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The exposure-response relationship between temperature and childhood hand, foot and mouth disease: A multicity study from mainland China

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Abstract

Background: Hand, foot and mouth disease (HFMD) is a rising public health issue in the Asia-Pacific region. Numerous studies have tried to quantify the relationship between meteorological variables and HFMD but with inconsistent results. We aimed to characterize the relationship between temperature and HFMD in various locations and to investigate the potential heterogeneity.

Methods: We retrieved the daily series of childhood HFMD counts (aged 0–12 years) and meteorological variables for each of 143 cities in mainland China in the period 2009–2014. We fitted a common distributed lag nonlinear model allowing for over dispersion to each of the cities to obtain the city-specific estimates of temperature-HFMD relationship. Then we pooled the city-specific estimates through multivariate meta-regression with city-level characteristics as potential effect modifiers.

Results: We found that the overall pooled temperature-HFMD relationship was shown as an approximately inverted V shape curve, peaking at the 91th percentile of temperature with a risk ratio of 1.30 (95% CI: 1.23–1.37) compared to its 50th percentile. We found that 68.5% of the variations of city-specific estimates was attributable to heterogeneity. We identified rainfall and altitude as the two main effect modifiers.

Conclusions: We found a nonlinear relationship between temperature and HFMD. The temperature-HFMD relationship varies depending on geographic and climatic conditions. The findings can help us deepen the understanding of weather-HFMD relationship and provide evidences for related public health decisions.

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1. Introduction

Hand, foot and mouth disease (HFMD) is a worldwide childhood infectious disease caused by Enterovirus. Although HFMD is normally characterized by mild symptoms of febrile illness and rashes (World Health Organization, 2011), some patients can develop severe central nervous system complications and even fatal cardiopulmonary failure (Sabanathan et al., 2014). Over the last few decades, a series of large HFMD epidemics, accompanied by abnormally high rates of severe and fatal cases, have occurred in countries of the Asia-Pacific region (Chan et al., 2003; Ho et al., 1999; Van Tu et al., 2007; Zhang et al., 2010). In mainland China, HFMD is one of the leading infectious diseases in children and is also responsible for hundreds of reported deaths every year since it has been made statutory notifiable in May 2008 (Xing et al., 2014). Given its threat to children and the potential for its emergence as a leading cause of enterovirus-related CNS disease after poliomyelitis, HFMD has raised huge public health concerns in the Asia-Pacific region (Regional Emerging Diseases Intervention Center, 2009).

It is well accepted that weather plays an important role in the transmission of many infectious diseases (Kuhn et al., 2005). Epidemiologists have performed a large amount of studies trying to quantify the relationships between meteorological variables and HFMD. Among them, the temperature-HFMD relationship is the most controversial one. Earlier studies normally assumed a simple linear relationship. A study in Northern Thailand (Samphuththanon et al., 2014) showed that the relationship with temperature was negative, whereas studies in Hong

Abbreviations: HFMD, hand, foot and mouth disease; TSR, time series regression; DOW, day of week; LR, likelihood ratio; AIC, Akaike information criterion.

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Kong (Ma et al., 2010) and mainland China (Chen et al., 2015; Feng et al., 2014; Li et al., 2014; Wei et al., 2015; Wu et al., 2014; Zhang et al., 2016) found a positive relationship. More recent studies relaxed the linear assumption to allow for non-linear relationships. A study in Singapore (Hii et al., 2011) suggested the presence of a threshold and a J-shape relationship; by contrast, studies in Japan (Onozuka and Hashizume, 2011), Taiwan (Chang et al., 2012), South Korea (Kim et al., 2016) and mainland China (Xu et al., 2015; Zhu et al., 2015) showed that the risk of HFMD increased below moderately hot temperature but declined at extremely hot temperatures, with an approximately inverted V shape. The inconsistency of findings can be partly attributable to the diversity of methodologies and data sources, but it also implies that the temperature-HFMD relationship might be modulated by various factors.

