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Advancing land use mix through complementarity: the Parcel Complementarity Model (PCM)

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Abstract

This paper introduces the Parcel Complementarity Model (PCM), a parcel-level analytical tool for evaluating and optimising land use mix through observed patterns of use and movement. Rather than relying on compositional measures such as land use mix diversity or proportional balance, PCM conceptualises land use mix as a system of functional complementary interaction shaped by asymmetric trip flows, visit frequency, and spatial adjacency. Using cadastral land use data and mobility survey data from the Madrid metropolitan area, the model quantifies both inter-parcel and intra-parcel complementarity through a Parcel Complementarity Index (PCI). PCM is applied to vacant parcels in Tres Cantos (Spain), which are treated as gaps within existing neighbourhood-scale functional complementarity sets rather than as isolated development opportunities. A multi-objective optimisation process is used to explore alternative land use allocation and configuration scenario under existing regulatory constraints. The results show that improvements in land use mix complementarity depend less on the presence of additional uses and more on how land uses are positioned and configured in relation to surrounding parcels and existing functional interaction patterns. PCM provides a transparent and replicable method for evaluating parcel-level complementarity and supporting early-stage planning decisions grounded in empirical use and movement relationships.

Keywords Land use mix, Functional complementarity, Evolutionary algorithms, NSGA-II, Data-driven planning, Evidence-based planning

1 Introduction

Land use mix (LUM) is a widely promoted principle in urban planning and is commonly framed as a strategy to support more sustainable, efficient, and livable cities (Zhuo et al., 2022). Conceptually, it refers to the spatial configuration and allocation of varied urban functions, such as living, working, shopping, and leisure, within the same neighbourhood or district, allowing residents to access multiple activities within relatively short distances (Duan et al., 2025; Vorontsova et al., 2016). In this context, allocation refers to the area and assignment of specific land use categories within a parcel, while configuration captures how these uses are distributed across different parcels within an urban area. This configuration may take the form of spatial structure between distinct single-use parcels or the integration of multiple functions within the same parcel through vertically or horizontally multi-use development (Al-Kodmany, 2019). Strategically planned mixed land uses are often associated with planning efforts that aim to foster more walkable environments by reducing spatial separation between activities and limiting the need for long-distance travel. Such planning approaches are also linked to broader objectives related to local economic vitality, reduced car dependence, social interaction, and environmental performance (Baeza et al., 2021). These principles underpin

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contemporary paradigms such as the 15-Minute City, which emphasizes neighbourhoods where daily needs can be met within a short walk or bicycle trip and promotes the decentralisation of urban services (Büttner et al., 2024; Moreno et al., 2021). More recently, the COVID-19 pandemic has further highlighted the relevance of LUM by illustrating how adaptable mixed-use environments can support community resilience during periods of disruption (Hejazi et al., 2023; Pentenrieder, 2025).

While LUM is often treated as a desirable planning condition, it is not sufficient on its own to guarantee successful urban outcomes. Practical challenges frequently arise, including land use conflicts, increased pressure on shared infrastructure, and unintended consequences such as rising property values that may displace long-term, lower-income residents (Ferm & Jones, 2016; Khan et al., 2022; Kim & Lee, 2024). In certain contexts, mono-functional areas such as industrial zones fulfill specific roles within the urban system, and introducing additional uses may undermine their operational effectiveness (Abel et al., 2015; Grodach & Guerra-Tão, 2024). Accordingly, decisions between maintaining single-use parcels and introducing multi-use ones must be evaluated in relation to their broader spatial, functional, cultural, and real estate context rather than treated as universally preferable (Gregorowicz-Kipszak et al., 2024; Zheng & Wang, 2024). Together, these limitations indicate that the effectiveness of LUM depends not merely on the presence or closeness of multiple functions, but on how these functions relate to one another through actual patterns of use and movement. In this sense, the success of LUM is shaped by context-specific factors, including infrastructure capacity, social conditions, and the functional relationships between land uses as revealed through observed mobility flow. This study focuses on the latter.

Building on this foundation, advancing LUM development requires moving beyond commonly used planning notions that treat mixed use primarily as the designation or co-location of multiple functions, towards a more operational understanding of how land uses are allocated and combined at a fine spatial scale, namely the parcel level. In largely built urban environments, opportunities to modify land use patterns are constrained, and planning interventions typically occur through the development of vacant or underutilised parcels rather than through comprehensive restructuring (Ahn, 2024; Nuissl et al., 2021). Under these conditions, the relevance of LUM depends on how specific uses, their floor areas, and their spatial distribution within and across parcels interact with existing urban functions and patterns of use (Wandl & Hausleitner, 2021). In parcel-based representations of land use, parcels that contain multiple uses are often represented solely by the land-use category that occupies the largest share of floor area, reducing internal multiuse to a single functional label (Hu et al., 2016). In practice, this simplification can influence redevelopment or infill decisions by obscuring how secondary uses within the same parcel contribute to surrounding activity patterns and functional relationships in the urban system (Jansen et al., 2007). This shifts attention from LUM as an abstract objective to LUM as a targeted infill strategy, where vacant parcels serve as the primary means through which functional relationships between uses can be adjusted within the existing urban fabric (Geyer, 2024; Gregorowicz-Kipszak et al., 2024; Somanath et al., 2025).

One way in which land-use mix operates is through the spatial and functional relationships that structure everyday activity patterns, including movements between residential areas and employment locations, access to services and amenities, and trips linking housing with education, retail, or recreational uses (Kockelman, 1997; Kuncheria et al., 2025; Vojnovic et al., 2013; Zhuo et al., 2025). Mixed-use configurations matter not merely because multiple uses coexist, but because they shape how people move between them, thereby reinforcing or weakening functional linkages across urban space (Casali et al., 2024; Lopane et al., 2023; Mackett, 1993; Shaw & Xin, 2003). In this sense, land-use mix becomes operational through the way spatial allocation and floor-area distribution structure observable interaction flows (Zhao et al., 2023). The direction and frequency of these flows influence whether mixed-use configurations operate as active urban systems characterised by sustained interaction, accessibility, and frequent cross-use engagement, or as relatively inactive systems in which uses coexist but generate limited everyday movement (Xing et al., 2022). Although land-use mix can also be examined through environmental, social, or economic lenses, mobility provides a measurable and behaviourally grounded perspective through which these interaction patterns become empirically observable (Chen & Lu, 2025; Chuang & Chen, 2025; Liu et al., 2021; Pastorino et al., 2022).

To advance the understanding and practical assessment of LUM, the notion of complementarity introduces a lens on functional interaction, understood here as the way specific land uses interact through observed patterns of use and movement between them, thereby positioning human mobility as the central operational dimension for evaluating LUM takes research beyond measures focused primarily on land use diversity presence towards measurable interaction-based assessment. Rather than focusing solely on the number or variety of uses, this approach highlights the importance of complementarity, acknowledging that not any LUM is valuable simply because of its diversity, but rather depending on whether the combined functions are functionally related through how people move between them (Hess et al., 2001).

Complementarity is defined by the functional and spatial relationships between land uses, specifically by examining how trip-generating uses operate as origins and how trip-attracting uses function as destinations, depending on the purpose of the trip and the observed flows between uses (Carpio-Pinedo et al., 2021). For instance, certain land use combinations, such as residential and employment-related uses, show strong functional complementarity because people frequently move between their homes and job locations. However, these origin–destination relationships are often asymmetric. Destinations may become new starting points for subsequent trips, but not in equal volume or direction. The number of trips from home to work, for example, is not necessarily matched by an equivalent number of trips returning directly home. This highlights how different land uses are functionally linked through uneven, yet connected, patterns of use and movement across the urban system (Kretzer et al., 2024; Louail et al., 2015; Minal et al., 2022). These continuous, multi-directional, and often asymmetric flows between land uses constitute the core of this paper's contribution.

In practice, the evaluation and implementation of LUM remain complex tasks for planners, particularly in urban contexts where opportunities for change are limited and interventions are largely confined to a small number of vacant or underutilised parcels (Hasan & Liu, 2025; Jacobs-Crisioni et al., 2014; Jinollo et al., 2025; Li et al., 2024). Under such infill conditions, decisions about land use allocation and configuration carry disproportionate importance, as adjustments affect not only the parcels themselves but also their interaction with the surrounding built fabric (Song & Ling, 2025; Soward & Li, 2021).

LUM evaluation and optimisation complexity is further shaped by socio-political dynamics, competing stakeholder interests, and normative judgments about acceptable urban change. Within these constraints, computational decision-support tools, including optimisation-based approaches, can assist planners by systematically generating land use allocation and configuration solutions under multiple regulatory and spatial constraints (Cao et al., 2020; Stewart et al., 2004; Xiao et al., 2002). When applied to LUM, such approaches allow planners to evaluate land use configurations in relation to existing functional interaction patterns (Drici & Carpio-Pinedo, 2025). These scenarios help assess whether specific mixes align with goals such as compactness, equitable access, or reduced single-use dominance (Wang et al., 2019). Although these solutions cannot be treated as direct prescriptions, they support data-driven decision-making by structuring land use allocation and configuration choices within existing planning constraints, while remaining open to broader social, cultural, and political considerations.

This study develops and implements the Parcel Complementarity Model (PCM), a parcel-level tool for evaluating and optimising LUM complementarity in largely built urban environments. PCM operationalises complementarity through the Parcel Complementarity Index (PCI), which captures asymmetric functional relationships between land uses based on observed origin–destination trip flows, visit frequencies, and parcel-level spatial adjacency. PCI comprises two components: inter-parcel interaction and intra-parcel allocation. Inter-parcel complementarity evaluates how parcels participate in asymmetric interaction structures across spatially separated uses, incorporating adjacency effects. Intra-parcel complementarity assesses whether the internal floor-area shares of co-located uses are proportionally aligned with the same directional interaction weights. Rather than rewarding uniform distribution, PCI evaluates internal allocation using this shared behavioural interaction structure. This distinction reflects the scale at which mixed-use designation and floor-area allocation are regulated within parcel boundaries. Building on this evaluative structure, the model applies a multi-objective optimisation process to explore LUM allocation and configuration for vacant parcels under existing planning constraints. The model is demonstrated through a case study in Tres Cantos, Madrid, illustrating how parcel-level LUM decisions can be systematically assessed and refined in relation to observed patterns of use and movement interaction.

2 Background

2.1 Assessment of urban land use mix

The relationship between land use patterns and transportation has been a long-standing focus in urban research, forming a core paradigm for understanding urban structure and activity distribution (Cervero & Kockelman, 1997; Ewing and Cervero, 2010). Yet, despite the existence of this literature, approaches to measuring LUM remain diverse in how LUM is conceptualised and operationalised, with no widely adopted framework that consistently operationalises functional interaction between land uses alongside their spatial configuration. These differences arise because LUM has been defined and measured in different ways: some studies conceptualise mix as proportional presence balance between land-use categories, most commonly through entropy-based indices that quantify evenness within a spatial unit; others as compatibility or suitability between specific land-use combinations based on planning or environmental criteria; others as functional interaction inferred from observed travel flow linking origin–destination uses; and others as spatial configuration or allocation at specific scales such as parcels or street blocks. These approaches measure different underlying constructs and are rarely combined within a single evaluative structure (Jiao et al., 2021a; Song et al., 2013).

