West Nile Virus Forecast Report for 2018-08-15
South Dakota

DEMO for Arbovirus Modeling and Prediction (ArboMAP): Synthetic Data
Not for Epidemiological Use

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Report compiled on June 01, 2022

Contents

1 Forecast results

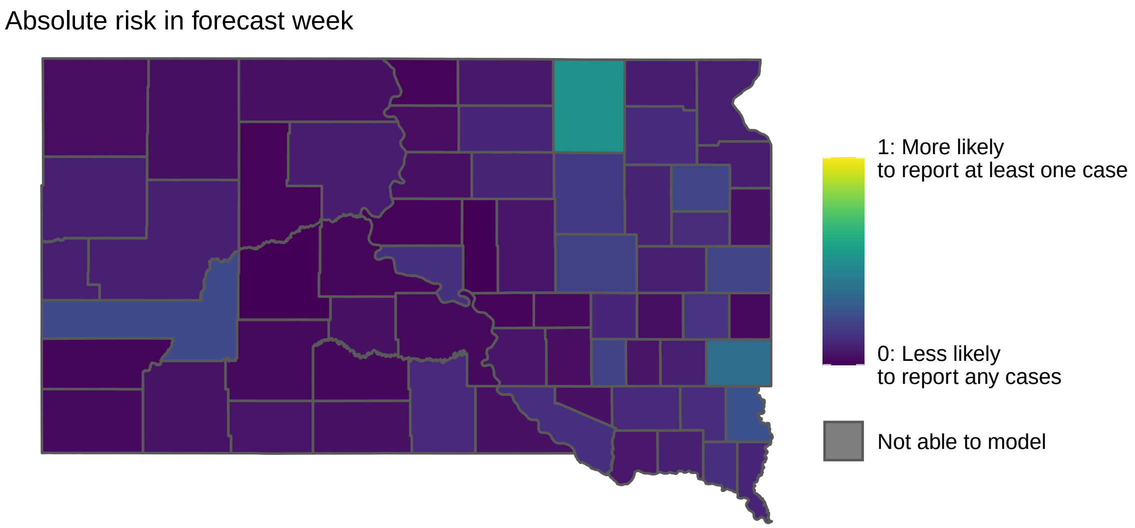
The Arbovirus Monitoring and Prediction (ArboMAP) system produces a weekly, county-level forecast of human West Nile virus (WNV) cases using environmental data combined with entomological data.

Modeling overview: The transmission of mosquito-borne diseases, such as WNV, is influenced by environmental conditions that affect many aspects of the disease transmission system. ArboMAP uses an ensemble of different mathematical models that each are predicting if a county will report at least one case in a given week ('positive county-week'). Results presented are an average of the models with ranges as appropriate. As part of the process, mosquito infection rate is also modeled based on the mosquito pool data, and is included in the default modeling. ArboMAP uses generalized additive models (GAMs) with smooths for seasonality, and also lagged weather data, which allows it to model the time-delayed effects of weather conditions. The appendix will expand all the results to show each individual model.

1.1 Forecast week WNV absolute risk

The following map displays the **absolute risk** of predicted positive counties during epidemiological week 33.

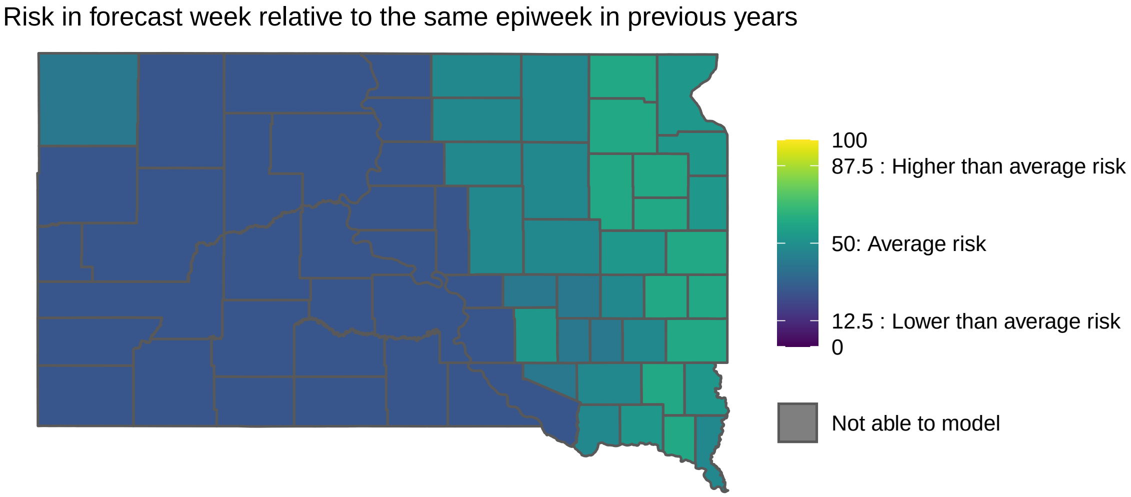
This map can be used in conjunction with the **relative risk** map. The absolute risk map shows the risk of a county reporting at least one WNV positive human case during this week, and the relative risk map shows if this risk is elevated (or not) as compared to previous years.



1.2 Forecast week WNV relative risk

In the forecast week there are 0 counties with higher than average risk as compared to the same epidemiological week in previous years (2004 through 2018).

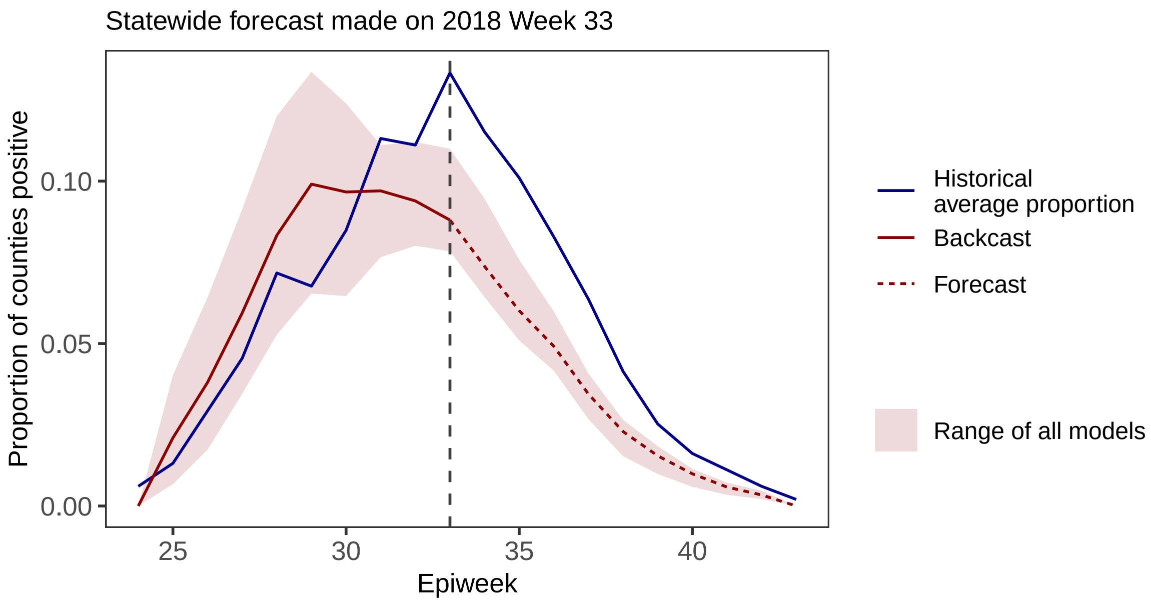
This **relative risk** map may be used in conjunction with the **absolute risk** map. The absolute risk map shows the risk of a county reporting at least one WNV positive human case during this week, and the relative risk map shows if this risk is elevated (or not) as compared to previous years.


Risk in forecast week relative to the same epiweek in previous years
100
87.5 : Higher than average risk
50: Average risk
12.5 : Lower than average risk
0
Not able to model

1.3 Forecast year

The following graph is the predicted epicurve of the forecast year: the average of all models is shown as a dark red line, with the range of all models in the shaded ribbon. Forecasts are shown as a dotted line and the predicted values from before the current forecast week ('backcast') are shown as a solid line. The appendix will have a version of this chart with a series for each model, rather than an average.

The historical **observed** proportion of counties positive, averaged over all known years, is also shown, here as a dark blue line. This is excluding human cases that occurred very early or very late in the season (temporal outliers), based on the percentage cut-off in the parameters, 0.02. This plotted curve allows a comparison between the timing and height of the predicted peak of cases as compared to averaged historical years. In the averaged year, 49% of the yearly cases would have been observed by this forecast week.



1.4 Case estimation

ArboMAP models are based on ‘positive county-weeks’, the probability that a county would have at least one human WNV case in a given week. These values can be used to predict a total number of **cases**, shown in the table below.

Table 1: Estimated number of WNV cases

Year	Predicted positive county-weeks	Average estimated cases (standard dev)	Range of estimated cases
2018	63	75 (+/-15)	56 - 89

1.5 Model fit statistics

The following table gives a summary of how well the model is fitting the historical years. The Area Under the ROC curve (AUC) is a statistic that ranges from 0 (model is right 0% of the time) to 1 (model is right 100% of the time). Scores above 0.5 are better than a random model, with >0.7 generally considered acceptable and >0.8 as good.

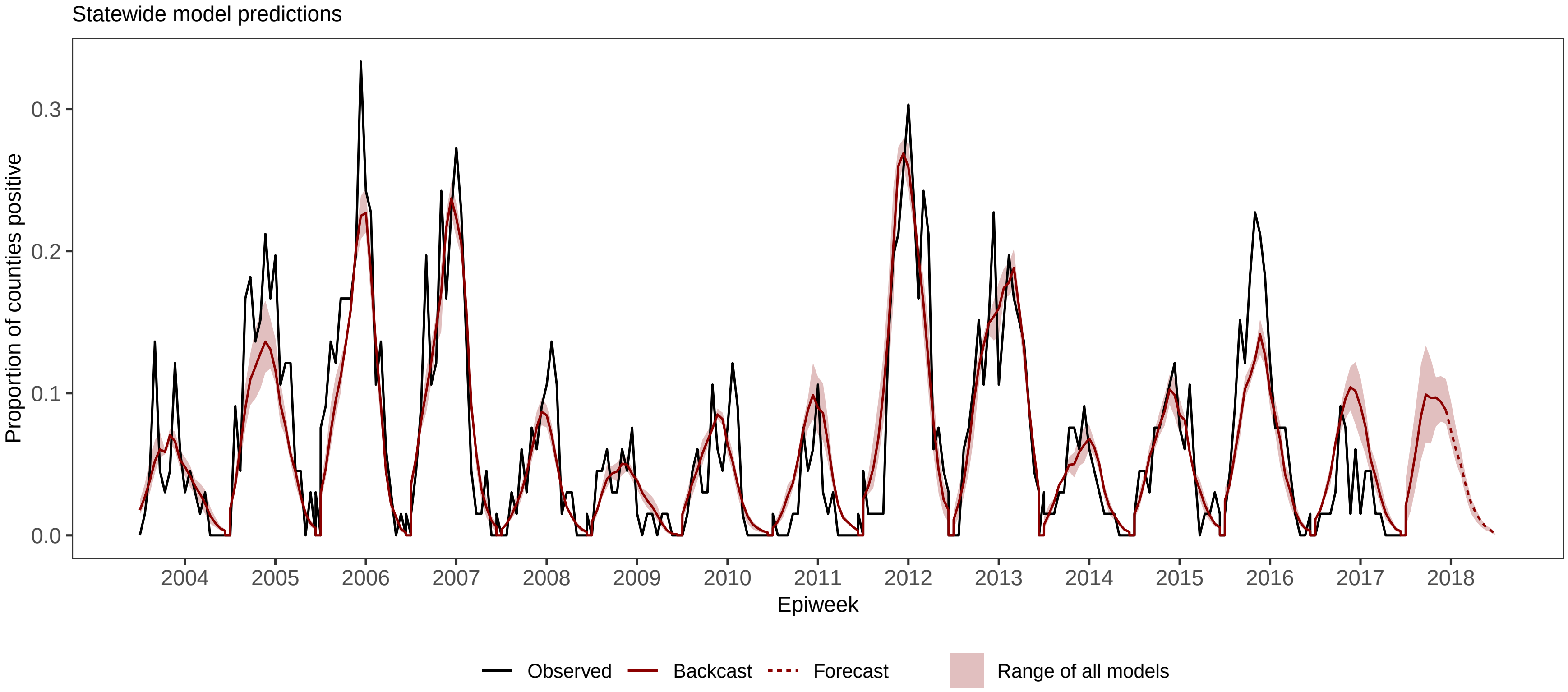
Table 2: Area Under Curve (AUC) statistics of all model fits

Model	Average AUC	Min AUC	Max AUC
Average of all models	0.84	0.84	0.85

1.6 Multi-year forecast

The following chart shows the model results for the entire modeled period from 2004 through 2018. Years prior to the forecast year that had human case data were used for fitting the model.

Similar to the previous forecast year chart, the average of all models is shown as a dark red line, with the range of all models as the shaded ribbon. Forecasts are shown as a dotted line and predicted values from before the current forecast week ('backcast') are shown as a solid line. The historical **observed** values are shown in black. The appendix will have a version of this chart with a series for each model, rather than an average.



2 Input data summaries

The report was requested for 2018-08-15, which is CDC/MMWR epiweek 33 in epiyear 2018.

2.1 Human cases

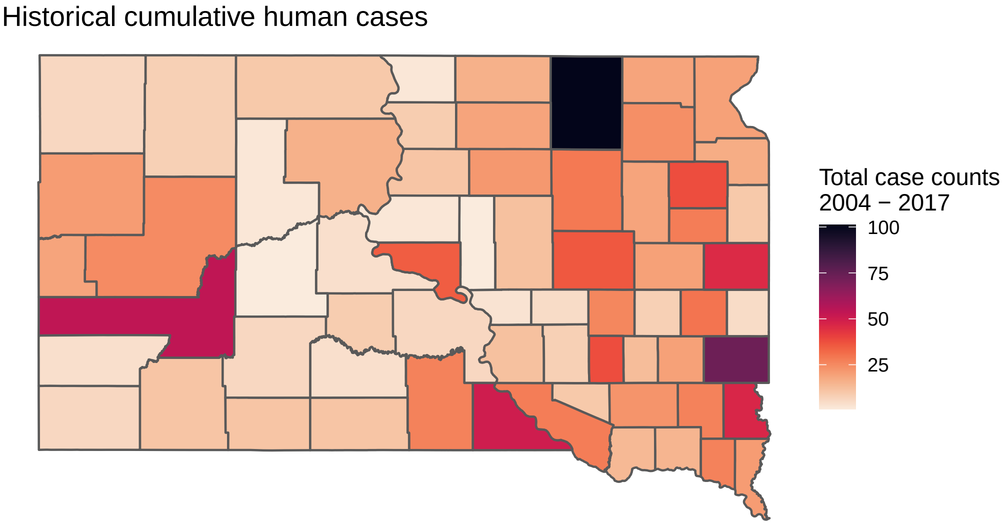
After data processing, the human case data contained a total of 1300 rows containing data from years: 2004, 2005, 2006, 2007, 2008, 2009, 2010, 2011, 2012, 2013, 2014, 2015, 2016, and 2017. Parameters were set to include human data from 2004 through 2017. Data from all years were found in the data file.

The human case data entries that were unmatched to spatial data during processing are in the table below. Please check for mispellings in the original file.

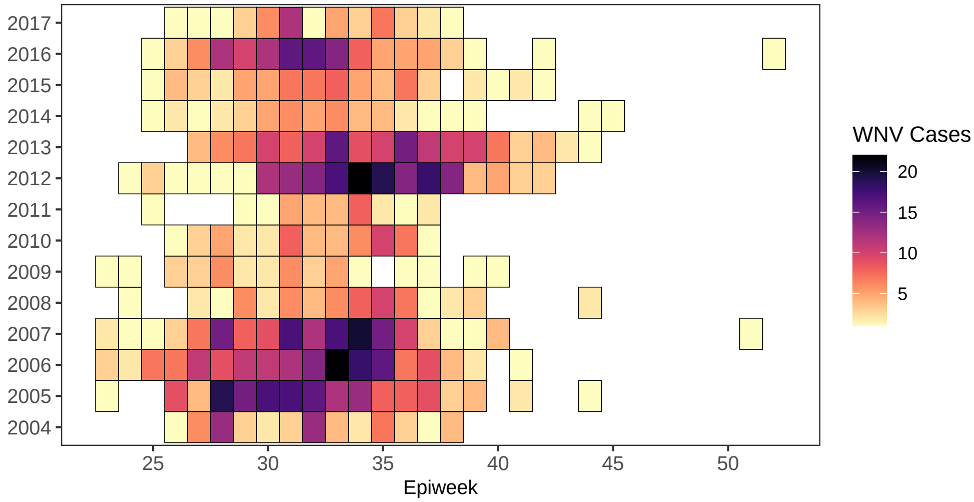
Table 3: Unmatched human case entries

arbo_ID	date
greg0ry	7/4/2004

Over all years, the state saw a cumulative total of 1300 human cases representing 1141 positive county-weeks from a total of 66 counties.



