Real-time analytical insights for disease surveillance and response during the severe drought and food security crisis, Somalia 2022-2023

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Abstract

Background

Decades of conflict, epidemics, and climatic shocks have severely weakened Somalia's health system. The failure of five consecutive rainy seasons in 2022–2023 led to the longest and most severe drought in recent history, resulting in an unprecedented nutrition and food security crisis. These conditions have heightened the risk of disease epidemics, particularly cholera and measles. To assess the effect of interventions on disease transmission in real time, make short-term projections of disease incidence, and inform response efforts, the World Health Organization Somalia Country Office developed the Somalia infectious disease explorer (WHO-SIDE).

Objective

To describe the development and application of WHO-SIDE and demonstrate its potential to identify high-risk areas for targeted public health interventions.

Description

WHO-SIDE is an interactive web-based application designed using the Shiny framework in R. It estimates the time-varying reproduction number (Rt), projects case incidence, and evaluates the impact of interventions on transmission. The application uses routine disease surveillance data, offering features such as data visualization, geographic analysis, and customizable epidemic projections.

Implementation

Since its deployment, WHO-SIDE has been used to monitor infectious disease trends, guide targeted interventions, and evaluate public health response efforts in Somalia. Outputs were reviewed jointly by WHO and Ministry of Health staff and formed part of the evidence base used to prioritise response activities. Challenges including limited access to technology, incomplete surveillance data, and a lack of trained personnel have hindered its full potential.

Implications

WHO-SIDE highlights the feasibility and utility of analytical tools for disease monitoring and response in resource-limited, crisis-affected settings. Realising this potential will require sustained investment in three areas: building analytical capacity among local health staff; improving the completeness and timeliness of surveillance data; and developing processes for integrating modelled outputs with field intelligence. Without progress in these areas, tools such as WHO-SIDE risk producing outputs that are difficult to interpret and act upon in operational contexts.

Key words
Epidemic, drought, cholera, measles, surveillance, Somalia, humanitarian crisis

Introduction

Somalia has been experiencing a protracted, complex humanitarian crisis for several decades, driven by internal armed conflict, political instability and, more recently, climatic shocks including the failure of five consecutive rainy seasons between 2022 and 2023, which resulted in the longest and most severe drought in recent history [1]. These overlapping factors have created a nutrition, livelihood, and food security crisis on an enormous scale, leading to the displacement of nearly a million people in 2022-2023, and more than 6.5 million people in need of humanitarian assistance [1]. The severe drought throughout 2022 and 2023 put more than 1.4 million children aged under 5 years at risk of severe acute malnutrition, caused extreme hunger among millions of people, and presented the looming threat of infectious disease outbreaks [2]. In 2022, a localized famine was anticipated in some of the worst-hit areas of the country because of the acute hunger and extreme loss of livelihood of the pastoral communities [3]. This placed the already fragile health system under enormous strain, weakened as it was by 30 years of protracted conflict, natural disasters, and large, deadly disease outbreaks including the COVID-19 pandemic [4, 5]. Although famine was narrowly averted, there has been considerable excess mortality, with recent estimates suggesting that an additional 43,000 deaths were attributable to the drought and food insecurity in 2022 alone [6].

Owing to the duration and scale of the drought and food security crisis, and the fragility of the health system, increasing incidences of infectious diseases were anticipated, particularly of cholera and measles, outbreaks of which have occurred throughout the country in recent years [7–9]. Cholera outbreaks have been recurring since 2017 in certain geographical hot spots, largely fuelled by: limited access to safe water and proper sanitation among the more than 2 million internally displaced persons; high levels of malnutrition among children younger than 5 years; limited access to health care and large-scale population movement within Somalia and to neighbouring countries [8, 10]. Armed conflict and the resultant insecurity in the country render many areas and populations inaccessible [10, 11]. As a result, early signs of ongoing community transmission of cholera are often missed [8, 10]. Furthermore, suspected cholera cases reported at the community level are often not reported through the country's disease surveillance system [12]. Indeed, most of the official case counts of cholera include only those cases reported by cholera treatment centres.

