USING WEATHER FORECASTS TO HELP MANAGE MENINGITIS IN THE WEST AFRICAN SAHEL

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Integrating research, operations, and community engagement, a multinational and multidisciplinary team uses relative humidity forecasts to better manage meningitis in the Sahel.

Within the meningitis belt, which stretches from Ethiopia to Senegal (Lapeyssonnie 1963; Greenwood 1999) as shown in red in Fig. 1, the endemic or background rate of *Neisseria meningitidis*, often referred to as meningococcal meningitis, is high enough to be considered an epidemic in the developed world (Molesworth et al. 2003). Against this background, larger epidemics occur every 7–14 years (WHO 2012). The largest epidemic in recent history, from 1996 to 1997, affected 250,000 people, caused 25,000 deaths, and left 50,000 people disabled (WHO 2012).

The epidemics have a devastating impact on the region and its people. Untreated meningitis is fatal 50% of the time (WHO 2012). Even with treatment, the fatality rate can exceed 10%, and 10%–20% of survivors experience long-term aftereffects including brain damage and hearing loss (Greenwood et al. 1987; Moore et al. 1989). Meningitis can push a family into severe poverty (Colombini et al. 2009), which is especially significant in a region where the annual per capita income ranges from US$500 to US$1500 (World Bank 2013).

Until 2010, polysaccharide vaccines were used to manage meningitis epidemics in the meningitis belt (WHO 2012). Because these vaccines are only effective for 2 years, are not protective for young children, and do not confer herd immunity, the polysaccharide vaccines were not used for preventive vaccination. Instead, vaccination campaigns employing the polysaccharide vaccines are initiated reactively in

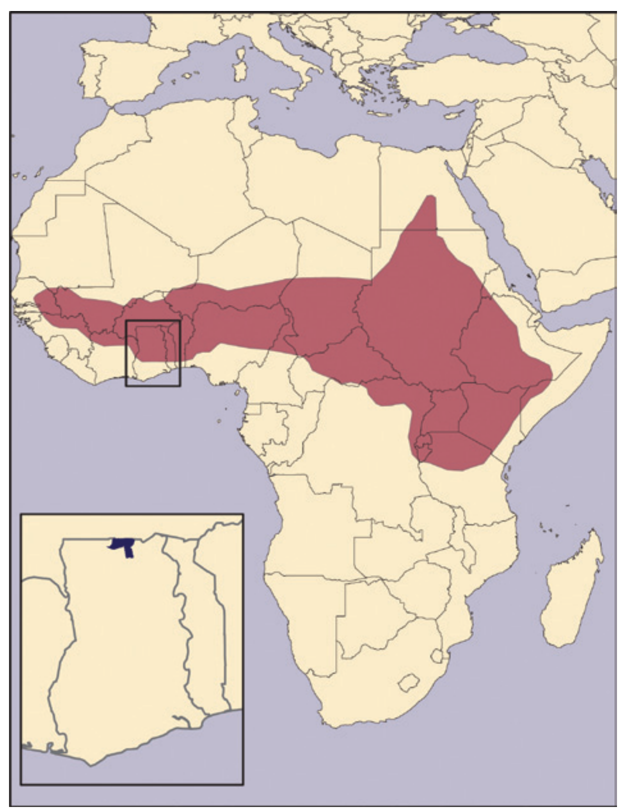

FIG. 1. Observed distribution of meningitis epidemics in Africa, compared to the location of the Kassena-Nankana District in northern Ghana. The red shaded region indicates the meningitis belt (based on Molesworth et al. 2003). The inset box in the lower left shows Ghana, with the Kassena-Nankana District highlighted in blue.

response to increases in the rate of disease within a public health district. If the number of confirmed cases of meningitis in a district exceeds the epidemic threshold defined by the World Health Organization (WHO 2012), the country in which the district is located can request emergency vaccines from the International Coordinating Group (ICG) on Vaccine Provision.

A conjugate vaccine was introduced in 2010 in Burkina Faso and parts of Mali and Niger (WHO 2012) to address the limitations of the polysaccharide vaccine and allow preventive vaccination. The conjugate vaccine appears to be very effective: 2011 saw the lowest number of meningitis cases ever recorded (WHO 2012). A beltwide mass vaccination campaign is underway and scheduled to be completed in 2016. However, the conjugate vaccine is only effective against the most common strain of meningitis, and the virulence of other strains requires continued surveillance and reactive management with the polysaccharide vaccine (S. Hugonnet 2013, personal communication).

The emergence and spread of meningococcal meningitis in the Sahel depends on a complex interplay of environmental, epidemiological, economic, and sociological factors. However, there are links to weather and climate that, if understood and operationalized, could be used to lessen the disease's impact.

All reported meningitis epidemics in the Sahel have occurred during the dry season, which runs from December to May (Lapeyssonnie 1963). Greenwood et al. (1984) first documented a correlation between low humidity and meningitis in the scientific literature (see Fig. 2). Higher humidity is associated with decreased meningitis transmission (Molesworth et al. 2003) and epidemics stop with the onset of the monsoon (WHO 2012). Our extensive interviews revealed that most people in northern Ghana associate meningitis with hot and dry conditions and its abatement with the onset of the rains.

Several studies have highlighted the correlation of dusty, dry conditions and meningitis (Cheesbrough et al. 1995; Besancenot et al. 1997; Molesworth et al. 2003; Sultan et al. 2005; Sultan 2005; Thomson et al. 2006; Cuevas et al. 2007; Yaka et al. 2008; Colombini et al. 2009). Airborne particulates have been linked to meningitis cases in the Sahel, including naturally occurring dust [Molesworth et al. 2003; Thomson et al. 2006; B. Sultan et al. (2007, meeting presentation)], dust borne by strong Harmattan winds (Sultan et al. 2005; Greenwood 1999), and particulates from smoke associated with cooking (Hodgson et al. 2001a).