To compare the epicurve of human cases in each year, the heatmap below shows when in each year the cases occurred.


2017
2016
2015
2014
2013
2012
2011
2010
2009
2008
2007
2006
2005
2004
25
30
35
40
45
50
Epiweek
WNV Cases
20
15
10
5

2.2 Mosquito pools

After data processing, the mosquito pool data contained a total of 16274 rows, containing data from years: 2004, 2005, 2006, 2007, 2008, 2009, 2010, 2011, 2012, 2013, 2014, 2015, 2016, 2017, and 2018. Overall during this time frame, a total of 29 counties reported mosquito data.

Parameters were set to include mosquito data from 2004 through 2018. Data from all years were found in the data file.

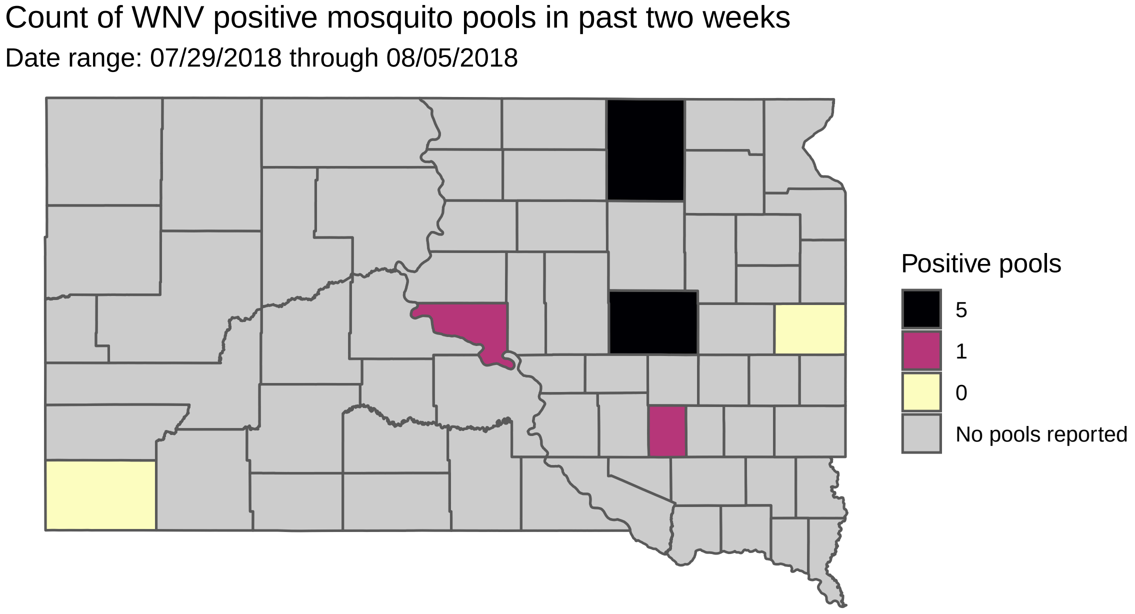
Note that even if there were no positive pools in a given year, if there were any pools tested then the data will be useful; zero infection rates do predict low-risk years and should be used.

Parameters were set to include mosquito data from day of year 140 through 366. The mosquito infection rate modeling is very sensitive to early mosquito pool results, which is why a cut-off is used. Sensitivity analyses indicate that a start day of year of 140 is a reasonable cut-off for a high modeling accuracy.

Modeling was done from 2004 through 2018. Years without mosquito data during these years are assumed to have average mosquito infection rates. This allows us to estimate relationships with environmental data even when mosquito data are not available. There were 6 years where mosquito infection rates were imputed. These years are: 2004, 2007, 2009, 2010, 2012, and 2013. In modeling years where sufficient mosquito data were present, the mosquito infection statistic was created using the model specified in the input parameter: stratifiedMIGR.

In the forecast year to date, there were 1697 pools reported from 12 counties. Of these pools, 66 (4%) were reported WNV positive.

Pool statistics for the past two weeks are also included. If pool data exists for the forecast epiweek, then the two weeks will be the forecast week and the week prior. If data does not exist yet for the requested forecast epiweek, then the weeks shown will be the two epiweeks prior to the forecast week. In this report, the two weeks are 07/29/2018 through 08/05/2018 (epiweeks 31 & 32) with mosquito data existing between 07/29/2018 through 07/31/2018.



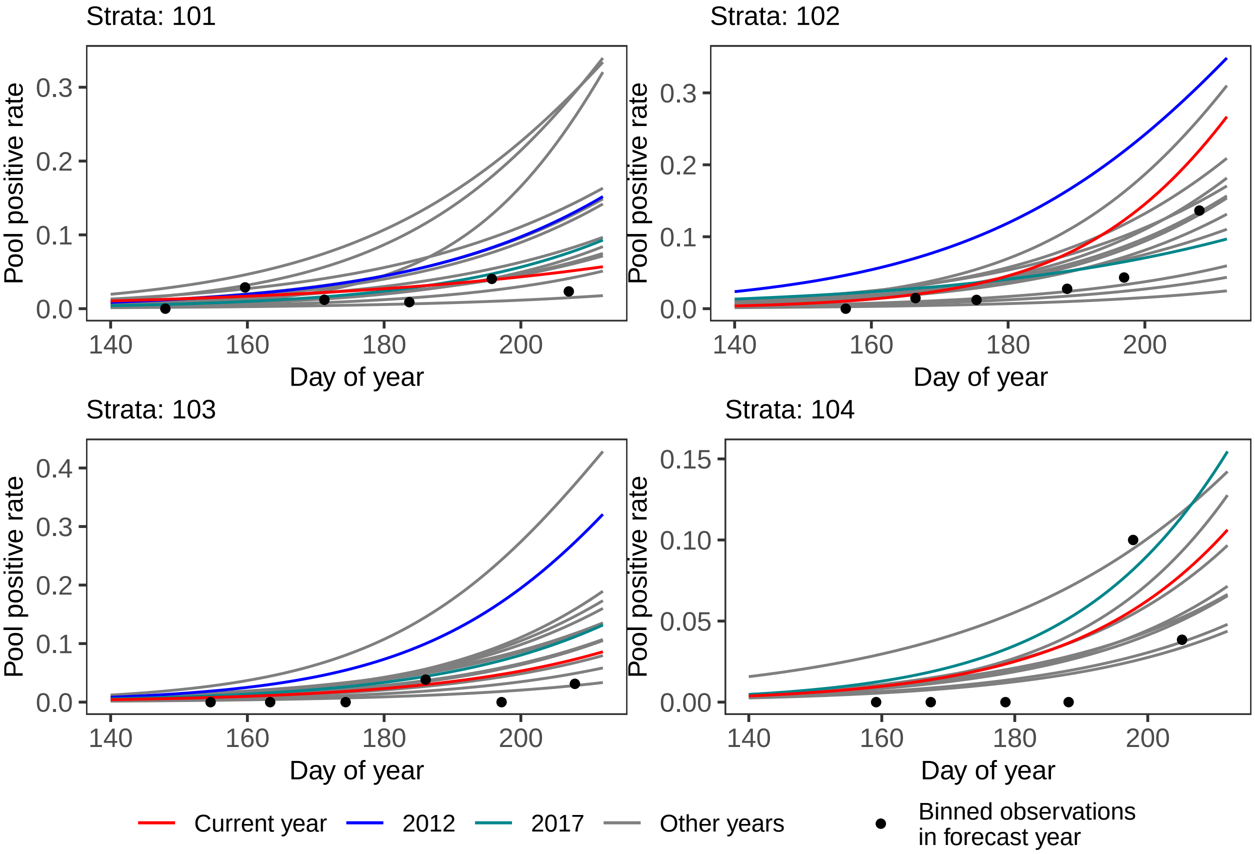
Count of WNV positive mosquito pools in past two weeks

Date range: 07/29/2018 through 08/05/2018

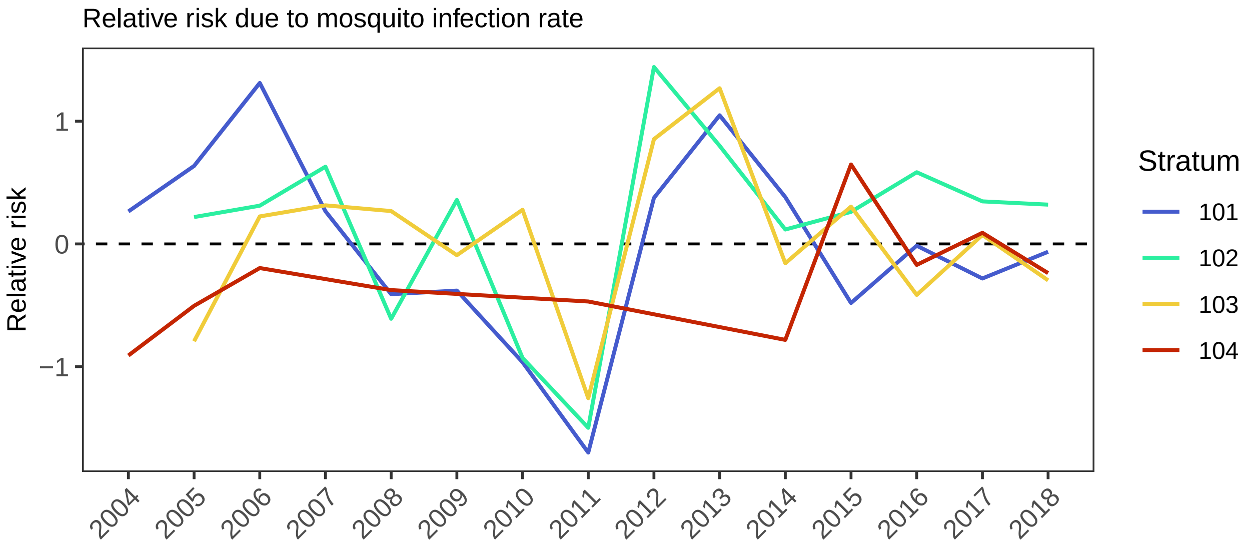
Table 4: Total reported and WNV positive mosquito pools: Past two weeks, and year to forecast week (YTD)

County	Pools reported last 2 weeks	Pools positive last 2 weeks	Pools reported YTD	Pools positive YTD
Beadle	30	5	161	11
Brookings	13	0	290	7
Brown	38	5	556	30
Custer	-	-	5	0
Davison	5	1	38	2
Edmunds	-	-	21	1
Fall River	2	0	57	2
Hughes	16	1	76	1
Lincoln	-	-	47	1
Minnehaha	-	-	372	10
Stanley	-	-	29	1
Todd	-	-	45	0

The next graph shows the percentage of predicted positive pools by year comparing the forecast year (in red) to the requested comparison years (shades of blue) and all other years (gray). If there is sufficient data in the forecast year, the observed pools rates are shown as black dots, binned into six different time points.



The last mosquito graph shows the relative risk due to the mosquito infection rate as a time-series of all known years. Mosquito strata are shown in different colors.

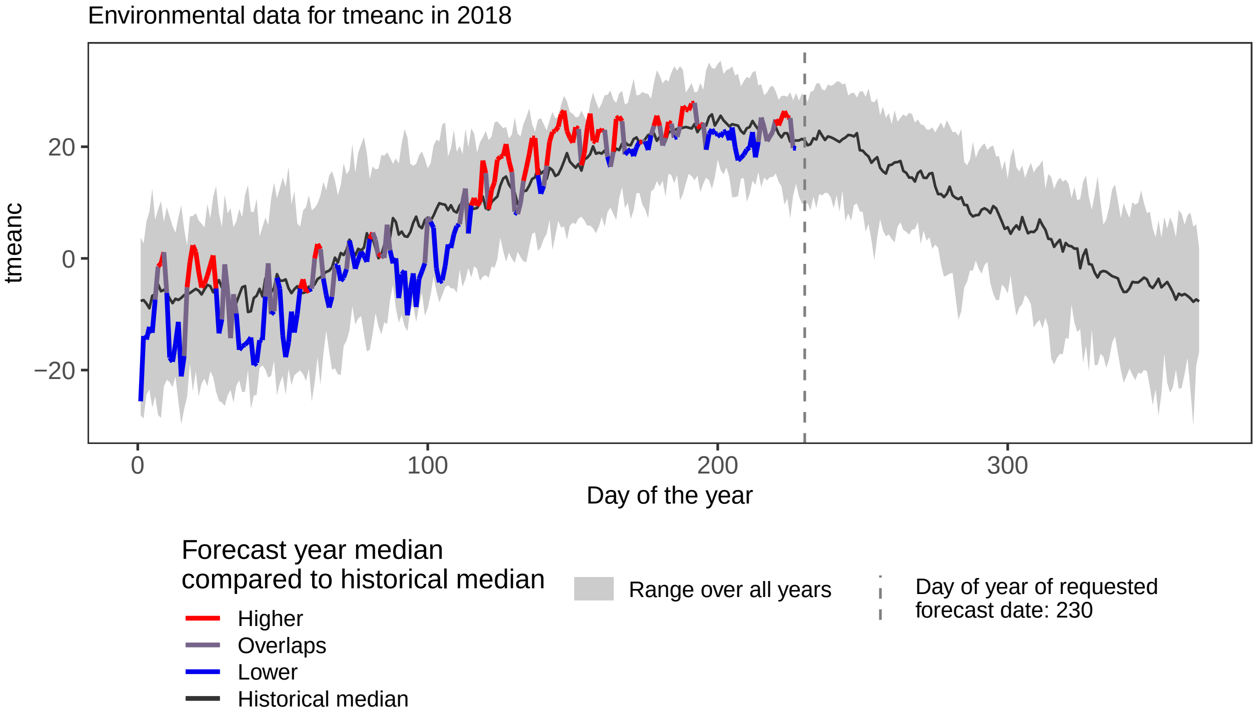

Relative risk due to mosquito infection rate
Relative risk
1
0
−1
2004
2005
2006
2007
2008
2009
2010
2011
2012
2013
2014
2015
2016
2017
2018
Stratum
101
102
103
104

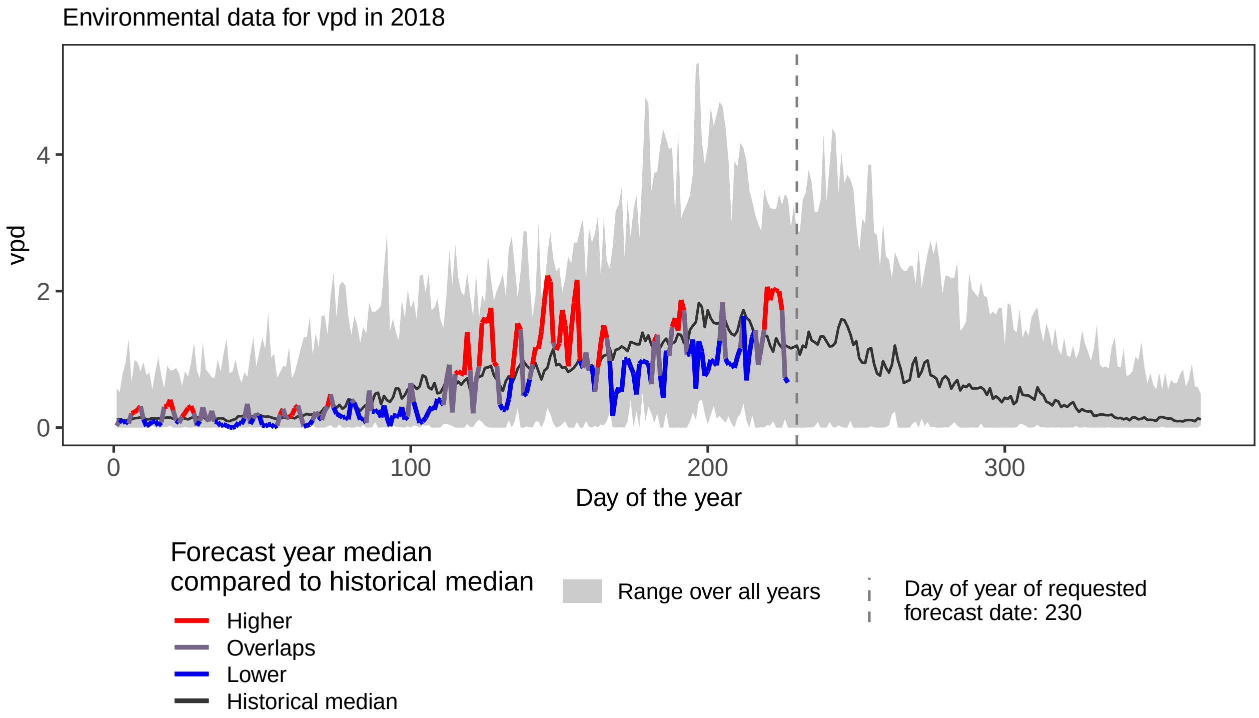
2.3 Weather

After processing, weather data existed from 2001-01-01 through 2018-08-15 for 66 counties. Environmental data are read and collated from all files in the base `data_weather` folder and if there are duplicate data entries for any particular day, the value from the latest file is used (i.e. the latest updated value).

