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Assessing wholesale market relocation decisions considering mobile vendor routing: A generalisable GIS-based spatial analytics model

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ABSTRACT

Urban wholesale market relocations often impose additional travel burdens on mobile vendors operating at low margins in the informal sector and create spatial inequities when guided by non-spatial criteria. This study, aiming at assessing the impact of market relocations on mobile vendors, presents a novel GIS-based framework that combines the Clarke and Wright Savings Algorithm for route optimisation with Kernel Density Estimation, a machine learning technique, to identify high intensity vendor corridors. Heatmap values of vendor activity and average distance metrics were normalised and candidate market sites were ranked using a new Equity-Efficiency Index measure which accounts for landuse policy preferences. Candidate sites were mapped further considering gain/loss in accessibility, for classifying the service area into improvement and degradation zones weighted by population. A case study based on the relocation of Segiri market in Samarinda, Indonesia has been developed to illustrate the method. Results show that there is a new location in Samarinda that can deliver large efficiency gains in key corridors but resulting in widespread service area losses. Other potential locations achieve moderate, evenly distributed accessibility improvements. The framework delivers spatially explicit evidence of benefit and burden distribution and supports relocation decisions that balance logistical efficiency, equitable access and urban resilience.

1. Introduction

Urbanisation and the rapid expansion of cities have dramatically increased demands on infrastructure systems, prompting the need for strategic urban planning that balances economic efficiency with fair resource distribution. While warehouse location has been widely studied, wholesale market siting and relocation remain relatively underexplored in integrated transport and urban development research (Balbontin and Hensher, 2021; Nugroho et al., 2024). Wholesale markets are critical nodes in urban logistics networks, linking producers, traders and mobile vendors to ensure a consistent flow of goods to customers (Agwu and Ibeabuchi, 2011; Esmizadeh et al., 2021; Schwarz and B, 2022; Smith, 2002). Two main buyer groups operate within these markets - *traders* with fixed retail premises who purchase in bulk (Terano et al., 2014) and *mobile vendors*; who procure smaller quantities daily to serve dispersed neighbourhoods (Giroux et al., 2021).

Mobile vendors, operating without fixed retail premises, depend on access to these markets for their daily stocks of fresh produce and essential commodities, making market relocation decisions critical to their operational effectiveness, service reliability and profitability. In practice, mobile vendors typically undertake daily travel cycles linking their residential locations, the wholesale market, and multiple customer areas across the city before returning home. Wholesale Market relocation is thus of particular theoretical and practical interest because changes in market location can have asymmetric impacts on these groups. While traders may be less sensitive to distance due to bulk purchasing and storage capabilities (Hau, 2002), mobile vendors are highly vulnerable to increased travel distances which directly affect their meagre profit margins, competitiveness and service reach.

Despite their importance, decisions on the siting or relocation of wholesale markets are often driven by economic objectives, political agendas or land use pressures rather than rigorous, data driven spatial analysis. As a result, market relocations can yield suboptimal outcomes for mobile vendors and the wider community, manifesting in increased

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travel distances, higher operating costs and uneven service provision across urban areas. Empirical studies show that poorly planned relocations exacerbate urban congestion, raise transportation costs and negatively affect vendor logistics, thereby undermining both vendor performance and overall urban accessibility (Balbontin and Hensher, 2021; Schwarz and B, 2022).

Mobile vendors usually operate with limited financial and logistical resources, planning daily routes to meet fluctuating customer demand across different urban zones. While this operational flexibility is advantageous in responding to consumer needs, it also makes vendors vulnerable to changes in market location. Centralised markets may offer short travel distances for some vendors but often generate bottlenecks and delivery delays during peak trading hours. Conversely, markets moved to peripheral areas may alleviate central congestion but inadvertently impose significant travel burdens on vendors based farther from the new site, reducing their service capacity and profit margins (Van der Ploeg et al., 2012). Given the increasing role of mobile vendors in urban food supply chains, especially in rapidly growing cities, there is a pressing need to ensure that market relocation decisions are not only efficient but also spatially just, supporting the operational sustainability of mobile vendors who are often among the most resource constrained actors in urban economies.

Beyond their direct impact on mobile vendors, market relocations can have ripple effects on wider community stakeholders. Access to fresh produce and everyday necessities often depends on the spatial distribution of wholesale markets (Lucan et al., 2015; Su et al., 2017). Relocations that overlook spatial equity risk creating food deserted areas with limited access to affordable, healthy food disproportionately affecting marginalised communities. Such disparities undermine social cohesion and exacerbate health issues related to nutrition (Black et al., 2011). Therefore, robust frameworks are needed to ensure that market relocation decisions promote equitable service distribution rather than entrenching existing inequalities.

This paper aims to develop a generalisable GIS-based spatial methodology that can capture the distributional consequences for urban residents and mobile vendors alike. Specifically, the objectives are: (i) to integrate route optimisation outputs with advanced spatial analytics in QGIS to evaluate vendor operational efficiency; and (ii) to assess the spatial/demographic impacts of alternative market locations through population weighted accessibility gain/loss analysis to support evidence-based prioritisation of market relocation sites.

The methodology in this study is designed to be generalisable and scalable across various urban contexts. By employing spatial analysis procedures and transparent data workflows, this framework can be replicated for market relocation assessments elsewhere. This approach ensures that city planners, local authorities and community stakeholders possess the capacity to undertake evidence-based infrastructure planning, thereby promoting sustainable and equitable urban development. Additionally, the study contributes empirical insights through a specific case-based analysis involving the relocation of Segiri market in Samarinda, Indonesia. Several candidate locations, reflecting plausible urban land use options were evaluated to demonstrate how market location choices affect vendor logistics and urban accessibility in different settings.

This research makes four main contributions. First, it offers an innovative integration of empirical vendor travel routing patterns with advanced spatial analytics, surpassing traditional site selection methods that often overlook the operational realities of mobile vendors. Second, it introduces a spatial framework enabling local authorities to systematically assess relocations and ensure equitable access to essential services. Third, through alternative location modelling, the study provides practical insights into how variations in urban context may influence relocation outcomes, supporting adaptive policy design. Finally, its findings empower policymakers with actionable information to generalise market locations that minimise vendor travel distances.

The structure of this paper is as follows. Section 2 reviews the literature on wholesale market relocations, mobile vendor logistics, and spatial equity. Section 3 describes the methodology, the optimised travel distance, the QGIS-based analytical workflow and analysis procedures. Section 4 presents a case study evaluation in Samarinda, illustrating the application of the framework to potential locations. Section 5 discusses the implications of the findings for urban planning, policy design and community engagement. Finally, Section 6 concludes with key recommendations, research limitations and suggestions for future spatially informed infrastructure planning studies.

2. Literature review

This section reviews and synthesises existing research to position the present study within the broader literature on wholesale market relocation, mobile vendor logistics, and spatial equity in urban systems. It begins by examining prior studies on wholesale market (re)location, followed by a discussion of the distinct operational vulnerabilities of mobile vendors. The review then considers spatial equity and accessibility concerns associated with market relocation before examining advances in routing optimisation and spatial density analysis. The section concludes by explicitly summarising the key research gaps that motivate the integrated spatial logistical framework proposed in this study.

2.1. Wholesale market relocation in urban logistics

Wholesale markets play a critical role in facilitating large scale transactions among producers, retailers and mobile vendors, thereby stabilising supply chains and regulating commodity prices (Schwarz and B, 2022; Smith, 2002). These markets promote a competitive trading environment by aggregating supply and demand, and they also contribute to fresh food access and local food security. However, many of them are historically located in city centre areas, and are known to cause congestion/ pollution, forcing the authorities to consider relocating the markets.

Research on siting and relocating distribution facilities has traditionally concentrated on warehouses and depots (Morganti and Gonzalez-Feliu, 2015); while wholesale market locations have received comparatively little attention. Integrated transport and urban development frameworks generally prioritise residential and warehouse siting issues; relegating wholesale markets to a secondary concern (Balbontin and Hensher, 2021). Recently; (Nugroho et al., 2024) developed an optimisation model to analyse the impact of market relocations using network modelling methods and assessed the change in traffic congestion and pollution levels. Other strands of the literature have examined wholesale markets and related distribution systems from descriptive or economic perspective; focusing on market performance (Agwu and Ibeabuchi, 2011; Esmizadeh et al., 2021). Nevertheless, most of the contributions remain descriptive or econometric in nature, lacking spatially explicit modelling of relocations.

2.2. Distinct vulnerabilities of mobile vendors

Wholesale market operations and urban distribution systems have largely examined market actors in aggregate terms, focusing on overall trading relationships, routing efficiency, and system level logistics (Håkansson and Snehota, 2006; Holz-Rau et al., 2014). Within this literature, traders and mobile vendors are often treated as functionally similar participants, despite the clear differences in their operating models. Traders typically operate from fixed retail locations and are relatively less sensitive to changes in market siting. In contrast, mobile vendors, a vital component of the informal urban economy (Giroux et al., 2021); rely on daily travel to wholesale markets and dispersed customer areas; making their profitability and service reach highly dependent on travel distance. This operational model creates distinct vulnerabilities. Mobile vendors typically rely on adaptive; often suboptimal routing which can lead to repeated journeys; overlapped service areas and elevated transport costs (Gano-An, 2019; Holz-Rau et al., 2014). While heuristic algorithms for vehicle routing problems have been reviewed, they generally assume depot based operations rather than reflecting mobile vendor needs (Segerstedt, 2014). This highlights the need to adapt routing optimisation methods to the context of mobile vendors.

2.3. Spatial equity considerations in market relocation

The concept of spatial equity in food access has attracted growing attention, with scholars introducing the notion of food desert areas in which residents lack access to affordable, nutritious food (Cummins and Macintyre, 2002; Walker et al., 2010). Yet such analyses remain rare in low- and middle-income urban settings. The relocation of wholesale markets can either alleviate or worsen these inequities: moving a market closer to underserved areas can improve access, whereas relocating to peripheral industrial zones risks deepening food deserts (Sadler, 2016). Mobile vendor distribution networks bridge retail gaps; making vendor travel burdens a proxy for consumer access (Cadilhon et al., 2006; Dharejo et al., 2022). Crucially, limited mobility among mobile vendors is not only an issue of efficiency, but also spatial equity. Increased travel requirements can exacerbate inequality in urban food and service accessibility (Geurs and van Wee, 2004). Despite this, most prior models have prioritised logistical optimisation, often overlooking the distributive consequences of wholesale market relocations, specifically which groups are advantaged or disadvantaged by changes in site location.

2.4. Advances in spatial analysis techniques

Spatial analysis has become a critical foundation for understanding and optimising urban distribution systems. The adoption of Geographic Information Systems is now indispensable for location allocation and accessibility modelling. Functional land use representations can inform siting decisions (Witlox et al., 2009); while network analyses have been employed to optimise urban freight delivery routes (Aljohani and Thompson, 2018). QGIS provides open source tools for gain/loss analysis; network based travel distance calculations and multi criteria decision making (Mancuso et al., 2023). Spatial trade off evaluations combining distance cost surfaces with demographic overlays enable planners to visualise the consequences of alternative site options.

In parallel, recent advances in spatial data science have seen the integration of *machine learning methods* such as Kernel Density Estimation (KDE) into urban analytics. KDE can be used innovatively to generate continuous surface density maps (Hu et al., 2018; Li et al., 2011), revealing spatial hotspots of vendor activity or customer demand that may not be captured otherwise by traditional distance-based analyses. The application of KDE in this context enables more granular identification of service concentration and undeserved regions, thereby supporting evidence-based decision making in site selection. To date, the use of machine learning based spatial techniques such as KDE remains limited in wholesale market relocation studies, despite their step-changing potential to complement a conventional GIS-based approach.

2.5. Routing optimisation of mobile vendors

Routing optimisation has long been applied to improve efficiency in distribution systems. The Clarke and Wright Savings Algorithm (CWSA) is a well established heuristic for the Vehicle Routing Problem, valued for its effectiveness in minimising total travel distance (Clarke and Wright, 1964). However; its standard form assumes vehicles depart from and return to a central depot (Segerstedt, 2018); which does not align with the operational patterns of mobile vendors who begin and end routes at their residences (Arifin et al., 2026). This limitation underscores the need to adapt classical routing algorithms like CWSA to reflect the decentralised nature of mobile vendor logistics. By modifying CWSA to treat vendor residences as route anchors and the wholesale market as an intermediate stop, this study bridges the gap between traditional logistics optimisation and the realities of informal vendor operations.