While it would be very helpful to use environmental factors to predict the onset of meningitis epidemics, our project shied away from that for two key reasons. First, it is extremely unlikely that environmental conditions alone can be used to predict an epidemic, because epidemics depend on the confluence of a myriad of environmental, social, and biological factors. Further, many of these factors lack comprehensive data sources that can be used to inform predictive models. In contrast, we found substantial evidence that environmental conditions alone, in particular high relative humidity, can end an epidemic. This meant that predicting high relative humidity allowed us to immediately produce information that public health decision makers can use to manage reactive vaccination campaigns. Indeed, members of the ICG already avoid launching vaccination campaigns near the end of the dry season, since they believe the epidemic will end naturally with the start of the monsoon. This highlights the second reason for focusing on the end of the season: it builds on existing practices in the public health community and therefore provides a clearer path for integrating new research findings into practice. Given limited supplies of vaccine, it makes sense to prioritize those vaccines toward dry areas where the epidemic is more likely to persist and away from areas where higher humidity contributes to the end of epidemics.

Our goal in this paper is to provide a multidisciplinary project-level overview of several interconnected and complementary research results for

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scientists from many disciplines. In some cases, while we summarize our original results here in a form meant for a more general scientific audience, we also refer to more detailed descriptions prepared, by members of our team, for other journals with more specialized audiences. In other cases, this paper is the first presentation of original results for which we intend to produce more detailed, discipline-specific manuscripts later.

Necessarily, the project team included a wide range of disciplines, including meteorologists, public health researchers and practitioners, as well as economists and medical anthropologists. It also included experts in the design of decision support tools and delivery and visualization of data. The Navrongo Health Research Centre (NHRC) was a key partner in this project. NHRC, as a part of the Ghana Ministry of Health, has a mandate to investigate Sahelian health problems and advise policy makers in Ghana and internationally. A foundation of the center's capability is the Demographic Surveillance System, started in 1992, which is a source of detailed, quality-controlled socioeconomic, demographic, epidemiological, health, and geographic information about northern Ghana. In addition to health information, NHRC researchers have digitized and quality-controlled 10 years of local meteorological data at two locations near Navrongo.

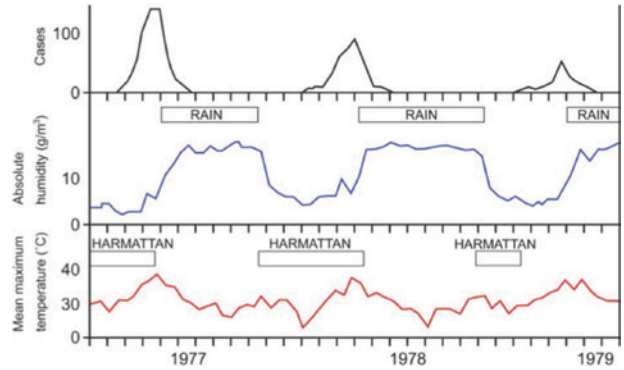

Fig. 2. A comparison of (bottom) mean maximum temperature (red line), (middle) absolute humidity (blue line), and (top) number of cases of meningitis (black line) in the Sahel. Figure was adapted from Greenwood et al. (1984).

VERIFYING THE LINK BETWEEN MENINGITIS AND HUMIDITY. Our team pursued three lines of evidence in order to confirm the long-observed connection between humidity and meningitis and define a relative humidity threshold associated with the end of meningitis transmission. These include i) an analysis of 10 years of weekly epidemiological and meteorological data taken in Navrongo, Ghana; ii) a differential-equation-based model of meningitis calibrated using 2 years of meteorological and epidemiological data from across the meningitis belt; and iii) a geospatial analysis of the relation of meningitis to bodies of water near Navrongo.

NHRC has a unique dataset of epidemiological and meteorological data collected for the same region and time period. The epidemiological data include total monthly counts of laboratory-confirmed meningococcal meningitis in Kassena-Nankana for the 11-yr period from 1998 to 2008. The meteorological data come from a local weather station operated by the Ghana Meteorological Agency. The analysis of these data is summarized below, and more detail is available in Dukic et al. (2012).

Figure 3 (from Dukic et al. 2012) provides a quick way to view the relationships between meteorological variables and meningitis cases using pairwise scatterplots. The scatterplots reveal that large numbers of meningitis cases occur when the maximum temperatures are high and the relative humidity is low, as indicated by the red boxes.

We also analyzed these data using generalized additive models (Hastie and Tibshirani 1990), which have been widely used to study air pollution and public health (e.g., Schwartz 1994). We found that including weather dependence in our generalized additive model improves in-season prediction of monthly laboratory-confirmed meningitis cases by up to 40%. In particular, the maximum monthly temperature of the current month and the previous month's relative humidity and carbon monoxide emissions due to fires showed the most influence on meningitis cases. This is consistent with the results of the survey of Kassena-Nankana residents, who indicated that meningitis is associated with hot conditions (Hayden et al. 2013), and with studies that suggest exposure to smoke increases the risk of meningitis (Hodgson et al. 2001a).

We also performed an analysis of meningitis cases across the entire meningitis belt using 2 years of data for the districts shown in Fig. 4. The epidemiological data were compiled from weekly district-level reports from the countries in the meningitis belt for the period from 2007 to 2009 (C. Lingani 2010, personal communication; Agier et al. 2013). Meteorological variables came from the National Centers for Environmental Prediction–National Center for Atmospheric Research (NCEP–NCAR) reanalysis (Kalnay et al. 1996). Population and georeferencing for the districts came from the LandScan 2008 High Resolution Global Population Data Set.

We modeled the transmission of meningitis using a differential-equation-based epidemiological model (Macal et al. 2012) and used these data to determine the coefficients of that model. [The model and our analysis are described in more detail in Hopson et al. (2014).] At the district level, the model distinguishes among three groups of people: those infected with meningitis, those susceptible to meningitis, and those who harbor the bacteria but do not have symptoms (i.e., a carriage population). It also assumes a homogenous mixing of people across the district and that the basic disease dynamics are the same across the Sahel (such that the model parameters apply uniformly). To make the model tractable, we assumed that the number of people infected is small compared to overall population, that changes in district population are negligible, that both the susceptible and carriage populations are proportional to the overall district population, and that the disease cycle is less than 2 weeks.

