Epidemiological modelling in refugee and internally displaced people settlements: challenges and ways forward

Aylett-Bullock, Joseph; Gilman, Robert Tucker; Hall, Ian; Kennedy, David; Evers, Egmond Samir; Katta, Anjali; Ahmed, Hussien; Fong, Kevin; Comes, Tina; Gaanderse, Mariken

DOI
10.1136/bmjgh-2021-007822

Publication date
2022

Document Version
Final published version

Published in
BMJ Global Health

BMJ Global Health

Epidemiological modelling in refugee and internally displaced people settlements: challenges and ways forward

Joseph Aylett-Bullock ,[1,2] Robert Tucker Gilman ,[3,4] Ian Hall,[3,5,6] David Kennedy ,[7] Egmond Samir Evers ,[8] Anjali Katta,[1] Hussien Ahmed,[9] Kevin Fong,[10] Keyrellous Adib ,[11] Lubna Al Ariqi,[11] Ali Ardalan,[11] Pierre Nabeth ,[11] Kai von Harbou,[8] Katherine Hoffmann Pham ,[1,12] Carolina Cuesta-Lazaro,[2] Arnau Quera-Bofarull,[2] Allen Gidraf Kahindo Maina ,[13] Tinka Valentijn ,[14] Sandra Harlass,[15] Frank Krauss,[2] Chao Huang,[16] Rebeca Moreno Jimenez,[17] Tina Comes ,[18] Mariken Gaanderse,[18] Leonardo Milano ,[14] Miguel Luengo-Oroz [1]

To cite: Aylett-Bullock J, Gilman RT, Hall I, *et al*. Epidemiological modelling in refugee and internally displaced people settlements: challenges and ways forward. *BMJ Global Health* 2022;**7**:e007822. doi:10.1136/bmjgh-2021-007822

Handling editor Seye Abimbola

► Additional supplemental material is published online only. To view, please visit the journal online (http://dx.doi.org/10.1136/bmjgh-2021-007822).

Received 27 October 2021
Accepted 23 January 2022

For numbered affiliations see end of article.

Correspondence to
Dr Joseph Aylett-Bullock;
joseph@unglobalpulse.org

ABSTRACT

The spread of infectious diseases such as COVID-19 presents many challenges to healthcare systems and infrastructures across the world, exacerbating inequalities and leaving the world's most vulnerable populations at risk. Epidemiological modelling is vital to guiding evidence-informed or data-driven decision making. In forced displacement contexts, and in particular refugee and internally displaced people (IDP) settlements, it meets several challenges including data availability and quality, the applicability of existing models to those contexts, the accurate modelling of cultural differences or specificities of those operational settings, the communication of results and uncertainties, as well as the alignment of strategic goals between diverse partners in complex situations. In this paper, we systematically review the limited epidemiological modelling work applied to refugee and IDP settlements so far, and discuss challenges and identify lessons learnt from the process. With the likelihood of disease outbreaks expected to increase in the future as more people are displaced due to conflict and climate change, we call for the development of more approaches and models specifically designed to include the unique features and populations of refugee and IDP settlements. To strengthen collaboration between the modelling and the humanitarian public health communities, we propose a roadmap to encourage the development of systems and frameworks to share needs, build tools and coordinate responses in an efficient and scalable manner, both for this pandemic and for future outbreaks.

Summary box

- Infectious diseases present many challenges in forced displacement contexts, particularly refugee and internally displaced people (IDP) settlements in which healthcare access is limited and crowded environments enable rapid disease spread.
- Epidemiological modelling is vital in supporting evidence-based and/or data-driven decision making, however, adapting and developing models for use in refugee and IDP settlements is challenging and has so far not been comprehensively addressed.
- Challenges include limitations in the availability of high quality data and the applicability of existing models; accurately modelling cultural differences and how these translate into social norms and behavioural patterns; communicating results and uncertainties; as well as aligning strategic goals between diverse partners in complex situations.
- We identify lessons learnt from existing modelling efforts and discuss ways to address these as a global community. We propose a roadmap describing both our current position and a global call to action to design new processes to share needs, build tools and coordinate responses in an efficient and scalable manner, both for this pandemic and for future outbreaks to ensure that no one is left behind.

INTRODUCTION

The spread of COVID-19 across the globe presents challenges to even the most advanced healthcare systems. In low-income and middle-income settings, it has had profound impacts, further exacerbating inequality and leaving the world's most vulnerable populations highly exposed. Refugee and internally displaced people (IDP settlements, especially those which have been rapidly created in response to humanitarian crises, often suffer from overcrowding and insufficient health and sanitation facilities. Epidemiological models to assess and guide potential public health interventions can be of vital importance for the people living in the settlements.[1 2] In this paper, we provide a first overview of the limited literature in this field, address some of the challenges and lessons learnt from conducting modelling efforts to simulate the spread of COVID-19 in refugee and IDP settlements, and discuss ways to better serve these vulnerable communities in the future.

BACKGROUND

Humanitarian responses to situations where people have been forced to flee their homes typically involve the provision of shelter, protection and aid. They generally involve bodies such as the United Nations (UN) and various non-governmental organisations (NGOs) and are organised following international frameworks for coordination, such as the 'cluster approach'[3] or the 'refugee coordination model',[4] which outline which entities are responsible for different components of the response. For example, the overall coordination for the Rohingya refugee response in Cox's Bazar, Bangladesh, the largest refugee settlement in the world, is led by the Inter-Sector Coordination Group which comprises sector leaders related to protection, health, water and sanitation, shelter and site management among others. In the case of managing COVID-19 in settlements, organisations responsible for overall coordination—for example, the UN refugee agency (UNHCR) and the International Organisation for Migration—and for leading the health sector—for example, the WHO—work closely together in designing strategies to support governments in managing and mitigating disease spread. Since crises and humanitarian disasters in general, and refugee and IDP settlements more specifically, are highly prone to infectious disease outbreak,[5] and, as we will show, available research on such disease outbreaks is currently limited, we see great potential in using epidemiological modelling to inform decision-making processes at all levels of settlement management. This potential can be realised via a collaboration between modelling teams and experts on the ground, while including the voices of local communities living in the settlements, and feedback mechanisms can be created to maximise the impacts of empirical data and modelling on population health.

