Influenza Seasonality Assessed Through Climatic Variables and Indoor Activity Across the United States

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Background

- Effective reproduction number (R_t): a measure of transmission; the number of infections caused at a given time by one infected individual.
- Virus stability is directly mitigated by dry bulb temperature (DBT) and relative humidity (RH). [1]
- Absolute humidity (AH) is implicated as a predictive variable for R_t. [2]

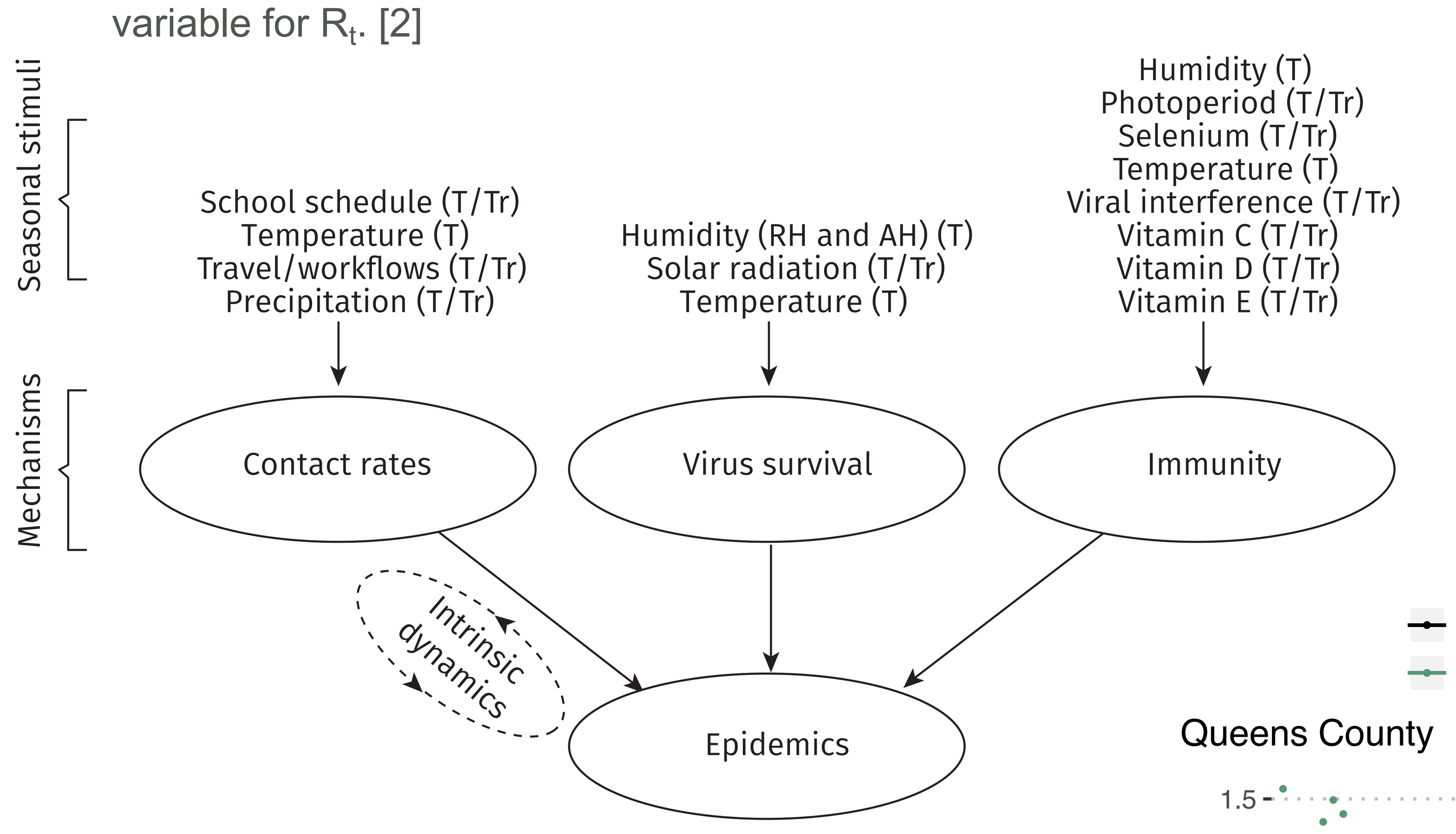


Figure 1. A flow chart depicting variables that contribute to influenza seasonality in temperate (T) and tropical (Tr) climates [3]

Objectives

It was hypothesized that weather variables and human interaction mitigate seasonal influenza patterns across climate zones as interconnected variables.

- To understand the predictive quality of AH on influenza epidemics in the United States.
- To determine a model combining behavioral and climatic variables to better define influenza seasonality across climate zones.

Methods

R and RStudio were used for all data cleaning and analysis. Exploratory data analyses were conducted with binomial linear regressions to determine the factors most related to an increase in R_t.

