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ORIGINAL ARTICLE

A Bayesian spatiotemporal approach to modelling arboviral diseases in Mexico

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Background: The objective of this study was to evaluate the spatial and temporal patterns of disease prevalence clusters of dengue (DENV), chikungunya (CHIKV) and Zika (ZIKV) virus and how socio-economic and climatic variables simultaneously influence the risk and rate of occurrence of infection in Mexico.

Methods: To determine the spatiotemporal clustering and the effect of climatic and socio-economic covariates on the rate of occurrence of disease and risk in Mexico, we applied correlation methods, seasonal and trend decomposition using locally estimated scatterplot smoothing, hotspot analysis and conditional autoregressive Bayesian models.

Results: We found cases of the disease are decreasing and a significant association between DENV, CHIKV and ZIKV cases and climatic and socio-economic variables. An increment of cases was identified in the northeastern, central west and southeastern regions of Mexico. Climatic and socio-economic covariates were significantly associated with the rate of occurrence and risk of the three arboviral disease cases.

Conclusion: The association of climatic and socio-economic factors is predominant in the northeastern, central west and southeastern regions of Mexico. DENV, CHIKV and ZIKV cases showed an increased risk in several states in these regions and need urgent attention to allocate public health resources to the most vulnerable regions in Mexico.

Keywords: Bayesian model, CARBayesST, chikungunya, dengue, spatiotemporal, Zika

Introduction

The re-emergence of dengue (DENV), chikungunya (CHIKV) and Zika (ZIKV) virus cases has resulted in a global public health crisis.[1] All three of these viruses are transmitted principally by *Aedes* (*Stegomyia*) *aegypti* and *Aedes* (*Stegomyia*) *albopictus* and are thus considered *Aedes*-borne viruses.

The most common arthropod-borne viral disease is DENV.[2] Several serotypes (e.g. DENV 1–4) have been reported globally, imposing a substantial disease burden on tropical and subtropical countries.[2] With an estimated 390 million DENV cases annually,[2] the burden of the disease has increased an estimated 30-fold over the past 50 y.[3] DENV is now endemic in >100 countries, exposing half of the world's population to the risk of infection.[2]

CHIKV causes high fever, muscle pain, headache and joint pain 3–7 d after infection. By 2013, CHIKV had spread throughout Europe, Africa, Asia, the Caribbean, Brazil, Canada, French Guyene, Guadalupe, Martinique, Mexico and USA.[4] ZIKV has mild symptoms (e.g. headache, fever, myalgias and joint and orbital pain),[5] however, it can be also associated with severe neurological complications, such as Guillain–Barré syndrome in adults[6] and microcephaly in neonates.[7]

In Mexico, the semitropical and tropical environment promotes infestation of large populations of *A. aegypti* and *A. albopictus*.[8] Mexico also has highly mobile human populations to fuel frequent disease outbreaks of DENV, CHIKV and ZIKV. Cases of DENV have been reported in 29 of the 32 Mexican states and up to 80% have occurred in southeast region states.[9] For CHIKV, the first case was observed in 2014 in the southern border state of Chiapas, a few months later it was found nine states of Mexico, affecting 34.8% of individuals between 25 and 44 y of age.[10] The first laboratory-confirmed case of ZIKV was reported in the central state of Querétaro, Mexico.[11]

Recent studies concluded that low socio-economic status independently increases the risk of arboviral (DENV, CHIKV and ZIKV) diseases. While some studies also evaluate the effect of gross domestic product in predicting the prevalence of disease, more granular socio-economic indicators like access to education, information and technological infrastructure are suggested as better prediction factors for disease distribution.[12]

It is essential to understand the effects of both socio-economic and environmental factors on these diseases in a local context to inform public health decision makers. In previous studies, different methods were used to predict the severity of arboviral diseases by using the climatic and socioeconomic factors individually,[13,14] but there has been no study conducted to evaluate the simultaneous effects of both ecological and socio-economic factors in the prevalence of arboviral diseases (DENV, CHIKV and ZIKV) at the local level using Bayesian spatiotemporal and conditional autoregressive settings.

