1   **Analyzing climate variations on multiple timescales can guide Zika**

2   **virus response measures**

3

4   *Á.G. Muñoz[1,2,3], M.C. Thomson[2,4,5], L. Goddard[2], S. Aldighieri[6]*

5   [1] Atmospheric and Oceanic Sciences (AOS)/Geophysical Fluid Dynamics Laboratory (GFDL). Princeton University.

6   NJ. USA.

7   [2]International Research Institute for Climate and Society (IRI). Earth Institute. Columbia University. NY. USA

8   [3] Latin American Observatory for Climate Events. Centro de Modelado Científico (CMC). Universidad del Zulia.

9   Venezuela.

10   [4] Mailman School of Public Health Department of Environmental Health Sciences. Columbia University. NY. USA

11   [5] WHO Collaborating Centre (US 306) on Early Warning Systems for Malaria and other Climate Sensitive Diseases.

12   USA

13   [6]International Health Regulations / Epidemic Alert and Response, and Water Borne Diseases (IR). Communicable

14   Diseases and Health Analysis Department (CHA). PAHO. DC. USA

15

16   **Abstract**

17   *Background*

18   The emergence of Zika virus (ZIKV) as a public health emergency in Latin America and the

19   Caribbean (LAC) occurred during a period of severe drought and unusually high temperatures.

20   Speculation in the literature exists that these climate conditions were associated with the

21   2015/2016 El Niño event and/or climate change but to date no quantitative assessment has

22   been made. Analysis of related *flaviviruses* –such as dengue and chikungunya, which are

23   transmitted by the same vectors– suggests that ZIKV dynamics is sensitive to climate

24   seasonality and longer-term variability and trends. A better understanding the climate conditions

25   conducive to the 2014-2016 epidemic may permit the development of climate-informed short-

26   and long-term strategies for ZIKV prevention and control.

27

28   *Results*

29   Using a novel timescale-decomposition methodology, we demonstrate that extreme climate

30   anomalies observed in most parts of South America during the current epidemic are not caused

31   exclusively by El Niño or climate change –as speculated–, but are the result of a particular

32   combination of climate signals acting at multiple timescales. In Brazil, the heart of the epidemic,

33   we find that dry conditions present during 2013-2015 are explained primarily by year-to-year

34   variability superimposed on decadal variability, but with little contribution of long-term trends. In

35   contrast, the extreme warm temperatures of 2014-2015 resulted from the compound effect of

36   climate change, decadal and year-to-year climate variability.

37

38   *Conclusions*

39   ZIKV response strategies adapted for a drought context in Brazil during El Niño 2015/2016 may

40   need to be revised to accommodate the likely return of heavy rainfall associated with the

41   probable 2016/2017 La Niña. Temperatures are likely to remain warm given the importance of

42   long term and decadal scale climate signals.

43

44   *Keywords*

45   Zika virus – epidemic - climate – timescales – climate change – decadal – inter-annual – El Niño

46   – Brazil – drought – vector control

47

48

49   **Background**

50   It has been postulated that the 2015/2016 El Niño-Southern Oscillation and long-term climate

51   change have contributed to the recent emergence of Zika virus (ZIKV) in Latin America and the

52   Caribbean (LAC) [1]. While plausible, analysis on the climate-ZIKV interaction is constrained by

53 the recent arrival of the virus in LAC and hence lack of historical time series of epidemiological

54 data [2] and the diverse nature of prior epidemics across the globe [3]. Evidence to date

55 suggests ZIKV is principally transmitted globally and in LAC by the container breeder mosquito

56 *Aedes aegypti* [4]*.* Because of its recent rapid spread, *Ae. albopictus,* alongside other *Aedes*

57 *spp.,* has been identified as a minor vector but one with significant transmission potential for the

58 future [5]. Although ZIKV transmission depends on several factors including human behaviour, it

59 is well established that the associated vectors are sensitive to variations in environmental

60 temperature and rainfall, and weather-based early warning systems for the related dengue virus

61 have been suggested in different regions of the world [6,7,8]. Temperature is a significant driver

62 of the development rates of juvenile mosquito vectors and adult feeding/egg laying cycles, along

