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A Neural Network Model to Predict the Effect of Climate Change on West Nile Virus (WNV) Epidemiology

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ABSTRACT

West Nile virus (WNV) is a mosquito-borne disease. The virus is transmitted cyclically between mosquitoes and avian hosts. It is influenced by a diverse array of environmental parameters. The prediction of WNV epidemic is challenging since any change in climate conditions and vector ecosystems affect the epidemiology of the WNV. In this study, a neural network (NN) model was developed to capture the non-linear effect of environmental parameters on WNV neuro-invasive disease by using historical disease data for four major cities in the USA. This NN model uses statistical and machine learning techniques to forecast spatial and temporal variation of WNV in other USA cities. This artificial intelligence framework was used further to quantify the correlation between various climate change parameters such as temperature, rainfall, season, and land coverage on WNV. This study addresses key questions on how projected climate change will affect the spatial and temporal dynamics of WNV disease epidemics which is critical to managing spread of the disease.

Introduction

West Nile virus (WNV) is one of more than 70 viruses of the family Flaviviridae of the genus Flavivirus (Paz, 2015). WNV has become the most prevalent mosquito-borne disease in the United States of America since its first occurrence in the year 1999 (Centers for Disease Control and Prevention, 2023). The disease is mainly (>80%) asymptomatic; however, some people (<20%) experience mild to severe symptoms (Githeko et al., 2000; Peterson et al., 2012; Ronca et al., 2019). In severe cases, occurring in approximately 0.67% of those infected, the disease can be neuroinvasive, leading to coma and death (Githeko et al., 2000). Treatment for WNV costs over $50 million neural network annually; often exceeding $700,000 per patient (Barrett, 2014; Staples et al., 2014). In addition to the heavy economic costs of WNV treatment, the unpredictability of the cases impediments proactive action. Human cases of the WNV in the USA vary significantly from year to year as shown in Figure 1. Furthermore, WNV cases are expected to be much notably greater than recorded, since most infected persons are asymptomatic and their cases go unreported (Peterson et al., 2012). For instance, from 1999 to 2021, over three million people were estimated to be infected with WNV (Centers for Disease Control and Prevention, 2023); however, only about 30,700 of these cases were reported (Peterson et al., 2012). Therefore, it is imperative to forecast WNV accurately so that health departments and municipalities can minimize loss through proactive actions.

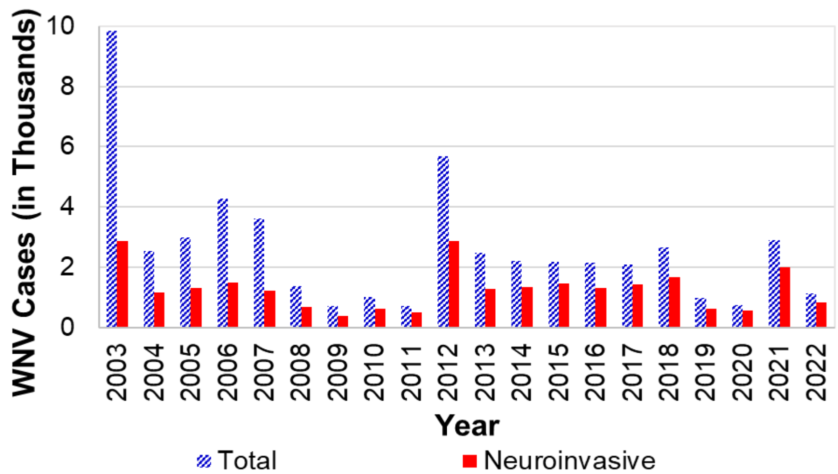


Figure 1. Reported total and neuroinvasive WNV disease cases in the USA.

West Nile Virus (WNV) Transmission Cycle

WNV spreads through cyclic transmission between mosquitoes and avian hosts. Figure 2 shows the transmission cycle of WNV. The WNV infects birds, humans, horses, and other mammals (Turell et al., 2001; Kilpatrick et al., 2005, Ewing et al., 2021; Fasano et al., 2022). However, human and mammal hosts are considered dead-end hosts, since they cannot further spread the disease due to limited viremia (DeFelice et al., 2018; McLean et al., 2006). WNV stems from some female mosquito species which need to feed on a vertebrate blood meal to produce eggs (Marra et al. 2004). These mosquitoes can become infected and transmit WNV pathogens. The enzootic cycle is driven by the continuous virus transmission between susceptible bird species and adult mosquito blood-meal feeding, which amplifies the virus. The number of birds and mosquitoes infected with WNV increases as mosquitoes transmit the virus to birds in spring. Human infections can occur from a bite of a mosquito that has previously bitten an infected bird. Peak transmission of WNV to humans in the USA typically occurs in summer or early autumn when temperatures are greater and mosquitoes have most activity.

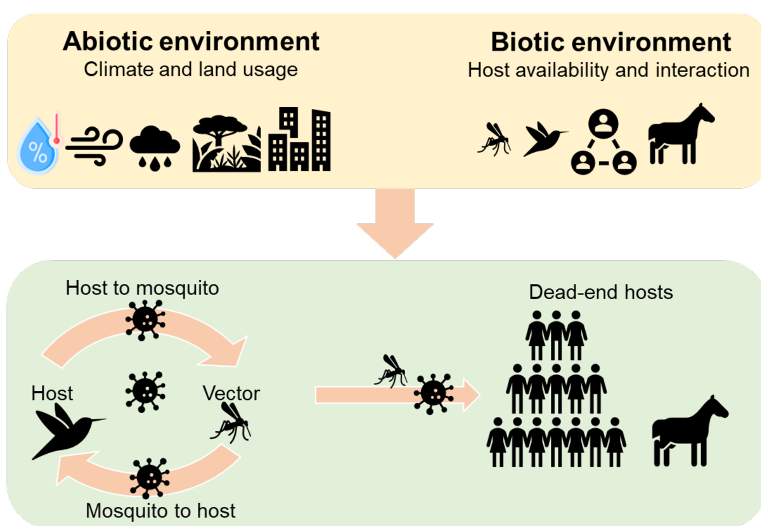


Figure 2. WNV transmission cycle and influence of abiotic and biotic factors.