One key challenge is that not all forms of land use diversity are functionally equivalent. Diversity-based indices, such as Shannon's entropy and Simpson's index, capture the evenness-based diversity of land use categories within an area but do not differentiate between distinct combinations of uses or their functional roles (Hu et al., 2025; Im & Choi, 2019; Noordzij et al., 2021; Noseir et al., 2023; Shi et al., 2022; Yue et al., 2017). In practice, entropy is a concept originally derived from ecological diversity, where it measures species evenness, and it is not calibrated to represent behavioural or mobility relationships between human activities (Carpio-Pinedo et al., 2021; Manaugh & Kreider, 2013). As a result, two areas may receive identical diversity scores while generating very different interaction patterns, since these metrics capture evenness rather than interaction linkage between land-use pairs (Im and Choi, 2019; Jiao, et al., 2021b; Manaugh & Kreider, 2013).

In addition to diversity measures, some studies assess land-use mix through compatibility or suitability matrices that evaluate whether specific land-use combinations are considered functionally or environmentally appropriate according to planning standards and expert criteria (La Rosa & Privitera, 2013; Luan et al., 2021; Pahlavani et al., 2020; Steiner et al., 2000; Yeh & Li, 1999). These approaches typically apply predefined weights to land-use pairings, focusing on the normative suitability of co-location rather than on empirically observed interaction structures between uses (Hashemkhani Zolfani et al., 2022; Mansourihanis et al., 2023).

Further, existing interaction-based approaches differ in how they represent relationships between land uses. Some studies model interaction complementarity through symmetric association measures, implicitly treating use-to-use interactions as reciprocal, which restrict their ability to capture the asymmetric nature of urban mobility (Cabanas-Tirapu et al., 2025; van Dam et al., 2023; Zhang et al., 2025). In contrast, other studies distinguish between trip-generating and trip-attracting functions, separating origin and destination flows when defining complementarity (Carpio-Pinedo et al., 2021; Ren et al., 2020), but typically assign land-use categories predefined roles as either trip-generating or trip-attracting functions within the travel system, rather than modelling variable bidirectional interaction profiles. Complementarity-based approaches therefore moves the attention from proportional balance to interaction between specific land-use pairs.

While much of the LUM literature operates at neighbourhood or grid scales(Jiang & Xiong, 2024; Song & Knaap, 2004; Xu et al., 2017), a few recent studies have emphasised the need for parcel-level assessment, as planning regulation and real estate change occur at this scale (Carpio-Pinedo et al., 2021; Fisu et al., 2024; Hu et al., 2024), Other research focused on the three-dimensional and morphological complexity of the built environment, combining diversity, accessibility, and compatibility indicators at fine spatial resolutions (Kumakoshi et al., 2021; Motieyan & Azmoodeh, 2021). Some studies have further incorporated economic pressures in hyper-dense contexts, where land values influence the dominance of commercially oriented uses, and have begun adapting such frameworks to optimisation-based approaches (Zhou et al., 2024).

While existing approaches capture specific dimensions of LUM, few simultaneously account for asymmetric, empirically observed movement between a wide range of land uses at the parcel-level in a form that can be directly embedded within LUM optimisation processes. This paper proposes and positions the Parcel Complementarity Index (PCI) within this landscape as an evaluative measure of LUM grounded in observed origin–destination flows, visit frequencies of land uses, and their spatial adjacency, designed to operate consistently at the parcel-level and to help inform subsequent land use allocation and configuration decisions.

2.2 Optimisation of urban land use mix

A growing body of urban planning research has addressed LUM through optimisation-based allocation models, where land use functions are assigned to discrete spatial units under multiple constraints. In these studies, the core planning task is typically formulated as a spatial allocation problem, in which land use categories are distributed across parcels, plots, or land cells based on predefined objectives and suitability conditions (Ding et al., 2021; Haque & Asami, 2011). Input data commonly include land suitability maps, zoning regulations, infrastructure capacity limits, and demand targets, while model outputs consist of optimised land use layouts indicating the assigned use or dominant function for each spatial unit.

Many parcel-level allocation models assign a single dominant land use to each parcel or spatial unit. These models often optimise criteria such as land suitability scores, compactness of land use patches, compatibility between neighbouring uses, or accessibility measures derived from distance thresholds or network proximity (Haque & Asami, 2014; Masoomi et al., 2013; Porta et al., 2013). Optimisation outputs typically take the form of optimised spatial layouts that satisfy regulatory constraints while improving one or more objective functions related to land use allocation and configuration. While effective for organising large-scale land use patterns, these approaches generally represent parcels as single-use entities, limiting their capacity to capture parcels that already contain multiple co-existing functions.

Other optimisation models extend parcel- or patch-level allocation by incorporating economic or environmental performance variables directly into the objective functions. In these cases, land use allocation is guided by variables such as land value, development cost, ecological suitability, carbon emissions, or habitat connectivity, often derived from remote sensing data, environmental indicators, or economic statistics (García et al., 2017; Liu et al., 2022; Pan et al., 2023). Model outputs typically prioritize spatial layouts that maximize or minimize these performance indicators at the system level, resulting in land use patterns optimised for economic return or environmental performance rather than for functional interaction between uses.

Heuristic and rule-based allocation frameworks represent another strand of work, where LUM is guided by predefined compatibility matrices or expert-defined rules that specify which land use types should co-locate or be separated (Eom et al., 2020). These models often rely on qualitative assumptions about land use interaction and produce deterministic allocation outcomes, offering transparency but limited flexibility in representing variations in use intensity or empirical patterns of movement between functions.

Across these approaches, evolutionary optimisation methods are widely used to search large solution spaces efficiently. Systematic reviews consistently report Genetic Algorithms and NSGA-II as the most commonly applied techniques in urban land use allocation due to their ability to handle discrete decision variables, multiple constraints, and competing objectives (Drici & Carpio-Pinedo, 2025; Rahman & Szabó, 2021).

Most optimisation-based land use models operate by assigning a single dominant land use to each parcel and producing allocation outputs accordingly. While this approach has been widely applied to address ecological, economic, or commercial compatibility objectives, comparatively limited attention has been given to how land uses interact through observed patterns of use and movement between parcels. As a result, parcels that already contain multiple functions are often simplified, and functional relationships embedded in observed mobility flows are not sufficiently investigated. This creates space for evaluative and multi-use optimisation approaches that first assess existing LUM conditions and then guide parcel-level allocation and configuration in ways that align more closely with observed patterns of movement between urban land uses.

3 Methodology

This section presents the study area and the data used in the analysis and then details the formulation of the Parcel Complementarity Model (PCM), including the construction of the Parcel Complementarity Index (PCI) and its integration within the NSGA-II optimisation framework.

3.1 Study area and data

Tres Cantos, a planned new town 27 km north of Madrid Fig. 1, spans 37.93 km^2 with a population of 51,453 (2023) (Agenda Urbana—Ayuntamiento de Tres Cantos, 2024). Located within the Madrid Metropolitan Area, it is accessible from the Madrid city centre within 30 min by private vehicle or frequent regional trains, enhancing connectivity to the capital. The city features a diverse range of land uses, including single- and collective housing, retail, offices, and industry, with well-integrated pedestrian and cycling infrastructure (Garcia-Garcia et al., 2020). However, residential areas remain distinct from office and industrial zones, reinforcing spatial separation of living and working spaces. As a relatively young city, Tres Cantos provides a unique case study for examining LUM strategies with potential implications for contemporary urban planning practices.

The PCM analysis relies on two primary datasets. The first one is the Spanish Cadastral database, which provides detailed parcel-level data Fig. 2, including coordinates, parcel area, and built floor areas per land use category, filtered to 2,591 parcels for comprehensive analysis (Sede Electrónica Del Catastro, 2024). The second dataset is the latest Mobility Survey of Madrid Region, initiated in 2018 and completed in 2020. Based on 75,208 respondents, this survey captures origin–destination trips and visit frequencies between urban functions (EDM2018VIAJES | Datos Abiertos Del Consorcio Regional de Transportes de Madrid, 2024). The survey covers the entire Madrid metropolitan area, including Tres Cantos, thereby capturing the mobility flows within which interaction patterns are formed. Conducted by an expert team of 320 members, the in-person household component followed a systematic sampling strategy with proportional allocation to ensure minimum representation across transport zones (Consorcio Regional de Transportes de Madrid, 2019; Encuesta domiciliaria de movilidad en día laborable de 2018 en la Comunidad de Madrid (edM2018). Documento I: Metodología y trabajo de campo, 2019). The complementary telephone survey employed a non-probability design structured around age and gender quotas. Proportional balance between

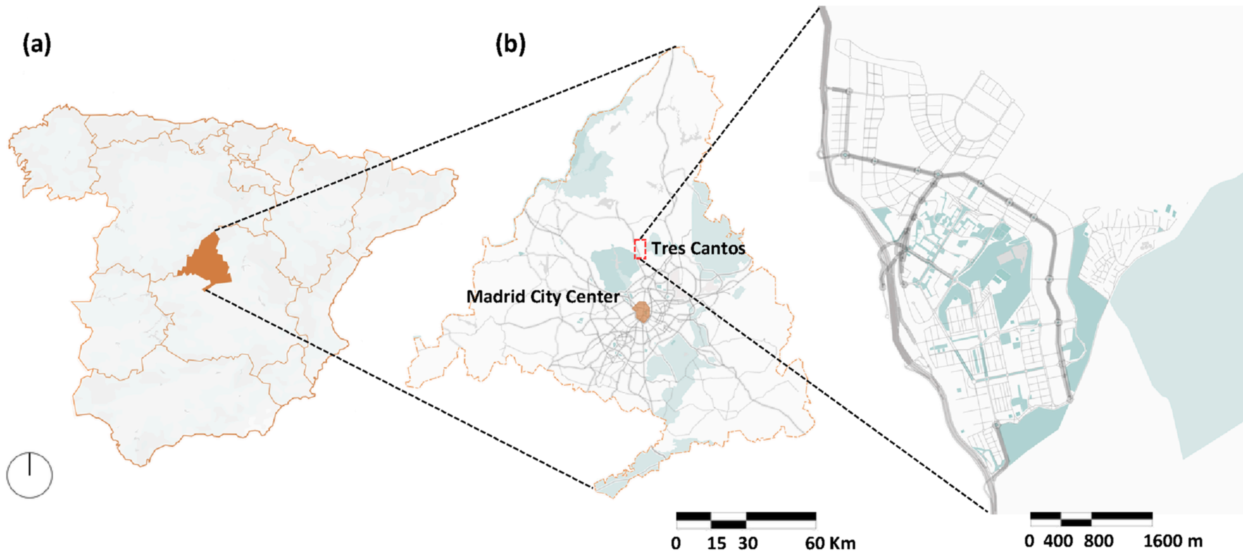


Fig. 1 **a** Location of Madrid region in Spain; **b** Tres Cantos City location in Madrid Metropolitan Area

