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Cross-regional analysis of the association between human mobility and COVID-19 infection in Southeast Asia during the transitional period of "living with COVID-19"

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ABSTRACT

Background: In response to COVID-19, Southeast Asian (SEA) countries had imposed stringent lockdowns and restrictions to mitigate the pandemic ever since 2019. Because of a gradually boosting vaccination rate along with a strong demand for economic recovery, many governments have shifted the intervention strategy from restrictions to "Living with COVID-19" where people gradually resumed their normal activities since the second half of the year 2021. Noticeably, timelines for enacting the loosened strategy varied across Southeast Asian countries, which resulted in different patterns of human mobility across space and time. This thus presents an opportunity to study the relationship between mobility and the number of infection cases across regions, which could provide support for ongoing interventions in terms of effectiveness.
Objective: This study aimed to investigate the association between human mobility and COVID-19 infections across space and time during the transition period of shifting strategies from restrictions to normal living in Southeast Asia. Our research results have significant implications for evidence-based policymaking at the present of the COVID-19 pandemic and other public health issues.
Methods: We aggregated weekly average human mobility data derived from the Facebook origin and destination Movement dataset. and weekly average new cases of COVID-19 at the district level from 01-Jun-2021 to 26-Dec-2021 (a total of 30 weeks). We mapped the spatiotemporal dynamics of human mobility and COVID-19 cases across countries in SEA. We further adopted the Geographically and Temporally Weighted Regression model to identify the spatiotemporal variations of the association between human mobility and COVID-19 infections over 30 weeks. Our model also controls for socioeconomic status, vaccination, and stringency of intervention to better identify the impact of human mobility on COVID-19 spread.
Results: The percentage of districts that presented a statistically significant association between human mobility and COVID-19 infections generally decreased from 96.15% in week 1 to 90.38% in week 30, indicating a gradual disconnection between human mobility and COVID-19 spread. Over the study period, the average coefficients in 7 SEA countries increased, decreased, and finally kept stable. The association between human mobility and COVID-19 spread also presents spatial heterogeneity where higher coefficients were mainly concentrated in districts of Indonesia from week 1 to week 10 (ranging from 0.336 to 0.826), while lower coefficients were

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mainly located in districts of Vietnam (ranging from 0.044 to 0.130). From week 10 to week 25, higher coefficients were mainly observed in Singapore, Malaysia, Brunei, north Indonesia, and several districts of the Philippines. Despite the association showing a general weakening trend over time, significant positive coefficients were observed in Singapore, Malaysia, western Indonesia, and the Philippines, with the relatively highest coefficients observed in the Philippines in week 30 (ranging from 0.101 to 0.139).

Conclusions: The loosening interventions in response to COVID-19 in SEA countries during the second half of 2021 led to diverse changes in human mobility over time, which may result in the COVID-19 infection dynamics. This study investigated the association between mobility and infections at the regional level during the special transitional period. Our study has important implications for public policy interventions, especially at the later stage of a public health crisis.

1. Introduction

COVID-19 is a highly contagious disease that has brought numerous challenges to our society. Ever since COVID-19 was first identified in Wuhan, China, it has spread rapidly worldwide and evolved as a global pandemic due to domestic and international population movements (Jia et al., 2020; Lemey et al., 2021). Many countries have struggled to prevent the importation and control the local transmission of the coronavirus by implementing lockdowns and social restrictions. These Non-Pharmacological Interventions (NPI) successfully reduced human mobility, which has been proven to limit the transmission of COVID-19 at the early stage of the pandemic (Lai et al., 2020). However, the continuous restriction could have an adverse effect on the economy, education, and people's mental well-being (Coccia, 2021; von Soest et al., 2022). Governments thus attempted to relax their restrictions to recover domestic socioeconomic development, while human activities resumed accordingly, and human contact would be more frequent. This would probably result in a long-term situation living with COVID-19 considering that the virus has not been eliminated thoroughly (Yin et al., 2021).

SEA is one of the most severe regions affected by COVID-19, with over sixty million confirmed cases to date (Nov-25, 2022) (World Health Organization, 2022). Noticeably, SEA experienced dramatically increasing infections and suffered from catastrophic damage in the second half year of 2021 due to rapid transmission of the Delta variant (Jaya et al., 2022). The situation varied due to the existing disparities in socioeconomic development and health resources among countries (Chu et al., 2022). For instance, the death rate was low in Singapore, whereas it was substantially higher in Malaysia, Brunei, and Indonesia. To mitigate the pandemic, countries in SEA had imposed various restrictions to reduce residents' mobility and connectivity, which have proven to successfully control the spread of COVID-19 in certain areas over the period (Luo et al., 2022). Since July and August 2021, many countries in SEA have shifted their strategies to "living with COVID-19", and people have begun to resume their normal mobility. For example, in 2021, Malaysia relaxed the lockdown restriction in five states in July, the Philippines eased restrictions in the capital areas in August, and Singapore eased border restrictions in August (Southeast Asia Covid-19 Tracker). Although vaccination is gradually progressing in all SEA countries, it is considered unwise to not implement any measures in response to the pandemic as the medical capacity is limited, especially for underdeveloped countries. Therefore, how to balance the restriction and corresponding costs thus became one of the major issues that governments must consider when implementing interventions. To better understand such situations, tracking the dynamics of the relationship between human mobility and COVID-19 infections during the period transiting to "live with COVID-19" in space and time has become significant for assessing the effectiveness of ongoing interventions.

The association between human mobility and the transmission of COVID-19 has received extensive attention in the past three years (Hu et al., 2021; Zhang et al., 2022). Specifically, many studies found that human mobility declined substantially due to restrictions implemented by the government to control the prevalence of COVID-19 (Abu-Rayash and Dincer. 2020; Borkowski et al., 2021; Huang et al., 2022; Shepherd et al., 2021; Jusup et al., 2022). On the other hand, human mobility was identified as a significant driving factor that positively correlated with the incidence of COVID-19 infections (Alessandretti, 2022; Habib et al., 2021; Kephart et al., 2021; Tokey, 2021; Zhu et al., 2022). Additionally, several studies further compared the association between human mobility and COVID-19 infections over the first two waves (Lison et al., 2022; Nohara and Manabe, 2022), and simulated the pandemic situation based on different scenarios of mobility restrictions (Franks et al., 2022; Chang et al., 2021). However, most of the previous studies predominantly focused on the stage with relatively strict restrictions before the uncontrollable transmission of the Delta variant. Even though several studies have suggested COVID-19 cases saw a marked increase after reopening and loosening restrictions (Sobiech Pellegrini, 2022; Aiano et al., 2021), few studies discussed the exact relationship between human mobility and COVID-19 infections over the transitional period of gradually relaxing the restrictions in most countries in the second half year of 2021. Previous studies investigated more at a city scale and a country scale (Badr et al., 2020; Kraemer et al., 2020; Chagas et al., 2021), but there is less attention focusing on such association over space and time at a regional scale in SEA. There are noticeable disparities in socioeconomic development and public health interventions across countries in SEA, which may lead to spatiotemporal heterogeneity of human mobility and the COVID-19 situation, especially during the transition period. Therefore, transregional analysis on the spatiotemporal association between human mobility and COVID-19 infections in SEA under the context of unrestricted mobility is warranted to be further examined.

To fill the gaps, this study aimed to investigate the spatiotemporal association between human mobility and COVID-19 infections in SEA regions during the period of the Delta variant transmission. Specifically, we first visualize the spatiotemporal dynamics of human mobility and COVID-19 infections in SEA during the Delta period, after which the variation of associations between human mobility and COVID-19 infections in space and time in SEA was identified. We aggregated weekly movement data and COVID-19 case data from June 2021 to December 2021 and adopted the geographically and temporally weighted regression (GTWR) model to detect their spatiotemporal association for 30 weeks across 207 districts within 7 countries. Our work shed light on understanding the impact of human mobility on COVID-19 infections in space and time during the transition period of shifting NPI from a regional perspective. Findings about the association between human mobility and COVID-19 infections over space and time will provide evidence and novel insights for researchers and public health authorities in public health policymaking.

2. Methods

2.1. Study areas and COVID-19 cases

Our studies focused on the period from Jun-1-2021 to Dec-27-2021, which is approximately the time of the Delta variant transmission in SEA. Seven countries were included in this study, namely, Brunei, Indonesia, Malaysia, Singapore, Thailand, the Philippines, and Vietnam as only these countries publicized the daily confirmed cases data at the district level. Noticeably, Indonesia was the earliest country that detected the Delta variant (March 2021), followed by Singapore and Vietnam, which detected the Delta variant in April 2021. Subsequently, Thailand, Malaysia, and the Philippines detected the Delta variant in May 2021, while Brunei was the latest country to detect the Delta variant (August 2021) (Luo et al., 2022). The Delta variant rapidly dominated mass infections in the next few months after first detection. Fig. 1 shows the temporal trend of daily confirmed cases in these countries during 2021. From June to December, the confirmed cases first increased and then decreased with fluctuations that might be attributed to the shift of different public health interventions. The confirmed COVID-19 case data at the district level were collected from various sources including the official websites of public health authorities of several countries and Johns Hopkins University's Center for Systems Science and Engineering GIS dashboard (Table 1). We treated both Brunei and Singapore as analytical units at the same level as the administrative districts of other countries due to their small territorial areas. Therefore, a total of 208 analytical units were included in this study.

