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The impact of COVID-19 pandemic on the fundamental urban mobility theories using transit data from Singapore

Rakhi Manohar Mepparambath [a,*], Hoai Nguyen Huynh [a], Jeremy Oon [a], Jie Song [a], Rui Zhu [a], Ling Feng [a,b,*]

[a] Institute of High Performance Computing (IHPC), Agency for Science, Technology and Research (A*STAR), 1 Fusionopolis Way, #16-16 Connexis, Singapore 138632, Singapore

[b] Department of Physics, National University of Singapore, 117551, Singapore

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ABSTRACT

The COVID-19 pandemic has caused changes in urban mobility patterns due to the temporary movement restrictive policies imposed by local governments and the long-term hybrid work arrangements adapted by companies. This study re-examines the fundamental theories of human mobility in Singapore at the pre-pandemic, pandemic and endemic stages. In particular, we estimated three well-established mobility models in complexity science: gravity model, radiation model and visitation law for investigating the effects of COVID-19 pandemic in different stages, using the transit Origin-Destination (O-D) data collected in Singapore. Overall, the results show that the three mobility theories remain valid throughout the different periods with visitation law outperforming the gravity and the radiation models. At the pre-pandemic stage, the performance of the gravity and radiation models were comparable. The performance of the gravity model has improved compared to its pre-pandemic performance, showing 6–18% improvement at the pandemic stage and 9–15% improvement at the post pandemic stage, whereas the performance of the radiation model hasn't changed much, making gravity model a better-performing model than the radiation model for these periods. Our results also show that in the gravity and radiation models, gross floor area is a better predictor for transit flows than the population, whereas in the visitation law use of population variable results in better predictions. Our study is a first attempt in providing a revised understanding of the performance of the fundamental human mobility laws in the post-pandemic world.

Introduction

The coronavirus disease 2019 (COVID-19) has caused a global health crisis unlike any other in modern history, and the World Health Organization declared it a global pandemic in March 2020. Before the widespread use of the vaccinations, the majority of pandemic prevention and control policies implemented by local governments focused on movement restrictions such as partial or complete lockdowns, which severely affected urban mobility during the pandemic (Long and Ren, 2022; Niu and Zhang, 2023). The pandemic has also brought about unprecedented changes in how people completed their daily activities like work, education, shopping, etc. (Li et al., 2021a). As a result, transportation demand, which is often called a derived demand due to the spatially separated activities has been heavily impacted. As the countries entered the endemic phase, the short-term restrictions on the movements were removed, but there might be long-term changes in how people work due to the large number of companies adopting hybrid work arrangements in the post-pandemic world.

Many studies have investigated the impacts of COVID-19 on urban mobility in different regions around the globe and reported varying levels of reduction in overall urban mobility during the pandemic (Zhu et al., 2022). Some examples of such studies include Fatmi (2020) for Kelowna region of British Columbia, Canada, Arimura et al. (2020) for Sapporo city, Japan, Aloi et al. (2020) for the city of Santander, Spain, and Rahman et al. (2021) for Riyadh and Jeddah in Saudi Arabia. Some of these studies also reported a higher reduction of transit trips or a modal shift towards private modes during the pandemic (Aloi et al., 2020; Fatmi, 2020; Oestreich et al., 2023; Rahman et al., 2021; Thombre and Agarwal, 2021) or slow return to public transit post-pandemic (de Séjournet et al., 2022).

* Corresponding authors.
E-mail addresses: rakhimm@ihpc.a-star.edu.sg (R.M. Mepparambath), fengl@ihpc.a-star.edu.sg (L. Feng).

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Studies in general showed that the COVID-19 pandemic has affected urban mobility patterns, in particular transit mobility. As the world has entered an endemic era, it is worth and timely to investigate the long-term impact of the COVID-19 pandemic on urban mobility. Although the impact of COVID-19 on urban mobility has been studied for different cities, the fundamental changes to the human mobility flows, if any, due to the pandemic is not well studied, which is the research gap that we try to address in this paper. As the urban mobility models describe the fundamental behaviour of mobility flows, adapting these models into different stages of the pandemic will help in revealing the changes in urban mobility patterns due to the pandemic.

As a key component that indicates social activities, mobility patterns have a huge impact on various aspects of the society, including the changing need for amenities and transport demand. Such changes have a direct influence on land use and transportation planning. Hence, it is pertinent to provide an in-depth understanding of the new urban mobility patterns due to the pandemic. With this goal, we study the three most prominent urban mobility models in the field, which are the gravity model, the radiation model, and the visitation law. The findings from our study show that even though there is a change in the transit mobility patterns during and after the pandemic, the fundamental human mobility models are still valid at different stages of the pandemic. But, the performance comparison between these models at different stages of the pandemic clearly indicates that the pandemic has varying impact on the performance of these models.

Related work

In this section, we briefly present the studies that discussed the impact of COVID-19 on urban mobility along with the studies on the three urban mobility models.

Fatmi (2020) studied the adjustment in daily out-of-home travel activities, in-home activities, and long-distance travel of individuals during the COVID–19 travel restrictions, using survey data from the Kelowna region of British Columbia, Canada. The analysis suggests that individuals' participation in out-of-home activities was reduced by more than 50% during COVID-19. Arimura et al. (2020) found—using mobile phone data—that there was a 90% reduction in the population density of Sapporo city during massive lockdowns. Mobile phone data from the same city was used by Ha et al. (2023) to model the population density of each facility type as a time series to find the impact of COVID-19 pandemic on peoples' mobility and found that commercial facilities had highest decline in visits. Aloi et al. (2020) reported a 76% reduction in overall urban mobility for the city of Santander in Spain. Rahman et al. (2021) also reported similar phenomenon in transit trips.

Huang et al. (2023) studied the changes in travel behaviour and trip characteristics under work-from-home (WFH) arrangements and found that a significant reduction in trip distance and travel time and travel frequency for those who worked from home indicating that WFH arrangement can be beneficial to the society in mitigating negative externalities of transport. Oestreich et al. (2023) also found that COVID-19 pandemic has led to significant changes in urban mobility patterns, including the preference for private vehicles over public transport, increased bicycle use, and the emergence of new mobility services through smartphone applications. Nikiforiadis et al. (2022) studied the travel patterns of young adults in Greece and reported reduced use of public transport especially for those who had access to car and those who travelled between cities.

Many studies have generated insights on the impact of the COVID-19 pandemic on urban mobility patterns (Aloi et al., 2020; Arimura et al., 2020; Rahman et al., 2021). Most of them focused on the stage when the pandemic was the most severe (Pullano et al., 2020; Venkatramanan et al., 2021), which has already ended in most locations in the world. As we enter the 'endemic' phase that people co-exist with the ongoing virus spread for the foreseeable future, it is imperative to re-examine the mobility patterns to facilitate long-term urban planning. While most of the existing studies focus on the aggregated statistical observations (Aloi et al., 2020; Fatmi, 2020; Pan et al., 2020; Vitello et al., 2021) during the pandemic period, like drastic decrease in travels—in particular, long-distance travels, shift in travel purposes, lower vehicle emission and energy consumption, very few (Luca et al., 2022; Takko et al., 2023) have paid attention to investigating the impact of the pandemic induced changes on the human mobility laws like gravity model (Erlander and Stewart, 1990), radiation model (Simini et al., 2012), the visitation law (Schläpfer et al., 2021), and other mobility models (Brockmann et al., 2006; González et al., 2008; Lenormand et al., 2012; Noulas et al., 2012; Pappalardo et al., 2015; Yan et al., 2017; Yan et al., 2014), which were universal across different locations in the world before the pandemic. Unlike the other descriptive patterns observed in human mobility, such universal laws are fundamental mechanisms that are supposed to hold regardless of the geographical idiosyncrasies, providing the necessary foundation for the understanding and modelling of human mobility patterns. However, the pandemic could have caused a dramatic shift in mobility patterns, which may have resulted in changes in these fundamental human mobility laws. Therefore, it is pertinent to re-examine them in the different stages of the pandemic before we develop any new mobility models.