There is a gap in knowledge about how geographic clusters, the rate of virus spread and risk factors vary for these three major arboviruses in Mexico. The goals of our current study were to assess the association between human disease with climatic and socioeconomic risk factors, analyse the extent of seasonality and trend of disease cases, assess the rate of spread of arboviruses and determine the spatiotemporal risk and space–time effects on the occurrence of DENV, CHIKV and ZIKV.

Methods

Study area

Mexico, with 32 states and 2469 municipalities, has an estimated 126 million inhabitants at risk for vector-borne disease transmission due to its dense population, rainfall and diverse weather conditions.[15] Northern Mexico is more arid, with hot summers and sporadic rainfall, while regions in southern Mexico receive >200 mm of rainfall annually.[15] *A. aegypti* can adapt to diverse environments in both dryer and wetter landscapes.[16]

Disease and climatic data

We obtained data from laboratory-confirmed DENV, CHIKV and ZIKV patients between January 2012 and December 2020 at the municipality level from the Mexico Ministry of Health.[17] Monthly temperature data were retrieved from the dataset of the National Centers for Environmental Prediction,[18] while rainfall data were obtained from the Climate Hazards InfraRed Precipitation with Station (CHIRPS) dataset.[19] We extracted the data at the municipality level by using post offices as centroids, which were then used to calculate mean estimates.

Primary climatic parameters for this study included minimum, average and maximum temperature data and daily average rainfall and relative humidity for the 9-y period between 2012 and 2020.

Population and socio-economic data

The Mexican National Council collected socio-economic data and used national census data for the evaluation of the Social Development Policy (Consejo Nacional de Evaluación de la Política de Desarrollo Social [CONEVAL]) for each municipality.[20] For the study period January 2012–2020, variables that were used as socio-economic parameters included illiteracy (ILL), population without health services (PWOHS), houses without pavement (HWFD), water pipelines (HWOWP), toilets (HWOT), a sewage system (HWOS) and electricity facilities (HWOE). Population density for each municipality was extracted from Consejo Nacional de Población and municipalities were classified as rural with a population size <10 000 or urban with a population size ≥10 000.[21]

Statistical analysis

Correlation tests

To evaluate the associations of climatic and socio-economic variables with confirmed arboviral cases, Pearson's (r), Spearman (ρ) and Kendall (τ) correlation coefficients were determined.

Seasonal and trend decomposition using locally estimated scatterplot smoothing (LOESS)

Seasonal and trend decomposition using LOESS (STL) is a method for decomposing a time series into its trend, seasonal and residual components.[22] The structure of the method is defined by the Holt–Winters and Ljung–Box tests and assesses the additive or multiplicative seasonality effect (i.e. stationary or non-stationary). Its index ranged from 0 to 1, with values close to 1 indicating strong seasonality and trend, while values close to 0 indicate weak seasonality and trend. STL decomposition analysis was used to estimate the extent of infection seasonality and trend.

Spatial analysis

The Getis-Ord Gi* statistic was used to analyse the geographical variation in arboviral diseases in Mexico using ArcGIS Desktop version 10.8.1 (Esri, Redlands, CA, USA). The computation of this method involves comparing the local mean count (sum for a municipality and its neighbour municipality) to the global mean