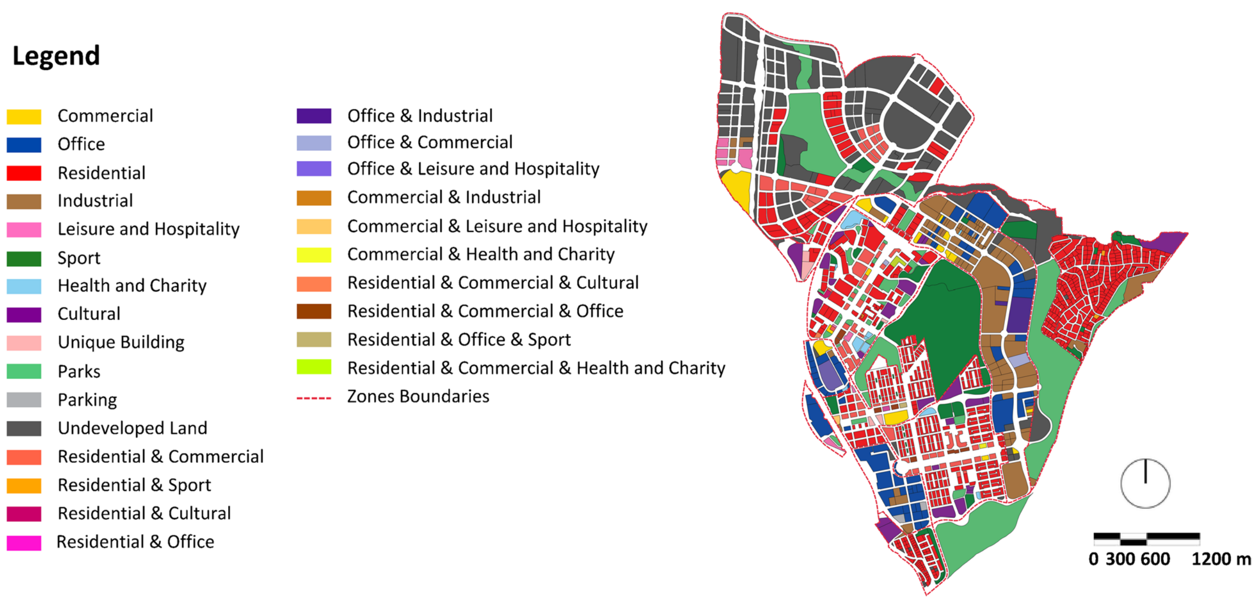


Fig. 2 Map of land use configuration of study area parcels

face-to-face household interviews and telephone surveys was maintained within each transport zone to preserve territorial representativeness in the combined dataset. Integrating these datasets enables an in-depth assessment of urban LUM complementarity, forming a foundation for optimising long-term LUM strategies vis-à-vis movement patterns between uses.

3.2 Parcel Complementarity Index (PCI)

The Parcel Complementarity Index (PCI) quantifies parcel-level land-use complementarity through two components: Inter-parcel PCI is computed using three inputs: Complementarity Weights (origin–destination flow weights allowing unequal magnitudes between land-use pairs), Visit Frequency Weights (measures of how frequently each function is visited as a destination), and Adjacency Weights (distance-based modifiers capturing spatial proximity between parcels).

Intra-parcel PCI is computed using Complementarity Weights and Visit Frequency Weights only, as it evaluates internal allocation without a spatial adjacency component. The following subsections first define these weights and then present the inter- and intra-parcel formulations.

3.2.1 Complementarity weights

Complementarity Weights for the Parcel Complementarity Index (PCI) are derived from the 2018 Urban Mobility Survey of Madrid, which records observed trips between urban functions as origin–destination (O–D) pairs, Table S1 in the supplementary material provides full complementarity weights values for the considered land use categories pairs in this study. Rather than modelling transport flows or travel demand, these data are used to characterize patterns of movement between land use types, reflecting how people move between different urban functions in urban space. The resulting complementarity weights are computed at the land-use category level from O–D counts and are not conditioned on the spatial distance between specific trip origins and destinations; spatial separation is introduced separately through the adjacency term defined in Section 3.2.3. Variations in observed trip count across function pairs capture directional asymmetries in use-to-use movement, indicating that certain destination functions receive a larger share of trips from specific origins than others. To account for these directional differences, trip counts are normalised by origin using the following formulation:

$$C_{w(f_o, f_d)} = \frac{(Trips(f_o, f_d))}{max(Trips(f_o))} \tag{1}$$

Complementarity weights.

Where:

- $\mathbf{C_{w(f_o, f_d)}}$ represents the Complementarity Weight for functions pair $\mathbf{f_o}$ and $\mathbf{f_d}$.
- $\mathbf{f_o}$ and $\mathbf{f_d}$ represent the origin and destination functions, respectively.
- $\mathbf{Trips(f_o, f_d)}$ denotes the number of trips from the origin function $\mathbf{f_o}$ to the destination function $\mathbf{f_d}$.
- $\mathbf{max(Trips(f_o))}$ is the maximum number of trips originating from $\mathbf{f_o}$ to any destination, providing a normalisation factor that scales each weight by the most active origin.

As illustrated in Table S1 in the Supplementary Material, complementarity weights are asymmetric across function pairs due to differences in origin-specific trip distributions. For example, trips from Residential origins to Commercial destinations yield lower normalised weights because Residential origins generate high overall trip volumes, resulting in a larger denominator. In contrast, trips from Commercial origins to Residential destinations may reach a weight of 1 when the destination corresponds to the dominant trip destination from that origin. This formulation ensures that complementarity reflects the relative magnitude of observed trips between functions rather than absolute trip counts.

3.2.2 Visit frequency weights

The Urban Mobility Survey of Madrid includes a visit frequency attribute for each recorded trip, indicating how regularly a destination function is visited Table S2 in the supplementary material provides full visit frequency weights values for the considered land use categories in this study. This information is used to construct Visit Frequency Weights, which capture how often a given land use function is visited, independent of trip origin. Unlike Complementarity Weights, which are directional and based on origin–destination trip counts, Visit Frequency Weights are destination-based and non-directional, reflecting visit frequency rather than movement between functions.

Survey-defined frequency categories are encoded as ordinal values: daily = 5, 2–4 times per week = 4, 1–2 times per week = 3, occasional = 2, and first-time = 1. For each destination function, a weighted average score is computed by multiplying the number of trips associated with each frequency category by its corresponding ordinal value and dividing by the total number of trips to that function. A detailed illustration of this calculation is provided in Supplementary Material Section 3.2.2.1. The formulation is:

$$\mathbf{VF(f)} = \frac{\sum_{\mathbf{i=1}}^{\mathbf{n}} (\mathbf{FrequencyWeight(i)} \cdot \mathbf{TripFrequency(i)})}{\sum_{\mathbf{i=1}}^{\mathbf{n}} \mathbf{TripFrequency(i)}} \tag{2}$$

Weighted average score of trips to destination function.

Where:

- $\mathbf{VF(f)}$ is the weighted average score of trips to function $\mathbf{f}$, which reflects reported visit frequency.
- $\mathbf{FrequencyWeight(i)}$ and $\mathbf{TripFrequency(i)}$ represent the assigned weight and the actual number of trips for the $\mathbf{i}$-th frequency type, respectively.

To ensure comparability across functions, the weighted average scores are normalised by dividing each function’s score by the maximum value observed across all functions:

$$VF_{w(f)} = \frac{VF(f)}{max(VF)} \quad (3)$$

Visit frequency weights.
Where:

- $\mathbf{VF_{w(f)}}$ is the normalised Visit Frequency Weight for function $\mathbf{f}$
- $\mathbf{VF(f)}$ represents the actual visit frequency score for function $\mathbf{f}$ before normalisation.
- $\mathbf{max(VF)}$ is the maximum weighted average score across all functions, which serves as the normalisation factor.

As shown in Table S2 in the Supplementary Material, visit frequency varies across functions. For example, schools classified as cultural functions exhibit high visit frequency values due to regular daily visits by a stable population, even when individual trip volumes are moderate. In contrast, stadiums classified as sports functions receive very high trip volumes on event days but show low visit frequency values because visits are episodic and limited to specific occasions.

3.2.3 Adjacency weights

Adjacency Weights (A_w) are used to account for parcel-level spatial adjacency by moderating land use complementarity based on centroid-to-centroid distance between parcels. The formulation follows distance-decay reasoning, whereby the potential for interaction between urban functions decreases with increasing spatial separation, consistent with gravity-inspired spatial logic commonly applied in urban analysis (García-Palomares et al., 2013; Hansen, 1959; Mitropoulos et al., 2023). Adjacency is treated strictly as a spatial condition and does not model accessibility, pedestrian behaviour, or transport flows. Complementarity weights are defined separately at the land-use category level and do not vary with parcel-to-parcel distance; spatial separation is introduced only through the adjacency term described in this section. Accordingly, Euclidean centroid-to-centroid distance is used as a parsimonious spatial measure to determine which parcels are treated as neighbours within the defined interaction envelope (Chen et al., 2024; Eikelboom et al., 2015; Leń et al., 2024; Maleki et al., 2017; Stewart & Janssen, 2014; Tepe & Guldmann, 2017), rather than to approximate network routing, travel time, or modal impedance.

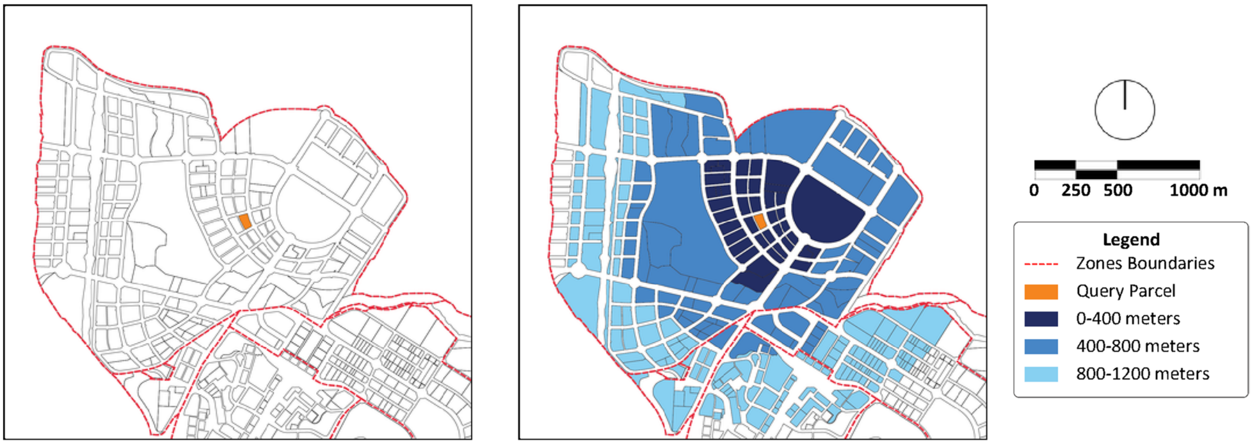
Discrete adjacency weights are assigned as follows: 1.0 for parcels within 0–400 m, 0.75 for parcels within 400–800 m, and 0.50 for parcels within 800–1200 m. These distance bands reflect stepwise approximations widely used in land-use mix, accessibility, and spatial interaction studies to operationalize adjacency effects without calibrated decay functions (Horak et al., 2022; Nelson & Robertson, 2012; Pot & Piesch, 2024; Sevtsuk & Kalvo, 2025; Sugiyama et al., 2019; Xu, 2019). Similar threshold ranges are commonly adopted in empirical studies of neighbourhood-scale interaction and walkable catchments, where discrete distance bands are preferred to calibrated decay functions when detailed behavioural calibration data are unavailable (Ewing & Cervero, 2010; Gori et al., 2014; Gunn et al., 2017; Li et al., 2020; Macioszek et al., 2022; Xia et al., 2018). In this case study, the outer band (1200 m) represents a neighbourhood-scale interaction range for parcel-to-parcel functional evaluation (Carpio-Pinedo et al., 2021; Wei et al., 2016; Yang & Vaughan, 2022), consistent with the model's emphasis on walkable interaction structure rather than larger-scale interaction patterns. Appendix A reports a sensitivity analysis of alternative spatial envelopes, with 1200 m retained as the most appropriate neighbourhood-scale threshold.

The selected values should therefore be understood as modelling proxies that represent declining interaction potential with increasing spatial separation between parcels. The magnitude and form of adjacency effects are likely to be context-specific and influenced by local urban structure; future work may replace these stepwise weights with empirically calibrated adjacency functions or network-based distance measures where suitable data are available, while retaining adjacency's role as a bounded spatial interaction filter within the PCI.

