A spatio-temporal analysis of house prices in Brunei Darussalam

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Abstract

This paper presents the first spatio-temporal analysis of property prices in Brunei Darussalam, a small, resource-rich economy with distinct housing market characteristics. Despite global interest in quantitative housing market analyses, Brunei's market remains underexplored, with prior studies predominantly qualitative. Addressing this gap, $N = 3,763$ residential transactions from 2015 to 2023 were analysed using Conditional Autoregressive (CAR) priors to model spatial dependencies and temporal trends in house prices accounting for other price determinants. Emerging Hotspot Analysis was then employed to classify price clustering across time. Key findings revealed significant spatial autocorrelation ($\rho = 0.43$) and temporal persistence best modeled by an autoregressive structure of order 2, indicating that market reactions to changes can extend up to six months. The results demonstrate the critical role of spatial and temporal factors in shaping property prices, providing actionable insights for policy interventions and real estate market analysis, particularly in addressing disparities between urban and rural housing markets.

Keywords: Spatio-temporal analysis, Conditional Autoregressive models, Housing market, Emerging Hotspot Analysis, Brunei Darussalam

1 Introduction

Studying the dynamics of the housing market is crucial for understanding economic trends, urban development, and effective policy-making. House prices are influenced by a complex interplay of property-specific characteristics, spatial dependencies, and temporal trends. Analyzing these complexities provides critical insights into market behavior, enabling policymakers, investors, and urban planners to make informed decisions. In the context of Brunei Darussalam, the housing market is shaped by a unique set of socio-economic, cultural, and geographic factors that distinguish it from other regional markets. Therefore, there is a pressing need for comprehensive spatial-temporal analyses to guide interventions. This study seeks to address this gap by investigating the determinants and spatial-temporal patterns of house prices across Brunei's Mukims, using advanced statistical and geospatial methodologies.

The country's high-income status and small population are coupled with socio-cultural preferences for detached, landed houses and living close to relatives, often in multigenerational households. These preferences significantly shape housing demand patterns. At the same time, two major economic hubs–Bandar Seri Begawan in the Brunei-Muara District and the oil town of Seria in the Belait District–concentrate economic activities and influence housing markets at opposite ends of the country. These hubs are complemented by the conservation areas and forest reserves, which limit land availability for development, further shaping the spatial distribution of housing demand and prices.

Despite being a high-income country, Brunei exhibits notable stratification in property prices based on location. Urban areas, particularly near economic hubs, tend to command significantly higher prices, while rural regions see lower demand and prices due to limited infrastructure and economic opportunities. Interestingly, high rates of car ownership[1] and a well-connected road network make most areas in Brunei accessible, suggesting that physical connectivity alone does not explain these disparities. Instead, socio-economic factors and proximity to key amenities and employment centers likely play a more substantial role. This has been suggested by previous studies on Brunei's housing landscape, which predominantly have been qualitative in nature focusing on urban geography, urban sprawl, and socio-cultural norms [Hassan et al, 2011, Hassan, 2023, Janaji and Ibrahim, 2020].

While these studies have provided valuable insights, there has been no quantitative exploration of the spatial-temporal dynamics of house prices in Brunei. Much of the existing literature on property price modeling focuses on large urbanised regions, giving relatively little attention to small, resource-rich economies like Brunei. This presents a novel opportunity to contribute to the growing body of literature on property price modeling amidst a growing global interest in understanding housing markets through quantitative modeling.

The research addresses three primary questions: What are the key determinants of house prices in Brunei, and how do spatial dependencies influence these relationships? Which spatial areas exhibit persistent or intermittent clustering of high or low house prices, and how do these patterns correlate with socio-economic factors, infrastructure, and policy interventions? Additionally, how do spatial-temporal patterns of property prices reflect the disparities between urban and rural regions, and what implications do these trends have for housing policy and market interventions?

To effectively answer the research questions, this study employs a multi-step approach. First, the challenge of data gaps in the collection process is addressed by applying spatio-temporal imputation techniques. This ensures a robust and comprehensive spacetime data "cube" for subsequent analyses, capturing both spatial and temporal dimensions of the housing market. Second, a spatio-temporal Conditional Autoregressive hedonic regression model was utilised to decompose house prices into their key determinants, such as square footage, land size, and type of property, while accounting for spatial dependencies between neighboring areas. This approach enables us to quantify how these factors contribute to variations in house prices across Brunei. Finally, an Emerging Hot Spot Analysis (EHSA) was conducted to identify and classify areas with persistent and intermittent clusters of high (hotspots) or low (coldspots) house prices over time. This provides insights into the long-term spatial-temporal dynamics of the housing market and highlights regions where policy interventions may be required.

This study serves as an exploratory analysis, marking the first quantitative investigation of spatial-temporal dynamics in Brunei's housing market. By providing a foundational framework, it hopes to address critical gaps in the literature and to spur further research on property price modelling, both locally and across the region.

[1] 92% of households own at least one car [DEPS, 2022], with around 1,027 registered vehicles per 1,000 population [JPD, 2021].

2 Literature review

Hedonic regression models have long been a staple in housing market analysis, used to decompose property prices into the contributions of various attributes, such as size, location, and amenities. These models are widely applied in urban planning and economic policy to understand how different property characteristics influence market prices.

At the property-specific level, features such as size, type, and building quality play a pivotal role in determining house prices. Larger properties or those with unique characteristics, such as detached houses or premium construction materials, often command higher prices [Zhou, 2024]. Similarly, the quality of construction and the age of a property are important factors, with newer and well-maintained buildings typically valued more highly than older or poorly maintained ones [Soltani et al, 2021, Zhou, 2024].

At the neighbourhood level, accessibility and amenities are critical determinants of house prices. Properties located near transportation hubs, schools, parks, and other amenities are generally more desirable and thus more expensive [Yao and Hu, 2023, Wu et al, 2018, Löchl and Axhausen, 2010]. Environmental and social factors also influence housing demand and valuation [Jamil et al, 2025]. Green spaces, neighbourhood safety, population density, and the reputation of an area can significantly impact property values [Li et al, 2021, Can, 1990].

Spatio-temporal analyses have become integral to understanding the complexities of housing markets, particularly in urbanised and rapidly developing regions. Spatial dynamics encompass the geographic distribution of house prices and the variation across different areas, often shaped by factors such as urbanization and infrastructure development. For instance, a study in Ecuador demonstrated that spatial hedonic models are more effective than non-spatial counterparts in capturing housing market variations and submarket dynamics, emphasising the importance of accounting for spatial dependencies [Valdez Gómez de la Torre and Chen, 2024]. Temporal dynamics, on the other hand, capture how house prices evolve over time, reflecting economic cycles, policy changes, and urban development [Gelfand et al, 2004, Hyun, 2017]. Conventional hedonic regression models, while effective for estimating property values based on intrinsic and extrinsic factors, often fall short of capturing spatial and temporal dynamics.

In regards to spatial dynamics of house prices, two components are essentially at play: *spatial dependence* and *spatial heterogeneity* [Anselin and Griffith, 1988]. The former refers to the phenomenon that the price of a house is influenced by the prices of nearby houses, while the latter means that factors influencing house prices can vary across different areas. Two spatial models stand out in the literature for modelling house prices: 1) The Spatial Autoregressive (SAR) Model [LeSage and Pace, 2009]; and 2) The Geographically Weighted Regression (GWR) Model [Brunsdon et al, 1998, Fotheringham et al, 2002]. SAR models are thought to be good at captural spatial dependence, while GWR for spatial heterogeneity [Jahanshiri et al, 2011].

SAR models incorporate spatial autocorrelation, capturing the influence of neighbouring properties on a given property's price. This feature is particularly useful for understanding how house prices in one location are affected by those in surrounding areas, making SAR models a popular choice for area-level data analysis [Soltani et al, 2021, Jahanshiri et al, 2011]. However, SAR models are limited by their focus on global spatial dependencies, often failing to capture localised variations in property price determinants.

GWR models allow for localised variations in relationships between property prices and their determinants. This approach enables a more granular understanding of spatial heterogeneity. For example, in Singapore, GWR models revealed how proximity to parks and transit stations significantly impacts public housing prices, demonstrating the importance of localised spatial factors [Cao et al, 2019]. Similarly, development mechanisms in the Greater Beijing Area exhibit spatial heterogeneity, with local variations in development factors, confirmed using GWR methodology [Yu, 2006].

Each of the SAR and GWR models are easily extended to incorporate temporal dynamics. In essence, the time element adds an additional dimension to the data, and are treated as a non-homogenous block in the model, which allows the estimation of time-related parameters. These models are particularly valuable in rapidly evolving urban markets where property values are influenced by dynamic factors like economic cycles and infrastructure development. In the interest of brevity, the key references are listed and the reader is invited to peruse them. See [Elhorst, 2014, 2022] for *Dynamic General Nested Spatial Models* (Dynamic GNSM), the time extension of SAR. See [Huang et al, 2010] for a discussion of *geographically and temporally weighted regresion (GTWR)*, the time extension of GWR.

Global applications of spatio-temporal analyses underscore the diverse factors driving property values. In Tehran, for instance, a GTWR model significantly outperformed traditional models in capturing both spatial and temporal variations in housing prices, offering deeper insights into market trends [Soltani et al, 2021]. In Beijing, the effects of property attributes like size and age vary significantly across urban and suburban areas, while proximity to amenities like schools and metro stations plays a crucial role [Duan et al, 2021, Crespo and Grêt-Regamey, 2013]. Similarly, in Islamabad, proximity to slum areas negatively affects property values, illustrating the influence of neighbourhood effects on housing markets [Hussain et al, 2019].

Several studies have also shown that incorporating spatial effects significantly improves the accuracy of models in terms of error reduction and predictive power [Pace et al, 1998, Liu, 2013]. The suitability of these models to analyse real life data is demonstrated by a multitude of studies: [Basu and Thibodeau, 1998, Abelson et al, 2013, Helbich et al, 2014, Cohen et al, 2016, Stamou et al, 2017]. These reference studies were conducted in different countries such as Australia, the United States, Greece, Austria, which show applicability across different economic conditions.

Despite intense research activity, application in small economies like Brunei remains under-explored, presenting a critical research gap that this study seeks to address. Such economies face unique challenges in analyzing housing markets. These challenges include limited geographic variability, concentrated economic activity in specific hubs, and significant government intervention, such as national housing schemes. These factors often create distinct spatial-temporal clustering patterns in property prices that are underexplored in existing literature. Additionally, data limitations–such as the availability of consistent, detailed information over time–further complicate the application of traditional spatial econometric methods.

