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THE IMPACT OF DIFFERENT DROUGHT METRICS ON WEST NILE VIRUS PREDICTION IN OKLAHOMA

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THE IMPACT OF DIFFERENT DROUGHT METRICS ON WEST NILE VIRUS PREDICTION IN OKLAHOMA

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BY THE COMMITTEE CONSISTING OF

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Abstract

West Nile virus (WNV) is an arbovirus originating in birds and transmitted to humans via infected mosquitoes. Since its introduction into the U.S. in 1999, research has concluded that weather variables, including temperature, precipitation, humidity, and wind speed, influence transmission. Previous research has also identified drought as a potential factor in arbovirus transmission, however, the metrics selected to represent drought in previous works are inconsistent and often chosen without sufficient exploration of alternatives. This study aims to explore which drought metrics have the most significant impact on WNV prediction in Oklahoma, while also expanding knowledge of how weather and land cover influence WNV transmission within the state. In order to accomplish this broad goal, this study presents three main objectives: (1) Identify the optimal meteorological predictors of WNV transmission in Oklahoma from the standard base weather variables (2) Identify the optimal drought metric predictor for WNV transmission in Oklahoma and determine whether it improves the base weather variable model, and (3) Determine which land cover classifications exhibit the most influence over the spatial patterns of WNV transmission in Oklahoma. Data was obtained on an epi-week timescale for each Oklahoma county between 2004-2023, and included Oklahoma State Department of Health de-identified human WNV case data, GridMet average minimum, maximum, and mean temperature, mean relative humidity, vapor pressure deficit, average and total precipitation, and the percentage of reclassified National Land Cover Database (NLCD) land cover classes. Drought metrics were similarly obtained through GridMet and included the Palmer Drought Severity Index (PDSI), Standardized Precipitation Index (SPI), Standardized Precipitation Evapotranspiration Index (SPEI), and Evaporative Demand Drought Index (EDDI). The SPI, SPEI, and EDDI were all obtained for 14 day, 30 day, 90 day, 180 day, one year, two year, and five year aggregations. Generalized additive models (GAMs) with embedded distributed lag nonlinear models (DLNMs) were used to test the relationships of the variables. Best performing models were selected using the Bayesian Information Criterion (BIC) and validated using the area under the curve (AUC) and Spearman's rank correlation coefficient (SRCC). The best overall model included minimum temperature, wind speed, developed land cover, and the EDDI at 30 day calculations. Furthermore, the model lags indicated that there were multiple pathways through which dry conditions could influence WNV risk. These findings solidify drought, especially in terms of evapotranspiration, as an important factor in WNV prediction, imply that models containing anomalies of weather variables and variables combining multiple weather phenomena may perform well for WNV prediction, and present a possible modelling scheme for Oklahoma that should be evaluated in other locations.

Keywords: West Nile virus, arbovirus, drought, distributed lag non-linear model

Introduction

Background

"West Nile virus is the leading cause of mosquito-borne disease in the contiguous United States" (U.S. Centers for Disease Control and Prevention, 2024b).

West Nile virus (WNV) is an arbovirus originating in birds and transmitted to humans via infected mosquitoes. Once a mosquito bites an infected bird and becomes infected itself, it can infect another bird and perpetuate the infection cycle, but may also bite and infect a human, which is a dead-end host unable to retransmit the virus (U.S. Centers for Disease Control and Prevention, 2025). Although most humans who contract the virus are asymptomatic, some can develop flu-like symptoms or, in rare cases, neurological illness that can result in death (U.S. Centers for Disease Control and Prevention, 2024b). The U.S. Centers for Disease Control and Prevention (CDC)'s ArboNET reports that there were 63,155 cases and 3,315 deaths in the U.S. caused by WNV between 1999-2025 (U.S. Centers for Disease Control and Prevention, 2026). Furthermore, following the initial epidemic in 2002-2003, the virus has become endemic and the occurrence of WNV can vary widely from year to year (Figure 1). For example, there were 3,493 cases in the outbreak year 2012, but only 454 cases in 2009 (U.S. Centers for Disease Control and Prevention, 2026). Because of this public health concern, predicting the spread of disease is valuable for health agencies within the United States.

The virus was introduced to the United States over two decades ago, and since then, research on the transmission and prediction of the virus has lead to the understanding that certain weather variables, including temperature, precipitation, humidity, and wind speed, are influential for both bird and mosquito habitats and lifecycles and, therefore, disease transmission and prediction (see Brown et al., 2023; Bump et al., 2025; Davis et al., 2018; Wimberly et al., 2014).

First, extreme cold and warm temperatures limit mosquito survival and development, influence mosquito behavior, such as biting rate, and partially determine the effectiveness of WNV transmission (Mordecai et al., 2019; Shocket et al., 2020). Kilpatrick et al. (2008) illustrated that increases in temperature not only "increased viral infection, dissemination, and transmission", but also give advantages to some WNV strains over others.

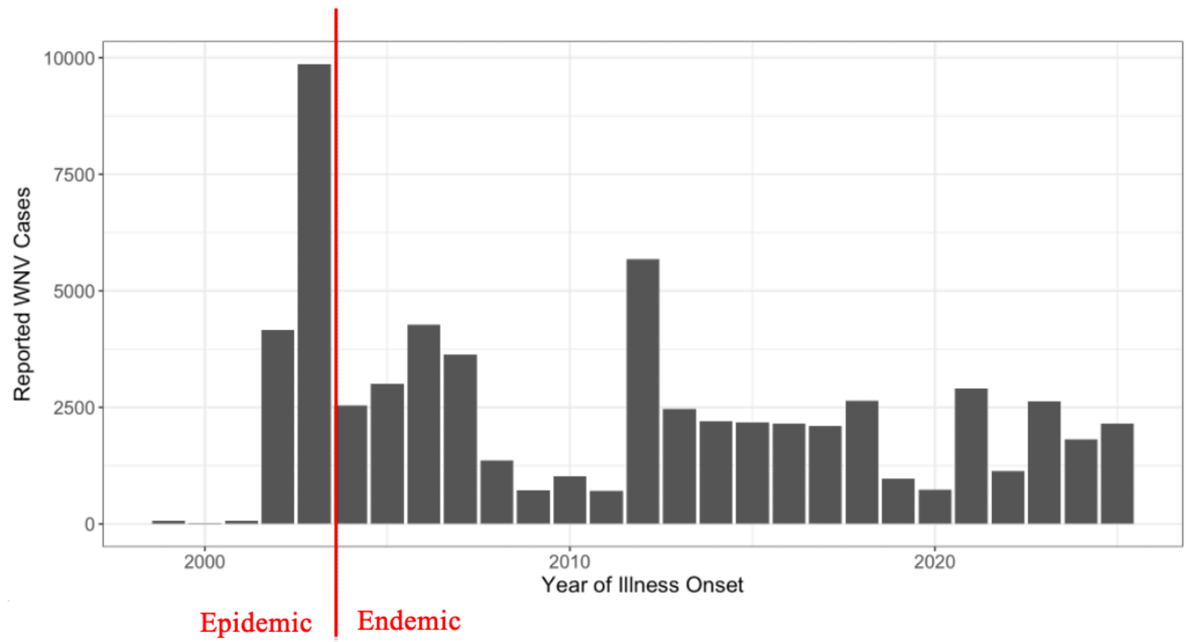

Figure 1: Time series of reported WNV human cases in the U.S. 1999-2025 derived from U.S. Centers for Disease Control and Prevention (2026) cumulative data

Second, both precipitation and humidity influence WNV transmission through their effects on the environment's moisture content. Mosquitoes require pools of water in order to breed, however, excess precipitation can lead to breeding sites being flushed out, meaning that the relationship of mosquitoes and WNV to precipitation is complex (Gardner et al., 2012). This relationship is also region specific, likely dependent upon local moisture conditions and vector and host species (Hahn et al., 2015; Landesman et al., 2007). Furthermore, the multiple mechanisms through which precipitation influences WNV may occur on different time scales (Caldwell et al., 2021). Similarly, humidity may influence mosquitoes through its relationship to evaporation at breeding sites and its potential to offset or worsen the stress effects of the given temperature; however, humidity is less studied than the previous variables (Brown, et al., 2023). Stilianakis et al. (2016) found a negative relationship between high humidity and WNV infection in Northern Greece, however, they acknowledge that this is in contrast to other studies, such as Paz (2006) in Israel, who found that the combination of high humidity and high temperatures increased infection. Stilianakis et al. (2016) suggest that their contrasting findings are due to complex and differing ecological factors in the studies.

Lastly, Bump et al. (2025) have recently identified wind speed as a key variable in WNV prediction in the United States. They suggest that strong winds may disrupt mosquito behavior and their ability to bite hosts and humans. This is consistent with the findings that wind can have an effect on mosquito dispersal (Atieli, et al., 2023), on WNV transmission in Northern Greece (Stilianakis et al., 2016), and on the transmission of malaria in Africa (Endo & Eltahir, 2018). Endo & Eltahir (2018) further argue that, while low wind speeds are associated with greater risk of malaria, wind direction also plays a role in transmission with upwind reservoir communities having an increased risk. They argue that this is due to the wind creating strong waves in the reservoir downwind, which causes greater larval mortality. Similarly, poor conditions caused by precipitation events, strong winds, or extreme temperatures may alter avian migration paths and timing, as well as the conditions of the prey and flora that they consume (McPherson, Alger, & Hofmeister, 2025).

Additionally, multiple studies have explored the possibility of connections between drought events and arboviruses (see Calzolari & Albieri, 2013; Chase & Knight, 2003; Kvit, 2017; Lowe et al., 2021; McMillian et al., 2025; Shaman, Day, & Stieglitz, 2005). Shaman, Day, & Stieglitz (2005) "show that the spatial-temporal variability of human West Nile (WN) cases and the transmission of West Nile virus (WNV) to sentinel chickens are associated with the spatial-temporal variability of drought and wetting in southern Florida". They further establish that, similar to findings for St. Louis encephalitis virus (SLEV), drought causes birds and mosquitoes to concentrate at water sources, resulting in a higher chance of WNV transmission. Ukawuba & Shaman (2018) examined WNV and hydrology in West Texas and found similar results that showed increased WNV particularly if dry summers were preceded by wet springs. Additionally, Paull et al. (2017) and Sambado et al. (2025) found that while droughts decrease mosquito abundance, they increase WNV infection, possibly through the concentration mechanism previously mentioned or reduced reproduction in the avian community. On the other hand, through surveys of both natural wetlands and experimental mesocosms, Chase & Knight (2003) found evidence to support that in wetlands that dry only in drought years, drought can reduce predators and cause mosquito populations to increase. Thus, there are multiple ways in which drought can influence WNV depending on the microclimates involved. The above studies highlight that drought can disrupt ecological processes, causing changes in host and vector behavior that either increases the vector population or forces vectors into closer proximity to hosts, and thereby increasing the chances of transmission.