3.2.4 Inter-parcel complementarity score

For each parcel (Parcel A), the Inter-Parcel Complementarity Score is computed by evaluating its interactions with all neighbouring parcels (Parcel B) within the specified adjacency distance thresholds. To identify neighbouring parcels within predefined distance thresholds, a k-dimensional tree (KD-tree) is employed to perform efficient spatial range queries. KD-trees hierarchically organize parcel centroid coordinates by recursively partitioning the data space along coordinate axes (Bentley, 1975), enabling faster identification of neighbouring parcels compared to naïve linear search approaches (Chen, Zhou, et al., 2019; S. Li et al., 2016; Wei et al., 2015).

In this study, KD-tree queries are applied to parcel centroids to retrieve all neighbouring parcels within the specified adjacency distance bands used in the PCI formulation Fig. 3. Adjacency is defined by distance rather than by administrative boundaries; all parcels within the specified thresholds are included irrespective of municipal borders, ensuring that cross-boundary interactions are not truncated (Stępniak and Jacobs-Crisioni, 2017). This boundary-independent definition is



Query Parcel Identification

Interactive Parcels within Maxmimum Distance

Fig. 3 Illustration for spatial parcel query process

consistent with established discussions of scale effects and the Modifiable Areal Unit Problem, which caution against allowing administrative zoning to artificially structure spatial interaction analysis (Manley, 2021). This approach improves computational efficiency when evaluating inter-parcel relationships across large parcel sets, while maintaining consistency with the centroid-based adjacency definition.

In Inter-parcel complementarity score interactions between neighbouring parcels are assessed across all directional pairwise combinations of urban functions, where each function f_a in Parcel A is evaluated against each function f_b in Parcel B. This decomposition ensures that parcels are not treated as single-use entities but are evaluated through the full set of cross-parcel functional relationships they contain. By considering all origin–destination pairings between coexisting functions, the model captures asymmetric use-to-use flow structures across adjacent parcels. A detailed illustration of the computational workflow and the corresponding implementation code are provided in Supplementary Material Sections 1.2.1.1 and 1.2.1.2.

For each function pair $(\mathrm{f_a}, \mathrm{f_b})$, the interaction score is calculated as:

$$\boldsymbol{Interaction\ Score} = \left(\boldsymbol{A_{f_a}} + \boldsymbol{A_{f_b}}\right) \times \boldsymbol{C_w(f_a, f_b)} \times \boldsymbol{VF_w(f_b)} \times \boldsymbol{A_w(d)} \tag{4}$$

Inter-parcel interaction score.
Where:

- $\mathrm{A_{f_a}}$ and $\mathrm{A_{f_b}}$ denote the floor areas of functions $\mathrm{f_a}$ (origin) in Parcel A and $\mathrm{f_b}$(destination) in Parcel B, respectively.
- $\mathrm{C_w(f_a, f_b)}$ is the Complementarity Weight for the function pair.
- $\mathrm{VF_w(f_b)}$ is the Visit Frequency Weight applied to the destination function.
- $\mathrm{A_w(d)}$ is the Adjacency Weight corresponding to the centroid-to-centroid distance d between parcels.

The additive area term $\left(\mathrm{A_{f_a}} + \mathrm{A_{f_b}}\right)$ represents the combined functional presence available for interaction between parcels, capturing exposure-based interaction potential without imposing balance or minimum constraints. The Visit Frequency Weight is applied only to $\mathrm{f_b}$ because visit frequency is defined in the survey as a property of destination functions. Weighting destinations increases the contribution of functions that are visited more regularly, while origins are already represented through the directional Complementarity Weight $\mathrm{C_w(f_a, f_b)}$. Across the full inter-parcel set, each function contributes through both roles because it appears as a destination in interactions with multiple origins.

The Inter-Parcel Complementarity Score for Parcel A is obtained by summing all interaction scores with neighbouring parcels and normalising by the total interacting functional area:

$$\boldsymbol{Inter - Parcel\ Score} = \frac{\sum \boldsymbol{Interaction\ Scores}}{\boldsymbol{Total\ Interaction\ Area}} \tag{5}$$

Inter-parcel complementarity score.

Total Interaction Area is defined as the sum of all $\left(\mathrm{A_{f_a}} + \mathrm{A_{f_b}}\right)$ terms across evaluated function pairs. This normalisation yields a relative, size-adjusted measure of inter-parcel complementarity that is comparable across parcels with different functional compositions and numbers of neighbours.

3.2.5 Computation of intra-parcel complementarity score

The Intra-Parcel Complementarity Score evaluates whether the floor-area shares of co-located uses are proportionally aligned with the directional complementarity and visit-frequency weights derived from observed mobility flows. It extends the behavioural interaction framework to the internal allocation scale and functions as a behaviourally grounded proxy for assessing how co-located uses are composed relative to the same asymmetric interaction structure applied throughout the PCI. A low intra-parcel score does not indicate weak neighbourhood integration; rather, it reflects limited alignment between internal floor-area distribution and the directional interaction weights. In this sense, intra-parcel complementarity evaluates internal allocation coherence without modelling within-parcel circulation. A detailed illustration of the computational process and the corresponding implementation code are provided in Supplementary Material Sections 1.2.2.1 and 1.2.2.2.

For each function pair (f_a, f_b) within the same parcel, the interaction score is calculated as:

$$\textbf{\textit{Interaction Score}} = (A_{f_a} + A_{f_b}) \times C_w(f_a, f_b) \times VF_w(f_b) \quad (6)$$

Intra-parcel interaction score.

Where:

- A_{f_a} and A_{f_b} denote the floor areas of functions f_a and f_b within the parcel.
- $C_w(f_a, f_b)$ is the Complementarity Weight for the function pair.
- $VF_w(f_b)$ is the Visit Frequency Weight applied to function f_b.

As in the inter-parcel formulation, intra-parcel interactions are evaluated asymmetrically through the directional Complementarity Weights, while Visit Frequency Weights and the additive area term are retained to ensure consistent weighting of functional presence and use within parcels.

The Intra-Parcel Complementarity Score is obtained by summing all intra-parcel interaction scores and normalising by the total functional area of the parcel:

$$\textbf{\textit{Intra}} - \textbf{\textit{Parcel Score}} = \frac{\sum \textbf{\textit{Interaction Scores}}}{\textbf{\textit{Total Functions Area}}} \quad (7)$$

Intra-parcel complementarity score.

This normalisation yields a relative, size-adjusted measure of internal functional complementarity that is comparable across parcels with different functional compositions.

3.3 Land use mix complementarity optimisation

3.3.1 Overview of NSGA-II in urban land use mix optimisation

NSGA-II is a computational evolutionary algorithm used to solve multi-objective optimisation problems by identifying non-dominated solutions within a constrained solution space, commonly referred to as a Pareto front, here used to retain jointly improving solutions rather than trade-off equilibria (Abdel-Basset et al., 2018; Deb et al., 2002). In this study, the NSGA-II framework is applied to urban LUM complementarity, where each individual solution represents a parcel-level LUM configuration, defined by the allocation of land use categories, locations, and areas, across all parcels. The optimisation simultaneously targets maximisation of Inter-Parcel and Intra-Parcel PCI, capturing LUM complementarity across and within parcels.

While machine learning and reinforcement learning approaches have been applied to LUM optimisation, they typically depend on large training datasets and reward-based processes that result in a black-box effect, limiting transparency in how solutions are produced (Yangzhi Li et al., 2025; Mirzahossein et al., 2022; Zhang et al., 2024). In contrast, NSGA-II operates directly on explicit objective functions and constraint structures, allowing the simultaneous exploration of multiple, non-conflicting objectives. For LUM optimisation, where inter- and intra-parcel complementarity are simultaneously evaluated rather than collapsed into a single aggregate objective, NSGA-II is adopted as a suitable optimisation framework due to its interpretability, reproducibility, and capacity for evolutionary-based evaluation (Drici & Carpio-Pinedo, 2025). However, the optimisation component is not intended to prescribe optimal land use outcomes, but to systematically explore parcel-level configurations that improve LUM complementarity under existing functional interaction and constraints.

3.3.2 Algorithmic urban land use mix complementarity optimisation

The NSGA-II algorithm explores alternative multi-use parcel-level LUM configurations that comply with existing zoning regulations, including Floor Area Ratio (FAR), ground coverage, and permitted uses, and building height limits as defined in the Plan General de Ordenación Urbana (PGOU) of Tres Cantos, which constitutes the legally binding municipal planning instrument regulating land use and development at the parcel and zone scale

(García, 2021). FAR defines the maximum total floor area that can be built on a parcel, ground coverage limits how much of the parcel can be occupied at ground level, and height restricts the number of storeys. An allocation is feasible only if the required floor area can physically fit within the footprint and height limits imposed by these regulations. Permitted uses act as a categorical filter restricting assignable land-use types. Configurations that exceed these constraints are repaired before evaluation, ensuring all solutions remain within the legally defined solution space. Each configuration represents a specific allocation of land uses and their areas across parcels within these regulatory constraints and is evaluated using the Inter-Parcel and Intra-Parcel PCI metrics, which quantify LUM complementarity based on use-to-use movement patterns, visit frequency, and spatial adjacency.

The optimisation follows a population-based evolutionary process in which a set of candidate land-use configurations is evaluated simultaneously at each iteration. During the initial population generation, parcel-level allocations are created within PGOU constraints, and any that exceed regulatory limits are adjusted prior to evaluation. The algorithm iteratively generates new configurations through genetic operations Fig. 4. Crossover combines land use allocations and area distributions from different configurations, producing new parcel configurations that inherit characteristics from multiple solutions. Mutation introduces small, controlled changes to land use types or their allocated areas within parcels, allowing the exploration of alternative arrangements not present in the initial population; where these operations produce allocations that exceed regulatory constraints, they are repaired to restore compliance before fitness values are computed and before entering the ranking stage.

