Exploring the effect of spatial scales in studying urban mobility pattern

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Abstract. Urban mobility plays a crucial role in the functioning of cities, influencing economic activity, accessibility, and quality of life. However, the effectiveness of analytical models in understanding urban mobility patterns can be significantly affected by the spatial scales employed in the analysis. This paper explores the impact of spatial scales on the performance of the gravity model in explaining urban mobility patterns using public transport flow data in Singapore. The model is evaluated across multiple spatial scales of origin and destination locations, ranging from individual bus stops and train stations to broader regional aggregations. Results indicate the existence of an optimal intermediate spatial scale at which the gravity model performs best. At the finest scale, where individual transport nodes are considered, the model exhibits poor performance due to noisy and highly variable travel patterns. Conversely, at larger scales, model performance also suffers as over-aggregation of transport nodes results in excessive generalisation which obscures the underlying mobility dynamics. Furthermore, distance-based spatial aggregation of transport nodes proves to outperform administrative boundary-based aggregation, suggesting that actual urban organisation and movement patterns may not necessarily align with imposed administrative divisions. These insights highlight the importance of selecting appropriate spatial scales in mobility analysis and urban modelling in general, offering valuable guidance for urban and transport planning efforts aimed at enhancing mobility in complex urban environments.

Keywords: Gravity model · Public transport flow · Spatial scales · Urban mobility pattern · Urban modelling.

1 Introduction

Urban mobility plays a crucial role in shaping the functionality and efficiency of cities, influencing economic activity, social interactions, and quality of life. An effective transportation system supports accessibility, reduces congestion, and enhances urban sustainability [4]. Public transport, in particular, serves as a backbone of mobility in dense urban environments like Singapore, where land

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constraints necessitate efficient transport planning. Understanding travel patterns within the public transport network is essential for optimising infrastructure, improving service provision, and informing urban development policies [27]. Analysing these patterns requires robust models that can capture the complex dynamics of urban mobility and provide insights into how people move across different spatial scales [23, 25].

A variety of models have been developed to study urban mobility, ranging from agent-based simulations to network-based approaches [2, 3]. Among them, the gravity model has been widely used due to its simplicity and effectiveness in capturing aggregate travel flows [15]. Inspired by Newton's law of gravity, it assumes that the interaction between locations is proportional to their population or activity levels and inversely related to the distance between them [5]. The gravity model has been successfully applied in various urban contexts to estimate mobility patterns and forecast transport demand [18]. However, while the model provides a useful approximation of mobility flows, its accuracy is arguably influenced by the spatial scale at which it is applied.

Spatial aggregation has been shown to play a critical role in urban mobility modelling, affecting both data representation and model performance [6, 9, 20]. At fine spatial scales, such as individual bus stops or train stations, the models may struggle to capture meaningful patterns due to high variability and noise in travel behaviour, leading to overfitting or poor generalisability. Conversely, at very coarse spatial scales, over-aggregation may lead to a loss of critical mobility details, obscuring important underlying dynamics and interaction patterns, and resulting in model underperformance. These challenges reflect the Modifiable Areal Unit Problem (MAUP), a well-known issue in spatial analysis where different zoning schemes or levels of aggregation can lead to significantly different analytical results (sometimes referred to as "Openshaw effect" [10]). In mobility research, this means that both the resolution and method of spatial aggregation must be carefully chosen to ensure accurate model interpretation and policy relevance.

Recent studies have sought to quantify and mitigate the effects of spatial scale in mobility modelling. For instance, it has been showed that while some mobility metrics (e.g. radius of gyration and entropy) remain relatively stable across scales, others vary significantly depending on the spatial resolution, influencing how individual activity spaces are characterised [7, 26]. Similarly, spatial boundaries can be argued to critically affect the predictive power of mobility models [22, 23], which means that spatial scale may not be merely a technical detail but a foundational element of mobility theory. However, while it has been acknowledged that model performance can vary significantly depending on the chosen spatial resolution, there is limited consensus on the optimal level of aggregation [8, 12]. Furthermore, spatial aggregation based on administrative boundaries may not necessarily align with actual urban movement patterns, potentially introducing biases in mobility analysis.