63 with the length of extrinsic incubation period and viral replication of arboviruses [8,9,10,11]. Both

64 excess rainfall and drought have been implicated in the creation of breeding sites for *Aedes*

65 vectors of ZIKV, and associated epidemics of dengue and chikungunya. Heavy rainfall may

66 result in the development of outdoor breeding sites in a wide range of artificial containers [12],

67 whereas droughts may also encourage changes in human behaviour to water storage that

68 results in increases in domestic breeding sites for *Aedes spp.* [13]

69

70 The climate at any location varies from its historical average on a number of time scales,

71 including natural year-to-year and decadal (10-20 year) variations as well as long-term trends,

72 the latter by construction compatible with anthropogenic climate change signals [14]. The

73 magnitude or persistence of the climate variations may enhance or decrease epidemic potential

74 in the region. In order to better understand how much of the total variance in rainfall and

75 temperature is explained by different timescales, and how those variations connect to recent

76 conditions that are connected in space and time to the emergence of ZIKV in LAC, we analyze

77 how anomalies over time can be approximately attributed to variations in climate drivers at

78 different timescales – an analysis referred to as "timescale decomposition" [14, 15]. This

79   methodology filters the associated anomalies of a climate time series into three components:

80   the inter-annual (year-to-year), decadal and long-term trend signals. The analysis shows how

81   important each timescale is for explaining the entire historical climate signal observed in any

82   particular location.

83

84   As indicated, the absence of long time series of ZIKV transmission indices or cases prohibits a

85   formal statistical assessment of the climate-ZIKV linkage including the epidemiological impact of

86   the 2015's climate on the epidemic. However, our study is based on the premise that climate is

87   likely an important driver of seasonal, inter-annual and longer-term trends in ZIKV transmission

88   given that 1) temperature impacts the development rates of related arbovirus' and the known

89   vectors, and 2) droughts or excess of rainfall influence vector breeding sites either directly or

90   through changes in human behavior. We therefore focus our analysis on the particular

91   contributions of climate signals at multiple timescales to rainfall and temperature in order to

92   support the development of climate-informed short- and long-term strategies for ZIKV

93   prevention and control [14].

94

95   **Data Description**

96   We chose two sources of climate data for our analysis as no single data set included the entire

97   time of interest. Timescale decomposition (Figures 1 and 2) was undertaken using the most up-

98   to-date long-term (1901-2014) rainfall and temperature data from University of East Anglia's

99   Climate Research Unit, product version 3.23 (CRUv3.23, 0.5-deg resolution) [16]. Recent

100   annual temperature and rainfall anomalies (2013-2015, Figure 3) were computed using the

101   Climate Prediction Center's Monthly Global Surface Air Temperature Data Set (0.5 deg) [17]

102   and Rainfall Unified Data Set (0.5 deg) [18], respectively. Years 1979-2000 were used to

103   compute the normal for Figure 3.

104

105   Time series, maps and data are freely available in the IRI's Timescale Decomposition Maproom

106   [19] and the Latin American Observatory's Climate and Health Maproom [20,21], and can be

107   obtained for any region in the world having long enough quality-controlled records. For details,

108   see [15].

109

110   **Analyses**

111   The 20th Century decomposition for annual rainfall totals (Figure 1ABC) and annual mean

112   temperature (Figure 1DEF) signals in LAC shows sharp differences in the variability explained

113   by each timescale. The part of South America delimited by the black box in Figure 1 exhibits the

114   highest number of reports associated with typical arbovirus vectors [22] and Zika cases [3], and

115   thus it was selected for further analysis. On average, our results for the selected region indicate

116   that the portion of variance in rainfall associated with the climate change signal is basically nil

117   (Figure 1A), whereas that for the inter-annual component is about 60%-90% throughout the

118   region (Figure 1C). Also, the decomposition reveals that all three timescale components for

119   surface air temperature are important (Figure 1DEF).

120

121   The temperature long-term trend signal is particularly important along the southeastern regions

122   of Brazil (Figure 1D). The decadal signal is in general more important for temperature than for

123   rainfall in the region, the contribution to precipitation being higher along the coast (20%-30%,

124   Figure 1B), whereas for surface air temperature the highest decadal component is found in the

125   Amazon (~50%, Figure 1E). Inter-annual variations for surface temperature show values over

126   30% in most locations, with a local maximum in Northeastern Brazil that explains at least 60% of

127   the variability (Figure 1F).

