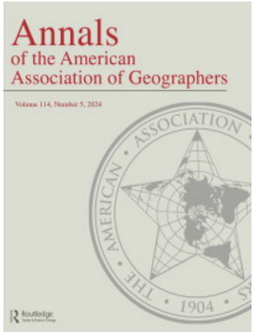

Taylor & Francis
Taylor & Francis Group

Annals of the American Association of Geographers

ISSN: (Print) (Online) Journal homepage: www.tandfonline.com/journals/raag21

Multiscale Complex Network Analysis of Commuting Efficiency: Urban Connectivity, Hierarchy, and Labor Market

Yue Jing & Yujie Hu

To cite this article: Yue Jing & Yujie Hu (22 Jan 2024): Multiscale Complex Network Analysis of Commuting Efficiency: Urban Connectivity, Hierarchy, and Labor Market, Annals of the American Association of Geographers, DOI: 10.1080/24694452.2023.2284296

To link to this article: https://doi.org/10.1080/24694452.2023.2284296

Published online: 22 Jan 2024.

ANNALS OF THE AMERICAN ASSOCIATION OF GEOGRAPHERS
https://doi.org/10.1080/24694452.2023.2284296

Multiscale Complex Network Analysis of Commuting Efficiency: Urban Connectivity, Hierarchy, and Labor Market

Yue Jing and Yujie Hu

Department of Geography, University of Florida, USA

This study employs the 2012 to 2016 commuting flows of Florida to reexamine excess commuting (EC) through multiscale complex network analysis. The results reveal significant discrepancies in urban connectivity, hierarchy, and labor market geography between the actual (ACN) and optimal commuting networks (OCN). Compared to ACN, OCN illustrates an overly simplified and isolated polycentric commuting system. This is evident through reduced overall network connectivity, a restructured centrality distribution pattern, and fragmented community divisions. Consequently, these results underscore the importance of delving into the economic implications of commuting within the conventional EC framework.
Key Words: commuting network, complex network analysis, excess commuting, labor markets, spatial network.

The work commute plays a vital role in shaping the spatial interaction between housing and labor markets, leading to significant economic implications (Hincks and Wong 2010). It is also closely associated with adverse environmental effects, however. Commuting contributes substantially to traffic congestion and air pollution, thereby posing significant challenges to urban sustainability (Horner 2004). Moreover, long commutes are associated with adverse health outcomes, negatively affecting individual well-being (Clark et al. 2020). Over the past fifteen years, the average one-way commute in the United States has steadily risen, peaking at 27.6 minutes in 2019 (Burd, Burrows, and McKenzie 2021). As commute times continue to increase, these issues are becoming more pressing, demanding policymakers' attention.

One unique perspective to tackle these issues is to explore the concept of excess commuting (EC; Hu and Li 2021), which examines the potential for reducing a city's overall commuting distance without changing its urban form. Using a set of global measures, EC quantifies commuting efficiency by comparing the actual commute distance C_{obs} with minimum commute distance C_{min}. The mainstream approach to deriving C_{min} uses a linear programming (LP) model specified to minimize the total commuting cost by assuming that people can freely switch their jobs or residences in the city (Horner 2004). A smaller C_{min} implies a theoretically more balanced land-use pattern with a greater mixture of jobs and housing (Giuliano and Small 1993). Therefore, C_{min} and EC serve as essential tools for evaluating land-use policies, including those related to jobs–housing balance and housing (Ma and Banister 2006). The versatile nature of EC allows for its integration with other dimensions (O'Kelly and Lee 2005), such as socioeconomic attributes and travel behaviors, providing valuable insights into addressing socioeconomic inequalities.

There are some issues with existing EC studies, however, which could lead to less meaningful measurements of EC and thus largely undermine the role of EC in informing spatial policymaking. First, most studies (e.g., Kanaroglou, Higgins, and Chowdhury 2015) focus on producing a set of global statistics that represent a city's overall commuting efficiency, whereas a few exceptions (Niedzielski 2006; Śleszyński et al. 2023) report spatially disaggregated measures at smaller zones. These global statistics, though, are unable to capture the internal variations of commuting

ARTICLE HISTORY
Initial submission, November 2022; revised submissions, July and October 2023; final acceptance, October 2023
CORRESPONDING AUTHOR Yujie Hu yujiehu@ufl.edu

efficiency, which refer to the spatial differences in commuting efficiency within a specific region or area. Second, traditional methods predominantly assess commuting efficiency through a singular focus on travel cost minimization. This approach, however, overlooks the structural properties of the underlying commuting network, such as the connectivity between centers, center hierarchies, and spatial extent of local labor market areas (LMAs). Incorporating this knowledge is essential for gaining a deeper understanding of the regional economic system's structure and developing spatially targeted policies. Third, existing studies often consider the minimum commute obtained through cost minimization as the "gold-standard" commuting scenario (or jobs–housing relationship) a city can achieve (Schleith et al. 2019). Its accuracy in representing the best possible scenario is largely unknown, however. Essentially, the minimum commute serves as a theoretical baseline for a city's commute and jobs–housing relationship, but it might deviate significantly from reality and be impractical to pursue. Furthermore, the measurement of the minimum commute is influenced by the scale of analysis (Horner and Murray 2002), and its value might not be accurately represented by calculations at a single scale. Finally, most existing studies have a limited spatial scope, focusing on the analysis of only one or a few cities. This practice will introduce edge effects whereby the increasingly prevalent cross-city commutes are ignored.

The primary goal of this study is to introduce a novel methodology to measure EC and understand commuting efficiency by addressing the previously mentioned issues. Given the networked structure of commuting data, the actual and minimum commuting scenarios are both converted into a network with zone (e.g., census tract) centroids as its nodes and commuter connections between zones as its edges. Next, using complex network concepts and metrics, structural properties of both actual and minimum commuting networks are examined at multiple scales to more fully identify differences between the two networks and reveal commuting efficiency patterns. The multiscale structural analysis also evaluates the accuracy of the minimum commute. The proposed methodology is applied to a commuting data set from the most recent 2012 to 2016 Census Transportation Planning Products (CTPP) for Florida.

