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A Bayesian Spatiotemporal Framework for Explaining Bus Ridership Dynamics in Singapore

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Summary

Bus networks serve as the backbone of urban public transport, significantly shaping daily mobility patterns. However, few studies have leveraged long-term high spatiotemporal resolution bus data to precisely analyze service demand and urban-scale ridership dynamics. This study proposes a Bayesian hierarchical spatiotemporal modelling framework that integrates structured and unstructured spatial and temporal components. Using Singapore — a city with a dense bus network — as a case study, we evaluate the framework's effectiveness, identify spatiotemporal trends and ridership hotspots, and assess the influence of key spatial covariables. The findings offer valuable insights for urban and transport planning.
KEYWORDS: Hierarchical Bayes, mobility pattern, transport planning, built environment, smart card data.

1 Introduction

The rapid development of cities over the past few decades has driven the diversification of public bus systems, thereby shaping emerging commuting trends (Klinger 2017; Nguyen-Phuoc et al. 2018; Huang et al. 2019; Chen et al. 2021). Buses play a vital role in improving social welfare (Åhman 2013), reducing traffic injuries (Kwan and Hashim 2016), and enhancing regional land values (Duncan 2011; Bocarejo, Portilla, and Pérez 2013; Kay, Noland, and DiPetrillo 2014). Consequently, studies have quantitatively analyzed bus ridership patterns, actual demand, and influencing factors in relation to the built environment.

Much of this previous research relied mainly on global or local spatial models, such as the Spatial Error Model (SEM) and Geographically Weighted Regression (GWR), to examine the relationship between bus ridership and the social environment (Blainey and Preston 2010; Cardozo, García-Palomares, and Gutiérrez 2012; D. Zhang and Wang 2014; Rahman et al. 2021). However, these practices heavily relied on cross-sectional or short-term ridership data, limiting analyses to discrete time points rather than continuous time series, despite the temporal non-stationarity on bus ridership (Zhong et al. 2016; Ma, J. Zhang, et al. 2018a).

Recent advancements in information and communication technology, including smart card data (M.

Zhou et al. 2017; Li et al. 2017) and GPS trajectories (Y. Zhou et al. 2015; Tu et al. 2016; Yang et al. 2018), has provided an abundance of high-precision transportation-related data. This development enables the assessment of travel behaviour at a city-wide scale with unprecedented temporal granularity (Ma, Wu, et al. 2013; Alsger et al. 2016). Researchers have leveraged this data to examine individual travel patterns (Tao, Rohde, and Corcoran 2014; Kieu, Bhaskar, and Chung 2015) and infer travel purposes and activities (Lee and Hickman 2014), integrating temporal non-stationarity and spatial characteristics. However, despite extensive research on spatiotemporal modelling, studies focusing on long-term bus ridership and its interactions with the urban environment remain limited.

To address this gap, our study proposes a Bayesian spatiotemporal framework using hierarchical modelling to capture spatial, temporal, and spatiotemporal dependencies. Using Singapore's bus ridership data as a case study, we examine the spatiotemporal evolution of monthly ridership from 2020 to 2023 and evaluate the potential impact of various built environment factors on ridership patterns.

2 Methodology

2.1 Bayesian hierarchical spatio-temporal models

We use a Bayesian hierarchical spatio-temporal framework to model monthly bus ridership at the Subzone (SZ) level in Singapore from 2020 to 2023. This framework accounts for spatial dependencies, temporal trends, spatio-temporal interactions, and the influence of urban spatial covariates. The observed bus ridership effect y_{it} for subzone i in month t is modeled as:

$$y_{it} \sim \text{Poisson}(E_{it}\theta_{it}), \tag{1}$$

where E_{it} represents the expected ridership from historical data, and θ_{it} captures deviations from this expectation due to spatial, temporal, and covariate effects. These effects are modelled on the log scale to allow additive decomposition. We compared four hierarchical models with varying of spatiotemporal variables to determine the best fit and overall representativeness.

