Mapping global environmental suitability for Zika virus

Messina, J.P.[1], Kraemer, M.U.G.[1], Brady, O.J.[2], Pigott, D.M.[2,3], Shearer, F.[2], Weiss, D.J.[1], Golding, N.[4], Ruktanonchai, C.W.[5], Gething, P.W.[1], Cohn, E.[6], Brownstein, J.S.[6], Khan, K.[7,8], Tatem, A.J.[5,9], Jaenisch, T.[10,11], Murray, C.J.L.[3], Marinho, F.[12], Scott, T.W.[13], Hay, S.I.[2,3]

1 Department of Zoology, University of Oxford; Oxford, UK
2 Wellcome Trust Centre for Human Genetics, University of Oxford; Oxford, UK
3 Institute for Health Metrics and Evaluation, University of Washington; Seattle, WA, USA
4 Department of BioSciences, University of Melbourne; Parkville, VIC, Australia
5 WorldPop project, Department of Geography and Environment, University of Southampton; Southampton, UK
6 Boston Children's Hospital, Harvard Medical School; Boston, MA, USA
7 Department of Medicine, Division of Infectious Diseases, University of Toronto; Toronto, Canada
8 Li Ka Shing Knowledge Institute, St Michael's Hospital; Toronto, Canada
9 Flowminder Foundation; Stockholm, Sweden
10 Section Clinical Tropical Medicine, Department for Infectious Diseases, Heidelberg University Hospital; Heidelberg, Germany
11 German Centre for Infection Research (DZIF), Heidelberg partner site; Heidelberg, Germany
12 Secretariat of Health Surveillance, Ministry of Health of Brazil
13 Department of Entomology and Nematology, University of California Davis; Davis, CA, USA

Abstract

Zika virus was discovered in Uganda in 1947 and is transmitted by Aedes mosquitoes, which also act as vectors for dengue and chikungunya viruses throughout much of the tropical world. In 2007, an outbreak in the Federated States of Micronesia sparked public health concern. In 2013, the virus began to spread across other parts of Oceania and in 2015, a large outbreak in Latin America began in Brazil. Possible associations with microcephaly and Guillain-Barré syndrome observed in this outbreak have raised concerns about continued global spread of Zika virus, prompting its declaration as a Public Health Emergency of International Concern by the World Health Organization. We conducted species distribution modelling to map environmental suitability for Zika. We show a large portion of tropical and sub-tropical regions globally have suitable environmental conditions with over 2.17 billion people inhabiting these areas.

Impact Statement

This global map of environmental suitability for Zika virus and the estimated population living at potential risk can help refine public health guidelines, travel advisories, and intervention strategies at a crucial time in the global spread of this arbovirus.

Introduction

Zika virus (ZIKV) is an emerging arbovirus carried by mosquitoes of the genus *Aedes* (Musso, Nilles and Cao-Lormeau 2014). Although discovered in Uganda in 1947 (Dick 1952, Dick 1953), ZIKV was only known to cause sporadic infections in humans in Africa and Asia until 2007 (Lanciotti et al. 2008), when it caused a large outbreak of symptomatic cases on Yap island in the Federated States of Micronesia (FSM), followed by another in French Polynesia in 2013-14 and subsequent spread across Oceania (Musso, Cao-Lormeau and Gubler 2015a). In the 2007 Yap island outbreak, it was estimated that approximately 20% of ZIKV cases were symptomatic. While indigenous transmission of ZIKV to humans was reported for the first time in Latin America in 2015 (Zanluca et al. 2015, WHO 2015), recent phylogeographic research estimates that the virus was introduced into the region between May and December 2013 (Faria et al. 2016). This recent rapid spread has led to concern that the virus is following a similar pattern of global expansion to that of dengue and chikungunya (Musso et al. 2015a).

ZIKV has been isolated from 19 different *Aedes* species (Haddow et al. 2012, Grard et al. 2014), but virus has been most frequently found in *Ae. aegypti* (Monlun et al. 1992, Marchette, Garcia and Rudnick 1969, Smithburn 1954, Pond 1963, Faye et al. 2008, Foy et al. 2011b, Dakar 1999). These studies were based upon ancestral African strains of ZIKV, but the current rapid spread of ZIKV in Latin America is indicative of this highly efficient arbovirus vector (Marcondes and Ximenes 2015). The relatively recent global spread of *Ae. albopictus* (Benedict et al. 2007, Kraemer et al. 2015c) and the rarity of ZIKV isolations from wild mosquitoes may also partially explain the lower frequency of isolations from *Ae. albopictus* populations. Whilst virus transmission by *Ae. albopictus* and other minor vector species has normally resulted in only a small number of cases (Kutsuna et al. 2015, Roiz et al. 2015), these vectors do pose the threat of limited transmission (Grard et al. 2014). The wide geographic distribution of *Ae. albopictus* combined with the frequent virus introduction *via* viraemic travellers (McCarthy 2016, Bogoch et al. 2016, Morrison et al. 2008, Scott and Takken 2012), means the risk for ZIKV infection *via* this vector must therefore also be considered in ZIKV mapping.

The fact that ZIKV reporting was limited to a few small areas in Africa and Asia until 2007 means that global risk mapping has not, until recently, been a priority (Pigott et al. 2015b). Recent associations with Guillain-Barré syndrome in adults and microcephaly in infants born to ZIKV-infected mothers (World Health Organization 2015, Martines et al. 2016) have revealed that ZIKV could lead to more severe complications than the mild rash and flu-like symptoms that characterize the majority of symptomatic cases (Gatherer and Kohl 2015). Considering these potentially severe complications and the rapid expansion of ZIKV into previously unaffected areas, the global public health community needs information about those areas that are environmentally suitable for transmission of ZIKV to humans. Being a closely related flavivirus to DENV, there is furthermore the potential for antigen-based diagnostic tests to exhibit cross-reactivity when IgM ELISA is used for rapid diagnosis. Although ZIKV-specific serologic assays are being developed by the U.S. Centers for Disease Control, currently the only method of confirming ZIKV infection is by using PCR on acute specimens (Lanciotti et al. 2008, Faye et al. 2008). Awareness of suitability for transmission is essential if proper detection methods are to be employed.

In this paper, we use species distribution modelling techniques that have been useful for mapping other vector-borne diseases such as dengue (Bhatt et al. 2013), Leishmaniasis (Pigott et al. 2014b), and Crimean-Congo Haemorrhagic Fever (Messina et al. 2015b) to map environmental suitability for ZIKV. The environmental niche of a disease can be identified according to a combination of environmental conditions supporting its presence in a particular location, with statistical modelling then allowing this niche to be described quantitatively (Kraemer et al. 2016). Niche modelling uses records of known disease occurrence alongside hypothesized environmental covariates to predict suitability for disease transmission in regions where it has yet to be reported (Elith and Leathwick 2009). Contemporary high spatial-resolution global data representing a variety of environmental conditions allows for these predictions to be made at a global scale (Hay et al. 2006).

Results

Figure 1a shows the locations of the 323 standardized occurrence records in the final dataset, classified by the following date ranges: (i) up until 2006 (before the outbreak in FSM); (ii) between 2007 (the year of the FSM outbreak) and 2014; and (iii) since 2015, the first reporting of ZIKV in the Americas. This map is accompanied by the graph in Figure 1b, showing the number of reported occurrence locations globally by year. These figures highlight the more sporadic

nature of reporting until recent years, with the majority of occurrences in the dataset (63%) coming from the recent 2015-2016 outbreak in Latin America.

The final map that resulted from the mean of 300 ensemble Boosted Regression Tree (BRT) models is shown in Figure 2a (with greater detail shown for each region in Figures 2b-2d). Figure 2 -- figure supplement 1 shows the distribution of uncertainty based upon the upper and lower prediction quantiles from the 300 models. We restricted our models to make predictions only within areas where i) mosquito vectors (in this case *Ae. aegypti*) were able to persist and ii) where temperature was sufficient for arboviral replication within the mosquito. The former of these was calculated by taking the *Ae. aegypti* probability of occurrence (Kraemer *et al*. 2015c) value that incorporated 90% of all known occurrences (Kraemer et al. 2015b) (giving a threshold value of 0.8 and greater) while the latter was evaluated using a mechanistic mosquito model (Brady et al. 2013, Brady et al. 2014), which identified regions where arboviral transmission could be sustained for at least 355 days (one year minus the human incubation period) in an average year. Figure 3 is a country-level map distinguishing between those countries that are currently reporting ZIKV, those which have reported ZIKV in the past, those which have highly suitable areas for transmission, and those which are unsuitable. Our models predicted high levels of risk for ZIKV in many areas within the tropical and sub-tropical zones. Large portions of the Americas are suitable for transmission, with the largest areas of risk occurring in Brazil, followed by Colombia and Venezuela, all of which have reported high numbers of cases in the 2015-2016 outbreak. In Brazil, where the highest numbers of ZIKV are reported in the ongoing epidemic, the coastal cities in the south as well as large areas of the north are identified to have the highest environmental suitability of ZIKV. The central region of Brazil, on the other hand, has low population densities and smaller mosquito populations, which is reflected in the relatively low suitability for ZIKV transmission seen in the map. Although ZIKV has yet to be reported in the USA, a large portion of the southeast region of the country, including much of Texas through to Florida, is also highly suitable for transmission. Potential risk for ZIKV transmission is high in much of sub-Saharan Africa, with continuous suitability in the Democratic Republic of Congo and surrounding areas and several sporadic case reports in western sub-Saharan countries since the 1950s. Although no symptomatic cases have yet been reported in India, a large portion of this country is at potential risk for ZIKV transmission (over 2 million square kilometres), with environmental suitability extending from its northwest regions through to Bangladesh and Myanmar. The Indochina region, southeast China, and Indonesia all have large areas of environmental suitability as well, extending into Oceania. While only representing less than ten percent of Australia's total land area, the area shown to be suitable for ZIKV transmission in its northernmost regions is considerable (comprising nearly 250,000 square kilometres).

Our models showed ZIKV risk to be particularly influenced by annual cumulative precipitation, contributing 65.0% to the variation in the ensemble of models. The next most important predictor in the model was temperature suitability for DENV transmission *via Ae. albopictus,* contributing 14.6%. These are followed by urban extents (8.3%), temperature suitability for DENV *via Ae. aegypti* (5.7%), the Enhanced Vegetation Index (EVI; 3.8%), and minimum relative humidity (2.5%). Effect plots for each covariate are provided in Figure 2 -- figure supplement 2. Validation statistics indicated high predictive performance of the BRT ensemble mean map evaluated in a 10-fold cross-validation procedure, with area under the receiver operating characteristic (AUC) of 0.829 (±0.121 SD). Due to the uncertainty about *Ae. albopictus* as a competent vector for ZIKV, we also provide results for an ensemble of models which did not include temperature suitability for dengue *via* this mosquito species in Figure 2 -- figure supplement 3.

