More specifically, the importance of involving stakeholders, particularly in LMICs context, has been underscored in several studies which points to the need for risk communication and incorporation of indigenous knowledge in scientific endeavours to safeguard environmental quality and human health (Sogbanmu et al. 2020). Recent systematic reviews (Macherera and Chimbari 2016, Marchezini et al. 2018, Sufri et al. 2019) examine cases of EWS that adopt a community-based or centric approach in order to characterise the ways, and the extent to which, communities are being involved in the design, development and implementation of EWS. These studies highlight the necessity and value of efforts to integrate traditional/local disaster knowledge with scientific knowledge development of community centred EWS. This requires engaging with local stakeholders and communities to identify their priorities and vulnerabilities, their local/indigenous and scientific strategies and co-creating an integrated strategy (Mercer et al. 2010). Scientists need to make deliberate efforts to integrate different knowledge systems using participatory and citizen-science approaches (Cieslik et al. 2019, Klimeš et al. 2019). Such efforts can result in improved disaster risk reduction tools (e.g., simulation models, conceptual frameworks, hazard maps, management plans) that are rooted in local realities, increase trust between communities and scientists, increase the ownership and responsibility of the community as well as greater engagement with risk reduction initiatives (Cieslik et al. 2019, Cochrane et al. 2019, Klimeš et al. 2019). Although the process of knowledge

integration is not without challenges, willingness to communicate and learn from the other, ongoing dialogue and collaboration, and mutual respect are vital (Mercer et al. 2010, Lin and Chang 2020). These processes should be set up as early in the design process as possible and can be aided by thorough context analysis (Ghariesifard et al. 2019). This context analysis links to and underpins all four of our pillars. Specific opportunities for stakeholder collaboration within each pillar are highlighted elsewhere in this manuscript (see Figs. 1 and 3 especially stages 1 and 2).

3.2.2. Socio-economic indicator suite

Careful identification of socio-economic drivers is required to establish thresholds at which bio-physicochemical markers respond to socio-economic change. This requires identification of stakeholder and community understanding of drivers of multi-hazard events, as well as the design of parameters for inclusion in spatiotemporal socioeconomic fingerprints. It also requires an understanding of stakeholder and community motivations and priorities, which may be complex and multifaceted, and not necessarily aligned with the goal of DUEF. Engagement with key city stakeholders (both official and citizens) will enable the construction of data repositories that will inform the design of site-specific communication strategies, based on the information provided by DUEF but tailored to the needs of the information recipients. For example, citizen science provides a specific opportunity to consider gender dimensions of environmental and public interventions, for example, targeting the inclusion of women in environmental and public health issues within their localities. Citizen science approaches should be harnessed to move community engagement beyond passive consumption of information towards active ownership of the EWS. Citizen science can be used as a tool to help co-create the purposes of particular DUEFs with citizens, providing opportunities for communities to highlight the facets within the system that are most relevant to them (Jolymore et al. 2017). A good knowledge of local language and dialects is essential in the socio-economic fingerprints and enhance rapid indication and warning signals for mitigation strategies of social disasters.

3.3. Mathematical modelling for hazard detection and diagnosis

Multivariate models that leverage the inherent geographic, temporal, and correlation structure of measurements will be essential in generating an effective, reliable EWS. Typical multivariate time-series models contain structural components – such as seasonal trends – and unstructured components to capture spatial-temporal auto- and cross-correlation in the markers. Importantly, these models require substantial initial or historic datasets to establish the baseline behaviour of a system before being incorporated in a DUEF. In resource-constrained settings, data for emerging biological and chemical markers is sparsely collected in both space and time. This makes it difficult to fully characterise normal conditions, in turn rendering it impossible to reliably detect abnormalities. An effective DUEF must identify the minimum amount of data necessary to inform the development of a sustainable monitoring strategy; the process of identifying the minimum necessary data will rely on modelling.

Statistical models can be enhanced while simultaneously reducing the burden on data collection by incorporation of first principles knowledge, specifically knowledge of causal relationships. In cases where these relationships are already known, they can be integrated into empirical models for improved predictions with lower data requirements. The DUEF may identify new causal relationships and environmental risk factors.