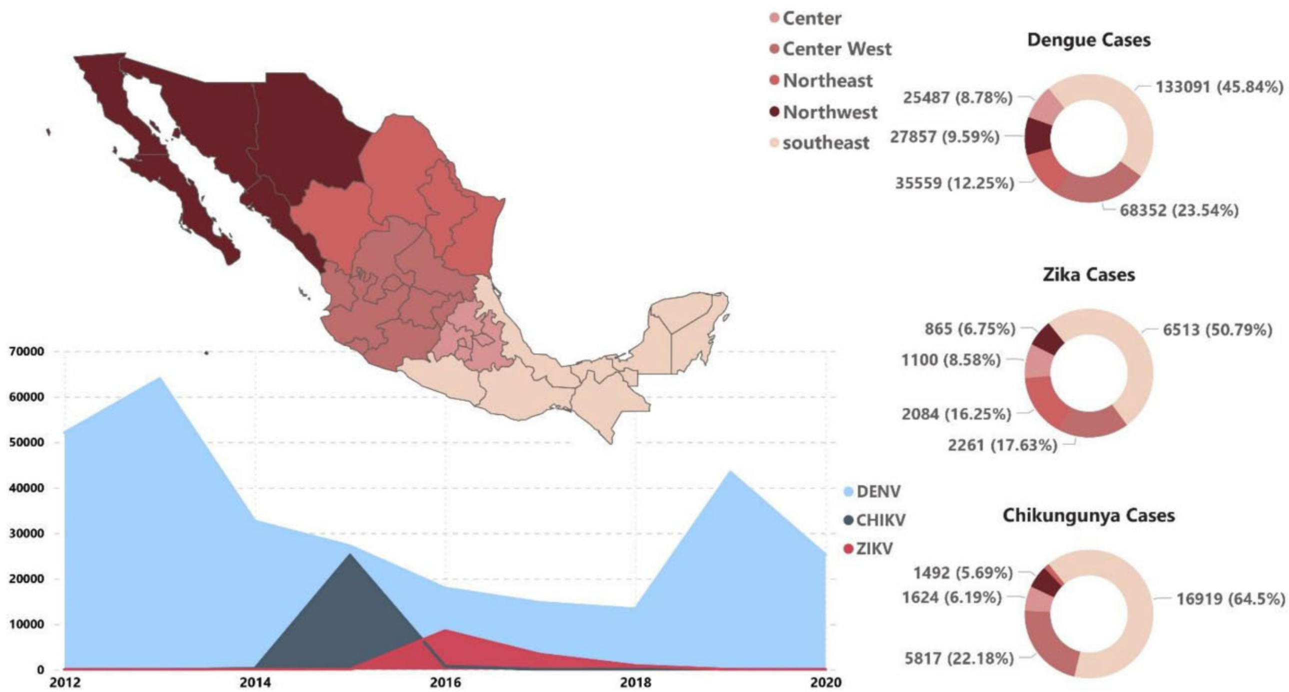

Figure 1. DENV, ZIKV and CHIKV cases classification by region.

count. For each municipality of interest, it generates a z-score, confidence interval and p-values. A high z-score and a small p-value indicate a significant high-value cluster (hotspot), while a small z-score and p-value indicate a low-value cluster (cold spot). A statistically significant positive z-score (hotspot) revealed the presence of clusters of high case counts, while low case counts were indicated by significantly negative z-scores. DENV, CHIKV and ZIKV cases were specified as input features and hotspots were determined yearly, then all years were combined to assess the persistence of disease hotspots.

Spatiotemporal approach for areal data

To assess the spatial effect, we ran three separate models for each disease outcome (DENV, CHIKV and ZIKV) and for each disease outcome we ran separate models, first by including socio-economic factors only, then environmental factors only, then a combination of socio-economic and environmental factors. Similarly, nine models were performed to assess the rate of viral occurrence. A Bayesian conditional autoregressive model was used to capture the spatial autocorrelation via random effects by assigning a conditional autoregressive prior distribution. In addition, Markov Chain Monte Carlo (MCMC) was used to estimate the parameters for each model.[23] The MCMC for obtaining the posterior distributions of model parameters for both spatial and non-spatial effect models was run with 220 000 iterations, with a burn-in period of 20 000. The log of the population density variable (p) and time variable (t) was used as an offset option in the model to estimate the risk and rate, respectively, for the three diseases. The output table of the model presents the parameter summaries, including a 95% confidence interval that was computed based on the highest density interval, and posterior median estimates. Geweke diagnostic (ranging from −2 to 2) results were used to assess the convergence of each model.[24] The deviance information criterion (DIC) and Watanabe–Akaike information criterion (WAIC) were used for the comparison of models, in which models with the lowest values of DIC and WAIC were chosen. The relative risk and rate were calculated based on the selected model. The graphs were displayed in two ways to easily understand the risk for each disease and detect a high-risk region.[25] The first graph depicts the risk for all states, while the second graph presents the probabilities (ranging from 0 to 1) for those regions where the relative risk is >1 (Supplementary Figure S4). We used the CARBayes and CARBayesST R packages to perform the models (R Foundation for Statistical Computing, Vienna, Austria).[23]

Results

DENV, CHIKV and ZIKV were most prevalent in the southeast region over the study period (2012–2020). The least affected region for DENV was the central region and for CHIKV and ZIKV it was the northwest region (Figure 1). Total laboratory-confirmed cases of all viruses are found in Supplementary Table S1. Additionally, the results of correlation coefficients (Pearson's, Spearman and Kendall rank correlation) with a p-value <0.05 indicate a statistically significant association between arboviruses and climatic and socio-economic variables (Table 1).