Independent Variables:

- RH, AH, DBT [4]
- Indoor activity, a measure of indoor interaction (based on cell phone location data) [5]

Outcome Measure:

- R_t (calculated using EpiEstim package and incidence counts from state health departments; SI = 3.6 σ = 1.6) [6]

A multivariate linear regression model was defined:

$$\bar{R} \approx \text{poly}\left(\frac{\text{DBT} \cdot \ln\text{RH}}{\text{Indoor Activity}}, 2\right)$$

Equation 1. A multivariate orthogonal binomial integrating RH, DBT, and indoor activity

A one-week lag was applied to the model to determine the predictive qualities of these variables as well.

Results

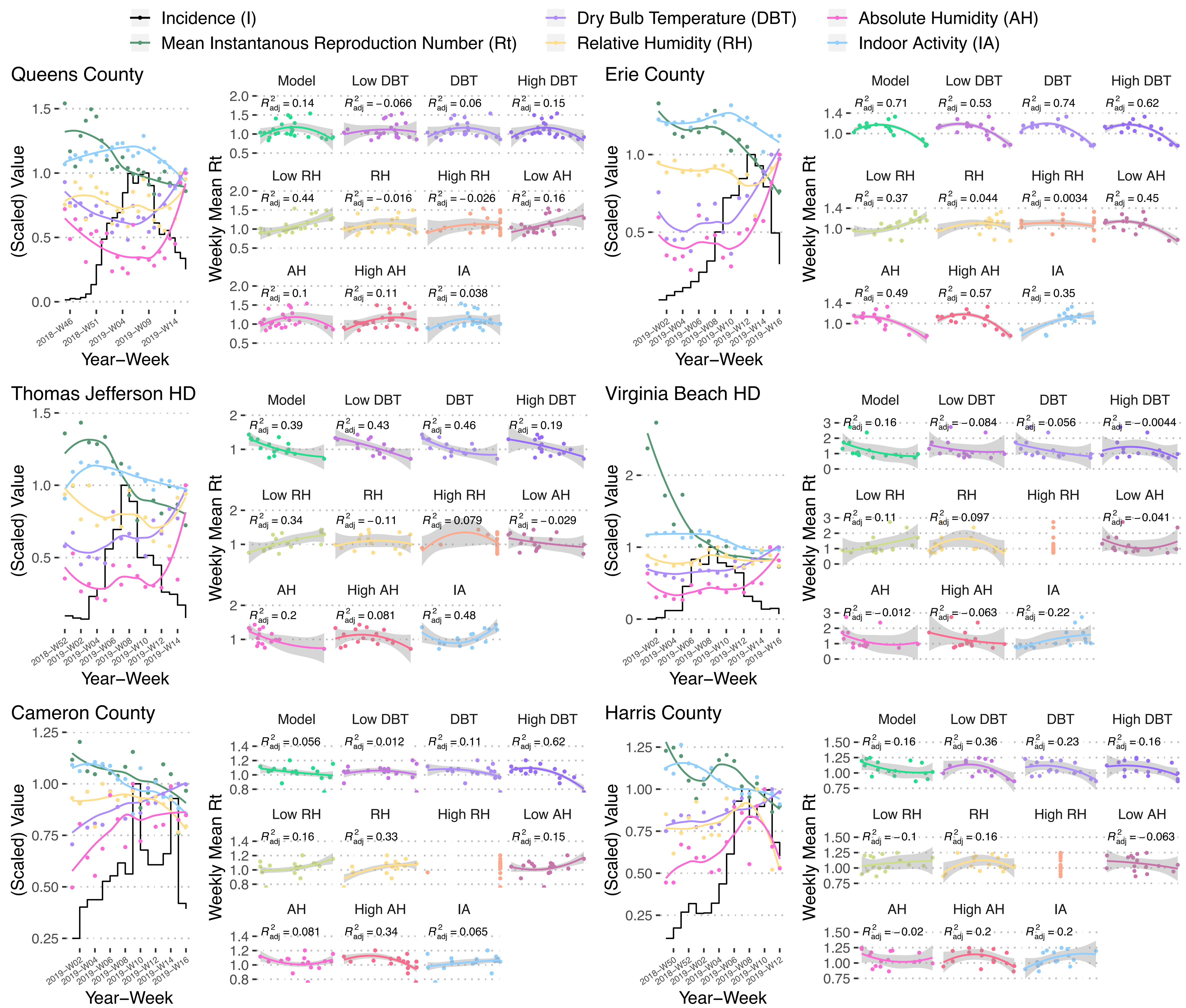
I. R^2 values are more significant in northern counties.
II. Incorporating a one-week lag on the model had consistent R^2 values among counties but did not show a northern trend.
III. Neither non-lagged AH nor lagged AH (not pictured) had a significant relationship with weekly mean R_t.

Table 1. R^2 adjusted values for each county between weekly mean R_t and models.