In this study, we re-examine the three most important human mobility theories—the gravity model (Erlander and Stewart, 1990), radiation law (Simini et al., 2012), and visitation law (Schläpfer et al., 2021), during the various stages of COVID-19, as a case study in Singapore. This helps us to distil the most fundamental human mobility laws that are invariant before, during, and after a pandemic. There exist other mobility models (Brockmann et al., 2006; González et al., 2008; Lenormand et al., 2012; Noulas et al., 2012; Pappalardo et al., 2015; Yan et al., 2017; Yan et al., 2014), but are not discussed in the current paper as we focus our attention to the selected three mobility models at different stages of the COVID-19 pandemic. A brief review of the three mobility models covered in this paper is provided below.

The gravity model (Barthélemy, 2011; Erlander and Stewart, 1990; Zipf, 1946), which is one of the earliest models for human mobility, suggests that the mobility between an origin and destination is proportional to the product of some form of mass variables of these two places and inversely proportional to the distance between them. The population at the origin and destination is used as the most common mass parameter in the gravity models found in the literature. The gravity model has found applications in different areas, some examples include predicting human mobility (Hong and Jung, 2016; Jung et al., 2008), trade and tourism flows (Bikker, 1987; Keum, 2010; Pöyhönen, 1963), communication flows (Expert et al., 2011; Krings et al., 2009), migration patterns or population flows (Barthélemy, 2011; Thiemann et al., 2010), and freight flows (Kaluza et al., 2010) to list a few.

As we study the urban flows using the mobility models, we briefly discuss similar studies found in the literature. Hong and Jung (2016) estimated a gravity model for intra-urban mobility flows on the Korean urban bus network for five cities in Korea and reported that the gravity model successfully estimates the intra-urban flows without universal exponents for cities. Goh et al. (2012) studied the subway system in Seoul using the gravity model and found that the subway flows can be better explained by modifying the distance-decay function in the gravity model.

The radiation law was proposed by Simini et al. (2012) to address some of the drawbacks of the gravity model, such as the dependency of adjustable parameters that vary from region to region, lack of a theoretical derivation for the model, the requirement of traffic flow data to fit the parameters of the model, etc. They analytically derived the radiation model and provided a parameter-free fundamental equation for the radiation model that can be used as an alternative to the gravity model. Simini et al. (2012) also showed that the predictive accuracy of the radiation model is better than the gravity model for a wide range of applications from long-term migration patterns to short-term communication flows.

A few studies compared the performance of the gravity and the radiation models. For example, Khan et al. (2017) compared the performance of the gravity and radiation models in modelling the human movement patterns in major Australian cities using mobility data collected from geo-tagged tweets and reported that the gravity model with cityspecific parameters provided the best results. Stefanouli and Polyzos (2017) also compared the performance of the gravity and radiation model in predicting the commuting flows in Greece using census data. They found that the parameter-free radiation model is able to describe the commuting pattern adequately in comparison to the gravity model. Similarly, Masucci et al. (2013) compared the radiation and the gravity model performance for commuting patterns using data from England and Wales. The authors found that the radiation model gives competitive results in comparison with the gravity model, but the thermodynamic limit assumption for the radiation model causes an underestimation of commuting flows for large cities.

Lenormand et al. (2016) also compared the performance of different variations of gravity models and radiation type models, making comparison across multiple cities, and found that the gravity approach outperforms the radiation approach in estimating the commuting flows. One of the few studies that attempted to compare the performance of the gravity and radiation models during the pandemic period is Luca et al. (2022), where the international mobility was modelled using mobile phone data. The results show that gravity model outperforms radiation model for outgoing flows for different periods of COVID-19 pandemic. Authors also proposed a new form of gravity model by explicitly including the movement restrictions as a variable in the model, which outperformed both the original gravity model and the radiation model. Using mobile phone data within the capital area of Finland for pre-pandmic, pandemic and endemic stages, Takko et al. (2023) constructed networks of exposure from the human mobility data and showed that the weights of the exposure can be modelled using gravity and radiation type models. Heydari et al. (2023) used a data fusion approach of using multiple sources of data including mobile phone data, traffic counts data and data from social networks in modelling mobility patterns in Finland before and early stages of the pandemic and found that by a model that combined a past baseline from mobile phone data with up-to-date road traffic data had the best performance, followed by the radiation and gravity models that were similarly augmented with traffic data.

The visitation law is relatively new and has yet to find wider applications in the literature. The visitation law states that “the number of visitors to any location decreases as the inverse square of the product of their visiting frequency and travel distance” (Schläpfer et al., 2021). The authors have demonstrated the universality of the distance-frequency distribution of population flows by using mobile phone data from five different cities across the world. Although the visitation law is developed to model individual-level flows, Schläpfer et al. (2021) suggested that the visitation law can be used in predicting aggregate flows and it outperforms both the gravity model and radiation flow in this aspect.

To sum up, it shows that the urban mobility models have been derived based on the pre-pandemic data or assumptions and have found a number of applications in the pre-pandemic mobility flow estimations. The studies on COVID-19 impact on urban mobility suggest that there were changes to the urban mobility patterns due to the pandemic. However, very few studies (Luca et al., 2022; Takko et al., 2023; Heydari et al.) have attempted to investigate the fundamental changes in the mobility patterns by developing urban mobility models since the start of the COVID-19 pandemic. Thus, the objective of this study is to investigate the validity of the urban mobility models at different stages of the COVID-19 pandemic. The contributions of the study include: (i) revealing the overall changes in the mobility patterns by descriptive analysis of transit data from Singapore at pre-pandemic, pandemic and endemic stages, (ii) estimating the gravity model, radiation model, and visitation law at pre-pandemic, pandemic, and endemic stages using the transit O-D data and comparing their performance, and (iii) comparing the performance of the mobility models while using population and land use variables at the three stages of the pandemic.

Data description

In this section, we discuss the different data sources that are used in this study which include COVID-19 related data, transport and mobility data, land use and population data. The details and usage of each category of data are discussed below.

Data on COVID-19 cases and policy measures

We collected information on the progression of the COVID-19 pandemic in Singapore and the control measures taken by the government using various online resources. The data on the number of COVID-19 cases over time in Singapore was collected from Dong et al. (2020), which is a continuously updated database of COVID-19 cases from different countries in the world. The first confirmed case of COVID-19 was reported in Singapore in January 2020. Since then, there have been a few waves of COVID-19 infection in Singapore, and the government has implemented adaptive policies to control the spread of the disease, as summarized in Table 1. The most restrictive measure was from April 2020 to May 2020, which is called the “circuit breaker“. During this period, there were restrictions on all non-essential travel and social gatherings. Following the circuit breaker, Singapore gradually removed the movement restrictions but tightened the restrictions again in May to November of 2021 due to an increase in the number of COVID-19 cases. The timeline of the COVID-19 pandemic in Singapore and the control measures implemented are shown in Table 1. It is used to understand the impact of various restrictive measures on the urban mobility flows and to decide on the time frame for the pandemic and endemic phase for the analysis. For the mobility model estimation purpose, data from the month of January 2019 is used for reconstructing the pre-pandemic mobility flows. Highest level of movement restrictions in Singapore happened during the circuit breaker period in April-May 2020. Although the total bus and train trips information is available for the circuit braker period, the detailed O-D based bus and train trips

Table 1
Timeline of COVID-19 pandemic and control measures in Singapore.

