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Impact of human mobility and weather conditions on Dengue mosquito abundance during the COVID-19 pandemic in Hong Kong

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ABSTRACT

Background: While *Aedes* mosquitoes, the Dengue vectors, are expected to expand due to climate change, the impact of human mobility on them is largely unclear. Changes in human mobility, such as staying at home during the pandemic, likely affect mosquito abundance.

Objectives: We aimed to assess the influence of human mobility on the abundance and extensiveness of *Aedes albopictus*, taking account of the nonlinear lagged effects of weather, during the COVID-19 pandemic in Hong Kong.

Methods: Google human mobility indices (including residential, parks, and workplaces) and weather conditions (total rainfall and mean temperature) along with *Aedes albopictus* abundance and extensiveness, monitored using Gravidtrap were collected between April 2020 and August 2022. Distributed lag non-linear models with mixed-effects models were used to explore their influence in three areas of Hong Kong.

Results: Time spent at home (i.e., residential mobility) was negatively associated with mosquito abundance. The model projected that if residential mobility in 2022 was returned to the pre-pandemic level, the mosquito abundance would increase by an average of 80.49 % compared to actual observation. The relative risk (RR) of mosquito abundance was associated with low rainfall (<50 mm) after 4.5 months, peaking at 1.73, compared with 300 mm. Heavy rainfall (>500 mm) within 3 months was also associated with a peak RR of 1.41. Warm conditions (21–30 °C, compared with 20 °C) were associated with a higher RR of 1.47 after half a month.

Discussion: Human mobility is a critical factor along with weather conditions in mosquito prediction, and a stay-at-home policy may be an effective intervention to control *Aedes albopictus*.

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1. Introduction

Dengue fever (DF) is one of the most widespread vector-borne diseases, with an estimated 390 million infections each year (Bhatt et al., 2013a). Along with climate change, human mobility has recently been identified as a critical factor in the spread of DF (Chen et al., 2022; Gibb et al., 2023). Since Dengue is transmitted by mosquitoes, these factors are likely to have an impact on mosquitoes as well. However, how human mobility influences the abundance of vectors is still unknown.

Hong Kong has faced an increased risk of DF outbreaks over the past few decades (Liu et al., 2019; Yuan et al., 2020), with *Aedes albopictus* identified as the primary vector. In response, Hong Kong has implemented a Gravidtrap system for vector surveillance since 2020. The Gravitrap was developed to capture the extensiveness and abundance of female *Aedes albopictus* (Lee et al., 2013). *Aedes albopictus* was found more frequently than *Aedes aegypti* in natural breeding sites and outdoor environments (Herath et al., 2022; Jin et al., 2023; Wijegunawardana et al., 2019). During the COVID-19 pandemic, changes in human mobility (Hu et al., 2021), such as staying at home, likely influenced mosquito behaviour and, consequently, their abundance.

While a warm condition has a known impact on mosquito development, breeding, survival, etc. (Reinhold et al., 2018), the effects of rainfall are diverse, with both heavier and lower rainfall being associated with increased DF risk. For example, rainfall was an important factor in mosquito growth and Dengue incidence (Bhatt et al., 2013b; Organization, 2023), but recent studies found that drought conditions were also associated with a higher risk of DF at long lead times of up to five months (Lowe et al., 2018, 2021). Similarly, springtime rainfall, which occurred a few months before seasonal DF outbreaks, appeared to be negatively associated with the risk of DF in Taiwan and Hong Kong (Yuan et al., 2019, 2020). Additionally, these previous studies suggested a varied relationship between hydroclimatic factors and DF with delay effects (Lowe et al., 2018, 2021; Yuan et al., 2019, 2020). However, whether these delay effects are linked to changes in mosquito abundance remains largely unknown.

Our study aimed to assess the influence of human mobility on the abundance and extensiveness of *Aedes albopictus*, taking account of the nonlinear lagged effects of total rainfall and mean temperature (Fig. 1). The results provided important insights for mosquito abundance prediction and control.

2. Methods

2.1. Weather data

Weather data in Hong Kong, including daily total rainfall and mean temperature, were collated from weather stations using records provided by the Hong Kong Observatory (Hong Kong Observatory). The study period spanned from April 2020 to August 2022, during which the data were divided into three regions (The Government of the Hong Kong Special Administrative Region, 2016): Hong Kong Island and Kowloon, New Territories East, and New Territories West (Table S1). We selected mean temperature and total rainfall for mosquito abundance prediction based on previous studies (Liu et al., 2019; Reinhold et al., 2018; Seidahmed & Eltahir, 2016). Monthly total rainfall and mean temperature (i.e., obtained by

