The impact of climate suitability, urbanisation, and connectivity on the expansion of dengue in 21st century Brazil

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22 Abstract

23 Dengue is hyperendemic in Brazil, with outbreaks affecting all regions. Previous studies 24 identified geographical barriers to dengue transmission in Brazil, beyond which certain areas, 25 such as South Brazil and the Amazon rainforest, were relatively protected from outbreaks. 26 Recent data shows these barriers are being eroded. In this study, we explore the drivers of 27 this expansion and identify the current limits to the dengue transmission zone. We used a 28 spatio-temporal additive model to explore the associations between dengue outbreaks and 29 temperature suitability, urbanisation, and connectivity to the Brazilian urban network. The 30 model was applied to a binary outbreak indicator, assuming the official threshold value of 300 31 cases per 100,000 residents, for Brazil's municipalities between 2001 and 2020. We found a 32 nonlinear relationship between higher levels of connectivity to the Brazilian urban network 33 and the odds of an outbreak, with lower odds in metropoles compared to regional capitals. The number of months per year with suitable temperature conditions for *Aedes* mosquitoes 34 35 was positively associated with the dengue outbreak occurrence. Temperature suitability 36 explained most interannual and spatial variation in South Brazil, confirming this geographical 37 barrier is influenced by lower seasonal temperatures. Municipalities that had experienced an 38 outbreak previously had double the odds of subsequent outbreaks, indicating that dengue 39 tends to become established in areas after introduction. We identified geographical barriers 40 to dengue transmission in South Brazil, western Amazon, and along the northern coast of 41 Brazil. Although a southern barrier still exists, it has shifted south, and the Amazon no longer 42 has a clear boundary. Few areas of Brazil remain protected from dengue outbreaks. 43 Communities living on the edge of previous barriers are particularly susceptible to future

outbreaks as they lack immunity. Control strategies should target regions at risk of future
outbreaks as well as those currently within the dengue transmission zone.

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48 Author summary

49 Dengue is a mosquito-borne disease that has expanded rapidly around the world due to 50 increased urbanisation, global mobility and climate change. In Brazil, geographical barriers to 51 dengue transmission exist, beyond which certain areas including South Brazil and the Amazon 52 rainforest are relatively protected from outbreaks. However, we found that the previous 53 barrier in South Brazil has shifted futher south as a result of increased temperature suitability. 54 The previously identified barrier protecting the western Amazon no longer exists. This is 55 particularly concerning as we found dengue outbreaks tend to become established in areas 56 after introduction. Highly influential cities with many transport links had increased odds of an 57 outbreak. However, the most influencial cities had lower odds of an outbreak than cities connected regionally. This study highlights the importance of monitoring the expansion of 58 dengue outbreaks and designing disease prevention strategies for areas at risk of future 59 60 outbreaks as well as areas in the established dengue transmission zone.

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63 Introduction

64 Dengue is considered one of the top 10 threats to global health (1), with around half the 65 world's population living in areas at risk of infection (2). Incidence rates have doubled each 66 decade in the past 30 years as a result of increased urbanisation, global mobility and climate 67 change (2–4). All 4 dengue serotypes are endemic to Brazil, which experiences frequent 68 outbreaks across the country (5). Previous studies identified geographical barriers to dengue transmission beyond which regions were relatively protected. This included South Brazil, 69 where seasonal temperatures are too cold for vectors to efficiently transmit the virus, areas 70 71 of high altitude in Southeast Brazil and remote regions of the western Amazon (6). However, 72 these barriers are being eroded and the dengue transmission area in Brazil has expanded over 73 the past decade. This expansion is thought to be linked to increased human mobility and 74 changes in climate (7,8).

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76 For dengue to become established in a new region, the environment must be suitable to support the propagation of the dengue vector, *Aedes* mosquitoes. There are two vectors 77 78 present in Brazil capable of transmitting the dengue virus: Aedes aegypti and Aedes 79 albopictus. Currently only Aedes aegypti are considered responsible for dengue transmission 80 in Brazil (9,10), however a recent study identified *Aedes albopictus* infected by dengue virus 81 in a rural area of Brazil during an outbreak, which could indicate their involvement in the 82 introduction of dengue to rural areas (11). Aedes aegypti have evolved to live in urban environments close to humans (12) but there is evidence to suggest they are becoming 83 84 established in peri-urban and rural regions of South America (13,14). Conversely, Aedes 85 albopictus are typically found in peri-urban areas but have been identified in densely

86 urbanised areas such as urban slums in Brazil (9,15). Aedes mosquitoes breed in pools of 87 standing, clean water created by water storage containers or uncollected refuse. These 88 conditions arise when rapid urbanisation occurs without adequate improvements to 89 infrastructure, such as access to piped water and refuse collection (16,17). There is evidence 90 that areas lacking reliable access to piped water are more susceptible to dengue outbreaks, 91 particularly in highly urbanised areas following drought (18). Suitable climate conditions are required for the mosquitoes to breed and transmit the virus. Aedes aegypti are unable to 92 93 survive in temperatures below 10°C or above 40°C (19) and can only transmit the virus between 17.8° and 34.5°C (20,21). Aedes albopictus are more suited to cooler temperatures 94 95 and can transmit the virus between 16.2° and 31.4°C (20,21). Recent outbreaks in temperate 96 cities of South America have shown that epidemics are still possible in regions that experience 97 seasonal temperatures outside of this range due to human movement (22–24).

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99 The expansion of Aedes aegypti and the arboviruses they transmit into rural parts of the 100 Amazon has been linked to connections to and within the area by air, road or boat (13,25). 101 Despite this, the investigation of spatial connections created by human movement is little 102 explored in the literature and the vast majority of spatial modelling studies of mosquito-borne 103 diseases assume connectivity is based on distance alone (26). Brazilian cities are connected 104 to one another within a complex urban network, described within the Regions of influence of 105 cities ("Regiões de Influência das Cidades", REGIC) studies carried out by the Brazilian Institute 106 of Grography and Statistics (27,28). People often travel great distances to reach large urban 107 centres as they contain important educational, business or cultural institutions. Failure to 108 account for long-distance movements may miss important drivers of dengue expansion, 109 particularly in areas such as the Amazon where the average distance travelled to Manaus, the

110 capital of Amazonas state, was 316km. Important cities can have influence over vast areas of

- 111 Brazil, for example the region of influence connected to the capital city of Brasilia corresponds
- to over 20% of the country and spans 1.8 million km² (28).
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114 Although previous studies have shown the expansion of dengue outbreaks in Brazil (7) and 115 the association between the dengue transmission zone and climate (6), neither formally investigated the link between this expansion and human movement. In this study, we use the 116 117 level of influence of cities from the REGIC studies (27,28) as a proxy for human movement, 118 and aim to better understand how climate suitability, connectivity between cities and socioeconomic factors have contributed to the recent expansion of dengue. It is hoped that 119 120 by understanding the drivers of dengue expansion in Brazil, we can identify its spatial trends and regions at risk from future outbreaks. 121

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123 Methods

124 Epidemiological data

Brazil is the 6th most populous country in the world with an estimated population of over 211 125 million in 2020. The country can be separated into 5 distinct geo-political regions (Figure S1a), 126 127 27 federal units (26 states and a federal district containing the capital city Brasilia, Figure S1b), 128 and 5,570 municipalities. We obtained monthly notified dengue cases for each of Brazil's 129 5,570 municipalities between January 2001 and December 2020 from Brazil's Notifiable Diseases Information System (SINAN), freely available via the Health Information 130 (http://www2.datasus.gov.br/DATASUS/index.php?area=0203). 131 Department, DATASUS 132 Cases were aggregated by month of first symptom and municipality of residence. Dengue

cases are considered confirmed if they test positive in a laboratory or, more commonly, based on the Ministry of Health's syndromic definition. Between 2001 and 2020, municipality boundaries in Brazil have changed and several new municipalities were created. To ensure data were consistent over the study period, we aggregated data to the 5,560 municipalities that were present in 2001 by combining the new municipalities with their parent municipalities. The data and code used to aggregate the dengue case data are available from https://github.com/sophie-a-lee/Dengue_expansion.