Timeline	Covid 19 phase	Social gathering	Work place arrangements
Jan ‘20	First confirmed case in Singapore	No size limit	No size limit
Mar ‘20	Safe distancing measures announced	No size limit	No size limit
Apr - May ‘20	“circuit breake”	Not allowed	All work from home
Jun ‘20	Phase 1 reopening.	Not allowed	All work from home
Jun – Dec ‘20	Phase 2 reopening.	Max. size = 5pax	Up to 50% staff can return
Jan - May ‘21	Phase 3 reopening	Max. size = 8pax	Up to 70% staff can return
May - July ‘21	Revert to Phase 2	Max. size = 5pax	Up to 50% staff can return
July - Aug ‘21	Phase 2 (Heightened Alert)	Max. size = 2pax	All work from home
Aug - Sep ‘21	Revert to Phase 2	Max. size = 5pax	Up to 50% staff can return
Sep - Nov ‘21	Stabilization Phase	Max. size = 2pax	All work from home
Nov - Dec ‘21	Transition Phase	Max. size = 5pax	All work from home
Jan - Mar ‘22	Transition Phase	Max. size = 5pax	Up to 75% staff can return
Mar -Apr ‘22	Transition Phase	Max. size = 10pax	Up to 50% staff can return
Apr ‘22 onwards	COVID-19 Resilient Nation Phase	No size limit	All can return

data that can be used in the estimation of the mobility models was not available for this period and hence we use data from the month of June 2020, which was a period with next highest level of movement restriction for estimation of mobility models during the pandemic. The data from the month of April 2022, when Singapore entered a COVID-19 resilient nation phase is used for analysing the mobility flows during the endemic phase.

Transport and mobility data sets

Public transport demand data that provide the transit Origin-Destination (O-D) flows is used in this study to develop the urban mobility models. The transit system in Singapore is multi-modal and consists of Mass Rapid Transit (MRT), Light Rail Transit (LRT) and the public bus network. Singapore has a high mode share for transit with 67% of trips made during the peak hours completed using transit (LTA, 2022). The travel demand data for both train and bus modes are maintained by the Land Transport Authority (LTA) of Singapore and are publicly available (LTA, 2023). This data is in the form of O-D flows between transit stops in the multi-modal transit network with hourly time resolution. Since the flows considered in this study are transit flows, we make use of the transit network to calculate the O-D distances. The details of the transit network such as the location of transit stations and route information for bus and train routes are also available in LTA (2023), using which we are able to construct a transit network for the study. The O-D distances used in this study are calculated as the distances in this transit network. More details on identifying the routes in Singapore transit network and finding the transit distances can be found in Mepparambath et al. (2023).

Land use and population data sets

The Urban Redevelopment Authority (URA) of Singapore makes long-term developmental plans for Singapore. The current Master Plan (2019) devised by URA divides Singapore into five regions, comprising 55 planning areas. The planning areas are further divided into 323 subzones. We study the transit flows at the planning area level. The URA Master Plan also provides the allowable land use types and Gross Floor Areas (GFA) for each land parcel. The GFA is used by URA in developmental control and gives an indication of the maximum floor area that can be developed in a land parcel. The GFA of the planning area can be derived directly by aggregating the GFA values for all the land parcels falling under each planning area. Since we examine the transit flows at the planning area level, it would be more appropriate to identify the principal land-use pattern for each planning area, instead of the actual land use at the plot level. Using a land-use clustering method proposed by Huynh (2022) (see also Jiang and Huynh (2022)), it can be shown that despite the complex land-use composition alongside variations, the 55 planning area can be classified into 6 different groups with distinctive land-use characteristics, which is shown in Fig. 1. The population based on 2020 census data is used in this study, which was obtained from the Singapore Department of Statistics (Department of Statistics Singapore, 2021). The data provides the total resident population at each planning area in Singapore, which includes 13 planning areas with zero resident population.

Urban mobility models

Gravity model

The gravity model (Erlander and Stewart, 1990) is a simple model developed as an analogy to Newton's law of gravity to capture the mobility flow between different geographical locations. It was originally designed to predict the flow between counties across a country but has been used to fit the data within urban areas as well (Hong and Jung, 2016; Li et al., 2021b). It is developed based on a simple assumption that the number of individuals that move from one location to other (T_{ij}) is proportional to some power of a mass variable at the source and destination and is inversely proportional to the distance between them, which is mathematically expressed as:

$$T_{ij} = G\frac{m_i^{\alpha} n_j^{\beta}}{r_{ij}^{\gamma}} \tag{1}$$

where m_i is the variable that influence the out-flow from origin i, n_j is the

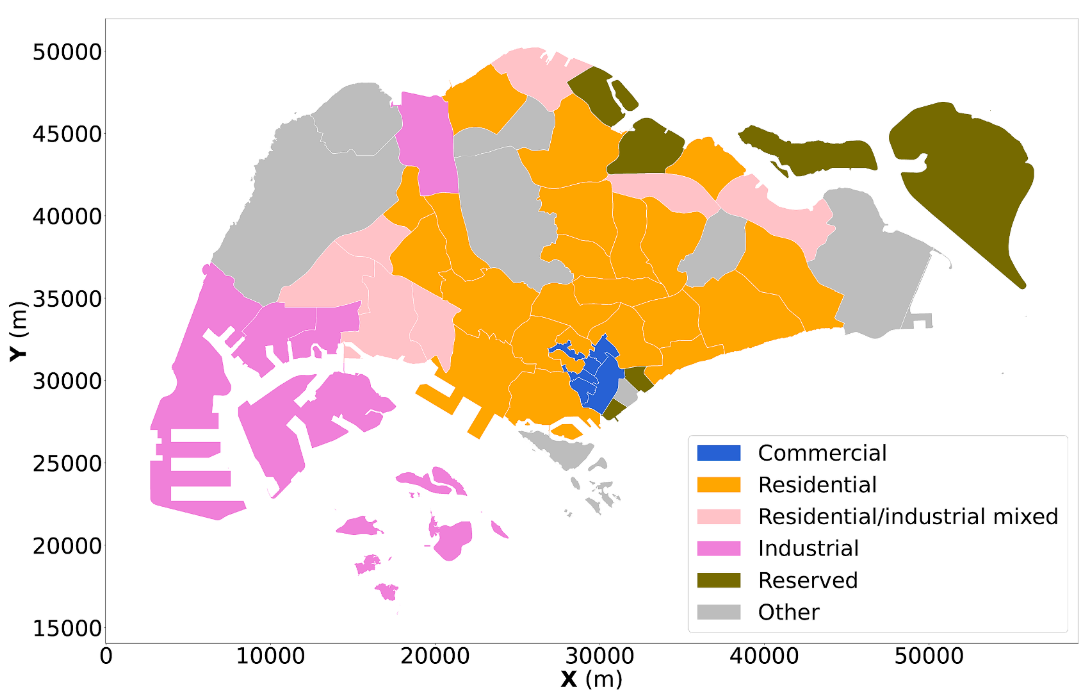

Fig. 1. Classification of planning areas in Singapore based on the composition of land-use types. The X and Y axes are in the Singapore SVY21 coordinate system (EPSG: 3414).

variable that influence the in-flow to destination j, r_{ij} is the distance between origin i and destination j and G, α, β, γ are the parameters calibrated using empirical data. This form of gravity model where all the parameters above are estimated is called the Type I gravity model. In some cases, α, β are kept as one and only G, γ are estimated. Such gravity models are called the Type II gravity model. In this study, we estimate the more generic Type I gravity models.

