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Post-pandemic COVID-19 estimated and forecasted hotspots in the Association of Southeast Asian Nations (ASEAN) countries in connection to vaccination rate

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Abstract

After a two-year pandemic, coronavirus disease 2019 (COVID-19) is still a serious public health problem and economic stability worldwide, particularly in the Association of Southeast Asian Nations (ASEAN) countries. The objective of this study was to identify the wave periods, provide an accurate space-time forecast of COVID-19 disease and its relationship to vaccination rates. We combined a hierarchical Bayesian pure spatiotemporal model and locally weighted scatterplot smoothing techniques to identify the wave periods and to provide weekly COVID-19 forecasts for the period 15 December 2021 to 5 January 2022 and to identify the relationship between the COVID-19 risk and the vaccination rate. We discovered that each ASIAN country had a unique COVID-19 time wave and duration. Additionally, we discovered that the number of COVID-19 cases was quite low and that no weekly hotspots were identified during the study period. The vaccination rate showed a nonlinear relationship with the COVID-19 risk, with a different temporal pattern for each ASEAN country. We reached the conclusion that vaccination, in comparison to other interventions, has a large influence over a longer time span.

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Introduction

The global outbreak of coronavirus disease 2029 (COVID-19) in early 2020 had a detrimental effect on public health throughout the world and provoked lockdowns in a number of countries, including China, Spain, India, Iran, United Kingdom, Italy, France, Germany, Brazil, Russia and the United States (Giuliani *et al.,* 2020; D'Angelo *et al.,* 2021; Mahmud *et al.,* 2021; Mohammad Ebrahimi *et al.,* 2021; Nikparvar *et al.,* 2021; Valente and Laurini, 2021).

The World Health Organization (WHO) proclaimed COVID-19 a pandemic on 11 March 2020, indicating that it is a serious crisis with severe health and economic consequences in around 270 nations (Cucinotta and Vanelli, 2020). Nearly two years later, on 15 December 2021, there were up to 273 million verified infections, 5.3 million deaths and millions of people undergoing treatment (WHO, 2021a). The Association of Southeast Asian Nations (ASEAN), which includes Brunei, Cambodia, Indonesia, Laos, Malaysia, Myanmar, the Philippines, Singapore, Thailand, Timor-Leste and Vietnam, were among the first to face major COVID-19 threats one year after the emergence of the disease. Since January 2021, there has been a further significant increase in confirmed cases, leading to uncontrolled breakouts in the ASEAN as well as other countries. Factors contributing to this onslaught include greater human mobility supporting the transmission of the various new COVID-19 variants, in particular the delta (Dyer, 2021; Sasongko, 2021). Two months after spreading through India in March 2021 (Mlcochova *et al.*, 2021), the delta variant was causing a rising catastrophe in ASEAN countries. Also, there was no vaccination program this time, which led to the uncontrollable spread of the virus.

Since March 2021, vaccination programmes were in place throughout the ASEAN countries, and by the end of 2021, the overall vaccination rate reached over 50% of the populations (WHO, 2021b). At this time, all ASEAN countries noted a considerable decline in the number of cases, which with all probability was the result of the vaccination programme. However, the chance of a rise in the number of cases remained because of the risk for new COVID-19 variants. However, knowing how the virus would spread over time is very important for preventing worst-case scenarios. To that end, an effective and efficient early warning system (EWS) is required. Such a system represents a collection of capabilities that enable at-risk individuals, communities and organizations to plan and respond effectively to the viral spread to avoid harm and loss of lives (Zambrano *et al.,* 2017; Watson *et al.,* 2021). Monitoring is the crucial component of EWS during a pandemic, purpose of which is to collect data for risk assessment.

Monitoring, which comprises observation, measurement and prediction (Zambrano *et al.,* 2017), three critical components that support the understanding when the different waves occurs. This helps determining the timing of case increases and provides an accurate spatiotemporal forecast for future periods, which assists the government in determining the timing and location of coming outbreaks. Armed with this information, governments can take the right steps to protect populations from future, severe COVID-19 outbreaks (Jaya and Folmer, 2021a).

Spatiotemporal disease mapping is meaningful for the identification of when and where an outbreak will occur (Jaya and Folmer, 2020, 2021, 2022). Spatiotemporal disease mapping models provide a reliable estimate of disease risk and can be used to identify the wave periods and forecast disease risk over multiple time periods (Jaya and Folmer, 2020, 2021). It is critically important in order to mitigate the worst consequences of a pandemic (D'Angelo *et al.,* 2021; Jaya and Folmer, 2020) and forecasting strategies can be used to improve planning and effective decision-making (Jaya and Folmer, 2021). Such strategies make use of historical data in order to generate more precise forecasts of future events and they also assist in planning for potential hazards and consequences (Massad *et al.,* 2005; Shinde *et al.,* 2020). On the other hand, forecasting COVID-19 risks is highly difficult due to the lack of knowledge about this novel disease, including risk factors and underreported cases (Ioannidis *et al.,* 2020).