Parameters were set to include weather data from 2000 through 2018. All necessary weather data were found in the data file.

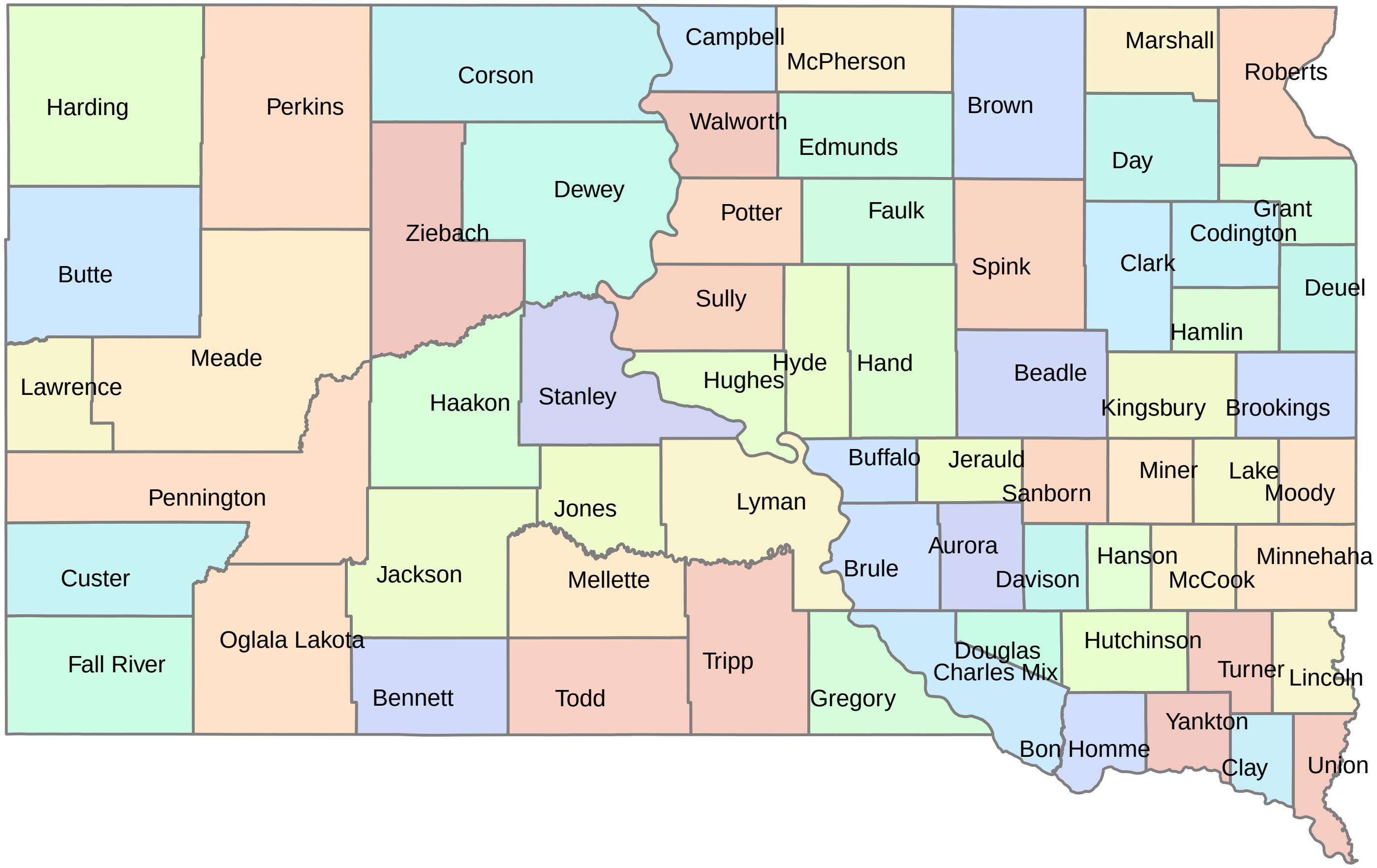
The report parameters set the two environmental predictor variables as tmeanc and vpd. The following two graphs show the median state-wide observed weather variables for the forecast year, compared to the historical median. Two or more consecutive days that are **greater than** the historical median are drawn in red and consecutive days that are **less than** the historical median are drawn in blue. Consecutive days that overlap the historical median (i.e. one day above and the next below, or the opposite) are in purple. The gray shaded region is a ribbon showing the historical range (min to max). The appendix will show the anomaly graphs (same timeseries, but the weather variable has been anomalized).




Environmental data for vpd in 2018
vpd
0
2
4
0
100
200
300
Day of the year
Forecast year median
compared to historical median
Higher
Overlaps
Lower
Historical median
Range over all years
Day of year of requested
forecast date: 230

2.4 Reference map

For South Dakota, the spatial data (shapefile) contained 66 counties: Aurora, Beadle, Bennett, Bon Homme, Brookings, Brown, Brule, Buffalo, Butte, Campbell, Charles Mix, Clark, Clay, Codington, Corson, Custer, Davison, Day, Deuel, Dewey, Douglas, Edmunds, Fall River, Faulk, Grant, Gregory, Haakon, Hamlin, Hand, Hanson, Harding, Hughes, Hutchinson, Hyde, Jackson, Jerauld, Jones, Kingsbury, Lake, Lawrence, Lincoln, Lyman, Marshall, McCook, McPherson, Meade, Mellette, Miner, Minnehaha, Moody, Oglala Lakota, Pennington, Perkins, Potter, Roberts, Sanborn, Spink, Stanley, Sully, Todd, Tripp, Turner, Union, Walworth, Yankton, and Ziebach



2.5 Parameters used

The report was run with the following parameters set.

Table 5: Parameters used

Parameter	Value
forecast_date	2018-08-15
state_name	South Dakota
state_code	SD
predictor_var1	tmeanc
predictor_var2	vpd
mosquito_model	stratifiedMIGR
mosquito_doy_start	140
mosquito_doy_end	366
file_human	data_human/simulated_human_data.csv
file_mosquito	data_mosquito/simulated_mosquito_data.csv
file_strata	data_strata/example_strata_SD.csv
file_county_sf	data_spatial/sd_counties.RDS
file_models	data_models/models.txt
folder_weather	data_weather
year_human_start	2004
year_human_end	2017
year_mosquito_start	2004
year_mosquito_end	2018
year_weather_start	2000
year_weather_end	2018
year_compare_vis1	2012
year_compare_vis2	2017
create_appendix	TRUE
lag_length	121
case_trim_alpha	0.02

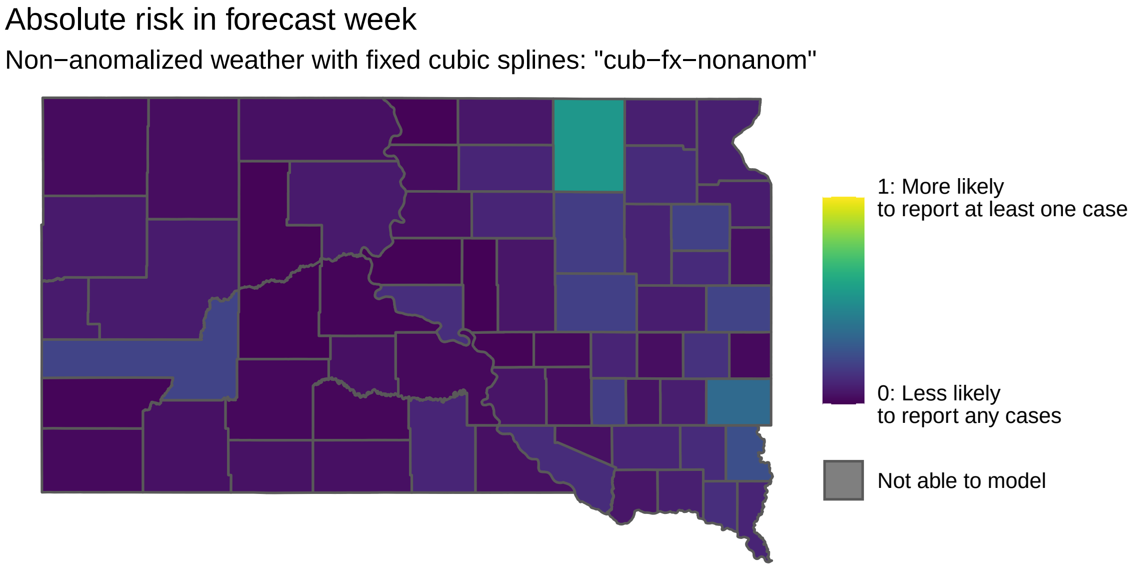
3 Appendix

This appendix will provide more details into some of the underlying forecast modeling and break out the results per model, rather than an average of all models run (as in the main report).

3.1 Forecast results

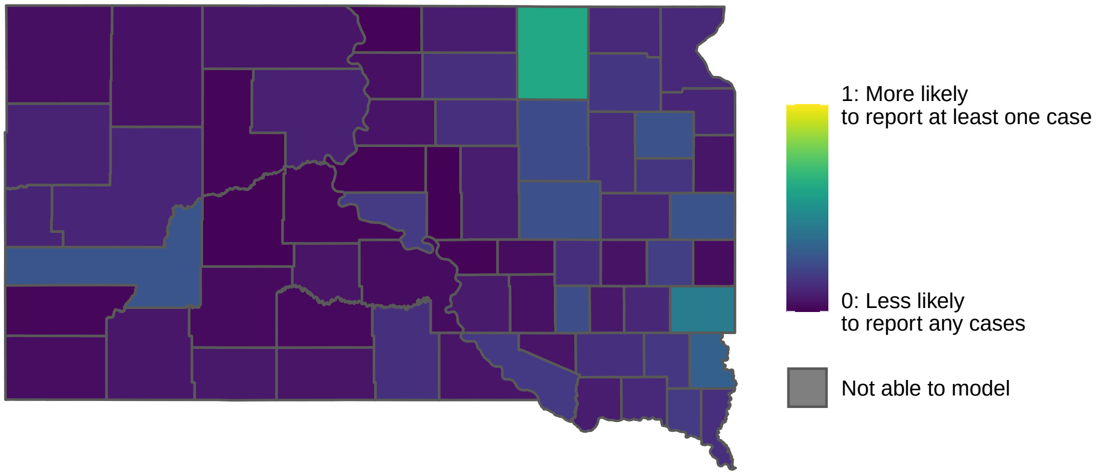
3.1.1 Current-week WNV absolute risk

Following are the absolute risk maps generated by **each** model:


Absolute risk in forecast week
Non−anomalized weather with fixed cubic splines: "cub−fx−nonanom"
1: More likely
to report at least one case
0: Less likely
to report any cases
Not able to model

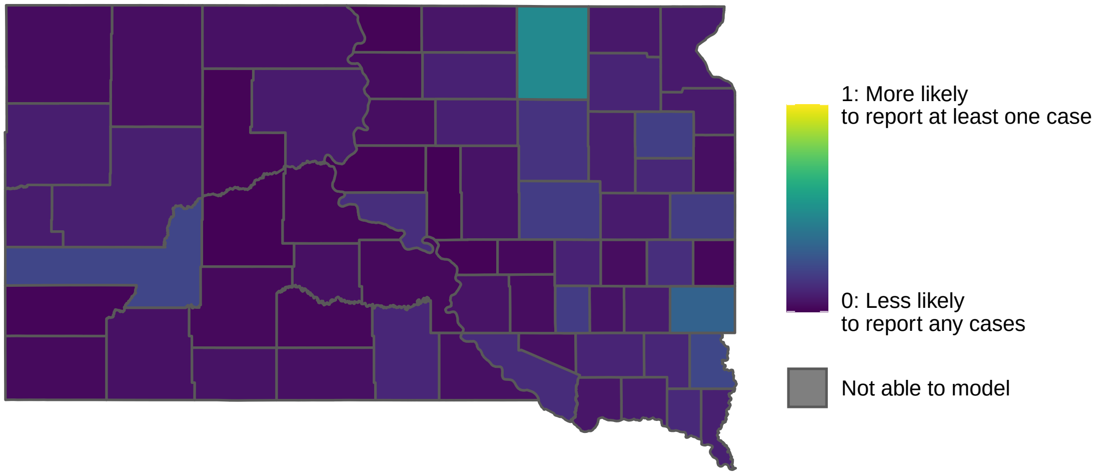
Absolute risk in forecast week

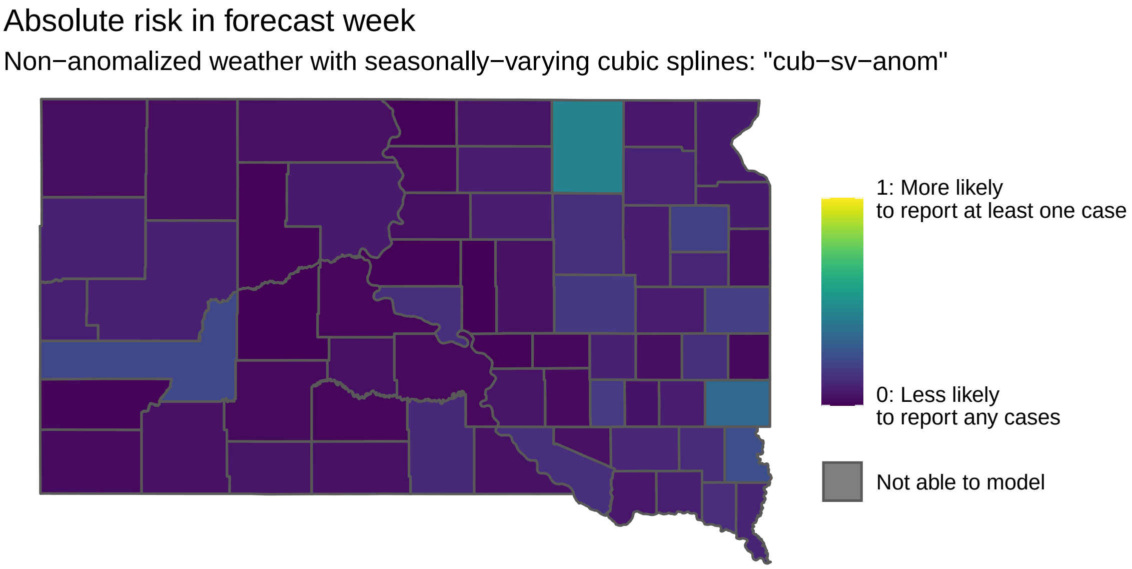
Anomalized weather with fixed cubic splines: "cub−fx−anom"

