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Combined effects of hydrometeorological hazards and urbanisation on dengue risk in Brazil: a spatiotemporal modelling study

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For the Portuguese translation of the abstract see **Online** for appendix 1

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Summary

Background Temperature and rainfall patterns are known to influence seasonal patterns of dengue transmission. However, the effect of severe drought and extremely wet conditions on the timing and intensity of dengue epidemics is poorly understood. In this study, we aimed to quantify the non-linear and delayed effects of extreme hydrometeorological hazards on dengue risk by level of urbanisation in Brazil using a spatiotemporal model.

Methods We combined distributed lag non-linear models with a spatiotemporal Bayesian hierarchical model framework to determine the exposure-lag-response association between the relative risk (RR) of dengue and a drought severity index. We fit the model to monthly dengue case data for the 558 microregions of Brazil between January, 2001, and January, 2019, accounting for unobserved confounding factors, spatial autocorrelation, seasonality, and interannual variability. We assessed the variation in RR by level of urbanisation through an interaction between the drought severity index and urbanisation. We also assessed the effect of hydrometeorological hazards on dengue risk in areas with a high frequency of water supply shortages.

Findings The dataset included 12 895 293 dengue cases reported between 2001 and 2019 in Brazil. Overall, the risk of dengue increased between 0–3 months after extremely wet conditions (maximum RR at 1 month lag 1·56 [95% CI 1·41–1·73]) and 3–5 months after drought conditions (maximum RR at 4 months lag 1·43 [1·22–1·67]). Including a linear interaction between the drought severity index and level of urbanisation improved the model fit and showed the risk of dengue was higher in more rural areas than highly urbanised areas during extremely wet conditions (maximum RR 1·77 [1·32–2·37] at 0 months lag *vs* maximum RR 1·58 [1·39–1·81] at 2 months lag), but higher in highly urbanised areas than rural areas after extreme drought (maximum RR 1·60 [1·33–1·92] *vs* 1·15 [1·08–1·22], both at 4 months lag). We also found the dengue risk following extreme drought was higher in areas that had a higher frequency of water supply shortages.

Interpretation Wet conditions and extreme drought can increase the risk of dengue with different delays. The risk associated with extremely wet conditions was higher in more rural areas and the risk associated with extreme drought was exacerbated in highly urbanised areas, which have water shortages and intermittent water supply during droughts. These findings have implications for targeting mosquito control activities in poorly serviced urban areas, not only during the wet and warm season, but also during drought periods.

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Introduction

Dengue fever is an arboviral infection, considered one of the top ten threats to global health.[1] Dengue is caused by four distinct dengue virus serotypes (DENV 1–4), which are transmitted to humans by *Aedes* mosquitoes.[2] The four dengue serotypes are endemic in most of Brazil, and large epidemics have occurred in the past 10 years with more than 1·5 million notified cases in 2019, an increase of 600% compared with 2018.[3] Dengue transmission is expanding beyond previous geographical ranges to regions further south, cities at higher altitudes, such as Brasilia (the capital of Brazil), and into remote regions of the Amazon as a result of environmental change, improved connectivity between regions, and increased urbanisation.[4,5]

Local living conditions, such as population density, human mobility, and sanitation are important collective risk factors for dengue. Poor sanitation conditions, such as inadequate water supply and refuse collection services, promote mosquito breeding sites.[6] The distribution of the main vector species *Aedes aegypti* and *Aedes albopictus* are widespread across the country. *A aegypti* is found predominantly in urban settings, breeding in artificial containers in and around the home, whereas *A albopictus* is more commonly found in rural and periurban settings.[7]

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Research in context

Evidence before this study

Temperature and rainfall are known to influence the magnitude and seasonality of dengue transmission in endemic regions. However, the timeframes in which extreme hydrometeorological events, such as droughts and extremely wet conditions, might affect the timing and intensity of dengue epidemics are poorly understood. Several drought severity indices have been developed by the meteorological community, assimilating data on rainfall and other water supply indicators. However, data on the potential use of such indices in dengue control and preparedness plans are scarce. We searched PubMed on Oct 15, 2020, using the terms "dengue", "drought", and "model". Our search yielded only one study that had used a drought indicator in a dengue prediction model and quantified the delayed effect of drought on dengue risk in Barbados.

Added value of this study

We found that extreme drought was associated with an increase in dengue risk in Brazil, 3–5 months later, and the risk of dengue was increased 0–3 months after extremely wet conditions. This study confirms that initial findings from Barbados on the delayed and non-linear effect of hydrometeorological extremes on dengue risk are robust across a large gradient of climate and urbanisation conditions across Brazil. Densely populated urban areas that have interrupted water supply during periods of water scarcity are more susceptible to dengue outbreaks after periods of drought. The effect of extremely wet conditions on dengue risk is more immediate and exacerbated in rural areas than urban areas, predominantly in the Amazon region.

Implications of all the available evidence

These findings highlight the importance of targeting mosquito control activities in urban areas with intermittent water supply, not only during the warm rainy season, but also during periods of drought. In the short term, a community effort is required to ensure improvised water storage containers do not serve as additional larval habitats during droughts. During wet periods,outdoor water storage containers should be well covered and maintained, and discarded waste should be cleared to avoid collecting water. In the longer term, governments must invest in local infrastructure to ensure permanent water supply and promote environmental hygiene in areas prone to epidemics of dengue and other mosquito-borne diseases.