Compartmental models, in which populations are divided into discrete groups and generally modelled as systems of differential equations, offer a flexible foundation for such analyses.[6] An example is the commonly used Susceptible-Exposed-Infected-Removed model, which enables rapid exploration of the dynamics of epidemics while providing high-level insights into possible mitigation strategies. In their simplest forms, these models are based on data aggregated at the national or subnational level, but models with additional compartments can be used to simulate transmission among specific regions and at-risk groups. Compartmental models can also be formulated to include demographic or environmental stochasticity such as by adding autocorrelated noise to parameters in the model. To capture more complex dynamics and allow for enhanced realism in simulations, especially in relatively small subgroups of the population, meta-population models or network models[7–9] have proved useful, with several recent applications of these techniques to modelling the spread of COVID-19.[10 11]

As a complement to compartmental models, agent-based models (ABMs) focus on the (inter)actions of individuals, and groups of individuals, in complex social networks and can be thought of as maximally compartmentalised models. They are able to capture social mixing by modelling direct contacts between individuals belonging to different subpopulations,[12] as well as the geographic and demographic heterogeneity of the populations. This implies that ABMs can record chains of transmission between individuals. Perhaps most importantly for an epidemic, ABMs are also able to capture individual behavioural and emotional adjustments which can change as agents interact with the wider complex system. This includes fear (and overcompliance) or epidemic fatigue (and a lack of compliance), which spread in social networks independently from disease prevalence.[13] Since ABMs model interactions in social networks, they are also able to capture the emergence of pockets of behaviour and new communities. However, capturing the behaviour of individuals, their activities and social networks, requires much more detailed data inputs and greater computing power than compartmental approaches. In addition, the complexity of ABMs, as well as the sometimes strong effects of stochasticity, can make the process of fitting models to make predictions more challenging. Therefore, there is a trade-off between the high resolution of ABMs, which enables interrogation of models at the individual level, and the relative ease of constructing and fitting compartmental models. In situations of data scarcity, exploratory and scenario-based (SB) modelling may, therefore, be preferable when using ABMs[12] (see below for more discussion of this topic).

LITERATURE REVIEW

Epidemiological models of populations in low-resource settings have been applied to a range of diseases including cholera and Ebola.[14–17] More recently, several models have focused on the spread of COVID-19 at the national level in countries with large numbers of refugees or IDPs. For example, van Zandvoort *et al.*[18] used a compartmental model to model the possible effects of non-pharmaceutical interventions (NPIs), such as self-isolation, physical distancing, shielding vulnerable populations and more stringent lockdown measures, in three African countries—Mauritius, Nigeria and Niger. Frost *et al.*[19] took a similar approach—modelling four gradations of lockdown using a compartmental model—over all African countries. Ferguson *et al.*[20] demonstrated an application of a compartmental model to a district within Bangladesh which is estimated to contain significant

Table 1 Articles included in the systematic literature review (see online supplemental material 1 for more details)

Authors	Year	Model type	Location	Population data	Comorbidities	Analysis type	Open-sourced
Truelove *et al*[23]	2020	C	Cox's Bazar, Bangladesh	Refugee census and settlement infrastructure data from UN agencies and government	N	SB	Y
Hariri *et al*[25]	2020	C	Northwest Syria	Total refugee counts - source unknown	N	SB	Y
Gilman *et al*[34]	2020	ABM	Moria, Greece	Refugee census data from UN agencies and NGOs	Y	SB	Y
Pascual-Garcia *et al*[29]	2020	C	Northwest Syria	Refugee census data from UN agencies and NGOs	Y	SB	Y
Hernandez-Suarez *et al*[30]	2020	C	Za'atari, Jordan	Refugee census data from UN agencies	N	SB	N
Aylett-Bullock *et al*[32]	2021	ABM	Cox's Bazar, Bangladesh	Refugee census and settlement infrastructure data from UN agencies and government	Y	SB	Y
Kamrujjaman *et al*[24]	2021	C	Cox's Bazar, Bangladesh	Refugee census data from UN agencies and government	N	P	N
Ssematimba *et al*[31]	2021	C	Uganda	Total refugee counts from UN agencies and government	N	SB	N
Fouad *et al*[27]	2021	C	Lebanon	Total refugee counts from UN agencies and government	N	SB	N

Papers are sorted in order of initial publication. Model type is categorised as: C or ABM. The type of analysis undertaken is categorised as: SB or P.
ABM, agent-based models; C, compartmental; NGOs, non-governmental organisations; P, predictive; SB, scenario based.

numbers of persons of concern. Here, the authors looked at similar NPIs as above, as well as the possible effects of testing capacities and mask wearing, and focused on assessing the hospital capacity requirements as well as the economic costs of different interventions. The UN Office for the Coordination of Humanitarian Affairs, in collaboration with Johns Hopkins University, has built on the approach of subnational modelling and developed a geographically disaggregated compartmental model to predict the spread of COVID-19 in six low-resource countries.[21] The approach uses official health, census and survey data and focuses on modelling at the second administrative (admin-2, e.g., governorates or states) level, linking routes between administrative units to capture mobility patterns. The model is fitted to the latest COVID-19 case data and provides near-term forecasts at the admin-2 level.

Despite this, few models have addressed the spread of COVID-19 in refugee or IDP settlements specifically. In this section, we present a systematic literature review to identify all relevant papers to date presenting epidemiological modelling of COVID-19 in such settlements. Details of the review process can be found in online supplemental material 1.

Searching over medRxiv and PubMed we found 10 articles which were deemed relevant as they presented findings of epidemiological modelling in refugee and IDP settlements and populations. We assessed the articles according to a range of criteria including: the type of model used, compartmental (C) or agent-based (ABM); which geographical region/settlement the modelling was conducted in; which data was used to model the population; whether comorbidities were included explicitly in the modelling; the type of modelling analysis undertaken, scenario-based (SB—exploring a range of possible scenarios without requiring data for fitting) or predictive (P—fitting to data to make forecasts over a given time horizon); and finally if the model code/materials were made publicly available. A summary of the articles included in this review can be found in table 1. Note that one paper, Musalam *et al.*,[22] was discovered during the review, but could not be accessed and so has not been included.

We identified two articles which used compartmental models to study the Cox's Bazar refugee settlement. Truelove *et al.*[23] constructed a compartmental model designed for rapid deployment and to inform initial resource planning. Their model analyses a large contiguous part of the settlement, and utilises census data to capture the overall demographic profile of the settlement, which is then used to calculate age-adjusted hospitalisation and mortality rates. The authors take a SB approach due to the incomplete nature of the epidemiological data. Kamrujjaman *et al.*[24] also modelled the Cox's Bazar settlement, however, the authors did not explicitly include information on age structure in their model and instead used reported case data from the settlement to attempt to fit models for predictions disaggregated by sex.