2.2. Human mobility data

Our data source of human mobility at the district level is the 'Movement between Tiles' dataset at Facebook Data for Good Partner Portal. The dataset was produced as a part of the Facebook Disaster Maps for crisis response and recovery and detailed explanations and methodology were described in its technical document (Maas, 2019). In short, it provides information on the locations of active Facebook users at an 8-h interval (i.e., 0:00, 8:00, and 16:00). The data was collected by the Facebook app, which recorded the locations of active users who were granted access to location services. These locations were assigned to a number of tiles based on the Bing Map Tile system (Schwartz, 2022). Due to the constraints of data collation of vast users from different countries, the resolutions for our studied countries were different with tile sizes ranging from Bing Tile level 14 (higher resolution) to level 11 (lower resolution). With this 'Movement between Tiles' dataset, we calculated the number of moved Facebook users at each tile per day and we interpolated the calculated data to respective Southeast Asia districts by taking the center coordinate of each Bing tile and matching it with the administrative region boundary in which it fell. The numbers of moved users at the centroids within each administrative region were aggregated to obtain the total human mobility volume of respective Southeast Asia districts.

2.3. Socioeconomic data and public health-related data

In addition to human mobility, COVID-19 transmission could be influenced by socioeconomic status, public health interventions, and

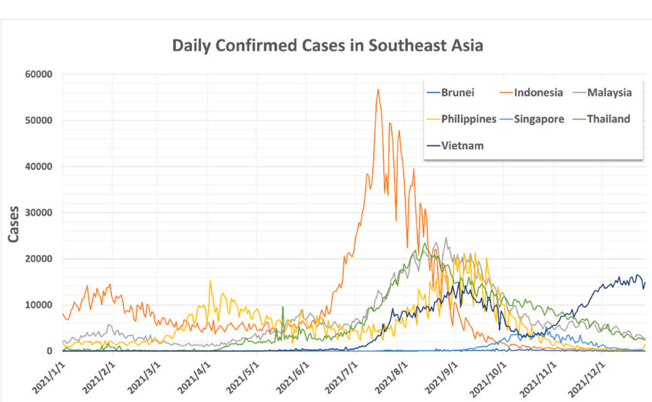

Fig. 1. Temporal trend of daily confirmed cases in SEA in 2021.

Table 1
Data source of COVID-19 cases.

Country	COVID-19 cases source
Brunei	Johns Hopkins University's Center for Systems Science and Engineering COVID-19 data
Indonesia	KAWALCOVID19 and the National Board of Confirmed Case Development
Malaysia	Ministry of Health, Malaysia
Singapore	Ministry of Health, Singapore
The Philippines	Department of Health, the Philippines
Thailand	Ministry of Public Health, Department of Disease Control Situational Reports
Vietnam	Ministry of Health, Vietnam

vaccination. Accordingly, we included population density (PD), gross domestic product per capita (PGDP), the proportion of elderly people (OLD), the poverty rate (PR), urbanization rate (UR), the number of hospitals per 10,000 people (HOS), and unemployment rate (UER) as control variables in the model because they were identified to be tightly related with the COVID-19 infections in previous studies (Grekousis et al., 2022; Mollalo et al., 2020). Besides, the Stringency index (SI) was included as an intervention-related variable since it represents the degree of implementation regarding public health intervention, which influences the transmission of COVID-19 (Ma et al., 2021). Furthermore, we also added vaccination rate (VR) in the model because vaccination is a significant factor in mitigating COVID-19 infections (Chen et al., 2022). Data on the socioeconomic variables were collected from statistic yearbooks in relevant countries, and the stringency index and vaccination data were derived from Our World Data (Table 2) (Department of Economic Planning and Statistics, Brunei, 2022; Department of Statistics Malaysia, 2022; Department of Statistics Singapore, 2022; General Statistics Office of Vietnam, 2022; National Statistical Office of Thailand, 2022; Philippine Statistics Authority, 2022). Considering the data availability, the socioeconomic data were all from 2020 to keep consistency. Noticeably, there were a few missing values in 2020 in several districts, which were supplemented by using linear interpolation according to the trend in previous years (Jang et al., 2021). Besides, due to the different units used to calculate the PGDP in different countries, we adjusted the value to US dollars using the exchange rate in 2020. All the socioeconomic variables were at district level static over time, while the SI and VR were time-variant variables at country level.

2.4. Geographically and temporally weighted regression model

The GTWR model is an extension of the GWR model, which considers both spatial and temporal non-stationary effects and thus improves the performance of the local regression model (Huang et al., 2010; Chu et al., 2015). Considering COVID-19 cases and human mobility are both sensitive in space and time (Chen et al., 2021), we employed the GTWR model to examine the spatiotemporal heterogeneity in the association between human mobility and COVID-19 cases across SEA regions at a weekly scale. The GTWR model is defined as:

$$Y_i = \beta_0(u_i, v_i, t_i) + \sum_{k=1}^{K} \beta_k(u_i, v_i, t_i) X_{ik} + \varepsilon_i$$

where Y_i is the dependent variable of the i^{th} observation, (u_i, v_i, t_i) is the space-time coordinates of the i^{th} observation; $\beta_0(u_i, v_i, t_i)$ is the intercept; $\beta_k(u_i, v_i, t_i)$ is the estimated coefficient of the independent variables X_{ik} and ε_i is the residual error term. With the spread of COVID-19 over time, the effects (β_k) of both time-variant independent variables (movement, SI, and VR) and time-invariant independent variables (socioeconomic indicators) on COVID-19 cases could be temporal dynamic (Fu and Zhai, 2021). Specifically, the local coefficient of the k^{th} independent variable of i^{th} observation can be estimated as defined below (Wang et al., 2021):

Table 2
Data source of independent variables.

Country	Human mobility	Socioeconomic data	Stringency index	Vaccination
Brunei	Facebook Data for Good	Department of Economic Planning and Statistic	Oxford COVID-19 Government Response Tracker (Hale et al., 2021)	Our World in Data: COVID-19 Vaccinations (Mathieu et al., 2021)
Indonesia		Statistics Indonesia		
Malaysia		Department of Statistics Malaysia Official Portal		
Singapore		Department of Statistics Singapore		
The Philippines		Philippine Statistics Authority		
Thailand		National Statistical Office Thailand		
Vietnam		General Statistic Office of Vietnam		