Studies have shown the geographical boundaries of *A aegypti* are expanding into rural and periurban areas across Latin America.[8,9]

Variations in temperature and rainfall are thought to contribute to the magnitude and seasonality of dengue transmission.[10] In Brazil, large outbreaks are typically observed after wet and warm periods, particularly in densely populated urban areas. Ambient temperatures influence dengue transmission by affecting mosquito development rates, reproduction, survival, biting rates, and viral replication in the mosquito, with warmer temperatures (optimum mean temperature range 26–29°C) increasing the risk of disease transmission, depending on the vector species.[11]

The effect of rainfall on dengue risk is more complex. Extreme hydrometeorological events, such as drought and heavy rainfall, interact with local living conditions, affecting mosquito infestation and the contact rate between humans and mosquitoes. Rainfall can increase mosquito density by creating additional larval habitats in rain-filled containers, particularly in areas with poor or irregular access to the water supply network. However, excess rain can result in larvae being washed away.[12] Periods of drought might lead to water supply shortages, encouraging improvised water storage for basic household washing and cooking, which can have the unintended consequence of creating additional breeding sites, thus increasing contact between mosquitoes and humans.[13]

In the past 10 years, a number of severe droughts and flooding episodes have occurred in the Northeast, Amazon, and Southeast regions of Brazil. The 2010–16 drought in the Northeast region was the most severe drought in the past 30 years. Studies have shown that the number of areas affected by these droughts is increasing, with up to 20 million people affected per year.[14] In the Amazon region, several hydrometeorological events with a supposed recurrence time of a century or more have occurred in the last decade or so, with record levels of flooding in 2009 and 2012, and record levels of drought in 2010.[15,16] Some of the most vulnerable populations in Brazil reside in the Northeast and Amazon regions, where much of the population have no access to water resources and rely on rainwater or wells.[17] Since the austral summer of 2014, southeast Brazil has had one of the most severe droughts in decades. The prolonged absence of rainfall resulted in water shortages and a water crisis that affected residents and local economies in the metropolitan region of São Paulo.[18] In more urbanised areas, access to the water network has increased in the past two decades, but without guaranteeing the continuity, safety, and quality of water supply for all households connected to distribution networks.[19] The interruption of water supply services can occur as a result of structural failures in the system, leading to insufficient supply to meet water demand, or the occurrence of prolonged droughts that compromise the water sources. A combination of these two factors result in households storing water in improvised reservoirs or barrels, especially during droughts, creating favourable conditions for *Aedes* mosquito breeding habitats.[20]

Although several studies have quantified associations between climatic factors and dengue risk, the association between hydrometeorological hazards (eg, extreme drought and extremely wet conditions) and outbreaks of mosquito-borne disease, and the delayed effects of such conditions on transmission, is poorly understood. The effect of climate variability and climate change on dengue transmission is complex, non-linear, and often delayed by several weeks to months, which limits the inferences that can be made from traditional linear modelling methods. A 2018 study developed a model to quantify the impact of drought on dengue transmission in Barbados between 1999 and 2016.[21] Dry conditions were found to positively influence the relative risk (RR) of dengue 3–5 months after extreme drought and higher minimum temperatures and heavy rainfall increased the risk within 0–3 months. Therefore, periods of drought followed by warm and wet weather several months later could provide optimum conditions for imminent dengue outbreaks. In this study, we aimed to extend this approach by designing a spatiotemporal model for Brazil to investigate the non-linear and delayed effects of hydrometeorological extremes across a large and varied geographical domain. We build on previous efforts to model the impact of climate and socioeconomic factors in Brazil by coupling spatiotemporal Bayesian hierarchical models[6,22] with distributed lag non-linear models (DLNM)[21,23] to simultaneously describe space-varying, non-linear, and delayed dependencies between dengue incidence and hydrometeorological factors. These exposure-lag-response associations can reveal how hydrometeorological extremes affect dengue risk in the months leading up to an outbreak. This association has implications for designing early warning systems that consider the cumulative effect of hydrometeorological variations in the months leading up to the peak season and to be ready to detect out-of-season anomalous events.

Methods

Study area and dengue data

Brazil is the sixth most populated country in the world, with a population of more than 209 million people. Brazil can be divided into distinct climatic and ecological zones spanning 8·5 million km². The country has five geopolitical regions, 27 states, and 5570 municipalities organised into 558 microregions, which consist of groups of municipalities surrounding a larger city. We obtained monthly notified dengue cases for each of the 558 microregions of Brazil between January, 2001, and December, 2019, from the Notifiable Diseases Information System, which is freely available via the Ministry of Health Information Department (DATASUS). The Brazilian Ministry of Health defines the monthly dengue incidence rate as the number of new dengue cases per 100 000 residents per month. To calculate dengue incidence for each microregion, we obtained yearly population estimates for the 558 microregions between 2001 and 2019, from the Brazilian Institute of Geography and Statistics via DATASUS.

