Chapter 22

Predicting Climate Impacts on Health at Sub-seasonal to Seasonal Timescales

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Variations in climate can have wide-ranging impacts on human health. These include direct impacts, involving immediate danger to human life resulting from weather extremes such as high winds, floods, storm surges, and weather-related accidents. Indirect impacts include nutritional deficiencies due to crop failures resulting from climate-induced pest outbreaks or drought in regions relying on rain-fed agriculture (World Health Organization, 2012). A wide range of diseases are also affected by climate due to the sensitivity of disease pathogens, vectors, or hosts to variations in climate.

Health impacts may be derived as a result of variations in rainfall, temperature, and humidity (and related factors) over multiple timescales, from weather variations (days to weeks) through seasonal variability (weeks to months) to decadal variability and climate change (years to centuries). Here, the focus is on the prediction of weather and its impacts over sub-seasonal to seasonal (S2S) time frames of weeks to approximately 2 months. This timescale is situated between short-term weather forecasts, which predict the evolution from accurate atmospheric initial conditions, and seasonal climate forecasts (SCFs). At each prediction timescale, modes of atmospheric and oceanic variability can provide predictability, such as the El Niño-Southern Oscillation (ENSO) at a seasonal timescale or the Madden-Julian Oscillation at sub-seasonal scales.

In this chapter, we explore the potential value of S2S forecasting for health decision makers and seek to identify opportunities for adding value to current uses of weather and SCFs in the development of health early warning systems (HEWSs). Operational requirements for effective S2S-based forecasts for health are introduced using four case studies contributed by the coauthors, where prior work has shown the potential for weather and SCFs to inform decision making. Our discussion compares the results of heat stress early warning with that of infectious diseases, including viral (dengue) and parasitic (malaria) vector-borne diseases, as well as an airborne bacterial infection (meningococcal meningitis). Despite the early stage of applying S2S predictions to support public health decision making, we believe that valuable lessons can be learned and applied to a wide range of climate-sensitive diseases.

While variations in climate affect health in both developed and developing countries, developing countries are more vulnerable. These countries lack protection against exposure to extreme temperatures in the home and workplace, and vector-borne disease outbreaks are more prevalent. Therefore, the case studies presented here predominantly focus on the developing regions of the globe.

1.1 Climate Impacts on Health

Variations in weather and climate affect health outcomes, and climate information is already implicitly or explicitly accounted for in health decisions, such as incorporating climate into the derivation of spatial risk maps for malaria (Hay and Snow, 2006; Omumbo et al., 2013) or accounting for the seasonal cycle of disease in intervention planning (Jancloes et al., 2014). Accurate predictions of climate thus can lead to valuable information that can help with preparation for a specific health consequence, provided that the link between climate and health is well understood. Often, the relationship between climate and health outcomes is determined
empirically, using a univariate or bivariate analysis with rainfall, temperature, or both as key determinants of many health outcomes, particularly those associated with vector-borne diseases. For example, documented malaria outbreaks in highland areas of Africa have long been known to be associated with ENSO events and have been attributed to both enhanced rainfall and warmer temperatures (Kilian et al., 1999; Lindblade et al., 1999). A simple empirical relationship between rainfall and malaria was used in an early, groundbreaking prototype of a seasonal forecast system (Thomson et al., 2006a). More recent work with statistical models has evolved to use general additive/linear models (Lowe et al., 2011, 2013a,b, 2016a; Colón-González et al., 2016).

An advantage of using statistical models is the ability to simultaneously consider the complex interaction of climate hazards, socioeconomic disparities, and human vulnerability with predictive disease risk in space and time (Lowe and Rodó, 2016). This approach attempts to predict health case data using a range of socioeconomic and environmental indicators, some of which can act as proxies for climatic variables, such as altitude (a proxy for temperature), location, or month of the year (a proxy for seasonality). These fields are static and do not vary from year to year. The model is then shown linear and nonlinear functions of temperature and rainfall to determine if the fit to the health data is improved. This approach thus focuses on the relationship between interannual variations in climate and health outcomes, which could be predicted at multiple timescales, including by S2S climate-forecasting systems. The drawback of statistical methods is the need for long datasets of high quality, as well as the fact that such a model is restricted to areas of similar social and eco-epidemiological conditions to those for which the model was developed. Often, models are shown to be skillful in the locale in which they are derived and are not necessarily transferable to new locations. This is particularly true for models driven by rainfall, which can have nonlinear and complex relationships with health outcomes depending on the context.

Table 1 gives examples of how rainfall has been found to affect some common health outcomes, and in each case, opposing impacts can be found depending on the environmental setting. For example, malaria is generally assumed to be associated with the rainy season,
as rainfall provides the water for temporary breeding sites for many of the key mosquito vectors. A study of malaria in a Sahelian village shows cases tracking rainfall with a delay of approximately 2 months (Bomblies et al., 2009). In contrast, in the vicinity of rivers, transmission can flare up during periods of drought. As river flow slows or halts, still ponds are created as a result (Kusumawathie et al., 2006; Haque et al., 2010). Extended drought can also affect population vulnerability through malnutrition, loss of herd immunity, or even through the loss of vector predators, causing more intense outbreaks once rains and transmission resume (Gagnon et al., 2002).

The relationship between rainfall and cholera also depends on the hydrological setting. Rainfall sometimes increases risk in dry regions, while the dilution effect of rainfall in estuarine locations may result in lower cholera incidence (Pascual et al., 2002). In East Africa, Rift Valley Fever (RVF) epidemics often follow rainfall anomalies during the short rainy season (October-December) associated with El Niño. In West Africa, the relationship between rainfall and RVF appears to be more complex, with a dry period between rainy events being identified as an outbreak trigger (Caminade et al., 2011). This would suggest a highly nonlinear dependence on sub-seasonal rainfall variability, which would be very challenging for S2S forecasting systems to predict accurately beyond the range of a few days. Finally, rainfall also can provide open-air breeding sites for dengue vectors, but dry periods increase water storage in urban areas with unreliable supplies, which can actually increase vector density if these facilities are poorly managed (Brown et al., 2014; El-Badry and Al-Ali, 2010; Padmanabha et al., 2010). Indeed, water storage and harvesting may have implications for other health outcomes, such as schistosomiasis and malaria (Boelee et al., 2013).

All these examples show why a statistical approach to modeling climate-disease interactions may be restricted to the area in which it is derived. If an improved understanding of the disease biology can be attained, empirical statistical approaches can be supplemented by mathematical models of diseases, which may be more generic and transferable in theory. However, such models also have their drawbacks, as the uncertainty of many biological processes can be large, partly related to the representativeness of controlled laboratory conditions to real-world situations and the fact that single laboratory experiments give little indication of parameter uncertainty. Moreover, location adaption of vector species also may hinder the ability of the model to be transferred from one location to another. Mathematical dynamical disease models thus often suffer from considerable structural and parameter uncertainty (Tompkins and Thomson, 2018).

