Report: Singapore HDB Carpark Information

**Introduction**

In this project, we aim to conduct a comprehensive point pattern analysis of HDB carparks in Singapore using spatial data analysis techniques. Spatial data analysis involves the study of data that is geographically or spatially referenced, allowing us to investigate patterns and relationships that may vary across different locations. The focus of our study is on understanding the distribution of HDB carparks across Singapore and identifying any spatial trends or patterns that may exist.

The analysis leverages techniques such as quadrat count analysis, kernel density estimation, nearest neighbour analysis, and *K*-function analysis. These methods are essential for examining spatial autocorrelation, clustering, or dispersion in the data, which can help reveal insights into how carparks are distributed across different regions. We utilise the HDB carpark dataset available on the Singapore government data portal (<https://data.gov.sg>), using the coordinate reference system EPSG:3414 (SVY21 / Singapore TM) for all spatial computations to ensure accurate distance and area calculations.

This project not only enhances our understanding of the spatial distribution of carparks but also provides a foundation for applying these spatial techniques to other geo-tagged datasets. Throughout the analysis, we use R programming language, focusing on packages such as spatstat, sf, and tmap, which are well-suited for spatial data analysis and visualisation. The findings from this study aim to contribute to urban planning and regional development initiatives by providing valuable insights into HDB carpark utilisation and accessibility across residential estates within Singapore.

**Data preparation**

The initial step in our analysis involves data preparation, which is crucial to ensure that the dataset is organised and ready for spatial analysis. We begin by setting the working directory and loading the necessary packages in R, including spatstat, sf, and tmap. These packages facilitate the handling of spatial data and the creation of visual maps.

We load two main datasets: the HDB carpark information file (HDBCarparkInformation.csv) and a shapefile representing the planning areas in Singapore (MP14\_PLNG\_AREA\_WEB\_PL.shp). The carpark dataset contains details on carpark type, parking systems, short-term parking availability, free parking, night parking, and physical characteristics like gantry height and carpark decks. The shapefile provides geographical boundaries for the various planning regions in Singapore, allowing us to visualise HDB carpark locations within these areas.

We convert the carpark dataset into a simple feature (sf) object using the coordinate reference system EPSG:3414, suitable for Singapore's geographic context. This transformation enables us to perform accurate spatial calculations, such as distance measurements and area calculations, necessary for the subsequent analyses. Additionally, we check for the alignment of the coordinate systems in both datasets to ensure consistency in spatial analysis.

To create a visual representation of the data, we generate a base map of Singapore and overlay HDB carpark locations as points as shown in **Figure 1**. This visualisation serves as the foundation for more detailed spatial analysis, where we explore patterns and trends in the distribution of carparks across different areas. By carefully preparing the data, we set a robust framework for applying advanced spatial statistical techniques in the later stages of the analysis.

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**Figure 1:** Distribution of HDB carparks in Singapore

**Spatial descriptive summary measures**

Spatial descriptive summary measures provide a statistical overview of the geographical distribution of HDB carparks in Singapore. These measures help to quantify central tendencies, dispersion, and other key aspects of the spatial distribution, laying the groundwork for further point pattern analysis. To understand the central location of the carpark distribution, we calculated the spatial mean and median of HDB carpark coordinates. The spatial mean represents the average position of all carparks, while the spatial median provides a more robust measure of central tendency that is less sensitive to outliers. Based on the data, the computed spatial mean coordinates were found to be around (28771.33, 37889.76), and the spatial median coordinates were found to be approximately (29429.19, 37444.64). These measures suggest that the concentration of carparks is centred within these coordinate points, which corresponds to the central region.

To analyse the spread of the carpark locations, we calculated the standard deviational distance (SDD) and the standard deviational ellipse (SDE). These metrics help us understand how dispersed the carpark locations are relative to the mean centre. From the data, the SDD radius was found to be approximately 9171.929 units, indicating the average distance of the carpark locations from the spatial mean. Moreover, the SDE provides a measure of the directional distribution of the carparks, revealing the extent to which the distribution is elongated in a specific direction. In our analysis, the SDE had a major axis aligned in the direction of *σy* with a moderate level of eccentricity, suggesting a slight directional trend in HDB carpark distribution. The SDD and SDE (**Figure 2**) together highlight that while there is some degree of clustering around the mean, the distribution of carparks exhibits a tendency to spread out more in certain directions, which could be due to the urban layout and planning of Singapore.

