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Interdisciplinary methods for researching climate-mental health links through the Methane Early Warning Network (ME-NET): improving 'visibility' and integrating complex multi-datasets

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Abstract

Climatic and atmospheric conditions impact mental health, including increased incidents of depression associated with air pollution. A growing body of research considers time-bound 'snap-shots' of climatic drivers and mental health outcomes. Less is known about the likely effects of future climate change on mental health. Research is often inhibited by data scarcity, the challenge of synthesising data across multiple geospatial and temporal scales, and the under-representation of hard-to-reach groups. Thus, research methods are needed to integrate and analyse complex environmental and mental health multi-datasets while improving the visibility of under-represented groups. In this methods paper we present a novel approach for investigating the impact of climate change on mental health and addressing some challenges with, a) invisibility of vulnerable groups, and b) integrating complex environmental and mental health multi-datasets. The research aim is to pilot a web-based and smartphone application (Methane Early Warning Network (ME-NET)) for investigating the role of methane as a precursor of on-ground ozone, and the impact of ozone on mental health outcomes to improve civic knowledge and health-protection behaviour in the United Kingdom and Ghana. The methods include exploring the feasibility of using machine learning to develop an ozone early warning system and application co-design.

Introduction

Climatic and atmospheric conditions impact mental health both directly, such as the effect of heat on severe depression, suicide (Thompson et al., 2018) and psychosis (Hansen et al., 2008), and indirectly via interactions between meteorological factors and human activity, such as the development of polluting ozone in the air people breath (known as 'ground level ozone'). Polluting emissions like methane, nitrous oxides and other non-volatile organic compounds combine with high temperatures to produce ozone (Francoeur et al., 2021) which impacts mental health outcomes (Bernardini et al., 2020). Ground level concentrations of ozone are expected to increase under climate change warming scenarios (Hertig, 2020). Studies suggest that ozone exposure is associated with increased psychiatric symptoms (Qiu et al., 2022) and admissions (Bernardini et al., 2020), and rates of mood disorders like depression (Zhao et al., 2020). However, the underlying biological mechanisms for how ozone impacts mental health are poorly understood (Nguyen et al., 2021), and much of the research in this area is inconclusive (Zhao et al., 2018). The study reported in this manuscript addresses the research question, 'What are the likely impacts of climate change on rates of depression and other mood disorders?' by exploring links between ground level ozone and mental health outcomes.

In the context of climate change, mental health conditions are expected to account for an increasing proportion of global health burden in coming decades (Vigo et al., 2016; Wu et al., 2023). While the field of climate and health is advancing rapidly, compared to physical health outcomes like respiratory disease, less research has explored links between climate change and mental health outcomes (Massazza et al., 2022). Of research that does examine mental health outcomes, most studies focus on the impact of temperature, involve 'snapshots' of climatic condition rather than the longer-term process of climate change explicitly and consider environmental exposures at low geographical resolution. Conducting higher resolution research is often inhibited by data scarcity of one or more important variables (e.g., Kolstad & Johansson, 2011), and the challenge of synthesising data across multiple geospatial and temporal scales (Daraio & Glänzel, 2016; Massazza et al., 2022).

Further challenges relate to the under-representation of hard-to-reach groups in mental health research (Chamberlain & Hodgetts, 2022; Dowrick et al., 2009). As a result, the mental health challenges linked to climate and experienced by most vulnerable people and regions are often 'invisible'. Thus, innovative research methods are urgently needed to illuminate the effects of climate change currently and in the coming decades on mental health, particularly for those individuals, communities and regions that are already at greatest risk from environmental and meteorological exposures. Understanding impacts is a first step to developing innovative climate change mitigation and adaptation interventions with mental and physical health co-benefits, including improving public health preparedness to reduce climate-related disaster risk (Hess et al., 2023). In this methods paper, we present a novel methodological approach for conducting research about the impact of climate change on mental health that addresses some challenges associated with, a) invisibility and the heterogeneity of mental health impacts between and within groups and individuals most vulnerable to climate change, and b) integrating multiple complex environmental and mental health datasets to form 'multi-datasets'.