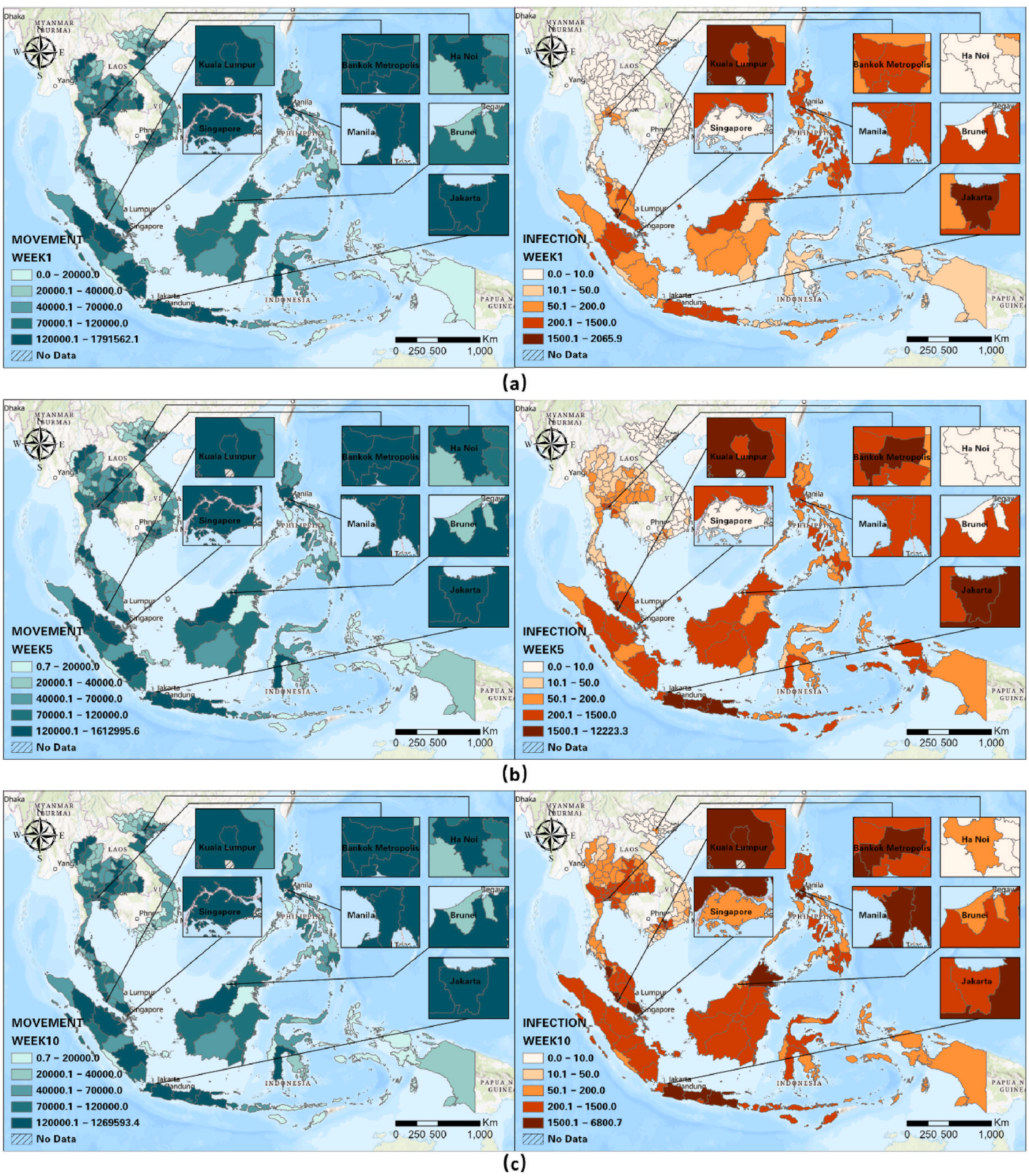

Fig. 2. Spatial distribution of weekly average human mobility volumes and COVID-19 cases ((a): week 1, (b): week 5, (c): week 10.

$$\widehat{\beta}(u_i, v_i, t_i) = \left[X^T W_i X\right]^{-1} X^T W_i Y$$

where X and Y denote matrices of the independent variables and the dependent variables, respectively; assuming that there are n observations, W_i is an $n \times n$ diagonal matrix of spatiotemporal weight, which can be calculated using a Gaussian kernel function (He and Huang, 2018):

$$w_{ij} = \exp\left(\frac{\lambda\left(d_{ij}^S\right)^2 + \mu\left(d_{ij}^T\right)^2}{h_{ST}^2}\right)$$

where λ and μ respectively denote scale parameters in the spatial metric system and the temporal metric system; d_{ij}^S and d_{ij}^T denote spatial distance and temporal distance between object i and j; h_{ST}^2 denotes spatiotemporal bandwidth satisfying the following relationships with spatial bandwidth h^S and temporal bandwidth h^T:

$$\begin{cases} \left(h^S\right)^2 = h_{ST}^2/\lambda \\ \left(h^T\right)^2 = h_{ST}^2/\mu \end{cases}$$

The period of our study is a total of 30 weeks from Jun-1, 2021 to Dec-27, 2021, during which we calculated the 7-day average movement accordingly as the key independent variable (human mobility). During the transition period, there were not only people infected by the Delta variant but also people infected by other variants. Given that the Delta variant of COVID-19 has an incubation period of approximately 2-7 days and the non-Delta variant of COVID-19 has an incubation period of around 2–10 days (Ogata et al., 2022; Liu et al., 2022; Grant et al., 2022), we considered the 7-days lag of spatiotemporal correlation between COVID-19 infections and human mobility. Specifically, the dependent variable was defined as the average confirmed cases in the following week of recorded movement. Moreover, other variables related to socioeconomic status and public health were added to control the influence of socioeconomic development, vaccination status, as well as intervention dynamics. The GTWR model was conducted by using ArcMap add-in, and a totally of 208 districts over 30 weeks, that is, 6240 samples, were included in the model fitting. Noticeably, we adjusted the local p-value to 0.047 to account for multiple local testing to maintain a global significance level of 5% (Oshan et al., 2019).

3. Results

3.1. Spatiotemporal dynamics of human mobility and COVID-19 infections in SEA

Fig. 2, Figure A1, and A2 visualized the average human mobility and COVID-19 cases on a weekly basis. The general volume of human mobility decreased first from week 1 (Jun-1 to Jun-7) to week 10 (Aug-3 to Aug-9) in many districts, and it then gradually increased from week 15 (Sep-7 to Sep-13) to week 30 (Dec-21 to Dec-27). Even though human mobility saw fluctuations during the transition period, its spatial patterns were similar in each selected week. Specifically, the capital regions of 5 countries including Kuala Lumpur, Bangkok Metropolis, Ha Noi, Jakarta, and Manila witnessed a relatively high volume of human mobility from week 1 (Jun-1 to Jun-7) to week 30 (Dec-21 to Dec-27). Besides, Singapore also experienced a relatively high volume of human mobility, while Brunei saw a relatively low volume of human mobility. In addition to the capital regions of countries, some districts such as Jawa Barat in central Indonesia, Ho Chi Minh City in southern Vietnam, Region IV-A in the central Philippines, Chiang Mai in northern Thailand, Selangor in western Malaysia also presented continuously high volume of human mobility during the transition period. On the contrary, some districts maintained a relatively low volume of human mobility during the transition period, such as Mae Hong Son in the west of Thailand, Ha Giang in the north of Vietnam, Region IV-B in the west of the Philippines, and Kalimantan Utara in the north of Indonesia.

In terms of COVID-19 infections, it presented noticeable spatiotemporal heterogeneity during the transition period. In week 1 (Jun-1 to Jun-7), relatively high COVID-19 infections (from 200 to 2066) were mainly concentrated in central Indonesia, the eastern coast and the west of Malaysia, capital regions in Thailand, and the Philippines, while most districts in Vietnam saw relatively low COVID-19 infections, with weekly average cases are close to 0. Even though the spatial pattern in week 5 (Jun-29 to Jul-5) was similar, COVID-19 infections experienced a dramatic increase in most districts, especially in northern Thailand. In week 10 (Aug-3 to Aug-9), COVID-19 infections in several districts in Indonesia experienced a significant decrease, for example, COVID-19 infections in Jakarta decreased from 12223 in week 5 (Jun-29 to Jul-5) to 1247 in week 10 (Aug-3 to Aug-9); COVID-19 infections of Jawa Barat decreased from 7225 in week 5 to 2533 in week 10 (Aug-3 to Aug-9). From week 15 (Sep-7 to Sep-13) to week 20 (Oct-12 to Oct-18), the relatively high values were mainly distributed in Singapore, Malaysia, the Philippines, and several districts in Thailand and Vietnam (e.g., Bangkok Metropolis and Ho Chi Minh City). Nevertheless, some districts in Indonesia such as Sulawesi Selatan, Sumatera Selatan, and Lampung, which experienced relatively high movement levels in previous weeks saw relatively low values in this period. From then on, many districts in Indonesia became the low-value groups while several districts in Vietnam such as Ha Noi, Khanh Hoa, and Bac Lieu saw a rapid increase in COVID-19 infections. Besides, districts in eastern Malaysia, the capital region in the Philippines, and Singapore witnessed relatively high values of COVID-19 infections in week 30 (Dec-21 to Dec-27).

In general, there were some similar patterns between human mobility and the number of infections. For instance, during the weeks, the Jawa island of Indonesia had relatively higher volumes of human mobility than other areas of the country. In comparison, higher numbers of COVID-19 infections were also observed on Jawa island in week 1 (Jun-1 to Jun-7), week 5 (Jun-29 to Jul-5), and week 10 (Aug-3 to Aug-9). Additionally, the capital regions which had the highest mobility level within each country observed a substantially greater number of infections than most of the other regions. For example, Bangkok Metropolis saw relatively high levels of human mobility and relatively large numbers of COVID-19 infections in each selected week. Moreover, Manila experienced high mobility levels and saw high COVID-19 infections each week. Besides, Ha Noi, with average mobility values of 846872 and 938290 in week 25 (Nov-16 to Nov-22) and week 30 (Dec-21 to Dec-27) respectively, observed weekly average COVID-19 cases of 295 and 1365 accordingly. By contrast, some other districts including Phichit of Thailand, Kalimantan Utara of Indonesia, and Dien Bien of Vietnam observed relatively low human mobility and low COVID-19 infections during this period.

3.2. Regression model results and comparison

To assess the global spatial autocorrelation of the dependent variable (i.e., COVID-19 infections), we estimated the Moran's I statistics for each week. Moran's I estimates turned out to be positive and statistically significant at the 5% level for all weeks (Table A1), which indicates that COVID-19 infections tended to be spatially clustered during our study period, and spatially and temporally explicit models were needed. Before implementing the GTWR model, we first adopted the global ordinary least square (OLS) regression model to investigate the relationship between COVID-19 cases and human mobility as a benchmark. The descriptive statistics of dependent and independent variables are shown in Table 3 and the OLS results are shown in Table A2. Given that the variance inflation factor (VIF) values of the independent variables were smaller than 5, the selected variables can avoid the issue of multicollinearity (Yellow Horse et al., 2022). From the global perspective, the coefficient of movement was 0.132 ($p<0.001$), indicating that a

Table 3
Descriptive statistics of the dependent variable and independent variables.