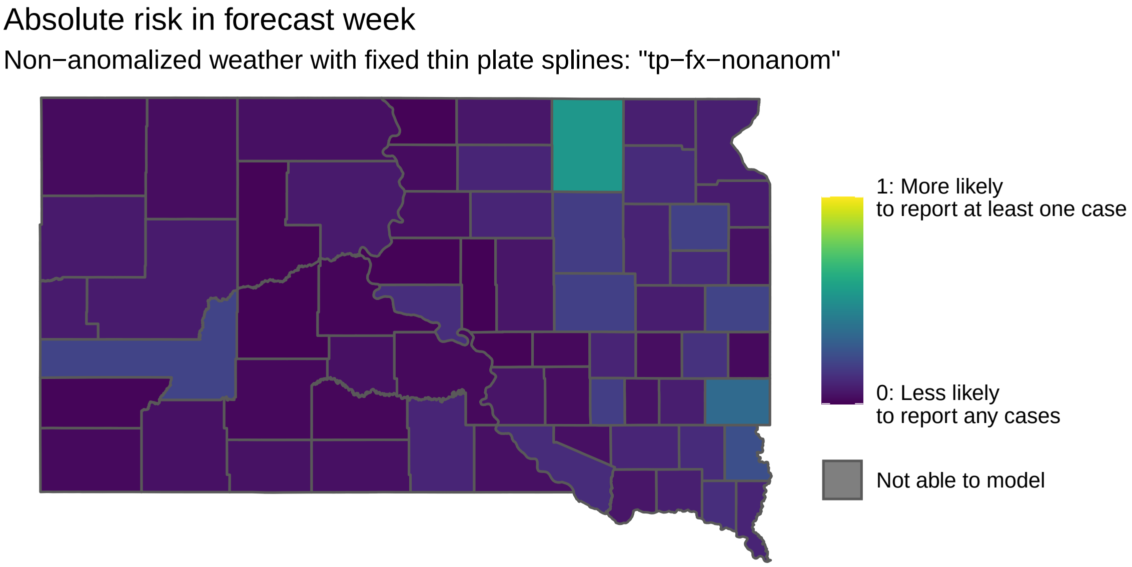


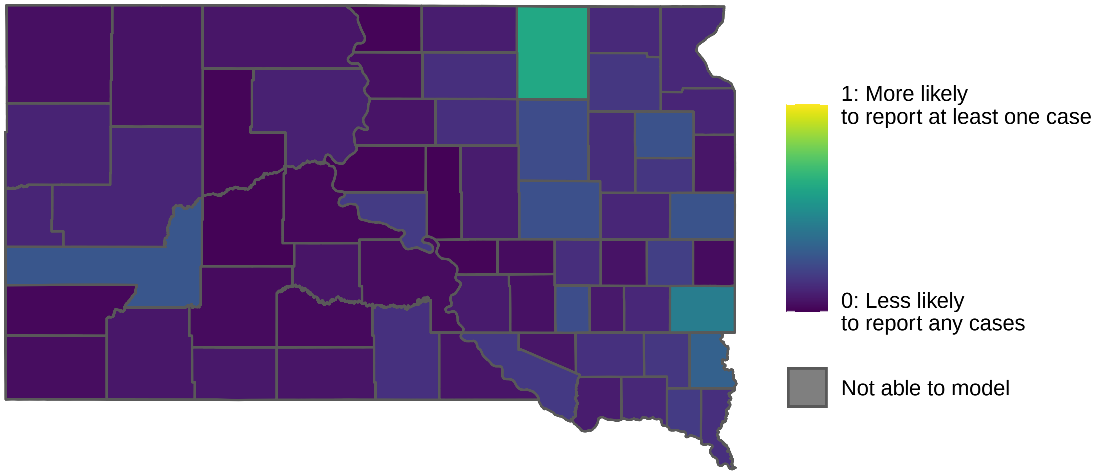
Absolute risk in forecast week

Non−anomalized weather with seasonally−varying cubic splines: "cub−sv−nonanom"



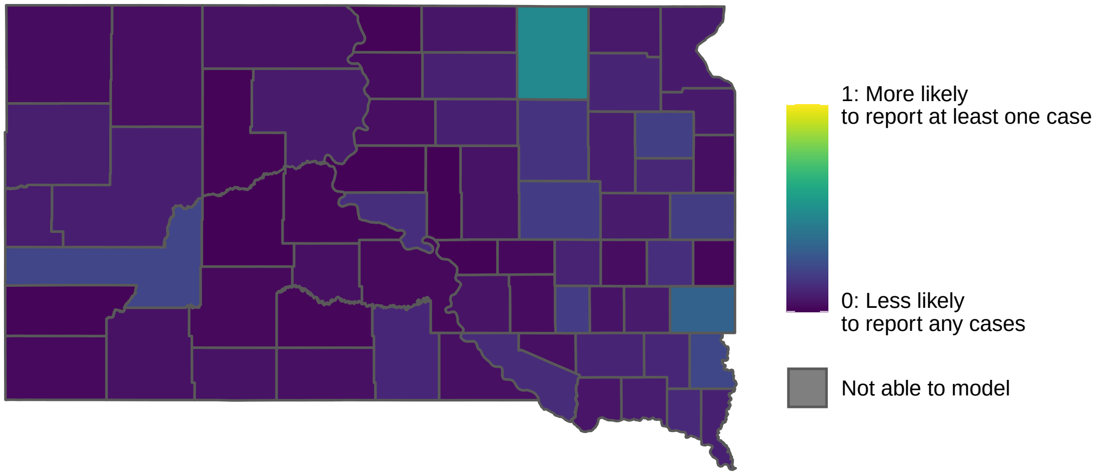

Absolute risk in forecast week
Non−anomalized weather with seasonally−varying cubic splines: "cub−sv−anom"
1: More likely
to report at least one case
0: Less likely
to report any cases
Not able to model


Absolute risk in forecast week
Non−anomalized weather with fixed thin plate splines: "tp−fx−nonanom"
1: More likely
to report at least one case
0: Less likely
to report any cases
Not able to model



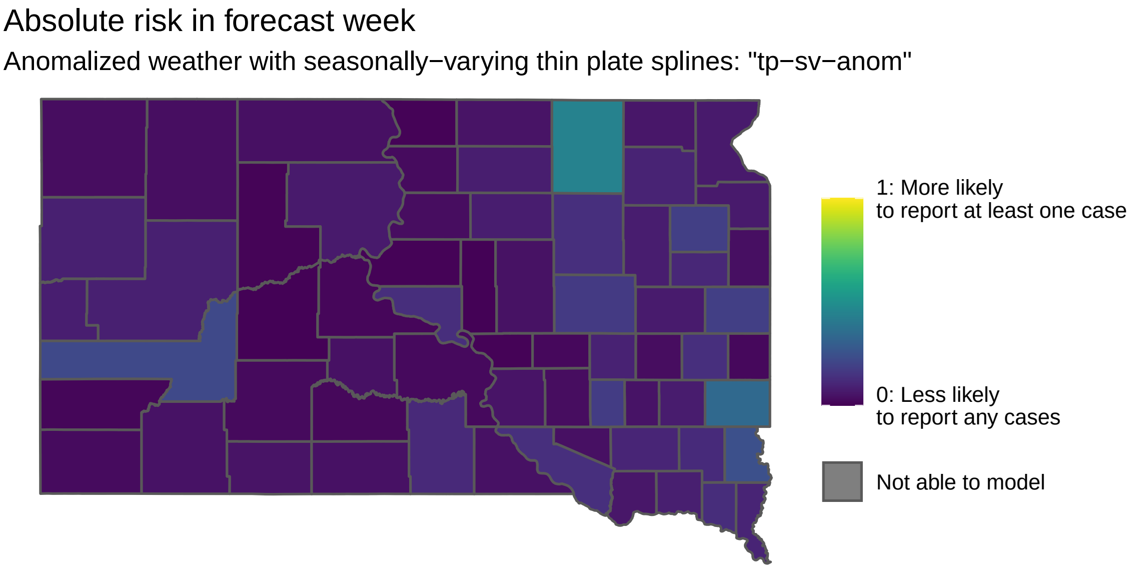
Absolute risk in forecast week

Anomalized weather with fixed thin plate splines: "tp−fx−anom"



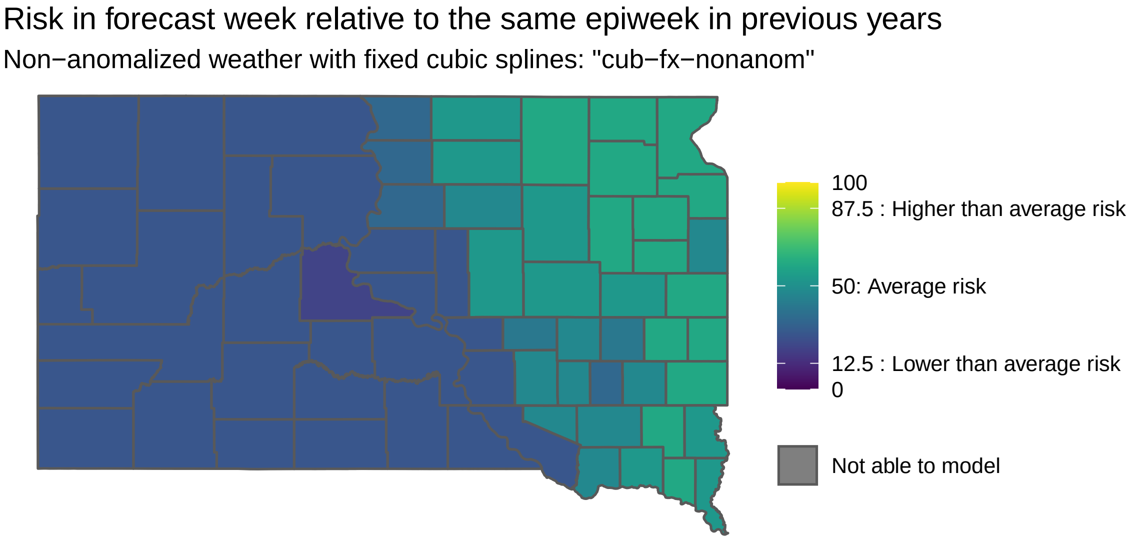
Absolute risk in forecast week

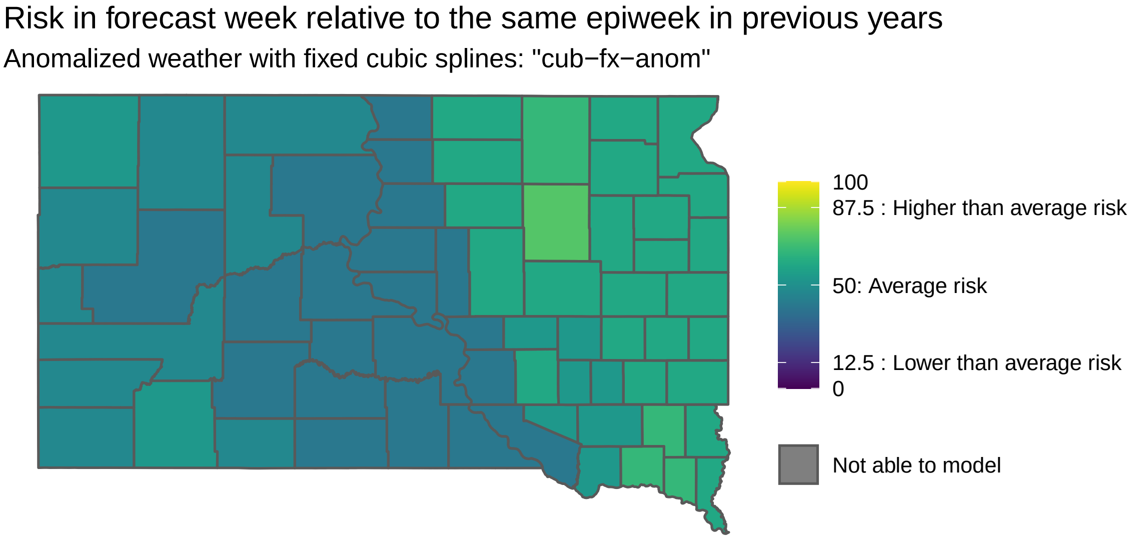
Non−anomalized weather with seasonally−varying thin plate splines: "tp−sv−nonanom"


Absolute risk in forecast week
Anomalized weather with seasonally−varying thin plate splines: "tp−sv−anom"
1: More likely
to report at least one case
0: Less likely
to report any cases
Not able to model

3.1.2 Current-week WNV relative risk

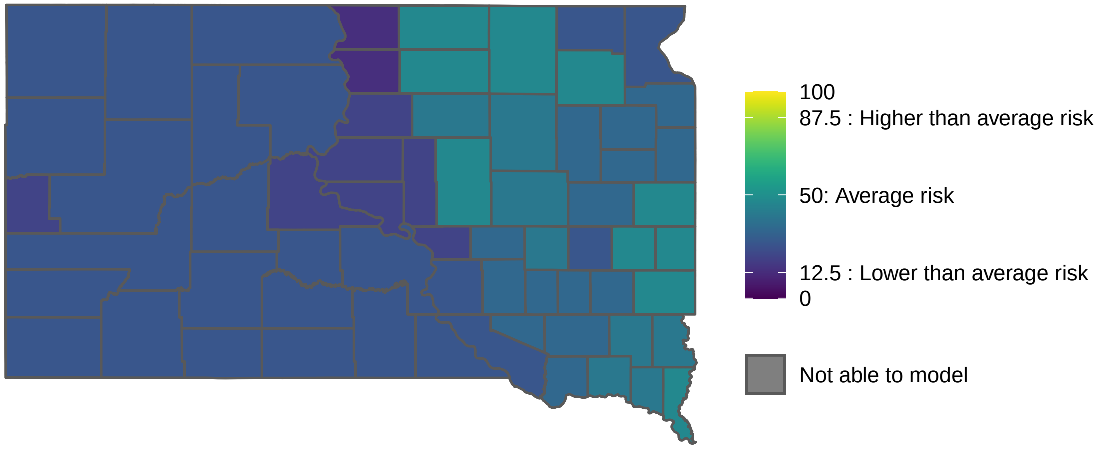
Following are the relative risk maps generated by **each** model:


Risk in forecast week relative to the same epiweek in previous years
Non−anomalized weather with fixed cubic splines: "cub−fx−nonanom"
100
87.5 : Higher than average risk
50: Average risk
12.5 : Lower than average risk
0
Not able to model


Risk in forecast week relative to the same epiweek in previous years
Anomalized weather with fixed cubic splines: "cub−fx−anom"
100
87.5 : Higher than average risk
50: Average risk
12.5 : Lower than average risk
0
Not able to model

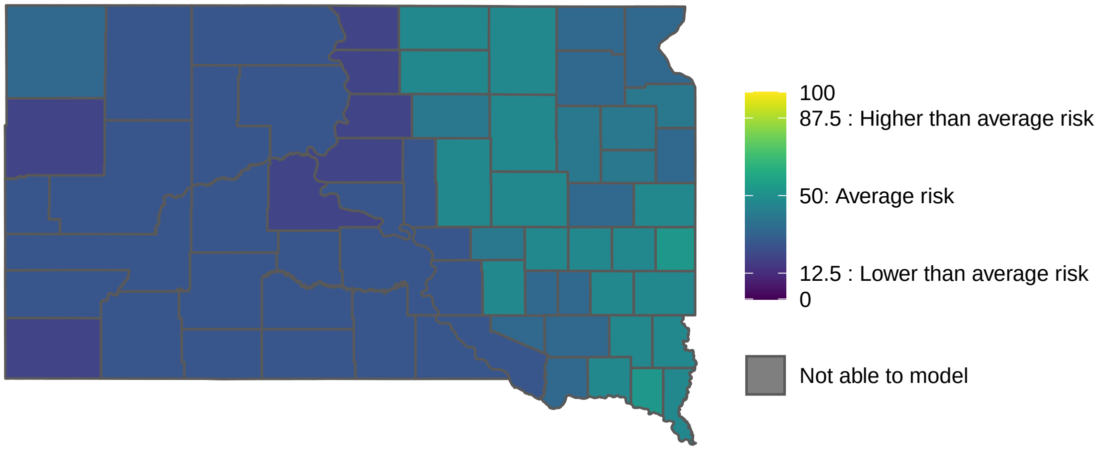
Risk in forecast week relative to the same epiweek in previous years