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To understand how the dengue transmission zone has expanded between 2001 and 2020, we 142 143 aggregated dengue cases by year and created a binary outbreak indicator. We used an 144 outbreak threshold of more than 300 cases per 100,000 residents, defined as 'high risk' by 145 the Brazilian Ministry of Health (29). We also tested a 'medium risk' indicator, defined as more 146 than 100 cases per 100,000 residents. The annual dengue incidence rate was calculated using 147 estimates of the annual population for each municipality obtained from the Brazilian Institute 148 of Statistics and Geography (IBGE) via DATASUS 149 (http://tabnet.datasus.gov.br/cgi/deftohtm.exe?ibge/cnv/poptbr.def). Further details about 150 the dengue surveillance system in Brazil and outbreak definitions are given in the supplementary material. 151

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154 Meteorological data

155 Monthly mean temperatures (K) were obtained from the European Centre for Medium-Range 156 Weather Forecasts' (ECMRWF) ERA5-Land dataset (30) for the period January 2001 - December 2020, at a spatial resolution of 0.1° x 0.1° (~9km). The ERA5-Land database was chosen because of its fine spatial scale, necessary when analysing small administrative units such as municipalities. Temperatures were converted from Kelvin to degrees Celcius (°C) by subtracting 273.15. Mean temperature was aggregated to each municipality using the exactextractr package (31) in R (version 4.0.3) by calculating the mean of the grid boxes lying within each municipality. Grid boxes partially covered by a municipality were weighted by the percentage of area that lay within the municipality.

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165 Due to its size, Brazil experiences a wide range of climate systems and ecosystems. The 166 northern part of the country lies on or close to the equator, meaning regions experience year-167 round high temperatures. In contrast, the South and Southeast regions have clear seasonality 168 in temperatures with cooler winters (Figure S2), often falling below the optimal temperature 169 range for dengue transmission (between 17.8°C and 34.5°C for Aedes aegypti and 16.2° and 170 31.4°C for Aedes albopictus (20,21)). To understand how temperature suitability has 171 contributed to the expansion of the dengue transmission zone in Brazil, we calculated the 172 number of months per year each municipality lay within the suitable temperature ranges 173 (between 16.2° and 34.5°C). Most of Brazil experiences year-round temperature suitability 174 except for the temperate South and mountainous regions in the Southeast (Figure S3), although the number of months suitable has increased in these regions over the past decade 175 176 (Figure 1). As *Aedes aegypti* is the only vector proven to transmit dengue in Brazil, we also 177 tested the number of months considered suitable for *Aedes aegypti* transmission (between 178 17.8°C and 34.5°C) within the model.

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Fig 1: The difference between the average number of months with suitable temperatures for dengue transmission in 2001 - 2010 and 2011 - 2020. The number of months with temperatures between 16.2 and 34.5°C has increased on average (shown in pink) in parts of South and Southeast Brazil which were previously considered 'protected' from dengue transmission.

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- 188 Urbanisation

189 We obtained the percentage of residents in each municipality living in urban areas from the 2000 and 2010 censuses via DATASUS. In 2010, just under 85% of Brazil's population lived in 190 191 urban areas, mostly concentrated in the large cities of South and Southeast Brazil. The North 192 region, except for some state capitals, has a larger rural population (Figure S4). The 193 percentage of residents living in urban areas was converted to the proportion to make 194 interpretation and comparison of model coefficients easier. Data from the 2000 census was 195 used for the years 2001 - 2009 and data from 2010 was used for the years 2010 - 2020 to 196 account for changes in urbanisation over the period. Further details on the socioeconomic 197 variables considered in this analysis are given in the supplementary materials.

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200 Hierarchical levels of influence of cities

As a proxy for human movement, we obtained the hierarchical level of influence of cities from IBGE's REGIC studies, carried out in 2007 and 2018 (27,28). REGIC aims to recreate the complex urban network of Brazil using information from surveys about the frequency and reasons for the movement of people and goods around the country. Part of this study

205 involved classifying cities based on their hierarchical level of influence within this network

206 (see the supplementary materials for more details). Cities were classified into five levels:

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209	1.	Metropolis: the largest cities in Brazil, with strong connections throughout the entire
210		country. This includes São Paulo, the capital Brasilia, and Rio de Janeiro.

- 2. Regional capital: large cities which are connected throughout the region in which they
- are located and to metropoles. This includes state capitals that were not classified as
- 213 metropoles, such as Rio Branco, Campo Grande and Porto Velho.
- Sub-regional capital: cities with a lower level of connectivity, mostly connected locally
 and to the three largest metropoles.
- 216 4. Zone centre: smaller cities with influences restricted to their immediate area, often217 neighbours.
- Local centre: the smallest cities in the network which typically only serve residents of
 the municipality and are not connected elsewhere.
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The REGIC study aggregated data to population concentration areas ("Áreas de Concentração de População", ACPs), defined in (32). Smaller or isolated ACPs consisted of a single municipality, while large urban centres consisted of multiple municipalities. Levels of influence were extracted for each municipality based on the ACP they belonged to, meaning small municipalities neighbouring large cities may have a high level of influence. The distribution of highly connected urban centres is uneven across the country; the South and Southeast regions are particularly well connected, while the North and Northeast contain

- fewer high-level centres (Figure 2, Table S1). To account for any changes in connectivity over
- the study period, we used the levels extracted from the 2007 study for the years 2001 2010,
- and levels from the 2018 study for the years 2011 2020.
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Fig 2: The level of influence of cities within the Brazilian urban network from REGIC 2018.
The Amazon region is far less connected to the urban network than the rest of the country.
As there is only one metropolis in North Brazil, people often travel great distances, far greater
than in other regions, to reach cities.

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239 Modelling approach

We formulated a binomial spatio-temporal generalised additive model (GAM) using the 240 241 binary outbreak indicator, defined as an annual dengue incidence rate of more than 300 cases 242 per 100,000 residents, as the response variable. We included the number of months per year 243 with temperature suitable for Aedes mosquitoes to transmit dengue, the level of influence 244 from REGIC, the proportion of residents living in urban areas, and a 'prior outbreak' indicator 245 which took the value 0 until the year of the first outbreak in a municipality and 1 in every year 246 after as covariates. To account for spatial and temporal patterns in the data, smooth functions 247 of the year and the coordinates of the centroids of municipalities were included in the model 248 (see the supplementary materials for further details). Inference was performed using an 249 empirical Bayesian approach with estimates calculated using restricted maximum likelihood 250 (REML) as part of the mgcv package in R (33).

