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Supplemental Material

Integrated Forecasts Based on Public Health Surveillance and Meteorological Data Predict West Nile Virus in a High-Risk Region of North America

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Table of Contents

Figure S1. Accuracy of lagged weekly West Nile virus predictions from zero to six weeks into the future from 2016-2019 measured as the area under the receiver operating characteristic curve (AUC).

Figure S2. Accuracy of South Dakota West Nile virus predictions from 2016-2019 in counties with no mosquito infection data measured as the area under the receiver operating characteristic curve (AUC).

Additional File- ArboMAP_Main_Code.Rmd

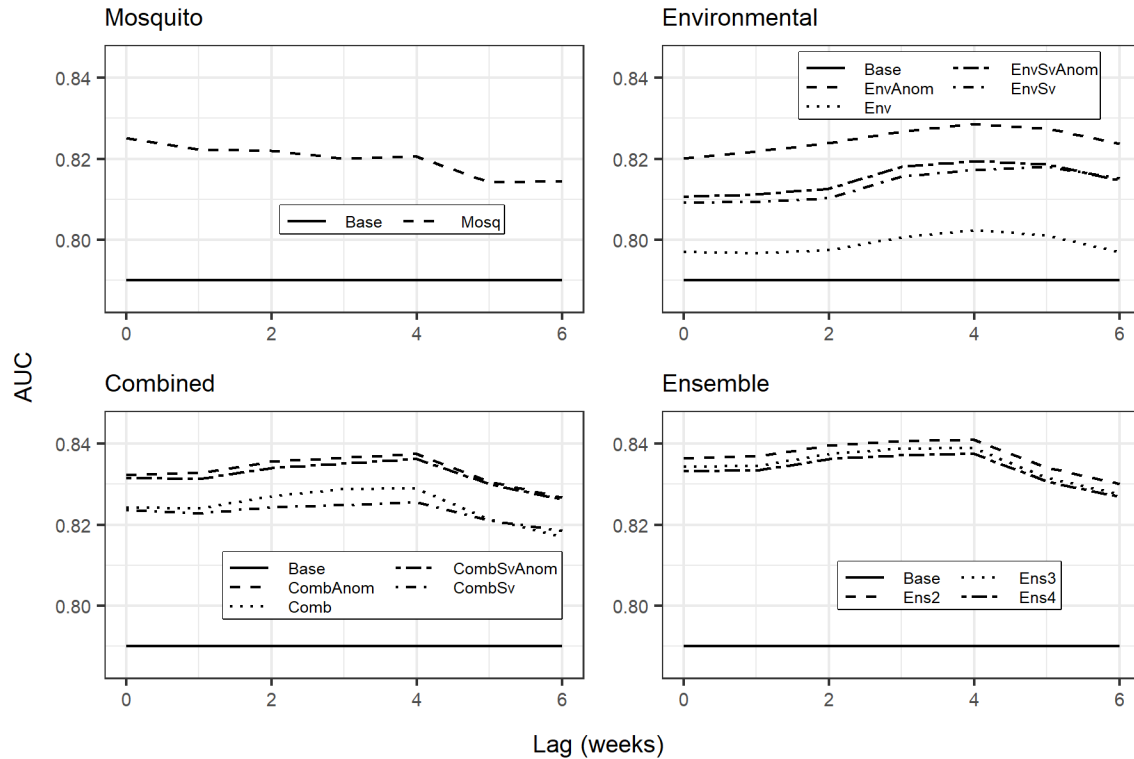


Figure S1: Accuracy of lagged weekly West Nile virus predictions from zero to six weeks into the future from 2016-2019 measured as the area under the receiver operating characteristic curve (AUC).

Predictions were generated using the Arbovirus Monitoring and Prediction (ArboMAP) software with thirteen different model formulations. Weekly predictions from weeks 28-40 were evaluated based on forecast weeks from zero to six weeks prior to the prediction week.

Each line represents the variation in AUC by forecast lead time for one model. The logistic regression models incorporated various combinations of mosquito infection variables and lagged meteorological variables (temperature and vapor pressure deficit) with different variable transformations and model structures. Model abbreviations: Base=baseline; Mosq=mosquito; EnvAnom=environmental with anomalies; Env=environmental; EnvSvAnom=environmental with anomalies and seasonally-varying distributed lags; EnvSv=environmental with seasonally-varying distributed lags; CombAnom=combined with anomalies; Comb=combined; combSvAnom=combined with anomalies and seasonally-varying distributed lags; CombSv=combined with seasonally-varying distributed lags; Ens2=two-model ensemble; Ens3=three-model ensemble; Ens4=four-model ensemble. Individual models are defined in Table 1 and mathematical forms are provided in Table 2 in the main text.