Due to the limited amount of accessible data and the difficulty of determining the risk factors associated with COVID-19 transmission, the hierarchical Bayesian pure (*i.e.* without covariates) spatiotemporal model approach is the most suited alternative solution (Jaya and Folmer, 2021). This method requires only the number of COVID-19 cases and the population at risk. Spatial and temporal random effects are introduced to account for unobserved risk factors (Jaya and Folmer, 2021). Hierarchical Bayesian estimation are widely used as they can be utilized to estimate the parameters of a spatiotemporal model and thus generate reliable risk estimates and accurate forecasts for COVID-19 (Carroll and Prentice, 2021; Jaya and Folmer, 2021; Sahu and Böhning, 2021). Additionally, there is the posterior exceedance probability (*i.e.* the probability that a COVID-19 risk will be exceeded at a certain threshold), which can be used to identify the suitable wave period (Lawson, 2010; Lawson and Rotejanaprasert, 2014).

The aim of this research was to identify the appropriate wave periods and provide an accurate space-time forecast of COVID-19 disease, as well as the relationship between vaccination and COVID-19 disease rates. The approaches used in this study included hierarchical Bayesian pure spatiotemporal model and locally weighted scatterplot smoothing.

Materials and methods

Data

We used data on the number of confirmed cases of COVID-19, number of populations and vaccination rates in each ASEAN country. The daily number of positive confirmed cases of COVID-19 was obtained from the Johns Hopkins University Centre for Systems Science and Engineering (2021). The data were collected from 22 January 2020 to14 December 2021 and can be found at https://github.com/datasets/COVID-19.git. We transformed these daily data into weekly data to avoid the problem of data reporting delays. The population numbers of the ASEAN countries were obtained from https://worldpopulationreview.com/country-rankings/asean-countries. The weekly vaccination rates were collected per 1000 inhabitants and obtained from https://ourworldindata.org/covid-vaccinations.

Statistics

The hierarchical Bayesian pure spatiotemporal-model

Hierarchical Bayesian pure spatiotemporal modelling has been used extensively to study disease transmission (Jaya and Folmer, 2020, 2021). We applied this approach to evaluate the spatiotemporal distribution of COVID-19 risk in ASEAN countries and to provide accurate forecasts of the COVID-19 risk for the period 15 December 2021 to 5 January 2022. In this section, we used the model established by Knorr-Held (2000) and assumed that the spatial dependence across countries does not exist as a result of human mobility limits in order to create three distinct models. Second, we assumed that the number of new COVID-19 cases followed the Poisson or negative binomial distribution in case of overdispersion: Let $y_{it} \sim Poisson(\lambda_{it})$ where λ_{it} denotes the expectation and variance of y_{it} at country *i* and time *t*.

To estimate the relative risk, we defined the mean $\lambda_{it} = E_{it}\theta_{it}$ with E_{it} denoting the expected COVID-19 case count and θ_{it} the relative risk at country *i* and time *t*. According to Abente *et al*. (2018) and Jaya *et al.* (2017), the expected number of confirmed cases E_{it} is then defined as:

$$E_{it} = N_{it}\frac{\sum_{i=1}^{n}\sum_{t=1}^{T} y_{it}}{\sum_{i=1}^{n}\sum_{it=1}^{T} N_{it}} \; i = 1, \dots, n \text{ and } t = 1, \dots., T \quad (1)$$

The relative risk θ_{it} is estimated using log-linear model, specifically:

$$\eta_{it} = \alpha + \phi_t + \delta_{it} \quad (2)$$

where η_{it} is (θ_{it}); α the intercept representing the overall relative risk; with ϕ_t and δ_{it} the temporally structured and the spatiotemporal interaction effect, respectively. A prior for the temporal trend (φ_t) was an order-1 random walk of (RW1) (Jaya and Folmer, 2020):

$$\varphi_{t+1} - \varphi_t | \tau_\varphi \sim \mathcal{N}\left(0, \frac{1}{\tau_\varphi}\right) \quad (3)$$

where τ_φ is the precision parameter of RW1; and δ_{it} the interaction component, which follows the type II interaction structure, an interaction that combines the spatially unstructured main effects and the temporally structured main effects according to Knorr-Held (2000).

We employed an exceeding probability approach to find spatiotemporal hotspots that can be used to determine the appropriate wave periods (Lawson, 2010; Lawson and Rotejanaprasert, 2014). This probability is obtained from the posterior spatiotemporal distribution of the relative risk and defined as the probability that the posterior mean of relative risk in region *i* at time *t* is greater than a threshold value *c* (*i.e.* $\Pr(\theta_{it} > c \mid \mathbf{y})$). It is estimated as:

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$$\widehat{\Pr}(\theta_{it} > c|\mathbf{y}) = 1 - \int_{\theta_{it}\le c}^{\square} p(\theta_{it}|\mathbf{y})\, d\theta_{it} \tag{4}$$

The spatiotemporal units were identified as hotspots if the exceedance probability in Equation (4) is greater than the γ cut-off. Hence, to identify the hotspots using the exceedance probability, the threshold value c and the cut-off value are necessary. The most frequently used values of c are 1 and 0.95. For a full discussion of hotspots, see Jaya and Folmer (2021). For forecasting purposes, we assumed the spatiotemporal units that must be forecast as missing (NA). Then, we applied an imputation scenario for missing values to obtain the forecast values. In Bayesian settings, the imputation procedure can be performed by using predictive posterior distribution $p(\mathbf{y}^*|\ \mathbf{y},\theta_{it})$ with $\mathbf{y}^*$ denoting the vector observation that will be forecast (Jaya and Folmer, 2020, 2021).