A threshold environmental suitability value of 0.397 in our final map was determined to incorporate 90% of all ZIKV occurrence locations. This was used to classify each 5km x 5km pixel on our final map as suitable or unsuitable for ZIKV transmission to humans. Using high-resolution global population estimates (WorldPop 2015, SEDAC 2015), we summed the populations living in Zika-suitable areas and have identified 2.17 billion people globally living within areas that are environmentally suitable for ZIKV transmission. Table 1 shows a breakdown of this figure by major world region, also showing the top four contributing countries to the potential population at risk. Asia has the most people living in areas that are suitable for ZIKV transmission at 1.42 billion, accounted for in large part by those living in India. In Africa, roughly 453 million people are living in areas suitable for ZIKV transmission, the largest proportion of which live in Nigeria. In the Americas, more than 298 million people live in ZIKV-suitable transmission zones, with approximately 40 percent of these people living in Brazil. Within the majority of environmentally suitable areas for ZIKV in the Americas, prolonged year-round transmission is possible. Southern Brazil and Argentina, however, are more likely to see transmission interrupted throughout the year, as is the case with the USA should autochthonous ZIKV transmission occur there. Using high-resolution data on births for the year 2015 (WorldPop 2015), we also estimate that 5.42 million births will occur in the Americas over the next year within areas and times of environmental suitability for ZIKV transmission.

Discussion

A large number of viruses (circa 219) are known to be pathogenic (Woolhouse et al. 2012). Of the 53 species of *Flavivirus*, 19 are reported to have caused illness in humans (ICTV 2014). Some flaviviruses, such as DENV, YFV, Japanese encephalitis virus, and West Nile virus, are widespread, causing many thousands of infections each year. The remainder, however, have been recognized as being pathogenic to humans for decades, but have highly focal reported distributions and are only minor contributors to mortality and disability globally (Hay et al. 2013, Murray et al. 2015). As a result, many are of relatively low priority when research and policy interest are considered (Pigott et al. 2015b). The recent spread of ZIKV across the globe highlights the need to reassess our consideration of these other flaviviruses, to gain a better understanding of the factors driving their spread and the potential for geographic expansion beyond their currently limited geographical extents.

Environmental suitability for virus transmission in an area does not necessarily mean that it will arrive and/or establish in that location. Arboviral infections in particular are dependent on a variety of non-environmental factors, with their movement having historically been largely attributed to human mobility from travel, trade, and migration, which introduce the viruses to places where mosquito vectors are already present (Murray, Quam and Wilder-Smith 2013, Weaver and Reisen 2010, Nunes et al. 2015, Gubler and Clark 1995). The identification of locations with permissible environments for transmission of emerging diseases like ZIKV is crucial, as importation could give rise to subsequent autochthonous cases in these locations (Hennessey, Fischer and Staples 2016, Zanluca et al. 2015). In order to identify places potentially receptive for ZIKV, we assembled the first comprehensive spatial dataset for ZIKV occurrence in humans and compiled a comprehensive set of high-resolution environmental covariates. We then used these data to implement a species distribution modelling approach (Elith and Leathwick 2009) that has proven useful for mapping other vector-borne diseases (Bhatt et al. 2013, Pigott et al. 2014a, Mylne et al. 2015, Messina et al. 2015b), allowing us to make inferences about environmental suitability for ZIKV transmission in areas where it has yet to be reported or where we are less certain about its presence. How the ongoing epidemic unfolds in terms of case numbers (or incidence) will depend on a range of other factors such as local transmission dynamics, herd immunity, patterns of contact among mosquitoes and

infectious and susceptible humans (Stoddard et al. 2013), and mosquito-to-human ratios as recently shown for dengue (Kraemer et al. 2015a) and chikungunya (Salje et al. 2016).

Globally, we predict that over 2.17 billion people live in areas that are environmentally suitable for ZIKV transmission. We also estimate the number of births occurring in the Americas only, as it is the region for which the most accurate high-resolution population data on births exists (Tatem et al. 2014, Sorichetta et al. 2015) and because it is the focus of an ongoing outbreak, which is the largest recorded thus far. In the Americas alone, an estimated 5.42 million births occurred in 2015 within areas and at times that are suitable for ZIKV transmission. It is important to recognize that not all individuals will be exposed to ZIKV. Like with other flaviviruses, a ZIKV outbreak may be temporally and spatially sporadic and, even in the most receptive environments, is unlikely that all of the population will be infected. Furthermore, increasing herd immunity of this likely sterilizing infection will rapidly reduce the size of the susceptible population at risk for infection in subsequent years (Dick, Kitchen and Haddow 1952) and work is ongoing to predict the likely infection dynamics after establishment. Instead, the estimates are intended as indicators of the total number of individuals or births that may require protection during the first wave of the outbreak. Specifically, these populations should be the focus of efforts to increase awareness and provide guidelines for mitigating personal risk of infection. In future analyses, our estimates could be extended to include ZIKV incidence and the virus' effect on incidence of associated conditions such as Guillain-Barré syndrome and microcephaly. Before appropriately caveated estimates can be generated, however, more information is needed regarding: (i) the background rate of these conditions due to other causes; (ii) how risk may vary throughout the course of a pregnancy; (iii) the proportion of the population exposed during outbreaks; and (iv) whether or not immunity acquired through a mother's prior exposure is protective.

For all arboviral diseases, public health education about reducing populations and avoiding contact with mosquito vectors is required in at-risk areas. Specific to ZIKV is the risk of microcephaly in newborns, which has led public health agencies to issue warnings for women who are currently or planning on becoming pregnant in areas suspected to have ongoing ZIKV transmission and the declaration of a Public Health Emergency of International Concern (Heymann et al. 2016). Due to the sensitive nature and implications of these warnings, it is important that levels of risk are rigorously estimated, validated, and updated. Transmission of related arboviral diseases still occurs in many areas we defined as at-risk for ZIKV, which highlights the need for improved vector control outcomes, particularly those targeting *Ae. aegypti*. Predicted levels of risk for ZIKV transmission are potentially helpful for prioritized allocation of vector control resources, as well as for differential diagnosis and, if a vaccine becomes available, delivery efforts. It should be noted that instances of ZIKV sexual transmission have been reported (Patino-Barbosa et al. 2015, Musso et al. 2015, Foy et al. 2011a). We did not incorporate secondary modes of transmission into the models we described here, but our map can help inform future discussions about the potential impact of this mode of transmission as its relative importance becomes better understood.

A great deal of basic epidemiological information specific to ZIKV is lacking. As a result, information must be leveraged from our knowledge about transmission of related arboviruses. Previous work has focused on mapping other vector borne diseases that share much of the ecology of Zika, such as DENV (Bhatt et al. 2013) and CHIKV, as well as for its primary vectors, *Ae. aegypti* and *Ae. albopictus* (Kraemer et al. 2015c). For this reason, temperature suitability for dengue (Brady et al. 2013, Brady et al. 2014) was entered into the models due to the greater number of field and laboratory studies available for parameterising this metric for DENV. Until more studies related to vector competence and temperature constraints on ZIKV transmission to

humans are conducted, this is the most accurate indicator of arboviral disease transmission *via* *Aedes* mosquitoes currently available. Indeed, all other covariates in our models could equally be applied to mapping DENV and CHIKV, and ZIKV-specific refinements to modelling covariates will be possible as the disease continues to expand to allow for improvements in future iterations of the map. The relatively smaller amount of occurrence data available for ZIKV (especially prior to recent outbreaks) means that this dataset should also be updated with new information as necessary, leading to a stronger global evidence base and improved accuracy of future maps. Better understanding of ZIKV transmission dynamics will eventually allow for further cartographic refinements to be made, such as the differentiation between endemic- and epidemic-prone areas. Still, all covariates included in the current study have been updated and refined since (Bhatt et al. 2013), and when combined with the most extensive occurrence database available for ZIKV, the resulting map we present here is currently the most accurate depiction of the distribution of environmental suitability for ZIKV. A map highlighting differences in predicted suitability for both diseases is provided in Figure 2 -- figure supplement 5.

Conclusion

In this study, we produced the first global high spatial-resolution map of environmental suitability for ZIKV transmission to humans using an assembly of known records of ZIKV occurrence and environmental covariates in a species distribution modelling framework. While it is clear that much remains to be understood about ZIKV, this first map serves as a baseline for understanding the change in the geographical distribution of this globally emerging arboviral disease. Knowledge of the potential distribution can encourage more vigilant surveillance in both humans and *Aedes* mosquito populations, as well as help in the allocation of limited resources for disease prevention. Public health awareness campaigns and advice for mitigation of individual risk can also be focused in the areas we have predicted to be highly suitable for ZIKV transmission, particularly during the first wave of infection in a population. The maps we have presented may also inform existing travel advisories for pregnant women and other travellers. The maps and underlying data are freely available online *via* figshare (http://www.figshare.com).

Methods

To map environmental suitability for ZIKV transmission to humans, we applied a species distribution modelling approach to establish a multivariate empirical relationship between the probability of ZIKV occurrence and the environmental conditions in locations where the disease has been confirmed. We employed an ensemble boosted regression trees (BRT) methodology (De'ath 2007, Elith, Leathwick and Hastie 2008), which required the generation of: (i) a comprehensive compendium of known locations of disease occurrence in humans; (ii) a set of background points representing locations where ZIKV has not yet been reported; and (iii) a set of high-resolution globally gridded environmental and socioeconomic covariates hypothesised to affect ZIKV transmission. The resulting model produces a 5km x 5km spatial-resolution global map of environmental suitability for ZIKV transmission to humans.

Assembly of the geo-referenced ZIKV occurrence dataset

Information about the locations of ZIKV occurrence in humans was extracted from peer-reviewed literature, case reports, and informal online sources following previously established protocols (Kraemer et al. 2015b, Messina et al. 2014, Messina et al. 2015a). To collate the peer-reviewed dataset, literature searches were undertaken using PubMed (http://www.ncbi.nlm.nih.gov/pubmed) and ISI Web of Science (http://www.webofknowledge.com) search engines using the search term “Zika”. No language restrictions were placed on these searches; however, only those citations with a full title and abstract were retrieved, resulting in the review of 148 references ranging in publication dates between 1951 and 2015. In-house

language skills allowed review of all English, French, Portuguese and Spanish articles for useable location information for human ZIKV occurrence. ProMED-mail (http://www.promedmail.org) was also searched using the term “Zika”, resulting in the review of 139 reports between 27 June 2007 and 18 January 2016. Additionally, the most current database of ZIKV case locations in Brazil was obtained directly from the Brazilian Ministry of Health. From all sources, only laboratory confirmation of symptomatic ZIKV infection in humans was entered into the dataset (mention of suspected cases was not entered). Serological evidence from healthy individuals could represent a past infection, with transmission potentially occurring in a different location to that where the individual currently resides (Darwish et al. 1983), or could be an artefact from possible cross-reactivity with a variety of different viruses (Smithburn et al. 1954). As a result, these less reliable diagnoses of ZIKV were excluded.