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**Figure 2:** The SDD and SDE computed from the spatial distribution of HDB carparks

We further explored additional descriptive statistics like the range, interquartile range, and variance-covariance matrix of the carpark coordinates to gain a deeper understanding of the HDB carpark data's spatial properties. Specifically, the range of the coordinates indicated that HDB carparks spanned from a minimum of (11539, 28123) to a maximum of (45265, 48691), showing a wide distribution across Singapore. On the other hand, the variance-covariance matrix provided insights into the variability of the HDB carpark locations in both the *x* and *y* directions, with larger values indicating a higher degree of spread in the east-west dimension compared to the north-south counterpart. These statistical measures collectively illustrate that the distribution of HDB carparks in Singapore is not uniform but exhibits a degree of spatial clustering, with certain areas having a higher density of carparks than others.

To visualise the spatial distribution of HDB carparks, we generated a density contour plot along with the plotted mean and median locations as shown in **Figure 3**. This plot helped to highlight areas of higher concentration and the overall pattern of HDB carpark distribution in Singapore. The contours illustrated that the highest density regions are closely aligned with the spatial mean and median, reinforcing the idea that these central measures are good indicators of where most carparks are situated.

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**Figure 3:** Density contour plot of HDB carpark locations with mean (red) and median (blue)

Overall, the spatial descriptive measures indicate that while HDB carparks in Singapore are somewhat clustered around central locations, there is a noticeable spread in specific directions, suggesting that urban design and land use patterns play a significant role in determining the distribution of these facilities.

**Quadrat count analysis**

Quadrat count analysis is a fundamental method in spatial point pattern analysis, used to study the distribution of points within defined spatial units or "quadrats." This approach helps determine whether the observed spatial pattern of HDB carparks deviates from a random distribution, indicating clustering or regularity in the arrangement of carparks. For our analysis, we converted the spatial points of HDB carparks into a planar point pattern object (ppp) as shown in **Figure 4**, which is necessary for conducting spatial analyses with the spatstat package in R.

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**Figure 4:** Plotted planar point pattern of the HDB carpark distribution in Singapore

We then defined a grid of quadrats, dividing the study area into 15 × 15 cells, as shown in **Figure 5**. Each quadrat represents a fixed portion of the geographical area, and we counted the number of carparks falling within each cell. The quadrat count analysis revealed a variation in the number of carparks across different quadrats, with some cells containing significantly more carparks than others. This initial observation suggested the presence of spatial heterogeneity in the distribution of carparks.

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**Figure 5:** 15 × 15 quadrat count analysis of the spatial distribution of HDB carparks in Singapore

To statistically evaluate whether the observed distribution of carparks follows a homogeneous Poisson process (HPP), we conducted a *χ*2 test using the quadrat counts. The null hypothesis for this test states that the carparks are randomly distributed across the study area. In this case, produced a *χ*2 statistic of 2371.4 with 74 degrees of freedom, and a *p*-value of less than 2.2 × 10–16. Given the extremely low *p*-value, we rejected the null hypothesis of complete spatial randomness. This outcome indicates that the carpark distribution is not random but exhibits significant clustering within specific areas of Singapore.

To ensure that the results of our quadrat count analysis were not overly dependent on the chosen grid size, we performed a sensitivity analysis using different quadrat dimensions. For instance, we used 5 × 5, 10 × 10, and 20 × 20 grids as shown in **Figure 6**. This analysis helps verify the robustness of our findings across varying levels of spatial resolution. For all tested quadrat sizes, the *χ*2 tests consistently showed significant *p*-values, reinforcing the conclusion that the spatial distribution of carparks is clustered rather than random. This robustness across multiple grid sizes suggests that the clustering observed in the data is not merely an artifact of the quadrat size but a genuine characteristic of the carpark distribution.

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**Figure 6:** Quadrat count analysis of the spatial distribution of HDB carparks in Singapore using 5 × 5 grids (left), 10 × 10 grids (centre), and 20 × 20 grids (right)

We visualised the quadrat count data to better understand the spatial pattern of carparks. The quadrat maps displayed the number of carparks in each cell, with darker shades representing higher counts. The visualisation clearly highlighted areas with a higher density of carparks, particularly in regions closer to Singapore's urban centres. The comparison between observed and expected quadrat counts (**Figure 7**) further illustrated that several quadrats contained significantly more carparks than expected under a random distribution, corroborating the test results that indicated clustering.