	Observation	Mean	Std. dev	Max	Min	Units
Dependent Variable						
INFECTION	6240	224.91	633.39	12223.29	0.00	Persons
Independent Variable						
MOVE[b]	6240	110230.30	182895.40	2221559.00	0.00	Persons
PD[c]	6240	598.79	2021.83	21765.28	9.00	Person/km^2
PGDP[d]	6240	4925.45	5783.81	48455.97	434.71	USD/person
OLD[e]	6240	8.57	3.26	16.76	1.73	%
PR[f]	6240	9.47	8.63	50.20	0.00	%
UR[g]	6240	37.41	21.85	100.00	6.65	%
SI[h]	6240	65.12	10.14	85.19	33.33	Scores
VR[i]	6240	0.62	0.49	2.13	0.01	Doses
HOS[j]	6240	1.61	0.63	3.50	0.35	Numbers
UER[k]	6240	2.82	1.95	9.32	0.10	%

a: Weekly cases per 100000 people.
[b]Weekly movement.
[c]Population density.
[d]Gross domestic product per capita.
[e]Proportion of elderly people.
[f]Poverty rate.
[g]Urbanization rate.
[h]Stringency index.
[i]Vaccination rate.
[j]Hospital per 10000 people.
[k]Unemployment rate.

100-unit increase in human mobility is associated with an increase of 13 in COVID-19 infection cases while holding all the control variables constant during the transition period. Additionally, human mobility had the largest coefficient, indicating that it had the strongest association with COVID-19 infections. However, the global model can only show the average effects of human mobility on COVID-19 infections in the whole study area, while local the model (e.g., GTWR) is able to detect the spatiotemporal heterogeneity of such effects. This enables us to further understand the dynamics of the association between human mobility and COVID-19 infections over space and time.

For comparison, the temporally weighted regression (TWR) model and the geographically weighted regression (GWR) model were also applied to the same dataset. As shown in Table 4, all the local regression models performed better than the OLS model as the temporal non-stationary effects and spatial non-stationary effects of the association between human mobility and COVID-19 infections are respectively considered in the TWR model and the GWR model. Among the local model, the GTWR exhibited the best performance as it simultaneously considers the spatial and temporal non-stationary effects of the aforementioned association, with the highest adjusted R^2, the lowest residual sum of square (RSS), and the lowest value of the Akaike information criterion with a correction (AICc). Specifically, the R^2 of the GTWR model was 0.697, indicating that the GTWR can explain 65.1% of the total variation in the weekly average confirmed cases. Therefore, the GTWR model constitutes an appropriate method for investigating the spatiotemporal association between human mobility and COVID-19 infections. The detailed results of GTWR including spatial bandwidth, temporal bandwidth, and estimated coefficients of each variable are presented in Table 5. Apart from the minimum value, the lower-quartile value, median value, upper-quartile value, and maximum value of the movement coefficient are positive, indicating the robust result of the positive association between human mobility and COVID-19 infections.

Table 4
Comparison of local model.

	Adj R^2	RSS	AICc
TWR	0.426	9.608	−22587.1
GWR	0.439	9.387	−22688.3
GTWR	0.651	5.834	−25469.0

Table 5
Estimate summaries of GTWR parameter.

	Minimum	Lower Quartile	Median	Upper Quartile	Maximum
Intercept	−0.351	−0.029	−0.026	−0.014	0.135
MOVE	−0.022	0.049	0.082	0.141	0.826
PD	−0.079	0.077	0.161	0.358	0.988
PGDP	−0.663	−0.055	0.018	0.040	0.264
OLD	−0.162	−0.036	−0.016	−0.007	0.308
PR	−0.044	0.007	0.018	0.027	0.102
UR	−0.118	0.022	0.043	0.068	0.190
SI	−0.151	0.013	0.022	0.039	0.351
VR	−0.537	0.019	0.037	0.155	1.443
HOS	−0.191	−0.017	−0.008	0.015	0.120
UER	−0.116	−0.026	−0.011	0.011	0.224

Diagnostic information.
Adj R^2 = 0.651.
RSS = 5.834.
AICc = -25469.0.
Temporal bandwidth = 0.119.
Spatial bandwidth = 0.115.

3.3. *Temporal variation of movement coefficients*

Our GTWR model could capture the spatiotemporal variation in the impact of mobility on infections over space and time. Fig. 3 presents the temporal variation of the average movement coefficient in each country. The average movement coefficient was calculated by taking an average of the statistically significant coefficients of all regions within a country. During the study period, the average coefficients of all 7 countries were positive, suggesting that human mobility positively influenced the number of infection cases. Among them, Indonesia, Brunei, the Philippines, and Singapore showed an overall higher coefficient (peaks from 0.408 to 0.609) than the other 3 countries, indicating a stronger impact of human mobility on COVID-19 infections. In comparison, Thailand (from 0.041 to 0.180), and Vietnam (from 0.025 to 0.126) observed a relatively lower coefficient, suggesting a relatively weaker correlation between movement with domestic infections. Nonetheless, the countries presented similar temporal variation patterns, that is, the movement coefficients for all the countries substantially increased before hitting their peak and decreased at the latter stage of the period

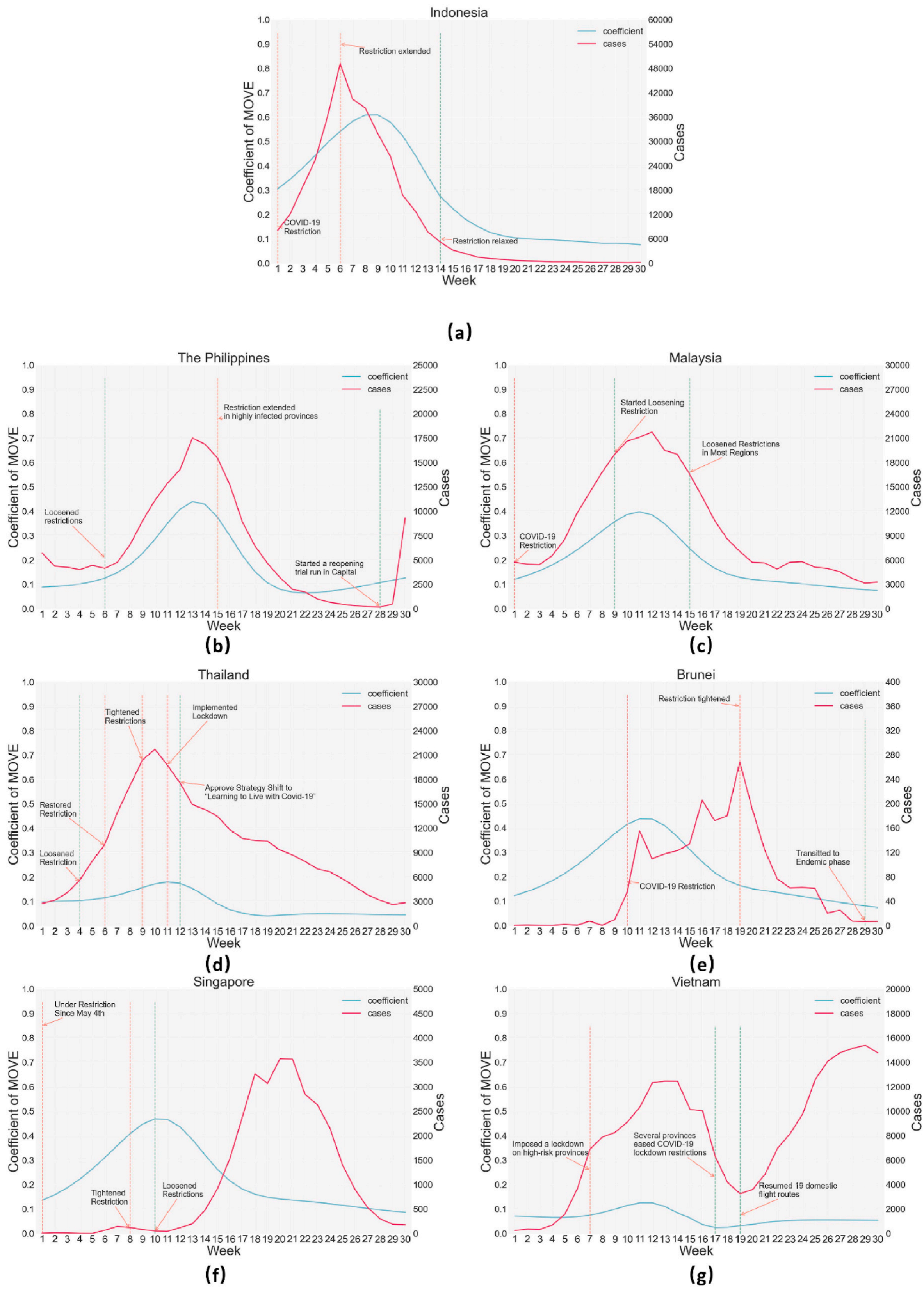

Fig. 3. Temporal heterogeneity of movement coefficient and comparison with Infection cases in SEA countries ((a): Indonesia, (b): The Philippines, (c): Malaysia, (d): Thailand, (e): Brunei, (f): Singapore, (g): Vietnam).

