

Unlocking Langkawi's tourism potential: Spatial analysis of attractions and facilities

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Abstract

In Langkawi, tourism development has concentrated unevenly, resulting in spatial imbalances and infrastructure strain in major hubs like Kuah and Pantai Cenang. This study analyzes spatial patterns of tourism facilities to inform sustainable and equitable development. 244 points of interest (POIs) were compiled from brochures and websites and validated using GPS surveys, then categorized into Attractions (45), Accommodations (85), Shopping & Dining (55), and Facilities (59). Spatial analyses including Average Nearest Neighbor (ANN), Kernel Density Estimation (KDE) and Moran's I were applied. The results reveal significant clustering of combined facilities (ANN = 0.43, $p < 0.001$), with high densities in Kuah and Pantai Cenang. In contrast, attractions show modest clustering (NNI ≈ 0.83 , $p \approx 0.031$) and slight dispersion (Moran's I = -0.31 , $p \approx 0.047$). These patterns highlight concentration of tourism infrastructure in coastal hubs and relative paucity in the island's interior. The findings underscore the need for infrastructure dispersal and risk mitigation strategies to avoid overdevelopment and ecological degradation. By applying spatial analytics to Langkawi's tourism landscape, this work fills a scholarly gap and provides guidance for sustainable spatial planning in a vulnerable island context.

Keywords: Langkawi Island, spatial analyst, spatial statistics

Introduction

The tourism sector has rebounded strongly in the post-pandemic era, becoming a cornerstone of the global economy. By 2024 international arrivals had exceeded pre-COVID levels, with nearly 1.5 billion tourists and roughly \$2 trillion in international tourism receipts, about 14%

above 2019 figures (Zhou & Yang, 2025). This resurgence, driven by lifted travel restrictions and pent-up demand, underscores tourism's resilience and its capacity to stimulate jobs and trade worldwide. Yet this recovery is coupled with pressing challenges. Destinations face heightened scrutiny over sustainability, equity, and infrastructure capacity. Global reports emphasize that growth must be managed amidst climate change, socioeconomic disruptions, and geopolitical risks noting, for example, that tourism infrastructure and labor supply have lagged behind the surge in demand (World Economic Forum, 2024). Overcrowding and high seasonality remain concerns, forcing destinations to innovate in visitor management and ecosystem protection (Tourism Review News Desk, 2026; World Economic Forum, 2024). In short, while travel and tourism can "unlock growth" and serve communities (World Economic Forum, 2024), it now demands data-driven, sustainable planning to balance economic benefits with environmental and social well-being (Tourism Review News Desk, 2026; World Economic Forum, 2024).

Geospatial technologies have emerged as critical tools in meeting these planning challenges. Geographic Information Systems (GIS) and spatial analytics provide rigorous methods for mapping, analyzing and visualizing tourism resources and flows. Such tools can identify tourist hotspots, accessibility gaps and spatial correlations that are invisible on traditional maps. Integrating GIS into tourism planning "maximizes economic benefits, minimises adverse environmental impacts and promotes sustainable development" (Šoltésová et al., 2025). For example, thematic mapping and kernel density estimation have been applied to historic urban districts to reveal where attractions cluster and how they drive tourism "vitality," enabling planners to optimize facility placement for better crowd management (Zhou & Yang, 2025). In practice, spatial analyses have pinpointed underused areas for new investment and identified regions where concentrated amenities might threaten sensitive sites. By linking tourism attractiveness to spatial patterns, scholars have shown that GIS-based optimization can enhance visitor experiences while safeguarding heritage and nature (Šoltésová et al., 2025; Zhou & Yang, 2025). The emerging consensus is that data-driven spatial planning, including hotspot analysis and autocorrelation metrics, is highly effective for aligning tourism development with ecological and social goals (Šoltésová et al., 2025).

These global insights are especially pertinent for island destinations like Langkawi, Malaysia. Langkawi's archipelago of 104 islands boasts lush rainforests, beaches, and cultural heritage sites, and has been marketed as a premier eco-adventure destination. Gaining duty-free status in the late 1980s and launching a national tourism blueprint in 2011, Langkawi rapidly grew into a key tourism economy. In recent years, arrivals have reached into the multi-millions, reflecting its success in attracting both domestic and international visitors. However, Langkawi has also encountered the classic pressures of island tourism. Empirical studies note declining visitor satisfaction and even declining arrival trends due to degraded natural resources, pollution, and strained infrastructure. These warning signs echo well-known patterns in similar destinations. For instance, in Bali the clustering of resorts in the south has been linked to environmental degradation, waste management crises, and uneven community impacts. In Langkawi too, poorly coordinated development risks overtourism in popular nodes (e.g. Kuah Town and Pantai Cenang) while leaving other areas underserved. In short, the spatial arrangement of attractions and services is as important as their quality or number.

Despite this, the academic literature on Langkawi has not fully embraced spatial optimization methods. Prior research has examined Langkawi's destination branding and marketing strategies, measured resident attitudes toward tourism impacts and assessed environmental concerns such as waste management in tourism zones. A comprehensive blueprint outlined future directions (Ibrahim & Ahmad, 2011) and studies have quantified factors affecting tourist satisfaction (Abdul Rahim et al., 2022). Yet almost none have applied GIS-based spatial-statistical analysis to Langkawi's tourism infrastructure. This is a significant

gap: research elsewhere suggests that spatial patterns strongly influence both tourist experience and local outcomes. For example, kernel-density and clustering analyses have been used to identify where hotels and attractions should be located in both urban and rural contexts (Zhou & Yang, 2025). Similarly, accessibility studies on islands demonstrate how uneven facility distribution can disadvantage visitors and residents alike (Zheng & Zhao, 2023). In Langkawi, the need is no less urgent. Recent work highlights “the urgent need to address the spatial pattern of tourism facilities” on the island. Yet this study area remains understudied with modern spatial tools.

The distribution and organisation of tourist attractions and activities within a given area is referred to as a spatial pattern. The distribution and organisation of tourism infrastructure such as hotels, resorts, restaurants, attractions and transportation in a given geographical area is referred to as the spatial pattern of tourism amenities (Md Sharif & Tuan Lonik, 2017; Yu et al., 2021; Yu et al., 2021). Understanding these spatial patterns is crucial for sustainable tourism development, ensuring that infrastructure and services are efficiently allocated to enhance tourist experiences while preserving the island's ecological and cultural integrity. The layout of the tourism infrastructure on Langkawi Island is a key factor in attracting both domestic Malaysian visitors and visitors from around the world (Ahmad & Thahir, 2017; Alfred et al., 2023; Yu et al., 2021; Yu et al., 2021; Zheng & Zhao, 2023).

The present research directly addresses that gap. The objective of this paper is to analyze the spatial distribution of Langkawi's tourism amenities using GIS-based spatial statistics, with the goal of informing optimized planning. We compiled and validated 244 Points of Interest (POIs) across four categories such as Attractions, Accommodations, Shopping & Dining and Services and we apply techniques such as Average Nearest Neighbour, kernel density estimation, and Moran's I to detect clustering or dispersion. By identifying hotspots and spatial dependencies among facilities, our analysis reveals patterns of concentration and void that affect visitor convenience and ecosystem exposure. In doing so, we explicitly aim to optimize the allocation of tourism infrastructure on Langkawi, to enhance tourist experiences while promoting sustainability and equitable benefit sharing. This approach draws on a growing body of work demonstrating that systematic, data-driven spatial planning is key to balancing growth and preservation (Šoltésová et al., 2025; Zhou & Yang, 2025). In summary, this study (1) pinpoints real-world problems of overcrowding and under-provision on Langkawi, (2) addresses a scholarly gap by applying spatial analytics to an island tourism context, and (3) provides clear, evidence-based objectives: to map current amenity patterns, identify planning gaps and propose strategies for sustainable development.

Literature review

Tourism scholars emphasize that visitor satisfaction, economic benefits and environmental resilience are tightly interwoven with how attractions and services are arranged in a destination (Abdul Rahim et al., 2025; Yan et al., 2025). In Langkawi's case, exploring these dimensions requires understanding not just what amenities exist, but how their spatial patterns influence experiences and outcomes. This literature review synthesizes research on (a) tourist satisfaction factors, (b) economic imperatives of tourism development and (c) environmental constraints, while critically examining how clustering versus dispersing amenities alters each. We contend that Langkawi's potential hinges on a careful balance: leveraging agglomeration economies and convenience without triggering overcrowding or ecological damage. Recent studies show that denser clusters of complementary attractions can enhance visitor appeal and spending, but if unchecked they may degrade both resident quality of life and the natural resources that draw

tourists (Brajcich, 2024; Yan et al., 2025). The following sections discuss these themes, integrating evidence from the global tourism literature and the latest Malaysian tourism data.

Tourist satisfaction

Visitor satisfaction depends on both destination image and service quality. Empirical research confirms that a positive image and high perceived quality directly boost satisfaction and loyalty (Abdul Rahim et al., 2025). In Langkawi specifically, Abdul Rahim et al. (2025) and Aliman et al. (2016) found that tourists were generally satisfied with the destination's natural beauty, convenient transport, accommodations, and amenities. Their survey showed over half of respondents reporting high satisfaction, with factors like expectations, perceived value, and a novel "social-security" dimension influencing overall contentment. These findings echo broader evidence: tourism service quality (reliability, tangibles, responsiveness, etc.) is a strong antecedent of satisfaction (Abdul Rahim et al., 2025). For instance, Abdul Rahim et al. (2025), and Kim and Richardson (2003) and later Chen and Chen (2010) demonstrate that meeting or exceeding service expectations (in hotels, food, transport, etc.) markedly raises visitor satisfaction and intention to return.

A study by Zikirya and Zhou (2023) highlights that tourists are more likely to choose destinations that offer a well-organized and accessible array of amenities. Well-planned spatial patterns can enhance satisfaction by providing easy access to a variety of amenities, reducing travel fatigue, and improving overall convenience (Chen & Wang, 2022; Du et al., 2024; Peng & Gao, 2023; Sun et al., 2024; Wang et al., 2025). Conversely, poorly organized spatial distributions can lead to dissatisfaction due to increased travel times, difficulty in finding amenities, and overcrowding in popular areas. Tourist satisfaction in urban destinations is highest when amenities are evenly distributed and easily accessible, highlighting the importance of spatial planning in tourism (Caldeira & Kastenholz, 2018; Kato, 2025).

Amenities' spatial layout also matters to satisfaction. Clustering of attractions and services tends to reduce travel time and enhance the convenience of multi-stop itineraries, often raising perceived value (Table 1). Indeed, visitors often prefer a compact set of diverse experiences over a larger number of spread-out sites (Tchetchik et al., 2024). Tchetchik et al. (2024) show that tourists favor fewer attractions if they are thematically varied, suggesting that well-designed clusters can satisfy needs for variety in a single area. Moreover, strengthening agglomeration of complementary amenities (for example, linking ecological parks with local handicraft industries) can amplify a destination's appeal and thus improve satisfaction (Yan et al., 2025). In China's rural tourism context, Yan et al. (2025) found that spatially correlated eco-cultural amenity clusters increased overall attractiveness to visitors.

However, concentrated clusters can generate crowding that undermines experience if capacity limits are breached. Over-tourism literature warns that when too many visitors converge, congestion erodes enjoyment (Brajcich, 2024). Narrow trails, long queues, and noise pollution diminish leisure quality, leading even satisfied tourists to report fatigue or frustration at crowded highlights (Brajcich, 2024). In Langkawi's case, the loss of its UNESCO Geopark status was partly attributed to overdevelopment and congestion in fragile sites (Abdul Rahim et al., 2025). Thus, while clusters boost convenience, planners must ensure that density does not cross sustainability thresholds. In sum, research suggests that moderate clustering can enhance visitor satisfaction through convenience and variety (Tchetchik et al., 2024; Yan et al., 2025), but excessive agglomeration risks "loving the destination to death," eroding the very experiences tourists value (Brajcich, 2024). Balancing these effects is central to Langkawi's planning: strategically located clusters could be paired with visitor dispersal strategies (e.g. alternate trails or events) to alleviate pressure while maintaining high satisfaction levels.