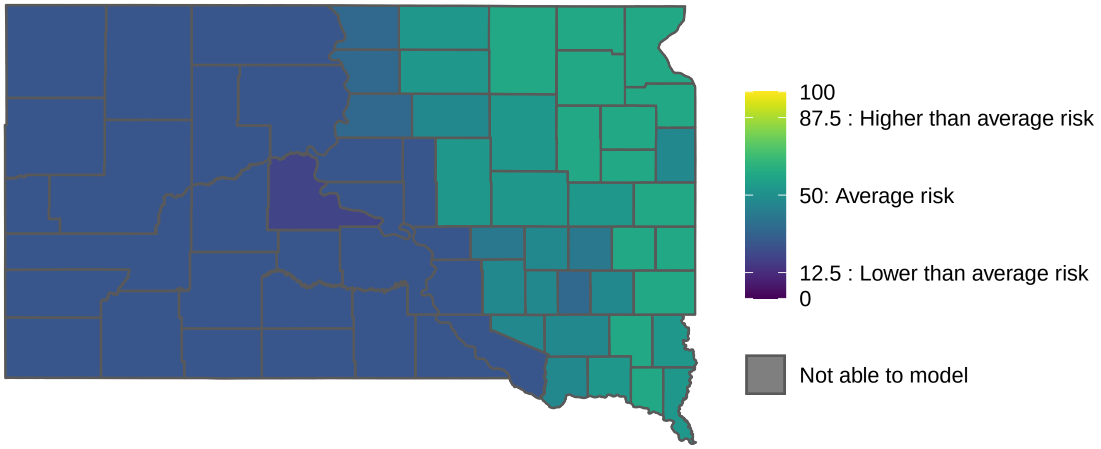
Non−anomalized weather with seasonally−varying cubic splines: "cub−sv−nonanom"


100
87.5 : Higher than average risk
50: Average risk
12.5 : Lower than average risk
0
Not able to model

Risk in forecast week relative to the same epiweek in previous years

Non−anomalized weather with seasonally−varying cubic splines: "cub−sv−anom"

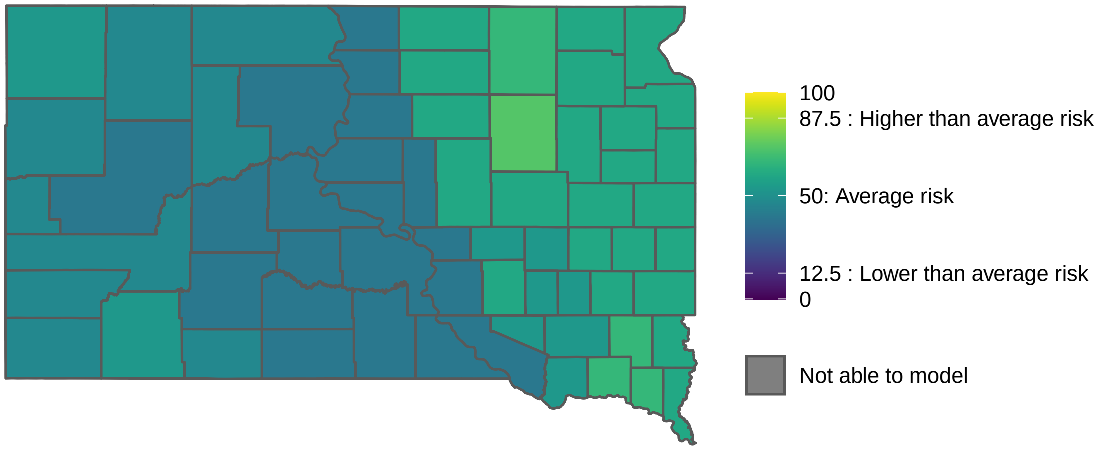

100
87.5 : Higher than average risk
50: Average risk
12.5 : Lower than average risk
0
Not able to model



Risk in forecast week relative to the same epiweek in previous years

Non−anomalized weather with fixed thin plate splines: "tp−fx−nonanom"

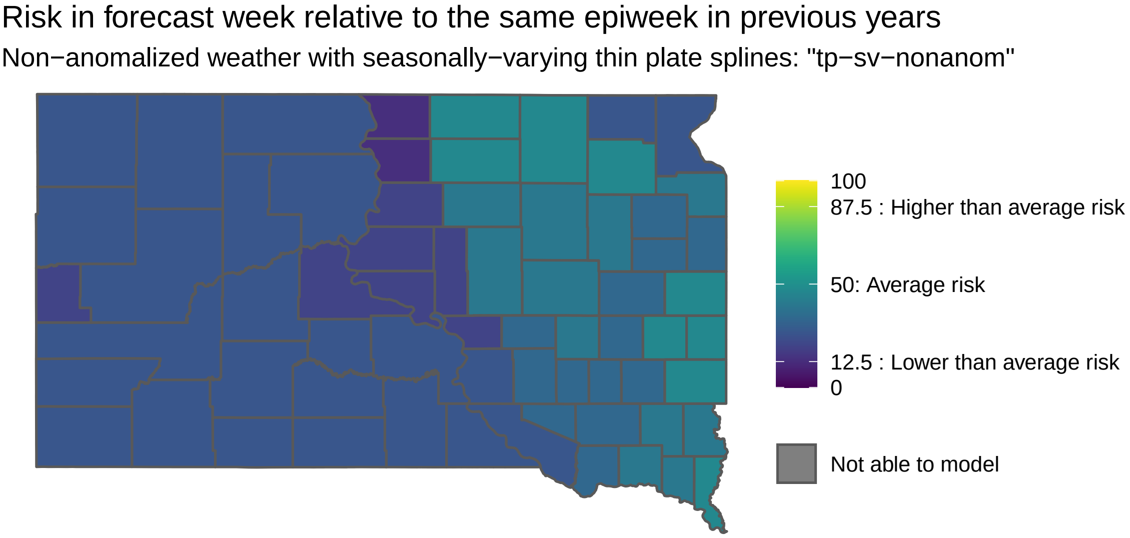
100
87.5 : Higher than average risk
50: Average risk
12.5 : Lower than average risk
0
Not able to model

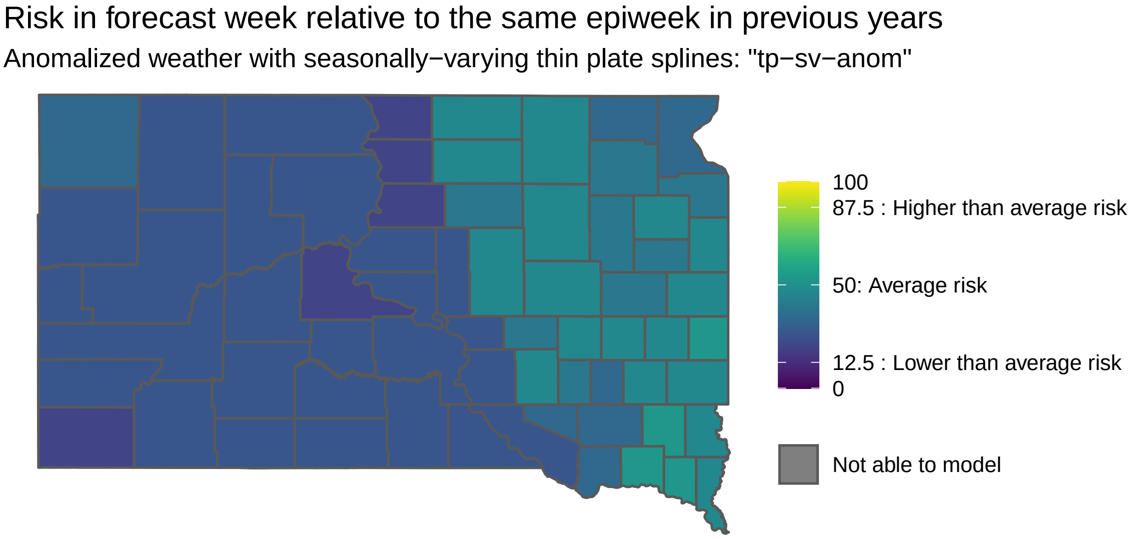


Risk in forecast week relative to the same epiweek in previous years

Anomalized weather with fixed thin plate splines: "tp−fx−anom"

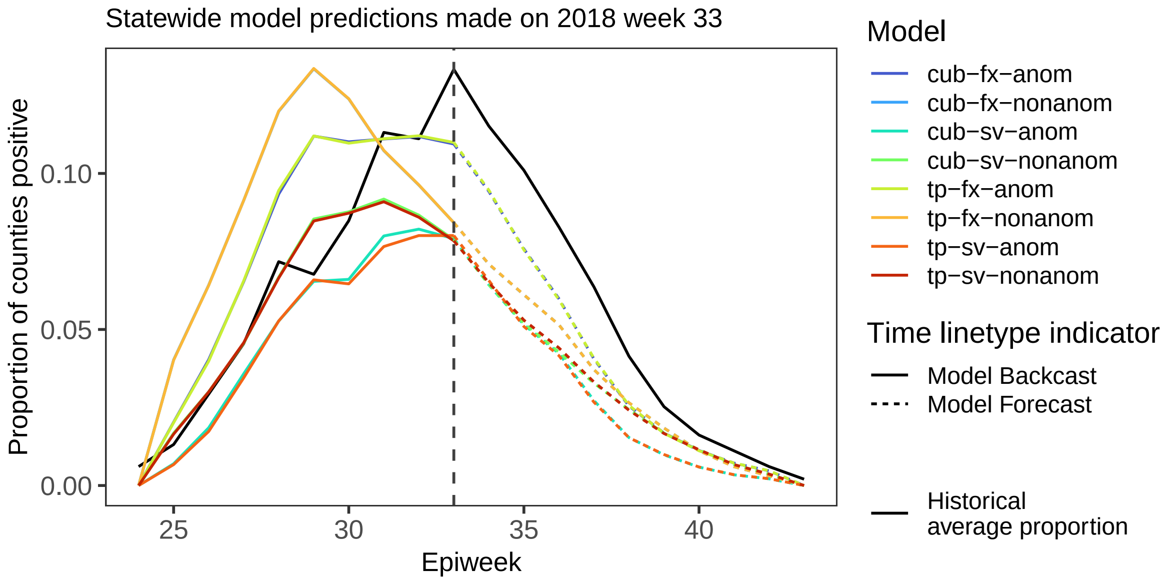
100
87.5 : Higher than average risk
50: Average risk
12.5 : Lower than average risk
0
Not able to model


Risk in forecast week relative to the same epiweek in previous years
Non−anomalized weather with seasonally−varying thin plate splines: "tp−sv−nonanom"
100
87.5 : Higher than average risk
50: Average risk
12.5 : Lower than average risk
0
Not able to model


Risk in forecast week relative to the same epiweek in previous years
Anomalized weather with seasonally−varying thin plate splines: "tp−sv−anom"
100
87.5 : Higher than average risk
50: Average risk
12.5 : Lower than average risk
0
Not able to model

3.1.3 Current-year forecasts

The graph below shows the current year forecast, with lines for **each** model:



3.1.4 Case estimations

The table below lists the estimated case counts per model.

Table 6: Estimated number of WNV cases

Year	Model	Predicted positive county-weeks	Estimated cases
2018	cub-fx-anom	73.2	86
2018	cub-fx-nonanom	75.7	89
2018	cub-sv-anom	46.8	56
2018	cub-sv-nonanom	55.7	66
2018	tp-fx-anom	73.3	86
2018	tp-fx-nonanom	75.7	89
2018	tp-sv-anom	46.2	55
2018	tp-sv-nonanom	55.7	66

3.1.5 Additional model fit statistics

The table below gives multiple model fit statistic per forecast model:

- AUC : Area Under ROC Curve, values range 0 - 1
- AIC : Akaike information criterion, relative fit statistic to other models
- Temporal MAE : Mean Average Error, mean of weeks (collapsed to state)
- Spatial MAE : Mean Average Error, mean of counties (collapsed all time)

Table 7: Fit statistcs by model

Model	AUC	AIC	MAE Temporal	MAE Spatial
cub-fx-nonanom	0.839	6728	1.837	0.772
cub-fx-anom	0.838	6749	1.791	0.766
cub-sv-nonanom	0.846	6634	1.622	0.743
cub-sv-anom	0.848	6645	1.539	0.729
tp-fx-nonanom	0.839	6728	1.837	0.772
tp-fx-anom	0.838	6749	1.790	0.766
tp-sv-nonanom	0.846	6634	1.620	0.743
tp-sv-anom	0.848	6644	1.538	0.729

3.1.6 Partial effects

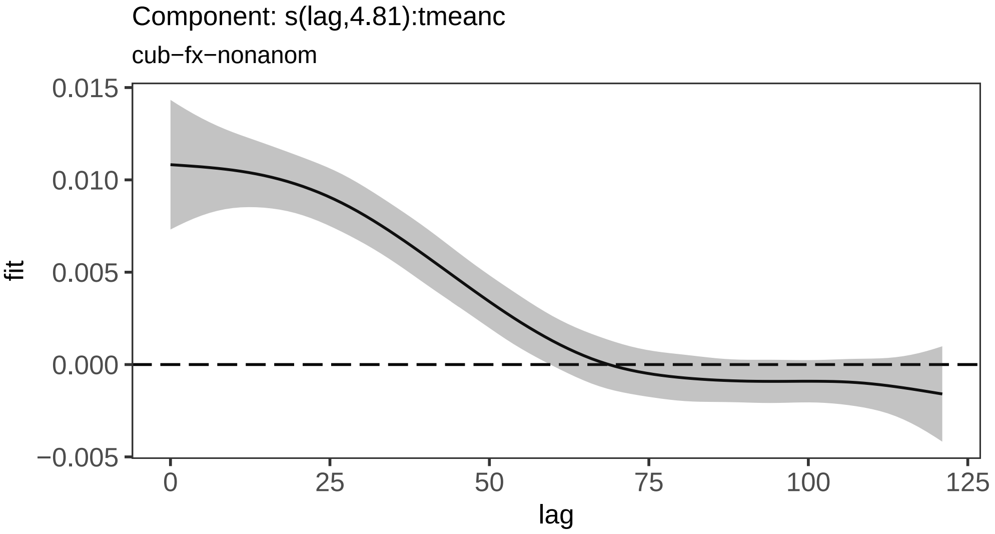
ArboMAP allows the user to write custom model formulas, and as such the plots below are the partial effects of all the smooth terms for each model. These show the component effect of the term. All components (not just smooths) added together would be the overall prediction. For a table of all formulas, see the section on "Models and formulas".

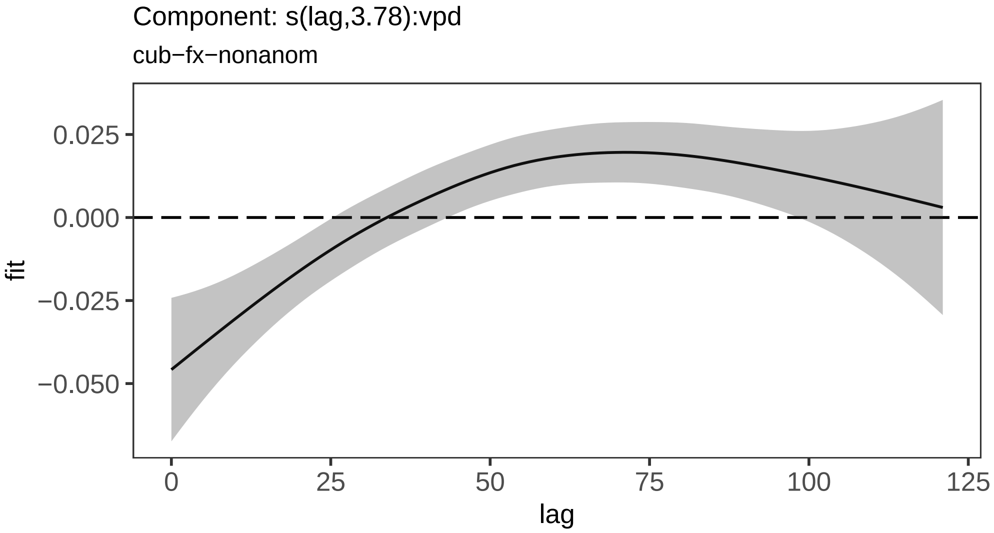
The number after the comma in the `s({item}, {number})` labels is the effective degrees of freedom (EDF). The EDF is a measurement of the complexity of the smooth term - a value of 1 is a straight line, higher values are more complex curves.

An easy way to check on the significance of the smooth term is if you cannot draw a horizontal line through the 95% confidence interval (value +/- se, shown in the gray shaded ribbon in the relevant graphs).