DENV case data showed a strong seasonality and trend throughout the study period, while CHIKV and ZIKV showed strong seasonality but weak trends. Additionally, climatic

Table 1. Correlation between DENV, CHIKV and ZIKV and both socio-economic and climatic variables.

	DENV			CHIKV			ZIKV		
Factors	Pearson	Spearman	Kendall	Pearson	Spearman	Kendall	Pearson	Spearman	Kendall
ILL	0.40***	0.50***	0.47***	0.21***	0.27**	0.23**	0.14*	0.07	0.06
PWOHS	0.28**	0.24*	0.19*	0.02	−0.28**	−0.23**	−0.16**	−0.38***	−0.28***
HWFD	0.39***	0.54***	0.40***	0.26**	0.09	0.07	0.04	−0.06	−0.05
HWOT	0.08	0.09	0.06	0.23*	0.07	0.05	0.06	−0.09	−0.07
HWOWP	0.50***	0.48***	0.37***	0.11	0.05	0.04	0.03	−0.08	−0.06
HWOS	0.32***	0.39***	0.30***	0.25**	0.22*	0.19*	0.11	0.02	0.01
HWOE	0.22*	0.35***	0.28***	0.05	0.08	0.06	0.01	−0.07	−0.05
MaxT	0.32***	0.45***	0.33***	0.26**	0.30***	0.26***	0.11	−0.11	−0.09*
MinT	0.32***	0.47***	0.34***	0.28**	0.32***	0.27***	0.22*	−0.09	−0.08
AvgT	0.32***	0.46***	0.33***	0.27**	0.31***	0.26***	0.22*	−0.10	−0.08
MaxR	0.41***	0.49***	0.36***	0.08	0.06	0.04	0.04	0.05	0.04
AvgR	0.44***	0.48***	0.36***	0.09	0.24*	0.20*	0.09	0.09	0.07
AvgRH	0.16***	0.19***	0.10*	0.29**	0.04	0.03	0.01	−0.06	−0.05

The covariates are ILL (illiteracy rate), PWOHS (population without health services), HWFD (house with floor of dirt), HWOT (house without toilets), HWOWP (house without water pipelines), HWOS (house without sewage system), HWOE (house without electricity), MaxT (maximum temperature), MinT (minimum temperature), AvgT (average temperature), MaxR (maximum rainfall), AvgR (average rainfall) and AvgRH (average relative humidity).
*p=0.05, **p=0.01, ***p=0.001.

Table 2. Time series STL Decomposition Results.

Time series feature	Seasonality strength	Trend strength
Dengue		
Monthly	0.87	0.83
Quarterly	0.81	0.77
Yearly	0.75	0.48
Zika		
Monthly	0.61	0.34
Quarterly	0.62	0.38
Yearly	0.34	0.02
Chikungunya		
Monthly	0.64	0.36
Quarterly	0.68	0.12
Yearly	0.41	0.02
Climatic parameters		
Minimum Temperature	0.94	0.82
Maximum temperature	0.89	0.69
Average Temperature	0.95	0.76
Minimum Rainfall	0.53	0.30
Maximum Rainfall	0.84	0.76
Average Rainfall	0.91	0.79
Relative Humidity	0.80	0.41

variables including minimum, maximum and average temperature and maximum and average rainfall values indicated a strong seasonality and trend. However, relative humidity and minimum rainfall values indicated a weak trend (Table 2).

Hotspot analysis of arboviral disease revealed that DENV is highly concentrated in the municipalities of the southeast, northeast, centre and northwest regions. In contrast, a clustering of low values (cold spots) was seen in centre and centre-west region municipalities (Figure 2A, Supplementary Figure S1). CHIKV case hotspots were detected across southeast, northeast, northwest and centre border region municipalities, while cold spots were found in the central and southeastern regions throughout the study period (Figure 2B, Supplementary Figure S2). Regarding Zika cases, the concentration of hotspot clustering was seen in the municipalities of the northeast, southeast, centre and northwest regions (Figure 2C, Supplementary Figure S3).

