Enhanced Forecasting of Mosquito-Borne Disease Outbreaks Using AMSR-E

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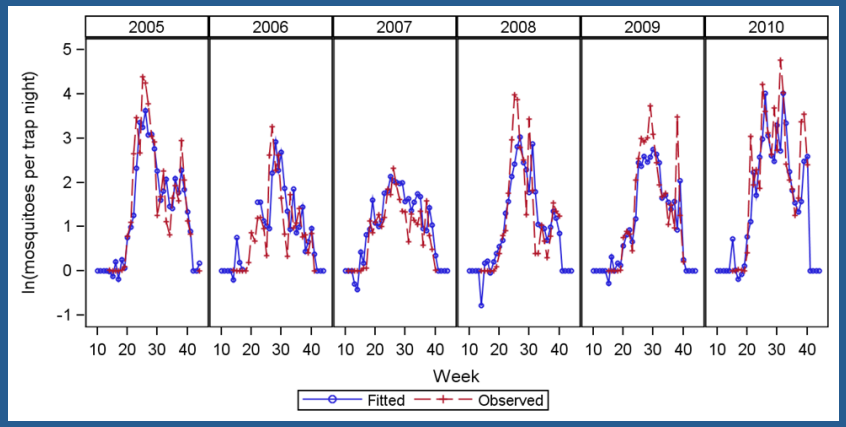
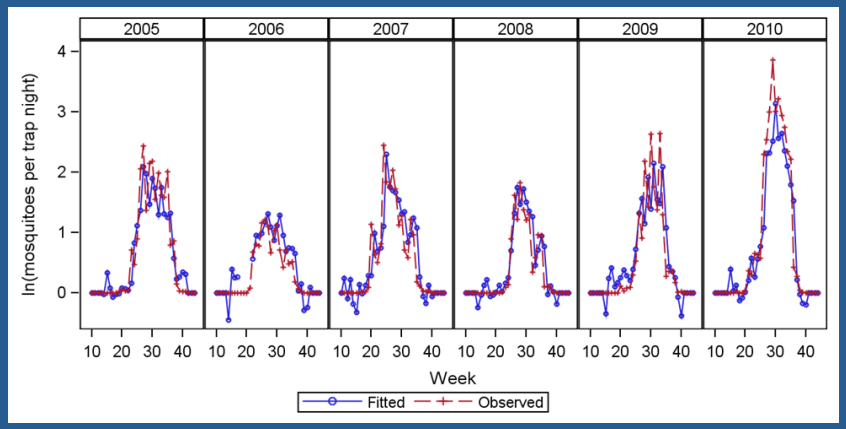
Research Objectives

- Objective 1: Develop statistical models of mosquito population dynamics and WNV incidence using AMSR-E land surface parameters.
- Objective 2: Compare the performance of the AMSR-E driven models with similar models derived from other sources of environmental monitoring data to quantify improvements in the forecasting of mosquito-borne disease outbreaks.
- Objective 3: Generate WNV risk forecasts from models based on AMSR-E variables, disseminate these predictions to public health practitioners, and obtain qualitative feedback on the value and utility of these predictions.

Objectives 1 and 2

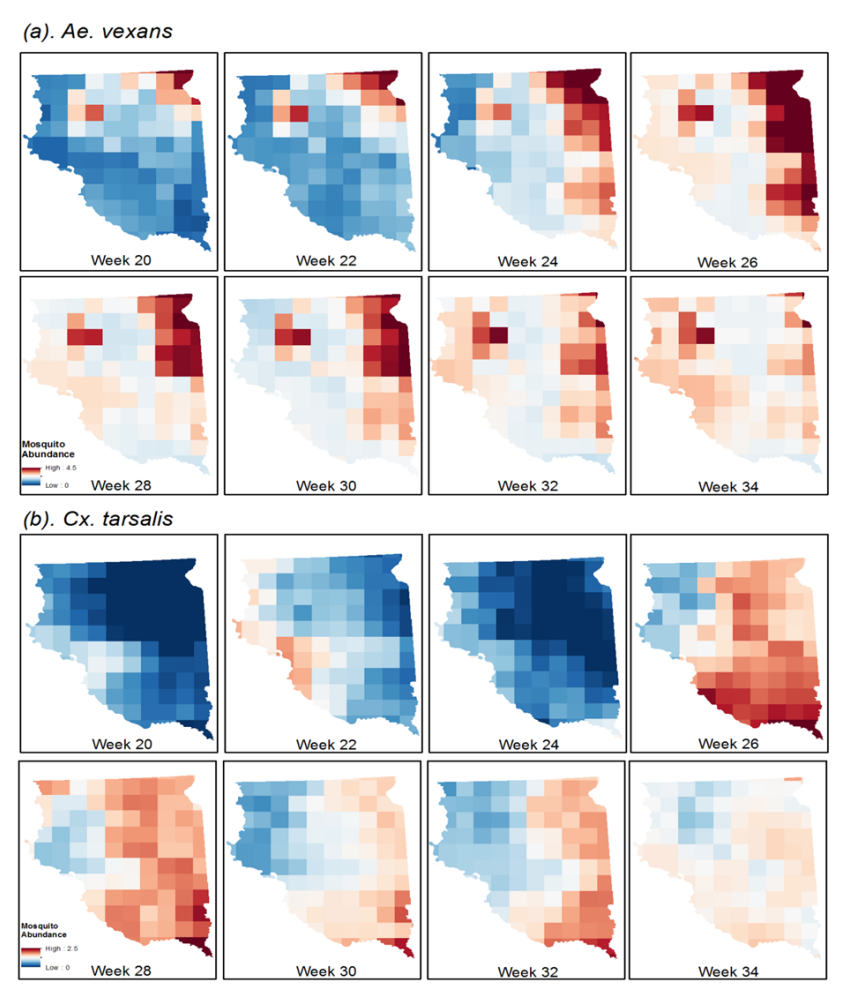
- Compared environmental models based on AMSR-E land surface parameters versus meteorological variables
- Models based on AMSR-E had better fits
  - Fractional water strongly associated with *Aedes vexans*
  - Vegetation opacity improved the fit of the *Culex tarsalis* model





Overview of Major Results

- Model evaluation
  - Cross-validation indicated high potential for predicting mosquito activity at the same location where the model was parameterized
  - Validation against data from an independent site indicated moderate potential for predicting seasonal and interannual variability at different locations

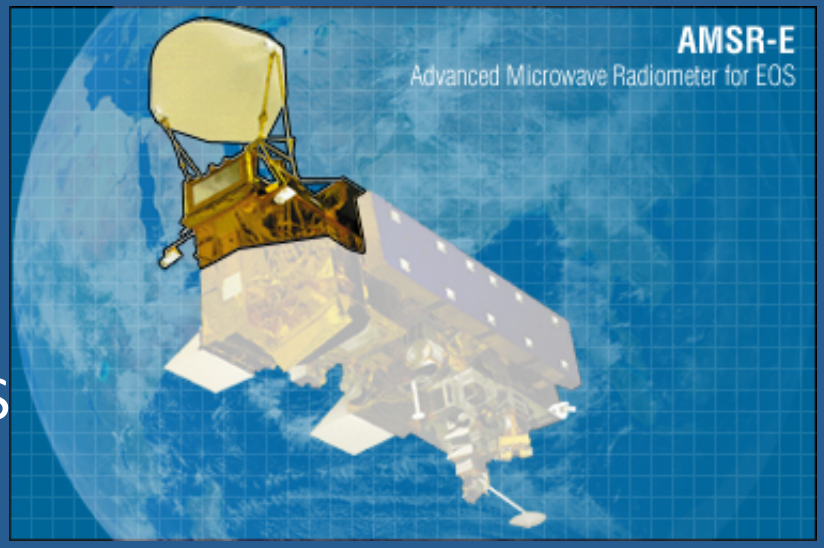


Summary – Mosquito Population Models

- Remote sensing data were as effective as weather station data for modeling mosquitoes
- Unique measurements of biophysical Earth-surface characteristics - not simply a remote "proxy" for ground data
- Integrates information over broad spatial extents