Solutions are ranked using non-dominated sorting, which groups configurations according to whether one solution improves both inter- and intra-parcel complementarity relative to another. The resulting set of optimised land use configurations forms a Pareto front, representing alternative non-dominated solutions that jointly enhance inter- and intra-parcel complementarity under the imposed spatial and regulatory constraints. Each generation corresponds to one full cycle of evaluation, ranking, selection, crossover, and mutation applied to the population, and the optimisation proceeds by repeating these generations sequentially. In this formulation,

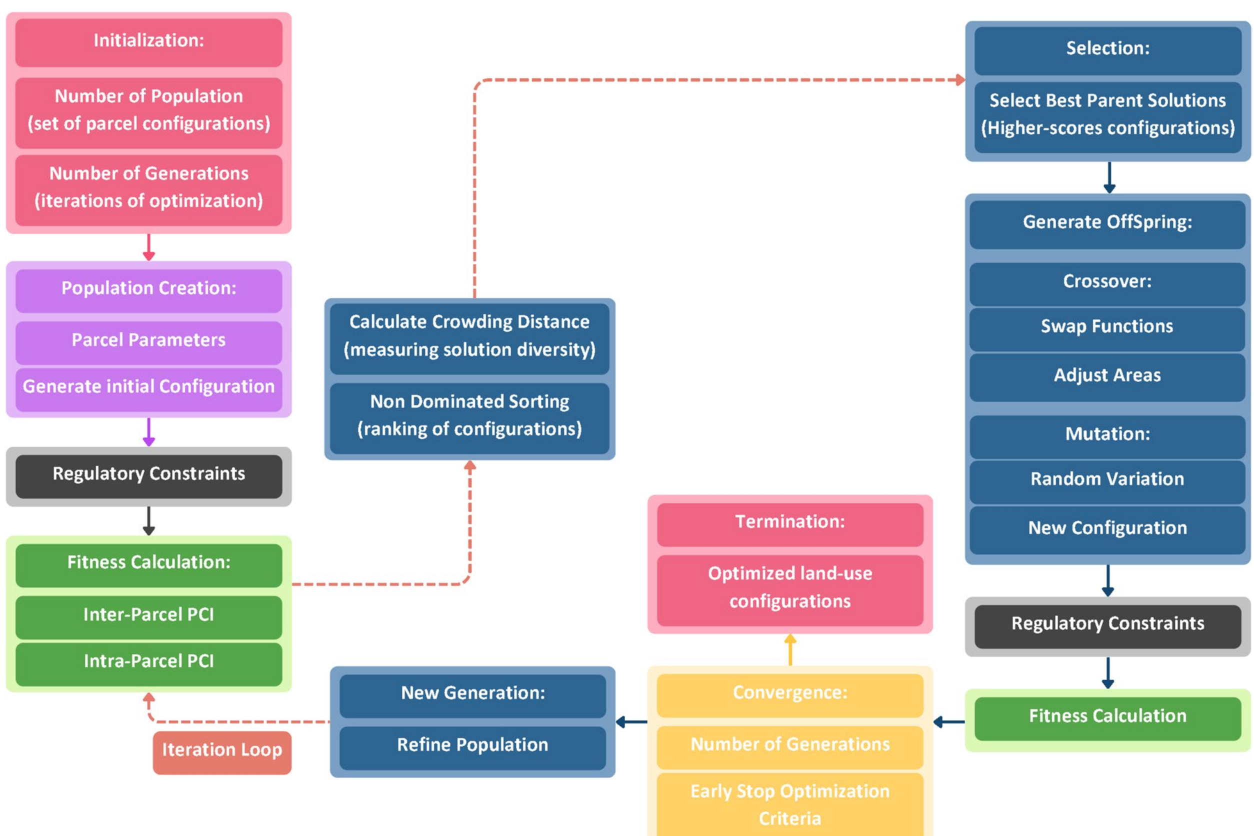


Fig. 4 Framework for NSGA-II optimisation of parcel complementarity

improvements in parcel-level LUM are expected to reinforce both components of complementarity; however, the Pareto front also reveals configurations where marginal trade-offs may emerge due to spatial structure or regulatory limits. A crowding distance criterion maintains diversity amongst solutions, and an early stopping rule terminates the optimisation once successive iterations no longer yield meaningful improvements in the solution set.

The Inter-Parcel Complementarity objective evaluates a parcel's external relational positioning by favouring allocations that increase directional interaction complementarity with surrounding parcels. Because interaction scores scale with floor area, optimisation based solely on inter-parcel PCI tends to concentrate allocation in a single high-interaction use, potentially reinforcing single-use dominance or generating disproportionate internal shares when multiple uses are permitted.

For instance, in a parcel containing residential, commercial, and parking uses, if parking exhibits comparatively strong external interaction, inter-parcel optimisation may allocate a large share of floor area to parking at the expense of the other uses. Intra-parcel complementarity counterbalances this effect by assessing whether the internal distribution of floor area aligns proportionally with the broader asymmetric interaction structure. In such a case, it would assign residential and commercial floor-area shares in proportion to their directional interaction weights, preventing the parcel from becoming predominantly parking with only minimal co-located uses.

4 Results

4.1 Statistical distribution and composition of PCI values

Table 1 reports descriptive statistics for inter- and intra-parcel PCI values to clarify the empirical scale of the index within the study area. Inter-parcel PCI values are highly skewed: while the mean is 0.65, the median is 0.30, indicating that half of all parcels score below 0.30 and that the average is influenced by a small number of high-value cases. The first and third quartiles (0.20 and 0.49) show that most parcels fall within a relatively narrow range. Ninety percent of parcels score below 0.96 and ninety-nine percent below 4.81, confirming that very high complementarity values are rare.

The maximum value (151.84) represents an extreme case corresponding to a large green park parcel located near residential, commercial, office, industrial, and sports uses. Its elevated score reflects both its substantial area and its strong complementarity with diverse surrounding uses within the 1200 m adjacency range. Because PCI accumulates weighted relationships across neighbouring parcels, large parcels embedded within diverse interaction environments can generate disproportionately high values. The pronounced skewness and kurtosis reported in Table 1 are consistent with this distributional pattern.

PCI should therefore be interpreted as a relative structural index whose magnitude reflects how a parcel both complements and is complemented within the observed mobility structure of the Madrid metropolitan area. While the methodological framework is transferable through recalibration with other mobility datasets, the numerical values function here as a context-specific comparative measure rather than as a universal benchmark.

Table 2 compares inter-parcel PCI values between single-use and multi-use parcels. Multi-use parcels exhibit systematically higher complementarity: their median inter-parcel PCI (1.04) is more than three times that of single-use parcels (0.29), and their 95th percentile (4.04) exceeds that of single-use parcels (0.73). Using the 95th percentile of the overall distribution (PCI = 1.62) as a reference, multi-use parcels account for 60% of the

Table 1 Distribution of PCI values within the study area

Statistic	Inter-parcel PCI	Intra-parcel PCI
Mean	0.65	0.09
Median	0.30	0.00
Std. Dev.	4.23	0.30
Variance	17.88	0.09
Min	0.00	0.00
Max	151.84	3.08
Q1 (25%)	0.20	0.00
Q3 (75%)	0.49	0.00
Interquartile Range	0.29	0.00
P90	0.96	0.49
P95	1.62	0.67
P99	4.81	1.22
Skewness	28.00	4.46
Kurtosis	869.47	26.64
Coeff. of Variation	6.51	3.35

Table 2 Inter-parcel PCI by parcel composition (Single-use and Multi-use)

Metric	Single-use	Multi-use
N	2,289	302
Mean	0.53	1.57
Median	0.29	1.04
Std. Dev.	4.43	1.96
Min	0.00	0.00
Max	151.84	18.96
P90	0.52	2.80
P95	0.73	4.04
P99	2.64	10.27

top 5% of values despite representing only 12% of parcels. This indicates a strong association between multi-use configuration and elevated inter-parcel relational complementarity.

However, high inter-parcel PCI values are not exclusive to multi-use parcels. As shown in Fig. 5, single-use parcels span the full value range, including relatively high scores. This suggests that while internal diversity increases the likelihood of stronger complementarity, spatial context positioning remains decisive. Because inter-parcel PCI reflects neighbourhood-scale interaction complementarity and scales with allocated floor area, a large single-use parcel assigned to a strongly interacting category can achieve high complementarity through spatial embedding alone. Internal allocation is evaluated separately within the PCI framework, and optimisation therefore considers both contextual positioning and internal composition in determining.

4.2 Spatial distribution of PCI scores

The study area is a planned new town whose urban structure has been largely consolidated through phased development. Unlike cities shaped by long-term historical layering, the centre of Tres Cantos reflects a coordinated planning framework in which mixed-use areas were intentionally allocated. While some peripheral parcels remain undeveloped, the urban structure is largely fixed, which places emphasis on evaluating existing parcel-level LUM complementarity.

The spatial distributions of Inter-Parcel and Intra-Parcel PCI scores differ significantly in their statistical characteristics, reflecting the distinct spatial and functional processes captured by each component of the PCI. This required separate classification strategies for visualisation in Fig. 6. Inter-Parcel PCI scores, shown in Fig. 6a, span a broad numerical range and include several outliers. An equal interval classification was therefore used to represent the full score distribution and to highlight areas with relatively high complementarity. This method divides the overall range into equal-width bins, which explains why the legend thresholds appear as values such as 0.13, 0.26, and 0.54 at the lower end. In contrast, most Intra-Parcel PCI scores, shown in Fig. 6b, are zero, with internal multiuse concentrated in a minority of parcels. To visualise these limited variations, a quantile classification was applied so that non-zero values were distributed across visual categories. In this case, the thresholds reflect parcel-count-based quantiles rather than equal numerical intervals.

As shown in Fig. 6a, central zones include parcels with comparatively high inter-parcel PCI values, most of which range between 0.63 to 1.6. This interval corresponds roughly to values above the upper quartile (0.49) and approaching the 95th percentile (1.62) reported in Table 1. These values reflect stronger complementarity between parcels that host mixed and frequently visited land uses, such as residential, commercial, and public services. In this sense, these parcels are identified