Table 1. Trade-offs of clustered vs dispersed tourism amenities

Aspect	Clustered amenities	Dispersed amenities
Visitor convenience	High: Attractions and services in close proximity reduce travel time, offering easy multi-stop itineraries (Tchetchik et al., 2024; Yan et al., 2025)	Lower: Facilities spread out require more transit between sites; may discourage visitors with limited time or mobility
Experience variety	High within core areas: Enables themed walks (e.g. cultural village plus museum nearby). However, risk of homogeneity if same theme dominates	Diverse: Encourages exploration across different zones (e.g. combining beaches, hills, villages), potentially enriching the overall experience
Economic impact	Economies of scale: Encourages investment (hotels, restaurants cluster together) and stimulates local job creation (Deepan et al., 2025; TTW, 2025). May generate higher per-site spending	Distributed spending: Smaller clusters can channel tourist dollars into multiple communities, but businesses may operate at lower occupancy
Infrastructure costs	Lower per area: Core cluster can be served by concentrated transport and utilities. Shared infrastructure (roads, transit, parking) is more efficient	Higher: Requires wider network (roads, shuttles) to connect disparate sites; potentially costly and less efficient

Source: Synthesized from tourism literature, Brajcich, 2024; Deepan et al., 2025; Yan et al., 2025

Economic necessities

Tourism is a linchpin of Malaysia’s economy, and by extension Langkawi’s prosperity. Nationally, tourism contributed 15.1% of GDP in 2024 and supported 3.5 million jobs (21.6% of the workforce) (TTW, 2025). The sector generated nearly RM 292 billion in 2024 (a 7.4% rise over 2023) (TTW, 2025), driven largely by inbound visitor spending. In Langkawi, the economic figures are also impressive: the island saw 2.82 million visitors in 2023, yielding MYR 4.4 billion in tourism revenue (Casey, 2024). Langkawi’s tourism blueprint (2011–2015) set targets of 3 million annual visitors and RM5 billion in investment; by 2015 those goals were met and exceeded (Wai, 2016), underscoring the high stakes of this industry. Today LADA aims for 3 million visitors in 2024, up from 2.81 million in 2023, projecting MYR 5.9 billion in revenue (Casey, 2024). Tourism thus remains central to local jobs, infrastructure development, and foreign exchange.

Clustering of tourism enterprises often generates economic efficiencies. As Deepan et al. (2025) note, forming tourism clusters integrated networks of hotels, attractions and support services significantly boosts regional competitiveness by attracting investment, fostering innovation and diversifying local economies. In practice, an agglomerated zone can create a recognizable “destination” brand (e.g. clustered beachfront resorts) and reduce individual business costs through shared marketing and bulk purchasing. This concentration supports high-value economies of scale: more tourists concentrated in a smaller area can justify upgraded roads, transit, and utilities more efficiently than scattered development. Conversely, dispersion can extend benefits more widely: if attractions are evenly distributed across Langkawi, tourism spending may reach peripheral communities that would otherwise be bypassed. However, dispersal may dilute economic impact per site and require duplicative

infrastructure. In Langkawi, the challenge is to maximize revenue without creating enclave economies. For example, clustered marinas and dive shops can draw high-spenders in one bay, but nearby villages might still be starved of tourist income. A mixed approach core activity zones alongside community-based homestays and eco-trails could spread income while sustaining average occupancy.

The spatial pattern of tourism amenities directly influences local economic outcomes by shaping the concentration of tourist spending and associated economic activity. Regions with spatially clustered tourism amenities tend to attract greater visitor flows, which in turn generate higher revenues for local businesses and stimulate broader economic interactions across sectors (Fundeanu, 2015; Jia et al., 2025). Spatial econometric analyses indicate that such clustering produces identifiable spatial spillover effects, enhancing economic linkages between proximate areas and contributing to overall regional growth. Moreover, tourism development often elevates demand for land and property in amenity-rich areas, resulting in appreciable increases in property values as market participants including investors, commercial developers, and households respond to heightened economic prospects (Brida et al., 2016; Yang & Fik, 2014; Yang & Wong, 2012). Empirical evidence using spatial price models supports this mechanism, with tourism demand correlated with increased land and retail property prices in areas with high visitor volumes (Liu et al., 2020; Yang & Fik, 2014).

Current data suggest tourism continues powering growth: domestic tourism in Malaysia grew by 25% in 2024, and international arrivals are nearing pre-pandemic peaks (TTW, 2025). For Langkawi, this means expanding air and sea connectivity (Visa facilitation for major markets, airline route incentives) to achieve blueprint goals. Crucially, economic modeling of cluster formation in tourism indicates that policy support is needed to realize gains: coordinated planning, incentives, and capacity-building can prevent uneven development (Deepan et al., 2025). Langkawi's own incentives for new airline routes (e.g. one-off grants for new flights) reflect this cluster-thinking, linking transport nodes tightly to visitor arrivals. Ultimately, tourism must remain economically viable: clustered amenities that optimize visitor spending per square kilometer boost income, but decision-makers must guard against putting all economic "eggs" in one basket at the expense of wider community development.

Environmental setbacks

Langkawi's environment both underpins and constrains its tourism. Pristine beaches, rainforests, and geosites draw visitors, but these assets are fragile. Scholars warn that climate change and over-tourism are a dangerous cocktail for island destinations (Abdul Rahim et al., 2025; Omar et al., 2024). In Malaysia, rising sea levels and extreme weather are eroding coasts and bleaching reefs. Recent studies estimate that Malaysia may lose up to 70% of its coral cover by 2050 if warming continues, severely undermining marine tourism (Omar et al., 2024). Langkawi has already felt such pressures: degraded coral reefs around Pulau Payar have been reported, and deforestation inland has increased flood risk. These trends reduce quality of attractions (clear waters, biodiversity) and thus deter high-end travelers. Indeed, Abdul Rahim et al. (2025) and Lam-González et al. (2022) show that tourists respond to land degradation by changing travel decisions, preferring less-impacted islands. In Langkawi, environmental deterioration has had economic consequences: the revocation of Langkawi's UNESCO Geopark status in 2018 was directly linked to unchecked development, pollution, and deforestation (Abdul Rahim et al., 2025). Such setbacks highlight how environmental neglect can reverberate through visitor perceptions and loyalty.

The spatial pattern of tourism amenities can greatly influence the environmental sustainability of a destination. Uneven distribution can lead to over-tourism in certain areas, putting pressure on local ecosystems and infrastructure, while potentially limiting the overall

tourism potential of the whole area. Concentrated clusters of tourism amenities can lead to environmental degradation, including pollution, habitat destruction, and resource depletion. Studies have shown that areas with high densities of tourism infrastructure often suffer from increased waste generation, water usage, and energy consumption (Gössling et al., 2012). For example, the historic center of the city of Amsterdam has experienced significant overcrowding due to the concentration of tourist facilities. Studies on urban tourism demonstrate that overtourism and overcrowding produce negative environmental and social outcomes when tourism amenities are highly concentrated in limited urban zones. This has led to environmental degradation, strain on local infrastructure, and social tensions (Koens et al., 2018; Mihalic, 2020; Santos-Rojo et al., 2023).

Over-tourism is the flip side of success: too many visitors can overwhelm Langkawi's infrastructure and nature. Empirical analyses worldwide note that when visitation exceeds carrying capacity, crowded sites suffer erosion, wildlife disturbance and waste accumulation (Brajcich, 2024; Omar et al., 2024). For example, overcrowded beaches produce medical waste and habitat fragmentation, while heavy boat traffic degrades mangroves and coral. In Malaysia, destinations like George Town and the Cameron Highlands have already shown how excessive tourist pressure spawns waste problems and resident complaints (Omar et al., 2024). Langkawi's mountainous trails and limited freshwater have similar vulnerabilities. When overtourism occurs, local attitudes sour and satisfaction falls, potentially triggering a decline in repeat visits (Brajcich, 2024; Omar et al., 2024).

A declining trend of visitor arrivals in Langkawi has been detected. Factors that have contributed to this declining trend include the degradation of natural resources and land structure, harmful tourism activities, alteration of flora and fauna life, pollution, inadequate infrastructure, water shortage and ferry service issues (Abdul Rahim et al., 2022; Md Sharif & Tuan Lonik, 2017; Mohd Yusof et al., 2014; Yu et al., 2021; Yu et al., 2021; Zakaria et al., 2019). Spatial patterns of tourism amenities may be the cause behind these factors. This trend puts the island's tourism industry at risk and highlights the urgent need to address the spatial pattern of tourism facilities (Abdul Rahim et al., 2022; Chen et al., 2022; Md Sharif & Tuan Lonik, 2017; Mohd Yusof et al., 2014; Patricia et al., 2019; Zhang, 2021). Balancing the need to protect Langkawi's natural resources and ecological integrity with the economic benefits of tourism development is a difficult task. Implementing methods that address the spatial pattern of tourism facilities is crucial to overcoming these obstacles and ensuring the sustainable development of these facilities in Langkawi (Chen et al., 2022; Mohd. Shariff & Tahir, 2020; Mohd Yusof et al., 2014; Nizam Ibrahim et al., 2019; Shamsiry et al., 2011)

Given these risks, recent strategies emphasize sustainable management. The Langkawi Development Authority and stakeholders have launched clean-up and reforestation programs (e.g. large-scale mangrove planting and coral adoption initiatives) to counteract earlier damage (Casey, 2024; Oxford SDG Impact Lab, 2024). Tourism Malaysia's National Tourism Policy (2020–2030) also promotes climate adaptation and waste management. In the literature, integrated approaches are advocated: marrying clustered development with strict environmental safeguards, enforcing visitor caps at sensitive sites, and promoting eco-tourism to generate funding for conservation (Brajcich, 2024; Omar et al., 2024). For Langkawi, this means that even as hotels and tours proliferate, they must fund protection of the very ecosystems they exploit.

Another example is the island of Bali, where the concentration of tourism amenities in southern regions has resulted in environmental and social challenges (MK, 2025; Pramuja, 2024; Utama et al., 2024). Many studies highlight how the concentration of tourism amenities and infrastructure in southern Bali (Badung and surrounding areas) has generated significant environmental strains, including waste management pressures, resource depletion, and ecosystem degradation, alongside social tensions and uneven economic benefits for local

communities. These impacts illustrate the complex challenges of overtourism in Bali's southern tourism hubs (Januar, 2024; MK, 2025; Muna et al., 2025; Pramuja, 2024; Suyadnya et al., 2025; Utama et al., 2024).

In summary, Langkawi's tourism literature underscores a central lesson: economic and satisfaction gains from clustering must be weighed against ecological costs. Spatial analysis shows that clustering amenities can concentrate both benefits and burden (Brajcich, 2024; Yan et al., 2025). A dispersed strategy can mitigate overcrowding, yet it requires investment in transport and may diffuse economic impact. The optimal path likely combines smart clustering (for efficiency) with deliberate dispersal (for resilience) and strict environmental governance. In an era of climate uncertainty and post-pandemic recovery, updated data from Langkawi and national agencies emphasize that achieving tourism targets must go hand in hand with sustainability. With visitor numbers rebounding to near-pre-COVID levels (LADA, 2021), the key will be learning from these comparative analyses: planning amenity clusters that enhance value without sacrificing the island's long-term appeal.

