West Nile Virus Prediction

Introduction:

- West Nile Virus:- disease transmitted through mosquito bite
- Develop severe symptoms leading death
- First reported in 2002 in Chicago

Problem:

- City of Chicago and Chicago Department of public health starts surveillance program to control the mosquitoes
- Identify the potential outbreak region and spray disinfectants to control the mosquitoes

Objective:

- Develop machine learning algorithm to predict when and where the mosquito will test positive for the West Nile virus

Methodology

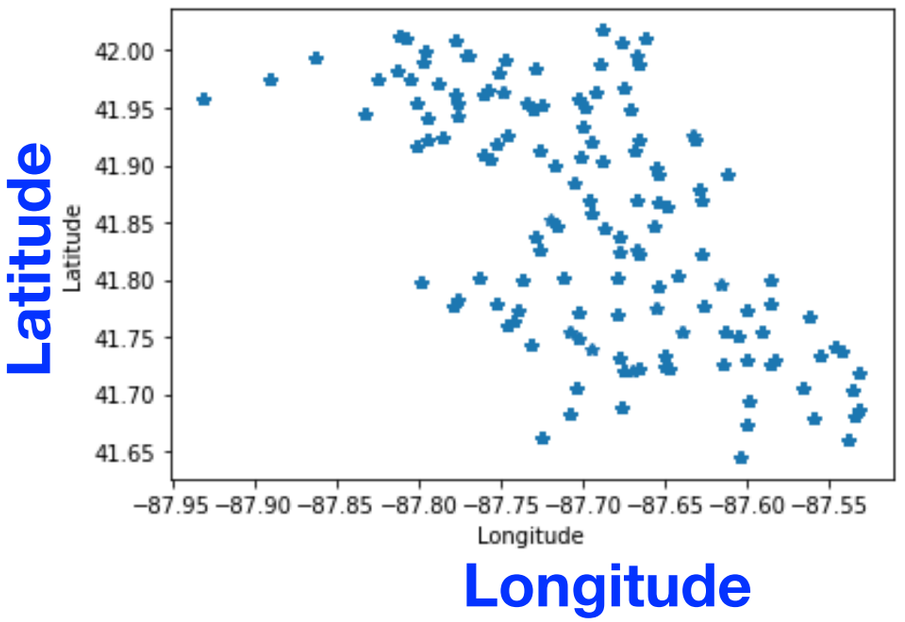
Data analysis:

- Two sets of data: GIS data and weather data
- GIS data:
  - provides location information, date, mosquito species and a label indicating presence or absence of virus features describing ticket prices
  - 10506 rows and 11 features
  - No missing data
- Weather data:
  - Weather parameters from two weather stations describing temperatures, pressure, precipitation, sunrise, sunset, etc
  - 2944 rows with 21 features
  - Missing parameters in rows and columns

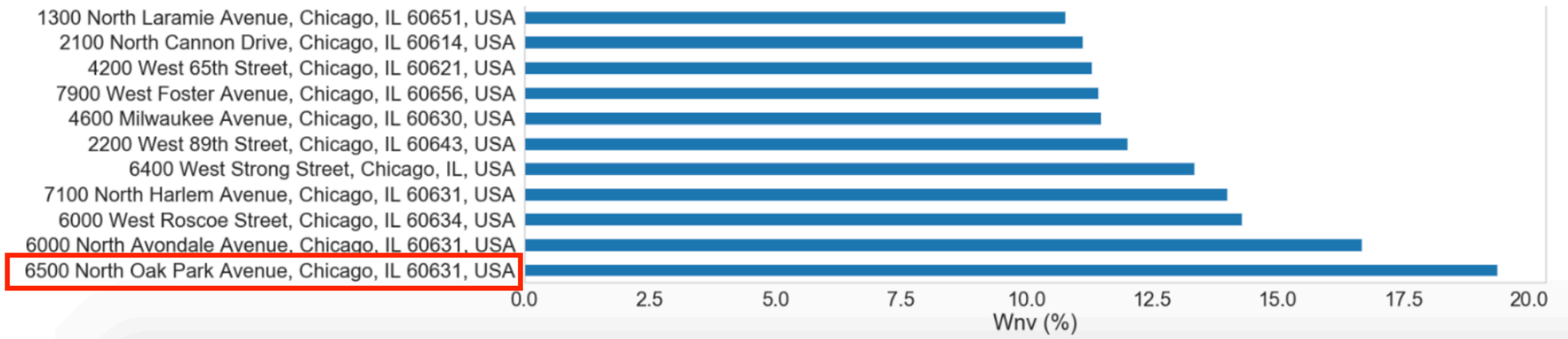
GIS data

- Samples collected from 136 locations every two years apart from 2007 to 2013
- Latitude and longitude of locations are provided along with street name, address and block number
- Mosquitoes are trapped from May to October
- Label 0 and 1 indicates presence and absence of virus
- The highest sample collected from O'hare international airport with 8.8% containing the virus
- The highest virus percentage as 19.35% was observed at 6500 North Park Avenue, Chicago IL, 60631, USA

City of Chicago



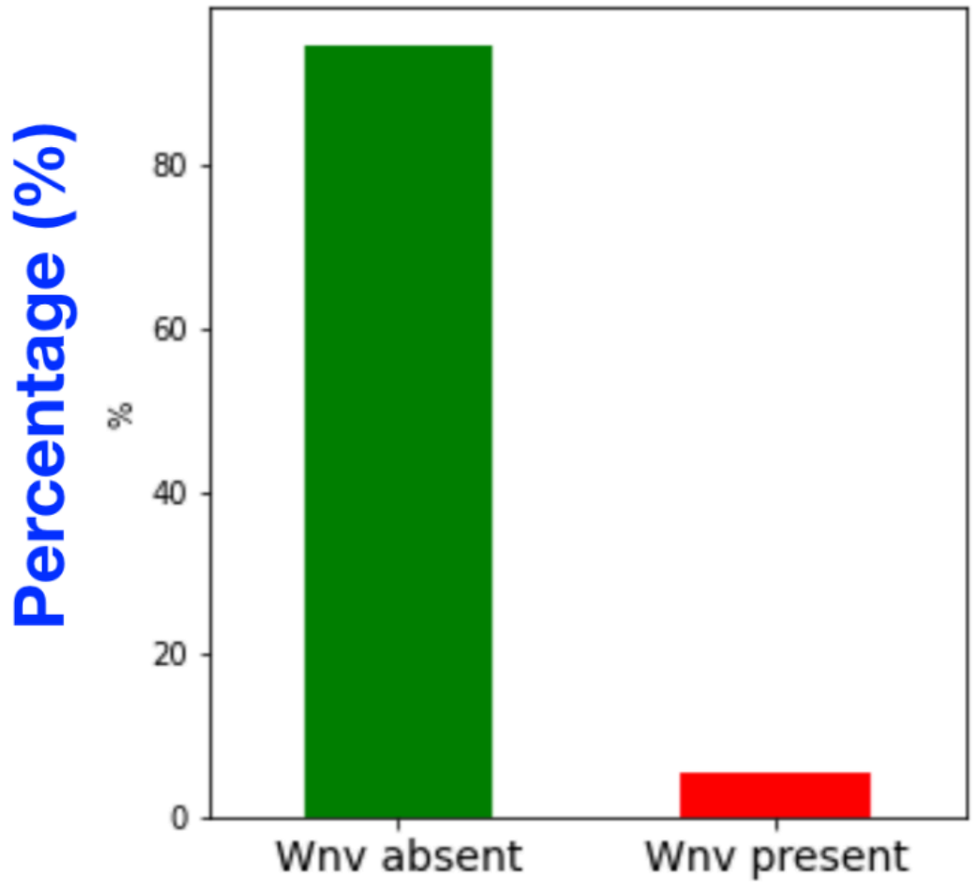
Address observing higher percentage of Wnv virus