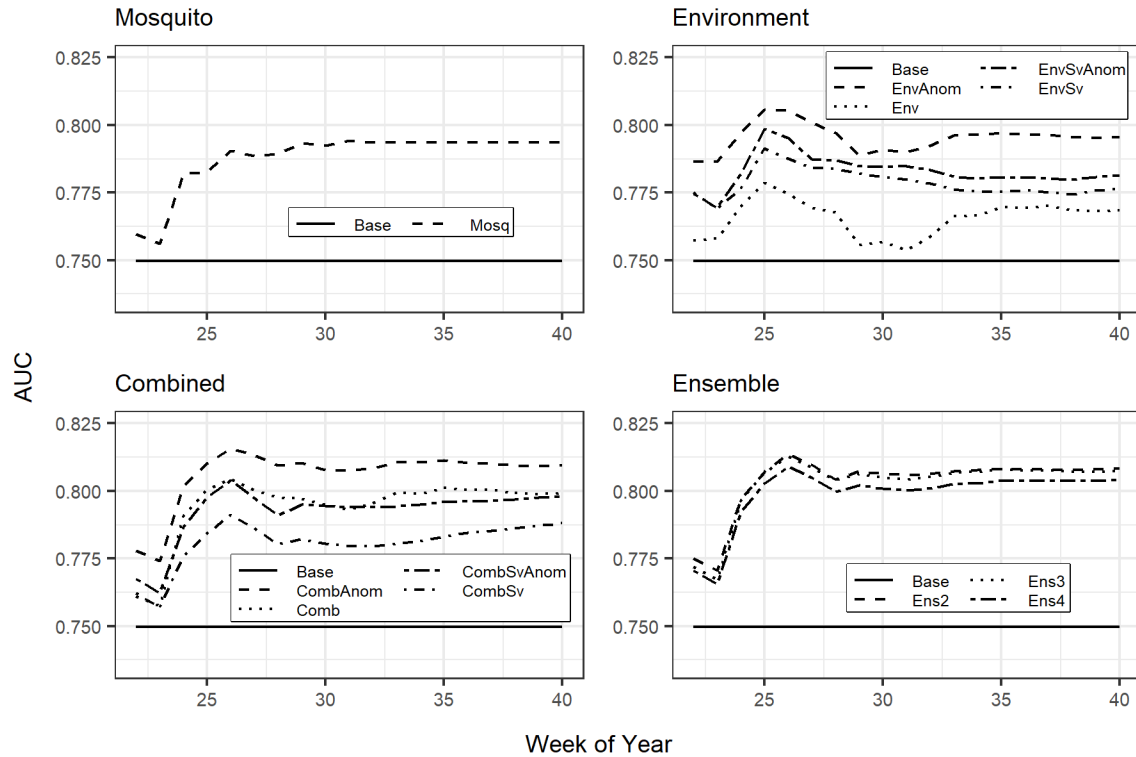


Figure S2: Accuracy of South Dakota West Nile virus predictions from 2016-2019 in counties with no mosquito infection data measured as the area under the receiver operating characteristic curve (AUC).

Predictions were generated using the Arbovirus Monitoring and Prediction (ArboMAP) software with thirteen different model formulations. Only the 43 South Dakota counties with no mosquito infection data from 2004-2019 were included in the accuracy assessment. Each line represents the variation in AUC by forecast week for one model. The logistic regression models incorporated various combinations of mosquito infection variables and lagged meteorological variables (temperature and vapor pressure deficit) with different variable transformations and model structures. Model abbreviations: Base=baseline; Mosq=mosquito; EnvAnom=environmental with anomalies; Env=environmental; EnvSvAnom=environmental with anomalies and seasonally-varying distributed lags; EnvSv=environmental with seasonally-varying distributed lags; CombAnom=combined with anomalies; Comb=combined; CombSvAnom=combined with anomalies and seasonally-varying distributed lags; CombSv=combined with seasonally-varying distributed lags; Ens2=two-model ensemble; Ens3=three-model ensemble; Ens4=four-model ensemble. Individual models are defined in Table 1 and mathematical forms are provided in Table 2 in the main text.