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A Real-Time, Multi-Method Approach to Functional Metropolitan Delimitation: The Case of Guatemala City

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ABSTRACT: *A different methodology has been developed for the functional delimitation of metropolitan areas, integrating the Gravity Model, Cluster Analysis, and Geographic Information Systems (GIS), along with real-time data to improve spatial and temporal precision. In contrast to conventional approaches dependent on static administrative boundaries; this method captures the dynamic behavior of urban systems by incorporating variations in mobility patterns, land use, accessibility, and economics. The collaborative integration of spatial modeling techniques with live data streams, allowing the continuous adjustment of metropolitan boundaries in response to actual urban transformations is an important contribution of this methodology. This methodology was applied to the context of Guatemala City and the approach reveals zones of functional interconnection that extend beyond political jurisdictions, thus offering a more flexible and transferable framework for metropolitan areas undergoing rapid growth. As a result, the method represents an important advance in urban planning practices—providing an adaptive, data-driven, and context-sensitive tool.*

KEYWORDS: *Functional delimitation, metropolitan areas, gravity model, cluster analysis, GIS, real-time data, Guatemala City Metropolitan Area.*

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I. INTRODUCTION

Guatemala City is in the central highlands of Guatemala, sits within a valley surrounded by mountains, ravines, and volcanic formations. This complex topography has historically limited urban expansion and fostered a pattern of fragmented and irregular growth, which is demonstrated over recent decades, the Guatemala City Metropolitan Area (GCMA) has experienced rapid demographic expansion, primarily driven by internal migration from rural regions and natural population increase; it is home to over 4 million people, with the Municipality of Guatemala City alone accounting for nearly 1 million residents. The demographic concentration of this metropolitan area has been increasing pressure on infrastructure, housing, mobility networks, and public services.

The delimitation of metropolitan areas has become a critical issue in contemporary urban planning, particularly in accelerated growing regions like Guatemala City, traditional approaches, which rely on administrative boundaries or statistical units defined by census data, often fall short in capturing the fluid and complex nature of modern urban systems. These methods are typically static, jurisdictionally bounded, and unable to account for the socio-spatial interactions and mobility patterns that extend beyond municipal limits; that's the reason, why Feria (2008), Tong & Plane (2014), Ouředníček et al. (2018), and Sánchez & Cebrián (2021) consider that these models fail to reflect the dynamic and trans-scalar processes that shape metropolitan spaces.

The dynamic and trans-scalar limitations had demonstrated that functional delimitation has emerged as a more responsive and spatially grounded alternative (Carvajal & Argueta, 2024); this approach emphasizes actual flows of people, goods, services, and capital, enabling a more accurate understanding of urban influence zones. Gómez et al. (2020) and Lui et al. (2021) have demonstrated how functional criteria, including land use and mobility behavior, can effectively delineate metropolitan extents. In those cases, techniques such as the Gravity Model, Cluster Analysis, and Geographic Information Systems (GIS) have proven particularly valuable because they allow urban influence to be measured based on interaction rather than legal-political boundaries (Orihuela & Sobrino, 2023).

Guatemala City provides a particular case for testing an integrated functional delimitation framework due to its complex territorial dynamics, socioeconomic characteristics, and lack of cohesive metropolitan governance; at the same time, the city's fragmented urban development is shaped by natural barriers (e.g., ravines, rivers, hills), dispersed settlements, and irregular connectivity. As a result, these characteristics underscore the need for a methodological approach that integrates structural and functional urban dimensions and adapts to temporal and spatial change.

There is a necessity of proposing a multi-method framework that combines the Gravity Model, Factor Analysis, Cluster Analysis, and GIS, improved by real-time data from GPS, mobile applications, and digital traffic platforms; because of that the Gravity Model serves to quantify the intensity of interzonal interactions based on population, land use, travel time, and distance—factors that traditional applications often fail to dynamically incorporate (Liu et al., 2010; Feria, 2004; Aguirre et al., 2023); then the Cluster Analysis complements this by categorizing areas with similar economic, infrastructural, and ecological characteristics, allowing for the identification of both contiguous and non-contiguous functional zones (Burneo & Ordoñez, 2023; Andrés et al., 2023).

The integration of real-time data introduces a critical temporal layer into the analysis. As shown by McMillen (2001) and Gómez et al. (2020), platforms such as Google Maps, Waze, and other GPS-based sources reveal daily fluctuations in travel behavior, congestion, and route performance—variables typically absent from conventional planning tools; the incorporation of dynamic data facilitates the identification of evolving urban hotspots, informal connections, and real-time patterns of accessibility, providing a more adaptable and accurate perspective on metropolitan connectivity. At the same time, uniting these elements into a single analytical framework fills an important gap in literature and responds to the growing demand for flexible, evidence-based tools in urban governance. Due to that, the Guatemala City case not only demonstrates the utility of this approach but also offers a replicable model for other metropolitan regions facing rapid change and spatial complexity across Latin America.

Table 1 illustrates the comparative advantage of this methodology and contrasts traditional administrative-based delimitation with the proposed functional approach; while conventional models rely on fixed, outdated data and produce static boundaries, the integrated methodology allows continuous updates using real-time data and spatial clustering. And this responsiveness is essential in contexts like Guatemala City, where urban transformation is ongoing and multifaceted.