even though the restrictions were eased. For instance, the movement coefficient of Indonesia increased constantly since week 1 (Jun-1 to Jun-7) and peaked at week 9 (Jul-27 to Aug-2). It then showed a rapid decrease and has been maintaining a low level (from 0.074 to 0.152) since week 20 (Oct 12 to Oct 18) despite Indonesia relaxing its restriction since week 14 (Aug-31 to Sep-6). Apart from Indonesia, other countries except for Vietnam and the Philippines also present this pattern. The coefficient for Vietnam has been fluctuating at a relatively low level. It first decreased before week 5 (Jun-29 to Jul-5) and increased since week 7 (Jul-13 to Jul-19) despite the lockdown. It reached the peak of 0.126 in week 11 (Aug-24 to Aug-30) and then decreased before increasing again during week 17 (Sep-21 to Sep-27) and 19 (Oct-5 to Oct-11) when several provinces eased their restrictions. Thereafter, several domestic flight routes were resumed, and the movement coefficient maintained at the level of around 0.500, while the COVID-19 cases saw a dramatic increase. In terms of the Philippines, the coefficient increased first during week 1 and week 13, after which the coefficient saw a significant decrease from 0.440 in week 13 to 0.065 in week 22. Noticeably, the movement coefficient subsequently increased from 0.670 in week 23 to 0.127 in week 30, indicating that the association between human mobility and COVID-19 infections slightly strengthened in the Philippines at the later stage of the transition period in spite of the fluctuation at the early stage.

Interestingly, despite that the range of movement coefficients varies across SEA countries, their temporal trends were aligned with the number of cases to some extent in Indonesia, the Philippines, Malaysia,

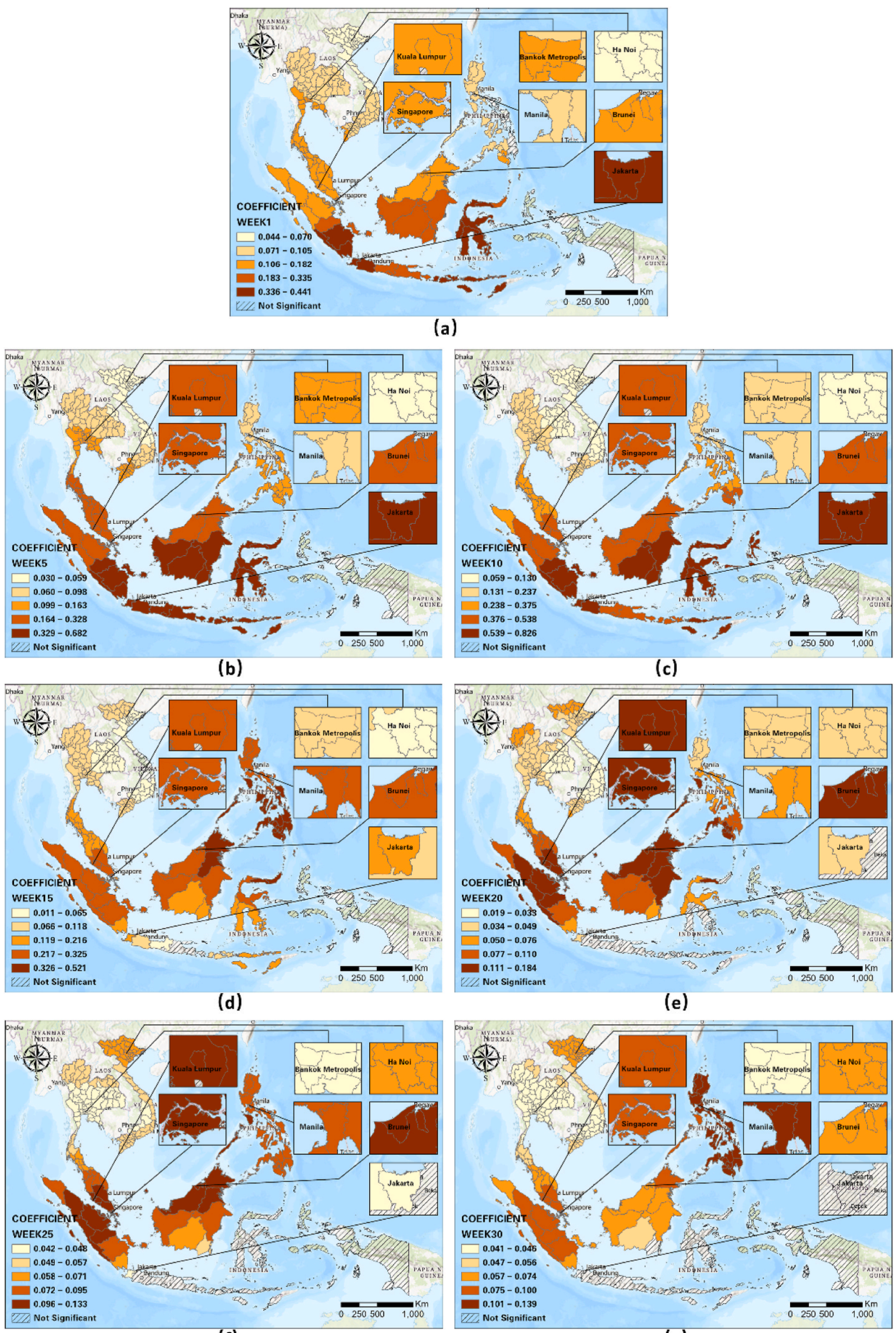

Fig. 4. Spatial heterogeneity of movement coefficient in SEA ((a): week 1, (b): week 5, (c): week 10, (d): week 15, (e): week 20, (f): week 25, (g): week 30).

and Thailand (Fig. 3(b), 3(c), 3(d)). This suggests that the more people were infected, the higher impact mobility could have in terms of facilitating disease transmission. In contrast, Singapore, Brunei, and Vietnam exhibited different patterns, showing the lags between movement coefficients and COVID-19 infection cases. For example, the trend of the coefficient in Brunei was partially consistent with the infection cases at the early stage of the period, after which the coefficient continuously declined despite the cases increasing with fluctuations. After tightening the restriction in week 19 (Oct-5 to Oct-11), the cases decreased markedly followed with a slight decrease in coefficient. Likewise, the coefficient in Singapore increased first then decreased after loosening the restrictions in week 10 (Aug-3 to Aug-9) and maintained at a relatively low level since week 17 (Sep-21 to Sep-27), while the COVID-19 cases maintained at a low level before week 10. However, the COVID-19 cases in Singapore markedly increased since week 12 (Aug-17 to Aug-23) and gradually decreased since week 21 (Oct-19 to Oct-25). These patterns indicated that the dynamics of COVID-19 infection cases were not always consistent with the temporal trends of human mobility for some countries over time during the transition period. The two noticeable outliners are Brunei and Singapore, partially attributed to their small sizes and a higher proportion of transnational human mobilities. Moreover, the coefficient of Vietnam was partially aligned with the COVID-19 infections from week 7 (Jul-13 to Jul-19) to week 17 (Sep-21 to Sep-27), while the infection cases rose dramatically and decoupled with the movement coefficient since week 19 (Oct-5 to Oct-11).

3.4. Spatial distribution of movement coefficients

Fig. 4 presents the weekly spatial variation of movement coefficients in 7 selected weeks at a five-week interval. In week 1 (Jun-6 to Jun-7), the relatively high coefficients were mainly located in Indonesia, ranging from 0.183 to 0.441. By contrast, the relatively low coefficients were mainly seen in the north of Vietnam, with values ranging from 0.044 to 0.070. Specifically, Sulawesi Selatan in Indonesia saw the highest coefficient with a value of 0.441, while Cao Bang in Vietnam witnessed the lowest coefficient with a value of 0.044. Additionally, a total of 8 districts (3.85%) showed insignificant results ($p>0.047$), which were mainly located in the eastern Philippines and eastern Indonesia (e.g., Maluku, Papua, Region V, Region VIII, etc.), which indicated that there were no statistically significant associations between human mobility and COVID-19 infections in these areas.

In week 5 (Jun-29 to Jul-5), despite the general increase of coefficients seen in most districts of SEA, the coefficients of most districts in Indonesia kept relatively high levels, ranging from 0.329 to 0.682. Specifically, some districts in the south of SEA showed a relatively significant increase in coefficients from week 1 to week 5 such as Riau (from 0.150 to 0.283), Jawa Timur (from 0.238 to 0.403), Brunei (from 0.123 to 0.213), and Sarawak (from 0.146 to 0269). Nevertheless, districts in northern Thailand and Vietnam kept relatively low coefficients in week 5, ranging from 0.030 to 0.098, which indicates the associations between human mobility and COVID-19 infections were relatively weak in these areas. Moreover, several districts in the Philippines showing an insignificant association between human mobility and COVID-19 infections presented significant coefficients in week 5, that is, Region V (0.085), Region VIII (0.102), Region XI (0.148), and Region XIII (0.135). However, some districts in western Indonesia showing insignificant results in week 1 such as Maluku, Maluku Utara, Papua, and Papua Barat still witnessed insignificant results in week 5 ($p>0.047$).