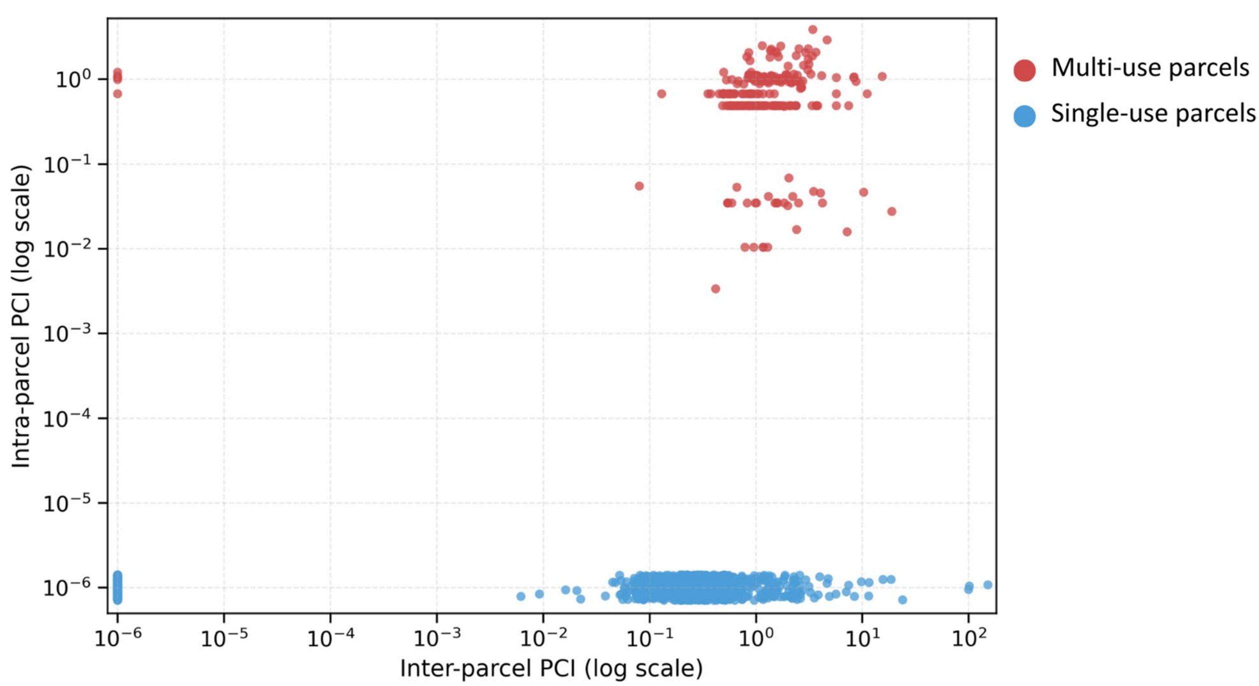


Fig. 5 Quadrant analysis of PCI scores

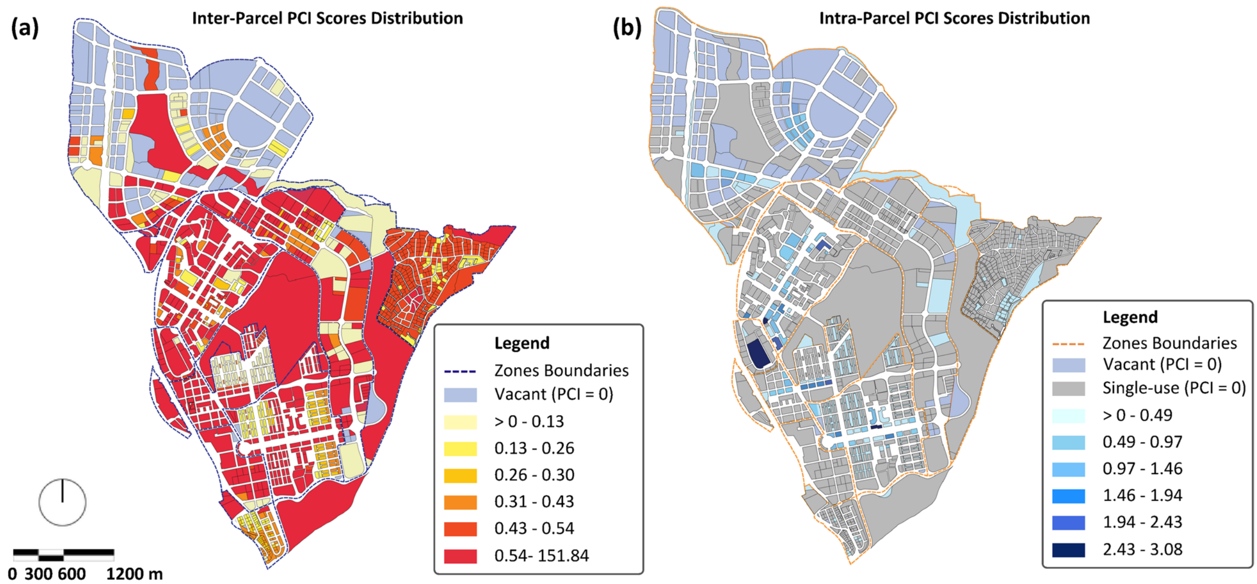


Fig. 6 Parcel Complementarity Index (PCI) scores distribution of for existing land use configuration, **a** Inter-parcel scores distribution, **b** Intra-parcel scores distribution

as highly complementary relative to the distribution observed in Tres Cantos, rather than against any universal benchmark. Across the study area, the median inter-parcel PCI value is 0.30, indicating that most parcels fall within a lower range of complementarity. Peripheral areas typically register inter-parcel PCI scores below 0.25, where land uses are more monofunctional and spatially dispersed. These conditions limit opportunities for functional interaction across parcels, particularly when complementary uses are absent in close spatial adjacency. The presence of numerous vacant parcels under the current configuration is associated with lower inter-parcel complementarity, reflecting gaps in functional interaction within the existing land use pattern. Inter-parcel PCI is calculated within bounded spatial adjacency thresholds that capture neighbourhood-walkable scale functional interaction around each parcel of up to 1200 m. Each parcel is evaluated relative to its own surrounding context, such that parcels located close to one another may exhibit different complementarity scores depending on the configuration of nearby land uses. By limiting the influence of more distant parcels, this approach reveals spatial patterns of complementarity and deficiency across the city.

Intra-parcel PCI values, shown in Fig. 6b, remain low across most of the study area and rarely exceed 0.49. The mean intra-parcel PCI value is 0.09, with a median of zero. This reflects the predominance of single-use parcels, particularly those allocated to office or industrial activities. Residential parcels, which account for approximately 60 percent of all parcels, also display low intra-parcel PCI values. Cultural, sports, and health parcels similarly exhibit low intra-parcel scores, consistent with their specialised functional roles. A small number of centrally located parcels show higher intra-parcel PCI values, ranging from 2.08 to 2.91. These cases reflect the presence of multiple co-located land uses within individual parcels. Their limited number indicates that internal parcel-level complementarity remains relatively uncommon, and that overall complementarity within the study area relies primarily on inter-parcel functional relationships.

4.3 Land use mix complementarity allocation and configuration optimisation

Parcels considered for land use optimisation were focused on vacant parcels, which were observed to be located within areas exhibiting low inter-parcel and intra-parcel PCI values, indicating locations where functional complementarity is currently limited possibly due to vacancy, thereby creating gaps in the surrounding parcel-level functional set. Parcel characteristics were obtained from the official Spanish Cadastral platform, including parcel identifiers, spatial coordinates, surface area, and recorded land use categories. For this analysis, only parcels recorded as vacant were included. This restriction confines the optimisation to realistic infill opportunities and avoids speculative intervention in built parcels, where reallocation or the introduction of new uses would require morphological restructuring of existing buildings, parcel subdivision or consolidation, and legal ownership adjustments beyond the scope of this analysis.

The parcels selected for optimisation represent approximately four percent of the total parcels within the study area. These parcels are not treated as independent intervention sites, but as spatial gaps embedded within existing neighbourhood-scale land use sets. The optimisation task therefore concerns how land uses may be assigned within these parcels in relation to their immediate spatial context, rather than whether development should occur.

The LUM optimisation process employed the NSGA-II algorithm to generate complete multiuse parcel-level configurations under existing development constraints, including permissible floor area ratios, and compatible uses indicated per zone defined by the local urban code. Each configuration represents an optimisation of land uses and associated floor areas and location across all selected parcels. The optimisation objective was to identify configurations that perform strongly on both inter-parcel and intra-parcel PCI, reflecting functional complementarity within parcels and between parcels and their surrounding context. The optimisation does not assume that allocating land uses to vacant parcels per se improves complementarity. Instead, it distinguishes allocation patterns that align with observed use and movement-based functional relationships from heuristic land use allocation and configuration approaches that are not explicitly grounded in empirical interaction patterns.

Land use allocations were scaled proportionally by area to reflect differences in functional presence across parcels and to ensure that allocated uses contribute to neighbourhood-scale functional interaction in a manner consistent with observed use and movement relationships. This approach avoids unrealistic concentration of multiple functions within individual parcels, while remaining consistent with the exposure-based logic of the PCI.

The NSGA-II algorithm was implemented with a population size of 500 and a maximum of 100 generations, in alignment with parameter settings commonly adopted in previous NSGA-II applications in urban studies (Ding et al., 2025; L Li et al., 2025; Peña et al., 2023; Xu et al., 2025; Yang & Jiang, 2020). A population size of 500 means that 500 candidate land-use allocation configurations are evaluated and evolved in parallel at each iteration, while 100 generations correspond to successive evolutionary cycles applied to the population as detailed in Sect. 3.3.2. This results in the evaluation of approximately 50,000 candidate solutions, allowing the algorithm to balance exploration of the solution space (via population diversity) with convergence towards the Pareto front (via iterative evolution). The optimisation process was terminated once the non-dominated solution set exhibited stable joint distributions of inter-parcel and intra-parcel PCI values, indicating that further iterations were no longer producing materially different allocation patterns within the defined solution space and that the resulting configurations were structurally consistent rather than algorithmically transient.

From the stabilised set of non-dominated solutions, a single representative configuration was selected for detailed examination. The selected configuration performs strongly on both inter-parcel and intra-parcel PCI without representing an extreme or edge-case solution that prioritises one dimension of complementarity over the other. It lies within a region of low variance on the Pareto front, where multiple configurations exhibit comparable complementarity levels. The configuration is therefore presented as an illustrative and interpretable outcome rather than as an optimal or unique solution.

Figure 7, presents the selected configuration, showing how land uses are allocated across the selected parcels in relation to their surrounding land use context. Table S3 in the supplementary material provides additional examples of parcel-level optimisation drawn from the stabilised solution set.

In the initial configuration generated by the optimisation process, functional floor area was predominantly allocated to parking and industrial uses. Parking accounted for 763,51 m^2, and industrial use for 443,39 m^2, together constituting the dominant share of allocated floor area. Commercial uses amounted to 116,10 m^2, offices to 94,96 m^2, and residential use to 85,07 m^2. Leisure and hospitality covered 75,42 m^2, unique buildings 61,14 m^2, sports facilities 37,67 m^2, and cultural uses 17,47 m^2. Health and charity functions (4,178 m^2) and green spaces (1,043 m^2) represented only marginal shares. Overall, the initial configuration allocated 1.70 million m^2 of functional floor area across the selected parcels.

In the selected configuration, a total of 2.36 million m^2 of functional floor area is allocated across the selected parcels. This includes approximately 1.17 million m^{2}of residential use, 759,458 m^2 of offices, 619,000 m^2 of commercial use, 526,000 m^2 of leisure and hospitality, 357,000 m^2 of parking, 328,017 m^2 of sports facilities, 299,000 m^2 of cultural uses, 271,000 m^2 of unique buildings, 265,000 m^2 of industrial use, 35,538 m^2 of health and charity functions, and 7,486 m^2 of green spaces. These values represent cumulative functional areas distributed across multi-functional parcels, reflecting allocation patterns rather than the creation of new single-use zones.

4.4 Impact of optimisation on inter- and intra-parcel complementarity

The spatial effects of the land-use complementarity optimisation are most clearly captured through the

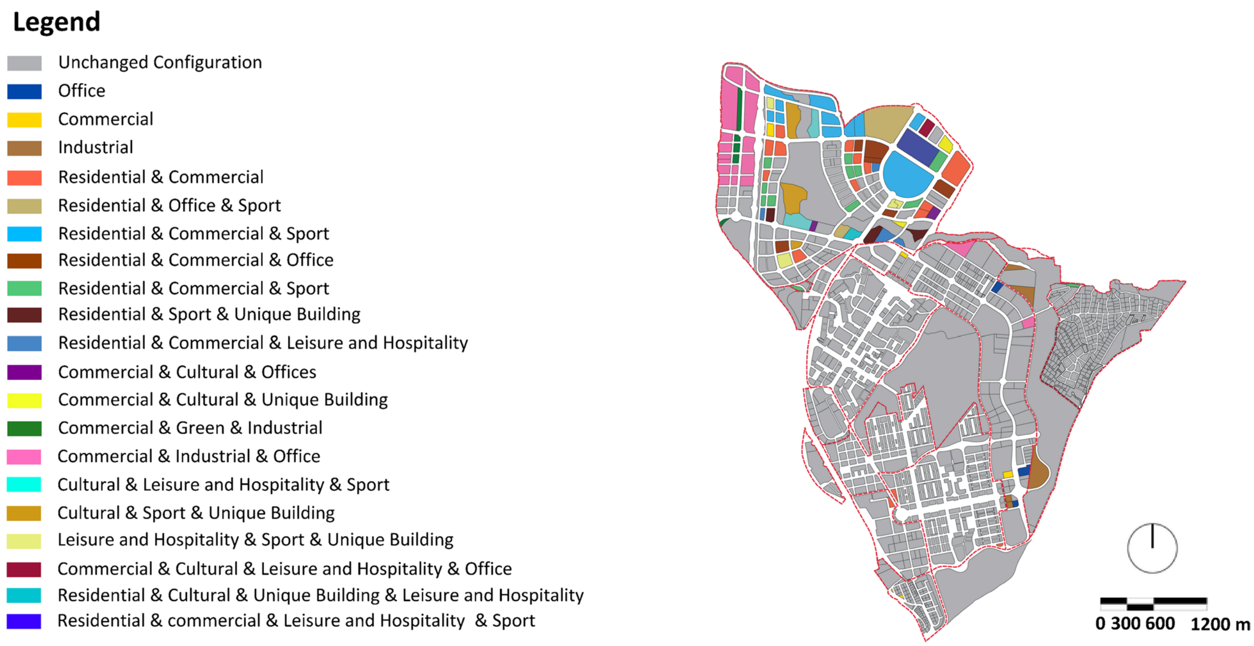


Fig. 7 Map of land use configurations of newly allocated parcels by NSGA-II optimising study area complementarity