We used integrated nested Laplace approximation (INLA) to estimate the parameter of the Bayesian spatiotemporal model and obtain the COVID-19 forecast values (Rue *et al.*, 2009). To perform Bayesian analysis, we applied a vague Gaussian prior distribution for α, *i.e.* $\alpha\sim N(0,10^6)$ and half a Cauchy (HC) prior with the scale parameter 25 for hyperparameter standard deviations of temporally structured $(1/\tau_\varphi^{1/2})$ and interaction effects $(1/\tau_\delta^{1/2})$ (Gelman, 2006; Jaya and Folmer, 2020). In order to find the best model given model (2) we applied a forward selection procedure with different likelihood distributions, *i.e.* Poisson and negative binomial. We used deviance information criteria (DIC), Watanabe Akaike information criteria (WAIC), marginal predictive likelihood (MPL), mean absolute error (MAE), root mean square error (RMSE) and Pearson correlation to choose the best model (r) (see Jaya and Folmer 2021 for detail) presenting a choropleth map to illustrate the geographical distribution of COVID-19.

Locally weighted scatterplot smoothing

To find out the relationship pattern between the number of COVID-19 cases and vaccination attainment in each ASEAN country, we used a non-linear regression analysis approach through locally weighted scatterplot smoothing techniques (LOESS) (Cleveland and Loader, 1996). Let assume we have mean regression model $E(\theta_{it}\mid x_{it}) = f(x_{it})$ where θ_{it} denotes the relative risk in region i at time t. For each value of vaccination rate (x_{it}), we estimated the value of $f(x_{it})$ by using its neighbouring sample (Cleveland and Loader, 1996). To estimate $f(x_{it})$ we needed the weight function $w(x_{it})$. The tricube weight function, which is frequently employed to fit LOESS, is defined as follows (Cleveland and Loader, 1996):

$$w(x_{ij}) = \begin{cases} \left(1-|x_{ij}|^3\right)^3 & |x_{ij}| < 1 \\ 0 & |x_{ij}| > 1 \end{cases} \tag{5}$$

All analyses were conducted using the open source R programming language, specifically the R-INLA package for Hierarchical Bayesian pure spatiotemporal models (Bakka *et al.,* 2018) and the R-stat package for LOESS.

The models considered were the following: i) one with time-structured effects (M1); ii) one with type II interaction effects (M2); and iii) one with temporally structured effects plus type II interaction effects (M3). We evaluated Poisson and negative binomial probabilities with a temporal trend similar to that of RW1.

Results

Incidence and vaccination rates in descriptive mode

Several nations, such as Malaysia and Thailand, appear to have a similar early COVID-19 incidence patterns. Pearson's correlation value between Malaysia and Thailand was approximately 0.90, indicating that the two countries are quite close. With the exception of Singapore and the Philippines, where the outbreak of COVID-19 began in early and middle 2020, most countries experienced an outbreak after March 2021.

It did not take very long for the delta variant virus to spread to all ASEAN countries. After two years, the cumulative number of cases during period 22 January 2020 to 14 December 2021 reached 14,413,946 (2156 per 100,000 inhabitants) with a vaccination rate of 121.67 per 1000 inhabitants. The rates of disease incidence and vaccination per 100,000 inhabitants in the different ASEAN countries by the end of 2021 are shown in Table 1. Singapore stands out with has the highest rates, both for COVID-19 incidence and vaccination.

Model comparison

Using model comparison criteria and applying a Poisson likelihood approach, we discovered that the model incorporating both time-structured and interaction effects (M3) outperformed both the model that exclusively analysing the temporal structures (M1) and the one with only the interaction structures (M2). The M3 model had a lower DIC, WAIC, MAE and RMSE, together with a higher MPL and r, indicating that it is more predictive than the other two models (Table 2). We employed in-out-sample prediction to evaluate the best model by the following selected weeks 5, 10, 15, 20, 25, 30, 35, 40, 45, 50, 55, 60, 65, 70, 75, 80, 85, and 90 as testing samples and the rest of the data as training set samples. Figures 1 and 2 show the observed and predicted relative risk based on M3 demonstrating that they are extremely near each other.

Table 1. COVID-19 cumulative incidence rates compared with vaccination rates in the Association of Southeast Asian Nations (ASEAN) countries.

Country	Cumulative incidence per 100,000 inhabitants	Vaccination rate per 100,000 inhabitants
Brunei	3508	173
Cambodia	207	173
Indonesia	1557	89
Laos	1228	79
Malaysia	8316	165
Myanmar	967	51
The Philippines	2589	83
Singapore	4673	174
Thailand	3107	138
Timor-Leste	1504	84
Vietnam	1451	173

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Model interpretation

We aimed at estimating and forecasting the relative risk. As seen in Table 3, the variation of the interaction effects is very much larger than the variance of the temporally structured effects, with former accounting for 95.7% of the spatiotemporal variation of the COVID-19 risk, while the latter accounts for just 4.3%. In addition, the temporal trend of the COVID-19 risk is significantly different among countries with no spatial dependence, according to type II interaction effects.