Radiation model

Highlighting the gravity law's limitations and analytical inconsistencies such as in predicting the number of trips when the populations in the origin or destination increase asymptotically, Simini et al. (2012) derived the radiation model as an alternative to the gravity model. According to the radiation model, the mobility flow from an origin i to a destination j is given by:

$$T_{ij} = T_i \cdot \frac{m_i n_j}{(m_i + s_{ij})(m_i + n_j + s_{ij})} \tag{2}$$

where T_i the total mobility out-flow from origin i, m_i, n_j are the number of opportunities at origin i, and destination j respectively, s_{ij} is the number of opportunities within the circle of radius r_{ij} centred at the origin i excluding the opportunities at the origin i and the destination j, and r_{ij} is the distance between the origin i and destination j.

Visitation law

The more recent universal visitation law proposed by Schläpfer et al. (2021) is an individual-level mobility model and the authors used mobile phone data to estimate the model parameters. Visitation law states that "the number of visitors to any location decreases as the inverse square of the product of their visiting frequency and travel distance". The visitation law is given by the following expression.

$$\rho_i(r, f) = \frac{\mu_i}{(rf)^{\eta}} \tag{3}$$

where $\rho_i(r, f)$, also referred to as the 'spatial flow' is the density of visitors to location i with frequency f from a distance r, η is the scaling exponent, the value of which was found to be nearly equal to two for different cities and μ_i is the proportionality constant that reflects the location-specific attractiveness. Based on some assumptions on the visitation law, Schläpfer et al. (2021) also proposed a method for finding the aggregate O-D flows using the population density, which is given by the following expression.

$$T_{ij} = \frac{\mu_j A_i + \mu_i A_j}{r_{ij}^2 \ln(f_{max}/f_{min})} \tag{4}$$

where μ_i and μ_j are the proportionality constants that reflect the location-specific attractiveness of origin i and destination j. μ_j is found as $\mu_j \approx \rho_{pop}(j) r_j^2 f_{home}$, where $\rho_{pop}(j)$ is the population density at the destination j, r_j is the distance to the boundary of j and f_{home} is the frequency of returning to home during the observation period. μ_j can also be found in a similar way. f_{home} is found as $f_{home} \approx \frac{1}{day}$, assuming that individuals return back home on a daily basis. A_i, A_j are area of location i, j respectively. f_{min}, f_{max} are the visitation frequency limits, which are set as $f_{min} = \frac{1}{T}$, where T is the observation period and $f_{max} = \frac{1}{day}$. Further details on the visitation law for aggregate flows can be found in Schläpfer et al. (2021).

Variables in the model

Population is the most commonly used variable to describe the flows in all three models discussed here. In the current study, we estimate the flows using both the population variable and the Gross Floor Area variable in all three models. Hence, m_i, n_j corresponds to the population at the origin and destination in the population-based model and it corresponds to GFA at the origin and destination in the GFA-based models. Similarly in the visitation law for aggregate flows (Equation (4)), we derive the μ_i and μ_j using both population and GFA to estimate the corresponding flows using the visitation law. Since our observations are for daily transit flows, the visitation frequency limits f_{min}, f_{max} are kept at one in the visitation law. All three urban mobility models explored in this study use the distance variable r_{ij} which is the distance between an origin i and destination j. As we use data on transit flows, the distances are also calculated in the transit network. We calculate the distance between two given zones as the weighted average distance in the transit network between all observed OD pairs between two zones. That is the distance between zone i and zone j, which is denoted by r_{ij} is calculated as:

$$r_{ij} = \frac{\sum_{od \in OD} w_{od} r_{od}}{\sum_{od \in OD} w_{od}} \tag{5}$$

where, w_{od} is the observed flow between OD pair o, d, where o is a transit stop in origin zone i and d is a transit stop in destination zone j. r_{od} is the shortest transit distance calculated on the transit network. OD is the set of all transit OD pairs observed between origin zone i and destination zone j. If the flows are not available at transit node level, distances between the zones can be estimated as the distance between the geographical centroids of the zones. Our analysis has shown that there is only negligible change in the urban mobility model estimation results between theses two methods of estimating the distances between the zones.

Performance comparison of models

The data used in calibrating the mobility models in this study are purely aggregate transit O-D demand data and no individual-level mobility data was used in the study. Parameters of the gravity model are fitted using linear regression in the log–log space making use of the aggregate transit O-D data. The estimated gravity model is used to predict the O-D flows between different zones, which is then compared against the observed flows. The radiation model is parameter-free, similarly for visitation law no parameters are estimated for the prediction of aggregate flows. Hence, the transit O-D flows between different zones are directly predicted using the radiation law and the aggregate visitation law. The predicted and observed flows are then compared.

For comparing the performance of the models, we use Sørensen–Dice similarity index (SSI), which has its origin in ecology (Dice, 1945; Sorensen, 1948), and was found to be one of the most common measures used in the literature to compare the mobility models (Luca et al., 2022; Ma et al., 2019; Masucci et al., 2013; Schläpfer et al., 2021). SSI quantifies the similarity between the predicted and observed number of trips and is calculated as:

$$SSI = \frac{2\sum_{i,j} \min(T_{ij}^{pred}, T_{ij}^{obs})}{\sum_{i,j} T_{ij}^{pred} + \sum_{i,j} T_{ij}^{obs}} \tag{6}$$

where T_{ij}^{pred} is the predicted flow between origin i and destination j by the respective model and T_{ij}^{obs} is the observed flow between the same origin and destination pair. The SSI takes values between zero and one with zero showing no agreement with the observed flow and the flow predicted by the model and one showing a perfect match with the predicted and observed flows.

Results and discussion

General changes in transit flow

To understand the general trends in transit mobility, we analysed the bus and train trip data before, during, and after the COVID-19 pandemic. In particular, we investigated how the total volume of trips, trip distances and the relative distribution of trip ends have changed over different stages of the pandemic.

The change in the average number of transit trips at different stages of the pandemic is shown in Fig. 2 along with the daily COVID-19 cases reported. The figure shows that the highest dip in the number of trips occurred during the first wave of COVID-19 infections, which was from April to June 2020. This was expected as Singapore was in partial lockdown during this period with the highest level of movement restrictions. The next major dip in the number of transit trips happened from May to June of 2021 when the second COVID-19 wave hit Singapore. With every subsequent wave, a slight decrease in the average number of trips is observed, with minimal decrease with the later waves. This pattern clearly shows that Singapore has entered the endemic stage of the COVID-19 pandemic with the number of COVID-19 infections no longer making much impact on transit trips. The average number of daily bus and train trips for the selected pre-pandemic period, Jan 2019, were 4.25 and 3.68 millions respectively. Similarly, for pandemic period (June 2020) the average daily bus trips were 2.13 millions and train trips were 1.35 millions, whereas the number of bus and train trips for endemic period (April 2022) were 3.44 and 2.78 millions respectively. This also shows that the number of daily bus and train trips has not reached pre-pandemic levels yet. This may be due to long-term hybrid work arrangements, adopted by many companies in Singapore.

The distribution of trip distances at different stages of the pandemic is shown as a box plot in Fig. 3. The figure shows that there is no major change in the distribution of the trip distances although the number of trips has come down as shown in Fig. 2. We also investigated the change in the number of trips originating and ending at each zone during the pandemic and endemic stages compared to the pre-pandemic stage and the results are shown in Fig. 4. The figure shows that there is a reduction in the in-flow and out-flow to most of the zones (blue zones) during the pandemic and also in the endemic stages. A comparison of land use of

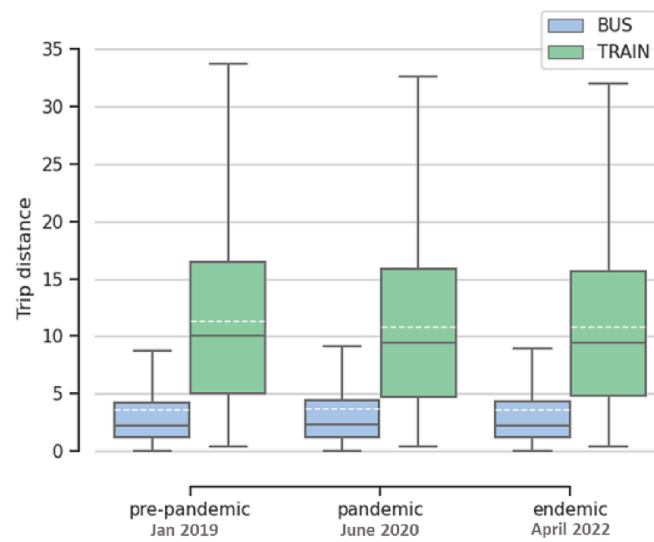

Fig. 3. Trip distances during different stages of pandemic.