Meteorological data

In this study, we used the Palmer drought severity index (PDSI), which is the most prominent standardised index for monitoring drought and long-term changes in aridity.[24] The monthly mean daily minimum temperature (T_{min}; °C), maximum temperature (T_{max}; °C), and the self-calibrated PDSI were obtained from the Climatic Research Unit gridded Time Series (version 4.04),[25] for the period January, 2000, to December, 2019, at a spatial resolution of 0·5° longitude × 0·5° latitude (data for 2000 were extracted to allow for a lag period before the first dengue observation in January, 2001). The gridded datasets were aggregated to each microregion using the exactextractr package in R (version 4.0.2), by calculating the mean of grid boxes lying within each microregion. Grid boxes that were partially covered by the microregion were weighted by the percentage that lay within the microregion. The PDSI is one of the most widely used measures of meteorological drought, providing a measure of dryness in a region relative to normal conditions. PDSI is calculated using moisture levels of the soil, expected evapotranspiration rate (ie, the amount of evaporation from soil that would occur if sufficient water levels were available, based on mean daily temperature and length of days in the month), and precipitation.[26,27] We used the self-calibrating PDSI, which provides a spatially comparable index by calibrating a different normal condition for each location.[28] The index ranges from –10 (very dry) to 10 (very wet), with values below –4 or above 4 classified as extreme. Brazil has had extreme and prolonged drought in several states located in the North (Amazon) and Northeast region, particularly since 2010 (appendix 2 p 8). Minimum temperature differs greatly across the country with the tropical north having consistently high temperatures, able to support year-round virus transmission, whereas the temperate south has cold winters, which sometimes do not sustain adult vector populations (appendix 2 p 9).

See **Online** for appendix 2

Urbanisation and access to water

To assess whether the associations between hydrometeorological events and dengue vary by level of urbanisation and access to water supply services, we obtained data on the proportion of residents living in urban areas and with access to the piped water network from the 2010 census, from DATASUS. Poor sanitation conditions, including limited access to water supply, can encourage mosquito breeding through use of improvised water storage containers. Accordingly, dengue risk is hypothesised to be higher in areas with poor sanitation. However, at the microregion level, the proportion of residents living in urban areas (figure 1A) is positively correlated with the proportion of residents with access to

For more on **DATASUS** see http://www2.datasus.gov.br/DATASUS/index.php?area=02 the piped water network (figure 1B). Therefore, at this level of aggregation, the water access variable is not useful due to collinearity between water access and level of urbanisation (Pearson correlation coefficient r=0·73, p<0·0001). Although improved access to the piped water network that accompanies increased levels of urbanisation might reduce dengue risk, the proportion of the population residing in urban areas is expected to increase dengue risk, because urban areas are ideal environments for mosquitoes and many people living in close proximity enables the establishment of a human–virus reservoir. The quality and reliability of water supply services is difficult to measure. One approach is to monitor supply system failures and interruptions, reported annually by service providers in the National Sanitation Information System. For this study, the number of reported interruptions in water supply per municipality between 2000 and 2016, was divided by the number of years and municipalities for each micro-region, to obtain the frequency of interruptions, ranging from 0 to 1. This variable has a weak positive correlation with urbanisation (r=0·13, p=0·0017). Some microregions with the highest levels of access to the water network also have the highest frequency of water supply shortages—eg, in urbanised areas in the southeast regions of Brazil (figure 1C; appendix 2 p 10).

For more on the **National Sanitation Information System** see http://www.snis.gov.br/

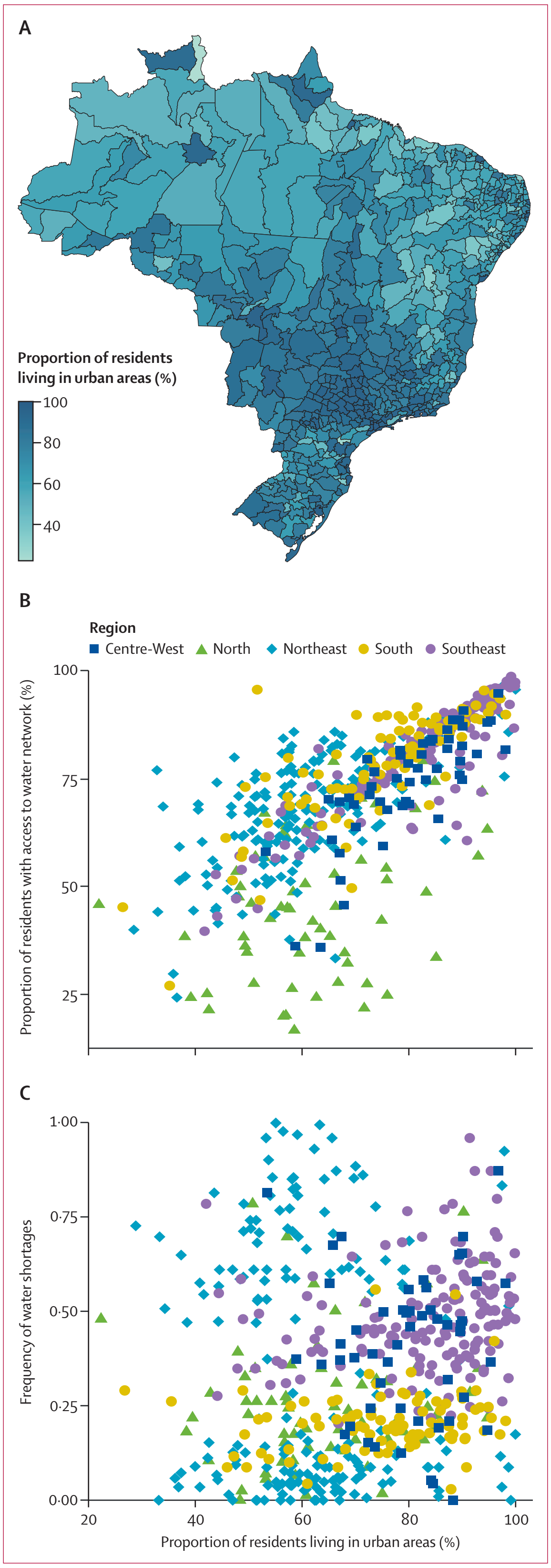

***Figure 1:* Distribution of urban areas and the association of urbanisation with water network access and frequency of water shortages by microregion**
(A) Proportion of residents living in urban areas. (B) Comparison of access to the piped water network with proportion of residents living in urban areas, stratified by geopolitical region. (C) Comparison of water shortage frequency with proportion of residents living in urban areas, stratified by geopolitical region.

