Climate services for health: from global observations to local interventions

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Abstract

A wealth of available climate information has prompted data integration into climate services for the health sector, reducing society's vulnerability to climate hazards. We discuss challenges related to product choice, highlighting that without consideration of biases, collaboration between climate and health sectors, reliability of climate-informed public health decisions is undermined.

Introduction

Human disruption to the Earth's natural systems presents a serious threat to human health and well-being. Fundamental changes to the global climate system as a result of anthropogenic activities and other non-anthropogenic drivers can directly affect health outcomes, for example through injuries and premature deaths as a result of extreme weather events, such as extreme heat, tropical storms and floods. Climate change can also affect health indirectly by altering the geographical distribution and burden of communicable and non-communicable diseases.

In particular, the impact of climate variation and climate change on vector-borne diseases, including malaria and dengue fever, is of growing concern. Vector-borne diseases are especially sensitive to climate conditions, which influence the life history of both the pathogen and the vector to determine the geographical distribution, seasonality and interannual variation of disease transmission. Dengue fever is a viral infection transmitted by *Aedes* mosquitoes and is prevalent in urban and peri-urban areas of tropical and sub-tropical climates. Temperatures within an optimum range of 28-30°C can increase *Aedes aegypti* mosquito development, survival and reproduction and decrease the time taken for the pathogen to develop inside the mosquito (the extrinsic incubation period)[1]. Rainfall can increase the availability of dengue mosquito larval habitats in the short-term (i.e. within a few weeks), whilst drought conditions can influence dengue risk over longer time periods (e.g. 3-5 months later), by altering water storage behaviours that increase dengue transmission[2]. Similarly, outbreaks of malaria, which is caused by *Plasmodium* parasites transmitted by *Anopheles* mosquitoes, are sensitive to climate conditions, and are closely related to predictable seasonal rainfall patterns, which have been used to develop early warnings of malaria outbreaks up to four months in advance[3]. Over longer time scales, the warming global climate has been implicated in the return of epidemic malaria to the East African highlands[4], warmer temperatures combined with urbanization are considered to favour the transmission of arboviruses including dengue in sub-Saharan Africa[5] and the expansion of the *Aedes aegypti* vector into temperate latitudes[6].

Climate services

The growing acknowledgement of the impacts of climate on human health and the urgent need to manage these risks from climate variability and change has led to the development and demand for climate services aimed at reducing human vulnerability to climate hazards. The WMO defines a climate service as a decision aide derived from climate information that assists individuals and organizations in society to make improved ex-ante decision-making[7]. For the health sector, climate services can improve the communication of climate-related risks to health professionals, identify those populations that are most vulnerable, as well as identify when and where climate associated health risks may be greatest, and effectively design and target interventions[8]. Climate services are crucial for strengthening the resilience of the health sector in a world with increasing frequency of climate extremes. For a climate service to be successful it must be based on credible scientific information, respond to user-requirements and result in timely and relevant information that can be easily incorporated into decision-making. The ability for a climate service to foster effective collaboration and communication between the users and service providers, including climate scientists and public health practitioners, is also a key component of success. Coproduction of a climate service, where climate and health sectors continually work together during development can ensure successful delivery of a climate service that can be truly useful for health decision making (Fig. 1). Climate services can be applied to public health decisions at many levels, from the local scale to global. For example, a nationwide predictive model framework was developed using seasonal climate forecasts to produce probabilistic dengue predictions in Brazil ahead of the 2014 FIFA World Cup, drawing on an interdisciplinary collaboration between climate scientists, epidemiologists, impact modellers and the Ministry of Health[9]. In highland areas of Ethiopia with periodic malaria epidemics, the Epidemic Prognosis Incorporating Disease and Environmental Monitoring for Integrated Assessment (EPIDEMIA) tool was developed to enhance integration between climate information and epidemiological surveillance, supporting early warning system development and improving outbreak detection at the regional level[10].

Earth observations

Earth observations are a critical component of climate services, providing timely production and delivery of climate information, which can be incorporated alongside epidemiological information to support public health decision-making. Earth observations are atmospheric, oceanic or terrestrial data and information collected about our planet via in-situ observations such as meteorological stations and atmospheric soundings and remote-sensing technologies, such as satellite imagery[11].

