Identifying Climatological Interactions in Global Influenza Across Temperate and Tropical Regions

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Abstract. Recently, global epidemic models that uses climatological factors have been shown to explain influenza activities for both temperate and tropical regions. In this paper, we extend these global models by including interactions of climatological factors. We find that countries in Europe and Australia have higher forecast skill, indicating the stronger relationship of influenza with climatological factors, than regions in other continents. The influenza activities of 47 (83%) countries can be explained with a closer match using multi-factor interactions along with original factors than only using the original factors.

Keywords: Multi-factor interaction · Influenza · Climatological factor

1 Introduction

Influenza outbreaks are affected by climatological factors, such as relative humidity [12], absolute humidity [11], temperature [7] and precipitation [16]. The survival and transmission rates of influenza outbreaks are affected by climatological factors. Due to geographic variations, different countries exhibit different climatological properties due to geographical variations [1,6]. The seasonality of influenza has been well studied in temperate regions, which are characterized by significant seasonal changes in climatological factors [15]. In contrast, tropical regions have much weaker annual climatological cycles with weak seasonality [9,10]. Climatological factors of absolute humidity and temperature were shown to improve the global models of influenza outbreaks, with different influence in different regions [16].

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When researchers drill down to the relationships between climatological factors and influenza, they find that climatological factors may interact with each other and thus eventually affect the influenza dynamics [1,16]. For example, the effect of absolute humidity on influenza was mediated by temperature with a U-shaped pattern [1]. In addition, the synthetic conditions of specific humidity and temperature were associated with the activity of influenza [16]. Previous studies enlighten us for the global phenomenon of climatological factors' interactions. However, the combined influences of factors' interactions on influenza transmission is not yet understood. Due to the geographic variations of climatological factors across different countries [4,5,8,14], factor interactions can be heterogeneous across countries. This study aims to identify all possible interactions of climatological factors in each country and to what extent these interactions are useful to explain the observed influenza epidemics than factors' main effects.

2 Methods

2.1 Study Design

We conduct a retrospective time series study of global influenza to highlight the major interactions of climatological factors across countries via the relationships of weekly influenza cases with climatological factors.

2.2 Data

Our data include both influenza incidences and climatological factors for 79 countries over at least 208 weeks (4 years), and such countries geographically cover an area of <1.5 million mi^2 [1]. In these countries, totally 57 countries have the concurrent period of weekly influenza cases and temperature, absolute/relative humidity and precipitation. More details can be found in the following subsections of influenza and climatological data.

Influenza Data. We use the open-access influenza data, released by the World Health Organization for the weekly laboratory confirmed influenza cases of type A and B on April 2014 in country level in the period of January 1, 1996 to March 26, 2014 [1]. To infer the risk of influenza, we use the incidence density (per capita) as the influenza index, which is estimated via counting the estimated population size and reporting rates.

Climatological Data. In the open-access climatological data , weekly temperature (T) and absolute humidity (AH) data are calculated for each country by taking the average value of all available stations in National Oceanic and Atmospheric Administration Global Surface Summary of the Day. Given the temperature and absolute humidity of a region, the relative humidity (RH) is calculated by assuming standard atmospheric pressure. In addition, the precipitation (PRCP) values of a region are taken from the combined National Centers for Environmental Prediction Climate Forecast System (http://cfs.ncep.noaa.gov/).

2.3 Forecast Analysis

The forecast skill refers to the accuracy of association of prediction to an observation. Here, it is represented in terms of the Pearson correlation between the predicted index and the observed influenza index. In order to calculate the forecast skill, we used the model-free method of multi-view embedding (MVE) to forecast, which is particularly effective in the scenario of noisy time series. This kind of methods is also popular in the relationship analysis of influenza and climatological factors.

Baseline models are taken as MVE with the four climatological factors as input together or separately through their main effects. A forecast is estimated via the average of the nearest neighbors of attractors, built from lags of factors [2,3,13] to enable influenza dynamics reconstructed.

To be specific, MVE is defined as:

$$y_{t+1} = \frac{1}{k}\sum_{i=1}^{k} y_{nn^i(t)+1} \tag{1}$$

where y_{t+1} represents the prediction at time $t+1$. $y_{nn^i(t)+1}$ is the i-th factor's attractor, ordered by the time index $nn^i(t)$.

As for the interactions of multiple factors, we consider the method of tensor product interaction (ti) [17], which uses different smoothing bases for factors and has a huge advantage of flexibility in comparison to the usage of single smoothing base. The factors are divided into two sets. One is M, involving the factors with only main effects. Another is TI with only multi-factor interactions. Thus, the influenza prediction can be written as

$$\frac{1}{4}\Big(\sum_{M_k \in M} y_{nn^{M_k}(t)+1} + \sum_{ti_l \in TI} y_{nn^{ti_l}(t)+1}\Big) \tag{2}$$

where M_k infers the main effect of the k-th factor in M and ti_l denotes the l-th multi-factor interaction in TI.

3 Results

We, first, study the forecast analysis of influenza across countries by choosing the best model in all 21 possible combinations of the four climatological factors with the highest forecast skill for forecasting, as shown in Fig. 1, ordered by the latitude.