In week 10 (Aug-3 to Aug-9), 98.56% of the districts showed a significant correlation between human mobility and COVID-19 infections and the correlation continuously strengthened compared to week 5. The extremely high coefficients (from 0.539 to 0.826) were mainly seen in Indonesia, and the moderately high coefficient (from 0.376 to 0.538) were mainly located in Singapore, Brunei, Malaysia, and the southern Philippines. In contrast, the relatively low coefficients (from 0.059 to 0.130) were mainly located in eastern Thailand and central and northern Vietnam. Specifically, the highest coefficient was located in Gorontalo of Indonesia (0.826), indicating that mobility had the strongest positive impact on COVID-19 infections in this district. On the contrary, the lowest coefficient was seen in Da Nang of Vietnam (0.059), indicating the weakest association.

Despite the general decline of the coefficients, various spatial patterns were presented in week 15 (Sep-7 to Sep-13). The relatively high coefficients were mainly concentrated in the Philippines (from 0.326 to 0.521) and dispersedly distributed in Sulawesi Utara of Indonesia (0.387), Gorontalo of Indonesia (0.398), Kalimantan Utara of Indonesia (0.361), and Sabah of Malaysia (0.425). Interestingly, some districts in central Vietnam presented a statistically insignificant correlation ($p>0.047$) between human mobility and COVID-19 infections (i.e., Quang Tri, Thua Thien Hue, Da Nang, Quang Ngai, Quang Nam, Kon Tum, Gia Lai, and Binh Dinh). Likewise, Jawa Tinur and Bali in Indonesia also presented insignificant results in week 15.

A total of 14 districts showed an insignificant association ($p>0.047$) between human mobility and COVID-19 infections in week 20 (Oct-12 to Oct-18), with the proportion increasing from 3.85% in week 1 to 6.73% in week 20. These districts were mainly located in Indonesia, some of which relatively high coefficients were seen from week 1 to week 10. Besides, the relatively high coefficients (from 0.111 to 0.184) were mainly distributed in southern and eastern Malaysia, Singapore, western Indonesia, the southern Philippines, and Brunei, while the relatively low coefficients (from 0.019 to 0.033) were also mainly distributed in eastern Thailand and central Vietnam. A similar pattern was seen in week 25 (Nov-16 to Nov-22) despite the proportion of districts showing insignificant association ($p>0.047$) between human mobility and COVID-19 infections continuously increased to 8.17%. In week 30 (Dec-21 to Dec-27), an increasing proportion of districts (9.62%) presented insignificant relation ($p>0.047$) between human mobility and COVID-19 infections, which indicated a disconnection between human mobility and COVID-19 infections in these regions (Fig. 4 (g)). Besides, coefficients in most districts decreased to a relatively low level (under 0.100) in week 30, indicating that the associations between human mobility and COVID-19 infections in many districts weakened. The relatively high significant coefficients were mainly located in the Philippines (from 0.101 to 0.139), while the relatively low significant coefficients were also seen in Thailand (from 0.041 to 0.045) and southern Vietnam.

4. Discussion

4.1. Principal findings

In this study, we visualized the spatiotemporal dynamics of COVID-19 infections and volumes of human mobility in 7 SEA countries at the district level, and further adopted the GTWR model to identify the varying associations between human mobility and COVID-19 infections across space and time during the period of transitioning to "living with COVID-19" in 2021. Our initial visualization showed that patterns of human mobility were somewhat aligned with those of COVID-19 infections. By constructing the GTWR model, we found that mobility had a considerable impact on infections, especially during the middle of the transition period. The movement coefficients for all countries increased substantially at the beginning of the transition period. Coefficients in countries peaked at a high level (exceeded 0.400), except for Thailand and Vietnam which peaked at 0.180 and 0.126, respectively. Nonetheless, the coefficients dropped at the later stage of the transition period and maintained a relatively low level (around 0.100) thereafter. The aligned variation trend of coefficient and cases in some countries (e.g., Indonesia, the Philippines, Malaysia, and Thailand) suggests that the impact of human mobility on COVID-19 spread was related to the local infection context. However, at the latter stage of the transition, mobility did not possess a significant contribution to the pandemic, presumably due to relatively low-level infections in these countries. Similarly, even though there was an increasing number of cases in Singapore and Vietnam, the association between human mobility and COVID-19 infections maintained at a low level.

Further inspecting the coefficients at a regional level, we found that the correlation between human mobility and COVID-19 infections in an increasing number of districts gradually became insignificant (from 3.85% in week 1 to 9.62% in week 30), and the coefficients in many districts continuously declined. To detect the similar temporal dynamics of movement coefficients in SEA, K-means clustering analysis was conducted to identify potential clusters in the data (Figure A3) (Li et al., 2020). The movement coefficients show relatively high value and sharper fluctuation over time in districts of central Indonesia (cluster 1 and cluster 2). The moderate value and temporal fluctuation were mainly seen in districts of southern and eastern Malaysia, Singapore, Brunei, and the southern Philippines (cluster 3 and cluster 4). By comparison, districts in Thailand and Vietnam (cluster 5 and cluster 6) experienced relatively low levels and slight fluctuation of movement coefficient. Despite the spatiotemporal variations in the movement coefficients of clusters, the movement coefficient of each cluster increased before decreasing and maintained at a relatively low level over time. This indicates that movement disconnected from the infections after the transition in many regions. The abovementioned patterns were probably attributed to fewer susceptible individuals because of immunity after recovering from infections and more people were vaccinated, especially with booster doses (Gupta and Topol, 2021; Krause et al., 2021). To further verify the hypothesis, we calculated the Pearson correlation coefficients between average movement coefficients and the vaccination rates in each country respectively (Table A3). The results show that the movement coefficient is negatively associated with the vaccination rate in the whole SEA (coefficient = -0.188, $p = 0.006$). In terms of the specific countries, all the countries except for the Philippines saw significant negative correlations between vaccination rate and movement coefficient, while the Philippines witnessed insignificant negative correlations (coefficient = -0.260, $p = 0.165$). This indicates that vaccination may weaken the association between human mobility and COVID-19 infections in SEA to some extent following the popularization of vaccination.

Based on our findings of the positive association between human mobility and COVID-19 infections, reduction of human mobility might be an effective way to control the transmission of the infectious diseases, especially at the early stage of the pandemic (Zhou et al., 2020; Askitas et al., 2021). For example, COVID-19 infections in Indonesia, the Philippines, and Thailand saw a noticeable decline after these 3 countries implemented restrictions in week 6, week 15, and week 11, respectively. However, followed by the reduction of socioeconomic activities, economic development, and human well-being suffered from substantial challenges, because of which governments would have to resume normal activities and re-open society (Zu et al., 2021; Franks et al., 2022). According to our findings, gradual and appropriate adjustment of movement restrictions would limit the number of infections during the transition period back to normal activities. This could prevent the health system from reaching its maximum capacity, especially for those severe COVID-19 patients that were in need of medical support. With a gradually established herd immunity after infections and vaccinations, countries would need to consider the restoration of the economy. Meanwhile, we suggest that the government should pay more attention to the reasonable allocation of healthcare resources and vaccination popularization, rather than only controlling human activities.

Moreover, we identified those living in vulnerable districts such as districts with high population density, high poverty people, and lower hospital resources were somewhat at higher risk of epidemic infections. Based on the GTWR result, more than 75% of the significant observations showed that COVID-19 infections were positively correlated to population density (lower quartile coefficient = 0.077) and poverty rate (lower quartile coefficient = 0.007), while more than half of the significant observations saw a negative association between hospitals per 10000 people and COVID-19 infections (median coefficient = -0.008). This suggested that it is important to allocate healthcare resources preferentially to those vulnerable areas after easing the restrictions as they are at the highest risk of COVID-19 outbreaks. (Stok et al., 2021). To further help those who are living in disadvantaged areas reduce the relatively high risk of infections during a public health crisis, regional collaboration should be important to realize the effective and equal allocation of healthcare resources such as vaccines and essential medicine (Jit et al., 2021).

Overall, apart from the control of human mobility, many efforts need to be made in different aspects to ensure that society could recover in the post-pandemic era, especially for those regions with issues of socioeconomic inequality. For example, China is experiencing a transition period and gradually relaxing the social restrictions from the strict zero COVID policy. Given that China has complicated and unequal resources and hospital ICU distributions, the popularization of vaccination, stocking up on antiviral drugs, and expanding healthcare facilities should be essential ways for Chinese society to avoid a wave of deaths (Mallapaty, 2022). Most importantly, there was a significant spatiotemporal heterogeneity related to effects of socioeconomic status and human mobility on regional infections according to our findings and previous research (Fu and Zhai, 2021; Maiti et al., 2021). Even though the effects of human mobility on infections in most areas gradually weakened, we suggest the relevant authorities continue to pay attention to equal allocation of health resources and active regional collaboration during the transitional period of such a public-health crisis, enabling effective recovery of normal life.