Figure 3 shows the relative risk in the ASEAN countries depicting: A) the estimated (chosen weeks) and B) the forecast ones (four weeks in advance from 15 December 2020 to 05 January 2021). In general, based on the estimated of the relative risk, the time of greatest risk for the majority of ASEAN countries was found to be from March 2021 to August 2021. Almost nine countries of the total eleven must be classified as high-risk areas, while Singapore and Brunei were at low risk zone during this time period. However, both these countries experienced outbreak between September and November 2021. As seen in Figure 3B, some of the countries remain at high risk of COVID-19 during the first week of the forecast period (15 December 2021-21 December 2021). Laos had a relative risk that was higher than one categorized as a high-risk country, while Malaysia falls into the moderately high range, with the risk of COVID ranging from 0.8 to 1.00. We calculated the exceedance probability with a threshold of 1 and a credible level of 0.80 to identify the hotspot countries

Figure 4 shows that there were no countries categorized as having COVID-19 hotspots during the forecast period. This indicates that the number of new cases can be reduced significantly.

The hotspots correspond to wave periods of COVID-19 as

Table 2. Model comparisons.

Model	Likelihood	DIC	WAIC	MPL	r	MAE	RMSE
M1	Poisson	6898816.453	4495614.760	–4580052.293	0.505	1.644	0.264
	Negative binomial	13686.355	13689.560	–7000.156	0.792	1.236	0.139
M2	Poisson	8007.788	7865.645	–6326.559	0.999	0.223	0.185
	Negative binomial	11777.635	12064.167	–7474.141	0.998	0.170	0.059
M3	Poisson	7991.383	7872.720	–6313.167	0.999	0.187	0.154
	Negative binomial	11207.740	11082.917	–6462.617	0.999	0.253	0.214

M1: $\eta_{it} = \alpha + \phi_t$; M2: $\eta_{it}\ \alpha + \delta_{it}+$ (Type II); $\eta_{it} = \alpha + \phi + \delta_{it}$ (Type II). DIC, deviance information criteria; WAIC, Watanabe Akaike information criteria; MPL, marginal predictive likelihood; r, Pearson's correlation to find the best model; MAE, mean absolute error; RMSE, root mean square error (Yang and Shaman, 2021).

Table 3. Posterior means and variance of the hyperparameters.

Hyperparameter	Variance	Mean	q(0.025)	q(0.975)	Fraction variance (%)
The temporally structured effect	σ_φ^2	0.023	0.023	0.023	4.28
The interaction effect	σ_δ^2	0.505	0.505	0.505	95.72

q denotes quantile. It divides the range of a probability distribution into equal-probability intervals.

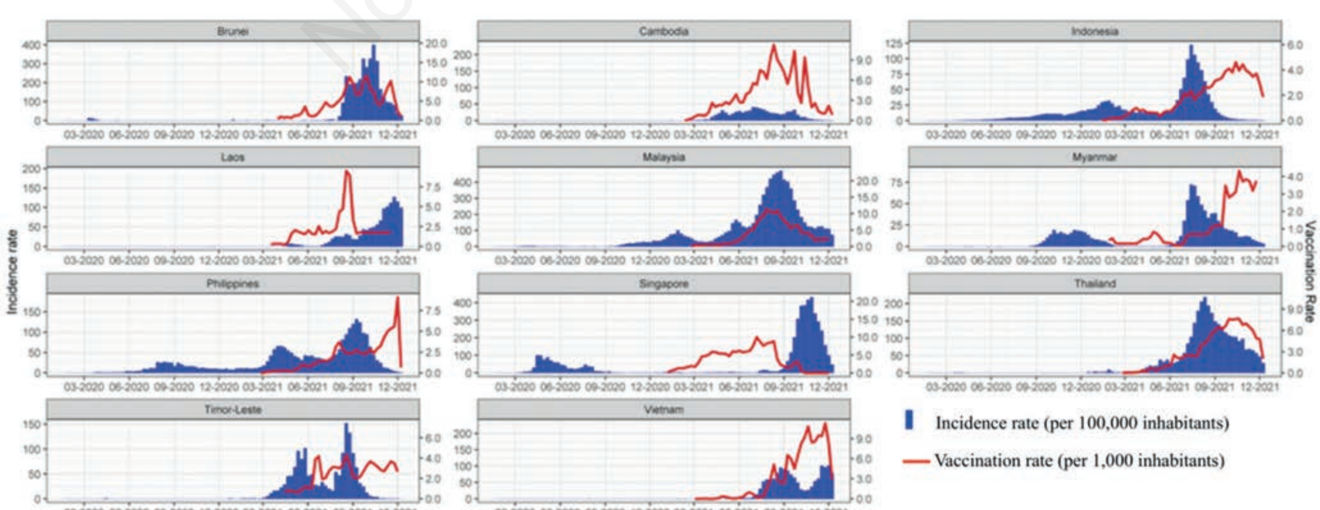

Figure 1. Incidence and vaccination rates of COVID-19 in the Association of Southeast Asian Nations (ASEAN) countries.

