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Multi-stream data-driven forecasting of influenza activity and associated hospital admission burden: an implication for impact assessment of COVID-19 pandemic on 2019/20 winter influenza season in Hong Kong



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The authors report no potential conflicts of interest

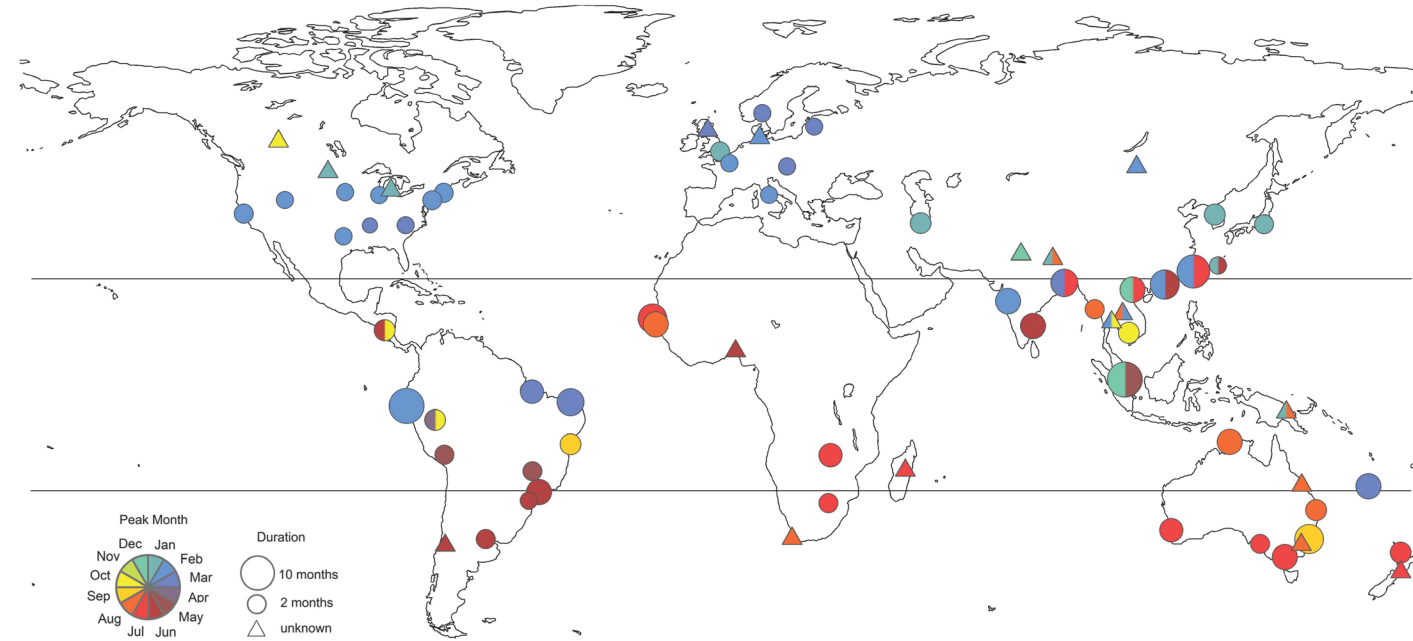
Health Research Symposium
November 26, 2024

Background & Motivation

Influenza in Subtropics vs Temperate

- Influenza dynamics and seasonality in **temperate** Vs **tropical and subtropical** locations (Tamerius et al., 2011; Azziz et al., 2012; Tan et al., 2014)
 - Winter vs year-round
 - Single and multiple peaks

Fig. 1 Bloom-Feshbach et al. (2013): Global map of influenza peak timing and epidemic duration (n = 77 locations).



Influenza in Subtropics vs Temperate

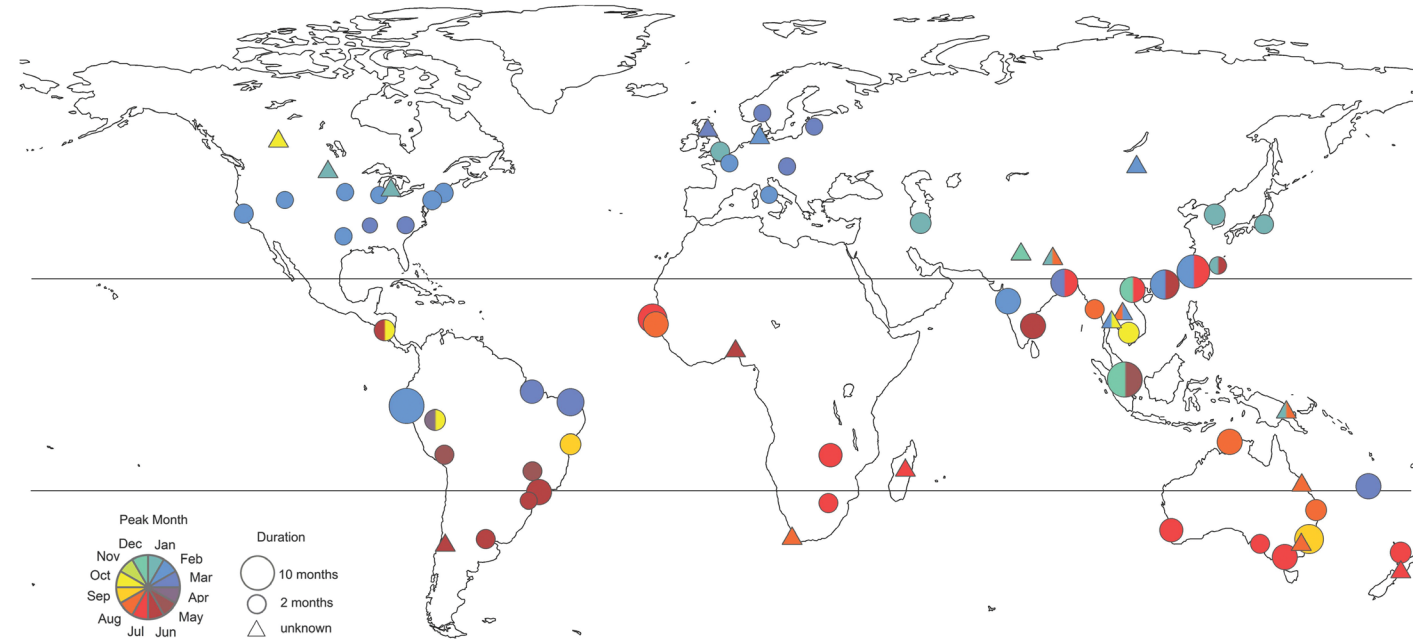
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- Various explanations have been put forward for such variations including.