The Excess Commuting Framework

The relationship between commuting and land use has been a subject of enduring interest in urban studies. A specific line of research focuses on the jobs–housing balance, seeking to understand how commuting patterns relate to the spatial distribution of jobs and housing (Cervero 1989; Giuliano and Small 1993). Within this framework, the concept of EC was proposed by Hamilton and Röell (1982) to test the fit of the classic monocentric city model in predicting commuting patterns. Unlike Hamilton's mathematical approach, White (1988) developed the LP-based method using actual land-use geography to measure EC (C_{ex}), which has since become the mainstream approach:

$$C_{ex} = \frac{C_{obs} - C_{\min}}{C_{obs}} \tag{1}$$

$$C_{\min} = \min\left(\frac{1}{N}\sum_{i}\sum_{j} X_{ij} D_{ij}\right) \tag{2}$$

$$\text{Subject to}: \sum_{j} X_{ij} = W_i,\ \sum_{i} X_{ij} = E_j,\ X_{ij} \geq 0 \tag{3}$$

where C_{min} is derived by reallocating zonal commuting flows to reduce the system-wide commuting cost while maintaining the total number of workers W_i and jobs E_j in each zone. X_{ij} denotes the number of workers commuting from zones i to j, D_{ij} is the travel cost between zones i and j, and N represents the total number of workers in the city. C_{ex} is then derived by comparing C_{obs} to C_{min}, and a larger C_{ex} indicates less efficient commuting. Most traditional analyses of EC only use these single numbers to demonstrate a city's commuting efficiency.

EC has been extensively used to inform land-use policymaking. Different theoretical commuting benchmarks and efficiency metrics provide complementary insights on policy effectiveness regarding jobs–housing balance, decentralization, and urban growth, especially through cross-sectional or longitudinal comparative studies (Schleith et al. 2019). The policy relevance of EC, however, could be compromised due to the issues discussed previously.

Methodology

Data and Commuting Distance Measurement

The study area is the state of Florida, comprising such major cities as Miami, Tampa, Orlando, and Jacksonville that serve as employment and residential centers (Figure 1). The primary data source is tract-to-tract commuting flows from the 2012 to 2016 CTPP. Geographic information systems (GIS) data for the tract boundary and road network are downloaded from the U.S. Census Bureau. In total, Florida has 4,245 tracts with 4,188 tracts having recorded commuting flows.

This research exclusively examines automobile commuting due to its predominant use in Florida, with around 94.4 percent of workers relying on cars for their daily commutes, as per the CTPP data. Hence, the car travel distance is used as the measure of commuting cost, which includes two components: interzonal and intrazonal distances (Hu et al. 2020). Interzonal distance is the shortest path distance along the road network between tract centroids, whereas intrazonal distance is the radius of a circle that approximates the area of the tract (Jing and Hu 2022). To capture only daily commutes, extreme commutes that are longer than 160 km (Nelson and Rae 2016) are excluded. The remaining flows account for 99 percent of the entire sample, and the average commuting distance is 19 km.

Construction of Commuting Networks

Structurally, the tract-to-tract commuting flows form a spatial network with its nodes representing residential and employment tract centroids and edges being commuter connections between tracts. Depending on the question at hand, different types of networks can be constructed. The network can be either undirected or directed. The former aggregates opposing directions of commutes between nodes to capture the total two-way commuting connections, whereas the latter differentiates between inward and outward commuting that relate to employment and residential functions, respectively. Likewise, the network can be either unweighted (edges are present when there are commuter connections between two nodes and absent if otherwise) or weighted (by the number of commuters between two nodes). The former can help reveal the topological structure of the network, whereas the latter further uncover flow patterns.

To better understand the commuting network structure, these different types of networks in terms of edge direction and weight are considered in constructing two commuting networks: (1) an actual commuting network (ACN) that corresponds to the observed commuting flow patterns between tracts, and (2) an optimal commuting network (OCN) that denotes the minimum commuting flow patterns solved by the LP model.

