Landscape mapping of software tools for climate- sensitive infectious disease modelling

Inter-American Institute for Global Change Research: IAI

Team

Anna M. Stewart Ibarra, Inter-American Institute for Global Change Research (IAI)

Scientific Director of the IAI, an inter-governmental organization based in Montevideo, Uruguay. She was formerly the Director of the Latin America and Caribbean Research Program of the Institute for Global Health and Translational Science at the State University of New York Upstate Medical University (SUNY UMU) from 2012 to 2019. She is also an Assistant Professor (voluntary faculty appointment) in the Department of Medicine at SUNY UMU.

Sadie J. Ryan, University of Florida

Associate Professor of Medical Geography at the University of Florida, with a joint appointment in Geography and the Emerging Pathogens Institute (EPI). PI of the Quantitative Disease Ecology and Conservation (QDEC) Lab. Research ongoing in Ecuador, NY State, and Southern Africa.

Rachel Lowe, The London School of Hygiene & Tropical Medicine (LSHTM)

Royal Society Dorothy Hodgkin Fellow based at LSHTM, her research is supported by the Global Challenges Research Fund. Rachel leads a group of researchers working between the Centre for Mathematical Modelling of Infectious Diseases and the Centre on Climate Change & Planetary Health.

Catherine A. Lippi, University of Florida

Postdoctoral Associate, Medical Geography, University of Florida. PhD in Medical Geography, University of Florida. MFAS in Fisheries and Aquatic Science, University of Florida. Graduate Certificate in Applied Biostatistics, University of South Florida.

Avriel Diaz, Walking Palms Global Health and Columbia University

Co-founder and Executive Director of Walking Palms Global Health Consultant. Climate and Health Research PhD Student at Columbia University in the City of New York.

Willy Dunbar, Florida International University

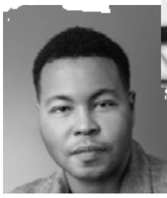
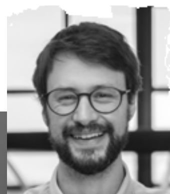
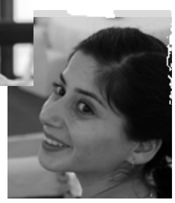
Postdoctoral Research Associate at the Department of Health Promotion and Disease Prevention, Florida International University (FIU). Visiting Scholar at the School of Public Health, Université libre de Bruxelles (ULB) in Belgium.

Simon Johnson, HetCo Design

Software developer who has worked on responses to infectious diseases for 7 years, starting with the West Africa Ebola outbreak. He has created open source software for infectious disease surveillance which has been deployed by Médecins Sans Frontières in multiple countries in conjunction with local departments of health.

Shruti Grover, HetCo Design

Shruti is a Human Centred Designer/Researcher who has led the conception, research, design and delivery of innovative products and services for BBC, King's College London, Wellcome Trust, Médecins Sans Frontières, Stannah Stairlifts, Proteus Digital Health, Chelsea and Westminster Hospital, Cerestim Therapeutics, Ford, Rio Tinto and the Seoul Design Foundation.



Index

Executive summary

Climate-informed infectious disease models have the potential to become powerful tools to support public health decision making. This project aimed to identify existing software tools at the intersection of climate and infectious diseases, and to identify opportunities for the development of tools.

After searching PubMed for papers published over the last 10 years, using a customized API and keywords for scoping climate and health software, we found 37 fully developed and named tools. We interviewed experts in modelling research and public health decision making to understand their perspectives on the software tools landscape.

We found very few robust, evidence-led operationalized models. This suggests that few studies progress from providing the initial evidence of climate-health linkages to the operationalization of a decision support tool that could inform actions to reduce the burden of disease.

The majority of tools identified in our review focused on vector-borne disease systems. There is a shortage of tools for respiratory, foodborne, and waterborne diseases, and no tools for soilborne diseases. This revealed an opportunity to develop tools for these neglected disease groups.

More than half of the tools were described as operationalized; however, only one quarter were freely available online and only one quarter had interfaces legible to decision makers. Those that did have legible interfaces were funded by an institutional or country-level partner. Transitioning research to public health practise must be accounted for from the project outset since the data that feed into the model and the model output (e.g., interfaces) need to align with decision-making processes.

Most tools were developed for, and implemented in, geographic regions where the infectious disease of interest is currently endemic. Tools are needed for regions where the risk of disease transmission will increase substantially (zones of emergence) due to climate change, demographic shifts, and other factors.

North American and European institutions are disproportionately represented as tool-creators (38% in the USA and UK alone). In the co-creation of tools, there is a need for greater representation of investigators from the Global South, where many of the tools were designed to be used.

The spatial and temporal scale of the 37 tools varied widely. Most tools used gridded climate data to inform models. Few models forecast disease risk beyond the seasonal climate outlook. It is important to develop models across a range of spatio-temporal scales to capture climate and disease processes at different scales and to support decision-making needs across scales.

Common barriers to tool implementation include lack of effective communication between modelers and decision makers, lack of personnel to maintain and operate systems, and lack of training for new users to operate the tools. We also identified a lack of information on climate-disease modelling tools for non-English speaking countries. There is an opportunity to improve science communications, to produce information in multiple languages, and to build the capacity of local experts who are tool users.

We found that climate datasets are readily available, but sharing of health datasets is politically sensitive. Most public health and climate sectors do not yet have a mandate to focus on the climate impacts on health. There is a need to influence and inform policy to support cross-sectoral collaborations, long-term resource allocation for work on climate and health, and dataset sharing.

These findings indicate clear opportunities to invest in the development and implementation of climate-driven infectious disease modelling tools.

Project Structure

PROJECT OVERVIEW

Climate Change

Infectious Disease

1

Literature Review of Software Tools

2

Interviews With Global Experts

3

Conclusions and Recommendations

Project Overview

Predicting the risk of infectious disease outbreaks is valuable for public health preparedness. Infectious disease transmission and incidence are affected by changes in the climate at local, regional and global scales [1]. Increasing global temperatures can lead to alterations in human behavior that result in increased transmission of pathogens and more frequent infectious disease outbreaks [2]. Climatic conditions also directly influence environmental suitability for pathogen transmission and disease vectors, affecting the spatial-temporal distribution of infectious diseases, like malaria and its mosquito vectors [3,4].

Climate forecasting systems that enable us to predict disease risk are in great demand for public health planning and early warning systems (EWS) [1,5].

These systems often rely on statistical tools and forecasting models to estimate the future likelihood of disease outbreaks. They can provide valuable lead time for public health decision makers to take action ahead of an outbreak and can support policies aimed at reducing medium- and long-term climate risks.

Climate-informed tools have been frequently used for the study of vector-borne disease systems, given the documented effects of climate conditions (e.g., rainfall, temperature) on vector biology and disease transmission [3]. Yet, many infectious diseases are modulated by climate conditions at various scales, including diseases with direct transmission pathways (e.g., influenza spread via respiratory transmission), waterborne diseases (e.g., cholera, giardiasis), and food-borne diseases (e.g., salmonellosis) [6–8].

There are a number of computational and statistical frameworks that are applied to climate-disease problems. Specifically, model-based approaches offer the opportunity to identify the direction of climate-disease relationships and quantify these relationships under natural conditions (i.e., not relying on experimental approaches that are unfeasible or unethical). This allows for predictions and climate-based disease forecasts that can inform policy in a timely and anticipatory manner. Software tools and packages are being created in a variety of coding languages (e.g., R, Python, Julia etc.) from a range of perspectives and specializations, reflecting the numerous disciplines contributing to this field. These include medical and health geography, disease ecology, applied climate science, data science, epidemiology, public health, and infectious disease medicine.

Although climate-informed modelling systems can be useful in public health planning, there can be considerable barriers to adoption and implementation, such as gaps in technological expertise, a mismatch between the model outputs and decision-making needs, and financial constraints [5]. User-friendly software tools can be developed so that forecast models are more accessible to public health practitioners and other stakeholders interested in climate-informed decisions.

Project Aims

This project aimed to identify the availability of, and need for, software tools amongst the climate-sensitive infectious diseases modelling community and public health tool users.

The objectives of this project were:

To identify tools by scoping the landscape of models addressing climate-sensitive infectious diseases, with an eye to identifying the current available set of tools for public health decision makers.

To understand expert perspectives on tools by engaging with researchers and policy stakeholders at key organizations in the fields of climate and infectious disease to understand their perspectives on the software tools landscape.

Report Categories

Section I of this report describes a comprehensive literature review and synthesis. Section II shares the results of interviews with global experts from research and policy communities. Section III provides conclusions and recommendations.

1

Scoping Climate-Health Software for Infectious Diseases: Literature Review and Synthesis

Identifying 37 tools from 30,000 papers and synthesizing key findings.

Introduction

Climate-sensitive infectious diseases pose an increasing threat under the combined trajectories of demographic and climatic changes [1,3,9]. As human populations push into both increasingly urbanized and dense spaces [10], and rural and wild interfaces, the frequency of potential interactions with environmentally linked diseases is also increased. When we add the prospect of a changing climate, we are faced with the question: when and where will the risk of outbreaks or rising disease incidence occur? To answer this question, we must rely on our current understanding of climate-sensitive diseases in order to forecast or predict likely outcomes in the short-, medium-, or long-term future, using available datasets, models and tools.

In this report, we aimed to identify tools that incorporate both climate inputs and epidemiological information to produce an output as a prediction or indicator of disease risk. We sought to identify accessible software platforms that are also implementation ready. We scoped the landscape of models addressing climate-sensitive infectious diseases, with an eye to identifying the current available set of tools for public health decision makers.

The ideal tool

for modelling climate-sensitive infectious diseases fulfills the following required qualifications:

- **Incorporate both climate inputs and epidemiological information.**
- **Produce an output as a prediction or indicator of disease risk in a single software package.**
- **Are transparently described and validated.**
- **Are named, for future searching and versioning.**
- **Are accessible - code is published, or available on a code repository, a web platform, or other.**

1.1 Methodology

A —

Automated Review

Using our application programming interface (API), we searched PubMed for papers published between 2011-2021 using search term triplets combining climate, infectious disease, and technological keywords (e.g., climate+epidemic+logistic, seasonal+influenza+forecast, etc). The full list of search terms is provided in the Appendix.