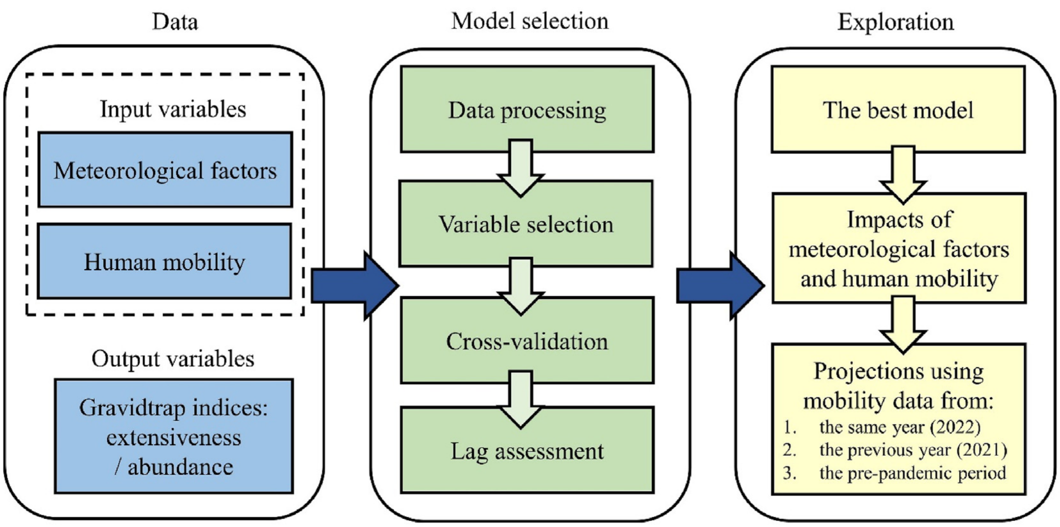

Fig. 1. Schematic flow for exploration of different factors in the mosquito extensiveness and abundance predictions. The Watanabe-Akaike information criterion (WAIC) was used for variable selection. The best model was determined after the results were cross-validated and compared with different lagged periods.

averaging the daily mean temperatures) were calculated from these daily measurements (Table S2). The weather factors for each region were the average values of selected weather stations within that region (Supplementary Methods).

2.2. Human mobility data

Three mobility indices, including ***residential***, ***parks***, and ***workplaces***, for Hong Kong were collected from Google to represent human behavioural changes and social distance measures in response to the COVID-19 pandemic during the study period (Google). Time spent in parks represents outdoor activity with a higher chance of mosquito contact. Moreover, both time spent at home and at work were likely to affect the risk of mosquito-transmitted diseases, according to a previous study (Phillips et al., 2023). On the other hand, we excluded human mobility in ***retail and recreation***, ***groceries and pharmacies***, and ***transit stations***, as these factors involve shorter time spent compared to that at home or work. All indices were computed relative to a baseline day. The baseline day is the median value for each corresponding day of the week during the five-week period between January 3 and February 6, 2020. The monthly human mobility index was calculated for model prediction (see Supplementary Methods).

2.3. Mosquito activity data

Mosquito activity data were provided by the Food and Environmental Hygiene Department (Food and Environmental Hygiene Department). The Hong Kong government has used Gravidtrap to replace Ovitrap since 2020 to monitor the activity of *Aedes albopictus*, the only Dengue mosquito species found in Hong Kong. In addition to the extensiveness (i.e., the distribution) of *Aedes albopictus*, the Gravitrap also monitored the abundance (i.e., the number) of mosquitoes. The mosquito Gravitrap surveillance measured two indices: The Area Density Index (ADI), defined as the number of mosquitoes captured in the traps (used to represent the abundance of *Aedes albopictus*); and the Area Gravidtrap Index (AGI), defined as the proportion of Gravidtraps that are found to have positive results in a specific area (used to represent the extensiveness of *Aedes albopictus*).

We calculated the abundance and extensiveness for each area during each month t. The index for each area was calculated as the average index for all Gravidtrap sites within that area. The average monthly mosquito extensiveness in area A is defined as:

$$\overline{AGI}^A(t) = \sum\nolimits_{m_i \in M^A(t)} \left(AGI^{m_i}(t)\right) \Big/ n_m^A(t) \tag{eq. 1}$$

where n_m^A represents the total number of mosquito monitoring sites in area A. AGI^{m_i} represents the AGI in the surveyed area m_i. $M^A = \{m_1, m_2, \dots, m_i\}$ is a collection of sites (surveyed areas), in which m_i represents each site in the area.

The monthly abundance $N^A(t)$ (per 1000 traps) in area A is defined as:

$$N^A(t) = \sum\nolimits_{m_i \in M^A(t)} \left(AGI^{m_i}(t) \cdot ADI^{m_i}(t) \cdot 1000\right) \Big/ n_m^A(t) \tag{eq. 2}$$

where $ADI^{m_i}(t)$ represents the mean ADI at the site m_i in month t.

