Climate services for health: predicting the evolution of the 2016 dengue season in Machala, Ecuador

Rachel Lowe, Anna M Stewart-Ibarra, Desislava Petrova, Markel García-Díez, Mercy J Borbor-Cordova, Raúl Mejía, Mary Regato, Xavier Rodó

Summary

Background **El Niño and its effect on local meteorological conditions potentially influences interannual variability in dengue transmission in southern coastal Ecuador. El Oro province is a key dengue surveillance site, due to the high burden of dengue, seasonal transmission, co-circulation of all four dengue serotypes, and the recent introduction of chikungunya and Zika. In this study, we used climate forecasts to predict the evolution of the 2016 dengue season in the city of Machala, following one of the strongest El Niño events on record.**

Methods **We incorporated precipitation, minimum temperature, and Niño3·4 index forecasts in a Bayesian hierarchical mixed model to predict dengue incidence. The model was initiated on Jan 1, 2016, producing monthly dengue forecasts until November, 2016. We accounted for misreporting of dengue due to the introduction of chikungunya in 2015, by using active surveillance data to correct reported dengue case data from passive surveillance records. We then evaluated the forecast retrospectively with available epidemiological information.**

Findings **The predictions correctly forecast an early peak in dengue incidence in March, 2016, with a 90% chance of exceeding the mean dengue incidence for the previous 5 years. Accounting for the proportion of chikungunya cases that had been incorrectly recorded as dengue in 2015 improved the prediction of the magnitude of dengue incidence in 2016.**

Interpretation **This dengue prediction framework, which uses seasonal climate and El Niño forecasts, allows a prediction to be made at the start of the year for the entire dengue season. Combining active surveillance data with routine dengue reports improved not only model fit and performance, but also the accuracy of benchmark estimates based on historical seasonal averages. This study advances the state-of-the-art of climate services for the health sector, by showing the potential value of incorporating climate information in the public health decision-making process in Ecuador.**

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Centre for the Mathematical Modelling of Infectious Diseases and Department of Infectious Disease Epidemiology, London School of Hygiene & Tropical Medicine, London, UK (R Lowe PhD); **CLIMA—Climate and Health Programme, Barcelona Institute for Global Health (ISGLOBAL), Barcelona, Spain** (R Lowe, D Petrova MSc, Prof X Rodó PhD); **Center for Global Health and Translational Science and Department of Medicine, SUNY Upstate Medical University, Syracuse, NY, USA** (A M Stewart-Ibarra PhD); **Predictia Intelligent Data Solutions, Santander, Spain** (M García-Díez PhD); **School of Maritime Engineering, Biological Sciences, Oceanic and Natural Resources, Escuela Superior Politecnica del Litoral (ESPOL), Guayaquil, Ecuador** (M J Borbor-Cordova PhD); **National Institute of Meteorology and Hydrology (INAMHI), Guayaquil, Ecuador** (R Mejía MSc); **National Institute of Public Health Research (INSPI) of the Ministry of Health, Guayaquil, Ecuador** (M Regato MSc); **and Institució Catalana de Recerca i Estudis Avançats (ICREA), Barcelona, Spain** (Prof X Rodó)

Correspondence to:
Dr Rachel Lowe, Department of Infectious Disease Epidemiology, London School of Hygiene & Tropical Medicine, Keppel Street, London WC1E 7HT, UK
rachel.lowe@lshtm.ac.uk

Introduction

The burden of dengue fever (family Flaviviridae, genus *flavivirus*) has increased globally over the last three decades, from an estimated 8·3 million apparent (symptomatic) cases in 1990, to 58·4 million cases in 2013.[1] WHO and others have advocated the use of climate information to manage the increasing burden of dengue as part of comprehensive early warning and response systems.[2–4] Predictions of higher than expected dengue incidence (eg, outbreaks) can optimise the allocation of scarce resources through targeted and focused interventions. Previous studies have shown that climate information, such as seasonal climate forecasts, can be used to improve predictions of dengue outbreaks months in advance.[5,6]

Dengue is sensitive to changes in climate conditions because temperature affects the physiology of the *Aedes aegypti* and *Aedes albopictus* mosquito vectors (eg, biting and larval development rates)[7,8] and the rate of viral replication in the mosquito.[9,10] Transmission of dengue, and other arboviruses by *Aedes* spp mosquitoes, has been found to occur between 18–34°C with maximal transmission in the range of 26–29°C.[11] Both rainfall and drought can increase the availability of larval mosquito habitats (ie, containers with standing water), depending on local water storage practices and piped water infrastructure.[12,13]

The El Niño Southern Oscillation (ENSO) is the strongest interannual climate cycle on Earth. It occurs in the equatorial Pacific Ocean, and affects weather patterns worldwide through atmospheric teleconnections. Typical examples include excess rainfall in Peru and Ecuador, dry conditions in Indonesia, and a decrease in the number of typhoons in the western Pacific during the warm phase of the cycle, and more or less symmetrical anomalies during the cold phase.[14] To monitor, assess, and predict ENSO, the climate research community has defined the Niño3·4 index, which is calculated as anomalies in sea surface temperature (SST) in the Niño3·4 region ([120–170°W, 5°S–5°N]). The warm phase, El Niño, occurs when the 3 month running mean Niño3·4 index is 0·5 or higher for a period of at least

Research in context

Evidence before this study

We searched PubMed on March 7, 2017, for studies using seasonal climate forecasts for dengue early warning. Our search terms included "climate", "dengue", "model", and "early warning system". Several studies have used climate data to formulate dengue models and produce dengue predictions. However, predictions are usually made in retrospective mode, using observed climate data, which would have been available only after the event being predicted had occurred.