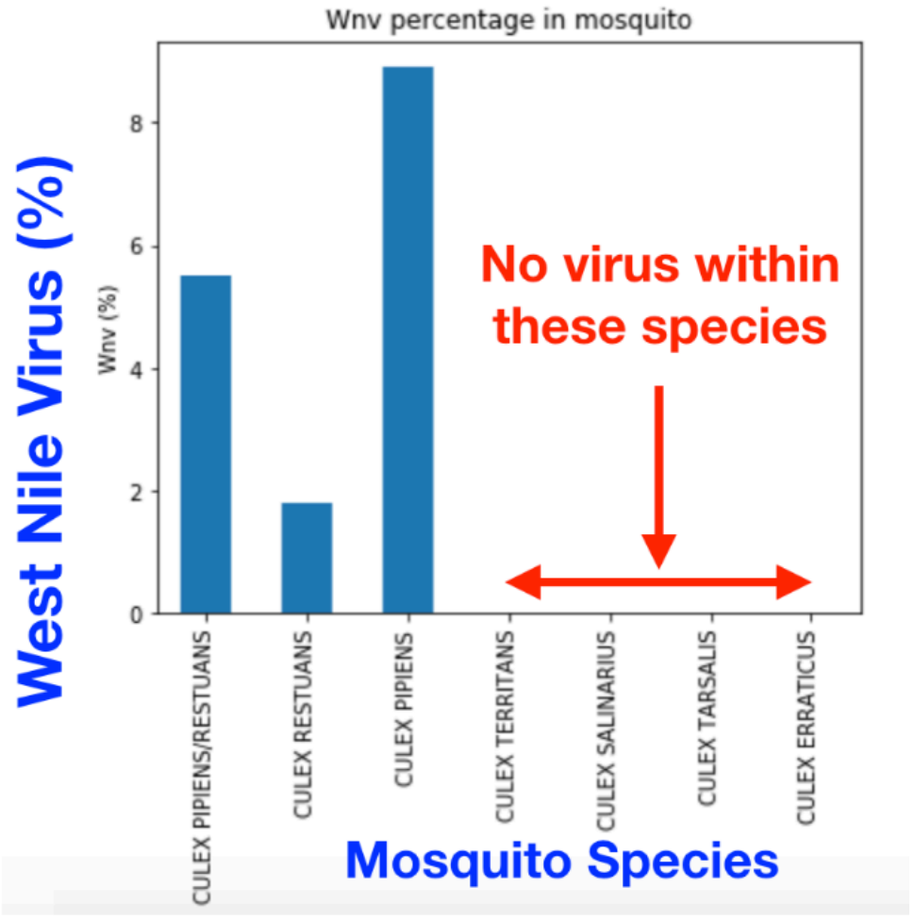
Exploratory data analysis

- Six species of mosquitoes with two frequently appeared together in most locations
- Virus present only in two species of mosquitoes:- Culex Restuans and Culex Pipiens
- Highly imbalanced data with 5.2% probability of observing virus