2.4. Model development

We developed prediction models for mosquito abundance and extensiveness based on distributed-lagged non-linear models (DLNM) (Gasparrinia et al., 2010; Liyanage et al., 2022), which effectively capture non-linear and lagged effects. The model parameters were estimated within a bayesian hierarchical regression framework using integrated nested laplace approximation (INLA) (Martino and Riebler), which efficiently approximates posterior distributions and allows for incorporating random effects and hierarchical structures. This approach enables robust uncertainty quantification while addressing temporal and spatial dependencies in the data. For mosquito abundance prediction, we assumed the mosquito number per 1000 traps follows the negative binomial distribution and selected the log function as the link function. Let λ_t be the mosquito number per 1000 traps in the month t, such as:

$$\lambda_t \sim NB(u_t, \kappa)$$

where u_t is the distribution mean of λ_t at month t and κ is the overdispersion parameter in the negative binomial distribution. λ_t in area A can be measured by monthly mosquito abundance $N^A(t)$ (see eq. (2)). Then, the regression model to predict mosquito abundance was:

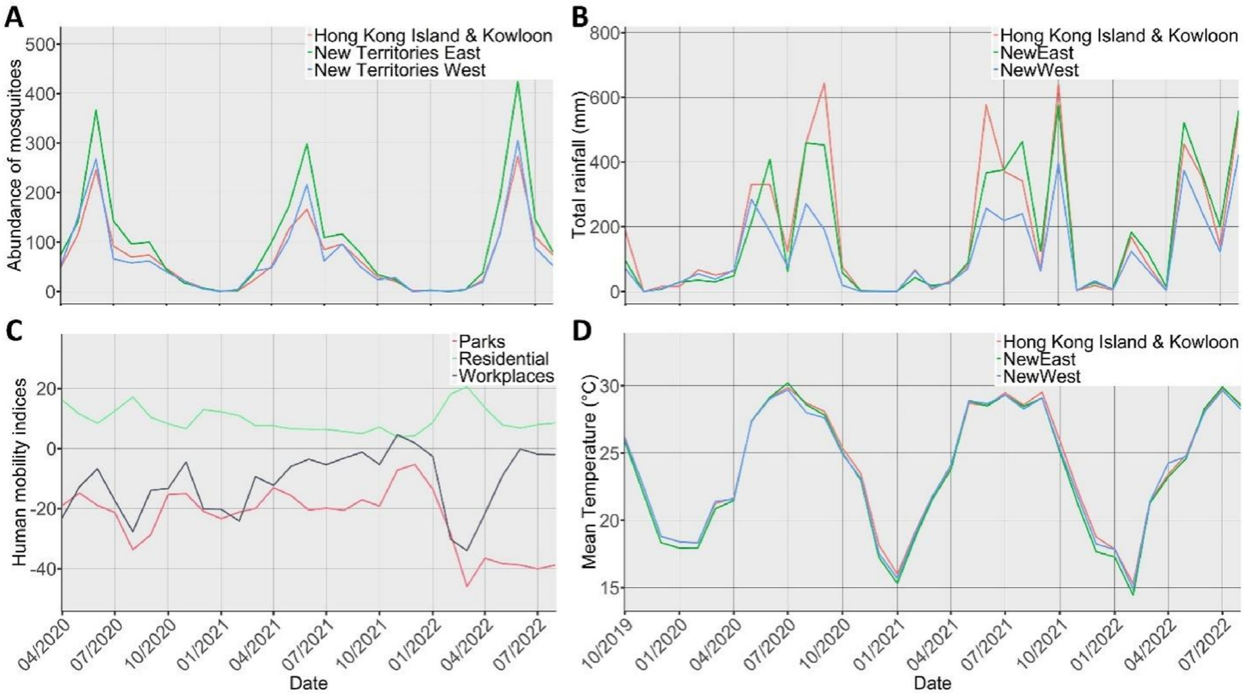

Fig. 2. Monthly changes in mosquito abundance and its predictors in Hong Kong. (A) Mosquito abundance; (B) Total rainfall; (C) Human mobility; (D) Mean temperature. In A, B, and D, red refers to Hong Kong Island and Kowloon; blue refers to New Territories East; and green refers to New Territories West.

$$\log(\lambda_t) = \beta + \gamma + S + f.w(R_t, l_1) + f.w(T_t, l_2) + m_t + \alpha \tag{eq. 3}$$

where $f.w(R_t, l_1)$ and $f.w(T_t, l_2)$ represent the nonlinear exposure-lag functions of total rainfall R_t from 0 to l_1 months and mean temperature T_t from 0 to l_2 months in t^{th} month, respectively; S is the area random effect to capture the spatial effect on mosquito abundance; γ is the monthly random effect to capture potential monthly fluctuations; β is the yearly random effect to capture potential yearly fluctuations; α is the intercept; and m_t is the human mobility index in one category (e.g., residential areas, workplaces, or parks) at t^{th} month.