Added value of this study

To our knowledge, this work constitutes the first demonstration of the use of seasonal climate and El Niño forecasts in a dengue early warning model for Ecuador. This study adds value to the body of literature on dengue modelling by using real-time climate forecasts to make long-lead dengue predictions and using active surveillance data to correct for misreporting.

Implications of all the available evidence

The results of this study contribute to an ongoing collaboration between the National Institute of Meteorology and Hydrology and the Ministry of Health in Ecuador to undertake studies on climate and dengue. Previous studies have focused on providing the evidence base of the effect of climate on dengue transmission and improvements in seasonal forecasts in the region. This study takes this collaboration one step further, by co-developing a dengue early warning system using forecast climate information, which could potentially be operationalised as a climate service for the public health sector.

five consecutive 3-month overlapping seasons, and the cold phase, La Niña, when the Niño3·4 index is –0·5 or less.[15] The recent El Niño in 2014–16 was one of the strongest on record, similar in magnitude to the prominent 1997–98 event. The warming in the Niño3·4 region started in October, 2014, and the Niño3·4 index reached a maximum value of +2·9 in November, 2015. The Niño3·4 index then gradually decreased with a transition to a weak La Niña by the autumn of 2016.[15]

Southern coastal Ecuador is an important region to study the effects of ENSO on dengue. El Niño events are usually associated with heavy rainfall and warmer than average air temperatures.[16–18] Previous studies have shown the effects of ENSO and climate on dengue transmission in Ecuador and surrounding regions.[13,19–21]

Dengue is hyperendemic in Ecuador and the main cause of mosquito-borne febrile illness. There is no official dengue early warning system in the country. Every year, the authorities tend to expect the same number of cases and a peak in transmission during the hot, rainy season as in previous years. Each local health district monitors the behaviour of dengue based on the endemic curve, which is calculated with retrospective dengue case reports from the past 5 years. The mean number of weekly cases and the upper 95% CIs are calculated and compared with cases reported in the current year. Current surveillance efforts do not formally incorporate climate information, although the public health sector has identified this as a priority area.

Chikungunya virus and Zika virus, which are spread by the same mosquito species (*A aegypti*) as dengue, now co-circulate in Ecuador. The first recognised autochthonous cases of chikungunya were reported in Ecuador at the end of 2014.[22] The first cases of Zika were confirmed in Ecuador on Jan 7, 2016, and currently (May 25, 2017) 3972 suspected and 1330 confirmed cases of Zika have been reported.[23]

See Online for appendix

In this study, we predicted monthly dengue incidence in the city of Machala, El Oro Province, Ecuador, from January to November, 2016. We incorporated seasonal climate forecasts of precipitation and minimum temperature and a novel ENSO forecast in a statistical model framework to make monthly probabilistic predictions of dengue. The forecasts were generated on Jan 1, 2016, to predict dengue from 1 to 11 months ahead (January to November, 2016). We accounted for misreporting of dengue due to the introduction of chikungunya virus, by using active surveillance data to correct reported dengue case data from the passive dengue surveillance system. We then evaluated the forecast retrospectively with available epidemiological information.

Methods

Study area

Machala is a midsized port city located in El Oro province in southern coastal Ecuador. Like many cities in Latin America, the city was settled through a process of rapid unstructured urbanisation, and is now in a process of consolidation. The city was settled on low-lying mangroves, resulting in a high water-table and poor drainage. The city is prone to flooding every year during the rainy season, and extreme flooding events occur when rainfall coincides with high tides (as seen in February, 2016), often during El Niño years. The economic base of the province is agriculture (banana coffee, and cacao), aquaculture (shrimp), mining, and commerce due to a large port and proximity to the Peruvian border (see land use on appendix p 1). The core of the city is highly urbanised and has access to improved urban infrastructure and municipal services, such as paved streets, piped water inside the home, sewerage, and garbage collection. Many communities at the margin of the urban area are often not legally incorporated into the city, because they were settled

through informal slum settlements. As a result, they do not have adequate coverage of urban infrastructure and services, resulting in populations highly vulnerable to mosquito-borne diseases and other pathogens.[24] Previous studies in Machala have shown that poor housing conditions, lack of access to piped water inside the home, interruptions in the piped water supply, high population density, water storage, low risk perception, and absence of knowledge about the mosquito vector are key risk factors for the presence of *A aegypti* and dengue transmission.[13,20] Many homes in the urban periphery store water due to frequent interruptions in the piped water supply. In addition, homes in the urban centre continue to store water as a backup water source despite adequate access to piped water.

Machala is a key dengue surveillance site,[25,26] due the high burden of dengue, seasonal transmission, and co-circulation of all four dengue serotypes (DENV 1–4). Further, the region experiences exceptionally high *A aegypti* vector indices, which has implications for the recent emergence of chikungunya in 2015 and Zika in 2016.[13,27] Through the region, there is substantial movement of people and goods, due to proximity to the Ecuador–Peru border, the presence of a major port, and the location along the Pan-America highway, probably resulting in frequent reintroductions of viruses and vectors.

Data

Passive surveillance data

Monthly clinically suspected cases of dengue from Machala from 2002 to 2016 were provided by the national surveillance system operated by the Ministry of Health. Dengue is a mandatory notifiable disease in Ecuador. Cases were converted to incidence per 100 000 population using population data provided by the 2001 and 2010 national censuses (National Institute for Statistics and Census [INEC] 2001, INEC 2010), and population projections generated by INEC from 2011 to 2016. Population estimates between 2001 and 2010 were generated by linear extrapolation.