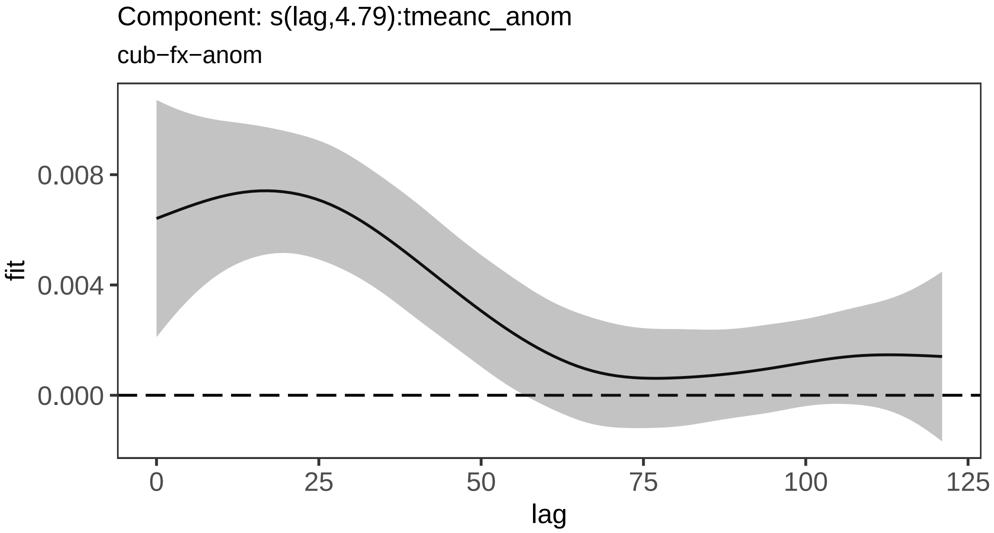
All models with smooths will have 1-D graphs. Seasonally-varying models will also have 2-D graphs (components with `doymat` in standard models), however a subset of y-values have been pulled out to plot as lines.

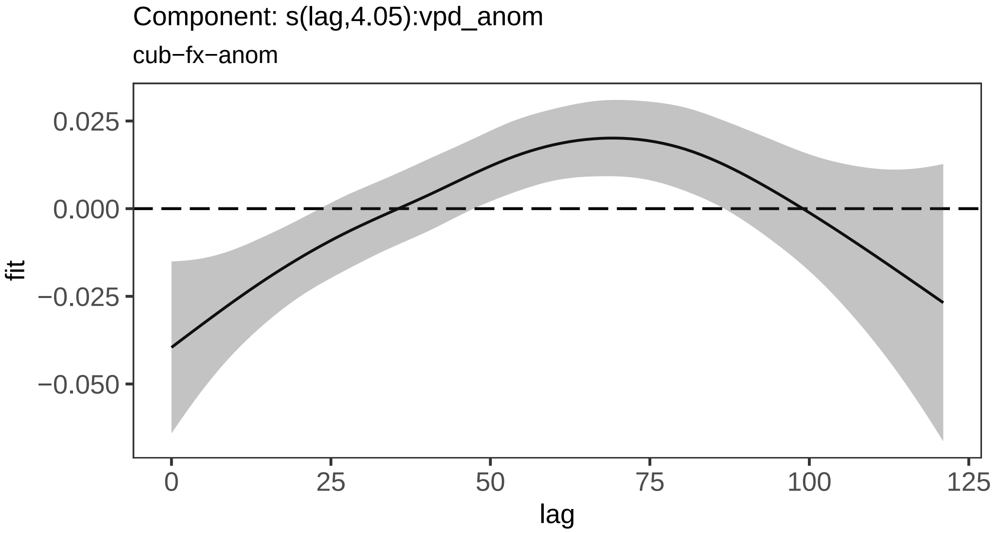
3.1.6.1 Non-anomalized weather with fixed cubic splines: "cub-fx-nonanom"

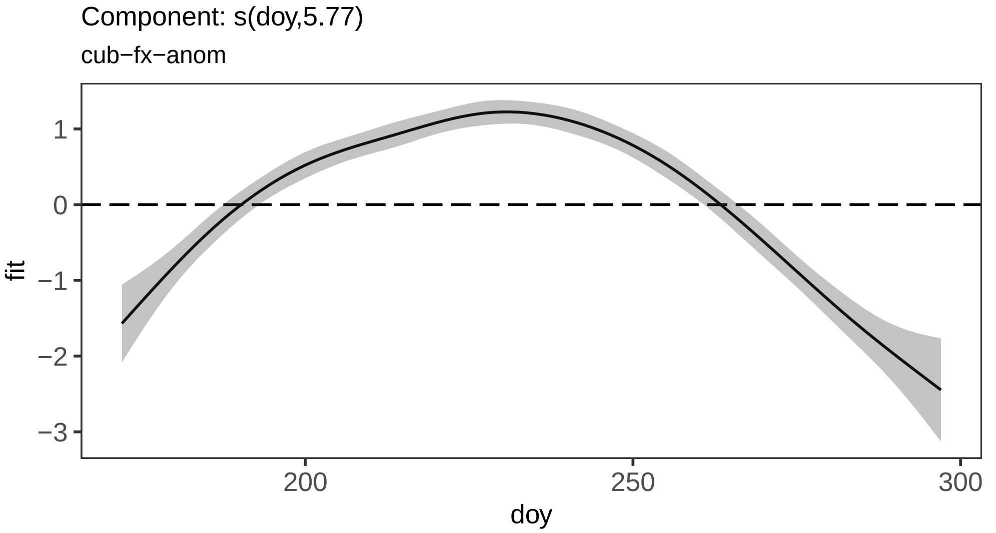




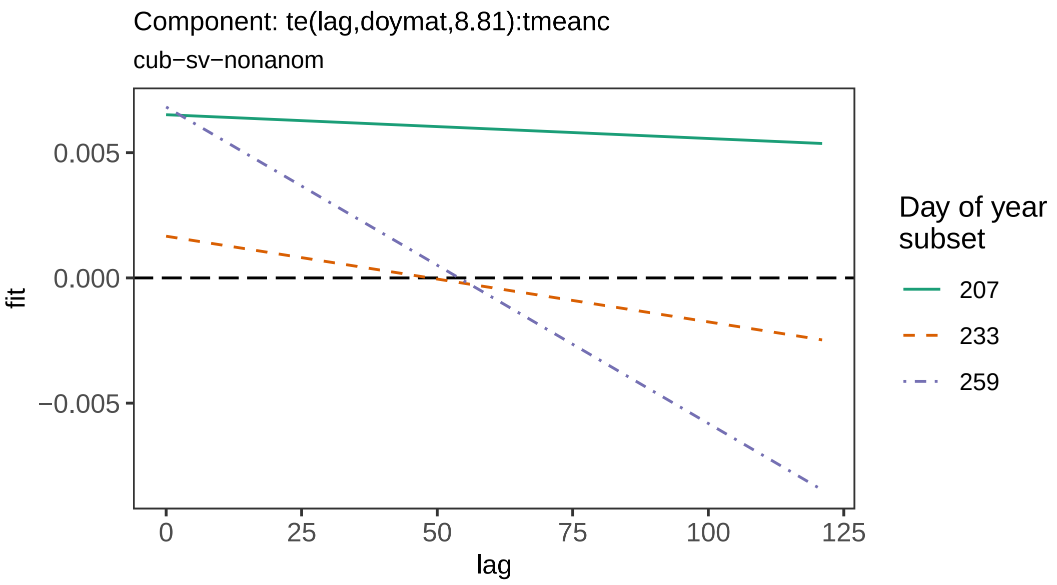
3.1.6.2 Anomalized weather with fixed cubic splines: "cub-fx-anom"

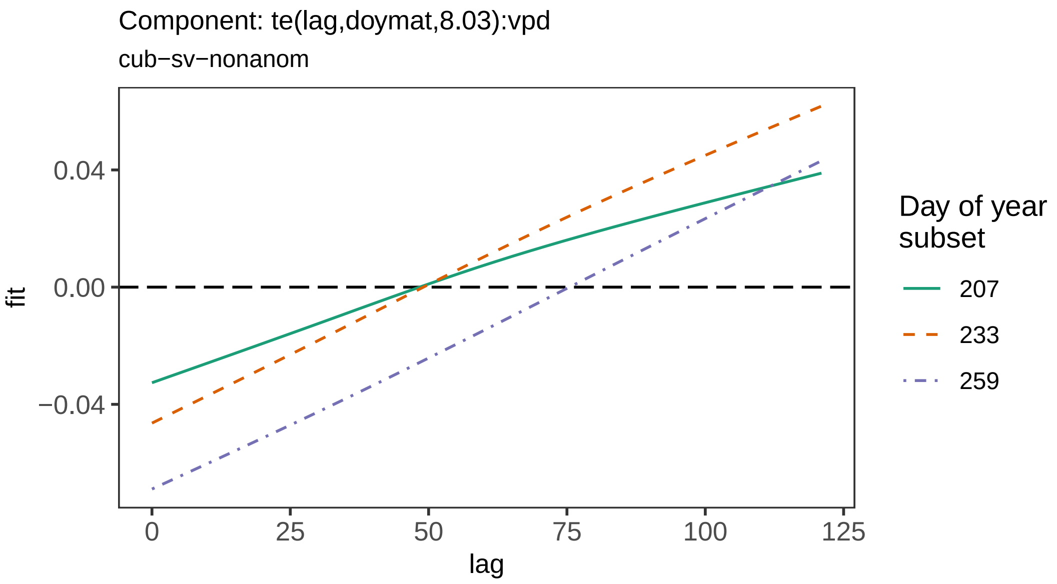




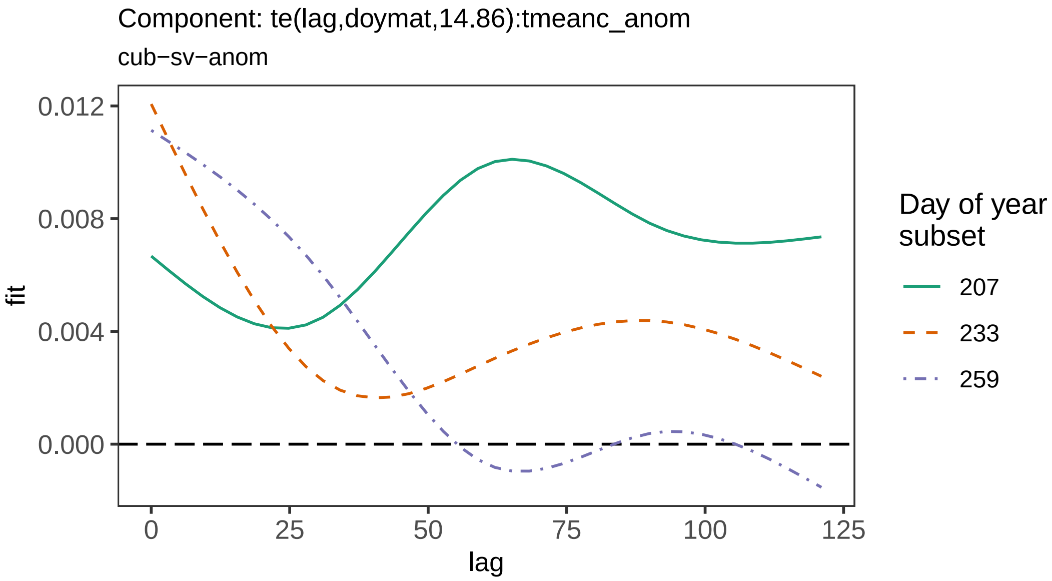


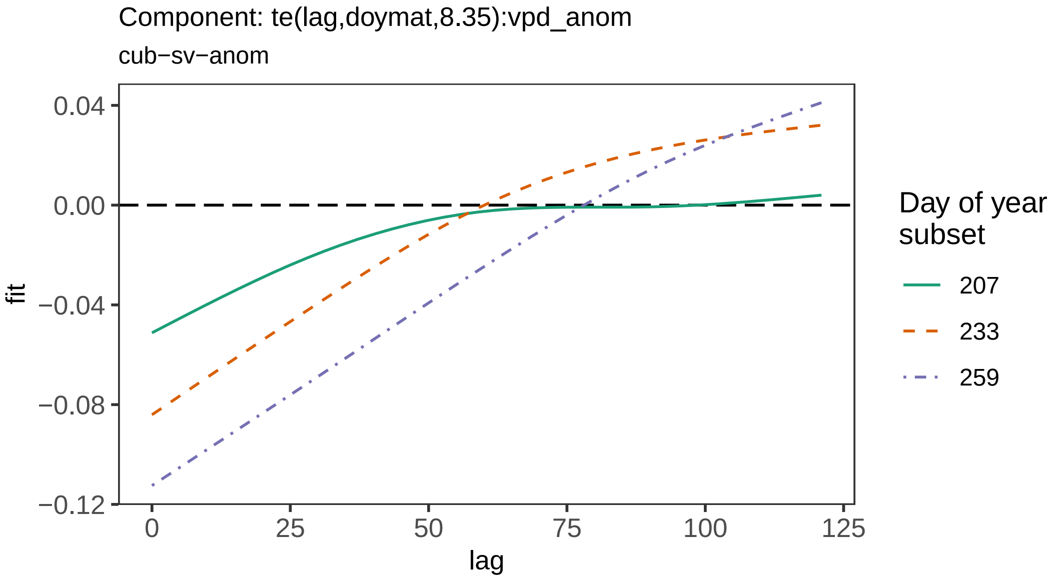
3.1.6.3 Non-anomalized weather with seasonally-varying cubic splines: “cub-sv-nonanom”

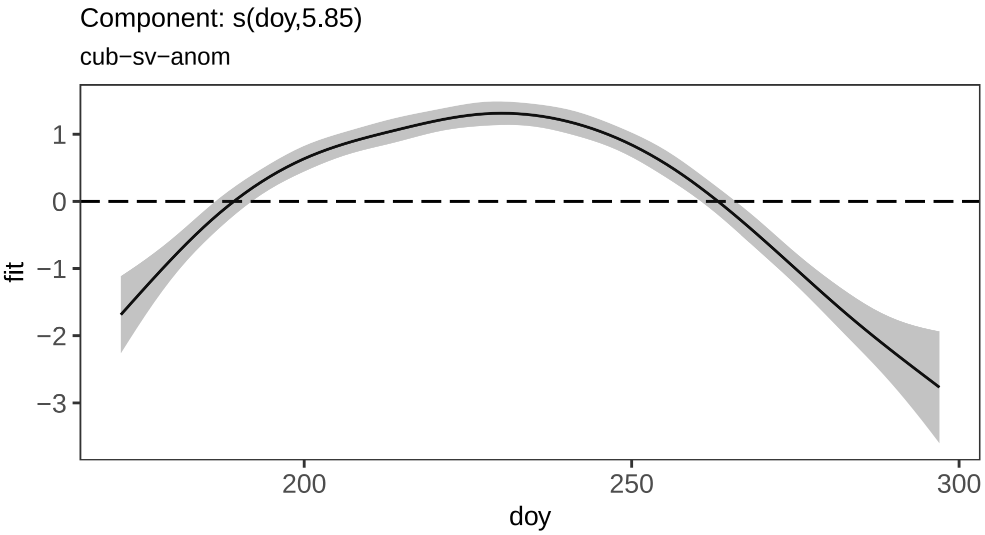




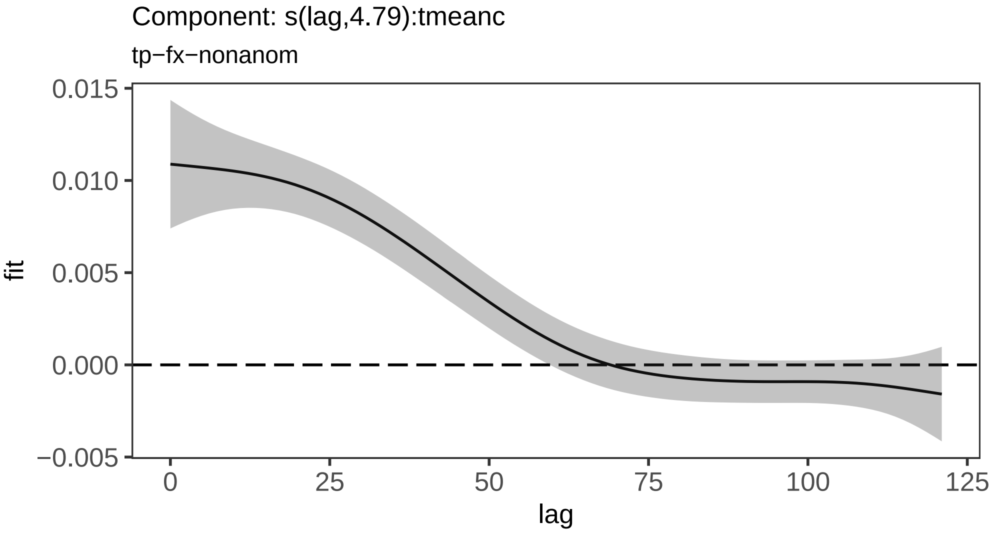
3.1.6.4 Non-anomalized weather with seasonally-varying cubic splines: "cub-sv-anom"