Probability



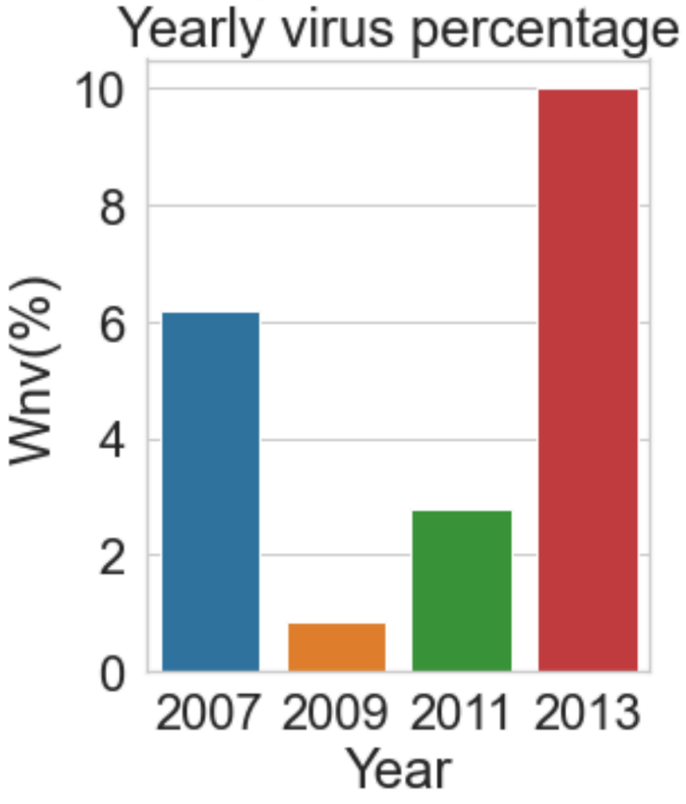
Mosquito species



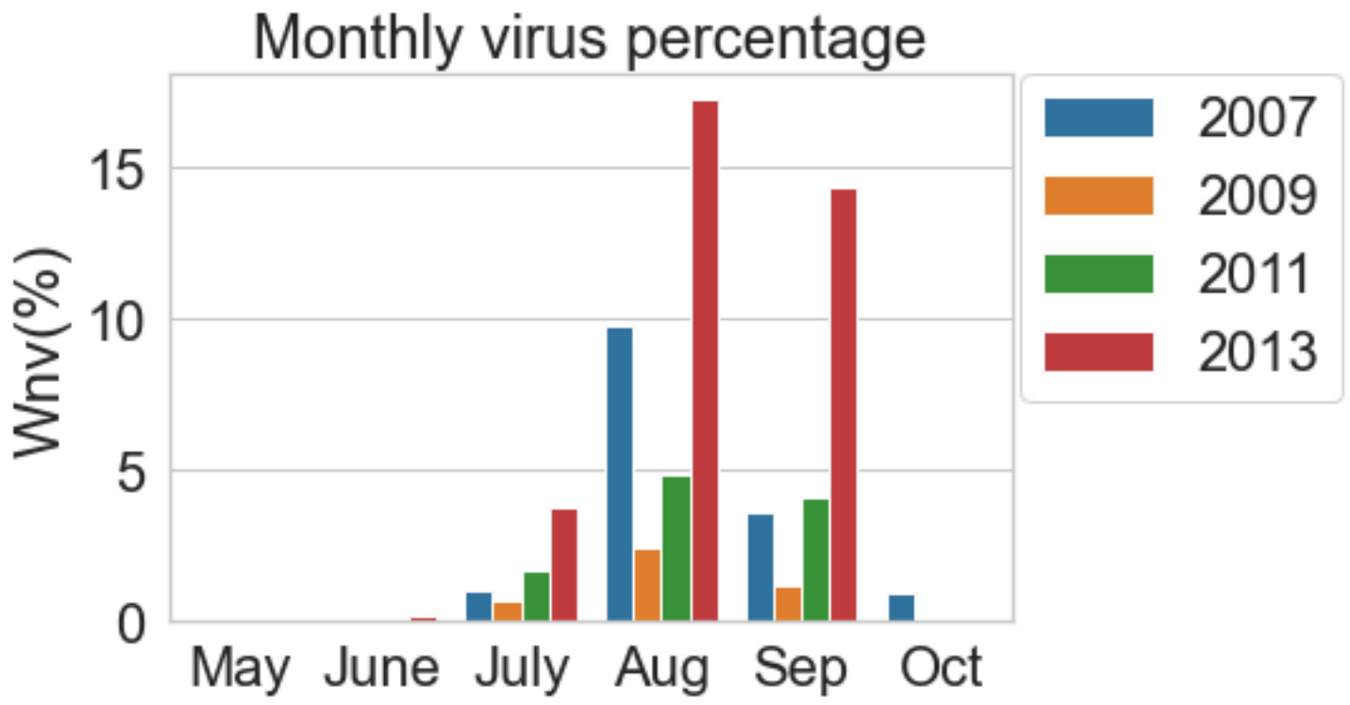
Exploratory data analysis

- Virus observation probability is higher in 2013 and fall season
- Virus appears in June, becomes critical in August and then disappears in October