Despite extensive research on urban mobility modelling, several gaps remain in understanding the interaction between spatial scale and model performance

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using public transport flow data. First, the impact of spatial scale on gravity model performance has not been systematically explored in the context of public transport networks, particularly in highly urbanised environments like Singapore. Second, while administrative boundaries are often used for spatial aggregation, their effectiveness compared to alternative aggregation methods like distance-based clustering remains unclear. Moreover, most of these studies have focused on either individual-level GPS [1], mobile phone records [16] or social media data [7], rather than formal public transport usage data, which reflects structured and policy-relevant travel behaviour. This study addresses these gaps by examining how spatial aggregation affects gravity model performance using public transport flow data in Singapore. Specifically, the influence of different spatial scales on model accuracy is investigated, and comparison between administrative boundary-based aggregation and distance-based methods is made to evaluate which better captures urban mobility patterns. The findings from this study can provide insights into optimal spatial resolutions for mobility analysis and inform urban and transport planning strategies.

The remainder of this paper is organised as follows. Section 2 describes the data and methods used in the study, including details on public transport flow data, spatial aggregation approaches, and gravity model fitting procedures. Section 3 presents the results and discussion, focusing on model performance across different spatial scales and aggregation methods, as well as comparison of mobility pattern between time windows. Finally, Section 4 concludes with key findings, implications for urban planning, and potential directions for future research.

2 Data and methods

2.1 Data

The datasets used in this study were obtained from relevant authorities in Singapore, and can be categorised by public transport and administrative boundaries.

The public transport related data was obtained from the Land Transport Authority (LTA) of Singapore, which provides comprehensive data on public transportation infrastructure and usage across the city-state [14]. The data contains the location of bus stops and train stations and the amount of traffic flow between them. As this study focuses on mobility pattern within Singapore, the bus stops in Johor (Malaysia) that are parts of the cross-border services between Singapore and Malaysia are excluded. The traffic flow data contains information on the number of trips made between a pair of origin and destination transport nodes during hourly time windows (from `HH:00` to `HH:59`) that will be merged to obtain the daily flow on a typical day of a month, for both weekdays and weekends. The public transport flow data used in this study is for October 2024, which was chosen to reflects recent typical mobility patterns without the anomalies and seasonal variations in travel behaviours during major holiday periods in Singapore.

In addition to transport flow data, administrative boundaries delineated in the Master Plan 2019 [24] by the Urban Redevelopment Authority (URA) are

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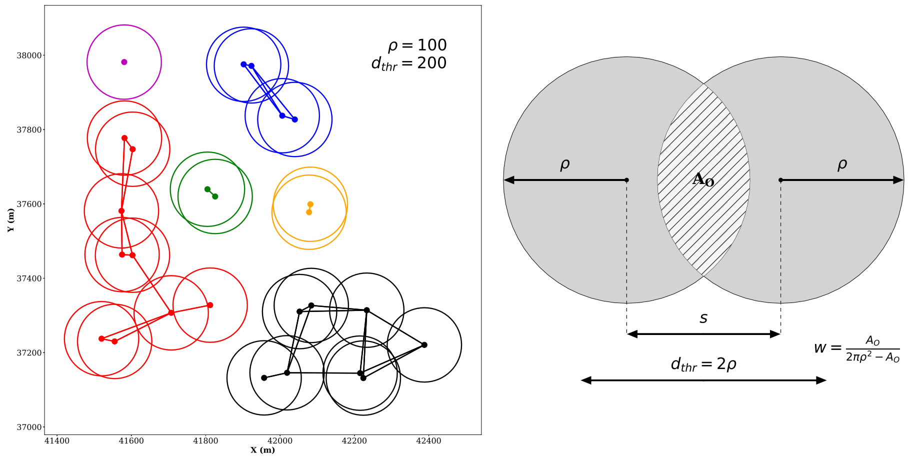

Fig. 1. Construction of network of transport nodes in which links and corresponding weights w are determined by the overlap area (hatched) of buffer circles of radius ρ centred at the nodes (right panel). The threshold distance for a pair of nodes to be considered in the same cluster is $d_{thr} = 2\rho$, beyond which the buffer circles do not overlap (left panel).

also used to compute different levels of spatial aggregation of transport nodes. These boundaries include three hierarchical levels: subzone, planning area, and region. Subzones represent the most granular administrative divisions in Singapore, while planning areas and regions provide broader spatial groupings.