The X axis represents the forecast skill, starting from 0 to 0.9, and the Y axis represents the latitude. We find that the higher the latitude of a country

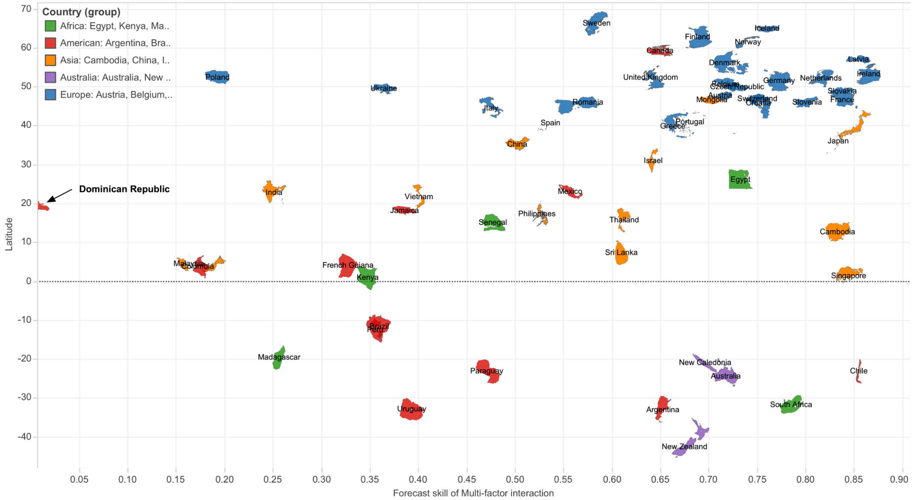

Fig. 1. Overview of the forecast skill over countries. Countries are ordered by with the latitude and colored by continents. For each country, we show its highest forecast skill for forecasting over 21 possible combinations of the four climatological factors as input together or separately. The X axis represents the forecast skill, starting from 0 to 0.90, and the Y axis denotes the latitude. There are 25 European countries with average forecast skill of 0.68, 5 African countries with 0.52, 12 American countries with 0.43, 12 Asian countries with 0.57, and 3 Australian countries with 0.70.

the higher the forecasting skill of the corresponding influenza forecasts. Most countries that are north of the 30° latitude appear to have forecast skill values around 0.75 with relatively small variation. In contrast, countries that are south of the 30° latitude show high variation in their forecast skill values. When we examine the results for countries in each continent separately, we find that the 25 European countries have an average forecast skill of 0.68; the 12 American countries have an average forecast skill of 0.43; the 12 Asian countries have an average forecast skill of 0.52; and the 3 Australian countries have an average forecast skill of 0.70. Forecasts for European countries exhibit high levels (0.55 to 0.85) of forecast skill, such as Netherlands, Slovenia, Ireland and France.

In Fig. 2, we show the relative improvement in forecast skill for each country by including the climatological interaction terms. The brighter the red color, the more the improvement in forecast skill for the corresponding country. We find that, including multi-factor interaction terms of climatological factors in our modeling results in improved forecast skill values for countries except part of Europe. Among the 57 countries, the epidemics dynamics for 47 (∼83%) countries can be explained with a closer match using additional multi-factor interactions. The mean forecast skill of the 47 countries is enhanced by 8.54% from 52.28% to 60.82%.

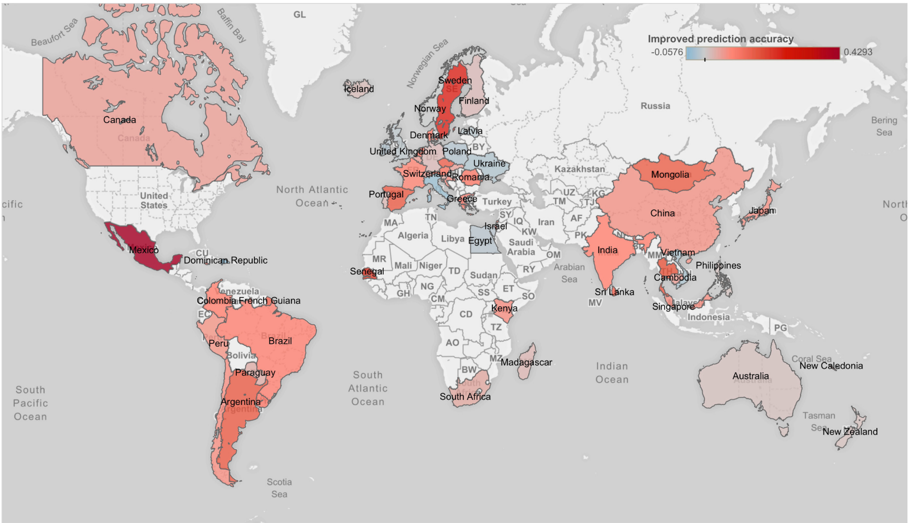

Fig. 2. Overview of the forecast skill enhanced. The forecast skill is enhanced by the best multi-factor interactions, in the contrast with the main effects of climatological factors. The redder the color, the greater the country's forecast skill is. Forecast with multi-factor interaction exhibits better forecast skills in most countries in North/South America, Africa, Asia and Australia. Among the 57 countries, the epidemics dynamics for 47 (∼83%) countries can be explained with a closer match using additional multi-factor interactions. The mean forecast skill of the 47 countries is enhanced by 8.55% from 52.28% to 60.82%.

4 Conclusion

Interactions of climatological factors correlate with influenza at the country level, which result in higher values of forecast skill than models that exclude interactions terms. Including multi-factor interactions increases the explanation of observed influenza time series, indicating the common interactions of climatological factors across countries. Tropical countries benefit from the interaction of absolute humidity and precipitation. In the contrast, temperate countries in the northern hemisphere benefit from by temperature and humidity. Our work extends previous studies from the analysis of multiple climatological factors to their additional interactions, revealing the disparity of different countries in the view of multi-factor interactions. to get better influenza surveillance and control through monitoring climatological factors and their interactions.

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