Active surveillance data

The proportion of reported clinically diagnosed dengue cases in 2015, which were later confirmed to be chikungunya infections, were removed from the passive surveillance dengue case dataset (appendix p 2). This proportion was determined from the results of a passive and active surveillance study of dengue infections in Machala, which has been described in detail elsewhere.[25] Briefly, patients were referred to the study if they were clinically diagnosed with dengue fever by physicians from sentinel clinics and the central hospital operated by the Ministry of Health in Machala. These individuals were registered as dengue cases in the Ministry of Health passive surveillance system. Serum samples from patients were tested by the study team for acute or recent dengue infections by non-structural glycoprotein-1 (NS1) rapid test, NS1 ELISA, Immunoglobulin M (IgM) ELISA, and RT-PCR, and for acute chikungunya and Zika infections by RT-PCR. All samples were negative for Zika virus. Based on these results, we calculated the monthly proportion of clinically diagnosed dengue cases that were dengue negative and chikungunya positive, and used this proportion to adjust the total number of Ministry of Health dengue cases reported in the passive surveillance system from the same period. This allowed us to account for over-reporting of dengue cases due to the recent introduction of a new febrile illness with similar clinical presentation as dengue.

Climate data

Local daily weather data (eg, rainfall, minimum temperature) were obtained from the Granja Santa Ines weather station located in Machala (3°17'26" S, 79°54'5" W, 10 m above sea level) and operated by the National Institute of Meteorology and Hydrology (INAMHI) of Ecuador. The Niño3·4 index (Extended Reconstructed Sea Surface Temperature [ERSST] version 4 SST anomalies in the Niño3·4 region) was obtained from the National Oceanic and Atmospheric Administration (NOAA) Climate Prediction Center (CPC) of NOAA/National Weather Service. SST anomalies in the Niño3·4 region are calculated using centred 30-year base periods updated every 5 years.

Figure 1 shows anomalies in dengue incidence in Machala, precipitation, and minimum temperature from the Granja Santa Ines weather station, at the monthly timescale from 2002 to 2015. Anomalies were calculated by subtracting the annual cycle of each variable (ie, the mean value for each month, calculated for 2002–15, appendix p 3) from the observed monthly data for each year. The Niño3·4 index from 2002 to 2015 is also shown. El Niño events (anomalous warming of SST in the Niño3·4 region, figure 1D) are, generally, associated with positive temperature (figure 1C), and precipitation (figure 1B) anomalies in Machala. These conditions can, in turn, create an ideal environment for dengue outbreaks (eg, the large dengue outbreak that peaked in February, 2010, see figure 1A). Alternatively, cool SSTs, cooler temperatures, and less than average rainfall might inhibit dengue outbreaks (see negative anomalies in figure 1A–D in 2013).

The epidemiological surveillance and climate data, outlined above, were used to formulate the dengue forecast model, described in the following section.

For **population data and projections** see http://www.ecuadorencifras.gob.ec/censo-de-poblacion-y-vivienda

Dengue forecast model

A statistical mixed model was used to produce probabilistic forecasts of dengue cases per month.[19,28] Dengue cases, y_t, were assumed to follow a negative