Earth observations provide a valuable and accessible resource for investigating the relationships between the environment and human health, including the impacts of climate variation on vector-borne disease risk. Satellite-derived environmental data can provide global estimates of land surface temperatures, rainfall and land cover classifications of particular relevance to the transmission of vector-borne diseases, enabling the development of timely disease forecasts and fine-scale intervention risk maps as well as tracking the health impacts of climate change. Earth observations are particularly desirable for addressing limitations in accessing and using local ground data, such as meteorological station data, which can be complemented with satellite-derived climate products. Remotely-sensed climate observations, such as temperature and rainfall estimates can be incorporated into disease modelling frameworks and have been used to develop forecasts for dengue early warning[12] and determine seasonal variation in malaria incidence due to local climate conditions[13].

Issues of scale

In regions of the world with incomplete historical coverage of meteorological stations, or where stations are situated far apart satellite-derived climate products provide a useful resource for obtaining spatially continuous historical climate observations. This provides an opportunity for the development of tailored climate services that do not need to rely on ground truth data, as satellite data can complement ground measurements. Incorporating globally derived climate information into a functioning locally relevant climate services can in practice be challenging[8]. These challenges include a lack of knowledge about which products are available and suitable and the challenge of providing climate information in a suitable format to be used by the health sector. Climate information is often required at a variety of spatial and temporal scales, to suit multiple needs. Tailoring these global scale products and translating them to be interoperable with localised data in order to provide information for local level decision making can be a challenge to the service success (Fig. 1). Health and epidemiological data are often reported by health centres and hospitals to health authorities and aggregated to administrative levels (i.e., district and province level). Climate information needs to be collated at the appropriate spatial and temporal scale to match epidemiological data. Coarse resolution gridded climate observations and forecasts often need to be aggregated, downscaled and bias corrected for use in a health impact model, which is not a straightforward task especially in areas with diverse topography, such as the Andes mountains and foothills.

Global climate products are desirable as they are easily accessible and provide a wide range of climatic variables. These products have good spatial and temporal coverage, which enables global comparisons across multiple timescales. These data vary from coarse scale resolution datasets (50 km) and datasets with finer resolutions (up to 1 km) (Table S1). For example, the ERA5-Land reanalysis dataset provided by the European Centre for Medium-Range Weather Forecasts (ECMWF) covers the period January 1981 to near real time, providing estimates of meteorological variables that include mean temperature, precipitation and humidity at a high spatial resolution of 9 km (0.08°). In addition, these data are available at an hourly timescale, enabling their use in defining climate indicators for disease forecasting, such as number of wet days and diurnal temperature ranges. Fine scale (<0.1°) spatial climate information can be especially useful to detect variations in microclimate that may be masked at coarser resolution products, which neglect in the effects of topography, presence of water bodies and land surfaces that may influence climate measurements. The spatial scale of climate information is an important aspect to consider when downscaling climate information to match epidemiological data to ensure the appropriate aspects of climate variability that may affect disease transmission processes are captured.

In contrast to the ERA5-Land, the Climate Research Unit (CRU) timeseries provided by the University of East Anglia has a coarser spatial resolution (0.5°/55 km) but has the advantage of providing monthly climate information covering an extensive time period from January 1901- December 2019, which may be useful for detecting historical and long-term climate impacts on disease risk. Given the diversity of global climate products available and differences in spatiotemporal resolution, the purpose of the climate service needs to be considered carefully before selecting the most appropriate source of climate information. For example, a climate product with the ability to detect fine scale variations in local climate may be useful for predicting differences in disease risk across an urban landscape. In contrast, long term climate products with coarser resolution may be more suitable to detect spatiotemporal associations between disease risk and climate variables over a wide geographical area with larger administrative units (e.g., regions or provinces), especially with global climate change.