All available location information was extracted from each peer-reviewed article and ProMED case report. The site name was used together with all contextual information provided about the site to determine its latitudinal and longitudinal coordinates using Google Maps (https://www.maps.google.com). If the study site could be geo-positioned to a specific place, it was recorded as a point location. If the study site could only be identified at an administrative area level (e.g. province or district), it was recorded as a polygon along with an identifier of its administrative unit. If imported cases were reported with information on the site of infection, they were geo-positioned to this site; if imported cases were reported with no information about the site of infection, they were not entered into the dataset. Informal online data sources were collated automatically by the web-based system HealthMap (http://www.healthmap.org) as described elsewhere (Freifeld et al. 2008). Alerts for ZIKV were obtained from HealthMap for the years 2014-2016, and then manually checked for validity. In total, usable location information was extracted from 110 sources. Information was also collected about the status of symptoms in each reported occurrence, distinguishing between those where symptomatic cases were being reported, versus those where only seroprevalence was detected in healthy individuals.

Due to the potential for multiple independent reports referring to the same cases temporal and spatial standardization was required, as we have described previously in detail for dengue mapping efforts (Messina et al. 2014). In brief, an occurrence was defined as a unique location with one or more confirmed cases of ZIKV occurring within one calendar year (the finest temporal resolution available across all records). Point locations were considered to be overlapping if they lay on the same 5km x 5km pixel, and polygon locations were identified by a unique administrative unit code. Furthermore, all polygons whose geographic area was greater than one square decimal degree (approximately 111 square kilometers at the equator) were removed from the dataset to avoid averaging covariate values over very large areas, and only those occurrences comprising symptomatic individuals were retained for modelling purposes to ensure an accurate location of infection. In total, the final occurrence dataset contained 323 unique occurrences to be entered into our BRT modelling procedure. A map of the final set of occurrence locations is provided as Figure 1a.

Generation of the background location dataset

Separate maps of the relative probability of occurrence of *Ae. aegypti* and *Ae. albopictus* (Kraemer et al. 2015c) were used to compute a combined metric of the relative probability of vector occurrence, by taking the maximum value from the two layers for all 5km x 5km gridded cells globally. The inverse of this combined-*Aedes* occurrence probability layer (higher values indicating greater certainty of absence) was then used to draw a biased sample of 10,000 background locations. As such, a greater number of background points were sampled in areas where we are more certain that *Ae. aegypti* or *Ae. albopictus* do not occur, and therefore where

ZIKV is less likely to be transmitted to humans. While it has been demonstrated that predictive accuracy from presence-background species distribution models can be improved by biasing background record locations toward areas with greatest reporting probabilities (Phillips et al. 2009), information on possible reporting biases, or proxies of such spatial bias, are currently unavailable for ZIKV. These 10,000 background locations were combined with the standardized occurrence dataset to serve as comparison data locations in the BRT species distribution modelling procedure. The background locations were weighted such that their total sum was equal to the total number of occurrence locations (n=237; pseudo-absence weighting=0.0237), in order to aid in the discrimination capacity of the model (Barbet-Massin et al. 2012).

Explanatory Covariates

A set of six covariates hypothesized to influence the global distribution of ZIKV transmission to humans were used in our models to establish an empirical relationship between ZIKV presence or absence and underlying environmental conditions. These six covariates included: (i) an index of temperature suitability for dengue transmission to humans *via Ae. aegypti;* (ii) temperature suitability for dengue transmission to humans *via Ae. albopictus*; (iii) minimum relative humidity; (iv) annual cumulative precipitation; (v) an enhanced vegetation index (EVI); and (vi) urban versus rural habitat type. The underlying hypothesis behind each of the covariates is discussed in more detail below, along with a description of data sources and any processing that was undertaken before entering these covariates into our models. Maps of each covariate layer are provided in the supplementary information in Figure 1 -- figure supplement 1.

Temperature suitability for dengue transmission to humans via Ae. aegypti *or* Ae. albopictus: Temperature affects key physiological processes in *Aedes* mosquitoes, including age- and temperature-dependent adult female survival, as well as the duration of the extrinsic incubation period (EIP) of arboviruses and the length of the gonotrophic cycle (Brady et al. 2013). While these parameters have yet to be measured experimentally for ZIKV, they have been for the closely related DENV. We obtained temperature data from WorldClim v1.03 (http://www.wordclim.org), which uses historic global meteorological station data from 1961-2005 to interpolate global climate surfaces. MARKSIM software (Jones and Thornton 2000) was then used to apply the coefficients of 17 Global Climate Models (GCMs) to estimate temperature values for the year 2015. This enabled us to incorporate the quantified effects of temperature on DENV transmission into a cohort simulation model that analysed the cumulative effects of both diurnal and inter-seasonal changes in temperature on DENV transmission within an average year, both for *Ae. aegypti* and *Ae. albopictus* separately. The models were then applied to the 2015 temperature data for each 5km x 5km grid cell globally. This resulted in maps of temperature suitability for DENV transmission by either *Aedes* species ranging from 0 (no suitable days) to 1 (365 suitable days). These measures were then used as a proxy for temperature suitability for ZIKV transmission to humans.

Annual cumulative precipitation: Presence of static surface water in natural or man-made containers is a pre-requisite for *Aedes* oviposition and larval and pupal development. While fine-scale spatial and temporal heterogeneities have been observed between precipitation, vector abundance, and incidence of human DENV infections, there is evidence that areas with greater amounts of precipitation are generally associated with higher DENV infection risk (Chandy et al. 2013, Chowell and Sanchez 2006, Dom et al. 2013, Pinto et al. 2011, Restrepo, Baker and Clements 2014, Sang et al. 2014, Sankari et al. 2012, Campbell et al. 2015). Although studies that directly connect levels of precipitation to ZIKV transmission have yet to exist, we assumed for Zika a similar association of precipitation as closely related flaviruses. WorldClim v1.03

precipitation data and MARKSIM software were used as described above for temperature, to estimate annual cumulative precipitation for the year 2015 for each 5km x 5km grid cell globally.

Minimum relative humidity: Greater relative humidity has been found to promote DENV propagation in *Ae. aegypti* mosquitoes in several localized settings (Colon-Gonzalez, Lake and Bentham 2011, Thu, Aye and Thein 1998), and has also been found to be an important contributor when predicting DENV risk at a global scale (Hales et al. 2002). Therefore, we again assumed a similar association for ZIKV in the absence of any direct studies, and included the minimum annual relative humidity in our models as a potential limiting factor to ZIKV transmission. Relative humidity (RH) was calculated as a percent of saturation humidity, or the amount of water vapour required to saturate the air given a particular temperature, using the temperature data from WorldClim v1.03 described earlier. The saturation, or "dew", point (T_{dew}) was calculated using a tabular relationship (Linacre 1977). RH was then calculated as follows:

$$RH = \frac{V(T_x)}{V(T_{dew})} \times 100$$

Where $V(T_{dew}) = 611.21 \times \exp(17.502 \times \frac{\mathrm{T}}{240.97 + \mathrm{T}})$ and $V(T_x)$ is the humidity at the given temperature. We then extracted the minimum annual RH for each 5km x 5km pixel globally for the year 2015.

Enhanced Vegetation Index (EVI): A close association has been shown between local moisture supply, vegetation canopy development, and abundance of mosquito reproduction (Linthicum et al. 1999), with previous studies highlighting the importance of moisture-related measures such as relative humidity to DENV occurrence (Hales et al. 2002). Although resistant to desiccation, both *Aedes* eggs and adults require moisture to survive (Cox et al. 2007, Sota and Mogi 1992, Reiskind and Lounibos 2009, Costa et al. 2010, Luz et al. 2008), with low dry season moisture levels substantially affecting *Aedes* mortality (Russell, Kay and Shipton 2001, Trpis 1972, Luz et al. 2008). Vegetation canopy cover has previously been associated with higher *Aedes* larvae density (Fuller et al. 2009, Troyo et al. 2009, Bisset Lazcano et al. 2006, Barrera et al. 2006) by reducing evaporation from containers, decreasing sub-canopy wind speed, and protecting outdoor habitats from direct sunlight. To account for these factors, we included a 5km x 5km resolution measure of the EVI derived from NASA's Moderate Resolution Imaging Spectrometer (MODIS) imagery (Wan et al. 2002, Lin 2012), summarized from gap-filled, 8-day, 1km x 1km resolution images acquired globally for years 2000 through 2014 (Weiss et al. 2014) to produce a mean annual EVI layer. This mean EVI product is indicative of amount of photosynthesis taking place in the environment over the course of a year, which is positively correlated with the density of vegetation, and is thus a proxy for the level of moisture available given the relationship between precipitation and vegetative growth.

Urban versus rural habitat type: There is a well-established link between urban areas, some vector borne diseases, and their vectors. In particular, *Ae. aegypti* is found in close proximity to human dwellings often breeding in artificial containers (Brown et al. 2011, Powell and Tabachnick 2013, Kraemer et al. 2015c). To identify the relationship between urbanisation and ZIKV presence we adapted probabilistic spatial modelling techniques to predict the spatial distribution of global urban extents at a 5km x 5km spatial resolution. We used urban growth rates from the United Nations Population Division (Division 2014), paired with urban extents measured and tested by the Moderate Resolution Imaging Spectroradiometer Collection 5 (MODIS C5) land-cover product for Asia (Schneider et al. 2015, Schneider, Friedl and Potere 2009, Schneider, Friedl and Potere 2010). A set of spatial covariate datasets hypothesized to influence the spatial

patterns of urban expansion was generated, including the time to travel from each 5km x 5km pixel to a major city (Nelson 2008), the proportion of urbanised land within a buffer of 20 km, human population density (Linard and Tatem 2012, Stevens et al. 2015, Gaughan et al. 2013), slope (Becker et al. 2009), and distance to water (Arino et al. 2008). A BRT modelling approach was then used to predict areas that would become urban in 2015 (Linard, Tatem and Gilbert 2013). Outputs were tested against a training dataset comprising points from Asia only, and showed good overall predictive performance (AUC=0.82). The output raster is a 5km x 5km gridded surface with urban (1) vs. rural (0) pixels.