The resulting linear finite difference equation relates the change in the number of new cases of meningitis to the number of cases in previous weeks and to the overall district population, through coefficients that were allowed to implicitly vary in time through their dependence on meteorological variables. These coefficients were determined using cross-validated logistic regression, and we asked whether the predictions for new cases of meningitis improved when the coefficients were allowed to vary with the weather. After testing over 90 meteorological variables with varying time lags, we found the most consistent improvement in the model's predictions came from including 2-week lagged relative humidity first and northeasterly winds second (the latter a possible surrogate for dry Harmattan winds and dust transport).

We found that a relative humidity of 40% marked an inflection point for the probability of a district exceeding the epidemic threshold (Fig. 5). Based on the 2 years of epidemiological data alone, the risk of a district experiencing an epidemic on any given week is only 2%. This represents background risk, an average risk that does not account for the meteorological influence on meningitis. If the relative humidity in the district is well below 40%, however, the risk of epidemic significantly exceeds the background risk, maximizing at 25%. Conversely, districts with a relative humidity above 40% have a lower risk of exceeding the epidemic threshold.

Based on the relationship shown in Fig. 5, we used a weekly average humidity below 40% to differentiate between a district at continuing risk of epidemic and one in which persistent humidity would end the epidemic naturally. In practice, the exact value of the time-averaged relative humidity is not that important; what is important is the large shift from hot, dry conditions to cooler, moister condition, and the 40% relative humidity represents a convenient way to mark the boundary between these two conditions.

It is interesting to note that relative humidity is a better predictor of epidemic risk than absolute

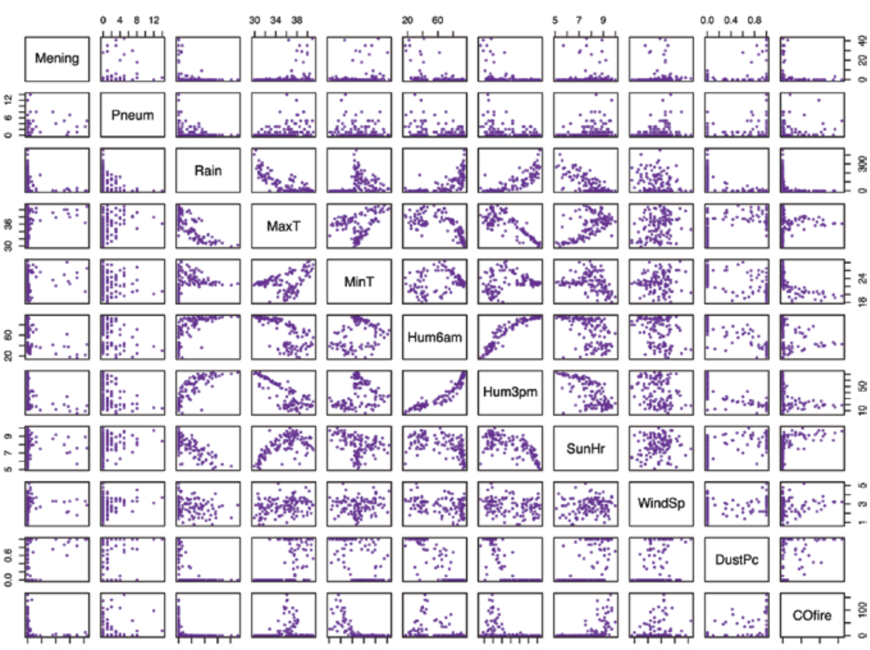

Fig. 3. Pairwise comparison of monthly meteorological and epidemiological data for Navrongo. Each position in the matrix shows a scatterplot between two variables, labeled by the box on the diagonal. From the top-left corner the variables are as follows: cases of *Neisseria meningitis*, cases of *Pneumococcal meningitis*, total daily rainfall (mm), maximum temperature (°C), minimum temperature (°C), relative humidity at 0600 local time, relative humidity at 1500 local time, hours of sunlight, wind speed (m s^{-1}), percentage of dusty days that month, and CO_2 from fires the previous month. (Note the lack of cases of *Neisseria meningitis* for high relative humidity in row 1, columns 6 and 7.) Figure was adapted from Dukic et al. (2012).

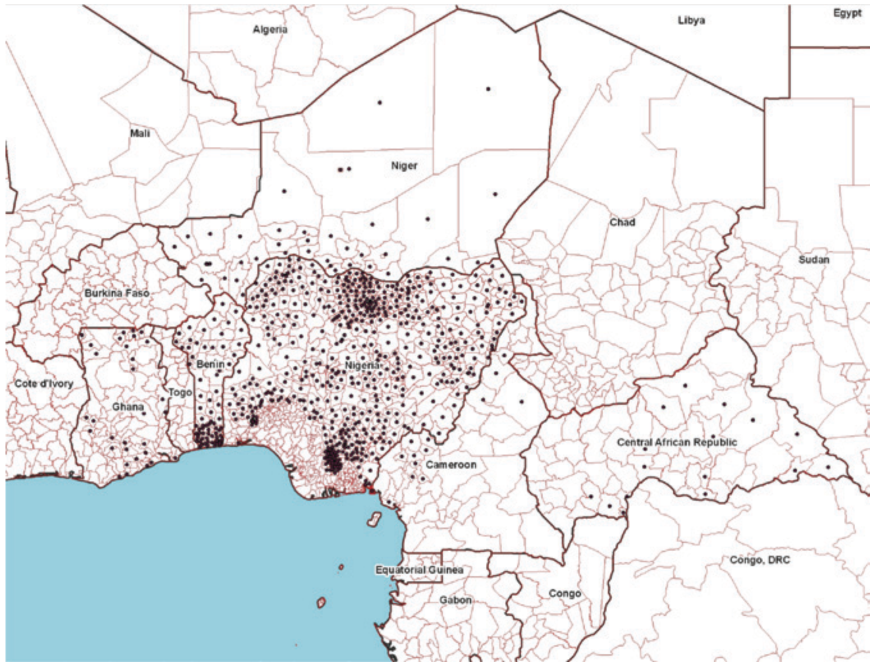

Fig. 4. Public health districts in Africa for which data were available between 2007 and 2009. Black dots highlight districts that crossed the epidemic threshold at least once in the 2-yr period. Note that not all countries are uniformly represented; this is because not all data from all parts of the country were available.