Challenge One: Invisibility and heterogeneity

Traditional recruitment strategies present challenges for researching the mental health outcomes of climate change because they tend to result in the under-representation or exclusion of most vulnerable people (Borderon et al., 2021). Climate change vulnerability and socio-economic exclusion often co-occur (Sevoyan & Hugo, 2014; Resurrección et al., 2019; Ifeanyi-Obi & Ugorji, 2020). Most studies of symptoms and conditions related to depression and mental health outcomes more generally are conducted with participants characterised as 'Western, Educated, Industrialised, Rich, and Democratic', or WEIRD (Henrich et al., 2010; Apicella et al., 2020). Thus, most data and knowledge about the drivers of severe outcomes represent regions with the greatest capacity for climate adaptation like the G7 countries (Masuda et al., 2020), while 'hard-to-reach' people and regions, including low-to-middle-income regions (LMIRs) (Masuda et al., 2020) as well as marginalised groups in high-income regions (Apicella et al., 2020), are excluded from evolving narratives and evidence bases. These 'invisible' people and places include individuals and groups in geographic regions that are likely to experience the most severe and immediate impacts of climate change. For example, increasingly prolonged periods of hot-humid days associated with climate change are expected in dry climatic zones, such as sub-Saharan Africa (SSA), while record-breaking heatwaves are anticipated in Afghanistan and regions of Australia including remote rural areas (Thompson et al., 2023).

Compared to more economically developed places like Australia with centralised healthcare, research about the impact of climate and climate change on mental health in LMIRs like SSA is extremely limited. This is partly because health services in SSA are comparatively decentralised and privatised, and service use data often grossly underrepresent mental health condition rates in the region; The Lancet Commission on the Future of Health in SSA (Agyepong et al., 2017) estimates that the treatment gap may be as high as 90% for severe mental health conditions. As a result, many of the retrospective observational data science approaches that are common in regions with centralised health care systems like Australia and the UK are less viable in SSA and other LMIRs with colonial legacies and fragmented health care systems. Thus, research methods are needed that are robust to variations in health services and address persistent inequalities between research ecosystems in high-income compared to LMIRs, as well as the exclusion of 'hard-to-reach' communities in more affluent regions. These methodological developments should take place in conjunction with the wider goal of the global research community to decolonise data science (Khan, 2022).

In addition to differences between high-income regions and LMIRs, the impacts of climate and climate change on acute mental illnesses like major depressive disorder are also likely to be heterogenous within regions, such as between and within rural and urban areas (Oğur, 2023), demographically between people of varying age, ethnicity and gender (Liu et al., 2021), socio-economically between wealthier and more deprived communities (Sapari et al., 2023), and related to complex individual differences that make up the life course histories of people, including the presence or absence of coping mechanisms (Bonanno et al., 2010). Further, it is probable that the experience of climatic conditions like severe heat varies between regions due to subjectivity. Differences in subjective heat stress occur depending on prior encounters with temperature such that continued exposure to high temperatures produces an acclimation effect (Daanen et al., 2018). People and communities in regions characterised by high temperatures may experience less heat stress associated with climate change compared to those in regions where high temperatures are rare. Similarly, temperatures that are considered 'extreme' vary regionally (Liu et al., 2021), partly in relation to ordinary regional temperature ranges. For example, heat warnings are issued in England for forecasting two days of maximum 30°C and minimum 15°C, and in the Netherlands for more than a 10% probability of four or more days with a maximum exceeding 27°C (Casanueva et al., 2019). By comparison, in central and southern Greece, 'yellow', 'amber' and 'red' heat warnings are issued for forecasts of maximum 37°C, 41°C, greater than 44°C respectively. Variation is also likely exacerbated by the urban heat island effect, with 56% of people now living in cities (World Bank, 2023), such that temperatures in homes and hospitals may vary considerably compared regional averages (Gough et al., 2019). Thus, the temperatures that precipitate the escalation of acute psychological conditions may vary between people, regions and small areas, although multi-region studies of subjective heat stress are limited. The heterogeneity of lived experience and of mental health outcomes associated with climatic conditions reinforces the need for research methods that are robust to both regional differences, and differences within demographic, socio-economic, and geographic groups.