Mosquito species from the genus *Culex* are the primary vectors of WNV (Turell et al., 2001). Studies find that mosquito biting behavior varies significantly within the *Culex* genus, spatially and temporally (Andrade et al. 2011; Ruiz et al. 2010; Kunkel et al. 2006; Hamer et al. 2008; Hort et al., 2023). Three *Culex (Cx.)* mosquito species are the main vectors of the disease across the United States. *Culex pipiens* is the primary West Nile vector in the eastern United States and is typically found in urban areas. It prefers breeding in standing waters with waste from nearby human settlements or farms (e.g., in storm sewers and ditches) (Farajollahi et al., 2011). *Culex salinarius* is another *Culex* species found in fresh and saltwater bodies. It generally prefers habitats close to human localities. *Culex tarsalis* is predominant in the western United States and prefers breeding in irrigated agricultural areas as well as temporary water areas. It is most active during dusk, when it preys on animals, humans, and birds. Differences in the *Culex* species' preferred breeding habitats implies that they impact human WNV disease risk differently across these regions.

Effect of Environmental Parameters on WNV Transmission

Environmental parameters such as temperature, season, humidity, precipitation, drought, storms, natural land coverage (e.g., wetlands and forests), urban ecology, population density, and geographic location significantly affect WNV transmission (Githeko et al., 2000). These environmental factors influence the vector populations' survival, reproduction rates, and habitats (Gould & Higgs, 2009). For instance, temperature plays a major role in every stage of a mosquito's life cycle. *Culex* mosquitos prefer temperatures between 50 ºF and 95 ºF with temperatures between 82 ºF and 89 ºF being most optimal for population growth (Beard et al., 2016). Higher temperatures typically reduce the duration for the WNV transmission. This is because the increased temperatures shorten the time it takes for the virus to replicate inside the mosquito.

Recent studies indicate that climate change will further magnify the spread of WNV, since increased temperatures along with changes in rainfall will alter mosquito and avian habitats (Beard et al., 2016). Loss of habitats will increase mortality of avian hosts, disrupting viral transmission. Global warming and climate change impacts are multifaceted as they can alter biological parameters, including vector population density, survival rates, and habitat. Also, the increase in WNV risk will vary regionally. With the immense economic impact and changes brought by climate change, it is essential to forecast WNV accurately so municipalities and hospitals can better prepare for the disease.

Current Status and Gaps in Understanding

Forecasting the WNV epidemic is challenging as any change in climate and ecosystem has pronounced effects on the spread of the virus. Various studies have investigated the relations between climate parameters and WNV cases. These studies postulated the effect of climate change, specifically temperature on WNV cases using a parameter called "mosquito days" (Langer et al. 2018). According to a report by Climate Central, mosquito days increase in the USA as temperatures rise (Langer et al. 2018). Figure 3 shows the variation of WNV cases with calculated mosquito days for five cities with diverse climates. From this figure, it is evident that there is a very weak correlation between WNV disease and mosquito days. Therefore, mosquito days is not an accurate parameter to predict WNV disease. Furthermore, the clustering of mosquito days based on the climate prevalent in these cities indicates that there may be a non-linear correlation or additional parameters affecting WNV spread. This work focuses on the development of a model to address these gaps by including additional environmental parameters.

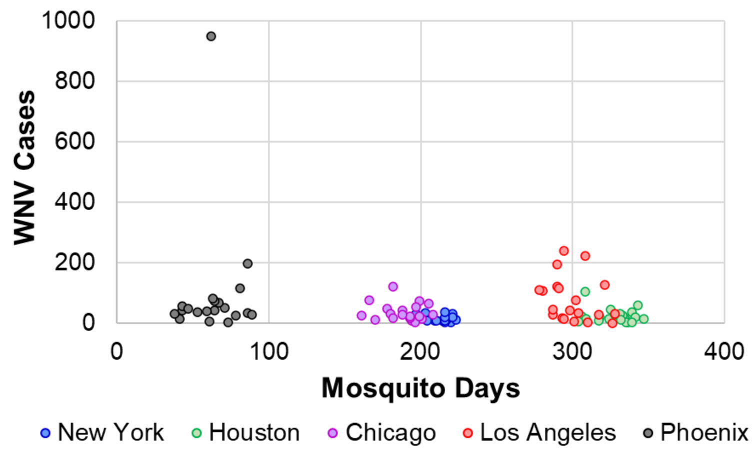


Figure 3. Variation of WNV neuroinvasive cases with mosquito days for five major cities.

Figure 4 summarizes the various types of WNV prediction models available in the literature. These models have different degrees of complexity ranging from simple analytical models (Bowman et al., 2005; Chen et al., 2013) to more developed models capturing the dynamic vector-host process (Ewing et al., 2021; Fasano et al., 2022; DeFelice et al., 2018; McLean et al., 2006). Deterministic data-driven models are relatively simple and reveal general trends in disease spread. On the other hand, mechanistic models typically simulate the complex process of viral transmission to understand epidemiological risk. However, the accuracy of these models depends on the vector species and requires abundant data on vector population, ecosystem, and temporal variation. Furthermore, most of these models capture very few environmental parameters and are not comprehensive. These models in the literature estimate the impact of temperature and precipitation on WNV; however, their applicability or spatial resolution is limited to a county or regional level. Furthermore, the explored models do not capture the geographic and climate variation across the USA. This paper addresses these gaps by developing a WNV epidemic model with spatial and temporal prediction capability for the USA.