Climatic or Meteorological effects: Temperature and humidity on the virus (Lowen et al., 2007; Shaman et al., 2009; Tamerius et al., 2013; te Beest et al., 2013)

Biological effects: Host immunity during winter (Dowell, 2001; Lipsitch, et al., 2009)

Social effects: Indoor crowding in winter (Lofgren et al., 2007), Holidays and School closures (Ferguson et al., 2006; Cowling et al., 2008; Wu et al., 2010)

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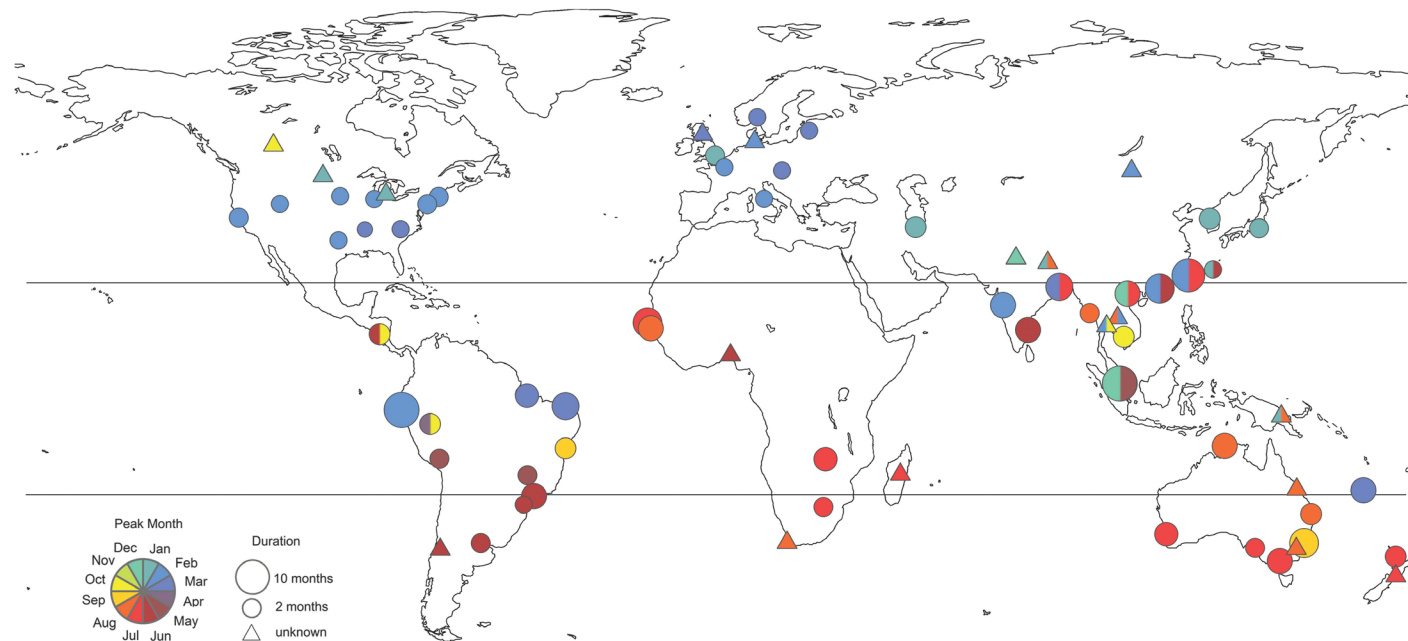
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- Where a tiny seasonal change in transmissibility by these drivers may cause a large sustained oscillation in incidence of influenza outbreaks (Dushoff et al,2004).

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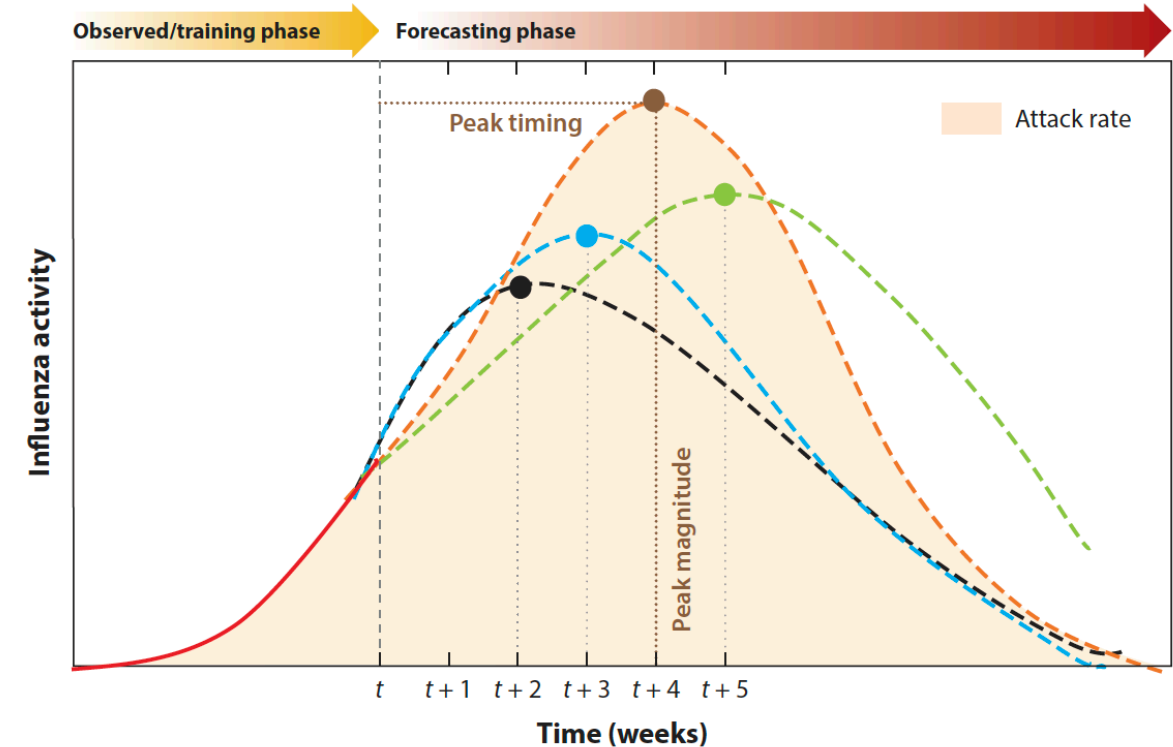
Objectives

Hong Kong is a subtropical location, having **year-round** influenza circulation with **multiple peaks**.

