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MULTIDIMENSIONAL NETWORK ANALYSIS OF PLACE–ROAD INTERDEPENDENCE IN PEOPLE-INFRASTRUCTURE SYSTEMS

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ABSTRACT

Urban settlements and transportation infrastructure jointly shape regional spatial organization, yet they are often analyzed as separate network systems. This study models their interdependence as a multidimensional network consisting of census-designated places and primary roads in Texas for the year 2010. The resulting place–road network integrates three types of relationships: place adjacency, road connectivity, and cross-layer links formed when road segments pass through places. Exponential Random Graph Models (ERGMs) are employed to analyze the link formation processes governing place–road connectivity by capturing the effects of node attributes and structural network configurations. The proposed multidimensional network representation and the ERGM framework provide a principled methodology for analytically investigating intra- and inter-system dependencies between urban settlements and transportation infrastructure. The modeling results recover qualitative patterns observed in Texas urban systems in 2010, providing evidence for the validity of the proposed representation and analytical framework. For example, larger and more populated places are significantly more likely to connect to primary roads, while Interstate and U.S. highways exhibit a higher probability of connecting with places than state highways. Regarding system interdependencies, geometrically weighted degree terms reveal hub-like connectivity patterns in which a small number of places and roads accumulate a disproportionate share of connections. In addition, cross-layer network configurations derived from place adjacency further indicate that geographically adjacent places are substantially more likely to share connections to the same roads, reflecting spatial clustering in place–road interactions. These results illustrate how the proposed framework can provide quantitative information on the formation of coupled urban-infrastructure systems and establish a foundation for future studies of system evolution, prediction, and engineering design of complex people-infrastructure systems.

Keywords: Urban systems, Bipartite networks, Multidimensional networks, Exponential Random Graph Models (ERGMs)

1. INTRODUCTION

Urban systems have increasingly been examined through the lens of complex systems and network science. A major strand of urban science research investigates urban scaling, which explores systematic relationship between city size and various socio-economics and infrastructural indicators [1, 2]. These studies suggest that urban systems emerge from interactions among individuals, firms, and infrastructure networks rather than from isolated urban entities. Network science offers a compelling framework for understanding the intricate dynamics of urban systems, where spatial entities such as cities or municipalities are modeled as nodes and connections represent spatial, economic, or infrastructural interactions [1, 3, 4]. Network representations allow researchers to analyze structural properties such as connectivity, clustering, and centrality, providing insights into how spatial interactions shape urban systems. In this context, the selection of spatial units is important. Many studies rely on metropolitan areas or counties due to data availability, but such aggregated units may obscure localized spatial interactions. In the United States, cities and towns function as autonomous jurisdictions with authority over land use and infrastructure decisions, making place-based units (i.e., cities or census-designated places) meaningful spatial agents for modeling regional urban interactions [5].

Transportation infrastructure plays a central role in facilitating these interactions. Road networks enable the movement of people, goods, and services across space and connect urban settlements with regional systems. They therefore have been widely modeled as spatial graphs, where nodes and edges represent physical elements of the transportation system and their connectivity [6]. Different graph representations have been proposed. In the conventional primal graph representation, intersections are modeled as nodes and road segments as edges. Alternatively, the dual representation models individual roads as nodes and intersections

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between roads as edges, capturing structural relationships among streets [7–9]. In this study, we adopt the dual representation and focus on primary roads, highlighting the backbone of regional transportation infrastructure and how it connects urban places across the region.

Despite the importance of both urban settlements and transportation infrastructure, these systems are often analyzed as separate networks. In reality, however, urban places and transportation infrastructure coexist within the same spatial system and jointly shape regional spatial organization. From a people-infrastructure systems perspective, infrastructure networks are not only physical assets, but components of socio-technical systems that interact with communities and support societal functions, such as mobility, economic activity, and public welfare across multiple spatial scales [10]. Understanding these systems therefore requires analytical frameworks that can represent both urban places and transportation infrastructure and capture their interdependence. To realize this perspective, this study conceptualizes the urban system as a multidimensional network composed of interacting spatial layers.

Fig. 1 illustrates this framework using examples from the Austin, Texas region and the primary road network. At the place layer, census-designated places such as Austin, West Lake Hills, and Sunset Valley are represented as nodes, and undirected edges are defined when two places share a geographic boundary, capturing reciprocal adjacency relationships among neighboring jurisdictions. At the road layer, the system is represented using a dual graph representation, where individual roads (e.g., I-35, State Highway 71) are modeled as nodes and intersections between roads form undirected edges. The two layers are connected through spatial embedding: when a road segment crosses or passes through a place polygon, an undirected link is formed between the corresponding road node and place node. In this way, the framework represents place adjacency, road connectivity, and place–road relationships within a unified multidimensional network structure. This representation enables the investigation of the following question: how can the structural dependencies between and within urban settlements and transportation infrastructure be analytically characterized to understand the underlying formation of regional connectivity patterns?