humidity, water content, or other measures of the absolute amount of water. This is consistent with the hypothesis that drying out the nasopharnyx increases the susceptibility to meningitis (Stephens et al. 1983; Moore 1992; Hart and Cuevas 1997), since drying depends on the relative, not absolute, humidity in the environment.

We also investigated whether meningitis cases could be correlated with proximity to water bodies and downwind direction, as described in more detail in McCormack et al. (2013). This investigation used meningitis data from the Navrango Health Research Centre, relative humidity data from 22 outdoor and indoor data loggers placed across the Kassena-Nankana District, and a simple advection–diffusion model driven by wind data extracted from the National Aeronautics and Space Administration (NASA) Modern-Era Retrospective Analysis for Research and Applications (MERRA) (Rienecker et al. 2011). While there was no significant correlation between distance from the reservoir and the incidence of meningitis, there was a small directional effect that may have been related to the advection of moisture from the lake, although the presence of a nearby city may have confounded the analysis. This strategy could be generalized to investigate whether locally high values of relative humidity offer some protection from meningitis. If so, household-scale interventions to raise humidity, like moistened curtains, might provide a new way to decrease meningitis risk.

To better understand the meteorology at the end of the meningitis season, our project included a team that analyzed the variability of the transition from dry to moist conditions in the western Sahel. This transition is largely driven by variations in the northward migration of the Intertropical Front (ITF) (Sultan and Janicot 2003; Le Barbé et al. 2002), but smaller-scale convective rains can modulate this zonal signal and alter the timing of the shift to a moister environment (Omotosho et al. 2000; Ati et al.

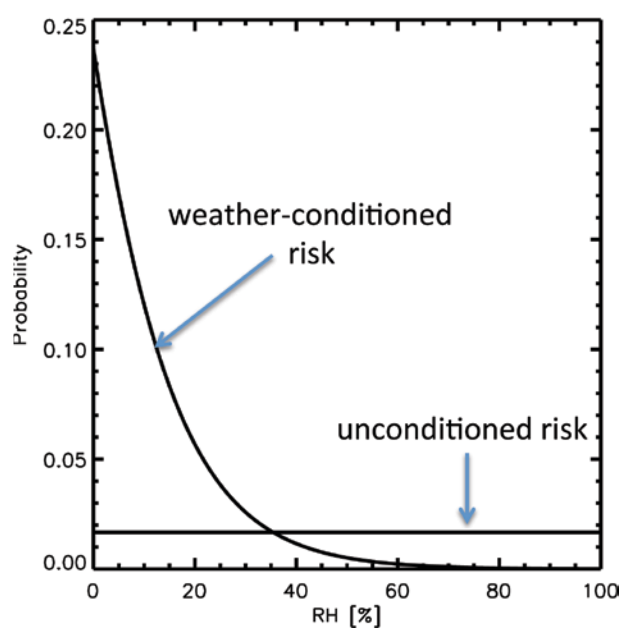

Fig. 5. A log plot of the probability of a district crossing epidemic threshold, in a version of the model using relative humidity and other weather variables (weather-conditioned risk) and without weather variables (unconditioned risk). The graphs of weather-conditioned risk shows an inflection point at about 40% relative humidity, with the probability of epidemic increasing significantly for relative humidity less than 40%.

2002). Using NCEP reanalyses, precipitation, and outgoing longwave radiation, members of our team showed that tropical depression–type disturbances of the same scale as African easterly waves, equatorial Kelvin waves, equatorial Rossby waves, extratropical cyclones, and the Madden–Julian oscillation all modulate the local- and regional-scale timing of the ITF-driven shift from dry to moist conditions. This work is described in considerably more detail in Mera et al. (2014), which also demonstrates that these large-scale disturbances are predictable and can influence cases of meningitis. In April 2009, for example, three different systems crossed over Kano, Nigeria. Together, these systems kept average weekly humidity above 40% and coincided with a sharp decline in the number of districts reporting meningitis (see Fig. 6).

UNDERSTANDING MENINGITIS IN NORTHERN GHANA. Investigating socioeconomic perspectives provides a more complete picture of the challenges of managing meningitis; provides context for developing, using, and evaluating environmental forecasts; and can suggest other interventions that could reduce the burden of the disease. Social–environmental factors to consider include external drivers, like climate change or patterns of human migration; environmental factors, like smoke from agricultural burning or indoor cooking; differing susceptibility based on age, poverty, and access to health care; and adaptive capacity. Adaptive capacity, in turn, can depend on community knowledge of meningitis symptoms and transmission dynamics, social behaviors such as sharing rooms or utensils with sick people, and the ways in which traditional medicine and western medicine are used to respond to the disease.