Additional modelling efforts have focused on Syrian refugees. Hariri *et al*.[25] deployed the WHO COVID-19 essential supplies forecasting tool,[26] which uses a compartmental model similar to that discussed above above (without explicitly including age-structured information), and assessed the effect of a rapid case doubling time (2.3 days) in the context of the IDP population of Northwest Syria. Fouad *et al*.[27] explored the potential spread of COVID-19 among the Syrian refugee population in Lebanon under different values of the basic reproduction number (R0), using the age-structured compartmental model presented by Ayoub *et al*..[28] Changes in the R0 value were mapped to changes in scenarios such as crowded environments, inadequate access to personal protective equipment and healthcare services, as well as different levels of community awareness of the dangers of the virus. Similarly, Pascual-García *et al*.[29] use a compartmental approach to model NPIs in IDP settlements in Syria, assuming a well mixed population with no spatial structure, but including different behavioural classes of the population in order to encode different mixing patterns. This allowed the authors to explore the effects of NPIs such as the introduction of safety zones for vulnerable populations, as well as case detection and isolation measures.

Compartmental models have also been implemented in other refugee and IDP settings. Hernandez-Suarez *et al*.[30] proposed a compartmental model to capture prototypical camp settings with a focus on the Za'atari camp in Jordan. Similar to the above, the authors explore the effects of quarantining and contact tracing, along with other NPIs. Ssematimba *et al*.[31] focused on explicitly exploring the impact of population density—which is extremely high in many settlements—and a variety of NPIs on the spread of COVID-19 in refugee populations in Uganda. Such studies could be important for informing not just the implementation of NPIs for mitigating disease spread, but also the construction of settlements to avoid dangerously dense living conditions.

We identified only two papers using ABMs. Aylett-Bullock *et al*.[32] present the results of a recent study in Cox's Bazar, for which UN entities and academic partners developed a generalisable approach for individual-leve ABM for refugee and IDP settings. The model, based on the JUNE framework[33]—an individual-based model which captures highly granular geographic, demographic and behavioural characteristics of a population to allow for the precise implementation of mitigation policies and behavioural changes—uses extensive available georeferenced data to construct a digital twin of the settlement, including the locations of key mixing points such as households, distribution centres and schools, and also uses demographic data on over 700 000 inhabitants. The simulator probabilistically determines what agents do during the day. Demographic characteristics, including comorbidities, are used to estimate disease spread and the likelihood of severe disease progression. The authors assessed a range of NPIs such as alternative care delivery mechanisms, mask wearing, and strategies for the reopening of learning centres.

Gilman *et al*.[34] present an ABM study of the Moria refugee camp on the island of Lesbos in Greece. At the time of modelling, Moria was the largest displacement camp in Europe. The goal of the model was to assess the potential of NPIs to slow the spread of COVID-19 in the camp. The model simulates the camp's spatial and demographic makeup and the movements of its 18 500 residents at the individual level. Similar to the above approach, disease progression depends on demographic attributes, with agents' routines controlled probabilistically. Interventions studied include lockdowns, removal and isolation of infected individuals, and altering the queueing structure for lines at crowded distribution centres.

Overall, we found that very few refugee and IDP settlements and populations have been the explicit focus of epidemiological modelling during the COVID-19 pandemic. In addition, the majority of models are compartmental in nature. This is understandable given the lower setup and computing costs for such models, as well as their need for less explicit input data and assumptions relative to ABMs. However, a diversity of modelling approaches is important for decision-making as each model contains its own implicit assumptions, uncertainties and biases. While it is encouraging that certain settlements and wider vulnerable populations (such as the Cox's Bazar settlement and Syrian refugees) have been served by multiple modelling efforts, we hope this will be more common in the future.

In the remainder of this article, we discuss some of the challenges posed to modelling refugee and IDP settlements, drawing on a wide range of experience and the literature presented above, and propose potential ways forward for overcoming these challenges as a community.

CHALLENGES

It is important that communities of public health decision-makers and modellers work closely together. In this section, we identify challenges facing current modelling efforts, and therefore wider collaborations between modellers and decision-makers, from two complementary perspectives: data and modelling, and strategic partnerships and communications.

Data and modelling challenges

Settlements are often dense and challenging environments, with sanitation and healthcare facilities that vary greatly across geographies.[35] NPIs, such as physical distancing and self-isolation for symptomatic individuals, can be difficult to implement due to overcrowding and the need to access shared resources such as water supplies and latrines.[36 37] The impact of differing healthcare access across and between regions is rarely incorporated in modelling efforts but should be included to properly estimate disease progression in individuals, and therefore better capture hospitalisation and death rates.[38] Modelling teams and public health decision-makers must iterate and design new approaches to data collection and disease mitigation, accounting for the local needs and contextual challenges faced by the populations. In addition, while outbreak scenarios in displacement settings usually require models that can be developed rapidly to guide decision-making, our experience from recent responses is that evolving situations often require adapting projections based on new data as the situation emerges and/or develops differently than expected. Methodologies that allow for dynamic adaptation of projections to new events such as fires or monsoon floods which cause displacement,[34] or major shifts in the population makeup, can be useful tools to guide the response strategy. These new methods require a mixture of new model types flexible enough to capture the changing situations, as well as high quality, and rapidly collected, data on such changes.

Modelling requires a minimum level of data quality for making predictions and building scenarios. This varies depending on the model construction and purpose. Throughout the COVID-19 pandemic there has been an unequal distribution of the data available and it is unclear to what extent data and results can be transferred between geographies. When fitted using data from the Global North, disease parameters such as transmissibility and clinical progression to severe disease do not necessarily translate to communities with very different demographic structures and cultural patterns. Indeed, the limited success in predicting the spread of COVID-19 in many parts of the African continent illustrates these challenges and highlights the need for a greater diversity of disease studies.[39 40]

Existing literature has attempted to compensate for this lack of information by adjusting COVID-19 health and symptom onset data from the Global North by using data on comorbidities in local populations, adjusting for age and sex differences[29 32 34] (see table 1). However, certain compound comorbidities, which are prevalent in displaced populations, impact the clinical progression of COVID-19, but this impact is poorly quantified.[41 42] Similarly, under-reporting of COVID-19 cases and deaths is a concern in many countries and settlements due to inadequate disease surveillance infrastructure[43] and the spread of misinformation.[44 45] To address this, SB modelling can be a powerful approach to explore possible futures under uncertainty. This involves exploring different scenarios based on clearly communicated assumptions and focusing on relative differences in infection curves and cumulative statistics, as opposed to precise predictions, thereby removing some dependencies on assumptions and missing disease data. While compartmental models may require fewer direct assumptions when data is scarce, they implicitly make aggregate assumptions about population dynamics due to their structure. Therefore, both compartmental models and ABMs are useful for assessing possible scenarios under uncertainty, and different approaches may be compared with each other to better express model structure uncertainty.