- To assess the impact of these drivers on influenza **transmissibility** and **seasonality** in Hong Kong
- To construct a statistical and mechanistic model based **predictive** frameworks using multi-stream data.
- To use these models to provide forecasts (short-term, medium-term and long-term) of influenza **outcomes**: activity/attack rate, peak timing and peak magnitude in subtropical city Hong Kong.

Fig. 2

Ali ST Ann. Rev. PH 2022



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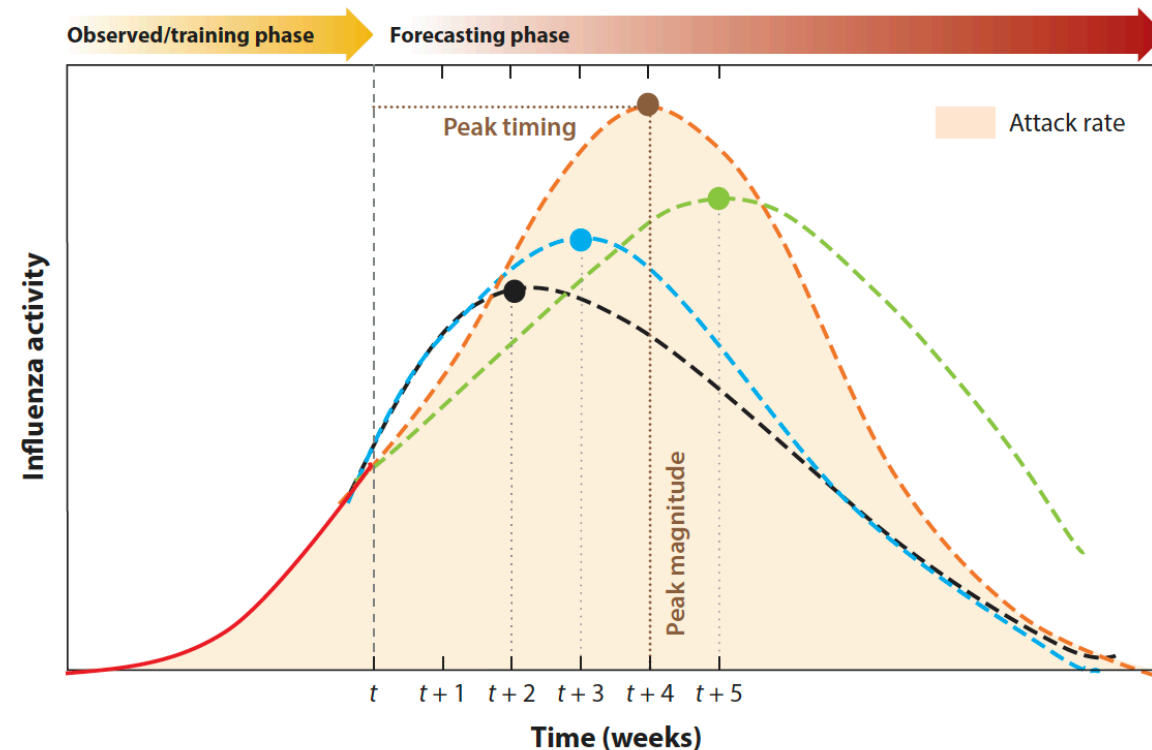
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Emergence of COVID-19 Pandemic

- To assess the impact of COVID-19 PHSMs on 2019/20 winter season in Hong Kong
 - Retrospective forecasting for influenza outcomes.
 - Associated hospital admission burden