2.1. Data sources

2.1.1. Daily series of HFMD counts and meteorological variables

We retrieved the surveillance data of reported clinical HFMD cases and meteorological variables in mainland China between 1 January 2009 and 31 December 2014.

We collected the reported clinical cases of HFMD from China Information System for Disease Control and Prevention. A clinical HFMD case is defined as a patient with papular or vesicular rashes on hands, feet, mouth or buttocks, with or without fever. All clinical cases were reported online within 24 h of diagnosis by use of a standardized form. More details of the surveillance data of HFMD have been described elsewhere (Xing et al., 2014). As over 99% of cases occurred among children under the age of 12 years (i.e. children in elementary school and below) according to our preliminary analysis, in this study we focused on the incidence of HFMD among children aged 0–12 years. The daily counts of HFMD clinical cases based on the date of onset of symptom were then aggregated at each of 293 cities in mainland China (Chen, 2009–2014). A city is defined as the main central urban area in each of the prefectures (i.e. prefectural-level city). A prefecture is an administrative division ranking below a province and above a county in China’s administrative structure, and a prefectural-level city corresponds to a middle to large size city in China.

We collected the daily monitoring data of meteorological variables, including mean temperature, mean relative humidity, mean air pressure, accumulated rainfall and sunshine hours, from China Meteorological Data Sharing Service System. We included 646 national ground meteorological stations which have daily records in the period 2009–2014. The missing values in the daily records were filled by different approaches depending on the nature of each meteorological variable. Specifically, for temperature, humidity and air pressure, the missing values were filled by the polynomial interpolation (Zeileis and Grothendieck, 2005); for sunshine hours and rainfall, the missing values were replaced by zero. However, the missing issue should be negligible given that the missing proportion is very small (<0.1%).

2.1.2. City-specific characteristics

We collected the geographic, climatic and social characteristics for each of the 143 cities. We used the coordinates of city/station to represent their differences in geographic locations, and we calculated the arithmetic mean of daily monitoring data of meteorological variables (including temperature, relative humidity, air pressure, rainfall and sunshine hours) at each city/station to represent their climatic differences. We collected the city-specific social characteristics from the China city statistical yearbook (Chen, 2009–2014), including demographic variables (population density and population increase rate), economic variables (GDP per person and GDP increase), health resources (licensed physicians and hospital beds per 1000 persons), traffic (total travel passengers a year) and number of elementary school students per 1000 persons. Besides, an indicator variable based on the national standard of meteorological and geographic division (China Meteorological Administration, 2006) was also used to group the 143 cities into eight regions.

2.2. Statistical analysis

We implemented a two-stage multisite time series analysis to first obtain the city-specific estimates of temperature-HFMD relationship, and then to pool the multicity estimates and study the heterogeneity.

2.2.1. First-stage analysis

In the first-stage analysis, we fitted a common time series regression (TSR) (Peng and Dominici, 2008) to each of the 143 cities to relate the daily series of HFMD counts and mean temperature. Given that multiple previous studies suggest that the temperature-HFMD relationship can be nonlinear and also their association can be delayed because of the incubation period of infectious disease, we incorporated distributed lag nonlinear model (Gasparrini et al., 2010) into the TSR to allow for bi-dimensional exposure-lag-response relationship. We determined our specific model parameters based on prior knowledge, followed by a systematic sensitivity analysis to further evaluate our choices. See more technical details and discussions of our model choices and related sensitivity analysis in Appendix, Text A.1.