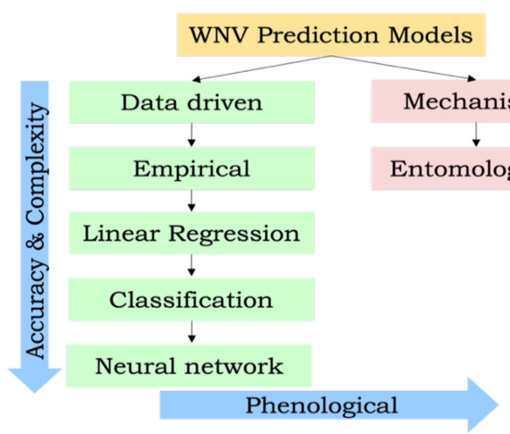


Figure 4. Classification of existing WNV disease prediction models.

Research Objective

In this study, a neural network model was developed to capture the non-linear effect of environmental parameters on WNV neuroinvasive disease by using historical disease data for four major cities in the USA. This neural network model uses statistical and machine learning techniques to forecast spatial and temporal variation of WNV in other USA cities. This artificial intelligence framework was used further to quantify the correlation between climate parameters, such as temperature, rainfall, season, and natural land coverage, and the virus. This study has several important strengths, including a large WNV data sample size, longer historical period, and geographic diversity. It answers the question: How accurately can environmental parameters, such as temperature, month, natural land coverage, location, precipitation wind speed, and humidity, be used to develop a model extrapolating WNV prevalence in American cities? The study also addresses key questions on how climate change will affect the spatial and temporal dynamics of WNV disease epidemics, which is critical to managing them. This work will help local municipalities, governments, and health organizations further understand the risk of WNV in their region and enable them to take proactive measures.

Methods

Five highly populated and climatically diverse regions of the US were chosen for this study (Table 1). The counties constituting these five cities represent ~10% of the USA population and encompass ~20% WNV neuroinvasive cases. Out of these five cities, four cities i.e., New York, Los Angeles, Chicago and Houston were used for neural network model development and validation, whereas Phoenix was used to test the model prediction performance and robustness.

Table 1. Five major cities selected for model development.

Cities	Counties	Population (2020 US Census)	Region
New York (NY)	Manhattan, Brooklyn, Bronx, Queens, Richmond	8.74 M	Northeast
Los Angeles (LA)	Los Angeles	9.99 M	West
Chicago	Cook	5.26 M	Midwest
Houston	Harris	4.73 M	South
Phoenix	Maricopa	4.44 M	West

Data Collection

WNV case data from the years 2003 to 2022 was obtained from the Centers for Disease Control and Prevention's ArboNET national surveillance system (2023). The database includes the annual WNV cases for each of the counties in the USA but does not provide the monthly breakdown at the county level. Instead, the database reports the monthly breakdown of the WNV cases for the USA. This data was used to obtain the monthly WNV cases for the cities investigated in this study. Climate data such as daily mean temperature, average humidity, precipitation and mean wind speed was obtained from the National Oceanic and Atmospheric Administration (NOAA, 2024). All these parameters' values were averaged over the month, since a monthly duration was used as the precision for temporal prediction. Years 2000, 2010 and 2020 census data (United States Census Bureau, 2023) were used to get the population for these cities. To get the monthly population during the intermediate time-period, the population was linearly interpolated. Similarly, data for wetland, grassland and forest coverage was obtained for years 2000 and 2020 from the U.S. Geological Survey (USGS) database managed by The Multi-Resolution Land Characteristics (MRLC) consortium (2024). Land coverage for intermediate periods was linearly interpolated to get monthly distribution. Furthermore, city location is categorical (or, ordinal) variable based on the geographical region classification defined by CDC (Geographic Division or Region - Health, United States, 2023). To aid the model, these categorical values were converted to continuous values by defining four major directions as numbers, i.e., Northeast =1; Midwest = 2; West = 3; and South = 4. Geographic location was considered in the model since it captures the racial, social, climate and land topography which have an influence on the incidence rate. In this work, JMP statistical software version-17 (SAS Institute Inc., 2022) was used for neural network model development.

WNV Neuroinvasive Cases

Figure 5 shows that WNV neuroinvasive cases are typically higher in Los Angeles and Phoenix compared to other cities. Furthermore, Figure 5 indicates that there is no continuous increasing or decreasing trend in the cases for any city on a year-to-year basis. Figure 6 depicts the cumulative WNV neuroinvasive cases from the year 2003 to 2022, aiding in comparisons between cities. For instance, Phoenix experienced a significant WNV epidemic in 2022, while Los Angeles experienced a WNV outbreak in 2011 that slowed down after 2017. Moreover, cases are lowest for New York, whereas western cities (Los Angeles and Phoenix) have relatively high cumulative cases. Variations in the slopes of the cumulative cases graph (Figure 6) provide meaningful information, since they highlight any annual increase or decrease in WNV cases.