Table. 1.
Contrasts of the traditional administrative-based delimitation with the proposed functional approach

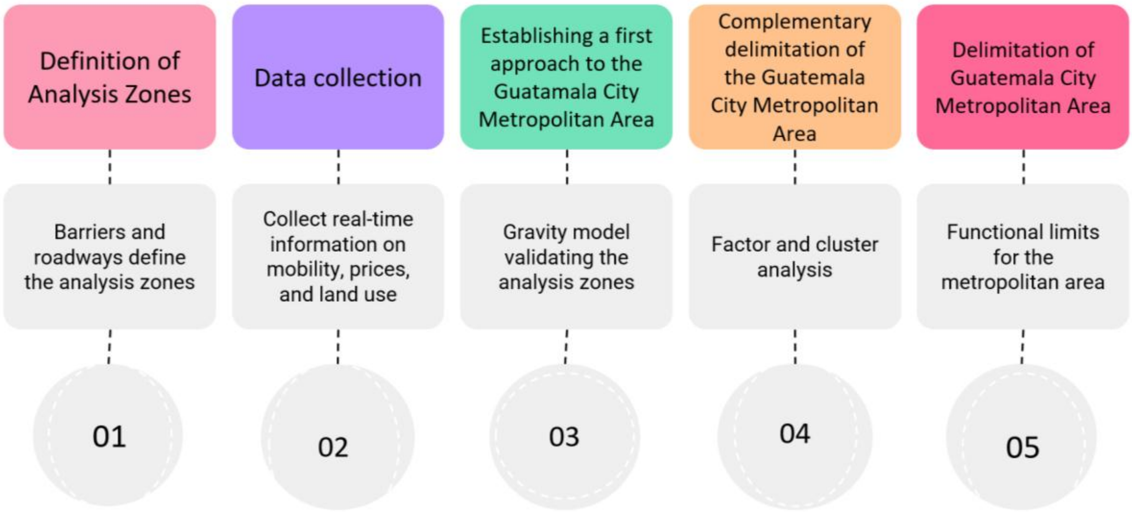
Criteria	Traditional approach	Proposed Methodology (Integrated)
Data Type	Static (Census, Plans)	Dynamic (Real-Time, GIS)
Boundaries	Fixed, Administrative	Flexible, Functional
Adaptability	Limited	High
Identification of interactions	Restricted	Comprehensive
Application Context	Predefined Areas	Continuously Updating

Note. Differences between the traditional administrative-based delimitation and the functional delimitation derived from the proposed methodology.

II. METHODOLOGY

This study proposes a multi-method and adaptive framework for the functional delimitation of metropolitan areas (Figure 1); this novelty approach lies in the seamless integration of spatial modeling techniques with real-time data, allowing for continuous refinement of urban boundaries in response to actual territorial dynamics. This approach as different of the traditional methodologies grounded in static census information, the proposed framework leverages both structural and functional indicators to define metropolitan space based on real interactions, accessibility, and spatial cohesion.

Figure 1.
Methodology to the functional delimitation of metropolitan area



Gravity Model of Urban Interaction

The Gravity Model is used to quantify the intensity of functional relationships between urban centers and surrounding zones and this model is based on the premise that interaction levels are directly proportional to the "mass" of each zone—measured through population or economic activity—and inversely related to distance or travel cost. That is the reason why González & Sarmiento (2009), López & Aguilar (2019), and Evans (2020), interaction flows between zones are operationalized through:

$$\ln V_{ij} = \ln G + \quad \alpha \ln(M_i) + \beta \ln(M_i) - \ln(D_{ij}) \qquad (1)$$

The model integrates both physical and behavioral variables and includes travel times, alternative routes, delays, land cover, and geographic coordinates (latitude and longitude), enhancing the conventional gravity structure through dynamic spatial inputs. These multidimensional variables are detailed in Table 2.

Cluster Analysis for Functional Zoning

To complement and validate the mobility-based findings, Cluster Analysis is applied to identify zones with similar structural and functional attributes. This technique groups areas according to shared characteristics in land use, land prices, and accessibility, revealing both contiguous and non-contiguous zones that exhibit core-periphery relationships. It enables the identification of monocentric and polycentric patterns, as demonstrated by Burneo & Ordoñez (2023) and Andrés et al. (2023). In this study, the clustering process reinforces the functional delimitation by capturing spatial heterogeneity and coherence beyond the predictive scope of the gravity model.

Geographic Information Systems (GIS)

GIS serves as the central platform for integrating, analyzing, and visualizing the diverse spatial data sets used in the study. Natural barriers such as ravines, hills, and rivers are georeferenced and mapped based on Fuentes & Cuberos (2014), providing insights into territorial discontinuities that may influence urban connectivity. Additionally, GIS overlays layers of land use, accessibility, and demographic data to support zoning and cluster validation.

Real-Time Data Integration

To incorporate temporal dynamism, the methodology includes real-time data from GPS devices, mobile applications, and traffic platforms such as Google Maps and Waze. This integration aligns with the work of Gómez et al. (2020) and McMillen (2001), providing a responsive layer of analysis capable of detecting evolving urban conditions. Real-time inputs enrich the gravity model and cluster analysis by offering granular data on travel speeds, congestion, route alternatives, and peak-hour behaviors—dimensions absent from traditional, static datasets (Feria, 2008; Liu et al., 2010).

Variables and Operational Definitions

The integrated methodology relies on a combination of conceptual and operational variables to capture the physical, functional, and socio-economic fabric of the metropolitan area. Table 2 summarizes the key indicators used for modeling and classification.