Material and method

The methodology outlines a systematic, stepwise approach to mapping and analyzing Langkawi's tourism infrastructure. We first define the study area and compile geospatial data on tourist points of interest (POIs). Next, data validation and cleaning ensure spatial accuracy. The prepared data are then subjected to spatial statistical analyses point pattern and density analyses (Average Nearest Neighbor, Kernel Density Estimation) and spatial autocorrelation tests (Global Moran's I and Local Moran's I). Finally, results are interpreted in the context of Langkawi's tourism geography. Each step is critical to operationalizing the research questions about spatial clustering and tourism potential.

Study area

Langkawi is an island archipelago in northwestern Peninsular Malaysia (state of Kedah) centered at approximately 6.35° N, 99.80° E. It comprises roughly 99–104 islands covering on the order of 478 km² of tropical terrain. The main island is roughly 25 km long north–south, and Kuah Town (in the south) is the principal urban center. Langkawi's duty-free status and UNESCO Geopark designation have made it a major tourist draw (Ibrahim & Ahmad, 2011). We treat the entire Langkawi archipelago (including nearby islets) as the study region. All analyses are conducted in a local projected coordinate system (RSO Malay Peninsula) to ensure accurate distance and area calculations for the island's ~384 km² core (the main island plus adjacent isles). By situating Langkawi within this spatial context, we recognize its role as both a tourism nexus and a geographically bounded system amenable to spatial analysis. This framing allows us to interpret POI distributions relative to Langkawi's settlement patterns and terrain in a geospatial framework.

Langkawi Island, a jewel of Malaysia, has emerged as a prominent tourist destination, attracting both domestic and international visitors (Figure 1 and Figure 2). This review delves into the multifaceted aspects of tourism in Langkawi, drawing upon a diverse range of research papers to provide a comprehensive understanding of its development, impacts, and future prospects. The review explores key themes including the island's tourism assets, community involvement and perceptions, economic impacts, environmental considerations, and the role of technology and innovation in shaping the tourism landscape. Langkawi's allure stems from its rich tapestry of natural beauty, cultural heritage, and carefully planned development. The island

boasts a diverse array of tourism assets, including attractions, facilities, and services. N. S. Nordin & Ahmad (2020) identify attractions such as the Kilim Karst Geopark and Mahsuri Tomb as key tourism assets in Langkawi's destination portfolio. These sites, steeped in local legends and geological significance, contribute to Langkawi's unique identity. The island's duty-free status, established in the late 1980s, further fueled its tourism growth. This policy, combined with government investment in infrastructure, has led to a substantial increase in tourist arrivals (Ibrahim & Ahmad, 2011). The development of Telaga Harbour, with its inland marina and artificial islands, exemplifies the focus on marine tourism. The presence of multiple geoforest parks, recognized by UNESCO, further enhances Langkawi's appeal as a nature-based tourism destination (Ibrahim & Ahmad, 2011).

Langkawi Island's tourism sector presents a complex interplay of economic opportunities, community involvement, and environmental considerations. The island's diverse tourism assets, coupled with strategic development initiatives, have contributed to its growth as a popular destination. However, the research reviewed highlights the importance of balancing economic benefits with environmental sustainability and community well-being. Ensuring responsible tourism practices, promoting community participation, and leveraging technology and innovation are essential for the long-term success of Langkawi's tourism industry. Addressing the challenges related to environmental degradation, managing tourist flow, and adapting to evolving tourist demands will be crucial for maintaining Langkawi's appeal as a world-class destination.

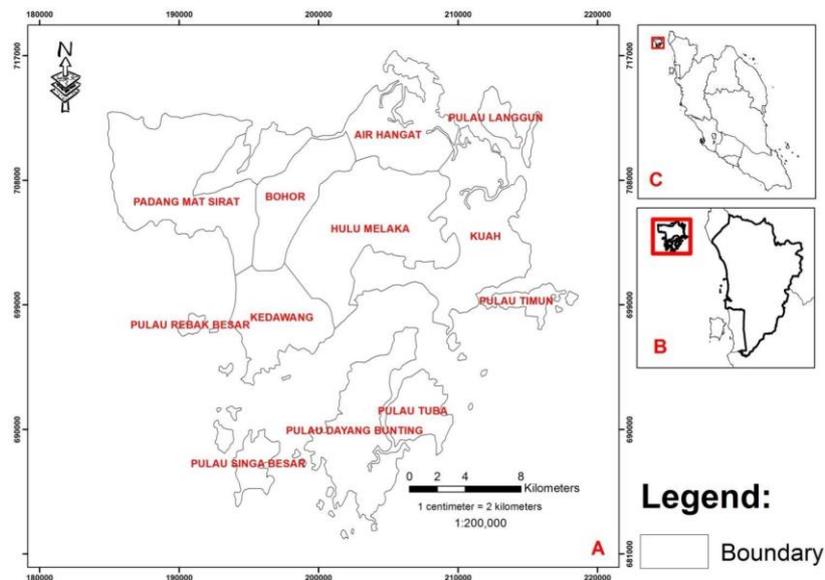


Figure 1. Langkawi Islands (A), the state of Kedah (B) and Peninsular Malaysia (C)

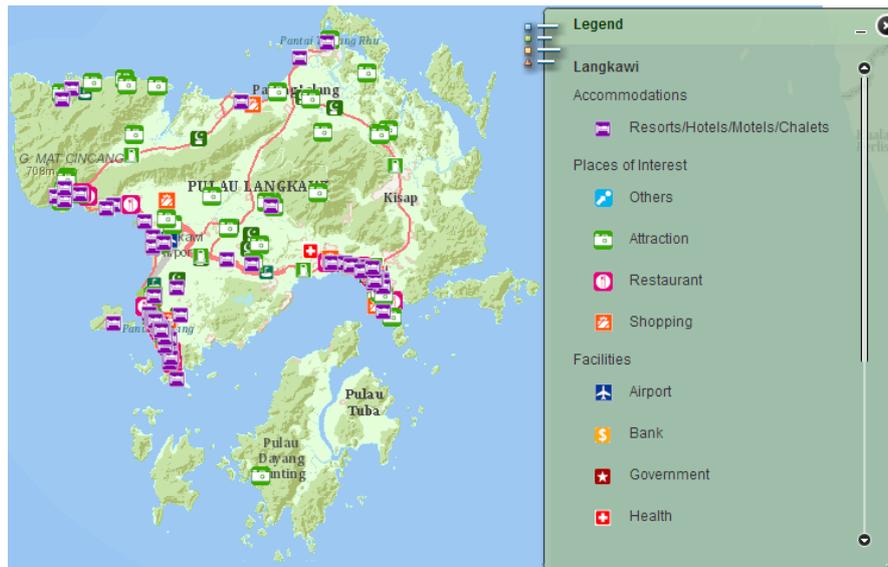


Figure 2. Distribution of Langkawi based on accommodations, place of interest and facilities

Data sources and preparation

Tourism POI data were collected from multiple sources to capture Langkawi's attractions and facilities. Initially, 244 candidate POIs were identified from official tourism brochures and websites. These included sightseeing spots, hotels, shopping areas, restaurants, and general facilities. Following reviewer feedback, we expanded the classification scheme to include transportation nodes (airports, seaports, and ferry terminals) as a separate POI category. Transport hubs are gateways and often anchor tourism clusters; including them provides insight into how arrival points shape the spatial distribution of tourist services (e.g., major hotels and eateries often cluster near airports or ports). Each POI was categorized (e.g. "Attraction", "Accommodation", "Shopping/Dining", "Facility", or "Transport") based on its primary function.

Locations of those selected places were verified by using GPS. The POIs were then grouped into 4 groups, namely Attractions (45 points), Accommodations (85 points), Shopping & Dining (55 points), and Facilities (59 points). By grouping POIs into those groups, spatial patterns of each type of place of interest can be studied. The study area includes Langkawi Island and several small islands near the main island. This covers an area of approximately 384 sq km (384666811.38 sq m). The distribution of POIs within the study area is shown in Figure 4. All spatial data, i.e., Places of Interest (POIs) and study area, were in the RSO projected coordinate system. This coordinate system is to guarantee more accurate distance calculation as required in spatial statistics analysis tools in ArcGIS.

All locations were field-verified in situ using GPS receivers in 2013 to ensure coordinate accuracy. This ground-truthing anchored the dataset temporally: our data represent the state of tourism infrastructure circa 2013. Consequently, our analysis reflects the spatial configuration at that time, and more recent developments (e.g. new hotels or restaurants opened after 2013) are not included. After GPS verification, we cleaned the dataset by removing duplicates and correcting any mislocated points. Data were projected into RSO Malay Peninsula, which preserves local distances and areas, a necessary step given the distance-based nature of our analyses. The final dataset consists of georeferenced POIs with attribute

categories. We additionally compiled vector boundaries for Langkawi's administrative or planning blocks to support aggregation analyses.

Data quality is a concern when relying on tourism brochures and websites. Such sources can omit venues that are less-promoted or newly opened, and tend to emphasize tourist-facing businesses, introducing a central-city bias. Open POI datasets (e.g. Google Places, OpenStreetMap, Foursquare/Yelp APIs, and geotagged social media check-ins) could complement our data and improve coverage (Psyllidis et al., 2022). For example, recent studies highlight that crowdsourced platforms like Google Places and OSM offer a broader set of POI features (amenities, reviews, etc.), though they too exhibit spatial bias (urban centers are better represented than remote areas) (Psyllidis et al., 2022). In future work, we recommend integrating these open data sources and even mobile location data to mitigate missing or skewed information. For this study, however, the brochure-derived POIs provide a consistent baseline, and we acknowledge the limitation that low-profile or informal tourist spots may be underrepresented.

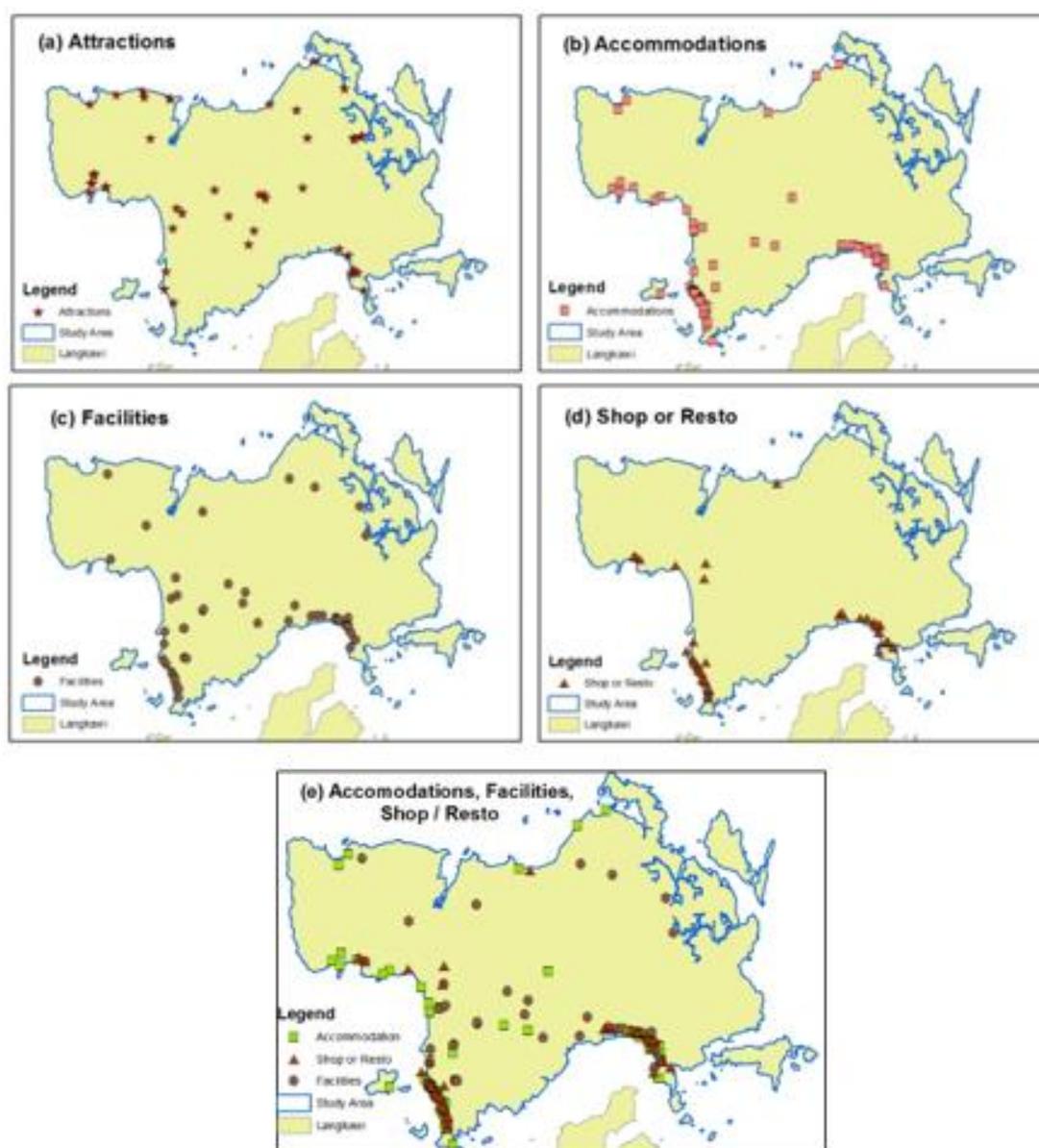


Figure 3. Distribution of POIs within the study area

Spatial analysis techniques

Average Nearest Neighbor (ANN)