Methodological and formatting differences

In addition to availability and spatiotemporal resolution, global climate products differ in the techniques used to scale products and methods used to produce continuous estimates. As previously mentioned, epidemiological data are often provided at much finer scales, usually aggregated to administrative units, whereas climate information is usually provided as a grid, which must be reconciled to a common spatial unit for use in health impact models. Gridded climate products and forecasts often need to be downscaled to approximate local conditions on the ground. These datasets are commonly affected by biases, which are systematic deviances from the local climate. Biases are caused by the lack of horizontal resolution as a result of computational constraints, simplifications of physics in the climate model and inaccuracies in static data, such as land cover. These biases can be addressed using bias-correction techniques and downscaling techniques to ensure that the climate model output produces data that better reflects local climate observations. Common downscaling techniques include dynamical and statistical downscaling that rely on statistical relationships between local climate variables and global scale predictors. Bias correction methods include the use of a change factor derived from a global climate model to historical observations to better capture local climate observations. These methods have a number of assumptions to be aware of, such as assuming the biases in climate models remains constant over time, and use of different bias correction techniques can affect the outcome[14].

Downstream impact of the choice of climate inputs to health specific decision-tools

The availability of fine scale climate information has led to an improved understanding of the local climate impacts on health outcomes, such as mosquito-borne disease transmission. However, using climate information in a climate product or service without due consideration and awareness of inherent biases and methodological differences between available products may undermine the appropriateness and reliability of the public health decisions made as a result. A significant challenge in the development of climate services is effectively identifying and conveying these methodological differences, their limitations and the impact they may ultimately have on public health decision making.

Despite the wealth of global climate products available there is no general consensus or guidance on the most appropriate data source to use for applications such as disease mapping and forecasting, and the reliability of sources to be used to inform public health decisions. In addition, there has been no direct comparison of different data sources, how to select the most appropriate resource and how the use of different products can impact climate-sensitive disease analyses.

Implications of different climate data sources on understanding vector-borne diseases in southern Ecuador

As a case study, we used simple temporal models adapted from previous studies to assess how the choice of climate product as a model input affected vector-borne disease model outputs[12,13]. We used Bayesian hierarchical models of monthly cases of dengue between 2002-2014 and malaria between 1990-2015 for the city of Machala, in southern Ecuador, a city at risk of the health impacts of climate change[15]. Prior studies found that dengue and malaria transmission were sensitive to changes in climate in this region[12,13]. We compared five global products of monthly mean temperature and precipitation, with local weather station data to investigate the impact of local climate variation on these two vector-borne diseases. In this example, we used global climate products of similar temporal coverage but differing spatial resolution, which included CHELSA timeseries, CRU timeseries version 4.04, monthly ERA5-Land, TerraClimate and WorldClim historical monthly timeseries. Mean temperature and precipitation from these sources differed in comparison to estimates from the local meteorological station (Fig. 2A-B). In particular mean temperatures from the CRU and ERA5-Land datasets were much cooler (up to 5°C lower) than those observed from the meteorological station, while seasonal dips in temperatures from the CHELSA dataset were much warmer than station observations (Fig. 2A, Fig. S1). The global climate products were able to capture peaks in rainfall over the time period as measured by the local meteorological station, although up 40 mm more rainfall per day was recorded in the ERA5-Land dataset (Fig. 2B, Fig. S1).

Comparison of model parameter estimates revealed differences in the modelled impact of climate variation on disease risk (Fig. 2C-D). The model showed that warmer temperatures would lead to increased risk of dengue. The magnitude of this effect was similar for WorldClim, TerraClimate and CHELSA models but was slightly reduced for models with ERA5 and CRU products. For malaria risk, there was a divergence in the impact of climate on malaria between the models (Fig. 2D). Whilst the observed station data and ERA5 models indicate a positive association between malaria cases with warmer temperatures, the credible intervals for the temperature parameter estimate contained zero. If these data were to be used, this could lead to the conclusion that variation in temperature does not have a significant impact on malaria risk, even though temperature has been previously demonstrated to be an important factor explaining malaria seasonality and interannual variability in southern Ecuador[13]. Whereas the credible interval for precipitation contained zero in the dengue and malaria models using the observed station data, CHELSA and ERA5 data showed a negative association between rainfall and malaria risk. In contrast to this the CRU model showed a positive association between rainfall and malaria (Fig. 2D). This result could be due to inherent biases in the underlying climate information and methods used to produce monthly precipitation estimates that cause differences between observed and modelled estimates.