128

129   Results are similar for the region of interest when particular seasons are considered [19, 21]: for

130   rainfall the most important scales are inter-annual and decadal, while for air surface temperature

131   the three timescales share similar importance, while locally one timescale may exhibit

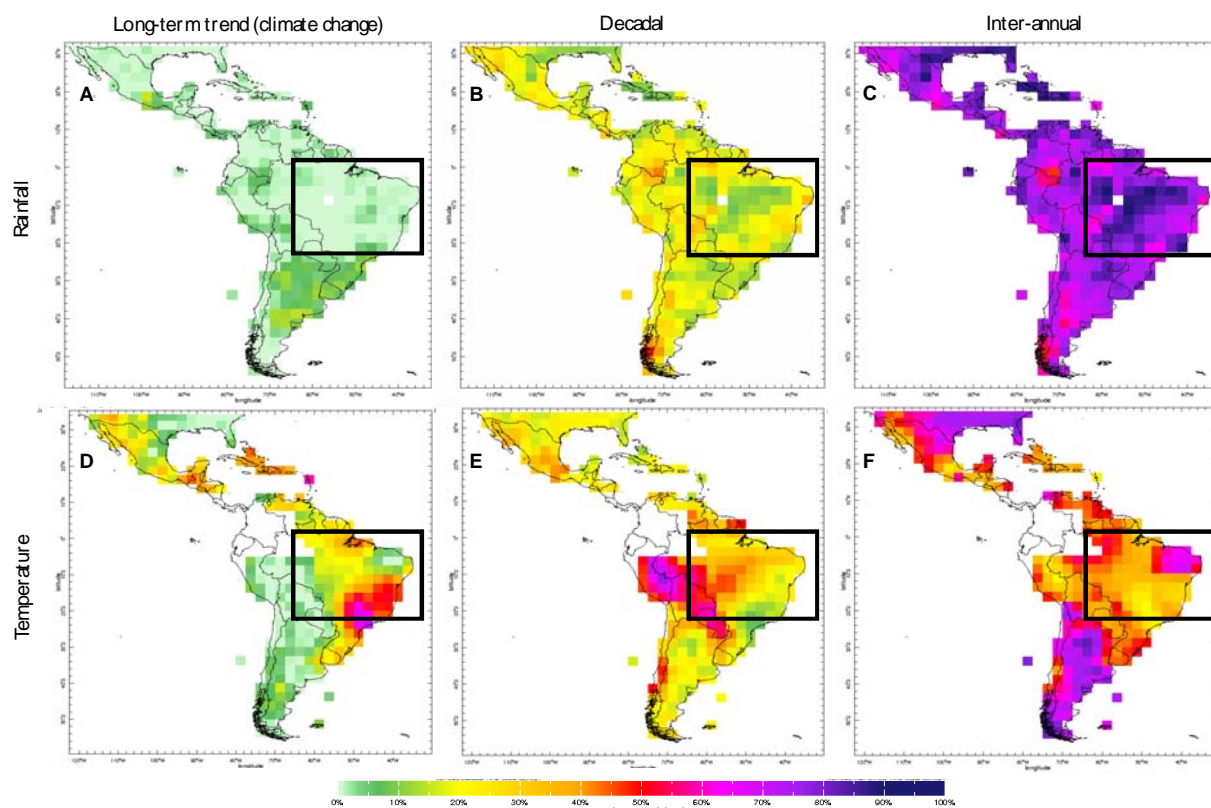132   greater importance than the others.

133

134

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 [15]. Analysis focuses in the region delimited by the black box (see main text).