This resulted in ~60,000 unique searches yielding over 30,000 unique papers. This list was reduced by analysing relevancy of keywords and Medical Subject Heading (MeSH) terms (i.e., terms used in PubMed to classify papers with keywords) and quality of search terms, resulting in 9,500 publications. A relevancy score was devised and the top ~2000 relevant papers were reviewed, in addition to papers that contained technological tool terms. A total of 2,380 relevant papers from the literature search were partitioned into seven sets for manual screening, to identify papers that potentially featured tools within the scope of the review.

B —

Paper Review

The full list of papers comprised 242 publications. Of these papers, 62 were identified as having potentially operationalized modelling tools. Following screening and data extraction, 48 of the papers featured a named infectious disease modelling tool that incorporated climatological or meteorological data. After accounting for studies that used the same models, we found a total of 37 unique tools (Table 2).

C —

Tool Enrichment

We investigated each of the 37 tools individually and created a database which contained additional attributes about each tool including: the models of infectious disease systems each tool utilised, the software packages used to build it, and whether or not the code repositories were openly accessible. The full list of attributes is presented below :

Publication Details

- Study ID
- Authors
- Institutions
- Publication Date
- Foundational Paper

Study Information

- Country
- WHO Region
- Disease or Vector
- Mode of Transmission

Tool Specifics

- Operationalized
- Availability
- Link to Tool Partners
- Tool Name
- Name Acronym
- Derived Model
- Name of Original
- Model
- Type of Model
- Software
- Scale of Study
- Input Data
- Climate Products
- Climate Variables
- Model Output

1.2 Result in Alphabetical Order

AeDES Aedes-borne Diseases	**albopictus package** Aedes-borne disease	**ANOSPEX** Malaria	**ArboMAP** West Nile virus	**BODA' package** Campylo bacteriosis	**CIMSiM, DENSiM** Dengue
Disease Monitoring Dashboard West Nile virus	**DyMSiM** West Nile Virus	**ECDC** Vibrio Map Viewer	**EPIDEMIA** Malaria	**epidemiar** Malaria	**EpiGraph** Influenza
EPIPOI Diverse health problems	**eRisk Mapper** Diverse health problems	**EWARS** Dengue	**FleaTickRisk** Transmitted by Rhipicephalus sanguineus ticks	**HYDREMATS** Malaria	**LIS-MAL** Malaria
Liverpool Malaria Model Malaria	**Liverpool Malaria Model 2010** Malaria	**Liverpool RVF model** Rift Valley Fever	**LMM_RO, MIASMA, UMEA MARA** Malaria	**MARA LITe** Malaria	**MGDrivE 2** Mosquito-borne diseases
MVSE Mosquito-borne viruses	**OMaWa** Malaria	**Open Malaria** Malaria	**Rapid Inquiry Facility** Diverse health problems	**RVF plug-in** Rift Valley Fever	**SCOPIC** Malaria
SLIM Malaria	**STEM** Influenza	**VECTRI** Malaria	**WNV_model** West Nile Virus	**yews4denv** Dengue	

List of unique tools with a climate component used for the analysis of infectious diseases.

Explore the online database: https://hetco.io/tools-for-climate-sensitive-diseases/tool-list/

1.3 Key Findings

We identified only 37 fully developed tools, but identified other models that represent an opportunity for tool development.

Of the 9,500 papers identified in the literature review, we found only 37 unique software tools meeting our criteria. This suggests that few studies progress from providing the initial evidence of climate-health linkages to the operationalization of a decision support tool that could inform actions to reduce the burden of disease. However, a number of models identified in this review could be rapidly transitioned to useful tools with additional development support.

The majority of tools focused on vector-borne disease systems

Most tools identified in our review (81.1%) focused on vector-borne disease systems. Of the tools dedicated to modelling vector-borne diseases (n=30), 53.3% focused on malaria, 13.3% on dengue, 13.3% on West Nile virus, and 6.7% on Rift Valley fever. There is a shortage of tools for respiratory, foodborne, and waterborne diseases, and no tools for soilborne diseases. This revealed an opportunity to develop tools for these disease groups.

More than half were described as operational; only one quarter had legible interfaces

Over half (n=20) of the papers in our reviewed list indicated that the featured tools were operationalized, either by presenting a tool as an accessible product (e.g., a software package available for download, such as the 'surveillance' package for R, which can be freely downloaded on the Comprehensive R Archive Network (CRAN) repository), or by using a tool in an applied capacity (i.e., generating results that were used to inform partners, rather than validation exercises). However, only one quarter were freely available online. Additionally, only one quarter had interfaces legible to finance, policy and regional decision makers. There is an opportunity to invest in the existing tools to increase their accessibility and to create user-friendly interfaces.

Mostly tools were developed for countries where the target infectious disease was endemic

Most of the tools were developed for, or implemented in, geographic areas where the infectious disease of interest was endemic. We also identified large variation in the spatial and temporal scales of the 37 tools. Most tools used gridded climate data to inform models. Few models forecast disease risk beyond the seasonal climate outlook. It is important to develop models across a range of spatio-temporal scales to capture climate and disease processes at different scales and to support decision making needs across scales.

Investigators from European / US institutions were the most common tool developers

North American and European institutions are disproportionately represented as tool-creators (38% in the USA and UK alone). There is a need for greater representation of tool developers from Global South, where many of the tools were designed to be used.

38%

of tool-creators are based in the west, however the tools are mainly designed to be used in the Global South.

1.3.1 Vector-Borne Disease Focus

Findings

Most tools identified in our review (81.1%) focused on vector-borne disease systems. Of the tools dedicated to modeling vector-borne diseases (n=30), 53.3% focused on malaria, 13.3% on dengue, 13.3% on West Nile virus, and 6.7% on Rift Valley fever.

Five tools for vector-borne disease systems (13.5%) focused on vectors more generally when modeling outcomes of interest, rather than focusing on a discrete pathogen (e.g., the AeDES model for habitat suitability of Aedes-borne disease transmission, where Aedes spp. mosquitoes are competent vectors for a variety of pathogens [11]).

Approximately 10% of modeling tools were applied to infectious diseases with other modes of transmission, including respiratory (5.4%), food-borne (2.7%), and waterborne (2.7%). Four of the tools identified (10.8%) were flexible in terms of health focus, where surveillance data from a wide variety of user-specified infectious disease systems could be used as data inputs for the tool (e.g., mapping platforms such as eRiskMapper, and user-driven analytical tools, such as the EPIPOI platform [12]).

81%

of tools focused on vector-borne disease systems.

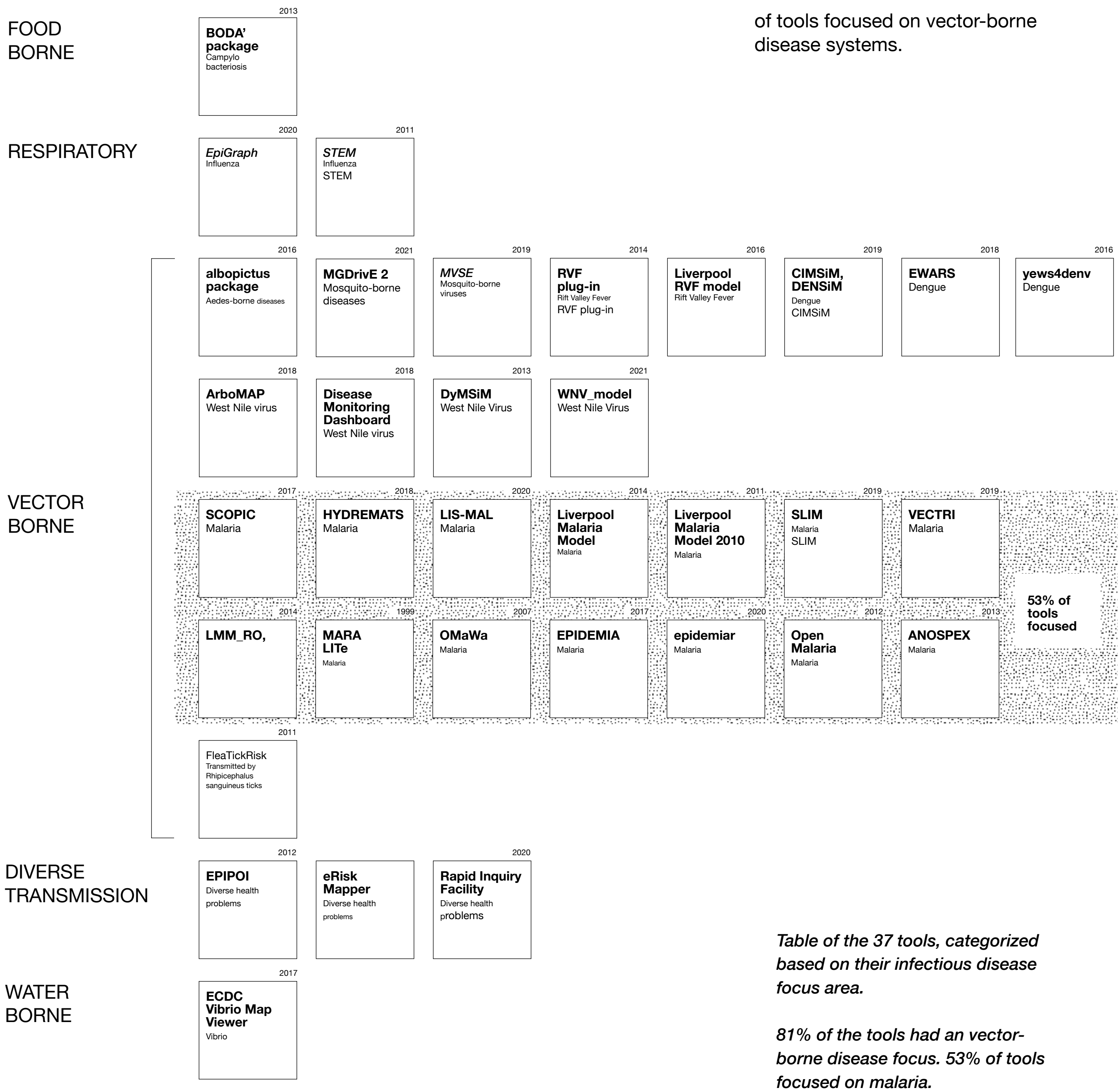


Table of the 37 tools, categorized based on their infectious disease focus area.

81% of the tools had an vector-borne disease focus. 53% of tools focused on malaria.