The aforementioned SAR and GWR models present additional limitations when applied to small economies. As mentioned, SAR models focus on global spatial dependencies, which may not adequately capture localised interactions critical in small datasets. GWR, while adept at modeling spatial heterogeneity, requires point-level data, which is often unavailable in small economies. These limitations necessitate alternative approaches better suited to Brunei's housing market, characterised by area-level data and localised spatial dependencies.

This study bridges the gap by employing a *Conditional Autoregressive (CAR)* model [Besag, 1974, Besag and Kooperberg, 1995] to analyse Brunei's housing market. The CAR model is particularly advantageous in this context due to its emphasis on local spatial dependencies. By defining property prices as conditionally dependent on neighbouring values [Leroux et al, 2000], CAR models effectively capture localised interactions, such as neighbourhood-level influences from infrastructure or socioeconomic conditions. This localised focus is crucial in Brunei, where property markets are small, transactions are limited, and aggregated data at the area level is the norm. Additionally, CAR models are computationally efficient and naturally integrate with Bayesian frameworks [Lee, 2013], enabling the incorporation of prior information to enhance robustness in data-scarce environments.

Early applications of the CAR model was found in fields such as agriculture [e.g. Besag and Higdon, 1999], ecology [e.g. Brewer and Nolan, 2007], and recently in epidemiology [e.g. Li et al, 2011, Xie et al, 2017]. In the context of property price modelling however, besides textbook examples and instructional articles [e.g. Lee, 2013, Moraga, 2019] the literature is severely lacking, with an overwhelming preference for the SAR model. This presents a ground breaking opportunity to examine the applicability of CAR-based models for property price modelling, with Brunei's case study being the first of its kind. Extensions to CAR-type models for spatio-temporal modelling will be elaborated further in Section 4.4.

3 Description of study area and data

This section provides an overview of the study area, Brunei Darussalam, and the data used in this study. A preliminary analysis of the data is also presented to better understand the unique distribution of property prices in Brunei.

3.1 Description of study area

Brunei Darussalam, a small country on Borneo Island in Southeast Asia, is bordered by the South China Sea to the north and is surrounded by the Malaysian state of Sarawak. The nation's 5,765 square kilometres territory is divided into two non-contiguous areas: The larger western section comprising Brunei-Muara, Tutong, and Belait districts; and the smaller eastern Temburong district. Connectivity between the two sections was enhanced in 2020 with the opening of the Sultan Omar Ali Saifuddien Temburong Bridge, which provided direct road access. Prior to the bridge's completion, travel to Temburong required either a journey by water or a detour through Limbang, Malaysia.

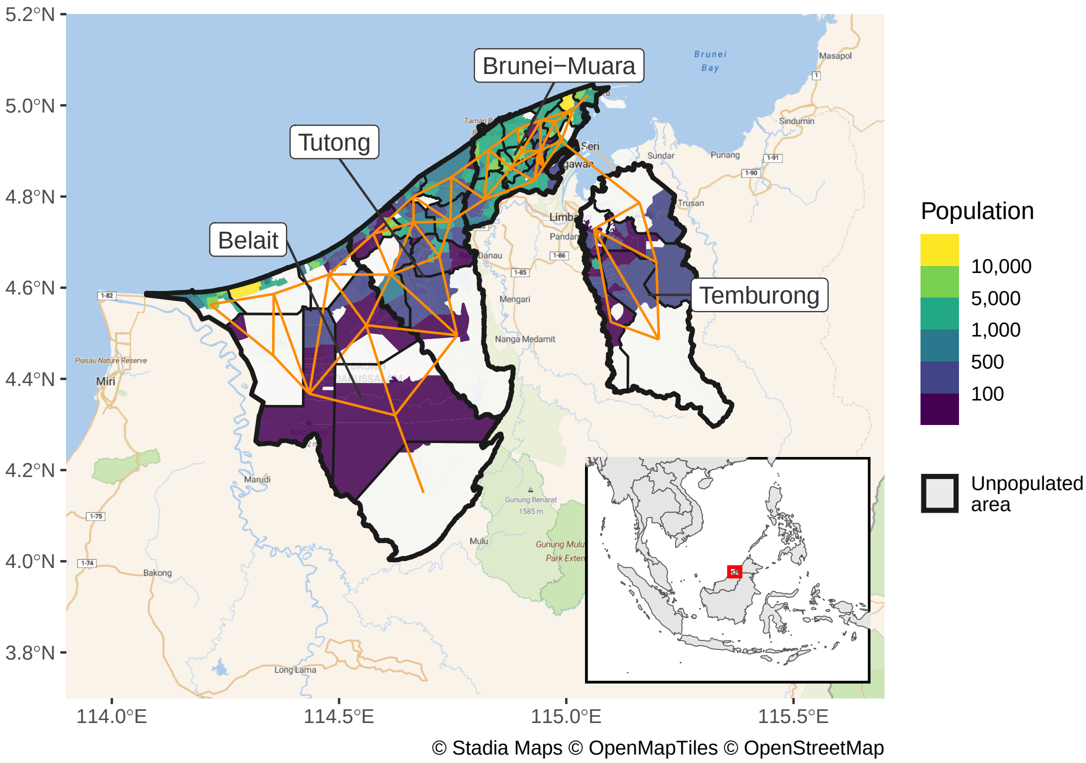

Figure 1: Administrative areas (black borders) in Brunei at the sub-district level (mukims), with an inset showing regional context in Southeast Asia. The overlaid orange graph represents spatial structure based on neighbourhood contiguity. The map also highlights variations in population distribution in Brunei.

Each of the four districts are further subdivided into smaller administrative areas known as *mukims* (sub-districts), delineated and shown in Figure 1. There are a total of 39 mukims in Brunei. For the purposes of this spatial study, these mukims are treated as non-overlapping polygons, and the neighbour contiguity structure of the mukims is defined by the common boundary between two mukims. The exception to this are the two mukims of Mukim Kota Batu (Brunei-Muara) and Mukim Labu (Temburong), which are separated by the Brunei Bay but contains the endpoints of the 26.3 km aforementioned bridge. In order to avoid separation of the areas into two disconnected graphs, a virtual link is created between these two mukims.

The population density distribution in Brunei provides further insight into the dynamics of its housing market, particularly through the growth rates observed in its top 10 mukims [DEPS, 2022] and seen on Figure 1. Notably, these mukims–such as Mentiri, Serasa, Telisai, Seria, and Liang–are predominantly coastal or located within the Brunei-Muara district. The significance lies in their proximity to the major road network facilitating seamless end-to-end connectivity across Brunei via a modern highway, allowing for country-wide travel in under two hours over a distance of 140km. The Brunei-Muara district, home to the central business district of Bandar Seri Begawan, stands out as the most populous yet smallest district, positioning it as a prime location for residential property demand. This demand is fuelled by the district's close access to major governmental, commercial, and financial hubs.

Conversely, the Belait district, as the second most populous region, anchors the nation's oil and gas industry, adding a different dimension to its real estate market. Furthermore, a significant portion of Brunei, especially in the southern parts of Belait and Temburong districts – amounting to 58% of the country's land [MIPR, 2012] – is dedicated to the Heart of Borneo initiative. This conservation effort, while crucial for environmental preservation, also shapes the landscape of the housing market by delineating areas for development and those reserved for ecological sustainability.

3.2 Data collection

The dataset encompasses $N = 3,763$ residential property transactions in Brunei Darussalam from 2015 to 2023. The data was collected by the Brunei Darussalam Central Bank (BDCB) for the purpose of constructing the national Residential Property Price Index (RPPI) [BDCB, 2021]. The data are sourced from licensed financial institutions as mandated by the Banking Order 2006 (amended 2010), and details each transaction, including sale price, property type, size, number of bedrooms and bathrooms, land type and area, the property's mukim and district location, as well as the transaction date.

It is critical to note the dataset's specific focus on financed transactions. While this provides a valuable and precise insight into property transactions that are formally recorded through regulated financial institutions, the exclusion of non-financed transactions such as cash purchases or those funded through personal or family loans potentially limits our understanding of the broader market dynamics. Nevertheless, the deliberate exclusion of transactions under government housing schemes is justified due to their heavily subsidized prices and restrictive eligibility criteria, which are not reflective of free market conditions.

The data has also been organised into $T = 34$ quarterly time periods (2015 Q1 to 2023 Q2). For analysis purposes, data aggregation at the desired spatial and temporal scales is essential, employing central tendency measures to typify the average property characteristics per mukim per time period. Continuous variables are summarized using either the median or mean, depending on the skewness of the data distribution, while the mode is applied for categorical variables. This aggregation process, however, highlights data sparsity across numerous mukims with absent transactions in specific periods (Figure 2). The need to impute the data set prior to modelling is therefore necessary, and is discussed in Section 4.4.

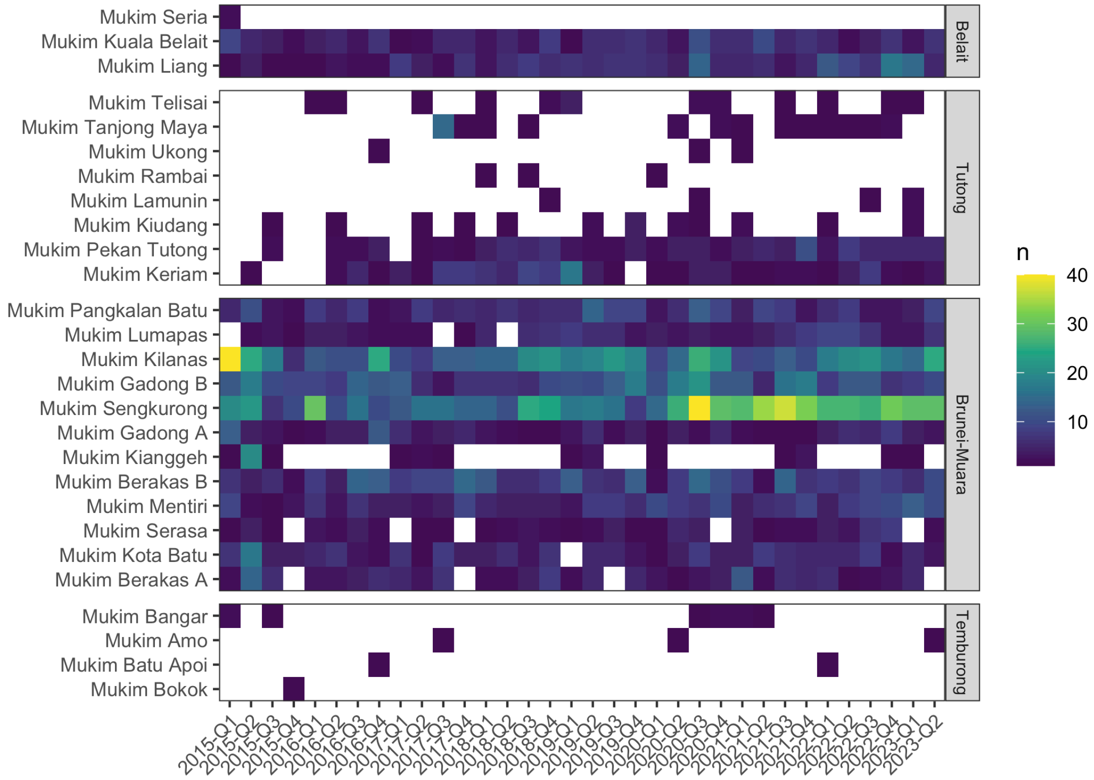

Figure 2: Sample size distribution among mukim and quarters, faceted by the four districts. Empty cells indicate no recorded transactions.