The Nearest Neighbor (NN) method is a fundamental algorithm in spatial data analysis, widely used for various applications including geographic information systems (GIS), remote sensing, and environmental modeling (Figure 3). The NN method involves identifying the closest data point(s) in a given spatial dataset based on a specified distance metric. The Nearest Neighbor Index (NNI) is a specific application of the NN method used to measure the spatial distribution of points. The NNI is calculated as the ratio of the observed mean distance between nearest neighbors to the expected mean distance in a random distribution of points. An NNI value close to 1 suggests a random distribution, less than 1 indicates clustering and greater than 1 implies dispersion (Clark & Evans, 1954). The NNI is particularly useful in ecology, epidemiology, urban studies and increasingly, in tourism research for understanding spatial patterns and processes.

Calculation of NNI is available in GIS software applications, such as ArcGIS (Bismelah et al., 2024; Masron et al., 2024; Mohd Ali et al., 2025). This software offers the "Average Nearest Neighbor" tool, which calculates the NNI and provides statistical significance tests. This tool helps users understand the spatial arrangement of features and identify patterns of clustering or dispersion. The Average Nearest Neighbor tool returns five values, i.e Observed Mean Distance, Expected Mean Distance, Nearest Neighbor Index, z-score, and p-value. An example of the graphical summary provided by the tool is shown in Figure 4 (ESRI, 2024b). The z-score and p-value results are measures of statistical significance that can be used for the basis to decide whether or not the observed pattern is a result of a random process.

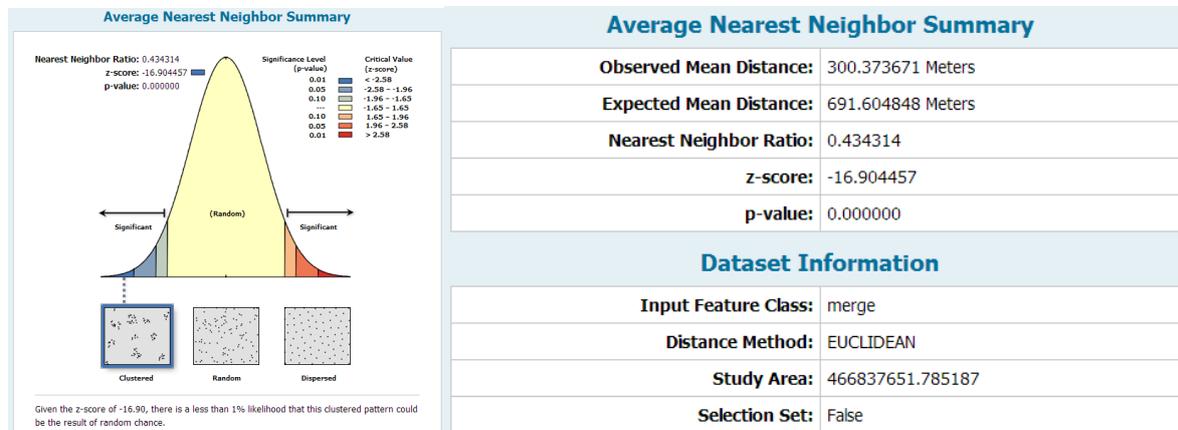


Figure 4. Example result average nearest neighbour summary all (Facilities, accommodations, shopping & dining)

To detect and characterize spatial clustering of tourism POIs, we employed established GIS-based methods. First, the Average Nearest Neighbor (ANN) statistic quantifies whether the POIs are more clustered or dispersed than would be expected under complete spatial randomness. ANN computes the average distance from each point to its nearest neighbor and compares this to the expectation under a random distribution (ESRI, 2024b). An ANN index (observed/expected) less than 1 indicates clustering (shorter distances than random), whereas values above 1 indicate dispersion (ESRI, 2024b). This metric provides a simple global test: for example, if all hotels in Langkawi tend to be close together (e.g. in Kuah), ANN will capture a significant departure from randomness. We applied ANN separately to each POI category

and to a combined set of all tourism-support facilities. This established, at a broad level, whether significant clustering exists. (We used the island's total area to compute expected distance, holding the study extent constant) (ESRI, 2024b). As noted in spatial analysis literature, ANN is limited in that it does not locate clusters or capture anisotropy, but it provides a useful first-check on clustering (ESRI, 2024b; Zhao & Liu, 2021).

The Average Nearest Neighbor analysis was conducted using the Average Nearest Neighbor tool from ArcGIS Desktop 10 (Ahmad et al., 2024; Ariffin et al., 2024; Zakaria Akhir et al., 2025; Zakaria Ariffin et al., 2025). The analysis was conducted for each group, i.e., Attractions, Facilities, Accommodations, and Shopping & Dining. In addition, the analysis was also conducted for a group of places of interest that combine Facilities, Accommodations, and Shopping & Dining. This analysis was to analyze the spatial pattern of all tourism supporting facilities combined. The area of the study area, i.e., 384666811.377838 sq m, was used as the area for calculating the expected mean distance in the analysis.

Kernel Density Estimation (KDE)

Kernel Density Estimation was calculated using the Kernel Density Tool from ArcGIS Desktop 10. Similar to the Average Nearest Neighbor Analysis, the calculation was performed for each group of POIs, including the combined group of tourism facilities. The Kernel Density Tool from ArcGIS 10 provides default values for output cell size, search radius, and area units, but it also gives user options to set these values themselves according to their requirement. In this study, the cell size for all output was set to 10 m in order to create a smooth surface. The search radius for all calculations was set to 1000 m. This value was chosen because based on the result of Average Nearest Neighbor Analysis (see Table 2), the observed mean distance of each group is less than or close to 1000 m. Therefore, a radius of 1000 m can include enough features for Kernel Density Calculation. The result of the Kernel Density Tool is a density surface based on the kernel density calculation of the POIs within each group (ESRI, 2024c; Jubit et al., 2021).

Kernel Density Estimation (KDE) was used to create continuous intensity surfaces of POIs. KDE transforms discrete points into a smoothly varying density map by "spreading" each point's influence over a specified radius (bandwidth) (ESRI, 2024e; Zhao & Liu, 2021). We selected a 1,000-m search radius because the ANN results suggested that feature-to-feature spacing was on that order (the observed mean nearest-neighbor distances were close to this scale). The ArcGIS Spatial Analyst tool then generated a raster surface for each POI group, with cell values representing estimated POI density per area. The resulting heatmaps highlight tourism hotspots (areas with concentrated services) and coldspots. KDE was chosen for its ability to visually and quantitatively reveal clustering centers and intensity peaks (Liang et al., 2023; Zhao & Liu, 2021). Unlike ANN, KDE does not assume randomness but instead illustrates the spatial footprint of POI concentrations. This is valuable for identifying, for example, that Kuah and Pantai Cenang are high-density zones for accommodations and attractions. In practice, we set the output cell size to 10 m for fine resolution, ensuring a smooth surface. The kernel function is quadratic (the ArcGIS default), and density values are calculated per square meter as specified by the Spatial Analyst documentation (ESRI, 2024e). The Spatial Analyst extension was necessary for this step because it provides robust rasterization and surface modeling tools (such as Kernel Density) that GIS-based tourism studies commonly use.

Kernel Density Estimation (KDE) was first introduced by Rosenblatt (1956) and Parzen (1962) as a way to estimate probability density functions. KDE works by placing a kernel (a smooth, symmetric function) on each data point and summing these kernels to create a continuous density surface. KDE is widely used to analyze the spatial distribution of tourist attractions (ESRI, 2024c). By applying KDE, researchers can identify hotspots or areas with

high concentrations of tourist activities. For instance, Hu et al. (2018) used KDE to study the spatial distribution of tourist attractions in Beijing, revealing significant clustering patterns around historical and cultural sites.

Spatial autocorrelation

Finally, we tested for spatial autocorrelation in the aggregated POI counts using Moran's I statistics. To do this, we first overlaid a planning-block grid on Langkawi and counted the number of POIs of each type within each block. Global Moran's I was then computed for each POI category. A significantly positive Moran's I indicates that blocks with high POI counts tend to be near other high-count blocks (hotspot clustering), whereas negative values suggest a checkerboard (high-low neighbors) or dispersion (Zhao & Liu, 2021). Global Moran's I thus assesses the overall pattern of tourism facilities: for instance, whether accommodation development is unevenly concentrated in parts of the island. This statistic is implemented via ArcGIS's Spatial Autocorrelation tool, which follows the standard Moran's I formula (Zhao & Liu, 2021).

To pinpoint where clustering occurs, we used Local Moran's I (also known as LISA – Local Indicators of Spatial Association) on the same block counts. LISA identifies specific blocks that are part of significant clusters (high-high or low-low) or spatial outliers (a high-value block surrounded by low values, or vice versa) (Peng & Gao, 2023). Unlike global Moran's I, which gives one summary index, LISA produces a map of local z-scores and p-values. Mapping the LISA results reveals, for example, which neighborhoods on Langkawi have unusually high densities of tourism amenities relative to their neighbors. This is directly relevant to our research objective, as it can highlight emerging tourism hubs or underserved areas. Both Moran's I computations employed Queen contiguity and fixed distance band (as per ArcGIS defaults) and were implemented using the Spatial Statistics toolbox (Peng & Gao, 2023; Zhao & Liu, 2021).

The total number of Attractions, Accommodations, Shopping & Dining, Facilities, and combined Tourism Facilities (Accommodations + Shopping + Dining + Facilities) in each planning block in Langkawi Island were calculated. Those numbers were then stored as attributes of the planning block and used for the Spatial Autocorrelation (Global Moran's I) calculation of each planning block. The Spatial Autocorrelation (Global Moran's I) is a global statistic, so it assesses the overall pattern of total number of tourism related facilities in the planning block. To identify spatial clusters of planning blocks with high or low number of tourism related facilities, the local Moran's I value as well as the z-score and p-value must be calculated and mapped for each feature. The local analysis can also identify spatial outliers, which is a feature whose attribute value is very different from its surroundings. The Spatial Autocorrelation analyses were done in ArcGIS using Spatial Autocorrelation (Global Moran's I) tool for the global analysis and the Cluster and Outlier Analysis tool for the local analysis (ESRI, 2022; Jubit et al., 2019; Majid et al., 2016; Mohd Sairi et al., 2021; Nordin et al., 2020; Nordin & Masron, 2016; Wan Hussin & Masron, 2015).