Ensemble Boosted Regression Trees approach

The boosted regression tree (BRT) modelling procedure combines regression trees with gradient boosting (Friedman 2001). In this procedure, an initial regression tree is fitted and iteratively improved upon in a forward stagewise manner (boosting) by minimising the variation in the response not explained by the model at each iteration. It has been shown to fit complicated response functions efficiently, while guarding against over-fitting by use of extensive internal cross-validation. As such, this approach has been successfully employed in the past to map dengue and its *Aedes* mosquito vectors, as well as other vector-borne diseases (Bhatt et al. 2013, Pigott et al. 2014b, Messina et al. 2015b, Kraemer et al. 2015c). To increase the robustness of model predictions and quantify model uncertainty, we fitted an ensemble (Araújo and New 2007) of 300 BRT models to separate bootstraps of the data. We then evaluated the central tendency as the mean across all 300 BRT models (Bhatt et al. 2013). Each of the 300 individual models was fitted using the gbm.step subroutine in the dismo package in the R statistical programming environment (Elith et al. 2008). All other tuning parameters of the algorithm were held at their default values (tree complexity= 4, learning rate= 0.005, bag fraction= 0.75, step size= 10, cross-validation folds=10). Each of the 300 models predicts environmental suitability on a continuous scale from 0 to 1, with a final prediction map then being generated by calculating the mean prediction across all models for each 5km x 5km pixel. Cross-validation was applied to each model, whereby ten subsets of the data comprising 10% of the presence and background observations were assessed based on their ability to predict the distribution of the other 90% of records using the mean area under the curve (AUC) statistic. This AUC value was then averaged across the ten sub-models and finally across all 300 models in the ensemble in order to derive an overall estimate of goodness-of-fit. Additionally, to avoid AUC inflation due to spatial sorting bias, a pairwise distance sampling procedure was used, resulting in a final AUC which is lower than would be returned by standard procedures but which gives a more realistic quantification of the model's ability to extrapolate predictions to new regions (Wenger and Olden 2012). We restricted our models to make predictions only within areas where either *Ae. aegypti* probability of occurrence (Kraemer et al. 2015c) is more than 0.8 or temperature is conducive to transmission for at least 355 days in an average year. A second ensemble of 300 models was executed which did not take into account temperature suitability for dengue transmission *via Ae. albopictus*, due to the uncertainty of this species as a competent ZIKV vector. The results of this ensemble of models are provided in Figure 2 -- figure supplement 3.

Population and births at risk

To calculate the number of people located in an area that is at any level of risk for ZIKV transmission, the global ZIKV environmental suitability map was combined with fine-scale global population surfaces (SEDAC 2015, WorldPop 2015). Firstly, the continuous ZIKV environmental suitability map (ranging from 0 to 1) was converted into a binary surface indicating whether there is any risk of transmission. To do this, we carried out a protocol previously used in (Pigott et al. 2015a), choosing a threshold environmental suitability value that encompasses 90% of the ZIKV

occurrence point locations. This threshold cut-off of 90% was chosen (rather than 100%) to reflect potential errors or inaccurate locations in the occurrence point dataset. Every 5km x 5km pixel in the suitability map with a value above this threshold value was considered at risk for ZIKV transmission. Finally, to estimate the population at risk, we multiplied this binary ZIKV risk map by the global population counts (aligned and aggregated to the same 5km x 5km grid) for the year 2015 and summed across all cells.

We next estimated the maximum number of births potentially affected by ZIKV in Latin America, as this region is the focus of the recent outbreak and the first to point to a possible association with microcephaly in newborn infants to mothers infected with ZIKV. In order to do this, we first identified the proportion of the year that is suitable for ZIKV transmission within areas that are predicted to be suitable in the binary ZIKV risk map. This proportion was derived from existing temperature suitability models (Brady et al. 2014, Brady et al. 2013), which predict the total number of days within an average year that arbovirus transmission can be sustained in *Ae. aegypti,* assuming there is a local human reservoir of infection. While the intra-mosquito viral dynamics in this model were parameterised for dengue virus, the limited information currently available on other arboviruses suggests that their dynamics are similar (Lambrechts et al. 2011). Using the resulting 5km x 5km map showing the proportion of the year suitable for ZIKV transmission to humans, we then multiplied this by a map (also at a 5km x 5km resolution) of the number of births in the Americas for the year 2015, updated from (Tatem et al. 2014, UNFPA 2014). The resulting map indicates the number of births in the Americas potentially at risk for ZIKV (for 2015), assuming ZIKV currently fully occupies its environmental niche and that births are evenly distributed throughout the year.

Figure Legends

Figure 1: (a) Map showing the distribution of the final set of 323 ZIKV occurrence locations entered into the ensemble Boosted Regression Tree modelling procedure. Locations are classified by year of occurrence to show those which took place (i) prior to the 2007 outbreak in Federated States of Micronesia; (ii) between 2007-2014; and (iii) during the 2015-2016 outbreak; (b) the total number of locations reporting symptomatic ZIKV occurrence in humans globally over time.

Figure 2: Maps of (a) global environmental suitability for ZIKV, ranging from 0 (grey) to 1 (red), showing greater detail for (b) the Americas, (c) Africa, and (d) Asia and Oceania.

Figure 3: Status of ZIKV reporting as of 2016 by country, showing countries that are highly environmentally suitable (having a suitable area of more than 10,000 square kilometres) but which have not yet reported symptomatic cases of ZIKV in humans. “Currently reporting” countries are those having reported cases since 2015.

Supplementary information:

Mapping global environmental suitability for Zika virus

Messina, J.P.[1], Kraemer, M.U.G.[1], Brady, O.J.[2], Pigott, D.M.[2,3], Shearer, F.[2], Weiss, D.J.[1], Golding, N.[4], Ruktanonchai, C.W.[5], Gething, P.W.[1], Cohn, E.[6], Brownstein, J.S.[6], Khan, K.[7,8], Tatem, A.J.[5,9], Jaenisch, T.[10,11], Murray, C.J.L.[3], Marinho, F.[12], Scott, T.W.[13], Hay, S.I.[2,3]

14 Department of Zoology, University of Oxford; Oxford, UK
15 Wellcome Trust Centre for Human Genetics, University of Oxford; Oxford, UK
16 Institute for Health Metrics and Evaluation, University of Washington; Seattle, WA, USA
17 Department of BioSciences, University of Melbourne; Parkville, VIC, Australia
18 WorldPop project, Department of Geography and Environment, University of Southampton; Southampton, UK
19 Boston Children’s Hospital, Harvard Medical School; Boston, MA, USA
20 Department of Medicine, Division of Infectious Diseases, University of Toronto; Toronto, Canada
21 Li Ka Shing Knowledge Institute, St Michael's Hospital; Toronto, Canada
22 Flowminder Foundation; Stockholm, Sweden
23 Section Clinical Tropical Medicine, Department for Infectious Diseases, Heidelberg University Hospital; Heidelberg, Germany
24 German Centre for Infection Research (DZIF), Heidelberg partner site; Heidelberg, Germany
25 Secretariat of Health Surveillance, Ministry of Health of Brazil
26 Department of Entomology and Nematology, University of California Davis; Davis, CA, USA

Figure 1 -- figure supplement 1

Maps of all covariates entered into the 300 BRT models: (a) probability of being urban, 2015; (b) enhanced vegetation index; (c) minimum relative humidity; (d) cumulative annual precipitation (mm); (e) temperature suitability for dengue *via Ae. aegypti*; (f) temperature suitability for dengue *via Ae. albopictus*

Figure 2 -- figure supplement 1

Uncertainty around Zika suitability predictions displayed in main manuscript – Figure 2, ranging from less than 0.01 (very little uncertainty) to 0.94 (greatest uncertainty).

Figure 2 -- figure supplement 2

Effect plots for each covariate entered into the ensemble of 300 BRT models: (a) minimum relative humidity; (b) cumulative annual precipitation (mm); (c) enhanced vegetation index; (d) probability of being urban (%); (e) temperature suitability for dengue *via Ae. aegypti*; (f) temperature suitability for dengue *via Ae. albopictus*

Figure 2 -- figure supplement 3

Environmental suitability for Zika virus transmission to humans, not taking into account temperature suitability for dengue *via Aedes albopictus*. Covariate effects are as follows: cumulative annual precipitation (67.4%); temperature suitability for dengue *via Ae.* aegypti (16.9%); probability of being urban, 2015 (8.2%); enhanced vegetation index (5.1%); minimum relative humidity (2.4%).

Figure 2 -- figure supplement 4

Map showing areas predicted to have greater dengue suitability (from Bhatt *et al.* 2013, Nature) vs. those which are predicted to have greater Zika suitability in the current study. These values are restricted to areas where both diseases had non-zero predictions.

Tables

Region/Country	Population living in areas suitable for ZIKV transmission (millions)
Africa	**452.58**
Nigeria	111.97
Democratic Republic of the Congo	68.95
Uganda	33.43
United Republic of Tanzania	22.70
Americas	**298.36**
Brazil	120.65
Mexico	32.22
Colombia	29.54
Venezuela	22.22
Asia	**1,422.13**
India	413.19
Indonesia	226.04
China	213.84
Bangladesh	133.29
World	***2,173.27***

Table 1. Population living in areas suitable for ZIKV transmission within each major world region and top four countries contributing to these populations at risk.

Competing Interests

SIH: Reviewing editor, eLife.

Funding

The other authors declare that no competing interests exist.

Acknowledgements

We thank the Secretariat of Health Surveillance, Ministry of Health of Brazil for providing access to the geographical coordinates of occurrence. J.P.M., M.U.G.K., and T.J. receive, and O.J.B. and S.I.H. acknowledge funding from the International research Consortium on Dengue Risk Assessment Management and Surveillance (IDAMS; European Commission 7th Framework Programme (21893)). O.J.B. and S.I.H. are supported by the Bill & Melinda Gates Foundation (OPP1053338). SIH is also funded by a Senior Research Fellowship from the Wellcome Trust (095066), and grants from the Bill & Melinda Gates Foundation (OPP1119467, OPP1106023 and OPP1093011). D.M.P. is also funded by the Bill & Melinda Gates Foundation (OPP1093011). D.J.W. and P.W.G. receive support from the Bill and Melinda Gates Foundation (OPP1068048, OPP1106023). N.G. is supported by a University of Melbourne McKenzie fellowship. C.W.R. is funded through the University of Southampton's Economic and Social Research Council's Doctoral Training Centre. T.W.S. is supported by grants from the National Institutes of Health (P01AI098670) and the Bill and Melinda Gates Foundation (OPP1081737). E.C. and J.S.B. are supported by the National Library of Medicine of the National Institutes of Health (R01LM010812).

References

Araújo, M. B. & M. New (2007) Ensemble forecasting of species distributions. *Trends Ecol Evol,* 22**,** 42-47.

Arino, O., P. Bicheron, F. Achard, J. Latham, R. Witt & J. L. Weber (2008) GLOBCOVER The most detailed portrait of Earth. *ESA Bulletin***,** 24-31.

Barbet-Massin, M., F. Jiguet, C. H. Albert & W. Thuiller (2012) Selecting pseudo-absences for species distribution models: how, where and how many? *Methods Ecol Evol,* 3**,** 327-338.