3.3 Preliminary data analysis

Table 1 provides the summary statistics for the study variables. The main response variable that is of interest is the sale price of the property, reported here in Brunei dollars. The mean sale price is BND 272,223 while the median is BND 255,000. The mean and median prices are quite different, suggesting that the distribution of sale prices is skewed, which is quite common for price data.

The private residential property market in Brunei consists of a range of options such as apartments, townhouses, and detached houses [Hassan, 2023]. The five categories considered in this data set are detached (52%), demi-detached (19%), terrace (19%), apartment (8%), and vacant land (2%). Evidently, the majority of transactions are landed property, with detached houses being the most commonly transacted property type. Besides the prevalence of multi-generational households, it could be argued that the demand for detached houses in Brunei is also fuelled by their contribution to socio-economic development, such as homestay initiatives [Janaji and Ibrahim, 2020]. On the flip side, the demand for apartments is relatively low, and this is consistent with the findings of Hassan et al [2011]. The reluctance to embrace apartment living stems from unmet cultural and lifestyle needs within high-density complexes, despite government efforts to promote vertical living as a solution to land scarcity and urban sprawl.

In terms of specific property characteristics, averaging across mukims and time periods, the median built-up area is found to be 2,284 square feet (212 square metres), giving an indication of the size of the typical house in Brunei. Such a size is logically associated with a two-storey house, comprising of 3-4 bedrooms and a similar number of bathrooms, and this is indeed the case. This "average" house is situated on a median land area of 0.121 acres (490 square metres).

Table 1: Summary statistics of property transactions ($N = 3,763$), including price, property type distribution, and key features such as built-up area, number of bedrooms and bathrooms, plot size, and land tenure type.

Variable	**N = 3763**	**Missing (%)**	**Mean (SD)**	**Median (IQR)**	**Range**
Price (BND 1,000)		0 (0%)	272 (123)	255 (200, 320)	24 - 2,006
Property type		6 (0.2%)			
Detached	1,968 (52%)				
Semi-Detached	700 (19%)				
Terrace	708 (19%)				
Apartment	310 (8.3%)				
Land	71 (1.9%)				
Built up area (sqft)		386 (10%)	2,400 (1,133)	2,284 (1,722, 2,798)	0 - 19,646
No. of beds		447 (12%)	4 (1)	4 (3, 4)	0 - 12
No. of baths		449 (12%)	4 (1)	3 (3, 4)	0 - 16
Plot size (acre)		370 (9.8%)	0.28 (0.60)	0.12 (0.07, 0.21)	0.01 - 5.19
Land tenure		0 (0%)			
Freehold	2,812 (75%)				
Leasehold	817 (22%)				
Strata	134 (3.6%)				

As noted by Hassan [2023], mukims do influence property prices as they denote distinct regions within the districts, with variations in prices across mukims attributed to differences in location, available amenities, and market demand. Table 2 tabulates, in decreasing order, the volume of transactions recorded during the data collection period across different mukims. Out of the total 39 unique mukims in Brunei, only $M = 27$ were recorded in the data set. This means the remaining 12 mukims, which comprise of areas in *Kampong Ayer* (water villages), reserved forests and non-populated areas, did not have any transactions during the data collection period, as is expected.

The data reveals that the three highest-volume transaction mukims, accounting for 44% of all transactions, are all situated in the Brunei-Muara district and are adjacent to one another, indicating a clustering effect. Moreover, among the top ten mukims by transaction volume, eight are in the Brunei-Muara district, with the other two in the Belait district. An examination of median prices shows that properties in Brunei-Muara and Belait districts command higher prices, while those in Tutong and Temburong districts are generally more affordable. While these observations don't control for the specific features of the properties, which will be analysed in the upcoming modelling phase, they offer an initial insight into the spatial patterns of property prices across Brunei.

4 Methods

This section outlines the methods employed in this study, integrating spatial and spatio-temporal statistical techniques to analyse the data.

4.1 Spatial weights matrix

Spatial autocorrelation is encoded by means of a *spatial weights matrix* $\mathbf{W} \in \mathbb{R}^{M \times M}$, where M is the number of distinct and non-overlapping study areas. In essence, the elements w_{kj} of W represent the "closeness" between areas labelled k and j ($k, j = 1, \dots, M$) using some weighting scheme. Arguably the simplest method, and the one used throughout this paper, is the *binary method*: Set $w_{kj} = 1$ if areas k and j satisfy a contiguity-based neighbourhood-defining rule (i.e. areas share one or more boundary point), and $w_{kj} = 0$ otherwise, including when $k = j$ (areas are not their own neighbours).

Table 2: Volume of transactions and the corresponding median price by mukim.

	Mukim	District	Median Price (BND)	Sales Volume
1	Mukim Sengkurong	Brunei Muara	268,000	726 (19.3%)
2	Mukim Kilanas	Brunei Muara	250,000	568 (15.1%)
3	Mukim Gadong B	Brunei Muara	290,000	373 (9.9%)
4	Mukim Berakas B	Brunei Muara	298,000	285 (7.6%)
5	Mukim Pangkalan Batu	Brunei Muara	209,000	215 (5.7%)
6	Mukim Mentiri	Brunei Muara	244,614	213 (5.7%)
7	Mukim Liang	Belait	270,000	199 (5.3%)
8	Mukim Kuala Belait	Belait	320,000	172 (4.6%)
9	Mukim Kota Batu	Brunei Muara	326,000	170 (4.5%)
10	Mukim Lumapas	Brunei Muara	199,500	138 (3.7%)
11	Mukim Berakas A	Brunei Muara	276,630	134 (3.6%)
12	Mukim Gadong A	Brunei Muara	300,000	130 (3.5%)
13	Mukim Keriam	Tutong	176,400	116 (3.1%)
14	Mukim Pekan Tutong	Tutong	190,000	114 (3.0%)
15	Mukim Serasa	Brunei Muara	225,500	78 (2.1%)
16	Mukim Kianggeh	Brunei Muara	223,700	37 (1.0%)
17	Mukim Tanjong Maya	Tutong	116,250	30 (0.8%)
18	Mukim Kiudang	Tutong	137,000	19 (0.5%)
19	Mukim Telisai	Tutong	252,000	18 (0.5%)
20	Mukim Bangar	Temburong	145,000	9 (0.2%)
21	Mukim Lamunin	Tutong	185,000	5 (0.1%)
22	Mukim Amo	Temburong	85,000	3 (0.1%)
23	Mukim Rambai	Tutong	50,500	3 (0.1%)
24	Mukim Ukong	Tutong	180,000	3 (0.1%)
25	Mukim Batu Apoi	Temburong	105,193	2 (0.1%)
26	Mukim Seria	Belait	177,500	2 (0.1%)
27	Mukim Bokok	Temburong	38,000	1 (0.0%)

4.2 Global tests for spatial autocorrelation

For areal data indexed by $i = 1, \dots, M$, the Moran's I test [Moran, 1948] is used as a measure of global spatial heterogeneity and overall clustering of the spatial data. The Moran's I test statistic is defined by

$$I = \frac{M}{\sum_{i=1}^{M}\sum_{j=1}^{M} w_{ij}} \frac{\sum_{i=1}^{M}\sum_{j=1}^{M} w_{ij}(x_i - \bar{x})(x_j - \bar{x})}{\sum_{i=1}^{M}(x_i - \bar{x})^2} \in [-1, 1], \tag{1}$$

where x_i is the value of the study variable for area i, $\bar{x}$ is the mean of the study variable, and w_{ij} is the spatial weight between areas i and j. Values of I close to 1 (c.f. -1) indicate positive (c.f. negative) spatial autocorrelation, whereas values close to 0 indicate no spatial autocorrelation. The null hypothesis of $I = 0$ is often compared against an alternative of $I > 0$. Under H_0, the mean and variance of I have closed form expressions, and the Central Limit Theorem is invoked to calculate p-values based on a Z score.

In practice however, the normality assumption is not always met. In such cases, the permutation test is used to calculate p-values. This involves shuffling the values of the study variable across the spatial units, and recalculating the Moran's I test statistic repeatedly [Cliff and Ord, 1981]. The p-value is then calculated as the proportion of times the permuted test statistic exceeds the observed test statistic.

4.3 Emerging Hotspot Analysis

Emerging hotspot analysis (EHSA) identifies spatial-temporal patterns of intensity in a dataset by classifying each location based on its historical and recent trends. The analysis uses a spacetime cube, where each spatial location i has time-series data divided into intervals

Table 3: Comparison of three spatio-temporal CAR models (Linear Time, ANOVA Decomposition, and AR) highlighting their brief explanations, advantages, and disadvantages.

Feature	Linear Time Model	ANOVA Decomposition	AR Model
Brief Explanation	Models spatially varying intercepts and linear time slopes.	Decomposes spatio-temporal variation into spatial, temporal, and interaction effects.	Incorporates temporal autocorrelation with an autoregressive structure of order up to 2.
Advantages	Simple to implement and interpret; Captures global and local linear trends.	Flexibly models non-linear time trends; Provides detailed decomposition.	Captures lagged temporal effects; Explicitly models time dependencies.
Disadvantages	Assumes linearity, which may not hold in complex datasets; Misses non-linear effects.	Computationally intensive; Interaction terms may not be identifiable (Gaussian likelihood).	Requires careful parameter tuning for stability; More complex to fit and interpret.

$t = 1, 2, \dots, T$. A Getis-Ord G_i^* statistic [Getis and Ord, 1992] for each location i is computed for each time step t, measuring local spatial autocorrelation:

$$G_i^* = \frac{\sum_{j=1}^{M} w_{ij} x_j - \bar{x} \sum_{j=1}^{M} w_{ij}}{s \sqrt{\left[\frac{M \sum_{j=1}^{M} w_{ij}^2 - \left(\sum_{j=1}^{M} w_{ij} \right)^2}{M-1} \right]}}$$

where x_j is the value at location j, w_{ij} is the spatial weight between locations i and j, $\bar{x}$ is the mean, s is the standard deviation, and M is the total number of locations.