Modelling approach

We specified a spatiotemporal Bayesian hierarchical model in which the response consisted of monthly counts of notified dengue cases for all 558 Brazilian microregions from January, 2001, to December, 2019.[6] A negative binomial distribution was assumed to account for potential overdispersion in dengue case counts. Spatiotemporal random effects were included to account for unobserved and unmeasured sources of variation and spatial and temporal dependency structures. We included DLNMs to account for exposure-lag response associations between the RR of dengue, temperature variations, and the drought severity index.[21,23] We tested a linear interaction between the drought severity index DLNM and level of urbanisation. The model parameters were estimated in a Bayesian framework using integrated nested Laplace approximations in R version 4.0.2 (appendix 2 p 2).[29,30]

We constructed a baseline model comprising state-level monthly autocorrelated random effects, to account for seasonality, and year-specific microregion-level spatial random effects to allow for interannual variability in unknown and unmeasured factors (eg, health care and vector control disparities) and dependency structures (eg, shared environmental and socioeconomic characteristics and human mobility) between microregions (appendix 2 pp 2–3). DLNMs were used to explore possible non-linear and delayed associations between dengue incidence, temperature (T_{min} and T_{max}), and the PDSI from 0 to 6 months.

We assessed the effect of hydrometeorological hazards on underlying socioeconomic conditions by including a

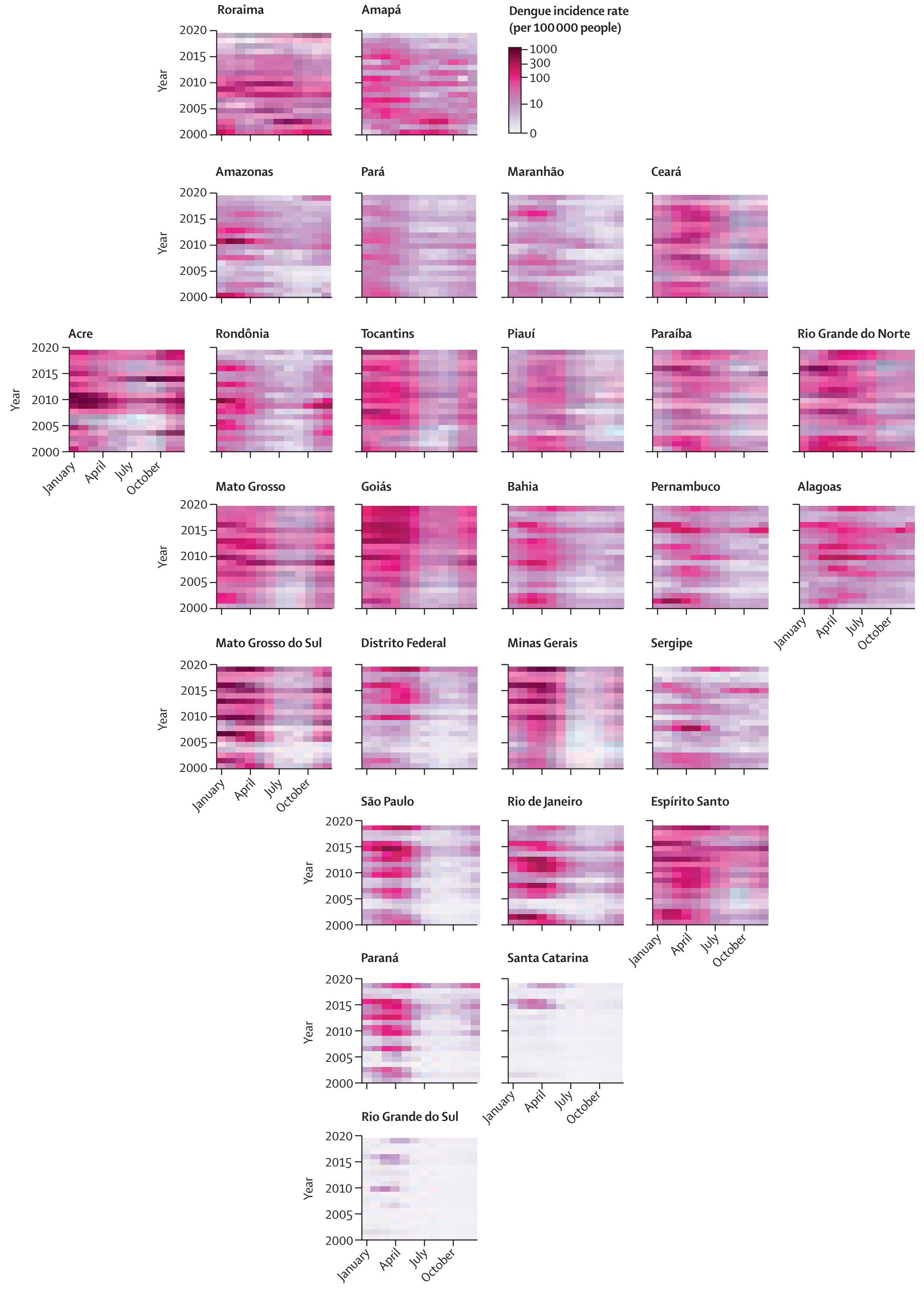

Figure 2: **Spatial and temporal variation in dengue incidence in Brazil, by state**

Monthly dengue incidence rate (per 100 000 people) between January, 2001, and December, 2019, aggregated at the state level (on a $\log_{10}$ scale). States are ordered by their geographical location.