There are multiple ways to define and measure drought, which impact how drought is accounted for in prediction models. For example, some drought metrics only consider lack of precipitation as their drought definition, while others include lack of soil moisture or atmospheric conditions. Drought metrics can also be calculated over multiple time periods from days to years, presenting another challenge in identifying the most relevant scale for defining drought in relation to WNV. However, studies connecting arboviruses to drought often select one drought metric or index without comparison to others and may also be outdated or not specific to WNV. For example, McMillian et al. (2025), Li et al. (2023b), Lowe et al. (2021), and Sambado et al. (2025) use the Palmer Drought Severity Index (PDSI) (see Palmer, 1965). In contrast, Li et al. (2023a), Calzolari & Albieri (2013), Lowe et al. (2018), and Landesman et al. (2007) use the Standardized Precipitation Index (SPI) (see McKee, Doesken, & Kleist, 1993) or the similar Standardized Precipitation Evapotranspiration Index (SPEI) (see Vicente-Serrano, Begueria, & Lopez-Moreno, 2010). On the other hand, Peters et al. (2020) uses the Evaporative Demand Drought Index (EDDI) (see Hobbins et al., 2016; McEvoy et al., 2016). Each drought metric includes slightly different phenomena with the PDSI incorporating evapotranspiration, precipitation, and soil moisture capacity, the SPI incorporating precipitation anomalies, the SPEI incorporating precipitation anomalies with evapotranspiration, and the EDDI incorporating anomalies of atmospheric demand (or "atmospheric thirst") ("Evaporative Demand Drought Index (EDDI): NOAA Physical Sciences Laboratory", n.d.; "Spi & Spei: Drought Indices Explained with Calculations", n.d.; "U.S. Gridded Palmer Drought Severity Index (PDSI) from Gridmet", n.d.).

Furthermore, land cover is thought to have an impact on WNV transmission as different mosquito species, as well as avian species, prefer different habitat types. In general, as humans change the landscape, for example through urbanization or the establishment of farmland, the type and extent of suitable habitats for mosquitoes and birds also change. Then, actions such as the use of pesticide or deforestation have further potential to affect biodiversity, including changes in host and vector species for arboviruses (Ferraguti et al., 2023). However, the effects of land cover may vary with each arbovirus and with the area in question (Ferraguti et al., 2023;

Bowden, Magori & Drake, 2011; DeGroote & Sugumaran, 2012). For example, Bowden, Magori, & Drake (2011) found that WNV incidence in the northeastern and western regions of the U.S. is positively influenced by urban and agricultural land cover respectively, and they argue that this difference could be driven by the presence of different vector species. Conversely, DeGroote & Sugumaran (2012) found that WNV in the northeastern region was influenced by agriculture and western regions were influenced by rural irrigated land cover. Hess, Davis, & Wimberly (2018) and Chuang et al. (2012) both found that low-lying rural areas with frequent ponding were at higher risk for WNV in South Dakota, likely due to increased mosquito breeding sites. These differences also may be due to variation in how regions were defined, datasets used, or modelling techniques.

In particular, the state of Oklahoma is home to multiple WNV vectors and hosts, making the relationships between different land cover types and the WNV transmission cycle complex. For example, Oklahoma has both *Culex tarsalis*, a WNV vector that prefers grasslands and forests, and *Culex pipiens*, a WNV vector that prefers urban settings (Bump & Wimberly, 2026; Hoback et al., 2017). Oklahoma is also home to robins, red-winged blackbirds, and grackles, examples of migratory avian hosts that may reintroduce WNV annually across multiple habitats in the state (Schwartz, Ibaraki, & Hort, 2025; Oklahoma Department of Wildlife Conservation, n.d. a-d). Johnson et al. (2015) found that WNV outbreak seasons in Oklahoma may manifest differently from year to year, likely due to differences in vector and host species abundance, as well as differences in the environment. Furthermore, Hess et al. (2020) found that *Culex tarsalis* and *Culex pipiens* abundance differs within each season, with August and October presenting the greatest abundance of each respectively.

On the avian side, Vaughan, Newman, and Turell (2022) found that some bird species are more effective hosts for transmitting WNV to *Culex pipiens* than others, with robins exhibiting much greater transmission than grackles. Consequently, different landscapes and the host and vector species that inhabit them within Oklahoma have the potential to shape WNV transmission differently each season. In terms of analysis, because Oklahoma lies in the central U.S. and contains multiple vectors, previous national studies have taken different approaches to including the state in larger regions within the U.S., such as incorporating it into predefined regions (e.g. South Central, Midwest, etc.) or splitting the state into pieces to fit within regions of vector habitats (see DeGroote & Sugumaran, 2012; Bowden, Magori, & Drake, 2011). However, this leads to inconclusive results for the effects of land cover on WNV in Oklahoma as an individual unit.

The goal of this research is to explore which drought metrics have the most significant impact on endemic WNV prediction in an effort to make future prediction models more accurate and further the understanding of the impact of drought on WNV transmission, while also expanding knowledge of how weather and land cover influence WNV transmission in Oklahoma. In order to accomplish this broad goal, this study addresses three main objectives:

(1) Identify the best predictors of WNV transmission in Oklahoma from the standard base weather variables (temperature, humidity, precipitation, and wind speed) known to influence transmission,

(2) Identify the best drought metric predictor for WNV transmission in Oklahoma and determine if it improves the base weather model, and

(3) Determine which land cover types exhibit the most influence over the spatial patterns of WNV transmission in Oklahoma.

Methods

Datasets

Deidentified human WNV case data at the county level was obtained from the Oklahoma State Department of Health (n.d) through a data sharing agreement. The human case data includes all reports (including both neuroinvasive and non-neuroinvasive cases) in the state between 2002-2023, the date of symptom onset reported, and the county of reporting. This dataset includes the initial epidemic outbreak years, during which the influence of weather patterns and other variables on WNV transmission was not yet established. In order to analyze solely the endemic years when the target variables would influence transmission in a regular manner, only 2004-2023 were considered. Epi-weeks (or Morbidity and Mortality Weekly Report (MMWR) weeks) are a standardized way to represent the weeks of the year within the epidemiological community that numbers the weeks of the year in a way that allows for comparison between years. The CDC's version of an epi-week begins on Sunday and ends on Saturday with the first week of the year containing at least four days of the current calendar year (U.S. Centers for Disease Control and Prevention, n.d. a). The sum of the human cases per county per epi-week was obtained in order to create an epi-week timescale in this study. Then, following the analysis methods used in previous studies (see Davis et al., 2018; Wimberly et al., 2022; Nekorchuk et al., 2024), the data was converted into a binary variable with 0 being no cases and 1 being at least one case in a given county in a given epi-week (henceforth called negative/positive county-weeks respectively). The previous studies mentioned above have used this type of binary variable to enhance analysis of human WNV datasets that are zero-inflated, and have demonstrated that the method is reasonable for WNV modelling. Additionally, to focus on modeling variability in WNV cases during the transmission season, only human case data from epi-weeks 17-47 (roughly May through November) were considered.

Daily weather variables for each Oklahoma county, including mean temperature, minimum temperature, maximum temperature, relative humidity, vapor pressure deficit (VPD), precipitation, and wind speed were derived from GridMet (Abatzoglou, 2011) via Google Earth Engine (GEE) for 2004-2023. The average of each weather variable was calculated for each county and epi-week, along with the sum of precipitation.

Drought metrics, including the PDSI, SPI, SPEI, and EDDI, were obtained from GridMet via GEE, which offers the metrics as precalculated data at five day intervals. These drought metrics were selected due their ease of access for future end-users, as well as their appearance in other arbovirus papers (For PDSI see McMillian et al., 2025; Li et al., 2023b; Lowe et al., 2021; Sambado et al., 2025, for SPI/SPEI see Lowe et al., 2018; Li et al., 2023a; Calzolari & Albieri, 2013; Landesman et al., 2007, for EDDI see Peters et al., 2020). The SPI, SPEI, and EDDI were all available for 14 day, 30 day, 90 day, 180 day, one year, two year, and five year aggregations, meaning that on any given day, the metric was calculated using weather data from the past 14 day, 30 day, 90 day, 180 day, one year, two year, or five year period to give one value for that day. For the PDSI, GridMet uses a modified equation with 30 day blocks of precipitation and potential evapotranspiration with static soil water holding capacity ("Palmer Drought Severity Index (PDSI)", n.d.; "GridMet Drought: Conus Drought Indices", n.d.). All of the above were obtained for the state of Oklahoma between 2004-2023 and averaged to obtain one value for each metric per county per epi-week over the time period. For PDSI, SPI, and SPEI, negative values represent drier conditions, while positive values represent wetter conditions (Table 1). Typically, the EDDI is interpreted with the reverse scale of the SPI/SPEI, with positive values representing drier conditions (see McEvoy et al., 2016). GridMet's dataset description lists the EDDI with the same interpretation as the SPEI and SPI, however, this is likely not the case, due to the opposite trends being exhibited in the present analysis (see Figure 7). Therefore, the EDDI is interpreted as usual with positive values indicating drier conditions.

Land cover data was obtained for Oklahoma from the National Land Cover Dataset (NLCD) via GEE (Dewitz & U.S. Geological Survey, 2021). At the time of this study, GEE only provided annual NLCD data for 2004, 2006, 2008, 2011, 2013, 2016, 2019, and 2021. Therefore, the categories from years that were available were assumed to be the same as the years after until the next available year (for example, the data from 2004 would be used for 2005). The values were reclassified so that open water and perennial ice/snow were one category, open space, low, medium, and high intensity developed land were one developed category, deciduous, evergreen, and mixed forests were one forest category, scrub/shrub, pasture/hay, and grassland/herbaceous land were one shrub/herbaceous category, and woody wetlands and emergent herbaceous wetlands were one wetlands category, and barren land and cultivated crops retained their own separate categories. The frequency of each class was calculated for each Oklahoma county and converted into a percentage of the total county land cover.

All of the above data were joined into one file with values for each variable being reported for every county and epi-week between 2004-2023.