4.2. Comparison with prior work

To the best of our knowledge, this is the first attempt to conduct a cross-regional study to investigate the spatiotemporal associations between human mobility and COVID-19 infections in SEA during the transition period of “living with COVID-19”. Our findings identified that human mobility is positively associated with COVID-19 infections in SEA, which is partially consistent with previous studies by Xiong et al., (2020), showing there was a positive correlation between mobility inflow and the number of COVID-19 infections in the US. Our study also showed that many districts gradually observed insignificant or weak associations between human mobility and COVID-19 infections at the later stage of the transition period. This is aligned with a study by Nouvellet et al. (2021), indicating that there was a decoupling relationship between human mobility and COVID-19 infections associated with lower transmission rates after a relaxation of intervention.

Even though prior studies have provided extensive evidence that the reduction of human mobility was effective in mitigating COVID-19 transmission (Wang et al., 2020; Abulibdeh and Mansour, 2022; Nohara and Manabe, 2022; Fang et al., 2020), people gradually resume their normal activities during the transition period of “living with COVID-19”, which resulted in an increase in human mobility. Our study thus identified the fluctuations in human mobility and COVID-19 infections over time in many districts of SEA countries during this special period. As shown in Fig. 2, for example, human mobility decreased first in most districts and increased later, which was probably due to the adjustment of health interventions. Accordingly, the COVID-19 infections in most districts increased first and then decreased later, while many districts in Vietnam and the Philippines saw increasing COVID-19 infections in week 30. The interesting dynamics did result in the spatiotemporal variation of the association between human mobility and COVID-19 infections during the transition period, which has not been discussed in previous studies. The findings in our study provided evidence for the researcher or policymakers to better understand the complicated association between human mobility and COVID-19 infections during the transition period and accumulate experience of recovering from the public health crisis at a later stage.

Moreover, this study shed light on the spatiotemporal association between human mobility and COVID-19 infections in the cross-region context in the understudied SEA countries, while existing studies mainly focused on other single countries such as the USA and China (Hou et al., 2021; Xu et al., 2022; Chen et al., 2022). Moreover, only a handful of existing studies considered the different socioeconomic development and public health interventions across regions (Sannigrahi et al., 2020). Therefore, our work contributes to cross-regional studies based on the hypothesis of the abovementioned transregional differences which might lead to various associations between human mobility and COVID-19 infections. Considering noticeable differences among countries in SEA (Chongsuvivatwong et al., 2011; Deutsch et al., 2020), our work identified the spatiotemporal association between human mobility and COVID-19 infections at a finer spatial scale (the first administrative district), which provided new insights for the relevant authorities to seek the regional collaboration of crisis responding and policy adjusting (Oka et al., 2021). On one hand, the restriction of human mobility across regions could play an important role in mitigating the transmission of COVID-19. On the other hand, local governments should make efforts to timely share surveillance information, healthcare resources, and vaccine allocation to balance unequal situation related to diverse implementations of public health interventions across regions, which has been proven to be effective in regional prevention of the pandemic (Flaxman et al., 2020).

4.3. Limitations

Some limitations in our work can be improved in future studies. First, 7 out of 12 countries of SEA were examined in this study because only these countries provided relevant data at the first administrative level. Nevertheless, we do note that the population of the 7 countries under study accounted for 88.3% of the total population in SEA. Second, due to data unavailability, control variables in this study were limited, which was insufficient to control the influence of other relevant factors including environmental and meteorological factors (Han et al., 2021; Yuan et al., 2021; Poirier et al., 2020). Besides, socioeconomic variables used in the regression calculations were at a district level and health-related variables were only at a national level. This inconsistent resolution might result in unavoidable bias. We strongly encourage the relevant authorities of all SEA countries to release data at a finer scale so that researchers can conduct more comprehensive studies related to public health, which is valuable for preventing and responding to the future public health crisis in SEA where the development has been unequal. Third, although the COVID-19 infections data were derived from the official website of the corresponding countries, the number of cases was probably underreported because of limited testing capacity in some regions and varied screening rates across regions (Chookajorn et al., 2021). Moreover, it was unnecessary for self-tested people with positive results to report to the government during the transition period, which might also lead to underreported cases.

In addition, the resolution of mobility data derived from Facebook was inconsistent, for example, the data resolution of Indonesia was relatively low while the data resolution of Brunei and Singapore was relatively high, which may result in an inaccurate estimate of human mobility. Moreover, the Facebook data only covered Facebook users, which means people who did not use Facebook were not included in the calculation of human mobility, resulting in an underestimation of actual human mobility. According to the Facebook Advertise Platform. There were approximately 469.2 million active Facebook users in Southeast Asia, taking up about 69 percent of SEA population (Maas et al., 2019). Nonetheless, movement data from Facebook was the most appropriate dataset with the finest resolution that we can access for cross-region analysis in Southeast Asia, and it has been widely used as a proxy of human mobility in previous studies (Ilin et al., 2021; Beria and Lunkar, 2021; Cowley et al., 2021; Reiner et al., 2021). In comparison with other mobility datasets (e.g., Google Mobility), the Facebook movement presents not only the temporal variation compared to the baseline, but also the actual number of moved Facebook users at a certain timestamp in a rather high spatial resolution. If there is sufficient data with higher accuracy (e.g., mobile phone data) in the future, the results of the cross-region analysis could be improved.

Lastly, previous studies indicated that the local epidemiological situation might influence the dynamics of human mobility, which was known as reverse causality (Boto- García, 2023; Glaeser et al., 2020; Mangrum and Niekamp, 2022). However, no extra instruments were built in this study to estimate the reverse causality between human mobility and COVID-19 infections as this is beyond the scope of our study. Our findings provided a whole picture of understanding the potential spatiotemporal dynamics of linkage between human mobility and COVID-19 infections during the transition period and should not be interpreted as pure causality between human mobility and COVID-19 infections. We also recommend future studies to detect the pure causality between human mobility and the spread of epidemic diseases over space and time by building more rigorous instruments to reduce bias.

5. Conclusion

There were significant spatiotemporal dynamics of human mobility and COVID-19 infections in SEA countries during the transition period of "living with COVID-19" in 2021. The GTWR model identified that the associations between human mobility and COVID-19 infections exhibited spatiotemporal heterogeneity. The associations in many regions strengthened over time at the early stage of the transition period, whereas gradually weakened and even became insignificant at the later stage of this period. Our work provided a comprehensive understanding of how human mobility was associated with COVID-19 infections over time and across space in SEA during the transition period. This inspires policymakers for adjusting interventions scientifically at the later stage of an analogous public health crisis and calls for local governments to collaborate to effectively respond to public health crises in the future.

Data availability

Data and code can be downloaded at https://github.com/GeoSpatialX/SEAsia_COVID_Mobility

Acknowledgement

We would like to acknowledge Facebook Data for Good at Meta (https://dataforgood.facebook.com/) for support with mobility data access.

Appendix

Table A1
Summary of Moran's I test

	Moran's Index	z-score	p-value
WEEK1	0.3735	16.4942	0.0000
WEEK2	0.3524	17.1027	0.0000
WEEK3	0.3371	18.3826	0.0000

(*continued on next page*)

Table A1 (*continued*)

	Moran's Index	z-score	p-value
WEEK4	0.3428	18.5625	0.0000
WEEK5	0.3549	18.9385	0.0000
WEEK6	0.4953	22.9001	0.0000
WEEK7	0.4050	17.9291	0.0000
WEEK8	0.3626	15.8996	0.0000
WEEK9	0.2879	12.8158	0.0000
WEEK10	0.2528	11.1714	0.0000
WEEK11	0.1939	8.5945	0.0000
WEEK12	0.1637	7.2147	0.0000
WEEK13	0.2030	8.9849	0.0000
WEEK14	0.1879	8.4081	0.0000
WEEK15	0.2094	9.3244	0.0000
WEEK16	0.1987	8.8924	0.0000
WEEK17	0.2213	9.6673	0.0000
WEEK18	0.2118	9.7227	0.0000
WEEK19	0.1981	9.5047	0.0000
WEEK20	0.1319	7.3125	0.0000
WEEK21	0.1198	6.7871	0.0000
WEEK22	0.1300	6.6274	0.0000
WEEK23	0.1827	8.8270	0.0000
WEEK24	0.2253	10.2356	0.0000
WEEK25	0.3116	13.5273	0.0000
WEEK26	0.3522	15.1097	0.0000
WEEK27	0.4065	17.2301	0.0000
WEEK28	0.3597	15.3005	0.0000
WEEK29	0.2667	11.5843	0.0000
WEEK30	0.2205	13.7028	0.0000