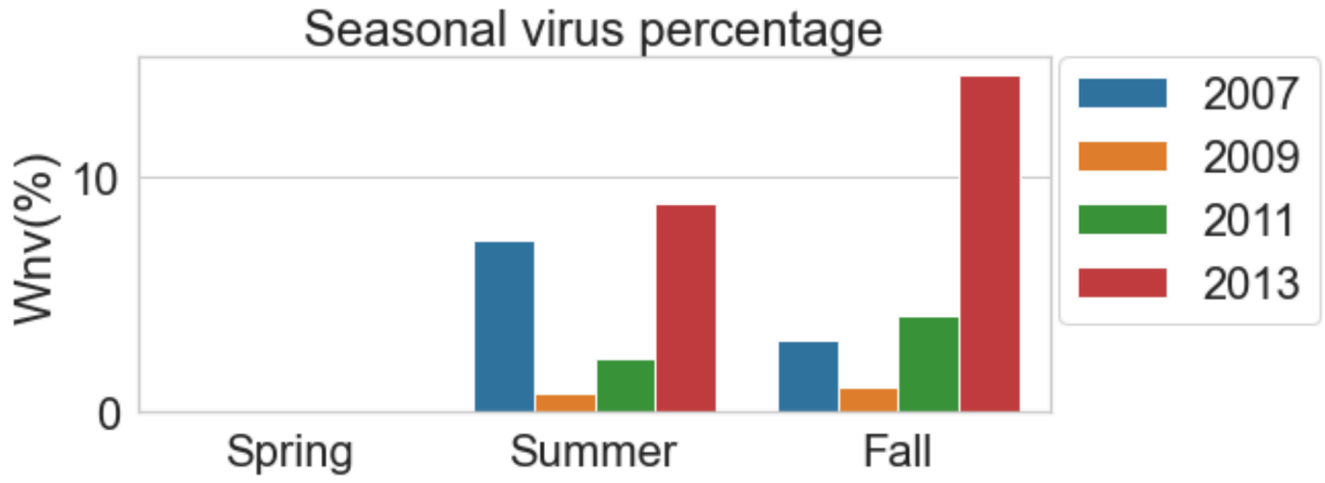
Yearly observation



Monthly observation



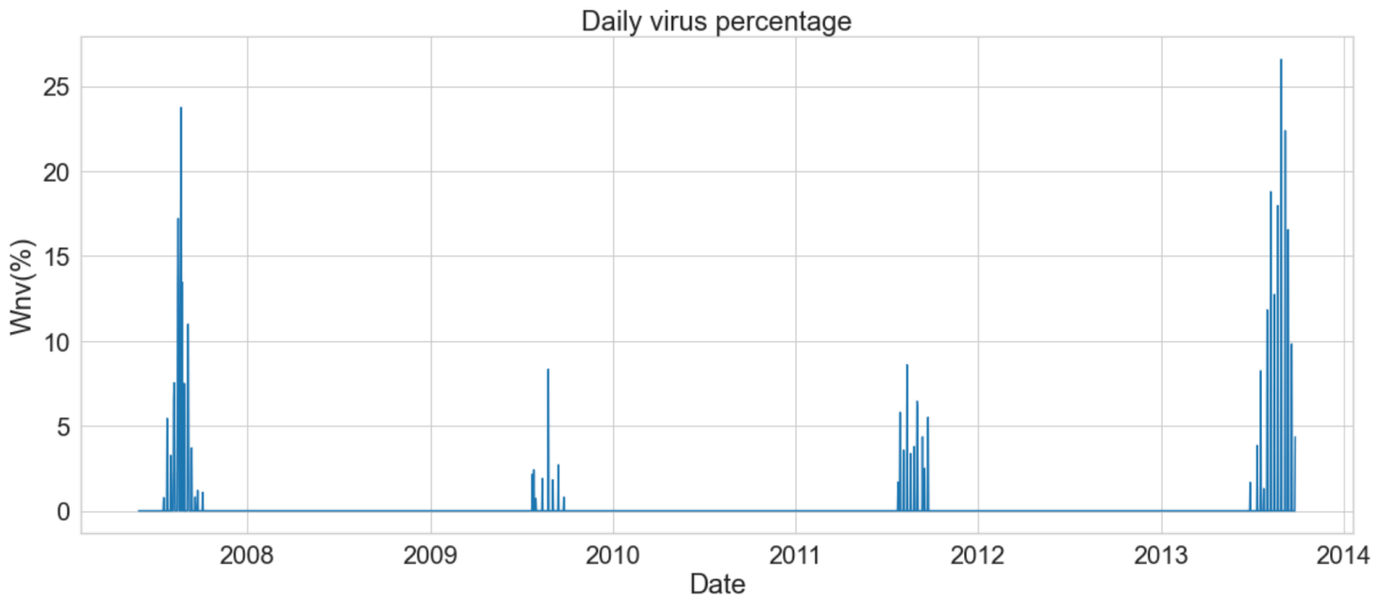
Seasonal observation

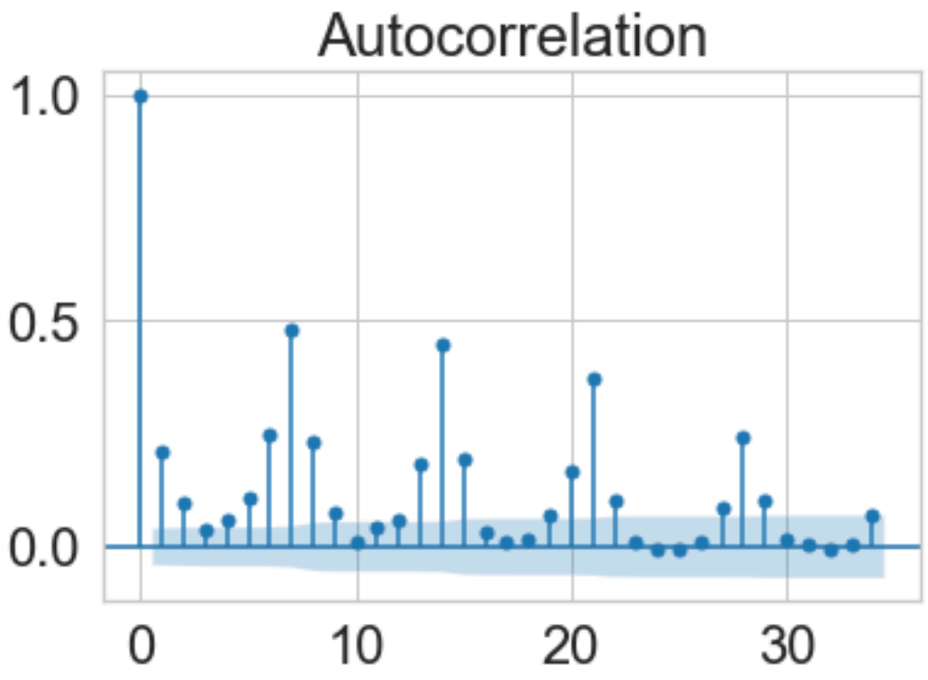


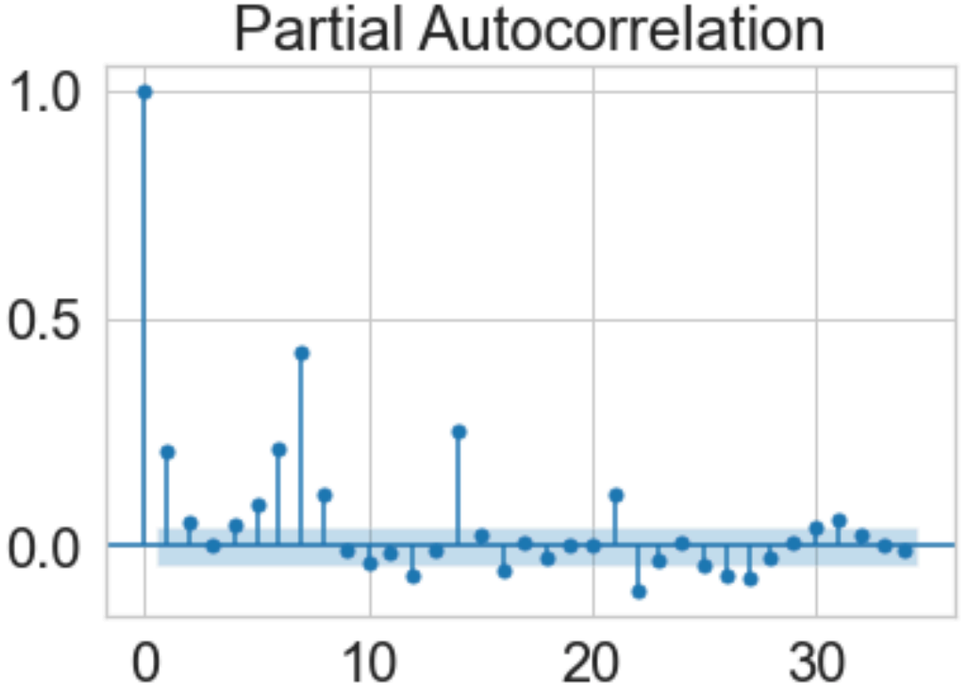
Exploratory data analysis

- Repeating pattern of virus
- Correlation with 7, 14 and 21 days are significantly higher than other days
- The pattern repeats in partial autocorrelation indicating periodicity in virus observation