In the face of these data uncertainties, studies of other infectious diseases, as well as seroprevalence studies in refugee settings to estimate population-level exposure to viruses, can help researchers and public health workers understand disease trends. Despite a few systematic studies in settlements,[46] these communities remain largely underserved by disease surveillance research. Indeed, a recent review focusing on studies of transmission, reinfection, and other health risks among migrants and forcibly displaced populations noted that there is significant heterogeneity in the design of existing studies, making the available data difficult to compare across settings and demonstrating the need for more robust, systematic, and comparative study designs[47] (see the WHO Unity Study protocol for an example of an attempt to harmonise such data collection[48]).

Consistent and regular reporting by UN entities and NGOs operating in the settlements ensures that regular demographic and needs-based data is gathered. Several humanitarian efforts exist to collect and collate this data, such as microdata libraries (e.g., the UNHCR Microdata Library[49]) and open data platforms. An example of such an open data platform is the Humanitarian Data Exchange,[50] which enables the use of data across organisations and crises by hosting a wide range of datasets and encouraging standard reporting formats and mandatory metadata. Nevertheless, because none of these platforms currently host all relevant humanitarian data, extensive data-hunting exercises must still regularly be undertaken to gather information across different metadata and reporting formats.

Context-specific behavioural and sociological information is key to understanding the interactions that allow infections to spread.[51] While demographic data are generally regularly collected in settlements, data on behavioural patterns of individuals, on cultural contextual factors affecting such patterns, and on compliance with public health recommendations, is often unavailable or challenging to access. For example, mixing patterns of individuals may be estimated from existing reports and surveys. However, this data is rarely systematically collected with the objective of assessing mixing in context, and therefore knowing which reports may be most useful in a given context can be challenging. In the case of the Cox's Bazar settlement, work is ongoing to analyse data on mixing and contact patterns in different locations collected from surveys conducted by the community-based protection (CBP) team. This team is part of the field-based protection staff and has direct contact with local communities; it seeks to address key protection issues such as child protection and issues surrounding age, gender, diversity, and education. These efforts should be replicated across different geographies.

Partnerships between modelling groups and teams on the ground are essential to understand the nuances and challenges of particular humanitarian contexts and to define coherent data collection and modelling strategies.[52] In settlements, liaising with various teams including the CBP, health, and management teams can enable the collection of more relevant data and provide insights into behavioural characteristics essential for modelling. New modes of data collection should also be explored. For example, mobile phone surveys of populations (which can be conducted by survey teams equipped with mobile devices in cases where mobile phone ownership is not widespread) may be able to provide both up-to-date disease data and population-related insights, such as household composition and behavioural changes, although these new data collection methods should be adapted to the relevant contexts.[53–55] Satellite imagery can also be employed to provide insights into excess mortality rates[56] and used in conjunction with computer vision techniques for rapid mapping of vulnerable and remote populations.[57 58] However, it is important that all data is validated, and good data quality is maintained, to ensure accurate modelling (see e.g., UNHCR's guidelines and standards[59] and the references therein). Well-designed mathematical models can highlight data gaps to policy makers (e.g., through sensitivity analyses), illustrate the projected impacts of these gaps, and help set priorities for further data collection.

Finally, researchers working with vulnerable populations must follow best practices, adopting the highest standards in data privacy and data protection and obtaining meaningful consent from the population on which data is collected. Systematic risks and harms assessments must be undertaken before and during the modelling work. Examples of such assessments include those developed by UN Global Pulse[60 61] and the Human Rights Impact Assessment.[62] These assessments consider factors such as data quality issues, modelling bias, the potential for individual and group reidentification, and possible misuses of the data and the models. Indeed, misuse of data may be particularly relevant in conflict regions and settings with marginalised, and often already persecuted, populations.

Strategic partnerships and communications challenges

The communication of modelling results and insights must be tailored to the relevant policy actors, which can be challenging in humanitarian situations where large numbers of parties are involved (e.g., there are over 80 partners engaged in the provision of health services alone in the Cox's Bazar settlement). Generating actionable insights requires aligning academic findings with operational questions co-designed by modelling teams, decision-makers and programme implementers. While public health experts and academic research communities may respond well to detailed technical reports, researchers must also be able to summarise model outputs for those with different expertise, and be able to provide timely and relevant insights for operational teams.

Engagement between researchers, health and protection teams, and refugee and IDP communities is essential to facilitate the timely sharing of information in a way that serves the best interests of the population. In addition, an understanding of information flows in the settlements and related social network structures is crucial to proper information sharing and delivery. Careful consideration must be given to the implementation, impacts and implications of certain insights, such as when models support the imposition of further restrictions on refugee and IDP movement. Health and protection teams are instrumental in engaging with persons of concern and deciding which interventions should be implemented given practical and cultural considerations. For example, they can identify linguistic and communication norms which may affect the delivery of communication strategies, societal norms around family structures which may influence the strategy of implementation around quarantining or shielding policies, and religious norms such as head and face covering which may affect practical use of masks and related communication strategies.

All models are constructed with biases and have their own limitations and caveats. For example, compartmental models assume a degree of homogeneity in the modelled population whereas ABMs may be overly sensitive to poorly supported assumptions about agent behaviour. Estimation, identification, and clear communication of inherent uncertainties, limitations and caveats are important and challenging tasks, and there is a need for continued development of approaches for decision-making under uncertainty.[63]

Bringing together actors from different communities to discuss challenges and share lessons learnt is essential for future supportive modelling efforts. There is an ongoing need to translate priorities and incentives between decision-makers and researchers, and problem scoping should culminate in concrete research questions that are of interest to both parties while allowing for time-sensitive, flexible and innovative cycles of model and approach improvement. Communication in both directions is essential for a holistic approach to data driven decision making and various methodologies can support this effort. For example, SB modelling approaches can help with the exploration of a wide range of assumptions and future events without the need for detailed epidemiological data for model fitting, while allowing for fast adaptation.