Barrera, R., M. Amador & G. G. Clark (2006) Use of the pupal survey technique for measuring *Aedes aegypti (Diptera: Culicidae)* productivity in Puerto Rico. *Am J Trop Med Hyg,* 74**,** 290-302.

Becker, J. J., D. T. Sandwell, W. H. F. Smith, J. Braud, B. Binder, J. Depner, D. Fabre, J. Factor, S. Ingalls, S. H. Kim, R. Ladner, K. Marks, S. Nelson, A. Pharaoh, R. Trimmer, J. Von Rosenberg, G. Wallace & P. Weatherall (2009) Global bathymetry and elevation data at 30 arc seconds resolution: SRTM30_PLUS. *Mar Geod,* 32**,** 355-371.

Benedict, M. Q., R. S. Levine, W. A. Hawley & L. P. Lounibos (2007) Spread of the tiger: global risk of invasion by the mosquito *Aedes albopictus*. *Vector Borne Zoonotic Dis,* 7**,** 76-85.

Bhatt, S., P. W. Gething, O. J. Brady, J. P. Messina, A. W. Farlow, C. L. Moyes, J. M. Drake, J. S. Brownstein, A. G. Hoen, O. Sankoh, M. F. Myers, D. B. George, T. Jaenisch, G. R. Wint, C. P. Simmons, T. W. Scott, J. J. Farrar & S. I. Hay (2013) The global distribution and burden of dengue. *Nature,* 496**,** 504-507.

Bisset Lazcano, J. A., M. C. Marquetti, R. Portillo, M. M. Rodríguez, S. Suárez & M. Leyva (2006) Ecological factors linked to the presence of *Aedes aegypti* larvae in highly infested areas of Playa, a municipality belonging to Ciudad de La Habana, Cuba. *Rev Pan Salud Pub,* 19**,** 379-384.

Bogoch, II, O. J. Brady, M. U. Kraemer, M. German, M. I. Creatore, M. A. Kulkarni, J. S. Brownstein, S. R. Mekaru, S. I. Hay, E. Groot, A. Watts & K. Khan (2016) Anticipating the international spread of Zika virus from Brazil. *Lancet,* 387**,** 335-6.

Brady, O. J., N. Golding, D. M. Pigott, M. U. Kraemer, J. P. Messina, R. C. Reiner, Jr., T. W. Scott, D. L. Smith, P. W. Gething & S. I. Hay (2014) Global temperature constraints on Aedes aegypti and Ae. albopictus persistence and competence for dengue virus transmission. *Parasit Vectors,* 7**,** 338.

Brady, O. J., M. A. Johansson, C. A. Guerra, S. Bhatt, N. Golding, D. M. Pigott, H. Delatte, M. G. Grech, P. T. Leisnham, R. Maciel-de-Freitas, L. M. Styer, D. L. Smith, T. W. Scott, P. W. Gething & S. I. Hay (2013) Modelling adult *Aedes aegypti* and *Aedes albopictus* survival at different temperatures in laboratory and field settings. *Parasit Vectors,* 6**,** 351.

Brown, J. E., C. S. McBride, P. Johnson, S. Ritchie, C. Paupy, H. Bossin, J. Lutomiah, I. Fernandez-Salas, A. Ponlawat, A. J. Cornel, W. C. t. Black, N. Gorrochotegui-Escalante, L. Urdaneta-Marquez, M. Sylla, M. Slotman, K. O. Murray, C. Walker & J. R. Powell (2011) Worldwide patterns of genetic differentiation imply multiple 'domestications' of *Aedes aegypti*, a major vector of human diseases. *Proc Biol Sci,* 278**,** 2446-54.

Campbell, K. M., K. Haldeman, C. Lehnig, C. V. Munayco, E. S. Halsey, V. A. Laguna-Torres, M. Yagui, A. C. Morrison, C. D. Lin & T. W. Scott (2015) Weather regulates location, timing, and intensity of dengue virus transmission between humans and mosquitoes. *PLoS Negl Trop Dis,* 9**,** e0003957.

Chandy, S., K. Ramanathan, A. Manoharan, D. Mathai & K. Baruah (2013) Assessing effect of climate on the incidence of dengue in Tamil Nadu. *Indian J Med Microbiol,* 31**,** 283-6.

Chowell, G. & F. Sanchez (2006) Climate-based descriptive models of dengue fever: the 2002 epidemic in Colima, Mexico. *J Environ Health,* 68**,** 40-4, 55.

Colon-Gonzalez, F. J., I. R. Lake & G. Bentham (2011) Climate variability and dengue fever in warm and humid Mexico. *Am J Trop Med Hyg,* 84**,** 757-63.

Costa, E. A. P. A., E. M. M. Santos, J. C. Correia & C. M. R. Albuquerque (2010) Impact of small variations in temperature and humidity on the reproductive activity and survival of *Aedes aegypti (Diptera, Culicidae)*. *Rev Bras Entomol,* 54**,** 488-493.

Cox, J., M. E. Grillet, O. M. Ramos, M. Amador & R. Barrera (2007) Habitat segregation of dengue vectors along an urban environmental gradient. *Am J Trop Med Hyg,* 76**,** 820-826.

Dakar, I. P. d. 1999. WHO collaborating center for reference and research on arboviruses and hemorrhagic fever viruses: Annual report. 143p. Dakar, Senegal.

Darwish, M. A., H. Hoogstraal, T. J. Roberts, I. P. Ahmed & F. Omar (1983) A sero-epidemiological survey for certain arboviruses (Togaviridae) in Pakistan. *Trans R Soc Trop Med Hyg,* 77**,** 442-5.

De'ath, G. (2007) Boosted trees for ecological modeling and prediction. *Ecology,* 88**,** 243-251.

Dick, G. W., S. F. Kitchen & A. J. Haddow (1952) Zika virus. I. Isolations and serological specificity. *Trans R Soc Trop Med Hyg,* 46**,** 509-20.

Division, U. N. P. 2014. World urbanization prospects: the 2014 revision. New York.

Dom, N. C., A. Ahmad, Z. Abd Latif, R. Ismail & B. Pradhan (2013) Coupling of remote sensing data and environmental-related parameters for dengue transmission risk assessment in Subang Jaya, Malaysia. *Geocarto International,* 28**,** 258-272.

Elith, J. & J. R. Leathwick (2009) Species distribution models: ecological explanation and prediction across space and time. *Annu Rev Ecol Evol S,* 40**,** 677-697.

Elith, J., J. R. Leathwick & T. Hastie (2008) A working guide to boosted regression trees. *J Anim Ecol,* 77**,** 802-13.

Faria, N. R., R. D. Azevedo, M. U. Kraemer, R. Souza, M. S. Cunha, S. C. Hill, J. Theze, M. B. Bonsall, T. A. Bowden, I. Rissanen, I. M. Rocco, J. S. Nogueira, A. Y. Maeda, F. G. Vasami, F. L. Macedo, A. Suzuki, S. G. Rodrigues, A. C. Cruz, B. T. Nunes, D. B. Medeiros, D. S. Rodrigues, A. L. Nunes Queiroz, E. V. Silva, D. F. Henriques, E. S. Travassos da Rosa, C. S. de Oliveira, L. C. Martins, H. B. Vasconcelos, L. M. Casseb, D. B. Simith, J. P. Messina, L. Abade, J. Lourenco, L. C. Alcantara, M. M. Lima, M. Giovanetti, S. I. Hay, R. S. de Oliveira, P. D. Lemos, L. F. Oliveira, C. P. de Lima, S. P. da Silva, J. M. Vasconcelos, L. Franco, J. F. Cardoso, J. L. Vianez-Junior, D. Mir, G. Bello, E. Delatorre, K. Khan, M. Creatore, G. E. Coelho, W. K. de Oliveira, R. Tesh, O. G. Pybus, M. R. Nunes & P. F. Vasconcelos (2016) Zika virus in the Americas: Early epidemiological and genetic findings. *Science*.

Faye, O., A. Dupressoir, M. Weidmann, M. Ndiaye & A. Alpha Sall (2008) One-step RT-PCR for detection of Zika virus. *J Clin Virol,* 43**,** 96-101.

Foy, B. D., K. C. Kobylinski, J. L. Chilson Foy, B. J. Blitvich, A. Travassos da Rosa, A. D. Haddow, R. S. Lanciotti & R. B. Tesh (2011a) Probable non-vector-borne transmission of Zika virus, Colorado, USA. *Emerg Infect Dis,* 17**,** 880-2.

Foy, B. D., K. C. Kobylinski, J. L. C. Foy, B. J. Blitvich, A. T. da Rosa, A. D. Haddow, R. S. Lanciotti & R. B. Tesh (2011b) Probable non–vector-borne transmission of Zika virus, Colorado, USA. *Emerging Infectious Diseases,* 17**,** 880.

Freifeld, C. C., K. D. Mandl, B. Y. Reis & J. S. Brownstein (2008) HealthMap: global infectious disease monitoring through automated classification and visualization of internet media reports. *J Am Med Inform Assoc,* 15**,** 150-7.

Friedman, J. H. (2001) Greedy function approximation: a gradient boosting machine. *Ann Stat,* 29**,** 1189-1232.