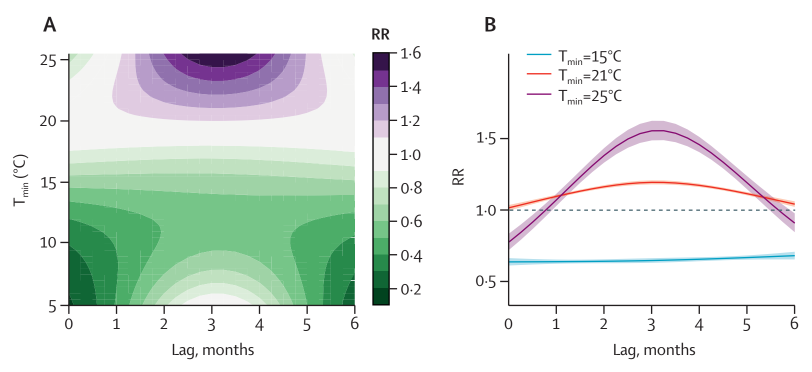

Figure 3: **Dengue lag-response for different temperature scenarios**
(A) Contour plot of the association between T_{min} and risk of dengue, relative to the overall mean T_{min} (19°C). The deeper the shade of purple, the greater the increase in RR of dengue compared with the overall mean T_{min}. The deeper the shade of green, the greater the decrease in RR of dengue compared with the overall mean T_{min}. (B) Dengue lag–response association for cool (15°C), warmer (21°C), and warmest (25°C) T_{min} relative to the overall mean T_{min} (19°C). Results are for the drought-severity model (with no interactions). RR=relative risk. T_{min}=minimum temperature.

linear interaction between the drought severity index DLNM, and a continuous variable of the proportion of residents living in urban areas.[31] To understand variations in dengue risk for different hydrometeorological scenarios by level of urbanisation, we centred the urbanisation variable at different points: high levels of urbanisation (upper quartile=87% of residents living in urban areas), intermediate levels of urbanisation (median quartile=73% of residents living in urban areas), and low levels of urbanisation (lower quartile=58% of residents living in urban areas). We also tested a linear interaction between the drought severity index DLNM and the frequency of water supply shortages variable per microregion over a 17-year period (2000–16). We centred this variable at high frequency (upper quartile=0·53), intermediate frequency (median=0·33), and low frequency (lower quartile=0·16; appendix 2 pp 3–4).

The final model was selected by comparing models of increasing complexity (with regard to input variables and model structure) to the baseline model. We calculated goodness of fit measures, including the deviance information criterion,[32] which balances model accuracy against complexity, by penalising for the number of effective parameters in the model, and the mean cross-validated log score,[33] which measures the predictive power of the model when excluding one datapoint at a time. For the deviance information criterion and log score, smaller values indicate better fitting models. We calculated the difference in mean absolute error between the baseline model and the selected model,[34] to identify the proportion of microregion for which a more complex, data-driven model improved model fit. We also did cross-validation, by refitting the selected model 19×12 times, excluding a month per year from the fitting process each time and compared observations to out-of-sample posterior predictive distributions for each state between January, 2001, and December, 2019.

Role of the funding source

The funders had no role in study design, data collection, data analysis, data interpretation, or writing of the report.

Results

The dataset included 12 895 293 dengue cases reported between 2001 and 2019 in 558 microregions in Brazil (figure 2). Over the 19-year period, dengue incidence rates have increased, and the dengue transmission zone has expanded further south, into the central-west region and Amazon region. Dengue seasonality varies across the country, with the peak transmission season occurring earlier in the year in the north (eg, in Amazonas state; figure 2) and later in the year in the Northeast (eg, in Ceará state; figure 2). Large nationwide epidemics occurred in 2010, 2013, 2015, 2016, and 2019 (appendix 2 p 7). To select the best fitting models, we included state-level monthly random effects, to account for varying seasonality between different areas (eg, Acre and Pernambuco; appendix 2 p 11), and year-specific microregion-level spatial random effects to account for unexplained interannual spatial variability per year (appendix 2 p 12). We then included DLNMs for T_{min}, T_{max}, and PDSI, lagged between 0 and 6 months. The inclusion of T_{min} and PDSI as DLNMs (drought severity model) resulted in a greater reduction in the deviance information criterion and mean logarithmic score compared with the baseline model (appendix 2 p 6). We then tested a linear interaction between the drought severity index DLNM and the continuous urbanisation variable (drought severity urban model). This model resulted in an improvement of the model fit compared with the drought severity model, with a reduction in the deviance information criterion despite the inclusion of 13 additional terms, comprising the additional cross-basis variables and the urbanisation variable as a fixed effect (appendix 2 p 6). The inclusion of the water supply shortage interaction also resulted in an improvement in model fit, similar to the drought severity urban model (appendix 2 p 6).

The mean absolute error of the drought severity urban model was smaller than the mean absolute error using the baseline model for 409 (73%) of the 558 microregions (appendix 2 p 13), suggesting the selected model improved the model fit above the baseline in these areas. When stratifying the added value by geopolitical region, the drought severity urban model performed best in the Southeast region (135 [84%] of 160 microregions with improved model fit) and the South region (75 [80%] of 94 microregions with improved model fit; appendix 2 p 13). In the microregions for which the baseline model fit better than the drought severity model, other unexplained factors are likely to dominate spatiotemporal dynamics in those areas.