In summary, a quasi-Poisson regression model was adopted to allow for over dispersion. The bi-dimensional exposure-lag-response relationship between temperature and HFMD was described through a cross-basis function (Gasparrini et al., 2010), using natural cubic splines with 5 degrees of freedom (df) for the exposure-response relationship and natural cubic splines with 4 df for the lag-response relationship. The lag range of 4 to 14 days was used to represent the lag structure of temperature-HFMD relationship. The start lag and the lag interval were informed by the median incubation period of HFMD infections (4 days) (Ministry of Health of China, 2009) and a preliminary analysis (see Appendix, Text A.1, Section 4), respectively. To control for the unmeasured time-varying...
confounding, we used the natural cubic splines of calendar time with 8 df per year to remove the long-term trends and seasonality. To control for the measured time-varying confounding, we incorporated the exponentially weighted moving average of relative humidity, air pressure, rainfall and sunshine hours in the same lag range of temperature. We also adjusted for the effect of day of week (DOW) and holidays (including the vacations for elementary school and national public holidays) as indicator variables. To account for autocorrelation in the residuals, we included the autoregressive terms of HFMD daily counts at lag 1 and 2 into the model based on the autocorrelation plot of residuals. The autoregressive terms were incorporated on the logarithm scale to better match the mechanism of infectious disease transmission (Imai et al., 2015).

2.2.2. Second-stage analysis

In the second-stage analysis, we meta-analyzed estimates of the exposure-lag-response association reduced to the unidimensional overall cumulative exposure-response by the application of multivariate meta-regression (Gasparrini and Armstrong, 2013; Gasparrini et al., 2012). To pool the exposure-response relationship, the exposure (i.e. temperature) should be distributed in a similar range in all sites, otherwise a common analysis will leave some parameters inestimable (Gasparrini et al., 2012). However, in our study the temperature ranges vary widely across cities. To address above issue, we adopted two separate approaches for different purposes.

In the first approach, we adopted a relative scale measurement of temperature by transforming temperatures to the related city-specific percentile, so that we can unify the temperature ranges across cities. Our main purpose is to combine all the city-specific estimates under the same model and provide us a better opportunity to capture the potential effect modifiers. We first fitted a multivariate meta-regression model with intercept only allowing for heterogeneity modelled through random effects (denote as intercept-only model). Then, we ran a single meta-predictor analysis by incorporating city-specific characteristics into the model separately (denote as single meta-predictor models) and compared it to the intercept-only model, in which we allowed the heterogeneity to be partly explained by meta-variables and modelled as fixed effects. Because different meta-predictors can be correlated with each other, we further ran a forward stepwise analysis to identify the optimum subset of meta-predictors.

To avoid the potential distortion of the above percentile-based approach, we also adopted another approach based on the absolute temperature measurement. In the second approach, we grouped the 143 cities into eight regions so that the temperature ranges can be similar within the subgroup. Our main purpose is to obtain the region-specific estimates of temperature-HFMD relationship while retaining the original measurement of temperature, which may be more interesting to public health practitioners. Because the city-specific characteristics were also similar after grouping, we pooled the city-specific estimates by regions without incorporating meta-predictors except intercept. The region-specific estimates were further combined with geographic maps for better interpretation. Although the second approach is limited in identifying effect modifiers directly, the indicator of regions can be seen as a categorized proxy variable of potential effect modifiers. Thus we compared the pooled estimates of temperature-HFMD relationship and the distributions of related effect modifiers between regions as a verification for the first approach.

For the second-stage analysis, we used the maximum likelihood estimation to obtain estimates and a multivariate extension of likelihood ratio (LR) test to test the significance of meta-predictors and differences between models (Gasparrini et al., 2012). Akaike information criterion (AIC) was used to measure the goodness of model fits. The residual heterogeneity was measured and tested by the multivariate extension of I² statistics and Cochran Q test (Gasparrini et al., 2012).

We did all statistical analysis with R software (version 3.2.3) using the packages dlm and mvmeta. The geographic maps were made by ArcGIS software (version 10.2.1, authorization number: EFL734321752).

3. Results

From 2009 to 2014, a total of 3,060,450 clinical cases of HFMD under 12 years of age were collected in the 143 cities of mainland China. Our study covered the majority of big cities in mainland China with the geographic region distributed from latitude 18.1° to 50.2° north, and longitude 4.5° to 130.6° east (Fig. 1). The western part is the least urbanized and sparsely populated area in China, thus only few data obtained from that area. The disease burden of HFMD (measured as the total number of clinical cases during our study period) varied geographically, with most cases occurring in densely populated large cities (Fig. 1). Shenzhen, Beijing, and Guangzhou were the top 3 cities in terms of the total number of HFMD cases reported. See Appendix, Table A.1 for the full lists of cities included and Table A.2 for the summary statistics of the city-specific characteristics.