2.2 Spatial clustering of nodes

Apart from the spatial aggregation by administrative boundaries, the transport nodes can also be clustered by spatial proximity. In this study, a procedure is devised to identify the clusters of transport nodes given a distance parameter. First, a network is contructed for all public transport nodes in Singapore with links added between pairs of nodes whose Euclidean distance is smaller than a given threshold d_{thr}. The weight of such links is calculated as the ratio between the overlap area of the buffer circles of radius $\rho = d_{thr}/2$ centred at the nodes and their union area (see Fig. 1). This area ratio reflects the strength of relationship between two nodes in terms of how close they are to one another. The network will then be divided into clusters using a procedure of community detection based on modularity (similar to previously employed in [11]). The clustering procedure is described in details in [13], involving multiple runs of the Louvain method for community detection and effective average of clustering patterns to identify the converged clusters of nodes.

Different levels of spatial clustering are obtained by varying the distance threshold parameter d_{thr} from 0 to 6,000 m in steps of 100 m. For every value of d_{thr}, the Louvain community detection algorithm is applied 100 times to yield

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the clusters of nodes. These distance-based clusters together with administrative boundaries (subzone, planning area and region) will serve as different kinds of spatial aggregation to assess the performance of the urban mobility flow model described in the next section.

2.3 Modelling the urban mobility flow

The gravity model has been widely used in transportation and urban studies to predict mobility flows between locations [18]. It is based on the analogy of Newton's law of gravity, where the interaction between two places is proportional to their population (or activity level) and inversely related to the distance between them. In the context of urban mobility, the model estimates the volume of trips between origin and destination locations and can be expressed as

$$F_{ij} = G\frac{M_i^\alpha M_j^\beta}{D_{ij}^\gamma} \tag{1}$$

in which F_{ij} denotes the traffic volume from location i to j, G is some scaling constant, M_i and M_j denote the corresponding activity level at these locations, and D_{ij} the distance between them, whereas α, β, and γ are associated parameters to be fitted using the mobility data. In this study, the total outflow traffic at location i and inflow traffic at location j are used as proxy for their activity level. The distance between the locations is taken as the Euclidean distance between the centroid of the cluster of transport nodes. It should be noted that in the case of administrative boundaries, the centroid is not the centroid of the polygon but the centroid of the cluster of transport nodes contained within the polygon.

The gravity model is then fitted using linear regression, where the logarithm of observed mobility flows is modelled as a function of explanatory variables including the activity level at origin and destination locations and the distance between them. This is achieved by employing the logarithmic form of Eq. 1

$$\log F_{ij} = \omega + \alpha \log M_i + \beta \log M_j - \gamma \log D_{ij} \tag{2}$$

in which the model parameters α, β, and γ are estimated using ordinary least squares (OLS) regression. Goodness-of-fit is evaluated using the coefficient of determination R^2 to assess how well the model explains variations in urban mobility flows between locations.

As the number of data points varies with different levels of spatial aggregation, the adjusted R^2 [21] is used to characterise the quality of model fitting instead of the usual R^2 to account for the data size and the complexity of the model (i.e. the number of independent variables). The formula for adjusted R^2 is given by $R^2_{adj} = 1 - (1 - R^2)(n - 1)/(n - p - 1)$ in which n is the number of data points and p the number of parameters. Given the gravity model has been shown to work very well with urban mobility pattern, aggressive test of the model in this study will be performed by using only 50% of the data for training and the model is tested on the remaining 50%.

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3 Results and discussion

3.1 Patterns of different levels of spatial aggregation

As the value of the distance threshold d_{thr} varies, different clustering patterns of transport nodes are observed. At $d_{thr} = 0$, every node forms its own cluster, whereas the nodes are grouped into 6 clusters at $d_{thr} = 6,000$ m. The clustering patterns of nodes at different values of d_{thr} are shown in Fig. 2. These patterns are also compared with clustering of nodes by subzones, planning areas and regions to assess their alignment with administrative boundaries. It could be observed that the distance-based aggregation does not necessarily align with imposed administrative boundaries, suggesting nuanced differences in patterns of spatial organisation across scales. The selected distance threshold values of 300 m, 600 m, and $4,400$ m in Fig. 2 show the clustering patterns that most closely match the clustering by administrative boundaries, as quantified by the mutual information score, which is commonly used to compare sets of different subset structures [19]. The identified clusters at different spatial aggregration levels will be used to assess the impact of spatial scale on the performance of the gravity model, providing insights into the relationship between spatial aggregation and urban mobility dynamics.