Table 2.
Variables, Conceptual Definitions, and Operational Definitions

Variables	Theoretical or Conceptual Definition	Operational Definition (Indicators)
Mobility	Collective social practice involving travel from residences to locations offering services and opportunities (López & Aguilar, 2019; Evans, 2020).	M_1=FORESTS, M_2=CROPLANDS, M_3=GRASSLANDS, M_4=URBAN, M_5=DISTANCE(KM), M_6=DISTANCE (MINUTES, real-time data), M_7=ALTERNATIVES ROUTES (real-time data), M_8=DELAYS (real-time data), M_9=BLUE SEGMENT OF ROUTE (MINUTES, real-time data), M_{10}=YELLOW SEGMENT OF ROUTE (MINUTES, real-time data), M_{11}=RED SEGMENT OF ROUTE(MINUTES, real-time data), M_{12}=PURPLE SEGMENT OF ROUTE(MINUTES, real-time data), M_{13}=Latitude, M_{14}=Longitude
Land Use	Functional occupation of a defined surface area.	Categories (km²): 1. Forested areas 2. Cultivated areas 3. Grassland areas 4. Water bodies 5. Urban areas 6. Other types of areas.
Land Prices	Market value of land depending on supply, demand, location, and urban pressure (Borrero, 2008).	Value in quetzales per m² of undeveloped land, located on the city outskirts and in traffic analysis areas, as of 2023.
Natural Urban Barriers	Structural physical elements of natural origin (e.g., rivers, ravines, hills) that define, condition, or restrict the fluid interaction of agents, ideas, conceptions, and lifestyles. (Fuentes & Cuberos, 2014).	Georeferenced location of hills, ravines, or rivers. Length (km) of the natural barrier.

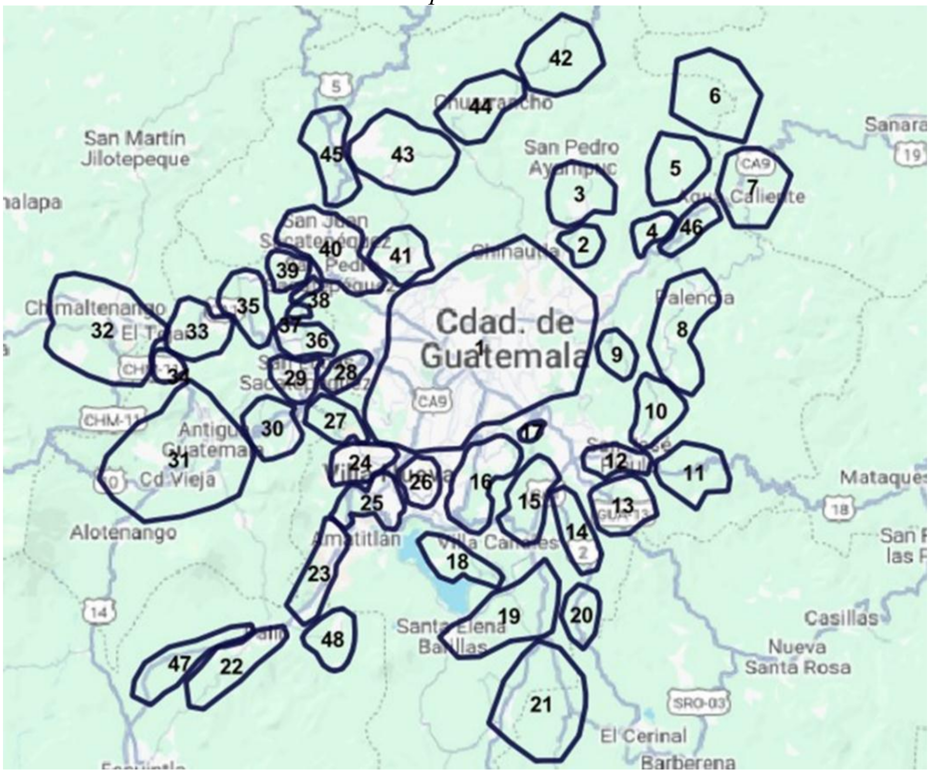
Despite advancements in each individual technique, prior studies have rarely integrated them into a unified, adaptive framework. This study addresses that gap by proposing a real-time, multi-method approach to metropolitan delimitation. By combining the strengths of the Gravity Model, Cluster Analysis, GIS, and real-time data, it captures both the structural and functional dimensions of urban systems. This integrated methodology provides a replicable model not only for Guatemala City but also for other rapidly transforming metropolitan regions.

Study Area: Guatemala City

Guatemala City's Metropolitan Area (GCMA) is the largest and most densely populated urban agglomeration in Guatemala. It serves as the country's political, economic, cultural, and social hub, hosting approximately 25% of the nation's total population within a relatively small geographical area. The metropolitan region encompasses the Municipality of Guatemala City along with several surrounding municipalities, forming a complex and interconnected urban system.

The delimitation of the analysis zones, as illustrated in the Figure 2, was guided by the identification of natural and infrastructural barriers that shape urban form and function in the Guatemala City Metropolitan Area. Hills, ravines, and bodies of water such as lakes were considered as physical obstacles that restrict urban continuity and influence settlement patterns. Additionally, the connectivity and accessibility of the roadway network played a crucial role in determining the extent and configuration of each zone. These criteria ensured that the zones represent internally cohesive units with meaningful spatial and functional relationships, forming a solid basis for subsequent modeling and clustering analysis.

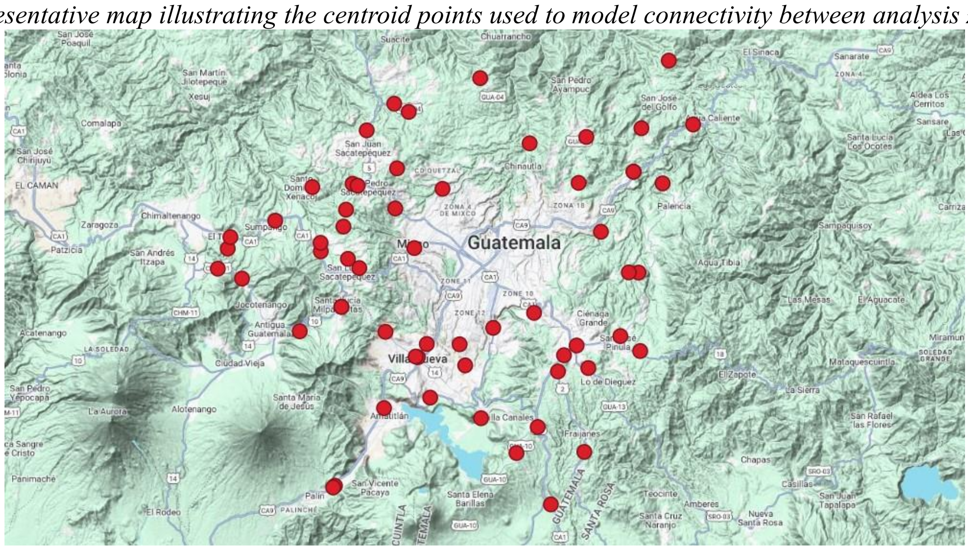
Figure 2.
Representative visualization image showing the analysis zones for data collection of the Guatemala City Metropolitan Area



Note. Illustration created by the authors with QGIS.