140

141   We performed a complementary analysis for the average climate over the boxed region of

142   interest (Figure 2). When summed, the specific contributions explain the observed anomalies for

143   each particular year. Our results show that a positive superposition between the rainfall inter-

144   annual and decadal signals and all three temperature components (climate change, decadal

145   and inter-annual) is key to understand the recent behaviour of the climate in the region. This

146   collection of drivers was responsible for the particularly warmer- and drier-than-normal

147   conditions present in the region during the last few years. The unprecedented positive

148   temperature anomalies that started in the 1990s are consistent with the positive sign of the

149   decadal component for that period, combined with the contributions of the long-term trend and

150   inter-annual variability.
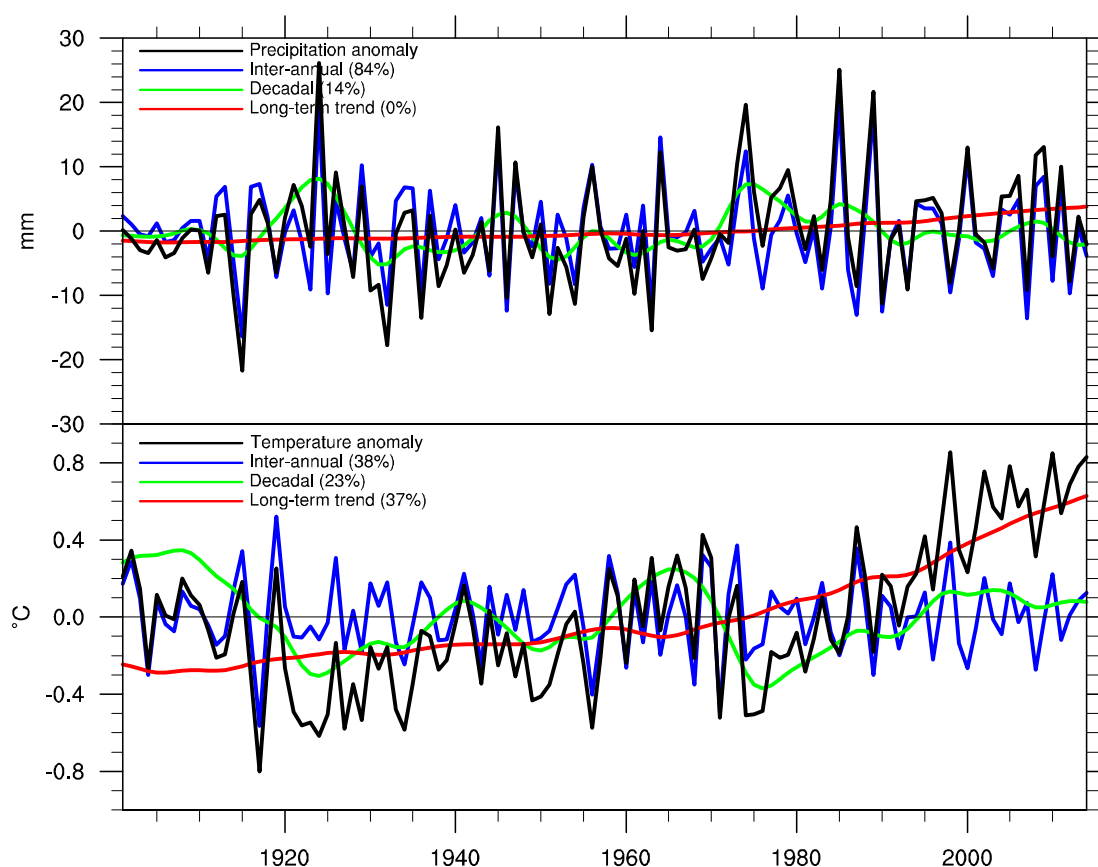

151
152   *Figure 2 Timescale decomposition for annual anomalies in the 1901-2014 period (black curves;*

153   *rainfall in the top panel, temperature in the bottom panel) averaged over the region indicated in*

154   *Figure 1 (black box). The anomalies correspond to the superposition of the long-term trend (in*

155   *red), the decadal signal (in green) and the inter-annual variability signal (in blue). Contribution of*

156   *each timescale to the total explained variance is shown in parenthesis.*

157   The spatial patterns for both temperature and rainfall anomalies in LAC were fairly similar in

158   2014 and 2015 (Figure 3), which were, at their respective terminus, the hottest years on record

159   [23,24]; 2015 marked also the start of one of the three most intense El Niño events on record. In

160   terms of temperature anomalies, the year 2013 was normal for most part of LAC, although the

161   warming pattern in the Amazon that extended through the study region in the following years