2.6. Relocation strategies and policy priorities

Evaluating wholesale market relocation requires moving beyond technical spatial analysis to consider broader strategic trade offs and policy priorities. Existing literature indicates that relocation decisions are often driven by limited economic, political or land use considerations (Balbontin and Hensher, 2021; Schwarz and B, 2022), frequently lacking comprehensive spatial analysis that accounts for operational impacts on key stakeholders particularly mobile vendors. Consequently, relocations can yield suboptimal outcomes, such as increased travel distances, higher operating costs, and uneven service distribution across urban areas.

Prevailing analytical approaches in the literature possess significant limitations that contribute to this gap. Many studies rely on static methods like buffer analyses or single criterion optimisation (Mykrä et al., 2023), which fail to concurrently address logistical efficiency and spatial equity. Furthermore, existing GIS-based relocation frameworks seldom integrate the actual routing patterns of mobile vendors into evaluation models. This is a critical oversight, as the operational sustainability of these vendors is highly sensitive to daily travel distance, making their needs a paramount concern for equitable relocation planning and inclusive urban policy.

2.7. Summary of review and the way ahead

To systematically synthesise the reviewed literature and clarify the contributions of this study, Table 1 provides a structured comparison on wholesale market relocation approaches. This comparison explicitly delineates what has been accomplished in prior research, what remains unexplored and how the current study advances the field through an integrated spatial-logistical framework that addresses both operational efficiency and spatial equity.

This review highlights several key research gaps: (i) limited integration of vendor route optimisation with GIS-based accessibility analysis for wholesale market relocations; (ii) scarcity of frameworks addressing both logistical efficiency and spatial equity; (iii) underdeveloped, replicable methodologies for integrated spatial–logistical analysis, constraining adoption by resource-limited authorities; (iv) limited application of machine learning techniques such as KDE in this context; and (v) rare evaluation of policy preference for landuse development to offer robust guidance.

To address these gaps, this study integrates CWSA with a QGIS-based spatial framework, incorporating KDE as an additional analytical layer. This enables an integrated assessment of efficiency and equity across varied relocation scenarios, with transparent and replicable outputs for adoption by local governments and stakeholders.

3. Methodology

This research employs an integrated methodological framework, combining mathematical route optimisation with advanced spatial analysis in QGIS, to evaluate the impacts of wholesale market relocation on mobile vendor logistics and urban accessibility. The workflow consists of four principal stages:

Stage 1: Data preparation and distance matrix construction;
Stage 2: Vendor route optimisation using the CWSA;
Stage 3: Geospatial processing and computing spatial statistics in QGIS; and
Stage 4: Accessibility and gain/loss analysis.

Table 1
Synthesis of literature on wholesale market relocation approaches.

Approach Type	System Characteristics	Analysis Method	Limitations	How This Study Addresses It	Key References
Traditional Warehouse Location	Single facility optimisation, fixed depot	Economic/cost-benefit analysis, descriptive	Focuses on the warehouse, wholesale markets are overlooked, ignores informal sector	Specifically targets wholesale market relocation with explicit focus on the informal mobile vendor	(Balbontin and Hensher, 2021; Morganti and Gonzalez-Feliu, 2015)
Efficiency-focused optimisation	Logistical efficiency prioritised	Single criterion optimisation (cost/distance)	Overlooks spatial equity and distributive impacts on vulnerable groups, typically operator centric	Complements efficiency metrics with spatial equity through gain/loss mapping and equity to assess distributive impacts	(Håkansson and Snehota, 2006; Holz-Rau et al., 2014)
Depot-based Vehicle Routing Problem (VRP)	Coordinated routing from a fixed depot	Clarke and Wright Savings Algorithm (CWSA), heuristic optimisation	Assumes centralised operations, does not account for mobile vendor daily routing, ignores multiple independent origins	Extends CWSA to the mobile vendor context	(Clarke and Wright, 1964; Segerstedt, 2014; Segerstedt, 2018)
Food Access and Equity	Geographic accessibility analysis	Buffer analysis, distance-based metrics	Often concentrated in high income contexts, limited integration with informal distribution networks and relocation scenarios	Applied to developing country context, integrates dynamic vendor travel patterns with demographic data	(Cummins and Macintyre, 2002; Sadler, 2016; Walker et al., 2010)
Traditional GIS-Based Accessibility	Spatial proximity analysis	Static buffer zones, network analysis	Conventional distance metrics, limited identification of service gaps, weak integration with operational/routing data	Combines GIS accessibility mapping with empirically derived vendor mobility and routing outputs to evaluate relocation impacts	(Aljohani and Thompson, 2018; Mykrä et al., 2023)
Spatial Density/ Hotspot Modelling	Continuous density surfaces (activity hotspots/ corridors)	Kernel Density Estimation (KDE)	Often used descriptively limited application for relocation and limited integration with routing outputs	Uses KDE to map vendor activity density and service corridors, then integrates this with efficiency metrics	(Hu et al., 2018; Li et al., 2022)
Relocation Strategies	Single site relocation and alternative configurations (e.g., split/multiple candidate sites)	Scenario evaluation/ site comparison	Limited systematic assessment of configurations and distributive impacts	Evaluates candidate relocation sites and discusses implications using gain/loss and equity and efficiency	(Balbontin and Hensher, 2021; Nugroho et al., 2024)
This Study: Integrated spatial-logistical framework	CWSA route optimisation and spatial equity analysis	QGIS-based spatial framework, KDE, gain/loss analysis	Prior approaches lack integrated efficiency and equity with replicable workflows and policy facing outputs	Unified framework linking vendor route optimisation with spatial equity mapping, transparent and replicable outputs, supports policy preference comparisons	(This Study)

The entire workflow is presented in Fig. 1. Each step in each stage is designed to ensure replicability and analytical rigour while reflecting the operational realities of mobile vendors as described in detail in this section.

3.1. Stage 1: data preparation and distance matrix construction

The model building commenced with the collation and validation of primary geospatial data obtained through a field survey. The survey captured detailed operational information, including vendor residential locations, daily travel routes and the set of customer neighbourhoods they serve. Customer locations were identified based on service areas reported by vendors, providing an empirical basis for representing vendor-service zone linkages. Accordingly, the proposed framework is grounded in observed spatial patterns of vendor operations.

From the survey responses, customer location points were identified by aggregating the neighbourhood locations, each point representing the centroid of sales activity within a service area. All spatial features, including coordinates of vendors, customers, the existing wholesale market (EWM), and candidate new wholesale markets (NWMs) were projected and visualised as point layers in QGIS, with a digital road network incorporated to ensure realistic travel conditions. Shortest path distances between all origin-destination pairs were computed using QGIS network analysis, producing a distance matrix that reflects minimum travel distances along the road network. This matrix was constructed under the assumption that each vendor-customer connection is visited *once* per day per route, reflecting typical daily operations with a fixed vehicle carrying capacity. This simplification facilitates the model to minimise total travel distance while preserving the observed spatial structure of vendor operations. The resulting distance matrix formed the basis for subsequent CWSA route optimisation, ensuring calculations were grounded in actual urban accessibility patterns and empirically observed vendor behaviour.

3.2. Stage 2: Vendor route optimisation with CWSA

The routing component of the framework adopts the CWSA, a widely used heuristic for solving the Vehicle Routing Problem, valued for its efficiency in producing cost-effective delivery routes by minimising total travel distance (Li et al., 2022; Mancini, 2017; Martins et al., 2020). In its standard form, CWSA assumes all vehicles depart from a central depot will visit assigned customers, and return, merging routes iteratively based on the greatest achievable distance savings (Clarke and Wright, 1964; Doyuran and Çatay, 2017). For example, consider a simple case where a wholesale market (WM) must serve customers C_k, C_j $(k \neq j)$ the algorithm computes potential distance savings for all customer pairs. The pair with the highest savings is merged first, and the process repeats until an efficient set of routes is formed, typically ending at the depot. This approach is well suited to traditional logistics operations centred on a fixed depot. However, mobile vendor operations differ significantly as they start from home every day and visit the market location for procurement and visit each customer location to sell the goods before returning home at the end of the day.

To realistically model the operational practices of mobile vendors, the CWSA is adapted such that each vendor's base location is treated as both the starting and ending node for the delivery route (Arifin et al., 2026). The wholesale market is represented as a dummy customer within the algorithm, thereby prioritising the vendor's spatial proximity to customers in the optimisation process. The CWSA operates by computing savings for all possible route segments, enabling efficient

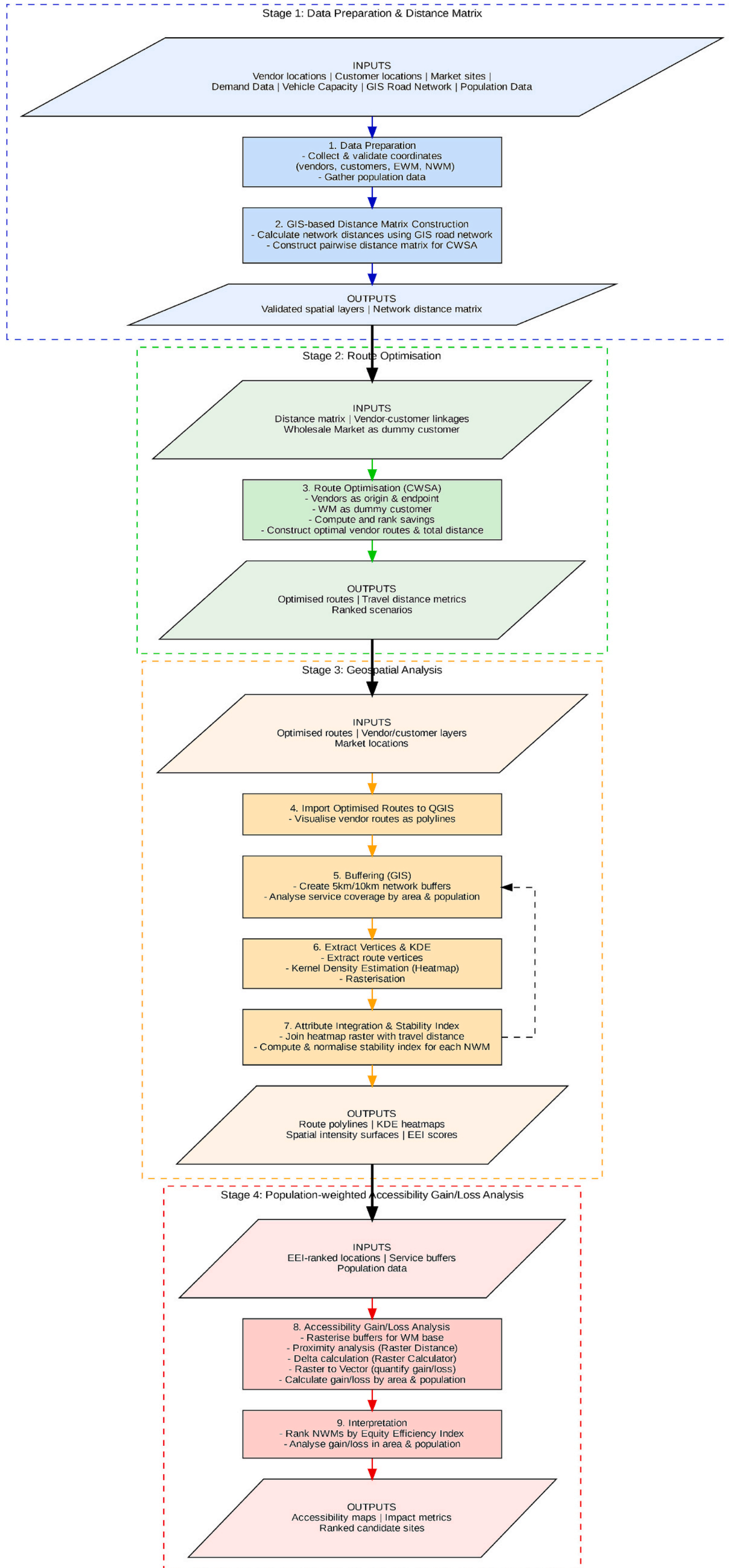


Fig. 1. Methodology flow chart.

route construction. Specifically:

a. For each pair of customers C_k, C_j:

$$S\left(C_k, C_j\right) = D\left(V, C_k\right) + D\left(V, C_j\right) - D\left(C_{k,} C_j\right) \tag{1}$$

where $D\left(V, C_k\right)$ and $D\left(V, C_j\right)$ are distances from V to each Customer C_k and C_j and $D\left(C_{k,} C_j\right)$ is the distance between C_k to C_j.

b. For each combination involving the Wholesale Market *WM* and Customers WM, C_k

$$\mathrm{S}\left(\mathrm{WM}, \mathrm{C_k}\right) = \mathrm{D}\left(\mathrm{V}, \mathrm{WM}\right) + \mathrm{D}\left(\mathrm{V}, \mathrm{C_k}\right) - \mathrm{D}\left(\mathrm{WM}, \mathrm{C_k}\right) \tag{2}$$

where $D(V, WM)$ is the distance from vendor to the market, $D\left(V, C_k\right)$ Distance between V *to* C_k, $D\left(WM, C_k\right)$ Distance between WM to C_k.

