Zika epidemic fueled by climate variations on multiple timescales

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Speculation exists that the emergence of Zika virus (ZIKV) as a public health emergency in Latin America and the Caribbean (LAC)[1] is partially related to high temperatures associated with the 2015-2016 El Niño event[2]. Analysis of related *flaviviruses* –such as dengue and chikungunya[3], which are transmitted by the same vectors[4]– suggests that ZIKV is sensitive to climate. Quantifying the climate contribution to ZIKV transmission is an important step in better understanding the conditions conducive to the 2014-2016 epidemic, and permits the development of climate-informed short- and long-term strategies for ZIKV prevention and control[5]. Using a novel timescale-decomposition methodology[6], here we demonstrate that extreme climate anomalies observed in most parts of South America during the current epidemic are not caused exclusively by El Niño or climate change –as speculated–, but are the result of a particular combination of climate signals acting at multiple timescales. In Brazil, the heart of the epidemic, we find that dry conditions present during 2013-2015 are explained primarily by year-to-year variability superimposed on decadal variability, but with little contribution of long-term trends. In contrast, the extreme warm temperatures of 2014-2015[7,8] resulted from the compound effect of climate change, decadal and year-to-year climate variability. The increasingly probable 2016-2017 La Niña[9] suggests that ZIKV response strategies adapted for a drought context in Brazil may need to be revised to accommodate the likely return of heavy rainfall. Temperatures are likely to remain warm given the importance of long term and short term trends.

While the postulated impact of the El Niño-Southern Oscillation and long-term climate change on ZIKV transmission is plausible[2], current analysis on the climate-disease interaction is constrained by the recent arrival of the ZIKV in the Latin American and Caribbean region[1] and the diverse nature of prior epidemics across the globe[3]. Evidence to date suggests ZIKV is principally transmitted globally and in LAC by the container breeder mosquito *Aedes aepgyti*[4]. Because of its recent rapid spread, *Ae. albopictus,* alongside other *Aedes spp.,* has been identified as a minor vector but one with significant transmission potential in the future[10]. Although ZIKV transmission depends on several factors including human behaviour, it is well established that the associated vectors are sensitive to variations in environmental temperature and rainfall, and weather-based early warning systems for the related dengue virus have been suggested in different regions of the world[11,12,13] . Temperature is a significant driver of the development rates of juvenile *vectors* and adult feeding/egg laying cycles, along with the length of extrinsic incubation period and viral replication of arboviruses[12,14,15]. Both excess rainfall and drought have been implicated in the creation of breeding sites for *Aedes* vectors of ZIKV, and associated epidemics of dengue and chikungunya. Both floods and droughts may result in the development of outdoor breeding sites in a wide range of artificial containers[15], whereas droughts may also encourage

changes in human behaviour to water storage that results in increases in domestic breeding sites for *Aedes spp.*[16]

The climate at any location varies from its historical average on a number of time scales, including year-to-year, decadal and long-term trends, the latter compatible with climate change signals. The magnitude or persistence of the climate variations may enhance epidemic potential in the region. In order to better understand how much of the total variance in rainfall and temperature is explained by different timescales, and how those variations connect to recent conditions, we analyze how anomalies over time can be approximately attributed to variations in climate drivers at different timescales – an analysis referred to as "timescale decomposition"[6]. This methodology filters the associated anomalies of a climate time series into three components: the interannual (year-to-year), decadal and long-term trend signals. The analysis shows how important each timescale is for explaining the entire climate signal observed in any particular location.

The 20th Century decomposition for annual rainfall totals (Figure 1ABC) and annual mean temperature (Figure 1DEF) signals in LAC shows sharp differences in the variability explained by each timescale. On average, our results for a large region involving most of Brazil (black box) indicate that the portion of variance in rainfall associated with the climate change signal is basically nil (Figure 1A), whereas that for the inter-annual component is higher than 80% throughout the region (Figure 1C). Also, the decomposition reveals that all three timescale components for surface air temperature are important (Figure 1DEF). The temperature long-term trend is particularly high along the coast, in the Northeast and Southeast regions of the country. The part of South America delimited by the box in Figure 1 exhibits the highest number of reports associated with typical arbovirus vectors[17] and Zika cases[3], and thus it was selected for further analysis.