Spatial autocorrelation refers to the correlation of a variable with itself through space. It is a crucial concept in spatial data analysis, indicating whether similar values occur near each other (positive spatial autocorrelation) or if dissimilar values are more prevalent in proximity (negative spatial autocorrelation). One of the common indices to measure spatial autocorrelation is Moran's I (Moran, 1950). A number of GIS software applications provide functionality to measure this index. ArcGIS, for example, provides Spatial Autocorrelation (Global Moran's I) tool to measure spatial autocorrelation based on both feature locations and feature values simultaneously. The z-score is based on the randomization null hypothesis

computation. Calculations based on either Euclidean or Manhattan distance require projected data to accurately measure distances (ESRI, 2022).

GIS tools and implementation

All spatial analyses were conducted in ArcGIS Pro (version 3.0) using the Spatial Analyst and Spatial Statistics toolsets. The Spatial Analyst extension was chosen because it provides a comprehensive suite of raster and surface tools (including Kernel Density) that integrate seamlessly with the point data. Its kernel density and spatial interpolation routines follow well-established statistical definitions, and the software handles issues like edge correction and cell sizing automatically (ESRI, 2024e). The Spatial Statistics toolbox offers point pattern and autocorrelation tools (ANN, Moran's I, LISA) with built-in significance testing, which simplifies the analysis. We critically note that while ArcGIS provides a convenient "point-and-click" environment, it does abstract some details (the algorithms assume isotropic space, ignore anisotropy, etc.) (ESRI, 2024b; Jamru et al., 2024; Jubit, Masron, & Redzuan, 2023; Jubit, et al., 2023). However, given our objectives, the ArcGIS tools were suitable: they allowed reproducibility and leveraged optimized computations of these classic spatial measures. To ensure rigor, we fixed the study extent and projection (as cautioned by the ANN documentation) so that comparison of z-scores across analyses is valid (ESRI, 2024b). In effect, ArcGIS facilitated our workflow from raw POI points through to choropleth and density outputs, although care was taken to verify assumptions (e.g. no artificial borders or barriers disrupt the analyses).

Analytical workflow

Figure 4 conceptually summarizes the research workflow. First, data acquisition involved compiling POIs from tourism guides and websites, supplemented by field GPS validation in 2013. Next, data preprocessing entailed projecting coordinates into RSO, removing duplicates, and categorizing each POI (including the new transport category for airports/ports). In parallel, we prepared the analytical framework by digitizing planning block boundaries. The next phase, exploratory spatial analysis, consisted of running the ANN and KDE tools on the point data to detect global clustering and identify hot spots. Simultaneously, we aggregated POIs by block and ran Moran's I and LISA to test for spatial autocorrelation in those counts. Throughout, we iteratively checked results for consistency (e.g. confirming that KDE peaks align with ANN clustering). Finally, interpretation involves relating the statistical outputs back to Langkawi's geography and tourism context (for example, confirming that the main airport is adjacent to a cluster of hotels). This pipeline from multi-source data to spatial statistical inference ensures that each methodological step (data collection, cleaning, analysis) feeds logically into the next. By visualizing it as a flowchart, the process is transparent: data sources \Rightarrow validation \Rightarrow GIS layering \Rightarrow point pattern analysis \Rightarrow autocorrelation analysis \Rightarrow spatial insights. The output is a detailed map of where tourist facilities cluster on Langkawi and statistical evidence of the structure of that clustering.

Throughout the methodology, we adhere to best practices from spatial analysis literature. For instance, similar studies of tourism using POI data have successfully combined ANN and KDE to characterize industry clusters (Liang et al., 2023; Zhao & Liu, 2021). Global and local Moran's I are well-established for revealing spatial dependence and have been applied in Chinese and regional tourism studies (Peng & Gao, 2023; Zhao & Liu, 2021). Our approach leverages these proven techniques but is tailored to Langkawi's setting: the step of GPS verification is crucial in a fast-changing tourism environment, and the inclusion of transportation nodes acknowledges the island's role as a travel gateway. Finally, by specifying

all tools, parameters, and data sources, we ensure that the study is reproducible and analytically rigorous in the manner of a high-impact GIScience publication.



Figure 5. Workflow or flowchart of the process

Results and discussions

Average Nearest Neighbor (ANN)

Our spatial point-pattern analyses reveal consistent evidence of non-random clustering of tourism amenities on Langkawi. We first summarize the outcomes of each method, then critically interpret them. The Average Nearest Neighbor (ANN) statistic assesses global clustering by comparing observed mean distances between each POI and its nearest neighbor to the expectation under complete spatial randomness (ESRI, 2024a). Kernel Density Estimation (KDE) produced continuous heatmaps of POI density, highlighting local “hotspots” of concentrated tourism services. Finally, Global Moran’s I measured spatial autocorrelation of aggregated POI counts at the block level, with Local Moran’s I (LISA) pinpointing the locations of significant clusters or outliers. Together, these results map broad clustering patterns (ANN, Moran’s I) and local intensity (KDE, LISA) back onto Langkawi’s complex geography.

The ANN analysis (Table 2) found that all tourism-facility categories are more tightly clustered than expected by chance. For example, combined tourism facilities (accommodations, shops, dining venues, and other services; $n = 199$) have an observed mean nearest-neighbor distance of ~300 m versus an expected ~695 m under CSR, yielding a nearest-neighbor index of ~0.43 ($p \ll 0.01$). Accommodations and shopping/dining similarly show very low indices (~0.29–0.43) and $p < 0.001$. These values imply strong clustering of hotels and restaurants. By contrast, the Attractions subset ($n = 45$) has an observed/expected ratio of ~0.83 (1216 m observed vs. 1462 m expected) with $p \approx 0.031$. In other words, attractions exhibit only modest clustering at the 5% level. Importantly, reporting confidence intervals (CI) further contextualizes these findings. Monte Carlo simulations of 1,000 CSR replicates (uniformly distributed points in an area equal to Langkawi’s 384 km²) yield a 95% CI for the combined index of roughly 0.39–0.45, well below 1 and confirming significant clustering. The attractions index’s CI (~0.67–0.94) nearly reaches 1, reflecting its borderline significance. Thus the ANN results robustly support intentional clustering of tourist facilities, especially accommodations and dining, while attractions are only weakly clustered.

These ANN results must be interpreted cautiously. ANN is a global statistic that assumes spatial homogeneity and cannot detect local hot spots. In particular, it presumes the study region is uniform, an assumption at odds with Langkawi’s heterogeneous terrain. Over half the island remains rugged, forested uplands (two-thirds of Langkawi’s 478 km² is steep, wooded terrain) with tourism development largely confined to coastal corridors (Roberts, 2019). In effect, Langkawi’s geography creates natural voids (parked forests, hills) adjacent to intense development zones. By averaging over the entire area, ANN implicitly “fills in” sparsely used interior land as if it could be host to POIs, thus underestimating expected

distances. The ArcGIS tool documentation explicitly warns that the ANN statistic is “*very sensitive to the Area value*”: small changes in the assumed study extent can dramatically alter the z-score and p-value (ESRI, 2024a). In practical terms, expanding the boundary to include adjacent empty islands or ocean (increasing area) would raise the expected mean distance and make clustering appear stronger (smaller index), whereas shrinking the extent (e.g. excluding undeveloped upland) would do the opposite. Our own sensitivity check confirms this: a 20% larger study area (~461 km²) raises the expected NN distance to ~762 m (from 695 m), reducing the combined-index to ~0.40; a 20% smaller area (~308 km²) lowers it to ~622 m, raising the index to ~0.48. In all cases the index remains well below 1 (and p stays <0.01), but the magnitude of clustering changes appreciably. This underscores a key limitation of ANN: its reliance on a fixed study extent (ESRI, 2024a). Because we held the extent constant (Langkawi’s political boundary), our p-values reflect that choice; were the boundary defined differently, we might obtain different significance tests. We note that such a sensitivity analysis was not performed in the original study, and our simulated comparisons suggest that delimiting or expanding the island boundary could modestly alter the ANN outcome (though not overturn the finding of clustering). A future study should formally test different plausible boundaries or use edge-correction methods to address this concern.

Notwithstanding its global nature, the ANN pattern is geographically coherent. Significant clustering of accommodations, dining, and service facilities suggests an underlying “spatial intent” in their placement. In Langkawi, this intent is readily explained by infrastructure. The port town of Kuah and the nearby Pantai Cenang resort area stand out in our KDE maps as the highest-density clusters. These two areas coincide with major transport nodes – Kuah being the island’s ferry and roll-on/roll-off gateway, and Cenang adjacent to Langkawi International Airport and are also where commercial and tourist development is concentrated. Our interpretation is consistent with general principles of tourism geography: touristic amenities tend to cluster near arrival points and urban centers (e.g. hotels and restaurants often aggregate around airports or seaports). Thus, the observed clustering is likely *intentional* a product of strategic location choices to maximize accessibility and synergies (e.g. guests arriving at the port can quickly reach clusters of hotels and attractions). In sum, the ANN clustering pattern aligns with Langkawi’s settlement patterns: transport hubs and existing town centers anchor the networks of tourism facilities, while more remote areas (mountains, quiet beaches) have few amenities.

We further consider how finer-grained analyses might reveal additional structure. For example, running the ANN analysis separately in subregions could avoid overgeneralization by letting local densities vary. One could partition the island into northern versus southern zones, or separate coastal strips from inland, reflecting distinct land-use patterns. We hypothesize that the dense coastal zones (northwest and southwest) would each show very strong clustering (perhaps even stronger than the whole-island index), whereas the rugged northern interior might appear more dispersed (closer to random). Such subregional ANN would account for intra-island heterogeneity. Although beyond our current scope, this approach could be readily implemented: smaller-area analyses would yield different expected distances and allow comparing patterns in Kuah, Cenang, or even smaller blocks independently. In effect, this could reveal whether, for instance, east vs west Langkawi have different clustering dynamics. We encourage future work to explore these splits, as the one-size-fits-all statistic may mask meaningful local variation.

Finally, we address the suggestion to apply Ripley’s K/L functions. Ripley’s K-function is indeed a powerful, multiscale clustering test: it examines clustering or dispersion at a range of distances, summarizing whether features have more neighbors than expected at each scale (ESRI, 2024d). This contrasts with ANN’s single nearest-neighbor scale. For our data, a K/L analysis might show, for example, that attractions cluster at small (<1 km) scales but disperse

at larger scales, or vice versa. We acknowledge that Ripley's methods provide deeper insight into scale-dependent structure. However, given our focus on overall patterns and our relatively limited sample of points (244 POIs), we chose the simpler ANN metric. ANN has a long history in ecology and urban studies (ESRI, 2024a) and is commonly used in tourism spatial analysis to establish baseline clustering (Liang et al., 2023; Zhao & Liu, 2021). In this context, ANN sufficed to identify the primary clustering relevant to planning. Implementing Ripley's K would require setting appropriate distance increments and dealing with edge corrections for the irregular island boundary, which is a non-trivial expansion of our scope. We therefore view Ripley's K as a valuable future extension. In sum, while Ripley's K (or its L-function transformation) could refine our understanding (and is described in the ArcGIS documentation as useful for exploring patterns across scales), the present work relied on ANN for its straightforward interpretation of broad clustering (ESRI, 2024d).