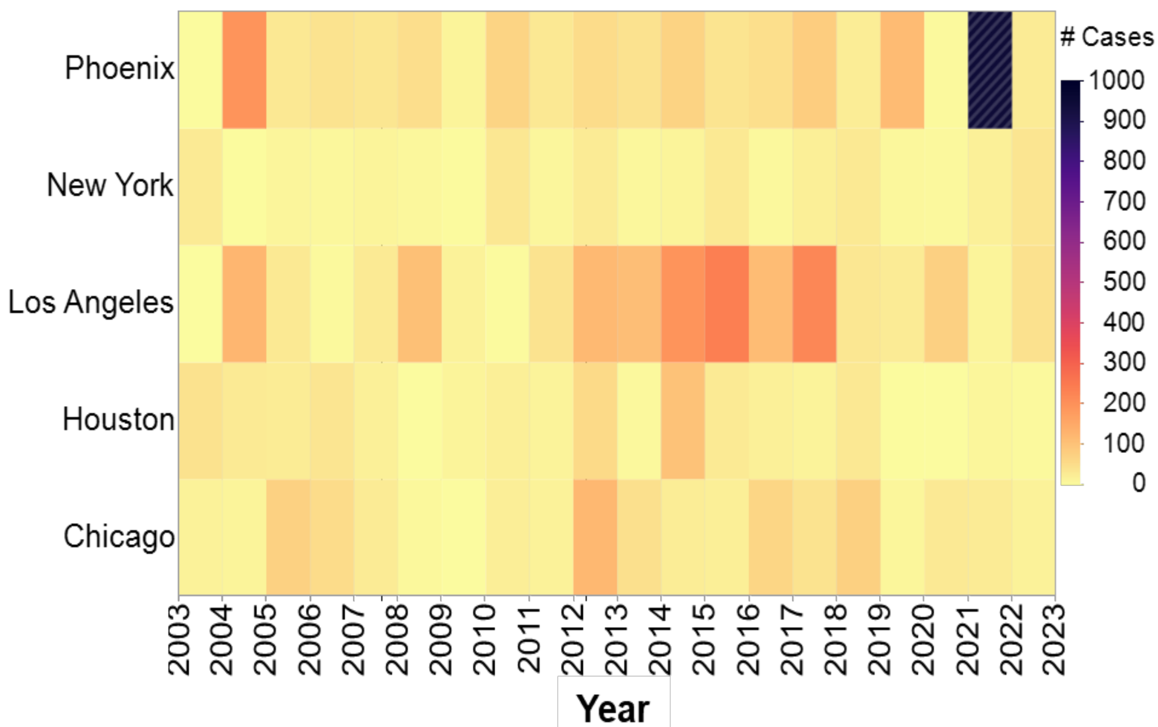


Figure 5. Heatmap of the annual WNV neuroinvasive cases for five cities in the USA.

WNV Incidence Rate

In the model, the WNV neuroinvasive data was converted into monthly incidence rate over a population size of one million using the following equation:

$$WNV\ Monthly\ Incidence\ Rate\ =\ (WNV\ Monthly\ Cases\ x\ 1{,}000{,}000)\ /\ (Population)$$

The incidence rate parameter adjusts for differences in population sizes among regions, allowing for fairer comparisons. This assists in creating a more robust and reliable model.

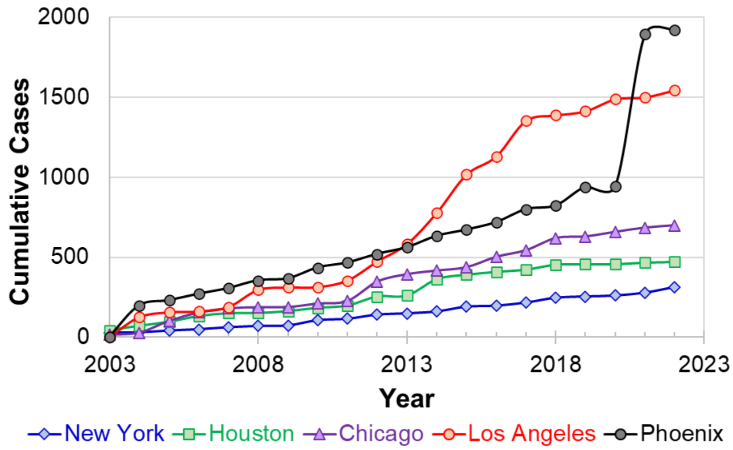


Figure 6. Cumulative WNV neuroinvasive cases from the year 2003 to 2022.

Results and Discussion

Correlation Coefficients

To identify a suitable modeling approach and a machine-learning algorithm, the correlations between WNV disease incidence rates and environmental parameters were calculated. These correlation coefficients provide insight into the relative effect of various variables on WNV disease incidence rate as shown in Figure 8. The correlation coefficients heatmap depicts the strength of the relationships between each pair of variables. The values of the correlation coefficients range from -1 to 1. A correlation coefficient of -1 indicates an absolute inverse correlation, with one variable increasing as the other variable decreases, and vice versa. The red color in the heatmap (Figure 7) indicates absolute positive correlation, whereas a blue color indicates a negative correlation. The red cells on the diagonal show the correlations of variables with themselves, and therefore, are unity. The first row in the heatmap (Figure 7) shows the correlation between WNV incidence rate and the input parameters. From this figure, it can be noted that the month, natural land coverage, and location have positive correlation, while wind speed, precipitation and humidity have negative correlations. Furthermore, temperature has the strongest correlation on the incidence rate. When effects are highly correlated, it is difficult to determine and include the effect of input parameters on the response using a simple regression model. Therefore, a neural network model was used to capture these correlations in this work.