3.2 Performance of gravity model across spatial scales

For every clustering structure of the transport nodes, the gravity model is fitted to the corresponding aggregated traffic flow pattern to assess its performance across spatial scales. In order to obtain a reliable measure of the performance, the model fitting is run 100 times with randomisation of 50:50 train-test split. Equation 2 is fitted using 50% of the data to estimate the parameters α, β, and γ, and the model performance is assessed based on its prediction of the remaining 50% of the data. The results for weekday mobility pattern (see Fig. 3, top panel) show that the fitting at the least aggregate level, the transport node, is the worst with R^2_{adj} being only around 0.35, meaning that less than 40% of variance in the traffic flow can be explained by the combination of total outflow at origin, total inflow at destination and the distance between them. The model performance quickly improves as the nodes become spatially aggregated. The same argument as in [12] could be made that the aggregation of nodes better reflects the underlying dynamics of traffic flows where commuters from a particular location may use multiple transport nodes within the vicinity.

As the spatial aggregation increases, the average quality of fitting reaches the peak value at $d_{thr} = 1,500$ m and starts to decline afterwards. This decline signals that the transport nodes may be over-aggregated and that further congregating nodes may indeed "dilute" the dynamics of traffic flows whereby the true pattern is not captured as well as by a smaller mass of nodes, i.e. the flows are aggregated more than necessary. It is worth pointing out that the quality of fitting at large spatial scales fluctuates significantly compared to smaller ones, indicating low reliability of the fitting. Apart from diluting dynamics, the fact

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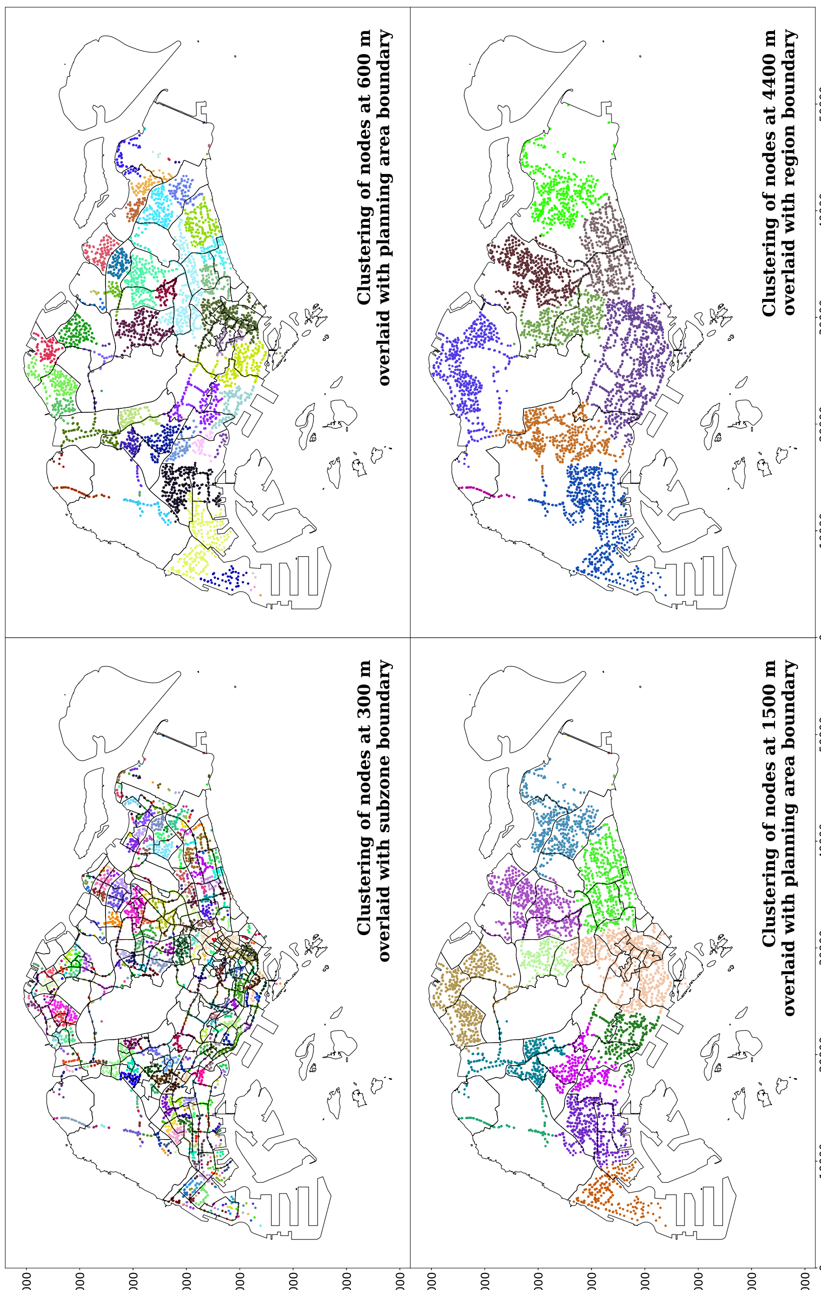