The risk models with combined socio-economic and climatic covariates have lower values of DIC and WAIC than the models with socio-economic and climatic covariates treated separately (Supplementary Table S2). The spatial (ρ_S) and temporal (ρ_T) dependence parameter values from the selected models for DENV, ZIKV and CHIKV are shown in Supplementary Table S3 and indicate the significant association between the response variable (DENV, CHIKV, ZIKV) and explanatory variables (socio-economic and climatic variables) both spatially and temporally over the study period.

The spatial heterogeneity of DENV, CHIKV and ZIKV cases is exhibited across Mexico (Figure 3). DENV relative risk was high in the southeast, northwest and central-west regions (Figure 3A), CHIKV relative risk was high in some states of the southeast region and the centre-west region (Figure 3B) and ZIKV relative risk was highest in the southeast and northeast regions (Figure 3C). The southeast region states had the highest risk for all three arbovirus diseases (Supplementary Figure S4).

An increase in maximum temperature leads to an increase in DENV cases of 23.3%, CHIKV by 9.3% and ZIKV cases by 18.9%.

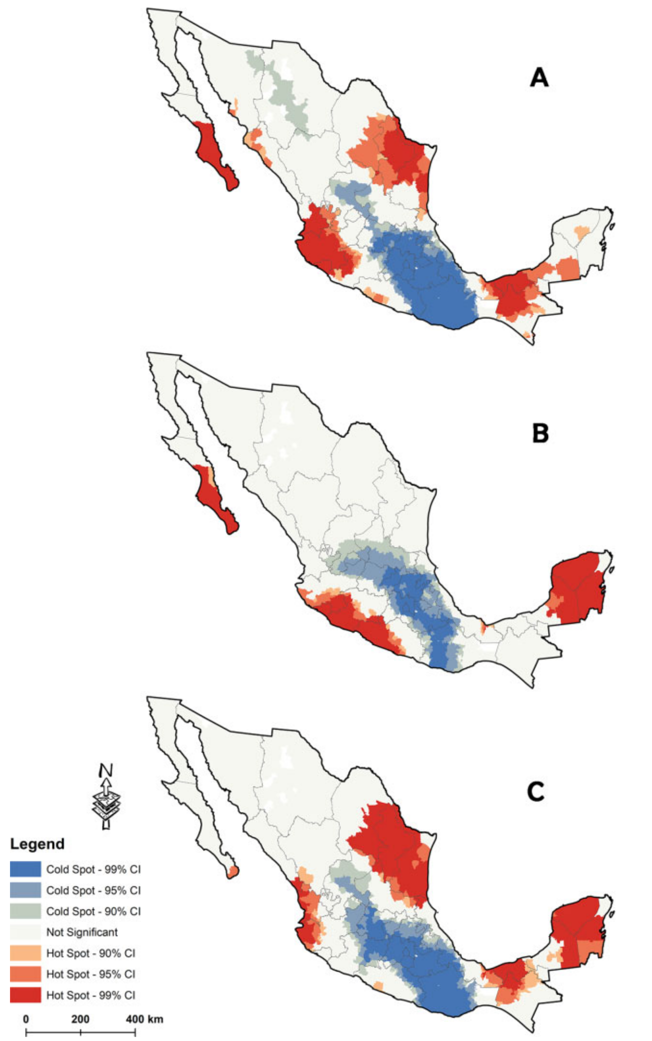

Figure 2. Hotspot of (A) DENV, (B) CHIKV and (C) ZIKV prevalence across Mexico over the study period.