Based on the relative scale measurement of temperature, the overall pooled estimates (i.e. intercept-only model) suggested a nonlinear relationship between temperature and HFMD with an approximately inverted V shape (Fig. 2a). We found a gradual increase in risk of HFMD until it peaked at 91th percentile of temperature with reference to 50th percentile (RR = 1.30, 95% CI: 1.23–1.37). Afterward, there was suggestive evidence of a dropping down of risk at extremely hot temperatures. Although all the cities were analyzed by a common time series model, the city-specific estimates still exhibited substantial variability (Fig. 2a). The residual heterogeneity indicated that 68.5% of the variation was attributable to true differences across cities (p-value of Q test < 0.001) (Table 1).

The single meta-predictor models showed that the geographic and climatic characteristics could explain part of the heterogeneity, whereas the social characteristics seemed to have no significant modification effects, except a borderline impact of economic variables (Table 1). Similar modification effects were found between temperature, relative humidity, sunshine hours, latitude and rainfall, so that did that between air pressure and altitude, mainly because they had similar geographic distributions and were highly correlated (see Appendix, Figs. A.1 and A.2 and Table A.3, which compared the results of different meta-predictors). For the sake of simplicity, we only displayed the modification effects of rainfall (p-value of LR test < 0.001) and altitude (p-value = 0.008) (Table 1) because they have the largest impact in their own category and have a more sensible interpretation. Rainfall had the best ability to explain the heterogeneity with the related I² statistic dropping from 68.5% (Intercept-only model) to 66.5% (Table 1). We found that rainfall could strongly elevate the association between temperature and HFMD, especially at hot temperatures (Fig. 2b). For altitude, we found that the temperature-HFMD relationship at hot temperatures changed from an inverted V shape to an approximately straight line by comparing low and high altitude (Fig. 2c). By incorporating both rainfall and altitude into the model, we could decrease the residual heterogeneity to 66.1% (p-value < 0.001) (Table 1).

The region-specific analysis can further confirm the modification effects of rainfall and altitude (Fig. 3). First, we found an upward trend of the temperature-HFMD relationship from northwest to southeast, with nearly null association in Inner Mongolia region, Northwestern and Northern China (Fig. 3a–b). The spatial variation of the temperature-HFMD relationship was highly in agreement with the geographic distribution of rainfall (Fig. 3a–c). Besides, we found the nonlinear behavior of temperature-HFMD curves can be explained by the distribution of accumulated rainfall at different temperatures as well (Fig. 3b and d). The turning points of temperature-HFMD curves were very close to those temperature points where rainfall changed rapidly, and the temperature-HFMD relationship elevated with the rising of rainfall. The exceptions were
found in Northeast, Southwest and Southern China, where the risk of HFMD went up continually with increasing of temperature, although substantial drop of rainfall was seen at extremely hot temperatures (Fig. 3b and d). In contrast, an approximately inverted V shape were estimated in Huang-Huai-Yangtze river basin and Jiangnan region. As the single meta-predictor model suggested, we found altitudes might play a role in explaining the discrepancy. In Huang-Huai-Yangtze river basin and Jiangnan region, the distribution of altitudes is positively skewed to zero (Fig. 3d) with plain as the dominant terrain (Fig. 3c) (most areas belong to the alluvial plain created by Huang, Huai and Yangtze rivers). Whereas, in the other three regions, the altitudes are distributed around a relatively high mean value (Fig. 3d) with mountains or hills as the dominant terrain (Fig. 3c). By applying region-specific intercept-only models, the residual heterogeneity varied from 41.5% to 66.4% with p-value ranging from <0.001 to 0.008 (Table 2).