744 Fuller, D., A. Troyo & J. Beier (2009) El Niño southern oscillation and vegetation dynamics as
745 predictors of dengue fever cases in Costa Rica. *Environ Res Lett,* 4**,** 014011.
746 Gaughan, A. E., F. R. Stevens, C. Linard, P. Jia & A. J. Tatem (2013) High resolution population
747 distribution maps for Southeast Asia in 2010 and 2015. *PLoS One,* 8**,** e55882.
748 Grard, G., M. Caron, I. M. Mombo, D. Nkoghe, S. Mboui Ondo, D. Jiolle, D. Fontenille, C. Paupy & E.
749 M. Leroy (2014) Zika virus in Gabon (Central Africa)–2007: a new threat from *Aedes*
750 *albopictus*. *PloS Negl Trop Dis,* 8**,** e2681.
751 Gubler, D. J. & G. G. Clark (1995) Dengue/dengue hemorrhagic fever: the emergence of a global
752 health problem. *Emerg Infect Dis,* 1**,** 55-7.
753 Haddow, A. D., A. J. Schuh, C. Y. Yasuda, M. R. Kasper, V. Heang, R. Huy, H. Guzman, R. B. Tesh &
754 S. C. Weaver (2012) Genetic characterization of Zika virus strains: geographic expansion of
755 the Asian lineage. *PLoS Negl Trop Dis,* 6.
756 Hales, S., N. de Wet, J. Maindonald & A. Woodward (2002) Potential effect of population and climate
757 changes on global distribution of dengue fever: an empirical model. *Lancet,* 360**,** 830-4.
758 Hay, S. I., K. E. Battle, D. M. Pigott, D. L. Smith, C. L. Moyes, S. Bhatt, J. S. Brownstein, N. Collier, M.
759 F. Myers, D. B. George & P. W. Gething (2013) Global mapping of infectious disease. *Philos*
760 *Trans R Soc Lond B Biol Sci,* 368**,** 20120250.
761 Hay, S. I., A. J. Tatem, A. J. Graham, S. J. Goetz & D. J. Rogers (2006) Global environmental data for
762 mapping infectious disease distribution. *Adv Parasitol,* 62**,** 37-77.
763 Hennessey, M., M. Fischer & J. E. Staples (2016) Zika virus spreads to new areas - region of the
764 Americas, May 2015-January 2016. *Morb Mortal Wkly Rep,* 65**,** 55-8.
765 Heymann, D. L., A. Hodgson, A. A. Sall, D. O. Freedman, J. E. Staples, F. Althabe, K. Baruah, G.
766 Mahmud, N. Kandun, P. F. C. Vasconcelos, S. Bino & K. U. Menon (2016) Zika virus and
767 microcephaly: why is this situation a PHEIC? *Lancet*.
768 ICTV. 2014. Virus taxonomy: 2014 release. ed. I. C. o. Taxonomy.
769 Jones, P. G. & P. K. Thornton (2000) MarkSim: Software to generate daily weather data for Latin
770 America and Africa. *Agronomy Journal,* 92**,** 445-453.
771 Kraemer, M. U., S. I. Hay, D. M. Pigott, D. L. Smith, G. R. Wint & N. Golding (2016) Progress and
772 challenges in infectious disease cartography. *Trends Parasitol,* 32**,** 19-29.
773 Kraemer, M. U., T. A. Perkins, D. A. Cummings, R. Zakar, S. I. Hay, D. L. Smith & R. C. Reiner, Jr.
774 (2015a) Big city, small world: density, contact rates, and transmission of dengue across
775 Pakistan. *J R Soc Interface,* 12**,** 20150468.
776 Kraemer, M. U., M. E. Sinka, K. A. Duda, A. Mylne, F. M. Shearer, O. J. Brady, J. P. Messina, C. M.
777 Barker, C. G. Moore, R. G. Carvalho, G. E. Coelho, W. Van Bortel, G. Hendrickx, F.
778 Schaffner, G. R. Wint, I. R. Elyazar, H. J. Teng & S. I. Hay (2015b) The global compendium of
779 *Aedes aegypti* and *Ae. albopictus* occurrence. *Sci Data,* 2**,** 150035.
780 Kraemer, M. U., M. E. Sinka, K. A. Duda, A. Q. Mylne, F. M. Shearer, C. M. Barker, C. G. Moore, R.
781 G. Carvalho, G. E. Coelho, W. Van Bortel, G. Hendrickx, F. Schaffner, I. R. Elyazar, H. J.
782 Teng, O. J. Brady, J. P. Messina, D. M. Pigott, T. W. Scott, D. L. Smith, G. R. Wint, N.
783 Golding & S. I. Hay (2015c) The global distribution of the arbovirus vectors *Aedes aegypti* and
784 *Ae. albopictus*. *eLife,* 4**,** e08347.
785 Kutsuna, S., Y. Kato, M. L. Moi, A. Kotaki, M. Ota, K. Shinohara, T. Kobayashi, K. Yamamoto, Y.
786 Fujiya & M. Mawatari (2015) Autochthonous dengue fever, Tokyo, Japan, 2014. *Emerg Infect*
787 *Dis,* 21**,** 517.
788 Lambrechts, L., K. P. Paaijmans, T. Fansiri, L. B. Carrington, L. D. Kramer, M. B. Thomas & T. W.
789 Scott (2011) Impact of daily temperature fluctuations on dengue virus transmission by Aedes
790 aegypti. *Proceedings of the National Academy of Sciences of the United States of America,*
791 108**,** 7460-7465.
792 Lin, Q. H. 2012. Enhanced vegetation index using moderate resolution imaging spectroradiometers.
793 In *5th International Congress on Image and Signal Processing (CISP)*, 1043-1046.
794 Linacre, E. T. (1977) Simple formula for estimating evaporation rates in various climates using
795 temperature data alone. *Agr Meteorol,* 18**,** 409-424.
796 Linard, C. & A. J. Tatem (2012) Large-scale spatial population databases in infectious disease
797 research. *Int J Health Geogr,* 11**,** 7.
798 Linard, C., A. J. Tatem & M. Gilbert (2013) Modelling spatial patterns of urban growth in Africa. *Appl*
799 *Geogr,* 44**,** 23-32.
800 Linthicum, K. J., A. Anyamba, C. J. Tucker, P. W. Kelley, M. F. Myers & C. J. Peters (1999) Climate
801 and satellite indicators to forecast Rift Valley fever epidemics in Kenya. *Science,* 285**,** 397-
802 400.

Luz, C., M. Tai, A. Santos & H. Silva (2008) Impact of moisture on survival of *Aedes aegypti* eggs and ovicidal activity of Metarhizium anisopliae under laboratory conditions. *Mem Inst Oswaldo Cruz,* 103**,** 214-215.

Marchette, N., R. Garcia & A. Rudnick (1969) Isolation of Zika virus from *Aedes aegypti* mosquitoes in Malaysia. *Am J Trop Med Hyg,* 18**,** 411-415.

Marcondes, C. B. & M. d. F. F. d. Ximenes (2015) Zika virus in Brazil and the danger of infestation by *Aedes* (Stegomyia) mosquitoes. *Rev Soc Bras Med Trop***,** 0-0.

McCarthy, M. (2016) First US case of Zika virus infection is identified in Texas. *BMJ,* 352**,** i212.

Messina, J. P., O. J. Brady, D. M. Pigott, J. S. Brownstein, A. G. Hoen & S. I. Hay (2014) A global compendium of human dengue occurrence: 1960-2012. *Sci Data,* 1:140004.

Messina, J. P., D. M. Pigott, K. A. Duda, J. S. Brownstein, M. F. Myers, D. B. George & S. I. Hay (2015a) A global compendium of human Crimean-Congo haemorrhagic fever virus occurrence. *Sci Data,* 2**,** 150016

Messina, J. P., D. M. Pigott, N. Golding, K. A. Duda, J. S. Brownstein, D. J. Weiss, H. Gibson, T. P. Robinson, M. Gilbert, G. R. William Wint, P. A. Nuttall, P. W. Gething, M. F. Myers, D. B. George & S. I. Hay (2015b) The global distribution of Crimean-Congo hemorrhagic fever. *Trans R Soc Trop Med Hyg,* 109**,** 503-13.

Monlun, E., H. Zeller, B. Le Guenno, M. Traore-Lamizana, J. Hervy, F. Adam, L. Ferrara, D. Fontenille, R. Sylla & M. Mondo (1992) Surveillance of the circulation of arbovirus of medical interest in the region of eastern Senegal. *Bull Soc Path Exot,* 86**,** 21-28.

Morrison, A. C., E. Zielinski-Gutierrez, T. W. Scott & R. Rosenberg (2008) Defining challenges and proposing solutions for control of the virus vector *Aedes aegypti*. *PLoS Med,* 5**,** e68.

Murray, C. J., R. M. Barber, K. J. Foreman, A. Abbasoglu Ozgoren, F. Abd-Allah, S. F. Abera, V. Aboyans, J. P. Abraham, I. Abubakar, L. J. Abu-Raddad, N. M. Abu-Rmeileh, T. Achoki, I. N. Ackerman, Z. Ademi, A. K. Adou, J. C. Adsuar, A. Afshin, E. E. Agardh, S. S. Alam, D. Alasfoor, M. I. Albittar, M. A. Alegretti, Z. A. Alemu, R. Alfonso-Cristancho, S. Alhabib, R. Ali, F. Alla, P. Allebeck, M. A. Almazroa, U. Alsharif, E. Alvarez, N. Alvis-Guzman, A. T. Amare, E. A. Ameh, H. Amini, W. Ammar, H. R. Anderson, B. O. Anderson, C. A. Antonio, P. Anwari, J. Arnlov, V. S. Arsic Arsenijevic, A. Artaman, R. J. Asghar, R. Assadi, L. S. Atkins, M. A. Avila, B. Awuah, V. F. Bachman, A. Badawi, M. C. Bahit, K. Balakrishnan, A. Banerjee, S. L. Barker-Collo, S. Barquera, L. Barregard, L. H. Barrero, A. Basu, S. Basu, M. O. Basulaiman, J. Beardsley, N. Bedi, E. Beghi, T. Bekele, M. L. Bell, C. Benjet, D. A. Bennett, I. M. Bensenor, H. Benzian, E. Bernabe, A. Bertozzi-Villa, T. J. Beyene, N. Bhala, A. Bhalla, Z. A. Bhutta, K. Bienhoff, B. Bikbov, S. Biryukov, J. D. Blore, C. D. Blosser, F. M. Blyth, M. A. Bohensky, I. W. Bolliger, B. Bora Basara, N. M. Bornstein, D. Bose, S. Boufous, R. R. Bourne, L. N. Boyers, M. Brainin, C. E. Brayne, A. Brazinova, N. J. Breitborde, H. Brenner, A. D. Briggs, P. M. Brooks, J. C. Brown, T. S. Brugha, R. Buchbinder, G. C. Buckle, et al. (2015) Global, regional, and national disability-adjusted life years (DALYs) for 306 diseases and injuries and healthy life expectancy (HALE) for 188 countries, 1990-2013: quantifying the epidemiological transition. *Lancet,* 386**,** 2145-91.

Murray, N. E., M. B. Quam & A. Wilder-Smith (2013) Epidemiology of dengue: past, present and future prospects. *Clin Epidemiol,* 5**,** 299-309.

Musso, D., C. Roche, E. Robin, T. Nhan, A. Teissier & V. M. Cao-Lormeau (2015) Potential sexual transmission of Zika virus. *Emerg Infect Dis,* 21**,** 359-61.

Mylne, A. Q., D. M. Pigott, J. Longbottom, F. Shearer, K. A. Duda, J. P. Messina, D. J. Weiss, C. L. Moyes, N. Golding & S. I. Hay (2015) Mapping the zoonotic niche of Lassa fever in Africa. *Trans R Soc Trop Med Hyg,* 109**,** 483-92.

Nelson, A. 2008. Travel time to major cities: a global map of accessibility ed. G. E. M. U.-J. R. C. o. t. E. Commission. Ispra, Italy.

Nunes, M. R., N. R. Faria, J. M. de Vasconcelos, N. Golding, M. U. Kraemer, L. F. de Oliveira, S. Azevedo Rdo, D. E. da Silva, E. V. da Silva, S. P. da Silva, V. L. Carvalho, G. E. Coelho, A. C. Cruz, S. G. Rodrigues, J. L. Vianez, Jr., B. T. Nunes, J. F. Cardoso, R. B. Tesh, S. I. Hay, O. G. Pybus & P. F. Vasconcelos (2015) Emergence and potential for spread of Chikungunya virus in Brazil. *BMC Med,* 13**,** 102.