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253 Model fit was assessed using a receiver operating characteristic (ROC) curve which plots the 254 true positive rate against the true negative rate at different thresholds to test the predictive 255 ability of the model. The area under the ROC curve was calculated as this gives a measure of 256 predictive ability compared to chance, which would return a value of 0.5. To assess the 257 relative contribution of the covariates, we compared the spatio-temporal structured residual 258 terms between the final model and a baseline model, containing only the spatio-temporal 259 smooth terms. If the covariates explained variation in the data, the smooth functions would 260 shrink towards zero in the final model and the difference between the absolute estimates of these functions would be negative. To assess the contribution of the covariates over the 261 262 entire period, we took the median difference for each municipality. The contribution of each 263 individual covariate was also assessed by taking the difference between the structured residuals from the baseline model and models with each covariate added in turn. 264

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267 Results

There were 13,860,348 cases of dengue notified between January 2001 and December 2020 268 269 in Brazil. The dengue incidence rate has increased across all regions of the country (Figure 3) 270 particularly in the Centre-West and Southeast. Outbreaks were more widespread since 2010 271 with around 80% of all municipalities in the Centre-West now regularly experiencing outbreaks (Figure S8). Although the South had the highest incidence in 2020, this was still 272 273 concentrated in a small number of municipalities in Paraná, around the fringe area of the 274 previously identified geographical barrier. The previous barriers to dengue transmission have 275 been eroded over the past decade. This is particularly noticeable in the western Amazon

276 where there are now very few municipalities yet to experience an outbreak. The erosion of 277 the barrier in the South was particularly noticeable in 2020 when Paraná had the highest 278 incidence rate of any state (Figure 4). We oberved that once dengue was introduced to 279 municipalities, the virus became established and future outbreaks were likely to occur (Figure 280 5). 281 282 283 Fig 3: Monthly incidence rate per 100,000 residents in regions of Brazil 2001 - 2020. 284 Incidence rates have increased in every region of the country across the 21st century. The first regional outbreak occurred in 2010, outbreaks have occurred more frequently and in 285 286 more regions since then. 287 288 289 Fig 4: The first year each municipality experienced an outbreak for the first time in the 290 period 2001 - 2010 and 2001 - 2020. The year each municipality first recorded over 300 cases per 100,000 residents. Recent data shows the previous barriers to dengue outbreaks in the 291 292 Amazon and South are being eroded. 293 294 295 296 Fig 5: The number of years each municipality experienced an outbreak between 2001 and 297 2020. Municipalities that experienced outbreaks earlier in the 21st century continued to 298 experience outbreaks throughout the period. This suggests that once dengue is introduced to 299 a region, it becomes established.

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302 Model results

303 We found municipalities that were highly urbanised, highly connected, and had temperatures 304 suitable for dengue transmission year-round had a significantly increased odds of an outbreak 305 (Table 1, Figure 6). Municipalities that had previously experienced outbreaks had around 306 double the odds of experiencing another compared to municipalities that were still protected 307 (adjusted odds ratio (aOR): 2.03, 95% credible interval (CI): 1.93, 2.15), supporting the 308 hypothesis that dengue outbreaks become established once the virus is introduced. We 309 compared this model to an alternative that only considered whether an outbreak had occured 310 in the previous year (rather than any previous year) and found that the model considering 311 any previous outbreaks performed better according to the model's AIC (any previous year AIC 312 = 76923.74, year before AIC = 77465.88). Experiencing an outbreak in the previous year did 313 not have a protective effect due to acquired immnunity as hypothesised, the odds of an 314 outbreak was expected to increase by 18% on average in municipalities the year after an 315 outbreak occured (Table S2). Municipalities with year-round temperature suitability had 316 increased risk of outbreaks, whether we consider suitabability for both species of Aedes 317 mosquitoes (Table 1) or just *Aedes aegypti* (Table S2). On average, the odds of an outbreak 318 increased by 42% (aOR: 1.42, 95% CI: 1.30, 1.55) for every additional month of suitable 319 temperature per year.

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323 Table 1: Posterior mean and 95% credible interval (CI) estimates for linear effect

324 parameters, shown on the adjusted odds ratio (aOR) scale

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Coefficient	aOR (95% CI)
Urbanisation	3.26 (2.85, 3.72)
REGIC level: metropolis	1.39 (1.22, 1.59)
REGIC level: regional capital	1.52 (1.38, 1.66)
REGIC level: sub-regional centre	1.23 (1.14, 1.33)
REGIC level: zone centre	1.23 (1.15, 1.31)
Prior outbreak: yes	2.03 (1.93, 2.15)
Months with suitable temperature	1.42 (1.30, 1.55)

326 Posterior mean and credible interval estimated taking the 50th, 2.5th and 97.5th quantiles 327 from the simulated posterior distribution. Urbanisation is the proportion of residents living in urban areas. REGIC covariates are in comparison to the reference group, local centre. A 328 329 suitable temperature is defined as between 16.2° and 34.5°C (suitable for both Aedes aegypti 330 and Aedes albopictus).

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333 Fig 6: The mean and 95% credible interval of the posterior distribution for each model

334 covariate. Results show that regions with a higher proportion of residents living in urban 335 areas, in cities with a higher connectivity than local centres, with a higher number of month

- 336 suitable for dengue transmission, which had previously experienced an outbreak have
- 337 significantly a higher odds of outbreak.

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Although higher levels of connectivity had significantly higher odds of an outbreak than local 340

centres, this difference was highest on average for regional centres (aOR: 1.52, 95% CI: 1.38, 341

342 1.66) despite being considered less connected to the urban network than metropoles (aOR: 1.39, 95% CI: 1.22, 1.59). This is potentially due to the structure of the urban network which connects smaller cities to larger centres until they converge to metropoles, meaning that regional capitals are important intermediate urban centres, that influences wide hinterland areas (28). Alternatively, despite the regional capitals having similar levels of access to basic services as metropoles when aggregated to the municipality level (Figure S7), metropoles have larger economies than regional capitals (28) which may mean improved infrastructure which is not reflected by census variables on this scale.

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351 Sensitivity analysis using an outbreak definition of over 100 cases per 100,000 residents 352 resulted in similar parameter estimates and led to the same conclusions (Table S2). The area 353 under the ROC curve for the final model was 0.86 (95% confidence interval: 0.856, 0.861, 354 Figure S9), indicating that the model fit the data well. The temporal smooth function showed 355 increasing odds of an outbreak over the period not explained by the model covariates (Figure 356 7a). The spatial smooth field showed that the risk around Rio Branco in Acre, the Centre-West 357 region, and in Rio Grande do Norte in Northeast Brazil were higher on average than explained 358 by the model covariates (Figure 7b). In contrast, areas in South Brazil, along the northern 359 Brazilian coast, and in parts of the Amazon had lower risk of dengue outbreak occurrence 360 than expected given the covariates.

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Fig 7: Temporal (a) and spatial (b) smooth functions from the final model transformed to show the change in odds. The odds of an outbreak has increased over the period due to unexplained factors not included in the model. The spatial random field highlights that more information is needed in the model to understand the explosive outbreaks that have taken place in Rio Branco, Acre and the Centre-West region as these hotspots are not fully explained
by the model covariates. Pink (green) regions of the map represent areas where the odds of
an outbreak was higher (lower) on average than estimated by the covariates.