The Figure 3 presents the centroidal points that represent each of the defined analysis zones within the Guatemala City Metropolitan Area. These centroids were not only instrumental in delineating spatial units but also played a critical role in shaping the analytical approach. As reference anchors for calculating inter-zonal distances, they facilitated the operationalization of the gravity model used to quantify urban interactions and flows. Moreover, the spatial logic underlying their distribution prompted a re-evaluation of variable acquisition strategies, ensuring that socio-spatial indicators were appropriately aggregated and spatially representative. Beyond serving as geometric proxies, the centroids effectively structured the modeling of territorial connectivity, thereby contributing to a more nuanced and functionally grounded understanding of the metropolitan configuration.

Figure 3.
Representative map illustrating the centroid points used to model connectivity between analysis zones

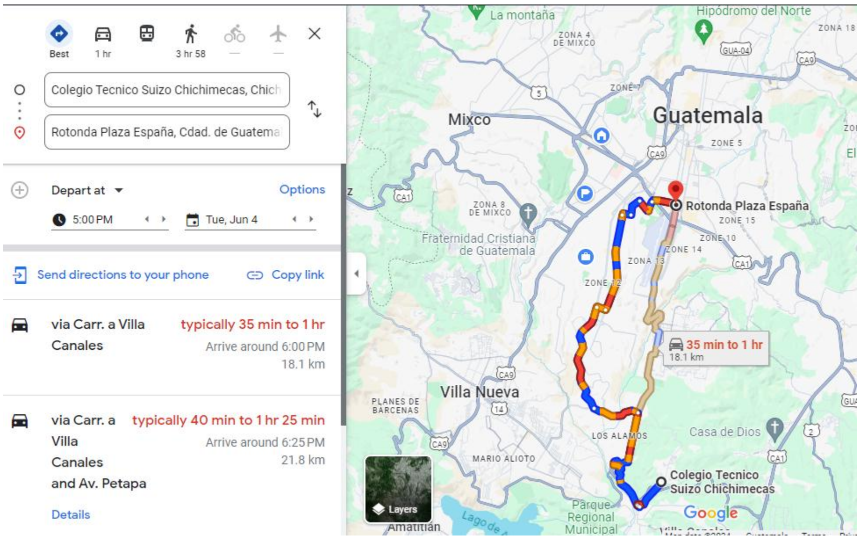


Note. These points serve as the basis for calculating inter-zonal interactions in the gravity model. Map developed by the authors using QGIS.

This figure 4 presents a sample route used to illustrate how real-time mobility data was integrated into the analysis. By capturing dynamic travel information—such as delays, route segments, and estimated durations during peak hours—this approach allowed for a more accurate understanding of commuting patterns and temporal variability within the metropolitan area. The data served to complement traditional sources by providing insight into actual travel behaviors, congestion hotspots, and the performance of the transport network under stress. This information was instrumental in enhancing the gravity model and refining the spatial interactions between analysis zones.

Figure 4.

Representative visualization image showing the routes between zones in terms of time and distance



Note. Created by the authors with Google Maps.