The decadal signal is in general more important for temperature than for rainfall in the region, the contribution to precipitation being higher along the Atlantic coast (20%-30%, Figure 1B), whereas for surface air temperature the highest decadal component is found in the Amazon (~50%, Figure 1E). Interannual variations in rainfall account for the majority of its overall variance (over 80%, Figure 1C); for surface temperature most locations show values over 30%, with a local maximum in Northeastern Brazil that explains at least 60% of the variability (Figure 1F).

Results are similar for the region of interest when particular seasons are considered (not shown): for rainfall the most important scales are interannual and decadal, while for air surface temperature the three timescales share similar importance, while locally one timescale may exhibit greater importance than the others.

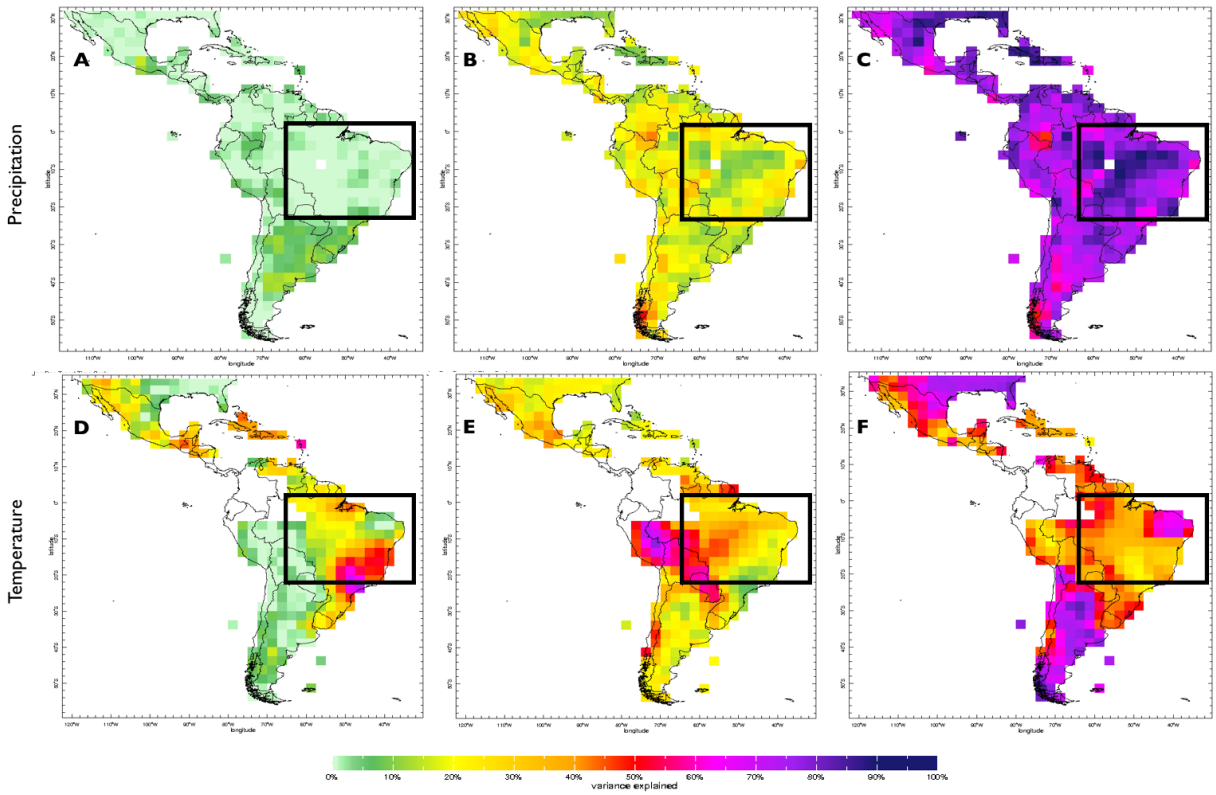

Figure 1 Timescale decomposition for annual precipitation (A,B,C) and air temperature (D,E,F), sketching the total explained variance for the long-term trend (A,D), decadal (B,E) and inter-annual variability (C,F) signals. Grid points in white indicate places where the lack of data would degrade the analysis and thus the corresponding signal has been removed by the screening process[6]. Analysis focuses in the region delimited by the black box (see main text).

We performed a complementary analysis for the average climate over the region of interest (Figure 2). When summed, the specific contributions explain the observed anomalies for each particular year. Our results show that a positive superposition between the rainfall interannual and decadal signals and all three temperature components (climate change, decadal and inter-annual) is key to understand the recent behaviour of the climate in the region. This collection of drivers was responsible for the particularly warmer- and drier-than-normal conditions present in the region during the last few years. The unprecedented positive temperature anomalies that started in the 1990s are consistent with the positive sign of the decadal component for that period, combined with the contributions of the long-term trend and inter-annual variability.