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The structured residuals for the full model were closer to zero on average for the vast majority 372 373 of the country than the baseline model (92.33% of municipalities, Figure 8), indicating that 374 the covariates are indeed explaining spatio-temporal variation in the data. The inclusion of 375 climate suitability into the baseline model shrank the structured residuals towards zero for 376 91.16% of municipalities. This was particularly noticeable in South Brazil (Figure 9a), 377 supporting the hypothesis that the dengue transmission barrier here was a result of lower 378 temperatures. The inclusion of the prior outbreak indicator also shrank the structured 379 residuals towards zero across Brazil (in 94.28% of municipalities, Figure 9b) showing its 380 relative importance in this model. The relative importance of urbanisation and REGIC levels 381 of influence were less clear; despite the model finding both these variables significantly 382 associated with increased odds of an outbreak, there were fewer municipalities in which the 383 structured residuals had shrank towards (57.5% for urbanisation, Figure 9c, and 45.08% for 384 REGIC levels of influence, Figure 9d). One potential reason for this is that both variables are 385 only measured once per decade and therefore do not differ annually; there may be changes in municipalities that contribute to dengue transmission but are not captured by these 386 387 stationary variables. Another potential reason is that these variables are not able to account for within-city variation at this spatial resolution that may contribute to outbreaks of dengue 388 389 (as highlighted by the other socioeconomic variables displayed in Figure S5).

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392	Fig 8: The median difference between abolute values of the smooth function estimates
393	calculated from the full model and from a baseline model. A reduction in the absolute
394	smooth functions (shown in green) indicates that the estimates have shrunk towards zero
395	when the covariates were added to the model and these covariates are explaining some of
396	the variability in the data.
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399	Fig 9: The median difference between absolute values of the smooth function estimates
400	calculated from the full model and models with a) the climate suitability covariate removed,
401	b) the prior outbreak indicator removed, c) the proportion of urbanisation removed, and d)
402	the level of connectivity covariate removed. A reduction in the absolute estimates of the
403	smooth functions (shown in green here) indicates that the functions have shrunk towards
404	zero and the covariate has explained variation in the data.
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407	To understand how the risk of outbreaks have changed over the period, we drew simulations
408	from the posterior distribution of the response and estimated the probability of an outbreak
409	for each municipality per year (Figure S10). These estimates were aggregated to the first
410	(2001 - 2010) and second (2011 - 2020) decade by taking the mean probability for each
411	municipality per decade to observe how the dengue transmission zone had changed after the
412	large scale outbreak of the 21st century in 2010. The probability of an outbreak increased
413	across most of Brazil since the first decade of the 21st century except for the 2 most southern
414	states and some areas of the Northeast (Figure 10a). The largest increases in risk were seen

415 in the Centre-West, which has been the epicentre of the explosive outbreaks taking place 416 since 2010. In the regions previously protected from outbreaks (the western Amazon (Figure 417 10b) and the South (Figure 10c)), the erosion of the geographic barriers can clearly be seen. Although a southern border still exists, it has shifted south, and the Amazon no longer has a 418 419 clear boundary. 420 421 422 Figure 10: The average probability of an outbreak 2001 - 2010 and 2011 - 2020 in a) Brazil, 423 b) Acre and Amazonas, and c) South Brazil. The probability of an outbreak estimated using 424 simulations from the posterior distribution of the response from the final model, averaged 425 over the firsrt and second decade of the time period. The probability of an outbreak has 426 increased across most of Brazil. The Amazonian barrier has almost completely been eroded

427 and the South Brazil border has moved further south.

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430 To determine the current dengue transmission barriers, we identified regions where the 431 average probability of an outbreak lay below 10% (Figure 11). We chose the threshold 10% as 432 this gave barriers comparable to those identified in a previous study (6) (Figure S11). The number of municipalities considered protected declined from 2689 in 2001 - 2010 to 1599 in 433 434 2011 - 2020. Between 2011 and 2020 there were no municipalities in the Centre-West region 435 that were considered protected, compared to 92 in 2001 - 2010. Northeast Brazil was the only region that had more protected municipalities in 2011 - 2020 than 2001 - 2020 (366 compared 436 437 to 315). The southern barrier to dengue transmission now begins in the southern part of 438 Paraná and extends through the west of Rio Grande do Sul and Santa Catarina. Areas of high

439 altitude in Southeast Brazil, mostly found in Minas Gerais, are still considered protected. 440 There are still areas of the Amazon protected from dengue outbreaks but this barrier is no longer clearly defined. In addition to the previously identified barriers in the South region and 441 442 Amazon rainforest, we found that there was a protected region along the north coast of Brazil 443 in northern Pará and Maranhão. This barrier was not explained by the covariates in our model indicated by the low values of the spatial smooth function (Figure 7b). This area is 444 predominantly warm and humid climate, with higher precipitation during winter ('Am' type 445 446 in Köppen climate classification) (34). Although temperature and humidity are relatively stable along seasons in this area, the interaction between these variables and increased 447 448 precipitation may inhibit the mosquito populations (35).

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Fig 11: Geographical barriers to dengue transmission in a) 2001 - 2010 and b) 2011 - 2020.
Maps showing areas where the probability of an outbreak was less than 10% on average in
each decade of the 21st century. In the second half of the decade, only the 2 most southern
states and the northern coast were fully protected from dengue transmission.

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456 Discussion

We found that the expansion of the dengue transmission zone is associated with temperature suitability, connectivity within the Brazilian urban network and urbanisation, and that these outbreaks become established in areas after both the vector and the virus have been introduced. This study builds on previous literature that showed the expansion of dengue across Brazil (6,7,17,25,36) and has updated the geographical barriers to transmission. The

462 most recent epidemiological bulletins have shown that this expansion has continued in 2021 463 into previously unaffected parts of Acre, Amazonas, and further south into Paraná and Santa 464 Catarina (37), highlighting the importance of monitoring the erosion of these barriers. To our 465 knowledge, this is the first epidemiological modelling study to use the REGIC's levels of 466 influence and show that there is an increased odds of dengue outbreaks in cities that are 467 highly connected within the Brazilian urban network. However this increase is not linear; 468 regional capitals are considered less connected than metropoles but we found that the 469 increase in odds were higher in these cities. Further investigation is needed to understand whether this is related to human movement, as people more often travel to regional capitals 470 471 from smaller cities than metropoles (28), or differences in socioeconomic factors that we 472 were unable to detect at the municipality level.

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474 Although this study focuses on Brazil, there is evidence that similar patterns are emerging in 475 other parts of South America. In Argentina, previously protected cities in temperate regions 476 are experiencing regular outbreaks, partially related to increasing temperatures but also as a 477 result of human movement importing cases from other parts of the continent (22,23). Rural 478 parts of the Amazon, which were previously isolated from infected hosts and vectors, are also 479 experiencing outbreaks, thought to be associated with increased connectivity between rural areas and larger cities (13,17). The introduction of dengue into Acre in the Brazilian Amazon 480 has been linked to increased connectivity across the state following the construction of a 481 482 highway between the two largest cities, Rio Branco and Cruzeiro do Sul (25). The impact of 483 this connection can be observed in the data as the outbreak appears to jump from Rio Branco 484 in the south of Acre to Cruzeiro do Sul in the north in 2014 rather than spreading to 485 neighbouring regions which appears to be the case in the South (Figure 5). The introduction

of dengue into the Amazon is particularly worrying as it is the ideal environment for the virus
to thrive: lower than average access to basic services such piped water and refuse collection,
and the ideal climate conditions for large epidemics (17,38).