Patino-Barbosa, A. M., I. Medina, A. F. Gil-Restrepo & A. J. Rodriguez-Morales (2015) Zika: another sexually transmitted infection? *Sex Transm Infect,* 91**,** 359.

Phillips, S. J., M. Dudik, J. Elith, C. H. Graham, A. Lehmann, J. Leathwick & S. Ferrier (2009) Sample selection bias and presence-only distribution models: implications for background and pseudo-absence data. *Ecol Appl,* 19**,** 181-197.

Pigott, D. M., S. Bhatt, N. Golding, K. A. Duda, K. E. Battle, O. J. Brady, J. P. Messina, Y. Balard, P. Bastien, F. Pratlong, J. S. Brownstein, C. Freifeld, S. Mekaru, P. Gething, D. George, M. Myers, R. Reithinger & S. I. Hay (2014a) Global distribution maps of the Leishmaniases. *eLife,* in press.

Pigott, D. M., S. Bhatt, N. Golding, K. A. Duda, K. E. Battle, O. J. Brady, J. P. Messina, Y. Balard, P. Bastien, F. Pratlong, J. S. Brownstein, C. C. Freifeld, S. R. Mekaru, P. W. Gething, D. B. George, M. F. Myers, R. Reithinger & S. I. Hay (2014b) Global distribution maps of the Leishmaniases. *eLife,* 3.

Pigott, D. M., N. Golding, A. Mylne, Z. Huang, D. J. Weiss, O. J. Brady, M. U. Kraemer & S. I. Hay (2015a) Mapping the zoonotic niche of Marburg virus disease in Africa. *Trans R Soc Trop Med Hyg,* 109**,** 366-78.

Pigott, D. M., R. E. Howes, A. Wiebe, K. E. Battle, N. Golding, P. W. Gething, S. F. Dowell, T. H. Farag, A. J. Garcia, A. M. Kimball, L. K. Krause, C. H. Smith, S. J. Brooker, H. H. Kyu, T. Vos, C. J. Murray, C. L. Moyes & S. I. Hay (2015b) Prioritising infectious disease mapping. *PLoS Negl Trop Dis,* 9**,** e0003756.

Pinto, E., M. Coelho, L. Oliver & E. Massad (2011) The influence of climate variables on dengue in Singapore. *Int J Environ Health Res,* 21**,** 415-26.

Pond, W. L. (1963) Arthropod-borne virus antibodies in sera from residents of South-East Asia. *Trans R Soc Trop Med Hyg,* 57**,** 364-371.

Powell, J. R. & W. J. Tabachnick (2013) History of domestication and spread of *Aedes aegypti*--a review. *Mem Inst Oswaldo Cruz,* 108 Suppl 1**,** 11-7.

Reiskind, M. & L. Lounibos (2009) Effects of intraspecific larval competition on adult longevity in the mosquitoes *Aedes aegypti* and *Aedes albopictus*. *Med Vet Entomol,* 23**,** 62-68.

Restrepo, A. C., P. Baker & A. C. Clements (2014) National spatial and temporal patterns of notified dengue cases, Colombia 2007-2010. *Trop Med Int Health,* 19**,** 863-71.

Roiz, D., P. Boussès, F. Simard, C. Paupy & D. Fontenille (2015) Autochthonous chikungunya transmission and extreme climate events in southern France. *PLoS Negl Trop Dis,* 9**,** e0003854.

Russell, B., B. Kay & W. Shipton (2001) Survival of *Aedes aegypti* (Diptera: Culicidae) eggs in surface and subterranean breeding sites during the northern Queensland dry season. *J Med Entomol,* 38**,** 441-445.

Salje, H., S. Cauchemez, M. T. Alera, I. Rodriguez-Barraquer, B. Thaisomboonsuk, A. Srikiatkhachorn, C. B. Lago, D. Villa, C. Klungthong, I. A. Tac-An, S. Fernandez, J. M. Velasco, V. G. Roque, Jr., A. Nisalak, L. R. Macareo, J. W. Levy, D. Cummings & I. K. Yoon (2016) Reconstruction of 60 years of chikungunya epidemiology in the Philippines demonstrates episodic and focal transmission. *J Infect Dis,* 213**,** 604-10.

Sang, S. W., W. W. Yin, P. Bi, H. L. Zhang, C. G. Wang, X. B. Liu, B. Chen, W. Z. Yang & Q. Y. Liu (2014) Predicting local dengue transmission in Guangzhou, China, through the influence of imported cases, mosquito density and climate variability. *PLoS One,* 9.

Sankari, T., S. L. Hoti, T. B. Singh & J. Shanmugavel (2012) Outbreak of dengue virus serotype-2 (DENV-2) of Cambodian origin in Manipur, India - association with meteorological factors. *Indian J Med Res,* 136**,** 649-55.

Schneider, A., M. A. Friedl & D. Potere (2009) A new map of global urban extent from MODIS satellite data. *Environmental Research Letters,* 4.

--- (2010) Mapping global urban areas using MODIS 500-m data: New methods and datasets based on 'urban ecoregions'. *Remote Sensing of Environment,* 114**,** 1733-1746.

Schneider, A., C. M. Mertes, A. J. Tatem, B. Tan, D. Sulla-Menashe, S. J. Graves, N. N. Patel, J. A. Horton, A. E. Gaughan, J. T. Rollo, I. H. Schelly, F. R. Stevens & A. Dastur (2015) A new urban landscape in East-Southeast Asia, 2000-2010. *Environmental Research Letters,* 10.

Scott, T. W. & W. Takken (2012) Feeding strategies of anthropophilic mosquitoes result in increased risk of pathogen transmission. *Trends Parasitol,* 28**,** 114-21.

SEDAC. 2015. Gridded Population of the World, v4 (GPWv4). Socio-economic Data and Applications Center.

Smithburn, K. (1954) Neutralizing antibodies against arthropod-borne viruses in the sera of long-time residents of Malaya and Borneo. *Am J Epidemiol,* 59**,** 157-163.

Smithburn, K., R. M. Taylor, F. Rizk & A. Kader (1954) Immunity to certain arthropod-borne viruses among indigenous residents of Egypt. *Am J Trop Med Hyg,* 3**,** 9-18.

Sorichetta, A., G. M. Hornby, F. R. Stevens, A. E. Gaughan, C. Linard & A. J. Tatem (2015) High-resolution gridded population datasets for Latin America and the Caribbean in 2010, 2015, and 2020. *Sci Data,* 2**,** 150045.

Sota, T. & M. Mogi (1992) Interspecific variation in desiccation survival time of *Aedes (Stegomyia)* mosquito eggs is correlated with habitat and egg size. *Oecologia,* 90**,** 353-358.

Stevens, F. R., A. E. Gaughan, C. Linard & A. J. Tatem (2015) Disaggregating census data for population mapping using random forests with remotely-sensed and ancillary data. *PLoS One,* 10**,** e0107042.

Stoddard, S. T., B. M. Forshey, A. C. Morrison, V. A. Paz-Soldan, G. M. Vazquez-Prokopec, H. Astete, R. C. Reiner, S. Vilcarromero, J. P. Elder, E. S. Halsey, T. J. Kochel, U. Kitron & T. W. Scott (2013) House-to-house human movement drives dengue virus transmission. *Proc Natl Acad Sci USA,* 110**,** 994-999.

Tatem, A. J., J. Campbell, M. Guerra-Arias, L. de Bernis, A. Moran & Z. Matthews (2014) Mapping for maternal and newborn health: the distributions of women of childbearing age, pregnancies and births. *Int J Health Geogr,* 13**,** 2.

Thu, H. M., K. M. Aye & S. Thein (1998) The effect of temperature and humidity on dengue virus propagation in *Aedes aegypti* mosquitos. *Southeast Asian J Trop Med Public Health,* 29**,** 280-4.

Troyo, A., D. O. Fuller, O. Calderón-Arguedas, M. E. Solano & J. C. Beier (2009) Urban structure and dengue incidence in Puntarenas, Costa Rica. *Singapore J Trop Geog,* 30**,** 265-282.

Trpis, M. (1972) Dry season survival of *Aedes aegypti* eggs in various breeding sites in the Dar es Salaam area, Tanzania. *Bull World Health Org,* 47**,** 433.

UNFPA, U. N. P. F. 2014. The state of the world's midwifery 2014: a universal pathway, a woman's right to health.

Wan, Z. M., Y. L. Zhang, Q. C. Zhan & Z. L. Li (2002) The MODIS land-surface temperature products for regional environmental monitoring and global change studies. *Int Geosci Remote Se***,** 3683-3685.

Weaver, S. C. & W. K. Reisen (2010) Present and future arboviral threats. *Antiviral Res,* 85**,** 328-45.