Fig. 2. Clusters of transport nodes at different values of threshold distance d_{thr}.

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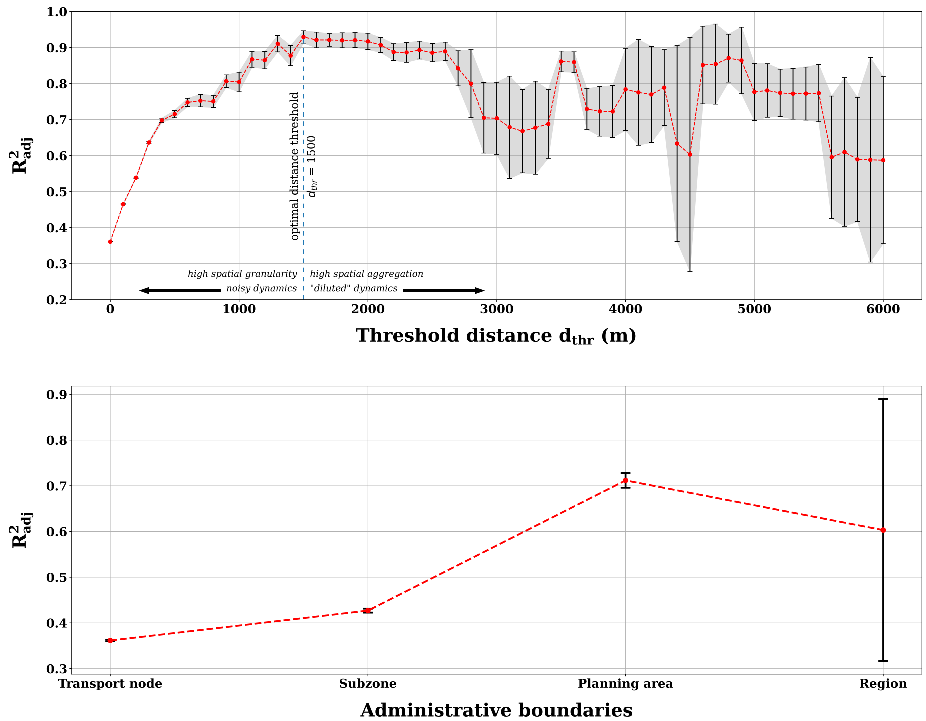

Fig. 3. Quality of fitting the gravity model to weekday mobility flows at different levels of spatial aggregation by distance threshold (top) and administrative boundaries (bottom). At each spatial aggregation, the average R^2_{adj} value and its error bar are computed over 100 runs with randomisation of 50:50 train-test split of the data.

that the number of data points decreases with higher level of spatial aggregation may also contribute to a poorer fitting of the model when its complexity is not justified by the amount of data available.

3.3 Comparison of mobility pattern across temporal windows

To further examine the temporal consistency of the gravity model performance, a stratified analysis is conducted based on time of day and weekday versus weekend travel patterns. The model is separately fitted to public transport mobility data from three distinct weekday periods, namely AM peak (6:00 AM to before 10:00 AM), PM peak (4:00 PM to before 8:00 PM), and off-peak hours (10:00 AM to before 4:00 PM), as well as to aggregated flows over the entire day on weekends. Across all time windows, the gravity model consistently shows the best performance when spatial aggregation is applied at 1,500 m (see Fig. 4, top panel). This suggests a robust spatial scale at which urban mobility dynamics in Singapore are optimally captured, regardless of temporal variation in travel behaviour. While minor fluctuations in model fitting are observed between time