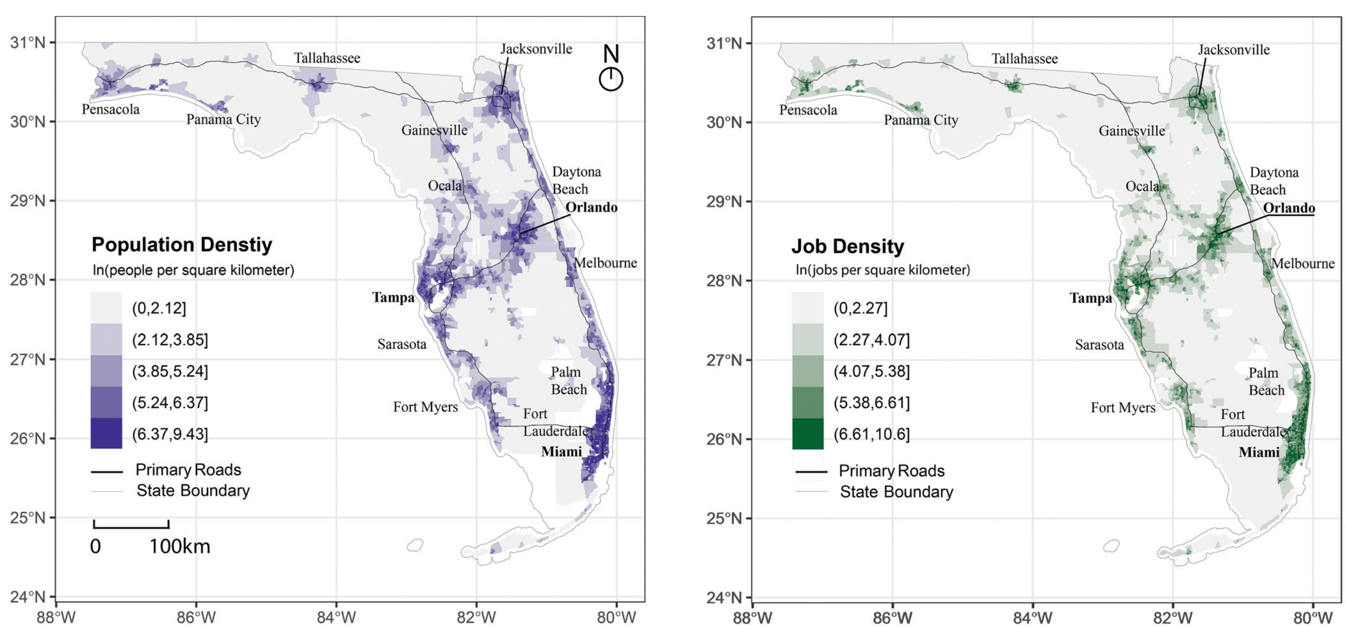

Figure 1. Spatial distributions of population and job densities in Florida.

Complex Network Metrics

A set of complex network metrics are applied to understand and compare structural properties between ACN and OCN at three scales. Table 1 describes these metrics in more detail. In short, two macroscale metrics—average path length and global clustering coefficient (Albert and Barabási 2002)—are employed to examine the overall connectivity of commuting networks, or the degree to which all pairs of nodes are interconnected. At the microscale, node degree is used to reveal the structural importance of each node for understanding the hierarchy of nodes in the networks. Finally, at the mesoscale, the modularity score based on the Louvain community detection algorithm (Blondel et al. 2008) is used to detect cohesive node groups in the network, a neighborhood-level structural property that metrics at the two other scales are unable to capture (Newman 2006; Zhang et al. 2020). In the context of commuting networks, the node grouping characterizes LMAs, the functional regions with essential economic geography implications.

To facilitate the comparison of results between ACN and OCN at different scales, several similarity indexes are calculated. The weighted Jaccard index (WJI; Frigo et al. 2021) assesses the structural similarity between two weighted networks at the macroscale:

$$WJI(X, Y) = \frac{\sum_{i=1}^{n} \min(x_i, y_i)}{\sum_{i=1}^{n} \max(x_i, y_i)} \tag{4}$$

where X and Y are two weighted networks, and x_i and y_i represent the weights of common edge i between X and Y. WJI is obtained by dividing the sum of minimum weights of common edges by the sum of maximum weights of common edges in both networks. The index ranges from 0 to 1. A value of 1 indicates that the two networks are identical in terms of their edge weights, whereas a value closer to 0 indicates lower similarity between the networks.

For node hierarchy results (microscale analysis), changes are captured using the coefficient of variation and Spearman's rank correlation coefficient. For LMAs (mesoscale analysis), the Fowlkes–Mallows Index (FMI; Fowlkes and Mallows 1983) measures the overall extent of agreement between two sets of community detection results A and B:

$$FMI = \sqrt{\left(\frac{TP}{TP + FP}\right) \times \left(\frac{TP}{TP + FN}\right)} \tag{5}$$

where TP is the number of node pairs that are present in the same community in both A and B; FP is the number of node pairs that are present in the same community in A but not in B; FN is the number of node pairs that are present in the same community in B but not in A. The FMI ranges from 0 to 1, where a value closer to 1 indicates a higher similarity between the two community detection results. Additionally, the Jaccard index (JI; Frigo et al. 2021) provides localized assessment of the similarity between two community detection results, quantifying the extent to which a node belongs to the same community in both A and B. The JI between A and B is calculated by dividing the size of their intersection (common elements) by the size of their union (all unique elements present in both sets). It ranges between 0 and 1, where 0 indicates no similarity and 1 represents complete similarity.

Results

Traditional Analysis of Excess Commuting

The traditional method for EC yields a 7-km C_{min} and a C_{ex} of 63.2 percent, indicating a large inefficient commuting system in Florida overall. In other words, existing land-use layouts in Florida cities and towns would allow for a much-reduced one-way commute of 7 km, compared to the observed 19-km commute, for general workers, and 63.2 percent of the observed commute could have been reduced through relevant policymaking balancing jobs–housing relationships. Clearly, the traditional method is of limited value as it only reports these global statistics about overall commuting distance and efficiency.

Complex Network Analysis of Excess Commuting

Figure 2A–B illustrates one configuration (weighted, undirected) of ACN and OCN, revealing a striking discrepancy in their layouts. This notable visual inconsistency is further supported by a quite low WJI value of 0.083, indicating poor similarity between ACN and OCN. These findings are in line with the 63.2 percent C_{ex} discussed earlier. Figure 2C presents the spatial pattern and distance

Table 1. Description of complex network metrics

Scale	Network configuration	Metric	Equation	Description	Interpretation
Macroscale	Unweighted, undirected	Average path length (l)	$l = \frac{1}{n(n-1)} \sum_{i \neq j} d(v_i, v_j)$	n is the number of nodes, calculated as the number of tracts in the commuting network; $d(v_i, v_j)$ denotes the shortest path length between tract i and j.	l measures the average shortest distance between any pair of tracts. A greater l signifies lower network connectivity within the commuting system.
		Global clustering coefficient (CC)	$CC = \frac{3 * number\ of\ triangles}{number\ of\ triads(both\ open\ and\ closed)}$ $0 \leq CC \leq 1$	—	CC measures the fraction of possible triangles with commuting flows through a tract that exist. A higher CC indicates an overall high level of cohesiveness of the commuting system.
Microscale	Unweighted, directed	In-degree (k_i^{in})	$k_i^{in} = \sum_{j=1}^{n} a_{ij}$	a_{ij} equals 1 when there is a commuting link from j to i, and 0 otherwise.	k_i^{in} is the sum of in-going commuting links. A higher k_i^{in} indicates stronger employment attractiveness.
		Out-degree (k_i^{out})	$k_i^{out} = \sum_{j=1}^{n} a_{ji}$		k_i^{out} is the sum of outgoing commuting links. A higher k_i^{out} signifies wider outreach of labor supply.
Mesoscale	Weighted, undirected	Modularity (Q)	$Q = \frac{1}{2m} \sum_{i,j} \left[W_{i,j} - \frac{S_i S_j}{2m} \right] \partial(c_i, c_j)\ -1 \leq Q \leq 1$	$W_{i,j}$ denotes the weight of the edge between nodes i and j, calculated as the total number of commuters between i and j. S_i is the sum of weights for node i. c_i is the community node i belongs to. $\partial(c_i, c_j)$ equals 1 if nodes i and j belong to the same community, and 0 otherwise. $m = \frac{1}{2} \sum_{ij} W_{ij}$.	Q measures the density of commuting flows inside communities as compared to commuting flows between communities. A higher Q suggests a higher partition quality.