1.2 Toward S2S Predictions in Health

Apart from disease model (statistical or dynamical) uncertainties, the efficacy of any climate-driven early warning system for health depends on the underlying skill of the driving climate-forecasting system. Approaching the climate-health nexus from the meteorological perspective, the focus of S2S system skill for health application is on near-surface meteorology, although of course, the skill in predicting these parameters depends on the whole meteorological system. Accurate representation of the near-surface temperature in S2S systems is the result not only of a good representation of the land surface and soil moisture, but also of the turbulence, convection, cloud microphysics, and large-scale dynamical processes.
The key near-surface parameters are rainfall, temperature, relative humidity, winds, and radiative fluxes. Reliable weather and climate predictions of these parameters in S2S forecast systems from 1 to 60 days ahead (see Chapter 1) could be used to drive statistical and/or dynamical modeling systems for health outcomes. The potential advance warning available will vary substantially according to the specific health impact. This may be contemporaneous with the meteorological anomaly (e.g., flooding or heat waves) or involve a delay of weeks to months (e.g., vector-borne disease risk). In the case of malaria, the early warning (lead time) of 1–2 months available from climate monitoring could be potentially extended by a further 2 months with the use of skillful S2S prediction systems. Indeed, SCFs have already shown predictive capacity in certain regions and seasons (Doblas-Reyes et al., 2013) and research has demonstrated the opportunity to incorporate forecast climate information into early warning systems for climate-sensitive diseases such as dengue and malaria (Connor and Mantilla, 2008; Thomson et al., 2006a; Lowe et al., 2014; Balleser et al., 2016). The advantage of S2S systems is that they are more frequently initialized, generally have a higher spatial resolution than the equivalent seasonal forecasting system from the same producing center, and in some cases, offers more frequent model upgrades (Vitart et al., 2008). A direct comparison between the European Center for Medium-range Weather Forecasts (ECMWF) S2S and seasonal forecast systems for Africa showed a significant improvement in skill, especially for 2-m temperature (Tompkins and Di Giuseppe, 2015).

In summary, an HEWS requires the identification of critical meteorological thresholds associated with adverse (or beneficial) health impacts, the ability to predict these meteorological conditions accurately in advance and translate them reliably to a particular potential health outcome. Forecasts should be issued to decision makers, indicating whether key thresholds are likely to be reached while effectively communicating the uncertainty associated with this prediction. Further, a set of standard operating procedures should be established, to implement risk reduction measures based on the forecast information provided. The system needs to be robustly evaluated over a set of past events to ensure its overall benefit. All of these steps represent significant research and operational challenges. Despite the obvious potential of S2S forecasts and the fact that policymakers are often well aware of the relationship between climate variations and health outcomes, it is perhaps unsurprising that climate information is still rarely exploited to help prevent and control such health risks. The four case studies described here attempt to determine the possible added value of incorporating climate information at S2S timescales in health early warning systems. The chapter highlights some of the barriers and bottlenecks that exist, which need to be overcome to effectively operationalize such systems. Possible steps are suggested to address these and ensure that the potential of present state-of-the-art climate observational and prediction systems are fully realized to complement public health decision-making and ultimately improve well-being.

2 CASE STUDIES

2.1 Malaria (Tompkins and Thomson)

Malaria has long been linked to the environment, with the association of pestilence with drying marshes identified in Roman times (O’Sullivan et al., 2008). After Ross discovered that
mosquitoes were the vectors for the disease, the direct link with rainfall that provides vector breeding sites was firmly established. By the World War I, environmental engineering techniques were employed to control the disease until the 1960s, when the focus was switched to the use of the insecticide dichlorodiphenyltrichloroethane (DDT) application (Konradsen et al., 2004; Tompkins et al., 2016b). While engineering solutions such as swamp drainage schemes can be classified as long-term abatement interventions, annual interventions such as the application of DDT are often carried out according to the seasonality of the disease.

One of the earliest studies that attempted to use rainfall anomalies to predict malaria transmission anomalies for the season ahead for guidance was conducted in the early 1920s (Gill, 1923), with the method employed for several decades afterward with claimed success in linking May rainfall in the Punjab province to late autumn transmission (Swaroop, 1949). The separation of India and Pakistan was cited as the cause of the cessation of this particular forecasting system in the province (Swaroop, 1949). However, after 1955, the introduction of insecticides and newly developed medicines aimed at malaria eradication resulted in decreased interest in forecasting and early warning systems (Rogers et al., 2002).

After the collapse of intervention efforts in the 1970s and the subsequent rebound of the disease, interest in early warning systems was rekindled in the 1980s and 1990s (Connor et al., 1998). Effective early warning of an outbreak in epidemic-prone areas or anomalous transmission in malaria-endemic regions could be used to manage decisions concerning indoor residual spraying (IRS) interventions, bed net distribution, ensuring that appropriate medical supplies in health clinics are available, and conducting public information campaigns, with the appropriate action or combination of actions depending on the disease transmission setting in question. Although it was known that temperature and humidity could impact the transmission of the disease (Mayne, 1930), the majority of studies into early warning were univariate, focusing on rainfall variability as the predictand for transmission. The widespread outbreaks in the African highlands resulting from the extreme El Niño event of 1998 greatly increased interest in the potential of malaria early warning systems, and while the focus was still on rainfall, some studies also noted that the warmer tropical temperatures associated with El Niño also could act to push transmission to higher altitudes and encourage highland outbreaks (Kilian et al., 1999; Lindblade et al., 1999; Hay et al., 2001). The delay between the rains and the peak in transmission of 1–2 months meant that many early efforts for early warning were based on rainfall monitoring, using in situ and/or remotely sensed data (Grover-Kopec et al., 2005), which provided additional advance warning compared to simply attempting to monitor cases. Case monitoring, especially prior to the implementation of the first- and second-generation digitized health management and information systems, was rarely close to real time due to the delay involved in collating paper records centrally.