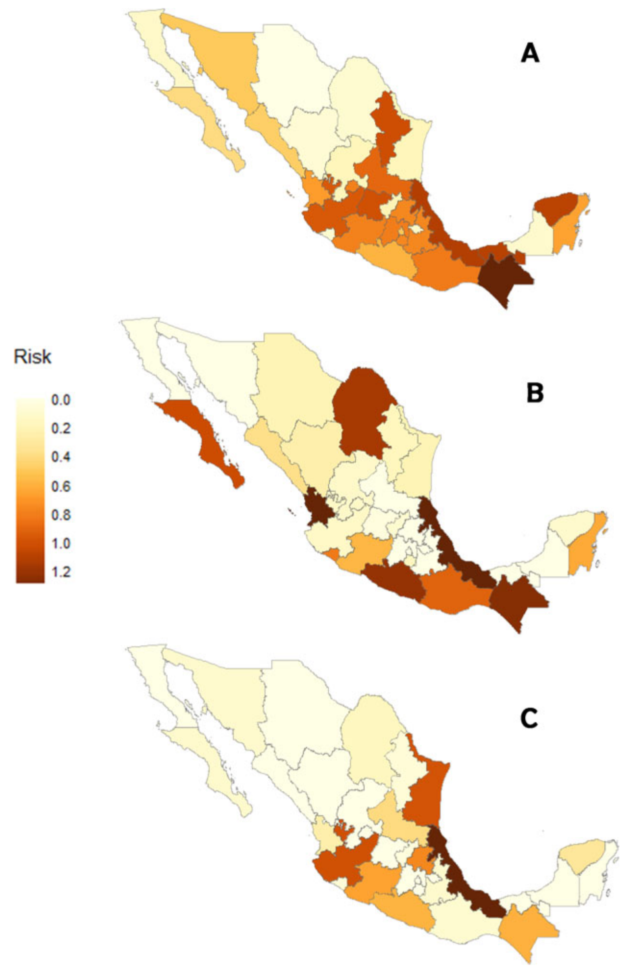

Figure 3. Spatial pattern of the risk of (A) DENV, (B) CHIKV and (C) ZIKV estimated by posterior median risk surface.

Mean temperatures had a significant effect on DENV, CHIKV and ZIKV, while minimum temperature had no significant effect on ZIKV cases. Maximum rainfall had a significant effect on DENV and ZIKV, but not on CHIKV cases. Furthermore, mean rainfall and relative humidity had a significant effect on all three arboviruses (Table 3).

Regarding socio-economic variables, a one-unit increase in illiteracy was associated with a 31.1% increase in the risk of DENV and a 31.6% in the risk of CHIKV. Further, a one-unit increase in the population without health services corresponded to a 38.6% increase in the risk of DENV and a 43.6% increase in CHIKV. An increase in the illiteracy rate and population without health services did not have any significant effect on ZIKV. The proportion of houses without pavement and houses without toilets were both significantly associated with an increase in DENV and ZIKV, but not CHIKV. However, the proportion of houses without water pipelines and sewage systems significantly predicted CHIKV and DENV, while the proportion of houses without electricity significantly predicted DENV and ZIKV, but not CHIKV (Table 3).

The models that were used to evaluate the rate of occurrence of DENV, CHIKV and ZIKV with all combined covariates have minimum DIC and WAIC values as compared with other models and were selected for further analysis (Supplementary Table S4).

After controlling other variables, the results of the models revealed that a 1-mm increase in minimum rainfall resulted in an increase in the occurrence rate of DENV (0.0007 [95% CI 0.0001 to 0.0009]), CHIKV (0.0005 [95% CI 0.0003 to 0.0009]) and ZIKV (0.0006 [95% CI 0.0004 to 0.0008]), indicating no statistical significance (Supplementary Table S5). Further, a 1-mm increase in mean rainfall revealed a significant increase in the rate of occurrence ($[1-\exp^{\text{median estimate}}]*100$) of DENV (16.6%), CHIKV (4.48%) and ZIKV (5.3%), when holding other covariates constant (Supplementary Table S5). A 1°C increase in the mean temperature caused an increase in the rate of occurrence of DENV (34.5%), CHIKV (47.5%) and ZIKV (23.7%) after controlling for other variables. After controlling for other variables (socio-economic and climatic variables except humidity), an increase in humidity caused an increase in DENV (16.7%), CHIKV (36.3%) and ZIKV (17.9%) rates. A one-unit increase in the houses without electricity and toilets index caused a decrease in all three

Table 3. Relative risk for DENV, CHIKV, and ZIKV with both socio-economic and climatic variables.