Temporal trends are evaluated using the Mann-Kendall trend test for G_i^* values over time. Locations are classified into categories such as intensifying, persistent, or diminishing hotspots based on significance levels and trend slopes. For the full classification of trends, consult the ArcGIS Pro 3.4 documentation.

4.4 Spatio-temporal regression models

Let Y_{it} denote the observed property price for area $i \in \{1, \dots, M\}$ at time period $t = 1, \dots, T$. In addition to the property prices, temporally-distributed area-level covariates are available. Collectively denote the covariates relating to area m at time period t as $\mathbf{X}_{it}^\top = (X_{1,it}, \dots, X_{p,it})$.

The main idea of spatio-temporal models is to be able to encode the spatial and temporal effects into the modelling process. This involves modification of the linear regression model to include latent spatio-temporal random effects ψ_{it} as a linear predictor. Specifically, the model becomes

$$\begin{gathered} Y_{it} = \beta_0 + \beta_1 X_{1,it} + \dots + \beta_p X_{p,it} + \psi_{it} + \epsilon_{it} \\ \epsilon_{it} \sim \mathrm{N}(0, \sigma^2). \end{gathered} \tag{2}$$

The errors are independently and identically normal conditional on observing the value of ψ_{it}. These latent effects ψ_{it} are further decomposed into spatial and temporal components, so that the each can be quantified separately. The spatial component can be modelled using the CAR prior (Equation 3), while the temporal component can be handled in several ways. Three are described in this article: 1) The linear effect of time, 2) the ANOVA decomposition, and 3) the time autoregressive process. A brief comparison of the three models is given in the table below.

4.4.1 Conditionally Autoregressive (CAR) Spatial Priors

Due to [Besag, 1974], the Conditionally Autoregressive prior distribution [Leroux et al, 2000] for a spatial random effect ϕ_i is the following:

$$\phi_i \mid \phi_{-i} \sim \mathrm{N}\left(\frac{\rho \sum_{j=1}^{M} w_{ij}\phi_j}{\rho \sum_{j=1}^{M} w_{ij} + 1 - \rho}, \frac{\tau^2}{\rho \sum_{j=1}^{M} w_{ij} + 1 - \rho} \right). \tag{3}$$

The parameters ρ and τ control the level of spatial dependence among the areal units and the variability of the spatial random effects, respectively. Although these can be fixed, both are typically set to be freely estimated parameters. Of note, the specification $\rho = 1$ refers to the intrinsic CAR model as outlined in Besag et al [1991], while the specification $\rho = 0$ implies no spatial dependence, and the model reduces to a vanilla random intercepts model. For convenience, (Equation 3) is referred to as the CAR prior $\mathrm{CAR}(\mathbf{W}, \rho, \tau^2)$.

4.4.2 Linear time model

Modelling a linear effect of time allows us to estimate the autocorrelated time trends for each areal unit, thereby estimating areas exhibiting changing linear trends in response over time [Bernardinelli et al, 1995]. The linear time model is

$$\begin{aligned} \psi_{it} &= \phi_i + (\alpha + \delta_i)t \\ \phi_i \mid \phi_{-i} &\sim \mathrm{CAR}(\mathbf{W}, \rho_1, \tau_1^2) \\ \delta_m \mid \delta_{-m} &\sim \mathrm{CAR}(\mathbf{W}, \rho_2, \tau_2^2) \end{aligned} \tag{4}$$

There are two main features of this linear time model. Firstly, this model facilitates the estimation of a spatially varying intercept $\beta_0 + \phi_i$, where the β_0 is the grand intercept coming from the coefficients in the linear predictor β. This allows average response variables to vary across space, while accounting for spatial dependencies. Secondly, the model also estimates spatially varying time slopes. Reminiscent of growth models, this allows for the study a linear temporal trend in the response variables, both globally (α parameter) and locally within each spatial area (δ_i parameter).

4.4.3 ANOVA decomposition

This model decomposes the spatio-temporal variation into its constituent parts of space (ϕ_i) and time (δ_t), with the goal being to estimate the overall time trends and spatial patterns exhibited by the data [Knorr-Held, 2000]. No assumption is made regarding the functional form of time (linear or otherwise). The model is

$$\begin{aligned} \psi_{it} &= \phi_i + \delta_t \\ \phi_i \mid \phi_{-i} &\sim \mathrm{CAR}(\mathbf{W}, \rho_S, \tau_S^2) \\ \delta_t \mid \delta_{-t} &\sim \mathrm{CAR}(\mathbf{D}, \rho_T, \tau_T^2) \end{aligned} \tag{5}$$

In this ANOVA model, both the autocorrelation of the spatial and temporal effects are governed by the CAR prior with their own set of (ρ, τ) parameters. The matrix $\mathbf{D}$ is the temporal adjacency matrix with elements $d_{tt'} = 1$ if $|t - t'| \leq 1$, and 0 otherwise. This is a simple design matrix that structures the temporal dependencies in the data by linking each adjacent time points (time lag of 1). The addition of a time-space interaction effect, $\gamma_{it} \sim \mathrm{N}(0, \tau_I^2)$ say, is possible for non-Gaussian likelihoods. However, for the Gaussian model, this parameter is not identifiable with the model errors ϵ_{it}.

4.4.4 Time autoregressive models

It is possible to estimate evolution of spatial random effects over time by considering autoregressive (AR) structure of time of order up to 2 [Rushworth et al, 2014]. As is common with AR models, the dependence of time is built into the model in such a way that the observation at any time point t is dependent also on previous observations. Let us say $\psi_{it} = \phi_{it}$, and define the spatial effects vector to be $\phi_t = (\phi_{1t}, \dots, \phi_{Mt})^\top$ for each time point. Then a vector autoregressive model is

$$\begin{aligned} \phi_t \mid \phi_{t-1}, \phi_{t-2} &\sim \mathrm{N}_M\left(\rho_1\phi_{t-1} + \rho_2\phi_{t-2}, \tau^2\mathbf{Q}(\mathbf{W},\rho_S)^{-1}\right) \\ \phi_1 &\sim \mathrm{N}_M\left(\mathbf{0}, \tau^2\mathbf{Q}(\mathbf{W},\rho_S)^{-1}\right), \end{aligned} \tag{6}$$

where the precision matrix $\mathbf{Q}$, as a function of the spatial weights $\mathbf{W}$ and a spatial dependence parameter ρ_S, is given as per Leroux et al [2000]:

$$\mathbf{Q}(\mathbf{W},\rho_S) = \rho_S\left(\mathrm{diag}\left(\textstyle\sum_i w_{ij}\right)_{j=1}^{M} - \mathbf{W}\right) + (1-\rho_S)\mathbf{I}_M.$$

It can be shown, using Brook's lemma, that this corresponds to the precision matrix of the joint distribution of the conditional spatial effects discussed earlier in (Equation 3) For this model, temporal autocorrelation is induced by the mean, while the spatial autocorrelation is induced by the variance [Lee et al, 2018]. The temporal autocorrelation is controlled by the ρ_1 and ρ_2 parameters, which are each constrained between 0 and 1 to ensure stability and stationarity.

4.4.5 Model estimation

Model estimation is done using Bayesian methods, where additional priors need to be chosen on the parameters to be estimated. For the present study, I default to the uninformative priors, i.e. uniform priors for ρ, $\Gamma^{-1}(1, 0.01)$ priors for variance/scale parameters, and independent flat normal priors for the coefficients. This happens to be the default choices in the `{CARBayesST}` R package [Lee et al, 2018] that is used to fit the models.

Inference is conducted on the posterior distribution of the parameters (e.g. posterior mean and 95% credible intervals). Posterior sampling is done by way of Markov chain Monte Carlo (MCMC) methods. All parameters whose full conditional distributions have a closed form distribution are Gibbs sampled (e.g. the regression coefficients β, the random effects ϕ, and variance parameters). Remaining parameters are updated using Metropolis or Metropolis-Hastings steps. Convergence is assessed by visual checks and using the convergence diagnostic proposed by Geweke [1992].

For model comparison purposes, the marginal log-likelihood value can be a useful metric, but they are not able to capture model complexities. Information criteria that penalises log-likelihood values based on the number of effective parameters, thereby giving preference to more parsimonious models. Examples include the Deviance Information Criterion (DIC) [Spiegelhalter et al, 2002] the Watanabe-Akaike Information Criterion (WIC) [Watanabe and Opper, 2010] (small values indicate better fit). Lastly, the log marginal predictive likelihood [LPML, Congdon, 2005] measures the ability of the model to predict new data using cross-validation techniques (higher values indicate better fit).

4.5 Spatio-temporal imputation

The spatio-temporal model and emerging hotspot analysis described above require a dense $M \times T$ spacetime data cube for implementation. Missing data due to sparseness in volume transaction (seen in Figure 2) hinders implementation, while a complete case analysis excludes spatial areas with missing covariates, leading to a loss of valuable information. The following is a description of a simple imputation process using averages (means, medians, and modes) that respect the spatio-temporal structure of the data, extending the interpretation of Tobler's first law of geography[2] to time as well as space. The imputation strategy is laid out in Algorithm 1.

Algorithm 1 Spatio-temporal mean imputation

input: Raw data $\mathbf{X}$, Neighbourhood structure $\mathcal{N}$
output: Imputed $\tilde{\mathbf{X}}$
procedure STMeanImputation($\mathbf{X}$, $\mathcal{N}$)
    for $m = 1, \dots, M$ **do**
        $\mathcal{N}(m) \leftarrow$ Spatial neighbours of m
        $\mathbf{X}_m \leftarrow \{\mathbf{X}$ at location $k \mid k \in \mathcal{N}(m)\}$
        if $\mathbf{X}$ continuous **then**
            $\tilde{\mathbf{X}}_m \leftarrow$ 3-quarter rolling window Mean or Median
        end if
        if $\mathbf{X}$ discrete **then**
            $\tilde{\mathbf{X}}_m \leftarrow$ 3-quarter rolling window Mode
        end if
    end for
    $\tilde{\mathbf{X}} \leftarrow (\tilde{\mathbf{X}}_1, \dots, \tilde{\mathbf{X}}_M)$ **return** $\tilde{\mathbf{X}}$
end procedure

$\tilde{\mathbf{X}} \leftarrow$ STMeanImputation($\mathbf{X}$, $\mathcal{N}$)
while $\tilde{\mathbf{X}}$ is not complete **do**
    $\tilde{\mathbf{X}} \leftarrow$ STMeanImputation($\tilde{\mathbf{X}}$, $\mathcal{N}$)
end while

In essence, the algorithm iteratively imputes missing values by taking the mean, median, or mode of the values of the spatial neighbours. A 3-quarter rolling window is used to smooth the imputed values and borrow strength from the adjacent time points. The process is repeated until there are no missing values in the data set. The imputation may be validated by visually and statistically testing the distribution of the original data set with the imputed data set to ensure that the imputation process has not introduced any significant bias. Statistical testing is done using the non-parametric Kolmogorov-Smirnov test, with large p-values indicating insufficient evidence to reject the hypothesis of a common distribution of the two samples.