Daily virus observation probability

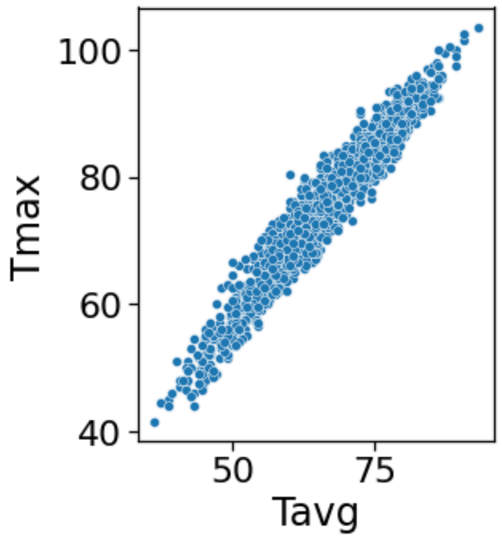


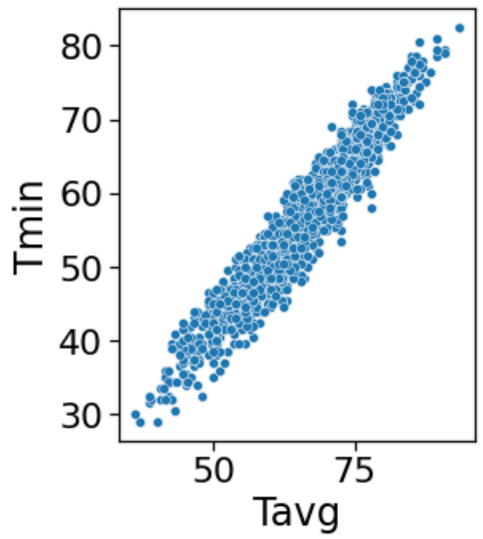


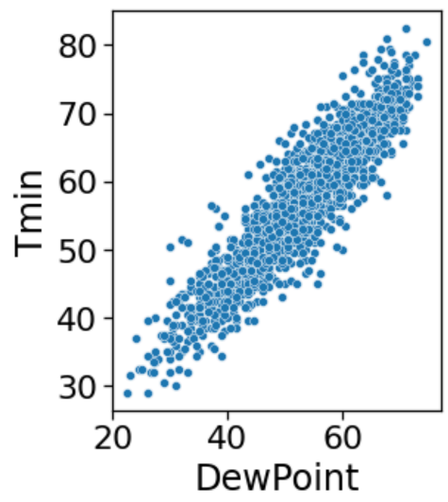


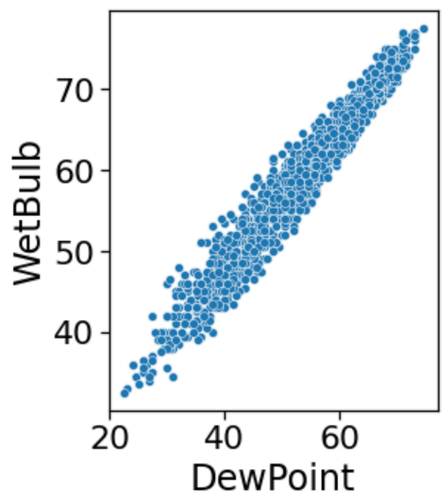
Weather data

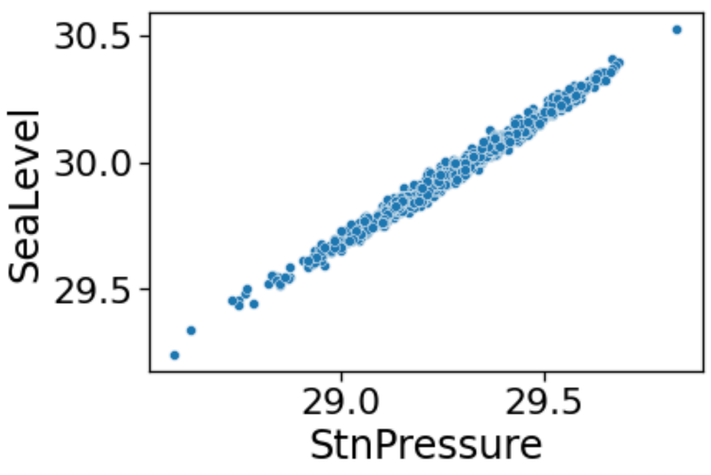
- Addition of new features such as wetbulb depression, dewpoint depression and relative humidity
- Many weather parameters are correlated in heat map and scatter plots
- Correlated weather parameters
  - Average, maximum and maximum temperature
  - Sea level and pressure
  - Result speed and Average speed
  - Dewpoint and bulb