To enable such communication and collaboration more broadly, there is a need for greater adoption of participatory modelling approaches, which engage a range of stakeholders from governments, the public health sector, academia, and national and international organisations throughout all stages of modelling to enable an iterative and adaptive modelling process. Within the participatory approach, several professional groups with different roles interact forming a three node structure. The three node structure comprises a model development node, an in-country experts node and a policy-making node. The involvement of professionals with all three types of expertise is useful in: framing meaningful research questions;

encouraging data sharing and discussing data limitations; formulating models including key aspects of the simulated population; promoting the translation of model results into actionable public health decisions; providing timely responses to decision-makers' policy questions; improving overall communication between modellers, policy-makers and implementers; and building trust in, ownership of, and support for the models.[64 65]

WAYS FORWARD

At present, there are more than 84 million forcibly displaced people, representing more than 1% of the worldwide population, and recent conflicts may further increase this figure.[66] Given the scale of this challenge, there is an increased need for attention to, and coordination among those, providing modelling support to public health decision-makers charged with protecting displaced populations. Over the course of the pandemic, thousands of papers have presented or discussed COVID-19 modelling work. However, our literature review identified only 10 papers that explicitly model refugees and displaced people.

While some nations are able to coordinate multiple modelling efforts simultaneously to produce consensus

Table 2 Roadmap of change for improved cooperation between the modelling and humanitarian public health communities

	Where we are	Call to global action
Data	► Multiple open data libraries ► Microdata libraries for sensitive data ► Several mechanisms for rapid data collection by humanitarian workers ► Wide selection of data privacy and protection practices ► Limited data in Global South	► Atlas of all available data libraries and their contents ► API/interface to discover, clean, aggregate and structure data from libraries for modellers ► Increased consultation on data requirements for disease modelling, in order to facilitate preemptive data collection and identify data gaps ► Mechanisms and procedures for systematic collection of disease surveillance data ► Global responsible data standards covering collection, processing, analysis, storage and (fair) re-use
Models	► Sparse collection of models from different groups with a few consortia ► Development of different modelling strategies: scenario-based, participatory, and predictive ► Limited access to hardware and/or cloud computing for field operations	► Library of available models and previous studies, fully documented as open-source packages ► Best practices to conduct full assessments and reporting of model uncertainty ► Model pooling and ensembling methods for decision-making ► Guidance on model types and approaches to use for different problems
Partnerships\ Coordination	► Cluster approach coordination framework and the refugee coordination model for humanitarian response, but which does not include modelling teams ► Wide variations in the level of involvement of public health humanitarian decision-makers in the modelling process and vice versa ► Disparate collection of legal/ collaboration agreements including data sharing agreements ► Risks, harms and benefits/ethical assessment tools	► Catalogue of stakeholders and roster of parties able to support public health decision-making (including modellers) ► Coordination and matchmaking mechanism between modellers and decision-makers to enable rapid activation of collaborations in emergencies ► Mapping of insights which could be derived from modelling and their possible impact and desired priority level ► Wide adoption of participatory modelling and methods through training sessions and capacity building ► Pre-arranged legal/collaboration and data sharing agreements with templates and clear processes for initiating new agreements ► Wide and systematic use of ethical assessment tools, with risk mitigation measures identified and implemented
Communications	► Wide range of available visualisation and communication platforms for displaying model results ► Limited engagement and communication with local community on use of models for decision-making ► Broad range of mechanisms for understanding and reporting on model caveats, limitations and uncertainties	► Suite of tested communication methods (visualisations, graphics, etc.) tailored to different audiences for ready deployment ► Development, dissemination and adoption of capacity building toolkit for decision-makers and modellers ► Mechanisms for community involvement in decision-making and appropriate communication of insights ► Guidelines and standards on communicating model uncertainty, caveats, and limitations ► Widely documented and collated reflective learning and lessons learnt ► Coordinated technical knowledge sharing activities

on scenarios and forecasts and thereby explore multiple assumptions and modelling approaches, only a handful of models exist for refugee and IDP communities globally. Developing pooling strategies and parallel modelling approaches in settlements will provide more robust insights for planning disease mitigation strategies, predicting disease progression and coordinating public health responses. Comparing multiple models with different underlying mathematical assumptions is critical to provide reassurance that outputs are not sensitive to hidden assumptions; seeking a single 'best' model should not be the ambition.[67]

For the sake of transparency and global cooperation, modelling teams should also publish their epidemiological models under open-source licenses which will help remove barriers to entry, facilitating and empowering new diverse and multidisciplinary teams to engage in modelling challenges related to underserved communities.[68] Indeed, in the literature reviewed, just over half of the models were open-sourced. Furthermore, releasing source code is not enough; any shared materials should be accompanied by clear documentation, use and setup instructions. Similarly, peer review of models will be best facilitated by further data sharing. In the case of modelling vulnerable populations, appropriate risks and harms assessments must be followed by mitigation strategies before open-sourcing all data freely, and so the further development of best practices and guidelines in this area are needed.

In the short term, as COVID-19 vaccines become increasingly available, national vaccination strategies are informed by multiple modelling efforts with a range of objectives such as minimising mortality or reducing transmission.[69 70] The WHO-led COVAX scheme for global equitable access to vaccines is enabling broader inclusion in vaccine distribution, with many countries deliberately including refugees and asylum-seekers in their vaccination plans. However, further modelling work is needed to support these operations. Refugees and IDPs have limited access to healthcare, increased vulnerabilities, and unique demographics, and addressing their needs presents particular logistical challenges. Therefore, models developed specifically for such settlements and populations should be used to design and execute vaccination strategies.[71] Similarly, new disease variants may quickly change the situation, for example due to faster transmission or reduced vaccine effectiveness, and models must be available to support a rapid response in this case.

In order to address the challenges and enable the necessary changes discussed in this paper, we believe that next steps include establishing a global framework for the modelling and the humanitarian public health community to share needs, develop tools and coordinate responses in an efficient and scalable manner, both for this pandemic and for future outbreaks. To facilitate the creation of such a framework, we present a roadmap (see table 2) which summarises where we currently stand as separate, and occasionally connected, communities, and which defines a set of future milestones to be achieved under a call to global action.