5 Results

Results of the spatio-temporal imputation are first discussed, before dissecting results of the modelling phase and subsequeny EHSA.

5.1 Spatio-temporal imputation

The aggregated spacetime data cube contains 39% missingness (see Figure 2). The spatio-temporal imputation algorithm described in the methods section was carried out on the original data set successfully, and a complete non-empty data set was obtained after two imputation cycles.

To evaluate the imputation's effectiveness, Figure 3 displays the distribution between the original and imputed datasets for comparison, and reports the Kolmogorov-Smirnov test of the difference. Here, large p-values are interpreted as an inability to reject the null hypothesis of no significant differences between the original and imputed datasets. For the continuous variables baths, beds, and built-up area, we see that the imputed values form a distribution that is similar to the original. The land size variable however shows some notable differences.

[2]"Everything is related to everything else, but near things are more related than distant things". Walder Tobler is said to have presented this seminal idea during a meeting of the International Geographical Union's Commission on Qualitative Methods held in 1969.

The discrepancy likely stems from the high variability in land size not adequately accounted for by property type during imputation, as evidenced by an increase in 1-2 acre properties in the imputed data distribution seen in Figure 3.

Upon further inspection, these properties are located in the rural Tutong and Temburong areas, where it is common for large tracts of land to be sold. However, such transactions are rare and not observed consistently across time in the dataset. Given that these areas are underdeveloped, it is reasonable to assume that similar land sizes would likely be sold if property transactions were to occur in these regions over time. Therefore, the imputation of land size values was retained as is.

For the categorical variables (type and land type), there are no significant deviation from the original dataset at a 5% significance level. However, it is noted that the type variable's Kolmogorov-Smirnov p-value of 0.074 approaches significance, hinting at a higher proportion of detached houses in the imputed dataset. Detached houses indeed are one of the most commonly purchased houses, so it is not surprising that this phenomenon is carried over during the imputation process.

Overall, the spatio-temporal imputation process generally reflects the original dataset accurately, and is felt to be a pragmatic approach of leveraging the available information without introducing too much bias in the data set, as seen by the result of the statistical tests.

5.2 Hedonic house price model

A spatio-temporal hedonic regression model accounting for both land and built-up properties simultaneously is proposed, as follows:

$$\texttt{price} = \begin{cases} \beta_0 + \beta_1\texttt{type} + \beta_2\texttt{built\_up} + \beta_3\texttt{beds} & \texttt{type} \neq \texttt{"Land"} \\ +\beta_4\texttt{baths} + \beta_5\texttt{land\_size} + \beta_6\texttt{land\_type} & \\ & \\ \beta_0 + \beta_5\texttt{land\_size} + \beta_6\texttt{land\_type} & \texttt{type} = \texttt{"Land"} \end{cases} \tag{7}$$

This model structure allows for a unified estimation of an overall grand intercept β_0, representing the average cost of owning a property, while simultaneously decomposing property values into their constituent components. By including data points for land-only properties, the approach maximises the utility of the dataset, ensuring that the unique characteristics of all property types contribute to the regression analysis.

After initially fitting an ordinary linear regression model (referred to as M0), its residuals were examined for spatial and temporal autocorrelation. Following Lee et al [2018], the data set is treated as spatial panel data, with Moran's test applied to each time period to assess autocorrelation. The Moran's I statistics, as shown in Figure 4, predominantly exceed zero, indicating positive spatial autocorrelation at each time period.

Consequently, four CAR-based spatio-temporal models are fitted: the linear time model (M1), the ANOVA model (M2), and the time AR(1) and AR(2) models (M3 and M4, respectively). The results of the model fit are shown in Table 4. For each model, 1,500,000 MCMC samples were obtained, and the first 500,000 samples discarded as burn-in. The remaining samples were thinned by a factor of 100, yielding a total of 10,000 samples used for inference. All diagnostics for the MCMC chains were satisfactory, and the Gelman-Rubin statistics were close to 1.0 for all parameters.

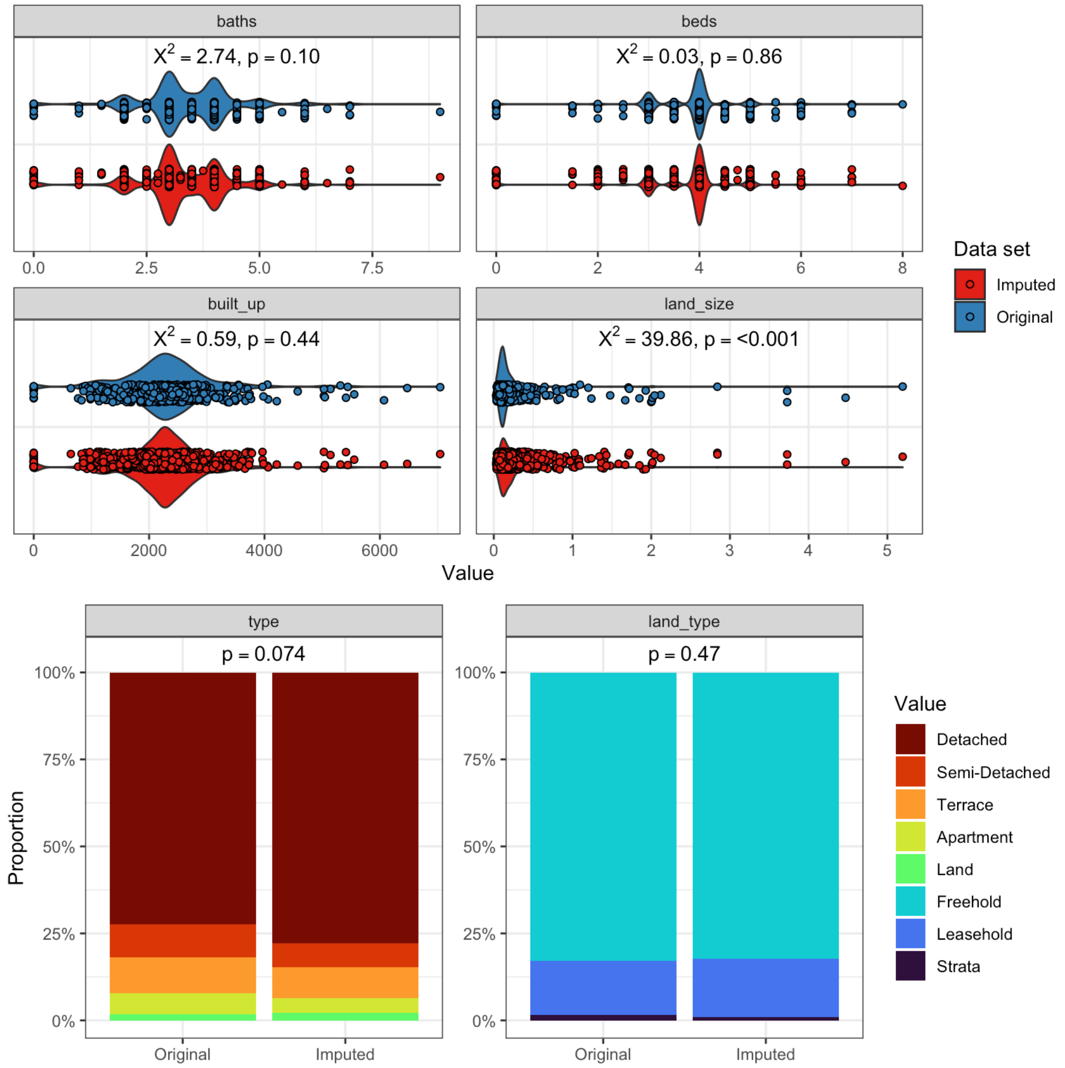

Figure 3: Comparison of the imputed data set with the original data set. The p-values are from the Kolmogorov-Smirnov test.

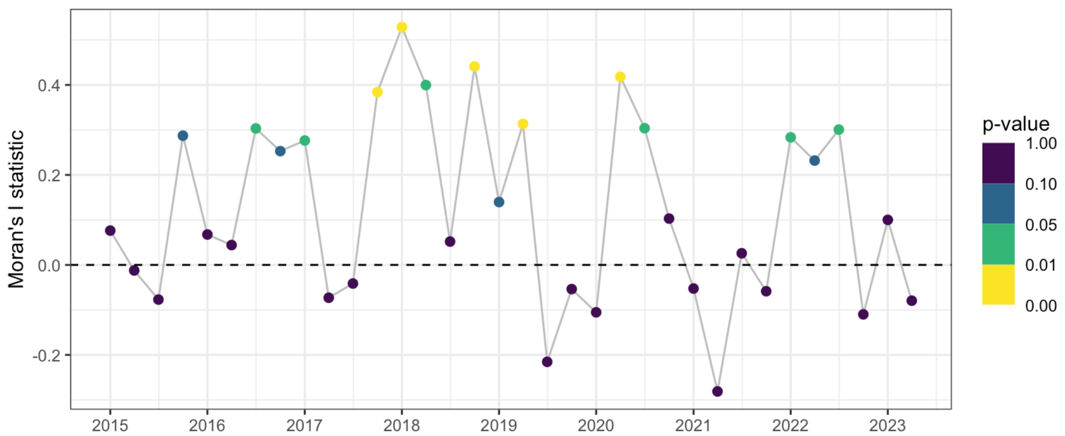

Figure 4: Spatio-temporal Moran tests.

Table 4: Comparison of model coefficients, spatio-temporal parameters, and variance estimates across all spatio-temporal regression models (M0 to M4), highlighting changes in fit and variable effects as model complexity increases.