Implications

Most of the tools and operationalized models identified in our review focus on malaria (e.g., EPIDEMIA and associated 'epidemiar' R package [13,14]). This is perhaps expected, as vector-borne disease systems are often studied in the context of climate, and malaria has been a global public health priority for decades.

The lack of dedicated tools for estimating outbreaks with other modes of transmission and other vector-borne transmission systems represents a major knowledge gap that could have tangible implications for climate-informed planning and response.

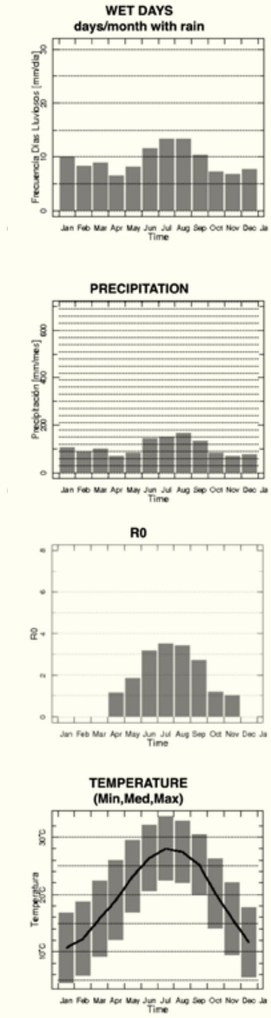
Further, expanding the foci of modelling tools may aid in developing resilient policies for neglected diseases, or emerging infectious diseases in light of climatic and demographic changes.

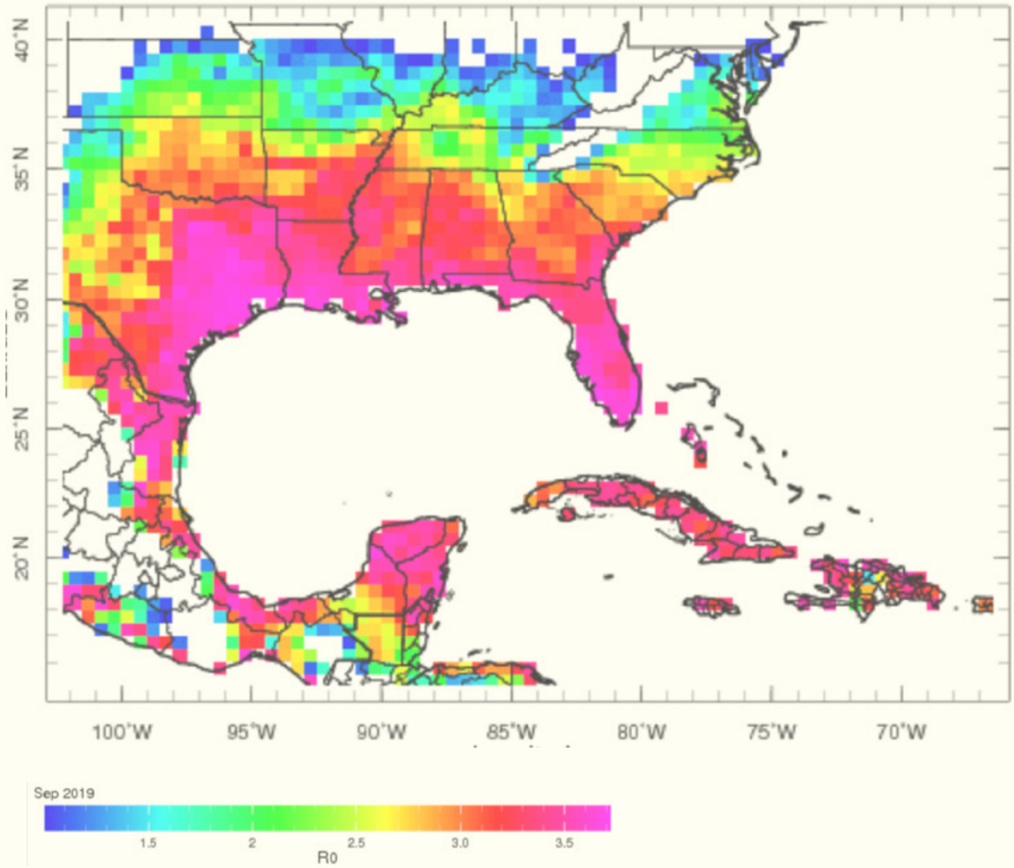
Case Study 1:

AeDES Map Room
a Vector-borne Disease
Focused Tool

Aedes-borne diseases' environmental suitability (AeDES) maproom

The Aedes-borne diseases' environmental suitability (AeDES) maproom allows decision makers to monitor and forecast diseases (including Zika, dengue, and chikungunya) transmitted by the Aedes albopictus and Aedes aegypti mosquitoes to better prepare their communities for future outbreaks. This tool incorporates four different environmental suitability models, considering climate factors and mosquito life cycle.





Muñoz, Á. G., et al. "Ae DES: a next-generation monitoring and forecasting system for environmental suitability of Aedes-borne

1.3.2 Implementation, Data Scales and Inputs

Data Scales

Findings

The tools found in this review have been implemented in several WHO regions, spanning Africa (43.8%), the Americas (14.6%), Europe (10.4%), the Western Pacific (10.4)%, South-East Asia (6.3%), and the Eastern Mediterranean (2.1%). Four tools (8.3%) had a global extent and did not focus on a single geographic region.

The spatial scale of tools in our final list varied considerably, ranging from highly localized foci (8.1%), for example simulations for individual villages, to tools with a global or continental extent (16.2%). The majority of tools (75.7%) produced output at some intermediary scale (e.g., health district, country, region, etc).

Scale was either dictated by the tool itself (e.g., simulation models designed to replicate disease transmission within a single town or community), or, in many cases, was dependent on user specifications, as determined by the spatial resolution of data inputs (e.g., epidemiological data reported by administrative units, or the spatial resolution of gridded climate products). Many studies (29.2%) that used epidemiological data from health departments or surveillance networks as data inputs for models also reported their findings using the same administrative units (e.g., provinces, counties, local health reporting districts).

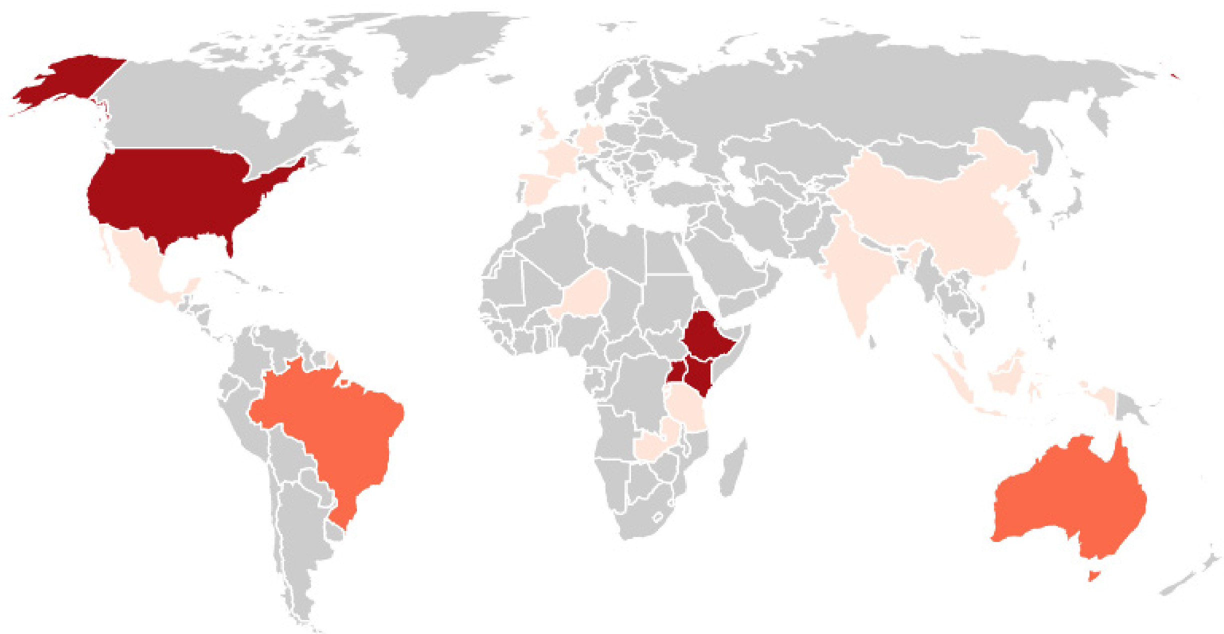
44%

tools found in this review have been implemented in African countries.

Legend

Darker colors represent countries that were the site of more tool related studies.

Map showing countries where tools have been implemented. Most of the tools were developed for, or implemented in, geographic areas where the infectious disease of interest was endemic.



Implications

Most of the tools were developed for, or implemented in, geographic areas where the infectious disease of interest was endemic and we noted large variation in the spatial scale. In general, it is important to encourage models across a range of spatial scales to support diverse decision-making needs.

Tools that are highly localized will have limited, if any, transferability across geographic regions. This potentially highlights a need for the development of tools with a broader spatial focus, particularly for diseases, or disease vectors, that are expected to undergo range shifts under climate change.

While localized tools (i.e., tools developed on a fine spatial scale) may limit operationalization to specific regions, these models may have the benefit of being well validated locally, which may lead to more accurate predictions for local health authorities. Conversely, tools with very coarse resolutions (e.g., global or continental model output) may be of limited use for local stakeholders.

16%

Operated on a continental spatial scale.