All savings values are ranked in descending order. The pair with the highest savings is selected to initiate the route, either *[Vendor, WM, Customer]* or *[Vendor, Customer 1, Customer 2]*. Additional customers are added iteratively based on the next highest savings, with the vendor remaining the anchor point. Once all customers are included, the route is closed by returning to the vendor's location, resulting in:

$$\mathrm{Route} = \left[\mathrm{V}, \mathrm{WM}, \mathrm{Customers}\ (\mathrm{ordered\ by\ savings}), \mathrm{V}\right] \tag{3}$$

The total travel distance for each vendor is calculated as the sum of all consecutive route segments, reflecting operational efficiency tailored to actual mobile vendor logistics.

3.3. Stage 3: geospatial analysis and spatial statistics in QGIS

The geospatial analysis in this study is designed to explicitly quantify both the operational efficiency and distributive equity of wholesale market relocation. The overarching aim is to provide a comprehensive, evidence-based spatial framework that supports decision makers in identifying market locations which max*imise service coverage* while *minimising negative impacts on existing communities*.

The analysis begins by importing coordinates of vendors, customers, EWM and NWM as spatial point layers in QGIS. Using the Buffer tool (Mykrä et al., 2023), circular zones with suitable radii e.g. 5 km and 10 km are generated around the EWM ensuring adequate service area coverage.

Following the mapping and buffering, optimised vendor routes from Stage 2 were imported into the GIS as polyline features. The 'Extract Vertices' tool generated dense point datasets along each route, capturing detailed vendor movement patterns (Mulrooney et al., 2017). These points were analysed using KDE to produce raster heatmaps that visualise vendor activity intensity, operational hotspots, and key distribution corridors.

These heatmap outputs are subsequently converted into raster format using the Rasterise (Vector to Raster) tool (Sato et al., 2019), where each raster cell value corresponds to local vendor density. For each NWM, the average travel distance of vendors is calculated by aggregating the CWSA optimised route distances for all vendors, providing a direct measure of operational efficiency in kilometres. As the heatmap and average travel distance metrics are measured in fundamentally different units and scales, normalisation is applied prior to integration. The normalised heat value for candidate *i* is defined as:

$$\mathrm{Normalised\ Heat_i} = \frac{\mathrm{Heat_i} - \min(\mathrm{Heat})}{\max(\mathrm{Heat}) - \min(\mathrm{Heat})} \tag{4}$$

where $heat_i$ is the heatmap value for candidate location *i*. This step rescales all heat values to fall within 0–1 range, with 1 representing the highest vendor density.

The average travel distances for all NWMs are standardised to 0–1 range, consistent with the normalised heat scores.The normalised distance for candidate *i* is calculated as:

$$\mathrm{Normalised\ Distance_i} = \frac{\max(\mathrm{avg\ Dist}) - \mathrm{avg\ Dist_i}}{\max(\mathrm{avg\ Dist}) - \min(\mathrm{avg\ Dist})} \tag{5}$$

where $avg\ dist_i$, is the average travel distance for candidate location *i*. This formulation ensures that a lower average travel distance yields a higher normalised score, so that higher values consistently indicate more efficient sites.

To facilitate systematic comparison among candidate market sites, a composite Equity-Efficiency Index (EEI) is calculated for each NWM *i* by integrating the two normalised metrics using the equation given below.

$$\mathrm{Equity-Efficiency\ Index_i} = (1-\alpha)\mathrm{Heat_i} + \alpha\mathrm{Dist_i}\ \ 0 \le \propto \le 1 \tag{6}$$

where α is a smoothing factor which can be interpreted as an indicator of a policy preference. For instance, $\alpha = 0$ represents preference for high vendor activity in an area prioritising the interest of vendors serving the communities along established corridors, whereas, $\alpha = 1$ puts larger weight on distance, indicating the preference for contained development, and $\alpha = 0.5$ indicates a balanced approach. This index can be thought of as a lever for policy preference representing (de)centralised land use development, as it allows the development to be contained within the core area of a city or otherwise. Descending EEI values from 1 (most preferred) to 0 (least preferred) provide a quantitative basis for ranking the candidate locations according to the combined spatial vendor activity and operational efficiency. Finally, a composite layer was produced using the Join Attributes by Table tool, enabling spatial visualisation and robust identification of market locations that demonstrate consistently strong performance across both criteria.

3.4. Stage 4: population-weighted accessibility gain/loss analysis

Each analytical step is purposefully chosen to enable the measurement and comparison of accessibility gain and losses in both spatial and demographic terms, ensuring that market relocation strategies are not only efficient but also equitable. The distributive impacts of each relocation were evaluated through a detailed gain/loss mapping process. The Proximity (Raster Distance) tool was used to generate distance rasters (Mulrooney et al., 2017); quantifying accessibility from all locations to the nearest market *before* and *after* relocation. The Raster Calculator (using Geo-spatial Data Abstraction Library- GDAL) computed the difference (delta) in accessibility; producing rasters that highlight zones of improved or diminished access attributable to each NWM. These delta rasters were then converted into vector polygons using the Raster to Vector tool to enable precise measurement of gain; loss; or unchanged accessibility over areas expressed in square kilometres. To ensure an equitable assessment; these polygons were overlaid with subdistrict-level demographic data; with gains and losses *weighted by resident population*. The population-weighted approach provides a robust measure of how accessibility benefits/burdens are distributed; enabling identification of communities likely to gain or be disadvantaged (Higgs and Langford, 2009). Integrating these geoprocessing steps in QGIS allows explicit quantification and mapping of spatial impacts; supporting evidence-based and socially equitable relocation decisions. Finally; we also have computed the value of Gini coefficient (Dadashpoor et al., 2016) for each NWM which helps summarising the equity involved.

3.5. Gini coefficient as a complementary equity measure

While the EEI and the population-weighted gain/loss analysis capture how wholesale market relocation affects mobile vendors and the populations they serve, these measures do not explicitly indicate how evenly accessibility impacts are distributed across individual subdistricts. To complement the primary equity assessment, this study employs the Gini coefficient as an additional indicator of spatial distributional balance. Gini coefficient is widely used in spatial planning and accessibility research to summarise the degree of inequality in the distribution of benefits and burdens across spatial units (Dadashpoor et al., 2016; Jang et al., 2016). The coefficient ranges from 0, indicating a perfectly even distribution of impacts across all subdistricts, to 1, indicating extreme spatial concentration, where impacts are confined to a small number of locations (Delbosc and Currie, 2011).

In this study, the Gini coefficient is calculated using a Lorenz curve (Delbosc and Currie, 2011; Kaplan et al., 2014; Sharma and Patil, 2021; Sharma and Patil, 2022) based approach applied to subdistrict level net population impact derived in Stage 4. Net population impact is defined as the difference between the population experiencing gain and loss within each subdistrict. For each candidate wholesale market and for each buffer size, subdistricts are ordered in ascending order of net population impact. The cumulative proportion of subdistricts is denoted by X_i, while the cumulative proportion of net population impact is denoted by Y_i. The Gini coefficient is then computed by approximating the area under the Lorenz curve:

$$G = 1 - \sum_{i=1}^{n} (X_i - X_{i-1})(Y_i + Y_{i-1}) \quad (7)$$

where n denotes the total number of subdistricts included in the analysis. The resulting Gini values serve as a complementary diagnostic tool to the earlier results.

4. Case study: Samarinda's wholesale market relocation

This section illustrates the application of the proposed GIS-based spatial logistical framework using the relocation of Segiri Wholesale Market in Samarinda, Indonesia, as an example. The case study is used to demonstrate how the methodology can be implemented in a real urban context, linking observed mobile vendor operations with spatial accessibility and equity analysis.

4.1. Study context and data description

Strategically located, acting as the principal distribution hub for key commodities such as vegetables, meat, other essential goods, Segiri Market spans more than 54,000 m^2 and handles the distribution of 8–10 t of vegetables daily. The market not only fulfils local needs but also serves as an entry point for goods arriving from a diverse range of regions, including South Sulawesi, Surabaya, Mamuju, and even Thailand. To evaluate potential outcomes, 12 candidate NWMs were identified across the city (Fig. 2), representing variation in the spatial positioning of wholesale market within Samarinda's urban structure. These candidate locations were used to systematically examine how different spatial configurations of wholesale markets influence vendor travel patterns, accessibility outcomes and the distribution of gains and losses across urban subdistricts.

Administratively, Samarinda is divided into 59 subdistricts, coded as L1 through L59 in this study. The city covers an area of approximately 718 km^2 and, according to 2023 population statistics, is home to over 860,000 residents, making it one of the largest urban centres in East Kalimantan. Samarinda's urban landscape is characterised by both densely populated residential neighbourhoods and extensive commercial zones, presenting unique challenges for wholesale distribution and market accessibility.

A field survey conducted by the authors in October 2024 involved talking to 50 mobile vendors operating in the vicinity of the Segiri Wholesale Market. Information was collected on vendors' residential locations and the areas in which they regularly conduct their selling activities. Vendors were asked to identify their home subdistrict and to report their operating subdistricts that they routinely serve during daily trading activities. In this study, each operating subdistrict is represented as a single spatial point, with one point corresponding to one service zone. The point location approximates the typical location of vendor selling activity within the subdistrict.

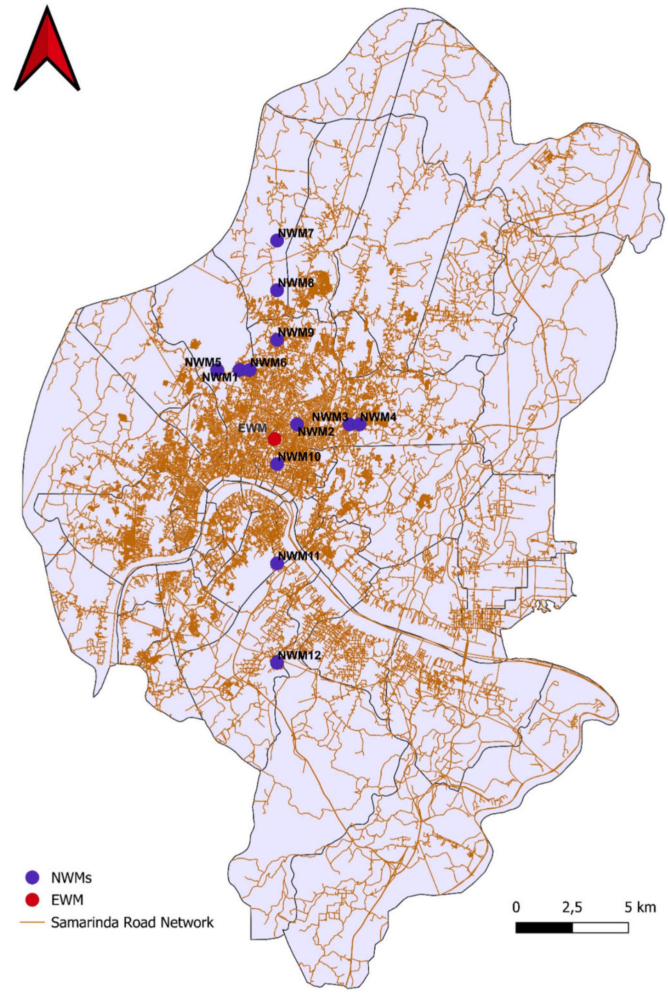


Fig. 2. Location of WM and NWMs.