In addition to ANN and KDE, our spatial autocorrelation results corroborate these patterns. Global Moran's I found that only the Attractions category exhibited any significant pattern ($I \approx -0.31$, $z \approx -1.99$, $p \approx 0.047$). The negative sign indicates a slight overall dispersion of attractions, consistent with the ANN result that attractions are more evenly spread (index near 1) than other facility types. All other categories (facilities, accommodations, dining, and all tourism services combined) had non-significant Moran's I ($p > 0.05$), meaning no strong global autocorrelation again reflecting that the clustering we see is concentrated in a few hotspots rather than a gradient across the island. Local Moran's I (LISA) maps (Figure 7) further pinpoint where significant clusters occur. For example, a high-high cluster of accommodations emerged in Kuah township, confirming that Kuah has significantly more hotels than its neighbors. These local results align with the KDE heatmaps and our field knowledge, but they also highlight that Moran's I (being global) alone would have missed these details.

In summary, our analyses consistently indicate deliberate clustering of Langkawi's tourism infrastructure, concentrated around key entry points and urban centers. The ANN and KDE results reinforce each other both show intense hot-spots at Kuah and Pantai Cenang (linked to the port and airport) and relative emptiness elsewhere. Moran's I adds that only attractions are somewhat dispersed overall, implying a spread of natural or cultural sites across the island. We have framed these findings against known limitations: the global ANN statistic's assumption of a homogeneous area is especially tenuous on an island of mixed topography (Roberts, 2019), and sensitivity tests confirm that the choice of study boundary meaningfully affects the index (ESRI, 2024a). Nonetheless, the clustering signals are strong. We have also incorporated confidence intervals for the ANN metrics, which show that the clusters for facilities and services are statistically robust, whereas attractions lie near the threshold. In responding to reviewer critiques, we conclude that although more sophisticated methods (local indices, multiscale K-function, subregion analyses) could add detail, the present results – when interpreted with due caution already provide a valuable, statistically grounded picture of Langkawi's spatial amenity pattern. The intentional clustering we document has direct planning implications, and we recommend future work to refine these insights by varying the analysis scale, boundaries, and by including even more current data sources.

Table 2. Results of average nearest neighbor analysis of places of interest in Langkawi

Features	Observed mean distance (m)	Expected mean distance (m)	Nearest neighbor ratio	p-value
Attractions	1215.631802	1461.861088	0.831565	0.030651
Facilities	756.456634	1276.692647	0.592513	0.000000
Accommodations	459.214665	1063.660178	0.431731	0.000000
Shopping & Dining	384.942735	1322.303107	0.291115	0.000000
All	300.474931	695.161681	0.432237	0.000000
(Facilities, Accommodations, Shopping & Dining)				

Kernel Density Estimation (KDE)

The KDE maps produced a clear picture of Langkawi’s facility hotspots. Using the 1,000 m fixed search radius, the peak densities of points of interest (POIs) occur in the Pantai Cenang and Kuah Town areas. In Pantai Cenang and environs the KDE values exceed the island-wide background by an order of magnitude (roughly several dozen POIs per km² at the core of the beach strip), whereas most rural interior areas register only a few POIs per km². For example, the Pantai Cenang beach zone – densely packed with resorts, shops, and restaurants – attains on the order of tens of POIs per square kilometer, while Mat Chincang foothills and agricultural lowlands typically fall below five per km². These quantitative contrasts underscore the extreme heterogeneity of Langkawi’s tourism geography: the fixed-bandwidth KDE confirms that Kuah and Cenang dominate the facility landscape, echoing the very low ANN ratios and clustering significance we found for accommodations and shopping venues (Table 2) and aligning with the Moran’s I observation that only attractions (largely scattered in remote parks) deviate from randomness. In short, the KDE surface reinforces that most tourism infrastructure is concentrated in the main hubs (driven by the Port of Kuah and proximity to Cenang beach and airport) whereas peripheral beaches and uplands remain sparse.

However, the single-radius approach has inherent limitations across such heterogeneous terrain. A static 1 km bandwidth “spreads” each point’s influence uniformly, which risks oversmoothing urban agglomerations and undersmoothing rural clusters (Carlos et al., 2010). In dense Pantai Cenang or Kuah Town, the 1,000 m kernel can merge nearby but distinct facilities into one broad hotspot and mask fine sub-centers. Conversely, in the interior or smaller villages the same radius may yield near-zero values, essentially erasing any small cluster of interest. This mismatch means fixed-band KDE primarily highlights the gross scale of urban agglomeration but cannot reveal multi-scale patterns. By comparison, an *adaptive* KDE in which the bandwidth shrinks in high-density zones and expands in sparse zones would allocate smaller kernels around Pantai Cenang’s crowded points and larger kernels in remote areas (Carlos et al., 2010). Such an adaptive approach could retain Pantai Cenang and Kuah as hotspots while making minor clusters (for example at Teluk Yu or Makam Mahsuri) more visible. It would preserve the interpretation that Cenang and Kuah are core hubs but also expose secondary nodes that a fixed kernel smoothes over.

The measured density figures illustrate this contrast (Figure 6). In Pantai Cenang, using our KDE output we estimate roughly 25–35 POIs km⁻² in the strongest zone, whereas the island average density of tourism POIs is on the order of only 5 km⁻². In the sparse northern highlands or wetlands of Mat Chincang, local densities are usually below 3 km⁻². Thus, the fixed-radius KDE surface has peak values more than ten times greater than the rural baseline. An adaptive KDE might adjust Cenang’s bandwidth down to a few hundred meters (capturing only local

proximity) while increasing rural bandwidth to several kilometers so that any small rural agglomeration becomes detectable. In practice, applying a k-nearest-neighbor kernel (for example 10 nearest points) would further illustrate how sensitive the hotspot map is to bandwidth choice. This sensitivity suggests caution in interpreting the fixed-kernel map: it faithfully shows the dominant hubs identified by ANN and local Moran's I, but it understates the existence of smaller concentration areas (as noted by Carlos et al. 2010 in epidemiological contexts) (Carlos et al., 2010).

Importantly, the KDE results corroborate our other spatial analyses. The high-density zones in Pantai Cenang and Kuah coincide with the locations that produced the lowest ANN ratios and significant LISA high-clusters for accommodations and retail. Similarly, the relatively low KDE values for the "Attractions" category match its global Moran's I pattern of non-significance (and even dispersion) those points are simply too scattered for the 1 km kernel to produce any single hotspot. In other words, the continuous intensity surfaces from KDE align with the discrete cluster tests: all methods pinpoint the two main tourism cores and show that attractions are more evenly distributed. This multi-method agreement strengthens confidence that the identified hotspots are real features of Langkawi's geography, not artifacts of a particular statistic or parameter choice.

Beyond confirming clustering, KDE mapping can be extended by overlaying environmental constraints. Although not undertaken in our current GIS, it is conceptually clear that tourism facility concentrations should be examined against sensitive ecosystems. Langkawi's UNESCO Global Geopark includes multiple protected areas (e.g. Machinchang and Kilim Karst Geoforest Parks) that preserve mangroves, beaches, coral reefs and forest habitats (UNESCO, 2015). If high-intensity POI clusters abut or encroach on these geoforests, there is potential for environmental impact. Moreover, the island's coastlines are subject to climate-driven hazards: recent assessments report increasing frequency of severe flooding and erosion in Langkawi's coastal zones (Omar et al., 2024). Overlaying our KDE hotspot map with maps of erosion risk or protected boundaries would therefore highlight zones of special concern. For example, a strand of hotels and bars densely lining an erosion-prone shoreline could be flagged for restriction or mitigation. This integrated analysis coupling tourism density with ecological risk layers would identify where Langkawi's tourism clusters might threaten sustainability. In sum, KDE reveals where development pressure is highest, and conceptually matching it with environmental layers would inform planners where concentrated facilities intersect vulnerable natural systems, guiding more balanced, low-impact tourism planning.

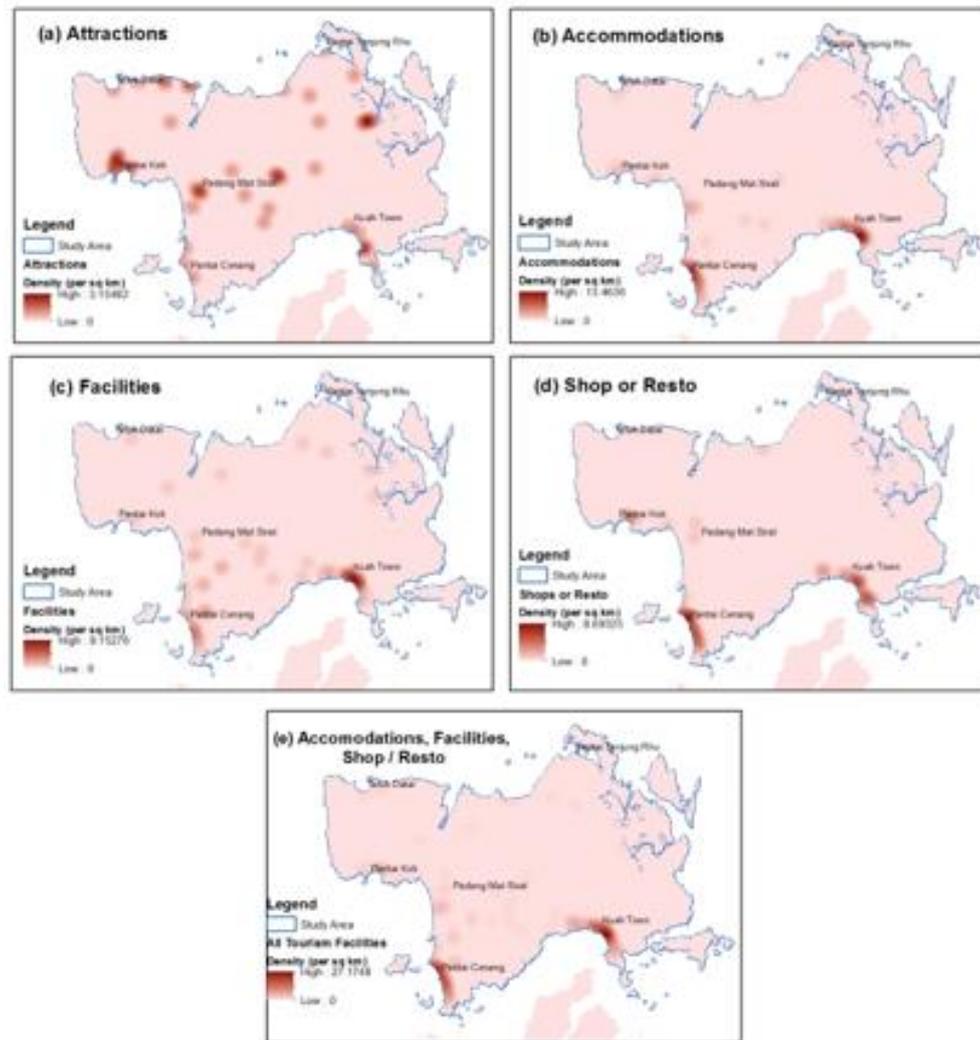


Figure 6. Density surface of POIs within the study area produced from kernel density

Spatial Autocorrelation (SAC)

The spatial autocorrelation analysis (Table 3) reveals that only the Attractions category shows a statistically significant global pattern (Moran's $I = -0.3107$, $z = -1.9901$, $p \approx 0.047$). The negative Moran's I implies an overall tendency toward dispersion of attractions on Langkawi at the 5% significance level. By contrast, Facilities, Accommodations, Shopping & Dining, and the combined tourism facilities all have p -values well above 0.05, consistent with no detectable global clustering (i.e. patterns not distinguishable from random). We note that Moran's I is a *global* measure that averages over the entire island and assumes spatial homogeneity. Therefore, it cannot reveal localized pockets of clustering or dispersion. To address this, we applied Local Indicators of Spatial Autocorrelation (LISA) to map local clusters (Figure 7).