Fig. 2

Ali ST Ann. Rev. PH 2022

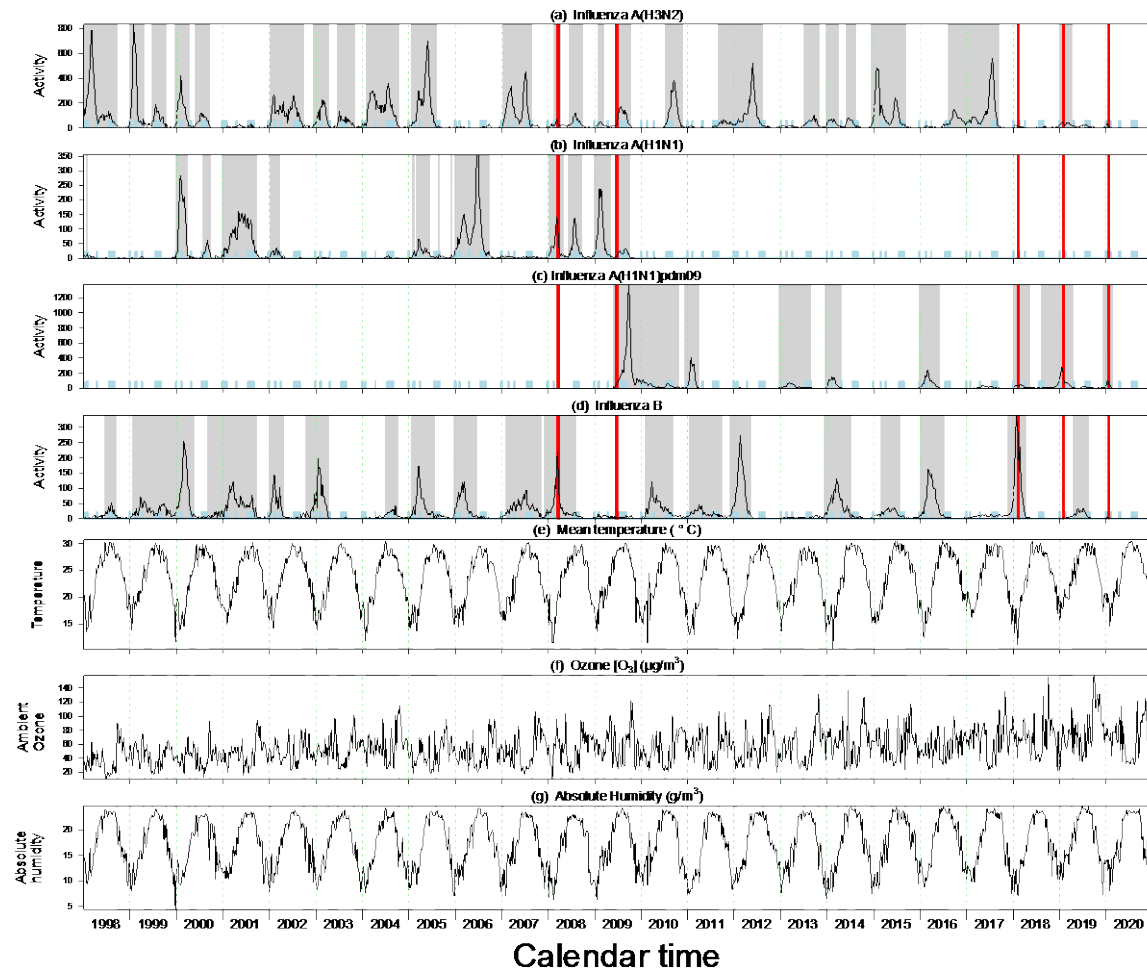


Materials & Methods

Influenza Activity : During 1998-2020

Fig. 3

Ali ST et al Sc Tot Envs 2022 and Lau YC et al PLoS Comp Bio 2024



– **ILI+ proxy** (in lines): (proportion of specimen tested **positive**) x (proportion of GP visits with **ILI**) [Wong JY et al., AJE 2013]. Grey shaded regions are identified epi-onset for influenza type and subtypes.

– Reactive school closure (**Red**) and holiday related school closure (small **Blue** bars).

– Extrinsic drivers (meteorological and environmental)

– **ILI+ proxy** $\rightarrow R_t$ [Cori et al., AJE 2013]

– $R_t \rightarrow \beta_t$ ($\beta_t = \frac{R_t}{S_t} \times \vartheta$ where, ϑ is recovery rate)

– Regression framework to identify the potential drivers and their form of association. [Ali ST et al., EID 2018]

Statistical modelling framework

– **Standard Generalized Linear Model (GLM)** with log link, $\ln(\lambda(t+k)) = \alpha_k \mathbf{B}(t-1) + \sum_{l=1}^L \beta_{k,l} y(t-l) + \sum_{j=1}^n \psi_{k,j}(t-1)$ where, ILI+ proxy $y(t) \sim$ negative binomial distribution with $\lambda(t+k)$ is the expected ILI+ proxy for the coming k week with $k \in \{0,1,2,3\}$ at week t .

Absolute Humidity: U-shaped form ($\psi_{k,j}(t) = \{\gamma_{k,1,j} C_j(t) + \gamma_{k,2,j} C_j^2(t)\}$)

Ozone: Non-linear power form ($\psi_{k,j}(t) = \{C_j(t)\}^{\gamma_{k,1,j}}$)

School closures: $\psi_{k,j}(t) = \begin{cases} 1, & (t) \text{ in regular week} \\ 1 - \varepsilon, & (t) \text{ in during the control} \end{cases}$

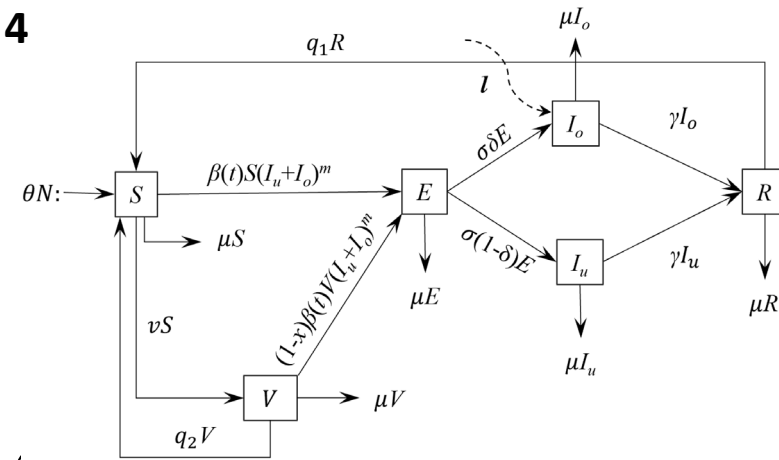
– *Evaluation (short-term, medium-term and long-term)*

- Outcomes
- Cross-validation
- RMSE, RMSLE, MAE, WIS

Mechanistic modelling framework

– *Compartmental Model Construction*

Fig. 4



$$\beta(t) = \beta_0 \left(1 + \beta_1 \sin\left(\frac{2\pi}{13}t + \phi\right) \right) \cdot \exp([a_1 q^2(t) + a_2 q(t)]) \cdot \left[\frac{-c}{T(t)} \right]^{\text{exp}} \cdot \exp(-cO_3(t)) d\Gamma$$