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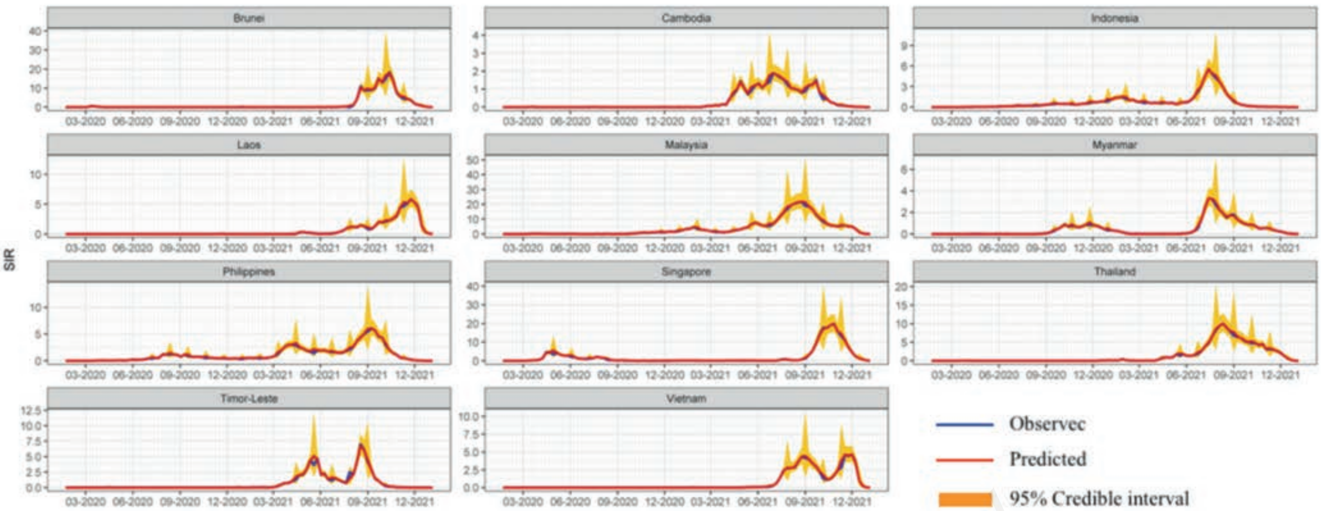

Figure 2. In-out sample prediction for selected weeks.