In addition to the issue of selecting the most appropriate climate product to best capture local climate variation, grid cell selection is also important. In a predictive dengue model developed previously, the climate conditions of the grid cell adjacent to the reference Granja Santa Ines meteorological station in Machala was found to be more representative of the local climate than the grid cell within which the station was located. Temperatures for the grid cell corresponding to the meteorological station location were consistently colder than the station observations. Therefore ensemble climate forecasts for the adjacent grid cell were used to predict the evolution of the dengue season in 2016, as a simple bias-correction to account for this difference[12]. In our analysis using the corresponding grid cell, which covers a topographically diverse area including the Andes foothills, we would expect a 40% increase in dengue cases for a 1°C increase in mean temperature. Using the adjacent grid, which is 4°C warmer we would expect a 46% increase in dengue cases for a 1°C increase in mean temperature (Fig. S2).

This simple example highlights the issues and considerations when selecting the most appropriate climate products for modelling climate-sensitive diseases. However, it exemplifies a single specific problem for one location that will not be universal for all applications. In some instances, global climate dataset models may not align with ground truth conditions in areas with incomplete weather station coverage. In this example, Machala is located on the coast of Ecuador and has the Andes mountains situated to the east. Orographic events mean the climate variables in the grid cell may not reflect actual conditions in the coastal city, where the weather station is located, and the majority of mosquito-borne disease transmission occurs. In summary, it is important to first compare remotely derived data to ground truth data and second to consider geographic sources of local variation in the absence of ground truth data when choosing the most suitable climate product. This can be achieved through close collaboration between experts and scientists from the health and climate sectors, enabling local biases in climate information to be detected and corrected for before incorporation into the health decision-making tools.

Conclusions

Earth observations and forecasts are helping to reduce society's vulnerability to climate hazards, through the development of tailored climate products and services for health and other sectors. The availability of and access to global data sources have allowed for gaps in local weather station data to be supplemented with global observations and provided estimates of environmental conditions in areas lacking locally observed data, which is useful for developing early warning systems over large geographical domains or in remote areas. However, as illustrated in examples for two climate-sensitive vector borne diseases - dengue and malaria – the choice of climate data product can have important downstream implications for interpreting the importance of climate as predictors of disease risk. These findings have implications for the health sector, as public health practitioners face decisions about how and when to respond to climate-associated health risks. For example, a misinformed conclusion about climate-malaria relationships that is used as the basis of an early warning system reliant on climate predictors that gives incorrect information about when and where to distribute bed nets to tackle an outbreak could lead to a misallocation of precious health resources. We have highlighted that simple off the shelf usage of climate data products, without thorough understanding and interrogation of methodological and scale issues can lead to such misinformed conclusions.

Coproduction of climate services is vital to ensure that a climate service is truly useful for health decision making. A strong partnership and interdisciplinary collaboration between the health and climate sectors that supports appropriate climate data selection and fosters continued sharing of information, skills and progress will also contribute to a sustained climate service to improve future decisions by health sector practitioners. When choosing a climate product to inform health impact models, it is important to consider inherent biases and methodological differences between climate products, variation in weather station coverage and local climate variations, which may not be captured by gridded products. Improved communication of methods used to conduct global climate projects, with guidance for users on their appropriate use and limitations is needed to enhance the uptake of these products and avoid misuse.

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Declaration of interests

The authors declare no competing interests.