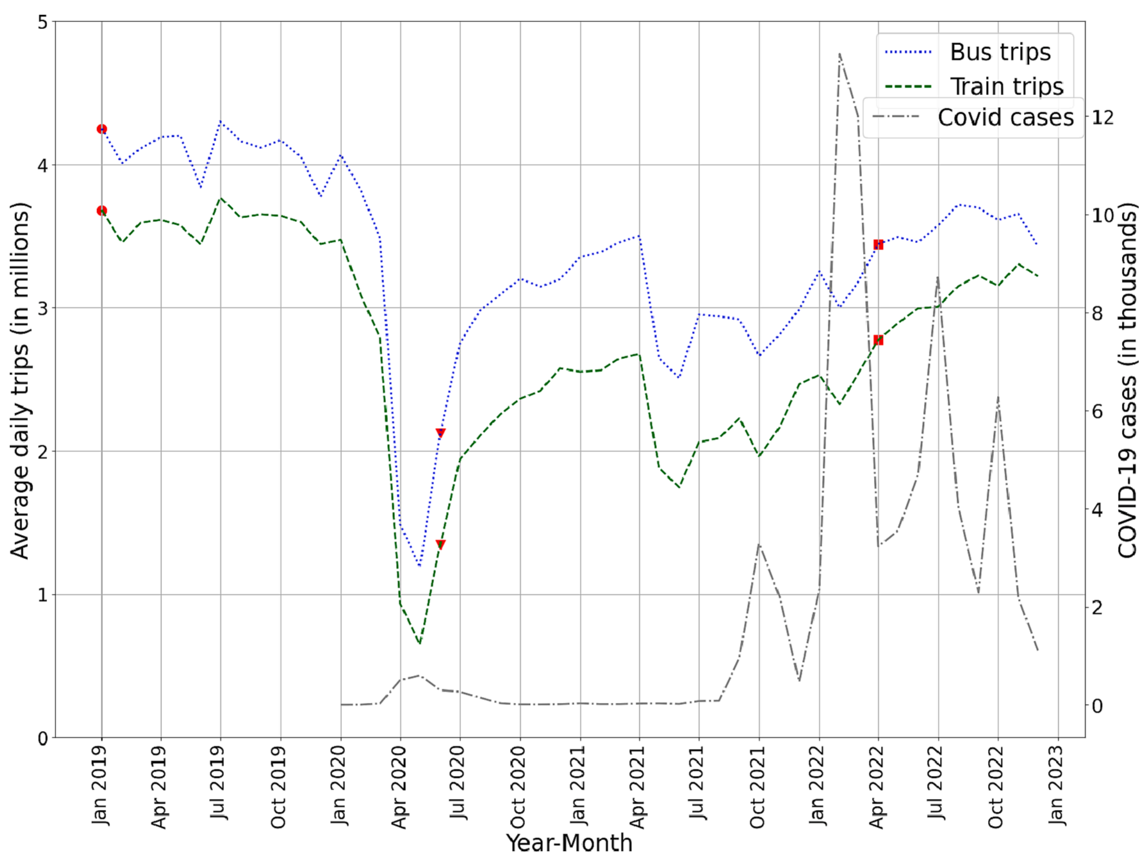

Fig. 2. Average daily transit trips from Jan 2019 to Jan 2023, with average daily bus and train trips for the selected pre-pandemic - Jan 2019 (red circle), pandemic - Jun 2020 (red triangle) and endemic - Apr 2022 (red square) stages highlighted. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

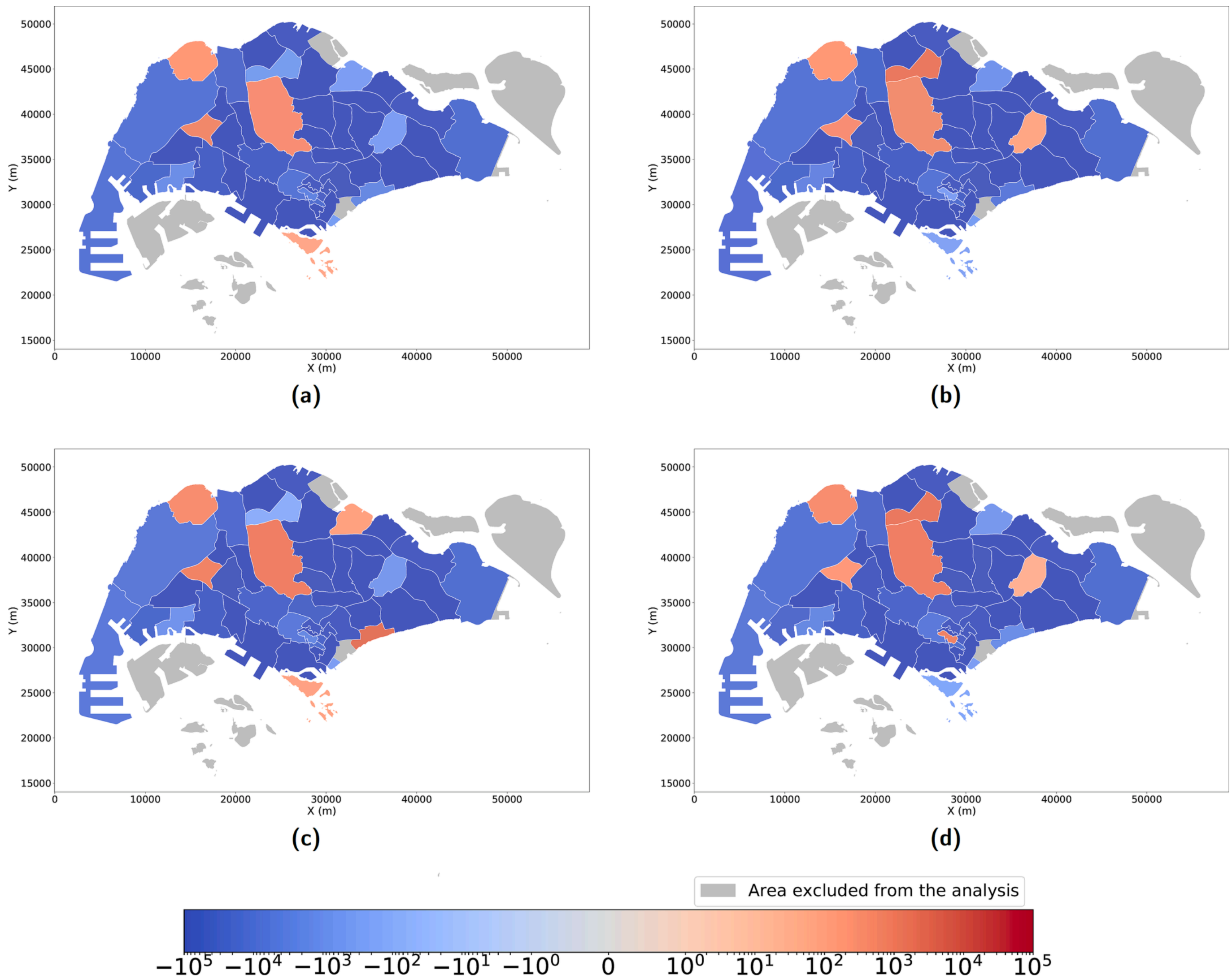

Fig. 4. Change in (a) trip origins from pre-pandemic to pandemic (b) trip destinations from pre-pandemic to pandemic (c) trip origins from pre-pandemic to endemic (d) trip destinations from pre-pandemic to endemic.

these zones as shown in Fig. 1 shows that the highest reduction in flow occurred in those zones with high residential and commercial land use.