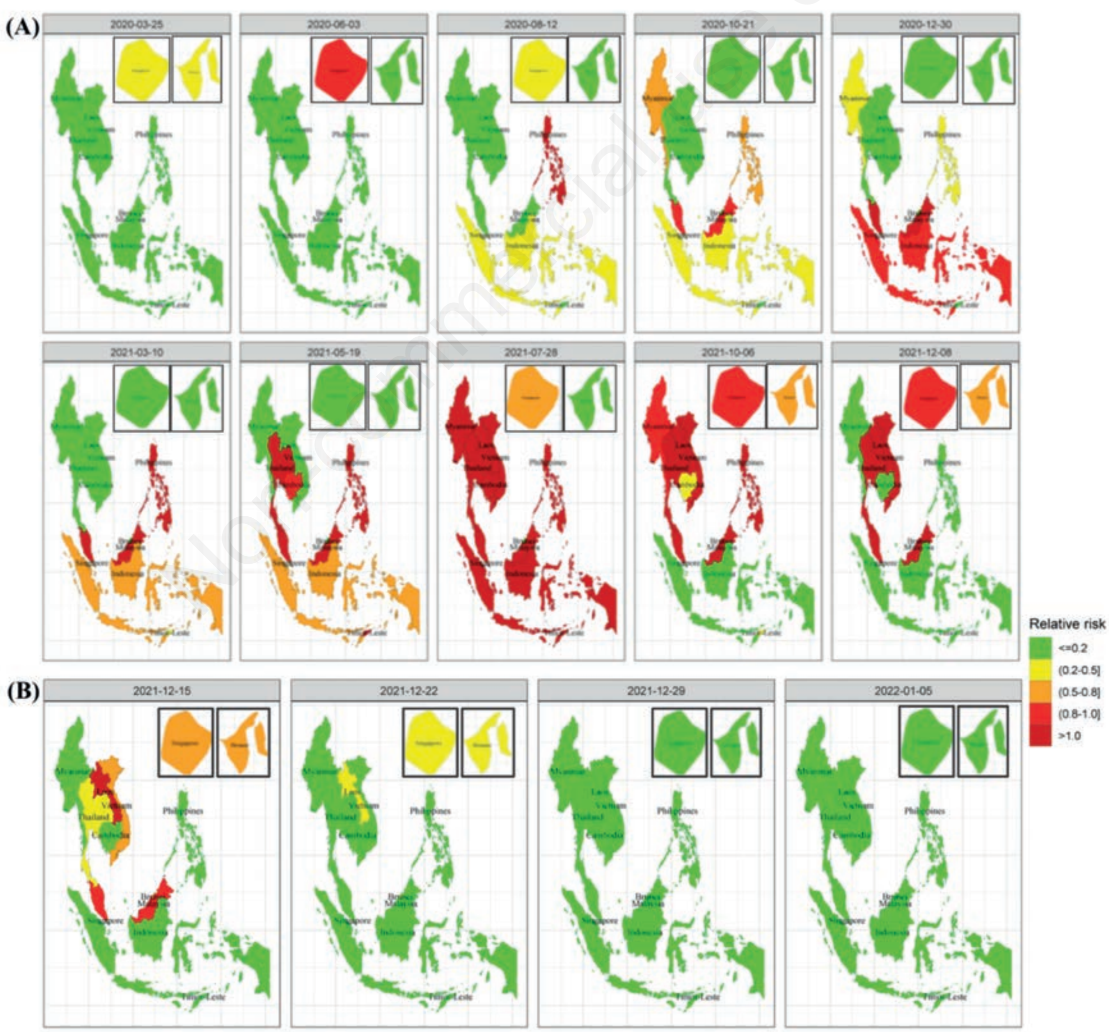

Figure 3. Mapping of the estimated spatiotemporal risk (A) and (B) forecast of the relative risk of COVID-19. The date indicated on each map corresponds to the start of each week.

emphasized and shown in Table 4. Each country had a unique number of waves and periods and it turns out that wave identification is critical for assessing critical risk indicators. Cambodia, Indonesia, Philippines, and Singapore are connected by experiencing three waves; Laos and Timor-Leste by two waves; while Brunei, Malaysia, Myanmar, Thailand and Vietnam by only a single wave.

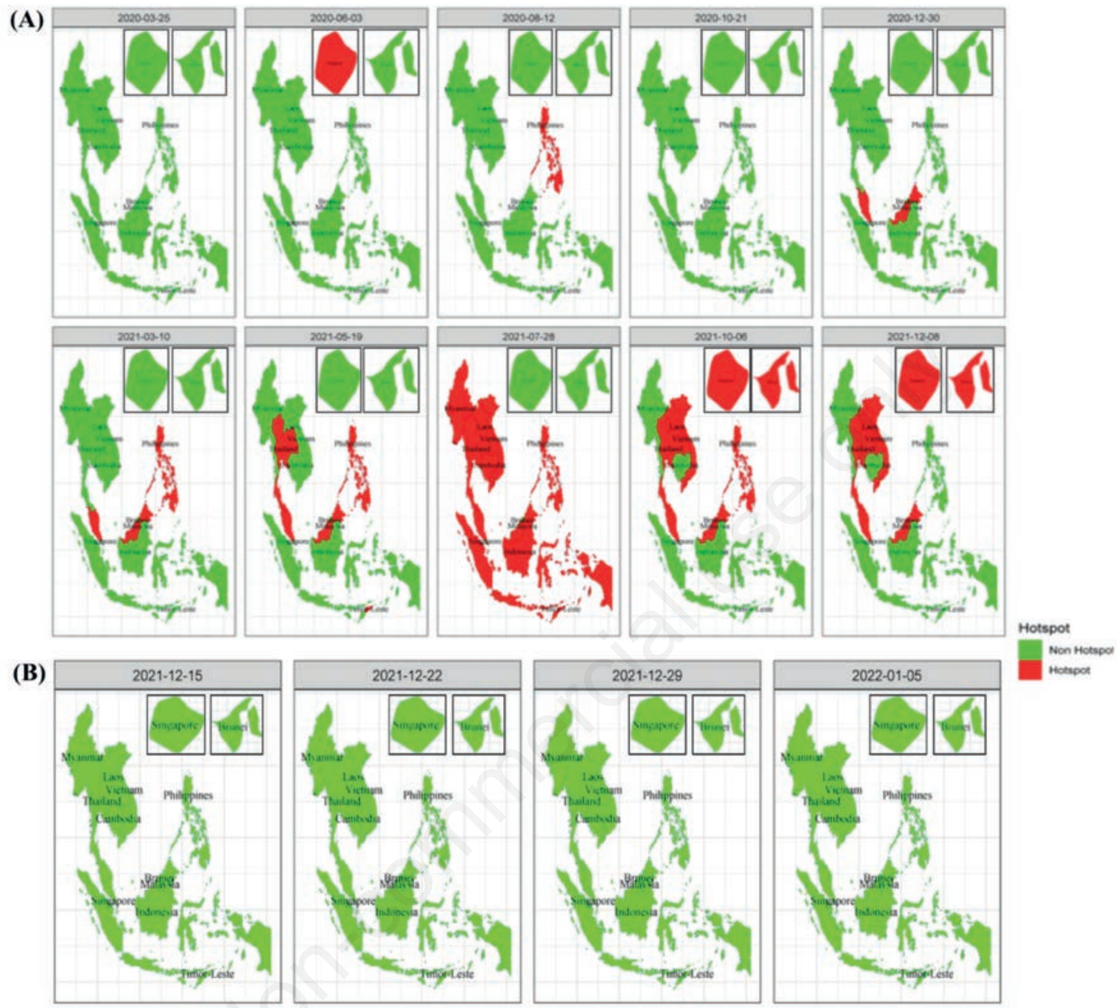

Figure 4. Mapping of the estimated spatiotemporal risk (A) and forecast hotspots of COVID-19. The date indicated on each map corresponds to the start of each week.