Data Inputs

CONTINENTAL

2016 **albopictus package** Aedesborne diseases	2017 **ECDC Vibrio Map Viewer** Vibrio	2020 **LIS-MAL** Malaria	2014 **LMM_RO,**					
AeDES Aedes-borne diseases	**ArboMAP** West Nile virus	**CIMSiM, DENSiM** Dengue	**Disease Monitoring Dashboard** West Nile virus	**DyMSiM** West Nile VirusDyMSiM		**Liverpool Malaria Model 2010** Malaria	**STEM** Influenza	**SCOPIC** Malaria
EPIPOI Diverse health problems	**MVSE** Mosquito-borne viruses	**Rapid Inquiry Facility** Diverse health problems	**BODA' package** Campylo bacteriosis	**EPIDEMIA** Malaria	**epidemiar** Malaria	**EpiGraph** Influenza	**EWARS** Dengue	**Liverpool RVF model** Rift Valley Fever
Liverpool Malaria Model Malaria	**Open Malaria** Malaria	**RVF plug-in** Rift Valley Fever	**yews4denv** Dengue	**eRisk Mapper** Diverse health problems	**MGDrivE 2** Mosquito-borne diseases	**VECTRI** Malaria	**MARA LITe** Malaria	**OMaWa** Malaria
SLIM Malaria		**ANOSPEX** Malaria						

LOCALIZED

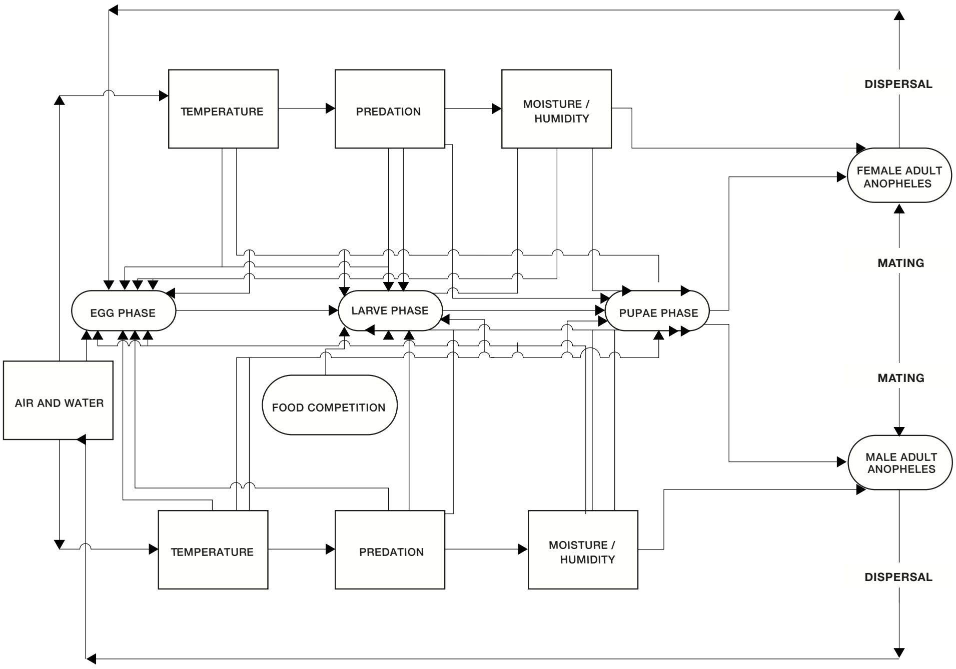
Table of the 37 tools, categorized based on their spatial focus. 16% operated on a continental spatial scale.

Findings

The climate products used as data inputs for risk predictions varied considerably, both with model type and study area. These included remotely sensed data products (e.g., NASA satellite imagery), interpolated weather station data (e.g., WorldClim, Global Historical Climatology Network (GHCN)), and modeled climate projections (e.g., IPCC global climate projections). A majority (58.3%) of models utilized gridded climate products. One third (33.3%) of the models utilized local meteorological datasets, either from national meteorological centers or local weather stations. Temperature (85.1% of studies) and precipitation (68.1% of studies) were the most commonly used climate indicators, either as model predictors or descriptive variables. Measures of humidity were used in nearly a quarter (25.5%) of the studies. Few models forecasted disease risk beyond the seasonal climate outlook.

Case Study 2:

ANOSPEX a tool at a localized scale.



Oluwagbemi, Olugbenga O., et al. "ANOSPEX: a stochastic, spatially explicit model for studying Anopheles meta-population dynamics." PloS one 8.7 (2013): e68040./

ANOSPEX is implemented as a grid representation of residential properties, where each property has one house and two larval habitats for mosquitoes to develop in. Adult mosquitoes can move from one property to another property. Weather parameters used in the model were maximum temperature, minimum temperature, average temperature, precipitation, saturation deficit and relative humidity.

1.3.3 Methodological Approaches and Technology

Types of Modelling Approaches

Diverse modelling approaches were incorporated into the tools found in the review. Of the 37 tools, the majority (59.5%) used either mechanistic or dynamical population modelling approaches. Other analytical methods included time series modelling, regression methods, Bayesian modelling, decision rules, and multi-model ensembles.

We did not consider species distribution modelling (SDM) frameworks, also described as ecological niche modelling (ENM), as standalone tools in this review since, with few exceptions, these are methodological approaches rather than standalone software tools. There are a number of algorithms, software packages, and programs used to build species distribution models [15– 17]. SDMs have been used in vector-borne disease modelling approaches, applied to describe vector occurrence, infected vector occurrence [18], and to human cases of disease [19]. Species distribution models do not inherently have any climate data as part of the algorithm. Environmental data are supplied by the user as static inputs, and these can include gridded climate summaries (e.g., mean temperature, mean rainfall, etc), but this input is not coded into the software.

Papers that used SDMs to describe disease or vector distributions as a function of climate variables were quite prevalent in our final results, where 17.8% (n=43) of our initial screening list of 242 papers used these methods, and thus, are worth noting. The most frequently used SDM was MaxEnt (Maximum Entropy algorithm, often implemented in the software of this name [20] or the R package distribution modelling ('dismo') [21]), which was used in more than half of the papers (65.1%, n=28). The prevalence of MaxEnt is likely due to the availability of an open source software package, in addition to options for implementation in R. Other SDM algorithms used in the initial screening results included BIOMOD, boosted regression trees (BRT), classification and regression trees (CART), GARP, and random forests (RF).

39%

were foundational publications.

40%

were derived from other existing tools.

Foundational vs Derived Publications

Nearly half (39.6%) of the studies in our final list were foundational papers, indicating the first use or description of a given tool in the literature.

Many of the tools in our list (40.5%) were explicitly derived from existing tools, including updates to previously published models, and new models that incorporated components of existing models.

Discrete Models vs Software Platforms

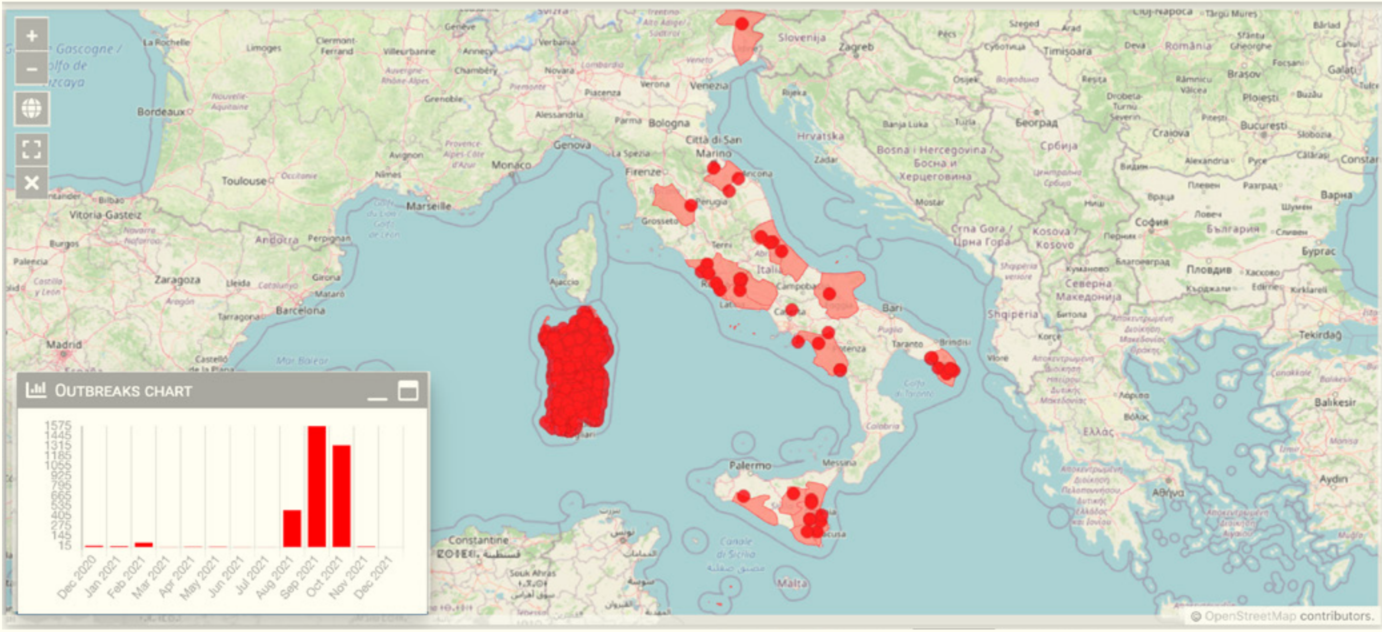
Some tools provided flexible platforms for analyzing or visualizing infectious disease systems, as opposed to discrete models. These included dedicated software packages (n=9), web-based applications (n=3), and a code repository (n=1).

Programming Languages

The R programming language was used to develop or implement almost one third (29.7%) of the tools. Other programming languages or software included Python (n=4), C++ (n=3), MatLab (n=3), and FORTRAN90 (n=1).

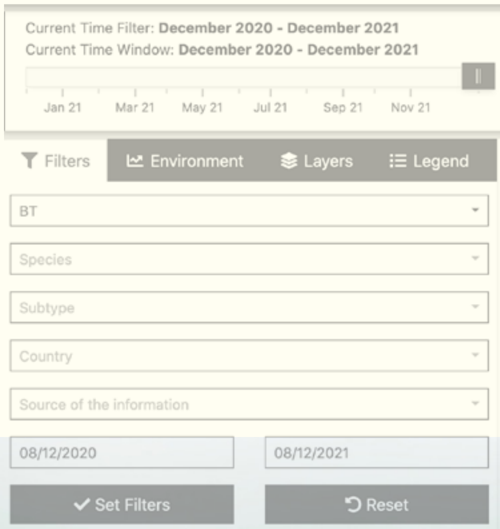
Case Study 3:

Disease Monitoring Dashboard, an openly accessible tool.