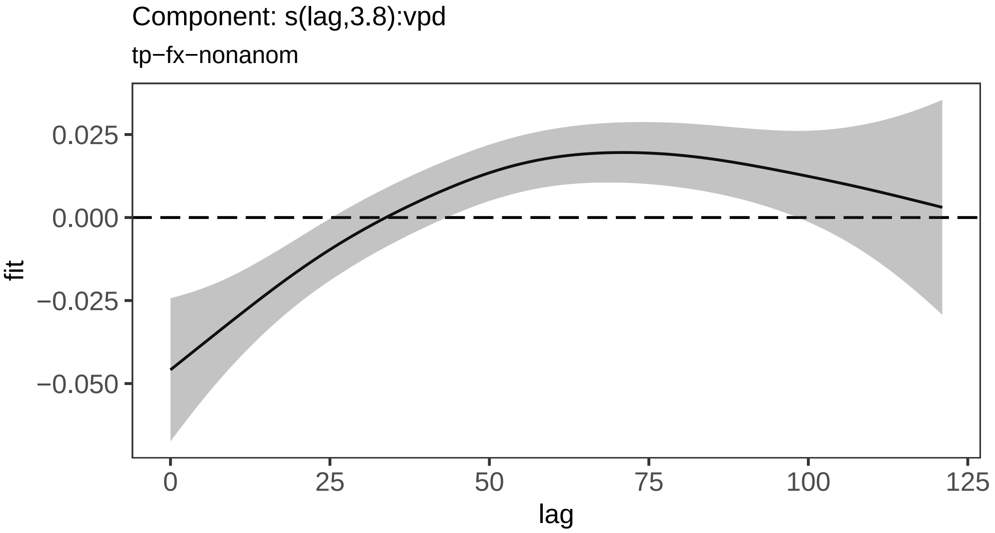

Component: te(lag,doymat,14.86):tmeanc_anom
cub−sv−anom
0.012
0.008
0.004
0.000
fit
0
25
50
75
100
125
lag
Day of year subset
207
233
259


Component: te(lag,doymat,8.35):vpd_anom
cub−sv−anom
0.04
0.00
−0.04
−0.08
−0.12
fit
0
25
50
75
100
125
lag
Day of year subset
207
233
259

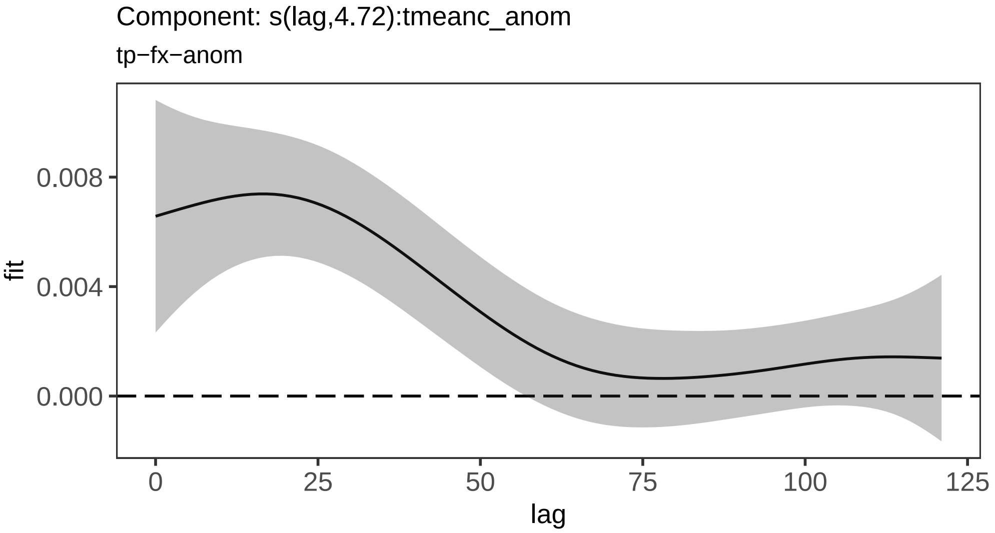


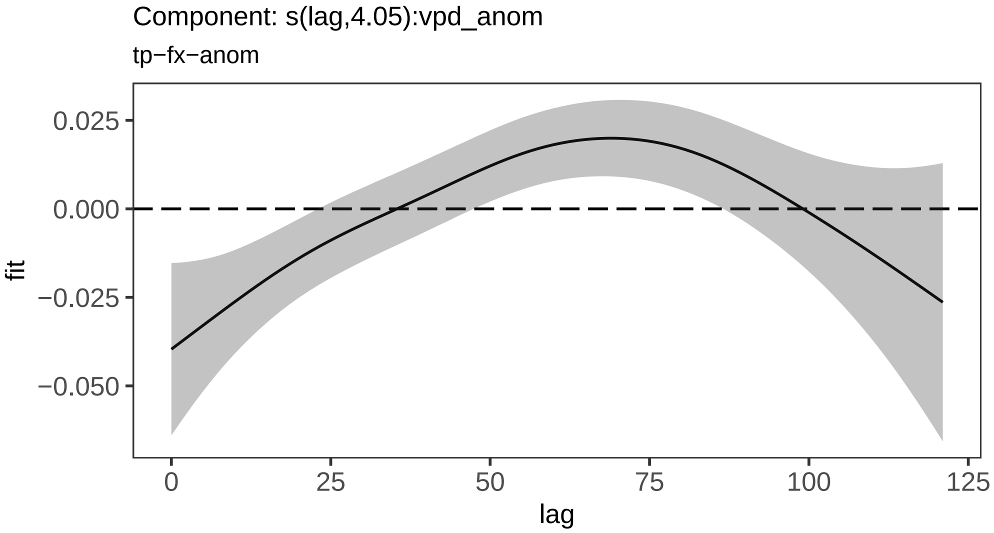
3.1.6.5 Non-anomalized weather with fixed thin plate splines: "tp-fx-nonanom"

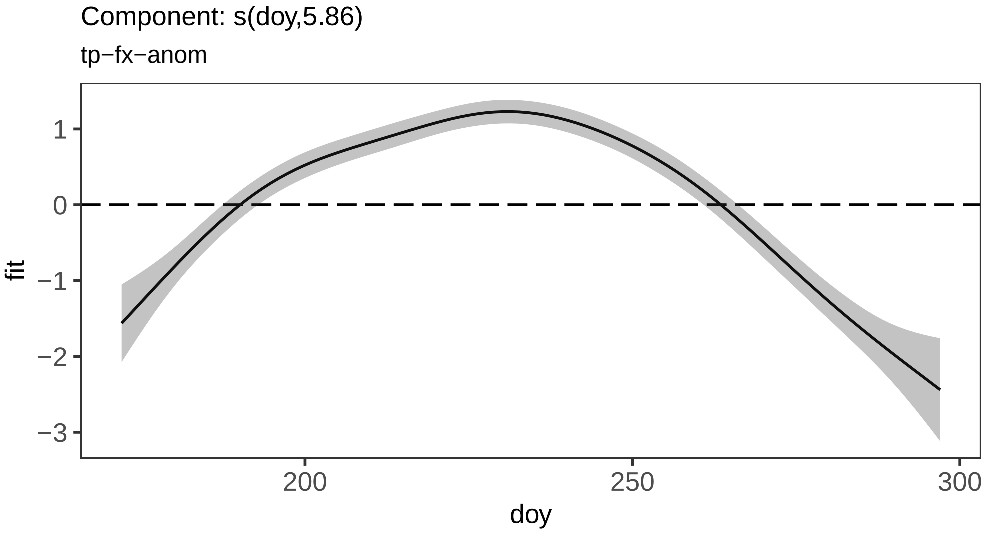




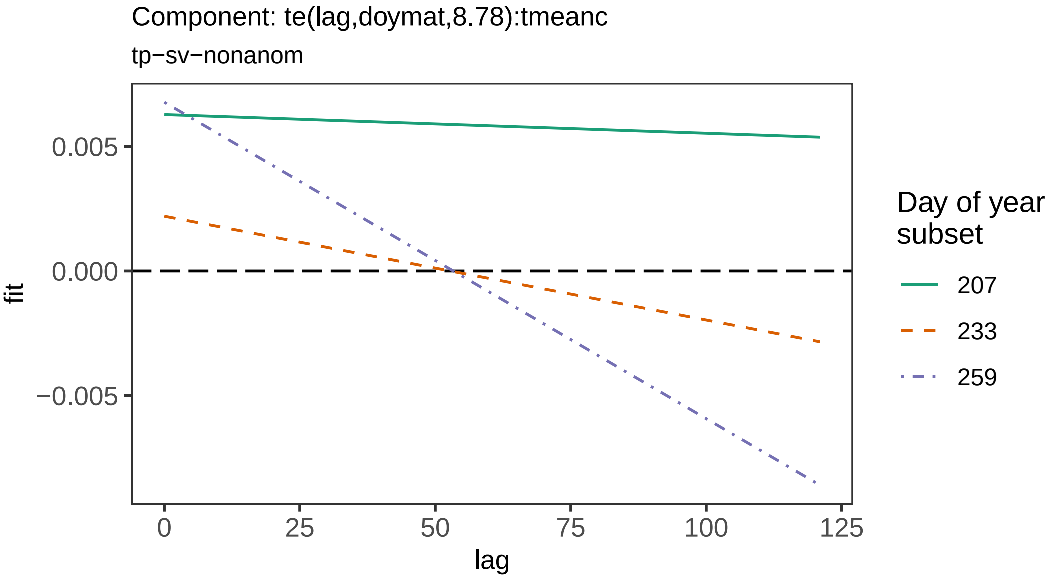
3.1.6.6 Anomalized weather with fixed thin plate splines: “tp-fx-anom”

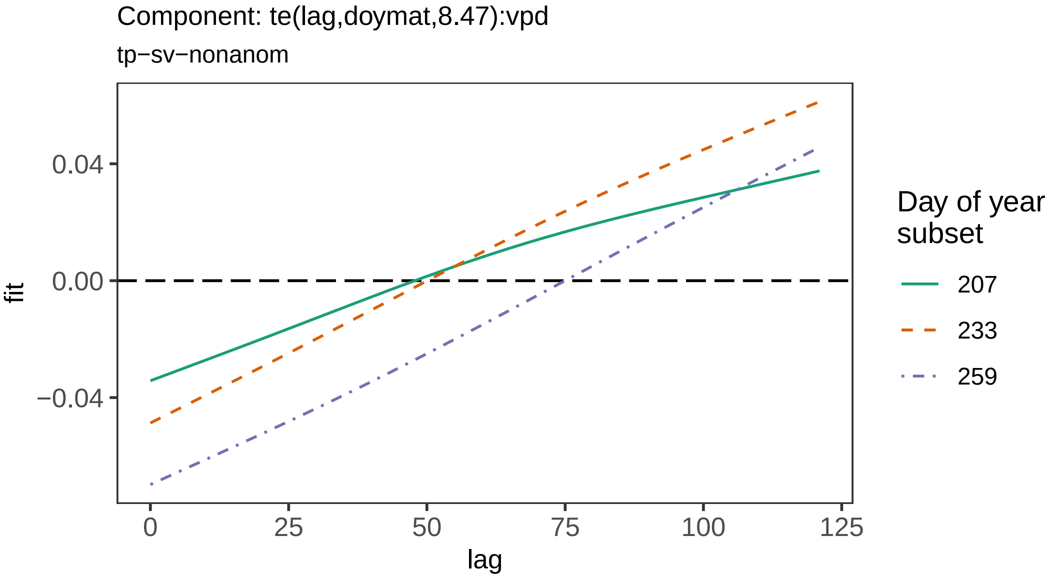




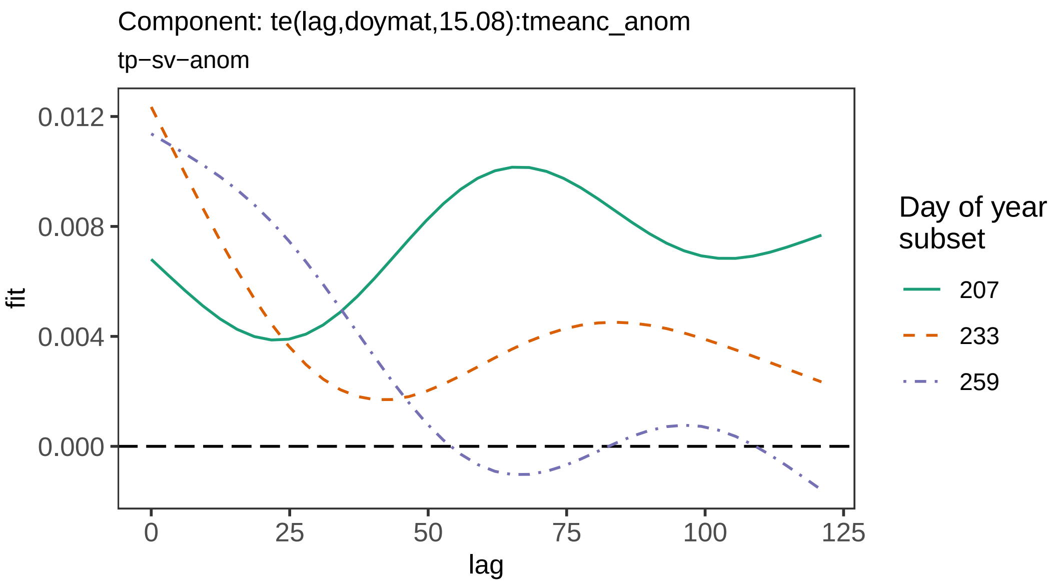


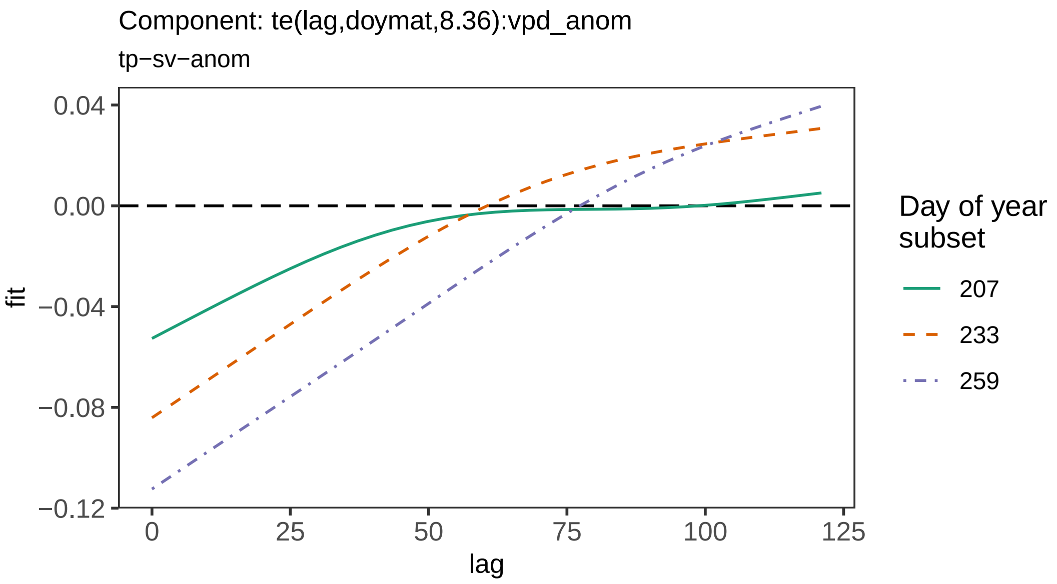
3.1.6.7 Non-anomalized weather with seasonally-varying thin plate splines: “tp-sv-nonanom”