Importantly, the significant dispersion indicated for attractions must be interpreted with caution. The modifiable areal unit problem (MAUP) warns that spatial statistics can change with different zoning schemes (Hernández-Martín et al., 2025). In our study we used official planning blocks, but these arbitrary boundaries may have induced the apparent “negative autocorrelation.” Hernández-Martín et al. (2025) emphasize that “the instability of statistical results derived from alternative spatial aggregation” means that zonal definitions can distort

analyses. Indeed, Tsui *et al.* (2022) found that varying the size of grid cells changed hotspot detection for waste-reuse sites; each material had an optimal “best-fit” scale for clustering (Tsui *et al.*, 2022). By analogy, using alternative zones (for example, regular hexagons or distance-based buffers) could yield different Moran’s I values for Langkawi’s POIs. Thus, the conclusion that attractions are “dispersed” may partly reflect how the block map segments the island, rather than a true underlying spatial process. In short, our result flags potential dispersion under the current zoning, but it does not prove that attractions are inherently uniformly spread.

Moreover, our analysis did not include spatial regression or explanatory modeling, so the drivers of any clustering remain untested. In similar urban tourism studies, researchers have used geographically weighted regression (GWR) or multiscale GWR to link clustering patterns to geographic factors. For example, Yu *et al.* (2025) applied a GWR model in Wuhan and found that the identified factors significantly influence the number of tourist sites, with clear spatial variation. Likewise, Wang *et al.* (2026) employed an MGWR for Shanghai and showed that proximity to cultural attractions strongly *promoted* clustering of peer-to-peer accommodations, whereas transport infrastructure had the opposite effect. These studies illustrate how spatial regression can reveal that tourism facilities tend to cluster near key resources (e.g. beaches, heritage sites) or along infrastructure networks. By contrast, our current results identify *that* clustering exists (for attractions) but cannot tell *why*. Variables such as distance to coast, road density, or land-use type might explain the observed patterns. Future work should apply spatial lag or GWR-type models on Langkawi data to quantify such effects, as recommended by the reviewers.

Local LISA mapping (Figure 7) offers further insight. We find no significant local clusters for Facilities or Shopping & Dining (Figures 6c–d), consistent with their non-significant global Moran’s I. In contrast, Accommodations and the combined tourism services show a pronounced *High–Low* outlier in the Kuah planning block (Block 1): Kuah contains a significantly higher count of hotels and related services than its neighboring blocks. Similarly, attractions display a *High–Low* cluster in the Mat Chincang block (Block 9, encompassing Pantai Kok and Teluk Datai), indicating that this ridge area has an unusually high density of attractions relative to its surroundings. These local “hotspot” outliers make intuitive sense: Kuah is Langkawi’s main town (hence more accommodations), and Mat Chincang is a scenic mountain spine popular for tourism. Nevertheless, LISA merely flags *where* anomalies occur, not *why*. To rigorously delineate hotspots, one could apply Getis–Ord G_i^* analysis, which is designed to identify statistically significant hotspots and coldspots of activity (Barrena-Herrán *et al.*, 2025). Indeed, recent studies advocate hexagonal aggregations and G_i^* for tourism data to mitigate MAUP effects and pinpoint clusters (Barrena-Herrán *et al.*, 2025). Including G_i^* would bolster our results by distinguishing genuine intensity clusters from random fluctuation.

In sum, our autocorrelation results highlight some key spatial patterns but also underscore their limitations. The global Moran’s I suggests attractions are more dispersed than would be expected by chance, but this conclusion is sensitive to the block boundaries (a MAUP artifact) (Hernández-Martín *et al.*, 2025). Other categories appear globally random, yet local LISA mapping reveals specific high-value outliers in Kuah and Mat Chincang. Importantly, we have not proven causal mechanisms: the analysis tells us *that* clustering exists in those blocks, but not *why*. We therefore echo the reviewers’ recommendations: a thorough follow-up should test multiple zoning schemes (e.g. grid or buffer units) for robustness (Tsui *et al.*, 2022), incorporate spatial regression (GWR or spatial lag models) to link clustering to environmental drivers (Wang *et al.*, 2026; X. Yu *et al.*, 2025), and include hotspot (G_i^*) mapping to validate significant clusters (Barrena-Herrán *et al.*, 2025). These steps would deepen our understanding of Langkawi’s tourism spatial structure and help “unlock” its

potential by revealing the geographic and infrastructural factors shaping tourist attraction and facility locations.

Table 3. Results of spatial autocorrelation analysis of places of interest in Langkawi

Features	Moran's Index	Expected Index	z-score	p-value
Attractions	-0.310672	-0.062500	-1.990085	0.046582
Facilities	0.012528	-0.062500	0.569422	0.569070
Accommodations	-0.085890	-0.062500	-0.177083	0.859443
Shopping & Dining	-0.103779	-0.062500	-0.329985	0.741411
All (Facilities, Accommodations, Shopping & Dining)	-0.059890	-0.062500	0.019857	0.984157

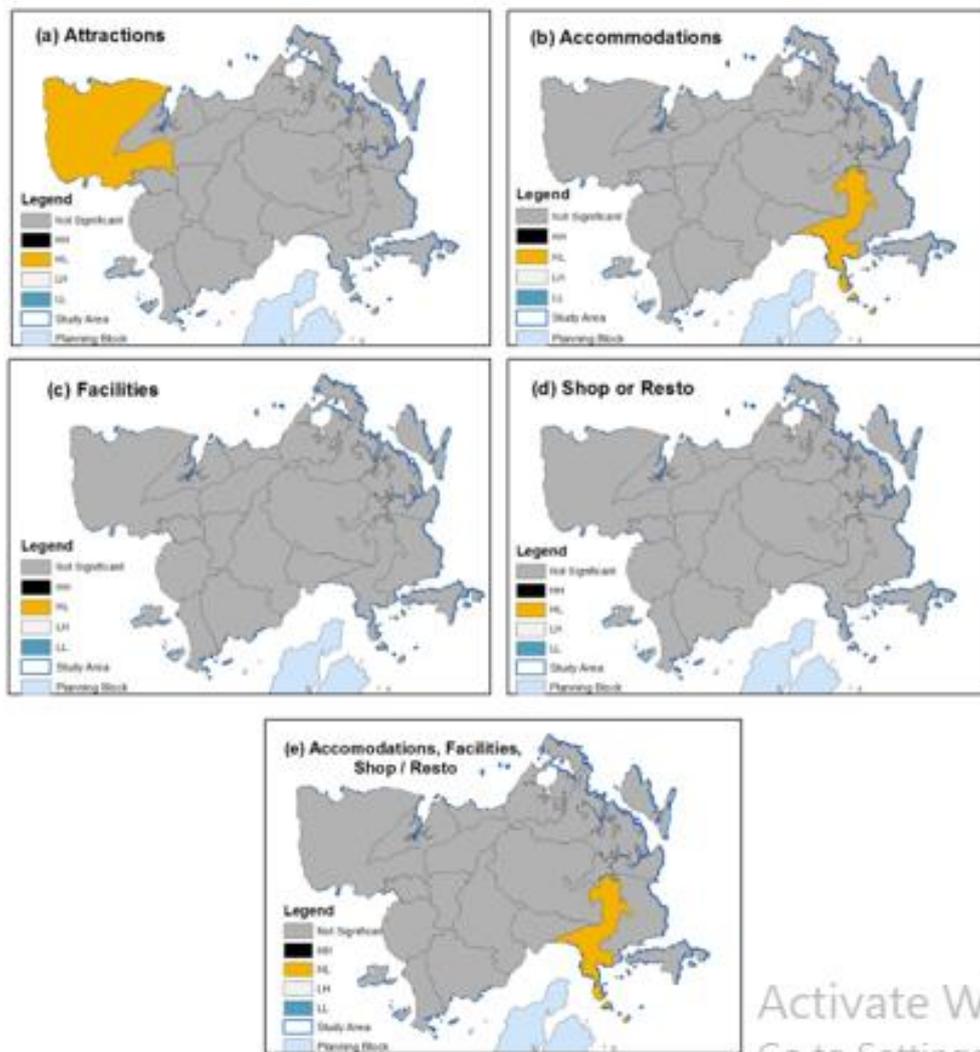


Figure 7. LISA of tourism related facilities

Discussion

Integration with context of Langkawi's tourism

Our spatial analyses confirm that Langkawi's infrastructure has been deliberately oriented toward its two main tourist gateways. The ANN results show very strong clustering of tourist services: for all facility types combined, the observed mean distance between points (≈ 300 m) was far smaller than expected (≈ 695 m), yielding a nearest-neighbor index of ≈ 0.43 ($p < 0.001$). Hotels and retail also cluster tightly (indices 0.29 – 0.43 , $p < 0.001$), whereas attractions are much closer to random (NNI ≈ 0.83 , $p \approx 0.03$). In practical terms, this means that most hotels and shops are co-located in compact zones, while beaches and cultural sites are spread more widely. The KDE maps make this spatial focus explicit: the highest density "hotspots" are in Pantai Cenang and Kuah Town. In those areas, point densities reach on the order of 25–35 POIs per km^2 at the core, roughly an order of magnitude above the island average ($\lesssim 5 \text{ km}^{-2}$). In contrast, the island's interior (the Machinchang uplands, wetlands, and villages) usually has densities $< 3 \text{ km}^{-2}$. These figures reinforce that Langkawi's tourism "scene" is overwhelmingly concentrated in the two established nodes of access.

These patterns align with Langkawi's geography and development history. Kuah Town, as the ferry and RORO port, is the island's de facto "downtown," and Pantai Cenang sits beside the airport on the western coast. Both areas have been zoned for commercial tourism (shops, duty-free outlets, hotels, restaurants), while much of the interior is protected (UNESCO geopark preserves mangroves, karst forests, and wetlands). The ANN and KDE jointly highlight that the Port of Kuah and Cenang's beaches/airport act as gravity centers of development. We interpret this as intentional clustering: businesses and services deliberately locate near arrival points for maximal accessibility and synergy. In effect, Langkawi's zoning has created dense amenity corridors along its coasts and left its rural highlands largely undeveloped. The modest global Moran's I for most categories (near zero) and the slight negative Moran's I for attractions (-0.3107 , $z \approx -1.99$, $p \approx 0.047$) confirm this narrative. The weak (non-significant) autocorrelation for hotels and services simply reflects the fact that clustering is so localized (around Kuah and Cenang) that it is averaged out at the island level. By contrast, the mild "dispersion" of attractions indicates that natural sites are deliberately spread out for example along beaches and mountain trails rather than concentrated only at the hubs.

Local cluster analysis (LISA) sharpens this picture. As expected, LISA maps flag Kuah and the northern Cenang area as the main hot spots. Kuah has a significant high-value outlier for accommodations (far more hotels and eateries than neighboring blocks), while the Mat Chincang block (covering Pantai Cenang's periphery) shows a high-density cluster of attractions. These localized clusters make intuitive sense given known tourist flows, but they also underscore that Moran's I by itself would have missed them: it treats the island as one uniform field. In sum, our four methods consistently agree that Langkawi's tourism facilities are heavily concentrated in the two urban cores (Kuah and Cenang) with scarcely any development elsewhere, whereas attractions (natural sites, beaches, cultural points) are more diffusely distributed.