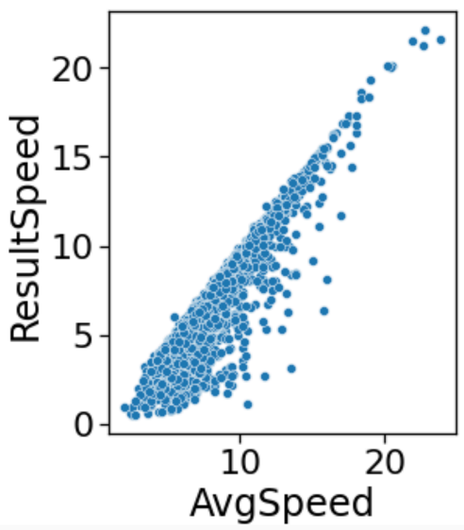


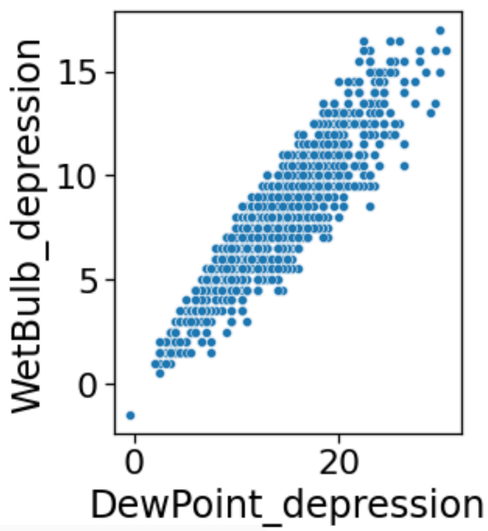






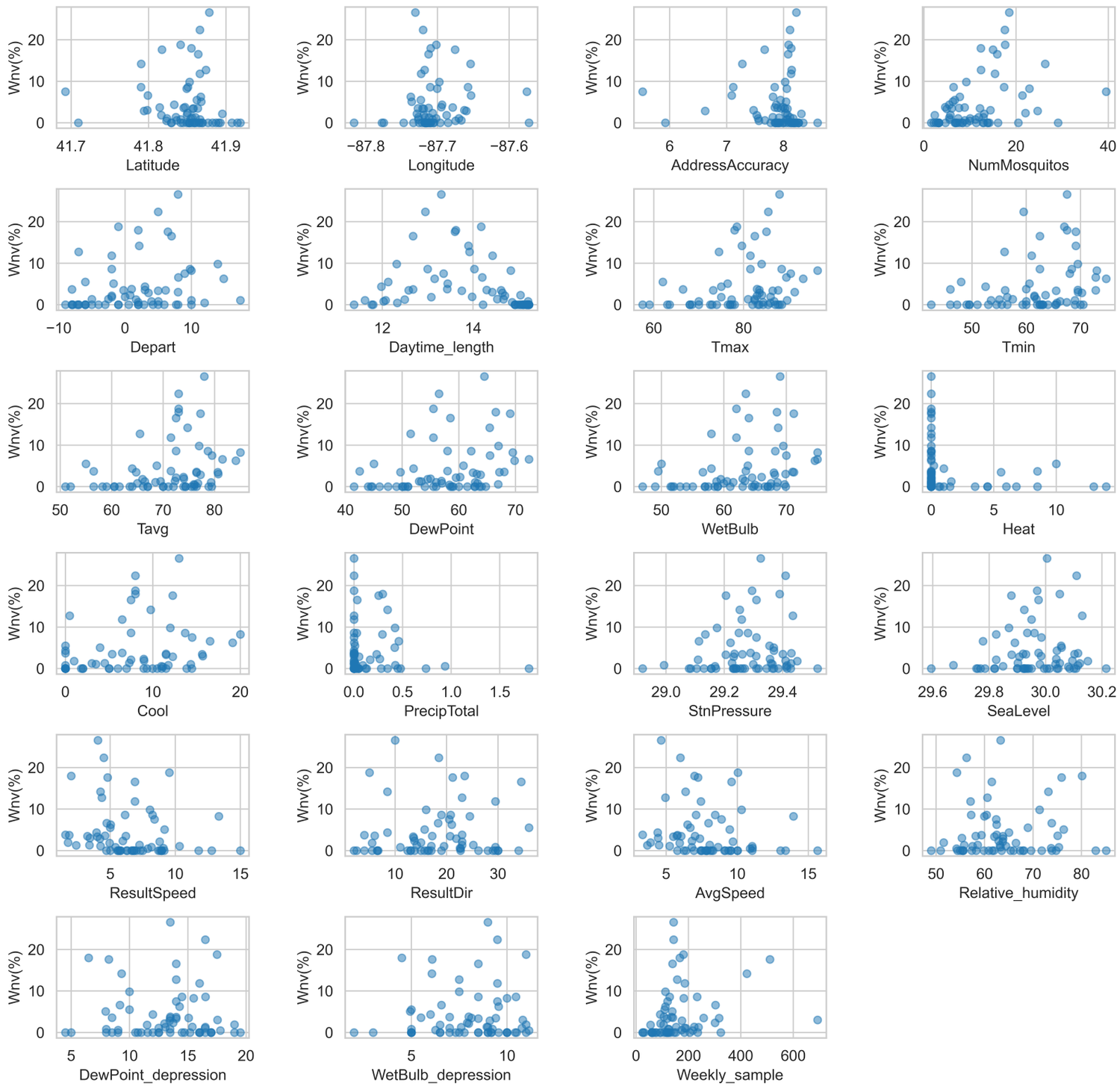






Exploratory data analysis

Relation between weekly virus observation probability and weather parameters

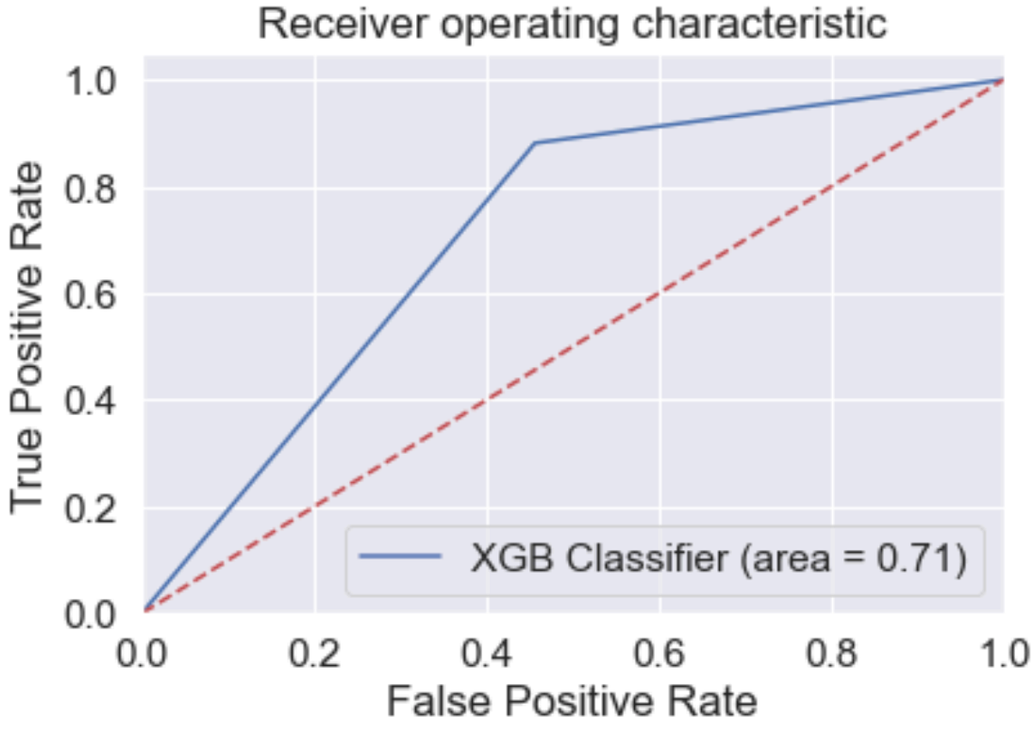


Feature engineering

- Available weather parameters from both stations are averaged
- Filled missing values with the average of backward and forward filling method
- Remove correlated weather parameters retaining only one
- Merged weather data with GIS data on date
- Additional features such as day of week, day of month, week of year, month, season and year for gaining seasonality on virus observation
- Addition of daily virus observation probability based on 7, 14 and 21 days lag
- Hot encoding of month, season and mosquito species
- Removal of hot encoded month and mosquito species without virus
- Drop object columns describing address retaining only latitude and longitude
- Applied information value (IV) technique for the selection of important features
- Used variance inflation factor technique to reduce multicollinearity issue among features