Covariates	Relative Risk (95% CI)[a]		
	DENV	CHIKV	ZIKV
Maxt	1.23 (1.11–1.44)	1. 09 (1.00–1.52)	1.19 (1.05–1.29)
MinT	1.09 (1.00–1.22)	1.31 (1.09–1.36)	1.00 (0.91–1.20)
AvgT	1.36 (1.21–1.52)	1.05 (1.04–1.06)	1.39 (1.22 –1.51)
MaxR	1.31 (1.22–1.52)	0.04 (0.01–0.09)	1.13 (1.10–1.16)
AvgR	1.10 (1.06–1.23)	1.09(1.03–1.18)	1.39(1.27–1.47)
AvgRH	1.27 (1.11–1.39)	1.13 (1.05–1.24)	1.22 (1.11–1.32)
ILL	1.31 (1.22–1.49)	1.32 (1.22–1.42)	0.45 (0.22–1.00)
PWOHS	1.39 (1.29–1.44)	1.44 (1.23–1.69)	0.61 (0.43–0.85)
HWFD	1.15(1.04–1.25)	0.68 (0.67–0.69)	1.03 (1.02–1.04)
HWOT	1.08 (1.07–1.09)	0.63 (0.62–0.64)	1.04 (1.03–1.04)
HWOWP	1.05 (1.02–1.08)	1.03 (1.02–1.06)	0.56 (0.55–0.57)
HWOS	1.15 (1.14–1.25)	1.07 (1.03–1.09)	0.41 (0.39–0.42)
HWOE	1.05 (1.02–1.06)	0.37 (0.20–0.47)	1.01 (1.00–1.01)

The covariates are MaxT (Maximum Temperature), MinT (Minimum Temperature), AvgT (Average Temperature), MaxR (Maximum Rainfall), AvgR (Average Rainfall), AvgRH (Average Relative Humidity), ILL (Illiteracy Rate), PWOHS (Population without health services), HWFD (House with floor of dirt), HWOT (House without toilets), HWOWP (House without water pipelines), HWOS (House without sewage system) and HWOE (House without electricity).
[a]95% Credible Interval of Relative Risk

arboviruses. However, a one-unit increase in houses without pavement and sewage systems was associated with an increase in the occurrence of DENV (12.2% and 2.84%), CHIKV (5.3% and 5.29%) and ZIKV (19.8% and 2.25%) (Supplementary Table S5). After controlling for other variables, an increase in the proportion of the population without health services was significantly related to an increase in the rate of DENV, CHIKV and ZIKV by 11.56%, 9.9% and 22.6%, respectively (Supplementary Table S5).

Discussion

The purpose of this study was to determine the spatiotemporal dynamics of DENV, CHIKV and ZIKV over 9 y in Mexico and determine the municipality-level environmental and sociodemographic risk factors that likely influence arboviral outbreaks.

The outbreak of CHIKV in 2014 and ZIKV in 2015 established transmission of three viruses in some municipalities of Mexico.[26] Our current study is based on analyses of laboratory-confirmed cases, thus bias from misclassification of cases is minimized.

This study reveals the epidemics of CHIKV and ZIKV that swept through Mexico, peaking in 2015 and 2016, respectively. The traveling epidemics of ZIKV that started in southern Mexico in 2015 and shifted north and west over the following 3 years. That followed an expected pattern of the virus entering immunologically naive populations, fuelling epidemics, and then herd immunity dampening them.[27] We also document a significant decline in the number of cases of DENV over time. The most populated and poor socio-economic status states of the centre-west and southeast regions observed more cases, whereas sparsely populated and more socio-economically stable states in the northwest and northeast region reported fewer cases. The cases of DENV, CHIKV and ZIKV peaked in 2013, 2015 and 2016, respectively, although DENV had another spike in 2019.

Clusters of DENV cases are significantly higher (hotspots) in the southeast, northeast, northwest and centre region municipalities. Furthermore, the pattern of CHIKV hotspots was identified in border area municipalities of the southeast, northwest and centre-west regions. As for ZIKV, accumulations of risk were concentrated in southeast, northeast and centre-west region municipalities.

In this study, different climatic factors were observed to determine the risk of arbovirus diseases. An increase in maximum, minimum and average temperature; maximum and average rainfall; and relative humidity was associated with an increase in the risk of DENV. However, increasing maximum rainfall was associated with a decrease in the risk of CHIKV, whereas minimum and average temperature were not associated with an increase in ZIKV risk across Mexico. The average temperature was significantly positively associated with an increase in the risk of arboviruses, consistent with previous findings.[28] Previous studies have shown that *Aedes* mosquitoes can transmit all arboviruses within an observed temperature range in Mexico,[29] and our results indirectly support the simultaneous spread of arboviruses within the same population and geographic areas.