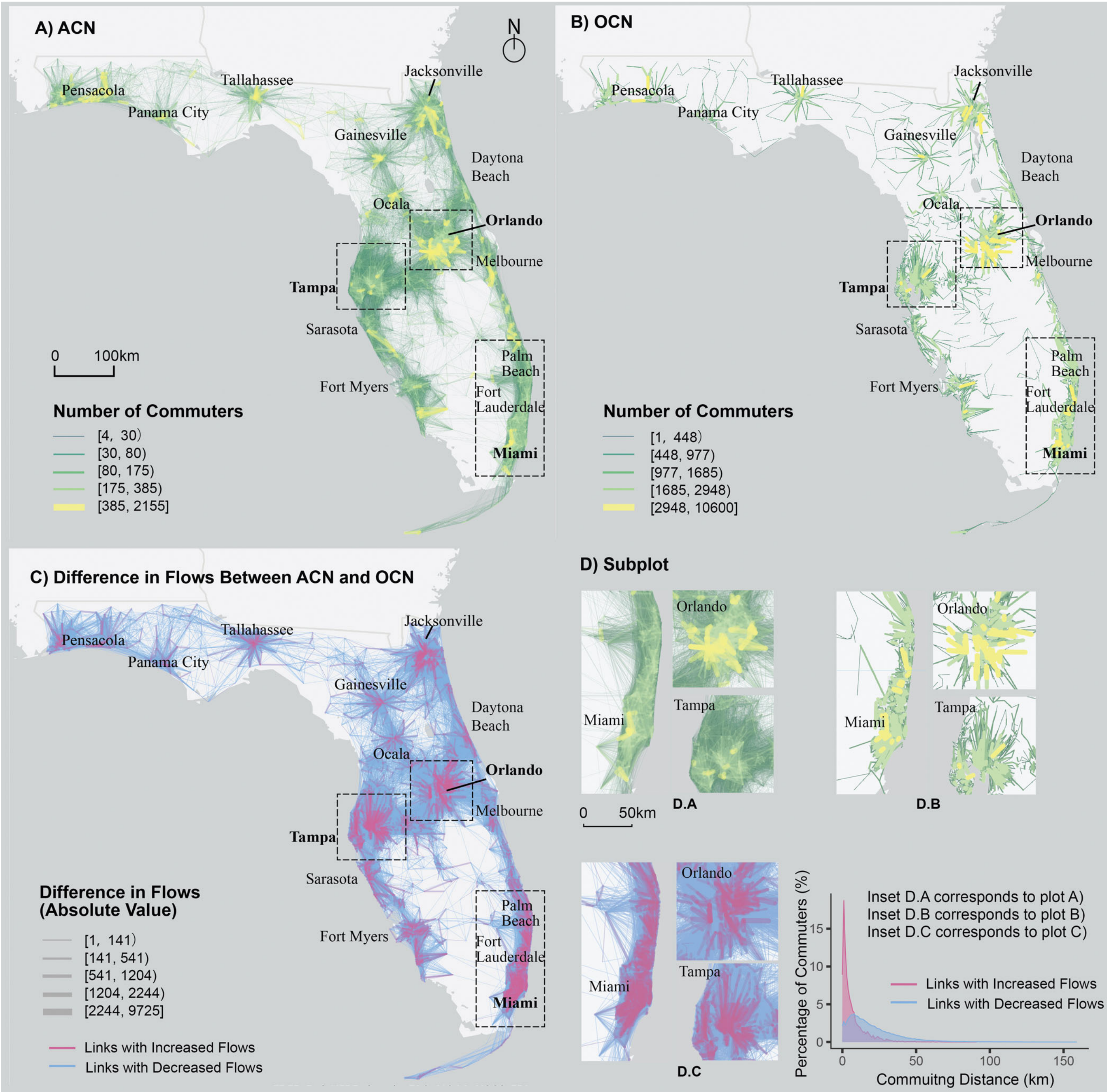

Figure 2. Network visualizations of actual commuting network (ACN), optimal commuting network (OCN), and their differences.

distribution of the differences in flows between ACN and OCN. To achieve C_{min}, a substantial 86.5 percent of the actual commuting flows are reallocated, leading to both decreased and increased flows among commuting connections. Commuting links with decreased flows are distributed throughout the region over a wide distance range of 0 to 160 km, and links with increased flows are more concentrated, primarily on shorter commutes less than 7 km.

Macroscale Analysis: Examining the Overall Degree of Connectivity. This subsection examines differences in the overall degree of connectivity between ACN and OCN. As the LP model reassigns a worker to an overall nearest job, the number of edges expectedly has a sharp decline from 210,324 in ACN to 8,347 in OCN. In OCN, workers are predominantly redistributed to nearby employment opportunities, resulting in a significantly sparser network. Moreover, the 96 percent edge reduction results in remarkable growth in l from 4.5 for ACN to 74.1 for OCN, indicating an average of seventy more commuting connections for any two tracts to be connected. This suggests a much-reduced overall connectivity for OCN over ACN. Although the minimum commuting scenario has the best overall spatial proximity between jobs and housing, the significantly lower connectivity of OCN indicates that places that are physically close can be further apart due to the lack of direct commuting connections. OCN, although having the shortest overall commute, is instead quite topologically inefficient.