The remainder of the paper is organized as follows. Section 2 reviews related work on network-based modeling of urban systems and the use of exponential random graph models (ERGMs). Section 3 presents the research methods used in this study. Section 4 reports the empirical results and a degree distribution analysis across network layers. Section 5 concludes the paper, discusses limitations, and outlines directions for future research.

2. REVIEW OF RELEVANT LITERATURE

2.1. Bipartite and Multidimensional Network Models in Urban Systems

Urban systems consist of multiple interacting components, including settlements, transportation infrastructure, and other built systems. To represent interactions among heterogeneous entities, researchers have proposed bipartite network models, where nodes belong to two distinct sets and edges occur only between nodes of different types [11]. The utility of bipartite networks lies in their ability to explicitly represent relationships between two functionally distinct classes of actors, such as plant and pollinator species in ecological networks [12, 13] and customers and products in market systems [14], while revealing emergent patterns of connectivity that would otherwise be obscured in a unipartite representation. This same logic extends naturally to people-infrastructure systems, where places and roads constitute two functionally distinct yet interdependent layers, and the interactions between them govern urban accessibility and mobility.

More broadly, multidimensional network models extend this concept by allowing multiple types of nodes and relationships to coexist within a unified network representation [15, 16]. These models have been increasingly applied to study interdependent infrastructure systems, including transportation, communication, and power networks, where failures or disruptions in one layer can propagate to others [17, 18]. Such approaches enable researchers to examine structural dependencies across systems and to analyze system-level resilience.

Despite these developments, applications of bipartite or multidimensional network models to urban settlement–infrastructure systems remain limited. Existing multilayer studies primarily focus on interactions among transportation modes or infrastructure layers, such as bus–metro or road–rail systems [19–21]. As a result, cities and transportation infrastructure are typically analyzed separately, either as networks of urban settlements or as networks of infrastructure elements. However, urban places and transportation infrastructure mutually shape regional spatial organization [22–24]. Modeling these systems jointly can provide new insights into how infrastructure connectivity structures interactions among urban settlements and how urban development influences the configuration of infrastructure networks.

2.2. Background on Exponential Random Graph Models (ERGMs)

Originally proposed by Frank and Strauss [25], ERGMs interpret global network structures as the outcome of multiple local network configurations [26]. An observed network y is treated as one realization from a set of possible networks (i.e., a distribution) Y. The probability of observing a particular network structure depends on a weighted combination of network statistics, given as

$$P(Y = y) = \frac{1}{\kappa(\theta)} exp(\theta^T g(y)), \tag{1}$$

where θ is a vector of model parameters, $g(y)$ is a vector of network statistics representing structural configurations or nodal covariates, and $\kappa(\theta)$ is a normalizing constant to ensure that the distribution sums to one over all possible networks. This formulation implies that the likelihood of observing a network increases when configurations associated with positive parameters occur more frequently.

A key feature of ERGMs is that the entire network is treated as a random variable, meaning that the model evaluates probabilities over complete network structures rather than individual edges. Within this framework, endogenous dependencies among links, such as degree concentration (the tendency for high-degree nodes to attract additional connections) or transitivity (the tendency for