Using this representation, the survey had identified that the mobile vendors operate from 16 residential subdistricts, reflecting the spatial clustering of vendor residences across the city. In addition, vendors serve customers located across 22 different subdistricts, derived from 66 empirically observed customer locations reported in vendors' daily operational records. All service zones were therefore modelled as point locations at the subdistrict level, ensuring a consistent spatial unit for routing and accessibility analysis.

From the survey, mobile vendors were found to operate at a carrying capacity of 60 kg per trip, consistent with the observed field practice in the area. This capacity acts as an operational constraint that defines the feasible scale of daily vendor activity. Routes were optimised between vendor home locations and end use customer locations, focusing on spatial structure and travel distance relevant to accessibility outcomes.

The analysis of vendor mobility and market accessibility began with geospatial mapping of all principal actors, existing and candidate wholesale market locations, vendor and customer locations. Each point was mapped precisely using latitude and longitude coordinates within the GIS. Four primary map layers were systematically integrated into the spatial analysis workflow, namely:

(i) location of the existing wholesale market (EWM) and 12 candidate new market locations (NWM1–NWM12);
(ii) spatial distribution of mobile vendors' residences and their operational areas;

(iii) distance data from mobile vendors to both existing and candidate market locations; and
(iv) administrative boundaries and population data across Samarinda serving as the fundamental layer for subsequent cartographic and analytical processes.

Finally, Segiri Market in Samarinda was selected for several reasons. First, it functions as a critical hub within the urban food supply chain handling high daily transaction volumes. Second, its current central urban location has increasingly generated planning concerns related to congestion, land-use pressure and operational inefficiencies making it a realistic candidate for relocation under prevailing urban development policies. Third, the market exhibits strong functional linkages with mobile vendors, whose daily travel patterns and service area are highly sensitive to market location. This makes Segiri an appropriate empirical setting for examining both logistical efficiency and spatial equity impacts. The case of the Segiri Wholesale Market in Samarinda serves as a tangible example of how a central marketplace underpins urban food supply chains and the livelihoods of mobile vendors.

4.2. Data adequacy asessment

Prior to the spatial and routing analysis, statistical assessment was undertaken to ensure that the number of vendors was sufficient to support robust quantitative evaluation. This assessment focused on evaluating whether the observed distribution of daily travel distances reported by mobile vendors was statistically significant and supported by an adequate data set size. The Chi-square test is a statistical method to analyse the relationship or correspondence between categorical variables (Fitts, 2018). A Chi-square goodness-of-fit test was applied to the distribution of daily vendor travel distances. The test results indicate that the observed distribution deviates significantly from a uniform distribution ($\chi^2 = 9.88, df = 2, p = 0.007$). The calculated test statistic exceeds the critical value of 5.99 at the 5% significance level, leading to rejection of the null hypothesis of uniformity. This confirms that the observed distance categories are not evenly distributed and exhibit significant variation, statistically.

To assess the significance of the results further, the effect size (ω) was calculated. Using the Chi-square statistic and data size, where $\chi^2 = 9.88$ and $N = 50$, the effect size was found to be 0.445. According to Cohen's guidelines, this value represents a moderate to large effect size, indicating that the deviations from the expected distribution are not only statistically significant but also practically meaningful. To ensure the adequacy of the data for detecting the observed effects, a power analysis was conducted. Power analysis is a statistical technique designed to determine the minimum sample size required for a study to detect a significant effect with a given confidence level (Vasileiou et al., 2018). Using the effect size ($\omega = 0.445$) and a significance level ($\alpha = 0.05$), the statistical power was calculated to be 0.882, exceeding the desired threshold of 0.8. This demonstrates that the data size was sufficient to reliably detect the observed deviations.

The analysis determined the minimum data required to achieve a power level of 0.8. With an effect size of $\omega = 0.445$, the required data was approximately 40 respondents. Given that the actual data was 50 respondents, there was a surplus of 10 respondents, further confirming the adequacy of the data. In conclusion, the results of the Chi-Square tests demonstrate significant deviations from the expected distribution, supported by a moderate to large effect size and robust statistical power. These findings confirm the reliability of the analysis, and no additional respondents are needed for further evaluation.

5. Results and discussion

We now describe the results beginning with the route optimisation.

5.1. Route optimisation results using CWSA

CWSA was implemented to determine optimal routing solutions aimed at minimising total travel distances. This method systematically evaluates and aggregates individual vendor routes into optimised travel sequences, thereby significantly reducing the overall distance travelled and consequently lowering transportation burdens faced by mobile vendors. Appendix A presents the complete routing patterns constructed for each mobile vendor when the EWM serves as the focal point. We then calculated the cumulative total distance travelled by all vendors as well as the average travel distance per vendor for each NWM too. The summary of the results is shown in Table 2 below:

Table 2 presents the total and average travel distances of mobile vendors for each candidate NWM location as calculated using CWSA. The results clearly indicate that NWM2 yields the lowest total travel distance (728.42 km) and the smallest average travel distance per vendor (14.57 km), positioning it as the most logistically efficient option among all candidate locations. These findings highlight the effectiveness of CWSA in optimising route configurations and minimising the aggregate travel distance and overall operational burden for mobile vendors.

Despite these advantages, it is important to note that the outcomes generated by the CWSA reflect efficiency in aggregate terms, focusing primarily on minimising overall distance travelled. While this approach is instrumental in identifying a leading candidate location based on logistical performance, it does not account for how the relocation might affect access to the market at the neighbourhood or subdistrict level. In other words, a site that minimises total travel distance may not necessarily offer equitable improvement in accessibility for all urban areas. Some neighbourhoods may benefit substantially, while others may experience reduced service coverage. Thus, further analysis is warranted to assess the distributive and spatial impacts of each candidate location. By integrating spatial datasets and conducting advanced analyses, including buffer creation, accessibility mapping, and gain/loss calculations, QGIS enables the evaluation of how each candidate market affects service reach and spatial equity across the city. The following sections therefore build on the CWSA findings by leveraging QGIS to visualise and quantify the spatial distribution of accessibility gains and losses, offering a more holistic basis for selecting the most appropriate relocation site.

5.2. Spatial generalisation of NWMs

The integration of optimised vendor routing configurations derived from CWSA into GIS environment enables a robust spatial comparison of travel distances for the existing and candidate wholesale market new locations. In this phase, baseline travel distances from the EWM were systematically contrasted with those projected for NWMs, providing a comprehensive assessment of the potential efficiency gains that could be realised through strategic relocation.

Table 2
Estimated distance travelled by mobile vendors.

Wholesale Market	Total Distance (km)	Average Travel Distance (km) per vendor
EWM	765.90	15.32
NWM1	1044.98	20.90
NWM2	**728.42**	**14.57**
NWM3	781.11	15.62
NWM4	810.86	16.22
NWM5	1067.61	21.35
NWM6	959.41	19.19
NWM7	1388.90	27.78
NWM8	1176.03	23.52
NWM9	982.26	19.65
NWM10	791.13	15.82
NWM11	1392.90	27.86
NWM12	1835.13	36.70

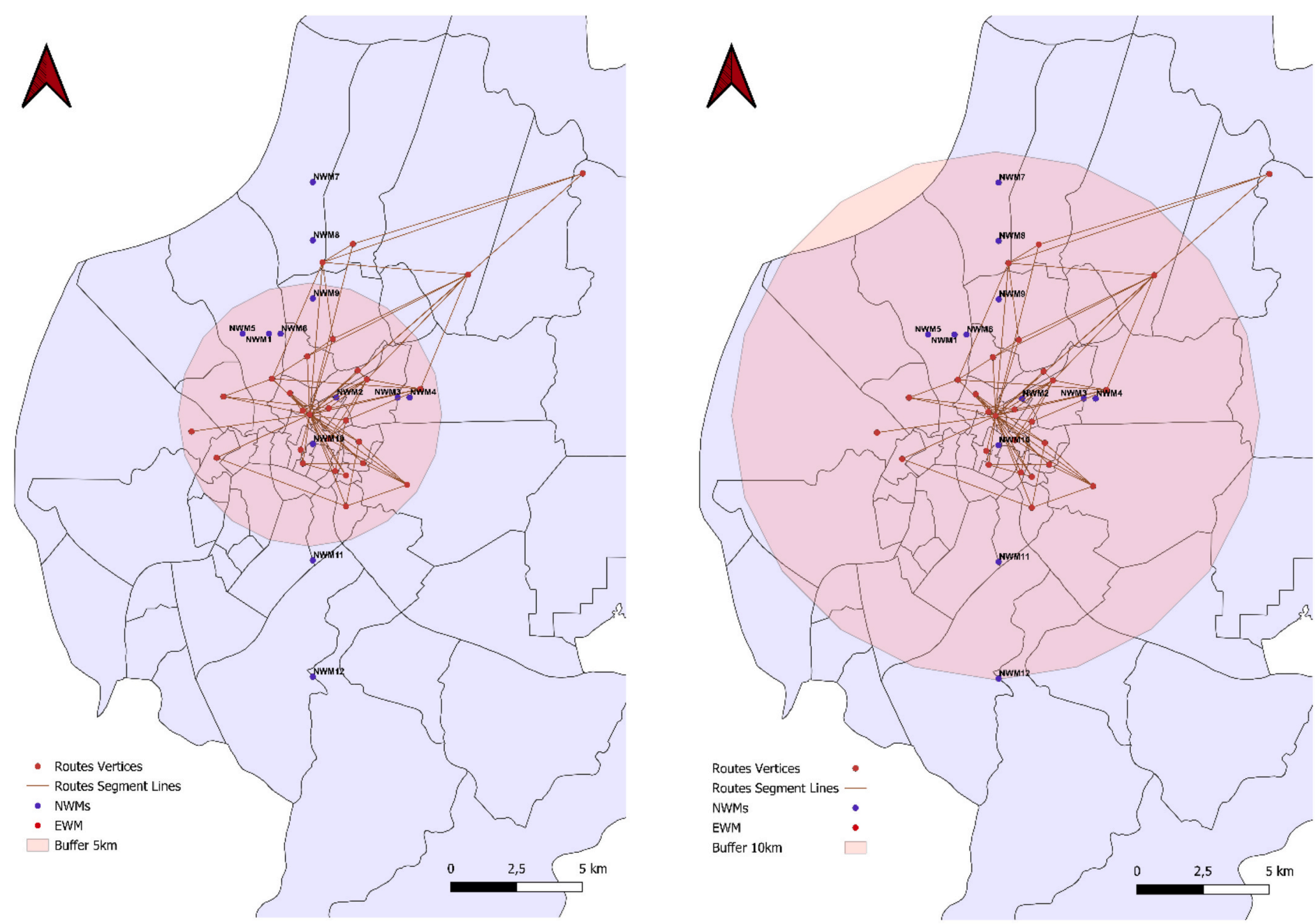
Fig. 3 (and Fig. 4) illustrate the spatial outcomes of this analysis by overlaying the optimised vendor route segments, route vertices for all candidate NWM sites onto the Samarinda urban area map. In both figures, EWM is centrally positioned, with vendor-customer route vertices (orange points) and route segments (orange lines) emanating outward to capture the true pattern of vendor movement and operational reach. Straight lines shown between vendors and customers are notional connectors, intended to show linkages and movement direction. All distance calculations rely on *network-based shortest routes* generated in QGIS (not crow-fly distances), meaning that the lines on the maps should be interpreted merely as schematic visualisation of origin-destination associations.