Additionally, CC drops from 0.31 in ACN to 0.12 in OCN with more open triads. The drastic increase of l and decrease of CC signify the structural change from a relatively small-world network (ACN), where nodes are closely connected to one another, to a more separated network of an overall less cohesive and efficient structure (OCN).

Microscale Analysis: Examining the Node Hierarchy. The in- and out-degree ($k_i^{in(out)}$) of ACN and OCN are compared to analyze the shifts in the employment and housing hierarchy within the commuting system. Figure 3A demonstrates significant changes in the distributions of $k_i^{in(out)}$. The mean values of $k_i^{in(out)}$ show a significant decrease from 50.22 in ACN to 1.99 in OCN, indicating a notable reduction in the overall intensity of spatial interaction within the commuting system after optimization. Moreover, the coefficient of variation (CV) shows contrasting trends between k_i^{in} and k_i^{out}. The CV for k_i^{in} declines from 1.15 in ACN to 0.94 in OCN, indicating that the variation in employment attraction among nodes in OCN has become less dispersed compared to ACN. In other words, the differences in the number of incoming commuters to different employment locations in OCN have become less pronounced. Nonetheless, the CV for k_i^{out} increases from 0.44 in ACN to 0.52 in OCN, suggesting that although the housing opportunities tend to be more evenly distributed than the employment opportunities (smaller CV for k_i^{out} than for k_i^{in}), housing opportunities become more dispersed or variable in OCN compared to ACN. These trends are also notable in Figure 3C. To further explore the structural changes in the node hierarchy (i.e., in- and out-degree ranking) between ACN and OCN, the Spearman's rank correlation coefficient (ρ) is calculated. The findings reveal a substantial reshaping of the node hierarchy concerning the housing function from ACN to OCN ($\rho = 0.23$ for k_i^{out}). A moderate level of consistency or similarity in the node hierarchy is observed, however, for the employment function between ACN and OCN ($\rho = 0.62$ for k_i^{in}). These trends are clearly evident in Figure 3B, which depicts the changes in ranks for $k_i^{in(out)}$ across metropolitan statistical areas (MSAs) in Florida, ordered by the number of workers. Overall, larger MSAs tend to undergo downgrades in rank, whereas smaller ones demonstrate upgrades in the commuting system.

Figure 3C provides a closer examination of the shift in the node hierarchy. For k_i^{in}, the employment hierarchical system in ACN showcases the dominant presence of three MSAs—Miami, Tampa, and Orlando—occupying the top-tier positions in the job market, followed by Jacksonville. Notably, the top 5 percent nodes with the highest k_i^{in} are primarily concentrated in these three MSAs, particularly in areas near central business districts (CBDs), regional airports, and theme parks (especially in Orlando). In OCN, although the top three MSAs still hold prominence at the regional level, their influence has diminished as indicated by a decreasing share of the top-ranked nodes, owing to the rise of other MSAs in the job market. Generally, OCN demonstrates a polycentric tendency characterized by the emergence of regional employment centers located in the CBDs of smaller MSAs including Tallahassee, Gainesville, and Ocala. This polycentric trend is further supported by the growing number of high–low clusters revealed through Moran's I analysis (Anselin 1995), distributed along the border areas between cities in OCN. For k_i^{out}, the four MSAs—Miami, Tampa, Orlando, and Jacksonville—with a broader reach of labor supply hold more prominent positions in ACN. Unlike k_i^{in}, however, nodes with the highest k_i^{out} tend to be dispersed over the suburbs. Similarly, k_i^{out} exhibits a reshaping into a more polycentric and uniform structure, indicated by the dispersion of high–high clusters throughout the suburbs of smaller MSAs.

Mesoscale Analysis: Examining Local Labor Market Geographies. As shown in Figure 4A, ACN exhibits sixteen geographically cohesive communities (LMAs) with a high modularity score of 0.84, indicating a robust division (Hu and Huang 2023). The within-LMA commutes across LMAs contribute to 93.9 percent of the total commutes in Florida, suggesting a high level of employment self-containment. Additionally, Figure 4A illustrates the proportion of the within-LMA commutes relative to the total commutes in Florida for each identified LMA.