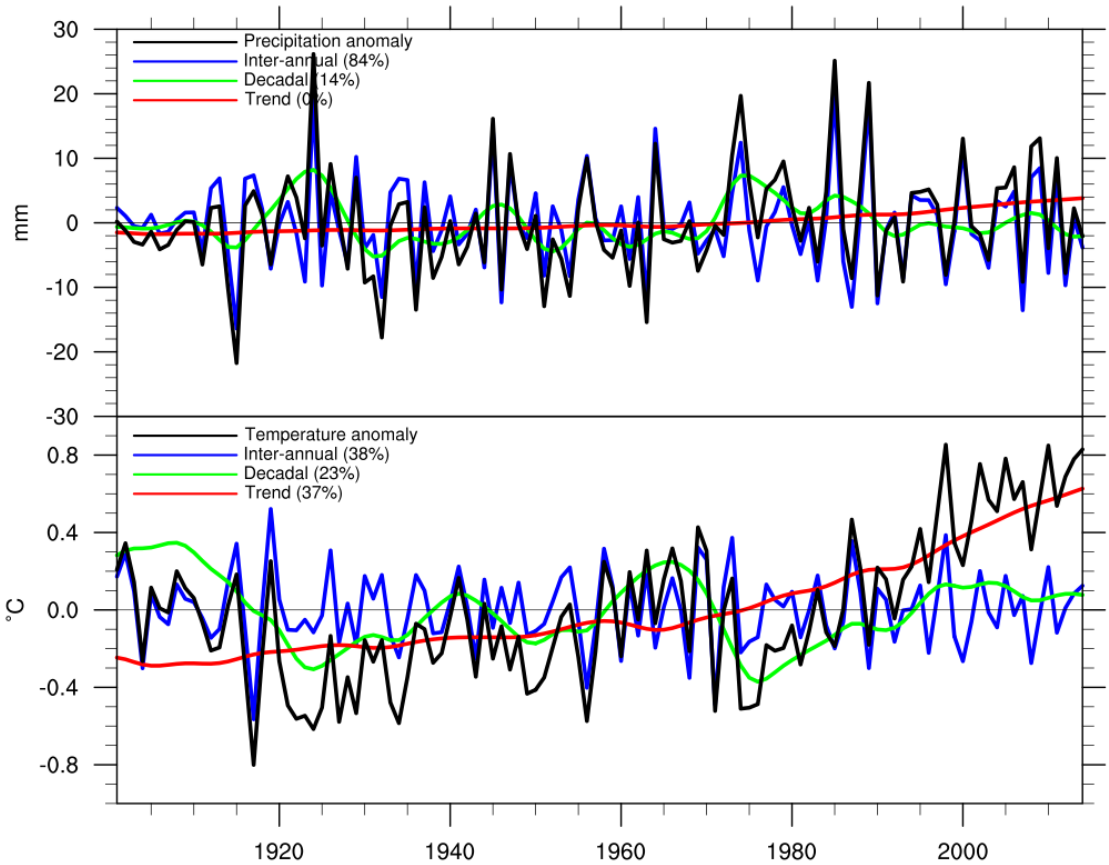

Figure 2 Timescale decomposition for annual anomalies in the 1901-2014 period (black curves; precipitation in the top panel, temperature in the bottom panel) averaged over the region indicated in Figure 1 (black box). The anomalies correspond to the superposition of the long-term trend (in red), the decadal signal (in green) and the inter-annual variability signal (in blue). Contribution of each timescale to the total explained variance is shown in parenthesis.

The spatial patterns for both temperature and rainfall anomalies were fairly similar in 2014 and 2015 (Figure 