Outbreaks | Distribution

Country	Region	Admin unit	Source	Outbreak	Start date	Confirm date	Disease	Species	Subtype	Cases	Susceptible	Deaths	Destroyed	Slaughtered
ITALY	SARDEGNA	SUD SARDEGNA	National Informati...	IT-2021-9-2971	03 Nov 2021	03 Nov 2021	BT	SHEEP	Subtype4	5	257	0		0
ITALY	SARDEGNA	SUD SARDEGNA	National Informati...	IT-2021-9-2968	03 Nov 2021	03 Nov 2021	BT	SHEEP	Subtype4	10	700	2		0
ITALY	SARDEGNA	SUD SARDEGNA	National Informati...	IT-2021-9-2968	03 Nov 2021	03 Nov 2021	BT	GOATS	Subtype4	0	60	0		0
ITALY	SARDEGNA	SASSARI	National Informati...	IT-2021-9-2973	03 Nov 2021	04 Nov 2021	BT	SHEEP	Subtype4	13	200	1		0
ITALY	SARDEGNA	SUD SARDEGNA	National Informati...	IT-2021-9-2967	03 Nov 2021	03 Nov 2021	BT	SHEEP	Subtype4	2	734	2		0



Disease Monitoring Dashboard

Disease Monitoring Dashboard system collects data through on-line forms and automated procedures and visualizes data as interactive graphs, maps and tables. The spatial and temporal dynamic visualization of disease events is managed by a time slider that returns results on both map and epidemiological curve. Climatic and environmental data can be associated to cases through python procedures and downloaded as Excel files.

Savini, L., Tora, S., Di Lorenzo, A., Cioci, D., Monaco, F., Polci, A., ... & Conte, A. (2018). A Web Geographic Information System to share data and explorative analysis tools: the application to West Nile disease in the

1.3.4 Operationalization and Availability

59%

of the tools were available freely in some form online.

Operationalization

Over half of the tools (n=21) were described as operationalized. The tool was either described as an accessible product (e.g., a software package available for download, such as the 'surveillance' package for R, which can be freely downloaded on the CRAN repository), or was described as being used in an applied capacity (i.e., generating results that were used to inform partners, rather than validation exercises). We note that, in this context, operationalization does not necessarily mean that available tools are actively used by the public health sector to inform decision making.

Only one quarter of the tools had interfaces legible to finance, policy and regional decision makers. Those that did were funded by an institutional or country-level partner. This suggests that transitioning research to public health practice must be accounted for from the project outset since the data that feed into the model and the model output (e.g., interfaces) need to align with decision making processes identified by public health professionals.

Availability

The majority of tools (59.5%) were freely available in some form online, with 16.2% available as R packages on the CRAN repository, 16.2% with available source code on GitHub, and 5.4% on GitLab.

Additionally, almost one third (n=11) of tools were associated with dedicated websites (e.g., a website for the tool or the project), sometimes together with instructions for use and links to download.

Usability

Although assessing the usability and actual use of tools was beyond the scope of this review, tools that were hosted on external websites (e.g., GitHub), with links included in the publication, or available as open access software packages (e.g.,R packages such as 'surveillance' [22] and 'epidemiar' [14]) appeared to be more readily accessible.

The accessibility of tools was not always apparent in the literature, as published papers often had no clear instructions on how to access tools or where tools were hosted, with some papers instructing to contact the study authors for more information (e.g., some applications of the VECTRI model [23]).

1.3.5 Institutions and Partners

Findings

There were 102 institutions represented in the author list of the 48 publications screened in our review. Over one third (38.2%) of these institutions were based in the USA or UK. Only 24 institutions were associated with more than one paper, which included universities and agencies located in Europe (n=11), the Americas (n=8), the Western Pacific (n=3), and South-east Asia (n=1).

Designated corresponding authors for the 37 tools were based in the USA (32.4%), UK (27.0%), other European countries (29.7%), Australia (5.4%), South-east Asian countries (5.4%), and Tanzania (2.7%). Nearly one quarter (22.9%) of papers listed institutional partners. Partners identified by study authors ranged from international organizations (e.g., WHO, PAHO), to national agencies (e.g., CDC, ECDC), and regional partners, such as local health departments or academic institutions.

Although the majority of papers reviewed did not explicitly name agency and institutional partners, it was noted that author affiliations on individual publications were quite diverse, possibly indicating the inclusion of partner organizations in the publication process.

38%

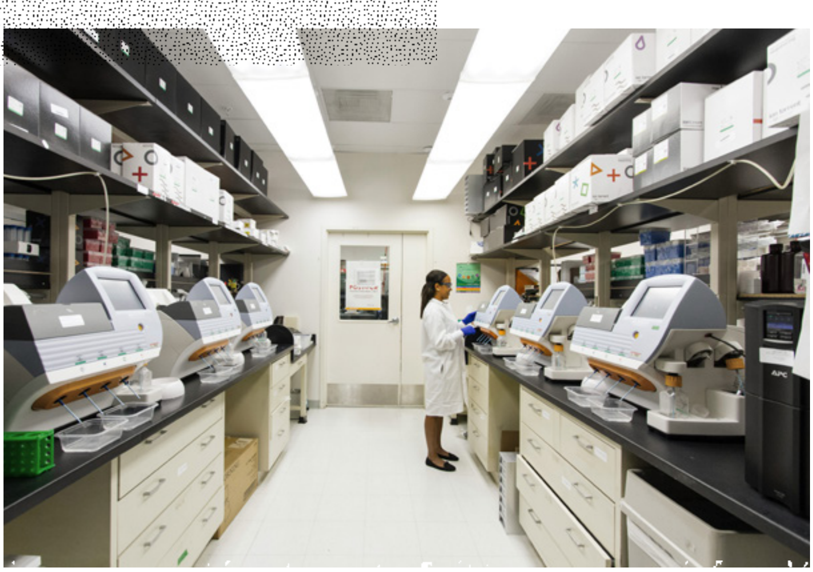
of institutions were based in the UK or US.

23%

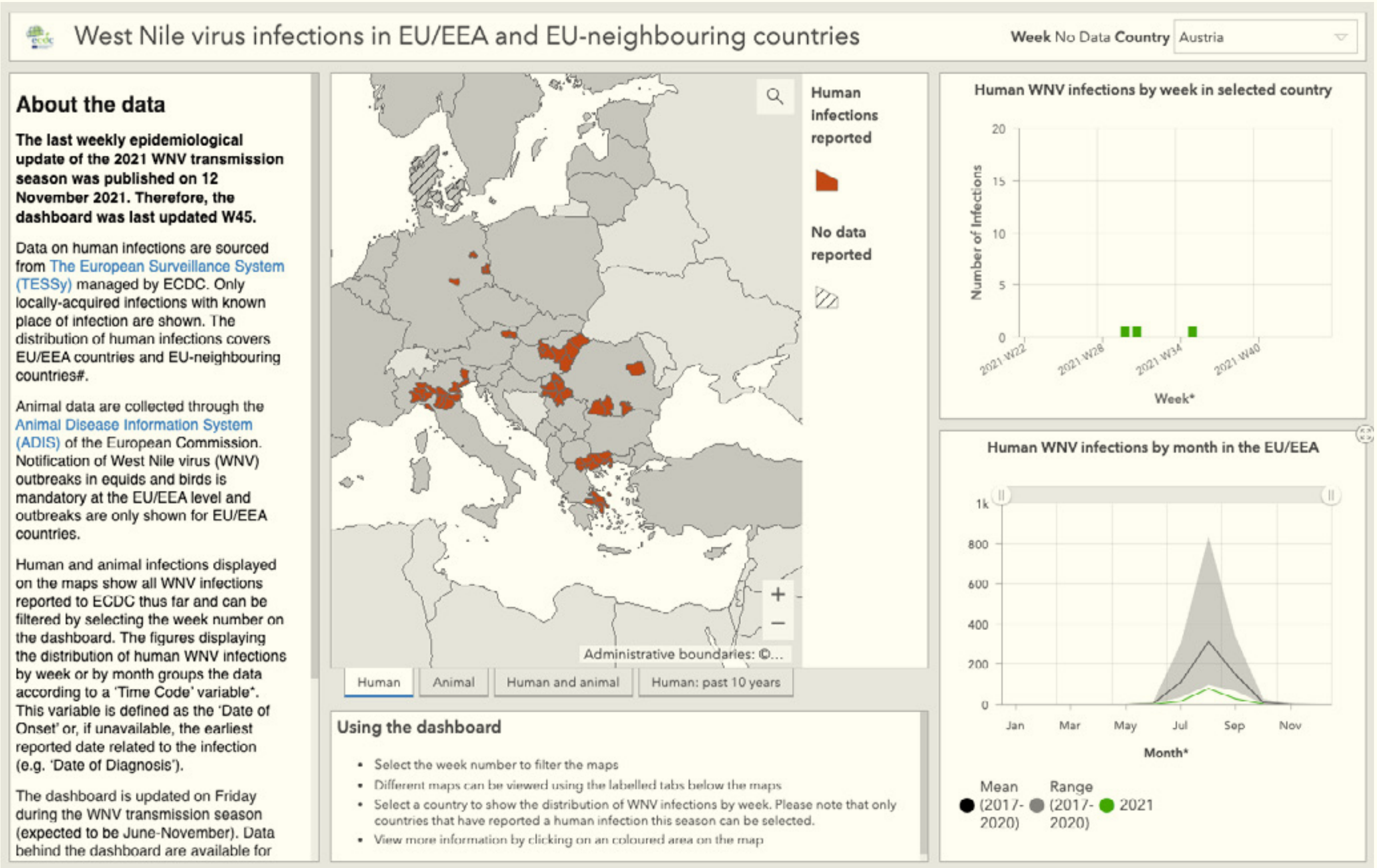
Papers listed an institutional partner.

Implications

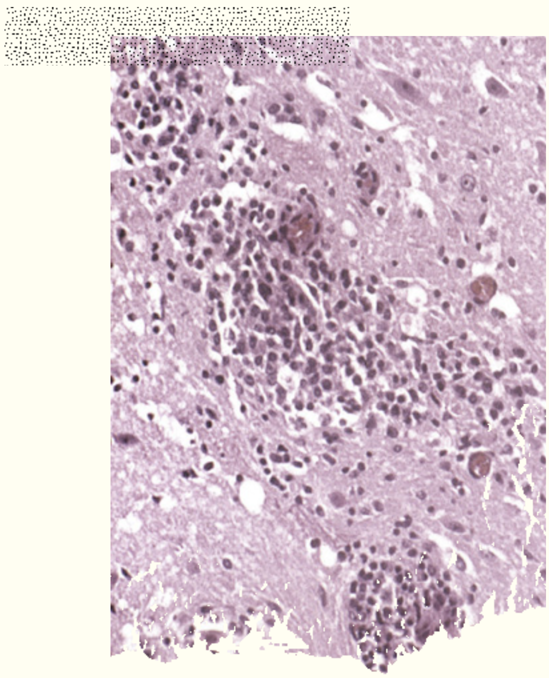
North American and European institutions were disproportionately represented in the production of tools. There is a need for greater representation of the Global South, where many of the tools were designed to be used.