Considering the use of dynamical monthly and seasonal forecasts for climate, skillful forecasts could potentially extend the available lead time for planning purposes (Cox and Abeiku, 2007). While this was discussed in the context of rainfall predictions, to maximize the potential benefit of dynamical climate predictions, a multivariate approach would be beneficial, accounting for all climate variables that affect the disease. Of course, rainfall provides breeding sites for malaria vectors, although the relationship is far from straightforward because extreme events on sub-seasonal timescales can flush breeding sites of early-stage larvae and even reduce vector density in the short term (Paaijmans et al., 2007). This might explain why statistical analysis of the malaria-rainfall relationship often reveals a highly nonlinear

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parametric relationship, with transmission peaking at a rainfall rate of approximately 3–5 mm/day over a month (Thomson et al., 2006a; Lowe et al., 2013a; Colón-González et al., 2016). Temperatures affect both the parasite and vector development rates, while higher temperatures affect vector mortality in both the larval and adult phases (Craig et al., 1999). Humidity also affects vector survival (Mayne, 1930; Thomson, 1938; Lyons et al., 2014) although the impact is less well understood. Uncertainties in these relationships are large, due to lack of experimentation, and more important, complex topography and heterogeneous land cover can imply considerable variations in climate spatially, and thus satellite or station measurements may not accurately reflect variations in microclimates in which adult mosquitoes and their larvae reside.

Recent reviews of early warning systems for malaria show that the majority of them are based on climate monitoring, and a small number use SCFs (Mabaso and Ndlovu, 2012; Zinszer et al., 2012). The connection to malaria in these systems consists of statistical models (Lowe et al., 2013a), mathematical compartmental Susceptible, Exposed, Infected, Recovered (SEIR) models that incorporate climate in idealized and sometimes ad hoc ways (Laneri et al., 2010), or full-process models that attempt to model the key elements of the full-vector and parasite life cycles, relying mostly on results from experiments using controlled laboratory settings to set the life-cycle parameters (Hoshen and Morse, 2004; Bomblies et al., 2009; Tompkins and Ermert, 2013).

One of the first attempts to demonstrate a prototype forecasting system using dynamic climate predictions used multimodel precipitation forecasts from the DEMETER seasonal forecasting project (Palmer et al., 2004) to drive a simple, univariate statistical model that fitted the national total laboratory-confirmed malaria cases in Botswana to monthly rainfall data (Thomson et al., 2006a). Cross-validation showed the system to be skillful in this region, which exhibits significant teleconnections with ENSO. The Botswana data were also recently used to test a system using newer climate forecasts to drive a dynamical malaria model, which had some success at prediction in high-transmission years (MacLeod et al., 2015). Other studies demonstrated the potential for malaria early warning systems driven by the new ENSEMBLES seasonal forecast system (Weisheimer et al., 2009; Jones and Morse, 2010, 2012). However, these demonstrations consist of a so-called tier 2 validation, where the malaria forecasts are validated against the malaria model driven by climate reanalysis (Dee et al., 2011) rather than actual case data.

Most dynamical malaria forecast demonstrations have used seasonal dynamical systems, but what is the potential of S2S systems that are the subject of this book? As stated previously, these systems have a number of configuration advantages that should imply enhanced skill relative to their seasonal forecast cousins at their 1- to 2-month lead times. As these systems are relatively new, there has been limited evaluation of their potential for malaria forecasting to date. One study (Tompkins and Di Giuseppe, 2015) has employed the S2S system from the ECMWF model (Vitart et al., 2008) in tandem with its seasonal forecasting system (Molteni et al., 2011). The study showed an increase in both precipitation and temperature skill for the monthly system relative to the system 4 seasonal forecast over Africa. It used the S2S system for the first 32 days of the forecast, which was then supplemented by the seasonal system. A novel aspect of the study was that, rather than spinning up the forecast system from an artificial state, the forecasts were initialized from a simple malaria analysis, created by driving the model with reanalysis data. In this way, wetter/warmer-than-average conditions in the
weeks and months preceding the forecast would lead to enhanced vector densities and higher parasite ratios in the initial conditions. The study showed that the S2S system skill extended the malaria advance warning from 1 to 2 months (available from simply using climate monitoring) out to 2–3 months; and in limited areas the seasonal system extended the lead time further still (Fig. 1). Analyzing the S2S skill separately demonstrated that most of the prediction skill with malaria was actually derived from the temperature forecasts, which tended to be more skillful than with rainfall. One limitation of this study, however, was that the evaluation was again of the tier 2 type; that is, the forecasts were evaluated against a reanalysis-driven model. A more recent study instead evaluated the forecast system against actual confirmed case data in Uganda and demonstrated significant skill out to 4 months (Tompkins et al., 2016a).

In summary, while some limited studies have demonstrated the potential use of one S2S system for the prediction of malaria, there has been limited uptake of S2S systems so far. Further use of S2S systems is expected as the database grows. Open access to the real-time forecasts with no operational delay may also increase the evaluation and development of S2S-based malaria early warning systems.

2.2 Dengue (Lowe)

Dengue is a mosquito-transmitted viral infection, widespread in tropical and subtropical regions (Guzman and Harris, 2015). Dengue epidemics in Brazil often occur without warning and can overwhelm the public health services (Lowe et al., 2016b). SCFs combined with early data from a dengue surveillance system provide the opportunity for public health services to anticipate dengue outbreaks several months in advance. This could improve the allocation of intervention measures, such as targeted vector control activities and medical provisions, to those areas most at risk.

In a recent study, Lowe et al. (2014) developed a prototype dengue early warning system for Brazil. Real-time SCFs and disease surveillance data were integrated into a spatiotemporal model framework to produce probabilistic dengue forecasts. The model was used to predict the risk of dengue 3 months ahead of the 2014 FIFA World Cup in Brazil, a mass gathering of more than 3 million spectators.

Brazil is divided into more than 550 microregions. The authors assessed the potential for dengue epidemics during the tournament by providing probabilistic forecasts of dengue risk for each microregion, with risk-level warnings issued for the 12 cities where the matches were played. The dengue early warning system was formulated using a Bayesian spatiotemporal model framework (Lowe et al., 2011, 2013b), allowing specific public health issues to be addressed in terms of probability. It was driven by real-time SCFs for the period March-April-May and the dengue cases reported to the Brazilian Ministry of Health in February 2014. This information was combined to produce a dengue forecast at the start of March 2014.

Predicted probability distributions of dengue incidence rates (DIRs) were summarized and translated into risk warnings, which were determined using dengue risk thresholds of 100 and 300 cases per 100,000 inhabitants, defined by the National Dengue Control Programme of the Brazilian Ministry of Health. The probability of dengue incidence falling into predefined categories of low, medium, and high risk was mapped using a visualization
FIG. 1  Points where forecast skill is significant for temperature, rainfall, and an analog of malaria cases at lead times from 1 to 4 months over Africa, using reanalysis-derived data for evaluation (see Tompkins and Di Giuseppe (2015) for details of the calculation methodology). Points are filtered to show only those areas where malaria transmission is highly variable for the month in question (i.e., where malaria is epidemic, or where the onset of the transmission is highly variable). The graph shows that in the first month, often all three variables are skillfully predicted, or just temperature and malaria are. From month 2 onward, only malaria is successfully predicted, due to the lag between rains and malaria. This highlights the importance of correctly initializing the malaria modeling system. This is a challenge because real-time information on vector densities, puddle availability, and parasite prevalence is not available. It also shows that the successful climate forecasts in months 1 and 2 extend the malaria predictability range.