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490 Although this study extends our understanding of the expansion of the dengue transmission 491 zone in Brazil, there are several limitations. Dengue case data used in this study was taken from Brazil's passive surveillance system, which has been found to differ in accuracy between 492 493 regions, and between epidemic and non-epidemic periods (39). To reduce the impact of 494 reporting bias in our model, we used an outbreak indicator rather than case data as a 495 response variable. The outbreak indicator used was chosen as it reflects the Brazilian Ministry 496 of Health's definition (29). However, the threshold of an outbreak is likely to differ across the 497 country. In regions that historically experienced little or no transmission, even a small number 498 of cases may be viewed as an outbreak. The choice of such a high threshold is likely to produce 499 more conservative estimates of the transmission zone. When our results were compared to 500 a lower outbreak threshold of 100 cases per 100,000 residents, we found the model 501 parameter estimates were consistent with the higher threshold. The model failed to pick up 502 some of the temporal trends in the data, which may be a result of using stationary indicators 503 of urbanisation and connectivity measured every 10 years. Information collected at a finer 504 temporal scale may provide more insights into the impact of sudden expansions such as the 505 effect of improved infrastructure in the Amazon (25).

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507 Our model used the level of influence extracted from the REGIC studies (27,28) to account for 508 the level of connectivity between cities within Brazil as a proxy for human movement. 509 However, this indicator may simplify the process and miss important patterns. The

510 hierarchical model assumed by REGIC assumes each small city is linked to a higher level urban 511 centre, such as the regional capitals and metropoles. It is evident that large and warm cities 512 may propogate epidemic waves and maintain dengue transmission in their hinterland, while temperate metropoles in the South (Porto Alegre, Curitiba and São Paulo) do not play a 513 514 relevant role in dengue diffusion in their region. Previous studies have found that imported 515 cases driven by human movement are responsible for dengue outbreaks in temperate cities 516 (23,24). The choice of spatial connectivity assumption and data can lead to very different 517 results and the use of the REGIC levels of influence as a spatial covariate rather than including 518 the direct links may miss some important patterns (26). Future work will aim to incorporate 519 the complex urban network from the REGIC studies into a statistical framework to account 520 for direct and indirect links between metropoles and regional capitals, and smaller urban 521 centres in their hinterland.

522

523 Despite these limitations, we have shown that the expansion of the dengue transmission zone 524 has continued into the 21st century, driven by increased climate suitability in the South, a 525 network of highly connected cities, and high levels of urbanisation. The introduction of 526 dengue outbreaks into an area more than doubles the odds of future outbreaks, which is 527 particularly concerning given the expansion has continued into 2021. Given the dynamic 528 nature of the growing dengue burden, the barriers identified here will be outdated very 529 quickly. We have highlighted the importance of focusing control strategies in areas at risk of 530 future outbreaks as well as those within the established dengue transmission zone.

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References 538

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540 Ten health issues WHO will tackle this year [Internet]. [cited 2021 Jun 10]. Available 1. 541 from: https://www.who.int/news-room/spotlight/ten-threats-to-global-health-in-2019

- 542 2. Wilder-Smith A, Gubler DJ, Weaver SC, Monath TP, Heymann DL, Scott TW. Epidemic 543 arboviral diseases: priorities for research and public health. Lancet Infect Dis. 2017 Mar 544 1;17(3):e101-6.
- 545 3. Stanaway JD, Shepard DS, Undurraga EA, Halasa YA, Coffeng LE, Brady OJ, et al. The global burden of dengue: an analysis from the Global Burden of Disease Study 2013. 546 547 Lancet Infect Dis. 2016 Jun 1;16(6):712–23.
- 548 4. Gubler DJ. Dengue, Urbanization and Globalization: The Unholy Trinity of the 21st 549 Century. Trop Med Health. 2011 Dec;39(4 Suppl):3–11.
- 5. 550 Fares RCG, Souza KPR, Añez G, Rios M. Epidemiological Scenario of Dengue in Brazil. 551 BioMed Res Int. 2015 Aug 30;2015:e321873.
- 552 6. Barcellos C, Lowe R. Expansion of the dengue transmission area in Brazil: the role of 553 climate and cities. Trop Med Int Health. 2014;19(2):159–68.
- 554 7. de Azevedo TS, Lorenz C, Chiaravalloti-Neto F. Spatiotemporal evolution of dengue 555 outbreaks in Brazil. Trans R Soc Trop Med Hyg. 2020 Aug 1;114(8):593–602.
- 556 8. Churakov M, Villabona-Arenas CJ, Kraemer MUG, Salje H, Cauchemez S. Spatio-557 temporal dynamics of dengue in Brazil: Seasonal travelling waves and determinants of 558 regional synchrony. PLoS Negl Trop Dis. 2019 Apr 22;13(4).
- 559 9. Ferreira-de-Lima VH, Câmara DCP, Honório NA, Lima-Camara TN. The Asian tiger 560 mosquito in Brazil: Observations on biology and ecological interactions since its first 561 detection in 1986. Acta Trop. 2020 May 1;205:105386.
- 562 10. Ministério da Saúde (BR). Secretaria de Vigilância em Saúde. Departamento de 563 Vigilância Epidemiológica. Guia de vigilância em saúde: volume único [Internet]. 2019;
- 564 11. Rezende HR, Romano CM, Claro IM, Caleiro GS, Sabino EC, Felix AC, et al. First report of 565 Aedes albopictus infected by Dengue and Zika virus in a rural outbreak in Brazil. PLOS 566 ONE. 2020 Mar 12;15(3):e0229847.
- 567 12. Powell JR, Tabachnick WJ. History of domestication and spread of Aedes aegypti - A 568 Review. Mem Inst Oswaldo Cruz. 2013 Dec;108(Suppl 1):11-7.
- 569 13. Guagliardo SA, Morrison AC, Barboza JL, Requena E, Astete H, Vazquez-Prokopec G, et 570 al. River Boats Contribute to the Regional Spread of the Dengue Vector Aedes aegypti 571 in the Peruvian Amazon. PLoS Negl Trop Dis. 2015 Apr 10;9(4):e0003648.

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572 14. Pérez-Castro R, Castellanos JE, Olano VA, Matiz MI, Jaramillo JF, Vargas SL, et al.
573 Detection of all four dengue serotypes in *Aedes aegypti* female mosquitoes collected in 574 a rural area in Colombia. Mem Inst Oswaldo Cruz. 2016 Apr;111:233–40.

575 15. Ayllón T, Câmara DCP, Morone FC, Gonçalves L da S, Barros FSM de, Brasil P, et al.
576 Dispersion and oviposition of Aedes albopictus in a Brazilian slum: Initial evidence of
577 Asian tiger mosquito domiciliation in urban environments. PLOS ONE. 2018 Apr
578 23;13(4):e0195014.

- 579 16. Kraemer MUG, Reiner RC, Brady OJ, Messina JP, Gilbert M, Pigott DM, et al. Past and
 580 future spread of the arbovirus vectors Aedes aegypti and Aedes albopictus. Nat
 581 Microbiol. 2019 May;4(5):854–63.
- 17. Lowe R, Lee S, Lana RM, Codeço CT, Castro MC, Pascual M. Emerging arboviruses in the
 urbanized Amazon rainforest. BMJ. 2020 Nov 13;371:m4385.