Unfavourable socio-economic conditions have been found to promote *Aedes* mosquito proliferation.[30] Our study provides further evidence that socio-economic factors, including the proportion of houses without pavement, as well as without toilets, water pipelines, electricity and sewage systems, and populations without health services, are significantly associated with an increase in the risk of these three arboviruses in Mexico. Thus these factors may predict an increase in the rate of DENV, CHIKV and ZIKV, depending on the location. Specifically, the socio-economic conditions in southeast states like Guerrero and Oaxaca are worse than in other regions, and significant hotspots of clustering of these three diseases were identified in these regions. An effective response necessitates the adoption of a set of well-planned and coordinated actions that are tailored to the endemic and epidemic patterns of disease.

Arboviral outbreaks are historically associated with southern tropical regions that provide the ideal ecological conditions related to vector competence and establishment.[28] Furthermore, our study supports the evidence that high-prevalence areas serve as the source of arbovirus seeding and spread, primarily located in the southern regions of Mexico.[28] Thus the southern regions of Mexico are an important hub of viral transmission and a source for outbreaks of DENV, CHIKV and ZIKV.[28]

Predicting arbovirus spatial spread patterns could play a crucial role in designing surveillance programs and public health interventions and several tools have been developed to control the transmission of arboviral diseases.[18,28] Our findings highlight the predictability of spatial invasion patterns and contribute to the current knowledge of arboviral dynamics in Mexico. Furthermore, the current risk maps may be improved by integrating our findings into epidemiological and spatial models for established and emerging arboviruses in Mexico.

The findings of this study were based on confirmed case data of DENV, CHIKV and ZIKV extracted from passive surveillance systems to eliminate the misclassification bias. This study also used aggregated data and the findings are ecological and not at the level of an individual. The distribution of *A. aegypti* may have an impact at the individual and household levels. However, it might be possible that some of the observed patterns are confounded by potential hidden factors. Future studies should identify and address these hidden factors and should consider other factors that would influence arboviral disease cases, such as the amount of mosquito control and other public health campaigns, which are likely to vary among states. Furthermore, considering the age and gender of human disease cases could reveal additional spatiotemporal patterns or associations with climate or socio-economic factors.

The initial findings from this study can be used to develop future studies to improve the spatial resolution of factors associated with arbovirus cases. A cohort-based study with standardized diagnostics will improve the ability to predict disease based on socio-economic and microclimatic factors. Future research at the individual and household level would increase our understanding of the dynamics of arbovirus transmission. Microclimate, urban environment and landscape ecology data can reveal more spatial precision and ecologically interpretable metrics of mosquito-borne disease transmission drivers in various landscapes.

Conclusions

Climatic and socio-economic factors predict the rate of occurrence and risk of DENV, CHIKV and ZIKV in Mexico. Higher temperature and relative humidity and increasing rainfall predicted the rate of occurrence of all three arbovirus diseases in Mexico. Further, socio-economic factors, including population without health services, houses without a sewage system, cleanliness and illiteracy rate, were all positive predictors for DENV, CHIKV and ZIKV, while houses without electricity and toilets predicted lower rates of occurrence of arboviral infection in Mexico. States like Guerrero and Oaxaca should be monitored closely for all three arboviral infections. Results also imply that using appropriate spatiotemporal approaches may help identify various geographic groups and the influence of both socio-economic and climatic covariates by time and population density.

Supplementary Data

Supplementary data are available at *Transactions* online.

Authors' contributions: MHB prepared and analysed the data and drafted the manuscript. MYS and UH supervised the analysis, contributed to data preparation, conceived the study design and contributed to writing. DK obtained and pre-processed climate data and contributed to writing and editing the manuscript. U-SDTN, JATC, WJ, WUB, ALG-H, RR, NSCF, GLH, PW, EA, and CKR contributed to the writing and editing of the manuscript.

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Competing interests: None.

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Data availability: All data will be made available by request to the corresponding author.

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