III. DISCUSSION

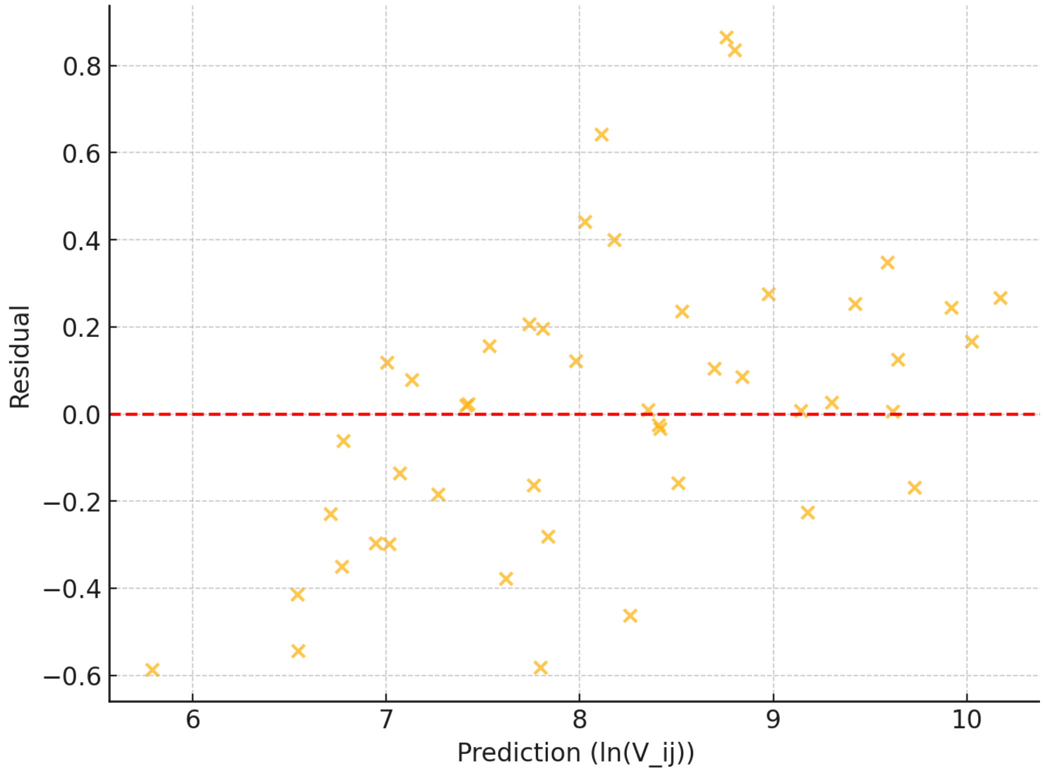
Gravity Model Application

The first approach to delineating a probable metropolitan area was developed by applying a gravity model improved through the Random Forest algorithm. This model estimated the intensity of trip generation from surrounding zones toward Zone 1, considered the central area of the urban region. By incorporating a wide range of predictors—including land cover types, travel distances and times, and geographic coordinates—the model effectively captured the spatial dynamics and functional linkages between zones. The resulting predictions, which achieved a high coefficient of determination ($R^2 = 0.933$), provided a reliable picture of the zones that exhibit strong daily interactions with the central core, offering a robust proxy for functional urban integration.

This mobility-based estimation allowed for the identification of zones that consistently generate high volumes of trips toward the central area, thereby forming a first, data-driven approximation of the metropolitan territory. The influence of spatial variables such as latitude and longitude, together with urban land use and accessibility indicators, revealed geographic trends that go beyond administrative boundaries (Carvajal & Argueta, 2025). These findings support the notion that metropolitan areas are best understood as functional entities shaped by interaction patterns, rather than fixed political delineations.

The Random Forest algorithm (Breiman, 2001) was employed due to its ability to capture non-linear relationships and handle a wide range of predictor variables. This approach offered a robust framework for modeling the complexity inherent in urban mobility patterns. The model delivered excellent performance, achieving a coefficient of determination (R^2) of 0.933, which reflects a strong explanatory power.

Figure 5.
Residuals of the Random Forest Model and its residual to select the Gravity Model

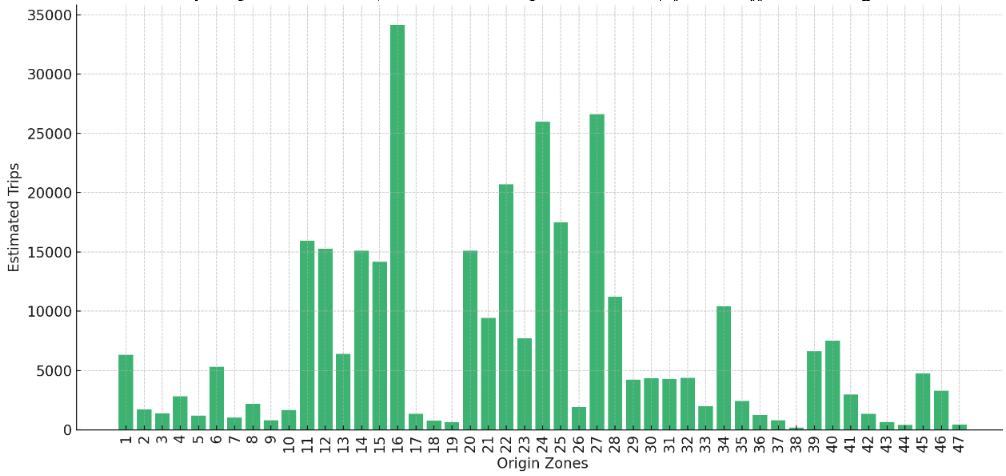


Traditionally, gravity models have been used to estimate flows between geographic zones. However, these models often rely on empirically derived parameters, which can be difficult to calibrate and may lead to imprecise predictions. To enhance predictive accuracy and leverage recent advancements in data science, a Random Forest model was applied to a set of variables that had been previously transformed using natural logarithms (Figure 5).

The gravity model developed through Random Forest demonstrated high performance in predicting trip generation between zones. In addition to capturing complex relationships among variables, the model's behavior was further clarified through a linear regression approximation, enabling interpretability and practical use in urban and transportation planning contexts.

$$\begin{aligned}\ln V_{1j} = 51.8893 &- 0.0775\ln(M_1) - 0.8076\ln(M_2) - 0.58\ln(M_3) + 0.56\ln(M_4) + 1.5279\ln(M_5)\\ &- 1.3318\ln(M_6) + 0.3869\ln(M_7) - 1.3586\ln(M_8) + 0.3967\ln(M_9) + 0.0970\ln(M_{10})\\ &- 0.2726\ln(M_{11}) - 0.1120\ln(M_{12}) + 2.7568\ln(M_{13}) + 0.8267\ln(M_{14}) \quad (2)\end{aligned}$$

Figure 6.
Estimated daily trips to zone 1 (Central metropolitan area) from different origin zones



A first approach to delineating (Figure 6) the metropolitan area can be based on the intensity of estimated trips from surrounding zones to Zone 1, the central urban core. By using trip volume as a proxy for functional integration, zones with high trip generation—such as those between zones 11 to 17 and 22 to 27—can be preliminarily included within the metropolitan boundary. This mobility-based criterion reflects strong daily interactions and urban dependency, offering a meaningful first delimitation grounded in actual movement patterns. To complement this approach, cluster analysis can be applied in the next stage to group zones with similar mobility behaviors and reinforce the consistency and validity of the metropolitan delimitation.