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technique in which color saturation expressed forecast certainty (Jupp et al., 2012). A verification map, expressing the past performance of the model, was provided along with the forecast. This indicated how “trustworthy” the model was in different areas of Brazil.

Following the tournament, the authors evaluated the prototype against the actual reported cases of dengue during the event. Fig. 2 shows a ternary probabilistic forecast map and the corresponding observed DIR categories (low, medium, and high). The model correctly predicted a high probability of low dengue risk in South Brazil and large areas of the Amazon (with certainty depicted by color saturation). High-risk microregions were also correctly detected in parts of Northeast Brazil. Observed DIRs were greater than expected in Brasília, although the likelihood of observing high levels of dengue for the surrounding region was relatively greater than observing lower levels. For some microregions in the state of São Paulo, the model was uncertain about the most likely category (depicted by pale colors). Some of these areas experienced high DIRs in June 2014.

The forecast model correctly predicted the dengue risk level in 7 of the 12 cities that hosted the World Cup games. The forecast model was compared to a null model based on seasonal averages of previously observed dengue incidence. When considering the ability of the two models to predict high dengue risk across Brazil, the forecast model produced more hits and fewer missed events than the null model, with a hit rate of 57% for the forecast model as compared to 52% for the null model.
opposed to 33% for the null model. Therefore, the forecast model, based on SCFs and early surveillance data, outperformed a simple seasonal profile, upon which decisions are typically based. The implementation of SCFs and early reports of dengue cases into an early warning system is now a priority for public health authorities (Lowe et al., 2016b). This action is likely to help them to prepare for and minimize epidemics of dengue and other diseases transmitted by the same mosquito vector, including Zika and chikungunya.

The prototype dengue early warning system for Brazil developed from a Leverhulme network project: EURO-Brazilian Initiative for Improving South American Seasonal Forecasts (EUROBRISA), which explored how SCFs could be better exploited to improve climate resilience in South America (Coelho et al., 2006). EUROBRISA is an operational forecasting system designed to produce 3-month average forecasts, issued 1 month ahead. To accommodate the design of the seasonal forecasting system in the dengue model framework, precipitation and temperature variables were averaged over the 3 months prior to the month in which dengue predictions were valid. However, climate data at the monthly, weekly, or daily scale, such as diurnal temperature range or number of days in a month with rainfall exceeding set thresholds, may better resolve the climate sensitivity of the mosquito life cycle (Lambrechts et al., 2011; Chen et al., 2012). Indeed, one of the challenges of moving toward the use of S2S systems is the need to use weekly rather than monthly averaged climate data as a driver.

In Ecuador, lag times ranging from several weeks to 2 months between dengue and rainfall and minimum temperature were found to be important for dengue prediction (Stewart-Ibarra and Lowe, 2013; Stewart-Ibarra et al., 2013). A recent study used SCFs to predict the evolution of the 2016 dengue season in the coastal city of Machala in Ecuador, following one of the strongest El Niño events on record (Lowe et al., 2017). The forecasts were obtained from the Climate Forecast System (CFSv2) model, developed by the National Center for Environmental Research (NCAR), using the grid point most representative of the climate in the coastal area of Machala. The forecasts were arranged as a 24-member ensemble initiated January 1, 2016, producing monthly averages of precipitation and daily minimum temperatures for the 10 months following the forecast start date.

Given a delay of 1 month between anomalies in climate variables and dengue incidence, dengue forecasts were produced up to 11 months ahead. These climate-driven forecasts successfully anticipated the peak in dengue incidence to occur 3 months earlier than expected, based on seasonal averages (Lowe et al., 2017). The temporal resolution of the dengue forecasts could be improved even further by incorporating sub-SCF information in the dengue model framework, which is an area of active investigation.

2.3 Meningitis (Martiny, Roucou, and Nakazawa)

Bacterial meningitis (meningococcus, or Neisseria meningitidis) is a highly contagious, person-to-person, infectious disease of the meninges, the thin layers that cover the brain and spinal cord. Some regions of the world are particularly exposed to epidemic risks, like the “African meningitis Belt” (Lapeyssonnie, 1963) a semiarid region that extends from Senegal to Ethiopia. This region suffers the highest incidence in the world, with both annual local epidemics and multiannual large waves affecting the whole meningitis belt (Broutin et al., 2007).
The Meningitis Environmental Risk Information Technologies (MERIT) initiative (Thomson et al., 2013) was established in 2007 as a multidisciplinary community of partners who conduct research to advance the use of climate-related information in strengthening public health strategies for the control of epidemic meningitis in Africa. Coinciding with this initiative, a new conjugate vaccine called MenAfriVac (Frasch et al., 2012), against the dominant serogroup A (NmA), was tested and rolled out across the region. The vaccine rapidly suppressed case numbers, but it has not eliminated the need for a meningitis early warning system or a better understanding of environmental drivers of disease. Serogroups other than A pose a significant epidemic threat and currently cannot be controlled by preventative vaccination (Agier et al., 2017).

The transmission and dynamics of meningitis can be influenced at different scales by host immunity, coinfections, household lifestyle, population density and dynamics, and socioeconomic conditions (Agier et al., 2017). Additionally, a link with climate was found in the 1960s, and the disease is now recognized as one of the most climate-sensitive in Africa. The World Health Organization (2012) stated in 2012 “While the temporal association between climate and meningitis is evident, what triggers or ends an epidemic is as yet unknown”. One assumption made by epidemiologists is that extremely low air humidity combined with high dust loadings that sometimes persist over many weeks may contribute to host susceptibility, including physical damage to the mucosa to the point where the colonizing meningococci are more likely to invade the nasopharyngeal epithelium (Mueller and Gessner, 2010). In any case, despite remaining uncertainty in the infection mechanism itself, the recognized climate risk factors of hot, dry, and dusty conditions are potentially predictable at S2S timescales, given accurate enough forecasting systems.

The geographic boundaries of the Belt are limited by the isohyet 300 mm to the north (approximately 15 degrees N) and 1100 mm to the south (7 degrees N) (Lapeyssonnie, 1963), which corresponds to the climate definition of the Sahel. It is well documented in previous studies that meningitis outbreaks occur in the dry season, from January to May, dominated by strong, warm, dry, and dust-laden northeasterly Harmattan winds, which blow from the Sahara Desert to the sub-Sahel regions, and that the premonsoon rainfall halts the outbreak (Sultan et al., 2005; Thomson et al., 2006b; Dukić et al., 2012; Broman, 2013; Pérez García-Pando et al., 2014; Pérez et al., 2014; Cuevas et al., 2015; Pandya et al., 2015; Diokhane et al., 2016). A recent review (Agier et al., 2017) reported the statistical methods (regression models, disease mapping, hypothetical explanatory models, mathematical modeling) employed to explain the meningitis incidences at different spatial (country/region/district/individual) and time (year/season/month/week) scales. The most commonly used climate factors are wind, humidity, temperature, and dust.