3), which were, at their respective terminus, the hottest years on record[7,8]. In terms of temperature anomalies, the year 2013 was normal for most part of LAC, although the warming pattern in the Amazon that occurred in the following years was already present. A similar claim can be made for the 2013 annual rainfall anomalies in the Amazon: the general drier-than-normal signal exhibited in 2014 and 2015 was already evolving.

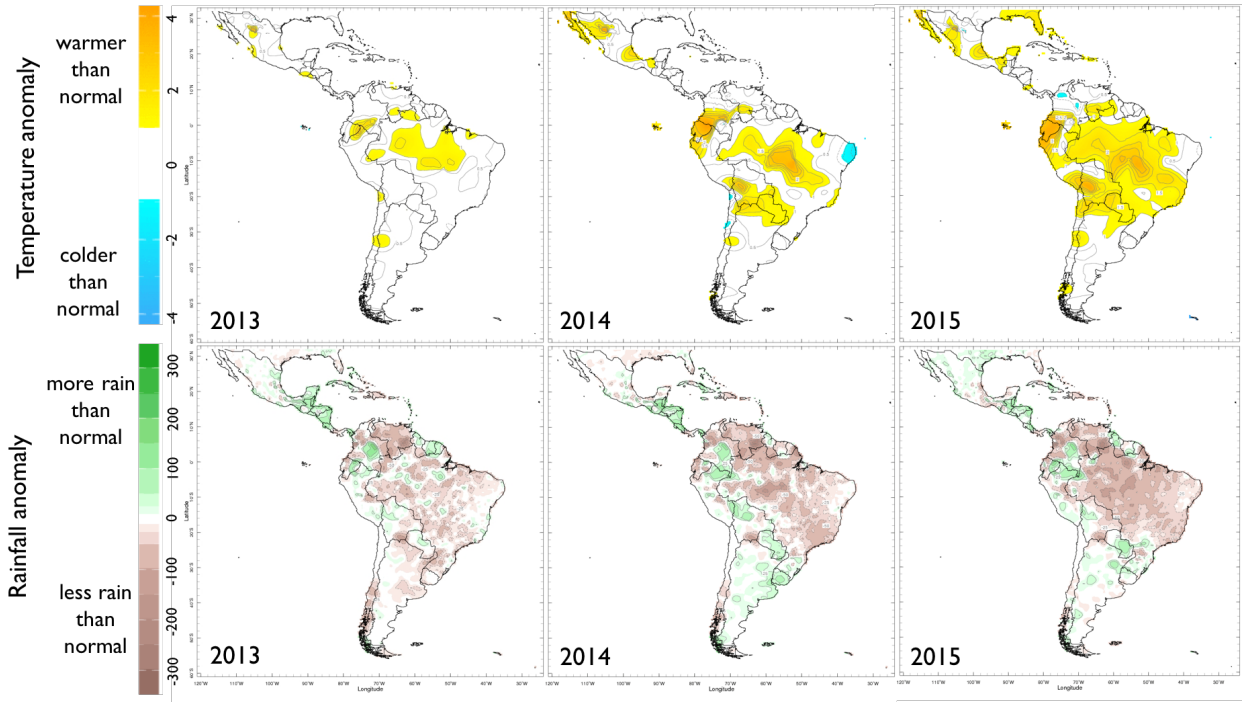

Figure 3. Annual temperature (upper row, in °C) and rainfall (lower row, in mm) anomalies for 2013-2015. White indicates near-normal values.