Prior knowledge can often be formulated in terms of mechanistic mathematical models, which can be leveraged to support the development of a DUEF monitoring system and the interpretation of the data it produces. Mechanistic models abstract key features and dynamical processes of the system into a mathematical framework. They may take the form of anything from a simple conceptual exploration to a complex microsimulation. Conceptual models may, for instance, consider infectious diseases spreading in a structured community that contributes to the wastewater in a sanitation network. The model structure may include spatial organisation, demographic characterisation, and wastewater networks with archetypal structures abstracted from those of real cities. This framework can be used to investigate how spatial patterns of the infectious disease dynamics manifest in wastewater samples and to identify generic network structures that contribute to resilient, healthy communities.

Microsimulation models may use geospatial mapping, hydrological and census data to construct a detailed representation of a city, its inhabitants, and waterways. The development of such models is a major undertaking since the analysis requires substantial computing power to run large numbers of simulations, and careful statistical analysis of the output. This framework can be used to experiment with surveillance systems before field implementation, generate short-term forecasts of outbreak dynamics from monitoring data and predict the impact of interventions such as new sanitation projects.

Significant challenges with microsimulation models include communication of the results they produce and generalisability to diverse settings. Active contribution of data via citizen science could go some way to aiding community scientific understanding (Bonney et al. 2016, Gaythorpe and Adams 2016). In depth pilot studies can be used to determine key mechanisms driving community health and thereby tailor data collection and microsimulation model development strategies. Analysis of mechanistic models can elucidate the underlying interactions and causal relationships of the system, how they shape the observed data and feedback processes (Bertuzzo et al. 2016, Gaythorpe and Adams 2016). Incorporating suitably parameterised models can facilitate more accurate forecasts with lower data inputs.

3.4. Information systems

Data collection, analysis, and modelling must be combined effectively to produce meaningful insights. GIS provides a well-established framework to analyse dynamic and geographically distributed data

and models, with examples including the comparative rates of diseases and other medical conditions across large areas, and the provision of early warning for outbreaks (Dangermond and Goodchild, 2020). GIS modelling can complement and support other models by integrating across locations both the biophysical data generated from autonomous sensing devices with social data collated from community engagement and existing health and disease records from archival sources. Through city profiling (that integrates physical, social, economic, health and governance variables) sampling sites can be determined for location of autonomous sampling devices as well as community engagements. The resulting biophysical and socioeconomic markers across the sites can be integrated for GIS and spatial analysis as well as statistics and modelling. Data exchange is possible between GIS and statistics through geostatistical modelling that produce cause-effect associations of community disease pattern and bio-physicochemical markers, spatial temporal mapping of bio-physicochemical and socio markers, spatial vulnerability maps and location-based predictive modelling of disease based on biophysical and social disease markers (Fig. 5). The end-result can be seamlessly integrated into the EWS platform including cloud-based services for time-dependent visualizations shared through mapping apps.

The effective implementation of information systems to support an EWS must consider the entire data supply chain. First, spatial-temporal data collected by sensors into Standard Data Models (SDMs) can form the basis of the data input hierarchy which supports GIS analysis, modelling, visualisation and communication. Sensor reliability and performance can be optimized if the sensor network, sensor availability and functionality can be continuously verified through monitoring processes, which would assist in the detection of gaps in recorded data.

An integral component of the data supply chain is the development of standardised Application Programming Interfaces (APIs) to facilitate data flows between sensors, curated data sources (e.g. scientific and governmental databases, earth observation, etc), analytical services, and even control actuators for instant responses to detected risks (e.g. cutting water supply when severe contamination is detected). Providing open data access through standard APIs encourages the development of applications by third parties and provides data for analysts and researchers, which could in turn facilitate more effective responses to early warnings, whereas data publishing mechanisms like CKAN (Comprehensive Knowledge Archive Network), can potentially monetise non-critical data and provide a business model for capital intense sensing technology. Good examples of established SDMs and Standardised APIs can be found on the FIWARE Foundation website (www.fiware.org).