- **Random Spatial Effects Model:**

  $$\log(\theta_{it}) = \alpha_0 + u_i + v_i, \tag{2}$$

  where α_0 is the global intercept representing the average ridership across all SZs and months. The model includes u_i, the structured spatial effects modelled using a conditionally autoregressive (CAR) prior to capture spatial dependencies between neighboring subzones, and v_i, the unstructured spatial random effects accounting for subzone-specific variability.

- **Random Temporal Effects Model:**

  $$\log(\theta_{it}) = \alpha_0 + u_i + v_i + \phi_t, \tag{3}$$

which extends the spatial effects model by incorporating ϕ_t, the temporal effects that reflect month-to-month trends. These temporal effects are modeled as a first-order random walk (RW1).

- **Full Model:**

$$\log(\theta_{it}) = \alpha_0 + u_i + v_i + \phi_t + \psi_{it}, \tag{4}$$

which includes ψ_{it}, the spatio-temporal interaction effects modeled using the Kronecker product of spatial and temporal structure matrices. This interaction term accounts for residual variation not captured by the main spatial and temporal components.

- **Full Model with Covariates:**

$$\log(\theta_{it}) = \alpha_0 + u_i + v_i + \phi_t + \psi_{it} + X_{it}\beta, \tag{5}$$

which extends the full model by adding $X_{it}\beta$, the fixed effects of other urban spatial covariates such as land use mix and bus stop density. Here, X_{it} is the covariates matrix for subzone i and time t, and β is a vector of regression parameters.

2.2 Study Data

Bus Ridership Data The Singapore bus ridership data, normalized to density, is sourced from the Land Transport Authority DataMall[1] and is based on smart card data originally obtained at the bus stop level, which was subsequently aggregated according to SZs. It includes monthly passenger volumes from March 2020 to December 2023, focusing on weekdays. Isolated SZs such as Jurong Island are excluded due to a lack of spatial neighbours and data availability, forming a final dataset of 326 SZs.

Spatial Variables To analyze the spatiotemporal influence of environmental variables on bus ridership, we selected ten representative variables, as shown in Table 1. Five types of Point of Interest (POI) data from OpenStreetMap represent the distribution of different urban facilities, while nighttime light intensity from NPP-VIIRS reflects urban nighttime economic activities. Demographic data from the Singapore Department of Statistics, transportation variables such as road density from OpenStreetMap, and land use data from the Urban Redevelopment Authority[2] are also included. All variable counts were converted into densities based on the area of SZ and subsequently standardized.

3 Results

3.1 Model comparison and selection

We compared the four Bayesian models using DIC and the Number of Effective Parameters (N.eff) to identify the best fit, where lower values indicate better performance and efficiency (Table 2). The

[1] https://datamall.lta.gov.sg/content/datamall/en.html
[2] https://www.ura.gov.sg/corporate

Table 1: Description of spatial covariates.

Variable	**Description**
Shopping & Food POI	POI for retail outlets, restaurants, and food courts
Cultural & Tourism POI	POI for cultural sites and tourist attractions.
Public Services & Amenities POI	POI for government and public service institutions.
Recreation & Sports POI	POI for sports complexes and recreational areas.
Health & Education POI	POI for health facilities and educational institutions.
Nighttime Light Intensity	Illumination captured from nighttime satellite images.
Road Density	The total length of all roads per unit area.
Bus Stop Density	The total number of bus stops per unit area.
Population Density	The number of residents per unit area.
Land Use Mix	The degree of heterogeneity in land use types.

baseline model included only spatial effects, while adding temporal effects (Model 2) significantly reduced DIC to -29819.0 and improved efficiency. Introducing spatiotemporal interactions (Model 3) further lowered DIC but increased complexity.

In the final model, we incorporated key covariates while mitigating uncertainty from weakly correlated variables. Using LASSO regression and VIF checks, we excluded covariates with absolute LASSO coefficients below 0.1 and ensured all retained variables had VIF values below 5. The selected features included *Land Use Mix*, *Cultural & Tourism POI*, *Public Services & Amenities POI*, *Health & Education POI*, *Road Density*, and *Bus Stop Density*. Achieving the lowest DIC and reduced N.eff, it proved the most optimal choice.