Neural Network Modeling Approach

In this neural network model, *TanH* and linear functions were used as activation functions to capture the non-linear effect of inputs on the incidence rate. An activation function is a mathematical transformation of input variables applied at hidden layer nodes. *TanH* is the hyperbolic tangent function that transforms input values to be between -1 and 1. The linear activation function is a combination of input variables similar to a linear regression model. The neural network model incorporated boosting methodology to build an additive neural network model by fitting a sequence of smaller models on the training dataset. Each of the smaller neural network models is fit on the scaled residuals of the previous model. The best-performing smaller neural network models were combined to form the final model. Figure 8 shows the neural network model architecture, which consists of 7 input parameters, one hidden layer containing 90 hidden nodes, and monthly incidence rate per million population as an output parameter. The 90 hidden nodes are a resultant of 30 small neural network models, each with 2 *TanH* hidden nodes and 1 linear hidden node boosted to form the final network. The neural network model performance quality was evaluated based on the R^2 (i.e., coefficient of determination) and RASE (root average squared error) values. To test the model performance and avoid overfitting of the neural, 85% of the dataset covering New York, Chicago, Los Angeles, and Houston was randomly assigned to training and the remaining 15% was assigned to the validation dataset. Furthermore, Phoenix city data was used to independently test model performance, since it was not included in the training or validation datasets. Table 2 shows the neural network model performance results in training, validation and test data.

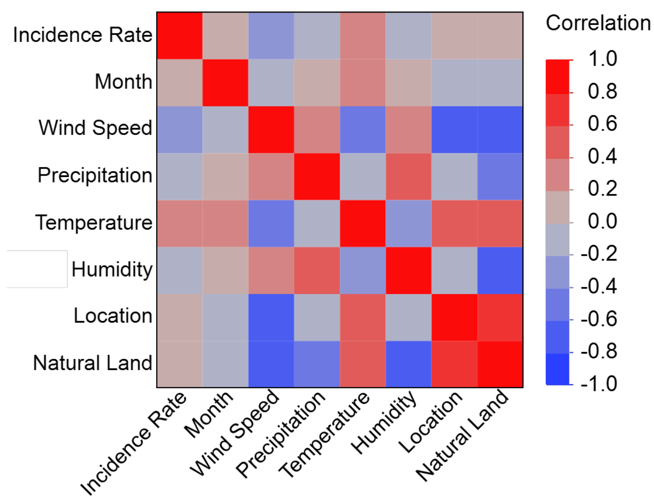


Figure 7. Heatmap showing correlation between input parameters and WNV incidence rate.

Table 2. Neural network model performance results on training, validation and test data.

Dataset	Training	Validation	Test
R^2	0.875	0.907	0.823
RASE	0.960	0.916	2.240

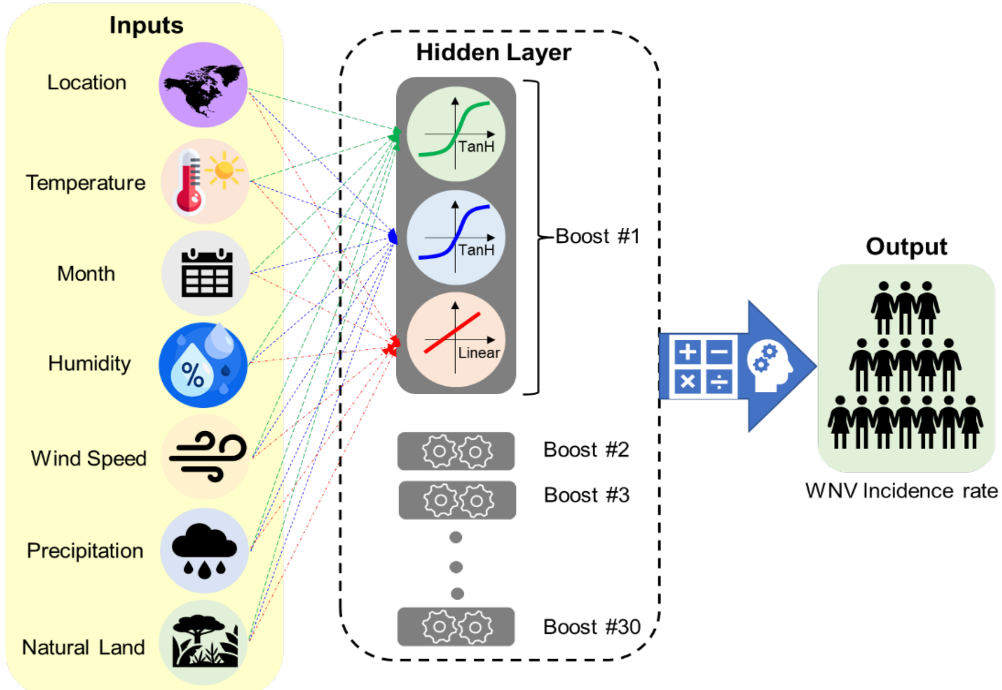


Figure 8. Neural network architecture.

Variables Importance in Incidence Rate Prediction

Figure 9 shows the calculated relative effect of each variable on the incidence rate in this neural network model. This figure indicates that temperature and month are the major factors affecting the WNV incidence rate. Other variables such as precipitation, wind speed, location and humidity have a relatively lower influence on the WNV incidence rate. Natural land coverage also has a minimal effect on the incidence rate which may be attributed to mosquito species favoring the urban environment for hatching and transmission. Furthermore, the natural land coverage used in the model represents cumulative area and may not be representative of the local environment.