162   was already present. A similar claim can be made for the 2013 annual rainfall anomalies in the

163   Amazon: the general drier-than-normal signal exhibited in 2014 and 2015 was already evolving

164   then. Similar anomaly patterns were present in other countries too; for example, warmer-and-

165   drier-than-normal conditions were observed in regions of Colombia, Venezuela, Ecuador and

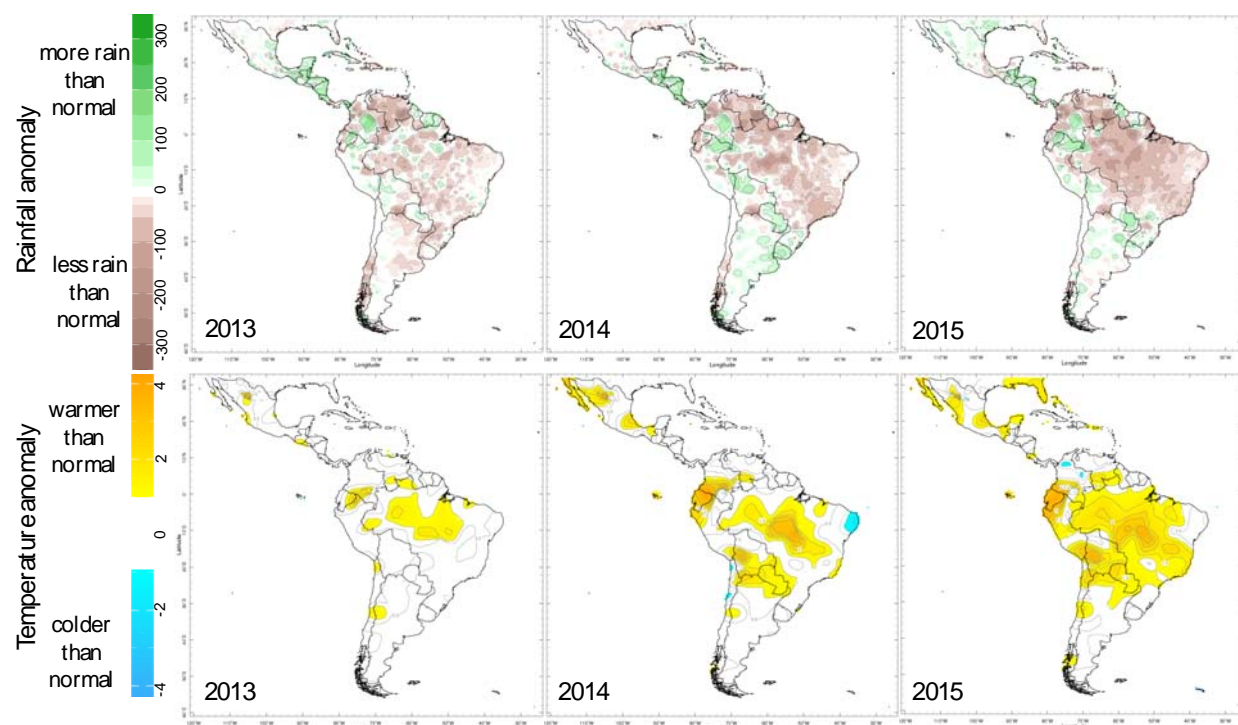166   Puerto Rico, that also have been impacted by the ZIKV epidemic.

167

168

Figure 3. Annual temperature (upper row, in ^{o}C) and rainfall (lower row, in mm) anomalies for

170   *2013-2015. White indicates near-normal values.*

171

Discussion

173   The warming observed in 2014-15 is therefore an outcome of positive temperature anomalies at

174   the year-to-year and decadal timescale superimposed on a long-term warming trend. This

175   superposition of timescales may have helped to set the climate scenario for local ZIKV

176   transmission via *Ae. aegypti* and other, less significant, vectors [4]. These patterns have also

177   been observed during the first few months of 2016, although some rainfall anomalies have been

178   changing as the year has progressed.