Table 2: Model comparison with DIC and number of effective parameters.

Model	**Components**	**DIC**	**N.eff**
Random spatial effects			
1. Spatial u_i and non-Spatial v_i random effects	$\alpha_0 + u_i + v_i$	-12972.2	1311
Random temporal effects			
2. Correlated time effects, ϕ_t	$\alpha_0 + u_i + v_i + \phi_t$	-29819.0	1157
Full Model			
3. Space-time interaction term, ψ_{it}	$\alpha_0 + u_i + v_i + \phi_t + \psi_{it}$	-32945.8	1724
Full Model with Covariates			
4. All components and covariates	$\alpha_0 + u_i + v_i + \phi_t + \psi_{it} + X'_{it}\beta$	-33320.3	1560

3.2 Model results

For the selected model, we analyzed the contribution of spatial, temporal, and spatiotemporal patterns to ridership variation (Table 3). The results indicate that spatial differences were the primary driver, while spatiotemporal effects played a smaller role, and temporal structures had minimal impact. This limited temporal influence may be due to the stable ridership trends observed during the study period.

Table 3: Variance analysis results.

Variance Type	**Spatial (%)**	**Temporal (%)**	**Spatio-Temporal (%)**
Variance	74.37	1.69	23.94

We further analyzed spatial random effects for each SZ, as illustrated in Figure 1 (a). An effect value greater than 1 indicates that the posterior mean ridership of the corresponding geographic unit exceeds the average of other SZs, identifying it as a spatial hotspot, whereas a value below 1 suggests the opposite, marking it as a spatial coldspot. High posterior means were concentrated in the centers and surrounding areas of residential towns, such as Yishun Central, Woodlands Regional Centre, Clementi Central, Toa Payoh Central, and Tampines East, reflecting Singapore's transit-oriented development (TOD) strategy. By integrating MRT stations, bus interchanges, and commercial hubs, these areas attract both commuters and shoppers. In contrast, industrial zones like Tuas North and Kian Teck, as well as less developed areas such as Lim Chu Kang and Marina South, had significantly lower effects. Interestingly, even high-density CBD areas like Raffles Place and Chinatown recorded values below 1, likely due to weekday commuting patterns. Many residents rely on MRT for travel, and given the compact size of these SZs, short-distance trips within them are often completed on foot, reducing bus dependency. This analysis helps identify high-demand SZs, offering insights for optimizing transit resources and improving transportation equity.

Next, we analyzed the temporal posterior mean variation from March 2020, coinciding with Singapore's pandemic lockdown (Figure 2). The temporal effect showed a sharp decline in the first two months but returned to baseline (posterior mean = 1) by July 2020 as restrictions eased. Over the next 40 time points, it remained stable, except for an increase in September–October 2023, likely due to the presidential election, before reverting to normal. This stability highlights Singapore's resilient transit system and minimal seasonal or travel fluctuations, indicating that ridership variability was mainly spatial.

Lastly, we selected four representative SZs to analyze their spatiotemporal patterns: a central business district (Raffles Place), two residential towns (Tampines East and Yishun Central), and an industrial area (Tuas North), as shown in Figure 3. Raffles Place exhibited a trend largely consistent with the overall temporal effect, showing a sharp decline before June 2020 due to the pandemic. It also experienced another drop in May–June 2021, likely influenced by the Phase Two Heightened Alert, which tightened restrictions and led to increased remote work in the CBD. The residential towns, Yishun Central and Tampines East followed similar trends. After an initial