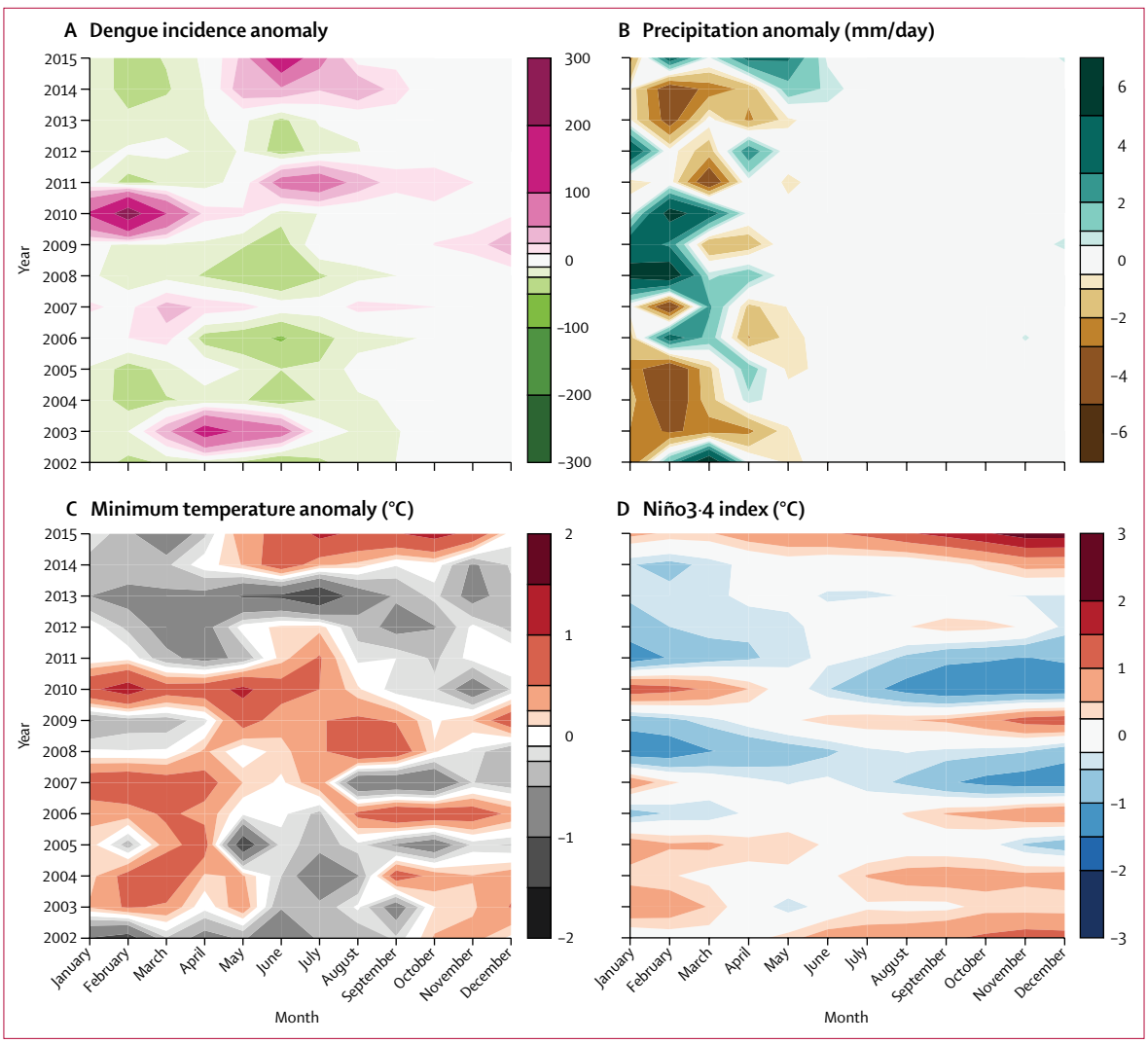

Figure 1: **Annual cycle of anomalies in dengue and climate variables, 2002–15**
(A) Dengue incidence anomalies in Machala, Ecuador per 100 000 population. (B) Precipitation anomalies (mm/day). (C) Minimum temperature anomalies (°C), from the Granja Santa Ines weather station, located in Machala. (D) Niño3·4 index (sea surface temperature anomalies [°C] in the Niño3·4 region).

binomial distribution with mean μ_t and overdispersion parameter κ. At the linear predictor scale, the log of the mean is equal to the log population $p_{T'(t)}$, T'(t)=1,...,n (n=14 years; included in the model as an offset) and log relative risk r_t for each time t:

$$y_t \sim \text{NegBin}(\mu_t, \kappa)$$

$$\log(\mu_t) = \log(\rho_{T'(t)}) + \log(r_t)$$

$$\log(r_t) = \alpha + f(\beta_{t'(t)}) + \Sigma\gamma_j x_{jt} + \delta_{T'(t)}$$

Using exploratory analysis and model selection criteria, such as the deviance information criterion, the best estimate of the log relative risk comprised a smooth function for the annual cycle $\beta_{t'(t)}$, t'(t)=1,...,m (m=12 months), using a first order autoregressive model. This term captures the seasonality in dengue, which is expected every year. This is partly attributable to climate conditions, but also other factors, such as human movement during holiday periods. The autoregressive model allows dengue in one calendar month to depend on dengue in the previous calendar month. The explanatory variables, x_{jt}, represent the selected climate covariates: precipitation (x_{1t}) and minimum temperature (x_{2t}), lagged by 1 month with respect to dengue, and Niño3·4 (x_{3t}), lagged by 3 months with respect to dengue (ie, 2 months with respect to the local climate). Note, we also tested maximum temperature in the model, but found a stronger association between minimum temperature and dengue incidence at all time lags, which was consistent with findings from previous studies.[13,19] To avoid overfitting the model (eg, representing an

anomalous warming event more than once in the model), we selected the best fitting temperature variable only. Exchangeable non-structured random effects for each year $\delta_{T'(t)}$, T'(t)=1,...,n (n=14 years) were included, to account for interannual changes in dengue risk attributable to unknown factors from 2002 to 2015, such as changes in vector control practices and the introduction of new serotypes and viruses (eg, introduction of chikungunya in 2015). In view of the introduction of another new virus (Zika) in 2016, the random year effect in 2015 was used to approximate the effect of a new virus (and associated misreporting) in 2016. To show the added value of our climate-based prediction model, we also formulated a null model using the annual cycle term as a predictor (ie, a submodel of the final predictive model) to represent current practice (ie, monitoring dengue incidence throughout the year compared to seasonal averages).

The model was trained using monthly dengue data from January, 2002, to December, 2015, and observed climate variables (precipitation, minimum temperature, and Niño3·4 index). The model was then used to produce forecasts for January to November, 2016, making use of seasonal climate forecasts of precipitation and minimum temperature, and Niño3·4 index forecasts from a new ENSO forecasting system (see below for details). Model parameters were estimated in a Bayesian framework using Integrated Nested Laplace Approximation (INLA) to generate samples from an approximated posterior of a fitted model.[29]

Seasonal climate forecasts

Seasonal forecasts of climate variables, such as precipitation and temperature, take advantage of the parts of the climate system with long-term memory, such as the oceans, to predict climate anomalies 1 or more months ahead of a given season.[30] To estimate uncertainty, each forecast consists of an ensemble of forecasts, obtained by perturbing the initial conditions. In this study, seasonal forecasts from the Climate Forecast System (CFS) model, developed by the National Center for Environmental Research (NCEP), were used.[31] The data were accessed via the International Research Institute for Climate and Society Data Library). The forecasts (1° zonal resolution) were arranged as a 24-member ensemble, initiated on Jan 1, 2016. The data consisted of monthly averages of precipitation and daily minimum temperatures, for the 10 months following the forecast start date (January to October, 2016, appendix p 4), taken at the grid point immediately to the west of the reference Granja Santa Ines weather station, located in Machala. The climate at this grid point, located over the sea, was found to be more representative of the climate of Machala, located at sea-level, than the nearest grid point (appendix p 5). The grid point in which the weather station is located has an average altitude of about 1200 m above sea level. Therefore, the forecasts for this grid point consistently underestimated the minimum temperatures recorded at the weather station, with a cold bias of 6–6·5ºC compared with a warm bias of 0·5–1ºC for the selected grid point (appendix p 5). Forecasts from the more representative grid point were then bias-corrected by subtracting the mean bias for each forecast time, to account for the model drift.[32,33] This was done using hindcasts (eg, retrospective forecasts) for the period 1982–2015, and corresponding observed data from the weather station.