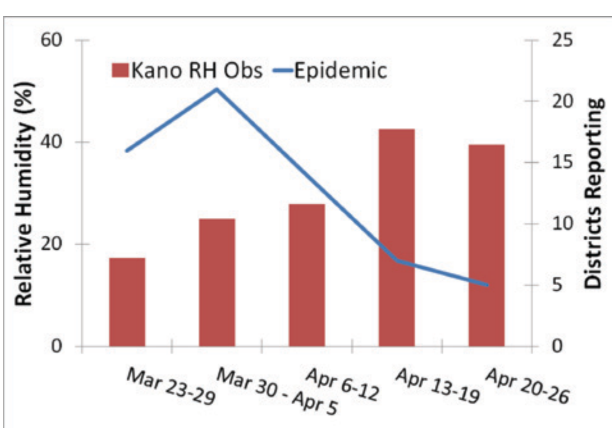

Fig. 6. A comparison of weekly average relative humidity (red bars) and cases of meningitis (blue line) in Kano in Mar–Apr 2009. Figure is from Mera et al. (2014).

A good way to understand these factors is via surveys that explore people's knowledge, attitudes, and practices (KAP). Working with the NHRC, we focused our surveys on the Kassena-Nankana District (which has recently been split into two districts, Kassena-Nankana West and East) in northern Ghana (see Fig. 1). Like much of the Sahel, the district is primarily rural. In these rural areas, extended families live in widely dispersed compounds surrounded by farmlands, like the example in Fig. 7. In the Sahel-wide meningitis epidemics between 1996 and 1997, the Kassena-Nankana District recorded 1396 cases with 65 deaths (Hodgson et al. 2001b).

In 2010 and 2011, our team conducted quantitative KAP interviews throughout the Kassena-Nankana District. These are described and analyzed in more detail in Hayden et al. (2013). We surveyed 74 people who had contracted meningitis between 2008 and the present and 148 people from a control group made up of people who had not had meningitis after 2008. This case-control methodology provides a way to remove variables known to be related to meningitis (in this case age, gender, and location) and isolate other factors that may correlate with meningitis and offer opportunities for intervention.

The interviews were based on a structured questionnaire administered by NHRC researchers in the preferred local language of the interviewee. The interviews were conducted in the dry season from November of 2010 through May of 2011. Individual survey participants gave informed consent, and all chiefs in the district approved the survey. NHRC, Ghana Health Service, and NCAR reviewed and approved the survey through their institutional review boards.

Over 85% of people surveyed indicated they would seek medical attention from either a clinic or hospital once they concluded that they or one of their family members had contracted meningitis. However, those who had experience with meningitis were much more likely to correctly identify the early symptoms of meningitis. Given the efficacy of early intervention, these results suggest that education about the early symptoms of meningitis would lead people to seek medical help sooner, improving health outcomes.

People who took the survey knew about the connection between meningitis and weather. Heat was the most commonly cited cause for meningitis among both cases and controls, and 70% of both groups selected hot and dry periods as the time of year meningitis is most severe.

The different histories of cases and controls revealed how migration and travel can influence meningitis risk. Many men from rural areas travel south during the dry season to seek farm-related work, essentially missing the entire meningitis season. However, these same men are more vulnerable if they return to northern Ghana during the dry season (e.g., to attend a funeral) as they will have missed any reactive vaccination campaign. Similarly, wealthier individuals who live outside the meningitis belt and in areas that do not routinely vaccinate for meningitis show increased risk when they return to the belt for visits. More generally, the survey found that wealthier individuals are more likely to report not having been vaccinated.

To help quantify the economic impact of meningitis and estimate the benefits of improved vaccination delivery, we included an additional set of survey questions for households who had experienced meningitis. This study and its results are described in more detail in Akweongo et al. (2013). These additional survey questions covered direct medical costs, like drugs, laboratory tests, and consultation fees as well as direct nonmedical costs associated with treatment like transportation, food, and lodging. Additional questions queried indirect costs associated with the lost ability to work while experiencing symptoms or taking care of family members. We did not collect data on the additional intangible costs that result from pain, discomfort, and changes in quality of life associated with the disease.

In Kassena-Nankana, we found that a household's expenditure on direct and indirect costs averaged US$101.70, about 3 times higher than the average income reported by those households. A study in Burkina Faso reported comparable household spending of US$90.00 (Colombini et al. 2009). In the Kassena-Nankana District, households without insurance paid approximately 4.6 times the amount paid by insured households seeking care at the same hospital. Since the poorest households were the least likely to have insurance, this means the financial burden of the disease is largest for those least able to absorb it.

USING HUMIDITY FORECASTS TO MANAGE MENINGITIS. Given the impact of meningitis in the region, the correlation between meningitis cases and the average relative humidity, and the predictability of subseasonal and meridional variations in humidity, our next step was to help public health decision makers use relative humidity predictions to inform their vaccination decisions. Current global models routinely predict relative humidity up to 14 days in advance; coupled with the observed 2-week lag between relative humidity and meningitis cases, this means it is possible to make a meningitis prediction as much as a month ahead of time, enough lead time to influence a vaccination campaign (S. Hugonnet 2013, personal communication).

Fig. 7. A household compound near Navrongo in the Kassena-Nankana District. Photograph is by Mary H. Hayden.

The forecast of relative humidity begins with the World Meteorological Organization (WMO) The Observing System Research and Predictability Experiment (THORPEX) Interactive Grand Global Ensemble (TIGGE; Bougeault et al. 2010), a real-time collection of ensemble forecasts from 10 global numerical weather prediction centers. We used quantile regression (QR) (Hopson and Webster 2010) to calibrate the probability distribution function of the relative humidity forecasts. QR is similar to regular regression but, instead of solving for the variation of the mean by minimizing the square error, QR finds the variation of any quantile of the distribution by minimizing a weighted absolute error. Further, the ensemble members can be used to define each quantile, thus avoiding assumptions about the form of the forecast probability distribution function. The result of QR is that the overall ensemble is better calibrated to observations, producing an improved forecast of the relative humidity and its variability. The benefits of using the full TIGGE set of ensembles is that, after calibration, we have a set of individual ensembles that represent equally likely weather scenarios and thus a range of humidity outcomes that are indicators of forecast uncertainty.