To provide a spatial benchmark of accessibility, circular buffers of 5 km and 10 km were constructed around the EWM. As the vendor operations are pivoted around EWM they serve as the most appropriate baseline for evaluating the change in accessibility and service reach due to NWMs. In our case, a 5 km buffer represents the core service area, reflecting most vendor-customer interactions and aligning with observed travel patterns. The 10 km-buffer extends coverage to peripheral districts and outliers, offering a broader view of market influence. Preliminary mapping confirms that the 5 km-buffer covers approximately 70% of the new market sites, while the 10 km-buffer encompasses over 95% enabling analysis of both immediate and extended spatial impacts. These buffers represent realistic ranges of daily vendor commute and enable direct comparison between different levels of service coverage.

Fig. 3a presents the spatial distribution of vendor activities relative to a 5 km-buffer centred on the EWM (shaded semi-transparent red), serving as the sole reference in this analysis. Many vendor route vertices fall within this buffer, indicating that the present EWM location generally supports practical and feasible vendor operations. However, some vertices and route segments extending beyond the buffer reveal specific urban subdistricts where vendors face excessive travel distances. Candidate locations NWM1-NWM12 were overlaid within the same spatial framework to provide positional context relative to the EWM service area.

Fig. 3b extends this analysis by visualising a 10 km service area buffer around the EWM. The broader buffer encompasses nearly all vendor route vertices and candidate NWM locations, providing an expanded perspective on the extent of market influence. This visualisation enables identification of those candidate sites that not only serve the existing vendor base but also have the capacity to reach peripheral neighbourhoods. By comparing the spatial coverage provided by 5 km and 10 km buffers, the analysis highlights the trade-offs between consolidating service in central urban zones versus expanding access to more distant districts.

Fig. 4 presents the kernel density heatmap generated from extracting the vendor route vertices, reconstructed with both 5 km and 10 km buffers. Kernel density indicates the intensity of vendor activity, estimated from the distribution of route vertices derived from the shortest path trajectories along the road network. Thus, on this map, dark red hue represents ‘hot’ corridors, indicating the areas of highest vendor



(a) (b)

Fig. 3. Buffer zone and mobile vendors routes in EWM and surrounding NWMs (a) 5 km (b) 10 km.

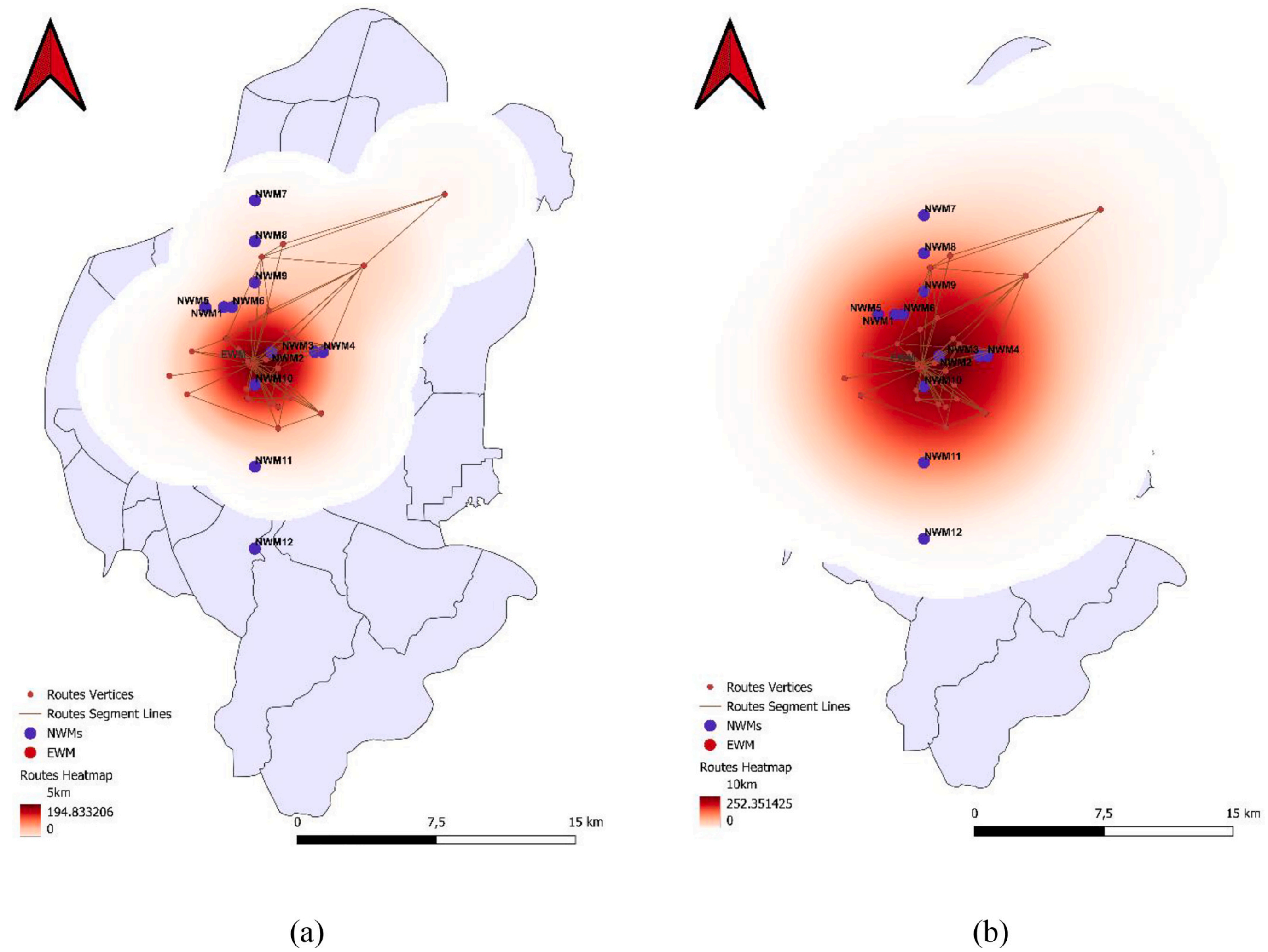


Fig. 4. Heatmap of mobile vendor route intensity (a) 5 km buffer (b) 10 km buffer.

movement intensity radiating outward from the EWM along the city's main thoroughfares, while lighter shades of red to white indicate 'cold' corridors, or zones with low levels of vendor activity. The outputs from the spatial analysis presented here have been used to prioritise the candidate market locations as explained in the ensuing paragraphs.

To provide an objective basis for prioritising wholesale market locations, we developed an index, EEI (Eq. 6), that integrates the two core criteria: the *intensity of vendor activity* and the *operational efficiency* of vendor travel routes. To ensure that the spatial (route intensity) and efficiency (travel distance) metrics are comparable and do not disproportionately influence the final assessment, both criteria were normalised to a standardised scale ranging from 0 to 1 using Eqs. (4) and (5).

The composite EEI for each candidate location is calculated by applying a simple weighting scheme to the two normalised attribute values viz., vendor activity intensity and average travel distance, and then summing the two weighted values to generate a single score. Five weighting schemes were tested: $\alpha = 0.1$ and $\alpha = 0.3$ (*heat biased*) and $\alpha = 0.5$ (*balanced*), $\alpha = 0.7$ and $\alpha = 0.9$ (*distance biased*). This analysis

Table 3
Composite EEI scores for potential New Wholesale Market locations (5 km buffer).

Wholesale Market Candidate	Heat value	Normalised Heat	Normalised Distance	EEI score for various values of α					EEI rank for α=0.5
				0.1	0.3	0.5	0.7	0.9	
NWM1	58.62	0.29	0.71	0.33	0.42	0.50	0.58	0.67	6
NWM2	**187.80**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**
NWM3	**99.91**	**0.52**	**0.95**	**0.56**	**0.65**	**0.73**	**0.82**	**0.91**	**3**
NWM4	79.75	0.41	0.93	0.46	0.56	0.66	0.77	0.87	4
NWM5	31.77	0.14	0.69	0.19	0.31	0.42	0.53	0.64	8
NWM6	69.05	0.35	0.79	0.39	0.48	0.57	0.66	0.75	5
NWM7	5.95	0	0.40	0.40	0.12	0.20	0.28	0.36	11
NWM8	14.18	0.05	0.59	0.10	0.21	0.32	0.43	0.54	9
NWM9	36.11	0.17	0.77	0.22	0.35	0.47	0.58	0.71	7
NWM10	**174.93**	**0.93**	**0.94**	**0.93**	**0.93**	**0.94**	**0.94**	**0.94**	**2**
NWM11	9.11	0.02	0.39	0.05	0.13	0.21	0.28	0.36	10
NWM12	0	0	0	0	0	0	0	0	12

enabled us to examine the robustness of candidate rankings under different policy preferences. For policy interpretation, the composite EEI scores were ranked from highest to lowest, with the highest EEI value assigned rank 1 and the lowest received rank 12. Tables 3 and 4 present the EEI scores for all potential new wholesale market locations and the resulting ranking for 5 km- and 10 km-buffers.

Tables 3 and 4 show that the role of α-value is critical for the local planning policy context. An α of 0.5 represents a balanced policy stance, giving equal weight to efficiency (distance minimisation) and equity of service coverage (heat intensity), making it suitable when authorities prioritise both vendor activity along corridors and the distance travelled. Higher α values (0.7 or 0.9) indicate policy preference towards travel distance minimisation, favouring sites that maximise operational efficiency reducing vendor travel costs. In other words, the development will be contained to the core area of the city. Such weighting might be most relevant in contexts when authorities aim for centralised urban development. Conversely, lower α values (0.1 or 0.3) bias the evaluation towards heat intensity, favouring sites located along vendor dense corridors even if travel efficiency is not at its best. Under this weighting, accessibility gains are anchored to existing areas of high vendor activity, thereby maintaining established service patterns beyond the urban core rather than redistributing development indiscriminately. This approach is therefore appropriate where authorities place greater emphasis on protecting vulnerable vendor groups whose livelihoods depend on proximity to established customer bases, protecting the equity by preserving the service to the communities.

The spatial results shown in Tables 3–4 largely align with CWSA findings shown in Table 2, which identified NWM2 as most efficient in total and average travel distance. However, numerical efficiency alone does not address wider spatial equity. By applying different α values, local authorities can transparently test how market relocation decisions might perform under alternative planning objectives, whether focused on minimising travel distances, maximising service inclusion, or achieving a balance between the two. In this way, integrating CWSA outputs with kernel density heatmaps and EEI scoring in QGIS embeds both efficiency and equity into the evidence base, supporting relocation choices.

5.3. Accessibility gain/loss analysis

We now turn our attention to population-based equity by assessing the gain/loss of accessibility due to wholesale market relocation. Using QGIS's advanced tools, we compared accessibility patterns for candidate sites by firstly quantifying the service areas and identifying zones gaining/losing accessibility. The gain/loss were then overlaid with subdistict population data to assess distributional impacts, allowing us to evaluate the consequence of each relocation on urban mobility, vendor logistics, and spatial equity.

A gain/loss analysis with a 5 km-buffer (Fig. 5) indicates that NWM2, NWM3, and NWM10 fall within the major vendor corridor, as reflected by the dominance of gaining zones (larger green areas) along the reconstructed core distribution routes. These market locations display relatively balanced profiles, generating accessibility improvements nearer to the new market, while expecting losses mainly in the opposite direction (red areas). In contrast, NWM1, NWM4, NWM5, NWM6 and NWM9 exhibit mixed results, characterized by adjacent pockets of gains and losses. Candidate sites situated further away from the vendor core NWM7, NWM8, NWM11, and NWM12 show concentric patterns with limited change, reflecting peripheral or isolated positions that do not substantially improve or diminish accessibility for the majority of the population.

Extending the analysis to the 10 km-buffer (Fig. 6) brings additional candidate sites into consideration, as NWM1, NWM4, NWM5, NWM6 and NWM9 beginning to show extensive gains, yet these are often accompanied by wider losses to other zones, signaling uneven redistribution of accessibility across subdistricts. In contrast, NWM2 and NWM10 remain comparatively stable as coverage extends. NWM7, NWM8, NWM11 and NWM12 continue to display marginal immediate impacts, reflecting their peripheral positions. Nonetheless, these sites may gain strategic importance in the longer term as urban growth and infrastructure expansion increase vendor and customer density in surrounding areas. Overall, the 5 km- and 10 km-buffer comparison highlights a clear trade off between consolidating service provision in central vendor corridors vs extending coverage to peripheral districts.

