# **Analysis of Spatiotemporal Dynamics** of Respiratory Syncytial Virus in Japan

Jingyi Liang, Harish Nair, Saturnino Luz, You Li

Usher Institute, The University of Edinburgh



### BACKGROUND

Respiratory syncytial virus (RSV) is the most common pathogen identified in lower respiratory tract infection in infants [1]. It poses a substantial burden of disease globally among children under five and elders. The traits of RSV activity are highly correlated with geographical location, with seasonal patterns varying significantly in different regions worldwide. The peak season of RSV occurs during autumn and winter in temperate regions and during rainy seasons in tropical regions. In Japan, RSV infection generally occurs during the autumn and winter.

The research intends to investigate the spatiotemporal patterns of RSV epidemics and identify climate drivers influencing RSV epidemics in Japan.



#### Figure 2. Time-series pattern of RSV cases in Japan during 2013-2019

Table 2. Pooled results of multivariate models for 47 prefectures in Japan

Meteorological Factor	Estimated Coefficients	95% CI	p-value	Heterogeneity (p-value)	0.2
Visibility	0.0546	[0.0396; 0.0697]	< 0.0001	< 0.0001	0.0 timation
Relative Humidity	0.0181	[0.0134; 0.0228]	< 0.0001	< 0.0001	<sup>ω</sup> -0.2
Average Temperature	-0.0238	[-0.0326; -0.0149]	< 0.0001	< 0.0001	-0.4
Precipitation	-0.0241	[-0.0435; -0.0047]	0.0161	0.2067	Relative IT Average Territy With Pr
Wind Speed	-0.0022	[-0.0164; 0.0120]	0.7562	< 0.0001	<b>Figure 4.</b> Distribution of associations prefecture-level models in Japan

### RESULTS



Figure 3. Spatial distribution of RSV cases in Japan during 2013-2019

### **OBJECTIVES**

Investigate spatiotemporal patterns of RSV epidemics in Japan

Identify the climate drivers that influence **RSV** epidemics in Japan

Assess the geographic distribution of such climate influences in Japan

Forecast the RSV epidemics in Tokyo, Japan

## **METHODS**





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Figure 5. Maps of relationships between meteorological factors and RSV cases in Japan during 2013-2019 
 Table 3. Forecasting performance

	N	lachine Learning Models	RMSE				
Autoregressive Integrated Moving Average (ARIMA(1,1,0)(0,1,1)[52])							
1D-Convolution and Long-Short Term Memory Network (Conv1D-LSTM)							
	Bi-directiona	al Recurrent Neural Network (BRNN)	59.87				
800 -	RSV Case Prediction by autoregressive integrated moving averag Training Data Validation Data Prediction Data	RSV Case Prediction by 1D Convolutional Long Short Term Memory Network RSV Case Prediction by Bi-direction 800 Actual Data Model Fitted Data 700 Prediction Data 600 Fitted Data	onal Recurrent Neural Networ				

Figure 1. Flowchart of the methodology

#### **Mixed-effect Generalized Linear Model**

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$$ln(E(Y_{ijt})) = \alpha_i + b_{ij} + c_{ij(t)} + \beta_{RH}X_{RH(ijt)} + \beta_{AT}X_{AT(ijt)} +$$

 $\beta_V X_{V(ijt)} + \beta_P X_{P(ijt)} + \beta_{WS} X_{WS(ijt)} + \varepsilon_{ijt}, \varepsilon_{ijt} \sim AR_1(\rho)$ 

Where  $Y_{iit} \sim Negative Binomial Distribution$ , is the number of RSV-confirmed cases in prefecture i, year j and week t,

 $\alpha_i$  is the overall mean of prefecture *i*,

 $b_{ij} \sim N(0, \delta_b^2)$  is the random main effect of year j of prefecture i,

 $c_{ii(t)} \sim N(0, \delta_c^2)$  is the random main effect of week t at year j of prefecture i,  $\beta_k$  is the fixed main effect of the meteorological factor k,

 $\varepsilon_{ijt} \sim N(0, \delta_e^2)$  is the error term, follows the stationary auto regressive

 $AR(1) \sim cov(\varepsilon_{ijt}, \varepsilon_{ijt*}).$ 



Figure 6. Forecasting plots of machine learning models of RSV cases in Tokyo, Japan

### CONCLUSION

Our research indicates no apparent spatial pattern in RSV cases in Japan from 2013 to 2019. Meteorological factors exhibited heterogeneous impacts on RSV transmission across different prefectures, resulting in evident spatial clustering effects in specific associations. Our forecasting analysis demonstrated that BRNNs surpassed both ARIMA and LSTM models in predictive accuracy. This highlights the substantial promise of BRNNs for anticipatory modelling of future RSV epidemics.

#### **REFERENCES.**

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[2] Li, Y., Wang, X., Cong, B., Deng, S., Feikin, D. R., & Nair, H. (2022). Understanding the potential drivers for respiratory syncytial virus rebound during the coronavirus disease 2019 pandemic. The Journal of Infectious Diseases, 225(6), 957–964. https://doi.org/10.1093/infdis/jiab606