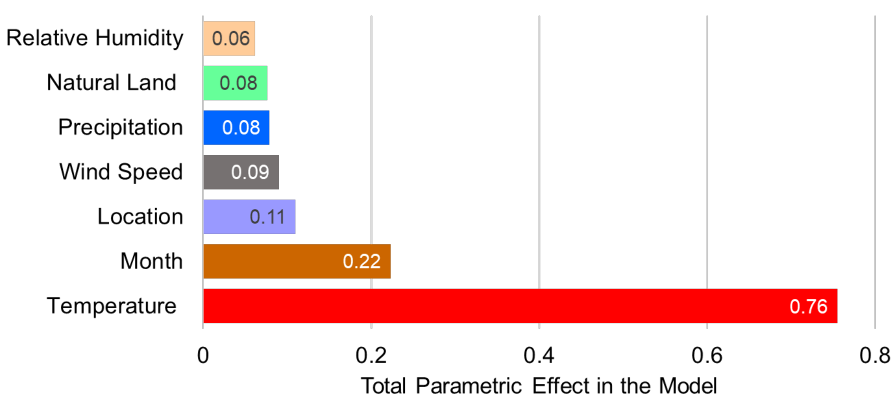


Figure 9. Variable contribution to the WNV incidence rate as per the neural network model.

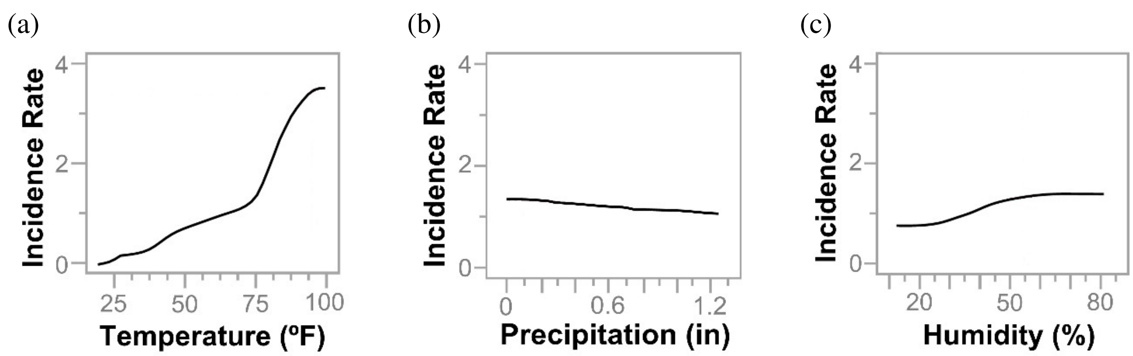
Figure 10 shows the WNV incidence rate prediction profiles for input parameters calculated using the neural network model. The positive and negative slopes in the prediction profiles reflect variables' effect on the incidence rate. It is to be noted that prediction profiles represent the trends at specific input values and will vary with change in input parameters. These prediction profiles provide valuable insight on how environmental parameters affect the incidence rate and are further discussed below.

Temperature

Figure 10(a) shows that the WNV incidence rate increases as temperature increases and achieves a peak around 95 ºF. After this critical temperature, further increase leads to stagnation in the incidence rate. This sigmoidal graph aligns with the mosquito life cycle and WNV transmission trend observed in the USA (Paz S and Semenza JC, 2013). Increased temperatures lead to proliferation of vector populations, and shorten the transmission cycle of the virus as mosquitoes are more active (Dohm et al., 2002; Paz S et al., 2013). However, extremely high temperatures reduce mosquito survival and slow down WNV transmission. Furthermore, temperature sensitivity varies with mosquito species. These results agree with the previous findings by various researchers which have reported a similar effect of temperature on the virus transmission cycle (Peterson et al., 2012; Ruiz et al., 2010).

Precipitation

Figure 10(b) shows that increased precipitation leads to lower WNV incidence rate. This trend may seem counterintuitive, since precipitation is generally assumed to support mosquito populations. However, these results can be justified based on the variations in ecology of mosquito vectors in different geographic locations as reported in the literature (Paz & Semenza, 2013; Landesman et al., 2007; Moudy et al., 2007). For instance, the population size of *C. pipiens* typically decreases with rainfall due to the flushing of catch basins (Koenraadt & Harrington, 2008). On the other hand, vector *C. tarsalis* generally sees surge in population with heavy precipitation, since it creates an optimal larval habitat (Wimberly et al., 2008; Reisen et al., 2008). Overall, drought conditions bring about favorable environments for most mosquitoes: standing water pools become rich in organic material that mosquitoes need in order to thrive (Paz et al., 2013) and have less mosquito predators like frogs (Chase & Knight, 2003). Drought conditions have also been shown to congregate birds and mosquitoes near remaining water sources, increasing transmission of the WNV (Wimberly et al., 2008). This trend can also be affirmed by the Centers for Disease Control and Prevention (CDC, 2023) findings on the WNV outbreak in the summer of 2022 in Texas where drought-like conditions were found to be the major cause (Roehr, 2012).