At the end of the data supply chain lies the mathematical models discussed earlier (which may include machine learning algorithms), communication with relevant stakeholders, and the automation of technical responses to optimise the detection and mitigation of risks in an efficient manner. The most valuable components of the information system would be the intelligent interpretation and visualization of data. In the context of an EWS, alerts should be provided to relevant stakeholders and could communicate predetermined operating procedures to ensure the fastest and most appropriate response while leaving room for respondents to justify a proposed course of action based on the evidence available. The resulting learning could be applied to improving systems as experience grows. Communicating context relevant alerts through instant messaging channels and dashboards to inform various stakeholders (like water management decision makers, health care authorities, water management technicians and the public and other stakeholders) can assist in influencing appropriate behaviour from water users and rapid response to potential threats and losses.

4. Building DUEF for Africa

A key consideration to build resilience in mitigation strategies for (non)communicable disease control and ecological conservation is the

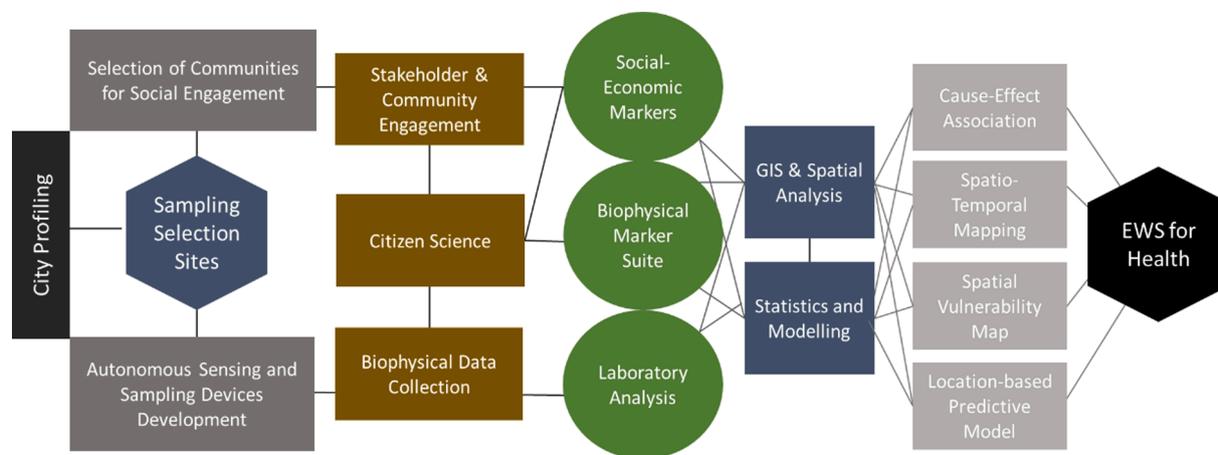


Fig. 5. Framework for DUEF data collection and Geospatial Modelling.

requirement for responsive systems of risk governance that attend to the day-to-day concerns of stakeholders and citizens that are country, region and city specific. In contrast to the challenges faced by LMICs, the established, resource rich, but aging infrastructure in HICs such as Europe would require different approaches in terms of setting the system up, reconciling existing processes with the uptake of new technology and management. To achieve this, DUEF needs an inherent degree of flexibility when exposed to geographically and/or socioeconomically contrasting areas (within- and between HICs and LMICs). For example, geographically contrasting, yet socio-economically comparable areas in Africa, such as Lagos (Nigeria) and Cape Town (South Africa) are subject to different stressors and resulting multi-hazard risks but have core common denominators, including resource stress driven by uncontrolled population growth, low resource availability, impact of poorly regulated industrial activities and unpredictable weather conditions.

Lagos is experiencing rapid growth (32.6 million by 2050) (Hoornweg and Pope 2017, Afolabi et al. 2019) that will bring sustainability challenges, for example, the spread of infectious diseases triggered by frequent flooding (Ajibade and McBean 2014, Olanrewaju et al. 2019). Cape Town regularly experiences events of water scarcity that are driven by climate change and increased anthropogenic water use within a rapidly-growing population (4.7 M in 2021), with a 2% annual population growth rate in the metropolitan area compared to continental growth rates of Asia (0.83%), Africa (2.45%), Europe (0.01%) (United and Nations). This growth is accompanied by expansion of informal settlements, which are prone to flooding with increased burden of disease (Madonsela et al., 2019). Moreover, the proximity of various communities of different socio-economic status, accessing different levels of infrastructure and exposed to different stressors provides an opportunity to investigate the socio-technical challenges of developing and implementing an EWS in such contexts. Health risks in Africa coexist and connect to existing vulnerabilities such as poverty, high population growth rates, low economic productivity, low access to basic services, formal education and skill/technology, poor government institutional collaborations and low awareness and access to information (including on health risks) by the citizens.