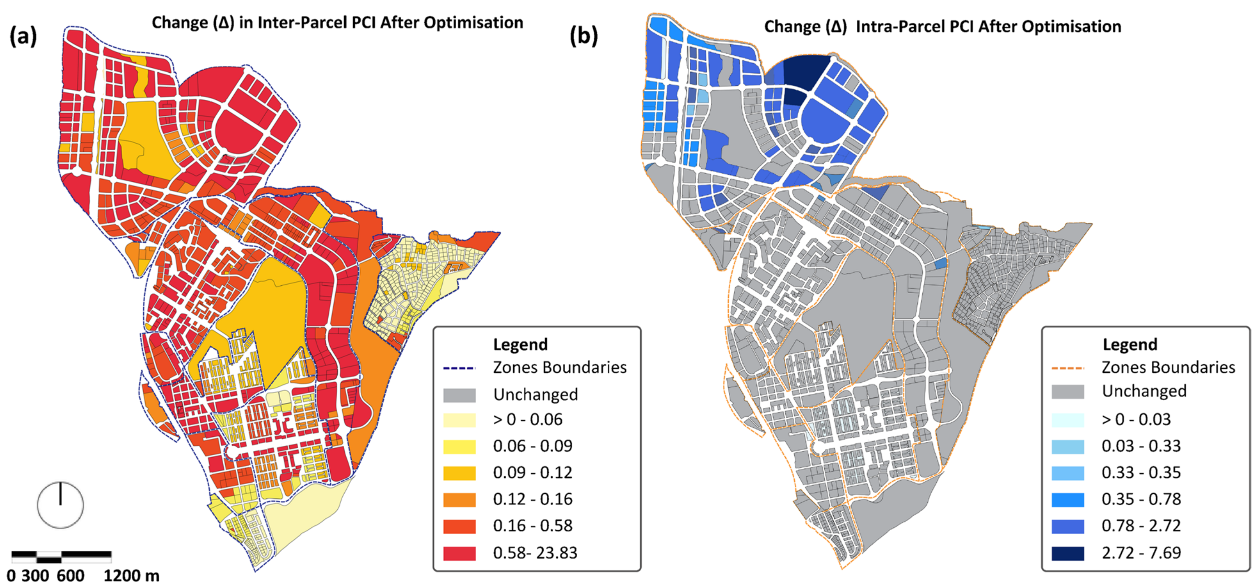


Fig. 8 Distribution of Parcel Complementarity Index (PCI) changes (Optimised – Baseline): **a** Δ Inter-parcel PCI, **b** Δ Intra-parcel PCI

parcel-level changes (ΔPCI) between the optimised and current situation configurations, as illustrated in Fig. 8. The results indicate a spatially differentiated pattern of change, with more pronounced and spatially clustered increases concentrated in the northern and central-north peripheral belts, while the consolidated inner core and the southern and eastern sectors exhibit comparatively limited and more dispersed increments.

Prior to optimisation, these areas exhibited low inter-parcel PCI values, reflecting the absence of functional interaction due to vacancy rather than merely the presence of land uses characterised by relatively low complementarity. Following optimisation, these parcels register positive ΔPCI values, as the newly allocated uses activated previously non-participating parcels within existing neighbourhood-scale functional sets. This PCI scores shift reflects the spatial activation of previously non-participating parcels rather than a qualitative transformation of the surrounding urban structure.

In northern peripheral zones, inter-parcel PCI values show a redistribution towards higher ranges, with mean and median values increasing from 0.23 and 0.02 to 0.96 and 0.73, respectively. These values should not be interpreted as indicating a more complementary configuration than central areas. Instead, they reflect the spatial concentration of vacant parcels within these zones and their proximity to already developed parcels, which allows optimisation effects to be expressed more clearly within the defined adjacency thresholds.

Across the study area as a whole, changes in inter-parcel PCI are more moderate. The overall mean increased from 0.65 to 0.68 and the median from 0.30 to 0.35, indicating that optimisation effects are spatially localised rather than uniform. Central areas, which contain few vacant parcels and already participate in dense functional sets, show comparatively limited inter-parcel PCI changes following optimisation. The observed ΔPCI values in these zones range approximately between 0.09 and 0.58, with only a small number of parcels exhibiting larger increases reaching up to 28.83. This pattern reflects the bounded spatial influence of the optimisation process and confirms that complementarity gains are primarily driven by adjacency to allocated vacant parcels adjacency and spatial availability rather than propagating uniformly across the city.

Changes in intra-parcel PCI values follow a similar spatial pattern. Prior to optimisation, both peripheral and central areas exhibited low intra-parcel PCI values, reflecting the predominance of single-use parcels. Following optimisation, increases in intra-parcel PCI are observed primarily in peripheral zones where vacant parcels were allocated multiple uses. These changes are spatially contained and do not affect central areas, as intra-parcel PCI captures internal parcel configuration rather than relational effects across parcels.

Observed intra-parcel changes are structurally linked to the allocation of previously vacant parcels. Because vacant parcels initially register zero intra-parcel PCI, any introduction of internal floor-area allocation generates positive ΔPCI. However, not all allocated parcels become mixed-use. In some cases, the optimisation assigns a single use, producing no intra-parcel change where mono-functional allocation yields stronger inter-parcel complementarity under prevailing spatial conditions. In others, internal floor-area shares are calibrated to align with the surrounding interaction structure, producing measurable intra-parcel gains.

Supplementary Sect. 3.3 further illustrates this trade-off: extreme Pareto-front solutions prioritise either inter-parcel or intra-parcel gains, indicating that the optimisation navigates a structured tension between neighbourhood-scale interaction and internal allocation rather than maximising both simultaneously.

Overall, the observed patterns demonstrate that parcel-level land use optimisation influences complementarity outcomes in a spatially contingent manner. The magnitude and spatial expression inter- and intra-parcel gains are conditioned by the parcel availability, location, and spatial adjacency, and the directional structure of empirically observed origin–destination flows, rather than being mechanically produced by optimisation alone. These results reinforce the interpretation of the model as a decision-support tool that clarifies where and how land use mix allocation and configuration can be functionally integrated, rather than as a mechanism for uniformly improving land use mix complementarity across the city. Allocation priorities within the optimised configuration therefore emerge from the interaction structure complementarity in the evaluation framework, rather than from an assumption that all land-use combinations may contribute equally.

5 Discussion

5.1 From land use mix to complementarity functional interaction

Land use mix (LUM) is commonly assessed through compositional measures that describe the presence, diversity, or proportional balance of uses within an area (Jiao et al., 2021). These approaches are useful for describing land use structure, but they do not directly capture whether co-located uses function as an interacting system in practice. The results of this study reinforce this distinction: Parcels that contain multiple uses tend to exhibit higher functional complementarity on average, although single-use parcels may also attain relatively high scores in specific spatial contexts. This suggests that LUM quality cannot be inferred from mix alone, but depends on the interaction structure that links uses through observed movement and use patterns (Carpio-Pinedo et al., 2021).

PCM aims to advance LUM assessment by modelling complementarity as an empirically grounded, explicitly directional relationship rather than a symmetric association between land-use categories. Symmetric approaches collapse origin–destination differences into mutual association, obscuring the directional imbalance that characterises observed mobility systems. In practice, urban functions generate uneven interaction flows, with some uses producing stronger outbound movements than they receive (Informatics et al., 2024). By retaining directional trip counts, PCM preserves these asymmetric interaction flows instead of assuming reciprocity.

This distinction has practical planning implications. Land-use allocation structures movement across space, not merely the coexistence of uses. A symmetric representation may treat categories as equally complementary despite uneven interaction patterns, whereas directional modelling aligns evaluation with observed behavioural structures. Preserving asymmetry differentiates interaction-dominant from interaction-receiving relationships, influencing parcel ranking and optimisation behaviour under the complementarity framework.

This helps explain why mixed-use environments often generate uneven outcomes: internal diversity may increase, yet functional integration may remain limited if the parcel is not situated within a surrounding configuration that supports coherent use-to-use relationships (Liu et al., 2024; Noordzij et al., 2021). This reframing is closely tied to the parcel as the unit of analysis. Urban change is typically realised through parcel-level interventions—such as infill, redevelopment, or incremental floor-area adjustments—rather than through wholesale restructuring (Ehrhardt et al., 2025). Yet, many LUM assessments remain anchored at neighbourhood or grid scales, obscuring the mechanisms through which allocation decisions are implemented. By distinguishing inter-parcel from intra-parcel complementarity at the parcel-level, PCM aligns LUM evaluation with the spatial unit where regulatory constraints apply and where allocation decisions occur.

5.2 Planning strategies and implications

The PCM functions as a parcel-level analytical and decision-support tool that operates within existing regulatory constraints. Its outputs are comparative scenarios for screening and prioritising land-use allocations under shared spatial and zoning conditions. Complementarity values are defined relative to the mobility-derived interaction structure of the study area rather than as universal benchmarks, consistent with other context-dependent spatial indices that derive meaning from local empirical distributions (Jaroszewicz et al., 2023; Jiménez-Espada et al., 2023; O'Driscoll et al., 2023; Yang et al., 2022). The model does not prescribe design outcomes but structures allocation choices within defined constraints. In this sense, PCM supports early-stage screening by narrowing broad allocation possibilities to a smaller set of evidence-aligned candidates that can subsequently undergo policy review, design development, and participatory evaluation.

In high-density cores, where debates on densification often concern how proximity and diversity influence travel behaviour and accessibility (Cervero & Kockelman, 1997; Ewing & Cervero, 2010). Empirical studies have shown that density and land-use diversity are associated with changes in mobility patterns, although these relationships vary across contexts and depend on local spatial conditions (Badland et al., 2017; Lu et al., 2018; Min et al., 2021). PCM provides a parcel-level lens for evaluating incremental redevelopment. It can assesses how proposed additions align with surrounding interaction patterns under regulatory and morphological constraints, including structural feasibility and ownership conditions. Inter-parcel complementarity identifies parcels embedded within established interaction structures, while intra-parcel complementarity evaluates whether added floor area is proportionally aligned with those patterns. Mobility is treated here as one structured analytical dimension rather than a comprehensive measure of land-use quality.

In established suburban contexts, where single-use parcels have structured mono-functional zones, the introduction of mixed-use development has produced varied outcomes of spatial responsiveness rather than absolute benefits (Filion, 2001; Grant, 2009). Diversification in this case at the parcel scale does not consistently translate into broader spatial interaction when surrounding configurations remain fragmented (Apparicio et al., 2007; Filion, 2001; Grant & Perrott, 2011; Gregorowicz-Kipszak et al., 2024). Alongside inter-parcel PCI component, intra-parcel complementarity functions as a proportional evaluation criterion rather than a mandate for diversification, clarifying how internal allocation relates to surrounding interaction structures without assuming inherent superiority of multi-use configurations.

In peripheral or expansion zones, where land-use configurations and interaction structures are still evolving, planning practice frequently relies on scenario comparison under shared regulatory frameworks (Debnath et al., 2023; Koomen & Beurden, 2011; Yilong Li et al., 2025; Wang et al., 2026). PCM can support scenario comparison under shared regulatory frameworks by evaluating how alternative allocations relate to emerging spatial-functional structures. Inter-parcel and intra-parcel complementarity together provide an additional analytical dimension alongside infrastructure, environmental, and growth management considerations.