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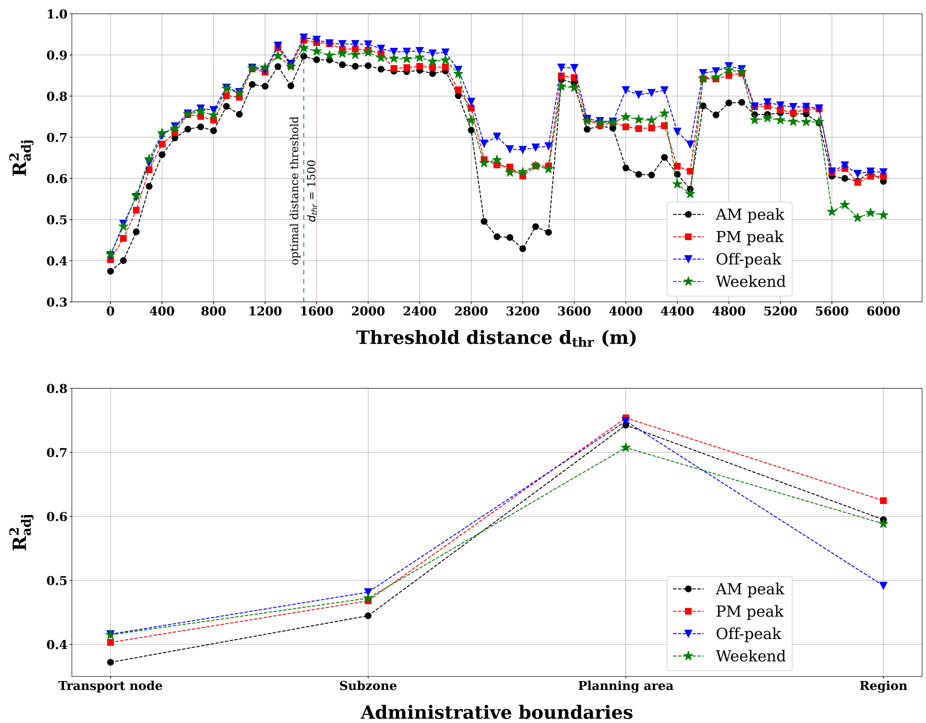

Fig. 4. Comparison of gravity model fitting by diffent periods: weekday AM peak, weekday PM peak, weekday off-peak, and weekend. Quality of fitting the gravity model at different levels of spatial aggregation by distance threshold (top) and administrative boundaries (bottom).

periods (likely due to differing trip purposes and passenger profiles), the spatial scale of 1,500 m provides a stable balance between granularity and aggregation. These findings reinforce the notion that intermediate spatial scales can effectively reduce noise in fine-grained data without oversimplifying travel patterns, making them suitable for both weekday commuting and weekend leisure mobility analysis.

3.4 Effect of different spatial aggregation methods

A similar trend in the quality of fitting the model is also observed using the administrative boundaries as the method of spatial aggregation (see Fig. 3, bottom panel). At the first level of subzone, the fitting shows some improvement with R^2_{adj} rising above 0.4. The improvement continues at planning area level when the average quality of fitting reaches 0.7. However the trend does not hold beyond planning area when the model performs poorer at region level, indicating over-aggregation of transport nodes. Recalling the corresponding patterns of clusters

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based on distance threshold and administrative boundaries in Sec. 3.1, grouping of transport nodes at subzone level is closest to the pattern of clusters at 300 m, at planning area level the distance is 600 m, and region level maps best to $4,400$ m (see Fig. 2). The corresponding quality of fitting at these distance also shows comparable values with similar trend as the spatial aggregation level increases. It should be noted that all of these administrative boundary-based clusterings perform worse than the spatial aggregation at $1,500$ m. The poorer performance of spatial aggregation based on administrative boundaries compared to distance-based aggregation indicates that these boundaries may not accurately reflect the true patterns of movement and interaction among transport nodes.