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Table 4. Identification of the number and timing of hotspots for each country of the Association of Southeast Asian Nations (ASEAN).

Country	No. of waves	First wave	Second wave	Third wave
Brunei	1	11 Aug.-8 Dec. 2021	-	-
Cambodia	3	28 April-5 May 2021	26 May-4 Aug. 2021	8-22 Sept. 2021
Indonesia	3	6 January-3 February 2021	17 February 2021	16 June-25 Aug. 2021
Laos	2	28 July-25 Aug. 2021	15 Sept.-8 Dec. 2021	-
Malaysia	1	4 Nov. 2020-8 Dec. 2021	-	-
Myanmar	1	30 June-15 Sept. 2021	-	-
Philippines	3	29 July-26 Aug. 2020	9 Sept. 2020	10 March-27 Oct. 2021
Singapore	3	8 April-24 June 2020	8 July-5 Aug. 2020	1 Sept.-8 Dec. 2021
Thailand	1	12 May-8 Dec. 2021	-	-
Timor-Leste	2	14 April-7 July 2021	28 July-22 Sept. 2021	-
Vietnam	1	14 July-8 Dec. 2021	-	-

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Relationship between relative risk and the vaccination rate

We conducted a nonlinear regression analysis using the LOESS method to determine the association between relative risk and vaccination rate in each ASEAN country.

The results are presented in Figure 5, which shows how the effects of vaccination rates differ by region. There is a strong non-linear association between the vaccination rate and the relative risk by location, indicating that vaccination does not reduce COVID-19 incidences rapidly. In general, the number of vaccinations was raised in response the increase in the number of incidents. In general, the positive correlation between vaccination rate and incidence rate of 0.577 indicates that vaccination does not directly reduce the number of incidents in a given time period. The vaccine programme, on the other hand, is a long-term option for controlling COVID-19 transmission and lowering the fatality rate (Haseltine, 2021; PTI, 2021).

Discussion

When researchers started to gain access to sufficiently large databases following the first COVID-19 outbreak in China two years ago, the development of statistical modelling was effective and rapidly led to illumination of key spatiotemporal patterns, demographic traits and their heterogeneity as the pandemic infection spread across regions and sub-regions. This, additionally resulted in the potential to estimate incidence patterns, create short-term forecasts, and indirectly assess the efficacy of early intervention strategies. This study represents an examination of post-pandemic country-level COVID-19 data for the outbreak in the ASEAN countries.

In the second semester of 2021, some ASEAN countries suffered their most severe COVID-19 conditions. A third deadly wave of the corona virus pandemic was sweeping over ASEAN countries as the delta variant invoked unprecedented levels of infection and fatality. The delta variant was first discovered in India in March

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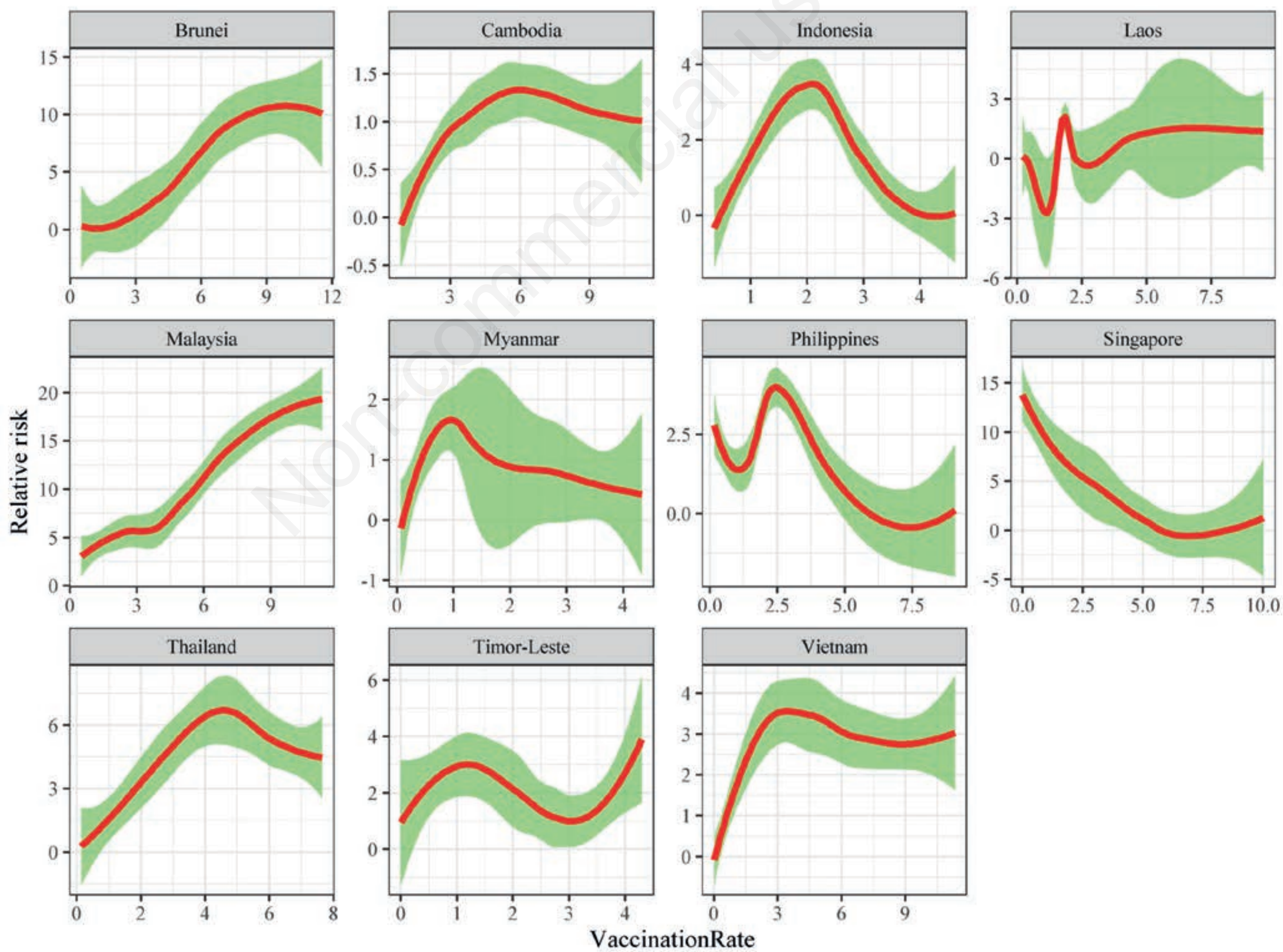