18. Lowe R, Lee SA, O'Reilly KM, Brady OJ, Bastos L, Carrasco-Escobar G, et al. Combined
effects of hydrometeorological hazards and urbanisation on dengue risk in Brazil: a
spatiotemporal modelling study. Lancet Planet Health. 2021 Apr 1;5(4):e209–19.

- 19. Reinhold JM, Lazzari CR, Lahondère C. Effects of the Environmental Temperature on
 Aedes aegypti and Aedes albopictus Mosquitoes: A Review. Insects. 2018 Nov 6;9(4).
- S89 20. Mordecai EA, Cohen JM, Evans MV, Gudapati P, Johnson LR, Lippi CA, et al. Detecting
 the impact of temperature on transmission of Zika, dengue, and chikungunya using
 mechanistic models. PLoS Negl Trop Dis. 2017 Apr 27;11(4):e0005568.
- 592 21. Mordecai EA, Caldwell JM, Grossman MK, Lippi CA, Johnson LR, Neira M, et al. Thermal
 593 biology of mosquito-borne disease. Ecol Lett. 2019;22(10):1690–708.
- Solution 22. Robert MA, Stewart-Ibarra AM, Estallo EL. Climate change and viral emergence:
 evidence from Aedes-borne arboviruses. Curr Opin Virol. 2020 Feb 1;40:41–7.
- Solution 23. Robert MA, Tinunin DT, Benitez EM, Ludueña-Almeida FF, Romero M, Stewart-Ibarra
 AM, et al. Arbovirus emergence in the temperate city of Córdoba, Argentina, 2009–
 2018. Sci Data. 2019 Nov 21;6(1):276.
- 599 24. Marques-Toledo CA, Bendati MM, Codeço CT, Teixeira MM. Probability of dengue
 600 transmission and propagation in a non-endemic temperate area: conceptual model
 601 and decision risk levels for early alert, prevention and control. Parasit Vectors. 2019
 602 Jan 16;12(1):38.
- Lana RM, Gomes MF da C, de Lima TFM, Honório NA, Codeço CT. The introduction of
 dengue follows transportation infrastructure changes in the state of Acre, Brazil: A
 network-based analysis. PLoS Negl Trop Dis. 2017 Nov 17;11(11).
- Lee SA, Jarvis CI, Edmunds WJ, Economou T, Lowe R. Spatial connectivity in mosquitoborne disease models: a systematic review of methods and assumptions. J R Soc
 Interface. 18(178):20210096.

- 609 27. Estatística IB de G e. Regiões de influência das cidades 2007. IBGE Rio de Janeiro; 2008.
- 610 28. Estatística IB de G e. Regiões de influência das cidades 2018. IBGE Rio de Janeiro; 2020.
- 611 29. Lowe R, Barcellos C, Coelho CAS, Bailey TC, Coelho GE, Graham R, et al. Dengue outlook
 612 for the World Cup in Brazil: An early warning model framework driven by real-time
 613 seasonal climate forecasts. Lancet Infect Dis. 2014;14(7):619–26.
- 614 30. Copernicus Climate Change Service. ERA5-Land monthly averaged data from 2001 to
 615 present [Internet]. ECMWF; 2019 [cited 2021 Jun 4]. Available from:
 616 https://cds.climate.copernicus.eu/doi/10.24381/cds.68d2bb30
- 617 31. Baston, Daniel. exact extractr: Fast Extraction from Raster Datasets using Polygons
 618 [Internet]. 2020. Available from: https://CRAN.R-project.org/package=exact extractr
- 619 32. IBGE. Arranjos populacionais e concentrações urbanas no Brasil. IBGE Rio de Janeiro;
 620 2016.
- 621 33. Wood SN. Generalized additive models: an introduction with R. CRC press; 2017.
- 622 34. Alvares CA, Stape JL, Sentelhas PC, de Moraes Gonçalves JL, Sparovek G. Köppen's
 623 climate classification map for Brazil. Meteorol Z. 2013 Dec 1;711–28.
- Spliego Pliego E, Velázquez-Castro J, Fraguela Collar A. Seasonality on the life cycle of
 Aedes aegypti mosquito and its statistical relation with dengue outbreaks. Appl Math
 Model. 2017 Oct 1;50:484–96.
- 627 36. Castro MC, Baeza A, Codeço CT, Cucunubá ZM, Dal'Asta AP, Leo GAD, et al.
 628 Development, environmental degradation, and disease spread in the Brazilian Amazon.
 629 PLOS Biol. 2019 Nov 15;17(11):e3000526.
- 37. Secretaria de Vigilância em Saúde. Boletim Epidemiológico Monitoramento dos casos
 de arboviroses urbanas causados por vírus transmitidos pelo mosquito Aedes (dengue,
 chikungunya e zika), semanas epidemiológicas 1 a 21, 2021 [Internet]. Ministério da
 Saúde; 2021. Available from: https://www.gov.br/saude/ptbr/media/ndf/2021/junbo/07/boletim_epidemiologico_sys_21 ndf
- 634 br/media/pdf/2021/junho/07/boletim_epidemiologico_svs_21.pdf
- 38. Huber JH, Childs ML, Caldwell JM, Mordecai EA. Seasonal temperature variation
 influences climate suitability for dengue, chikungunya, and Zika transmission. Althouse
 B, editor. PLoS Negl Trop Dis. 2018 May 10;12(5):e0006451.
- Silva MMO, Rodrigues MS, Paploski IAD, Kikuti M, Kasper AM, Cruz JS, et al. Accuracy of
 Dengue Reporting by National Surveillance System, Brazil. Emerg Infect Dis. 2016
 Feb;22(2):336–9.
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643	Supporting information captions
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645 646 647 648	S1 Document: Methods and materials. Additional information about methods and materials used in this study.
649 650 651	S2 Document: Portuguese translation of the abstract
652 653 654 655 656 657 658 659 660	Fig S1: The organisation of Brazil into a) 5 geo-political regions, and b) 27 federal units . Abbreviations: AC = Acre, AL = Alagoas, AP = Amapá, AM = Amazonas, BA = Bahia, CE = Ceará, DF = Distrito Federal, ES = Espírito Santo, GO = Goiás, MA = Maranhão, MT = Mato Grosso, MS = Mato Grosso do Sul, MG = Minas Gerais, PA = Pará, PB = Paraíba, PR = Paraná, PR = Pernambuco, PI = Piauí, RJ = Rio de Janeiro, RN = Rio Grande do Norte, RS = Rio Grande do Sul, RO = Rondônia, RR = Roraima, SC = Santa Catarina, SP = São Paulo, SE = Sergipe, TO = Tocantins.
661 662 663 664	Fig S2: Average monthly mean temperature (°C) in each Brazilian state January 2001 - December 2020.
665 666 667 668 669 670 671	Fig S3: The average number of months suitable for dengue transmission per year a) 2001 - 2010, and b) 2011 - 2020. The average number of months with mean temperature between 16.2 and 34.5°C aggregated to the two decades of data. Most of Brazil experiences suitable temperatures year-round apart from areas of South Brazil and areas of high altitude in the Southeast which experience cool winters.
672 673 674 675 676 677	Fig S4: The percentage of residents living in urban areas of each municipality from the 2000 (a) and 2010 (b) censuses. Levels of urbanisation differ greatly across Brazil, with the majority of Southeast and South Brazil living in urban areas in comparison to the North and Northeast which has a larger rural population.
678 679 680 681 682 683	Fig S5: Scatterplot comparing the percentage of residents with access to piped water (top) and refuse collection (bottom) to the percentage living in urban areas from the 2010 census. Access to basic services was highly correlated to the level of urbanisation: highly urban areas had highest access to piped water and refuse collection.
684 685 686 687 688 689	Fig S6: The proportion of cities in each region at each level of influence in the a) 2007 and b) 2018 REGIC study. The proportion of high-level cities has increased across the country but the North and Northeast still have noticeably less well-connected cities than other regions. The Southeast and South are by far the most connected regions.