In the mosquito extensiveness prediction, we assumed the number of positive traps follows the binomial distribution and selected the logit function as the link function. Let Y_t be the number of positive traps in the t^{th} month, following the binomial distribution with the total number of the traps (n_t), and the probability of a positive trap (p_t) in the t^{th} month, such as:

$$Y_t \sim B(n_t, p_t)$$

where p_t at each surveyed area A can be measured by $\overline{AGI}^A$ (see eq. (1)). n_t can be calculated as the product of the number of surveyed sites and the average number of traps per site. In Hong Kong, an average of 55 traps were placed in each selected site. Similarly, the regression model to predict mosquito extensiveness was:

$$\text{logit}(p_t) = \beta + \gamma + S + f.w(R_t, l_1) + f.w(T_t, l_2) + m_t + \alpha \tag{eq. 4}$$

2.5. Model selection criteria

To determine the best model (best-prediction model) among different combinations of predictors, in a two-stage selection approach, the Watanabe-Akaike information criterion (WAIC) was used in the first stage to select different sets of variables (candidate models) (Vehtari et al., 2017). Besides the yearly, monthly, and area random effects, variables include the lag effects of total rainfall and mean temperature and three human mobility indices (see Table S3). In the second stage, leave-one-out cross-validation (LOOCV) based on mean square error (MSE) was performed for the candidate models to compare the model's predictions to the observed data. In LOOCV, the observed data were divided into k parts (i.e., the total number of months), where k-1 parts were used as the training set, and the remaining part was used as the validation set. The procedure was repeated until every part (i.e., month) had been used for validation.

2.6. Comparison between mosquito abundance and extensiveness

For comparing the predictive performance among mosquito abundance and extensiveness, we used two standardised mosquito indices to unify the scales of different indices: the standardised abundance index (SAI) and the standardised extensiveness index (SEI). The SAI was:

$$SAI = \lambda / \sigma_{\lambda}$$

where λ and σ_{λ} represent mosquito abundance and standard deviation of mosquito abundance, respectively. Similarly, the SEI was:

$$SEI = p / \sigma_p$$

where p and σ_p represent mosquito extensiveness and standard deviation of mosquito extensiveness, respectively.

3. Results

3.1. Data analysis

In Hong Kong, mosquito abundance exhibited strong seasonal patterns, growing in the spring (March–May), peaking in the early summer (June or July), and remaining nearly at zero in the winter (December–February) (Fig. 2A). Among three predefined regions, New Territories East recorded higher mosquito abundance (i.e., the number of *Aedes albopictus*) than others. Mosquito extensiveness (i.e., the distribution of *Aedes albopictus*) had a similar pattern of variation to abundance (Figure S1 and Figure S2). Two standardised mosquito indices were proposed for mosquito abundance and extensiveness prediction (Fig. S3). During the study period, human mobility generally fluctuated at the beginning but showed rapid declines in parks and workplaces and a sharp increase in residential since January 2022. This rapid change reflected the behavioural changes and social distancing measures introduced during the COVID-19 Omicron wave (Fig. 2B).

The monthly total rainfall typically exceeded 300 mm during summer and early autumn (June–October) and was generally lower than that during winter and early spring (November–April) but varied substantially between regions and years. For example, in 2020–2021, Hong Kong Island and Kowloon had the most total rainfall, while New Territories West had the least (Fig. 2C). In 2022, all the regions experienced higher levels of total rainfall in February than the previous year. The monthly mean temperatures across these three regions was similar, with the highest at about 30 °C around July and the lowest at about 15 °C in January or February (Fig. 2D).

3.2. Model selection of mosquito abundance and extensiveness

After initial variable selection, a baseline model for mosquito abundance prediction (Model A; see Table 1) was obtained. The candidate models in mosquito abundance prediction (see eq. (3)) include Model A, Model A-M_p, Model A-M_w, and Model A-M_r. After incorporating human mobility in residential, the best model for abundance prediction (Model A-M_r) was obtained using LOOCV (Table 1). Moreover, the autocorrelation function of residuals demonstrated the independence of the residuals (Fig. S6), implying that autocorrelation of the mosquito abundance has been explained by the Model A-M_r. The best model for extensiveness prediction (Model E-M_r) also contained the same set of variables (Table S4).

Table 1
Comparison of candidate models for mosquito abundance.The top six rows represent the results of variable selection to obtain the best model. The bottom six rows represent the results of sensitivity analysis to ensure the best time lag of total rainfall and mean temperature. Model A comprised the total rainfall with lags from 0 to 6 months, mean temperature with lags from 0 to 2 months, and random effects for years, months, and regions were used as a baseline model. Model A-M_p, Model A-Mw, and Model A-Mr were models incorporating the human mobility index in parks, workplaces, and residential based on Model A, respectively.