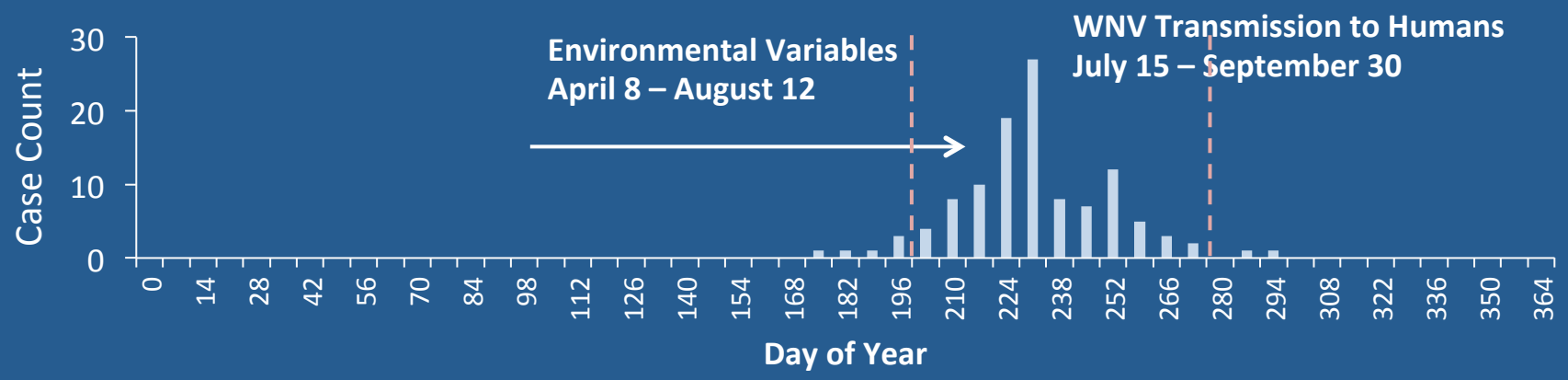
Objective 3

- *The AMSR-E antenna stopped spinning at 0726GMT Oct 4, 2011 most likely due to aging lubricant in the mechanism...*
- Overcame the loss of AMSR-E:
  - Developed and tested forecasting models using MODIS and other sources of optical-IR RS data
  - Used NLDAS data to scale up to the national level and improve temporal resolution in SD



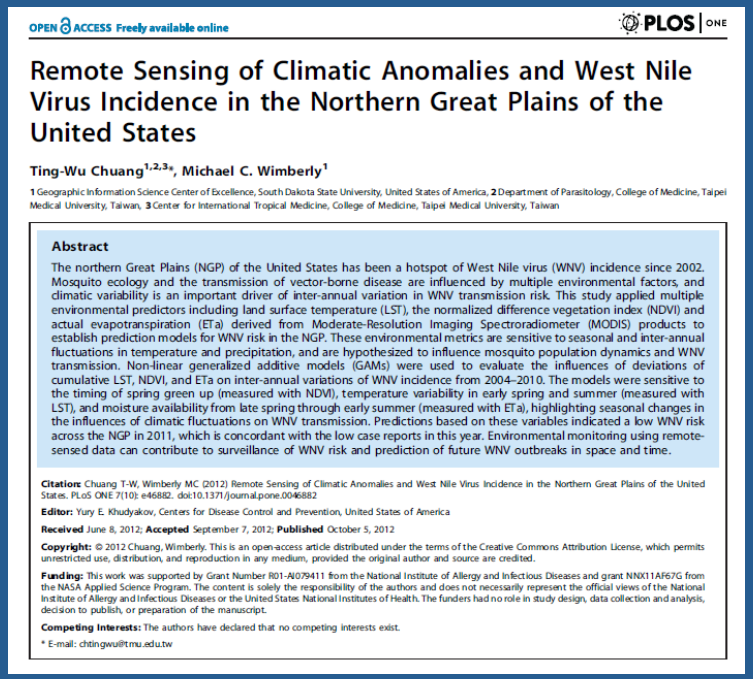
Modeling WNV Incidence in Humans Across the Northern Great Plains

- Response Variable – Log relative risk (LRR) computed for each county in each year
- Predictor Variables – Cumulative environmental metrics for different days of the year (DOY 105-217 at 8-day intervals).
- Fit generalized additive models (GAMs) to historical environmental and case data
- Predict using 2011 environmental data



Ecological Forecasting

- Models developed using lagged environmental indices from MODIS
  - Land surface temperature
  - Vegetation indices
  - Actual evapotranspiration
- Regional predictions
  - 2011: Low risk
  - 2012: High risk
  - 2013: Low risk



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Remote Sensing of Climatic Anomalies and West Nile Virus Incidence in the Northern Great Plains of the United States

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Abstract

The northern Great Plains (NGP) of the United States has been a hotspot of West Nile virus (WNV) incidence since 2002. Mosquito ecology and the transmission of vector-borne disease are influenced by multiple environmental factors, and climatic variability is an important driver of inter-annual variation in WNV transmission risk. This study applied multiple environmental predictors including land surface temperature (LST), the normalized difference vegetation index (NDVI) and actual evapotranspiration (ETa) derived from Moderate-Resolution Imaging Spectroradiometer (MODIS) products to establish prediction models for WNV risk in the NGP. These environmental metrics are sensitive to seasonal and inter-annual fluctuations in temperature and precipitation, and are hypothesized to influence mosquito population dynamics and WNV transmission. Non-linear generalized additive models (GAMs) were used to evaluate the influences of deviations of cumulative LST, NDVI, and ETa on inter-annual variations of WNV incidence from 2004–2010. The models were sensitive to the timing of spring green up (measured with NDVI), temperature variability in early spring and summer (measured with LST), and moisture availability from late spring through early summer (measured with ETa), highlighting seasonal changes in the influences of climatic fluctuations on WNV transmission. Predictions based on these variables indicated a low WNV risk across the NGP in 2011, which is concordant with the low case reports in this year. Environmental monitoring using remote-sensed data can contribute to surveillance of WNV risk and prediction of future WNV outbreaks in space and time.