ENSO forecast model

A structural time-series model, which uses subsurface ocean temperature, wind stress, and sea surface temperature as predictor variables, was used to forecast the Niño3·4 index in 2016.[34] We chose this ENSO forecast model based on its ability to predict El Niño events in the past (figure 2C). The model is comparable in performance to some of the most skilful dynamical ENSO models and generally performs better than other statistical schemes in terms of common skill metrics such as the root mean square error.[34,35] The ENSO prediction model is run with different predictor variables at different lead times. All forecasts of the 2016 Niño3·4 index were calculated using the observed Niño3·4 index data for December, 2015. For example, the Niño3·4 index forecast for January, 2016, was obtained from a 1-month-ahead forecast. Similarly, the Niño3·4 index forecast for February, 2016, was obtained from a 2-month-ahead forecast. The model is designed to produce very long-lead forecasts[34] (eg, 2 years ahead), but for the purpose of this study the last forecast used here was an 8-month lead forecast (eg, forecast for August, 2016, used to predict dengue incidence in November, 2016).

For the **Integrated Nested Laplace Approximation** see http://www.r-inla.org

Probabilistic dengue predictions for 2016

To account for uncertainty in the response variable, given the model parameters, the posterior predictive distribution of dengue cases, y_t, for each month (January to November, 2016) was estimated by drawing 1000 random values from a negative binomial distribution with mean corresponding to the elements of μ_t and scale parameter corresponding to the elements of κ, estimated from the model (note, the time lag of 1 month between the local climate variables [minimum temperature and precipitation] and dengue incidence allowed us to extend the dengue forecast 1 month beyond the maximum lead-time provided by the seasonal climate forecasts). To account for uncertainty in the model input (explanatory variables), we initiated the model 24 times for each ensemble member of the CFS forecasts of precipitation and minimum temperature. Therefore, for each month, we created a probability distribution of 576 000 samples (ie, 1000×24×24; note, as the ENSO model is deterministic, we do not account for uncertainty in the Niño3·4 index forecast). These data were summarised using the posterior predicted median and prediction interval (2·5% and 97·5% percentiles of the

For the **International Research Institute for Climate and Society Data Library** see http://iridl.ldeo.columbia.edu/SOURCES/.NOAA/.NCEP/.EMC/.CFSv2/index.html