Annual summaries of out-of-sample posterior predictive mean estimates of dengue incidence, simulated from the drought severity urban model fitted in the cross-validation model that excluded one month per year at a

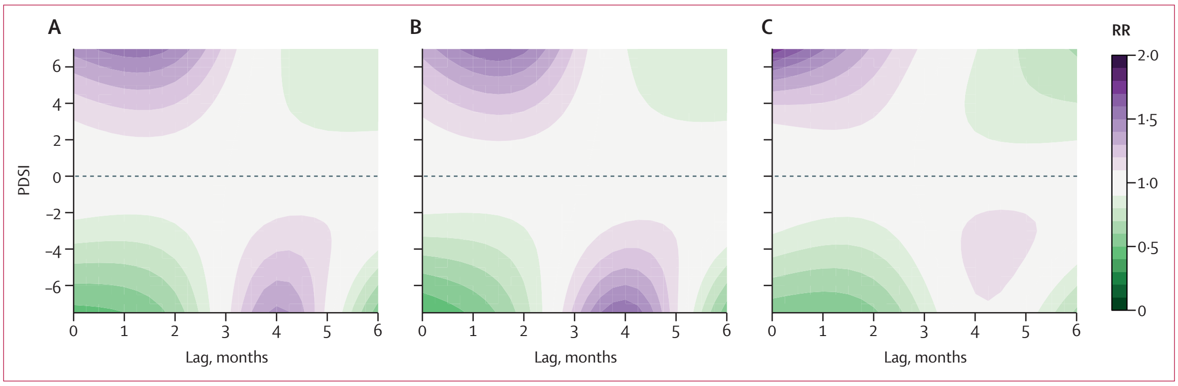

Figure 4: **Association between risk of dengue and drought severity index at different time lags overall, and for high and low levels of urbanisation**
Contour plots of the exposure–lag–response association between the PDSI and dengue, relative to normal conditions (PDSI=0) overall, using the drought severity model (with no interactions; A), and for high levels of urbanisation (upper quartile of residents living in urban areas=87%; B), and low levels of urbanisation (lower quartile of residents living in urban areas=58%) using the drought severity urban interaction model (C). The PDSI ranges from −10 (very dry) to 10 (very wet), with values below −4 or above 4 considered as extreme. The deeper the shade of purple, the greater the increase in RR of dengue compared with normal conditions. The deeper the shade of green the greater the decrease in RR of dengue compared with normal conditions. RR=relative risk. PDSI=Palmer drought severity index.

time, are shown in appendix 2 (p 14). The model correctly identified widespread dengue outbreaks in 2010, 2013, 2015–16, and 2019, and years with low incidence—eg, 2004 and 2017 (appendix 2 p 7). Overall, the model successfully distinguished interannual variability in dengue incidence between states (appendix 2 p 15). One notable exception was the estimate of an unobserved dengue peak in Acre in 2014.

Figure 3 shows the RR of dengue gradually increased as T_{min} increased. The greatest RR of dengue was found at the maximum T_{min} of 25·5°C at a lag of 2–4 months (appendix 2 p 16). The inclusion of T_{min} and PDSI resulted in improved model adequacy statistics compared with the use of T_{max} and was used for further model exploration of drought severity and socioeconomic interactions (appendix 2 p 6).

Output from the drought severity model (with no interactions) can be interpreted as the average effect across the whole of Brazil and the drought severity urban model distinguishes the average effect along an urban gradient, depending on the value at which the urbanisation value is centred. Overall, extremely wet conditions increased the risk of dengue within 3 months and drought conditions increased the risk 3–5 months later (figure 4A). When considering an interaction with level of urbanisation, the risk of dengue was greater in highly urbanised areas 3–5 months after extreme drought than in areas with a low level of urbanisation (figures 4B, 5A) but greater in more rural areas within 3 months of extremely wet conditions (figures 4C, 5B). The maximum RR and associated time lags for both dry and wet conditions are shown in the table. The association between drought and dengue incidence estimated from both the drought severity model and the drought severity urban model was highest 4 months after extreme drought (table). The greater the level of urbanisation, the higher the risk of dengue after extreme drought (RR 1·6 [95% CI 1·33–1·92]; table; figures 4B, 5A). The relative risk of dengue after extremely wet conditions was greater and more immediate at lower levels of urbanisation (RR 1·77 [1·32–2·37]; table; figures 4C, 5B). We also found an increased risk of dengue following drought in areas with high frequency of water supply shortages compared with a low frequency of water supply shortages (appendix 2 pp 17–19).

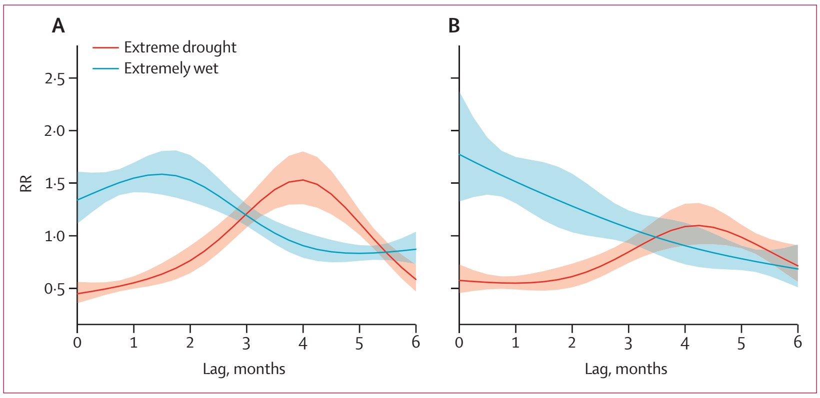

Figure 5: **Dengue lag-response association for hydrometeorological hazard scenarios, by level of urbanisation**
Lag-response association for extreme values of the PDSI in exceptionally wet (PDSI=7; blue line) and extreme drought (PDSI=−7; red line) conditions relative to normal conditions (PDSI=0) at high levels of urbanisation (upper quartile of residents living in urban areas=87%; A) and low levels of urbanisation (lower quartile of residents living in urban areas=58%; B). Shaded areas represent 95% CI. RR=relative risk. PDSI=Palmer drought severity index.