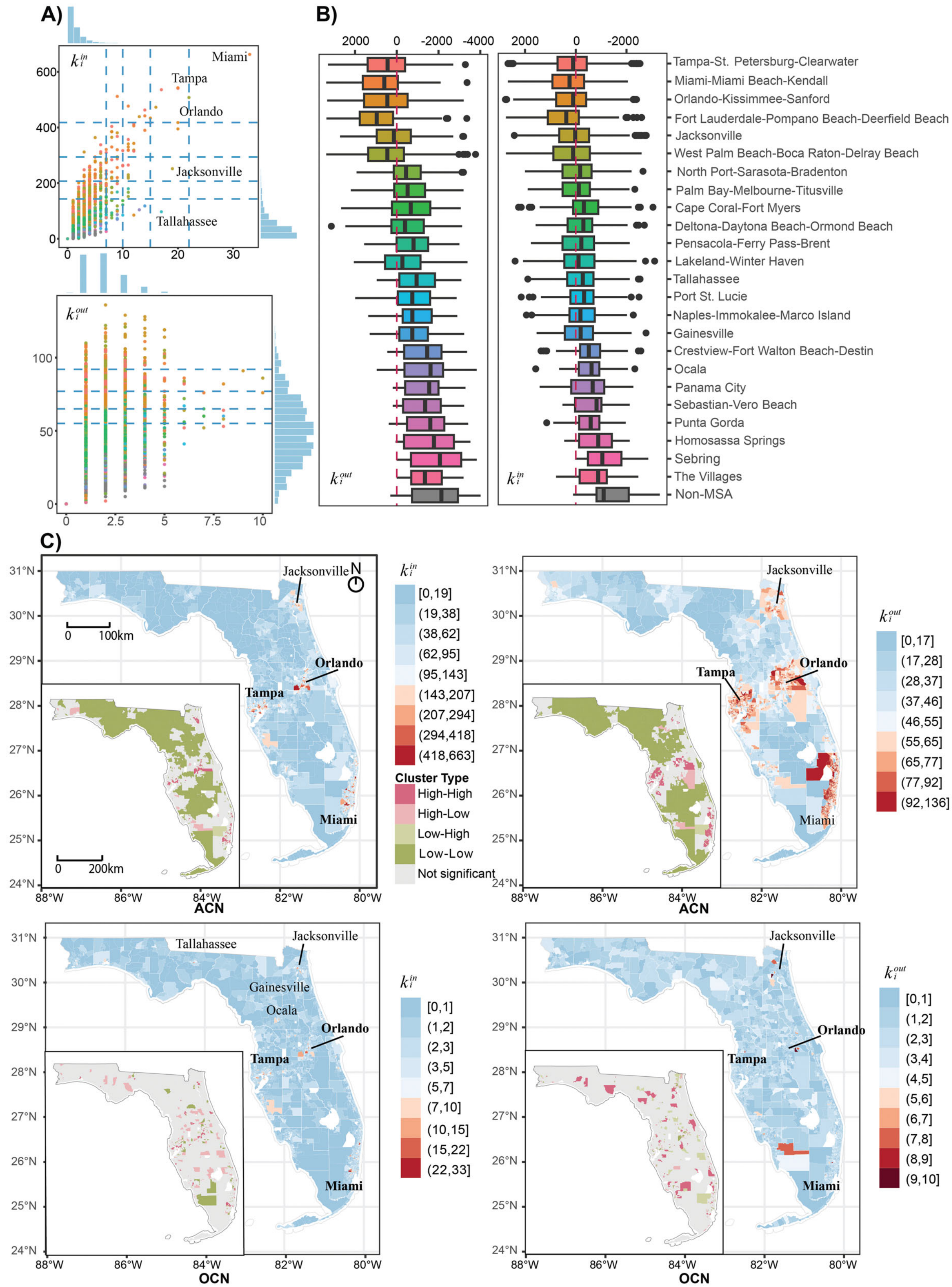

Figure 3. (A) Distributions of $k_i^{in(out)}$ in actual commuting network (ACN) and optimal commuting network (OCN). (B) Changes in node ranking associated with $k_i^{in(out)}$ between ACN and OCN. (C) Spatial distributions of $k_i^{in(out)}$ in ACN and OCN (the four insets show spatial patterns of local Moran's I statistics of $k_i^{in(out)}$).

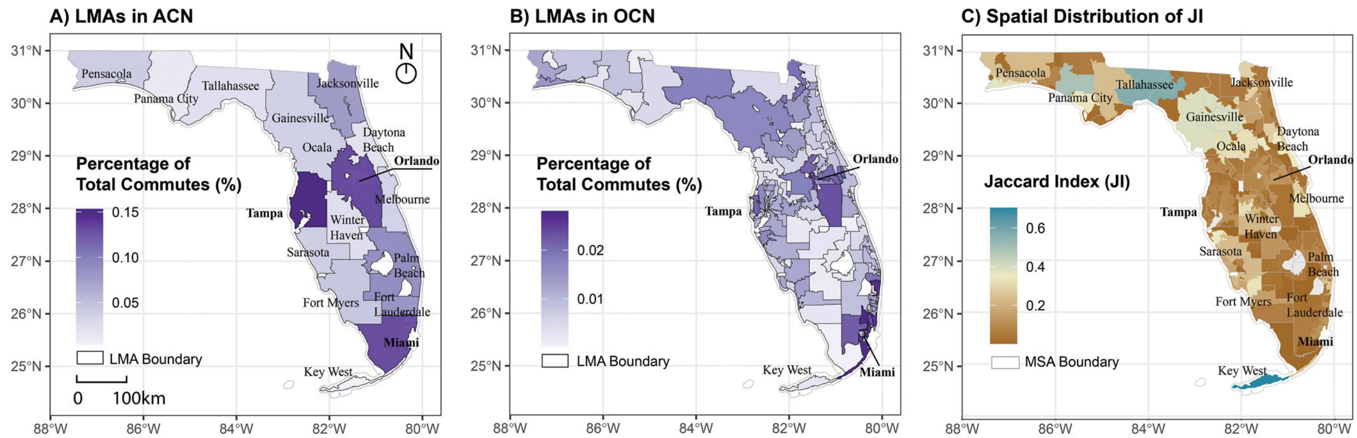

Figure 4. Labor market area (LMA) geographies in actual commuting network (ACN) and optimal commuting network (OCN).

Notably, approximately 41.4 percent of the total commutes concentrate in the top three largest LMAs centered around Tampa (15.3 percent), Orlando (13.1 percent), and Miami (13.0 percent), followed by three medium-sized LMAs surrounding Fort Lauderdale, Palm Beach, and Jacksonville, each capturing 8 percent to 10 percent of the total flows. In contrast, OCN comprises 118 significantly smaller and isolated LMAs, each accounting for less than 3 percent of the total commutes in Florida (Figure 4B). With a higher modularity score of 0.97, it indicates an even more pronounced degree of employment self-containment, as evidenced by an even higher share (98.9 percent) of total within-LMA commutes across LMAs in relation to the total commutes in Florida.

The notable difference in LMA geography between ACN and OCN is supported by a moderately low FMI value of 0.35, indicating a lower level of agreement between the two LMA delineations overall. The JI further provides a more detailed examination of the similarity between two LMA delineations for each node (tract). As shown in Figure 4C, tracts in Tallahassee, Key West, and Panama City exhibit higher JI values, suggesting higher consistency in LMA delineations between ACN and OCN. Conversely, tracts within the top three MSAs, particularly those located in the outskirts, show more pronounced changes, as indicated by lower JI values.