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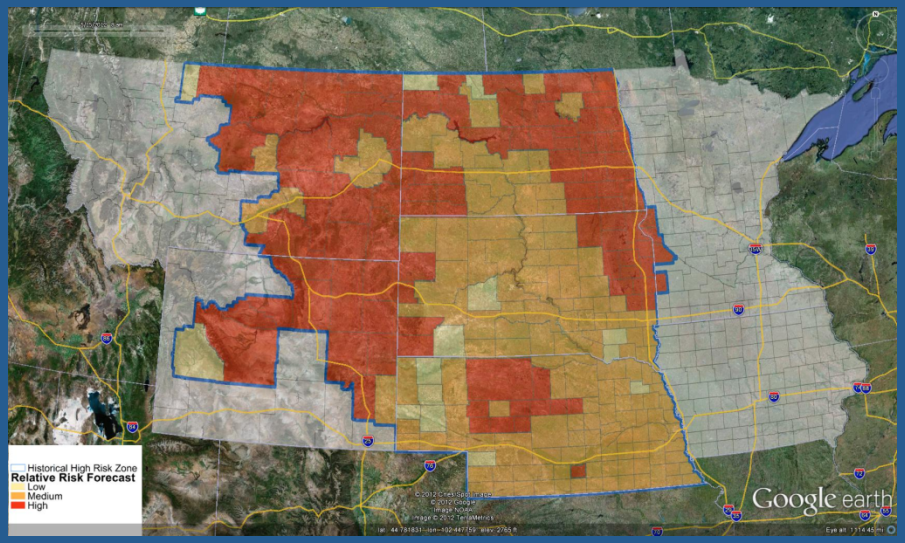
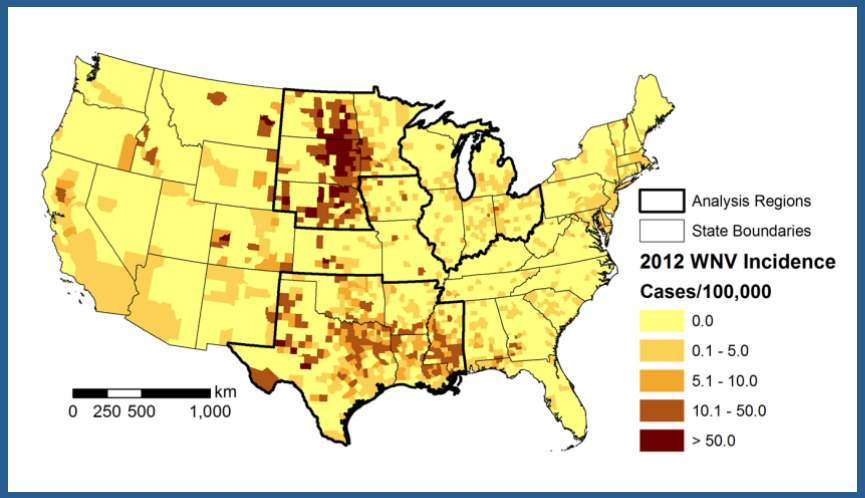


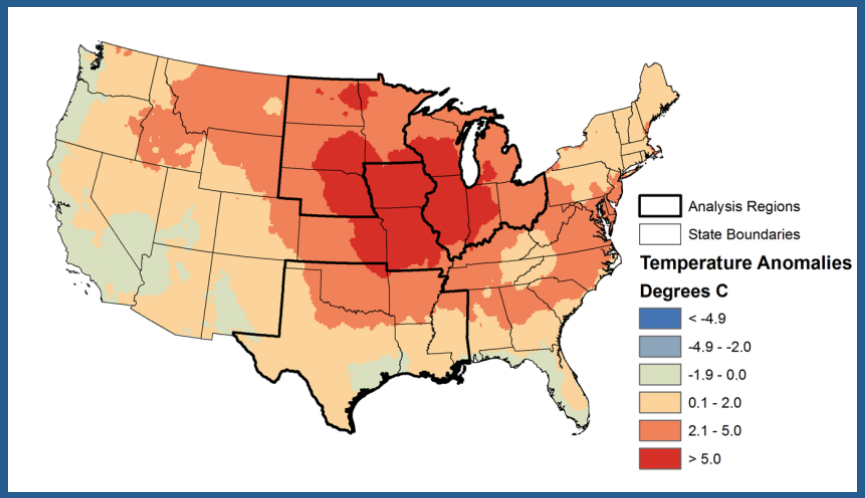
National-Level Analysis

- Three zones with large WNV clusters in 2012
  - Upper Midwest
  - Northern Great Plains
  - South Central
- Is interannual variability in human WNV cases associated with climate?
- Used monthly NLDAS data
  - FORA0125M.002