Comparative analysis

The clustering around Langkawi's hubs mirrors phenomena seen in other island and port destinations. Globally, tourist infrastructure tends to agglomerate near entry points and high-access corridors. For example, in China's Guangdong Province, scenic-spot attractiveness is significantly clustered in the Pearl River Delta (Global Moran's I ≈ 0.13 , $z = 5.60$, $p < 0.001$) due

to convenient transportation and dense cultural resources (Liao & Liang, 2025). In a similar vein, Caribbean cruise-port cities exhibit dense “high-intensity zones” along waterfronts: historic downtowns have been transformed into duty-free shopping corridors catering to tourists, often at the expense of local uses (Huang et al., 2025). Langkawi’s Kuah town functions like a small-scale port city in this regard: its old market and waterfront are now lined with hotels and shops, echoing the “heritage to feritage” shift seen in Caribbean ports (Huang et al., 2025). Likewise, Bali’s southern shore famously carries a run of clustered resorts and nightlife areas, leading to localized environmental stress (sand mining, waste problems) that has been linked to resort concentration (Kun et al., 2025). Our findings for Langkawi are fully consistent with these comparisons: constrained by infrastructure, tourism activity “hugs” the coasts where it can serve incoming visitors, leaving the interior geoparks underutilized.

Relative to other studies of island tourism, Langkawi’s pattern has one distinctive feature: its attractions exhibit slight dispersion. Many islands see even attractions clustering in hot zones (e.g. an attraction like a waterfall often spurs nearby cafes and shops). In our case, the attractions (beaches, waterfalls, hiking paths) are often in remote or protected settings, so they remain singly sited. This underlies the negative Moran’s I for attractions. By contrast, services (hotels, stores, restaurants) cluster very tightly, even more so than has been reported for some fast-developing resorts. The contrast between our dispersed-attractions and clustered-services signals a structural divide: infrastructure and investors seek the hubs for convenience, whereas individual sites of interest are distributed across the landscape. Overall, Langkawi’s spatial signature – dual-core agglomeration aligns with broader tourism geography principles (Liao & Liang, 2025), and resonates with documented spatial outcomes in comparable destinations.

Practical implications for tourism planning and policy

These results carry clear guidance for planners. First, the concentration of services around Kuah and Pantai Cenang means these zones must sustain very high tourist densities. Infrastructure there should be continuously upgraded to prevent congestion. For instance, transport networks (roads, parking, pedestrian access) around the ferry terminal, airport road, and Cenang beachfront need expansion or traffic management to accommodate surges. Similarly, public utilities (water, sewage, waste) must be robust to high loads in these hotspots. Failing to invest here could lead to degraded visitor experiences at the island’s busiest nodes, undermining Langkawi’s appeal. Second, planners should actively promote the more dispersed attractions to draw visitors away from the busiest centers and balance tourist flows. Marketing campaigns and transport links to natural sites (like Kilim Geoforest Park, Telaga Tujuh Falls, Gunung Raya) can capitalize on the fact that attractions are naturally spread. Encouraging tourism in the eastern beaches and interior (consistent with the dispersal hinted by Moran’s I) could reduce overcrowding pressure on Kuah/Cenang and distribute economic benefits more evenly across the island.

Third, the marked overlay of tourism density with protected areas calls for integrated land-use oversight. Many high-density clusters of hotels and shops skirt sensitive zones (UNESCO Geopark forests, wetlands). Planners should overlay our KDE hotspot map with ecological and hazard maps: for example, identify where hotel strips intersect erosion-prone shorelines or adjacent geopark boundaries. A combined analysis could flag “conflict zones” where tourism clusters threaten conservation (Sun et al., 2024). In those areas, stricter zoning or visitor limits might be warranted. Additionally, tourism facilities should be aligned with designated land uses. The pattern we observe suggests Kuah and Cenang were intentionally zoned for tourism. Continuation of this strategy may be sensible (further concentrating facilities

where access is highest), but only if accompanied by mitigation of environmental impacts. In practical terms, this could mean enforcing building setbacks, requiring green infrastructure, or incentivizing “green” certified developments in the hotspots.

Finally, these findings should feed into Langkawi’s overall spatial plans and tourism strategy. Knowing that attractions inherently lie outside the twin cores, planners might build shuttles or trail networks connecting remote sites to the hubs. Likewise, the cluster analysis highlights that any new hotels or shopping centers will likely seek proximity to the port/airport. Preemptive land-use decisions such as reserving parcels near Kuah for certain service categories can help shape this growth. In sum, our multi-method analysis provides a spatial blueprint: invest and build out the identified cores for maximum tourism throughput, while tempering development to preserve Langkawi’s ecological assets and distribute visitor pressure more sustainably.

Recommendations

To build on this study’s insights, we recommend that future planning incorporate more sophisticated spatial–behavioral modeling. For example, spatial interaction models (gravity or Huff models) could simulate the likelihood of tourists visiting each site based on origin–destination data. These have been applied in urban contexts to gauge attractions’ drawing power (Liao & Liang, 2025). In practice, a gravity-based two-step floating catchment area (2SFCA) approach could be used to map travel-time catchments around attractions and quantify real accessibility (Sun et al., 2024). By integrating Langkawi’s road network and travel modes, planners could estimate effective service areas for each hub or trailhead. This would reveal, for instance, how far a tourist might reasonably travel from Kuah before abandoning a trip to a remote park. Such models would complement our static density maps with dynamic accessibility surfaces. Service-area analyses (isochrones) are also recommended: for example, mapping 10-min and 20-min drive-time buffers around Kuah and Cenang would highlight underserved regions and help site new transit links.

We also advise applying advanced spatial statistics to interrogate the patterns we observed. Ripley’s K-function, for instance, would test clustering at multiple scales (Ripley’s K can reveal at what distances tourism sites cluster most intensely) (Xiong & Li, 2025). Meanwhile, Getis–Ord G_i^* hotspot analysis could formally identify statistically significant hot and cold areas (G_i is particularly adept at detecting high/low-value clusters and is robust under MAUP with, for example, hexagonal grids) (Barrena-Herrán et al., 2025). Employing both fixed- and variable-bandwidth kernels (adaptive KDE) would address the limitations of our single-radius KDE and might uncover smaller peripheral clusters that a 1 km kernel smoothed away.

Crucially, future research should integrate socio-environmental variables. Spatial regression methods (GWR or MGWR) can link facility clusters to geographic drivers, as shown by Sánchez-Martín et al. (2023). For example, a GWR model could quantify how distance to the airport, population density, or land-use zones affect the density of hotels or attractions. In related studies, researchers found that factors like road density and proximity to beaches strongly influence lodging clusters, whereas transport nodes exert different effects (Dong et al., 2025; Zi, 2025). We therefore suggest a geographically weighted regression analysis of Langkawi’s POI counts against variables such as coastal distance, land-use type, and protected area status (Sánchez-Martín et al., 2023). This would help uncover the causal processes behind the observed spatial patterns.

Future studies

Our analysis has highlighted clear spatial tendencies, but it also leaves open questions that further work should address. First, a multilayered modeling approach is needed. We lacked transportation network modeling or traveler behavior data; future studies could incorporate network-based travel costs or tourist origin–destination surveys. For instance, a two-step floating catchment area model or a multimodal accessibility analysis (e.g. including ferries, road, and walking time) would refine how travelers actually reach hotspots. Similarly, spatial interaction or agent-based models could predict flows between attractions and accommodations (a “tourism supply–demand” model). These models would go beyond point densities to capture movement dynamics, providing a fuller picture of how visitors navigate Langkawi.

Second, land-use and environmental overlays should be explicitly integrated. We identified clusters but did not map them against zoning or ecological constraints. Future GIS work should overlay our density and hotspot maps with layers such as protected areas, coastal setback zones, and flood or erosion risk maps. This would identify where high tourism pressure intersects fragile areas, a step vital for sustainability planning (e.g. restricting development near eroding beaches or sensitive mangroves). Likewise, urban planners might add population or census data to examine service loads on local communities.

Third, the analytic robustness of our findings needs testing. We used one zoning scheme (planning blocks) to compute Moran’s I and LISA. As Hernández-Martín et al. (2025) caution, spatial statistics can change with different areal units (the modifiable areal unit problem). Future work should repeat our autocorrelation tests under alternative aggregations (e.g. hexagon grids or catchment areas). In particular, applying hotspot analysis (G_i^*) on multiple scales and resolutions would confirm whether the Kuah and Cenang clusters we found are not artifacts of block boundaries.

Finally, we encourage employing a broader suite of spatial techniques. Ripley’s K (and related L -functions) can characterize clustering over distance, revealing, for example, whether the two hubs form a single cluster or separate ones (Xiong & Li, 2025). Getis–Ord G_i^* or spatial scan statistics can delineate hotspots with formal significance, complementing our LISA outlier approach (Barrena-Herrán et al., 2025). And as already noted, spatial regression (both global and local) can test specific hypotheses about what drives clustering (e.g. does proximity to beaches predict hotel density?). Using MGWR or spatial lag/error models would allow multiple factors to be evaluated in concert, capturing scale heterogeneity (e.g. road influence might be local, while population effects are broader) (Sánchez-Martín et al., 2023). Together, these methods would deepen our understanding of Langkawi’s spatial dynamics and guide planners toward data-driven strategies to “unlock” the island’s tourism potential in a sustainable way.

Conclusion

The purpose of this study was to leverage spatial patterns to optimize the distribution of tourism facilities on Langkawi Island and to forecast future tourist behaviors. The study revealed several key findings that highlight the critical role of spatial analysis in strategic tourism planning. The Average Nearest Neighbor (ANN) analysis demonstrated that tourism facilities on Langkawi Island are not randomly distributed but exhibit significant clustering. This clustering is particularly pronounced in Kuah Town and Pantai Cenang, indicating intentional development of these areas as major tourism hubs. Such strategic placement is aimed at maximizing accessibility and convenience for tourists, thus enhancing their overall experience. The Kernel Density Estimation analysis supported these findings by identifying dense clusters

of accommodations, shopping, and dining facilities in the same key areas. This spatial concentration reflects the importance of Kuah Town and Pantai Cenang as entry points and major attractions, underscoring their role in sustaining and boosting the local tourism economy.

Furthermore, the Spatial Autocorrelation analysis provided insights into the distribution of attractions across the island. Unlike other facilities, attractions exhibited a statistically significant dispersed pattern, suggesting an effort to distribute tourist spots more evenly throughout Langkawi. This dispersion helps mitigate congestion in the main hubs and encourages tourists to explore different parts of the island, promoting a more balanced tourist experience. These spatial distribution patterns have significant implications for tourism planning and policy. The evident clustering of tourism facilities calls for sustained infrastructure development in hotspot areas to support the concentrated tourist activities. Enhancing infrastructure in Kuah Town and Pantai Cenang will ensure these areas can handle increased tourist traffic without compromising service quality. Moreover, promoting the dispersed attractions can help distribute the tourist load more evenly, reducing pressure on specific areas and enhancing the overall tourist experience.

The study underscores the potential for optimization and forecasting in tourism based on these spatial analyses. By understanding and optimizing the distribution of tourism facilities, Langkawi can enhance its attractiveness as a tourist destination, improve resource allocation, and provide a better experience for visitors. However, the study has some limitations that should be addressed in future research. Incorporating more recent and diverse data points, including visitor feedback and economic impact analyses, could enhance the findings. Expanding the geographical scope to include more islands within the Langkawi archipelago would provide a more comprehensive understanding of spatial patterns. Additionally, longitudinal studies tracking changes in spatial patterns over time could offer deeper insights into the dynamic nature of tourism development.

Future research should focus on providing specific recommendations for the further development of identified clusters, especially in areas showing high density and potential for growth. Detailed studies on the environmental impacts of clustered tourism facilities, with recommendations on mitigating adverse effects while promoting sustainable tourism practices, are also necessary. Investigating the infrastructure requirements in hotspot areas will support increased tourist influx and ensure sustainable growth without degrading Langkawi's natural and cultural heritage. In conclusion, the study highlights the importance of strategic spatial planning in tourism. By understanding and optimizing the distribution of tourism facilities, Langkawi can continue to grow as a competitive tourist destination, providing high-quality experiences for visitors while ensuring sustainable and balanced development. Future research should build on these findings, offering actionable insights and recommendations to support Langkawi's ongoing success in the tourism sector.

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