– *Parameters estimation: POMP, particle filtering*

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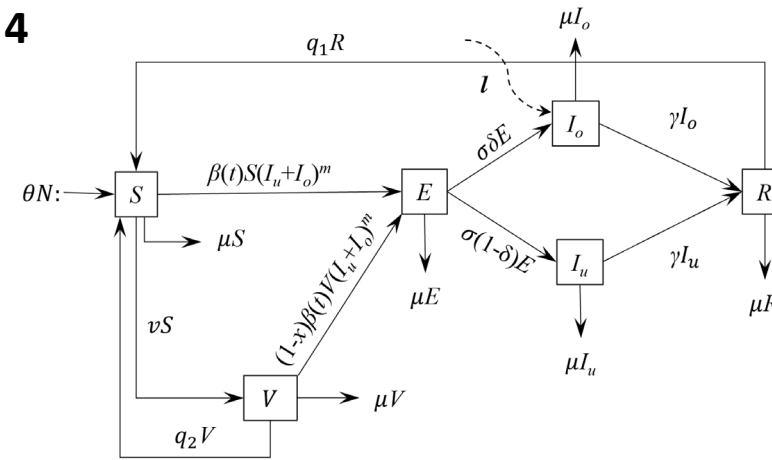
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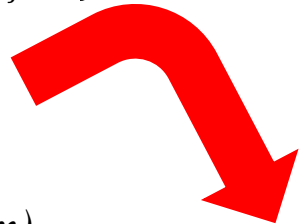
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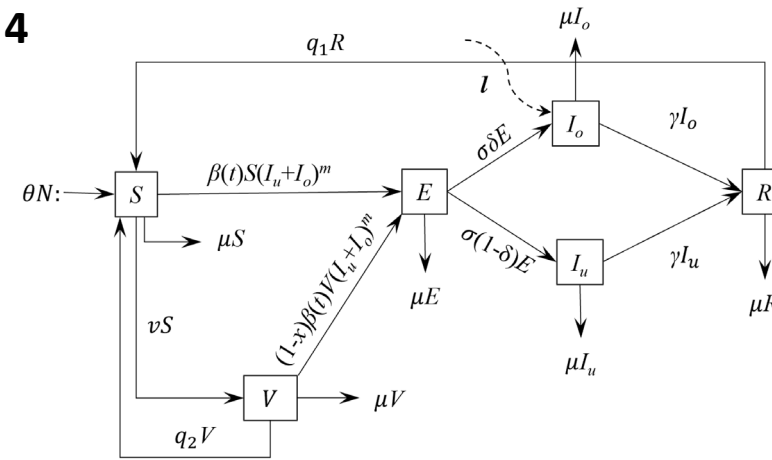
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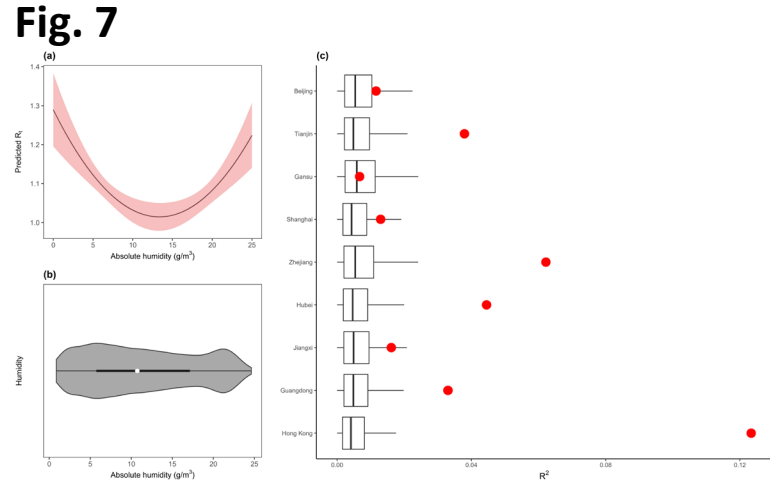
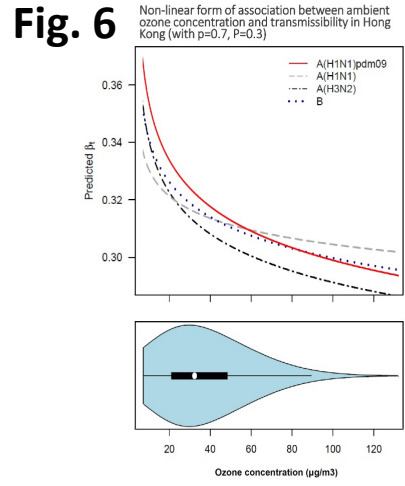
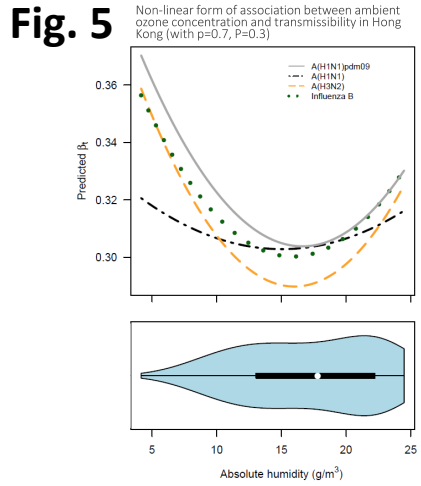


Impact assessment of COVID-19 PHSMs on influenza transmission

- Retrospective forecast
- Training data (2010 to 2019) for forecast (2020)
- Reduction in transmissibility, attack rate, peak magnitude and delay peak timing

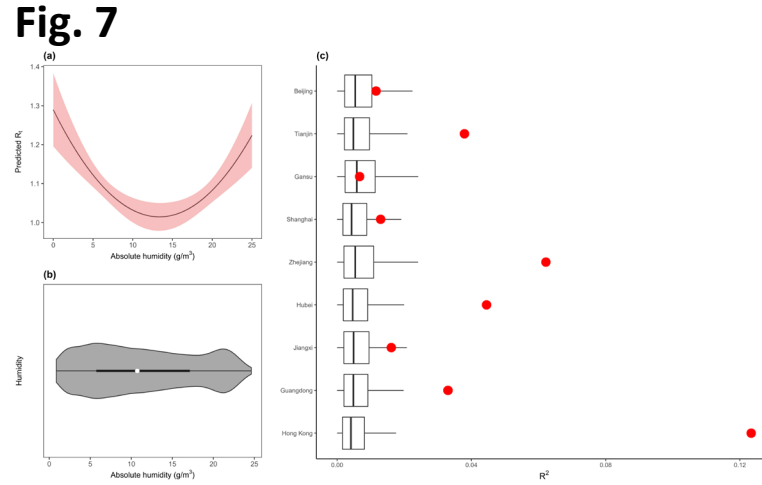
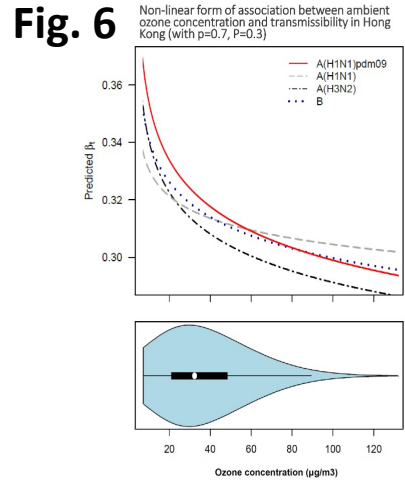
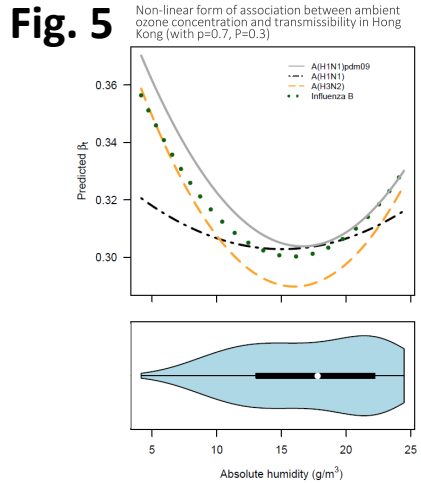
Results & Discussion