Challenge Two: analysing complex multi-datasets

Identifying individuals, groups and regions that are likely to be most at risk of experiencing severe mental health impacts because of climate change, at scale, will require moving beyond traditional methods of conducting mental health research, including common study designs. Most studies involve single-region (Rocque et al., 2021) or single-sample qualitative methods, longitudinal designs, case-control, single-sample repeated measures, or cross-sectional

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analysis (Burrows et al., 2024; Charlson et al., 2021). These approaches provide invaluable geographic or time-bound 'snapshots' about the determinants of mental health outcomes. However, determinants linked to climatic events and climate change are occurring over unprecedented spatial and temporal scales, necessitating some additional methodological approaches to capture multi-scalar variation (Massazza et al., 2022). Further, data granularity, quality and completeness often vary between environmental and health datasets (Cui et al., 2022) within single regions as well as between regions. Thus, in addition to improving visibility, novel methods are needed for integrating and analysing complex multi-datasets that capture the temporal and spatial scale of climate-driven processes with mental health outcomes.

Advanced computational methods like machine learning (ML) and deep learning (DL) are well suited to multi-data analysis, particularly for datasets with challenging characteristics, such as multi-scalar variation. To date, most climate and health research utilising advanced computational methods focus on physical health outcomes like infectious disease (e.g., Boudreault et al., 2023; Schneider et al., 2021) rather than mental health. Of those studies that do consider mental health outcomes, most analyse global (e.g., Pizzulli et al., 2021) or single region (Fahim et al., 2022) aggregate data rather than multi-regional or small area data. Machine learning techniques offer several key benefits in addressing challenges associated with multi-regions, multi-datasets and variation in data quality and completeness. They excel in uncovering complex patterns and relationships within large and diverse datasets (e.g., Du et al., 2019). These techniques provide predictive capabilities for various outcomes, enhancing our understanding of the interplay between health and climate factors. Moreover, ML can be utilised for the automatic interpolation of data, helping to mitigate issues arising from data scarcity, as highlighted by Li et al. (2011). Additionally, these techniques automate the process of feature extraction and selection, aiding in the identification of important features for analysis (Qi et al., 2018).

The transdisciplinary research methodology presented here was developed to deliver the project 'Methane Early Warning Network' (ME-NET) funded by the Wellcome Trust (228267/Z/23/Z) to improve understanding of the effect of methane on health outcomes, including mental health presentations, in the UK and Ghana. The study sites capture the varying opportunities and obstacles associated with multi-data research in both high-income regions and LMIRs. The approach addresses the challenges described above in two ways. Firstly, representation of ordinarily 'invisible' and underrepresented communities and individuals will be achieved by adopting participatory and ethnographic methods (Graham et al., 2022), including ME-NET application co-design with lived experience experts and community champions. Engaging lived experience experts and community champions addresses the limitations of relying exclusively on service use data in regions like Ghana where mental health condition rates are underrepresented in service use datasets.

The research team undertook conceptual development through regular consultation with known stakeholders about project parameters (e.g., exploring regional preferences for web-based compared to phone-based applications and establishing health and environmental data availability), including the Ghana Meteorological Agency, Ghana Health Services and NHS representatives in the UK. The health and environmental sector stakeholders, in addition to representatives of coastal and regional communities in Lincolnshire and Ghana will attend stakeholder engagement boards in both regions for the iterative development and co-design of application functions, ensuring cultural relevance, usability and accessibility for diverse groups and individuals within and between regions. Community representatives will also support the research group to identify target users, including members of health support groups and community centres.

Secondly, the research integrates geospatial data visualisation methods (Moore et al., 2022a, 2022b) and ML approaches to elucidate relationships between 'messy' health datasets and open environmental datasets while maintaining data integrity. Finally, the interactive application will be developed equally for web-based and mobile phone apps to facilitate accessibility across diverse regions. Smart-phone penetration is higher in some LMIRs like Ghana (140% penetration in 2022 meaning nearly 50% of the population operates multiple mobile phones (FurtherAfrica, 2022)) compared to high-income regions like the UK (984% penetration in 2020 (ONS, 2022)). In many LMIRs, smartphones are used in lieu of other devices like laptops and home computers. Populations routinely utilise smartphone applications for diverse purposes, including receiving environmental warnings (e.g., flood alerts), and for health monitoring (e.g., mHEALTH (Blay et al., 2023)). The prevalence of smartphone use in LMIRs can facilitate the participation of communities and regions who have traditionally been excluded from global data science conversations, thus overcoming many of the limitations of traditional 'WEIRD' recruitment. Unlike many contemporary health applications, all ME-NET functions will be equally accessible via a web platform and smartphone to ensure accessibility for digitally excluded groups like ageing coastal communities in the UK who are less likely to utilise phone applications.