We hope that the roadmap presented in table 2 will enable a future in which the joint work of the modelling and humanitarian public health communities scales to be able to serve, in a timely manner, all people living in refugee and IDP settlements. Modellers will have clear mechanisms to offer support and expertise in close collaboration with decision-makers; participate in contingency planning and rapid response to disease outbreaks in settlements; and contribute both foundational theoretical knowledge as well as applied, needs-based insights. Humanitarian public health workers will be able to call on modelling teams for support through global rosters, as well as run their own models for immediate insights through available open-source modelling platforms. Humanitarian teams will receive capacity building training in the development, deployment and interpretation of models. These models will be enabled by the improved, systematic collection of population, behavioural and disease data. To enable model creation and evaluation, this data will be made available in standardised formats through prearranged and/or rapidly deployable legal collaboration agreements between modelling and public health teams. Communication between these teams will be enhanced by a clear presentation of model assumptions, uncertainties and results, and local populations will be empowered through the development of public engagement tools and consultations.

As we continue to progress towards an ever more connected global society, frameworks for efficient and effective cooperation, and necessary stakeholder engagement, must be developed to ensure that IDPs and refugees are considered in the development of epidemiological models to fight currrging threats, and ensure that no one is left behind.

Author affiliations
[1]UN Global Pulse, United Nations, New York, New York, USA
[2]Institute for Data Science, Durham University, Durham, UK
[3]Centre for Crisis Studies and Mitigation, The University of Manchester, Manchester, UK
[4]Department of Earth and Environmental Sciences, The University of Manchester, Manchester, UK
[5]Division of Informatics, Imaging and Data Sciences, The University of Manchester, Manchester, UK
[6]Department of Mathematics, The University of Manchester, Manchester, UK
[7]UK Public Health Rapid Support Team, London School of Hygiene & Tropical Medicine/Public Health England, London, UK
[8]WHO Cox's Bazar Emergency Sub-Office, United Nations, Cox's Bazar, Bangladesh
[9]UNHCR Cox's Bazar Sub-Office, United Nations, Cox's Bazar, Bangladesh
[10]Department of Science, Technology, Engineering and Public Policy, University College London, London, UK
[11]WHO Eastern Mediterranean Regional Office, United Nations, Cairo, Egypt
[12]Stern School of Business, New York University, New York City, New York, USA
[13]UNHCR Public Health Unit, United Nations, Cox's Bazar, Bangladesh
[14]OCHA Centre for Humanitarian Data, United Nations, The Hague, The Netherlands
[15]UNHCR Public Health Unit, United Nations, Geneva, Switzerland
[16]UNHCR Global Data Service, United Nations, Copenhagen, New York, USA
[17]UNHCR Innovation, United Nations, Geneva, Switzerland
[18]Faculty of Technology, Policy, and Management, Department of Engineering Systems and Services, Delft University of Technology, Delft, The Netherlands

Twitter Joseph Aylett-Bullock @josephpbullock and Robert Tucker Gilman @GilmanTucker

Acknowledgements The authors would like to thank the many colleagues who participated in useful feedback and discussions which helped shape this work. In particular, much of this paper grew out of a wider consultation and informal discussion in December 2020 hosted by United Nations Global Pulse which included a broad range of participants all of whom we are extremely grateful to. The authors would also like to thank Cassandra Hendricks for administrative and operational support in completing this work.

Contributors JA-B, ML-O conceived the project. All authors contributed to the writing of this manuscript. JA-B is the guarantor.

Funding United Nations Global Pulse work is supported by the Governments of Sweden and Canada, and the William and Flora Hewlett Foundation. JA-B, AQ-B and CC-L are also supported by the UKRI-STFC grant number ST/P006744/1. The UK Public Health Rapid Support Team is funded by UK Aid from the Department of Health and Social Care and is jointly run by Public Health England and the London School of Hygiene Tropical Medicine. IH is a principal investigator of the NIHR Policy Research Programme in Operational Research for Emergency Response Analysis (OPERA, PR-R17-0916-21001) and supported by JUNIPER (Joint UNiversities Pandemic and Epidemiological Research) and PROTECT COVID-19 National Core Study on Transmission and Environment. FK gratefully acknowledges funding as Royal Society Wolfson Research fellow.

Disclaimer The authors alone are responsible for the views expressed in this article and they do not necessarily represent the views, decisions or policies of the institutions with which they are affiliated including the Department of Health and Social Care, NIHR, the WHO, or the United Nations.

Competing interests No competing interests expressed.

Patient consent for publication Not applicable.

Ethics Ethics approval was not required for this study as no data was collected or analysed.

Provenance and peer review Not commissioned; externally peer reviewed.

Data availability statement No data was collected or analysed.

ORCID iDs
Joseph Aylett-Bullock http://orcid.org/0000-0001-7551-3423
Robert Tucker Gilman http://orcid.org/0000-0003-2000-7966
David Kennedy http://orcid.org/0000-0003-0004-6167
Egmond Samir Evers http://orcid.org/0000-0001-8382-9946
Keyrellous Adib http://orcid.org/0000-0001-9995-8400
Pierre Nabeth http://orcid.org/0000-0002-1567-6252
Katherine Hoffmann Pham http://orcid.org/0000-0002-1022-6025
Allen Gidraf Kahindo Maina http://orcid.org/0000-0002-7995-5445
Tinka Valentijn http://orcid.org/0000-0002-1109-1484
Tina Comes http://orcid.org/0000-0002-8721-8314
Leonardo Milano http://orcid.org/0000-0003-1563-640X
Miguel Luengo-Oroz http://orcid.org/0000-0002-8694-2001