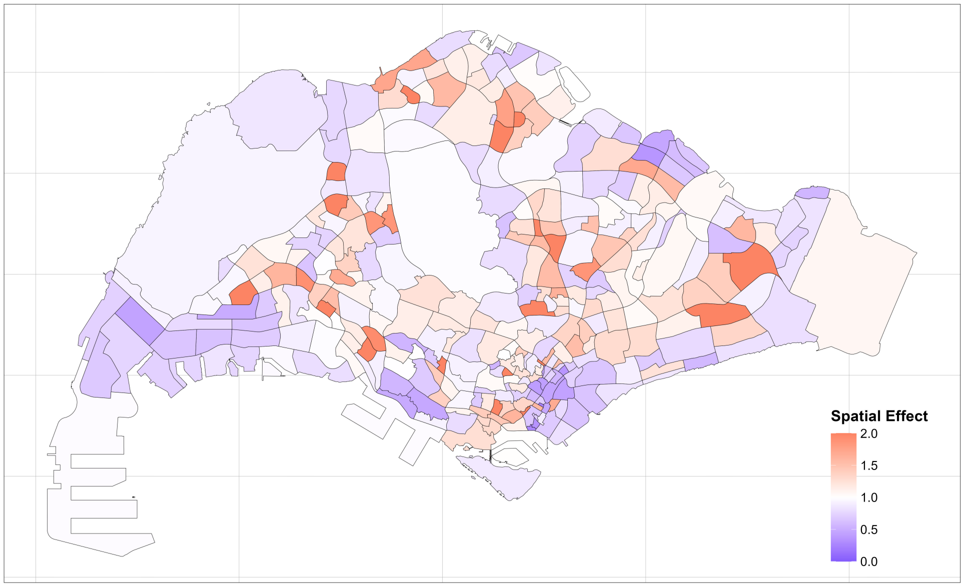

Figure 1: Distribution of spatial effect posterior mean.

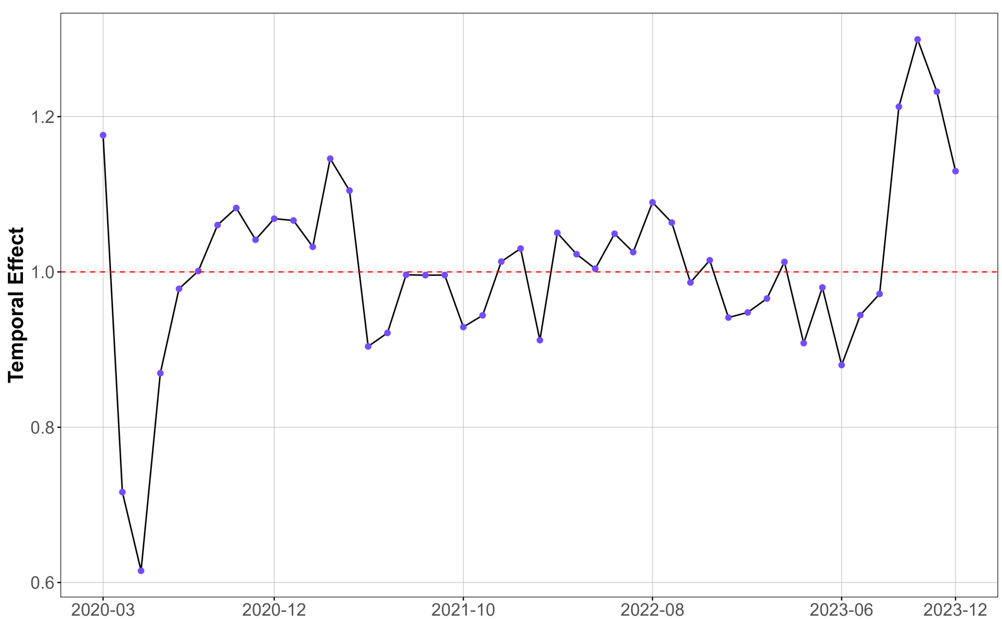

Figure 2: Temporal effect posterior mean from 2020-3 to 2023-12.

pandemic-induced decline, ridership stabilized over time. In contrast, Tuas North exhibited the opposite pattern, with a significant increase in ridership compared to other SZs during the early pandemic phase. This was likely due to its role as one of Singapore's key industrial zones, where essential industries continued operations during the stay-at-home order to maintain critical supplies and services.