Similarly, Somalia did not implement measles case-based surveillance until the end of 2023, with suspected cases only reported within healthcare facilities and excluded those reported in the community [9, 13]. Data quality is also questionable due to the use of inconsistent and/or inappropriate case definitions at healthcare facilities. Compounding these surveillance challenges, laboratory diagnostic capacity for both cholera and measles is very limited, with most reported infections being unconfirmed, particularly in remote and inaccessible areas [9, 13]. Therefore, the number of cases of both diseases officially reported is likely a substantial underestimate.

Such underreporting and underestimation of the true burden of disease poses challenges in using surveillance data to inform public health response activities [14]. A major concern for public health agencies operating in resource-limited and crisis-affected settings characterised by poor access to populations is how to make use of sparse and, in some cases, biased surveillance data to guide public health activities [14–17]. To continue to advocate for effective and timely public health interventions, to be able to target geographical areas where the maximum public health benefits can be achieved, and to detect emerging health risks early to guide outbreak response efforts, it is crucial to establish systems to assess the effect of these interventions on disease transmission, estimate transmissibility in real time and make short-term projections of disease incidence [18]. To this end, the WHO Somalia Country Office developed the WHO Somalia infectious disease explorer (WHO-SIDE) to anticipate the trajectory of outbreaks and inform response efforts by identifying high-risk areas where targeted interventions may be implemented to minimize deaths and interrupt transmission. Given that cholera and measles are endemic in Somalia and their early detection and timely implementation of response efforts could save many lives, these two diseases were included by default in this application.

This article This article describes WHO-SIDE and its use during the 2022–2023 response, illustrating how routine surveillance data can be translated into operational guidance under crisis conditions..

WHO Somalia infectious disease explorer

WHO-SIDE is an interactive web-based data application built using the Shiny framework for the R statistical computing programming language [19, 20] and hosted by the WHO Country Office. The application code is available on request from the corresponding author. It consists of five sections: a quick-start user guide; data selection; data exploration; intervention impact; and transmissibility and projections.

Data selection and exploration

As cholera and measles are endemic in Somalia, and prompt implementation of response efforts has the potential to avert considerable morbidity and mortality, data on these two diseases are included by default in the application. During the loading process, WHO-SIDE imports the latest cholera and measles surveillance data, which are stored as anonymized line-listed data on a WHO Somalia server. The key variables used for analysis are geographical administrative variables (region and district), date of onset of disease, and case confirmation by laboratory test. The user determines the level of geographic aggregation of analysis (national, regional, or district).

The application also permits users to upload data, which crucially can also be temporally aggregated (i.e. surveillance data reported daily, weekly, or monthly). These data may relate to any disease in any geographical location. The user inputs the estimated mean and standard deviation of the serial interval, a key parameter for the estimation of transmissibility and forward projections. These can either be those values reported in the published literature (e.g. from systematic reviews) or estimated using the specific dynamics of ongoing disease transmission in a particular setting. Default parameter values for measles and cholera are included in the application and were derived from multiple review articles [21–24].

Following data selection, the data are presented descriptively as tables, maps, and epidemic curves, all of which can be explored interactively and downloaded.

Transmissibility and projections

Real-time understanding of the epidemiological situation is achieved by estimating the time-varying reproduction number (R_t) and making short-term projections of case incidence.

The time-dependent transmissibility of a pathogen, as estimated by R_t, is a critical metric, indicating whether incidence is increasing, decreasing or stable within a population. R_t is the average number of secondary infections arising from each primary case. Therefore, if R_t is about equal to 1, incidence is stable, as each case gives rise to one additional case, on average. By contrast, if R_t is >1, the incidence is increasing, while if R_t is <1, the incidence is decreasing. R_t therefore provides real-time insights into the transmissibility of diseases, thus helping to design effective control measures and offering a gauge of the effectiveness of an intervention [18, 25].

WHO-SIDE makes use of recent advances to *EpiEstim*, a widely used estimation framework, to rapidly estimate R_t from the daily incidence reconstructed from temporally aggregated data [25–28].

The range of estimated R_t values from the recent past can be sampled to make short-term forward projections of the incidence via a branching process modelling framework that uses a Poisson-distributed number of new cases per day to make projections of the epidemic trajectory [29]. In addition to R_t, the method uses the latest case counts and the serial interval parameters provided earlier to make 1000 simulations of the epidemic trajectory, from which the central estimate and 95% confidence interval is drawn.