REFERENCES

1 Altare C, Kahi V, Ngwa M, *et al*. Infectious disease epidemics in refugee camps: a retrospective analysis of UNHCR data (2009-2017). *J Glob Health Rep* 2019;3:e2019064.
2 Kondilis E, Papamichail D, McCann S, *et al*. The impact of the COVID-19 pandemic on refugees and asylum seekers in Greece: a retrospective analysis of national surveillance data from 2020. *EClinicalMedicine* 2021;37:100958.
3 OCHA. What is the cluster approach? 2020. Available: https://www.humanitarianresponse.info/en/coordination/clusters/what-cluster-approach
4 UNHCR. UNHCR refugee coordination model, 2020. Available: https://www.unhcr.org/excom/icm/53679e2c9/unhcr-refugee-coordination-model.html
5 Charnley GEC, Kelman I, Gaythorpe KAM, *et al*. Traits and risk factors of post-disaster infectious disease outbreaks: a systematic review. *Sci Rep* 2021;11:5616.
6 Brauer F. Compartmental models in epidemiology. In: *Mathematical epidemiology*. Springer, 2008: 19–79.
7 Hanski I, Gilpin M. Metapopulation dynamics: brief history and conceptual domain. *Biol J Linn Soc Lond* 1991;42:3–16.
8 Rohani P, Earn DJ, Finkenstädt B, *et al*. Population dynamic interference among childhood diseases. *Proc Biol Sci* 1998;265:2033–41.
9 Grenfell BT, Bolker BM. Cities and villages: infection hierarchies in a measles metapopulation. *Ecol Lett* 1998;1:63–70.
10 Gatto M, Bertuzzo E, Mari L, *et al*. Spread and dynamics of the COVID-19 epidemic in Italy: effects of emergency containment measures. *Proc Natl Acad Sci U S A* 2020;117:10484–91.
11 Arenas A, Cota W, Gómez-Gardeñes J, *et al*. Modeling the spatiotemporal epidemic spreading of COVID-19 and the impact of mobility and social distancing interventions. *Phys Rev X* 2020;10:041055.
12 Epstein JM. Modelling to contain pandemics. *Nature* 2009;460:687.
13 Bedson J, Skrip LA, Pedi D, *et al*. A review and agenda for integrated disease models including social and behavioural factors. *Nat Hum Behav* 2021;5:834–46.
14 Merler S, Ajelli M, Fumanelli L, *et al*. Spatiotemporal spread of the 2014 outbreak of Ebola virus disease in Liberia and the effectiveness of non-pharmaceutical interventions: a computational modelling analysis. *Lancet Infect Dis* 2015;15:204–11.
15 Anderson J, Chaturvedi A, Cibulskis M. Simulation tools for developing policies for complex systems: modeling the health and safety of refugee communities. *Health Care Manag Sci* 2007;10:331–9.
16 Crooks AT, Hailegiorgis AB. An agent-based modeling approach applied to the spread of cholera. *Environ Model Softw* 2014;62:164–77.
17 Augustijn-Beckers E, Useya J, Zurita-Milla R. Simulation of cholera diffusion to compare transmission mechanisms. *Proceedings of the 11th International Conference on Geocomputation*, University College London, 2011:39–42.
18 van Zandvoort K, Jarvis CI, Pearson CAB, *et al*. Response strategies for COVID-19 epidemics in African settings: a mathematical modelling study. *BMC Med* 2020;18:1–19.
19 Frost I, Craig J, Osena G, *et al*. Modelling COVID-19 transmission in Africa: countrywise projections of total and severe infections under different lockdown scenarios. *BMJ Open* 2021;11:e044149.
20 Ferguson EA, Brum E, Chowdhury A. Modelling to inform the covid-19 response in Bangladesh. *medRxiv* 2021.
21 OCHA. Bucky: a covid-19 model to inform humanitarian operations, 2020. Available: https://data.humdata.org/dataset/2048a947-5714-4220-905b-e662cbcd14c8/resource/2d9592f8-2980-4466-96f5-f0de23ea7ffa/download/ochabucky_final.pdf
22 Musalam AMA, El-Ashgar NM, Al-Agha M, *et al*. Sheltering and quarantine measures for risks that threaten the village of Umm AL-Nasr, Gaza strip. *J Emerg Manag* 2021;18:127–39.
23 Truelove S, Abrahim O, Altare C, *et al*. The potential impact of COVID-19 in refugee camps in Bangladesh and beyond: A modeling study. *PLoS Med* 2020;17:e1003144–15.
24 Kamrujjaman M, Mahmud MS, Ahmed S, *et al*. SARS-CoV-2 and Rohingya refugee camp, Bangladesh: uncertainty and how the government took over the situation. *Biology* 2021;10. doi:10.3390/biology10020124. [Epub ahead of print: 05 02 2021].
25 Hariri M, Obaid W, Rihawi H. The COVID-19 forecast in northwest Syria the imperative of global action to avoid catastrophe. *medRxiv* 2020.
26 WHO. WHO COVID-19 essential supplies forecasting tool (COVID-ESFT), 2021. Available: https://www.who.int/publications/i/item/WHO-2019-nCoV-Tools-Essential-forecasting-2021-1
27 Fouad FM, McCall SJ, Ayoub H, *et al*. Vulnerability of Syrian refugees in Lebanon to COVID-19: quantitative insights. *Confl Health* 2021;15:13.
28 Ayoub HH, Chemaitelly H, Mumtaz GR, *et al*. Characterizing key attributes of COVID-19 transmission dynamics in China's