Climatic variability explains 25% of the year-to-year variability of meningitis according to previous analysis (Yaka et al., 2008). The meridional wind component in October, November, and/or December seems particularly important: An enhancement of the Harmattan flow at the beginning of the dry season may affect the number of cases in meningitis and provoke epidemics several months later. The climate conditions in the October-to-December season sometimes may permit early cases in meningitis that could, in turn, influence the final size of the epidemics through contacts between people and the increased size of the reservoir. This statistical model was refined at the health sanitary district scale in Niger by adding as new predictors dust at the beginning of the dry season, early cases of meningitis, and population density.
density (Pérez et al., 2014). The next key challenge is to explain the meningitis incidence at specific points of the epidemics (most notably the onset) in order to get closer to the operational needs.

Burkina Faso is one of the countries most affected by meningitis in the Belt (Agier et al., 2008). Based on the attack rate (number of cases in meningitis/population × 100,000), 7 years are identified as epidemic in the country for the period 1979–2014: 1984, 1996, 1997, 2001, 2002, 2006, and 2007. Monthly climate composites (epidemic years minus all years) highlight specific synoptic conditions in epidemic years. The November composite highlights a significant reinforcement of the surface wind in the northeasterly direction (Fig. 3A). This affects relative humidity, which experiences significant dry anomalies in the area (Fig. 3B).

The work of Agier et al. (2008) then used a standarized WHO weekly meningitis incidence dataset at the sanitary district scale for the 1997–2007 period to determine the onset week of the meningitis epidemic years. The average onset date falls between the fifth and sixth weeks of the year (±1.6 weeks). Weekly climate composites (epidemic years minus all years) were constructed to highlight specific conditions that may occur prior to the epidemic onset. A significant Harmattan wind reinforcement was found in the weeks before the averaged onset date.

Sultan et al. (2005) developed an HEWS meningitis index in Mali, demonstrating that the week of the epidemic onset is highly correlated to the week of the winter maximum (the sixth week of the year, ±2 weeks). Their strategy for an HEWS involves both a longer lead-time seasonal prediction made in November preceding the transmission season, supplemented by weekly updated predictions based on wind, temperature, and humidity predictions from the end of January onward. It is in this second phase of shorter lead-time weekly updates where the newly available S2S systems would naturally fit. Indeed, more recent analysis of the disease in Niger demonstrated that both zonal wind and dustiness could be used to predict cases on a local and district scale (Pérez García-Pando et al., 2014), emphasize the role that S2S systems could play in forecast meningitis incidence at a finer weekly timescale, initially using the winds produced by the systems directly. Because most S2S systems do not presently provide aerosol information in their output, the S2S system winds also could be used to drive an offline dust model as an input to the early warning system.

A differential equation for meningitis incidence was applied to the multivariate log-linear regression analysis using four meteorological variables (northeasterly surface wind, relative humidity, rainfall, and temperature, and one of four dust products over Burkina Faso), to determine their respective contribution to the number of cases of meningitis (Nakazawa and Matsueda, 2017). They showed that northeasterly wind makes a major contribution to the rate of change of the number of cases. Although the highest correlation coefficient between the estimated and observed tendency was for the regression models using all four meteorological variables in addition to the dust surface mass concentration data, even a single-parameter model using just wind was significantly skillful, simplifying the development of HEWSs. Other recent studies have compared dust to other climate variables as drivers of meningitis in the January-March season (JFM)—(i.e., concomitantly with the epidemics. At the country scale (Niger and Mali), the variability in the weekly number of cases in meningitis seems to be triggered by that of dust, with a 1- to 2-week time-lag between dust and meningitis (Martiny and Chiapello, 2013). Humidity observations also have been used in early warning systems

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with a 2-week lead time (Pandya et al., 2015). This time-lag, confirmed at the district spatial scale in Niger (Agier et al., 2008) and using different aerosol datasets (Deroubaix et al., 2013) is consistent with the incubation time period of the Nm bacteria of around 14 days (Stephens et al., 2007). In India, Sinclair et al. (2010) highlighted the relationship between the end of the meningitis epidemics and the increase in relative humidity, and it is possible that S2S-driven forecast systems may have applications outside the African continent, subject to rigorous local epidemiological study and evaluation.

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If observations of meteorological conditions and aerosol loadings can predict case numbers on a 2-week lead time, then the skillful prediction of these parameters by S2S systems may extend the lead time by a further 4–8 weeks, depending on the limitation of the S2S skill. Thus, relative to diseases such as malaria that usually have longer lags with climate, the impact of S2S on the length of the advance early warning could be significant for meningitis.

2.4 Heat Waves (Nissan and Lowe)

Extreme heat is the leading cause of weather-related deaths in the United States and Europe (Changnon et al., 1996; Klinenberg, 2015; Lowe et al., 2015), and was responsible for 4 of the 10 deadliest natural disasters worldwide in 2015 (UNISDR and USAID and Centre for Research on the Epidemiology of Disasters, 2015). However, heat-related illness and deaths are largely preventable. Heat action plans (HAPs) are operational in many locations worldwide and have been shown to save lives by improving preparedness (Ebi et al., 2004; McGregor et al., 2014; Natural Resources Defense Council et al., 2017; Bittner et al., 2013).

Reliable weather and climate forecasts can facilitate better short- to medium-term resource management when incorporated into a broader strategy to implement measures over a range of timescales, from long-term disaster risk reduction and seasonal preparedness to early warning systems and emergency response and recovery. A heat HEWS, when paired with appropriate actions to reduce risk, can be an effective component of such a strategy. As stated in the introduction, a heat HEWS involves the identification of critical meteorological thresholds associated with adverse health impacts for the location in question, the issuance of a forecast indicating whether these thresholds are likely to be reached, and a set of standard operating procedures to implement risk-reduction measures.

An effective heat HEWS is tailored to the local context, with thresholds determined according to the vulnerability of the local population and forecasts relating to these thresholds issued at lead times appropriate to the local capacity to take action. Vulnerable sections of the population can be identified through research on heat-health relationships (where sufficient data are available) and through surveys and community consultations. Appropriate actions to take in response to an alert vary depending on the target vulnerable populations, capacity of local government and stakeholders to respond, available resources, and skill of the forecast.