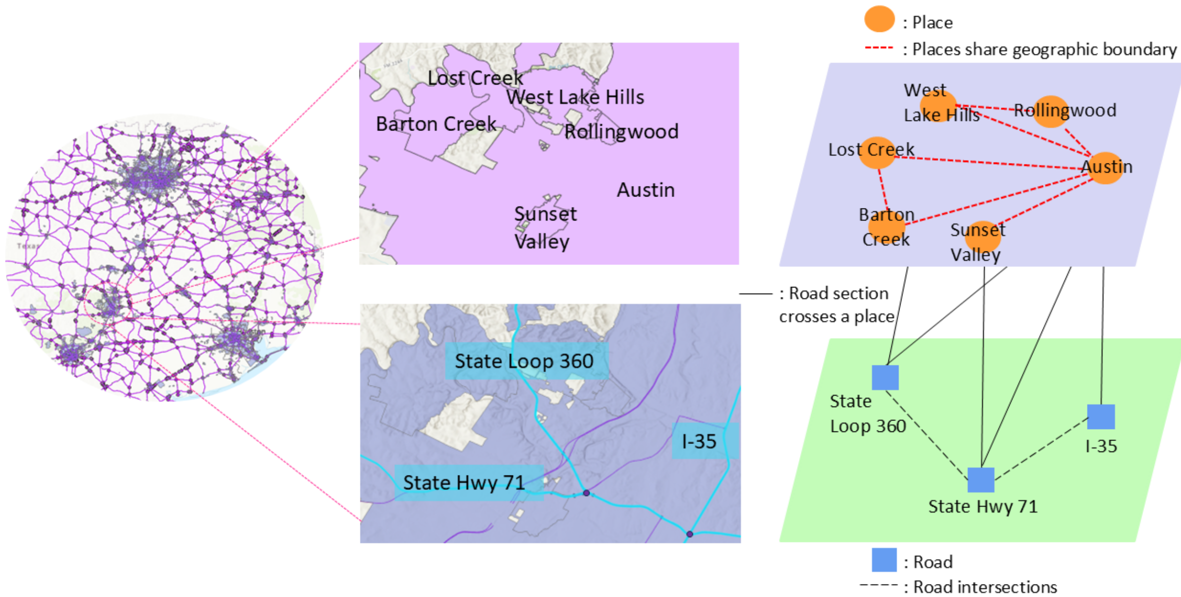


FIGURE 1: An example of multidimensional network representation for places and roads in area of Austin, Texas.

triangles and clustering to form among connected nodes), can be represented through network statistics, while exogenous attributes can be included as nodal or dyadic covariates (i.e., nodal or edge attributes) [26, 27]. In practice, researchers iterate through different combinations of network configurations that reflect theoretically meaningful mechanisms of network formation. The θ parameters can be estimated using maximum likelihood methods or Markov Chain Monte Carlo (MCMC) algorithms [28] given the observed network, i.e., the data.

ERGMs have been developed for several types of network structures, including one-mode or unidimensional networks, bipartite networks, and multidimensional networks [26, 27, 29]. In this study, the bipartite specification is appropriate as a foundation because the network consists of two types of nodes, places and roads, and the model seeks to explain the formation of links between these two node sets. In addition, we explore an extension that incorporates relationships within each layer, allowing place-place and road-road relationships to be considered within a multidimensional network framework.

2.3. Exponential Random Graph Model in Regional Studies

ERGM is most widely applied in the social network research [26, 27, 30–32]. It models network formation by relating observed network structures to underlying local configurations and node or dyadic attributes [26]. This framework allows researchers to examine mechanisms that drive edge formation, i.e., the probability that a connection between two nodes exists, rather than only describing observed network patterns.

In urban and regional studies, ERGM has been applied more selectively. Existing work has focused on intercity relational networks, where edges represent socio-economic or institutional interactions between cities or regions. For example, ERGM has been applied to several intercity socio-economic and environmental networks, including sustainable development cooperation network [33] and interregional resource or environmental interaction networks [34, 35]. These studies demonstrate that ERGM can identify how both endogenous network structures and exogenous spatial or economic attributes influence the formation of intercity connections.

However, most urban ERGM applications focus on functional relationships among city, rather than spatially embedded infrastructure systems. Infrastructure elements themselves are rarely represented as nodes within the network structure. Consequently, ERGM has seldom been applied to urban systems that explicitly integrate settlements and infrastructure within the same network representation. This is a notable gap since urban places and infrastructure networks are inherently interdependent: infrastructure structures accessibility between places, while urban development influences the configuration and expansion of infrastructure systems. In this study, ERGM is applied to a place–road multidimensional network framework, allowing the formation of links between urban places and transportation infrastructure to be analyzed within a unified probabilistic network model.

3. METHODS

This section provides an overview of the dataset and network configurations adopted in this study (sec. 3.1.1 and 3.1.2).

3.1. Network Construction

3.1.1. Data Source To examine the interactions between urban places and transportation infrastructure, this study constructs a multilayer undirected network composed of census-designated places and primary roads (highway networks) in Texas, United States, for the year 2010. Place-level demographic and spatial

TABLE 1: Summary statistics of variable in each network layer.

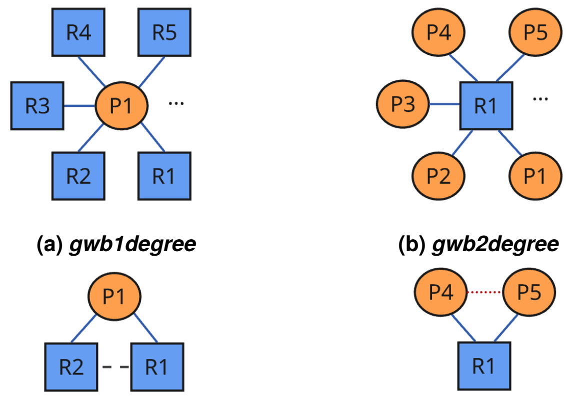
	Variables	Statistics
Place	Area (acres)	Min: 3.23, Max: 400,627.88 Avg: 4,810.29, Std: 17,564.73
	Population (# people)	Min: 0, Max: 2,099,451 Avg: 11,244.57, Std: 75,842.25
Road	Interstate highway, I	Count: 67
	U.S. highway, U	Count: 270
	State highway, S	Count: 857