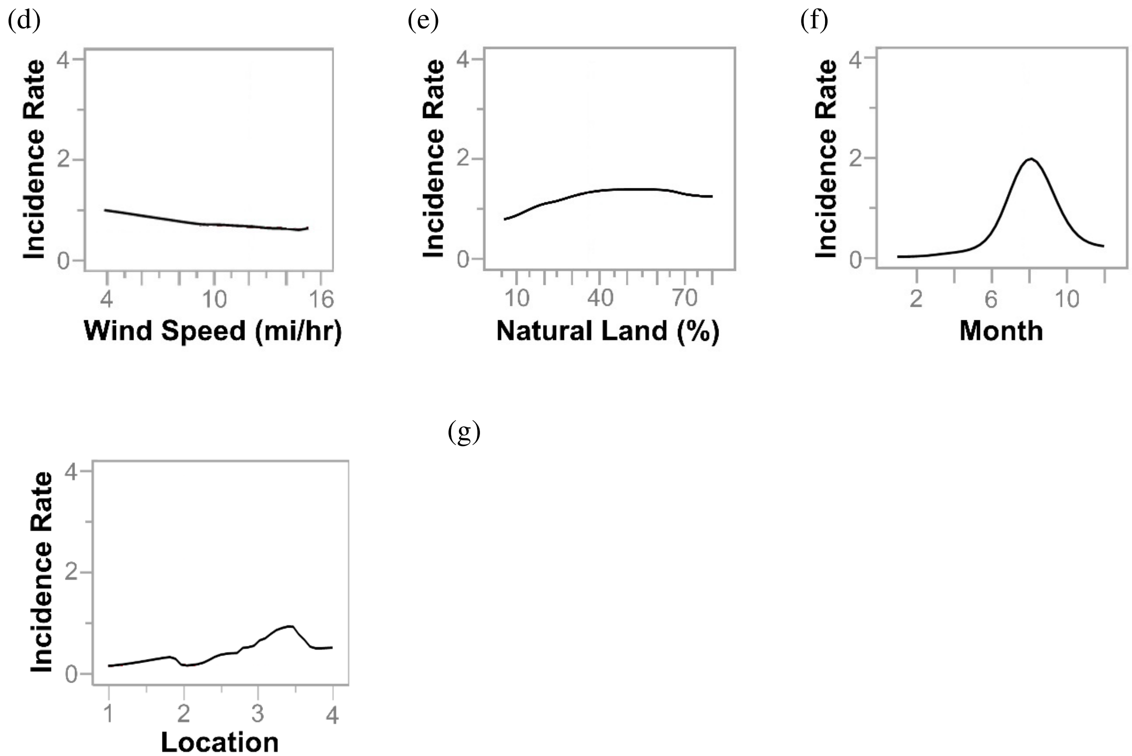


Figure 10. Prediction profiler for (a) temperature, (b) precipitation, (c) relative humidity, (d) wind speed, (e) natural land coverage, (f) season and (g) geographic location.

Relative Humidity

As expected, the WNV incidence rate increases as humidity increases but has a very weak association as shown in Figure 10(c). Higher relative humidity supports mosquito life cycle and enhances mosquito activities. Furthermore, humidity influences people's lifestyle and their involvement in outdoor activities, further increasing or decreasing their exposure to mosquitoes.

Wind

There was a scarcity of information about the effect of wind speed on WNV incidence rate in the literature. The results (Figure 10(d)) show that as wind speed increases, the WNV incidence rate decreases. Wind speed affects mosquitoes' flight and virus spread (Mackenzie et al., 2004; Sellers & Maarouf, 1990; Reisen et al., 2004). For example, *Culex* mosquitoes use wind as a means of migration (Min & Xue, 1996) and their dispersion will be affected with wind speed. Furthermore, the storms might impact virus dispersal by altering the dynamics of bird's flight and migration (Paz & Semenza, 2013).

Natural Land Coverage (Wetland, Grassland & Forest)

Natural land coverage has a very weak association with WNV incidence rate as shown in Figure 10(e). Typically, greater natural land coverage i.e., wetlands, grasslands and forests will increase the mosquito and bird population, and therefore will lead to a higher WNV incidence rate as observed in this model. However, it is very difficult to accurately quantify its effect in the model since natural land coverage areas can vary spatially and will require fine spatial resolution. To capture it accurately, city regions need to be split into smaller subzones with similar geographic conditions and grouped based on the mosquitoes predominant in those regions.

Season

WNV transmitting mosquitoes are ectotherms, which means that their life cycle and activity are heavily influenced by the ambient temperature. Figure 10(f) shows the incidence rate follows a gaussian or bell curve distribution with the months. The WNV incidence rate is maximum during the summer and early autumn since the outdoor conditions are optimal for mosquito breeding. Furthermore, more people are exposed in the summer since they indulge in outdoor activities. The incidence rates drop during winter because mosquitoes enter a dormancy stage due to low temperatures.

Geographic Location

Figure 10(g) shows that regional location coupled with climate factors affect the WNV incidence rate. For example, western USA has a higher incidence rate compared to the eastern USA. This geographic variation can be attributed to the varied distribution of bird hosts and mosquito species (Kilpatrick et al., 2006). Moderate temperature in the Western USA may also support mosquito life-cycle and enhance their interaction with birds. Moreover, mosquitoes that transmit WNV are more prevalent in areas where winters are short enough for them to survive (Eldridge, 1987; Nelms et al., 2013).

WNV Incidence Rate Forecast

The JMP software (SAS Institute Inc., 2022) was used to forecast the mean monthly temperature, precipitation, wind speed, population and natural land coverage area from the years 2021 to 2025, since these parameters are required as inputs to predict the future WNV incidence rates. A time-series forecast was first calculated for these environmental parameters using data from the years 2003 to 2020 as input parameters. These forecasted values were then used as inputs in the neural network model to predict the WNV incidence rate. Figure 11 shows forecasted annual WNV neuroinvasive cases which was calculated by multiplying the forecasted monthly incidence rate with population and summing it over a yearlong period. Good agreement between forecasted values and actual cases provide confidence in model capabilities in capturing temporal distribution of WNV incidence rate.

Summary and Conclusions

A neural network model was developed to forecast the incidence rate of WNV in the USA based on climate and geographical variables which include mean monthly temperature, wind speed, precipitation, humidity, land forest area, and the month. The following conclusions can be drawn from this model:

- The neural network model shows that temperature and month predominantly affect WNV incidence rate. Temperature follows an asymmetric sigmoidal distribution with a peak in incidence rate around 95ºF. Beyond this threshold temperature, the incidence rate becomes relatively stagnant. Month follows a Gaussian bell curve distribution with a peak in incidence cases during autumn.
- WNV incidence rate varies with geographical regions. Climate conditions in Western USA are more conducive for WNV. The Eastern USA has relatively lower incidence rates.
- Other environmental parameters have a marginal impact on WNV incidence rates. For instance, humidity and natural land coverage have a weak positive correlation with WNV incidence rate. Meanwhile, precipitation and wind speed have a weak negative correlation with WNV incidence rate.