Table 1: Guide for drought metric interpretation, information adapted from GEE's "GridMet Drought: Conus Drought Indices" (n.d.) with corrected EDDI interpretation

Drought Metric	**Interpretation**
PDSI	5.0 or more (extremely wet) 4.0 to 4.99 (very wet) 3.0 to 3.99 (moderately wet) 2.0 to 2.99 (slightly wet) 1.0 to 1.99 (incipient wet spell) -0.99 to 0.99 (near normal) -1.99 to -1.0 (incipient dry spell) -2.99 to -2.0 (mild drought) -3.99 to -3.0 (moderate drought) -4.99 to -4.0 (severe drought) -5.0 or less (extreme drought)
SPI, SPEI	2.0 or more (extremely wet) 1.6 to 1.99 (very wet) 1.3 to 1.59 (moderately wet) 0.8 to 1.29 (slightly wet) 0.5 to 0.79 (incipient wet spell) -0.49 to 0.49 (near normal) -0.79 to -0.5 (incipient dry spell) -1.29 to -0.8 (mild drought) -1.59 to -1.3 (moderate drought) -1.99 to -1.6 (severe drought) -2.0 or less (extreme drought)
EDDI	2.0 or more (extreme drought) 1.6 to 1.99 (severe drought) 1.3 to 1.59 (moderate drought) 0.8 to 1.29 (mild drought) 0.5 to 0.79 (incipient dry spell) -0.49 to 0.49 (near normal) -0.79 to -0.5 (incipient wet spell) -1.29 to -0.8 (slightly wet) -1.59 to -1.3 (moderately wet) -1.99 to -1.6 (very wet) -2.0 or less (extremely wet)

Modeling Approach

Generalized additive models (GAMs) (see Hastie & Tibshirani, 1986) with embedded distributed lag nonlinear models (DLNM) (see Gasparrini, Armstrong, & Kenward, 2010) were used to test the relationships of the variables. GAMs are similar to generalized linear models (GLMs), however, GAMs allow for non-linear relationships, allowing for greater flexibility in the modeling of complex variable relationships. Likewise, DLNMs allow for variables to be input into a model at different lagged time intervals in order to test whether lags have an effect on the outcome. This approach is useful in WNV prediction as weather variables may not have an immediate impact on WNV transmission. For example, precipitation may create pools of water for mosquitoes to breed, but there is a lag between the date of precipitation and the date those newly hatched mosquitoes become infected and in turn infect a human. Additionally, these lags can be difficult to pinpoint for each variable as they may be different for each and are not known at the time of modelling. DLNMs allow for the models to select the best lag functions as part of the modeling process and then assess the effects of the lag on the given variables. Furthermore, using lagged models is a well established approach in arbovirus research that has shown success in determining the timing and effects of predictor variables (see Bump et al., 2025; Davis et al., 2018; Nekorchuk et al., 2023; Lowe et al., 2018; Lowe et al., 2021).

This study allowed for 1-15 weeks of lag for each variable. To implement the lagged effects, DLNMs require that crossbases of the variables be created, in which the functions of the variable and the lags must be defined. The present study used natural splines for both. The optimal number of degrees of freedom for each variable and lag in the crossbases were determined by running models consisting of only the given crossbasis as a predictor for human WNV with county fixed effects using degrees of freedom from 1 to 10 for each. The degrees of freedom used for the crossbasis of the best performing model according to the Bayesian Information Criterion (BIC) were then considered for further use. BIC is similar to the Akaike Information Criterion (AIC), which estimates the likelihood of model fit to the given dataset, however, BIC presents a likelihood that is stricter for more complex models with multiple terms (Dziak et al., 2020). Due to the large number of variables in this study, BIC was chosen in order to further reduce the chance of overfitting. In order to perform evaluation tests, years 2004-2018 were used for training the model, and years 2019-2023 were used for testing. The DLNM crossbases were rebuilt for the testing data with the same number of degrees of freedom used in training. Only the training data was used to create the model, resulting in BIC values and model plots based solely on the training data.

To address objective (1), the relationship between human WNV and the base weather variables was tested by modelling every possible combination of temperature, humidity, precipitation, and wind speed (EQ1). Following the procedure of Bump et al. (2025), no two variables of similar type were used together in order to "minimize collinearity and maintain interpretability" (see Table 2). For example, minimum temperature and maximum temperature were not allowed to be combined. All models contained county fixed effects to account for the spatial variation of the data (see Davis et al., 2018; Wimberly et al., 2022).

(EQ1) Human WNV ~ gam(county fixed effects + (base weather variable crossbasis 1) + …+ (base weather variable crossbasis n))

Once the best performing base weather model was established by identifying the model with the lowest BIC (i.e. the model with the most likely fit to the data), objective (2) was addressed by testing the drought metrics in two ways: (1) adding each drought crossbasis to the base weather model individually, (2) modelling each drought crossbasis with temperature and wind speed only (EQ2 &3). The same procedure as the base weather model was used to find the best performing model that included drought.

(EQ2) Human WNV ~ gam(best base weather model variables + drought crossbasis)

(EQ3) Human WNV ~ gam(county fixed effects + temperature crossbasis + wind speed crossbasis + drought crossbasis)

Then, in order to address objective (3) smoothed land cover percentages (not put through crossbases) were added to the best performing drought model and tested for every possible combination of the seven land cover categories (EQ4). The county fixed effects were not used in the land cover models, as the land cover variables instead account for spatial effects. The best performing land cover model was also identified through the lowest BIC.

(EQ4) Human WNV ~ gam(best drought model variables + s(percent landcover type 1) + … + s(percent landcover type n))

Following the methods of previous literature, the top ten models presented for each objective were further validated during the testing period (2019-2023). Validation included the area under the curve (AUC), which was used to test the model's ability to distinguish between positive and negative county-weeks, and Spearman's rank correlation coefficient (SRCC), which was used to test the correlation between the average observed positive county-weeks and the average number predicted (see Davis et al., 2018; Wimberly et al., 2014; Wimberly et al., 2022).

Table 2: Guide for the variables used in the prediction models

Variable	**Type**	**Use**
average min. temperature, average mean temperature, average max. temperature	temperature	predictor
average relative humidity (RH), average vapor pressure deficit (VPD)	humidity	predictor
total precipitation, average precipitation	precipitation	predictor
average wind speed	wind speed	predictor
average PDSI, average SPI_14d, average SPI_30d, average SPI_90d, average SPI_180d, average SPI_1y, average SPI_2y, average SPI_5y, average SPEI_14d, average SPEI_30d, average SPEI_90d, average SPEI_180d, average SPEI_1y, average SPEI_2y, average SPEI_5y, average EDDI_14d, average EDDI_30d, average EDDI_90d, average EDDI_180d, average EDDI_1y, average EDDI_2y, average EDDI_5y	drought	predictor
percent open water and perennial ice/snow land cover	water/snow land cover	predictor
percent open space, low, medium, and high intensity developed land	developed land	predictor
percent deciduous, evergreen, and mixed forests	forests	predictor
percent scrub/shrub, pasture/hay, and grassland/herbaceous land cover	grass/shrub land cover	predictor
percent woody wetlands and emergent herbaceous wetlands	wetlands	predictor
percent barren land	barren land	predictor
percent cultivated crops	cropland	predictor
binary county-weeks	WNV	dependent

Study Area

The present study focuses on the U.S. state of Oklahoma, where WNV was first reported in 2002 and has since become endemic. By the end of 2023, there were 1,013 cases reported, with 2007, 2012, 2013, and 2015 being outbreak years experiencing over 100 cases each. The greatest total number of WNV cases reported in Oklahoma since the virus was first detected occurs in counties that have high populations and large cities: Tulsa County and Oklahoma County (Figures 2 & 3). However, incidence rate (i.e the number of cases in a given county divided by the population of the county) of WNV is highest in the panhandle, which is consistent with a swath of higher incidence rates in the broader Great Plains region (Figure 4).