The city of Ahmedabad, in India, is the site of South Asia’s first HAP (Knowlton et al., 2014a). The plan was developed in response to a devastating heat wave in 2010, during which nearly 1350 additional people died, compared with the same period in previous years (Azhar et al., 2014). Similar HAPs are now being rolled out across 13 other cities in India (Council, 2016). Analyses of daily maximum temperature data, all-cause mortality, hospital admissions, and ambulance calls, plus focus groups and sampling surveys, identified people living in slums, outdoor workers, the elderly, and neonates as the most vulnerable population groups. Critical maximum temperature thresholds for different levels of alert, from “no alert” to “extreme heat health alert” were determined by consensus after analyses of temperature and mortality data during the 2010 heat wave (Knowlton et al., 2014a; Azhar et al., 2014). Once an alert is issued, the plan outlines a series of actions to be taken, which include alerting key stakeholders such as community workers and hospitals, opening cooling centers and circulating warnings via text messages and radio broadcasts. In addition to an early warning
system to respond to forecasts of an imminent heat wave, the HAP involves seasonal activities including a community outreach and awareness raising program, training of key personnel, and procurement of ice packs and other supplies.

The Ahmedabad HAP now uses 7-day deterministic forecasts for maximum temperatures issued daily by the Indian Meteorological Department (IMD). Warnings are issued at the discretion of a dedicated nodal officer from 1 to 7 days in advance, in consultation with forecasters. More established heat HEWSs utilize probabilistic forecasts. In the United Kingdom (UK), heat alerts are triggered when there is a 60% probability of critical daytime and nighttime temperature thresholds being reached on at least 2 consecutive days (England et al., 2015). False alarms can be costly and damaging to the credibility of the key individuals and institutions responsible for implementing adaptation measures (Coughlan De Perez et al., 2015). Using a probabilistic forecast can maximize the time available to prepare, while minimizing the risk of a false alarm to a level considered acceptable by decision-makers. A compromise is struck between having confidence in the forecast and obtaining adequate lead time to take action. UK forecasts usually reach the minimum 60% confidence level approximately 2–3 days before a heat-wave hit.

Many risk-reduction actions require more advanced warning than the few days provided by weather forecasts. Fig. 4 illustrates some of the measures that could be taken to prevent the health impacts of extreme heat if the lead time of forecasts could be extended. For this reason, extending the lead time of forecasts beyond the weather timescale is an important method of improving disaster preparedness for a range of hazards (Knowlton et al., 2014a; IFRC, 2008; England et al., 2015; Letson et al., 2007; Vitart et al., 2012). At longer lead times, forecast reliability becomes critical for early warning systems. Deterministic forecasts give no indication of the degree of confidence in the prediction, which is a particular concern with sub-seasonal timescales, where skill is lower. A reliable probabilistic forecast is one where the probability assigned to a certain outcome corresponds to the observed probability of that outcome. For example, when heat-wave conditions are forecast with 70% probability, a heat wave should occur exactly 70% of the time (refer to chapter 16 for further detail). Reliable forecasts are essential because they allow decision makers to pair appropriate actions with forecast skill. Low-regret interventions, such as recapping emergency response procedures or closely monitoring weather forecasts, can be paired with low-probability forecasts. Actions that incur a higher cost, which might include rescheduling outdoor sporting events or setting up emergency drinking water stations, can be contingent on a higher probability trigger.

In some ways, heat waves present a good test case for the use of sub-seasonal forecasts in early warning systems. Adaptation measures for hydrometeorological hazards like flash floods and cyclones can involve high-cost interventions such as evacuations and flood defense reinforcements. By contrast, there are many low-cost, no-regret adaptation options appropriate to coping with extreme heat, from refreshing training for medical staff and community outreach officers to procuring emergency drinking water (Indian Institute of Public Health Ganghinagar et al., 2017).

At longer lead times it becomes difficult to specify the precise location of hazards, so forecasts must be issued for a larger region than is possible for high resolution weather forecasts for a few days ahead (Vitart et al., 2014). A forecast covering a larger area presents a challenge for early warnings of hydro-meteorological hazards like flooding or heavy rainfall, which are often highly localized. By comparison, hot and cold conditions do not occur in

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adjacent neighborhoods of a city. For heat waves, vulnerability and exposure are more important factors in determining risk than the hazard, which will be felt across a fairly broad spatial area. Therefore, assistance can be targeted toward the most vulnerable (e.g., the elderly or young children) and exposed (e.g., construction workers), reducing pressure on long-range forecasts to provide information at a fine spatial scale.

Furthermore, predictability of heat waves has been demonstrated on sub-seasonal timescales for some regions. Strong coupling between atmospheric temperatures and land surface conditions has been noted in several studies, with low soil moisture playing a role in the major European and Russian heat waves of 2003 and 2010 (Miralles et al., 2014; Hirschi et al., 2011). The persistent memory of the land surface suggests that forecast skill could be extended beyond weather timescales where soil moisture plays a role. In Bangladesh, low soil moisture conditions are detectable for several weeks on average before a heat wave (Nissan et al., in press).

**FIG. 4**  Preparedness and risk-reduction strategies for extreme heat that could be undertaken in a city based on short-term, S2S forecasting systems. Specific measures would vary according to local needs, but these examples were taken from heat action plans in India, the UK and elsewhere, and from a climate services workshop in South Asia (Knowlton et al., 2014b; McGregor et al., 2015; PHE, 2015). Seasonal preparedness measures also can be initiated without climate forecasts, based on an understanding of the seasonality of heat-wave risk in a given location. Items in gray indicate actions that may become possible as sub-seasonal forecasts improve in skill and become operationally available.

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A recent study developed a climate-driven mortality model to simulate the probability of exceeding emergency mortality thresholds for heat-wave and cold-spell scenarios in 54 European regions across 16 countries (Lowe et al., 2015). The model showed good skill when driven by observed apparent temperature data from reanalyses (in other words, to simulate heat-wave impacts in near-real time). Next, the extent to which S2S climate forecasts could be incorporated into HAPs to support timely public health decision-making ahead of imminent heat-wave events in Europe was assessed (Lowe et al., 2016). Forecasts of apparent temperatures at different lead times, ranging from 1 day up to 3 months, were used to generate probabilistic mortality forecasts for the 2003 heat-wave event in Europe and compared with the mortality forecasts driven by observed apparent temperatures. The model showed that after 1 week, skill decreased rapidly at forecast lead times longer than 1 week. Nonetheless, in some regions in Spain and the United Kingdom, excess mortality was detected up to 3 months ahead. In general, the skill of the mortality forecast was not limited by the mortality model, but rather by the predictability of the climate variables at S2S timescales over Europe.