After optimizing commuting flows, most LMAs in ACN undergo significant contraction, especially for the top three MSAs, which possess greater capacity in reorganizing flows due to higher job and population densities. The optimal commuting system now exhibits a more fragmented functional system comprised of numerous loosely connected small LMAs. It is important to note, however, that these smaller LMAs in OCN tend to exhibit a more balanced jobs–housing relationship.

Discussion

On Commuting Efficiency

The multiscale complex network analysis of EC proposes an alternative perspective for understanding commuting efficiency. The overall inefficient commuting system with a 63.2 percent C_{ex} emerges from two distinct underlying spatial interaction processes—ACN and OCN—reflected at multiple scales. At the macroscale, ACN and OCN exhibit divergent urban connectivity patterns due to significantly reduced commuting connections over longer distances after commuting cost minimization. ACN demonstrates a highly connected and topologically efficient structure manifesting small-world network properties, whereas OCN is more simplified, topologically distant, less cohesive, and less efficient. At the microscale, the cost minimization reshapes the node hierarchy of the commuting system. ACN exhibits a centralization of nodes mainly in three major MSAs—Miami, Tampa, and Orlando—at the regional level, whereas OCN demonstrates a polycentric tendency characterized by emerging regional employment and residential centers in smaller MSAs like Gainesville, Ocala, and Tallahassee. Another striking difference arises in the delineation of LMAs at the mesoscale. ACN is divided into sixteen larger-sized LMAs, whereas OCN displays a more fragmented pattern with 118 significantly smaller and isolated LMAs, primarily based on smaller labor sheds with limited mobility opportunities. The striking distinction between ACN and OCN highlights the paradox between commuting efficiency and labor mobility behind the single statistic, which, to some extent, reveals the dual nature of commuting behavior. Commuting produces various externalities and is often urged to be minimized for promoting sustainability, but it is essential for spatial interactions that facilitate economic growth and regional development through transmitting information, capital, and people across space (Goetz et al. 2010). In this sense, this paradox highlights the need to reexamine the theoretical foundation of the traditional EC framework, which has predominantly focused on the negative aspects of commuting while overlooking its benefits.

On the Accuracy of Minimum Commute

By redistributing workers to nearby employment opportunities, the LP method achieves the best overall spatial proximity between jobs and housing at the expense of reducing topological efficiency. Hence, pursuing the resulting OCN obtained by solely minimizing travel cost might not be a practical approach. It would lead to an oversimplified and fragmented commuting system, lacking vital commuting connections among large centers. Such a system could be less adaptable to external changes like COVID-19 lockdowns and might impede regional integration, reinforce regional disparities, and strengthen the urban–rural dichotomy. In this regard, the traditional EC framework might underestimate the minimum commute and potentially lead to ineffective jobs–housing policy recommendations. Nevertheless, this research does not seek to dismiss the practical significance of C_{min} as a benchmark for assessing spatial structure or advocate for longer commutes to achieve greater mobility. Rather, its purpose is to present an alternative perspective on understanding EC by exploring its underlying spatial interaction process. Moreover, this pilot study attempts to spark further discussions on designing a more appropriate commuting benchmark by capturing the trade-off between spatial proximity and labor mobility.

Conclusions

Using commuting flows from the 2012 to 2016 CTPP of Florida, this study reexamines EC through multiscale complex network analysis, delving into the underlying spatial interaction patterns behind the single global statistic. The findings reveal striking divergences in urban connectivity, node hierarchy, and labor market geography between ACN and OCN. Compared to ACN, OCN exhibits noteworthy reductions in both its average path length and global clustering coefficient, indicating a less connected and cohesive structure. The spatial distribution of degree centrality in OCN has undergone a transformation, illustrating a polycentric trend characterized by the emergence of regional employment and residential centers. Additionally, OCN demonstrates a more fragmented and isolated division of LMAs, which in turn limits labor mobility and regional integration. Although OCN results in cost savings for commuting, it might not represent a practical commuting objective, as it does not fully consider the economic significance of commuting. Hence, there is a critical need to delve deeper into the economic implications of commuting within the traditional LP model.

This study has several limitations. First, it does not consider the heterogeneity in jobs, workers, and transportation modes that can influence commuting patterns during the flow reallocation process (e.g., Niedzielski et al. 2020). A disaggregated analysis of workers across various employment, socioeconomic, and transportation mode groups could address this issue. Second, this study is based on a single aggregated commuting data set for Florida between 2012 and 2016, potentially limiting the generalizability to other regions and time periods. Nevertheless, the versatility of our proposed methodology allows for future investigations to easily extend the analysis to alternative data sets, thereby enhancing the understanding of EC and its temporal dynamics across different geographic contexts.

Acknowledgments

We thank the editor and the anonymous referees for their valuable comments that greatly improved this article.

Disclosure Statement

No potential conflict of interest was reported by the authors.

Funding

This study was undertaken with partial support from the U.S. National Science Foundation under Award #2319551.

ORCID

Yujie Hu http://orcid.org/0000-0001-5814-0805

References

Albert, R., and A. L. Barabási. 2002. Statistical mechanics of complex networks. *Reviews of Modern Physics* 74 (1):47–97. doi: 10.1103/RevModPhys.74.47.

Anselin, L. 1995. Local indicators of spatial association—LISA. *Geographical Analysis* 27 (2):93–115. doi: 10.1111/j.1538-4632.1995.tb00338.x.

Blondel, V. D., J. L. Guillaume, R. Lambiotte, and E. Lefebvre. 2008. Fast unfolding of communities in large networks. *Journal of Statistical Mechanics: Theory and Experiment* 2008 (10):P10008. doi: 10.1088/1742-5468/2008/10/P10008.

Burd, C., M. Burrows, and B. McKenzie. 2021. Travel time to work in the United States: 2019. American Community Survey Reports ACS-47. U.S. Census Bureau, Washington, DC.