Cluster Analysis Results

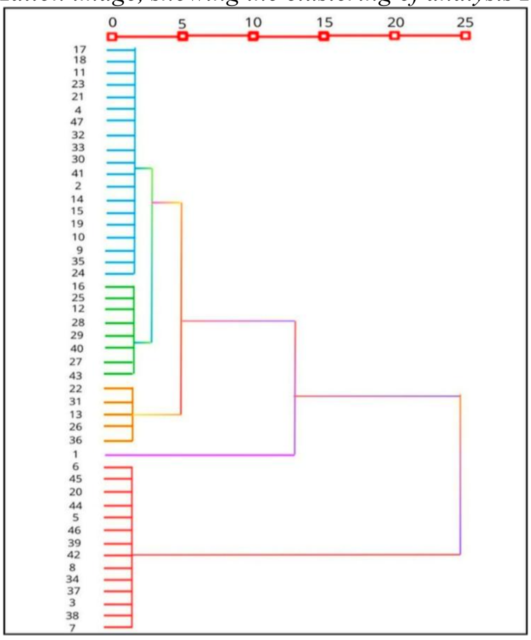
The definition of the Metropolitan Guatemala City was achieved by integrating four key factors that combine variables related to land use, accessibility, economic value, and ecological connectivity (Table 3). Factor 1 focuses on urban areas' accessibility to water bodies and other lands, measured by travel distances and times (outbound and return), highlighting connectivity to the urban core. Factor 2 combines grasslands and urban areas with return distance and land price, reflecting the economic valuation of urbanized and semi-urbanized zones. Factor 3 emphasizes the spatial relationship between crops, grasslands, and water bodies, identifying agricultural and natural areas that interact functionally with the metropolitan region. Factor 4 groups forests and grasslands, capturing ecological connectivity and identifying natural peripheries. These combined factors provide a comprehensive framework that integrates urban functionality, economic valuation, accessibility, and natural landscape interactions to define the extent of the Metropolitan Guatemala City.

Table 3.
Combinations of variables and an explanation about each factor

Factor	Variables
1	Water - Urban - Other lands - Outbound km - Outbound min - Return km - Return min
2	Grasslands - Urban - Return km - Price
3	Crops - Grasslands - Water
4	Forests - Grasslands

The dendrogram displayed (Figure 7) is a hierarchical clustering representation that groups different analysis zones by their similarity based on a combination of various factors (Vichi, Cavicchia, & Groenen, 2022). These factors include land use, land price, and distance to the center of Zone 1 (measured in both kilometers and minutes). The y-axis lists the analysis zones represented by numbers, while the x-axis indicates the linkage distance or dissimilarity between clusters. The colors of the branches signify different clusters formed during the hierarchical clustering process.

Figure 7.
Representative visualization image, showing the clustering of analysis zones by their distance



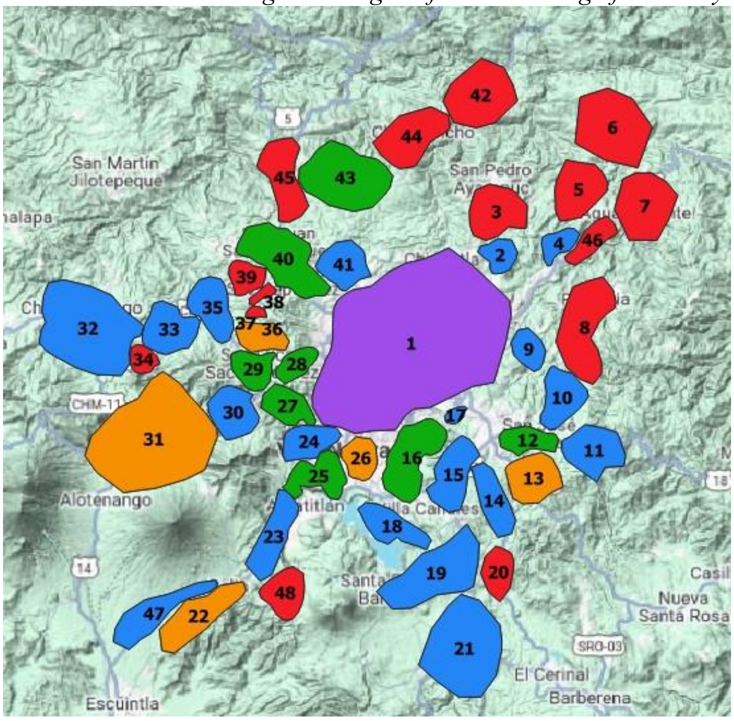
Note. Created by authors with IBM SPSS v26 and Canva.

Zones positioned at the top of the dendrogram (connected with shorter horizontal lines) are closely related or share similar characteristics according to the combined factors of land use, land price, and proximity to Zone 1. These zones have been grouped early in the clustering process, indicating high similarity or homogeneity. For instance, clusters represented by blue and green branches are likely to have similar land use patterns, comparable land prices, or similar distances to the central area of Zone 1.

On the other hand, zones located towards the bottom of the dendrogram (connected by long horizontal lines such as those in red) are more distinct from the others. This suggests that these areas differ significantly in terms of land use, have considerably different land prices, or are located farther away from the central area of Zone 1. The longer linkage distances required to merge these zones indicate that they are outliers or exhibit unique characteristics compared to the more cohesive clusters above.

The Figure 8 illustrates the functional classification of zones within the Guatemala City Metropolitan Area, based on cluster analysis results. At the center, Zone 1 (in purple) represents the urban core, characterized by high accessibility, density, and strong interaction with surrounding areas. The remaining zones are grouped by color according to their functional similarity: green and orange zones indicate areas with moderate to high connectivity and transitional urban characteristics; blue zones, generally farther from the center, reflect lower integration and more rural or peripheral features; and red zones stand out due to their distinct land use patterns, geographic constraints, or limited urban interaction. This spatial configuration highlights the varying degrees of metropolitan integration and supports a more nuanced, data-driven understanding of urban structure beyond administrative boundaries.