Model	Model formula	WAIC	MSE in LOOCV
Model A1	$\beta+\gamma+S+\alpha$	741.12	–
Model A2	$\beta+\gamma+S+f.w(R_t,6)+\alpha$	727.31	–
Model A	$\beta+\gamma+S+f.w(R_t,6)+f.w(T_t,2)+\alpha$	681.60	0.63
Model A-M_p	$\beta+\gamma+S+f.w(R_t,6)+f.w(T_t,2)+m_p+\alpha$	677.92	0.65
Model A-M_w	$\beta+\gamma+S+f.w(R_t,6)+f.w(T_t,2)+m_w+\alpha$	658.89	0.46
Model A-M_r	$\beta+\gamma+S+f.w(R_t,6)+f.w(T_t,2)+m_r+\alpha$	**651.87**	**0.37**
Model A-M_r1	$\beta+\gamma+S+f.w(R_t,5)+f.w(T_t,2)+m_r+\alpha$	666.57	–
Model A-M_r2	$\beta+\gamma+S+f.w(R_t,4)+f.w(T_t,2)+m_r+\alpha$	668.37	–
Model A-M_r3	$\beta+\gamma+S+f.w(R_t,3)+f.w(T_t,2)+m_r+\alpha$	664.26	–
Model A-M_r4	$\beta+\gamma+S+f.w(R_t,2)+f.w(T_t,2)+m_r+\alpha$	671.56	–
Model A-M_r5	$\beta+\gamma+S+f.w(R_t,1)+f.w(T_t,2)+m_r+\alpha$	669.79	–
Model A-M_r6	$\beta+\gamma+S+f.w(R_t,6)+f.w(T_t,1)+m_r+\alpha$	653.22	–

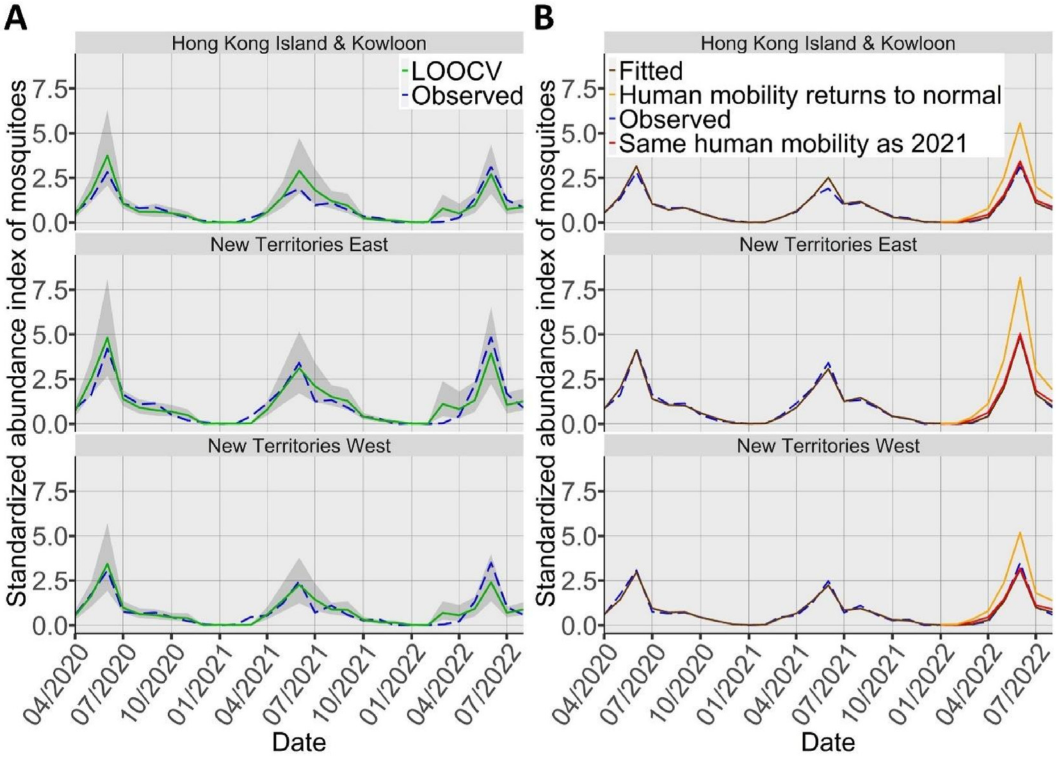

Fig. 3. Comparison of observed and predicted results using the best model for mosquito abundance. (A) Predicted results of mosquito abundance using leave-one-out cross-validation (LOOCV) with Model A-M_r. The grey shaded area represents the 95 % confidence interval. The blue dashed line represents observed data and the green solid line is the leave-one-out cross-validation result. (B) Projected results of mosquito abundance in the year 2022 under different scenarios in human mobility (residential category): human mobility returns to the COVID-19 pre-pandemic period (orange) and the same human mobility as year 2021 (red). The blue dashed line represents observed data and the brown solid line represents fitted data.