	Coef.	95% CI	Coef.	95% CI	Coef.	95% CI	Coef.	95% CI	Coef.	95% CI
Coefficients										
(Intercept)	231.2	[174, 288]*	190.5	[142, 240]*	190.0	[141, 239]*	179.8	[133, 227]*	176.3	[130, 222]*
Type (ref: Land)										
Detached	-149.5	[-215, -83.4]*	-104.3	[-163, -49.6]*	-103.1	[-160, -46.6]*	-75.4	[-129, -21.9]*	-78.9	[-134, -25.2]*
Semi-Detached	-151.5	[-220, -82.7]*	-119.4	[-178, -62.0]*	-119.8	[-178, -61.8]*	-89.4	[-145, -33.6]*	-92.9	[-149, -37.3]*
Terrace	-177.0	[-246, -109]*	-152.0	[-211, -95.4]*	-152.7	[-211, -95.0]*	-111.0	[-167, -54.8]*	-113.7	[-170, -57.4]*
Apartment	-51.2	[-118, 15.8]	-83.1	[-141, -26.8]*	-84.7	[-141, -28.4]*	-51.7	[-105, 2.75]	-49.7	[-104, 3.40]
Built up area (1000 sqft)	22.7	[10.3, 35.0]*	18.2	[8.48, 28.1]*	16.6	[6.95, 26.4]*	19.3	[9.99, 28.6]*	20.0	[10.7, 29.2]*
No. of beds	5.7	[-7.53, 19.1]	12.7	[2.50, 22.9]*	13.0	[2.63, 23.3]*	10.3	[0.64, 20.1]*	11.0	[0.76, 21.0]*
No. of baths	27.6	[16.6, 38.4]*	14.9	[6.38, 23.6]*	15.5	[6.77, 24.0]*	14.6	[6.31, 23.1]*	14.6	[6.14, 23.0]*
Land area (0.1 acre)	-8.1	[-26.5, 9.78]	14.6	[0.32, 28.9]*	13.3	[-1.03, 27.6]	14.2	[0.15, 28.1]*	13.7	[0.15, 27.0]*
Land type (ref: Freehold)										
Leasehold	18.6	[-1.22, 38.2]	1.5	[-18.7, 21.6]	2.0	[-17.4, 22.0]	0.4	[-19.0, 20.1]	1.2	[-18.0, 21.1]
Strata	92.9	[33.1, 153]*	37.1	[-10.3, 86.0]	38.6	[-8.89, 86.4]	7.8	[-38.0, 54.1]	3.5	[-42.8, 49.9]
Spatio-temporal parameters										
ρ_S			0.50	[0.10, 0.91]*	0.49	[0.08, 0.91]*	0.40	[0.13, 0.75]*	0.43	[0.15, 0.69]*
α			14.8	[-3.45, 33.2]						
$\rho_{1,T}$			0.41	[0.02, 0.91]*	0.39	[0.02, 0.91]*	0.99	[0.97, 1.00]*	0.48	[0.27, 0.84]*
$\rho_{2,T}$									0.51	[0.15, 0.73]*
Variances										
σ^2	6,380	[5681, 7155]*	3,574	[3162, 4039]*	3,578	[3170, 4040]*	2,713	[2324, 3160]*	2,389	[1892, 2913]*
τ_S^2			9,400	[4594, 17510]*	9,357	[4596, 17436]*				
τ_T^2			0.02	[0.00, 0.09]*	0.01	[0.00, 0.06]*				
τ^2							656	[390, 1040]*	1,483	[820, 2318]*
Model fit criterion										
DIC (p_d)[1]	6,509	(11.9)	6,208	(36.6)	6,208	(35.5)	6,143	(126.3)	6,120	(175.5)
WAIC (p_w)[1]	6,524	(25.2)	6,224	(47.3)	6,224	(46.3)	6,160	(119.9)	6,140	(159.1)
LMPL	-3,262		-3,113		-3,113		-3,089		-3,090	
Loglik.	-3,242		-3,067		-3,068		-2,945		-2,884	

Note: Asterisks (*) indicate significance at the 5% level.

[1] p_d and p_w are the estimated number of effective parameters.

Not surprisingly, Model M0 demonstrates the poorest fit among the models tested. The inclusion of spatial effects leads to a notable decrease in error variance, underscoring the linear model's failure to encompass the spatio-temporal heterogeneity of the price variable, instead attributing all discrepancies to the error term. The linear time model M1 and the ANOVA model M2 show a marked improvement in fit, as evidenced by reduced DIC and WAIC values. The AR(2) spatio-temporal model M4 appears to provide the best fit, though its DIC and WAIC values are not too different from those of the AR(1) model M3, particularly when considering the LPML statistic. The estimation of the temporal autoregressive parameter $\rho_{1,T}$ approaching the upper limit of 1.0 in the AR(1) model suggests an attempt to capture a level of persistence in the time series that exceeds the model's constraint. A boundary estimate implies a strong temporal dependency, potentially hinting at the model's inclination to express an even stronger relationship. Consequently, the AR(2) model is identified as the most appropriate choice to provide a better fit by accommodating greater persistence within the data's temporal structure.

Interpreting model M4, we observe that all coefficients in the linear predictor are significant, with two exceptions. The first is the land type variable (and its associated dummy variables), where no significant difference in average price, holding other factors constant, is observed among different land types (freehold, leasehold, and strata titles). This could be attributed to a potential collinearity effect, as land types and property types are closely related; for instance, most apartments are strata titled, whereas detached houses are likely to be freehold. The second is the dummy variable for apartments, which indicates no significant difference in average price between apartments and the base category (vacant lands). However, the upper 95% confidence interval (CI) actually approaches 0, suggesting a possible rationale for retaining this variable in the model.

Notably, property type is a strong predictor, with detached, semi-detached, and terrace houses commanding premiums over apartments. Coefficients for built up area, number of beds and baths are all positive, reflecting the value placed on larger living spaces and amenities. This relationship is quantified as follows: For every 1000 square feet increase in built up area accompanied by the addition of an en suite bedroom, the price increases by approximately BND 46,000.

The spatial effect, with an estimated value of $\rho = 0.43$, highlights the degree of price dependency on neighbouring properties. A positive ρ indicates evidence of a clustering effect, which is seen here. Being significant at the 5% level, this observation reinforces the concept of geographical influence on property prices, even after controlling for other factors.

The temporal autoregressive parameters for lag 1 and 2 are 0.48 and 0.51 respectively. Both of these effects are positive, which means that any current price point is expected to increase if past values increase as well, with effects from two prior time points affecting the current value almost equally. As the sum of these coefficients is less than 1, the impacts of any past shocks will gradually diminish over time rather than persist indefinitely or amplify.

5.3 Spatial and temporal trends in house prices

In this section, the AR(2) model M4 will be used to predict property prices in Brunei to get a sense of the spatial and temporal dynamics of the housing market. The model will be used to predict the typical house price in Brunei, which, based on the previous preliminary data analysis in Section 3.3, is found to have the characteristics described in Table 5. These will be the (time-invariant) $\mathbf{X}$ values and plugged into the Equation 6. Parameter values for the model are obtained from the posterior sample, thus allowing us to generate the posterior predictive distribution [Gelman, 2014] of the typical house in Brunei.

The map in Figure 5 overlays the predicted property prices for each mukim in Brunei, averaged across all time periods. According to the fitted model M4, the top three most expensive properties are located in Mukim Kianggeh (BND 486,000), Mukim Gadong A (BND 331,000), and Mukim Kuala Belait (BND 314,000). The cheapest properties are found in Mukim Rambai

Table 5: The typical property characteristics in Brunei (for prediction purposes).

Characteristic	Value
Property type	Detached
Built up area (sqft)	2284.2
No. of beds	4
No. of baths	3
Land size (acre)	0.121
Land type	Freehold

(BND 130,000), Mukim Amo (BND 140,000), and Mukim Kiudang (BND 162,000). Evidently, the spatial effect is quite pronounced, with the most expensive properties being clustered in the urban areas of Brunei-Muara and Kuala Belait districts, while the cheapest properties are located in the rural areas of Tutong and Temburong districts. These patterns seem to reflect the underlying socio-economic disparities between urban and rural regions.

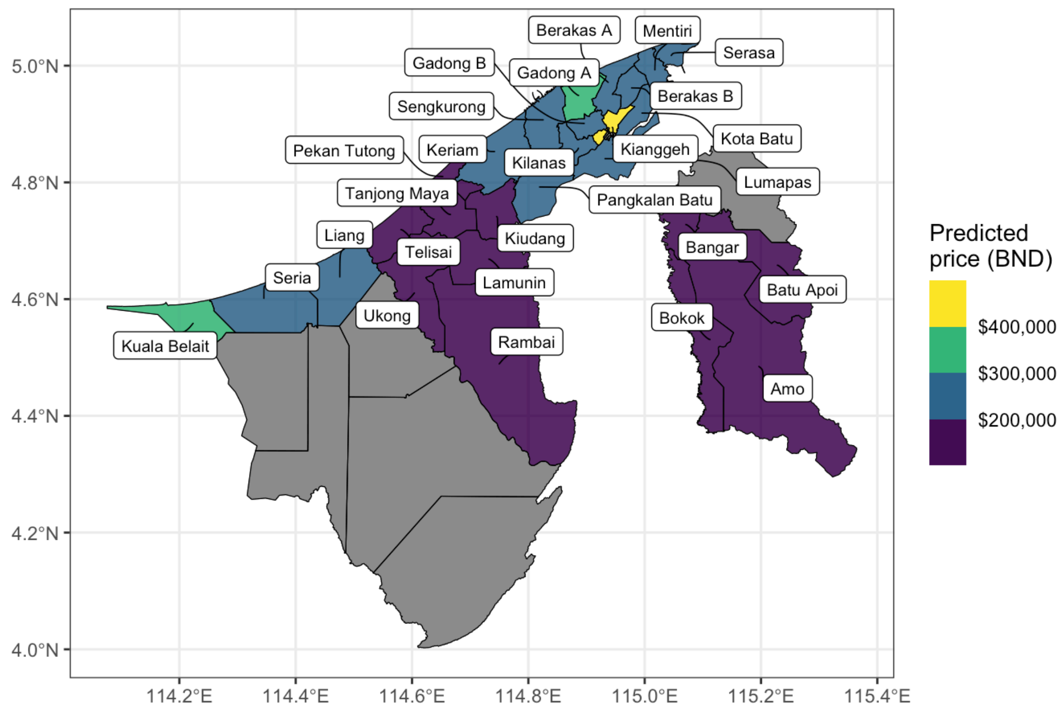

Figure 5: Predicted property prices in Brunei segregated by mukim and average across all time periods.

To further understand the spatial patterns of house prices, the analysis is extended to examine whether significant spatial patterns persist over time. EHSA provides insights into spatial-temporal trends, identifying areas with consistent patterns (persistent "hotspots" or "coldspots") as well as those with intermittent dynamics. These trends reflect underlying socio-economic and geographic factors influencing housing demand across Mukims, revealing the evolving nature of property values over time. Together with the Mann-Kendal tau statistics, the temporal trends within each spatial unit can be inferred to either be increasing ($\tau > 0$), decreasing ($\tau < 0$) or stable ($\tau = 0$). The EHSA highlights clusters of high or low prices

(Figure 6), offering a comprehensive view of how spatial patterns interact with temporal changes in Brunei's housing market.

