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Combined influence of multiple climatic factors on the incidence of bacterial foodborne diseases

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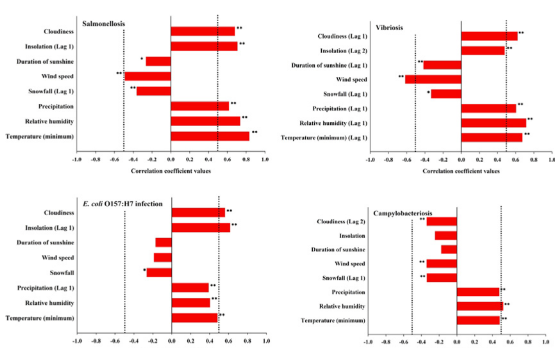
HIGHLIGHTS

- Multiple climatic factors can influence bacterial foodborne diseases (FBD) incidence.
- Relationships between 8 climatic factors and 13 bacterial FBD incidences were analyzed.
- Temperature, relative humidity, precipitation, insolation, and cloudiness were noted.
- These results are useful in designing preventive strategies for FBD.

GRAPHICAL ABSTRACT



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ABSTRACT

Information regarding the relationship between the incidence of foodborne diseases (FBD) and climatic factors is useful in designing preventive strategies for FBD based on anticipated future climate change. To better predict the effect of climate change on foodborne pathogens, the present study investigated the combined influence of multiple climatic factors on bacterial FBD incidence in South Korea. During 2011–2015, the relationships between 8 climatic factors and the incidences of 13 bacterial FBD, were determined based on inpatient stays, on a monthly basis using the Pearson correlation analyses, multicollinearity tests, principal component analysis (PCA), and the seasonal autoregressive integrated moving average (SARIMA) modeling. Of the 8 climatic variables, the combination of temperature, relative humidity, precipitation, insolation, and cloudiness was significantly associated with salmonellosis ($P < 0.01$), vibriosis ($P < 0.05$), and enterohemorrhagic *Escherichia coli* O157:H7 infection ($P < 0.01$). The combined effects of snowfall, wind speed, duration of sunshine, and cloudiness were not significant for these 3 FBD. Other FBD, including campylobacteriosis, were not significantly associated with any combination of climatic factors. These findings indicate that the relationships between multiple climatic factors and bacterial FBD incidence can be valuable for the development of prediction models for future patterns of diseases in response to changes in climate.

1. Introduction

Climate change has an impact not only on crop production and food security but also on food safety and the incidence and prevalence of foodborne diseases (FBD) (Gregory et al., 2005). Several studies have

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suggested an association between climate change or conditions and bacterial FBD (Jacxsens et al., 2010; Kim et al., 2015; Semenza and Menne, 2009), including salmonellosis (Kovats et al., 2004), vibriosis (Craig et al., 2012), pathogenic *Escherichia coli* infections (Liu et al., 2013), and campylobacteriosis (Kovats et al., 2005).

Most research to date has focused on specific climatic factors (either alone or in a combination of two variables) instead of the combined effect of many climatic factors. However, there are many climatic factors that can affect the incidence of foodborne illness (Semenza et al., 2012; Tirado et al., 2010), and the relationships between FBD and the majority of climatic factors, except temperature and rainfall (or relative humidity), remain poorly understood. Understanding the combined influence of climate variability on foodborne illness may improve the ability to predict the effect of climate change on these diseases (Young et al., 2015). Furthermore, regional differences in climatic variables likely affect the regional presence of foodborne pathogens (Kim et al., 2015) and, therefore, the incidence of foodborne illnesses and FBD outbreaks (Patz et al., 2005). South Korea is a small territory with a complex terrain and four seasons; its climate is affected by numerous meteorological factors. Therefore, an assessment of the impact of climate factors on human health is very important to establish national environmental health policies.

The aim of the present study was to examine the combined effects of 8 climatic factors, used to indicate regional climate variability, and the monthly incidence of 13 bacterial FBD in South Korea during 2011–2015.

2. Methods

2.1. Climate data and region

The 8 climatic factors were temperature (mean minimum, mean, and mean maximum), relative humidity, precipitation, snowfall, wind speed, duration of sunshine, insolation, and cloudiness (Supplementary Fig. S1), based on data published by the Korea Meteorological Administration (KMA, 2016). Based on the monthly bacterial FBD incidence data from the Health Insurance Review and Assessment Service (HIRA), we calculated mean values for the climatic factors for each month from January 2011 to December 2015. The included regions of South Korea are positioned between latitudes of 33°06′ and 38°27′ and longitudes of 125°04′ and 131°52′. South Korea is part of the East Asian monsoonal region, and the country has a temperate climate with 4 distinct seasons.