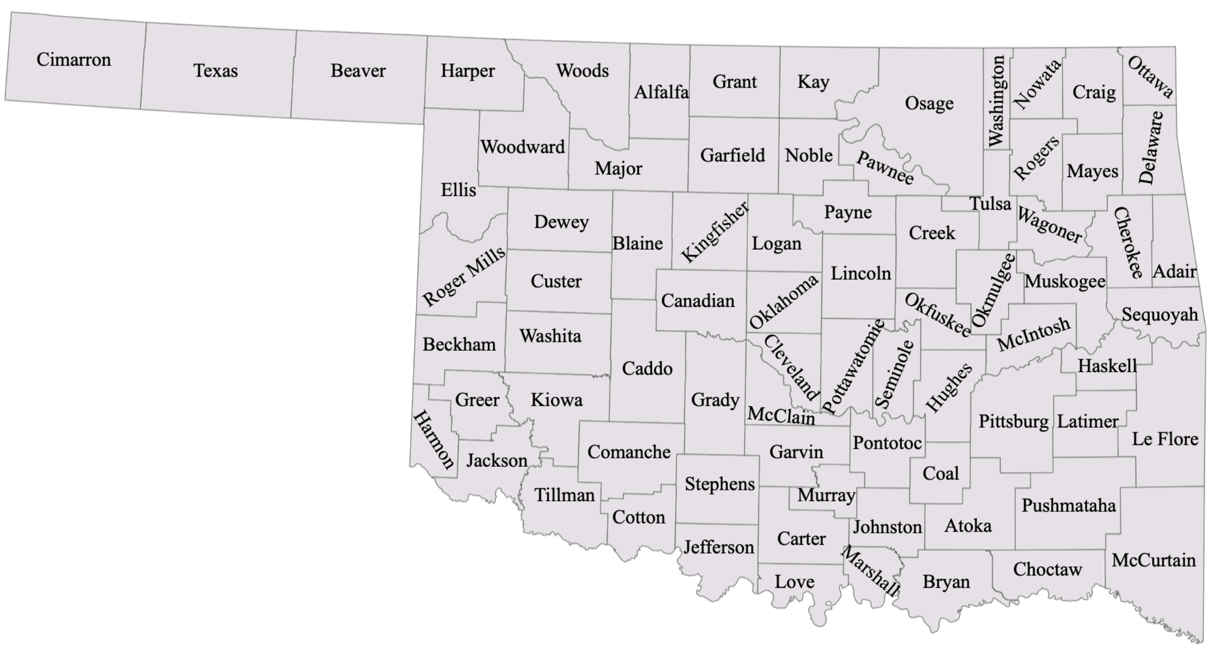

Figure 2: Reference map for Oklahoma counties

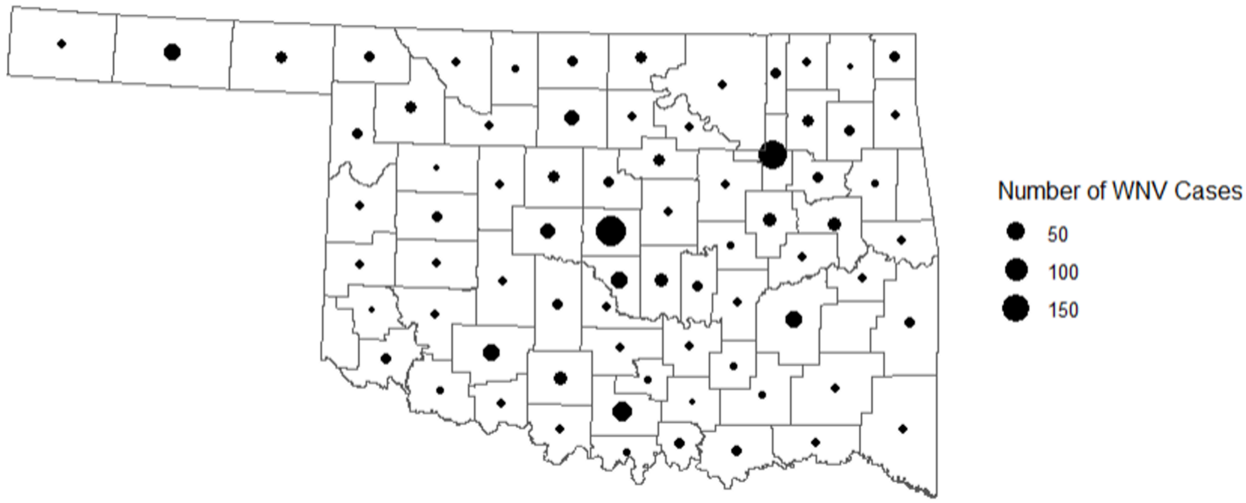

Figure 3: Map of all reported WNV cases in Oklahoma counties 2002-2023

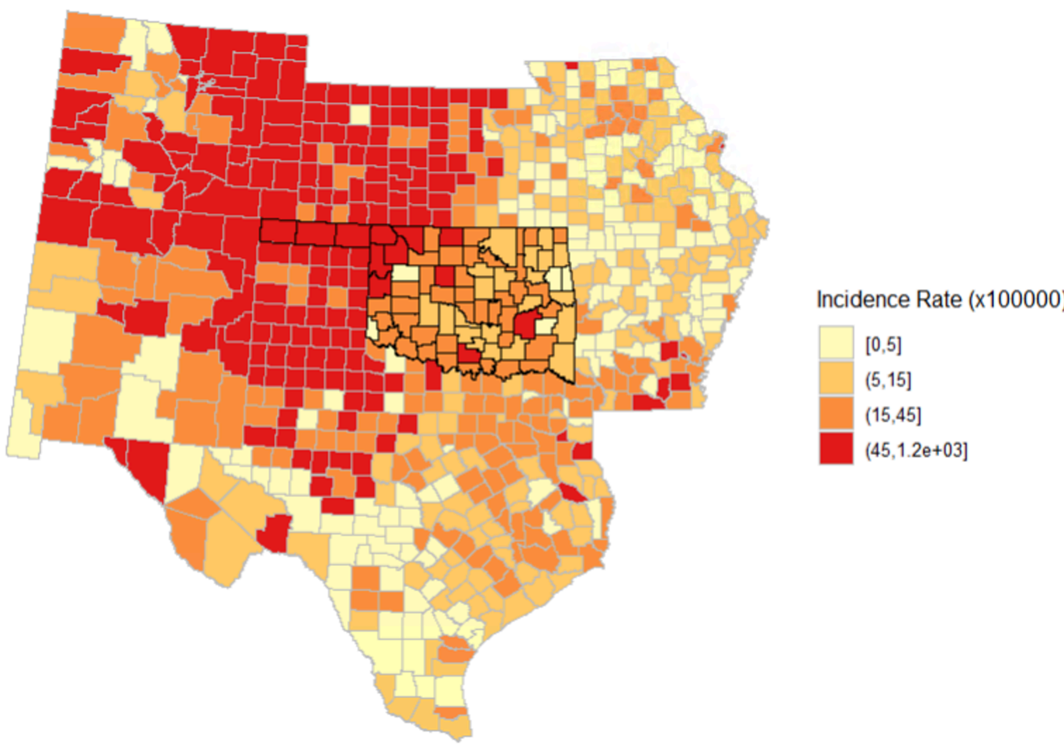

Figure 4: Map of incidence rate of all reported WNV cases in Oklahoma and the surrounding region 2002-2023, population derived from the 2010 Census (U.S. Census Bureau, n.d.), national WNV case data derived from the CDC ArboNET database (U.S. Centers for Disease Control and Prevention, 2026)

Oklahoma is situated in the midlatitudes and experiences a range of seasonal weather conditions that may influence WNV transmission. Upon examining temporal trends from 2003-2023 and spatial trends from 2012, average epi-weekly temperatures are warmest May-September and daily averages are a bit cooler in the Northwest (Figures 5A & 6A); daily temperatures can range from around -28℃ to 46℃. Average epi-weekly total precipitation is greatest in April-June, and the eastern portion of the state tends to receive greater amounts of total annual precipitation (Figures 5B & 6B); precipitation ranges from around 0 to 239 mm daily. Average epi-weekly evaporative demand, measured by vapor pressure deficit (VPD), is highest during the summer months and higher in the western portion of the state daily, particularly the Southwest (Figures 5C & 6C); VPD can range from around 0 to 6 kPa daily. Average daily wind speeds are generally higher in the central portion of the state and average epi-weekly wind speeds peak in the spring (Figures 5D & 6D); wind speeds can range from around 0 to 14 m/s daily.

Additionally, the state experiences varying degrees of drought from year to year, with the early 2010s being a particularly drought-prone period (Figure 7). Spatially, different drought metrics identify different regions of the state as being impacted during drought periods. For example, while PDSI and the EDDI calculated at 30 day intervals identify the eastern and central portions of the state as having the worst drought conditions in 2012 (a drought year), there is disagreement on how far those conditions extend and their magnitude. Furthermore, the EDDI calculated at 5 year intervals appears to indicate completely different results with the south and west indicated as the regions most affected by drought (Figure 8).

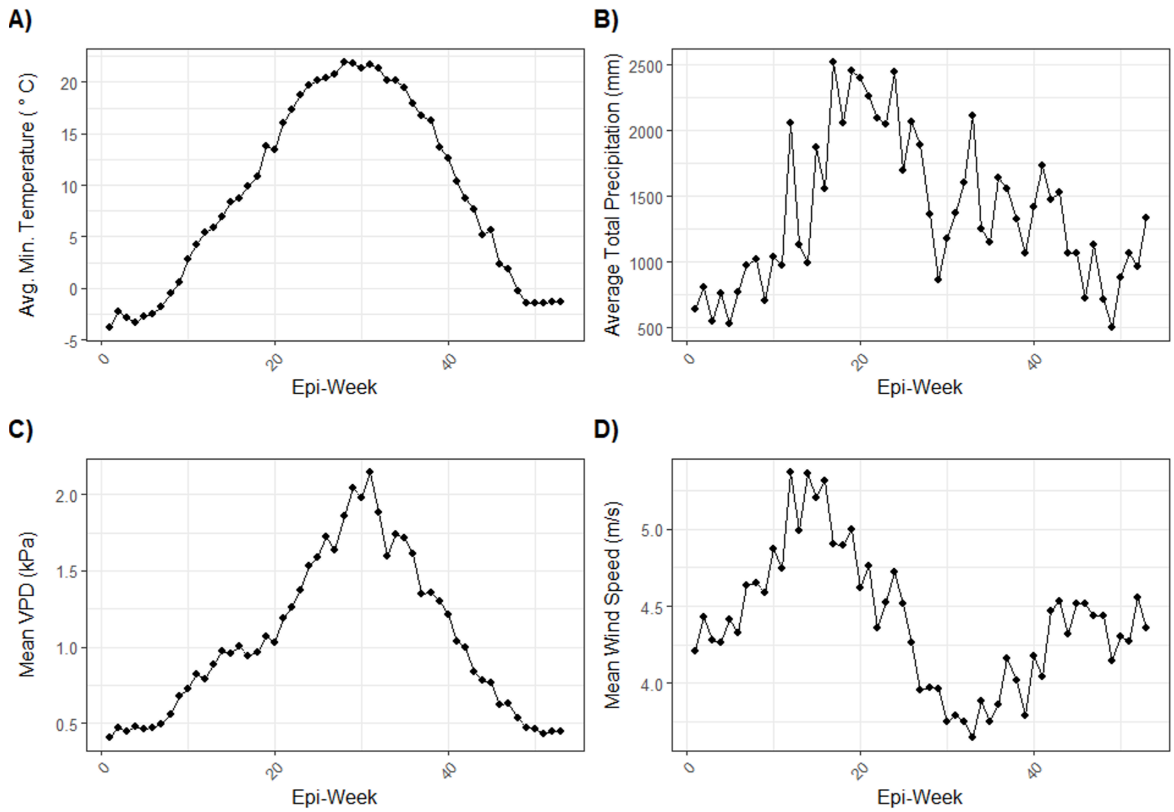

Figure 5: Time series of average epi-weekly conditions in Oklahoma 2003-2023 for A) minimum temperature, B) total precipitation, C) vapor pressure deficit, and D) wind speed

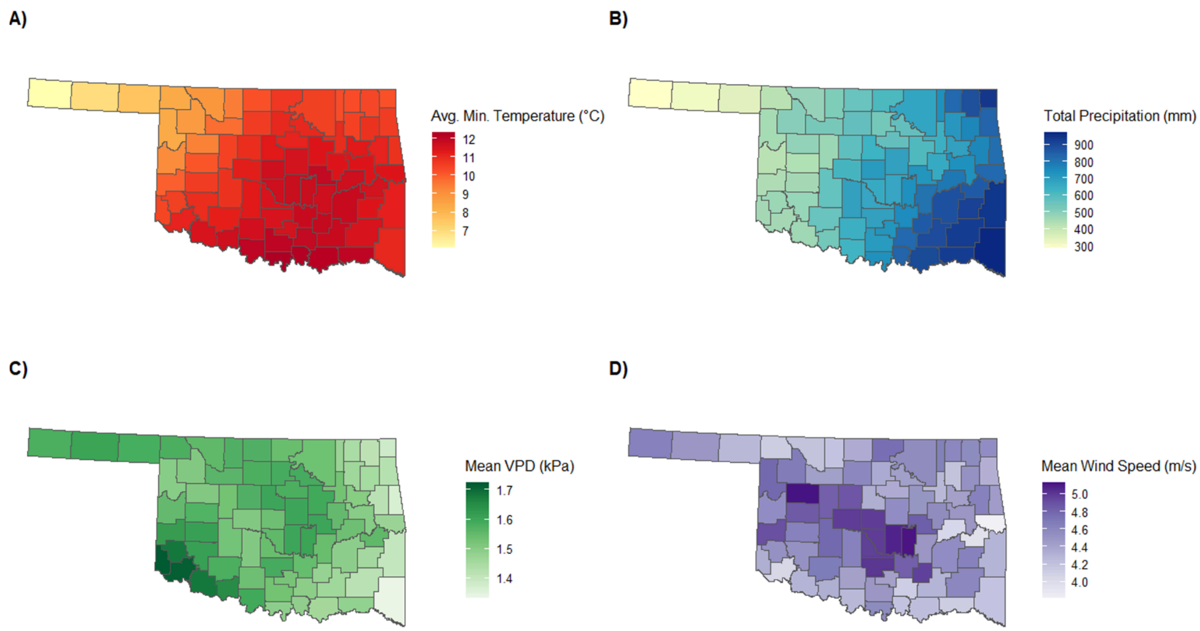

Figure 6: Map of meteorological conditions in Oklahoma counties in 2012 for A) daily average minimum temperature, B) annual total precipitation, C) daily average vapor pressure deficit, and D) daily average wind speed