We also observed a few zones which received higher flow during the pandemic and endemic periods, compared to the pre-pandemic period (orange zones). Our analysis shows that these zones have a relatively higher land use of type parks or green spaces as shown by other land-use category in Fig. 1. This analysis indicates that the pandemic may have brought about a long-term change in the trip generation rates for different land use types. This may partially be driven by the more flexible work arrangements in the post-pandemic world.

Model estimation results

The estimated parameters of the gravity models using the population and GFA variables for the three different time periods are presented in Table 2. The results show that the exponents of the mass variables for the origin and destination which are denoted by α and β in the gravity model show a slight decrease in both pandemic and endemic stages with the GFA variable. This gives us an indication that there is a slight reduction in the influence of the GFA variable of the origin and destination on the flow between them due to the changes in mobility patterns since the start of the pandemic. For the model with the population variable, there is a slight increases in values of α, β during the pandemic phase, but decrease during the endemic phase. More interestingly the influence of these variables has been less than their pre-pandemic level at the endemic stage, providing preliminary evidence that the trip generation rates of different land-use types may have changed post-pandemic.

Table 2
Parameter estimates for the gravity model.

Time	α	β	γ	G
Gravity Model 1 (GM1): Mass parameter = Population				
Pre-pandemic	0.373	0.364	1.375	exp(14.224)
Pandemic	0.384	0.411	1.710	exp(15.950)
Post-pandemic	0.351	0.356	1.642	exp(16.610)
Gravity Model 2 (GM2): Mass parameter = Gross Floor Area				
Pre-pandemic	0.829	0.731	1.545	exp(-0.758)
Pandemic	0.716	0.695	1.810	exp(3.279)
Post-pandemic	0.719	0.661	1.779	exp(3.806)

The results also show an increase in the value of the exponent for the distance variable or the γ parameter, especially during the pandemic. In the endemic stage, the value of the γ parameter has slightly reduced from the pandemic levels but hasn't reached to the pre-pandemic levels yet. This shows that the influence of the distance variable on the flow between an origin and destination has increased since the start of the pandemic. People are more sensitive to travel distances during the pandemic and the endemic phase compared to the pre-pandemic phase. The value of the constant G has also increased after the start of the pandemic. In the log–log space where the gravity model parameters are estimated, $\log G$ is the constant or the y-intercept of the linear regression model. Therefore, the value of G provides an indication of the influence of other factors on the flow that is not captured by the variables in the model. An increase in the value of the constant G in the pandemic and endemic stages gives an indication of the increased influence of factors other than the population, GFA, and the travel distance in the urban mobility flows during the pandemic and endemic stages compared to the pre-pandemic stage.

The predictive performance of gravity models at different stages of the pandemic with population and GFA variables are shown as a scatter plot of predicted and observed flow along with the SSI values in Fig. 5. From the SSI values, it is evident that the overall predictive performance of the gravity model has improved in the pandemic and the endemic stage in comparison to the pre-pandemic stage. Also, the GFA-based gravity model has similar or better performance than the population-based gravity model in all three stages. Although the population is the most commonly used variable in the gravity model the results from our investigation show that the use of land-use-related variables can provide similar or better prediction of urban mobility flows.

Since the radiation model is parameter-free, we directly used the model given by Equation (2) to estimate the transit flows between different zones and the results on the radiation models' predictive performance at different stages of the pandemic using the population and GFA variables are shown in Fig. 6. The results show that, unlike the gravity models, the performance of the radiation model has not changed much during the pandemic and endemic periods compared to the pre-pandemic period. Similar to the results for the gravity model, the GFA variable provides similar or slightly better results for radiation models as well. Even though the original radiation model proposed the use of population variables in the model, our results show that the use of land-use variables can provide equally good results for the radiation model.

By analysing the characteristics of ODs with higher error for radiation model with population variable, we found out that the radiation model is under-predicting the flows from residential land use type to industrial land use type. This is due to the negligible population residing in the industrial zones. Similar under prediction of flows from residential to industrial zones were observed in radiation model with GFA variable also due to the lower GFA in industrial zones compared to residential zones.

As described in Section 4, the parameters of the visitation law for aggregate flows given by Equation (4) are derived based on the population and GFA values in the respective models and are able to predict the OD flows between different zones without any estimated parameters. The prediction results for visitation law for different stages of the pandemic using the population and GFA variables are shown in Fig. 7. The performance of the visitation law remains similar during the three stages of the pandemic with a slight decrease in performance of the population-based visitation law during and after the pandemic compared to the pre-pandemic performance. Unlike the gravity and radiation models, the use of the GFA variable only worse-off the