179

180   As of August 2016, seasonal forecasts of sea surface temperatures suggest about 55%

181   probability of a La Niña event to be in place later this year [25], which is significantly higher than

182   the corresponding climatological threshold (~35% for the same period). La Niña events typically

183 lead to wetter than average conditions over the northern part of Brazil and Northern South

184 America [26]. Since precipitation in this region is dominated by inter-annual variability, climate

185 drivers at longer timescales are not likely to offset that response to La Niña. For temperature,

186 the tropics tend to be relatively cooler during La Niña events, particularly relative to El Niño.

187 However, given the comparable magnitude of decadal variability, which currently appears to be

188 in a warm phase, and the strength of the long-term trend, warmer than average temperatures

189 are still the most likely outcome over the coming year.

190

191 The characterization of year-to-year variability and longer term climatic trends is important for

192 strategic ZIKV outbreak preparedness activities in LAC and across the border into the USA. For

193 countries where variability and short and long-term trends are in part predictable, climate

194 information could support the planning of prevention and control activities for different high risk

195 areas, such as training of personnel in different aspects of the outbreak early warning and

196 response system [27].

197

198 For example, the response strategies for ZIKV vector control in a warm and dry year, where

199 high levels of water storage provide domestic breeding sites, may need revision in a wet year

200 when outdoor breeding sites may be more common. Current speculation about the climate

201 drivers that may impact ZIKV transmission (see for example [1]) are based on plausible

202 assumptions regarding the dynamics of the disease but lack an in-depth understanding of the

203 climate. However, using climate knowledge to improve health outcomes must be based on an

204 understanding of the climate system itself and its interaction at multiple spatial and temporal

205 scales. The timescale decomposition approach [15] used here allows a robust assessment of

206 complex climate components to be made for any time period, season and region [19,21]. It

207 provides a basis for considering climate as a resource to decision-maker efforts, not only for

208 ZIKV, but also for other vector-borne diseases like chikungunya and dengue.

209

Methods

211 Timescale decomposition consists of screening the individual gridbox values for filled data and

212 for very dry seasons and regions; detrending in order to extract slow, trend-like changes; and

213 filtering, to separate high and low frequency components in the detrended data. Detrending

214 involves regressing the local time series on multi-model global surface air temperature from the

215 Twentieth Century Climate in Coupled Models [28] and low-pass filtering. The decadal

216 component is obtained through low-pass filtering of the residual, using an order-five Butterworth

217 filter with half-power at a period of 10 years, while the inter-annual component is computed as

218 the difference between the residual from the detrending step and the decadal signal [15]. For

219 additional details, see the International Research Institute for Climate and Society (IRI)

220 Timescale Decomposition Maproom [19].

221

222 For the maps in Figure 1, data are processed gridbox by gridbox, meaning that results in

223 adjacent gridboxes are not compared or combined. For the graph of the regional timeseries

224 (Figure 2), averaging over gridboxes is performed prior to the decomposition. Total explained

225 variance for each component is computed for the area-averaged time series, and not as

226 averages of the spatial variance maps.

227

Availability and requirements

229 • Project name: Climate and Health Maproom

230 • Project home page: http://iridl.ldeo.columbia.edu/maproom/Health/index.html and

231 http://datoteca.ole2.org/maproom/Sala_de_Salud-Clima/index.html.es

232 • Archived version: http://doi.org/10.1029/2011EO450001

233 • Operating system(s): Platform independent

234   • Programming language: Ingrid

235   • Other requirements: none

236   • License: Open Database License (ODbL) v1.0

237

238   **Abbreviations**

239   **LAC**: Latin America and the Caribbean   **ZIKV**: Zika virus

240

241   **Availability of supporting data**

242   Data and figures supporting the results of this research are freely available online in the IRI's

243   Timescale Decomposition Maproom [19] and the Latin American Observatory's Climate and

244   Health Maproom [20,21].

245

246   **Declarations**

247   ***Acknowledgements***

253   ***Competing interests***

254   Authors declare no competing financial interests.

255   ***Author's Contributions***

256   Á.G.M., M.C.T. and S.A established the concept of the study. Á.G.M. obtained the data. Á.G.M.,

257   M.C.T and L.G undertook the analysis and interpretation of results. Á.G.M., M.C.T and L.G.

258   drafted the manuscript. All authors critically reviewed and revised the manuscript and agreed

259   the final submission.

260

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