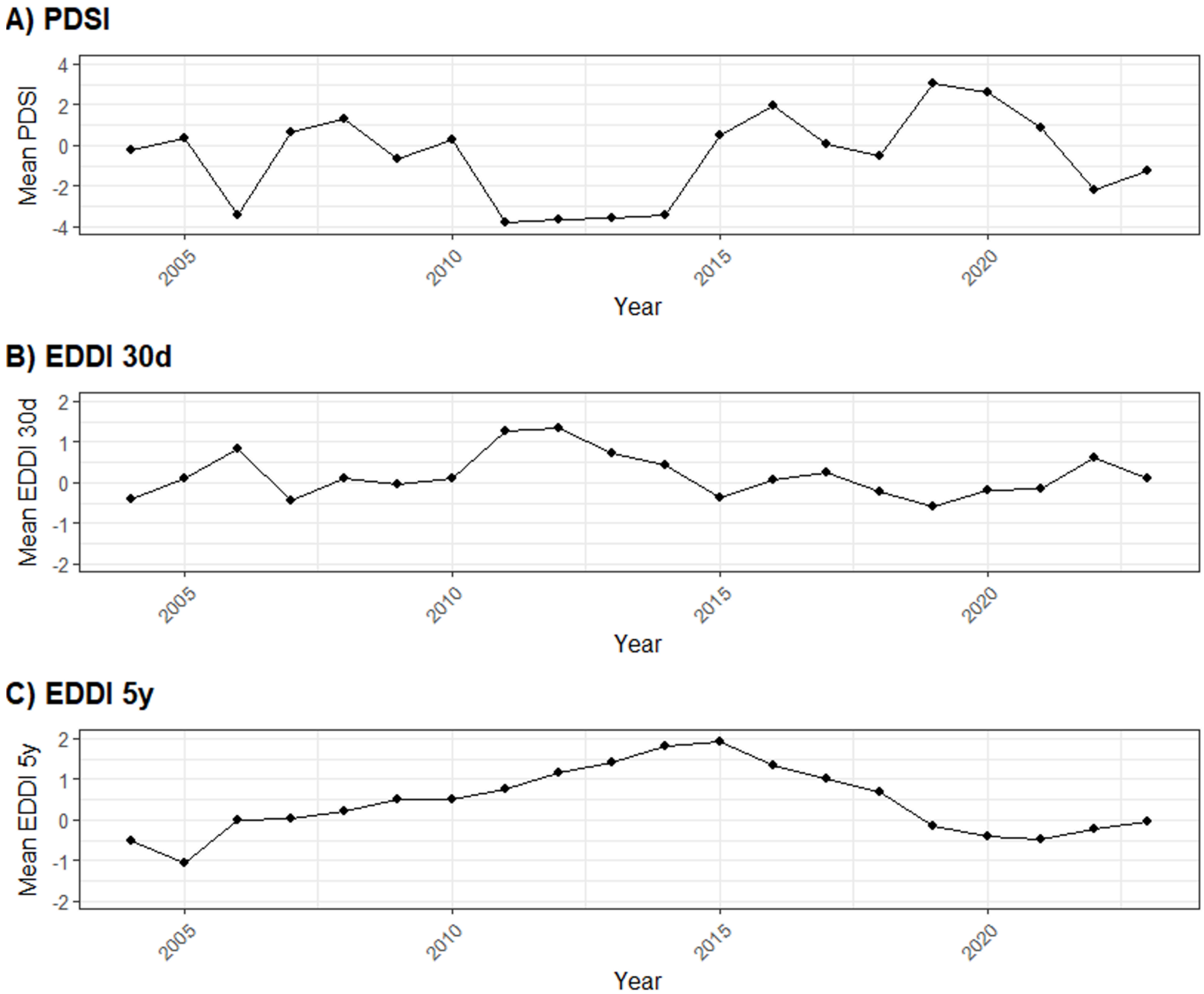

Figure 7: Timeline of annual average of drought using A) PDSI, B) the EDDI at 30 day calculations, C) the EDDI at 5 year calculations (negative PDSI, positive EDDI = drier conditions)

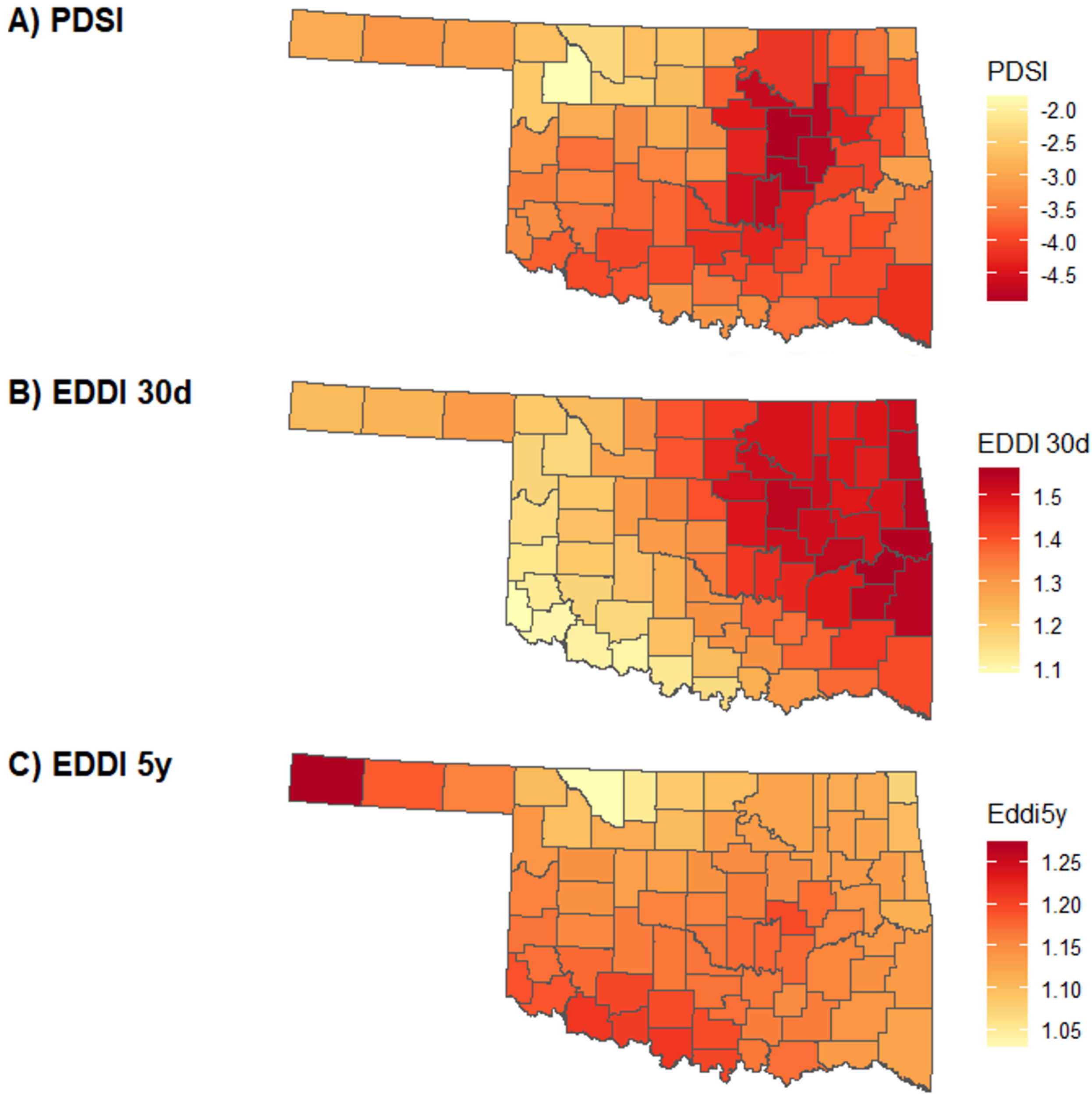

Figure 8: Map of mean weekly drought conditions in Oklahoma counties in 2012 using A) PDSI, B) the EDDI at 30 day calculations, C) the EDDI at 5 year calculations (negative PDSI, positive EDDI = drier conditions)