2012 WNV Incidence Rates

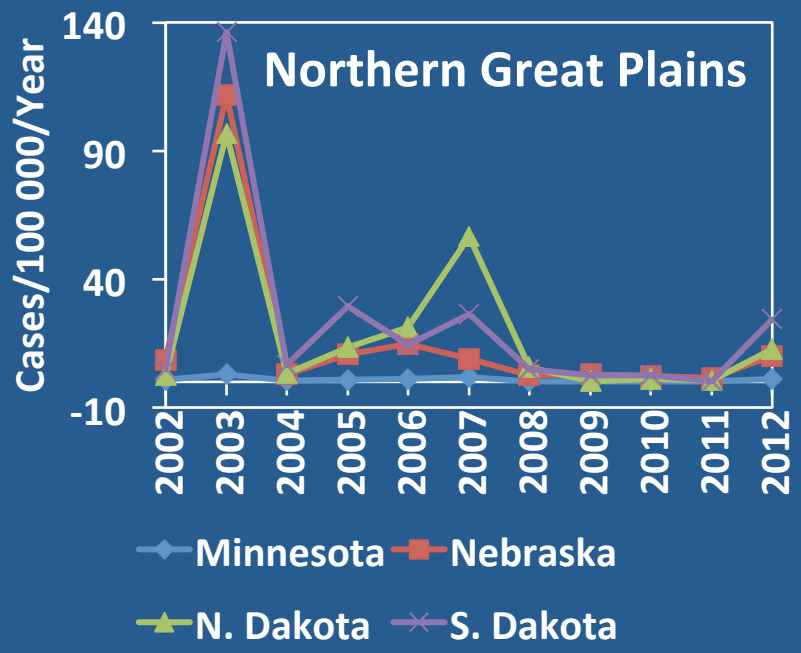


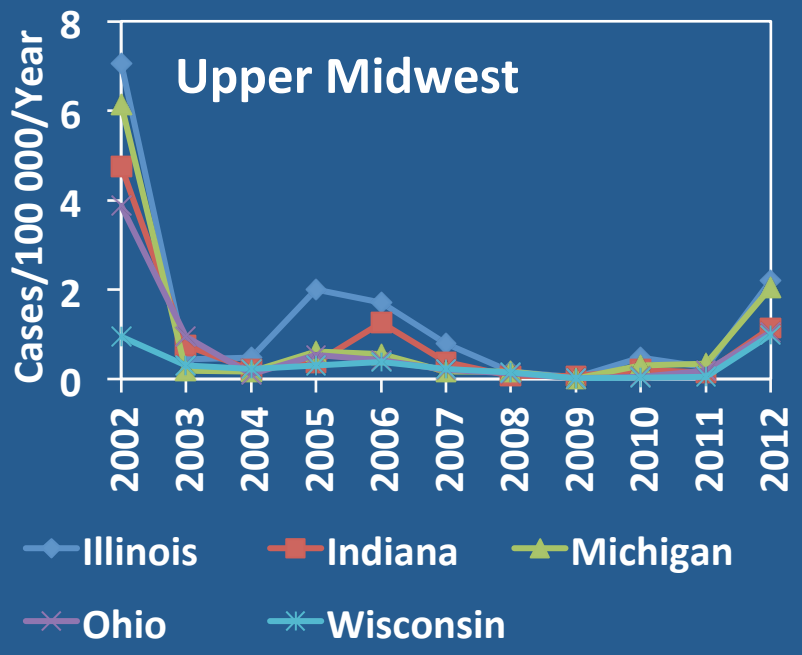
July 2012 NLDAS Temperature Anomalies

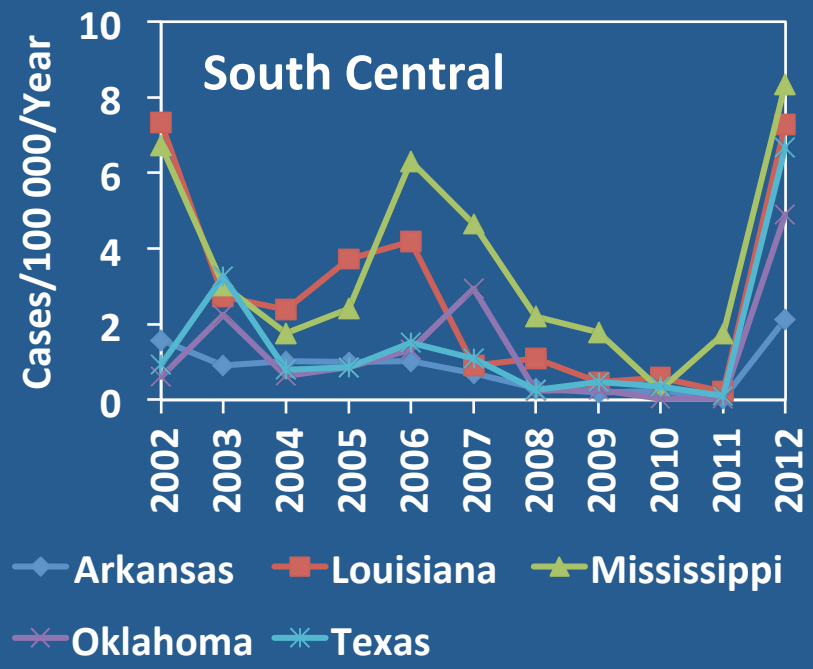


Time Series of WNV Cases by State

Includes both WNV fever and neuroinvasive disease. Note the different scales on the y-axes.





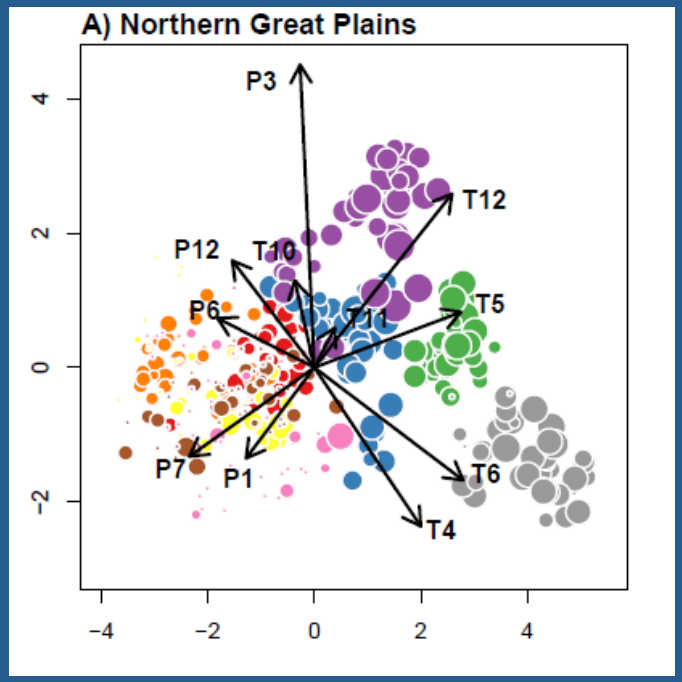


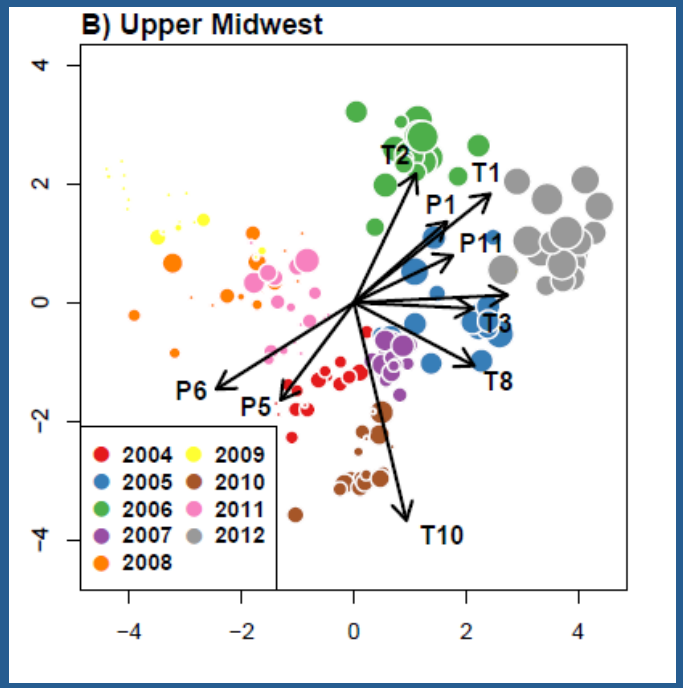
Statistical Analysis

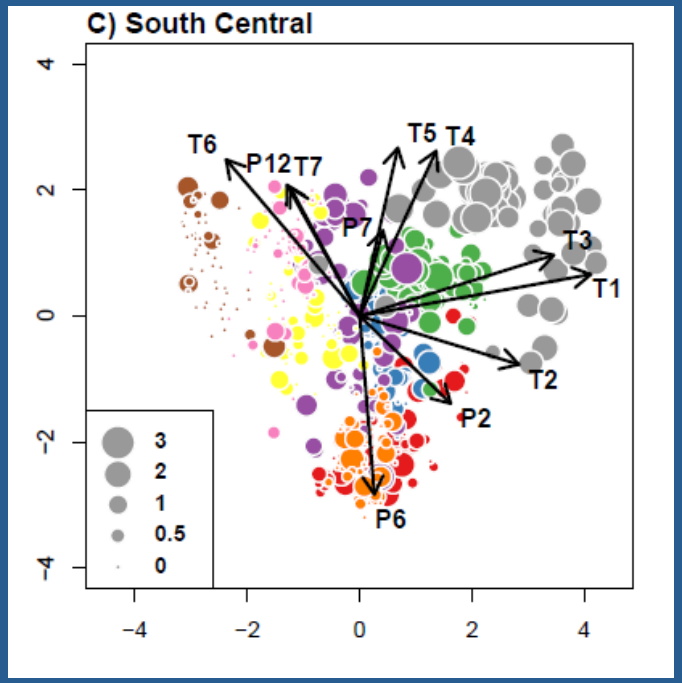
- Dependent Variable:
  - WNV relative risk based on data from the USGS disease map archive (CDC ArboNET surveillance program)
- Independent Variables:
  - Monthly precipitation and temperature anomalies computed using monthly North American Land Data Assimilation System (NLDAS) data
  - Summarized for the twelve months (October-September) encompassing and preceding the main WNV transmission season (July-September)
- Partial least squares regression (PLSR) used to extract a small number of independent latent climate variables that maximized the explained variance of *LRR*.