3.3. Prediction of mosquito activity using weather and human mobility

Overall, both models, A-Mr and E-Mr, showed similar predictive performances, but the model performance for mosquito abundance prediction appeared to be slightly better than that for mosquito extensiveness prediction. More observed data points were within a 95 % confidence interval (CI) of the predicted values for mosquito abundance (Fig. 3A and Fig. S4A). It might be because mosquito abundance is more weather-related, while mosquito extensiveness is more related to the presence of potential breeding places or the placement of the traps (Table 1 and Table S4).

The model estimated that residential mobility change has a negative effect on mosquito abundance (correlation coefficient = −0.075 (95 %CI, −0.118-0.033); see Table S5). On the other hand, park mobility and workplace mobility had a positive effect on mosquito abundance. The effects of the human mobility indices on mosquito extensiveness were consistent with mosquito abundance.

3.4. Effects of weather conditions

Higher relative risks in mosquito abundance were observed in the conditions of extremely low (<50 mm) or heavy rainfall (>500 mm) (Fig. 4A). Compared with the reference (300 mm), a reduction in total rainfall was associated with a higher relative risk (RR) after about 4.5 months, reaching a maximum of 1.73 (95 %CI, 1.19–2.51). However, heavy rainfall conditions (>500 mm) were associated with a higher RR within 3 months, reaching a maximum of 1.31 (95 %CI, 0.99–1.73). When lagged effects were accumulated, the maximum RR occurred at no rainfall (Fig. 4B). The accumulated RR decreased with total rainfall to about 500 mm but increased again thereafter.

Compared with the reference mean temperature (20 °C), the warm conditions (21–30 °C) were associated with an increased risk of mosquito abundance after about half a month, leading to a maximum RR of 1.47 (95 %CI, 0.94–2.32) at 25.5 °C (Fig. 4C). When lagged effects were accumulated, the RR increased with mean temperatures from 15 °C to 26 °C but decreased at warmer conditions (>26 °C) (Fig. 4D). The associations between total rainfall and mean temperature with mosquito extensiveness were similar to that of mosquito abundance (Fig. S5).

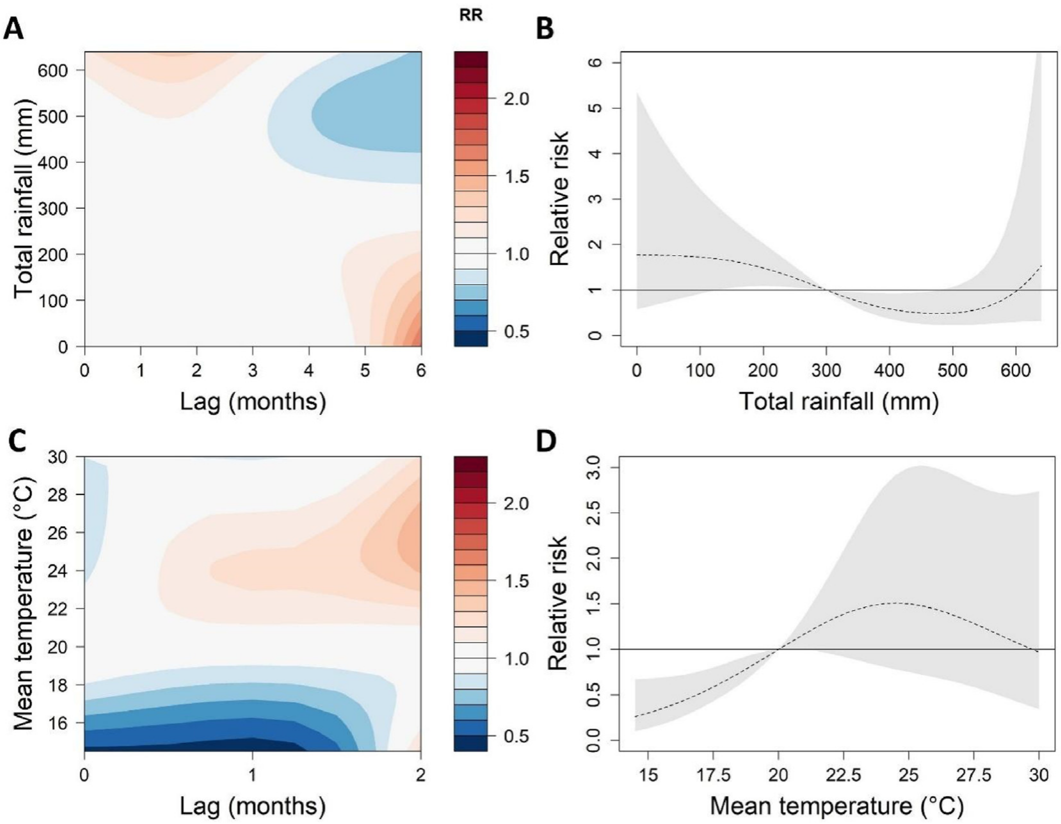

Fig. 4. Effects of total rainfall and mean temperature on mosquito abundance using the best model. (A) Relative risk (RR) by total rainfall and lag months; (B) Cumulative RR for total rainfall; (C) RR by mean temperature and lag months; (D) Cumulative RR for mean temperature. The reference of total rainfall and mean temperature are 300 mm and 20 °C, respectively. The deeper the shade of red, the greater the increase in RR compared with the reference. The deeper the shade of blue, the greater the decrease in RR compared with the reference. The black dashed line represents the cumulative exposure-response association. The grey shaded area represents the 95 % confidence interval.