Figure legends

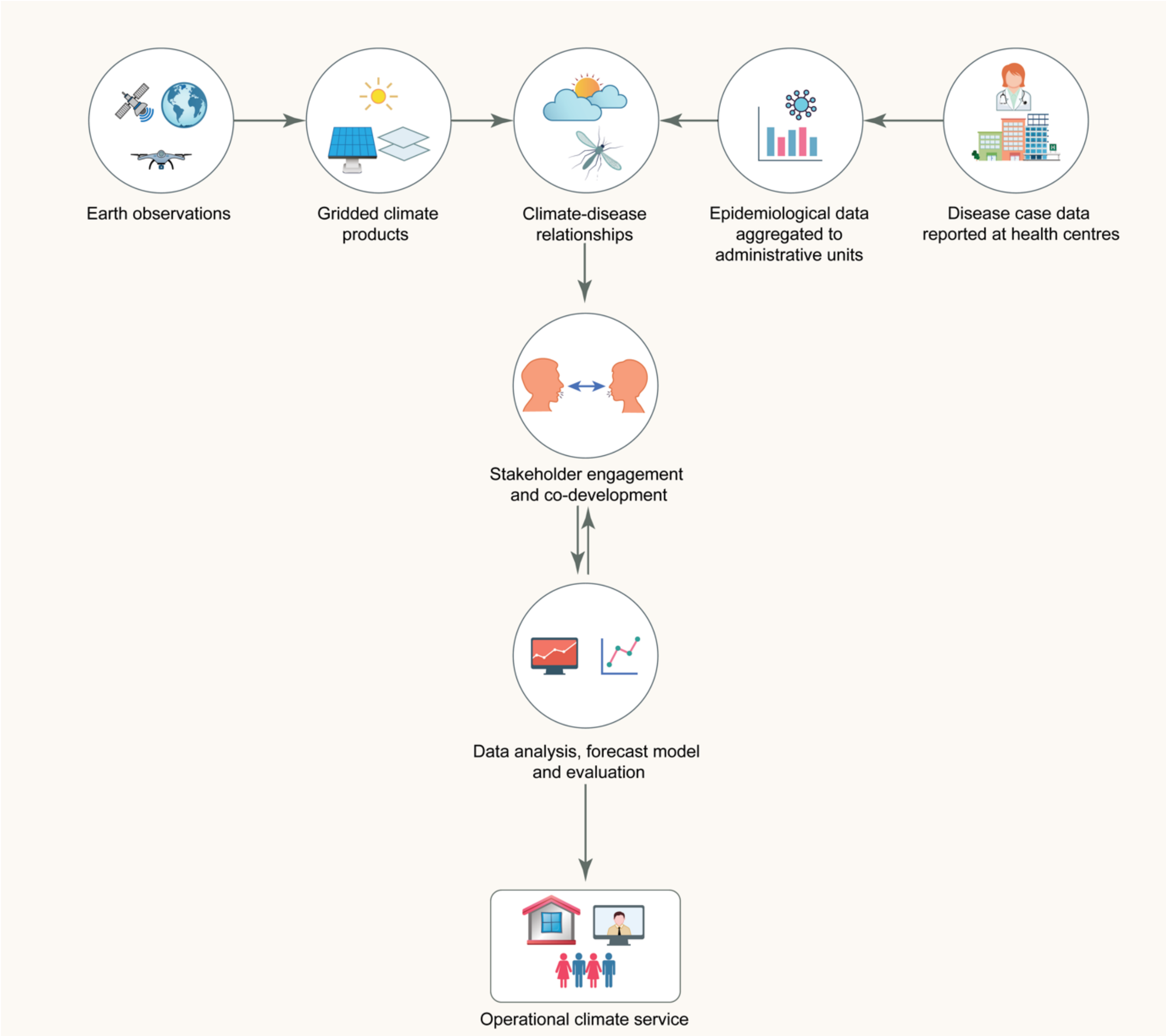

Fig. 1. Cross-disciplinary processes involved in coproduction of an operational climate service. Evidence for climate-disease relationships can be informed global climate products that can supplement lacking ground truth data. Earth observations, such as remotely sensed climate data often provided as global climate products, have to be combined with administrative-level epidemiological data such as cases of dengue for data-analysis. At this point co-development of the climate service, with continual sharing of information between climate scientists and public health officials as well as engaging stakeholders, can ensure methodological and data biases are addressed and the resulting climate service suits the user's needs. Collaboration between sectors to verify resulting forecasts and evaluate their success for climate-sensitive diseases is an iterative process to reach the final operational climate service.