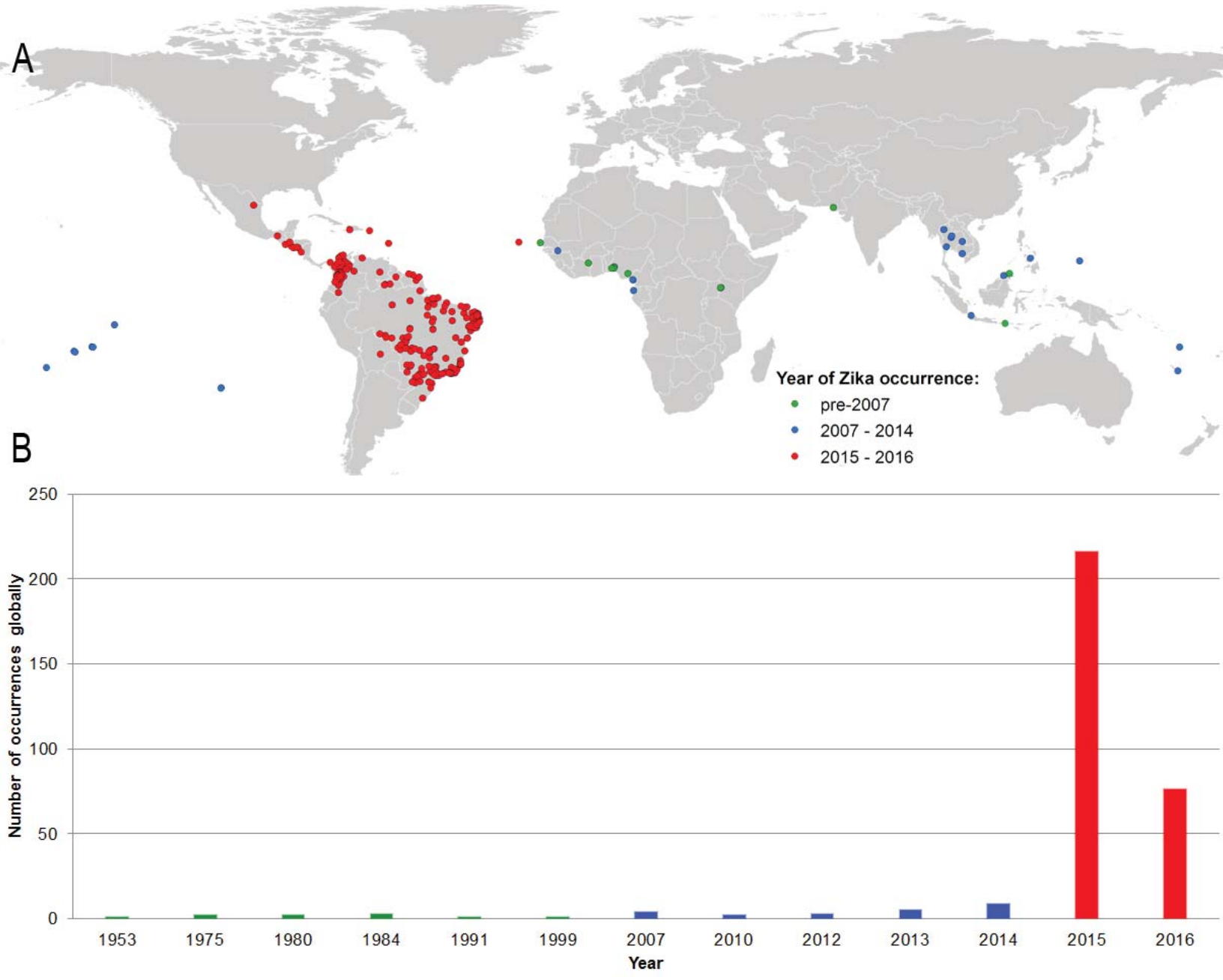
Weiss, D. J., P. M. Atkinson, S. Bhatt, B. Mappin, S. I. Hay & P. W. Gething (2014) An effective approach for gap-filling continental scale remotely sensed time-series. *Isprs Journal of Photogrammetry and Remote Sensing,* 98**,** 106-118.

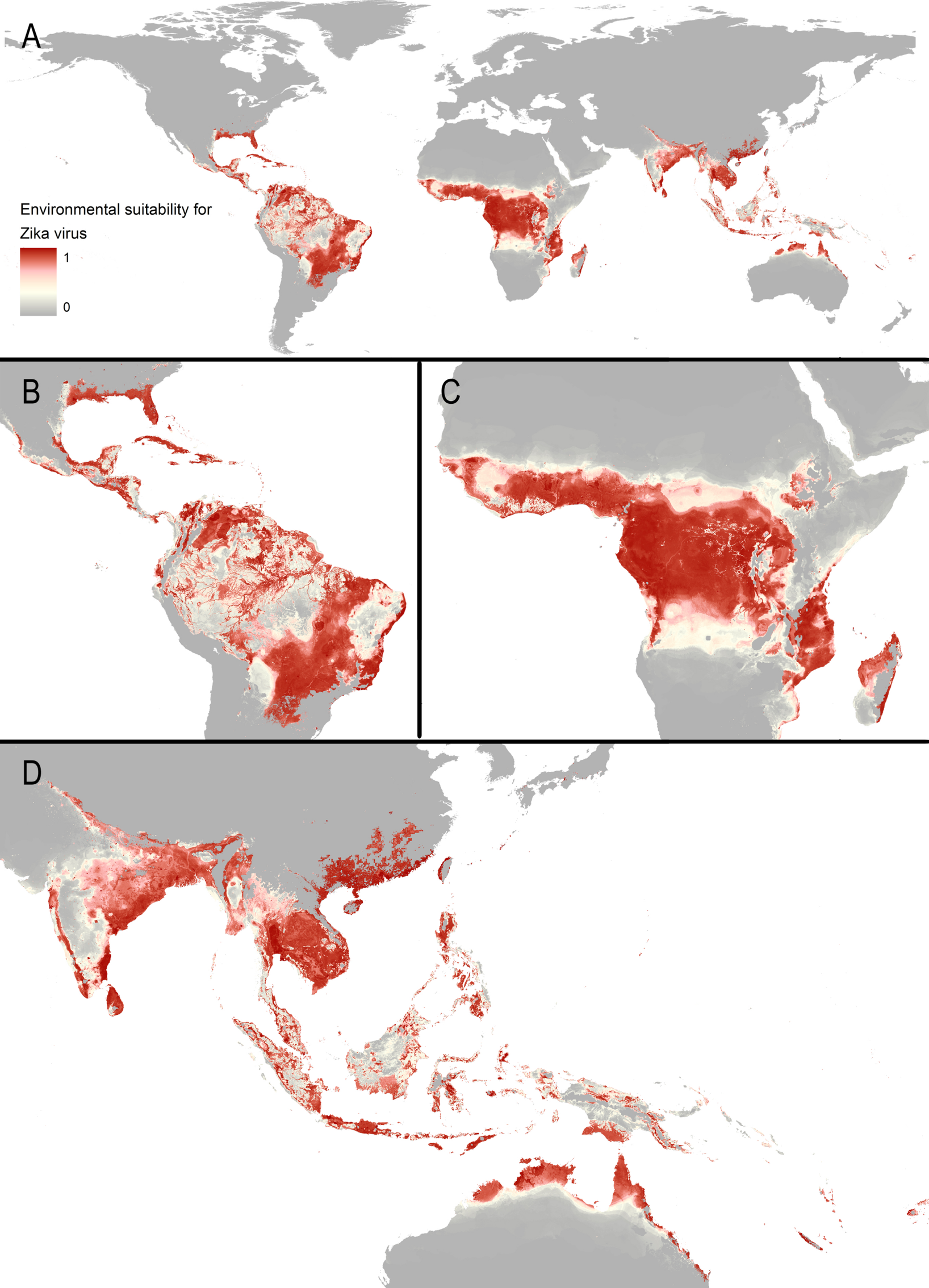
Wenger, S. J. & J. D. Olden (2012) Assessing transferability of ecological models: an underappreciated aspect of statistical validation. *Methods Ecol Evol,* 3**,** 260-267.

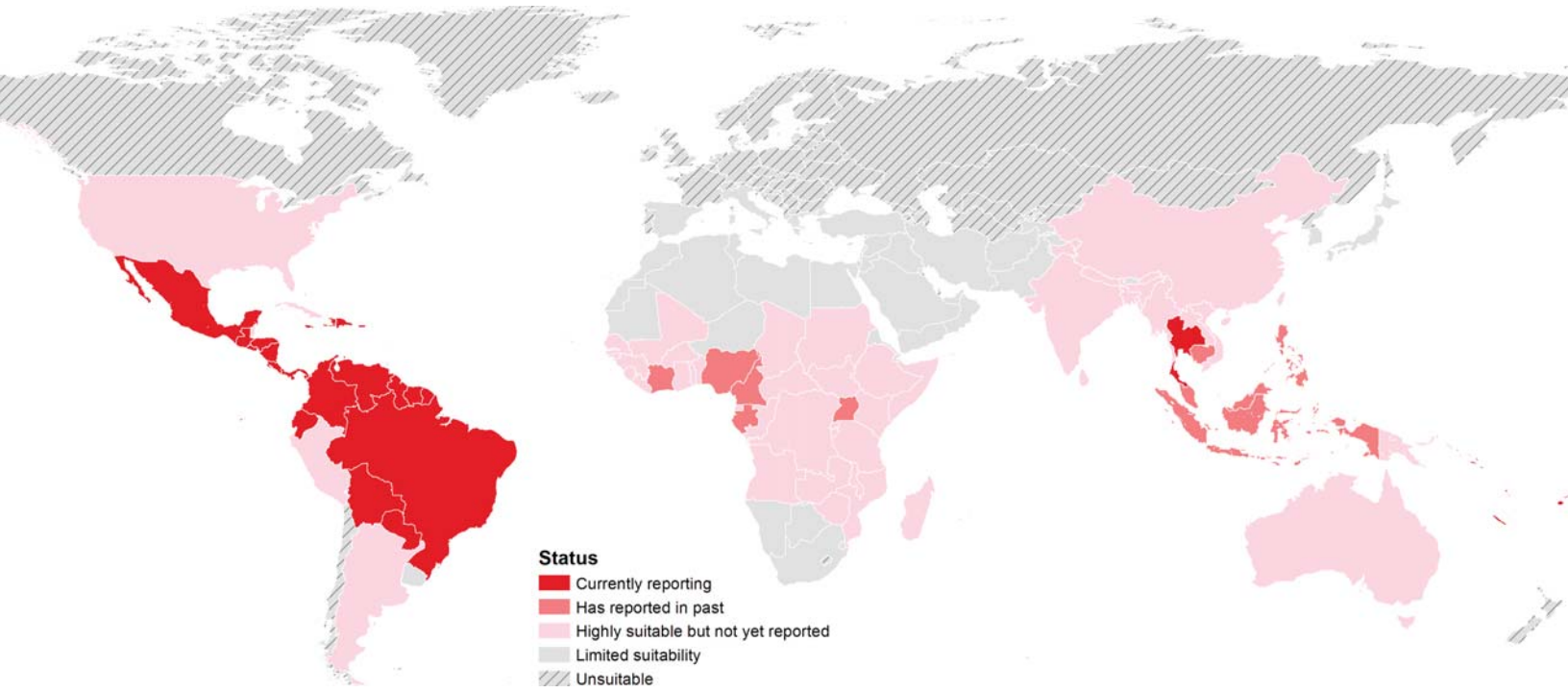
Woolhouse, M., F. Scott, Z. Hudson, R. Howey & M. Chase-Topping (2012) Human viruses: discovery and emergence. *Philos Trans R Soc Lond B Biol Sci,* 367**,** 2864-71.

WorldPop. 2015. High resolution age-structured population distribution maps. ed. U. o. S. GeoData Institute.

Zanluca, C., V. C. A. de Melo, A. L. P. Mosimann, G. I. V. dos Santos, C. N. D. dos Santos & K. Luz (2015) First report of autochthonous transmission of Zika virus in Brazil. *Mem Inst Oswaldo Cruz,* 110**,** 569-572.


A
Year of Zika occurrence:
pre-2007
2007 - 2014
2015 - 2016
B
Number of occurrences globally
250
200
150
100
50
0
1953
1975
1980
1984
1991
1999
2007
2010
2012
2013
2014
2015
2016
Year


A
Environmental suitability for
Zika virus
1
0
B
C
D


Status
Currently reporting
Has reported in past
Highly suitable but not yet reported
Limited suitability
Unsuitable