The quantitative analysis of travel distance changes, categorized into discrete gain and loss zones, provides a robust framework for evaluating how each candidate location would reshape vendor service areas in Samarinda. As presented in Tables 5 and 6, this approach moves beyond descriptive mapping to deliver actionable, evidence-based guidance for relocation policy.

Within the critical 5 km-buffer zone (Table 5), NWM10 demonstrates superior performance, achieving the largest area (33.02 km^2) gaing accessibility while affecting the highest population positively (214,557 people, representing 52% of the total affected population). Simultaneously, NWM10 minimises negative impacts, with an expected 195,710 people facing the prospect of reduced accessibility to the market. The spatial configuration is visually confirmed in Fig. 7(a), which illustrates how NWM10's gain zones align with established urban corridors while areas losing accessibility are predominantly distributed at the periphery. NWM2 also performs well in area metrics but with a smaller population affected positively (146,150 people) while leaving a larger population with reduced access (266,558 people).

To complement the accessibility gain/loss assessment, a supplementary equity check was also undertaken using the Gini coefficient, which summarises the degree of inequality in the distribution of accessibility impacts across subdistricts. As shown in Table 5, Gini coefficients within the 5 km-buffer are relatively high across all candidate locations (ranging from 0.11 to 0.14), reflecting the inherently localised

Table 4
Composite EEI scores for potential New Wholesale Market locations (10 km buffer).

Wholesale Market Candidate	Heat value	Normalised Heat	Normalised Distance	EEI score for various values of α					EEI rank for α=0.5
				0.1	0.3	0.5	0.7	0.9	
NWM1	**190.21**	**0.75**	**0.71**	**0.75**	**0.74**	**0.73**	**0.72**	**0.72**	**=6**
NWM2	**252.15**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**
NWM3	**222.97**	**0.88**	**0.95**	**0.89**	**0.90**	**0.92**	**0.93**	**0.95**	**3**
NWM4	**213.19**	**0.84**	**0.93**	**0.85**	**0.87**	**0.88**	**0.90**	**0.92**	**4**
NWM5	**166.11**	**0.65**	**0.69**	**0.65**	**0.66**	**0.67**	**0.68**	**0.69**	**8**
NWM6	**198.09**	**0.78**	**0.79**	**0.78**	**0.78**	**0.78**	**0.78**	**0.79**	**5**
NWM7	37.01	0.13	0.40	0.15	0.21	0.26	0.32	0.38	11
NWM8	101.23	0.39	0.59	0.41	0.44	0.49	0.53	0.58	9
NWM9	**177.80**	**0.69**	**0.77**	**0.71**	**0.72**	**0.73**	**0.75**	**0.76**	**=6**
NWM10	**239.72**	**0.95**	**0.94**	**0.95**	**0.95**	**0.95**	**0.95**	**0.94**	**2**
NWM11	119.21	0.46	0.39	0.45	0.44	0.42	0.42	0.40	10
NWM12	6.30	0	0	0	0	0	0	0	12

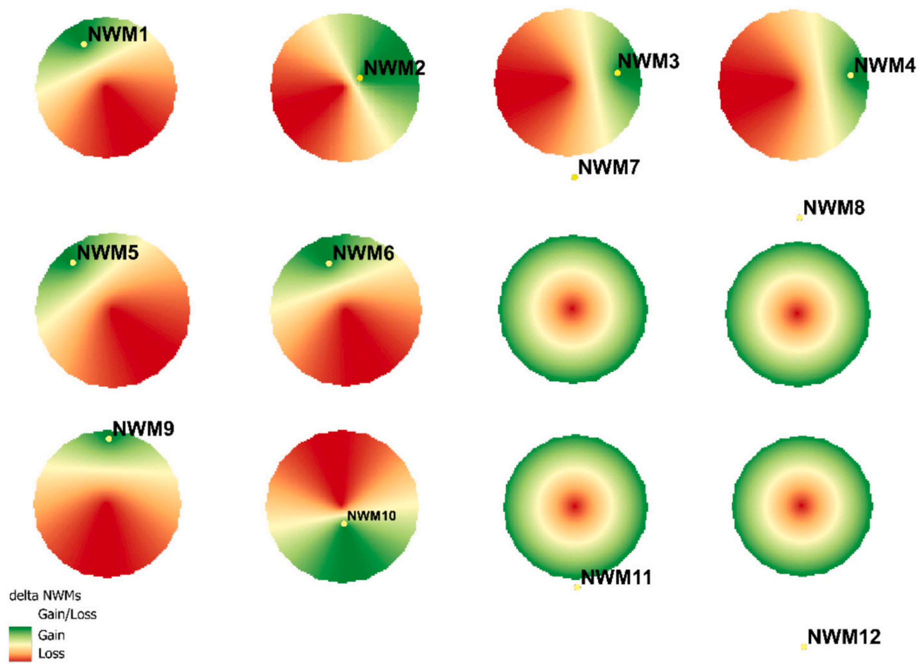


Fig. 5. Delta distances map in 5 km buffer.

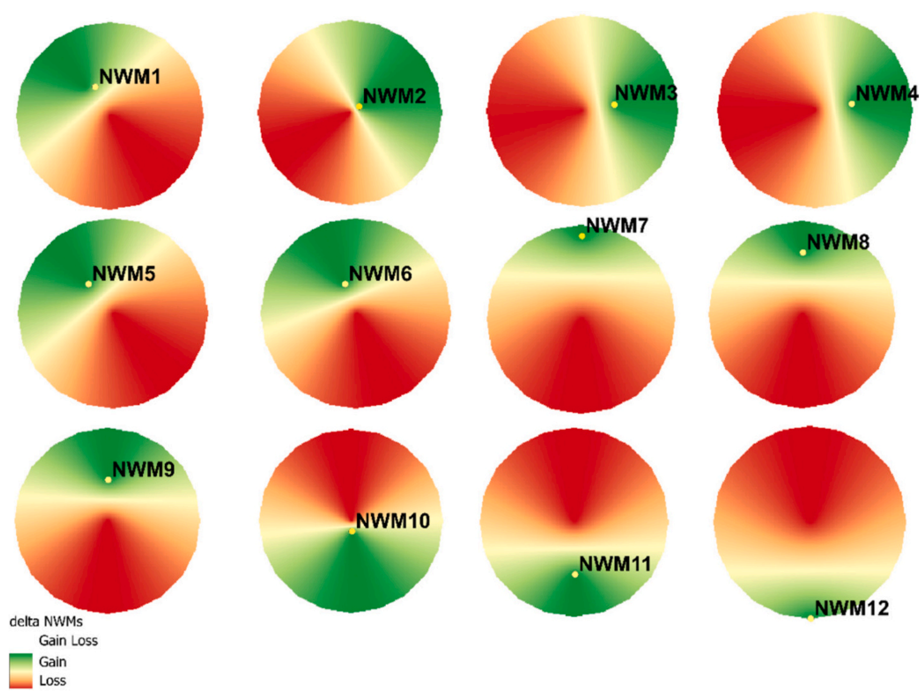


Fig. 6. Delta distances map in 10 km buffer.

nature of accessibility changes at this scale. This indicates that, regardless of the candidate site, gains and losses within the immediate vicinity of relocation are concentrated within a limited number of subdistricts. Importantly, although NWM10 exhibits a Gini coefficient comparable to other candidates (0.14), it achieves substantially larger population gains and lower losses, suggesting that its superior performance is not driven by disproportionately concentrating impacts in a small number of neighbourhoods.

Expanding the analysis to the 10 km-buffer (Table 6) further reinforces these findings while providing additional insights. NWM10 maintains its superior position with the largest area (143.58 km^2) with population (388,563 people) benfitting, while the smallest population losing accessibility among candidate locations. Fig. 7(b) visually represents the impact, showing how NWM10's accessibility benefits extend broadly across urban subdistricts. Notably, while some candidates (NWM1, NWM5, NWM6) show improved metrics at a broader scale, though these come at the cost of substantially increased areas of loss (and affected populations), representing poor trade-offs.

Furthermore, for NWM10 within 10 km buffer, the calculated Gini coefficient is 0.17 indicating a low level of spatial inequality in the distribution of accessibility impacts. This result suggests, relative to alternatives, NWM10's accessibility impacts are less spatially concentrated

Table 5
Gain/loss of accessibility to residents within 5 km buffer zone.

Wholesale Market Candidate	Area (km^2)		Affected Population (people)		Gini Coefficient
	Gain	Loss	Gain	Loss	
NWM1	21.63	55.43	45,572	366,398	0.11
NWM2	**32.67**	**44.63**	**146,150**	**266,558**	**0.22**
NWM3	**22.23**	**55.03**	**85,671**	**326,836**	**0.18**
NWM4	20.31	56.70	75,643	336,076	0.19
NWM5	19.08	57.98	40,959	371,011	0.11
NWM6	22.37	54.69	46,345	365,626	0.12
NWM7	Not Available	Not Available	Not Available	Not Available	Not Available
NWM8	Not Available	Not Available	Not Available	Not Available	Not Available
NWM9	16.97	60.05	31,655	380,233	0.15
NWM10	**33.02**	**43.87**	**214,557**	**195,710**	**0.14**
NWM11	Not Available	Not Available	Not Available	Not Available	Not Available
NWM12	Not Available	Not Available	Not Available	Not Available	Not Available

Table 6
Gain/loss of accessibility to residents within 10 km buffer zone.

Wholesale market candidate	Area (km^2)		Affected population (people)		Gini coefficient
	Gain	Loss	Gain	Loss	
NWM1	**108.68**	**193.77**	**117,580**	**566,764**	**0.16**
NWM2	**138.97**	**163.26**	**231,200**	**451,999**	**0.29**
NWM3	**120.32**	**182.22**	**178,174**	**506,346**	**0.27**
NWM4	**116.46**	**186.08**	**166,841**	**517,679**	**0.26**
NWM5	**108.68**	**193.77**	**117,580**	**566,764**	**0.16**
NWM6	**115.29**	**186.89**	**123,832**	**559,899**	**0.16**
NWM7	62.65	239.93	47,717	636,785	0.16
NWM8	82.69	219.85	69,311	615,209	0.16
NWM9	**103.68**	**198.87**	**101,196**	**583,324**	**0.21**
NWM10	**143.58**	**158.96**	**388,563**	**295,957**	**0.17**
NWM11	100.74	201.80	204,178	480,342	0.17
NWM12	60.64	241.94	92,851	591,651	0.17

and are distributed across a wider set of subdistricts. When considered alongside Fig. 7, the EEI results, and the aggregate population impacts, the Gini based assessment provides additional quantitative support for the interpretation that the effects of the NWM10 relocation scenario are broadly distributed rather than highly localised.

5.4. *Discussion*

The spatial pattern in Fig. 7 reinforces the gain/loss dynamics for NWM10, where zones gaining accessibility with the relocation are concentrated along the primary distribution corridors, while zones losing are clustered at the urban periphery. This pattern underscores the inherent trade-off between expanding the service coverage and maintaining equitable access. It is important to note that both NWM2 and NWM10 are situated in close proximity to the existing central market, which whilst delivering the greatest overall accessibility benefits, may contribute minimally to the objective of alleviating congestion and over concentration of activity in the city centre.

Within this context, the gain/loss analysis not only identifies which alternative sites offer the most immediate operational advantage but also provides strategic guidance regarding the direction of future market relocations. While NWM3, NWM4 support development in the east, NWM1, NWM5, NWM6 envisage developing the west. Similarly, NWM7, NWM8, NWM9 support the markets in the north, wheareas NWM11, NWM12 could potentially alter the development pattern in the south. The city authorities whilst aiming for decongesting the city centre, they also would like to relocate the market to a place to support broader urban development strategy. Thus relocating the market to, say, NWM8 might fulfil the objective of decongesting the city centre while also providing the impetus to developing the north. One may also extend the argument to support market relocations to NWM5, NWM8 and NWM11 to encourage development in the west, north and the south.

In Samarinda, this approach aligns with ongoing urban development priorities, where the city government is actively promoting integrated urban planning and economic expansion in new growth areas. Considering these development priorities, relocating markets to areas such as NWM4 and NWM11, where significant infrastructure and residential growth is anticipated, may dramatically increase vendor and customer density in the vicinity over time, thereby transforming current low gain locations into future high accessibility hubs.