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**Figure 7:** Plot of observed vs expected quadrat counts obtained from spatial HDB carpark data

In essence, the quadrat count analysis provided strong evidence that the distribution of HDB carparks in Singapore is not random but exhibits a significant level of clustering. This clustering pattern suggests that factors such as urban planning, population density, and land use play a critical role in determining the locations of carparks. Understanding these spatial patterns can inform more effective urban design and infrastructure development strategies, ensuring that carparks are optimally located to meet the needs of Singapore's residents.

**Kernel density estimation (KDE)**

KDE is a non-parametric method used to estimate the probability density function of a spatial point pattern. In the context of our study, KDE helps to visualise the density of HDB carparks across Singapore, highlighting areas with higher concentrations of carparks. This method provides a smoother representation of the spatial distribution compared to the discrete results from quadrat count analysis. The choice of bandwidth (known as the smoothing parameter) is crucial in KDE, as it determines the level of smoothing applied to the density estimation. A smaller bandwidth captures finer details in the distribution but may lead to overfitting, while a larger bandwidth produces a smoother density surface at the risk of oversimplifying the data. We used several approaches to determine the optimal bandwidth for our KDE analysis:

1. Fixed bandwidths

We initially used fixed bandwidth values of 500 and 1000 units to generate density plots shown in **Figure 8**. These values allowed us to observe the impact of different levels of smoothing on the estimated density of carparks. While a bandwidth of 500 units produced a more detailed density map, highlighting localised clusters of carparks, a bandwidth of 1000 units resulted in a smoother density surface, showing broader areas of high carpark concentration but at the cost of losing some localised details.

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**Figure 8:** KDE plots of the HDB carpark distribution with bandwidth 500 units (left) or 1000 units (right)

2. Automatic bandwidth selection methods

To refine our analysis, we employed automatic bandwidth selection techniques, including Diggle’s method, which is designed to minimise the mean square error of the density estimate. This method provided an optimal bandwidth of approximately 177.27 units, which balanced the trade-off between detail and smoothness. Other methods such as point pattern likelihood (ppl) cross validation, Scott’s rule of thumb, Cronie and van Lieshout’s (CvL) cross validation criterion, and the use of window geometry, were also used. The use of these methods yielded optimal bandwidths of 210.43, 2148.94, 6562.32, and 10010.55 units, respectively. In essence, each of the five methods offered a different perspective on the level of smoothing, from detailed to very smooth density surfaces, as shown in **Figure 9**.

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**Figure 9:** KDE plots of the HDB carpark distribution with optimal bandwidths generated by Diggle’s method (top left), ppl cross-validation (top centre), Scott’s rule of thumb (top right), CvL criterion (bottom left), and window geometry (bottom right)

To further enhance the KDE analysis, we tested different kernel functions (e.g., Gaussian, Epanechnikov, quartic, and disc kernels). While the bandwidth determines the extent of smoothing, the kernel shape influences the distribution of density around each data point. Specifically, the Gaussian kernel provided a smooth and continuous density surface, making it a preferred choice for general density estimation. On the other hand, the Epanechnikov, quartic, and disc kernels produced slightly different shapes in the density estimate but did not significantly alter the overall distribution pattern compared to the Gaussian kernel. The density plots generated are shown in **Figure 10**. Here, the kernel choice did not drastically affect the KDE results, indicating that the bandwidth selection plays a more crucial role in shaping the density estimate.

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**Figure 10:** KDE plots of the HDB carpark distribution generated via Diggle’s method using the Gaussian (top left), Epanechnikov (top right), quartic (bottom left), and disc (bottom right) kernels

We plotted the kernel density estimates using different bandwidths and kernel functions (**Figures 9-10**) to visually compare their effects. The density maps clearly showed that certain areas, particularly in the central and more densely populated regions of Singapore, had a higher concentration of HDB carparks. These areas correspond to the urban centres where demand for parking facilities is naturally higher due to greater population density and commercial activities. These maps also revealed that the carpark density gradually decreases as we move toward the outer regions of Singapore, indicating a lower concentration of carparks in suburban and less developed areas. This pattern aligns with Singapore's urban planning, where denser infrastructure is concentrated in central locations.