690 691	Fig S7: Raincloud plots exploring the relationship between REGIC level of influence and a) urbanisation, b) access to piped water, and c) refuse collection. Metropoles and regional
692	capitals have higher levels of urbanisation and access to basic services than municipalities
693	that had lower levels of connectivity within the urban network. Local centres were more
694	varied in terms of basic services and urban levels than the other levels and covered a wide
695	range of city types.
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697	
698	Fig S8: The proportion of municipalities in each region of Brazil experiencing an outbreak
699	per year 2001 - 2020. The proportion of municipalities affected by outbreak has increased
700	since 2010 in every region of the country, although outbreaks in South Brazil are still
701	focused on a small part of the region.
702	
703	
704	Fig S9: Receiver operating characteristic (ROC) curve for the final model (solid line)
705	compared to chance (dashed line). The closer to the top-left corner, the better the
706	predictive ability of a model. As the ROC curve lies above the dashed reference line, this
707	model performs better than chance.
708	
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710	Fig S10: The probability of an outbreak estimated from the model for each year 2001 -
711	2020. The mean probability of an outbreak estimated by taking 1000 simulations from the
712	posterior distribution of the response and transforming the outcome using a probit
713	function.
714	
715	
716	Fig S11: Comparison of different risk thresholds to define current geographical barriers to
717	dengue outbreaks. Municipalities were considered 'protected' if the probability of an
718	outbreak was less than or equal to the threshold a) 0%, b) 5%, c) 10% or d) 15%. The
719	threshold of 10% was chosen as it was the most comparable with previous studies.
720	
721	
722	Table S1: Distribution of municipalities at each level of influence in the urban network,
723	2007 (1) and 2018 (2). The number of municipalities classified as metropoles (largest cities
724	in Brazil, connected throughout the entire country), regional capitals (large cities connected
725	regionally and to metropoles), sub-regional capitals (cities connected locally and to the
726	three largest metropoles), zone centres (smaller cities generally connected only to their
727	neighbours), and local centres (smallest cities typically disconnected from the urban
728	network).
729	
730	
731	Table S2: Posterior mean and 95% credible interval (CI) estimates for linear effect
732	parameters, calculated using an outbreak threshold of 100 cases per 100,000 residents,
733	shown on the adjusted odds ratio (aOR) scale.

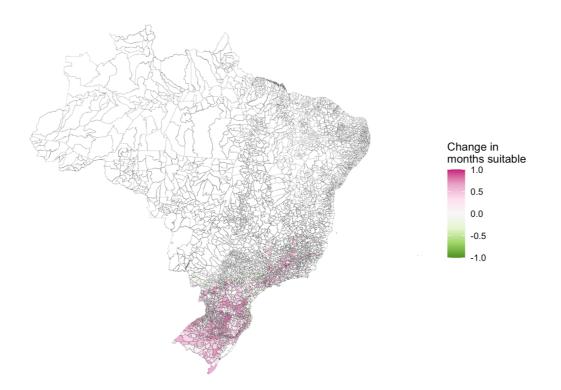


Fig 1: The difference between the average number of months with suitable temperatures for dengue transmission in 2001 - 2010 and 2011 - 2020. The number of months with temperatures between 16.2 and 34.5°C has increased on average (shown in pink) in parts of South and Southeast Brazil which were previously considered 'protected' from dengue transmission.

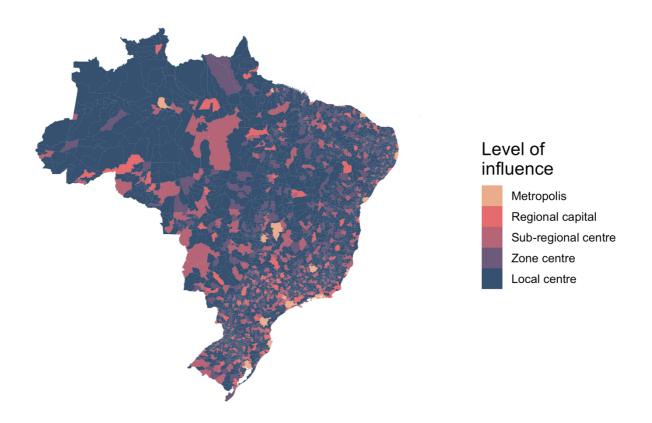


Fig 2: The level of influence of cities within the Brazilian urban network from REGIC 2018.

The Amazon region is far less connected to the urban network than the rest of the country. As there is only one metropolis in North Brazil, people often travel great distances, far greater than in other regions, to reach cities.

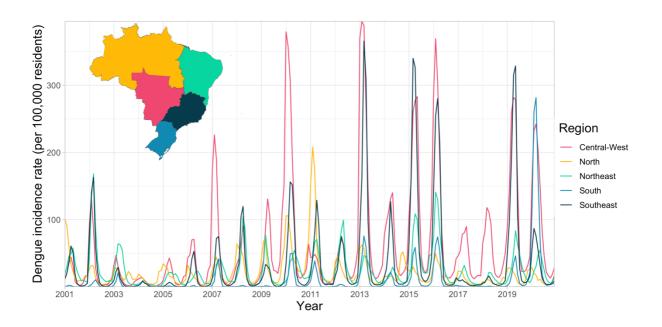


Fig 3: Monthly incidence rate per 100,000 residents in regions of Brazil 2001 - 2020. Incidence rates have increased in every region of the country across the 21st century. The first regional outbreak occurred in 2010, outbreaks have occurred more frequently and in more regions since then.

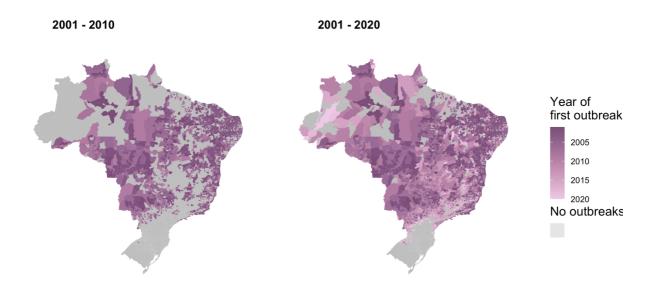


Fig 4: The first year each municipality experienced an outbreak for the first time in the period 2001 - 2010 and 2001 - 2020. The year each municipality first recorded over 300 cases per 100,000 residents. Recent data shows the previous barriers to dengue outbreaks in the Amazon and South are being eroded.