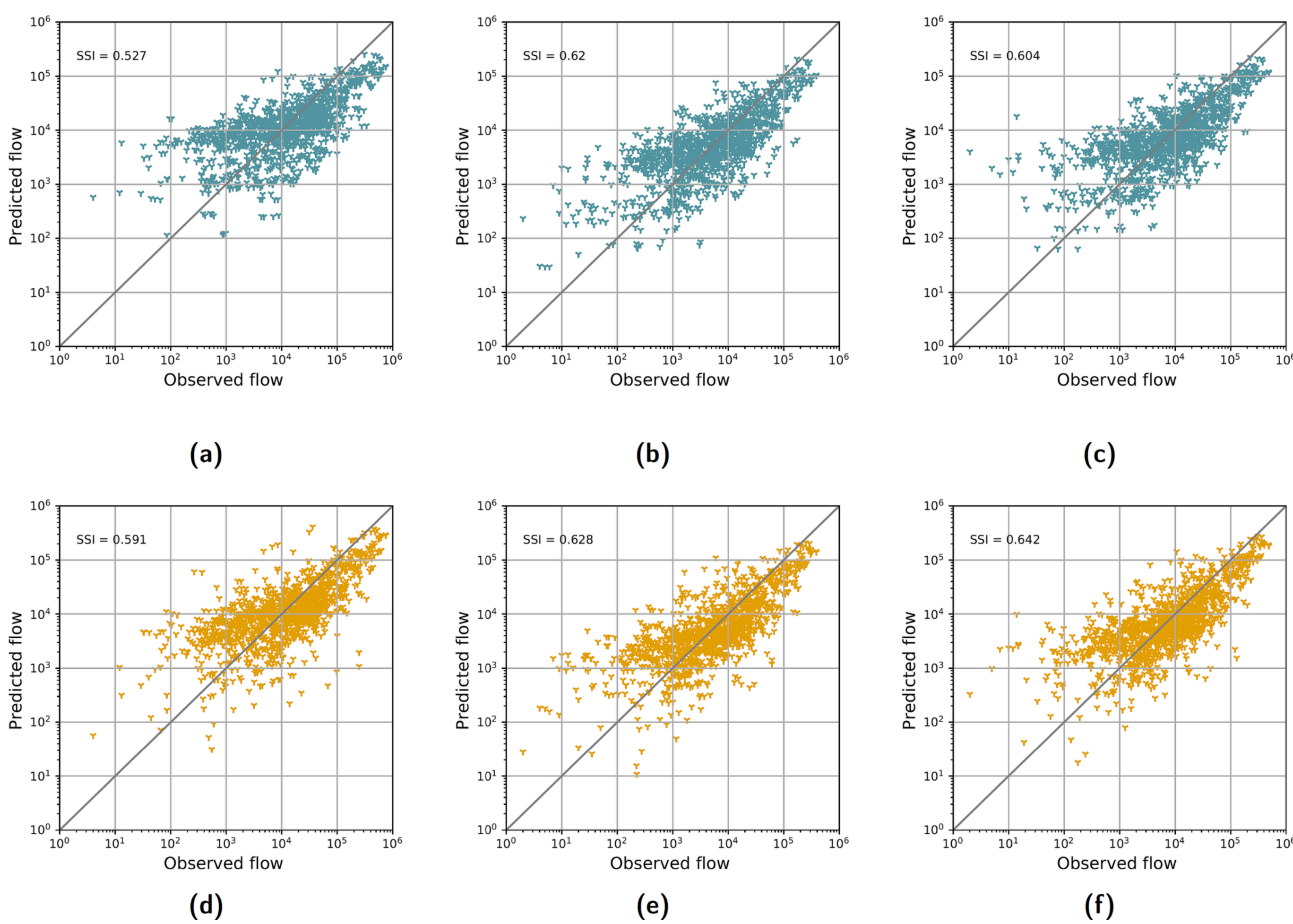

Fig. 5. Predictive performance of gravity model (a) during pre-pandemic using population variable (b) during pandemic using population variable (c) during endemic using population variable (d) during pre-pandemic using GFA variable (e) during pandemic using GFA variable (f) during endemic using GFA variable.

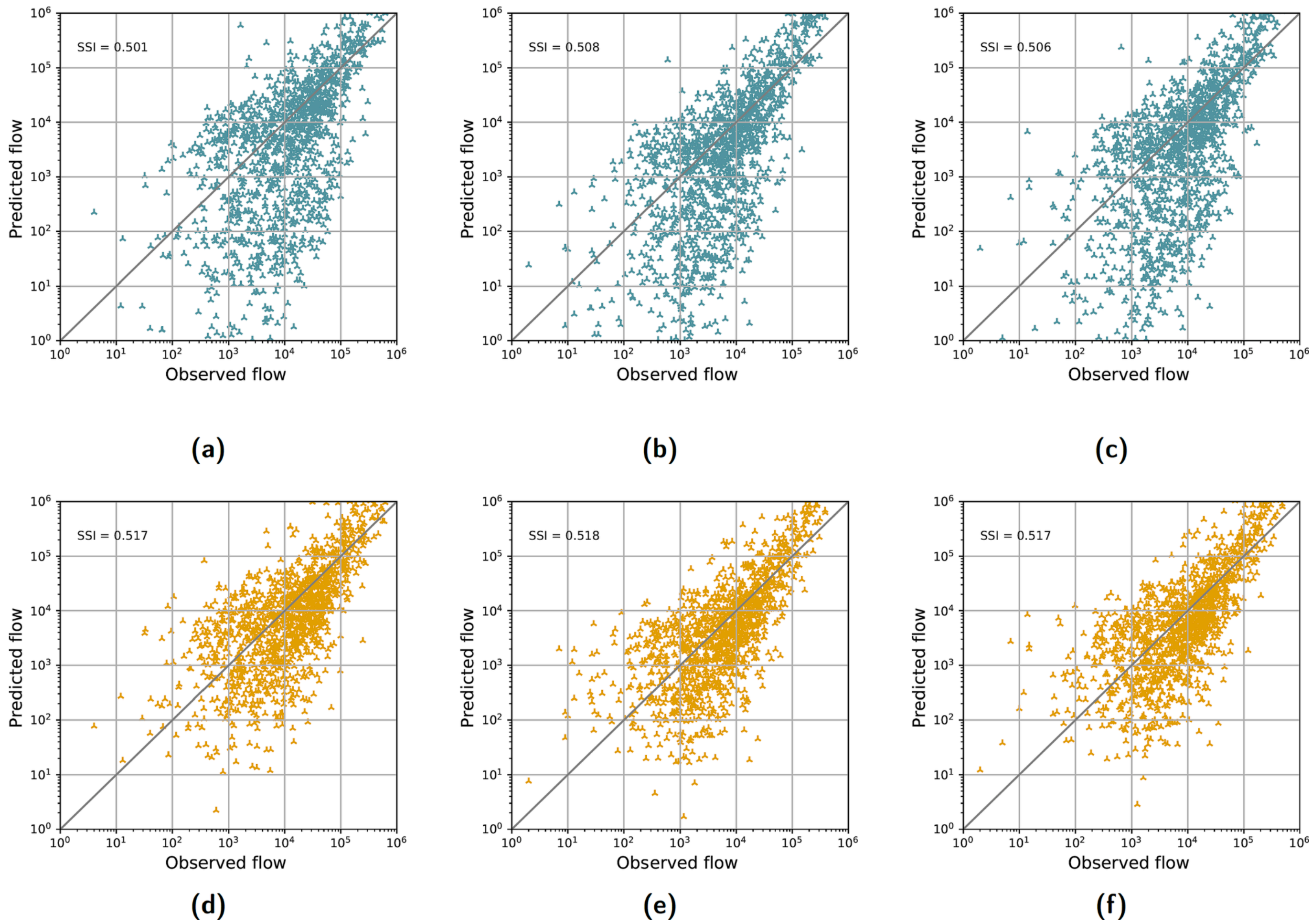

Fig. 6. Predictive performance of radiation model (a) during pre-pandemic using population variable (b) during pandemic using population variable (c) during endemic using population variable (d) during pre-pandemic using GFA variable (e) during pandemic using GFA variable (f) during endemic using GFA variable.

performance of the visitation law in all three stages of the pandemic. One potential reason we identified for the worsened performance of GFA based visitation law is that the original visitation law for O-D flows was derived based on population density and was based on the assumption of people returning to their home daily. Since these assumptions are not valid for land use types other than residential, direct use of GFA variable in place of population density in radiation model weakens the performance of the model.

For visitation law based on population and GFA, it was observed that the model over predicts the flows to and from industrial zones if the flow is from or to a zone with higher population density or GFA. In both cases, under predictions were observed between zones of high density residential land use. The analysis of ODs with higher error for both radiation and visitation models indicate that the inclusion of land use type along with population and GFA variable in these models can potentially improve the performance of the mobility models. The effect of this is lesser in gravity model due to the calibrated parameters for both origin and destination (α, β).

To compare the performance of the three different mobility models in predicting the transit flows, we present a summary table of the SSI values for these models at different stages of the pandemic using the population and GFA variable in Table 3. The results show that visitation law using population variable is consistently giving better predictions of transit mobility flows compared to the gravity and radiation law at different stages of the pandemic. Gravity model shows considerable improvement in performance compared to the pre-pandemic performance, which is about 6–18% improvement at pandemic stage and 9–15% improvement at endemic stage. In spite of the radiation model giving comparable performance to the gravity model at the pre-pandemic stage, its performance has not improved like that of the gravity model in the pandemic and endemic stages and the gravity model is outperforming the radiation model at these stages.

The performance comparison of models for the pre-pandemic period is consistent with other studies, where Khan et al. (2017), Lenormand et al. (2016), Masucci et al. (2013), Schläpfer et al. (2021)and Stefanouli and Polyzos (2017) found that the radiation and gravity models have very similar performance with gravity model giving slightly better results than the radiation model. Schläpfer et al. (2021) also found that the visitation law outperforms both the gravity and radiation models in the pre-pandemic stage. For the pandemic period, Luca et al. (2022) found that gravity model performs better than radiation model in predicting international outflows. Takko et al. (2023) compared the performance of gravity and radiation models for representing the human exposure network for years 2019, 2020 and 2021 in the capital region of Finland and found that the performance of gravity and radiation model slightly improved since the start of the pandemic, where we found that performance improvement for gravity model is much more that of the radiation model. The contribution of our study is in comparing the performance of the three urban mobility models during the pandemic and the endemic stages, which shows that the performance gap between the radiation and gravity models has widened since the start of the pandemic with the visitation law still outperforming the radiation and gravity models.