PLSR Biplots

Points close together have similar climatic anomalies and point size reflects the relative WNV rate for each county/year. Arrows represent correlations of climatic variables with each component (T=Temperature, P=Precipitation, Month=1-12).

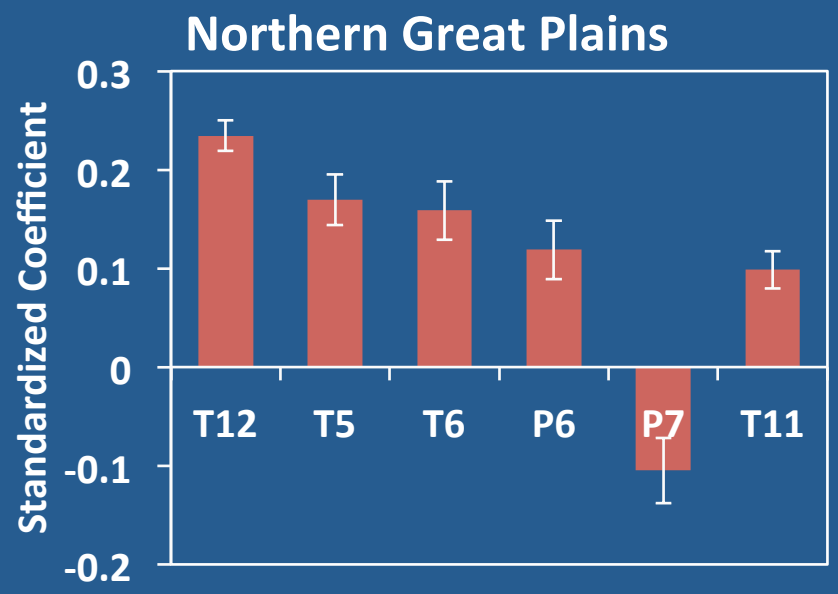


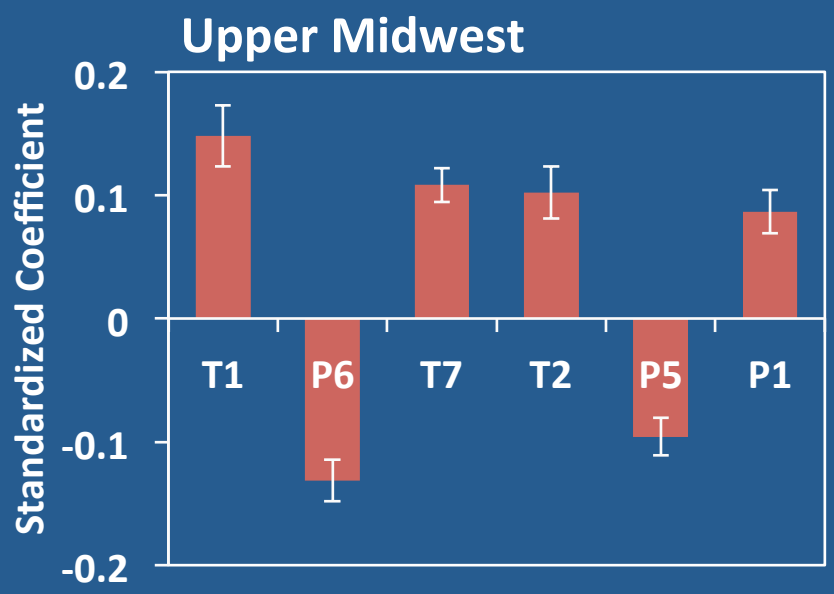


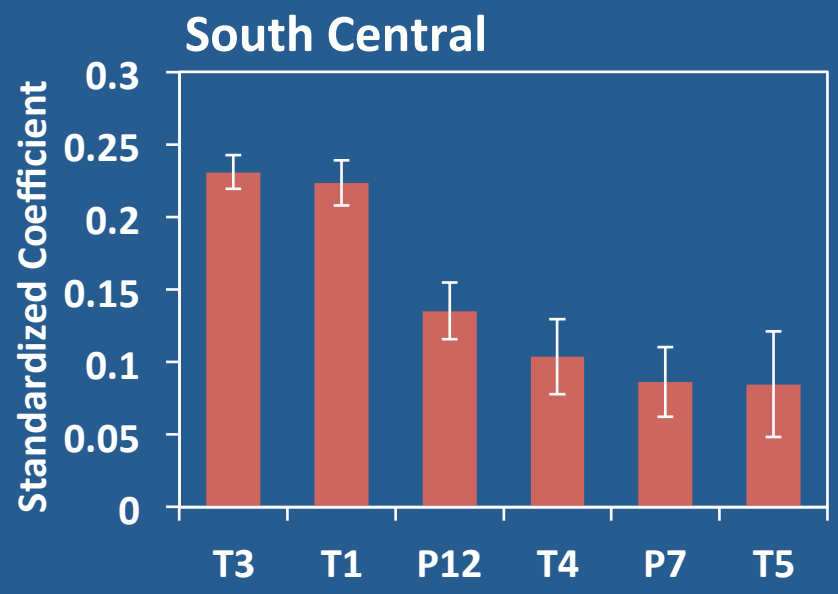


PLSR Coefficients

Standardized coefficients reflect the relative importance of each variable in the PLSR regression







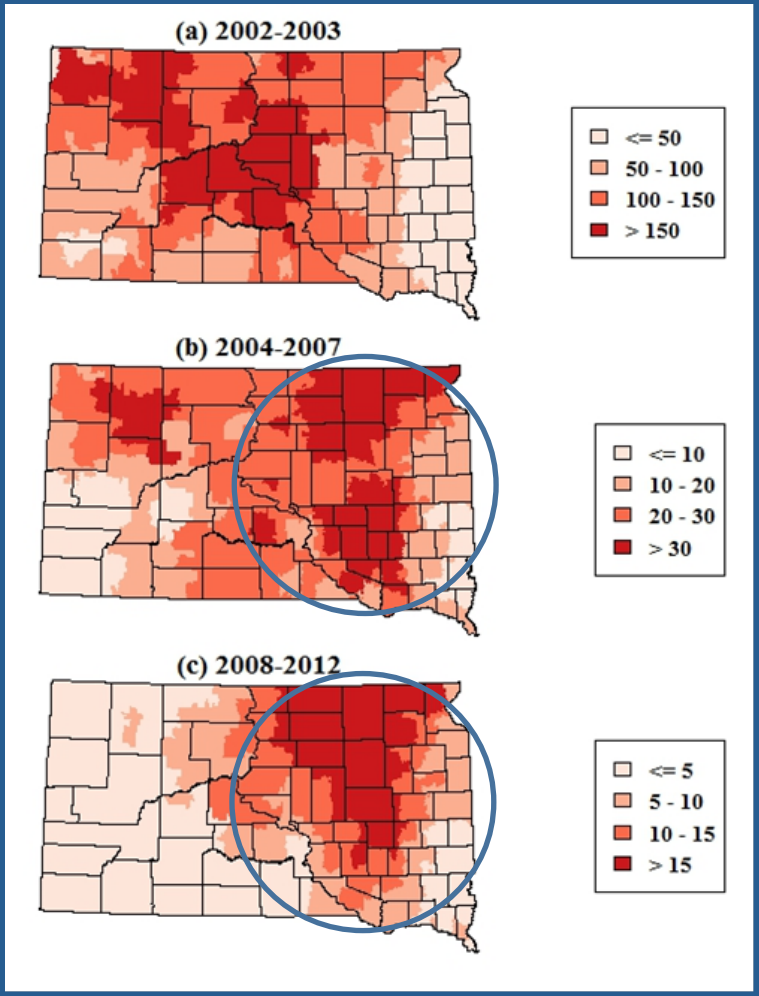
Summary – National-Level Analysis

- Interannual variability in WNV incidence was positively associated with temperature anomalies in three regions of the United States.
- The strongest associations with temperature variables occurred during the winter and early spring (December-March) preceding the main transmission season (July-September).
- The seasons of strongest climatic associations with WNV varied between regions, likely reflecting differences in vector species, host species, and geographical context.