Discussion

We used a spatiotemporal modelling analysis to investigate the delayed and non-linear effects of extremely wet and extreme drought conditions on dengue risk across Brazil, an area of 8·5 million km², which spans six different biomes. To our knowledge, this is one of the most comprehensive assessments of the effects of drought on dengue risk across a large gradient of climate zones and levels of urbanisation. We investigated the interaction between hydrometeorological hazards and underlying socioeconomic characteristics and human

	Wet conditions			Dry conditions		
	Maximum PDSI, n	Maximum lag, months	RR (95% CI)*	Maximum PDSI, n	Maximum lag, months	RR (95% CI)*
Overall†	7·0	1	1·56 (1·41–1·73)	–7·5	4	1·43 (1·22–1·67)
Level of urbanisation						
High‡	7·0	2	1·58 (1·39–1·81)	–7·5	4	1·60 (1·33–1·92)
Intermediate§	7·0	1	1·56 (1·43–1·70)	–7·5	4	1·40 (1·20–1·65)
Low¶	7·0	0	1·77 (1·32–2·37)	–4·0	4	1·15 (1·08–1·22)

The PDSI ranges from –10 (very dry) to 10 (very wet); values below –4 or above 4 are considered as extreme. RR=relative risk. PDSI=Palmer drought severity index. *RR of dengue compared with normal conditions (PDSI=0). †From the drought severity model without interactions. ‡From the drought severity urban interaction model with 87% of residents living in urban areas. §73% of residents living in urban areas according to the drought severity urban interaction model. ¶From the drought severity urban interaction model with 58% of residents living in urban areas.

Table: **Risk of dengue for different hydrometeorological conditions by level of urbanisation**

behaviour to determine the risk of dengue outbreaks. Extreme drought conditions were positively associated with risk of dengue 3–5 months later, and dengue risk was increased within 3 months after extremely wet conditions. Although the risk of dengue was highest during extremely wet conditions in more rural areas, the effect of extreme drought was exacerbated in highly urbanised areas and areas with a higher frequency of water supply shortages.

The effects of hydrometeorological events on dengue transmission are dependent on the local social and ecological conditions that determine the types of larval habitat available in the environment, and household water supply and storage practices. Some studies have shown that rainfall shortages can increase dengue risk in regions where people store water.[12,13,35] The 3–5 month delay between drought events and increased dengue risk observed might arise from the gradual change in human behaviour in response to drought, which can lead to households taking measures to store water in improvised containers around the home once they become aware of water scarcity. Changes in water storage practices can increase the availability of larval habitats for *A aegypti*, whose eggs have been found to be able to survive for 120 days in dry conditions.[36] The presence of additional mosquito breeding sites might also affect surrounding households regardless of water storage practices, reinforcing the importance of considering contextual socioeconomic factors when modelling associations between hydrometeorological hazards and dengue.

After heavy rainfall, the availability of larval habitats increases (eg, rain-filled abandoned containers, plastic waste), and within a few weeks, eggs hatch and adult mosquito populations grow (depending on ambient temperatures). The risk of dengue transmission subsequently increases several weeks later, representing a lag associated with the intrinsic and extrinsic viral incubation periods.[37] In more rural areas, we observed an immediate increase in the risk of dengue during extremely wet conditions, compared with normal conditions, which persisted for 2–3 months. In the short term (ie, within a month), heavy rainfall could temporarily decrease the risk of dengue due to flushing of water containers that are out in the open.[38] However, the relative availability of indoor versus outdoor breeding containers is likely to strongly affect the potential impact of flushing. A small reduction in the increased risk of dengue was observed immediately after extremely wet conditions in highly urbanised areas. These areas might have more outdoor breeding sites, such as discarded waste, and are therefore more impacted by flushing immediately after extremely wet conditions than more rural areas. However, we are unable to postulate further due to unavailability of data on vector habitat at this scale and over the time period.

This study supports findings from a previous study in Barbados that showed an increase in dengue risk 3–5 months after drought and up to 3 months after extremely wet conditions.[21] This research builds on the time series approach developed by Lowe and colleagues,[21] by imbedding DLNM methodology in a Bayesian spatiotemporal model framework, while simultaneously accounting for spatial heterogeneity and autocorrelation. The models used in our study were developed using an extensive open-access database of more than 12 million reported dengue cases, and applied to a varied geographical domain. This study provides additional and robust evidence on the potential delayed effects of drought on dengue risk over a large gradient of climate conditions and urbanisation. This work also advances previous efforts to model spatiotemporal dynamics of dengue in Brazil and provide early warnings for dengue risk by allowing the model to consider delayed and non-linear climatic exposures, interacted with underlying socioeconomic conditions. This study provides additional evidence to motivate the incorporation of drought monitoring and seasonal climate forecasts in vector surveillance and dengue early warning systems, to effectively intervene and engage at the community level not only during the wet and rainy seasons, but also during anomalous drought conditions. The use of predefined climatic indicators, such as the self-calibrated

PDSI, can enhance capacity to predict the timing and intensity of dengue outbreaks.