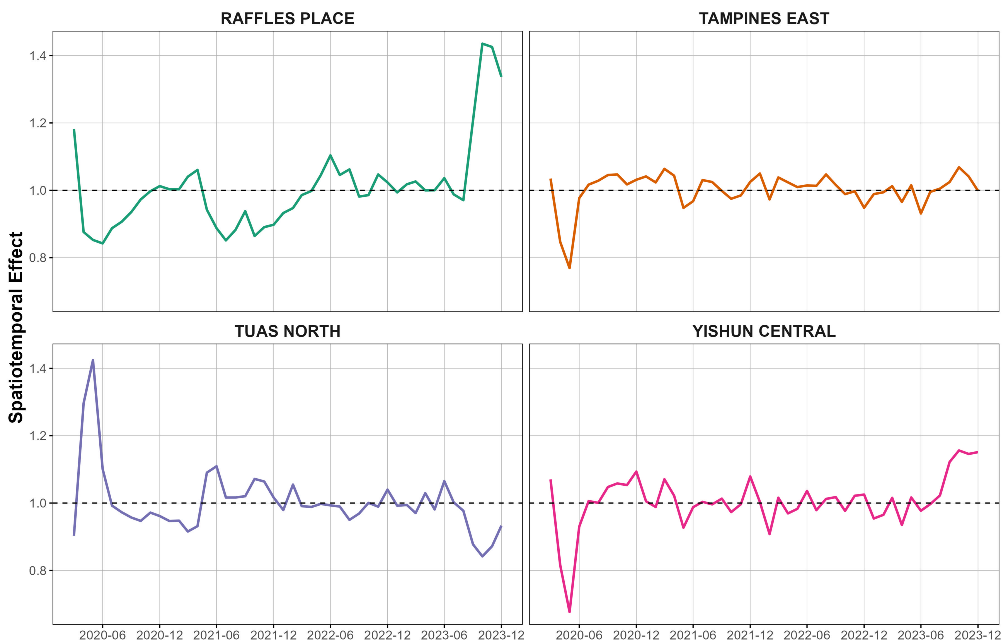

Figure 3: Spatiotemporal effect posterior mean for example SZs.

3.3 Association with spatial covariates

The inclusion of covariates enhances the predictive power of small area estimation models by accounting for spatial heterogeneity. The estimated fixed effects (Table 4) indicate that *Land Use Mix* (0.194), *Public Services & Amenities POI* (0.491), *Health & Education POI* (0.484), and *Bus Stop Density* (0.501) positively influence ridership, suggesting that land use diversity and access to public amenities promote public transport usage (Ma, J. Zhang, et al. 2018b; An et al. 2019).

Conversely, *Cultural & Tourism POI* (-0.560) and *Road Density* (-0.626) negatively impact ridership. The former is likely due to the concentration of tourist attractions in non-residential areas with lower commuting demand, while the latter may stem from the inclusion of all road types, diluting its relevance to bus accessibility.

Table 4: Model Results for Spatial Covariates

Variable	**Mean**	**SD**	**2.5% Quant**	**50% Quant**	**97.5% Quant**
(Intercept)	-2.256	0.677	-3.585	-2.256	-0.927
Land Use Mix	0.194	0.121	-0.043	0.194	0.431
Cultural & Tourism POI	-0.560	0.130	-0.816	-0.560	-0.304
Public Services & Amenities POI	0.491	0.114	0.268	0.491	0.713
Health & Education POI	0.484	0.099	0.291	0.484	0.678
Road Density	-0.626	0.413	-1.436	-0.626	0.184
Bus Stop Density	0.501	0.708	-0.887	0.501	1.890

4 Conclusion

This study proposes and evaluates a Bayesian hierarchical spatiotemporal framework for analyzing high-resolution bus ridership data. Using Singapore as a case study, we examined ridership patterns across spatial, temporal, and spatiotemporal dimensions as follows.

Firstly, spatial patterns accounted for most of the model's explanatory power, with transit-oriented developments in residential towns emerging as hotspots, while industrial and less developed areas exhibited lower spatial effects. Secondly, temporal patterns remained relatively stable, except for disruptions during the 2020 pandemic. Thirdly, spatiotemporal patterns varied across different SZs with different urban functions, even displaying opposing trends. Lastly, diverse land use and urban amenities positively influenced ridership distribution.

These findings provide valuable insights for urban and transport planning, supporting more equitable resource allocation and improved mobility access.

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