Case Study 4:
ECDC Geo-portal Dashboard,
a Tool funded by ECDPC



Levy, Sharon. "ECDC Vibrio map viewer: Tracking the whereabouts of pathogenic species." Environmental health perspectives 126.3 (2018): 034003.



The ECDC Vibrio Map Viewer

The ECDC Vibrio Map Viewer displays coastal waters with environmental conditions that are suitable for Vibrio spp. growth internationally.
It is based on a real-time model that uses daily updated remotely sensed sea surface temperature and sea surface salinity of coastal waters as inputs to map areas of high suitability for Vibrio spp. that are pathogenic to humans.

1.3.6 Keyword Analysis

Findings

A number of methodological approaches were commonly used throughout the relevant papers to assess the relationship between climatic factors and infectious disease outcomes. Regression methods were used in many studies, where terms commonly used to describe statistical analyses included logistic regression (n=78), linear regression (n=29), generalized linear model (n=27), hierarchical model (n=11), multiple linear regression (n=8), and stepwise regression (n=6). Methods used to estimate pathogen distributions and machine learning algorithms were also frequently encountered in the literature search results, with studies using the terms including MaxEnt (n=77), ecological niche model (n=77), species distribution model (n=41), boosted regression trees (BRT) (n=15), habitat suitability model (n=9), GARP (n=5), random forests (n=5), BIOMOD(n=1), classification and regression trees (CART) (n=1), and exploratory niche factor analysis (ENFA) (n=1). These keywords captured some of the most commonly implemented methodologies used in the relevant literature.

We note that studies not using common keywords to describe analyses would not necessarily be captured in the keyword analysis, emphasizing the need for standardized terminology in climate- health research. This becomes particularly evident when working across specializations, which may have different conventions for describing methodology. Very broad terms, for example 'regression analysis', could be used to describe a vast array of methodological approaches. Conversely, some methods that are fundamentally similar may be described by several terms (e.g., ecological niche modelling and species distribution modelling; mathematical modelling and dynamical modelling; simulation and stochastic modelling), making it at times difficult to categorize statistical methods across studies.

Implications

Studies with well defined statistical frameworks could potentially be leveraged for the development of new tools in the future. Existing climate models for infectious diseases could serve as the basis for new software development in the future. This underscores the need for investment to transition existing models to become useful tools. To illustrate this point, we have identified some examples from the scientific literature that did not meet our final criteria for named tools, yet have great potential for future tool development.

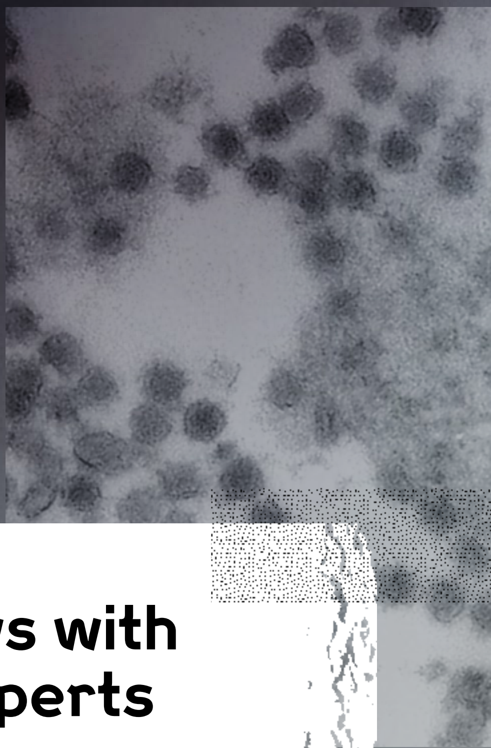
- Ryan et al. (2019) used temperature- dependent models of transmission to produce projections of dengue transmission risk under different scenarios of future climate change. This model provides a means to analyze and visualize climate-mediated range shifts in disease transmission and risk, and to describe regional population impacts [24]. This work has clear value for climate adaptation planning by the public health sector. However, although the model output is freely accessible, code and software to implement the model are not currently available.

- In another example, a climate-informed dengue forecasting system was developed for Vietnam as part of the Dengue forecasting MOdel Satellite-based System (D-MOSS) project [25]. In this example, the forecasting model was explicitly developed to be used as part of an early warning system, with R code to run the model openly available on GitHub. In this case, the existing model could clearly be developed into a discrete, named tool with little additional effort, or further developed into a standalone software package or modelling platform

- Another example is a model that was developed for Brazil to understand the delayed and nonlinear impacts of hydrometeorological extremes on the space-time distribution of dengue outbreaks [26]. The model was adapted from a previous model developed for Barbados [27] and the model code was shared on GitHub. Although the methodology is being reproduced by researchers and non-governmental organizations for Colombia and Peru, the model itself was not named or packaged due to human resource and technological capacity constraints.

Moving forward, partnerships between climate-infectious disease researchers and software engineers may help increase the number of models that are developed into standalone tools.

2



Interviews with global experts

Introduction

We engaged with global researchers and policy stakeholders at key organizations in the fields of climate and infectious disease to better understand their perspectives on the software tools landscape. To undertake this, we used a mixed methods approach to exploratory sequential research (28,29). We conducted semi-structured interviews to identify the current gaps that might be addressed by targeted investments in software-based tools. Following the interview, we conducted a survey with those who worked directly with models, software or tools to assess software quality, usability, efficiency and reproducibility at the user level. These findings elucidate the successes and challenges in the implementation and operation of these tools.

2.1 Methodology

A —

Sampling and Interview Approach

We identified interviewees working in institutions across the six WHO regions, with an emphasis on those who had experience in low and middle income countries (30). Eligibility was met if they were researchers, policy stakeholders and civil society and cross-sectoral collaborators working on issues related to climate and health.

Interviewees were asked about:

- Personal views, opinions and experiences on datasets and tools that are used;
- The way through which data and tools are accessed and curated;
- The principal steps of modelling processes (from data collection to results dissemination, including the software packages used);
- Key barriers preventing the process being done efficiently (i.e., physical and human resources, institutional/political barriers to climate-health partnerships such as limited political mandates);
- Software tools that would help address the missed opportunities defined through engagement with the policy makers;
- Where the current approaches to modelling the impact of climate-sensitive infectious diseases fall short of what is required as a policy maker (e.g., what decisions do policy practitioners actually need to make);
- How could this gap be most usefully addressed by science/software tools; and, opportunities where software development would have an impact.

B —

Data Protection

Compliance with UK GDPR requirements was confirmed in collaboration with the Wellcome Trust legal and data protection teams. Prior to interviewing, the project purpose and expectations of involvement were explained to the participants. We obtained oral and written informed consent from all participants. Data was stored in a secure place and the anonymity was maintained through de-identification. All participants were adults (>18 years of age) and no personal identifiable information was recorded.

C —

Data Analysis

Data from the recorded interviews were analyzed thematically in line with the project aims (31,32). Relationships and comparisons between themes were conducted in an iterative process. This ensured that attention was given for consistent patterns within the data focusing on similarities and differences on responses given by participants to aid analysis and interpretation.

Regular meetings were held among the team and with Wellcome Trust staff prior to conducting interviews in order to understand the contextual factors that would frame potential participants' opinions and perspectives. The researchers who conducted the interviews were familiar with the context and the process of stakeholder engagement and tool creation as well as implementation, thus establishing credibility. Dependability was established by describing the data analysis in detail and providing direct citations. Conformability and consistency of the analysis were established by holding meetings for the research team to discuss preliminary findings and emerging themes until a consensus was reached. To enhance the transferability of the findings, we have provided a description of the contexts, selection and background of participants, data collection and analysis process (33,34).

2.2 Key Findings

We interviewed twenty-one researchers, tool developers, cross-sectoral collaborators, policy and decision makers working in Africa, the Americas, Eastern Mediterranean, Europe, South-East Asia and the Western Pacific.

21 interviews

Inter-sectoral sharing of datasets

Inter-sectoral sharing of climate and disease datasets is limited. Interviewees described various datasets and tools that are being used for climate-sensitive infectious disease forecasting and prediction. These collaboration processes involve multiple stakeholders, however, data sharing remains a barrier to tool development and implementation.

Principal challenges to obtaining key datasets

The principal challenges to obtaining datasets for climate-disease modelling are related to the incompleteness of the data and lack of access despite formal partnership and multilateral agreements. Most public health and climate sectors don't have a mandate to focus on the climate impacts on health, thus limiting the resources dedicated to support these efforts over the long term.

"As health sectors don't have a mandate to focus on climate impact on health, I suspect that having political mandates would be very important."

Barriers to the effective use of disease forecast models

Key barriers preventing the use of climate-disease models as decision-support tools are poor data quality, miscommunication between researchers and decision makers, lack of expertise, and lack of funding.

"As researchers, we would like everyone to use the software of our choice, it's not going to happen… We need to adapt to what people on the ground are using and make the most of it."