NLDAS Application: Weekly Prediction of WNV Risk in Eastern SD

- Focused on temporal pattern of WNV cases in eastern SD
- Used hourly NLDAS product (FORA0125H.002) summarized at a weekly level
- Developed multilevel Poisson regression models incorporating lagged epidemiological and environmental data

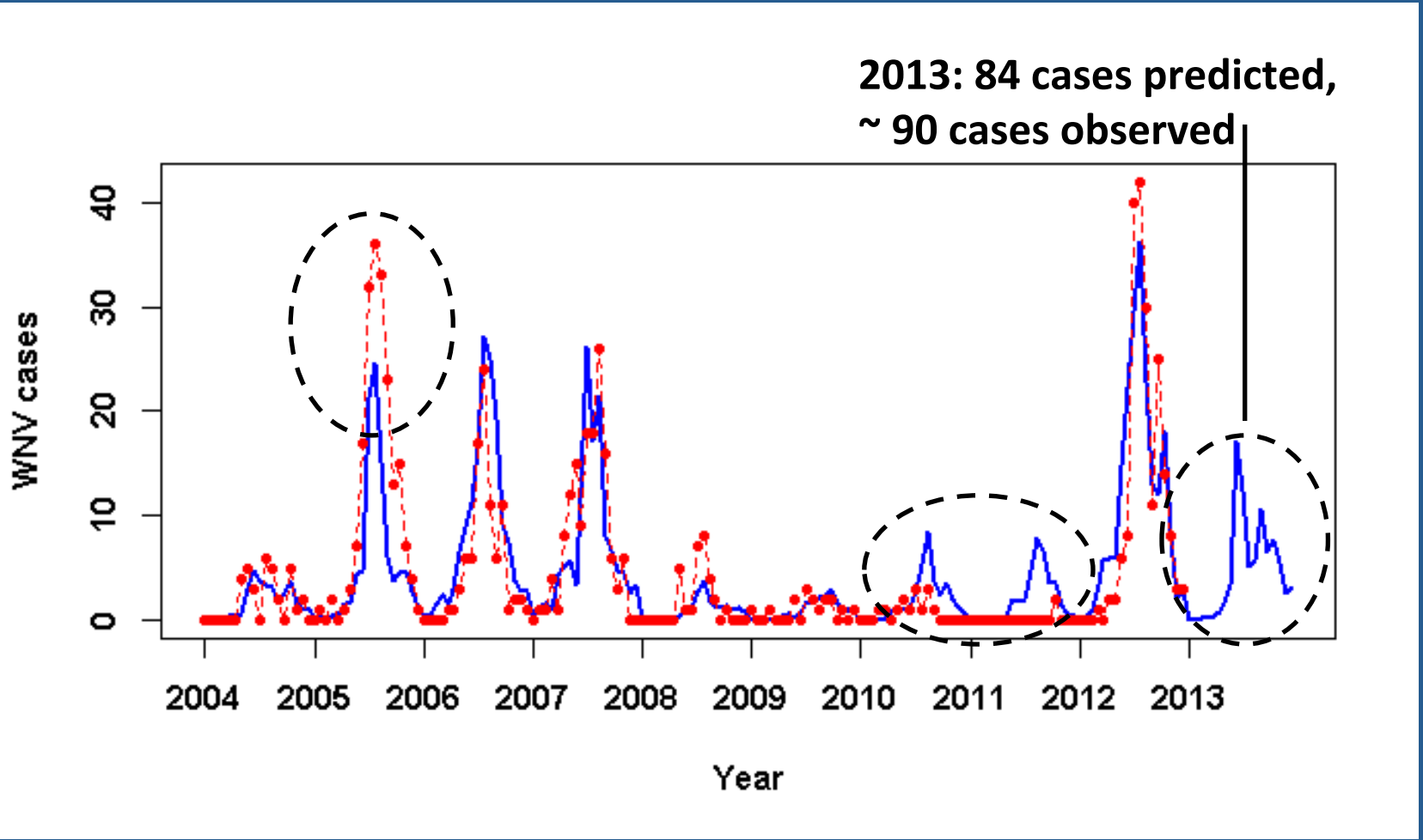
Annual WNV Incidence/100,000



Model 1: Includes Total WNV Cases from the Previous Year

- Weekly WNV case numbers were associated with:
  - Previous years WNV cases (+)
  - Previous Dec-Jan mean temperature (+)
  - Mean temperature at 1, 2, and 5 week lags (+)
  - Precipitation at 6, 7, and 8 week lags (+)