In conclusion, these studies suggest that predictability for extreme heat exists on sub-seasonal timescales in some regions, indicating that incorporating S2S forecasts into existing heat-health action plans could improve preparedness. Skillful and reliable forecasts are an important component of an HAP, but they can be effective only when paired with a coordinated awareness campaign and engagement with a range of institutions and individuals across different sectors of society.

3 OPERATIONALIZATION: CHALLENGES AND OPPORTUNITIES

Despite the obvious and growing potential to apply S2S forecasts of surface climate parameters to predicting health outcomes and plan mitigating actions, there has been a dearth of operational implementations to date. Many demonstration projects that successfully show the potential of such systems have not developed beyond the research phase or led to benefits for health and more efficient allocation of health resources. Some of the potential reasons for these operational bottlenecks are discussed next.

3.1 Data Access and Usage

One of the key impediments to operationalizing health prediction systems is a simple lack of access to high-quality observations for climate and health. Pay-for-access information hampers operational development in two ways. Not only does it prevent the operationalization of health forecasting systems directly, it inhibits the research needed to develop these systems in the first place. Research is held back by the difficulty in accessing in situ data for national networks of station data, which is often difficult to obtain for a health ministry from the national agency of the country. Similarly, while some countries lead the way in making aggregated health datasets openly available and easily accessible through the health ministry websites, this remains the exception rather than the rule, and access to health data for research remains elusive. Often health data are available only through specific research projects and
are subject to strict third-party conditions despite the possibility of applying rigorous anonymization techniques to ensure that ethical privacy concerns are met.

Several developments are underway that are in the process of improving this situation. Concerning climate observations, most reanalysis datasets produced by operational centers, which combine a variety of observations, have been free to use for research, such as those by National Centers for Environmental Prediction (NCEP) (Kistler et al., 2001) and ERA-Interim (Dee et al., 2011). While invaluable, these products are available on coarse grids on the order of 100 km; the high-resolution operational analyses (8 km at ECMWF as of 2017) remain closed. However, improved reanalysis products will soon become available as part of the climate services of the Copernicus program funded by the European Union (EU) (e.g., ERA-5). Another current development is the Enhancing National Climate Services (ENACTS) project, an initiative of the international Research Institute for climate and society (IRI) (Dinku et al., 2014; Thomson et al., 2014). This project aims to merge satellite data with all available national station data in order to produce a high-quality, gridded rainfall dataset that can be used by national services. The ENACTS products are already available for Rwanda, Kenya, Madagascar, Tanzania, Ethiopia, Zambia, Mali, Ghana, and soon Uganda as well.

Access to health data also should improve as more countries are introducing second-generation, web-based, digital information systems (Karuri et al., 2014). In addition to improving the reliability of data, these systems allow health data to be quickly and easily aggregated for wider use, which should facilitate their use for research, ultimately benefiting health organizations.

Concerning the forecasts themselves, the commercial value of weather forecast information has resulted in operational centers outside the United States implementing a closed-access data policy the short-range forecasts, which has been extended to S2S products as these were progressively added to the operational catalog over the past two decades. Where forecast information is made available, it often takes the form of graphical maps, which cannot be used to drive downstream statistical or dynamical models. Again, several developments are underway to address this. Sub-seasonal and seasonal systems must run large sets of forecasts for past periods to allow them to be calibrated for biases and errors. These datasets represent an invaluable resource for research, and several efforts have been made to release them from multiple centers in a single location. The World Climate Research Programme’s (WCRP) Working Group on Sub-seasonal to Interdecadal Prediction (WGSIP) has the flagship Climate-system Historical Forecast Project (CHFP), which makes seasonal hindcasts publicly available from a large number of operational centers (Tompkins et al., 2017). Since 2015, the S2S database has been established to provide access to sub-seasonal prediction systems (Vitart et al., 2016). Since late 2017, the EU program known as the Copernicus Climate Change Service (C3S) has made digital data from three operational seasonal forecast systems available in real time, in addition to the associated datasets of hindcasts. We are thus entering an era of unprecedented climate forecast data access for both research and operational activities.

3.2 Operationalization of Climate Information

In some respects, the greatest impediment to the uptake of climate information in health planning may not be the barriers to developing the systems, but the adaptation of operational

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strategies required to make effective use of them. While the seasonality of many diseases is well understood and the annual cycle of disease interventions already takes account of this known history (Tompkins et al., 2016b), the use of predictions of monthly or seasonal anomalies of the occurrence of a specific health impact represents a new operational paradigm. Endemic diseases with a well-defined seasonal cycle are tackled with a regular set of interventions; or where a disease may be subject to irregular epidemic outbreaks, the focus is on surveillance and reaction. Using forecasts to plan intervention or stockpile medicines for the months ahead requires unfamiliar operational procedures to be adopted.

To integrate climate information into planning, effective communication about the spatial scales and uncertainties of the forecasts may be required. In our experience of running workshops interacting with both academics and health officials, a frequently raised objection to the use of climate information concerns the spatial scale of the information. The argument is that health outcomes are usually highly heterogeneous over small spatial scales, and thus the coarse spatial scale of the forecast system driven by O (10–100 km) scale climate information may provide limited useful guidance at the local level. This argument confounds mean risk with risk anomalies. The climate-driven anomaly, which will likely occur on a scale of tens or even hundreds of kilometers, is superimposed upon a heterogeneous vulnerability surface that reflects changes in the vicinity of water, income levels, availability of health care and so on. Mapping efforts such as Kienberger and Hagenlocher (2014) aim to help project the climate-driven hazard to smaller spatial scales. Moreover, at the local and district scales, health district officers are familiar with the disease incidence landscape within their jurisdiction. Naturally, factors that affect both vulnerability and transmission intensity also change from year to year, but these are usually inherently unpredictable, providing one of many sources of error in model predictions. One of the tasks of an S2S forecast system, therefore, is to attempt to determine the locations and months where climate may determine a high proportion of the interannual variability in transmission (Tompkins and Di Giuseppe, 2015).

A second aspect relates to the confidence that can be placed in forecasts. Information at S2S timescales is uncertain and is assessed using ensemble forecasting techniques, as introduced in this book, which could also be applied to models of impacts (Ruiz et al., 2014; Caminade et al., 2014). Accounting for uncertainty in decision-making is highly challenging, and accurately assessing and effectively communicating forecast uncertainty are crucial. One aid to this process is the concept of cost-loss economic analysis (Murphy, 1977). This assesses ensemble or deterministic skill in terms of the cost benefit if a mitigating action is correctly taken on the basis of the forecast, therefore avoiding a loss (e.g., preventing an outbreak by rolling out interventions, or mitigating the impacts of heat waves). This is offset against the losses incurred when the forecast was incorrect, leading to the wasted cost of an intervention, or worse still, an outbreak that was not prepared for. While such an analysis can offer guidance, it is often difficult to precisely define a threshold for a mitigating action and to associate costs by translating health outcomes into equivalent disability-adjusted life years (DALYs).