2.2. Bacterial foodborne disease incidence data

Data regarding bacterial FBD cases for 2011–2015 were obtained from the HIRA (2016) using the method by Park et al. (2015), which considered accurate diagnoses based on the 10th Revision of the International Classification of Diseases (ICD-10) codes for 13 foodborne pathogens (*Salmonella* spp., *Shigella* spp., enteropathogenic *E. coli* [EPEC], enterotoxigenic *E. coli* [ETEC], enteroinvasive *E. coli* [EIEC], enterohemorrhagic *E. coli* [EHEC] O157:H7, *Campylobacter* spp., *Yersinia enterocolitica*, *Staphylococcus aureus*, *Clostridium perfringens*, *Vibrio parahaemolyticus*, *Bacillus cereus*, and *Listeria* spp.) (Supplementary Table S1 and Supplementary Fig. S2). The estimated bacterial FBD cases were then grouped on a monthly basis according to inpatient stays (i.e., hospitalizations) and outpatient visits. However, the pre-analysis resulted in a higher correlation between inpatient data and climatic variables than with the outpatient data or the sum of outpatient and inpatient data; therefore, we used only inpatient data for the analysis.

2.3. Statistical analysis

Fig. 1 shows the statistical process used for analyses. First, to quantify the strength of associations between climatic factors and the incidence of bacterial FBD, the Pearson correlation analysis was conducted. This pre-analysis indicated the correlation with each of the climatic factors decreased rapidly 2 months before the FBD cases; therefore, we used climatic data from 2 months prior to the FBD outbreak to account for this time lag. Second, to investigate the multicollinearity between climatic factors and bacterial FBD incidence, variance inflation factors (VIFs) were calculated; eliminating or combining factors with VIF values >10, which are indicative of high multicollinearity (O'brien, 2007).

Next, principal component analysis (PCA) was used to reduce the effect of higher order multicollinearity, investigate the combined effects of climatic variables on bacterial FBD, and explore the structure that identifies the similarities and differences in the climatic data. PCA reduces and extracts the dimensionality of the data and rates the variation present in the original data set, as much as possible (David, 2002). As a result, the manifest variables, and the set of components are reduced to new components called PC1, PC2, and PC3 (for the first, second, and third principal components, respectively), and so on, that are independent and decrease the amount of variance from the original data set. PC1 captures most of the variance, PC2 captures the next highest variance, and so on, until all of the variances are accounted for (Edwards, 1991).

Finally, to determine the relationship between the climatic variables and the time-series FBD incidence data, the seasonal autoregressive integrated moving average (SARIMA) model was used to estimate the parameters of the regression model through pre-processing (log transformed and differenced) of a stationary time series. SARIMA handles time-series modeling and forecasting by taking into account the impact of seasonality and autocorrelations (Helfenstein, 1996). A SARIMA model can be described as ARIMA (p, d, q) multiplied by (P, D, Q) and is defined by Eq. (1) (Suhartono, 2011).

$$\varphi_p(B)\Phi_p(B^s)(1-B)^d\left(1-B^S\right)^D Z_t = \theta_q(B)\Theta_Q\left(B^S\right)a_t \qquad (1)$$

where:

$\phi_p(B) = 1 - \varphi_1 B - \varphi_2 B^2 - \cdots - \varphi_p B^p$
$\Phi_p(B^s) = 1 - \theta_1 B - \theta_2 B^2 - \cdots - \theta_q B^q$
$\theta_q(B) = 1 - \theta_1 B - \theta_2 B^2 - \cdots - \theta_q B^q$
$\Theta_Q(B^S) = 1 - \Theta_1 B - \Theta_2 B^{2S} - \cdots - \Theta_Q B^{QS}$

where B is the backward shift operator, d and D is the non-seasonal and seasonal order of differences, respectively and usually abbreviated as SARIMA (p,d,q)(P,D,Q). The terms p, d, and q represent ordinary components, where p denotes the AR (autoregression), d the differencing order, and q is the MA (moving average) order that was used. The terms P, D, and Q represent seasonal components, where P denotes the seasonal order of AR, D the differencing order, and Q the MA order that was used. These terms were determined by the autocorrelation function (ACF) and partial autocorrelation function (PACF). The Akaike Information Criterion (AIC) and log-likelihood were used to assist the model fits, and the residuals were further examined for autocorrelation by scatter plots and the figures of ACF and PACF (Hu et al., 2007).

All analyses were performed using the SPSS 12.0 (Data Solution Inc., Seoul, South Korea), and $P = 0.05$ was considered significant.

3. Results

In the correlation analysis, 9 of the 13 bacterial foodborne pathogens (*Shigella* spp., EPEC, ETEC, EIEC, *Yersinia enterocolitica*, *Staphylococcus aureus*, *Clostridium perfringens*, *Bacillus cereus*, and *Listeria* spp.) were not correlated ($P > 0.05$) or had a weak correlation with most of the climatic factors. The remaining 4 bacterial foodborne pathogens (*Salmonella* spp., EHEC O157:H7, *Campylobacter* spp., and *Vibrio parahaemolyticus*) showed relatively high correlation with a majority of the climatic factors (Supplementary Table S1).