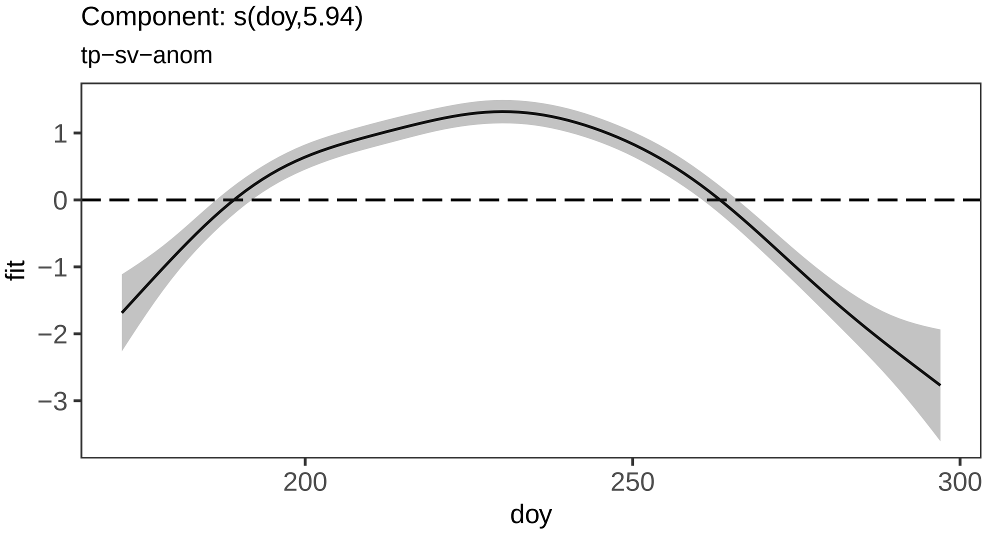




3.1.6.8 Anomalized weather with seasonally-varying thin plate splines: “tp-sv-anom”

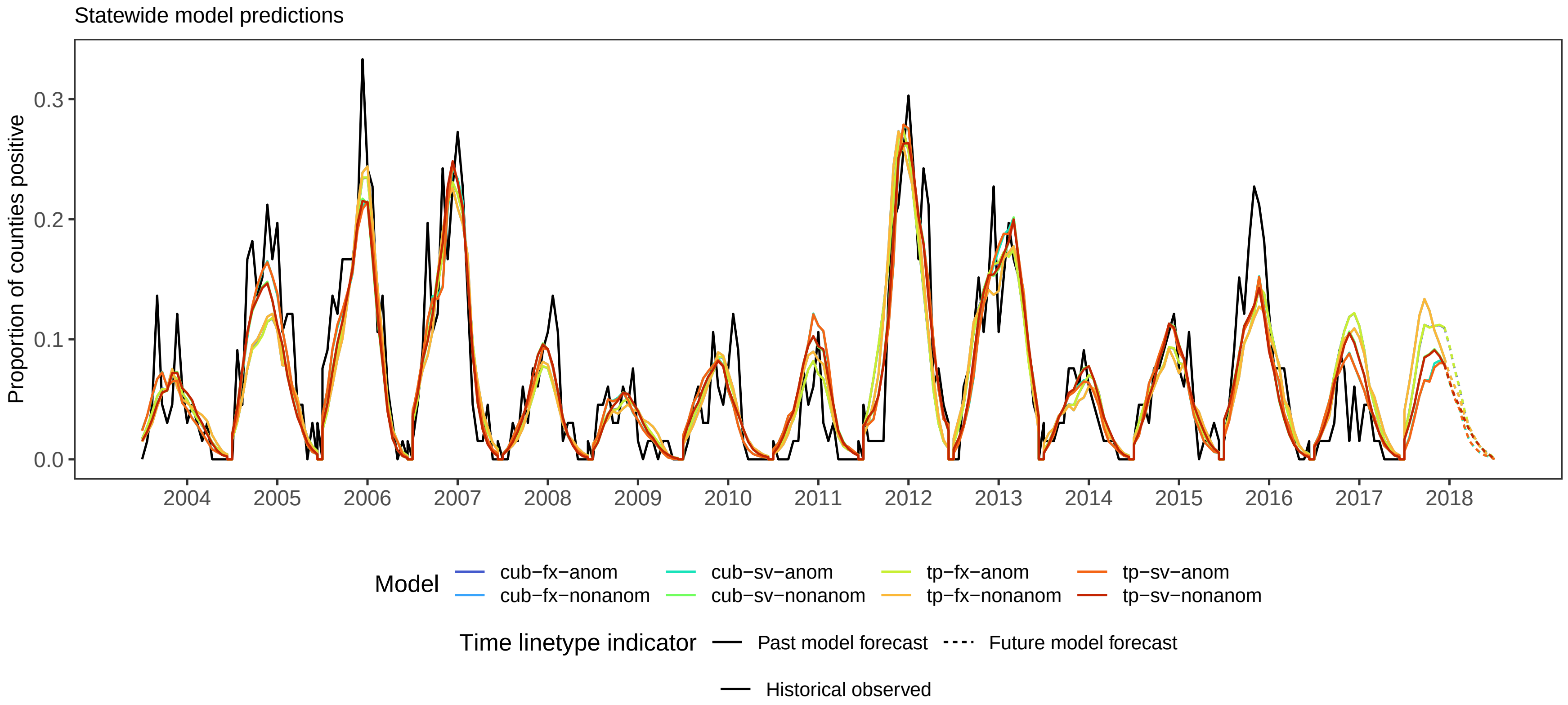

Component: te(lag,doymat,15.08):tmeanc_anom
tp−sv−anom


Component: te(lag,doymat,8.36):vpd_anom
tp−sv−anom


Component: s(doy,5.94)
tp−sv−anom
fit
1
0
−1
−2
−3
200
250
300
doy

3.1.7 Multi-year forecasts

The graph below shows the full forecast for all years, with lines for **each** model:



3.1.8 Models and formulas

The table below lists the models that were found in the data_models/models.txt file. Standard models will have a text description, but all models run should appear in the table along with their formula.

The following fields may be present:

- `any_cases` : positive county-week
- `arbo_ID` : internal field for identifying counties
- `mir_stat` : the mosquito infection rate statistic
- `s(lag, by=var...)` : fixed smooth term for the environmental variable over the distributed lag period
- `te(lag, doymat, by=var...)` : seasonally-varying smooth term for the environmental variable over the distributed lag period
- `var1` : variable for tmeanc, observed value
- `var2` : variable for vpd, observed value
- `var1_anom` : variable for tmeanc, anomalized value
- `var2_anom` : variable for vpd, anomalized value
- `s(doy,...)` : smooth term for day of year, for seasonality

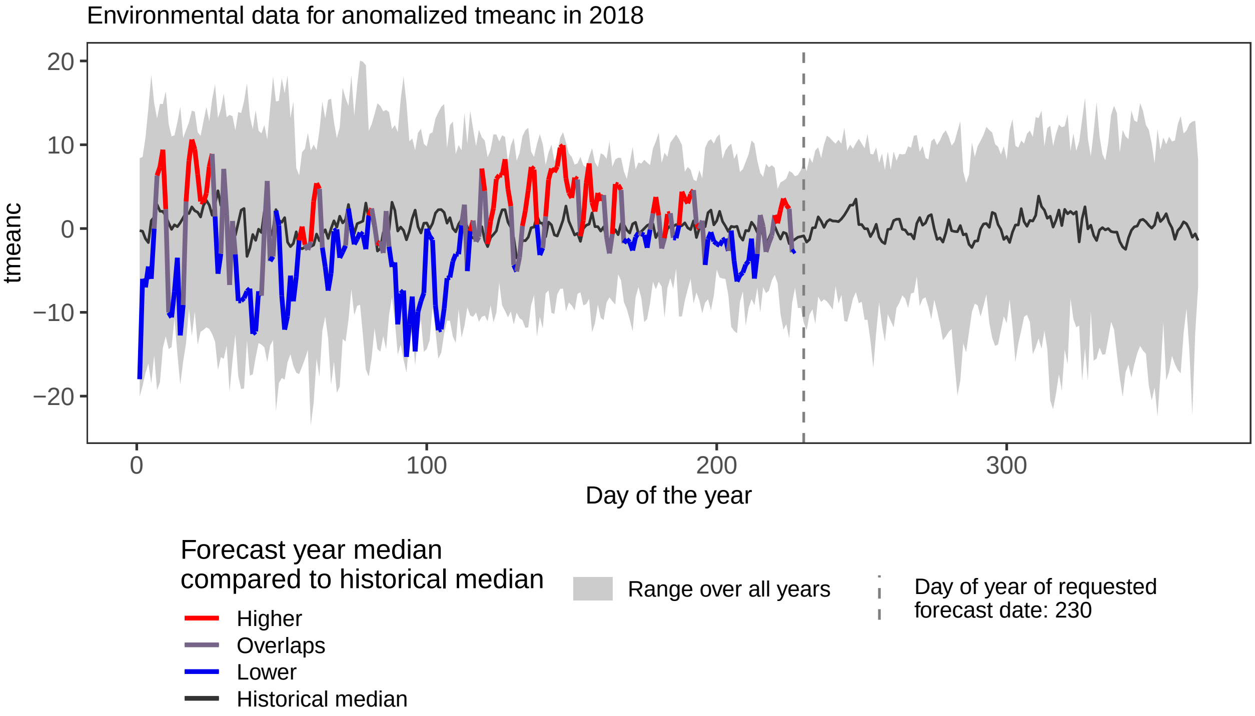
Model	Description	Formula
cub-fx-nonanom	Non-anomalized weather with fixed cubic splines	any_cases ~ 0 + arbo_ID + mir_stat + s(lag, by=var1, bs=‘cr’) + s(lag, by=var2, bs=‘cr’)
cub-fx-anom	Anomalized weather with fixed cubic splines	any_cases ~ 0 + arbo_ID + mir_stat + s(lag, by=var1_anom, bs=‘cr’) + s(lag, by=var2_anom, bs=‘cr’) + s(doy, bs=‘cr’)
cub-sv-nonanom	Non-anomalized weather with seasonally-varying cubic splines	any_cases ~ 0 + arbo_ID + mir_stat + te(lag, doymat, by=var1, bs=‘cr’) + te(lag, doymat, by=var2, bs=‘cr’)
cub-sv-anom	Non-anomalized weather with seasonally-varying cubic splines	any_cases ~ 0 + arbo_ID + mir_stat + te(lag, doymat, by=var1_anom, bs=‘cr’) + te(lag, doymat, by=var2_anom, bs=‘cr’) + s(doy, bs=‘cr’)
tp-fx-nonanom	Non-anomalized weather with fixed thin plate splines	any_cases ~ 0 + arbo_ID + mir_stat + s(lag, by=var1, bs=‘tp’) + s(lag, by=var2, bs=‘tp’)
tp-fx-anom	Anomalized weather with fixed thin plate splines	any_cases ~ 0 + arbo_ID + mir_stat + s(lag, by=var1_anom, bs=‘tp’) + s(lag, by=var2_anom, bs=‘tp’) + s(doy, bs=‘tp’)
tp-sv-nonanom	Non-anomalized weather with seasonally-varying thin plate splines	any_cases ~ 0 + arbo_ID + mir_stat + te(lag, doymat, by=var1, bs=‘tp’) + te(lag, doymat, by=var2, bs=‘tp’)
tp-sv-anom	Anomalized weather with seasonally-varying thin plate splines	any_cases ~ 0 + arbo_ID + mir_stat + te(lag, doymat, by=var1_anom, bs=‘tp’) + te(lag, doymat, by=var2_anom, bs=‘tp’) + s(doy, bs=‘tp’)

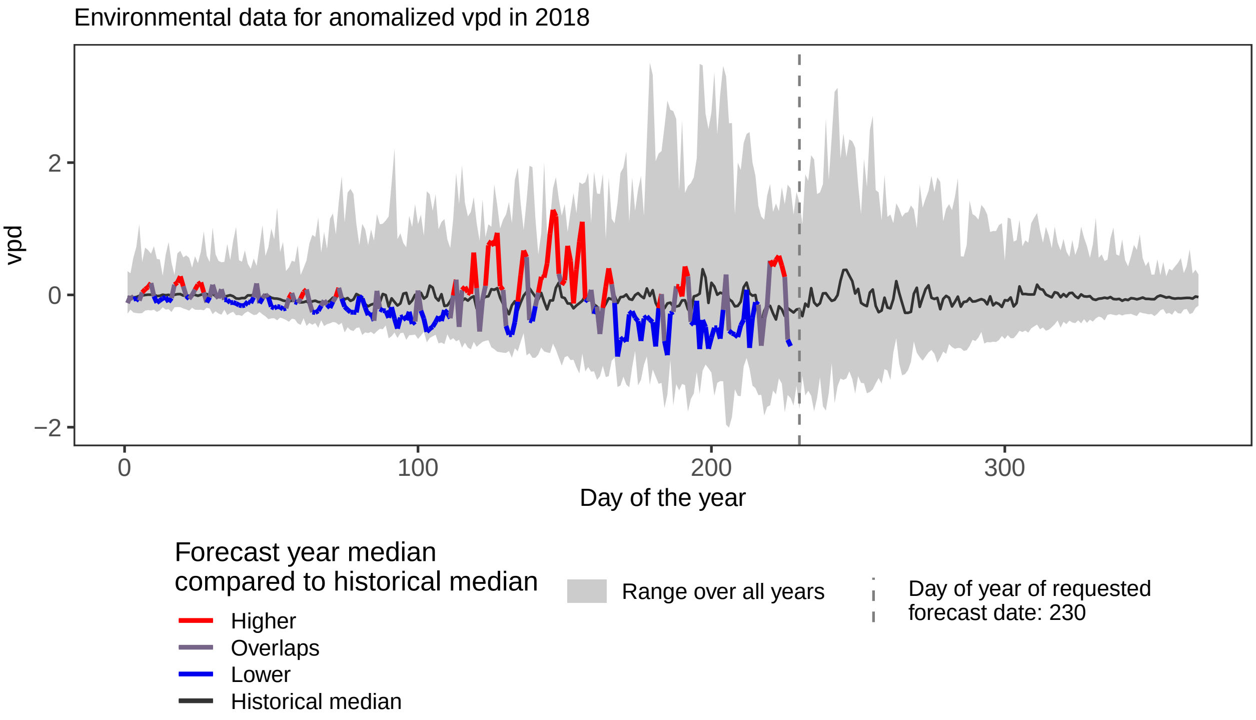
3.2 Data summaries

3.2.1 Anomalized environmental variables

The report parameters set the two environmental predictor variables as tmeanc and vpd. The following two graphs show the median state-wide anomalized weather variables for the forecast year, compared to the historical median. Anomalies are calculated using deviance between the observed value and the predicted value from a GAM regression model using county and a smooth on day of year (seasonality) and county. An anomaly is the observed minus the predicted.

Two or more consecutive days that have anomalized values **greater** than the anomalized historical median are drawn in red and consecutive days that are **less** than the historical median are drawn in blue. Consecutive days that overlap the historical median (i.e. one day above and the next below, or the opposite) are in purple. The gray shaded region is a ribbon showing the historical range (min to max).




Environmental data for anomalized vpd in 2018

3.2.2 Modeled mosquito infection rate

In modeling years where sufficient mosquito data were present, the mosquito infection rate (MIR) statistic was created using the model specified in the input parameter: stratifiedMIGR. The following table presents the calculated centered MIR values that were used in the forecast modeling.

Table 9: Mosquito model summary statistic

Year	Stratum	Centered MIR stat
2004	101	0.265
2004	104	-0.909
2005	101	0.635
2005	102	0.219
2005	103	-0.793
2005	104	-0.505
2006	101	1.312
2006	102	0.312
2006	103	0.224
2006	104	-0.197
2007	101	0.266
2007	102	0.629
2007	103	0.314
2008	101	-0.410
2008	102	-0.610
2008	103	0.268
2008	104	-0.376
2009	101	-0.380
2009	102	0.359
2009	103	-0.092

Year	Stratum	Centered MIR stat
2010	101	-0.964
2010	102	-0.929
2010	103	0.278
2011	101	-1.700
2011	102	-1.498
2011	103	-1.257
2011	104	-0.469
2012	101	0.375
2012	102	1.442
2012	103	0.853
2013	101	1.048
2013	102	0.799
2013	103	1.268
2014	101	0.381
2014	102	0.117
2014	103	-0.158
2014	104	-0.782
2015	101	-0.481
2015	102	0.261
2015	103	0.304
2015	104	0.647
2016	101	-0.014
2016	102	0.584
2016	103	-0.415
2016	104	-0.171
2017	101	-0.282
2017	102	0.347
2017	103	0.073
2017	104	0.091
2018	101	-0.064
2018	102	0.320
2018	103	-0.297
2018	104	-0.238