To deliver these forecasts to public health decision makers, we developed a prototype decision support system (Fig. 8). Using the Unidata Local Data

Manager (Rew and Wilson 2001) and the Internet data delivery (Yoksas et al. 2006), we ingest forecast data automatically as soon as they become available and calibrate the forecasts using QR. Epidemiological data are collected manually by public health officials in various countries, and shared using commercial cloud services, currently Dropbox. The two data are combined in a visual interface called the Africa Decision Information System (ADIS; Fig. 8). This web-based interface provides up-to-date QR-corrected relative humidity forecasts in a map view designed to highlight the boundary between dry and moist conditions. Users can step through historic and future humidity, zoom in and out, and look at time series at specific locations. ADIS also shows which districts are reporting meningitis alert and epidemic levels of meningitis with orange and red filled circles, respectively.

During the 2011/12 meningitis season, we participated in a weekly teleconference led by the World Health Organization (WHO), which included public health officers who manage meningitis in Benin, Togo, Nigeria, Chad, and Burkina Faso. Our team members regularly briefed this group on the predicted humidity and its potential impact on meningitis, and that briefing was part of the knowledge used to manage vaccine distribution. These teleconferences were also linked to the regular sharing of epidemiological data. This is significant because the lack of reliable and available epidemiological data has been one of the biggest challenges for researchers interested in working on meningitis. The teleconference also provided a context in which to try out specific forecast products and refine our overall approach.

From the teleconferences, we learned to present our findings so that they could be integrated into existing knowledge and support existing decision processes. For example, public health officials were willing to include meteorological forecasts as one of several factors they would consider when making vaccination decisions according to the existing protocol. Purely statistical models that predicted future cases were used less by the decision makers; they were reluctant to cede their vaccination decisions to a model and concerned about the influence of many confounding factors for which the models failed to account explicitly.

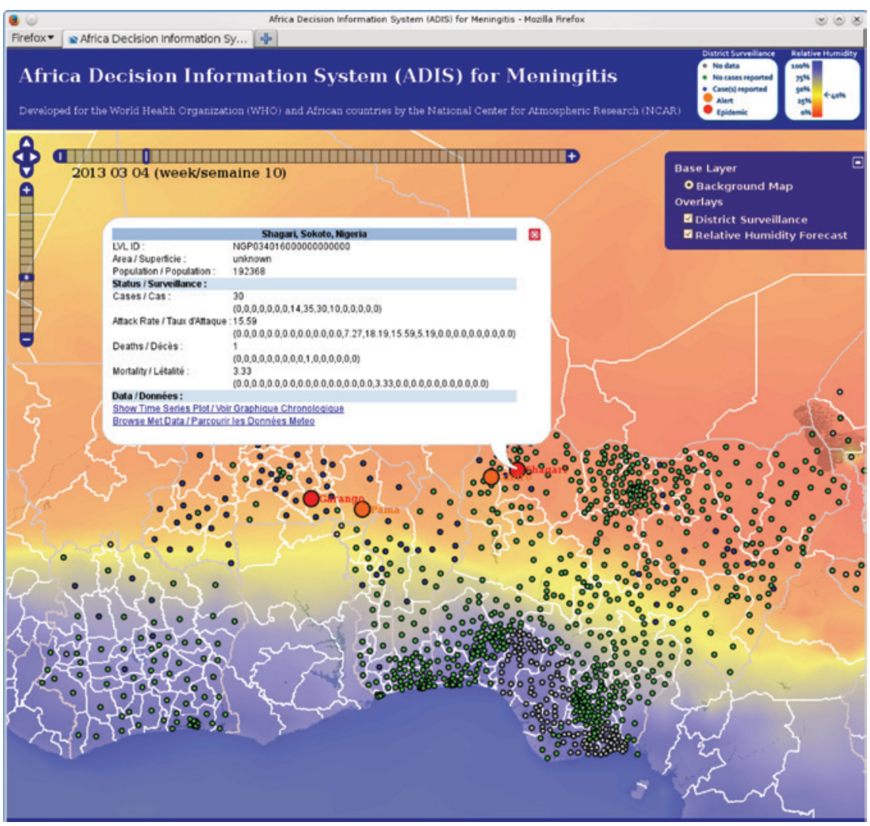

Fig. 8. A screenshot of the decision support system where the threshold of 40% relative humidity is highlighted by the transition from blue to orange. District centers are indicated by circles, with green circles indicating no cases in the district that week, orange indicating a district in alert status (between 5 and 10 cases per 10,000 people), and red circles marking districts currently in epidemic (more than 10 cases per 10,000 people). Black circles indicate a district that is not reporting data.

We also learned to present information simply and concisely. For example, we modified our color table in the display to have a tight gradient around 40% average relative humidity (Fig. 8) because we found decision makers liked having a straightforward rule of thumb: decreased risk of meningitis when average humidity exceeds 40%. While our forecasts had the capability of looking at the spread in forecast relative humidity from TIGGE ensemble members, none of the public health officials were interested in using this capability.

To ensure this work continues and grows, and to ensure that it fulfills the University Corporation for Atmospheric Research (UCAR) goals of enhancing research and operational capacity in Africa (Lamptey et al. 2009), we signed a memorandum of understanding with the African Center for Meteorological Applications for Development (ACMAD). ACMAD, which already produces disease-relevant weather forecasts, plans to incorporate these techniques and operationalize the production of these relative humidity forecasts for the entire meningitis belt.

To assess the potential impact of the relative humidity forecasts, we also estimated how many vaccinations could have been saved had perfect relative humidity forecasts predicting the natural end of the epidemic been used to avoid launching vaccination campaigns. The value of these avoided vaccinations can be considered in terms of cost savings that can be reallocated toward treating meningitis, an opportunity to reallocate vaccines to more at-risk districts, or the ability to conserve vaccine for future epidemics. This methodology is imperfect, since it does not account for errors in the humidity prediction, including the negative impact of incorrectly anticipating high humidity and prematurely ending a vaccination campaign, but it does provide an upper bound for the value of the meteorology forecasts, which can be used to compare to the potential benefit of other interventions.