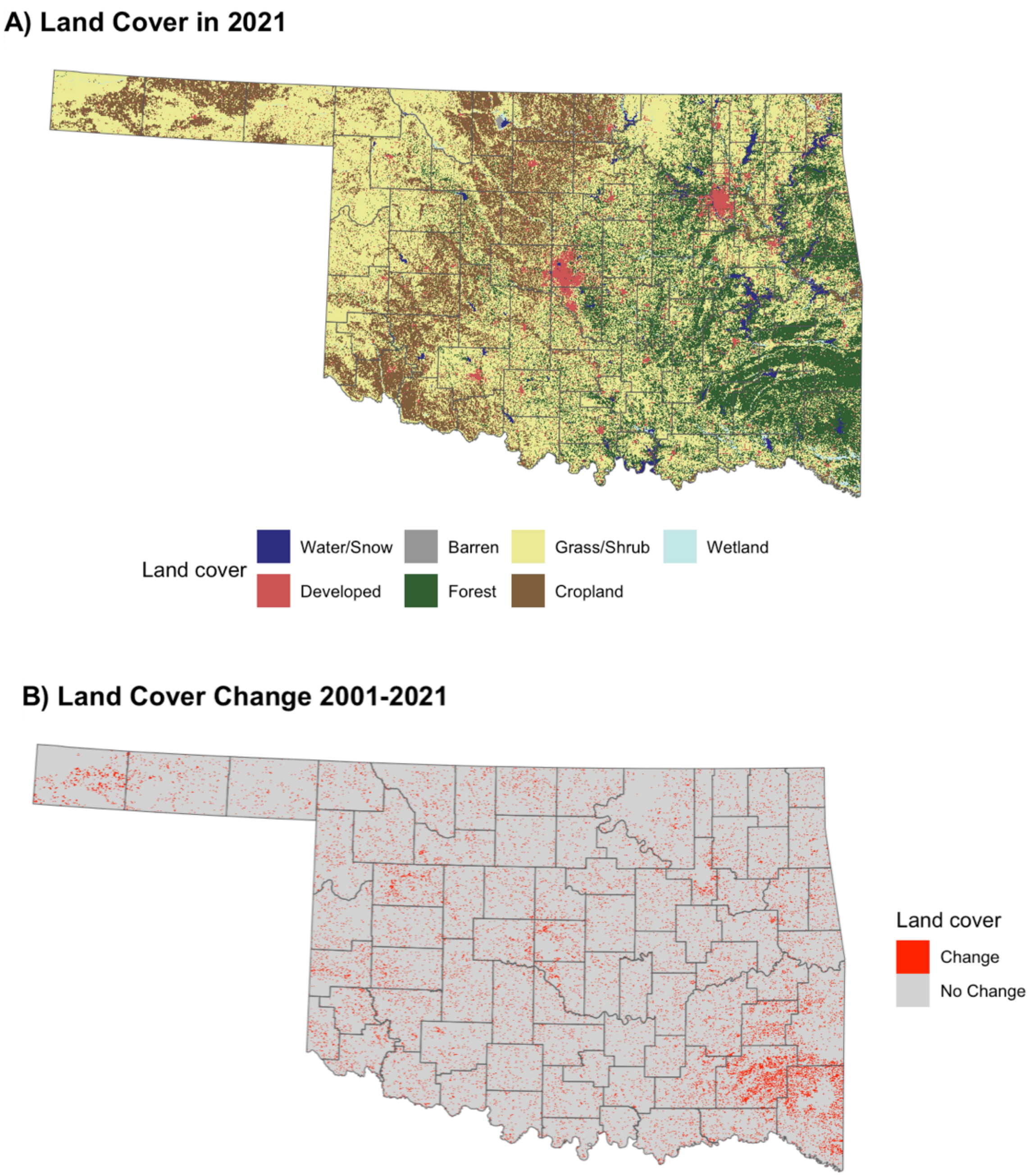

Figure 9: Maps of A) land cover in Oklahoma in 2021, and B) land cover change in Oklahoma 2001-2021

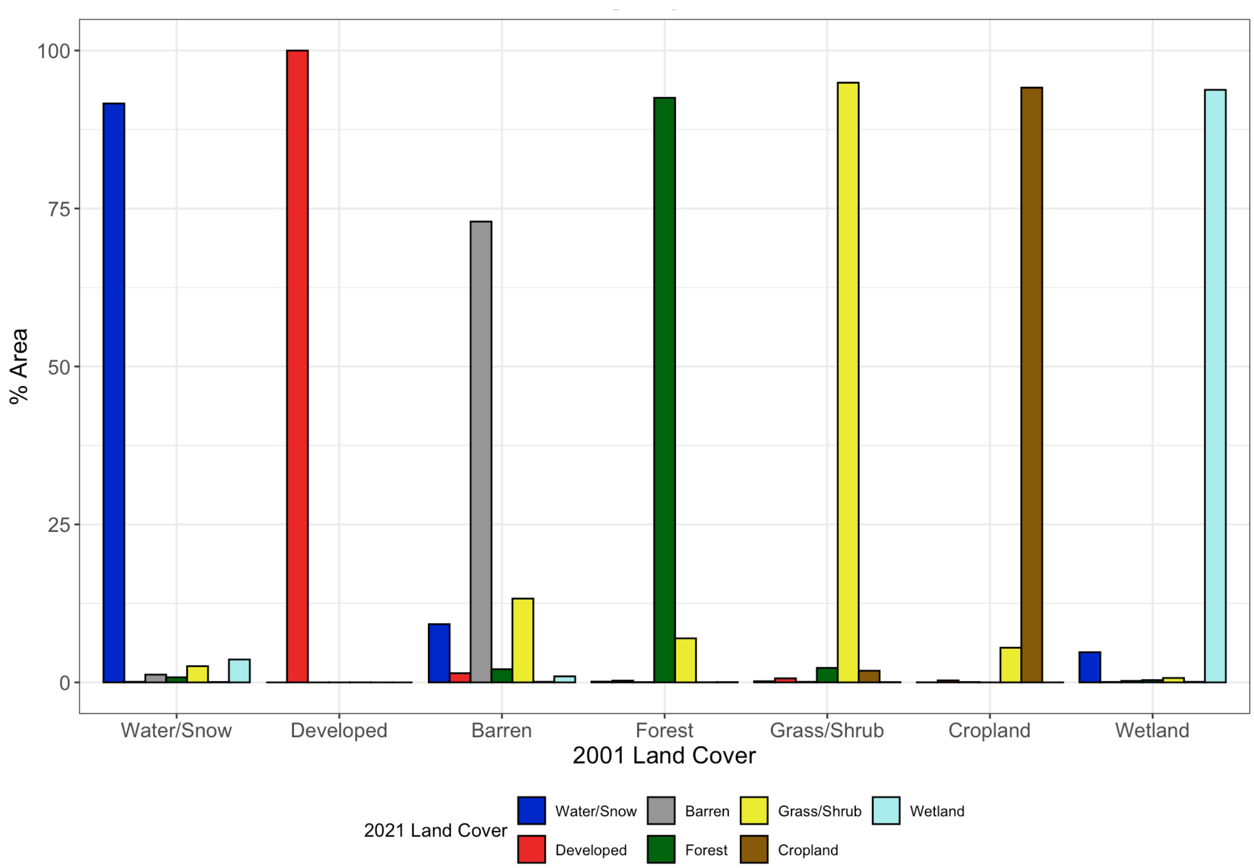

Figure 10: Bar chart of percent class area change in land cover 2001-2021 in Oklahoma

Land cover in Oklahoma is distinctive in the East and West, as the western part of the state is mostly grassland and cropland, while the eastern part is more forested with a mix of grassland and larger water bodies. The Oklahoma City and Tulsa metropolitan areas are the largest urban centers and are located in the center and northeastern parts of the state respectively (Figure 9). Between 2001-2021, the general percentages of each type of land cover in Oklahoma were mostly consistent, with ~ 100% of developed, 95% of grassland, 94% of cropland, 94% of wetland, 93% of forest, 92% of open water/snow, and 73% of barren areas remaining in the same category. However, areas where change did occur tended to be around urban centers, such as Oklahoma City and Tulsa, and in the largely forested southeastern region (Figure 9). Barren areas experienced the most change, and were mostly converted to grasslands and open water/snow (Figure 10).

Results

The top ten best base weather models (e.g. the models with the lowest BIC values) are presented in Table 3 with their respective AUC, SRCC, and SRCC p-values. A lower BIC indicates a better fit, and a BIC difference greater than two between models is considered support for the best model. Models that contained only a different precipitation variable (average versus total) resulted in the same BIC, indicating that the type of precipitation variable used did not affect the outcome. Because these models were redundant, the duplicates were excluded from Table 3. Minimum temperature appeared in nine of the remaining top base weather models with the other variables varying. The difference between the top model and the next model (other than precipitation duplicates) was greater than two, resulting in support for the model containing minimum temperature, VPD, the sum of precipitation, and wind speed as the best base weather model, which was then used in the drought model testing.

Table 4 shows the top ten drought models. The top five models contained the EDDI at various intervals, with the top two at 30 days. Other top models included SPEI at various longer intervals. Only two of the top models included the base weather model, while the rest contained only temperature and wind speed. The difference between the BIC of the first and second model was greater than two, resulting in support for the model using the EDDI at 30 days without precipitation and humidity as the best drought model. This model was also supported as having a better fit than the base weather model (the best drought model BIC, 5018, is more than two less than the best base weather BIC, 5226), and was used in land cover testing.

Table 3: Results for the top ten best base weather models according to BIC (BIC rounded to nearest integer, AUC, SRCC, and SRCC P-Value rounded to nearest thousandth), yellow highlight indicates best model

Model	BIC	AUC	SRCC	SRCC P-Value
Min. Temp. + VPD + Precip. + Wind Speed	5226	0.896	0.490	0.000
Min. Temp. + Precip.	5232	0.877	0.419	0.000
Min. Temp. + VPD + Precip.	5239	0.892	0.463	0.000
Min. Temp.+ Precip. + Wind Speed	5241	0.867	0.431	0.000
Min. Temp. + VPD + Wind Speed	5244	0.882	0.497	0.000
Min. Temp. + Wind Speed	5249	0.857	0.445	0.000
Min. Temp. + RH + Wind Speed	5252	0.878	0.485	0.000
Min. Temp. + RH + Precip.	5252	0.887	0.461	0.000
Min. Temp. + RH + Precip. + Wind Speed	5253	0.891	0.482	0.000
Mean Temp. + Wind Speed	5268	0.872	0.488	0.000

Table 4: Results for the top ten best drought models according to BIC (BIC rounded to nearest integer, AUC, SRCC, and SRCC P-Value rounded to nearest thousandth), yellow highlight indicates best model

Model	BIC	AUC	SRCC	SRCC P-Value
Min. Temp. + Wind Speed + EDDI_30d	5018	0.842	0.425	0.000
Best Base Weather Model + EDDI_30d	5049	0.856	0.437	0.000
Min. Temp. + Wind Speed + EDDI_90d	5084	0.842	0.429	0.000
Min. Temp. + Wind Speed + EDDI_5y	5139	0.877	0.449	0.000
Best Base Weather Model + EDDI_90d	5145	0.879	0.481	0.000
Min. Temp. + Wind Speed + SPEI_5y	5176	0.877	0.533	0.000
Min. Temp. + Wind Speed + SPEI_2y	5184	0.887	0.441	0.000
Min. Temp. + Wind Speed + SPEI_1y	5198	0.888	0.505	0.000
Min. Temp. + Wind Speed + EDDI_1y	5198	0.870	0.479	0.000
Min. Temp. + Wind Speed + EDDI_2y	5204	0.891	0.483	0.000

Table 5 shows the top ten land cover models. All of the top models contained developed land. Other land cover types presented in the top models were barren land in five models, and grassland/shrubs, wetland, water/snow, and forests in two models each. The top two models had a BIC difference less than two, which indicates they were competing models. In this case, the least complex model was considered the best fit. Therefore, the model containing only developed land cover was chosen as the best land cover model. This model was also supported as the best model in the study overall (the best land cover model BIC, 4538, is more than two less than the best drought BIC, 5018).