Model 1: Includes Total WNV Cases from the Previous Year

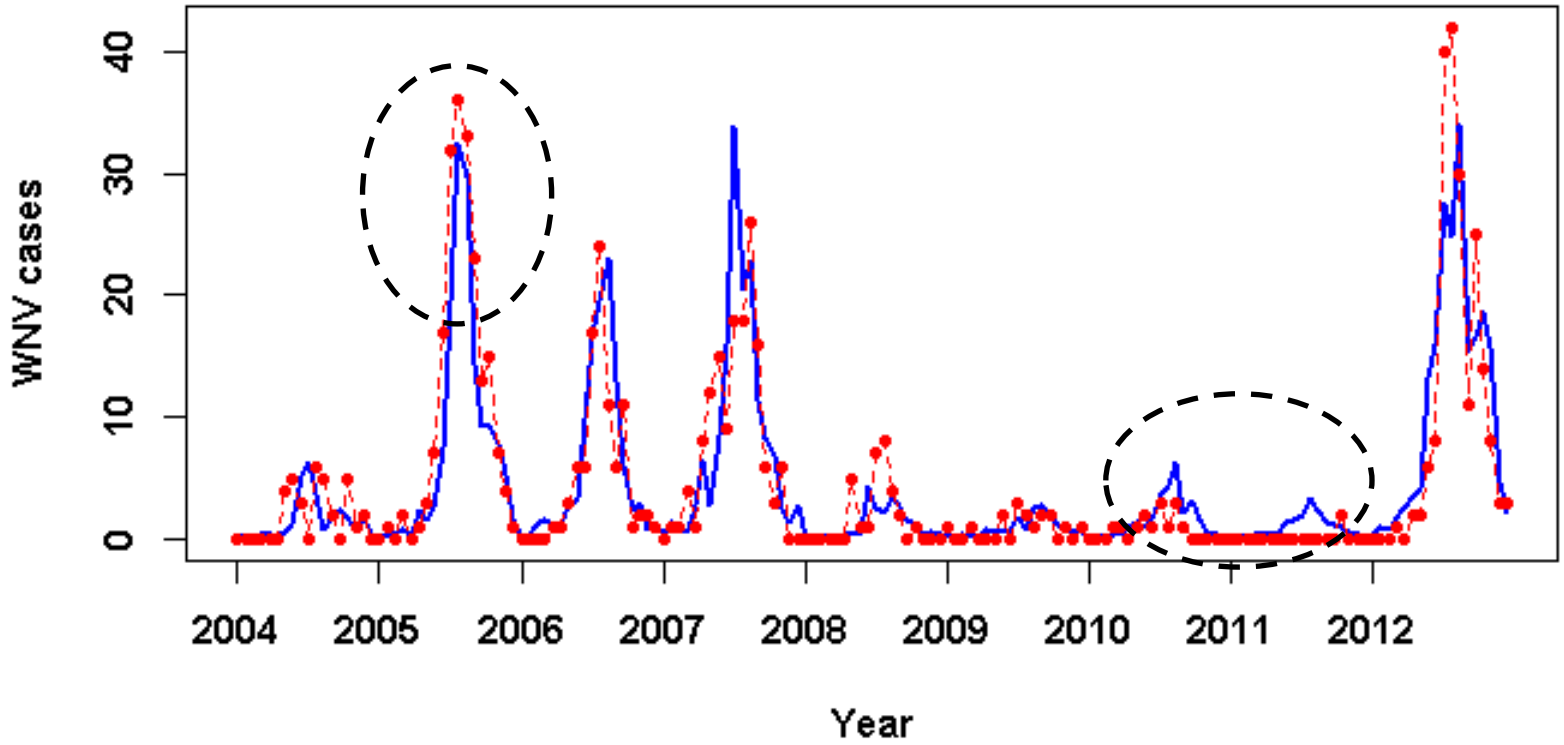


Truncated 20-week time series for each year

Model 2: Includes WNV Cases at a 2-Week Lag

- Weekly WNV case numbers were associated with:
  - WNV case numbers at a 2 week lag (+)
  - Previous Dec-Jan mean temperature (+)
  - Mean temperature at 1 and 2 week lags (+)
  - Precipitation at 6, 7, and 8 week lags (+)

Model 2: Includes WNV Cases at a 2-Week Lag

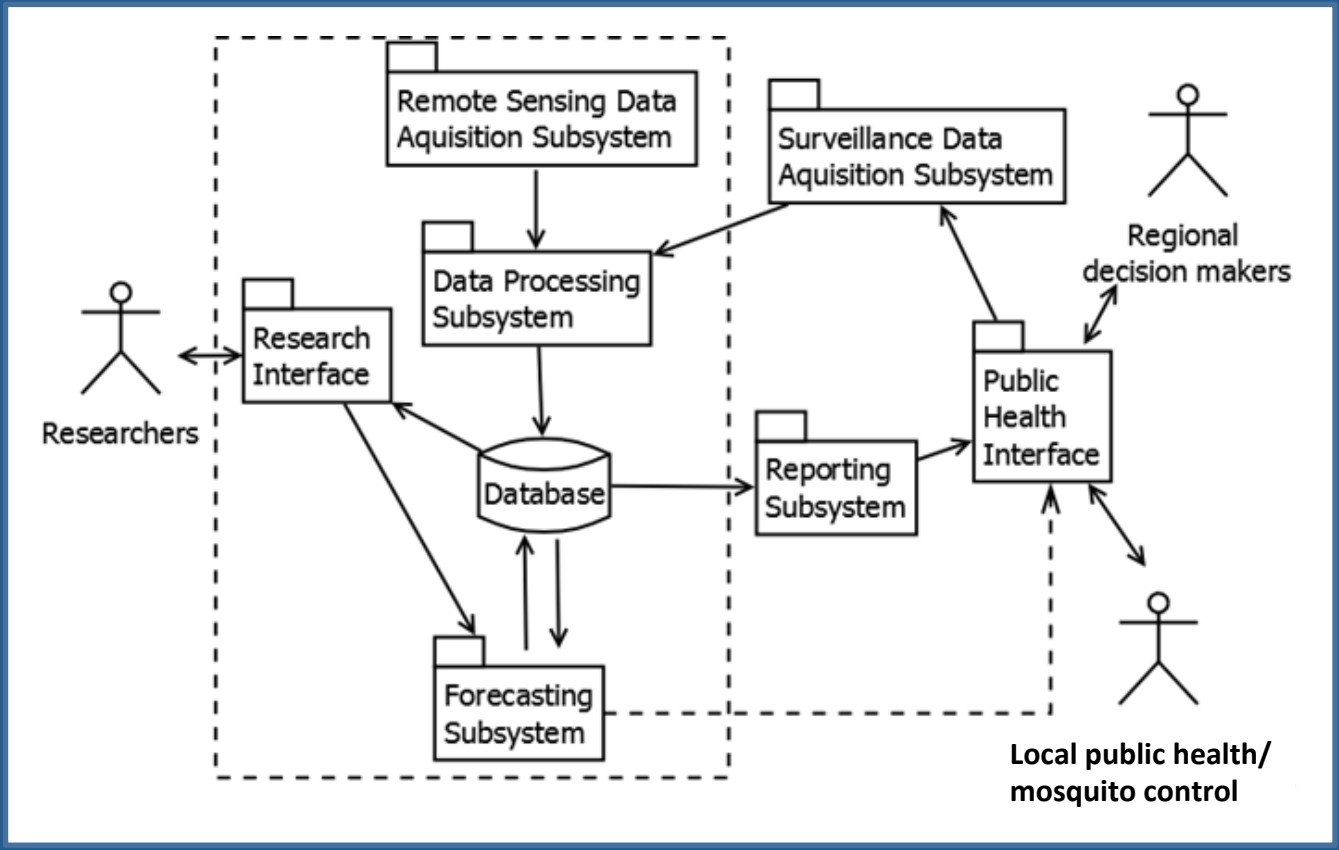


Truncated 20-week time series for each year

Links to Public Health Decision Support

- Mechanisms for providing information to public health decision makers in SD
  - Presentations at annual West Nile virus/mosquito control conferences (2012, 2013)
  - Participation in regular statewide conference calls during the West Nile virus season
  - Dissemination of risk maps and forecasts via the internet
- Importance of blending ecological forecasts with other sources of surveillance data
  - Epidemiological surveillance
  - Entomological surveillance

Epidemic Prognosis Incorporating Disease and Environmental Monitoring for Integrated Assessment (EPIDEMIA)



Connect remotely-sensed environmental monitoring with epidemiological and entomological surveillance

Links to Public Health Decision Support

- Invest in public awareness and education campaigns
- Allocate resources for adult mosquito control efforts (prevent transmission to humans)
  - Nuisance mosquitoes (*Aedes vexans*)
  - Vector mosquitoes (*Culex tarsalis*)
- Trigger larval control efforts to prevent amplification

West Nile

Researchers help public health officials combat West Nile virus

Photo: Bob Peterson, Montana State University

West Nile virus has found a home in South Dakota; the 2012 season proved that, says epidemiologist Lee Kightlinger of the South Dakota Department of Health. Over the past 10 years, he has worked with SDSU researchers to anticipate outbreaks and help cities plan spraying tactics.