To ensure a reliable estimate of the bandwidth for our KDE, we also applied cross-validated bandwidth selection using the CvL criterion. This approach selects the bandwidth that minimises prediction error, providing a more data-driven way to determine the optimal level of smoothing. The KDE generated with the cross-validated bandwidth (**Figure 11**) showed a consistent pattern of carpark density, reinforcing the observations from earlier analyses. This method helps confirm that our density estimation accurately reflects the spatial distribution of HDB carparks.

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**Figure 11:** KDE plots of the HDB carpark distribution generated via the CvL criterion using the Gaussian (top left), Epanechnikov (top right), quartic (bottom left), and disc (bottom right) kernels

Overall, the KDE analysis revealed significant clusters of HDB carparks in central and densely populated areas of Singapore, indicating higher demand and utilisation of carpark facilities in these regions. The choice of bandwidth was critical in capturing these patterns, with the optimal bandwidth providing a balance between detail and smoothness. While the type of kernel function had a minor effect on the density estimate, the overall findings consistently pointed to the central regions as hotspots for carpark concentration. This insight is valuable for urban planners and policymakers aiming to optimise carpark allocation and manage congestion in high-demand areas.

**Nearest neighbour distance analysis**

Nearest neighbour distance analysis is a technique used to assess the spatial arrangement of points by examining the distances between each point and its closest neighbour. This analysis helps determine whether the points (in this case, HDB carparks) exhibit a pattern of clustering, randomness, or dispersion across the study area. For our analysis, we computed the nearest neighbour distances for each HDB carpark location in Singapore using the nndist function from the spatstat package. This function calculates the distance between each carpark and its nearest neighbour, providing a statistical measure of spatial relationships. The mean nearest neighbour distance was found to be approximately 133.52 units, with the minimum distance being 18.03 units and the maximum distance reaching 623.17 units. This wide range in distances suggests variability in how closely carparks are positioned relative to each other across Singapore. The histogram of nearest neighbour distances in **Figure 12** revealed a left-skewed distribution, indicating that many carparks have relatively short distances to their nearest neighbour, a sign of clustering.

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**Figure 12:** Histogram of nearest neighbour distances between HDB carparks in Singapore

To quantitatively assess whether the distribution of carparks is significantly clustered, we performed the Clark-Evans test. The test compares the observed average nearest neighbour distance to the expected distance under a null hypothesis of complete spatial randomness (CSR). From the data, we showed that the calculated R-value was 0.452, which is significantly less than 1, suggesting a strong tendency towards clustering of carpark locations. Moreover, the *Z*-test (standard normal) statistic was highly significant (*p*-value < 2.2 × 10–16), leading us to reject the null hypothesis of complete spatial randomness in favour of clustering. Different corrections for edge effects, such as guard and cdf, were also applied to ensure that the test results were not biased by the study area boundaries. The results remained consistent across all corrections, confirming the presence of significant clustering among the carpark locations.

We extended our nearest neighbour analysis by plotting the cumulative distribution function of the nearest neighbour distances, also known as the *G*-function. The *G*-function compares the observed nearest neighbour distances to the expected distances under a theoretical Poisson distribution, providing insight into clustering or regularity at various distance scales. The *G*-function plot in **Figure 13** showed that the observed curve was consistently above the theoretical curve, indicating a higher frequency of short distances than expected under randomness. This pattern is a strong indicator of clustering, as points are more closely spaced than would be the case if they were randomly distributed.

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**Figure 13:** Plot of a series of *G*-functions obtained from the spatial HDB carpark distribution

The results of the nearest neighbour distance analysis and the Clark-Evans test strongly indicate that the HDB carparks in Singapore are not randomly distributed but are significantly clustered. This clustering pattern suggests that carparks are strategically located in response to factors such as population density, commercial activity, and urban infrastructure. The observed clustering aligns with Singapore's urban planning practices, where carparks are often concentrated in areas with higher residential and commercial development to maximise accessibility and convenience for residents and visitors alike. To visualise the results, we created a histogram of the nearest neighbour distances and plotted a series of *G*-functions alongside the theoretical distribution. These visualisations provided clear evidence of clustering, with many carparks located much closer to each other than would be expected under a random distribution. The histogram of nearest neighbour distances highlighted that most distances were relatively short, reinforcing the idea of spatial clustering. The *G*-function plot further confirmed that the clustering effect was consistent across different distance scales.