Cervero, R. 1989. Jobs–housing balancing and regional mobility. *Journal of the American Planning Association* 55 (2):136–50. doi: 10.1080/01944368908976014.

Clark, B., K. Chatterjee, A. Martin, and A. Davis. 2020. How commuting affects subjective wellbeing. *Transportation* 47 (6):2777–2805. doi: 10.1007/s11116-019-09983-9.

Fowlkes, E. B., and C. L. Mallows. 1983. A method for comparing two hierarchical clusterings. *Journal of the American Statistical Association* 78 (383):553–69. doi: 10.1080/01621459.1983.10478008.

Frigo, M., E. Cruciani, D. Coudert, R. Deriche, E. Natale, and S. Deslauriers-Gauthier. 2021. Network alignment and similarity reveal atlas-based topological differences in structural connectomes. *Network Neuroscience* 5 (3):711–33. doi: 10.1162/netn_a_00199.

Giuliano, G., and K. A. Small. 1993. Is the journey to work explained by urban structure? *Urban Studies* 30 (9):1485–1500. doi: 10.1080/00420989320081461.

Goetz, S. J., Y. Han, J. L. Findeis, and K. J. Brasier. 2010. US commuting networks and economic growth: Measurement and implications for spatial policy. *Growth and Change* 41 (2):276–302. doi: 10.1111/j.1468-2257.2010.00527.x.

Hamilton, B. W., and A. Röell. 1982. Wasteful commuting. *Journal of Political Economy* 90 (5):1035–53. doi: 10.1086/261107.

Hincks, S., and C. Wong. 2010. The spatial interaction of housing and labour markets: Commuting flow analysis of North West England. *Urban Studies* 47 (3):620–49. doi: 10.1177/0042098009349777.

Horner, M. W. 2004. Spatial dimensions of urban commuting: A review of major issues and their implications for future geographic research. *The Professional Geographer* 56 (2):160–73. doi: 10.1111/j.0033-0124.2004.05602002.x.

Horner, M. W., and A. T. Murray. 2002. Excess commuting and the modifiable areal unit problem. *Urban Studies* 39 (1):131–39. doi: 10.1080/00420980220099113.

Hu, Y., and J. Huang. 2023. Delineating and comparing local labor market geographies of Millennials, Generation Xers, and Baby Boomers. *Travel Behaviour and Society* 30:325–34. doi: 10.1016/j.tbs.2022.10.012.

Hu, Y., and X. Li. 2021. Modeling and analysis of excess commuting with trip chains. *Annals of the American Association of Geographers* 111 (6):1–17. doi: 10.1080/24694452.2020.1835461.

Hu, Y., C. Wang, R. Li, and F. Wang. 2020. Estimating a large drive time matrix between ZIP codes in the United States: A differential sampling approach. *Journal of Transport Geography* 86:102770.

Jing, Y., and Y. Hu. 2022. The unequal commuting efficiency: A visual analytics approach. *Journal of Transport Geography* 100 (C):103328. doi: 10.1016/j.jtrangeo.2022.103328.

Kanaroglou, P. S., C. D. Higgins, and T. A. Chowdhury. 2015. Excess commuting: A critical review and comparative analysis of concepts, indices, and policy implications. *Journal of Transport Geography* 44:13–23.

Ma, K. R., and D. Banister. 2006. Excess commuting: A critical review. *Transport Reviews* 26 (6):749–67. doi: 10.1080/01441640600782609.

Nelson, G. D., and A. Rae. 2016. An economic geography of the United States: From commutes to megaregions. *PLoS ONE* 11 (11):e0166083. doi: 10.1371/journal.pone.0166083.

Newman, M. E. 2006. Modularity and community structure in networks. *Proceedings of the National Academy of Sciences of the United States of America* 103 (23):8577–82. doi: 10.1073/pnas.0601602103.

Niedzielski, M. A. 2006. A spatially disaggregated approach to commuting efficiency. *Urban Studies* 43 (13):2485–2502. doi: 10.1080/00420980600970672.

Niedzielski, M. A., Y. Hu, and M. Stępniak. 2020. Temporal dynamics of the impact of land use on modal disparity in commuting efficiency. *Computers, Environment and Urban Systems* 83:101523. doi: 10.1016/j.compenvurbsys.2020.101523.

O'Kelly, M. E., and W. Lee. 2005. Disaggregate journey-to-work data: Implications for excess commuting and jobs–housing balance. *Environment and Planning A: Economy and Space* 37 (12):2233–52. doi: 10.1068/a37312.

Schleith, D., M. J. Widener, C. Kim, and M. W. Horner. 2019. Categorizing urban form for the largest metro regions in the US using the excessive commuting framework. *Built Environment* 45 (4):450–61. doi: 10.2148/benv.45.4.450.

Śleszyński, P., P. Olszewski, T. Dybicz, K. Goch, and M. A. Niedzielski. 2023. The ideal isochrone: Assessing the efficiency of transport systems. *Research in Transportation Business & Management* 46:100779. doi: 10.1016/j.rtbm.2021.100779.

White, M. J. 1988. Urban commuting journeys are not wasteful. *Journal of Political Economy* 96 (5):1097–1110. doi: 10.1086/261579.

Zhang, W., C. Fang, L. Zhou, and J. Zhu. 2020. Measuring megaregional structure in the Pearl River Delta by mobile phone signaling data: A complex network approach. *Cities* 104:102809. doi: 10.1016/j.cities.2020.102809.

YUE JING is a PhD Student in the Department of Geography at the University of Florida, Gainesville, FL 32611. E-mail: jingyue@ufl.edu. Her research interests include GIS and transportation studies.

YUJIE HU is an Assistant Professor in the Department of Geography at the University of Florida, Gainesville, FL 32611. E-mail: yujiehu@ufl.edu. His research interests include spatial networks, urban transportation, human mobility, and spatial accessibility.