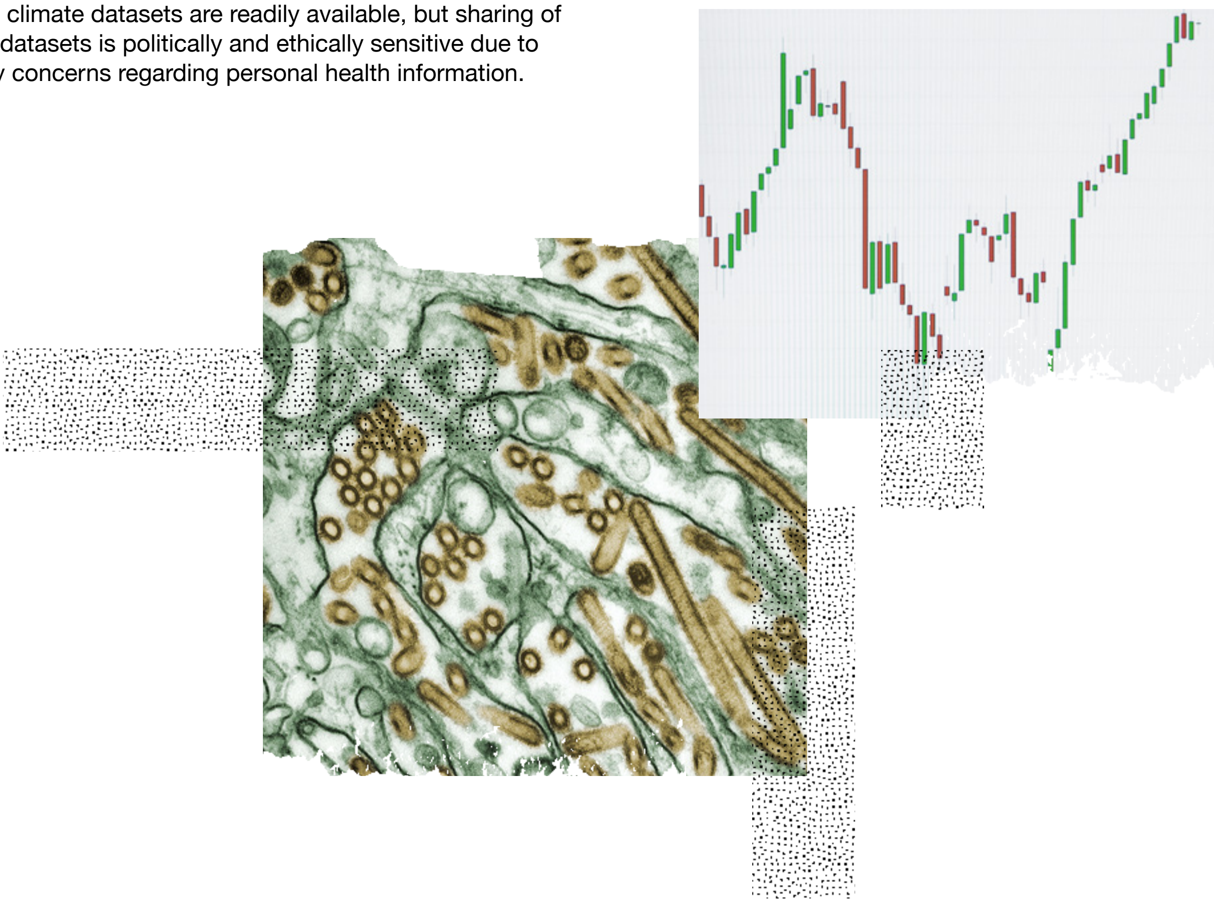
In summary, the development of cutting edge tools is important, but even more important are the multi-sectoral collaborations, strengthening of local capacities, and the ability of tool developers to clearly communicate with decision makers.

2.3.1 Inter-sectoral Sharing of Datasets

Participants explained that sharing of datasets can be difficult due to a lack of knowledge and motivation about the importance of inter-sectoral collaboration. They also highlighted the lack of automated data sharing protocols and formal collaboration agreements between the climate and health sectors. Participants also pointed out that data sharing agreements are sometimes limited to the duration of specific projects.

However, efforts are underway in some regions to put in place permanent inter-sectoral agreements. In South-East Asia and the Western Pacific, interviewees described government regulations and specific agreements that establish automatic data sharing. In the Americas, regional organizations such as CARPHA and PAHO are supporting national-level collaborations and data sharing agreements across the climate-health sectors. In some cases, strong networks have been established among researchers and cross-sectoral partners to share relevant datasets and to advocate for data sharing.

Interviewees also reported that the climate sectors may be more inclined to share datasets than health sectors. In other words, climate datasets are readily available, but sharing of health datasets is politically and ethically sensitive due to privacy concerns regarding personal health information.



2.3.2 Principal challenges to obtaining key datasets

The experience of obtaining different datasets is contingent to the region, the country, as well as the type of data that are required. Interviewees indicated that lack of access and poor quality and completeness were major barriers to obtaining datasets to inform the development and implementation of climate-disease modelling tools.

Access

Access to health data was deemed one of the largest constraints. Most participants agreed that data involving informed consent or sensitive personal information takes long periods of time to request and may never actually be shared. In some cases, countries may err on the side of caution when sharing data on infectious disease outbreaks, as a forecast of a future epidemic could reflect poorly and could have major consequences for the national economy. One respondent shared that countries are protective of this data because they do not want to be red listed for travel advisories.

Respondents also shared that a lack of human resources may limit the capacity of some sectors to engage in a new modelling project. This has been especially apparent during the COVID-19 pandemic, when health sectors were over stretched. Finally, participants shared that setting up data-use agreements can be challenging when there are limited or no national level mandates to support climate and health collaboration, thus making this work a lower priority.

"In the last year and a half we may have no data reported for some areas due to shift in personnel to COVID-19 work."

Quality and Completeness

Quality and completeness of data was the other major challenge reported for obtaining key datasets to inform climate-disease modelling. This is mainly due to a lack of proper tools and/or knowledge required for the collection and storage of long-term datasets. For example, key monitoring and surveillance data may be missing due to a lack of collaboration between the sectors which would establish common goals, follow-up and quality control. Interviewees also reported a lack of regularly released health datasets at sufficiently fine spatial and temporal scales needed to develop meaningful models. In some places, health datasets are released every 5 to 10 years. Moreover, there can be difficulty in reading data that are collected on paper forms and researchers may have confusion about what is being reported when working with cumulative data that is hard to unpack. Finally in some cases, data are not always generated using best practices for collecting and reporting.

Furthermore, although some countries in the Americas and Europe now have electronic records of health and climate data available for at least two decades, electronic databases of epidemiological records in other countries may remain limited, with reporting from 2016 onward. The same patterns are observed in Asia, as complete datasets are available in Thailand (40 years) and Vietnam but other parts of the region have many more limitations. Major data gaps are reported from countries in Africa, where long-term records of climate and health data may be rare or unavailable. In addition, participants identified a mismatch in the spatial and temporal scale of climate and disease data.

2.3.3 Barriers to the Use of Climate-Disease Models

Respondents identified barriers to the use of climate-disease models including issues in translating scientific models into common language useful to decision makers, lack of political will and national mandates for climate and health work, lack of funding for training and infrastructure, and poor planning. Some places lack personnel with the technical skills and expertise required to gather, process, and publish data despite tremendous will.

In most parts of the world, interviewees reported a lack of sustained funding for climate and disease modelling initiatives. This lack of funding makes it difficult to set up long-term training programs to promote local expertise. This leads to short-term consultancies which can produce the models but maintaining / operationalizing the modelling tools becomes very challenging for local partners.

"...but people don't know how, it's not a matter of tools but it's how to use them..."

WTSSI_001

The lack of funding also results in inadequate infrastructure for data entry, processing, storing, and analysis. In some areas, computing infrastructure may be limited, with frequent loss of internet and power. As a result, data can be lost and backups may not be available.

Interviewees also described the impact of the COVID19 pandemic and other disasters on stretched health systems. During periods of crisis, such as the COVID-19 pandemic and other disasters, the health sector response has required essential personnel to be redirected, which has made data sharing and multi-sectoral projects extremely difficult to sustain.

2.3.4 Ways To Increase Engagement With Policy And Decision Makers

Interviewees recommended the following actions to increase engagement and improve communication between the modelling community and decision makers:

1 —

Training Programs

Invest in local training programs: Training in the proper use of R, Python, and Microsoft Office (Excel) is needed for local tool users from the public health sector and other sectors. This sort of training will allow local partners to adapt existing tools, develop their own tools, and translate available tools for local decision making needs.

2 —

The next generation

Invest in the next generation of climate-health scientists and practitioners through the creation of new university programs and supported career paths at the climate-health nexus, particularly in countries that are already bearing the greatest burden of climate-sensitive infectious diseases. Create a supported cohort of climate-health professionals that can work collaboratively across sectors at the science-policy interface. These experts will ensure that modelling tools can be co-created and implemented to meet local needs.

3 —

Accessible interfaces

Invest in user friendly interfaces: Participants also suggested applications or user-friendly interfaces such that model outputs are easier for the public to understand. Such an application should adopt best practices in scientific communication, using accessible language and visuals.

2.3.5 Modelling Experts Take On Existing Tools

General Findings

Researchers reported that tool usage depended on the level of training of the user. They noted that most software has a steep learning curve, which is difficult to learn in a few technical training workshops. Participants also noted the importance of discussing software preference with the tool users from the beginning of the co-development process to ensure sustainability.

Researchers agreed that modelers need to adapt to the location in which they are working and not vice versa. In some areas of the world there are limited resources for data entry or reporting (i.e., lack of electronic data entry). However, some participants reported that using paid software can sometimes be beneficial (i.e., powersym or Stella). These software may help decision makers to better understand the modelling process from the beginning, more than some open-source software such as R. Interviewees also noted that some software may not be appropriate for creating operational models in countries with limited resources, but can be useful for initial discussions.

Researchers recommended incorporating a computer scientist or software engineer into project teams. Having these experts on the team can be especially useful to debug the model and smoothly transition the model into a tool.

Modelers indicated that the ultimate goal would be a multi-pathogen platform that can simultaneously serve different regions of the world. However, there are many challenges, including the lack of uniform protocols for health data collection, cleaning, quality control, etc. Researchers hope to be able to use the initial existing forecasting systems as pilots that can inform the development of more adaptive and versatile platforms.

Researchers also noted that more secure funding for countries to manage and operate their own systems is key. Without sustained funding, the tool development is limited to an academic exercise.

Modelers also noted the lack of existing modelling tools for regions of the world where infectious diseases are expanding or are projected to emerge in the future.

"There are a lack of tools to assess climate-ID linkages in areas of potential disease expansion, such as dengue in the southern cone of South America and other temperate latitudes around the world."

WTSSI_002

2.3.6 How Can Tools Better Serve Decision Making?

We identified three major gaps in the development and implementation of tools for climate-sensitive infectious disease 1) the level of miscommunication between researchers and policymakers, 2) lack of training of tool users to ensure sustainability and usefulness of models for local decision making needs, and 3) the lack of useful public visuals and display of findings.

1. Promoting political mandates for climate and health research and practice.

2. Enhanced communication and information exchange to align technical vocabulary across different sectors to ensure co-creation and user-led research/tool development.

3. Proper training of users. Workshops may work in the short-term, but a long-term investment in university programs and the creation of supported career paths at the climate-health interface will ultimately aid in sustainably developing and maintaining tools that reflect local needs.