Impact of drivers on influenza transmissibility



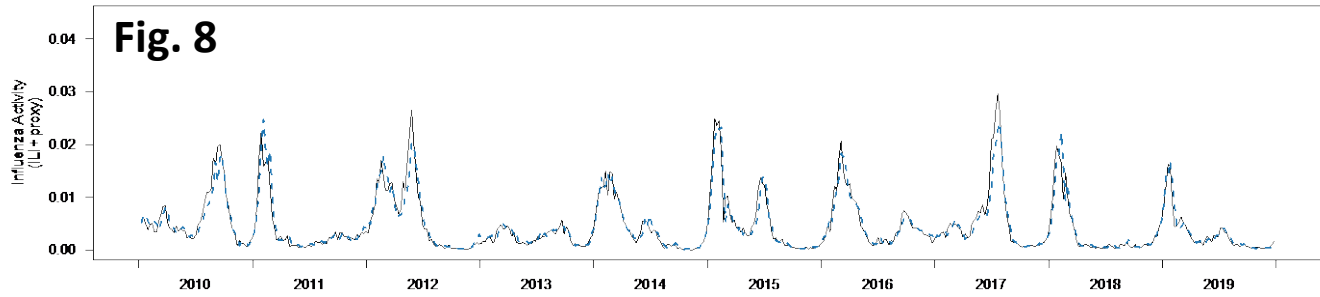
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Impact of drivers on influenza transmissibility

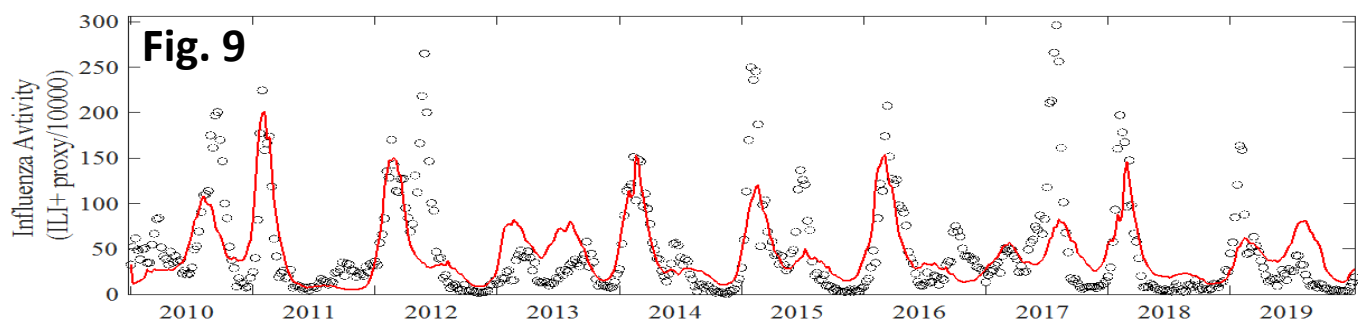


- Absolute humidity (U shape)
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Statistical and mechanistic model based prediction of influenza activity



- Both frameworks show comparable predictive performance
- Suggests some other potential drivers need to be included



Forecasting influenza activity in 2020 and assessing the impact of COVID-19 PHSMs

Fig. 10

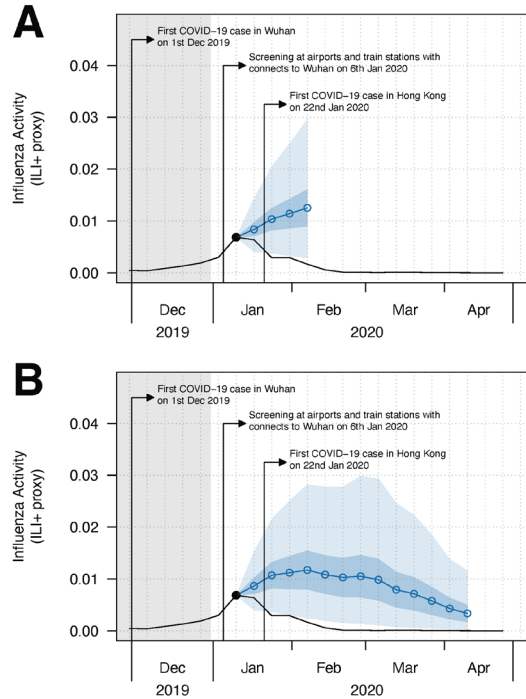
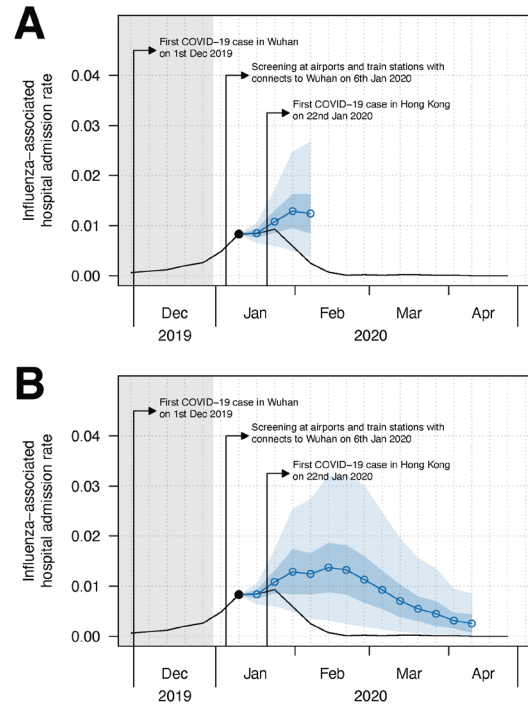


Fig. 11



– Short term (1-4 weeks), medium-term (13 weeks) and long-term (beyond a season)

– Influenza infection and hospital burden

– Peak for 2020 influenza winter-spring season could have peak in early February.