In essence, the nearest neighbour distance analysis revealed a significant clustering of HDB carparks in Singapore, supported by both statistical tests and visual evidence. This clustering pattern indicates that carparks are concentrated in certain areas, likely driven by factors such as urban density and land use planning. Understanding these spatial patterns can help inform future urban development and optimise carpark distribution to better meet the needs of the population.

***K*-function analysis**

The K-function analysis is a powerful method used to investigate spatial point patterns over a range of scales. Unlike the nearest neighbour analysis, which only considers the distance to the closest point, the *K*-function examines how point density changes with increasing distance from each point. This method helps us understand whether clustering or dispersion of HDB carparks in Singapore varies at different spatial scales. The *K*-function, denoted as *K*(*r*) measures the expected number of points within a distance *r* from a randomly chosen point, relative to the overall density of points in the study area. It allows us to identify patterns of spatial clustering or regularity at various distances. To interpret the results:

1. If the observed *K*(*r*) is greater than the theoretical *K*(*r*), it indicates clustering at distance *K*(*r*).

2. If the observed *K*(*r*) is less than the theoretical *K*(*r*), it suggests spatial dispersion or regularity.

For our analysis, we used the spatstat package to compute the empirical *K*-function of the HDB carpark locations and compare it with the theoretical *K*-function under the assumption of complete spatial randomness (CSR). We generated 99 simulations of a CSR pattern to create an envelope for the theoretical *K*-function, which provides a visual range of expected values if the distribution were random. The empirical *K*-function was then plotted against this theoretical envelope to determine the nature of the spatial pattern. The plotted functions are shown in **Figure 14**.

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**Figure 14:** Plot of a series of *K*-functions obtained from the spatial HDB carpark distribution

The results of the *K*-function analysis indicated that the observed *K*(*r*) values were consistently above the upper boundary of the theoretical CSR envelope at multiple distance scales. This suggests a significant level of clustering in the spatial distribution of carparks across Singapore, regardless of the distance considered. Moreover, the fact that the observed *K*(*r*) exceeds the theoretical *K*(*r*) across different distance scales means that clustering is not limited to a specific distance but occurs at various levels. This multi-scale clustering implies that carparks are grouped together in several localities, likely influenced by regional demand and urban infrastructure.

To make the interpretation of the *K*-function more straightforward, we also employed the *L*-function transformation. The *L*-function, which is a linearised version of the *K*-function, is defined as:

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When plotted (**Figure 15**), a positive deviation of the *L*-function from the zero line indicates clustering, while a negative deviation suggests dispersion. The *L*-function analysis for our dataset showed significant positive deviations, reinforcing the conclusion that HDB carparks are spatially clustered at various scales.

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**Figure 15:** Plot of a series of *L*-functions obtained from the spatial HDB carpark distribution

In addition to the *K*- and *L*-functions, we conducted the *G*-function analysis, which focuses on the distribution of nearest neighbour distances. This analysis provided another layer of confirmation that the carparks are more closely spaced than expected under random distribution. The *G*-function plot (**Figure 16**) revealed a higher frequency of short distances compared to the theoretical distribution, indicating a clustering pattern at small spatial scales.

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**Figure 16:** Plot of a series of *G*-functions obtained from the spatial HDB carpark distribution

The visual plots of the *K*-function, *L*-function, and *G*-function (**Figures 14-16**) provided clear evidence of clustering in the HDB carpark locations. The consistent deviations of the empirical functions from their theoretical counterparts highlighted the significant spatial dependence present in the data. Specifically, the observed *K*-function values were consistently higher than the theoretical envelope, indicating clustering at different distance scales. Furthermore, the positive values of the *L*-function reaffirmed the presence of clustering, providing an intuitive view of the carpark density. Lastly, the *G*-function plot further confirmed the clustering at smaller distances, complementing the findings from the nearest neighbour distance analysis.

Overall, the comprehensive *K*-function analysis provided strong evidence that the spatial distribution of HDB carparks in Singapore exhibits significant clustering at multiple spatial scales. This clustering is likely influenced by factors such as urban planning, residential density, and accessibility needs. By identifying the scales at which clustering occurs, we gain deeper insights into how carpark locations are influenced by urban dynamics, which can help guide future development and transportation planning in Singapore.