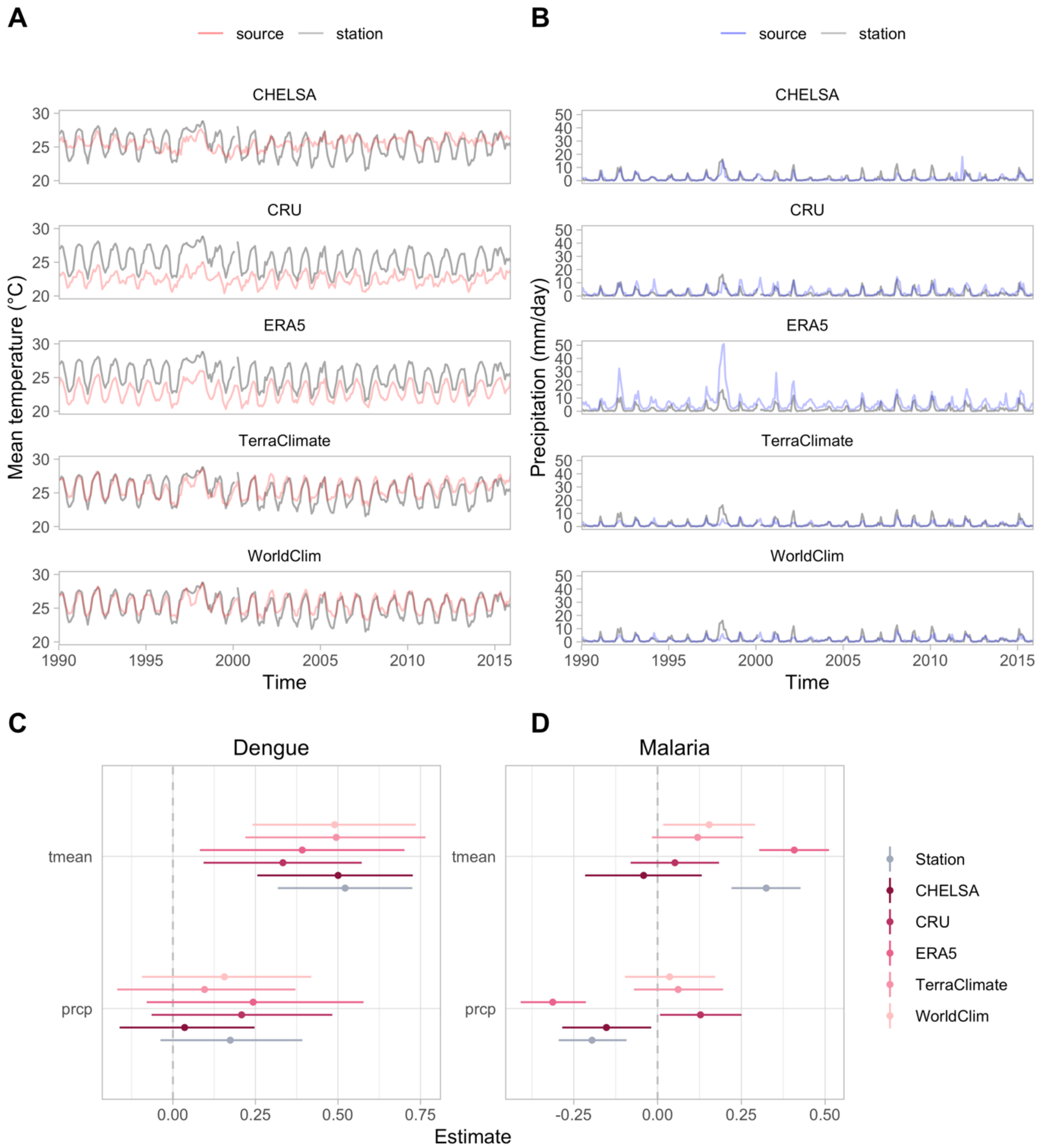

Fig. 2. Global climate observations using different global climate datasets and impact on parameter estimates in climate-sensitive disease models. A) Monthly mean temperature and B) precipitation from the Granja Santa Ines meteorological station in Machala, Ecuador and corresponding location estimates from five global climate datasets; CHELSA timeseries, CRU TS v.4.04, ERA5-Land monthly, TerraClimate and WorldClim historical timeseries. Posterior mean and 95% credible intervals of mean temperature (tmean) and precipitation (prcp) variables in temporal models of monthly C) dengue cases 2002-2014 and D) malaria cases 1990-2015 in Machala. Estimates in grey are for models using climate data from the Granja Santa Ines meteorological station and estimates in shades pink are for models using climate data from five global climate datasets; CHELSA timeseries, CRU TS v.4.04, ERA5-Land monthly, TerraClimate and WorldClim historical timeseries.

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