– COVID-19 PHSMs could reduce

➔ 44.6% (95% CrI: 38.6% - 51.9%) in transmissibility

➔ 75.5% (95% CI: 73.0% - 77.6%) in attack rate

➔ 41.5% (95% CI: 13.9%– 55.7%) peak magnitude.

➔ 63.1% (95% CI: 59.3% - 66.3%) in the admission rate during the winter-spring season in 2019/20

Forecasting influenza activity in 2020 and assessing the impact of COVID-19 PHSMs

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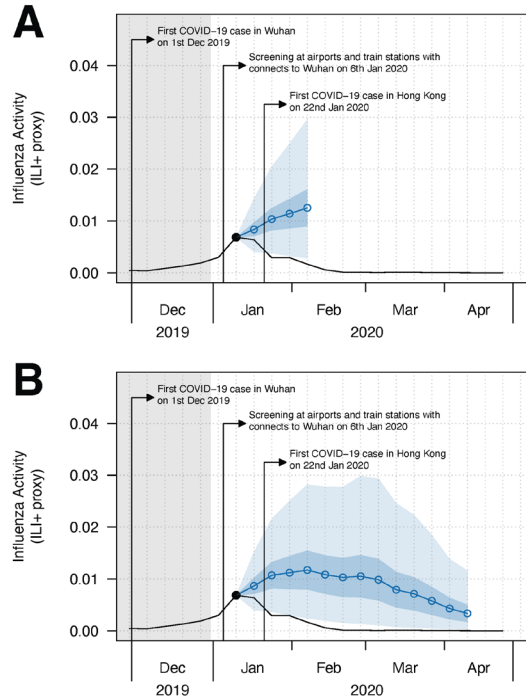


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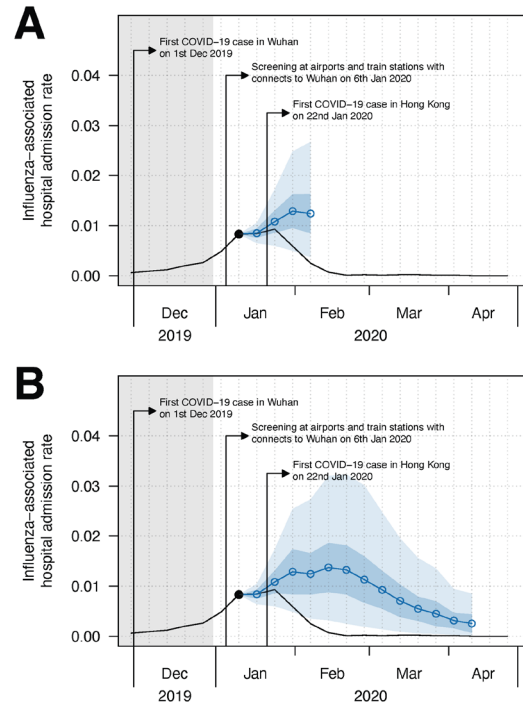
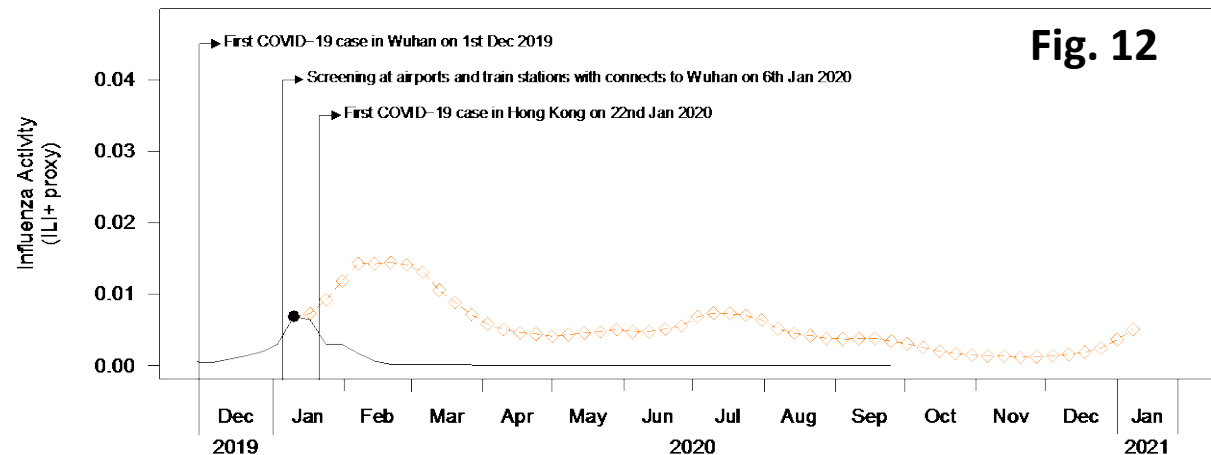


Fig. 12



– Short term (1-4 weeks), medium-term (13 weeks) and long-term (beyond a season)

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– Long term forecast suggested a peak in February, followed by a summer epidemic with lower magnitude

Forecasting influenza activity in 2020 and assessing the impact of COVID-19 PHSMs