Table 5: Results for the top ten best land cover models according to BIC (BIC rounded to nearest integer, AUC, SRCC, and SRCC P-Value rounded to nearest thousandth), yellow highlight indicates best model

Model	**BIC**	**AUC**	**SRCC**	**SRCC P-Value**
Best Drought Model + developed	4538	0.814	0.411	0.000
Best Drought Model + barren + developed	4539	0.818	0.412	0.000
Best Drought Model + developed+ grass/shrub	4554	0.819	0.411	0.000
Best Drought Model + barren + developed + grass/shrub	4554	0.822	0.412	0.000
Best Drought Model + developed + wetland	4579	0.811	0.418	0.000
Best Drought Model + water/snow + developed	4581	0.819	0.418	0.000
Best Drought Model + barren + developed + wetland	4582	0.814	0.414	0.000
Best Drought Model + barren + developed + forest	4582	0.819	0.413	0.000
Best Drought Model + developed + forest	4582	0.814	0.414	0.000
Best Drought Model + water/snow + barren + developed	4583	0.821	0.415	0.000

All top models tested in the study had an AUC > 0.8, indicating that the models performed well when differentiating positive county-weeks from negative county-weeks (Tables 3-5). Additionally, the SRCC remained around the 0.4-0.5 range across the top models (Tables 3-5). This indicated a slightly positive relationship between the predicted and observed county-week results for the testing years. The SRCC declined slightly between the best base, drought, and land cover models respectively. This may indicate slightly diminished predictive power or differences between the training and testing periods that resulted in altered variable relationships. All SRCC p-values were significant.

Upon examining the lagged effects generated by the best overall model, higher minimum temperatures appeared to have generally higher relative risk of resulting in a positive county-week regardless of the lag used, with a dip around 5℃ and in extreme warm temperatures (Figure 11A-C). Wind speeds at shorter lags had almost an exponentially positive relationship with the relative risk of a positive county-week, while the relative risk of a positive county week remains low but peaks around 5 m/s for wind speeds at longer lags (Figures 11D-F). The EDDI at 30 day calculations showed a slightly negative relationship with positive county-weeks for wet (negative) conditions and a slightly positive relationship for dry (positive) conditions (Figures 11G-I). At longer lags, the EDDI at 30 day calculations exhibited higher relative risk of a positive county week for both wet and dry conditions (Figures 11G & 10I).

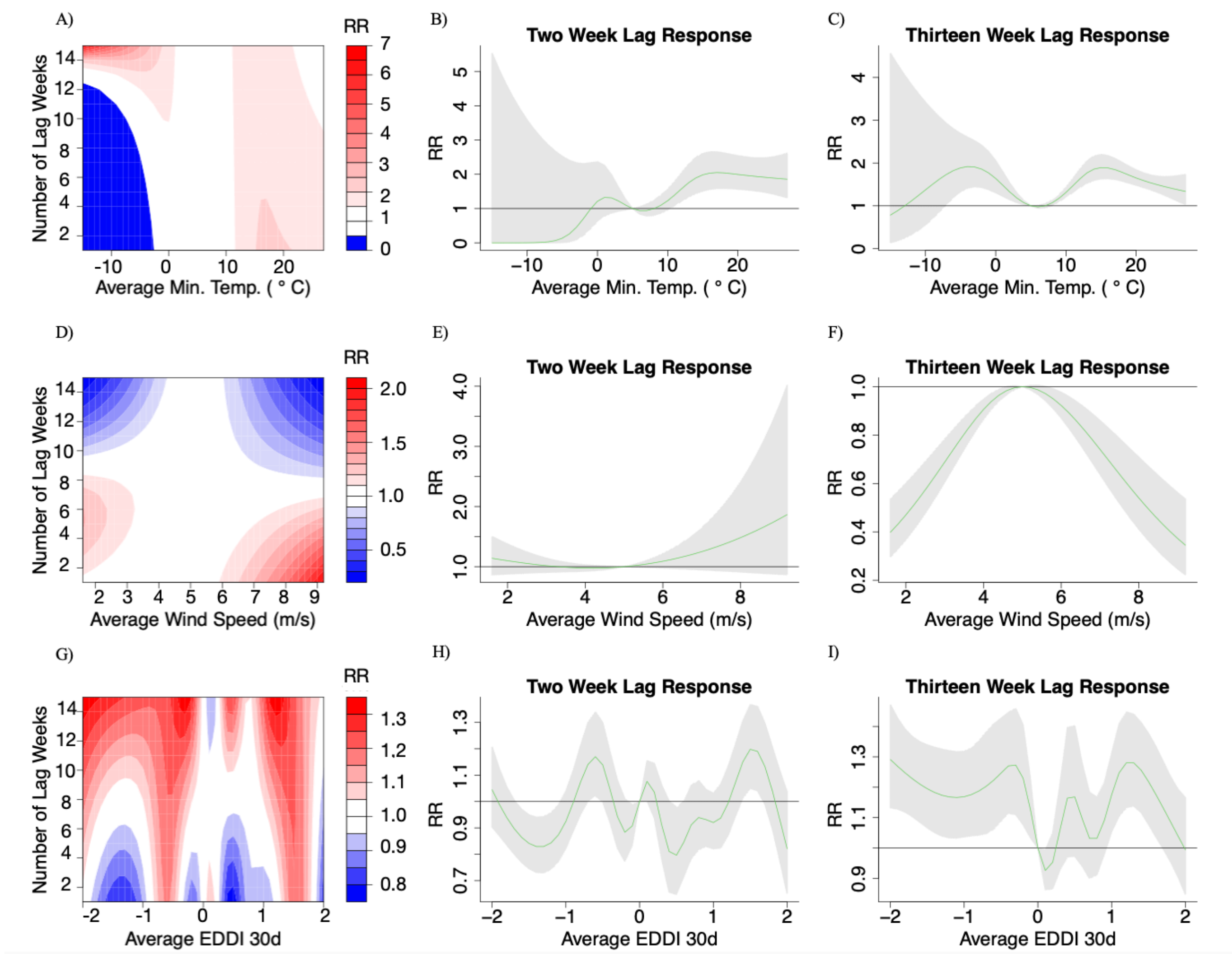

Figure 11: Contours of full lag response and plots of lags response at two weeks and thirteen weeks for A-C) minimum temperature, D-F) wind speed, and G-I) EDDI at 30 day calculations

Figure 12 shows the relationship of percent developed land with positive county-weeks generated by the GAM. There were peaks at around 8 and 25% developed land cover, indicating a bimodal fit. The second peak had a much higher magnitude, which suggested that the overall risk of WNV had a positive relationship with the percentage of developed land.

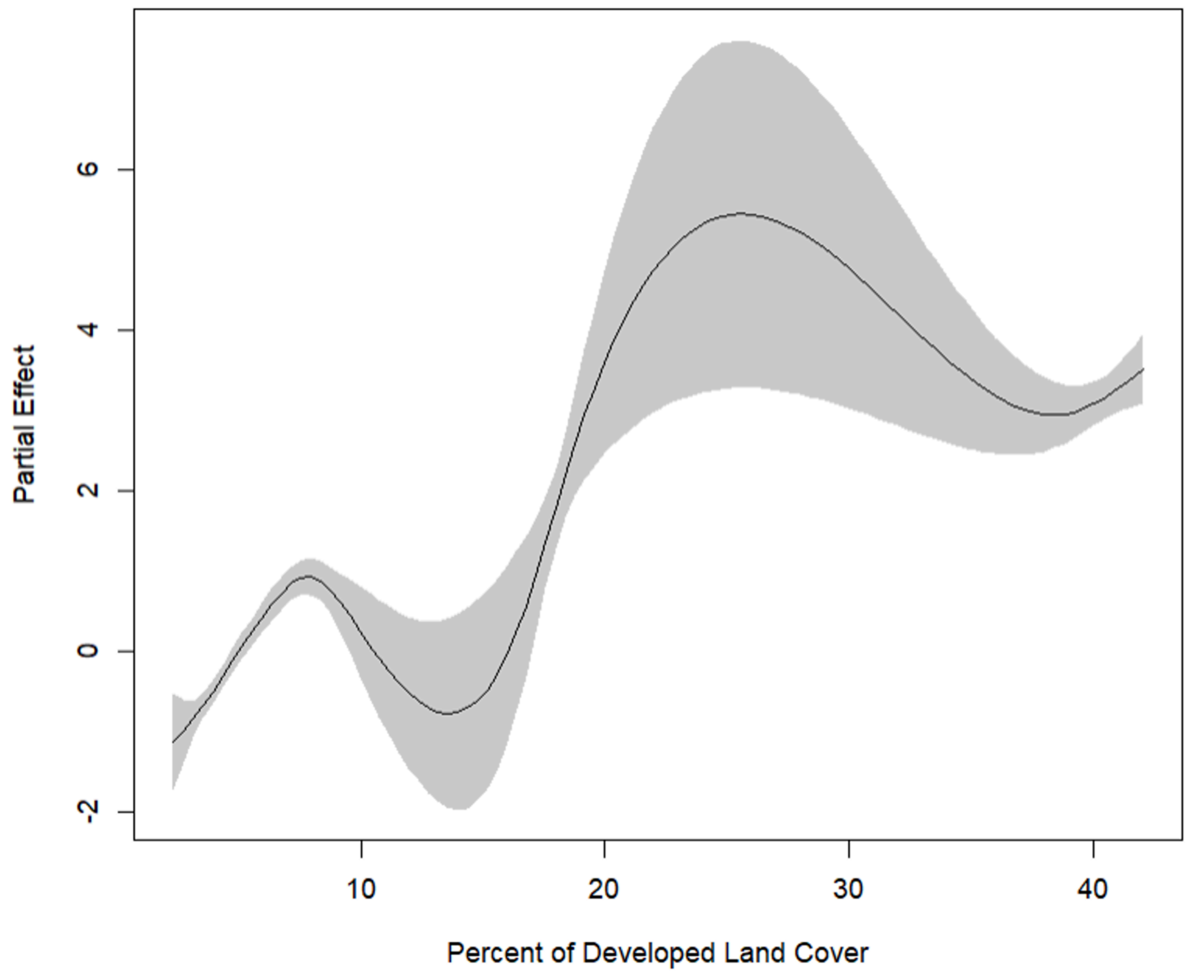

Figure 12: Plot of the GAM fit of percent developed land in the best model overall

Discussion

The variables contained in the best performing model (temperature, wind speed, drought, and developed land cover) all have support in previous literature, and the comparison of drought metrics presents a novel way of understanding their connections to WNV in Oklahoma and in general. Because minimum temperature was present in most of the top base weather models, it likely has a stronger connection to WNV transmission than other temperature metrics; this suggests that mosquitoes are more sensitive to cooler nighttime temperatures than to hotter daytime temperatures. The optimum temperatures for WNV transmission vary based on the mosquito species involved, however, they generally range from 23.8-25.2℃, with 11.0-34.9℃ being the general full range of temperatures possible (Shocket et al., 2020). The minimum temperature lags indicate that higher minimum temperatures increase the relative risk for a positive county-week, which would support the idea that, regardless of how high temperatures are during the day, if nighttime temperatures cool enough, there could be a reduced risk. Because mosquitoes are more active at night (U.S. Centers for Disease Control and Prevention, 2025) and temperatures tend to reach a minimum at night, it is plausible that this timeframe and temperature metric are the most crucial for WNV prediction and prevention.