4. Improving engagement and communication between researchers (tool developers) and policy makers through collaborative co-creation processes

5. WMO/WHO task forces to increase adapted services and establish multinational, regional and multi-sectoral collaboration.

6. Systematically encouraging implementation science.

7. Sustained funding opportunities that go beyond academic exercises.

8. Capacity building focused on co-learning processes for tool development and implementation.

9. Focus efforts on tools that are pragmatic, simple, usable and sustainable to ensure that tools can be useful over the long-term to local decision makers.

10. Creation of tools that are multi-functional and can be repurposed.

3

Conclusions and recommendations

3. Conclusions and recommendations

Conclusions: Key funding recommendations

The findings from this project indicate a number of opportunities to invest in the development and implementation of climate driven infectious disease modelling tools.

Transition validated models into tools and improve the interfaces of existing tools.

There are useful models and code associated with publications that exist on online repositories like GitHub, but there is a gap in translating this research into automated, packaged tools. Researchers who are developing these models can be connected to software engineers. An investment in these validated models could result in the rapid creation of new tools. Existing tools can also be improved through an investment in the creation of user friendly interfaces.

Tools for neglected disease groups.

There is an opportunity to develop tools for climate sensitive disease transmission modes that have been neglected (e.g., respiratory, foodborne, soilborne, waterborne). There is also an opportunity to develop tools for regions of disease emergence, which currently lack tools. These investments will increase the preparedness of the public health sector for the next pandemic.

Equity and diversity of investigators from the most affected regions.

There is a need to support teams that are led or co-led by researchers and other partners from the Global South, where the impacts of climate sensitive infectious diseases are the greatest. This would also increase the opportunity to cross-pollinate knowledge and experiences between regions that are currently endemic for climate sensitive diseases and regions of projected disease emergence due to climate change.

Co-creation of tools.

Transitioning research to public health practise must be accounted for from the project outset since the data that feed into the model and the model output (e.g., interfaces) need to align with decision making processes identified by public health professionals. To achieve this, transdisciplinary project teams can include academic partners with sectoral partners, to ensure that researchers and end-users co-create models, eliminating the last mile problem.

Multi-scalar tools.

There is a need to develop tools across a range of spatio-temporal scales to capture climate and disease processes at different scales and to support decision making needs across scales. An analysis of the gaps in the spatial and temporal data infrastructure would provide important guidance on gold standards.

Policy action.

There is interest from the climate and health sectors to work together to co-create modelling tools. However, often the sectors lack clear mechanisms for data sharing or lack a political mandate to engage in these efforts. There is a need to influence and inform policies that encourage intersectoral collaboration and data sharing to address climate impacts on health.

Science communication needs.

There is an opportunity to improve the communication between modelers and decision makers, such as the creation of useful public visuals that decision makers can use to create and enact evidenced based policy. Science communication experts and graphic designers should be incorporated into research teams. There is also an opportunity to translate available information on tools for non-English speaking countries.

Capacity building for tool users.

There is a critical need to train and sustain the next generation of tool users, such as local experts in ministries of health, through training materials that are freely available in different languages, the creation of university training programs, and supported career paths at the climate-health interface.

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Appendix

ABC

Appendix A
Key Search Terms

Climate Terms

Altitude
Climate Change
Climate Sensitivity
Climatic Processes
Diurnal Drought
Eutrophication
Extreme Weather
Flooding
Global Warming
Humidity
Hydrometeorolgical
Meteorological
Meterology
Precipitation
Rainfall
Storms
Temperature
Thunderstorm
Vector Borne Diseases
Warming
Weather
Wildfires
Wind

Infectious Disease Terms

Aedes
Allergic Disease
Alphaherpes Virus
Anaplasmosis
Anopheles
Anthrax
Babesiosis
Borreliosis
Botulism
Campylobacter Infection
Chagas
Chikugunya
Cholera
Climate-Sensitive Infectious Diseases
Clostridiosis
Clostridiosis
Cryptosporidiosis
Culex
Dengue
Diarrhea
Disease-Escalation
Drug-Resistant Infections
Ebola
Epidemic
Filariasis
Gammaherpes Virus
Giardiasis
Hantavirus Pulmonary Syndrome
Hemorrhagic Fever With Renal Syndrome
Influenza
Leishmaniasis
Leprospirosis
Malaria
Necrobacillosis
Neglected Tropical Diseases
New And Emerging Infectious Diseases
Onchocercosis
Pandemic
Parapoxvirus
Pasteurellosis
Pestivirus
Plague
Rabies
Respiratory Syncytial Virus (Rsv)
Rift Valley/ Rift Valley Fever
Salmonellosis
Schistosomiasis
Tick Borne Disease
Trypanosomiasis (Tsetse Flies - Glossina Sp)
Tuberculosis
Vector Borne Diseases
Vibrio
West Nile Fever
Yellow Fever
Zika

Technical Terms

Artificial Intelligence
Bayesian
Bayesian Regression Tree (Brt)
Compartmental Model
Data Mining
Deep Learning
Differential Equations
Dynamic Model
Dynamic Modeling
Early Warning System
Ecological Modeling
Ensemble
Forecast
General Circulation Model (Gcm)
Geospatial
Glm
Inla
Logistic
Machine Learning
Mathematical
Maxent
Maximum Likelihood
Mechanistic
Model
Model Framework
Natural Language Processing
Neural Network
Niche Model
Open-Source
Prediction
Predictive Analytics
Process-Based
Random Forests
Regression
Representative Concentration Pathway (Rcp)
Simulation
Sir
Spatial
Species Distribution Model
Statistical
Stochastic Modeling
Suitability
Supervised Machine Learning
Support Vector Machine
Time Series
Transmission
Unsupervised Machine Learning

Appendix B
Expert Interviews

B.1 : Datasets and tools used for climate-sensitive infectious disease forecasting and prediction

When working on climate-sensitive infectious disease forecasting and prediction, researchers, policy and decision makers often face a lack of quality data required for optimal targeting of the intervention and surveillance. Although some cross-sectoral collaborators working at regional levels collect data from specific countries involved in projects and integrated surveillance, researchers and tool developers mentioned the use of various datasets including:

- Epidemiological bulletins and case data from governmental agencies such as ministries of health (contingent upon institutional agreements)
- World Health Organization and Regional Offices Database
- Institutional data libraries
- GitHub
- Climate data store
- National Oceanic and Atmospheric Administration (NOAA)
- Regional climate data archive center [Climate Data Online (NOAA)]
- The Climate explorer
- Worldclim
- Dataclim package
- Observational satellite systems
- The North American Multi-Model Ensemble (NMME)
- Census and auxiliary data from Governments such as the national arboviral surveillance system managed by US-CDC and state health departments (ArboNET)

B.2: How organizations access and curate data and tools

Although it can be complicated to establish formal partnership and multilateral agreements to access data, in many places, memorandum of understandings (MoU) are set up among sectors. As examples, participants mentioned agreements with the European Centre for Disease Prevention and Control (ECDC) and the World Health Organization (WHO). However, in some European countries, the Ministries of Health (MOH) release data publicly. Data is curated before being posted into their systems.

They went further to explain that in other settings, data are provided directly by sectoral stakeholders after agreements through contracts with strict close on data privacy. In some cases, data is gathered directly from open websites and repositories.

B.3: Person in charge of data acquisition

Gathering dataset varies depending on the institutions and settings. Individual researchers, PhD students or Postdoctoral researchers are in charge of gathering data for each project. For regional works, hired consultants or project coordinators are responsible to gather data after stakeholder engagement meetings.

B.4: Storage of dataset after acquisition

Once a dataset is acquired, storage methods depend on the data agreement:

- If it is publicly available it can be stored on any computer or online repository.
- If it is confidential and has an agreement, special requirements such as double encryption and no right to copy onto local disks - are required.
- Encrypted servers in some organizations.

B.5: Description of a typical modelling processes (from data collection to results dissemination, including the software packages used)

Prior to the description, participants indicated the importance of collaboration between sectors towards co-creation processes.

- The process, generally, starts by bringing the stakeholders on the same table to identify exactly what they want and what is feasible. Although this phase is crucial, sometimes it is skipped.

  “Another way to go about it instead of asking, is what decisions do you make on a daily business and how we can support those decisions.” WTSSI_002

- Data gathering from different sources and in different formats.
- Initial inventory and consistency check. Sometimes, this part may lead to restarting the process in an iterative way.
- R Project for Statistical Computing is widely used for data cleaning, processing and modelling.
- Meetings with stakeholders for testing and validation.
- Training for users and policy makers.
- Technical reports, scientific publications and websites are used for dissemination.

* Many participants noted that sustainability was a huge issue in the modeling process as funding usually does not support long-term updating of the system leaving the platform highly unusable for policy makers.

Appendix C
Logistical Insights from Interviews

C.1: Task efficiency

In R there are no standard packages to check efficiency, but there are some codes available that aim to check data for issues. Depending on what functions you are using, R does not have very efficient updates and this can interfere with usage.

C.2: What tasks could be performed

In R you can perform anything you could imagine, any kind of model, however it is not as simple as plug and play which may be better for decision makers. R can also run statistical models, transmission models, processed based models, visualize data, R markdown-html, R Shiny apps. You can also run basic stats, times series analysis, GIS mapping , projection, raster manipulation. The online apps created in R are good for research demos but not great for decision makers. Powersym can take complex systems with complicated feedback mechanisms and create very visual depictions of the model and conduct multiple realizations at same time. It can also make a very powerful set of graphics and plots whereas this kind of work would not be as intuitive with R.

C.3: Level of difficulty in training of new users

Participants reported that coding in general is challenging and has a steep learning curve particularly in R. Paid platforms like Stella and Powersym are more intuitive because they use more design framework for visualization along with the option to view the mathematical formulas. R requires a lot of practice, trial, and error to learn how to navigate the software and learn its full capabilities. There are lots of free teaching tools available but many times it can present language barriers.

C.4: Real-time nature of the system (i.e. live streaming capabilities)

- R has real time live streaming capabilities
- Paid options for these systems are also available but less commonly used

C.5: Crashing/ lagging, ability to debug, report generating

Users must have a strong internet connection when downloading any data from online

Users that have more powerful computers will have less lagging and an overall smoother work process

Using cloud-based servers (i.e. Amazon Web Services and GitHub repositories) can allow for usage on more powerful computers than the average person may own. (Gaining access to these computers can be challenging in resource limited areas).

Crashing and lagging occur less often when the user has more experience to know what triggers these outcomes.

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