Fig. 13

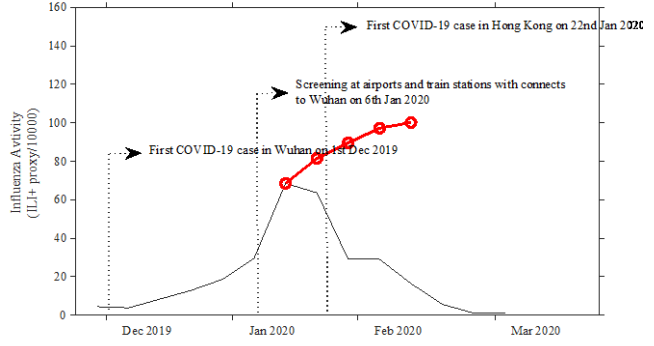
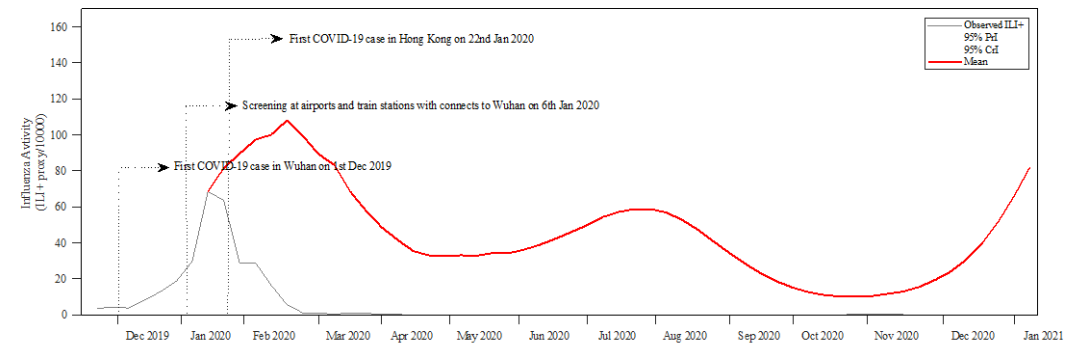


Fig. 14



- Mechanistic framework
- Comparable results for short-term and long-term

Forecasting influenza activity in 2020 and assessing the impact of COVID-19 PHSMs

Fig. 13

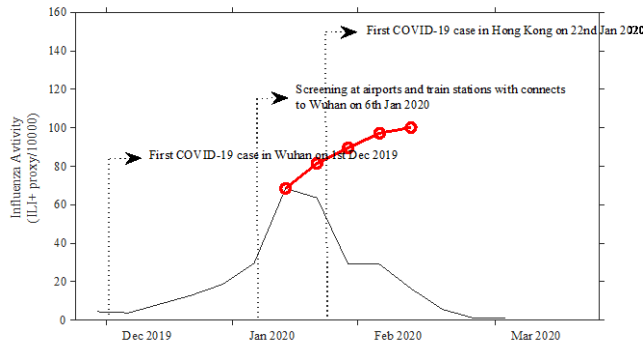
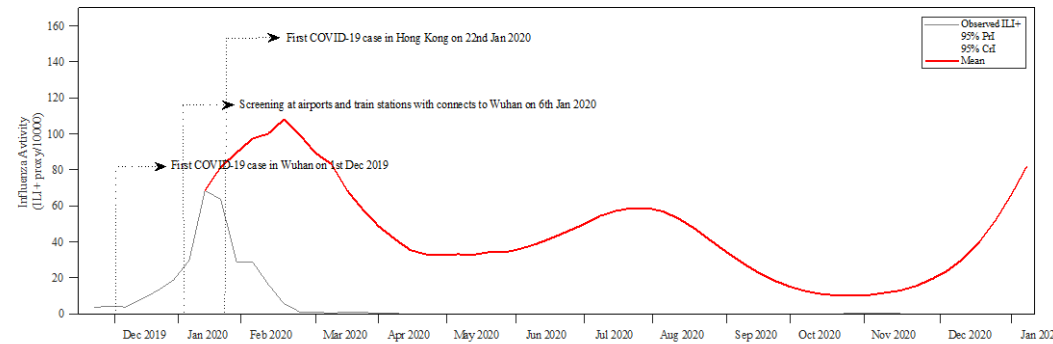


Fig. 14



- Mechanistic framework
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Conclusion

- Data-driven statistical frameworks to predict and forecast less regular dynamics of seasonal influenza and associated hospital admissions burden in Hong Kong
- To early detection of the influenza outbreak and enabled timely decision-making for the public health policymakers with better healthcare preparedness including stockpiling, implementation of better interventions (PHSMs) and vaccination scheme to mitigate the upcoming epidemics.
- Such forecasting frameworks also has the potential to quantify the direct/indirect impact of interventions for similar directly transmitted diseases (e.g. COVID-19 and influenza) on their associated burden of infections and hospitalization

Limitation and Future opportunities

- We have not considered **other drivers** into the model (population immunity, antigenic changes, importation risks etc.)
- Post-COVID-19 pandemic, interaction, co-existence, co-circulation of respiratory viruses

Acknowledgements

Health and Medical Research Fund (Ref. No. 18171202), Health Bureau, Government of the Hong Kong Special Administrative Region

Publications and Dissemination

1. Ali ST, Cowling BJ, Wong JY, Chen D, Shan S, Lau EHY, He D, Tian L, Li Z, Wu P; Influenza seasonality and its environmental driving factors in mainland China and Hong Kong, *Science of the Total Environment*, 2022, 818, 151724. [IF 8.00 (2021), rank 25/274 Environmental Sciences].
2. Ali ST, Cowling BJ; Influenza Virus: Tracking, Predicting and Forecasting. *Annual Review of Public Health*, 2021, 42:43-57. [IF 21.98 (2021), rank 4/203 Public Health, Environmental and Occupational Health (Science)]
3. Lau, YC, Shan S, Wang D, Chen D, Du Z, Lau EYC, He D, Tian L, Wu P, Cowling BJ, Ali ST[†]; Forecasting of Influenza Activity and Associated Hospital Admission Burden and Estimating the Impact of COVID-19 Pandemic on 2019/20 Winter Season in Hong Kong. *PLOS Computational Biology*, 2024. 20(7): e1012311. [IF 4.78 (2021), rank 3/20 Bioinformatics and computational Biology]

Results of the study were presented in international conferences including **Epidemics7** 2019, USA, **Epidemics8** 2021, Italy; and **Option XI** 2022, Belfast, UK.

References

- Ali ST, Cowling BJ, Lau EHY, Fang VJ and Leung GM; Mitigation of influenza B epidemic with school closures, Hong Kong, 2018. *Emerging Infectious Diseases* (2018); 24(11), 2071-2073.
- Bracher J, Ray EL, Gneiting T, Reich NG. Evaluating epidemic forecasts in an interval format. *PLoS Comput. Biol.* 2021; 17(2):e1008618.
- Shaman J, Karspeck A. Forecasting seasonal outbreaks of influenza. *Proc Natl Acad Sci U S A* 2012; **109**(50): 20425-30.
- Du X, King AA, Woods RJ, Pascual M. Evolution-informed forecasting of seasonal influenza A (H3N2). *Sci Transl Med* 2017; **9**(413).

Thank YOU!