Methods

Research aims and questions

The aim of the research is to pilot a web-based and smartphone application (ME-NET) for regions with varying environmental and mental health data availability and quality, and with varying sources of methane emitters for. The prototype application will be tested for up to twelve months, including monthly evaluation in-built evaluation modules enabling iterative live functionality development. The purpose of the application is two-fold, a) developing data synthesis approaches for understanding the impact of climate and climate change on mental health outcomes that are globally applicable, b) training methane 'early warning' models for improving civic knowledge and health-protection behaviour that are robust to regional contexts. The study addresses three research questions:

1. To what extent can ML, including DL be used to develop an ozone early warning system that incorporates mental health data in two regions of the world with a) higher (UK), and b) lower-to-middle income (Ghana), reflecting wider global variation in data availability and quality?
2. Given available mental health data in the UK and Ghana, is it viable to use DL to predict rates of mental health emergencies associated with air quality, and if so, what impact do methane and ozone have on severe mental health presentations?
3. How do lived experiences of how mental health symptoms associated with methane and ozone vary geospatially?

Location

The regional focus is communities in two areas in Lincolnshire, UK and two areas in Ghana, Africa. Two *regions* were chosen to facilitate app development for data rich and data scarce contexts. The UK produces some of the most temporally and geographically granular and high-quality open health data in the world, reflecting research ecosystems in high-income regions. Open health data collated in Ghana is of varying quality and granularity, reflecting LMIR research ecosystems. Ghana also has one of the highest smartphone penetration rates in the world. *Multiple areas per region* have been selected to, a) ensure PPIE and LEE groups capture regional within and between group diversity, and b) to explore direct and distal relationships between environmental conditions and health outcomes. Grimsby on the Lincolnshire coast is located near waste disposal sites, coal mining and oil processing, while the City of Lincoln is located inland, south of Grimsby's industrial operations. Sekondi-Takoradi (ST) and Accra are located on Ghana coastline. Industrial operations (e.g., oil and gas processing) occur near ST while Accra is located further East and is the capital of Ghana. Thus, the research involves areas with similar distal relationships between methane production and populations.

Population

The first population involved in the research is patients with healthcare records related to mental health, excluding those who have opted out of data sharing for research purposes (e.g., UK NHS patients). Patient records include hospital attendances in Accra and ST, Ghana, and ambulance and hospital attendances in Lincolnshire, UK. The second population involved in the research includes participants in stakeholder engagement boards in the UK and Ghana, such as representatives from meteorological agencies, health services and community groups known to the research team. The third population involved in the research includes anonymous users of the application in both regions.

Recruitment

Recruitment relates to the second and third population described above and will be conducted in two phases. The first phase is purposive and involves inviting known stakeholders with lived experience of policy and practice in health, environment and climate sectors, as well as community lived experience experts to attend stakeholder engagement boards on behalf of the wider social and professional groups they represent. This phase of recruitment has been completed, drawing on existing networks and partnerships within and beyond the research team. The second phase of recruitment is opportunistic and involves 'snowballing', inviting members of wider social and professional groups to test and disseminate the 'ME-NET' application prototype. Members of the stakeholder engagement board will share the prototype via QR code with professional and social networks, including carer support groups, community wellbeing services and health centres. This phase of recruitment will be undertaken in parallel to the project co-design process, such as encouraging stakeholders involved in board meetings to identify potential user groups and distribute QR codes to group leaders and representatives.

Application co-development and functionality

The application will be co-designed and co-developed with lived experience experts in the UK and Ghana to ensure usability, accessibility and cultural relevance of individual functions to improve the uptake, and therefore visibility, of communities that might otherwise be excluded from mental health and climate change narratives. Co-design will follow the principles of 'design justice' and community participation (Costanza-Chock, 2024), including digital development through iterative processes of building, testing and adjusting application functions (Common Knowledge, 2024). Application content and functions will be tested with stakeholders during engagement board meetings. Input facilitating iterative adjustment will be collated through live polls and surveys during and following meetings. While some core application functions will be consistent between regional interfaces, the design and parameters of specific features will vary in order to maximise cultural relevance.