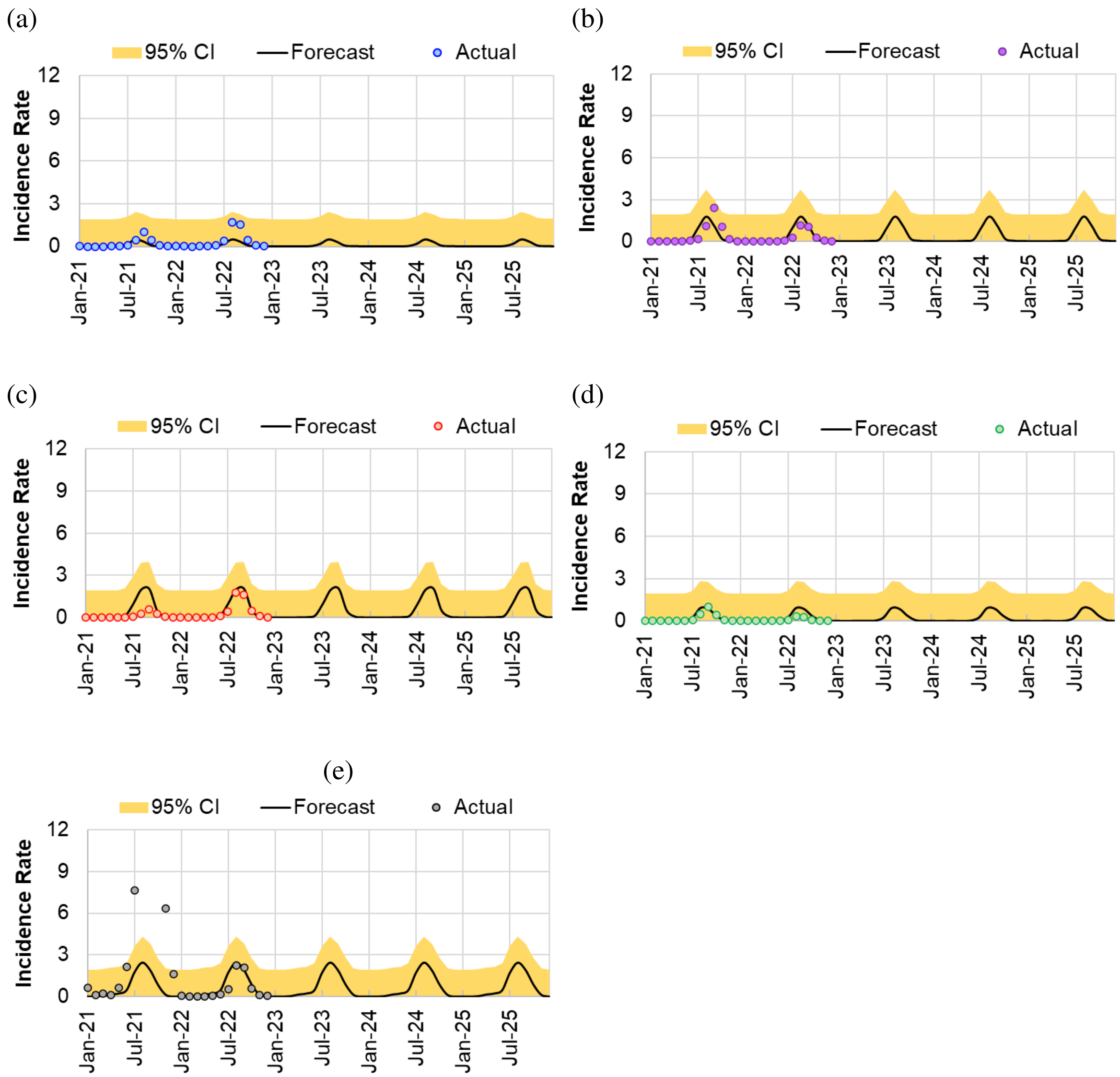


Figure 11. Forecasted incidence rate for (a) New York, (b) Chicago, (c) Los Angeles, (d) Houston, and (e) Phoenix. Note. Symbols represent actual data from January 2021 to December 2022, lines show the forecasted values, and shaded regions represent 95% CI (confidence interval).

In the future, climate change will further influence environmental parameters such as drought, rainfall and storms in addition to adaptability of birds which are predominant WNV disease carriers. This will influence WNV incidence rate, and some regions may experience a surge in the WNV disease if municipalities and local communities do not take proper precautions.

Limitations

The relationship between climate conditions and vector-borne disease risk is extremely complex due to variability in vector species, virus host populations, daily meteorological conditions, geographic location, and the life cycle of mosquitoes. Furthermore, social and environmental factors are interrelated, and they are extremely difficult to quantify. To simplify the model, the effects of age demography, race, health care infrastructure, socio-economic status, housing, people migration, and vector species population, etc. on the WNV incidence rate were not considered explicitly in the study. Moreover, the monthly time resolution and average climate conditions may not accurately capture the effect of daily extremes on vectors. Also, land usage characterization requires very fine resolution of the urban areas, grasslands and wetlands, etc. to accurately assess their impact on WNV epidemics. Any delay or underreporting of WNV cases will affect the model prediction quality, since the Centers for Disease Control and Prevention's ArboNET national surveillance database (2023) is a passive surveillance system. Future research with focus on reliable data and mechanistic model development may address some of the existing gaps in understanding the effect of climate parameters on WNV disease.

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