The warming observed in 2014-15 is therefore an outcome of positive temperature anomalies at the year-to-year and decadal timescale superimposed on a long term warming trend. This superposition of timescales may have helped to set the climate scenario for local ZIKV transmission via *Ae. aegypti* and other, less significant, vectors[4]. These patterns have also been observed during the first few months of 2016, but they are expected to change as the year progresses. As of May 2015, seasonal forecasts of sea surface temperatures suggest a 75% probability of a La Niña event to be in place later this year[9]. La Niña events typically lead to wetter than average conditions over the northern part of Brazil and Northern South America[18]. Since precipitation in this region is dominated by inter-annual variability, climate drivers at longer timescales are not likely to offset that response to La Niña. For temperature, the tropics do tend to be relatively cooler during La Niña events, particularly relative to El Niño. However, given the comparable magnitude of decadal variability, which currently appears to be in a warm phase, and the strength of the long-term trend, warmer than average temperatures are still the most likely outcome over the coming year.

The characterization of year-to-year variability and longer term climatic trends is important for strategic ZIKV outbreak preparedness activities in LAC and across the border into the USA. For countries where variability and short and long-term trends are in part predictable, climate information could support the planning of prevention and control activities for different high risk areas, such as training of personnel in different aspects of the outbreak early warning and response system[19]. For example the response strategies for ZIKV vector control in a warm and dry year, where high levels of water storage provides domestic breeding sites, may need revision in a wet year when outdoor breeding sites may be more common. Current speculation about the climate drivers that may impact ZIKV transmission are based on plausible assumptions regarding the dynamics of the disease but lack an in-depth understanding of the climate. Using climate knowledge to improve health outcomes however must be based on an understanding of the climate system itself and its interaction at multiple spatial and temporal scales. The timescale decomposition approach[6] used here allows a robust assessment of complex climate

components to be made for any time period, season and region. It provides a basis for considering climate as a resource to their efforts.

Methods

Timescale decomposition (Figures 1 and 2) used long-term (1901-2014) rainfall and temperature data from University of East Anglia's Climate Research Unit, product version 3.23 (CRUv3.23, 0.5 deg resolution)[20]. Most recent annual temperature and rainfall anomalies (Figure 3) were computed using Climate Prediction Center's Monthly Global Surface Air Temperature Data Set[21] (0.5 deg) and Rainfall Unified Data Set[22] (0.5 deg), respectively. Years 1979-2000 were used to compute the normal for Figure 3.

Timescale decomposition consists of screening the individual gridbox values for filled data and for very dry seasons and regions; detrending in order to extract slow, trend-like changes; and filtering, to separate high and low frequency components in the detrended data. Detrending involves regressing the local time series on multi-model global surface air temperature from the Twentieth Century Climate in Coupled Models[23] and lowpass filtering. The decadal component is obtained through lowpass filtering of the residual, using an order-five Butterworth filter with half-power at a period of 10 year, while the inter-annual component is computed as the difference between the residual from the detrending step and the decadal signal[6].

For the maps in Figure 1, data are processed gridbox by gridbox, meaning that results in adjacent gridboxes are not compared or combined. For the graph of the regional timeseries (Figure 2), averaging over gridboxes is performed prior to the decomposition. Total explained variance for each component is computed for the area-averaged time series, and not as averages of the spatial variance maps.

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