3.5. Model projections for human mobility change

The model projected the mosquito abundance in two alternative scenarios for the year 2022: 1) same residential mobility as before the COVID-19 Omicron wave, indicating returning to a normal state, and 2) same residential mobility as the year 2021, indicating a weak social distancing. In the first scenario, when human mobility returned to normal (before the COVID-19 pandemic), cumulative mosquito abundance in all areas significantly increased by an average of 80.49 % compared to the actual situation. The cumulative mosquito abundance in Hong Kong Island and Kowloon is increasing at 83.41 %. In the second scenario, cumulative mosquito abundance in all areas was only slightly higher than the actual situation by an average of 10.96 % (Fig. 3B). The projection results of mosquito extensiveness were similar to those of mosquito abundance (Fig. S4B).

3.6. Sensitivity analysis

Prediction models in mosquito abundance and extensiveness were sensitive to both the selection and the time lag of the key predictors, such as the human mobility indices, the total rainfall lag, and the mean temperature lag (Table 1 and Table S4). In Model A, the WAIC decreased from 681.60 to 651.88 after adding the residential mobility index. When the total rainfall lag reduced from 6 months to other lengths, WAIC increased. Similarly, when the mean temperature lag reduced from 2 months to 1 month, WAIC increased.

4. Discussion

4.1. Influence of human mobility on mosquito activity

Understanding the association between human mobility and mosquito activity helps in predicting mosquito abundance and, hence, the risk of DF. Our results showed that a reduction in the residential index correlated with an increase in mosquito abundance, while reductions in the mobility indices for parks and workplaces were associated with a decrease in the abundance. The results can be explained by the increase in outdoor activities, which provides more chances for *Aedes albopictus* to bite humans (Bonizzoni et al., 2013; Wijegunawardana et al., 2019), thus raising mosquito abundance. The model projected that if human mobility (e.g., residential) returned to normal (i.e., the pre-pandemic level) in 2022, mosquito activity would increase significantly during its peak. Changes in mosquito activity can influence the spread of vector-borne infectious diseases. For example, without border restrictions, DF can spread further when travellers return from high-risk areas (Li et al., 2021). Hence, the risk of DF is expected to be larger after the pandemic.

Recently, Chen et al. reported that using Google mobility data, the reduced time spent in non-residential areas had the strongest evidence of association with reduced risk of DF during the COVID-19 pandemic period in Southeast Asia and Latin America (Chen et al., 2022). This aligns with our finding that a decrease in indoor time was associated with an increase in mosquito abundance. While no significant result for the residential index was found in their study, the non-residential indices were generally negatively correlated with the residential index. High collinearity between covariates may make attribution challenging. Moreover, residential mobility may have different impacts on different Dengue mosquito species. For instance, as *Aedes aegypti* prefers indoor breeding (Herath et al., 2022; Wijegunawardana et al., 2019), focusing on multiple countries without differentiating between *Aedes* species may obscure the estimation of the impact of human mobility.

4.2. Impact of total rainfall lags and mean temperature on mosquito activity

Rainfall may influence mosquito activity through different mechanisms. Both dry and wet conditions were associated with an increased risk of DF in China (Li et al., 2023). We found that heavy rainfall (>500 mm) within 3 months was associated with a higher risk of *Aedes* mosquito abundance. Low rainfall (<50 mm) was associated with a higher risk but with a longer lag of about 4.5 months (Fig. 4A). This supports the recent findings of the delayed effects of weather on DF (Lowe et al., 2018, 2021). A possible explanation is that during late winter or spring, mosquito populations were primarily in eggs or larvae rather than adults. The limited rainfall during this period reduced the flushing effect on these developmental stages (Seidahmed & Eltahir, 2016). After a dry period, increased rainfall in a warmer environment triggers mass hatching of eggs, boosting mosquito populations. This is particularly relevant in subtropical regions in Asia, where the mosquito population peaks from spring to the pre-monsoon (Zhao et al., 2007). Our results suggest that extreme hydroclimatic events, such as delayed monsoons or droughts in spring, can increase mosquito abundance in the summer. Similarly, drought conditions were observed in spring 2018 in Hong Kong, and 2015 and 2023 in Taiwan, each followed by significant DF outbreaks (Yuan et al., 2019; The Year's Weather - 2018, 2019; Wong, 2023).