Our historic analysis used disease data from Niger, Burkina Faso, Benin, Togo, and Chad from 2006 (Agier et al. 2013) until the conjugate vaccine was introduced in the region (roughly 2010–11). Adapting the approach used by Leake et al. (2002), we identified the districts that reached the epidemic threshold defined by WHO (WHO 2000). Then we identified the subset of those districts where the relative humidity would have naturally ended the epidemic within the next 3–6 weeks, according to the linearized regression model we developed. We did this by estimating the number of cases of disease that would have occurred in the absence of a vaccination campaign and using that number of cases, as well as relative humidity, to identify districts where the risk of epidemic fell below the background risk predicted without accounting for relative humidity. While this methodology required a number of assumptions about the timing and efficacy of vaccination campaigns, the results were relatively insensitive to the realistic range of those assumptions and more robust than simply using the 40% relative humidity threshold to determine where a campaign would have been unnecessary.

During our study period, 474 noncontiguous epidemics occurred. Of these, there were 18 instances where the risk of continuation of epidemic levels dropped below the background risk because of the actual onset of high relative humidity, as shown in Fig. 9. Given that the accumulated population living in these districts was 3 million people, this implies that roughly 2.6 million doses of vaccine (about 3 million × 0.85 coverage) could have been more effectively positioned elsewhere around the meningitis belt if accurate weather forecasts had been provided and heeded. At an average cost of US$0.45 per vaccine, this translates into nearly US$1 million in savings over 4 years and five countries, enough to cover the average medical expenses due to meningitis for 11,000 families. More importantly, those 3 million vaccines, properly deployed, are enough to prevent as many as 24,000 cases of meningitis and 2,400 fatalities.

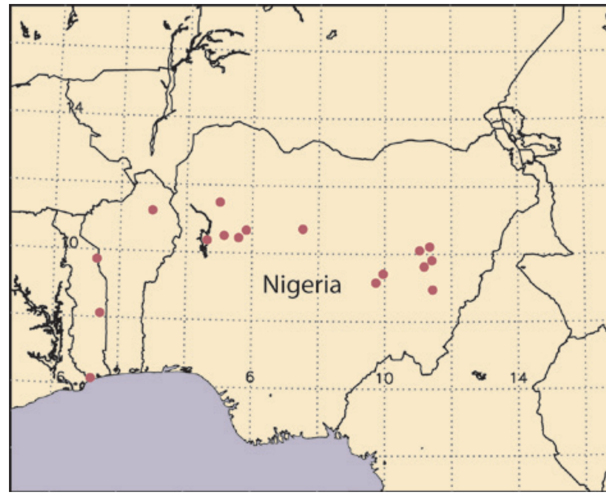

Fig. 9. A map showing avoidable vaccination campaign (red dot) between 2006 and 2011. In each of these places, a vaccination campaign was launched less than 6 weeks before the onset of high relative humidity would have ended the epidemic naturally. Given the population of these districts, this accounts for about 2.6 million vaccines at a cost of over US$1 million.

COMMUNITY-INSPIRED METEOROLOGY.

One outcome of this project is difficult to quantify: a subtle change in the way the U.S. scientists involved think about science and generate research questions and methods. Part of this came from interaction with the project sponsor, Google.org. The original driver for this project was a desire to improve meteorological capacity in Africa, premised on the idea that meteorological capacity was worthwhile in its own right and any investment in meteorology would automatically protect lives and livelihood. Google.org insisted on specific measurable impacts and steered us toward public health–oriented impacts.

Simultaneous conversations with several African scientists emphasized the need to tie the research question to clear societal benefit; reserve project funds for education, training, capacity building; and develop plans for sustaining the solution after funding ends (Lamptey et al. 2009). Finally, the collaboration with public health officials introduced us to the idea that research projects can involve community members as partners in defining the project, collecting data, and applying the results (Israel et al. 1998).

This mode of generating research has been called community-inspired research, in contrast to the more familiar mode of scientist-inspired research. While the general project was generated in response to community input and priorities from people throughout the Sahel, the core participating community was the community of public health practitioners who work in the Sahel.

From this simple difference in who asks the research question come considerable differences in the research process, and these differences are evident in this project. First, because community challenges seldom organize around traditional scientific disciplines, answering those challenges requires the integration of several disciplines. To develop an economic, pragmatic, and culturally appropriate solution, this project included epidemiologists, meteorologists, anthropologists, and economists. Second, data collection and analysis was a shared effort, with public health practitioners bringing epidemiological data and local knowledge and meteorologists contributing environmental data. Third, community-inspired research is often local or regional, and local knowledge is essential to the research. We saw in this study how local intuition provided the inspiration for researching the relation between humidity and meningitis. Another aspect of the importance of local knowledge showed up in the survey, where we found that a better understanding of early symptoms of meningitis might improve health outcomes. Fourth, community-inspired research is iterative and involves learning by both researchers and community members. If we understand the participating community to be the community of public health practitioners and decision makers who work in the Sahel, then the weekly teleconferences to inform decision making about vaccine deployment represented an interactive and co-learning environment that refined the research focus and improved its applicability. Finally, our project collaborated with and was inspired by the Meningitis Environmental Risk Information Technologies (MERIT) Consortium, a nongovernmental organization that owned the job of fostering regular interaction between researchers and decision makers. These kinds of boundary organizations have been shown to enhance the success of community-inspired research and its usability (Dilling and Lemos 2011).

CONCLUSIONS. This project produced several original results: it clarified and quantified the long-observed relationship between relative humidity and meningitis; revealed and documented knowledge, attitudes, and practices related to meningitis in rural Ghana; and provided one of the first estimates of the household costs of meningitis. It also produced operational results, including a rule of thumb public health decision makers can use in allocating vaccine (if the average relative humidity exceeds 40% in a district for a few weeks, the epidemic will end naturally with no vaccine) and a decision-informing tool that leverages existing forecasts to predict future average relative humidity. The results also suggest several potential interventions that merit further investigation: use of moistened curtains to raise the humidity within a compound, improved education about early symptoms of meningitis so that people seek medical attention sooner, and use of cookstoves to reduce local and regional carbon monoxide. In fact, a follow-up project examines the social and economic factors around the adoption of cleaner-burning cookstoves and the change in local and regional air quality that would result from widespread use of these cookstoves.