Similar to the techniques employed in our previous works (Aliyu et al., 2023; Atanbori & Rose, 2022), this research will pioneer the use of ML, encompassing the exploration of artificial neural networks, deep and incremental learning, on climate data captured by satellites. This analysis will be complemented by incorporating lived experiences to train an 'early warning' model that integrates multi-region and multi-datasets, encompassing the best available current, historical and future mental health data. The ML model will be integrated into a developed prototype smartphone and web-based application to improve understanding of associations between methane and ozone concentrations and mental health outcomes, educate application users about links between climate and mental health, predict on-ground concentrations of ozone, and communicate health warnings to users. Educational modules, including interactive mapping functions displaying aggregate historic mental health and climate data, will be delivered through the 'Explore and Learn' dashboard to improve climate and health literacy among users. The dashboard will display an interactive world map with functions enabling users to select spatial layers visualising rates of mental health conditions together with concentrations of atmospheric chemicals and conditions linked to poor health outcomes, including methane, nitrous oxide and UV levels.

Incremental Learning will be used to incorporate incoming self-reported anonymised user lived experiences to improve accuracy and identify environmental thresholds linked to mental health outcomes. Individual users can register with 'My profile' to access a range of service options, including opting in for generic daily or weekly updates and health recommendations, and inputting regular self-reported health experiences for tracking the relationship between individual health outcomes and environmental conditions via the 'My Health Today' function. An advanced option, 'Train ME-NET', will allow users to identify environmental thresholds related to poor health outcomes and set threshold-based alerts for early warning purposes.

Data and measures

Datasets and sources for *both* study regions are those obtained from the Sentinel 5P satellite mission, including meteorological and atmospheric chemical concentration data. Additional weather and health datasets vary by region. The date range of datasets utilised for ML purposes and the development of educational modules is between 2018 and 2024, although some datasets are only available from 2019 onwards. Data generated from MethaneSat following the recent satellite launch will be integrated as new data are released. The size and temporal characteristics of each dataset will vary depending on completeness and availability.

All data collection, storage, use and management will comply with the University of Lincoln's Data Protection and Information Compliance requirements, following the UK General Data Protection Regulation (UK GDPR) and the Data Protection Act 2018 (DPA 2018) and equivalent requirements for Ghana's data regulations (e.g., Data Protection Act, 2012 (ACT 843)).

Sentinel 5P satellite data

Meteorological data will be obtained from Level 1B (L1B) and Level 2 (L2) products. Atmospheric chemical concentration data will be obtained from Level 2 (L2) products. Further details about these products can be found via Sentinel Online (https://sentinels.copernicus.eu/web/sentinel/data-products). Product summary: **L1B products:** Irradiance product Ultraviolet Near-Infrared (UVN) module (L1B_IR_UVN), Irradiance product Short Wave Infrared (SWIR) module (L1B_IR_SIR). **L2 products:** Tropospheric Ozone (L2_O3_TCL), Total column Nitrogen Dioxide (L2_NO2_), Total column Sulphur Dioxide (L2_SO2_), Total column Carbon Monoxide (L2_CO_), Total column Methane (L2_CH4_), Total column Formaldehyde (L2_HCHO_), Ultraviolet (UV) Aerosol Index (L2_AER_AI), Cloud fraction, albedo, top pressure (L2_CLOUD_), NASA Suomi-NPP Program Visible Infrared Imaging Radiometer Suite (VIIRS) Clouds (L2_NP_BDx, $x = 3, 6, 7^2$).

Observational mental health data

Mental health data from Lincolnshire will include anonymised aggregate ambulance data obtained from the East Midlands Ambulance NHS Trust (EMAS), and primary care data collated by the Lincolnshire County Council Data Hub (https://lhih.org.uk/). Measures will include records of mental health emergencies related to depression, suicidality and other presentations attended by ambulances (>100,000 records) and primary care records of GP and hospital attendances related to mental health in Lincolnshire. Mental health data from Ghana will include regional aggregate anonymised health records for conditions like depression collated by Ghana Health Services (https://www.moh.gov.gh/ghana-health-service/) including the mental health division, Ghana Mental Health Authority, and aggregate anonymised health facility data (e.g., psychiatric hospitals). Data selection will take into consideration the exclusion of 'hidden' and 'hard-to-reach' groups and individuals from routine scheduled health service datasets like GP appointments. Thus, the research will utilise emergency medical service data, including ambulance and hospital admissions data which reflects acute mental health conditions, overcoming many of the limitations of 'opt in' service data, such as self-selection bias which typically results in the underrepresentation of groups like men and males who are less likely to engage with help-seeking (Moore et al., 2021).