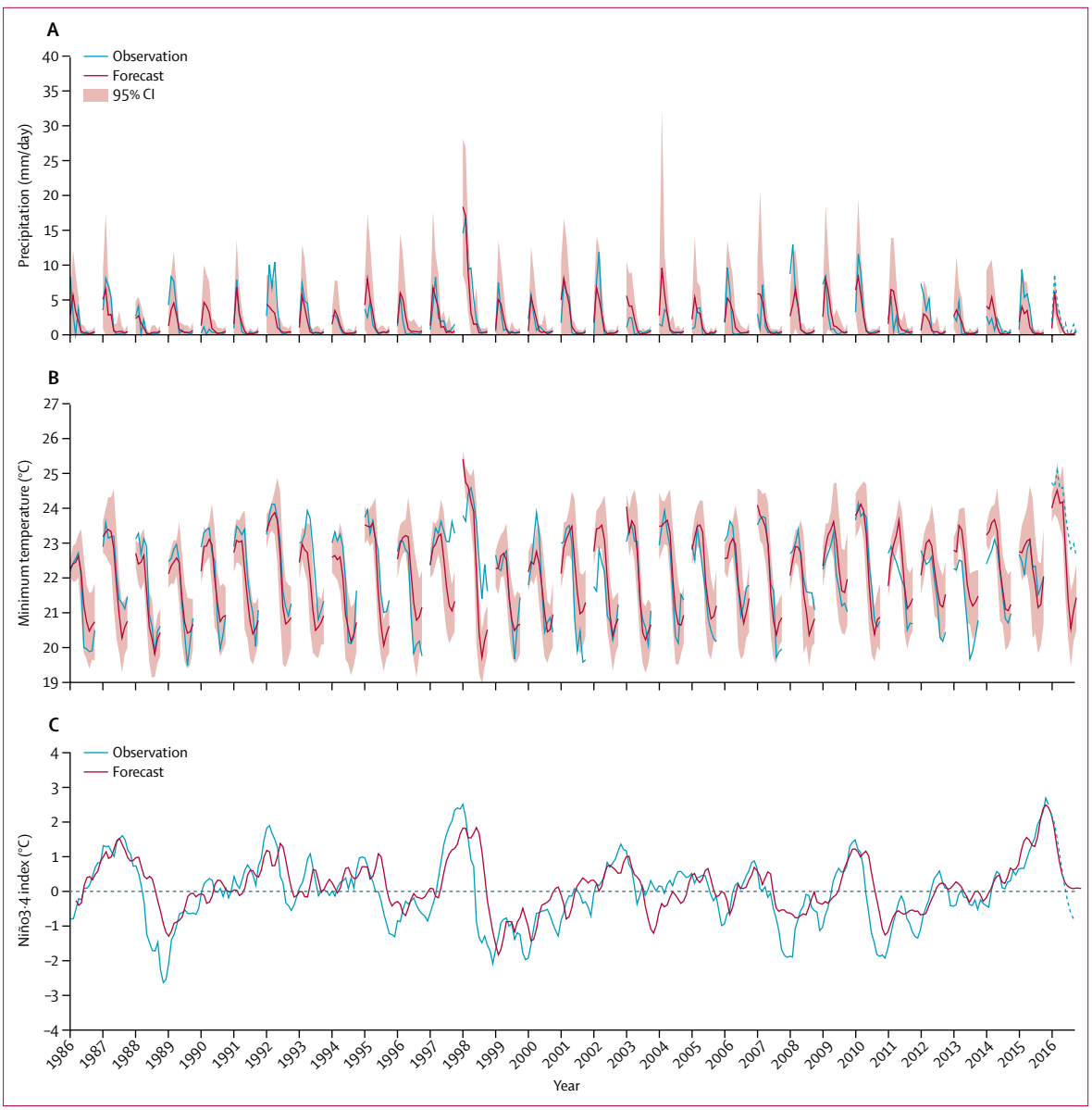

Figure 2: **Forecast and observed climate variables, 1986–2016**
Bias-corrected monthly forecasts from the Climate Forecast System version 2 model for Machala, Ecuador, from January to October, 1986–2016, for (A) precipitation (mm/day) and (B) minimum temperature (°C). The shaded areas represent the 95% CIs for the ensemble forecast (24 members). Observations from the weather station located in Machala for 1986–2015 (solid lines) and 2016 (dashed lines) are included. Forecasts are produced in January every year to predict climate conditions up to 10 months in advance. (C) Forecast Niño3·4 index (sea surface temperature anomalies in the Niño3·4 region), 1986–2016. Forecasts are produced using a structural time-series model with a 6-month lead time. Observed values for 1986–2015 (solid lines) and 2016 (dashed lines) are included.

posterior predicted distribution). For each month, the probability distribution was used to provide probabilistic forecasts of exceeding (1) the mean dengue incidence and (2) the upper 95% CI for the mean dengue incidence over the previous 5 years (2011–15; appendix p 6).

Role of the funding source

The sponsors of the study had no role in the study design, data collection, data analysis, data interpretation, or writing of the report. The corresponding author had full access to all the data in the study and had final responsibility for the decision to submit for publication.

Results

A set of analyses were done and visual aids were co-designed with climate and public health specialists in Ecuador, to communicate the predicted climate and dengue situation for Machala, at the beginning of 2016. This consisted of (1) the climate forecasts for 2016, along with hindcasts (retrospective forecasts) to indicate how

well climate models had forecast climate variations over the past 30 years; (2) the dengue prediction for the 2016 season, along with a comparison of observed and predicted dengue over the past 14 years; (3) a detailed forecast of dengue for each month in 2016, from January to November, showing the 2016 model prediction, and the mean and 95% upper CI dengue incidence thresholds, based on observed dengue incidence over the previous 5 years.

The bias-corrected mean monthly climate forecasts of precipitation and minimum temperature (and 95% CIs, based on the 24-member ensemble) for Machala, Ecuador, from January to October, 1986-2016, are shown in figure 2. Observed values from the Granja Santa Ines weather station in Machala are also shown. The forecasts were produced on Jan 1 every year to predict climate conditions from 1 month to 10 months ahead. The observed and forecast Niño3·4 index (SST anomalies in the Niño3·4 region), from 1986 to 2016, produced using the structural time-series ENSO model with a 6-month lead time are also included.[34] The ENSO model successfully predicted the peak in El Niño in November and a decrease in SST anomalies throughout 2016 (figure 2C). All 24 forecasted ensemble members from CFS for precipitation and minimum temperature in 2016, along with observations, are shown in the appendix (p 4). The forecasts were reasonably accurate, particularly for the first 6 months of the year. For example, the climate model predicted a peak in precipitation in February, 2016, the month in which Machala was subject to an extreme flooding event.

Observed, posterior predicted median and 95% prediction (credible) intervals for dengue incidence per 100 000 population in Machala, for the period 2002–16 are shown in figure 3. The posterior median estimate from the null model is also included. This shows the added value of using the proposed model to predict interannual variability in dengue incidence, rather than relying on seasonal averages. The model predicted, with some success, the interannual variability in dengue incidence. For example, the model accurately predicted the epidemic that occurred in 2010 and low dengue incidence in 2013. However, the model did underestimate incidence in 2003 and 2015, although observed incidence fell within the 95% prediction interval. Figure 4 shows the out-of-sample posterior predicted mean and 95% prediction (credible) interval for log dengue incidence (per 100 000 population) for 2016, January to November. The 5-year mean dengue incidence and upper 95% CI, calculated for the period 2011–15, are also shown. This shows the typical thresholds used by the Ministry of Health in Ecuador to assess the severity of a dengue season. The probability of exceeding the mean and upper 95% CI, calculated using incidence over the preceding 5 years (2011–15), is provided in the table. The model predicted an early peak in dengue incidence in March, 2016 (compared with the previous 5 years), with a 90% chance of exceeding the mean dengue incidence and an 85% chance of exceeding the upper 95% CI threshold (calculated for the previous 5 years). From June to November, the posterior mean prediction was less than the 5-year mean incidence, with probabilities of exceeding the mean less than 35%. The observed dengue incidence, obtained after the forecast had been made, is also included in figure 4. Although the posterior predicted median overestimated the observed dengue incidence for each month, the model correctly predicted that the peak incidence would occur 3 months earlier than expected, in March, 2016. The model also correctly predicted with confidence that dengue incidence would be greater than the 5-year mean incidence between January and April and less than the 5-year mean incidence from June onwards. Therefore, by using forecast climatic covariates, the model could identify key features of the transmission season, including an earlier-than-normal peak, and a lower-than-normal second half of season.