In our study, the mean temperature was positively associated with mosquito activity until exceeding a threshold. We observed an increased mosquito activity risk after about a half-month, similar to the time that *Aedes albopictus* may use to develop from eggs to adults. Peak activity occurred about two months later when the mean temperature ranged between 25 and 26 °C (Fig. 4C). These findings in Hong Kong align with a previous study using DF data (Lowe et al., 2021).

4.3. Implications

The spread of diseases such as DF, COVID-19, Malaria, and Zika diseases poses significant risks to human health, with the potential for large-scale fatalities. Residential mobility indicates the change in the time people spend at home as the outcome of social distancing measures during the COVID-19 pandemic period. Our results suggest that such measures might be a key factor in predicting or altering mosquito abundance. Mobility may be affected by many factors, such as socioeconomics, weather conditions, etc. (Hu et al., 2023). Consequently, many factors may contribute to varying DF risks through human mobility. Social distancing measures may be an important intervention to change mosquito abundance. To address this, integrating mosquito surveillance systems and human mobility can enhance the prediction of mosquito activities. When there is a significant predictive change in human mobility that indicates a higher mosquito activity, mosquito monitoring should be strengthened in a timely manner. At the same time, how to predict human mobility will be an important task (Xiong et al., 2020). Increased outdoor activities correlate positively with increased mosquito activity, suggesting that public caution and strengthened mosquito control are needed in the post-pandemic era, as mobility is expected to rebound. Vector control efforts can be adjusted during periods of higher human activity to mitigate the potential risks of vector-borne diseases.

In vector control efforts across Southeast Asia, the Global Vector Control Response prioritised enhancing vector surveillance, forecasting, and monitoring (World Health Organization, 2020). Extreme weather or hydroclimatic events, such as heavy rains or droughts, are becoming increasingly frequent worldwide (Fischer et al., 2021). They might have critical influences on the dynamics of the mosquito population depending on the time of their occurrences (Liyanage et al., 2022). Incorporating extreme hydroclimatic events (such as drought conditions) together with human mobility patterns helps to forecast mosquito risk.

4.4. Limitations and future works

Several limitations exist within this study. Firstly, mosquito activity may also be influenced by other human-induced factors, such as land use type and urbanisation process (Lee et al., 2020; Zahouli et al., 2017). The impact of control measures has not been considered, specifically around those Gravidtrap sites. However, during the COVID-19 pandemic in Hong Kong, these mosquito control measures were expected to be less frequent. Secondly, our analysis focused on identifying associations using population-level data, which cannot establish causal relationships. Thirdly, spatial differences such as different human activity areas (suburban, urban) may also affect mosquito activity. In our study, we combined multiple monitoring stations into three regions in Hong Kong for analysis without further regional refinement. Fourthly, human mobility patterns frequently fluctuate in response to weather events, potentially complicating the analysis of observed relationships between mobility dynamics and mosquito abundance. For example, individuals may reduce outdoor activities during periods of heavy rainfall or extreme weather, which could indirectly alter their rates of exposure to mosquitoes. In this study, we did not consider such complex interactions. Moreover, this study focuses on the special circumstances during the pandemic, during which measures such as lockdowns and travel restrictions significantly changed human mobility patterns, leading to atypical human behaviour patterns. However, the impact of human mobility in the post-pandemic era remains uncertain, highlighting the need for future studies to incorporate more data from human mobility to validate models. Furthermore, extreme weather events can affect a variety of climatic factors, some of which might be important factors for mosquito activity, such as typhoons (Kao et al., 2023). We only chose two important weather factors according to the previous studies (Bhatt et al., 2013b; Organization, 2023). Future studies should consider other weather variables (Gasparrinia et al., 2010; Gibb et al., 2023).

5. Conclusion

As the COVID-19 pandemic ends and borders reopen, the risk of mosquitoes is expected to be higher in many parts of the world. The study found that social distancing measures were associated with reduced abundance and extensiveness of *Aedes albopictus*. Additionally, lower rainfall was associated with increased abundance and extensiveness with a 4.5-month lag. Our findings offer insights into how human mobility and low rainfall conditions influence the abundance and control of the *Aedes albopictus*, thereby aiding in the prediction and mitigation of mosquito risk.

CRediT authorship contribution statement

Yufan Zheng: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Data curation, Conceptualization. **Keqi Yue:** Software, Methodology, Data curation, Conceptualization. **Eric W.M. Wong:** Writing – review & editing, Funding acquisition. **Hsiang-Yu Yuan:** Writing – review & editing, Resources, Project administration, Methodology, Funding acquisition, Conceptualization.

Declaration of competing interest

The authors declare they have no conflicts of interest related to this work to disclose.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.idm.2025.04.002.

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