Table A2
Summary of the OLS result

	Coefficient	p-value	VIF
Intercept	−0.042	0.000***	
Explanatory variable:			
MOVE	0.132	0.000***	1.437
Control variables:			
PD	0.084	0.000***	1.324
PGDP	−0.003	0.667	1.602
OLD	0.013	0.002***	2.338
PR	0.013	0.001***	1.363
UR	0.052	0.000***	2.763
SI	0.039	0.000***	1.879
VR	0.004	0.216	1.514
HOS	−0.003	0.370	1.605
UER	0.010	0.009***	1.888
Adj $R^2 = 0.236$	AICc = -20900		

Table A3
Summary of Pearson correlation results

Country	Coefficient	Significance (P-value)
Brunei	−0.546**	0.002
Indonesia	−0.841**	0.000
Malaysia	−0.475**	0.008
The Philippines	−0.260	0.165
Singapore	−0.378*	0.040
Thailand	−0.770**	0.000
Vietnam	−0.463*	0.010
7 countries in SEA	−0.188**	0.006

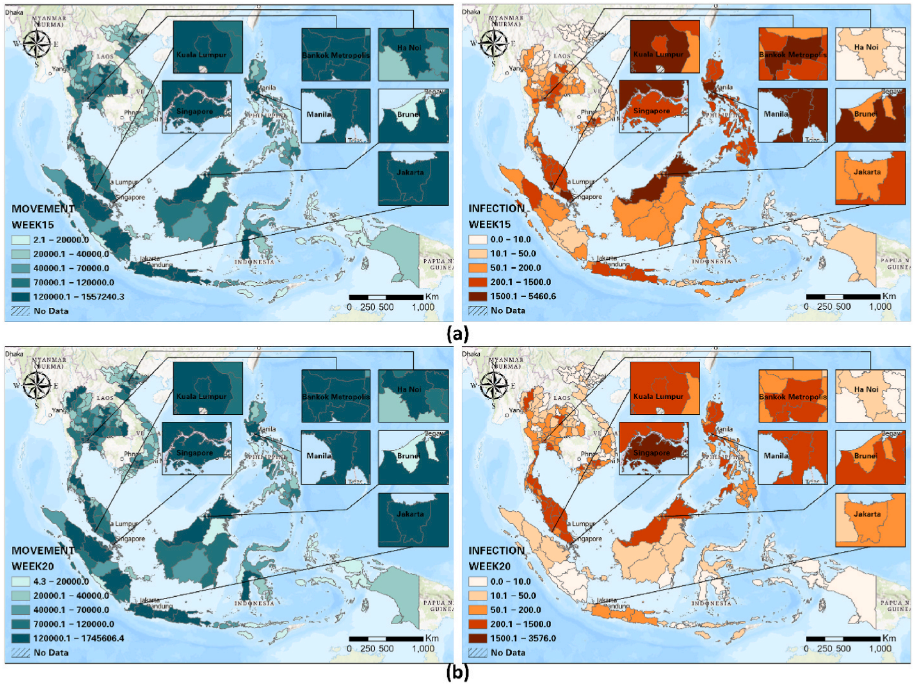

Figure A1. Spatial distribution of weekly average human mobility volumes and COVID-19 cases ((a): week 15, (b): week 20.

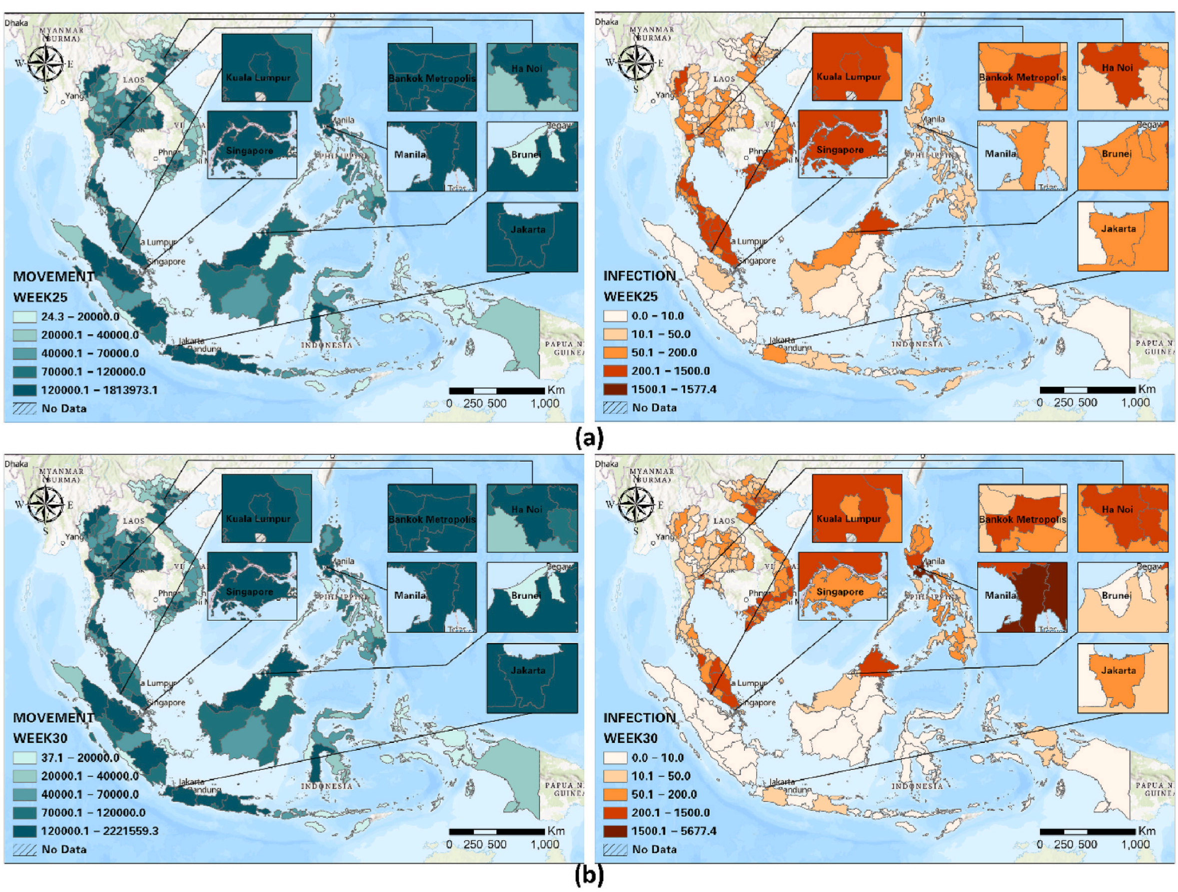

Figure A2. Spatial distribution of weekly average human mobility volumes and COVID-19 cases ((a): week 25, (c): week 30.

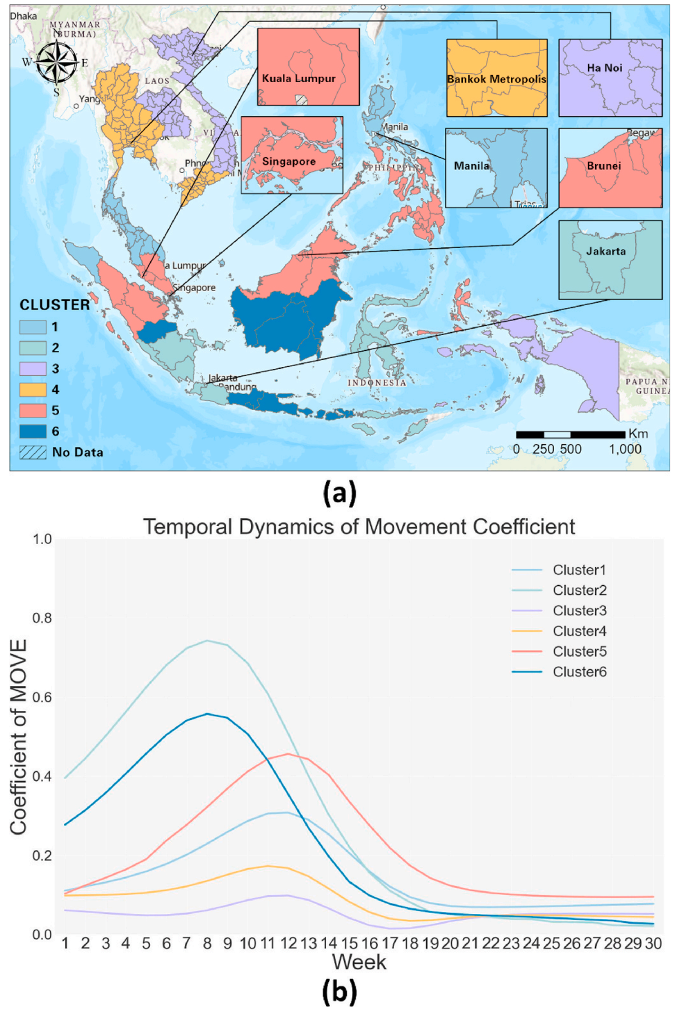

Figure A3. 6 Clusters of movement coefficient in Southeast Asia

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