In health, not only economic losses (e.g., lost productivity) arise, but also serious and possibly fatal health implications. If funds are adequate, a health officer may always err on the side of caution and take precautionary action, rather than risk appearing unprepared for a heat wave or disease outbreak. Moreover, if action is taken, it is difficult to certify whether a health crisis consequentially has been avoided, or it would not have happened in the first place (Lowe et al., 2016b). While forecasts of extreme temperatures can be validated subsequently, it is not possible to say whether interventions have prevented an otherwise predicted
outbreak of a disease such as dengue or malaria, unless neighboring regions with similar climate anomalies and no interventions are subjected to an anomalous disease outbreak. Our present understanding of the efficacy of disease interventions still rests heavily on idealized modeling, which cannot easily account for the situation on the ground.

This disconnect between the information potentially provided by climate-driven early warning systems and the reality of a health officer’s decision-making process is perhaps one reason why there is slow uptake of climate information in early warning systems in most cases. Heat-wave early warning systems are perhaps the exception, as they can be instantly and easily validated and have high proven skill in the shorter lead times of a few days, which still can provide useful warning. More effort is required to project climate-based forecast information onto health decision processes. Does the probability of an upper-tercile event or outcome (a commonly used criterion to designate “above normal” conditions in meteorological ensemble forecasts) relate to a particular decision process in health? In general, this has not been demonstrated. This disconnect can partially explain low demand from the health sector for early warning products. This relates not only to the coarse spatial scale of the forecast data, but also to the limitations in terms of the lead time provided at an adequate skill.

As an operational example, the time taken to acquire stocks and subsequently distribute vaccinations in the field during the rainy season for the 2006/2007 RVF outbreak that occurred in Kenya implied that the intervention came too late to affect the outbreak significantly (Jost et al., 2010). The difficulty in acquiring sufficient vaccines (with a limited shelf life) indicates that accurate S2S-based prediction at a 1 month lead time would not provide sufficient lead time for intervention. In this case, seasonal forecasts with longer lead times of several months would be required to be effective with presently available vaccines and distribution infrastructure.

3.3 Interaction Through Workshops

Underlying some of these bottlenecks to the uptake of climate information is a communication breakdown between the multifaceted players in this interdisciplinary issue. Health officials may lack understanding concerning the potential of climate data to improve public health outcomes, and how to access/interpret climate data or climate-based forecast products. Additionally, small-scale research demonstration projects may be dismissed as unfeasible to implement over larger scales (Awoonor-Williams et al., 2004). Likewise, climate and weather experts may often have a poor understanding of health-planning needs and the decision-making processes within a national or regional health hierarchy. Health planning is frequently top-down in nature, with interventions and mitigation actions planned at the national or regional level based on the advice of international bodies such as the WHO, or funding agencies and donors. This leaves limited scope to benchmark and possibly introduce new methodologies and technologies on smaller national or subnational scales without explicit WHO backing.

Within this context, the WHO is increasingly recognizing the importance of integrating climate into planning and has established a joint office with the World Meteorological Organization (WMO) to sustain these efforts. The WMO has also made health a key priority in its Global Framework for Climate Services (GFCS), a program that aims to coordinate and communicate research and observational developments to stakeholders at national, regional and
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Forecasting always need to be considered in context. If a hypothetical forecast is issued for “above-normal” conditions, then the user must have a good understanding of what “normal” is and how the observed climate influences the health issues that they care about. Forecasts for vector-borne diseases can be made with 2 months or more lead time using observed rainfall and temperature, due to the time that it takes for vector populations and pathogen cycles to build an epidemic cycle once climate conditions are conducive. In these predictions, uncertainty results from the quality of the observations rather than the inherent stochasticity of predictions. Until recently, the importance of health-sector researcher and practitioner access to historical and monitoring climate data has been ignored by the climate community, with restrictive data policies operating in many countries. We argue that familiarity with and use of observed data at appropriate temporal and spatial scales (such as provided by ENACTS) provide the foundation for the uptake of less certain, but forward-looking forecast information.

Progress in this matter can occur through increased communication, which is most readily facilitated through workshops. The development of new curricula for health practitioners that introduce climate information as a possible resource is also needed. It is imperative to stress the necessary two-way communication that must take place, so that experts in climate can understand the ways in which their forecasts might be potentially used, while at the same time attempting to communicate the usage and uncertainties that climate products have. Once again, involvement of, and sponsorship from, pan-national organizations such as WHO are invaluable through the support and coordination of the GFCS. Scaling up such events to increase their value and penetration may require further involvement of e-training resources in tandem with traditional in situ workshop settings (Barteit et al., 2015). Documentation of successful events provides helpful blueprints for duplication (Tompkins et al., 2012; Lowe et al., 2016c).

4 OUTLOOK

This chapter has attempted to summarize the opportunities that now exist to increase the uptake of S2S forecast information on the 2-week to 2-month timescale in health applications.
Four case studies have highlighted potential areas in which S2S could be employed or where pilot or preoperational systems are already in place. Often, the final step from a pilot to an operational system is the most challenging, and some of the key impediments for this uptake have been discussed. Despite this, S2S and related initiatives will lead to ever-increasing access to forecast and hindcasts in (near) real time. This will help demonstrate the potential and raise awareness of these systems and aid the rethinking of health policy to take advantage of this untapped source of predictability of health outcomes. The successful implementation of climate services for health requires political will and close collaboration among a range of partners, including climate scientists and practitioners, data managers, medical professionals, hospitals, public health agencies, and governments.

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Abstract

The potential to use sub-seasonal to seasonal (S2S) prediction systems for outcomes in health is presented, using four case studies of malaria, dengue, heat waves, and meningococcal meningitis. While promising, many such applications are currently in the demonstration phase, and examples of operationalizing S2S-based early warning systems, fully integrated with decision support, have yet to emerge. Potential reasons for this operationalization bottleneck are discussed, which include restrictions on open access to health and climate data, the unfulfilled requirement for training in the use of such systems, and the mismatch between the prediction paradigm and the decision entry points in health-planning systems. The S2S project sponsored by the World Meteorological Organization may help to demonstrate the potential application of climate information, but the lack of real-time access inhibits the operationalization of evaluated systems. It is recommended that partnership platforms, established through the Global Framework for Climate Services and related mechanisms, enable the climate and health academic and operational communities to work together on real-time provision and assessment of health early warning systems. This is particularly important in developing countries where climate-driven health outcomes can be severe.

Keywords: Malaria, Dengue, Heat waves, Meningococcal meningitis