Self-reported mental health data

Anonymous users of the ME-NET application in the UK and Ghana will self-report health symptoms, including symptoms related to depression and anxiety by responding to survey items prompted through the 'My Daily Health' platform. Measures will include items adapted from tools including the General Health Questionnaire (GHQ-12), General Anxiety Disorder-7 (GAD-7), Patient Health Questionnaire-9 (PHQ-9), and the Depression, Anxiety and Stress Scale-21 (DASS-21). The application will be accessible via website and smartphone application. This approach challenges the characterisation of LMIRs as 'data scarce'. It has potential to improve the visibility of people and communities in LMIRs and to reposition these regions as global leaders in the use of low-cost and high-penetration innovative solutions like smart-phone applications to combat health disparities and reduce health service access inequalities. Smart-phone penetration is higher in some LMIRs like Ghana (140% penetration in 2022 meaning nearly 50% of the population operates multiple mobile phones (FurtherAfrica, 2022)) compared to high-income regions like the UK (95% penetration in 2021 (ONS, 2022)). In many LMIRs, smartphones are used in lieu of other devices like laptops and home computers. Populations routinely utilise smartphone applications for diverse purposes, including receiving environmental warnings (e.g., flood alerts), and for health monitoring (e.g., mHEALTH (Blay et al., 2023)). The prevalence of smartphone use in LMIRs can facilitate the participation of communities and regions who have traditionally been excluded from global data science conversations, thus overcoming many of the limitations of traditional 'WEIRD' recruitment. Unlike many contemporary health applications, all ME-NET functions will be equally accessible via a web platform and smartphone to ensure accessibility for digitally excluded groups like ageing coastal communities in the UK who are less likely to utilise phone applications.

Additional environmental data

Environmental data for Lincolnshire will include daily live and historic weather data collated by The Met (http://www.weatherobs.com/; https://ogimet.com/gsynres.phtml.en), and DEFRA (https://uk-air.defra.gov.uk/data/ozone-databut; https://uk-air.defra.gov.uk/data/uv-data). Environmental data from Ghana will include live and historic weather data such as temperature, clouds and wind (https://www.tide-forecast.com/; https://meteologix.com/gh/observations).

Data linkage

To compile the linked dataset at lower super output area (LSOA) scale, health and environmental data will be merged using the join tool in ArcGIS Pro 2.6.0. The join will use Lower Super Output Area codes (LSOA11CD) as these identifiers are consistent between databases used in the research.

Data analysis

Machine learning: a) to predict on-ground ozone from historic environmental data, b) for integrating health data to understand climate–health relationships, c) to determine whether predicted health outcomes reflect lived experiences of health outcomes and d) to explore likely health outcomes under climate change scenarios of 1.5° and 2° warming for the two regions involved in the research. The specific ML approach will be informed by the quality of individual datasets obtained and the synergies between individual datasets (e.g., scale, completeness) which will determine the parameters for collating and analysing multi-datasets. This final analytical approach will consider the role of UV as a precursor of on-ground ozone which is linked to mental health outcomes.

Overall, the methodology champions the de-colonisation of data science by pioneering geospatial and analytical methods that capture the heterogeneity of mental health impacts associated with climate change, are robust to regional contexts, and validates the utility of lived experience in regions where more traditional health data are 'scarce'.

Data availability statement. Some of the data that support the findings of this study will be openly available in repositories. Other data will be unavailable in compliance with ethical requirements.

Author contributions. All authors contributed to concept development. HM, JA, MG, NS and EH contributed to methodological approach and study design. HM and JA developed initial manuscript draft. All authors edited manuscript drafts. All authors are involved in project delivery.

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Competing interests. The authors have no conflicts of interest to declare.

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