4. Discussion

In this paper, we conducted a multisite two-stage time series analysis including 143 cities in mainland China to examine the relationship between temperature and HFMD and related effect modifiers. As some previous studies suggested, we found that the surveillance data could be better explained by a nonlinear relationship between temperature and HFMD. The nonlinear behavior of the temperature-HFMD relationship implies that the impact of temperature on HFMD may involve with
HFMD can be transmitted either by exposure to infectious individuals or contaminated environmental reservoirs (Wang et al., 2011). It is believed that temperature can affect the trans-infectious individuals or contaminated environmental reservoirs. HFMD can be transmitted either by exposure to infectious individuals or contaminated environmental reservoirs. Multivariate meta-regression models for meta-predictors.

Table 1

<table>
<thead>
<tr>
<th>Meta-predictors</th>
<th>LR test Stat</th>
<th>df</th>
<th>p</th>
<th>AIC</th>
<th>Cochran Q test Stat</th>
<th>df</th>
<th>p</th>
<th>F (%)</th>
</tr>
</thead>
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<td></td>
<td></td>
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<td></td>
</tr>
<tr>
<td>Intercept only</td>
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<td>-</td>
<td>-</td>
<td>527.9</td>
<td>2253.3</td>
<td>710</td>
<td>&lt;0.001</td>
<td>68.5</td>
</tr>
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<td>Single meta-predictor model</td>
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<td></td>
<td></td>
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<tr>
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<td>514.8</td>
<td>2136.7</td>
<td>705</td>
<td>&lt;0.001</td>
<td>67.0</td>
</tr>
<tr>
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<td>2217.7</td>
<td>705</td>
<td>&lt;0.001</td>
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<td>0.006</td>
<td>522.4</td>
<td>2180.3</td>
<td>705</td>
<td>&lt;0.001</td>
<td>67.7</td>
</tr>
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<td>2130.4</td>
<td>705</td>
<td>&lt;0.001</td>
<td>66.9</td>
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<td>2140.0</td>
<td>705</td>
<td>&lt;0.001</td>
<td>67.1</td>
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<td>Air pressure</td>
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<td>2175.5</td>
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<td>GDP per person</td>
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<td>0.001</td>
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<td>Rainfall + altitude</td>
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<td>10</td>
<td>&lt;0.001</td>
<td>501.2</td>
<td>2065.1</td>
<td>700</td>
<td>&lt;0.001</td>
<td>66.1</td>
</tr>
</tbody>
</table>

All models were based on the relative scale measurement of temperature with reference at 50th percentile of temperature.

4 LR test was used to test the significance of meta-predictors with the Intercept-only model as reference.

b Cochran Q test was used to test the significance of residual heterogeneity with the null hypothesis as no heterogeneity.

complex mechanisms. HFMD can be transmitted either by exposure to infectious individuals or contaminated environmental reservoirs (Wang et al., 2011). It is believed that temperature can affect the transmission of HFMD. Previously proposed theories mainly fall into two categories, which have opposite impacts on the transmission of HFMD. Previously proposed theories mainly fall into two categories, which have opposite impacts on the transmission of HFMD. Recently, extremely hot temperatures cannot be seen in areas where the natural reservoirs of enterovirus, such as providing more shelters to keep water from evaporating and keep the natural reservoirs can be attributable to its impact on the enterovirus survival. Water environment is known as the main natural reservoir for enterovirus (Rajtar et al., 2008). In the water environment, enterovirus is able to tolerate various factors leading to virus inactivation, such as temperature, salinity, pH and etc. (Saló and Cliver, 1976). By providing water in the environment, rainfall may directly weaken the negative impact of temperature (i.e. virus inactivation) so that its positive impact (i.e. increasing contacts) can hold a leading position. In the contrary, we would expect the temperature-HFMD relationship decline if the rainfall dropped. It is interesting to note that the decrease of the temperature-HFMD relationship with the dropping of rainfall at extremely hot temperatures cannot be seen in areas where the terrain was dominated by mountains or hills. One possible reason might be that mountain or hills have a better ability to protect the natural reservoirs of enterovirus, such as providing more shelters to keep water from evaporating and keep the natural reservoirs from being exposure to the ultraviolet radiation. Therefore, the drop of rainfall may have less impact in those areas. However, further studies are needed to verify this hypothesis.