Wind speed has recently been investigated in relation to WNV transmission in Louisiana and South Dakota, with both regions presenting decreased WNV risk with higher wind speeds (Bump et al., 2025); high winds speeds were also associated with decreased malaria transmission in reservoir communities in Africa (Endo & Eltahir, 2018). This study confirms that wind speed plays an important part in WNV transmission and prediction in Oklahoma, but the lags suggest a different type of relationship. Shorter lags appear to be more influential than longer lags, indicating that the effects of wind on mosquitoes are more immediate. However, the positive relationship with wind speed at shorter lags contradicts what has been found in the other regions (Bump et al., 2025). This could be the result of different regions experiencing different relationships, or the result of analysis at different time scales (daily versus weekly). It is possible that high wind speeds on a given day may reduce the relative risk of a positive county week as mosquitoes struggle to fly in the conditions, but also that high wind speeds followed by low wind speeds may increase the chance of mosquitoes traveling farther or needing to feed after remaining in protected habitats during high winds (see Atieli et al., 2023; Bump et al., 2025).

Furthermore, while Endo & Eltahir (2018) identified wind direction as a predictor for malaria, their analysis was on a smaller local community scale, which could not be analyzed at the present study's county level. The incorporation of wind direction is, however, recommended for local WNV analyses conducted in the future.

This study also confirms the importance of drought in WNV prediction in Oklahoma, and the EDDI at 30 day calculations had the strongest relationship with WNV case occurrence. The selection of the 30 day calculation interval may stem from both the timescale of mosquito lifecycles and abundance and the chain of infection. Mosquito populations fluctuate, and time is required to complete each step in the process. Suppose a precipitation event causes pools of water to form and a mosquito lays eggs in one of the pools. Then, it will take at least a few days for the eggs to hatch, at least five days for larvae to become pupas, and at least two days for the pupas to become adult mosquitoes (U.S. Centers for Disease Control and Prevention, n.d.b). Even if one of the mosquitoes immediately becomes infected with WNV by biting an infected bird, it will take around a week for the virus to reach levels within the insect that allow it to transmit the virus back to birds (U.S. Centers for Disease Control and Prevention, 2024a), however this incubation period varies with temperature, WNV strain, and potentially species (Vollans et al, 2024). Then, if the infected mosquito bites a human, it can take 2-15 days for symptoms to appear (Rossi, Ross, & Evans, 2010). Finally, depending on the severity of their symptoms, it may take an infected human some time to report their condition and receive a diagnosis. The chosen EDDI interval may be just long enough to capture this lag from weather event to WNV report.

Because the EDDI measures anomalies of atmospheric evaporative demand, it can be inferred that that view of drought is useful for WNV transmission and prediction theory.

Precipitation can result in multiple outcomes for the environment, from drought relief to flooding, making the relationship between mosquitoes and precipitation complex (Gardner et al., 2012; Caldwell et al., 2021), and its connection to other environmental factors, such as humidity and soil moisture, important. In this way, precipitation (or lack of precipitation) alone is not enough to indicate WNV transmission. Additionally, while VPD was identified in the base weather model, the EDDI presents anomalies of atmospheric moisture demand, which results in a metric that is more unique to the area in question. Anomalies of predictor variables present a measure of how different conditions are from the local norm, presenting a better view of how those conditions may affect the area and WNV transmission than untransformed meteorological variables. These results are similar to those found by Wimberly et al. (2022), who found that WNV models with predictor variable anomalies performed better than models with untransformed predictor variables in South Dakota. The absence of precipitation and humidity in the best drought model may be the result of BIC's tendency to penalize more complex models and/or the possibility that only one measure of moisture was needed for the prediction, and the EDDI presented the best option. The latter may also suggest that the EDDI's characterization of moisture is more relevant than other characterizations, such as precipitation and humidity as independent variables.

Furthermore, the model lags indicated that there are multiple scenarios involving dry conditions that can influence WNV risk. Although wet conditions appear to have a negative relationship with relative risk of a positive county-week at short lags, they have a positive relationship at longer lags, meaning that wet conditions followed by drier conditions could present a higher WNV risk. On the other hand, dry conditions appear to have a positive relationship with WNV risk regardless of the lag interval. This would confirm that mosquitoes prefer moist (but not flooded) conditions and support the previous theory in Shaman, Day, & Stieglitz (2005) and Ukawuba & Shaman (2018) that drought increases the risk for WNV, possibly through the concentration of vectors and hosts at water sources. These results are also similar to those found for dengue by Li et al. (2023a) and Li et al. (2023b) in China, Lowe et al. (2018) in Barbados, and Lowe et al. (2021) in Brazil, where both extreme wet and dry conditions were associated with increased risk. They suggest that wet conditions increase mosquito abundance, while dry conditions cause changes in how humans store water, leading to more mosquitoes in populated areas. Lowe et al. (2021) also suggest that there are differences in the relationship between drought and dengue in urban and rural communities. Thus, because there are also multiple ways in which the moisture timeline can evolve and impact mosquitoes and WNV both in one community and across communities, the relationship between drought and WNV remains complex. Overall though, the inclusion of the EDDI allows the prediction model to better capture the environmental conditions that influence mosquitoes and WNV transmission.

Developed land was shown to strongly influence WNV transmission, which is not surprising given that most WNV cases occur in counties with high populations and large cities, namely OKC and Tulsa. However, the bimodal fit of percent developed land cover is interesting because it suggests that both high levels of development and lower levels of development (around 8%) are associated with peaks of WNV transmission. Counties in the panhandle, a hotspot for WNV incidence rate, only have ~2-4% developed land cover, making it possible but unlikely that the model has picked up on this factor. The lack of other land cover types in the best model may be the result of the strict penalization of the BIC, the effects of developed land being overpowering in model, or the broad NLCD classifications not capturing the nuanced habitat associations of WNV vector and host species present within Oklahoma. For example, as previously mentioned, Oklahoma is home to both *Culex tarsalis* and *Culex pipiens*, vector species with different habitat preferences (Bump & Wimberly, 2026; Hoback et al., 2017). Perhaps the model could not rectify that both urban and rural areas can be infected through different transmission paths. Similarly, slight differences within a land cover category may have significant impacts on WNV transmission. For instance, “small green islands” within urban areas have been linked to greater abundances of mosquitoes in Rome (Manica et al., 2016). Different urban areas have different amounts of green/blue space with different plant/water feature compositions, and they may handle water management differently, creating differences in suitability for mosquitoes and birds alike. Likewise, irrigated areas have been shown to have an increased risk for arbovirus transmission compared to non-irrigated areas, and irrigation may also lengthen the infection season in areas that would otherwise be too arid (Jardine et al., 2004; Jiang et al., 2023; Ondeto et al., 2022).

Additionally, there are limitations to the methods and findings presented in this study. First, BIC is not the only criterion that may be used to select models. It was used here in an attempt to reduce overfitting with the large number of variables included in the study, however, there are methods that may select different outcomes. Second, the inclusion of mosquito infection data as a predictor would likely enhance the human WNV risk results, but could not be used as Oklahoma does not yet have enough widespread historical mosquito data. Third, the spatial scale of county and temporal scale of epi-week may not capture relationships on finer scales, leading to over- or undergeneralization of the influences of the included variables. The presented models also assume temporal stationarity, that is, they may not capture a difference in the environmental factors influencing WNV within the same WNV season. Fourth, because most

WNV patients are asymptomatic, there is a likelihood of underreporting, resulting in the human case dataset presenting an incomplete picture of the WNV footprint.

Conclusion

WNV affects Oklahomans every year, and the need for more accurate predictions is ever-present. Previous studies have made advancements in prediction techniques for arboviruses, however, those studies have often overlooked drought or not considered multiple options for their drought metric. This study has presented a WNV modelling scheme for Oklahoma counties and identified the EDDI at 30 day calculations as the most fitting drought metric and basis for drought definition in the region, while also solidifying drought as an important factor in WNV prediction. However, the relationship between drought and WNV remains complex, with both extreme dry and wet conditions exhibiting an increased risk given longer temporal lags. Additionally, the study identified temperature, wind speed, and developed land cover as contributing factors in WNV transmission.

Future work may aim to include data that could not be obtained here, such as mosquito and bird infection data, as well as expand to other regions of the U.S. and the world. This study limited itself to GridMet drought metrics for ease-of-use in collaborations with data partners, but future work may aim to include more than those presented here, such as data from the U.S. Drought Monitor. NLCD data from GridMet was chosen for a similar reason, however, other land cover classifications that are more specific to WNV and mosquito habitat variations would likely enhance the results. There is also room to investigate the connections between different drought metrics and other mosquito-borne diseases, such as malaria. Locally, more work is needed in order to improve the accuracy of the predictions before they can be integrated into a dashboard or other public health tool.

Overall, these results support a recommendation to include drought and possibly other composite meteorological variables in WNV prediction that may better capture the transmission environment than traditional base weather variables. The findings in this study contribute to a larger effort to improve WNV surveillance and prediction in Oklahoma and across the country. The inclusion of the EDDI at 30 day calculations in this state model is a step forward that provides insight and opportunity to further the collective WNV prediction and prevention public health goal.

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IRB Statement

This thesis is part of a larger project for the advancement of WNV surveillance in Oklahoma, which has been deemed exempt from oversight by the OU Institutional Review Board (IRB).

Conflict of Interest

The author declares no conflict of interest for this study.