Intervention impact

Evaluation of the effect of the intervention is achieved through exploration of the impact on case incidence using interrupted time-series analysis [30], implemented using the forecast R package [31]. In this approach, two independent negative binomial models are fitted to the data, before and after a

user-supplied intervention date, which include estimates of the trend and any seasonality detected in the data. The difference between the model estimates provides a visual measure of the existence and magnitude of any impact of the intervention.

Surveillance systems and data quality

Cholera surveillance

Cholera surveillance in Somalia has relied primarily on facility-based reporting, with case counts largely limited to those presenting at cholera treatment centres. Community-level transmission is systematically undercaptured. Contributing factors include insecurity in many areas (making active case-finding impossible), low community awareness of reporting pathways, and the absence of a formal community reporting infrastructure in much of the country [8, 10, 12]. In practice, outbreaks in geographically remote or conflict-affected areas may not come to the attention of the surveillance system until they have been ongoing for weeks. Completeness of reporting has also been variable across regions and over time, reflecting differences in health facility density, staff availability, and supply of reporting materials. Timeliness of reporting has similarly been inconsistent, partly because data from peripheral facilities often had to be transcribed and aggregated manually before upload.

Measles surveillance

Prior to the introduction of measles case-based surveillance in late 2023, suspected cases were reported only from healthcare facilities using an aggregate format that precluded individual-level analysis. Case definitions were applied inconsistently across facilities, and community-level cases were not captured. Laboratory confirmation rates were very low, particularly in remote areas, limiting the ability to distinguish measles from other febrile rash illnesses [9, 13].

Implications for interpretation

Taken together, these surveillance limitations mean that the data feeding WHO-SIDE systematically undercount true disease burden, with the degree of undercounting varying by geography and time. Areas with poor surveillance infrastructure, which are often the same areas affected by insecurity, may appear to have low disease burden when cases are simply not being detected. Throughout the implementation period, users were explicitly advised that Rt estimates and case projections reflected reported rather than true epidemic size, and that apparent low case counts in regions with known surveillance gaps warranted particular caution.

Implementation

Analytical workflow and decision-making

During the 2022–2023 drought response, WHO-SIDE outputs were reviewed regularly by WHO epidemiologists and Ministry of Health (MoH) staff within the context of broader outbreak response coordination. Analyses were produced weekly during periods of active transmission, with more frequent updates during rapidly evolving situations. Results were presented at national and subnational coordination meetings alongside contextual information from field teams — including reports of access constraints, population displacement, and vaccination coverage — that could not be captured within the application itself but were essential for interpreting the outputs. This integration of modelled outputs with contextual intelligence was central to the application's utility. A district with stable or declining modelled Rt but known field reports of barriers to care-seeking would not be deprioritised on the basis of the application's outputs alone. The workflow therefore relied on users exercising judgement, and the application served as a tool to structure and quantify that judgement rather than to replace it.

Practical use cases

The application supported decision-making across several phases of the outbreak response. During the preparedness phase, trend analyses were used to identify districts where case counts were rising, enabling pre-positioning of supplies and mobilisation of rapid response teams ahead of a potential escalation. Subnational Rt estimates helped prioritise which of several simultaneously deteriorating districts warranted the most urgent attention given limited response capacity. During active outbreak response, short-term projections provided a basis for estimating the scale of additional resources likely to be required over the following two weeks — including oral rehydration solution stocks, treatment centre capacity, and workforce deployment. These projections explicitly communicated uncertainty through confidence intervals, enabling planners to consider both optimistic and pessimistic scenarios rather than relying on a single point estimate. Interrupted time-series analyses were used retrospectively to evaluate whether specific interventions — notably vaccination campaigns and water, sanitation, and hygiene activities — appeared to be associated with reductions in case incidence, informing decisions about whether to sustain, scale up, or redirect those interventions.

Illustrative examples

The application was used to assess the impact of a nationwide measles vaccination campaign conducted in October 2021. Preliminary analyses suggested that a 2023 outbreak of measles on the scale of that observed in 2017 may have been averted through the rapid roll-out of a mass immunization campaign when cases started to increase (Figure 1).