In our study, social characteristics were not significant in explaining the heterogeneity. By contrast, a recent similar study in Shandong province (China) including 17 cities (Zhu et al., 2016) suggested that number of healthcare institutions and household income could modify the temperature-HFMD relationship (geographic and climatic variables).
were not considered in their study). However, the proportion of heterogeneity they could explain was limited, with the related $I^2$ decreasing from 98.31% to 98.09% and 98.07%, respectively. Although we also found a borderline impact of GDP, the modification effects of social characteristics were negligible compared to that of geographic and climatic variables. Another study in Guangdong province (China) including 8 cities (Guo et al., 2016) agrees with our conclusions. They found that the city’s latitude and longitude were the most two important effect modifiers.

It is worth noting that there is still substantial heterogeneity that cannot be explained by the identified effect modifiers. The unexplained heterogeneity can be attributable to several reasons. First, the way how the city-specific characteristics were modelled may be not sufficient to fully represent their modification effects. Taking rainfall as example, both the mean and distributions of rainfall may have impact on the temperature-HFMD curve. However, we only incorporated the city-specific mean of rainfall into the meta-model. Second, there might exist some other important effect modifiers that we failed to take into account. City-specific variables like vegetation coverage, features of soil, local customs, public-health intervention, differences in data quality and etc. may have the potential to explain some part of heterogeneity, but we do not have the related information. Third, the relative scale analysis can induce heterogeneity by itself because various temperature ranges were forced to be on the same scale. A comparative study (Gasparrini et al., 2012) showed that, given the identical data and meta-predictor, the decrease of residual heterogeneity was much higher in the absolute scale analysis than that in the relative scale analysis. However, our findings can still explain the major discrepancies seen in previous single-site studies.

This study has three main limitations. The first one is to do with the intrinsic nature of time series analysis and ecological study. It should always bear in mind that what we really captured is the short-term associations at the population level before any further inference is made. The second limitation is related to the data quality. The weaknesses of surveillance data of HFMD in mainland China have been described elsewhere (Xing et al., 2014). The most relevant one is the potential bias caused by under-reporting. However, because time series analysis used its own previous observations as reference and removed the long-term trends and seasonality, the impact of under-reporting bias should be limited. The third limitation is to do with the spatial correlation. Spatial correlation is normally an issue which needs to be considered in pooling the multistie estimates (Peng and Dominici, 2008). In the context of pooling nonlinear relationship, incorporation of the spatial correlation will increase the complexity of models dramatically. Related methodologies are still under development which is far beyond the scope of this study. However, we believe that the spatial correlation may not have a significant impact on our conclusions for three main reasons. First, the main consequence of spatial autocorrelation is to bias the variances rather than the estimators (Dubin, 1998). Thus, we believe that the pooled estimates of temperature-HFMD relationship are still valid. Besides, for the identified effect modifiers, their $p$ values of LR test are far away from the significant level. So, it is very unlikely that our conclusions will change substantially after the incorporation of spatial correlation. Second, the identified effect modifiers can be confirmed by both the overall relative scale analysis and the region-specific absolute analysis, which implies our conclusions are robust. Third, because the meta-predictors have also shown spatial correlation, therefore we expect that the spatial correlations can be partly explained by the meta-predictors.

5. Conclusions

In conclusion, our study provides estimates of temperature-HFMD relationship based on a large dataset including 143 cities of mainland China. We found the temperature-HFMD relationships varied from region to region. Rainfall and altitude may play an important role in modifying the temperature-HFMD relationship. Our findings can help deepen the understanding of how meteorological variables affect the transmission of HFMD. Furthermore, this evidence can provide implications for the related public-health decision, such as the establishment of weather-based disease early warning systems.

Conflict of interest

The authors declare that they have no conflict of interest.

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Appendix A. Supplementary data

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