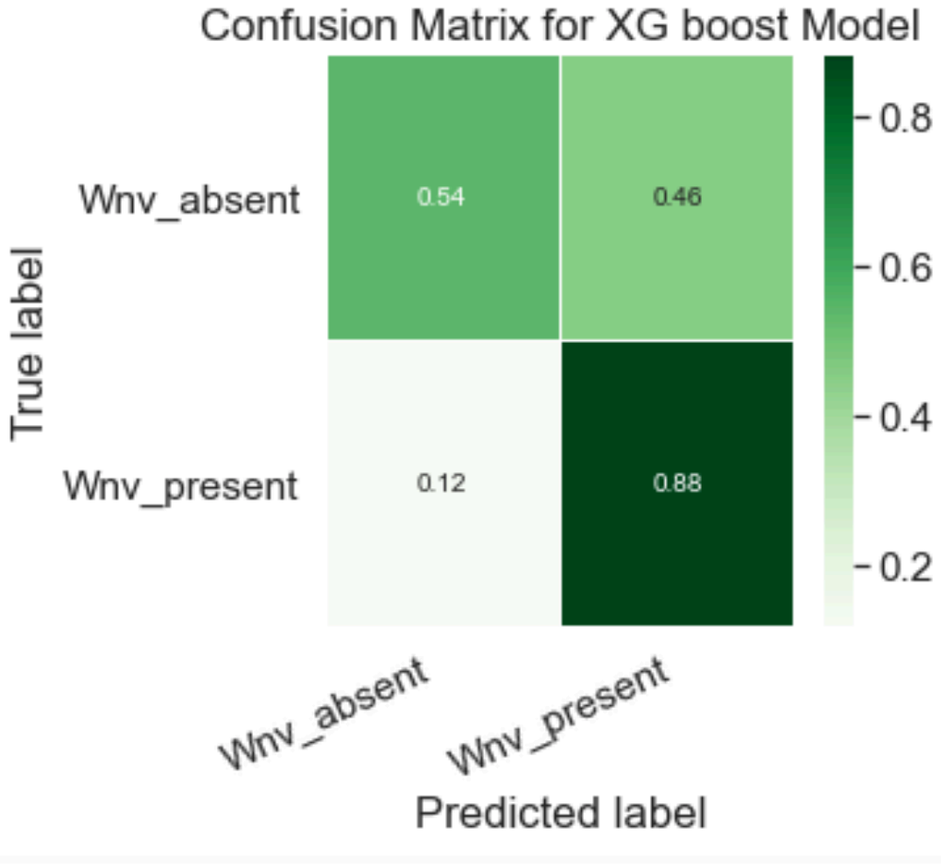
Data Modeling

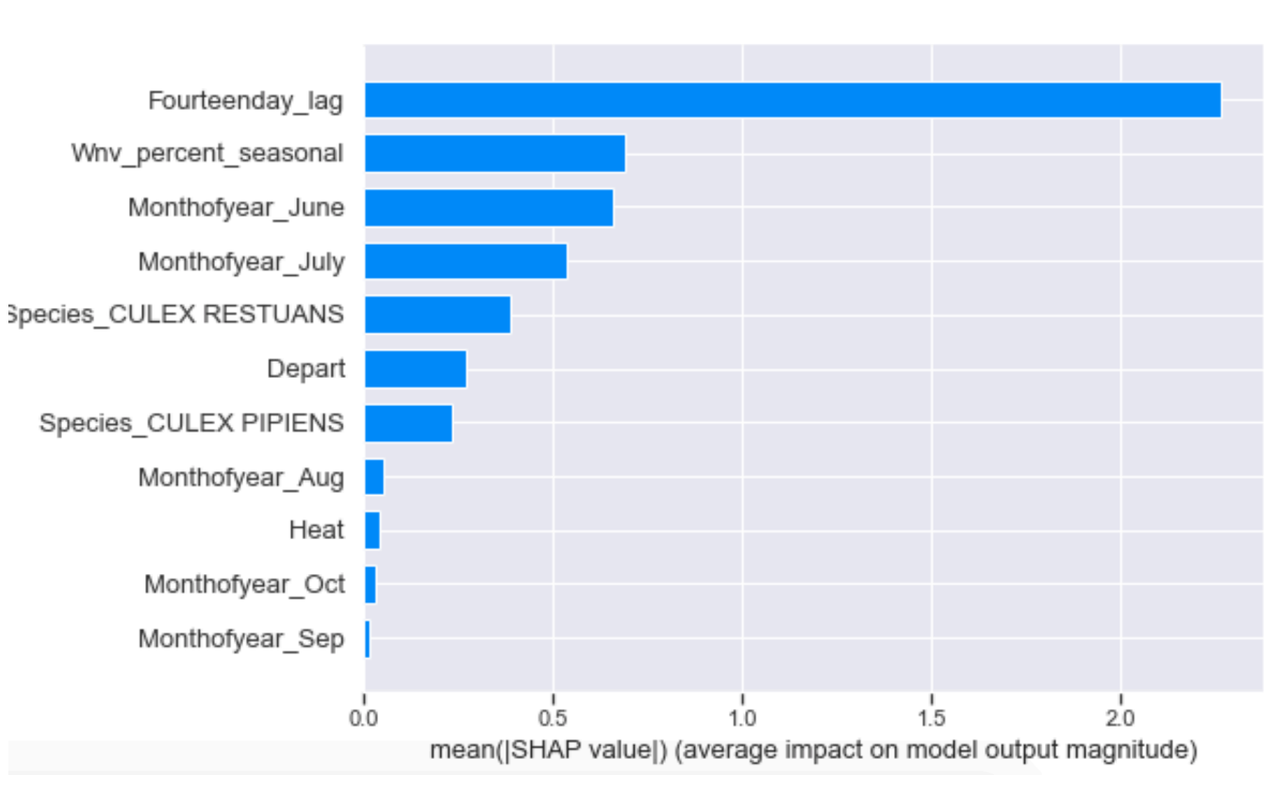
- Partitioning of data into training and test sets with ratio 7/3
- Data modeling using XGB classifier
  - Selection of best parameters using grid search method with five fold cross validation
  - Best score: 0.81
  - metric - area under the curve
- Model prediction:
  - AUC of 0.71 on test set



Results:

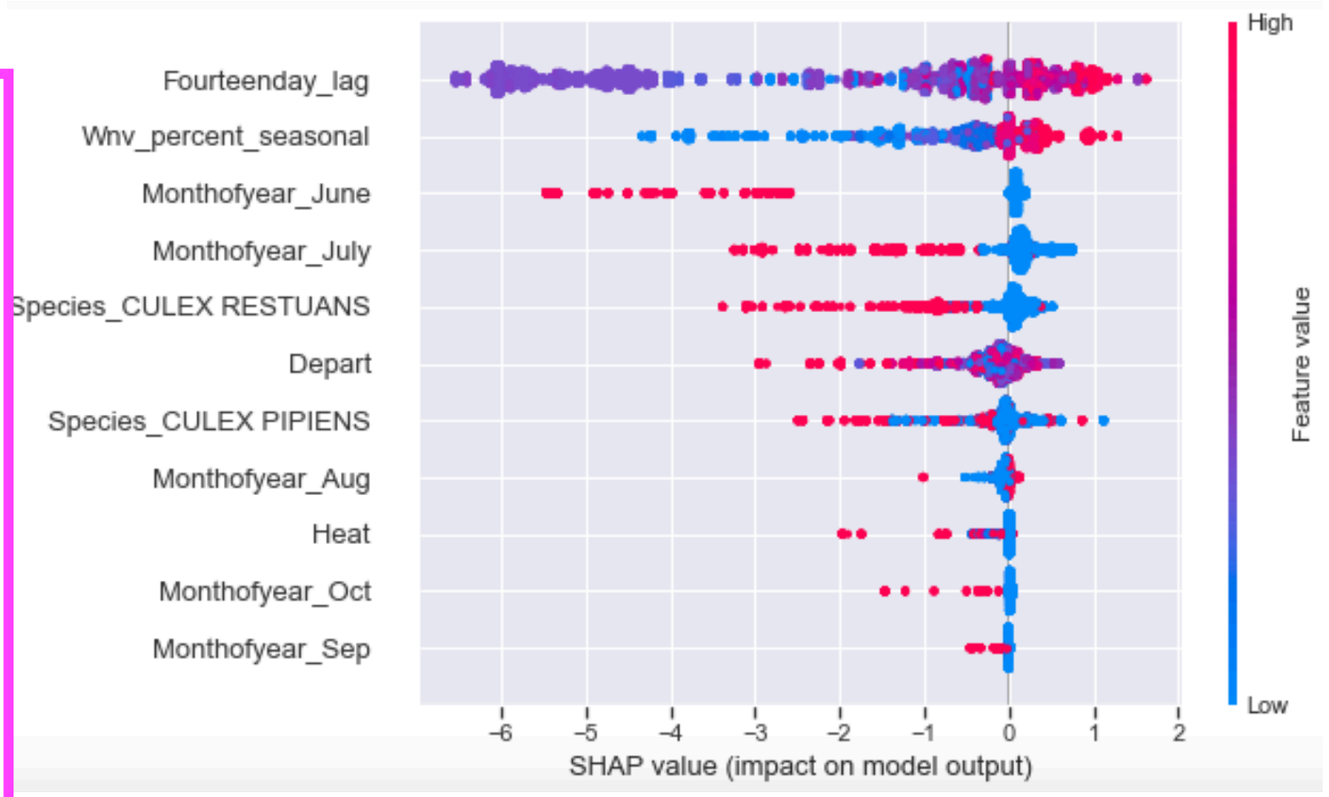
- Model predicts the presence of virus with probability 0.88
- The cost of incorrectly classifying the presence of virus (false negative) is riskier for virus outbreak than false positive
- Smaller magnitude of false negative. Thus, the model is critical in predicting the virus although the precision for virus absence is low.
- Fourteen day lag is the most important feature in classification decision

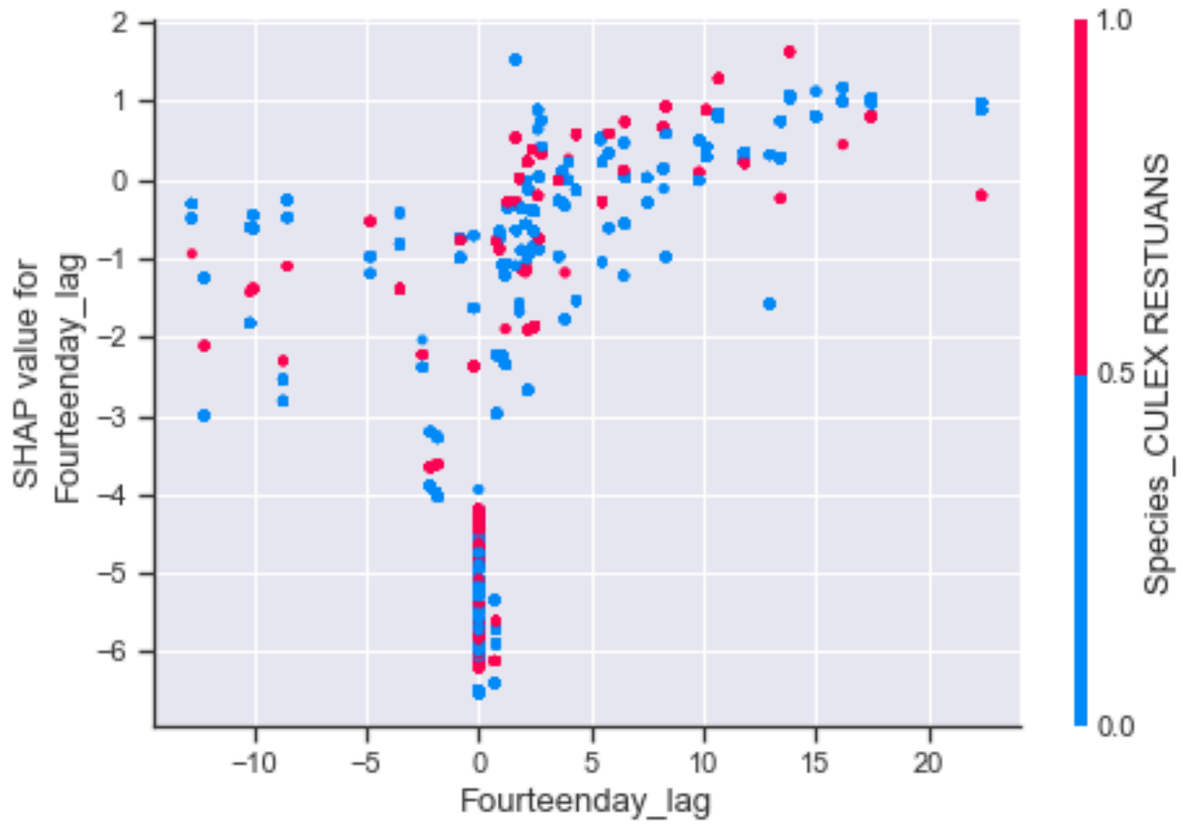




Results:

- Fourteen day lag and seasonal virus observation probability are positively correlated with the presence of virus
- Partial dependence plot of fourteen day lag exhibits some sort of linear relationship with the target variable and the spread suggests it's interaction with the mosquito species, Culex Restuans
- Months alone are negatively correlated except August but their interaction with lag values and mosquito species increases virus predictions
- Impact of weather parameters depart and heat index are minimum compared to lag, seasonal and months





Conclusions

- Virus prediction depends on time series data.
- Prediction increases if the virus has been observed two weeks prior (fourteen day lag)
- In June and July, virus prediction depends on fourteen day lag value.
- In August, virus prediction increases for mosquito species Culex Restuans and Culex Pipens
- Weather parameters have minimum affect for virus predictions in the developed model