Beyond the Samarinda case, these findings offer more insights on general planning. Wholesale market relocation strategies in rapidly urbanising cities should not be evaluated as isolated, single site interventions, but as part of broader spatial reconfiguration of urban distribution systems. Cities with similar characteristics, such as strong dependence on informal mobile vendors, centralised wholesale facilities, and emerging peri-urban growth corridors, are likely to face comparable trade-offs between efficiency and equity mitigation.

5.5. *Policy preferences*

A policy relevant reading of the results suggests that wholesale market relocation decisions can be guided through a set of structured decision levers. These levers can be interpreted at two levels: first as case-specific recommendations for Samarinda and second, as general policy guidance applicable to other urban contexts.

5.5.1. *Policy implications from Samarinda case study*

In the context of Samarinda, three specific policy implications emerge from the analysis.

- First, the weighting parameter α in the composite EEI should be treated explicity as a policy preference dial. A balance stance ($\alpha = 0.5$) is appropriate where planners must trade off operational efficiency against spatial equity in roughly equal measure, the default for routine city wide decisions. Distance biased ($\alpha = 0.7$ *and* $\alpha = 0.9$) approach is defensible when congestion pressures dominate whereas heat biased ($\alpha = 0.3$ and $\alpha = 0.1$) decisions are warranted when protecting vulnerable vendors and consolidating service in established corridors is paramount.
- Second, spatial preferences should reflect the diffentiated roles of candidate sites as indicated by the EEI evidence, heatmaps and gain/loss results. In our Samarinda case, NWM10 is the recommended relocation site because it consistently maximises accessibility gains in both area and affected population whilst containing losses and it remains stable across α settings. NWM2 is a credible alternative when a distance biased relocation is required by congestion constraints, aligning with the CWSA minimum distance outcome.
- Third, as NWM10 and NWM2 are both proximate to the urban core, selecting either will not in itself decongest the city sentre. Accordingly, spatial preferences should combine immediate relocation to

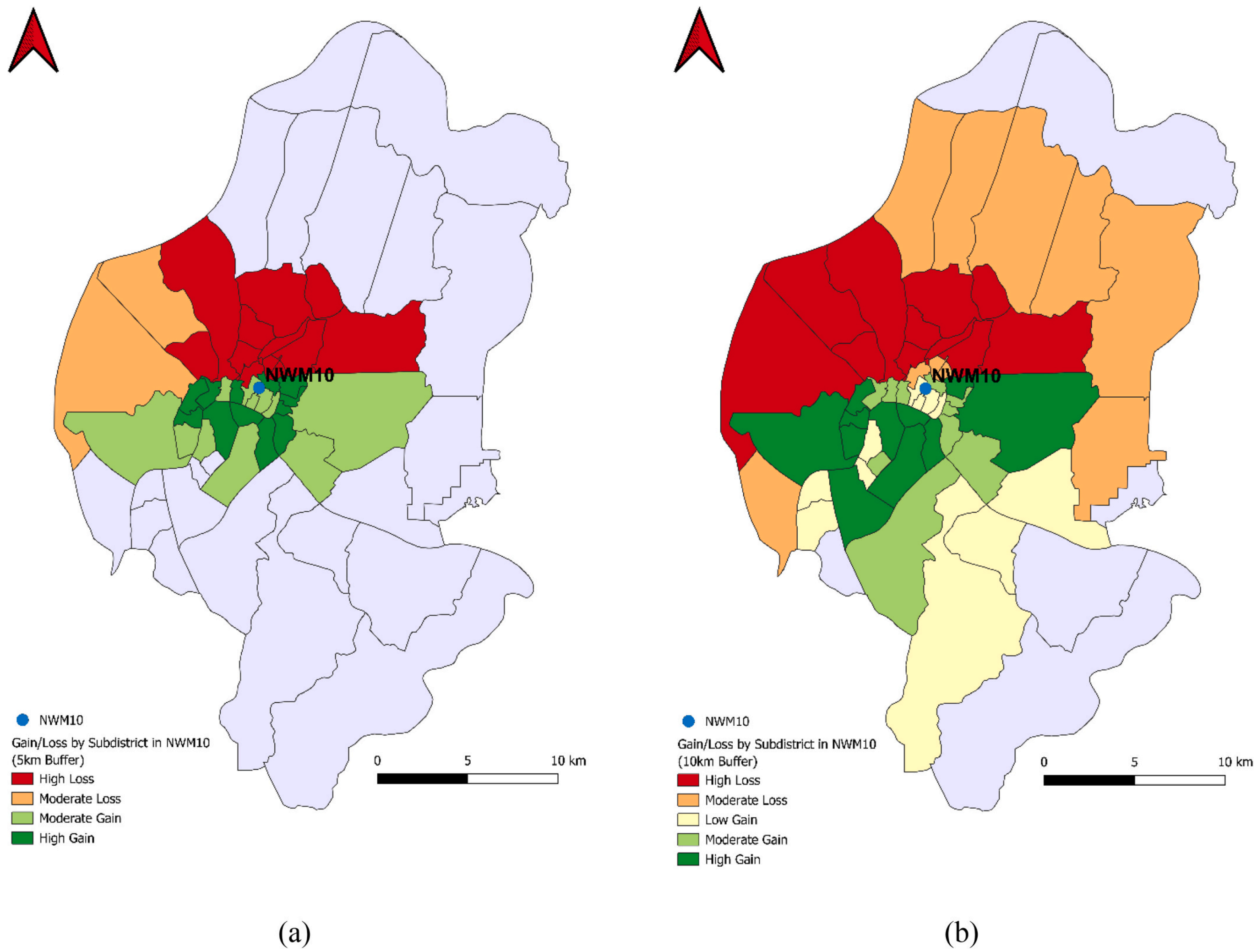


Fig. 7. Gain/loss of accessibility in subdistricts for NWM10 - (a) 5 km buffer (b) 10 km buffer.

NWM10 with planning for a market development in designated growth corridors, NWM4 or NWM11 to redistribute activity, extend equitable access, and shape future demand in locations anticipated to experience infrastructure and residential expansion.

In addressing the importance of methodological robustness, the policy driven variation of the α parameter can be regarded as a form of integrated sensitivity analysis, illustrating how the prioritisation between efficiency and equity shapes site selection. The stability observed in the rankings, particularly the consistent performance of NWM10 across different α values, indicates that certain locations remain robust under varying policy preferences, while others exhibit greater sensitivity. Beyond α, further sensitivity testing could systematically examine key factors such as the service area buffer radius and capacity constraints in multi market configurations. Explicit analysis of these parameters would help clarify the conditions under which relocation recommendations hold, thereby enhancing the model's applicability for evidence based and adaptive urban planning.

5.5.2. General policy implications for wider urban application

Beyond the Samarinda case, the results offer transferable policy insights for other rapidly urbanising cities where wholesale activities remain centralised and mobile vendors play a critical role in last mile food distribution.

- First, the EEI framework provides a generalisable decision support tool that allows policy makers to explicitly articulate their preference for efficiency, equity, or a balance of both through the α parameter. Rather than prescribing a single optimal outcome, this approach enables cities to tailor relocation strategies to their specific development priorities, fiscal constraints, and social objectives.
- Second, the differentiation of candidate sites based on their functional roles, core accessibility hubs versus long-term growth corridor investments, offers a general planning logic applicable across diverse urban contexts. Cities facing similar trade-offs between central congestion and peripheral accessibility can use this logic to plan their relocations rather than treating site location as a one-off decision.
- Third, the consideration of multiple new market relocations highlights the importance of viewing wholesale market relocation as part of a broader spatial reconfiguration of urban distribution systems. In many cities, phased or split market configurations may offer more equitable and resilient outcomes, particularly where informal vendors and dispersed populations are central to urban food access.

The proposed framework offers a transferable analytical template for evidence-based urban logistics planning, enabling cities to move beyond purely cost driven relocation decisions towards more transparent consideration of distributive impacts under varying policy priorities.

6. Concluding remarks

This study develops a generalisable GIS-based framework for evaluating wholesale market relocations by integrating the results from the CWSA routing algorithm with advanced spatial analytics, including kernel density mapping and population-weighted gain/loss analysis. Applied to Samarinda, the paper demonstrates how relocation decisions involve inherent trade-offs between logistical optimisation and spatial equity, thereby reshaping vendor service areas and accessibility outcomes across the city. While the empirical application focuses on Samarinda, the analytical structure is designed to be transferable to other urban contexts facing similar wholesale market relocation challenges.

Empirical results show that while NWM2 is identified by the CWSA as the most operationally efficient, NWM10 consistently delivers the greatest accessibility gains in terms of both area and affected population, while maintaining stable performance across multiple evaluation criteria. Importantly, the supplementary Gini coefficient analysis shows that the accessibility gains and losses associated with the NWM10 are not highly concentrated spatially, indicating a relatively even distribution of impacts across neighbourhoods. This makes NWM10 the strongest candidate for immediate relocation. However, the close proximity of both NWM2 and NWM10 to the existing wholesale market means that their relocation alone may have limited effect in decongesting the city centre. To address this, the analysis points towards the value of a market development strategy that integrates immediate relocation to NWM10 with future development of secondary markets in designated growth corridors such as NWM4 and NWM11. Although their current gain/loss performance is modest, these sites are strategically positioned within areas projected for infrastructure and residential expansion and could evolve into important accessibility hubs over time. This sequencing logic illustrates how short term efficiency gains and longer term spatial rebalancing objectives can be jointly accommodated within a single planning framework.

From a policy perspective, the strength of this framework lies in its flexibility. Rather than prescribing a single solution, it equips authorities with the evidence to select candidate sites that best align with their policy preferences, whether prioritising operational efficiency, spatial equity, or a balance of the two. The results suggest that prioritising NWM10 offers the most inclusive gains, but policymakers may legitimately adopt alternative weightings if fiscal constraints, congestion pressures, or equity concerns dominate their agenda. By making these trade-offs transparent, the framework supports more accountable and participatory decision making. Ultimately, this research underscores that wholesale market relocation is not simply a technical optimisation exercise, but a strategic urban intervention where efficiency and inclusivity must be considered in tandem. This policy flexibility enhances the framework relevance beyond the case study city.

While the empirical results are grounded in a single case study, the analytical logic and decision support structure developed in this research are transferable to other cities facing similar challenges, particularly in rapidly urbanising contexts where informal distribution systems play a central role in food access. These findings further underscore the necessity of incorporating spatial equity and distributive impact analysis alongside of operational efficiency in market relocation decisions. By doing so, policymakers can ensure that relocation strategies do not inadvertently exacerbate inequalities, but instead advance both logistical optimisation and the broader goals of equitable urban service provision.

The spatially explicit metrics and maps produced in this study provide actionable intelligence for city planners, enabling the design of supportive interventions such as targeted subsidies, improved feeder services, or staggered implementation to safeguard vulnerable groups. More broadly, the study affirms the indispensable role of advanced spatial analytics in urban infrastructure planning. Integrating route optimisation, spatial EEI, and distributive impact assessment not only supports more equitable and resilient market relocation strategies but also serves as a replicable model for addressing similar facility location challenges in rapidly urbanising settings.

Nevertheless, limitations of the study should be acknowledged. First, the framework relies on observed vendor travel behaviour and service coverage derived from survey data, without incorporating explicit measures of transaction frequency or shipment volume. Second, travel distances are represented using shortest-path network distances rather than time dependent travel conditions. Finally, although scalability is implicitly examined through twelve alternative market locations which exhibit substantial variation in spatial configuration and operational complexity, the study does not include formal computational benchmarking under systematically varied problem sizes. Despite the limitations mentioned, the method developed in this study is highly suitable for application in wider urban contexts, offering help to local authorities facing the problem of relocating wholesale markets.

CRediT authorship contribution statement

Triana Sharly Permaisuri Arifin: Writing – original draft, Methodology, Formal analysis, Data curation, Conceptualization. **Chandra Balijepalli:** Writing – review & editing, Validation, Supervision. **Anthony Whiteing:** Writing – review & editing, Validation, Supervision.