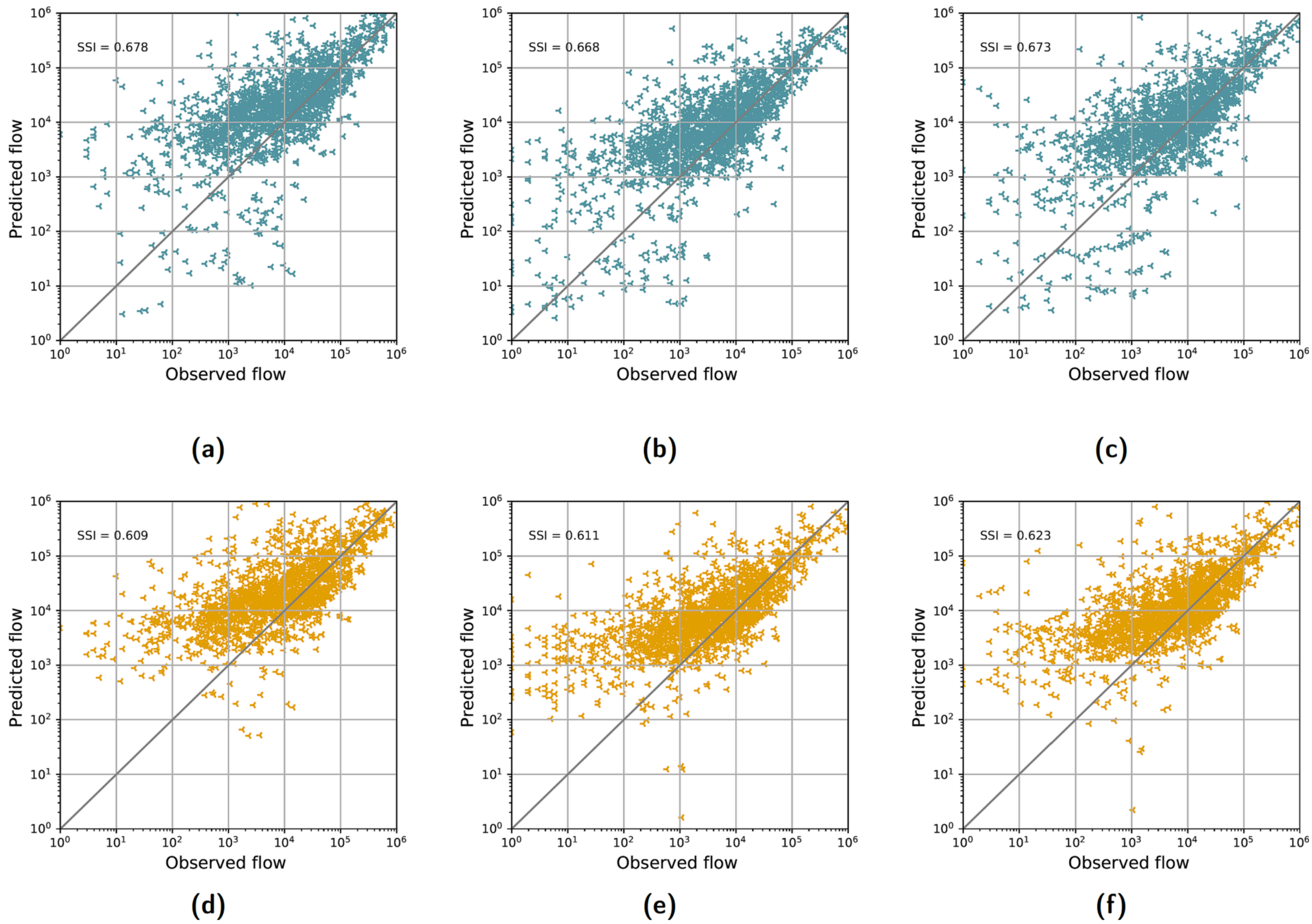

Fig. 7. Predictive performance of visitation law (a) during pre-pandemic using population variable (b) during pandemic using population variable (c) during endemic using population variable (d) during pre-pandemic using GFA variable (e) during pandemic using GFA variable (f) during endemic using GFA variable.

Table 3
Model comparison.

Mass variable	Time	Gravity Model SSI	Radiation Model SSI	Visitation law SSI
Population	Pre-pandemic	0.527	0.501	0.678
	Pandemic	0.620	0.508	0.668
	Endemic	0.604	0.506	0.673
Gross Floor Area	Pre-pandemic	0.591	0.517	0.609
	Pandemic	0.628	0.518	0.611
	Endemic	0.642	0.517	0.623

Conclusions

The COVID-19 pandemic has reshaped urban mobility by making both short-term and long-term impacts on the urban mobility patterns that are not captured by our existing knowledge on human mobility developed for the pre-pandemic scenario. This study investigated the fundamental urban mobility theories using transit data from Singapore before, during, and after the COVID-19 pandemic. In this study, we re-examined three prominent human mobility theories: the gravity model, radiation law, and visitation law, by integrating the use of the transit data throughout the whole periods of COVID-19 in Singapore. We also compared the performance of the models using population and land use variables during various stages of the pandemic.

The results show that the more recently proposed visitation law outperforms earlier models like the radiation model and the gravity model in the pre-pandemic, pandemic, and endemic stages. During the pandemic, the performance of the gravity model has improved whereas the performance of the radiation law show only very small improvement. The performance of the radiation model was comparable with that of the gravity model in the pre-pandemic stage, while the gravity model was much better in the pandemic and endemic stages. In terms of the predictors used in these models - gross floor area, which provides an indication of the intensity of the land-use has better predictive performance than the population variable in both gravity and radiation models. Whereas in the visitation law, the population variable provides better performance.

This study contains two limitations. Our study is mostly data-driven and only used transit O-D data, which cannot reflect the entire mobility patterns in a city. This is because personal mobility via multiple ways, such as walking, driving private vehicles, and travelling with personal mobility devices, can also be an important component affected by COVID-19. Although this study did not model personal mobility due to data limitations, our study is significant and reliable since transit mobility takes up a vast majority of urban mobility in Singapore. On the other hand, this study did not customize and advance the models for analyzing, which might impede an accurate reconstruction of directional traffic flows adapting to the transit data. Future work may analytically derive new equations for the three models to respectively investigate different periods of an infectious disease. Nevertheless, the results obtained from our study are significant in revealing the changed patterns of mobility.

To conclude, this study adapted fundamental human mobility theories to unravel and understand the changes in public transit-based mobility patterns, influenced by COVID-19. The results reveal that while COVID-19 has made profound impact on the public mobility patterns which are likely to be permanent, the fundamental mobility theories have remained valid, at least in the context of Singapore. However, the structural changes of the mobility patterns do show up in the certain parameters of the fitted models. Understanding such structural changes in the context of these mobility theories can stimulate urban planners and decision-makers to rethink and redesign resilient urban mobility for the next decade, with further advancement of dynamic mobility models and integration of both public and personal mobility data.

CRediT authorship contribution statement

Rakhi Manohar Mepparambath: Conceptualization, Methodology, Data curation, Writing – original draft. **Hoai Nguyen Huynh:** Conceptualization, Methodology, Data curation, Writing – original draft. **Jeremy Oon:** Data curation, Writing – original draft. **Jie Song:** Data curation, Writing – original draft. **Rui Zhu:** Methodology, Writing – original draft. **Ling Feng:** Conceptualization, Methodology, Data curation, Writing – original draft, Funding acquisition.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Datasets used are openly available, links to which are provided in the paper.

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