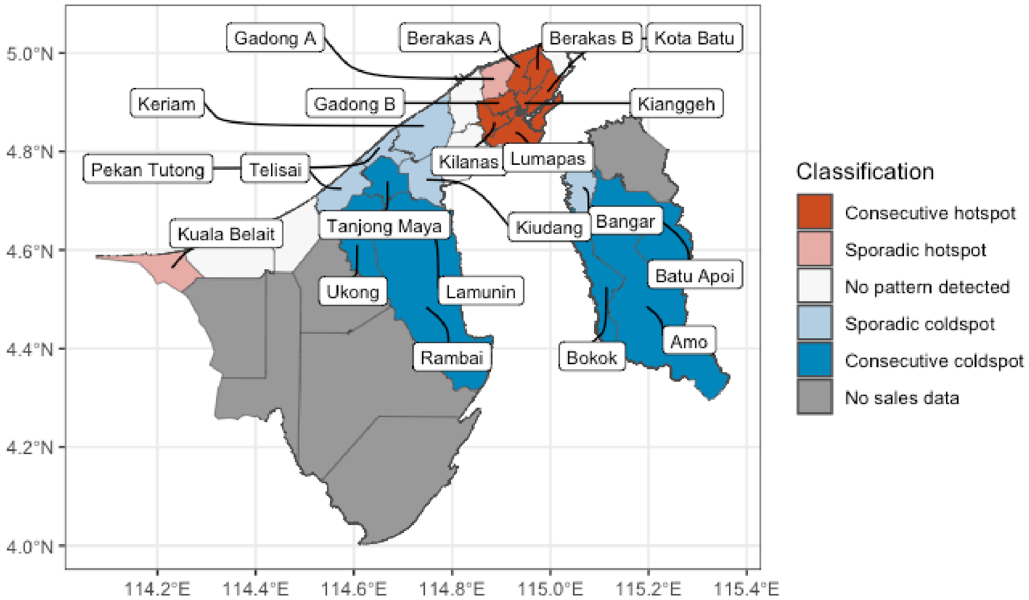

Figure 6: Emerging hotspot analysis of house prices in Brunei

Consecutive hotspots are predominantly concentrated in urban and suburban areas within the Brunei-Muara District. Mukims such as Kilanas ($\tau = 0.472$, $p < 0.001$), Lumapas ($\tau = 0.697$, $p < 0.001$), and Gadong B ($\tau = 0.369$, $p = 0.002$) demonstrate consistent high-price clustering over time, with increasing trends. Additional consecutive hotspots, including Berakas A and B, Kota Batu, and Kianggeh, indicate a strong and stable demand for housing in urbanised areas.

Consecutive coldspots, primarily located in rural regions, highlight persistent low-price clustering. Mukims such as Rambai ($\tau = -0.676$, $p < 0.001$) and Batu Apoi ($\tau = -0.419$, $p < 0.001$) exemplify this pattern, alongside areas like Amo, Lamunin, and Ukong. These results suggest consistent low demand driving decreasing property prices in these underdeveloped regions.

Sporadic patterns provide evidence of intermittent clustering dynamics. For instance, Mukim Gadong A ($\tau = -0.348$, $p = 0.004$) and Kuala Belait ($\tau = -0.291$, $p = 0.016$) are identified as sporadic hotspots, reflecting localized and transient increases in house prices. The negative τ value however uncovers an overall decreasing trend in prices. Conversely, Mukims such as Telisai ($\tau = 0.529$, $p < 0.001$) and Pekan Tutong ($\tau = 0.387$, $p = 0.001$) are classified as sporadic coldspots, suggesting occasional clustering of low-price properties, but with an increasing trend.

6 Discussion

A discussion of the results and implications of the study is presented, before highlighting certain limitations that should be taken under consideration.

6.1 Determinants of house prices in Brunei

The findings of this study provide valuable insights into the determinants of house prices in Brunei and the influence of spatial dependencies on these relationships. The spatio-temporal modelling of house prices reveals that spatial dependencies are a significant factor in the

Brunei housing market, as evidenced by a clustering effect ($\rho = 0.43$) of house prices even after controlling for other factors. This is consistent with previous studies that have highlighted the importance of spatial effects in hedonic price models [Holly et al, 2010, Helbich et al, 2014], although, such studies typically focus on a more concentrated study area such as a city or metropolitan area. In the context of Brunei, the data volume does not permit such a granular analysis, but the results suggest that spatial dependencies are a crucial consideration in understanding house price dynamics across the country. Certainly, ignoring spatio-temporal factors may result in biased and inefficient parameter estimates that can drastically affect the interpretation of property price determinants, leading to invalid inferences. This is clearly demonstrated by the substantial differences seen in the estimated coefficients between M0 (no spatial effects) and the other spatial models, particularly our model of choice M4.

Moreover, it stands to reason that from a prediction standpoint, it is important to account for spatial considerations, especially when analysis involving predicted house prices is paramount. An example is in the calculation of the Residential Property Price Index (RPPI) by the Brunei Darussalam Central Bank, which currently uses a hedonic regression model not fully accounting for spatial variability. Given the significant spatial dependencies identified in this study, it is recommended that RPPI calculations account for spatial factors, such as weighting by spatial areas, to ensure that the contributions of regions with disproportionately higher activity are properly reflected. Without this adjustment, the net effect on house price trends may be misrepresented, leading to incomplete or skewed insights.

Several key interpretations from the spatio-temporal hedonic regression model can be made. Firstly, the intercept in this model represents the estimated average price when all continuous variables are set to zero and categorical variables are at their reference levels. This average value, estimated to be BND 176,000 (95% CI 130,000–222,000), represents the "baseline value associated with owning freehold land". This encompasses various *minimum* costs associated with constructing a liveable property, including planning permission, legal fees, and infrastructure expenses such as access roads, water, electricity, and high-speed broadband [Basu and Thibodeau, 1998, European Commission. Eurostat, 2013].

Secondly, the analysis also identifies significant price differentials across property types. Comparing baseline costs again, the price ranking in ascending order is terrace (BND 62,000), semi-detached (BND 83,000), detached (BND 97,000), apartment (BND 126,000). This ranking highlights the relatively poor value proposition of apartments, further reinforcing the strong cultural preference driving demand for landed properties and larger living spaces in Brunei [Hassan, 2023, Ng et al, 2022]. The price hierarchy also suggests that buying land to develop properties independently is an economically unfavorable option for buyers in Brunei. The scarcity of land transactions in the data supports this and also past observations by [Ng et al, 2022, Jamil et al, 2025]. One explanation is due to the challenges in securing financial loans for land purchases, which banks may view as riskier compared to ready-built properties.

Thirdly, temporal dynamics in the housing market reveal an autoregressive structure of order 2 (AR(2)) influencing the spatio-temporal random effects. Previous studies have indeed found that the housing market is characterized by a lagged response to market changes [Cohen et al, 2016, Nagaraja et al, 2011, Wang and Ready, 2005]. Effectively, the housing market in Brunei potentially takes up to two quarters to fully incorporate the effects of market changes or economic shocks. The relationship between past and present prices is not simply linear, but rather more complex. This could be due to factors such as market cycles, seasonality, or unexpected events that can cause sudden price swings [Elhorst, 2022]. This finding underscores the importance of considering both recent and slightly older market conditions when predicting property prices and highlights the necessity of timely yet measured regulatory adjustments to stabilize the housing market.

6.2 Clustering of house prices in Brunei

The spatial dynamics of house prices in Brunei reveal a complex interplay of urban stability, rural challenges, and economic variability. Hotspots are concentrated in the Brunei-Muara district, particularly in Kianggeh and its neighbouring mukims. Situated in the capital city of Bandar Seri Begawan, Kianggeh serves not only as a hub of modern amenities and infrastructure but also as the geographical epicenter of the surrounding region. It borders two Berakas mukims to the north, Kota Batu to the east and south, and Lumapas to the south, while also being adjacent to Kilanas and Gadong B, with all of these mukims classified as a cluster of hotspots. All of these areas benefit from strategic urban locations with strong connectivity, modern infrastructure, and proximity to key government institutions and amenities [Ng et al, 2022].

The case of Lumapas is most interesting. Lumapas stands out with the strongest Mann-Kendall trend test result, indicating a significant increase in house prices over time. This upward trend coincides with the completion of the RIPAS Bridge in 2017, which directly connected the Kianggeh region to Lumapas, greatly reducing travel time that previously required a much longer route around the Brunei River. This case highlights the empirical relationship between key infrastructure investments and rising property values in the surrounding areas. Historically perceived as “rural” due to its limited accessibility, Lumapas has benefited from its newfound connectivity to the capital, seemingly making it an attractive option for buyers seeking more affordable alternatives to central urban areas.

Conversely, the predominance of coldspots in the Tutong and Temburong districts is not surprising, given their distance from key economic centers and limited infrastructure. Furthermore, much of the land in both districts are designated as forest conservation areas, limiting the availability of property for sale and further constraining market activity. This highlights a key disparity between rural and urban housing markets in Brunei, where remoteness, restricted land use, and limited economic opportunities make these regions less attractive to prospective buyers.

Sporadic clustering patterns provide additional insights into the role of transient economic and urban factors. Kuala Belait, for instance, given its proximity to major oil and gas operations and its role as an economic hub in the Belait District. The sporadic clustering of high house prices could reflect localized demand tied to the fluctuating fortunes of the oil industry. Unlike Seria and Liang, which exhibit no clear patterns, Kuala Belait’s position as a center for commercial and administrative activities in the district may attract intermittent demand for higher-value housing. This could be influenced by transient factors, such as the relocation of oil industry personnel or localized economic booms, contributing to its sporadic hotspot classification.

The lack of patterns in Seria and Liang, despite their industrial significance, may suggest that housing demand in these areas is more evenly distributed or constrained by national housing schemes in the vicinity. While this is an interesting theory, it does not hold true everywhere. For instance, Gadong A, primarily composing of national housing schemes, in fact show sporadic hotspot clustering (albeit a lowering of house price trend), and Mukims Berakas, Lumapas, Mata-Mata all containing natikonal housing schemes, provide evidence to the contrary.

In Tutong, areas such as Telisai and Pekan Tutong exhibit sporadic coldspot behavior, while others like Rambai and Lamunin are classified as consecutive coldspots. This pattern reflects the rural character of the region, where fewer amenities and economic activity constrain housing demand. In Temburong, a similar picture is seen, with Bokok, Batu Apoi, and Amo all classified as consecutive coldspots, suggesting a stronger and enduring clustering of low house prices in these areas. Interestingly, Bangar is classified as a sporadic coldspot, which could point to the potential influence of the Temburong Bridge completed in 2020. This classification raises questions about whether the bridge has begun to impact housing demand in Bangar or if its status as the most important town in the Temburong district accounts for this variation.