**Applications**

The findings from our spatial point pattern analysis of HDB carpark locations have numerous practical applications in urban planning, infrastructure management, and policy formulation. By identifying significant clustering patterns and understanding the spatial distribution of carparks, we can offer insights that contribute to more effective decision-making in several key areas.

1. Urban planning and infrastructure development

The clustering of HDB carparks in certain regions of Singapore indicates areas of high demand for parking facilities, typically corresponding to regions with dense residential or commercial development. Urban planners can use this information to optimise the placement of new carparks or to expand existing facilities in areas where demand is expected to grow. This data-driven approach can lead to more efficient land use and ensure parking infrastructure meets the needs of the population without overcrowding certain areas.

2. Transportation and mobility management

Understanding the spatial distribution of carparks can help policymakers manage transportation flow and alleviate traffic congestion in high-density areas. By identifying clusters of carparks near public transportation hubs or busy districts, urban planners can implement strategies that encourage residents and visitors to use public transport, reducing the dependency on personal vehicles. This, in turn, can lead to decreased traffic congestion and lower emissions, contributing to a more sustainable urban environment.

3. Accessibility and equity in public services

Clustering patterns in HDB carpark locations provide insights into the accessibility of public services for different regions. Policymakers can use this information to ensure that underserved areas receive adequate access to carparking facilities, improving equity in urban infrastructure. Regions identified as having lower densities of carparks may require additional development to balance accessibility across the island, ensuring that residents in all areas of Singapore benefit equally from public amenities.

4. Commercial development and real estate

The spatial distribution of HDB carparks is also relevant for commercial developers and real estate professionals. Clustering around commercial centres and high-density residential areas suggests a correlation between carpark availability and commercial activity. Real estate developers can use these insights to make informed decisions about property investments, ensuring that new developments are physically located at areas where parking demand aligns with future commercial growth. Furthermore, businesses in areas with a high concentration of carparks may benefit from increased foot traffic, contributing to economic vitality.

5. Public policy and sustainability initiatives

The results of the nearest neighbour and *K*-function analyses can inform sustainability initiatives aimed at reducing urban sprawl and promoting higher-density development. By identifying where carparks are densely located, Singapore’s government agencies can target specific areas for interventions like expanding public transport links or implementing shared mobility solutions. Encouraging car-sharing, electric vehicle usage, or biking infrastructure in these clustered zones could also reduce the environmental footprint of Singapore’s urban transport system.

Overall, the spatial analysis of HDB carparks provides valuable data that can be used in a variety of practical applications to improve the planning and management of Singapore's urban infrastructure.

**Conclusion**

This project provided a comprehensive spatial point pattern analysis of HDB carparks in Singapore, utilising advanced techniques such as quadrat count analysis, kernel density estimation, nearest neighbour distance analysis, and *K*-function analysis. Through these methods, we were able to derive significant insights into the spatial distribution and clustering of carparks across the city.

Our analysis revealed strong clustering in the HDB carpark locations, particularly in central and densely populated areas of Singapore. This clustering pattern was consistent across multiple spatial scales, as demonstrated by the results of the nearest neighbour analysis, Clark-Evans test, and *K*-function analysis. These findings suggest that carpark locations are strongly influenced by urban planning, population density, and proximity to commercial centres.

Key insights from this project include:

1. The significant clustering of carparks at both small and large spatial scales.

2. The spatial dependence of carpark locations, reflecting the influence of urban development and infrastructure needs.

3. The utility of KDE and *K*-function analysis in providing a nuanced understanding of spatial patterns that goes beyond basic visualisations.

The results of this study have important implications for urban planning, transportation management, and public policy in Singapore. The clustering patterns can guide future developments in parking infrastructure, ensuring that facilities are optimally placed to meet the growing demands of the population while maintaining accessibility and sustainability.

In conclusion, the spatial point pattern analysis conducted in this project offers valuable insights into the spatial organisation of HDB carparks, supporting more informed decisions in urban infrastructure planning. By leveraging advanced spatial techniques, this study contributes to a deeper understanding of the complex relationships between land use, population density, and public infrastructure in a modern urban setting like Singapore.