From a planning perspective, parcel-level decisions involve not only the permissibility of uses but also their proportional floor-area allocation (Berawi et al., 2020; Sharmin et al., 2019). Although zoning may allow multiple uses within a parcel, authorities and developers must still determine their relative shares (Díaz-Pacheco & García-Palomares, 2014). In the absence of a behavioural reference, these allocations are typically guided by fixed proportional requirements or heuristic standards (Liu et al., 2016). Intra-parcel complementarity provides a behaviourally grounded proxy for such decisions, evaluating whether internal floor-area shares align with the broader interaction roles those uses perform within the urban system. It neither mandates equal presence nor requires multi-use configurations; rather, it introduces an evidence-based criterion for proportional calibration that is not consistently reflected in development practice.

In development contexts structured around single-use investment models and segmented real-estate market (Gyourko & Rybczynski, 2000), dominant-use configurations may align with financial and programmatic simplicity. However, concentrating floor area in a single-use category can produce mono-functional environments prone to temporal gaps in activity (Barbosa & Baptista Neto, 2015; Li et al., 2024). Integrating multiple functions within a parcel requires coordinated financial, regulatory, and architectural strategies (Al-Kodmany, 2018; Grodach & Martin, 2025; Ilgın, 2023; Khan et al., 2022). yet proportionally calibrated multi-use configurations can sustain interaction across different times of day and reinforce continuous neighbourhood engagement. The balanced configurations identified in this study illustrate how external relational strength and internal proportional calibration can be reconciled, supporting coordination between planning objectives and development practice in incremental redevelopment settings.

5.3 Model constraints, and next steps

PCM evaluates land use complementarity using parcel-level land use data and observed mobility flows. Because complementarity is computed from asymmetric trip and visit frequencies, it captures empirical spatial interactions among residential, employment, commercial, and service parcels (Shen & Karimi, 2016). Mobility therefore reflects spatial manifestations of economic, social, and environmental conditions without directly measuring them (Barbosa et al., 2021; Benoussaïd et al., 2025; Dong et al., 2017).

The complementarity weights are derived from a metropolitan mobility survey designed to ensure representativity by gender, age, and transport zone. Proportional allocation across transport zones captures mobility behaviours across the full metropolitan structure rather than a partial or homogeneous sample. This is particularly relevant in the Madrid metropolitan area, where socio-economic segregation is among the highest in Europe, both in residential terms (Musterd et al., 2017). Sharp contrasts between the wealthier city centre and north/northwest sectors and the comparatively disadvantaged south and southeast sectors are evident in income levels, educational attainment, and employment patterns (Mazorra Rodríguez, 2024). Because all transport zones are proportionally represented, the resulting weights incorporate mobility behaviours shaped by these differentiated socio-economic contexts.

In economic terms, the measure reflects observed trip connections between housing and workplaces, retail destinations, and daily services within the defined spatial range (Zhao et al., 2011; Zheng et al., 2019), but it does not measure productivity, wages, land values, development costs, or market feasibility. In social terms, flows to cultural, recreational, educational, and health-related destinations indicate the extent to which such uses are embedded within everyday movement networks (Khan et al., 2025). However, the model does not explicitly differentiate individuals by socio-economic group and therefore cannot directly evaluate distributional equity across specific populations. In spatial-environmental terms, complementarity within bounded adjacency thresholds describes the concentration of interactions over shorter pedestrian and cycling distances, consistent with neighbourhood-scale accessibility and reduced spatial separation between uses (Carpio-Pinedo et al., 2021; Mouratidis, 2021; Nuuyandja et al., 2025; Zhou et al., 2018). Yet the model does not quantify overall energy consumption or associated environmental externalities at the building or area scale, such as greenhouse gas emissions, air pollutant concentrations, or noise exposure.

This enables a structured assessment of how parcels interact functionally within neighbourhood-scale spatial contexts. The model does not attempt to predict demand, accessibility, or behavioural intensity, nor does it substitute for transport modelling or urban design analysis. Its evaluative component is therefore most informative where parcel-level land use data and mobility information are available at sufficient resolution, while its optimisation component is necessarily bounded by the quality and availability of these inputs. Where comparable datasets exist, the same workflow can be applied by re-estimating complementarity and visitation relations from local use and movement patterns rather than relying on fixed assumptions.

Spatial interaction within PCM is represented through bounded parcel adjacency relationships rather than through explicit street network modelling. The 1200 m threshold defines the neighbourhood-scale envelope (Alawadi et al., 2025a, b; Bahale et al., 2025), within which complementarity is evaluated, enabling consistent comparison of interaction potential across parcels. While travel distances vary by trip purpose, with commuting typically extending further than daily service-oriented activities (Elldér, 2014), everyday pedestrian movement remains shaped by embodied walking ranges and time constraints (Yang & Diez-Roux, 2012). The threshold is not intended to replicate routing behaviour or network impedance, but to constrain functional interaction to a clearly defined spatial range.

The current implementation assumes fixed cadastral boundaries and does not address parcel subdivision, land assembly, or morphological restructuring. Similarly, PCM does not operate at the architectural or design scale. While the model proposes which land uses and floor areas may be allocated to a parcel, it does not specify vertical distribution, ground-floor placement, internal layout, or spatial arrangement within the parcel. These aspects remain within the domain of urban design, architectural planning, and local regulatory interpretation.

Mobility inputs used in PCM reflect observed trip origins and destinations and do not capture multi-stop journeys, temporal sequencing, or daily activity chaining. This limits representation of temporal dynamics but preserves stable and interpretable functional relationships. Extensions that incorporate temporal dimensions or richer mobility datasets may further refine complementarity assessment, particularly in contexts where time-of-day variation plays a significant role.

Optimisation outcomes presented in this study reflect convergence within a bounded solution space defined by the selected objectives and constraints. Multiple non-dominated configurations exhibit comparable complementarity levels, reinforcing PCM's role as an exploratory rather than prescriptive tool. The selected configuration is therefore illustrative and representative, not definitive. Moreover, because the model does not incorporate financial feasibility constraints, the resulting configurations should be interpreted as structurally aligned under mobility-based criteria and would require subsequent economic and financial assessment prior to implementation. Future work should examine the behaviour of PCM through targeted sensitivity and comparative analyses with alternative land use mix evaluation and optimisation approaches. Such analyses would help clarify how modelling choices related to interaction definitions, spatial thresholds, and objective formulation influence complementarity outcomes across different urban contexts. Such analyses should also progressively integrate feasibility-related constraints to assess how complementarity outcomes perform under different implementation conditions.

Within these boundaries, PCM supports planning practice by revealing where functional relationships are weak, where complementarity deficits exist, and where alternative land use configurations may strengthen neighbourhood-scale interaction patterns. Its value lies in structuring land use mix evaluation around observed use and movement relationships, while remaining compatible with existing planning frameworks and open to further methodological extension as part of broader planning workflows.

6 Conclusion

This study introduced the Parcel Complementarity Model (PCM) as a parcel-level analytical tool for evaluating and optimising land use mix complementarity based on observed patterns of use and movement. By conceptualising land-use mix as a system of directional functional relationships derived from mobility data, PCM evaluates both a parcel's position within the surrounding interaction structure and the coherence of its internal floor-area allocation with observed use-to-use flows. Rather than assuming reciprocal equivalence between land-use categories, the model retains asymmetric origin–destination relationships, treating complementarity as directional dependence. This formulation shapes optimisation outcomes by distinguishing between proportionally distributed and directionally dominant interaction structures, influencing how land-use allocations respond to observed mobility patterns.

PCM operates at the scale where most incremental urban change occurs and supports both the evaluation of existing land use configurations and the optimisation of alternative allocation and configuration scenarios. Its value lies not in prescribing optimal outcomes, but in enabling transparent comparison between feasible configurations under existing spatial and regulatory constraints, functioning as an early analytical filter for parcel-level decision-making.

The application to Tres Cantos illustrates how parcel-level complementarity can be evaluated jointly within parcels and across their surrounding context, and how vacant or underutilised parcels can be examined as part of wider functional systems rather than as isolated development sites. The results show that improvements in complementarity depend less on the introduction of additional uses and more on how land uses are allocated and configured in relation to existing functional interaction patterns.

Future work should examine the behaviour of PCM through sensitivity and comparative analyses alongside other land use mix evaluation and optimisation approaches and explore extensions that incorporate temporal dynamics or network-based spatial relationships. By reframing land use mix evaluation around functional complementarity rather than co-location, the study provides an explanatory lens for understanding why land use mix effects are often weak, inconsistent, or context-dependent across empirical settings.

Appendix A

To assess the sensitivity of inter-parcel PCI to the selected walkable neighbourhood interaction range, three alternative adjacency envelopes were tested while keeping the same stepwise decay structure (1.00, 0.75, 0.50). Only the distance bands were modified. The baseline (B) configuration applies weights of 1.00 for 0–400 m, 0.75 for 400–800 m, and 0.50 for 800–1200 m. The shorter-envelope scenario (S1) (800 m maximum range) applies weights of 1.00 for 0–300 m, 0.75 for 300–600 m, and 0.50 for 600–800 m. The first larger-envelope scenario (L1) (1600 m maximum range) applies weights of 1.00 for 0–500 m, 0.75 for 500–1000 m, and 0.50 for 1000–1600 m. The largest-envelope scenario (L2) (2000 m maximum range) applies weights of 1.00 for 0–600 m, 0.75 for 600–1200 m, and 0.50 for 1200–2000 m.

Figure 9a presents the distribution of inter-parcel PCI values under each envelope. Reducing the range to 800 m lowers the median PCI (0.208) relative to the baseline (0.247), indicating that restricting the interaction radius reduces the number of neighbouring parcels contributing to complementarity. Expanding the envelope to 1600 m and 2000 m produces only modest increases in median values (0.254 and 0.248). At the same time, the interquartile range progressively narrows as the envelope expands (from 0.178 at 800 m to 0.126 at 2000 m), reflecting a smoothing effect as more distant parcels are incorporated.

Figure 9b reports parcel-level deviations in inter-parcel PCI scores for all parcels relative to the baseline scenario, with the horizontal zero line indicating no change. The shorter envelope yields predominantly negative deviations, while the larger envelopes show small positive shifts concentrated near zero. The upper tail of the distribution remains stable across all scenarios (P95 between 1.61 and 1.71), indicating that parcels identified as highly complementary relative to the Tres Cantos interaction structure are consistently recognised regardless of moderate changes in spatial extent.

Overall, these results show that the 1200 m threshold operates within a stable neighbourhood-scale range. Reducing it truncates local interaction sets, whereas expanding it yields limited changes in central tendency and primarily smooths variation rather than altering structural patterns.

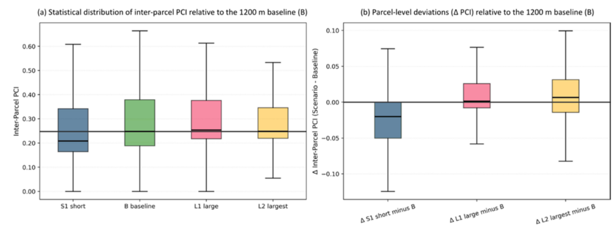


Fig. 9 Sensitivity of inter-parcel PCI to interaction envelopes. **a** Statistical distribution of inter-parcel PCI relative to the 1200 m baseline (B). **b** Parcel-level deviations (Δ PCI) relative to the 1200 m baseline (B)

Supplementary Information

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Supplementary Material 1

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Declarations

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