Declaration of competing interest

None.

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Appendix A. Mobile vendor route segment distances under the Existing Wholesale Market (EWM)

Vendor (V)	From	To	From Longitude	From Latitude	To Longitude	To Latitude
V1	L11	EWM	117.1603	−0.48779	117.1479	−0.48578
V1	EWM	L58	117.1479	−0.48578	117.1675	−0.47365
V1	L58	L57	117.1675	−0.47365	117.1857	−0.47695
V1	L57	L11	117.1857	−0.47695	117.1603	−0.48779
V2	L36	EWM	117.2019	−0.43760	117.1479	−0.48578
V2	EWM	L20	117.1479	−0.48578	117.1544	−0.49413
V2	L20	L11	117.1544	−0.49413	117.1603	−0.48779
V2	L11	L58	117.1603	−0.48779	117.1675	−0.47365

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Vendor (V)	From	To	From Longitude	From Latitude	To Longitude	To Latitude
V2	L58	L36	117.1675	−0.47365	117.2019	−0.43760
V3	L20	EWM	117.1544	−0.49413	117.1479	−0.48578
V3	EWM	L52	117.1479	−0.48578	117.1811	−0.50990
V3	L52	L20	117.1811	−0.50990	117.1544	−0.49413
V4	L14	EWM	117.1647	−0.49513	117.1479	−0.48578
V4	EWM	L12	117.1479	−0.48578	117.1603	−0.51725
V4	L12	L52	117.1603	−0.51725	117.1811	−0.50990
V4	L52	L14	117.1811	−0.50990	117.1647	−0.49513
V5	L38	EWM	117.1523	−0.43345	117.1479	−0.48578
V5	EWM	L27	117.1479	−0.48578	117.1351	−0.47345
V5	L27	L38	117.1351	−0.47345	117.1523	−0.43345
V6	L58	EWM	117.1675	−0.47365	117.1479	−0.48578
V6	EWM	L58	117.1479	−0.48578	117.1675	−0.47365
V7	L38	EWM	117.1523	−0.43345	117.1479	−0.48578
V7	EWM	L37	117.1479	−0.48578	117.1627	−0.42711
V7	L37	L38	117.1627	−0.42711	117.1523	−0.43345
V8	L13	EWM	117.1662	−0.50249	117.1479	−0.48578
V8	EWM	L33	117.1479	−0.48578	117.1412	−0.47841
V8	L33	L13	117.1412	−0.47841	117.1662	−0.50249
V9	L14	EWM	117.1647	−0.49513	117.1479	−0.48578
V9	EWM	L12	117.1479	−0.48578	117.1603	−0.51725
V9	L12	L14	117.1603	−0.51725	117.1647	−0.49513
V10	L55	EWM	117.1544	−0.48361	117.1479	−0.48578
V10	EWM	L57	117.1479	−0.48578	117.1857	−0.47695
V10	L57	L58	117.1857	−0.47695	117.1675	−0.47365
V10	L58	L55	117.1675	−0.47365	117.1544	−0.48361
V11	L49	EWM	117.1162	−0.50061	117.1479	−0.48578
V11	EWM	L12	117.1479	−0.48578	117.1603	−0.51725
V11	L12	L49	117.1603	−0.51725	117.1162	−0.50061
V12	L36	EWM	117.2019	−0.43760	117.1479	−0.48578
V12	EWM	L36	117.1479	−0.48578	117.2019	−0.43760
V13	L41	EWM	117.2411	−0.40291	117.1479	−0.48578
V13	EWM	L37	117.1479	−0.48578	117.1627	−0.42711
V13	L37	L41	117.1627	−0.42711	117.2411	−0.40291
V14	L13	EWM	117.1662	−0.50249	117.1479	−0.48578
V14	EWM	L52	117.1479	−0.48578	117.1811	−0.5099
V14	L52	L13	117.1811	−0.5099	117.1662	−0.50249
V15	L41	EWM	117.2411	−0.40291	117.1479	−0.48578
V15	EWM	L38	117.1479	−0.48578	117.1523	−0.43345
V15	L38	L41	117.1523	−0.43345	117.2411	−0.40291
V16	L58	EWM	117.1675	−0.47365	117.1479	−0.48578
V16	EWM	L30	117.1479	−0.48578	117.1455	−0.48445
V16	L30	L58	117.1455	−0.48445	117.1675	−0.47365
V17	L49	EWM	117.1162	−0.50061	117.1479	−0.48578
V17	EWM	L49	117.1479	−0.48578	117.1162	−0.50061
V18	L15	EWM	117.1603	−0.50673	117.1479	−0.48578
V18	EWM	L18	117.1479	−0.48578	117.1456	−0.50258
V18	L18	L15	117.1456	−0.50258	117.1603	−0.50673
V19	L13	EWM	117.1662	−0.50249	117.1479	−0.48578
V19	EWM	L18	117.1479	−0.48578	117.1456	−0.50258
V19	L18	L13	117.1456	−0.50258	117.1662	−0.50249
V20	L14	EWM	117.1647	−0.49513	117.1479	−0.48578
V20	EWM	L52	117.1479	−0.48578	117.1811	−0.5099
V20	L52	L14	117.1811	−0.5099	117.1647	−0.49513
V21	L15	EWM	117.1603	−0.50673	117.1479	−0.48578
V21	EWM	L33	117.1479	−0.48578	117.1412	−0.47841
V21	L33	L15	117.1412	−0.47841	117.1603	−0.50673
V22	L15	EWM	117.1603	−0.50673	117.1479	−0.48578
V22	EWM	L16	117.1479	−0.48578	117.1449	−0.49785
V22	L16	L18	117.1449	−0.49785	117.1456	−0.50258
V22	L18	L15	117.1456	−0.50258	117.1603	−0.50673
V23	L14	EWM	117.1647	−0.49513	117.1479	−0.48578
V23	EWM	L30	117.1479	−0.48578	117.1455	−0.48445
V23	L30	L14	117.1455	−0.48445	117.1647	−0.49513
V24	L58	EWM	117.1675	−0.47365	117.1479	−0.48578
V24	EWM	L58	117.1479	−0.48578	117.1675	−0.47365
V25	L14	EWM	117.1647	−0.49513	117.1479	−0.48578
V25	EWM	L33	117.1479	−0.48578	117.1412	−0.47841
V25	L33	L14	117.1412	−0.47841	117.1647	−0.49513
V26	L58	EWM	117.1675	−0.47365	117.1479	−0.48578
V26	EWM	L58	117.1479	−0.48578	117.1675	−0.47365
V27	L39	EWM	117.1558	−0.45977	117.1479	−0.48578
V27	EWM	L39	117.1479	−0.48578	117.1558	−0.45977
V28	L57	EWM	117.1857	−0.47695	117.1479	−0.48578
V28	EWM	L27	117.1479	−0.48578	117.1351	−0.47345
V28	L27	L57	117.1351	−0.47345	117.1857	−0.47695

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Vendor (V)	From	To	From Longitude	From Latitude	To Longitude	To Latitude
V29	L46	EWM	117.1076	−0.49159	117.1479	−0.48578
V29	EWM	L46	117.1479	−0.48578	117.1076	−0.49159
V30	L36	EWM	117.2019	−0.43760	117.1479	−0.48578
V30	EWM	L20	117.1479	−0.48578	117.1544	−0.49413
V30	L20	L58	117.1544	−0.49413	117.1675	−0.47365
V30	L58	L36	117.1675	−0.47365	117.2019	−0.4376
V31	L58	EWM	117.1675	−0.47365	117.1479	−0.48578
V31	EWM	L36	117.1479	−0.48578	117.2019	−0.43760
V31	L36	L58	117.2019	−0.43760	117.1675	−0.47365
V32	L57	EWM	117.1857	−0.47695	117.1479	−0.48578
V32	EWM	L27	117.1479	−0.48578	117.1351	−0.47345
V32	L27	L57	117.1351	−0.47345	117.1857	−0.47695
V33	L31	EWM	117.1471	−0.46576	117.1479	−0.48578
V33	EWM	L55	117.1479	−0.48578	117.1544	−0.48361
V33	L55	L28	117.1544	−0.48361	117.1185	−0.47959
V33	L28	L27	117.1185	−0.47959	117.1351	−0.47345
V33	L27	L31	117.1351	−0.47345	117.1471	−0.46576
V34	L55	EWM	117.1544	−0.48361	117.1479	−0.48578
V34	EWM	L28	117.1479	−0.48578	117.1185	−0.47959
V34	L28	L55	117.1185	−0.47959	117.1544	−0.48361
V35	L36	EWM	117.2019	−0.43760	117.1479	−0.48578
V35	EWM	L36	117.1479	−0.48578	117.2019	−0.43760
V36	L36	EWM	117.2019	−0.43760	117.1479	−0.48578
V36	EWM	L36	117.1479	−0.48578	117.2019	−0.43760
V37	L30	EWM	117.1455	−0.48445	117.1479	−0.48578
V37	EWM	L30	117.1479	−0.48578	117.1455	−0.48445
V38	L11	EWM	117.1603	−0.48779	117.1479	−0.48578
V38	EWM	L58	117.1479	−0.48578	117.1675	−0.47365
V38	L58	L11	117.1675	−0.47365	117.1603	−0.48779
V39	L36	EWM	117.2019	−0.43760	117.1479	−0.48578
V39	EWM	L57	117.1479	−0.48578	117.1857	−0.47695
V39	L57	L36	117.1857	−0.47695	117.2019	−0.43760
V40	L36	EWM	117.2019	−0.43760	117.1479	−0.48578
V40	EWM	L55	117.1479	−0.48578	117.1544	−0.48361
V40	L55	L58	117.1544	−0.48361	117.1675	−0.47365
V40	L58	L36	117.1675	−0.47365	117.2019	−0.43760
V41	L38	EWM	117.1523	−0.43345	117.1479	−0.48578
V41	EWM	L38	117.1479	−0.48578	117.1523	−0.43345
V42	L13	EWM	117.1662	−0.50249	117.1479	−0.48578
V42	EWM	L18	117.1479	−0.48578	117.1456	−0.50258
V42	L18	L13	117.1456	−0.50258	117.1662	−0.50249
V43	L58	EWM	117.1675	−0.47365	117.1479	−0.48578
V43	EWM	L59	117.1479	−0.48578	117.1643	−0.47061
V43	L59	L58	117.1643	−0.47061	117.1675	−0.47365
V44	L58	EWM	117.1675	−0.47365	117.1479	−0.48578
V44	EWM	L58	117.1479	−0.48578	117.1675	−0.47365
V45	L11	EWM	117.1603	−0.48779	117.1479	−0.48578
V45	EWM	L17	117.1479	−0.48578	117.1566	−0.50517
V45	L17	L11	117.1566	−0.50517	117.1603	−0.48779
V46	L36	EWM	117.2019	−0.43760	117.1479	−0.48578
V46	EWM	L31	117.1479	−0.48578	117.1471	−0.46576
V46	L31	L39	117.1471	−0.46576	117.1558	−0.45977
V46	L39	L36	117.1558	−0.45977	117.2019	−0.43760
V47	L57	EWM	117.1857	−0.47695	117.1479	−0.48578
V47	EWM	L11	117.1479	−0.48578	117.1603	−0.48779
V47	L11	L57	117.1603	−0.48779	117.1857	−0.47695
V48	L57	EWM	117.1857	−0.47695	117.1479	−0.48578
V48	EWM	L55	117.1479	−0.48578	117.1544	−0.48361
V48	L55	L57	117.1544	−0.48361	117.1857	−0.47695
V49	L36	EWM	117.2019	−0.43760	117.1479	−0.48578
V49	EWM	L31	117.1479	−0.48578	117.1471	−0.46576
V49	L31	L36	117.1471	−0.46576	117.2019	−0.43760
V50	L36	EWM	117.2019	−0.43760	117.1479	−0.48578
V50	EWM	L31	117.1479	−0.48578	117.1471	−0.46576
V50	L31	L39	117.1471	−0.46576	117.1558	−0.45977
V50	L39	L38	117.1558	−0.45977	117.1523	−0.43345
V50	L38	L36	117.1523	−0.43345	117.2019	−0.43760

Data availability

The data that has been used is confidential.

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