6.3 Policy implications

The spatial-temporal patterns of property prices in Brunei reveal significant disparities between urban and rural regions, with far-reaching socio-economic implications. Persistent clustering of high prices in urban hotspots such as Kianggeh and Kilanas reflects strong demand driven by economic opportunities, robust infrastructure, and access to amenities. Conversely, persistent coldspots in rural Mukims like Tanjong Maya and Rambai highlight limited development, weak housing demand, and insufficient infrastructure investment. While these price disparities are not unexpected, they offer critical insights into Brunei's functioning housing market. They signal the need for strategic regional planning to balance growth and address the challenges faced by underdeveloped areas.

These disparities exacerbate social and economic inequality, potentially marginalizing rural residents and limiting their access to urban opportunities. High urban property prices can lead to overcrowding, unaffordable housing, and strained infrastructure, while rural areas risk depopulation, undermining the viability of local services and infrastructure. This cycle of inequality reinforces the urban-rural divide, perpetuating underdevelopment in rural regions and overburdening urban areas.

Policy interventions are critical to addressing these challenges. The findings suggest a dual approach: managing urban affordability while promoting rural development. In urban hotspots like Kianggeh and Kilanas, policies should encourage mixed-income housing developments and regulate speculative activity through zoning reforms, based on previous strategies proposed for advance economy countries [Wetzstein, 2021]. Similar strategies have been proposed in advanced economy countries Incorporating affordable housing into commercial redevelopment projects, as seen in Gadong A, could mitigate the growing housing burden in urban areas, which may also include direct price or rent controls and promoting non-market-based housing supply [Talen, 2010]. It is noted that promoting non-market-based housing supply is an outcome achieved through the government's National Housing Scheme iniative. Further studies could look at the specific impact of this initiative on residential property prices in Brunei and its effectiveness in addressing housing burden in urban areas.

For rural coldspots such as Tanjong Maya and Rambai, targeted investments in infrastructure and amenities are essential to attract residents and spur economic activity. Improved transportation networks, enhanced access to healthcare and education, and the creation of employment opportunities can help stimulate housing demand [Barrios, 2008, Gebre and Gebremedhin, 2019]. In China, the Coordinated Urban-Rural Development (CURD) strategy has been successful in balancing urban and rural needs by granting rural residents property rights over their farmland, allowing them to subcontract user rights to urban entities [Li, 2017]. This reduces rural-to-urban migration pressures and supports sustainable urbanisation. Additionally, offering tax incentives [Wijburg, 2024] or subsidies to developers and landowners alike for projects in underdeveloped areas can encourage private investment in rural housing markets. The high baseline cost of owning land identified in the model highlights a need for policies that make it easier for individuals to develop their land, particularly in rural areas. Reducing financial barriers, such as easing loan accessibility [Hodge, 1991] or providing grants for self-development, could unlock the potential of rural regions and narrow the urban-rural divide.

All in all, the most critical aspect of policy design is the establishment of a robust monitoring framework that goes beyond traditional central bank indices like the RPPI. By integrating spatial and temporal analyses, this framework would enable the early detection of emerging hotspots and declining regions, allowing for proactive resource allocation and adaptive interventions. Such an approach ensures that housing policies remain responsive to market shifts, fostering sustainable and equitable development across Brunei's housing landscape.

6.4 Limitations

This study faced several limitations that warrant discussion. One major challenge was the issue of missing data, which is far from ideal but genuinely reflects the realities of data availability in the Bruneian context. Given the nature of the housing market in Brunei, it is unlikely that additional data collection would significantly improve coverage, as the observed volume of transactions is not uniform across all areas. Complete case analysis, while a potential alternative, would exclude a majority of areas with missing observations, leading to a significant loss of spatial coverage. As a result, imputation was necessary to ensure a robust analysis. While the spatio-temporal imputation approach employed in this study was largely satisfactory and backed by prior studies [Baker et al, 2014], future research could explore more sophisticated imputation methods to further improve accuracy and reliability.

Another limitation lies in the granularity of the data. This study aggregated data at the mukim level, which, while appropriate for the scope of this analysis, may mask finer spatial variations. A more granular, multilevel spatio-temporal modeling approach [Lee, 2013] could better account for variability at the Mukim level and provide deeper insights into localized housing market dynamics. However, such approaches would require more detailed and consistent data, which is currently unavailable.

The study also encountered challenges in comparing different spatial models more commonly used in the literature, such as SAR and GWR. While GWR requires point-level data, adjustments to fit mukim-level data were deemed impractical due to minimal data points in some mukims, which would hinder the robustness of localized regressions. Similarly, implementing the SAR model was not feasible due to missing response variables. Although imputing the missing response values could allow SAR to be applied, this would undermine the model's purpose of analysing actual observed data.

7 Conclusion

This study represents the first quantitative spatial analysis of house prices in Brunei Darussalam, offering new insights into the dynamics of the housing market within the context of a small, resource-rich economy. By employing a spatio-temporal Conditional Autoregressive (CAR) model, this research contributes a novel methodological framework for analysing housing data, effectively capturing localised spatial dependencies and temporal trends. The CAR model proved to be a suitable approach, going against the tide of the oft-used SAR or GWR models. The Bayesian framework paved the way for ease of model comparison and robust inferences. This work also addressed the challenge of data sparsotu using a spatio-temporal mean imputation method, which worked will with the proposed CAR models.

Key findings of this research highlight the real and quantifiable effects of spatial dependencies on house prices, evidenced by significant coefficient discrepancies between non-spatial and spatial models. The analysis also uncovered a significant AR(2) temporal dynamic, indicating that the housing market in Brunei incorporates the effects of market changes or shocks over a period of two quarters. Additionally, the application of EHSA revealed persistent and intermittent clustering effects, offering a nuanced understanding of how urbanisation, infrastructure, and socio-economic factors shape the spatial-temporal patterns of property values.

While this study provides a foundational understanding of Brunei's housing market, there are opportunities for future improvements. Incorporating a Bayesian framework for a one-shot imputation process could enhance the robustness of data handling, especially in the presence of high sparsity. Additionally, conducting a sensitivity analysis of the spatial weight matrix would further refine model specifications and provide deeper insights into the spatial dynamics of property prices.

The findings of this study have practical implications for housing policy and market interventions in Brunei. They emphasise the need for spatially adjusted measures, such as incorporating spatial weights into the Residential Property Price Index (RPPI), to better capture regional variations and provide more representative insights into housing market trends. The hotspot analysis also revealed persistent pricing disparity between urban and regional areas, which policymakers can take into account in order to foster sustainable and equitable market development.

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Appendix

Predicted property prices over time

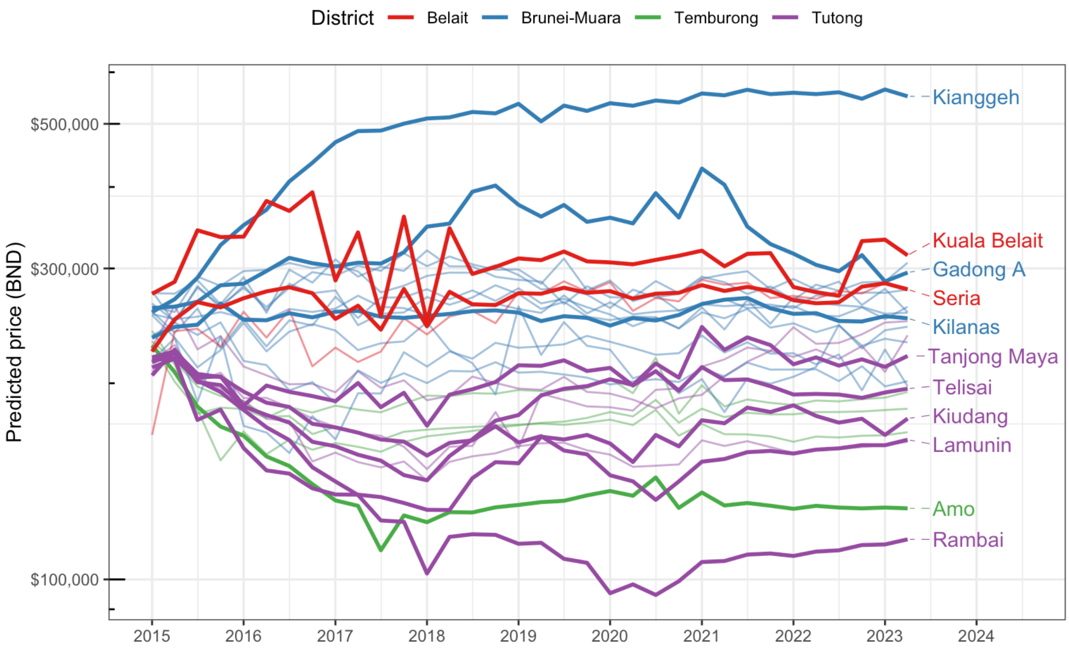

Figure 7: Evolution of predicted property prices over time for each mukim. Selected areas are highlighted with a bold line.

EHSA Results

Table 6: Emerging hotspot analysis of house prices in Brunei. Mann-Kendall tau values and associated p-values are given for each spatial area.

Mukim	District	τ	Classification	p-value
Berakas A	Brunei-Muara	0.119	Consecutive hotspot	0.3
Kota Batu	Brunei-Muara	0.141	Consecutive hotspot	0.2
Berakas B	Brunei-Muara	0.116	Consecutive hotspot	0.3
Kianggeh	Brunei-Muara	0.187	Consecutive hotspot	0.12
Gadong B	Brunei-Muara	0.369	Consecutive hotspot	0.002
Kilanas	Brunei-Muara	0.472	Consecutive hotspot	<0.001
Lumapas	Brunei-Muara	0.697	Consecutive hotspot	<0.001
Gadong A	Brunei-Muara	-0.348	Sporadic hotspot	0.004
Kuala Belait	Belait	-0.291	Sporadic hotspot	0.016
Bangar	Temburong	-0.291	Sporadic coldspot	0.016
Keriam	Tutong	0.112	Sporadic coldspot	0.4
Pekan Tutong	Tutong	0.387	Sporadic coldspot	0.001
Kiudang	Tutong	0.148	Sporadic coldspot	0.2
Telisai	Tutong	0.529	Sporadic coldspot	<0.001
Bokok	Temburong	0.116	Consecutive coldspot	0.3
Batu Apoi	Temburong	-0.419	Consecutive coldspot	<0.001
Amo	Temburong	-0.066	Consecutive coldspot	0.6
Lamunin	Tutong	-0.116	Consecutive coldspot	0.3
Rambai	Tutong	-0.676	Consecutive coldspot	<0.001
Ukong	Tutong	-0.055	Consecutive coldspot	0.7
Tanjong Maya	Tutong	0.212	Consecutive coldspot	0.080