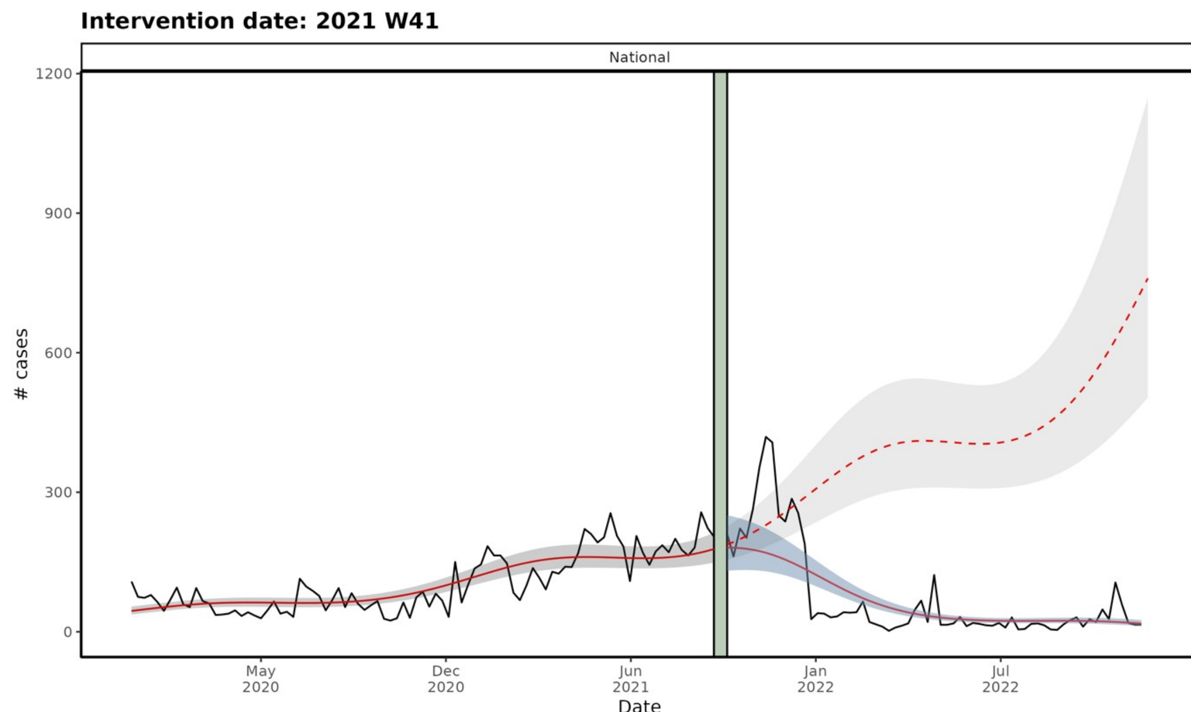

Figure 1. Impact of a nationwide measles vaccination campaign using interrupted time-series analysis, Somalia, January 2020–December 2022.

Notes. Black line: reported case incidence. Green bar: intervention period. Left of green bar — solid red line and grey shading: pre-intervention model fit and 95% CI. Right of green bar — dashed red line and light grey shading: projected trajectory absent the intervention; solid red line and blue shading: post-intervention model fit and 95% CI.

The application was also used to provide granular understanding of the measles epidemiological context in Banadir and Lower Shabelle regions, where local factors were known to restrict population access to health services. R_t was estimated between June and November 2023, with short-term projections through December 2023 (Figure 2). In both regions, R_t was oscillating at or just below 1, with incidence projected to be stable (Banadir) or declining (Lower Shabelle).