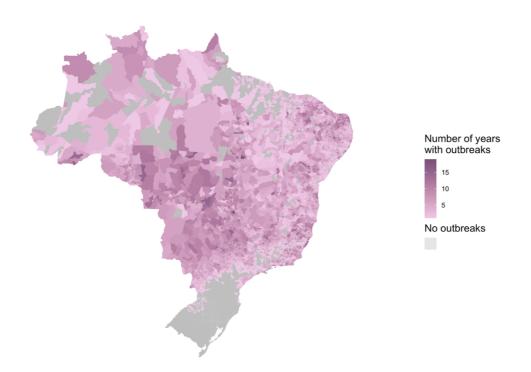


Fig 5: The number of years each municipality experienced an outbreak between 2001 and 2020. Municipalities that experienced outbreaks earlier in the 21st century continued to experience outbreaks throughout the period. This suggests that once dengue is introduced to a region, it becomes established.

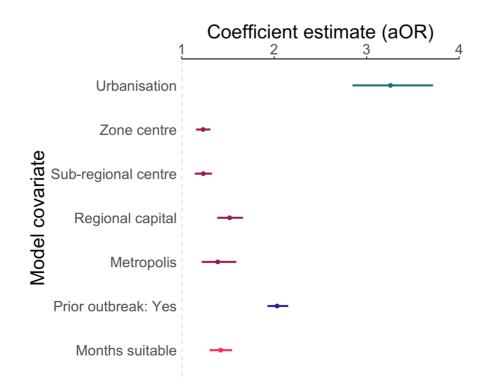


Fig 6: The mean and 95% credible interval of the posterior distribution for each model covariate. Results show that regions with a higher proportion of residents living in urban areas, in cities with a higher connectivity than local centres, with a higher number of month suitable for dengue transmission, which had previously experienced an outbreak have a significantly higher odds of outbreak.

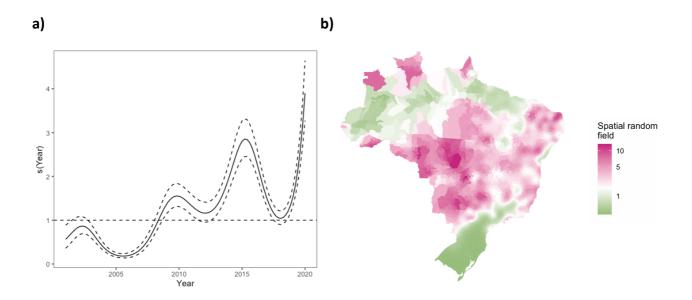


Fig 7: Temporal (a) and spatial (b) smooth functions from the final model transformed to

show the change in odds. The odds of an outbreak has increased over the period due to unexplained factors not included in the model. The spatial random field highlights that more information is needed in the model to understand the explosive outbreaks that have taken place in Rio Branco, Acre and the Centre-West region as these hotspots are not fully explained by the model covariates. Pink (green) regions of the map represent areas where the odds of an outbreak was higher (lower) on average than estimated by the covariates.

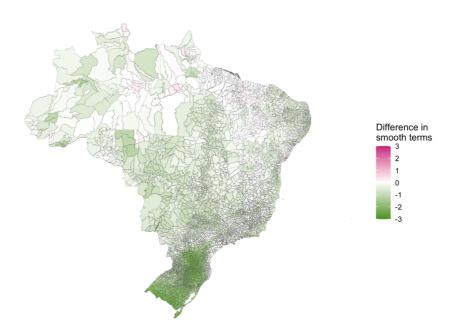


Fig 8: The median difference between abolute values of the smooth function estimates calculated from the full model and from a baseline model. A reduction in the absolute smooth functions (shown in green) indicates that the estimates have shrunk towards zero when the covariates were added to the model and these covariates are explaining some of the variability in the data.

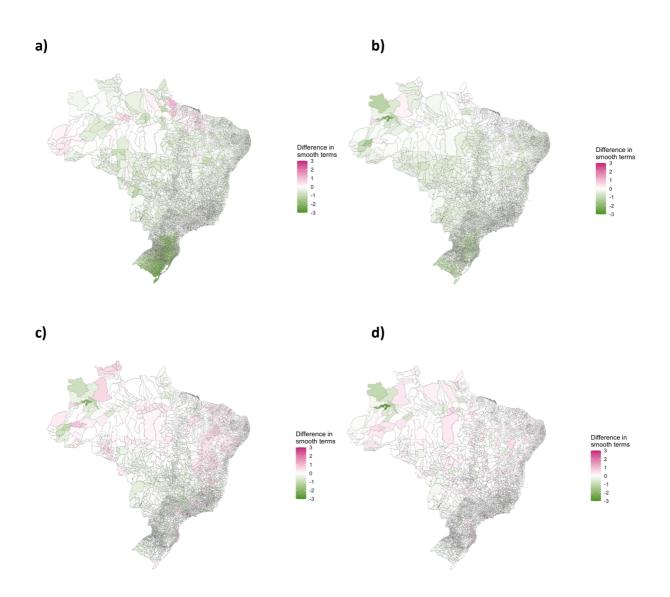


Fig 9: The median difference between absolute values of the smooth function estimates calculated from the full model and models with a) the climate suitability covariate removed, b) the prior outbreak indicator removed, c) the proportion of urbanisation removed, and d) the level of connectivity covariate removed. A reduction in the absolute estimates of the smooth functions (shown in green here) indicates that the functions have shrunk towards zero and the covariate has explained variation in the data.

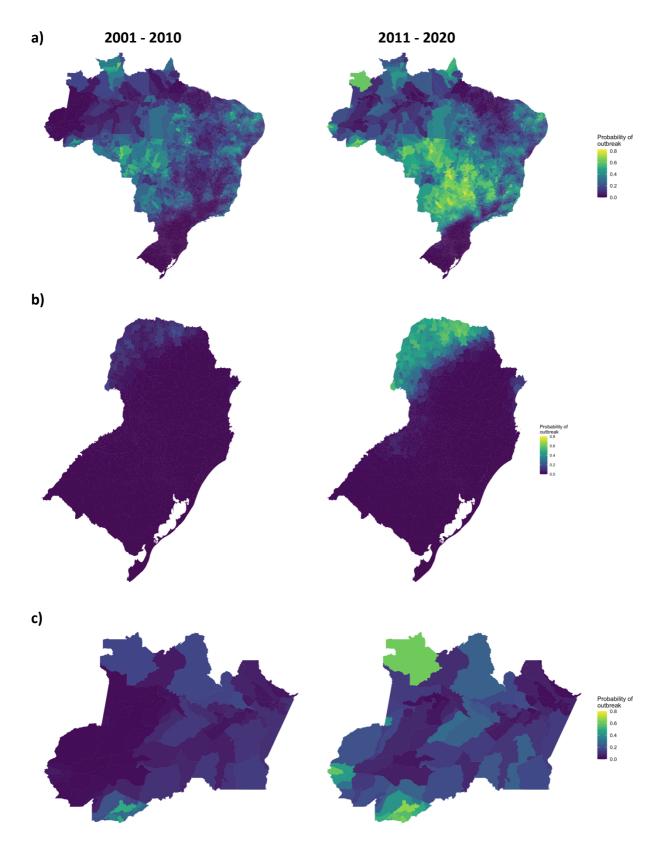


Figure 10: The average probability of an outbreak 2001 - 2010 and 2011 - 2020 in a) Brazil, b) Acre and Amazonas, and c) South Brazil. The probability of an outbreak estimated using simulations from the posterior distribution of the response from the final model, averaged over the first and second decade of the time period. The probability of an

outbreak has increased across most of Brazil. The Amazonian barrier has almost completely been eroded and the South Brazil border has moved further south.