These results are also consistent across temporal windows when fitting mobility data from different periods of weekdays (AM peak, PM peak, and off-peak) as well as on weekends (see Fig. 4, bottom panel). Similar to the results for weekday mobility data, the gravity model exhibits the best performance at planning area level among the administrative boundaries when fitting stratified data from these windows, with the average R^2_{adj} value peaking around 0.7. Notably, while the whole-day data on weekdays (Fig. 3, bottom panel) and weekends (green star marker in Fig. 4, bottom panel) show similar peak R^2_{adj} value of 0.7, the sub-weekday periods all show slightly higher peak value. This hints at the variability in mobility behaviour throughout the day affecting the model performance. In the same vein, the noticeably worse performance of the gravity model at region scale for off-peak period (blue triangle marker in Fig. 4, bottom panel) compared to whole days or peak periods could be due to irregular large-scale movement pattern when long-distance travel appears to be rare outside rush hours. Nevertheless, these observations require further substantiation which is beyond the scope of the current study.

3.5 Contribution to mobility research and future directions

This study employs the gravity model as a mean to illustrate the effect of spatial scales and units in urban modelling. While the gravity model offers a simple and intuitive framework for modelling urban mobility, it is not without limitations. It assumes that flows between locations depend solely on size and distance, overlooking other influential factors such as land use mix, transport connectivity, and individual travel preferences, which may influence local variations and dynamic behaviours inherent in real-world mobility. Despite these limitations, this study contributes to the field by systematically evaluating how spatial scale affects the model performance, offering practical guidance on appropriate aggregation levels for transport analysis. Furthermore, it highlights the mismatch between administrative boundaries and actual mobility patterns, suggesting that data-driven, distance-based approaches may yield more accurate representations of urban movement. Future research could build on these findings by incorporating additional variables into the model, such as socio-demographic factors or transport service attributes. The role of spatial scale can also be explored in other modelling approaches like radiation [17] or machine learning-based models [25]

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to provide more comprehensive understanding of complex travel behaviours in urban systems.

Moving toward practical applications of these findings, actionable insights can be derived by combining mobility patterns with contextual knowledge of the actual urban organisation. In the case of Singapore, the clustering pattern observed at the 1,500-m aggregation level (see Fig. 2, bottom left panel) suggests strong functional integration between areas such as Jurong East and Bukit Batok (violet cluster around X=16,000 and Y=35,000). Similarly, northern neighbourhoods like Woodlands, Sembawang, and Yishun, or northeastern areas such as Serangoon, Hougang, Sengkang, and Punggol, may benefit from being considered as cohesive planning units. These spatial patterns highlight the potential for more integrated planning strategies that align with how residents actually move through the city-state. Further analysis, such as incorporating the spatial distribution of amenities, residential density, and public transport infrastructure like bus routes and train stations, could provide deeper insights into mobility demand and service accessibility. While such integration lies beyond the scope of the current study, it represents a promising direction for future research. In other urban contexts, similar approaches could offer powerful tools for urban planning by combining mobility data with additional layers of urban organisation, such as land use and the spatial distribution of services and infrastructure.

4 Conclusion

In this study, a computational method is developed to analyse the urban mobility pattern in Singapore. The findings reveal that while the gravity model can generally capture the flow dynamics, its performance quality varies significantly when different spatial units are used to calculate the amount of traffic between origin and destination locations in the model. It is found that the model fits poorly at the transport node level and performs best at some intermediate level of spatial aggregation corresponding to a threshold distance of $1,500$ m between nodes. Beyond that scale, the model performance decreases, signaling over-aggregation. Similar pattern is observed if the administrative boundaries are used, where the model fits poorly at the lowest level of subzone and improves at the intermediate level of planning area before decreasing at the highest level of region. However, the spatial aggregation at these administrative boundaries perform poorer than the distance-based aggregation, indicating that the administrative boundaries are artificial and not reflective of the actual organisation of mobility patterns on the ground.

The findings here offer valuable insights into the spatial organisation of urban areas in Singapore. The method developed in this study could be used to identify functional urban areas at different scales when combined with other relevant datasets. Additionally, this approach can help reveal latent mobility patterns and interactions between different parts of a city, offering a data-driven lens through which to interpret urban dynamics. Both the methodology and results can be useful for relevant urban and transport planning authorities in understanding the

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impact of physical infrastructure on urban mobility behaviours so that future land use and transport network can be effectively developed. Future research could build on this work by incorporating additional layers of spatial information, such as the distribution of amenities, residential densities, and the structure of public transport network. This would allow for a more comprehensive analysis of urban function and accessibility, ultimately contributing to the development of more inclusive and efficient urban environments.

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