Figure 8.
Representative visualization image showing the final clustering of the analysis areas



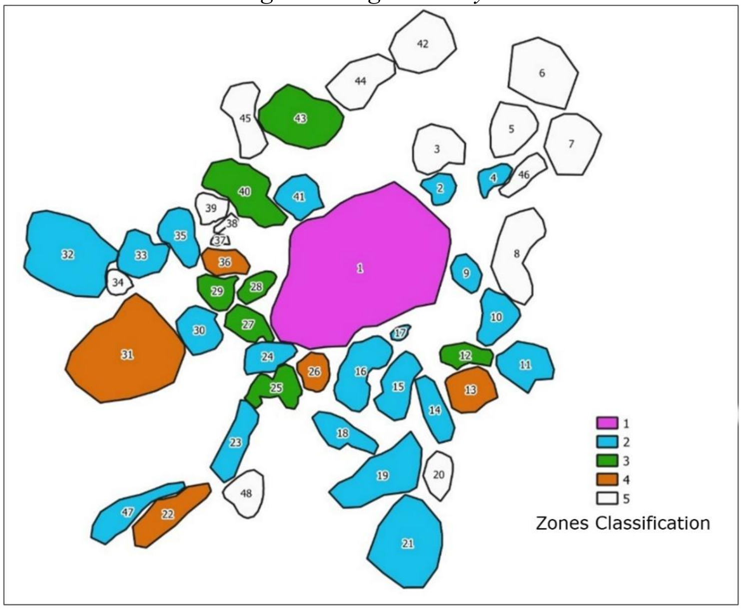
Note. Made by authors with QGIS.

IV. FINDINGS

The map in Figure 9 introduces a spatial classification of the analysis zones surrounding Guatemala City, derived from the integration of spatial, economic, and functional indicators. This visualization does not simply reflect proximity to the urban core but rather reveals a hierarchy of territorial integration based on the interplay between land use, land value, and accessibility. Each color-coded polygon represents a functional grouping identified through cluster analysis, signaling varying levels of metropolitan connectivity.

Zone 1, shown in purple at the center, operates as the system's core—not only in geographic terms but also in terms of intensity of interaction and urban centrality. Surrounding it, green and orange clusters delineate areas that, while not fully consolidated, exhibit a high degree of functional attachment, likely driven by infrastructural continuity or socio-economic flows. These areas suggest corridors of urban expansion and emerging sub-centers.

Figure 9.
Representative visualization image showing the analysis areas included in the GCMA

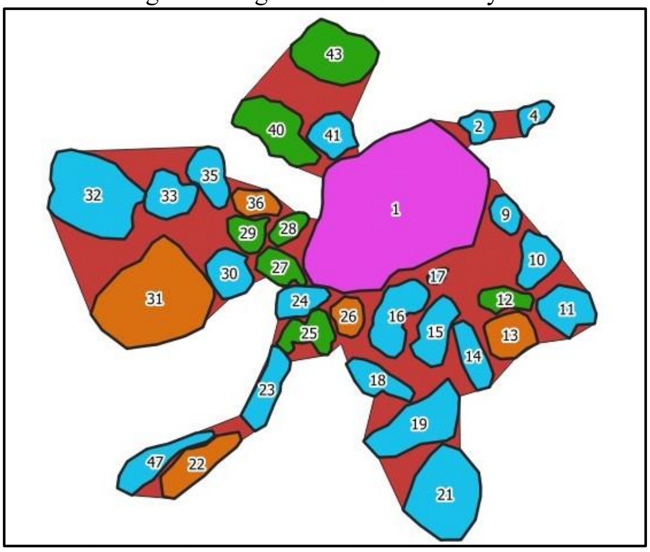


Note. Made by authors with ARCGIS.

In contrast, the blue and red zones—positioned toward the outer ring—highlight territories with weaker ties to the metropolitan core. These classifications capture more than distance: they reflect spatial discontinuities, such as natural barriers, and distinct land use profiles, such as rural or transitional zones. The white zones are excluded from the functional definition entirely, as they lack sustained interaction patterns with the metropolitan system, underscoring the importance of differentiated territorial treatment in regional planning.

The Figure 10 further consolidates these insights by presenting the finalized boundary of the Guatemala City Metropolitan Area (GCMA) as defined by functional criteria. This boundary moves beyond traditional administrative delineations by adopting a dynamic perspective, sensitive to real patterns of mobility and territorial behavior. The result is a responsive and evidence-based delimitation, capable of guiding spatial planning, investment prioritization, and governance structures in a more targeted and equitable manner.

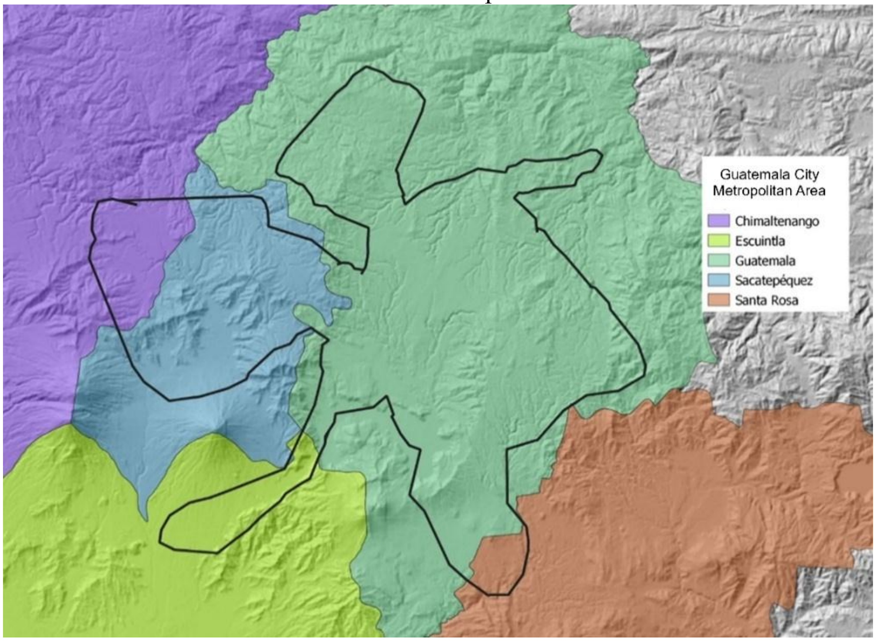
Figure 10.
Representative visualization image showing the AMCG boundary with the included analysis areas.