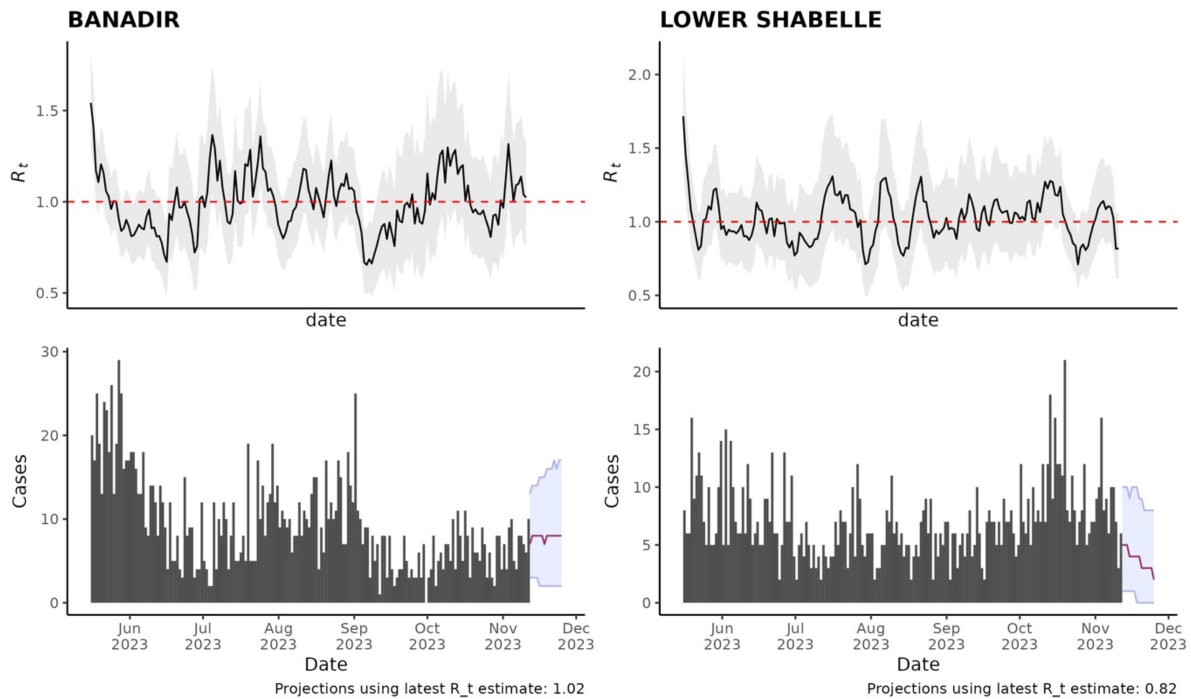

Figure 2. Estimation of measles time-varying reproduction number (R_t) for the preceding 6 months (upper panels) and epidemic curves with 14-day forward projections of incidence (lower panels) for Banadir and Lower Shabelle regions, Somalia

Notes. Upper panels — solid line: Rt estimate; grey shading: 95% CI. Lower panels — solid red line: projected incidence; blue shading: 95% CI.

Similarly, a measurable reduction in morbidity and mortality was reported following the scaling-up of cholera-specific interventions in five districts of Jubaland state, which borders Ethiopia and Kenya, during 2023. The application helped anticipate the rapid evolution of an explosive cholera epidemic in early April 2023. This early signal prompted targeted interventions, including localized cholera vaccination campaigns in districts with sporadic cases, enhanced surveillance, active case finding, and intensified community-level case management. WHO-SIDE was used throughout to monitor trends and communicate the evolving epidemiological situation to response partners.

Discussion

WHO-SIDE is a decision-making tool that makes use of routine disease surveillance data to perform close to real-time monitoring of transmissibility, make short-term projections, and evaluate the impact of interventions. In a context of intersecting political, public health, and climate crises, this approach was shown to be both feasible and useful when accompanied by robust efforts to strengthen surveillance systems to report with greater completeness and timeliness. The analytical approaches were used to identify high-risk areas for targeted interventions, to monitor disease transmissibility and promptly identify deteriorating trends, and assess the impact of interventions including vaccination campaigns and activities related to water, sanitation, and hygiene.

During this period, WHO supported national and subnational health authorities to reach approximately seven million people, roughly 75% of those estimated to need assistance, through a coordinated programme spanning immunisation, community nutrition screening, cholera treatment, and mass vaccination campaigns for cholera, measles, and polio.. Although it is difficult to know the counter-factual scenario, it is believed that these public health interventions were critical in averting a greater public health crisis than that already observed. In 2022-2023, there were no major disease epidemics in Somalia, and, despite its greater intensity, the number of excess deaths attributable to the ongoing

drought was substantially lower than that observed during the 2011/2012 drought [6, 32]. This was achieved in a country with one of the most fragile and weakened health systems globally [5].