County	Model	Lag Model (1 week)
Queens County	0.14	0.12
Erie County	0.71	0.59
Thomas Jefferson Health District	0.39	0.22
Virginia Beach County	0.16	0.029
Cameron County	0.056	0.35
Harris County	0.16	0.28

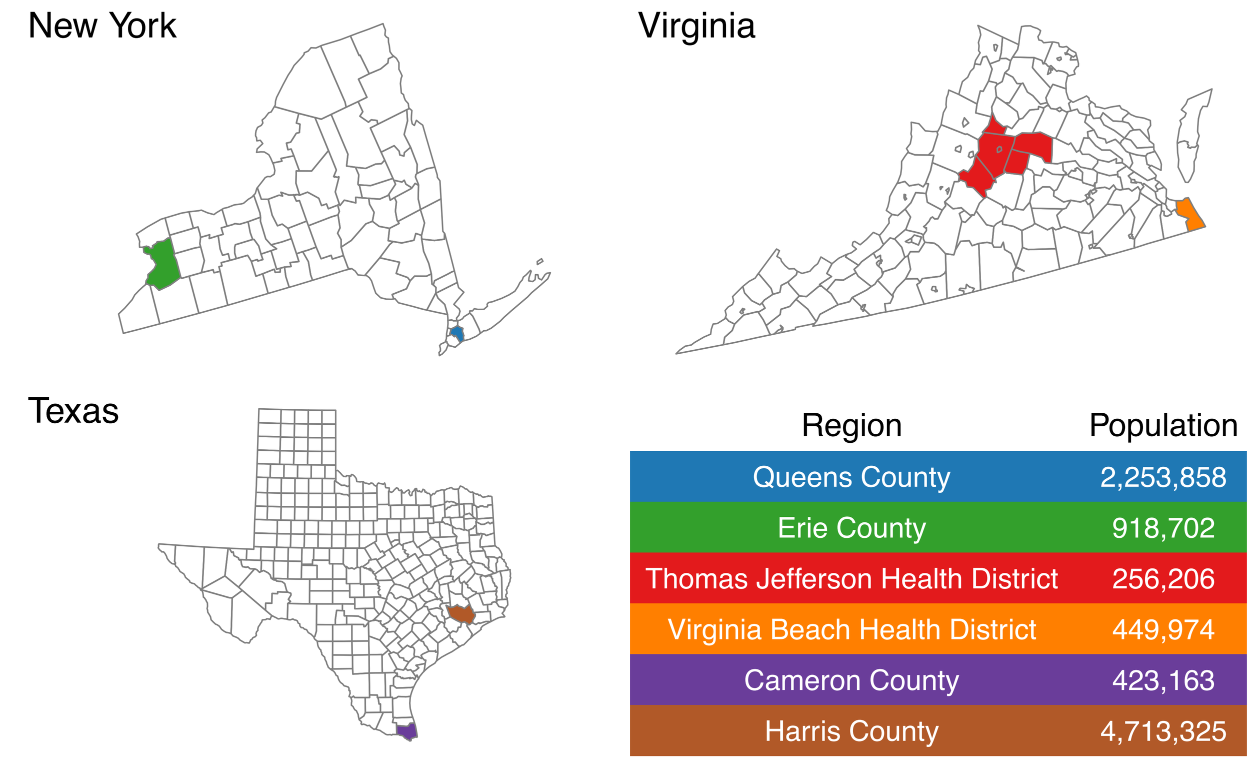
Table 2. Distribution of weekly mean R_t and optimal lags of the model for each county found using the Cross Correlation Function in the R feast package.

County	Shapiro-Wilk Normality Test	Optimal Lag (days)
Queens County	0.01181	42
Erie County	0.164	7
Thomas Jefferson Health District	0.5188	0
Virginia Beach County	0.0252	14
Cameron County	0.046	7
Harris County	0.4285	7



Incidence, DBT, RH, and AH normalized by maximum value. Orthogonal binomial fit.

Figure 2. Exploratory data analysis for each county studied including the R^2 values between variables and weekly mean R_t, not including the lag model.



Region	Population
Queens County	2,253,858
Erie County	918,702
Thomas Jefferson Health District	256,206
Virginia Beach Health District	449,974
Cameron County	423,163
Harris County	4,713,325

Figure 3. A map illustrating the three states and six counties chosen to represent temperate (NY and VA) and near-tropical (TX) regions.

Conclusion

The large range in R^2 values implies there is a difference in how variables contribute to seasonality across states. Although incorporating a lag did not result in a latitudinal trend, it proved important in consideration of real-time factors leading to outbreaks. The integration of both environmental and behavioral variables can be applied to public health measures to lower the morbidity of seasonal influenza outbreaks.

Future Directions

- A larger sample size will depict a clearer latitudinal trend in the model fit.
- A geographical expansion will better represent all climate zones (specifically more tropical and subtropical locations) and increase accuracy in the latitudinal trend of the model.
- A retrospective study to include a larger temporal range is required to increase statistical significance.

References

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