original outbreak: model-based estimations. *Glob Epidemiol* 2020;2:100042.
29 Pascual-Garcia A, Klein J, Villers J. Empowering the crowd: feasible strategies to minimize the spread of covid-19 in high-density informal settlements. *medRxiv* 2020.
30 Hernandez-Suarez C, Verme P, Radyakin S. Covid-19 outbreaks in refugee camps. *medRxiv* 2020.
31 Ssematimba A, Nakakawa JN, Ssebuliba J, *et al*. Mathematical model for COVID-19 management in crowded settlements and high-activity areas. *Int J Dyn Control* 2021:1358–69.
32 Aylett-Bullock J, Cuesta-Lazaro C, Quera-Bofarull A, *et al*. Operational response simulation tool for epidemics within refugee and IDP settlements: A scenario-based case study of the Cox's Bazar settlement. *PLoS Comput Biol* 2021;17:e1009360.
33 Aylett-Bullock J, Cuesta-Lazaro C, Quera-Bofarull A, *et al*. June: open-source individual-based epidemiology simulation. *R Soc Open Sci* 2021;8:210506.
34 Gilman RT, Mahroof-Shaffi S, Harkensee C, *et al*. Modelling interventions to control COVID-19 outbreaks in a refugee camp. *BMJ Glob Health* 2020;5:e003727.
35 Claude KM, Serge MS, Alexis KK, *et al*. Prevention of COVID-19 in internally displaced persons camps in War-Torn North Kivu, Democratic Republic of the Congo: a mixed-methods study. *Glob Health Sci Pract* 2020;8:638–53.
36 Kluge HHP, Jakab Z, Bartovic J, *et al*. Refugee and migrant health in the COVID-19 response. *The Lancet* 2020;395:1237–9.
37 Raju E, Ayeb-Karlsson S. COVID-19: how do you self-isolate in a refugee camp? *Int J Public Health* 2020;65:515–7.
38 Winskill P, Whittaker C, Walker P, *et al*. *Report 22: equity in response to the covid-19 pandemic: an assessment of the direct and indirect impacts on disadvantaged and vulnerable populations in low-and lower middle-income countries*. London: Imperial College London, 2020.
39 Nordling L. The pandemic appears to have spared Africa so far. scientists are struggling to explain why. *Science* 2020;26.
40 Mbow M, Lell B, Jochems SP, *et al*. COVID-19 in Africa: dampening the storm? *Science* 2020;369:624–6.
41 Williamson EJ, Walker AJ, Bhaskaran K, *et al*. Factors associated with COVID-19-related death using OpenSAFELY. *Nature* 2020;584:430–6.
42 Urrutia-Pereira M, Mello-da-Silva CA, Solé D. Household pollution and COVID-19: irrelevant association? *Allergol Immunopathol* 2021;49:146–9.
43 Watson OJ, Alhaffar M, Mehchy Z. Report 31: estimating the burden of covid-19 in Damascus, Syria: an analysis of novel data sources to infer mortality under-ascertainment; 2020.
44 WHO. Bangladesh: who strengthening community-based surveillance to address covid-19 related misinformation, 2020. Available: https://www.who.int/news-room/feature-stories/detail/bangladesh-who-strengthening-community-based-surveillance-to-address-covid-19-related-misinformation
45 Mistry SK, Ali ARMM, Yadav UN, *et al*. Misconceptions about COVID-19 among older Rohingya (forcefully displaced Myanmar nationals) adults in Bangladesh: findings from a cross-sectional study. *BMJ Open* 2021;11:e050427.
46 Malani A, Shah D, Kang G, *et al*. Seroprevalence of SARS-CoV-2 in slums versus non-slums in Mumbai, India. *Lancet Glob Health* 2021;9:e110–1.
47 Hintermeier M, Gencer H, Kajikhina K, *et al*. SARS-CoV-2 among migrants and forcibly displaced populations: a rapid systematic review. *J Migr Health* 2021;4:100056.
48 WHO. The unity studies: who sero-epidemiological investigations protocols, 2020. Available: https://www.who.int/emergencies/diseases/novel-coronavirus-2019/technical-guidance/early-investigations
49 UNHCR. Microdata library. Available: https://microdata.unhcr.org/index.php/home
50 OCHA. Humanitarian data exchange. Available: https://data.humdata.org
51 Rhodes T, Lancaster K, Lees S, *et al*. Modelling the pandemic: attuning models to their contexts. *BMJ Glob Health* 2020;5:e002914.
52 Aguas R, White L, Hupert N, *et al*. Modelling the COVID-19 pandemic in context: an international participatory approach. *BMJ Glob Health* 2020;5:e003126.
53 Flatten. Flatten in Somalia. Available: https://www.flatten.ca/somalia
54 Lapointe-Shaw L, Rader B, Astley CM, *et al*. Web and phone-based COVID-19 syndromic surveillance in Canada: a cross-sectional study. *PLoS One* 2020;15:e0239886.
55 Facebook Data for Good. Symptom survey. Available: https://dataforgood.fb.com/tools/symptomsurvey/
56 Koum Besson ES, Norris A, Bin Ghouth AS, *et al*. Excess mortality during the COVID-19 pandemic: a geospatial and statistical analysis in Aden governorate, Yemen. *BMJ Glob Health* 2021;6:e004564.
57 Quinn JA, Nyhan MM, Navarro C, *et al*. Humanitarian applications of machine learning with remote-sensing data: review and case study in refugee settlement mapping. *Philos Trans A Math Phys Eng Sci* 2018;376:20170363.
58 Logar T, Bullock J, Nemni E, *et al*. PulseSatellite: a tool using Human-AI feedback loops for satellite image analysis in humanitarian contexts. *Proc Conf AAAI Artif Intell* 2020;34:13628–9.
59 UNHCR. The 10-point plan, chapter 2: data collection and analysis, 2007. Available: https://www.unhcr.org/uk/protection/migration/50a4c0829/10-point-plan-action-chapter-2-data-collection-analysis.html
60 UN Global Pulse. Risks, harms and benefits assessment, level 1, 2016. Available: https://www.unglobalpulse.org/policy/risk-assessment/
61 UN Global Pulse. Risks, harms and benefits assessment, level 2, 2020. Available: https://www.unglobalpulse.org/policy/risk-assessment/
62 The Danish Institute for Human Rights. Human rights impact assessment guidance and toolbox, 2020. Available: https://www.humanrights.dk/tools/human-rights-impact-assessment-guidance-toolbox
63 Christley RM, Mort M, Wynne B, *et al*. "Wrong, but useful": negotiating uncertainty in infectious disease modelling. *PLoS One* 2013;8:e76277.
64 Adib K, Hancock PA, Rahimli A, *et al*. A participatory modelling approach for investigating the spread of COVID-19 in countries of the eastern Mediterranean region to support public health decision-making. *BMJ Glob Health* 2021;6:e005207.
65 RiskAware. Crystal cast product sheet: advanced disease forecasting to predict outbreaks and anticipate population impact, 2020. Available: https://www.riskaware.co.uk/wp-content/uploads/BioAware-CrystalCast-Product-Sheet.pdf
66 UNHCR. Refugee data finder, 2021. Available: https://www.unhcr.org/refugee-statistics/
67 Shea K, Borchering RK, Probert WJM, *et al*. COVID-19 reopening strategies at the county level in the face of uncertainty: multiple models for outbreak decision support. *medRxiv* 2020. doi:10.1101/2020.11.03.20225409. [Epub ahead of print: 05 Nov 2020].
68 Amant KS, Ballentine BD. Open source software, access, and content creation in the global economy. *J Tech Writ Commun* 2011;41:341–6.
69 Hogan AB, Winskill P, Watson OJ. Report 33: modelling the allocation and impact of a covid-19 vaccine; 2020.
70 Bubar KM, Reinholt K, Kissler SM, *et al*. Model-informed COVID-19 vaccine prioritization strategies by age and serostatus. *Science* 2021;371:916–21.
71 Thomas CM, Osterholm MT, Stauffer WM. Critical considerations for COVID-19 vaccination of refugees, immigrants, and migrants. *Am J Trop Med Hyg* 2021;104:433–5.