Limitations

The most important limitation of WHO-SIDE is data quality. As described above, the surveillance systems feeding the application are characterised by systematic undercounting, variable completeness and timeliness, and geographic gaps that correlate with insecurity and access constraints. These issues are not trivial: areas with the greatest disease burden are often precisely those where surveillance is least complete, meaning that application outputs could inadvertently direct attention away from the populations most in need. Users were advised to treat outputs as one input among several, interpreted alongside field reports and qualitative intelligence. Explicit communication of this limitation at coordination meetings was an important component of the implementation, though more structured safeguards, such as data quality indicators displayed within the application, would be a valuable addition in future iterations.

Neither Rt estimates nor case projections have been formally validated against ground-truth data in this context. The surveillance gaps described above preclude this: constructing the reference series against which projections would need to be assessed requires a level of data completeness that was not available here, and the degree of undercounting varies sufficiently across geography and time to make retrospective comparison unreliable. The claim that the application supported outbreak anticipation should therefore be interpreted with this absence in mind, and validation studies in settings with more complete surveillance data would be an important step for future work. Assessing intervention impact through interrupted time-series analysis of routinely collected data is similarly limited compared with dedicated study designs, though the latter were not feasible given access constraints and the operational intent of the tool.

A further challenge relates to sustainability. During the implementation period, analytical capacity resided primarily with WHO technical staff, with more limited involvement from MoH counterparts. Sustainable use of WHO-SIDE, particularly given ongoing efforts to localise humanitarian response, will require investment in training local health professionals to use and interpret the application independently. The MoH was engaged as a partner throughout, reviewing outputs and co-chairing coordination meetings at which results were presented; increasing its analytical ownership of the tool is a priority for future phases. The application was developed and maintained with WHO staff time, and planning for its longer-term handover to national authorities represents a real operational challenge that must be accounted for from the outset of similar tool development efforts.

Conclusions

WHO-SIDE demonstrated that real-time analytical tools can meaningfully support outbreak response in crisis-affected settings, helping health authorities track transmission trends and pre-empt deteriorating situations in geographic areas that might otherwise have been overlooked. While the importance of outbreak analytical tools, including R_t estimation, is clear, their implementation in the context of protracted, complex crises has many challenges. Limited access to technology, trained personnel and reliable data sources is further compounded by the crisis setting, which necessitates rapid life-saving activities without always having the time to develop tailored analyses. In this context, broadly applicable outbreak analytical tools are a practical necessity.

The development of broadly applicable, open-source outbreak analytics tools can help lower the technical barriers to adoption. Sustained use, however, requires investment in three complementary areas: local capacity-building (including training health professionals to operate and interpret such tools, and to communicate uncertainty to decision-makers); improvements to the underlying surveillance systems, without which analytical outputs will remain of limited reliability; and explicit processes for integrating modelled outputs with contextual intelligence from field teams, as a safeguard against over-reliance on quantitative outputs in settings where data are inherently imperfect.

Somalia is unlikely to be the last setting in which conflict, disease, and climatic stress converge. The lessons from this implementation, both its utility and its limitations, are relevant wherever surveillance systems are imperfect and analytical capacity is scarce [18, 33, 34].

Declarations

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Annex: Technical requirements for WHO-SIDE

Software requirements

WHO-SIDE is built on R (version 4.2 or later) and requires the following packages: shiny, EpiEstim, projections, forecast, ggplot2, dplyr, leaflet, and DT. All packages are freely available from CRAN. The application can be run locally using R and RStudio, or hosted on any server capable of running Shiny applications (including shinyapps.io or a locally configured Shiny Server).

Hardware requirements

The application can be run on a standard laptop or desktop computer. A minimum of 4 GB RAM is recommended; 8 GB or more will improve performance for large datasets. No specialised hardware is required.

Connectivity requirements

A stable internet connection is required when accessing the centrally hosted version. Connection speeds of 1 Mbps or above are typically sufficient. For use in low-connectivity environments, the application can be configured to run locally using pre-downloaded data, removing the dependency on continuous internet access during analysis. This configuration has been used in field settings where connectivity is intermittent.

Data requirements

The minimum data requirements are: a date variable (onset or report date), a geographic identifier (at minimum country level), and a case count or individual-level record. The application accepts both line-listed and temporally aggregated data formats. For Rt estimation and projections, approximately two to three weeks of data are recommended for stable estimates; the application will produce outputs from smaller datasets, but with correspondingly wider uncertainty intervals.