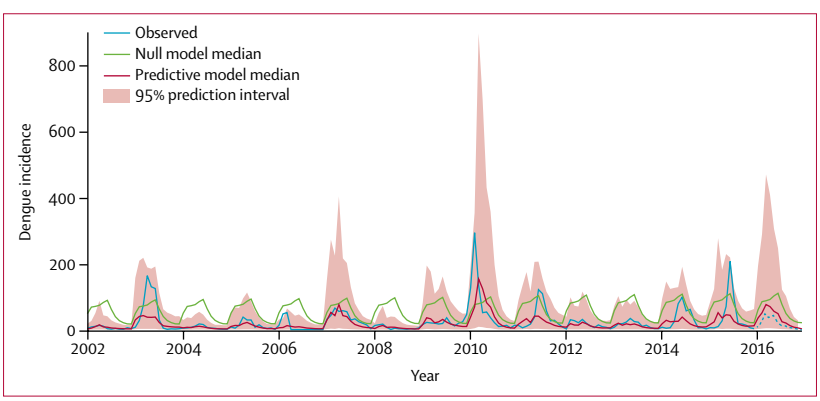

Figure 3: **Observed versus predicted dengue incidence 2002–16**
The posterior predicted median and 95% prediction (credible) interval (shaded area) for dengue incidence per 100 000 population in Machala, Ecuador, 2002–16; posterior median dengue incidence from a null model; and observed values for 2002–15 (solid line) and 2016 (dashed line) are shown.

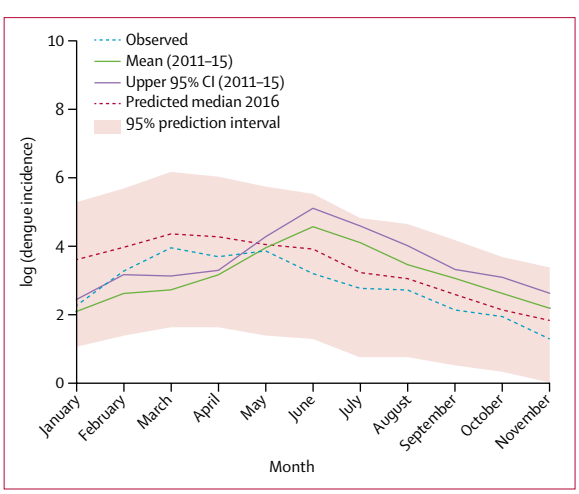

Figure 4: **Probabilistic dengue forecast 2016**
The posterior predicted median and 95% prediction (credible) interval (shaded area) for log dengue incidence per 100 000 population in Machala, Ecuador, January to November, 2016; 5-year mean dengue incidence and upper 95% CI, for the period 2011–15; and observed dengue incidence are shown.

	Mean (2011–15)			Upper 95% CI (2011–15)		
	Cases	Incidence	Probability of exceeding mean	Cases	Incidence	Probability of exceeding upper 95% CI
January	18	8	90%	27	11	84%
February	33	13	87%	58	23	76%
March	37	15	90%	56	22	85%
April	59	23	82%	68	26	79%
May	133	51	54%	186	71	41%
June	248	95	24%	430	162	9%
July	154	59	17%	251	97	5%
August	79	31	33%	140	54	13%
September	52	21	31%	69	27	21%
October	33	13	29%	53	22	13%
November	20	9	34%	32	14	17%

Mean and upper 95% CI of dengue (cases and incidence per 100 000 population) for the last 5 year period 2011–15. Probability of dengue incidence exceeding both the 5 year mean and upper 95% CI are shown.

Table: **Monthly probabilistic dengue risk forecasts for Machala, Ecuador, January–November, 2016**

To illustrate the benefit of incorporating active surveillance data, to correct for dengue misreporting, the model predictions were reproduced using the uncorrected dengue data—ie, before removing the confirmed chikungunya cases from the dataset in 2015 (appendix p 7). By using the original reported data, both the predicted dengue incidence and 5-year benchmark thresholds were inflated.

Discussion

Using a probabilistic dengue prediction model, driven by climate forecasts, dengue incidence in Machala was correctly predicted to be greater than the mean incidence over the previous 5 years (2011–15) at the start of the season (between January and April, 2016). The model successfully predicted the peak to occur 3 months earlier than expected, in March, with a 90% chance of exceeding the mean dengue incidence and an 85% chance of exceeding the upper 95% prediction interval. From June, 2016, the model also correctly predicted dengue incidence to be less than the mean incidence observed during the previous 5 years.

In Ecuador, the Ministry of Health informally monitors dengue incidence based on historical passive surveillance data averaged over the previous 5 years. When case reports exceed the upper 95% CI, the local public health authorities are aware that there is potential for an epidemic. By incorporating forecast climate information, the model provided a more accurate dengue outlook for the upcoming dengue season, than relying on the benchmark risk thresholds of the mean and upper 95% CI over the previous 5 years. Based on the 5-year average alone, public health officials would have expected the peak to occur later in the season.