Despite these scientific advances, several limitations exist. Using national-level data has advantages for exploring the effect of hydrometeorological hazards on dengue risk across a wide range of climatic and socioeconomic conditions, but has disadvantages in terms of data quality and representation of the true dengue burden. Dengue case data were obtained from the Brazilian Ministry of Health Notifiable Diseases Information System, which is a passive surveillance system, thus patients with mild or asymptomatic infections, who are thought to represent the majority of dengue cases,[39] might be missed. Additionally, only a small proportion of notified cases are laboratory confirmed (ranging from 10% in the Northeast region to 30% in the South region), although this might be even lower during epidemics.[40] One study estimated that only around one in 40 dengue cases were identified in Brazil during a period of low transmission.[41] The absence of laboratory confirmation also increases risk of misclassification, particularly since 2016, with the widespread circulation of Zika virus and chikungunya virus, which are spread by the same vector and often have similar symptoms to dengue. Furthermore, cross-protection might have suppressed incidence of dengue in 2017, following the 2015–16 Zika epidemic.[42] The dengue case data or population offset are not stratified by age group or serotype. Unequal population growth rates across the country, due to increased birth rates and internal migration, and previous dengue or Zika infection, might affect overall susceptibility.[43] Scarcity of data on serotype and seroprevalence studies hinders our ability to account for immunity other than via the year-specific spatial random effects, which account for unmeasured interannual spatial heterogeneity and dependencies between microregions. The formulation of the spatial component of the model assumes connectivity exists between neighbouring regions in Brazil. Microregions located along the inland border have neighbours in bordering countries, which are not accounted for in the neighbourhood matrix. In reality, the movement of people, goods, and services between large metropolises in Brazil creates an urban network connecting distant regions.[44] Human mobility has been shown to influence the spread of dengue.[45] We aim to improve the representation of spatial connectivity in future iterations of the model using the hierarchical urban network, combined with transport and mobility data.

Although we tested the hypothesis of an association between risk of dengue and hydrometeorological hazards along an urban gradient and in relation to water supply shortages, we acknowledge that these indicators are crude and might oversimplify the many other factors that influence specific landscape characteristics that determine dengue transmission potential. The proportion of the population residing in urban areas is a static variable, obtained from the 2010 census and is likely to have changed in the past decade. The water supply shortage variable is dependent on water service providers declaring water system failures to the National Sanitation Information System and is susceptible to reporting error. However, this variable provides an indication of where piped water is not reliable and alternative sources must be used. For example, the Southeast region was affected by a prolonged drought between 2014 and 2016. Although this region has good access to the water supply system, lowering of water body level (eg, reservoir, rivers, streams) in relation to the level of the pipes led to water supply shortages in many urban areas, including São Paulo. These shortages resulted in households storing water in improvised indoor reservoirs leading to an unprecedented dengue outbreak in the city in 2015.[46] Bias towards increased reporting of dengue cases could exist in urban areas (ie, better access to health-care facilities). Furthermore, we did not have access to data on vector density or vector surveillance at the microregion level of this study to formally assess the exposure-lag-response associations between hydrometeorological hazards and the vectors themselves, which limited the conclusions we could draw regarding the involvement of vectors as mediators between hydrometeorological extremes and dengue risk. To make this work useful for developing prevention strategies, alternative finer scale studies (ie, studies at the community level) are needed to detect basic hygiene disparities within urban areas and to assess interventions at a community level, which might include improved water storage care where piped water is unavailable or the supply is irregular.[20]

Despite these limitations, this research provides an indicative time period for implementing mosquito control activities and preparing health facilities for an increase in dengue cases following extreme hydrometeorological events. This work also highlights that hydrometeorolgical hazards can affect regions differently depending on the socioeconomic conditions. This analysis highlights the importance of supporting local communities to prevent dengue outbreaks, by providing alternative water storage options and increasing the reliability of water supply, particularly in areas in which the frequency of water supply failures is high. Monitoring and forecasting the occurrence, intensity, and evolution of hydrometeorological hazards will be crucial for public health agencies in their efforts to prepare, mitigate, and manage responses to epidemics of dengue and other climate-sensitive diseases. The advantage of our approach is the ability to capture cumulative effects of hydrometeorological hazards in the months leading up to a dengue epidemic. Our study shows that both extremely dry and wet conditions can increase risk of dengue with different delays. This provides stakeholders with usable timelines for planning and targeting mosquito control activities in poorly serviced areas, not only during the wet and warm season, but also during and following periods of drought.

Contributors

RL was responsible for the study design, model development, data analysis, and wrote the manuscript. SAL collated and managed the database and helped with visualisation and drafting of the manuscript. CB, RdCC, and MSC collected data and did a literature search. AG and HR contributed to the methodology and code development. SAL, LB, and FJC-G reviewed the code. All authors contributed to the study design, discussed the results, and reviewed and approved the final manuscript. RL and SAL had full access to all the data in the study and the corresponding author had final responsibility for the decision to submit for publication.

Declaration of interests

We declare no competing interests.

Data sharing

All data used in this study is open access and freely available on the internet, see the methods section for details. The data and code used to produce the analysis is available from https://github.com/drrachellowe/hydromet_dengue and archived in a permanent repository.[47]

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