"We feel West Nile is pervasive in

Targeting the culprit

All this makes a difference when it comes to spraying for mosquitoes.

The insecticide spray must land on the mosquito to kill it,

explains Hildreth, "so if the mosquitoes are not out looking for food, chances of those droplets killing them decrease

Lee Kightlinger

Michael Hildreth

Yi Liu

"Giving a warning is easy, but what comes down to is resources," ghtlinger says.

Small communities can strategically get their spraying before big events, ch as a baseball tournament or the urth of July, Kightlinger explains, hich will lower the risk considerably."

edicting outbreaks of the virus

mmitedly, the early warning system s not yet been perfected. Wimberly s only been making yearly predictions ce 2010, but he's been right two out three years.

"Our research has shown that mperature is an extremely strong ver," he says.

Wimberly found associations tween West Nile virus and mperature at two different times of e year. First, an earlier spring green , like this past year with the warm ril, gives the virus a longer plification period, he says. "In neral, mosquitos develop more idly, are more active and tend to bite ore when it's hotter."

The virus originates in the bird pulation but is transmitted to mans through the mosquito, mberly explains. After the mosquito as an infected bird, the virus must cubate in the mosquito before it can transmitted to humans.

Professor Michael Wimberly pulls up another map that he and his colleagues have made available online at http://globalmonitoring.sdstate.edu/projects/westnile/WestNileVirus.php.

This process is also temperature dependent, Wimberly says. During a warmer than normal summer, the mosquitoes become infectious more quickly.

When it comes to moisture and rainfall, Wimberly says, the relationship is complicated. As evidenced last year, lack of rainfall does not necessarily mean fewer West Nile cases.

The West Nile mosquito breeds in small water puddles, such as wheel ruts in a pasture or irrigated alfalfa. Wimberly calls it the "Goldilocks effect-the water needs to be just right."

Wimberly's next step will be to incorporate additional sources of environmental information to more precisely map the places where transmission risk is highest.

"Over time, we get better," Wimberly says of the ability to predict West Nile outbreaks. As a result, the public health community will begin to trust the forecasts. The ultimate goal is to provide useful and reliable information that can be applied to support West Nile virus prevention and control efforts.

Each county in the Northern Plains is color-coded on this 2012 West Nile Virus Risk Forecast map based on the risk of human infections. Orange counties have the highest risk, gold ones, a medium risk and yellow, the lowest risk.

Test your West Nile virus knowledge with the quiz on the back page.

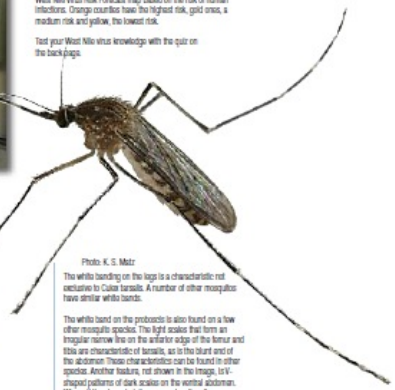
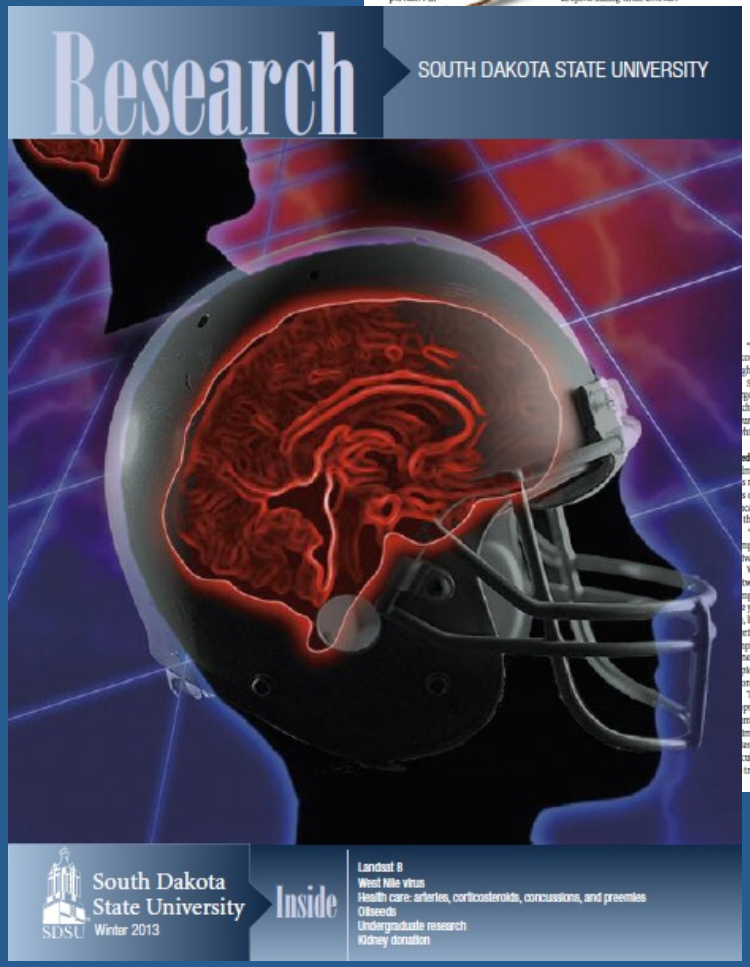


Photo: K. S. Metz

The white banding on the legs is a characteristic not exclusive to Culex tarsalis. A number of other mosquitos have similar white bands.

The white band on the proboscis is also found on a few other mosquito species. The light scales that form an irregular narrow line on the anterior edge of the femur and tibia are characteristic of tarsalis, as is the blunt end of the abdomen. These characteristics can be found in other species. Another feature, not shown in the image, lyre-shaped patterns of dark scales on the ventral abdomen. When all the characteristics appear together, the specimen will probably be Culex tarsalis.



Major Accomplishments and Lessons Learned

- Achieved our overarching goal of improving WNV forecasting applications for incorporating novel streams of earth observing data
- Demonstrated how applications can help drive the science
  - Value of making and critically evaluating real forecasts
  - Importance of "staying in the game"
- Strengthened relationships with public health end users
  - Public health professionals understand the potential of remote sensing
  - Remote sensing scientists understand decision support needs

Major Research Outputs

- Publications
  - Chuang, T., G. M Henebry, J. S. Kimball, D.L. VanRoekel-Patton, M. B. Hildreth, and M. C. Wimberly. 2012. Satellite microwave remote sensing for environment modeling of mosquito population dynamics. *Remote Sensing of Environment* 125: 147-156.
  - Chuang T., and M. C. Wimberly. 2012. Remote Sensing of Climatic Anomalies and West Nile Virus Incidence in the Northern Great Plains of the United States. *PLOS One* 7:e46882.
  - Wimberly, M. C., Giacomo, P., Kightlinger, L., and M. B. Hildreth. In Press. Spatio-temporal epidemiology of human West Nile virus disease in South Dakota. *International Journal of Environmental Research and Public Health*.
- Proposals
  - Wimberly, M. C. (PI), and Y. Liu (Co-I). Expanding Earth Science Data Access for Public Health Research and Applications. Submitted to NASA Roses 2013: Advancing Collaborative Connections for Earth System Science (NNH13ZDA001N-ACCESS), June 3, 2013.
- Website
  - http://globalmonitoring.sdstate.edu/eastweb/

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