The main advantage of this new dengue prediction framework is the use of seasonal climate and El Niño forecasts, which allows a prediction to be made at the start of the year for the entire dengue season. This provides advanced warning of the timing and magnitude of peak dengue incidence, which could greatly aid the management of scarce resources by the Ministry of Health, which is the institution responsible for dengue control. The planning period for the following fiscal year occurs during the last trimester of the calendar year. The new fiscal calendar begins on Jan 1, and budget allocations are finalised during the first trimester of the year. There are also emergency funds that can be allocated at a shorter timescale in the case of an emergency, such as an earthquake or epidemic. If the Ministry of Health was warned at the start of the calendar year that the peak in dengue would occur several months earlier than expected due to forecast climate conditions, they could adjust their budgets, and more effectively mobilise resources to strengthen vector control and surveillance, such as personnel, insecticide, diagnostic reagents, and vehicles, ahead of the peak season. With sufficient lead time, the public health sector could also implement community communication and mobilisation campaigns to promote behavioural change, such as health care seeking behaviour and the elimination of uncovered containers with standing water.

Dengue transmission in Ecuador is seasonal, with most cases occurring during the hot and rainy season, and sporadic transmission during the rest of the year. Over the past 5 years, the peak in dengue has shifted from the first trimester to the second trimester. This study shows the predicted evolution of the epidemic curve in 2016 was only possible due to the incorporation of forecast climate information in the model. However, this might not be the case every year. Other factors intrinsic to the local population dynamics are likely to play a more dominant part for certain years. For example, interannual variations in human mobility patterns, population immunity status, and the intensity of vector control measures. These factors are not explicitly accounted for in the model. However, we do include yearly random effects to crudely quantify variability resulting from unmeasured factors from 1 year to the next. This allows us to better quantify the effect of climate variation on dengue interannual variability and make more realistic predictions of future risk, based on climate information.

The efficacy of a climate-based dengue early warning system depends on the availability of accurate climate information and skilful climate forecasts. Seasonal climate forecasts are found to be more accurate during El Niño and La Niña episodes and in ENSO-affected regions, such as southern coastal Ecuador.[36] When these events occur, there is a clear opportunity to incorporate climate information into decision-making processes for climate-sensitive sectors. The presence of a strong El Niño towards the end

of 2015 increased our confidence in the seasonal climate forecasts for 2016. Furthermore, the 2015–16 El Niño was of similar magnitude to the 1997–98 and 2009–10 El Niño events, which were followed by dengue outbreaks in El Oro province.[19] This provided an ideal opportunity to test El Niño and climate forecasts in a pseudo-operational dengue modelling framework. However, seasonal climate forecasts can be less reliable during ENSO-neutral years. The skill of climate model simulations and predictions still represents a major research area for improving the usefulness of health early warning systems to public health decision makers, particularly in those regions and timescales for which climate forecast skill is low or non-existent. Further work is in progress to explore different sources of predictability of local meteorological conditions in coastal Ecuador, to improve the skill of seasonal climate forecasts in this region.[37]

Despite these limitations, this work advances the state-of-the-art of climate services for the health sector in Ecuador, by transitioning from proof of concept to application. The successful implementation of climate services for health depends on availability of relevant, high-quality climate data, as well as the institutional and human capacity to transform the data into reliable and tailored climate products and services.[38] In our case, this relied on close collaboration between public health specialists, climate scientists, and mathematical modellers to find a compromise between the quality and resolution of the climate and epidemiological datasets.

As well as taking advantage of the lead times provided by climate information, the model also considered active surveillance data in the city to correct the dengue dataset, in view of the introduction of chikungunya virus in the region in 2015. This was a unique opportunity, because active surveillance data are not readily available in many dengue-endemic regions. By removing the estimated number of chikungunya cases from the dataset, which had been erroneously recorded as dengue cases, both the model prediction and the benchmark mean estimates were more realistic (appendix p 7). The surveillance study showed that dengue case data in 2015 was in fact made up of dengue, chikungunya, and other febrile diseases. These individuals were also screened for active Zika virus infections, and were negative, which is consistent with Ministry of Health reports. We decided to remove chikungunya cases from the dataset, rather than using confirmed dengue cases only. This is because chikungunya was first introduced to the region in 2015. In previous years, other febrile diseases were likely to have been misreported as dengue cases. Therefore, to be consistent with misreporting practices in the years before 2015, we did not correct for diseases other than chikungunya.

In 2016, Zika virus also began to circulate in Machala but only ten cases of Zika were confirmed in the city. The epidemic has escalated in 2017 and as of May 25, 2017, there have been three confirmed cases of congenital syndrome associated with Zika virus infection in Ecuador.[23] Because we did not have data for the proportion of dengue infections that were misclassified as Zika virus, we did not adjust the dataset for the introduction of Zika. Although it is likely that some Zika virus infections were classified as dengue, we anticipate that this proportion was much lower than for chikungunya in 2015. The severe symptoms associated with chikungunya led to a substantial increase in misreported dengue cases that were captured by the Ministry of Health passive surveillance system. After accounting for chikungunya infections, the model well reproduced the evolution of dengue cases in 2016. Therefore, further correction for Zika was considered less essential than for chikungunya. Based on our experience, fewer people with suspected Zika virus infections attended health centres in 2016, due to mild symptoms. Analyses of active surveillance data from 2016 are ongoing to understand the prevalence and co-infections of Zika, chikungunya, dengue, and other febrile illnesses.

Ultimately, future predictions of dengue outbreaks in areas co-endemic for dengue, chikungunya, and Zika require laboratory confirmation of cases for accurate differential diagnosis. This study highlights the need to combine climate information and active surveillance data to strengthen early warning systems for arboviruses in Ecuador and other El Niño-sensitive areas, experiencing co-circulation of arboviral diseases.

Contributors

RL was responsible for the study design, model development, data analysis, and wrote the report. AMS-I collated the data, contributed to the study design, and helped write the report. DP provided the ENSO forecasts. MG-D provided the bias-corrected climate forecasts. All authors contributed to the study design, discussed the results, and reviewed and approved the final report.

Declaration of interests

We declare no competing interests.

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