Disease outbreak, water and sanitation, waste management, flooding, air pollution, poor housing conditions, and climate change impacts constitute serious health and well-being issues in Lagos (LASG 2020) and Cape Town, which are exacerbated by lack of monitoring data which weakens the governance capacity and decision structure on surveillance, detection, prevention, and elongate the response time. The DUEF approach integrating city profiling data (including physical, social, economic, health, and governance) and citizen science/social engagement with environmental health indicators measured from autonomous sampling devices provides a workable framework for socializing the science of WBE. The result will generate both biophysical and socio-

economic markers for location-based predictive disease modelling, cause-effect associations, and spatial population risks and vulnerability which are vital to a robust EWS.

The clamour for multi-stakeholder cooperation in combating Africa's health and environmental challenges has recently been on the front burner of regional and governmental discussions particularly with the advent of the COVID-19 pandemic (Mugabe et al., 2020). The strong call for research and innovation in providing early warning systems for environmental and health epidemics on the African continent has provided an impetus for digital innovations such as the DUEF for evidence-informed decision making by policymakers at the local, national and regional levels. In Lagos, the government is strongly encouraging and driving research and innovation for sustainable development in the state through the T.H.E.M.E.S agenda (<https://lagosstate.gov.ng/>). Particularly, the Lagos Resilience Strategy emphasises the key focus areas or priorities of the Lagos state government including capacity strengthening for information management and disaster preparedness (Pillar 2, Goal 2) and improving disease surveillance to support Lagos residents in times of shock (Pillar 2, Goal 3) (Lagos Resilience Strategy, 2020). Likewise, the City of Cape Town's Water Strategy aims to find an integrated and transversal approach in order to ensure safe and adequate supply of water to its citizens. The Strategy's five commitments are to 1) provide safe access to water and sanitation, 2) promote wise use of water; 3) provide reliable, sufficient water to its users; 4) ensure shared benefits from regional water resources by building collaborative partnerships and 5) transition the City towards a Water Resilient City by 2030 and Water Sensitive City by 2040. An early warning system such as the DUEF proposed in this manuscript thus aligns strongly with the development priorities at the state, national and regional levels. A successful DUEF will require initial investment in infrastructure building, but as we have seen during COVID pandemics, the need triggers investment and innovation. South African response to SARS-CoV-2 surveillance has, as in many HIC countries (UK National Network), provided a South African Collaborative COVID-19 Environmental Surveillance System (SACCESS) network using the principle of wastewater-based epidemiology (WBE) to address community-wide infection and to support clinical testing in localised communities (Lynn Bust et al., 2020). This network consists of a range of collaborators/members from academia, municipalities, private laboratories, research councils, as well as health departments and epidemiologists at both regional and national level. The rapid expansion and sharing of knowledge within this network since the start of the pandemic established a foundation of interdisciplinary collaboration and establishment of the logistics and epidemiological metadata needs to address health challenges as a collective. Moreover, the network has clearly illustrated the need for not only the rapid evaluation of infectious disease patterns, but also evaluation of other health biomarkers within a WBE platform. This network

will serve as grounds for DUEF development by means of using the advances and challenges that are shared between the organisations from various localised settings and identifying the biomarker and metadata needs that will serve as the most credible and verifiable information to be used by governing bodies and decision makers/end-users.

5. Conclusions

This manuscript critically evaluated the knowledge-base and preparedness for building early warning systems focused on environment fingerprinting in a rapidly urbanising world, with particular attention to Africa, which experiences rapid population growth and urbanisation. We have proposed a DUEF, Digital Urban Environment Fingerprinting platform in hazard forecasting and early-warning systems for global health risks. We have identified four key pillars required for the establishment of a DUEF framework: (1) Environmental fingerprints, (2) Socioeconomic fingerprints, (3) Statistics and modelling and (4) Information systems and critically evaluated the current knowledge base within each pillar and provided recommendations for further developments with an aim of laying grounds for successful development of global DUEF platforms.

CRedit authorship contribution statement

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Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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