This project also enhanced capacity and offered educational opportunity. Several students, from high school through graduate school, in both Africa and the United States, participated in this work and this project served as the foundation for two Ph.D. theses. The partnership between NCAR and African Centre of Meteorological Application for Development (ACMAD), using the decision-information tool and sharing the technology, data, and knowledge that supports the tool, has set the stage for ongoing collaboration that spans continents and bridges the divide that separates research from operations. ACMAD, in turn, provides support and training to several African national meteorological and hydrological services, so these innovations and technologies will be spread across the continent. Finally, the project inspired a new way of thinking about and organizing research: community-inspired research.

Much still remains to be done. Scientifically, while we have identified several weather-related factors that correlate with meningitis (including low relative humidity, high temperature, increased carbon monoxide, northeasterly winds, and enhanced local and regional smoke), we do not have a complete-enough understanding of transmission dynamics of the disease to determine the causal links behind these correlations (Trotter and Greenwood 2007) or understand how weather might interact with other social or biological factors. This paper also has not discussed the ongoing research investigating longer-time-scale interactions between meningitis and the environment, which, while harder to identify and act on, could provide significantly more benefit. There are several decision needs that guide this research, including (from discussion at the 2012 MERIT meeting) the following: What kinds of correlations are significant and actionable on seasonal or climate time scales? What kind and quality of information do public health officials need to help them minimize the impact of future outbreaks within a season or in future seasons: for instance, by scaling their purchase of vaccine or prepositioning available vaccine? How could changing environmental conditions, including climate change, change the regions that are most vulnerable to meningitis?

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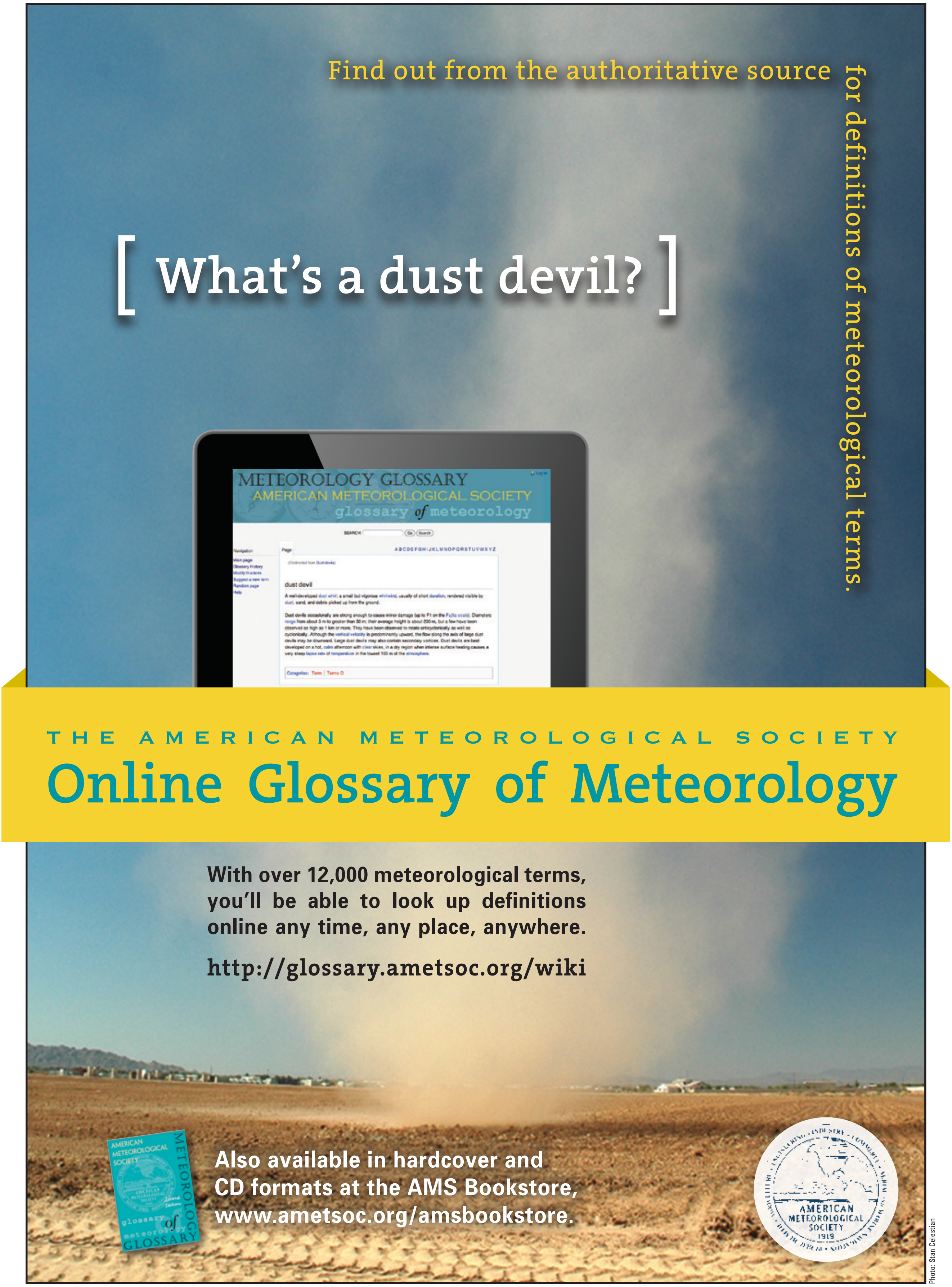

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