Figure 5. The relationship between vaccination rate and relative risk by regions.

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2021 (Yang and Shaman, 2021) and rapidly spread to other countries, including the ASEAN group. The temporal hotspots were consistently found after the second semester of 2021, with each ASEAN country experiencing different, in fact unique, numbers and time of waves. The peaks usually occurred one to two months after an official holiday as noted by Zipfel and Bansal (2020). The COVID-19 experience varied considerably among the ASEAN member states. Some of them, such as Vietnam, Laos and Thailand, avoided early significant outbreaks but are now battling new outbreaks, while Indonesia and Myanmar continue to struggle with low vaccination rates, insufficient oxygen supplies and overcrowded hospitals. According to experts, the healthcare systems in Indonesia and Myanmar are near the point of collapse. With China having overcome the worst characteristics of COVID-19 threat, the epicentre no longer in Wuhan, and the high number of daily cases in Indonesia has made some researchers (Dyer, 2021; Widadio, 2021) predict this country to be the new Asian COVID-19 epicentre.

WHO (2021b) states that adequate access to a safe and effective vaccine is important for resolving the COVID-19 pandemic. We found that the vaccination programme has a nonlinear relationship with the probability of contracting COVID-19, at least in the in this study. The relationship between the vaccination rate and COVID-19 risk varied by country investigated but, in the short term, there seemed to be no meaningful effect on the risk. In other words, substantially increased vaccination rates do not result in any immediate, significant decrease in COVID-19 cases. Unequal access to vaccines may explain why the vaccination strategy does not result in a direct case reduction. In the fight against the COVID-19 pandemic, equitable vaccination delivery throughout ASEAN and the rest of the world is crucial (Wagner *et al.,* 2022). According to Zhao *et al.* (2021), approximately 85% of the total population must be vaccinated in order to create a strong enough immunological barrier that would allow considering border restrictions removal. Additionally, virus containment requires efficient vaccines that have been found to prevent symptomatic infection and severe disease. However, as the virus evolves, so does our understanding of whether vaccinations alone will ever be sufficient to eradicate it.

Vaccination programme should have a long-lasting impact but based on what we know now, vaccines alone will not suffice, (Haseltine, 2021). Thus, it is still necessary to strengthen health standards and restrict community movement in order to avert the fourth, fifth, and following waves. This pandemic must be ended since it is wreaking havoc on the health system and economy of the country. Numerous countries are also seeing an increase in their poverty rates (Nicola *et al*., 2000). This is similar to the findings of research conducted in the United States on predicting vaccine effectiveness (Webb, 2021).

Conclusions

This study provides a regional perspective on the post-epidemiological characteristics and trends of the COVID-19 outbreak in ASEAN countries. A Bayesian spatiotemporal study of COVID-19 reveals that the temporal trend of COVID-19 grew dramatically following the COVID-19 tsunami that hit India in March 2021. While a broad pattern of temporal trends exists, each ASEAN country had its own temporal trend, and each country encountered a unique number of waves. Various ASEAN countries met different numbers of waves where, usually, later waves were worse than the preceding ones. The vaccination programme is known to have no short-term effect but should have a long-term effect in controlling the transmission of COVID-19. Short-term forecasts show a decline in the number of COVID-19 cases in early 2022.

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