Note. Made by authors with interpolation using Voronoi-Thiessen polygons, ARCGIS.

The delineated metropolitan area of Guatemala City, as illustrated in the Figure 11, now spans across five distinct departments: Guatemala, Sacatepéquez, Escuintla, Chimaltenango, and Santa Rosa. This functional expansion transcends conventional political-administrative borders, highlighting the need to reassess metropolitan governance and coordination mechanisms. While the core remains within the Department of Guatemala, the incorporation of adjacent territories—particularly from Escuintla and Sacatepéquez—reflects dynamic socio-spatial interactions such as commuting flows, land use intensification, and infrastructural connectivity. This underscores the importance of approaching metropolitan planning from a territorial systems perspective, rather than being constrained by department-level jurisdictions.

Figure 11.
Representative visualization image showing the delimitation of the Guatemala City Metropolitan Area (GCMA) in relation to the departments.



Note. Made by authors with ARCGIS.

An important spatial insight from this visualization is the westward orientation of metropolitan growth. The black boundary defining the functional urban area shows a notable concentration toward the west of the traditional urban core. This asymmetric expansion suggests an emerging reconfiguration of the geographic and functional center of the metropolitan region. Key factors behind this trend may include highway corridors, lower land prices, and topographical suitability for urban development. This westward bias not only challenges the centrality of historic core zones but also points to potential future nodes of metropolitan influence, such as in Sacatepéquez and western Chimaltenango. Recognizing this shift is crucial for anticipating new patterns of accessibility, infrastructure demand, and territorial inequality in the metropolitan region.

V. CONCLUSIONS

The proposed methodology offers a dynamic alternative to conventional administrative-based delineation of the Guatemala City Metropolitan Area (GCMA) by focusing on functional urban relationships rather than static political boundaries. One of the main characteristics of the new functional delimitation that the metropolitan area has an extension of approximately 1,451 km², encompassing parts of 40 municipalities across the departments of Guatemala, Sacatepéquez, Escuintla, and Santa Rosa. In contrast to previous delimitations, which has included 2,557 km² and the entirety of 26 municipalities; those delimitations often incorporate areas with limited or no functional ties to the metropolitan core. In that case, such overgeneralization leads to spatial inconsistencies, as it includes agricultural lands, steep slopes, and ravines—features that disrupt urban continuity, accessibility, and the effective delivery of public services.

The integration of a gravity model and real-time mobility data enabled the identification of zones with high functional interaction, particularly from the west and southwest corridors leading into the city; these zones exhibit shorter travel times and distances (generally under 30 km and 80 minutes, respectively), although they can extend beyond 43 km and 90 minutes in more remote cases. At the same time, the use of real-time data sources such as Google Maps and Waze enhanced the predictive power of the model, capturing dynamic patterns that traditional static datasets cannot. So, the first approach using the gravity model, which has a based-on mobility intensity and spatial accessibility, provided a robust foundation for delineating functionally connected zones within the GCMA.

On that basis and to strengthen and validate this initial approximation, cluster analysis was applied as a complementary method, integrating additional variables such as land use, land prices, accessibility, and ecological conditions. This second analysis allowed for the identification of spatially and functionally cohesive groups of zones, distinguishing between urban cores, transitional areas, and natural peripheries. At the same time, Cluster analysis revealed the CGMA's diverse spatial composition, showing that while the central zones are predominantly urban, peripheral areas display a mix of agricultural, forest, and pasture lands. As a complement, Land value gradients further reinforced these spatial distinctions, with the highest prices concentrated near the urban core and secondary peaks in regional hubs like Chimaltenango and Antigua Guatemala.

In the end, the combined methodology demonstrates that understanding metropolitan structure requires a multivariate, real-time, and spatially explicit approach and the gravity model alone provides strong evidence of functional interactions, but it is the complementary integration of cluster analysis that captures the complex socio-spatial fabric of the metropolitan area. As a result, this dual approach ensures that the resulting delimitation is not only accurate in terms of mobility flows but also reflective of territorial, economic, and environmental dynamics.

The new gravity model developed is notable important because it does not only quantifies the intensity of interactions between zones but also reveals how different variables—such as land use, travel time, distance, accessibility, and geographic position— but contribute to shaping the functional structure of the metropolitan area; that is the reason why, traditional gravity models that rely on static parameters characterized by incorporating a broader set of spatial and real-time variables, allowing for a deeper exploration of how specific territorial and infrastructural conditions influence urban connectivity. At the end, by identifying which variables most strongly drive trip generation toward the urban core, the model provides valuable insights into the underlying dynamics of metropolitan integration and this evidence-based approach supports more accurate and responsive planning decisions, helping define a metropolitan area that reflects actual mobility behavior and spatial interdependence rather than relying solely on political boundaries.

The incorporation of real-time data plays a pivotal role in refining the functional delimitation of the Guatemala City Metropolitan Area, and, at the same time, the real-time inputs—such as live traffic conditions, GPS mobility traces, and digital commuting behaviors—capture temporal fluctuations and emergent patterns of accessibility that static datasets overlook. In conclusion, within the gravity model, these dynamic variables directly influenced the estimation of interzonal interactions by revealing actual travel times, route choices, and congestion levels, all which condition urban connectivity in practice and the temporal sensitivity enabled the detection of short-term mobility trends and persistent flow corridors, thereby improving accuracy of the metropolitan boundary.

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