attributes are obtained from the National Historical Geographic Information System (IPUMS NHGIS) [36], while primary road network data in Texas are derived from U.S. Census Bureau transportation datasets [37]. The resulting dataset contains 1,752 place nodes and 1,194 road nodes, representing the settlement and transportation layers of the network, respectively. As discussed previously, census-designated places are used as the unit of analysis. Place-level data are available on a decennial basis, whereas road network data are available annually. In this study, we construct a network snapshot for 2010, in light of data availability, to evaluate which ERGM specifications best capture the structural characteristics of the place-road network.

For place nodes, we consider two attributes: area (measured in acres) and population (number of residents). These variables capture fundamental characteristics of places. Area represents the spatial extent of a place and reflects differences in geographic size and land coverage, while population captures the demographic scale of the place and serves as a proxy for potential transportation demand and urban activity, such as commuting and economic transactions.

For road nodes, we consider the road types including Interstate highways (I), U.S. highways (U), and state highways (S). These categories represent the functional hierarchy of highways and reflect different levels of transportation infrastructure importance. Interstate highways is the highest class of arterial highways designed for high-speed and long-distance travel, forming the backbone of the U.S. transportation system. U.S. highways provide interregional connectivity, and state highways serve more localized transportation functions [38]. Incorporating these classifications allows the analysis to account for differences in the roles that various road types play within the transportation network. Table 1 summarizes the descriptive statistics of the variables included in each layer. These attributes are incorporated into the ERGM specification as nodal covariates, accounting for heterogeneity in node characteristics that may influence connectivity patterns.

3.1.2. Network Configurations In addition to nodal covariates, we draw on the set of ERGM configurations documented in Ref. [39] to model structural dependencies within the place-road network. The choice of configurations is guided by the spatial and functional relationships expected between places and road segments, as well as the hypotheses being examined regarding how these entities interact. In this study, we incorporate two types of configurations: the geometrically weighted



(a) ***gwb1degree*** **(b)** ***gwb2degree*** **(c)** ***b1twostarb2network*** **(d)** ***b2twostarb1network***

FIGURE 2: Network configurations used to model interdependence between places and roads.

degree (*gwdegree*) to capture heterogeneity in place and road connectivity. In addition, we introduce two custom configurations, *b1twostarb2network* and *b2twostarb1network*, representing cross-layer triangular motifs. These configurations jointly account for within-layer and between-layer connections, effectively forming triangular structures composed of place-road links together with either place-place or road-road connections.

Geometrically weighted statistics were introduced to improve model stability and interpretability in ERGMs, particularly when networks exhibit heterogeneous degree distributions where nodes vary widely in the number of connections they form, with some nodes being highly connected hubs and others having very few connections [26, 40, 41]. The *gwdegree* statistic (see Fig. 2a and 2b) applies a geometrically decaying weight to higher-degree nodes, allowing the model to represent broad degree distributions with a single parameter rather than modeling each k-star configuration individually, thus reducing model instability and degeneracy [41]. Formally, Hunter [41] proposed the statistic as

$$g_{\text{gwdegree}}(Y;\tau) = \sum_{i=1}^{n} \left(1 - (1 - e^{-\tau})^{d_i(Y)}\right), \tag{2}$$

where $d_i(Y)$ denotes the degree of node i (i.e., the number of edges connecting to node i) in network Y, and $\tau > 0$ is a decay parameter controlling how strongly higher-degree nodes contribute to the statistic. Smaller decay values place relatively greater weight on low-degree nodes, whereas larger values allow higher-degree nodes to contribute more strongly to the statistic. This formulation effectively represents a geometrically weighted sum of k-star configurations centered at nodes, thereby modeling higher-order dependence associated with node popularity.

To capture higher-order, dyadic dependencies between the the place and road networks, we incorporate *b1twostarb2network* (see Fig. 2c) and *b2twostarb1network* (see Fig. 2d). The term *b1twostarb2network* represents a two-star configuration centered on a node in the first partition of a bipartite network (*b1*), where the two connected nodes in the second partition (*b2*) are related through an external network or adjacency matrix, and vice versa for *b2twostarb1network*.

Consider *b1twostarb2network* as an example, say we have a bipartite network $G = (P, R, Y)$, where P denotes nodes in the place layer (i.e., first mode) and R denotes nodes in the road layer (i.e., second mode). Y_{ij} is a binary variable indicating whether an edge exists between $i \in P$ and $j \in R$. Let X_{jk} denote an adjacency matrix representing relationships among nodes in R (i.e., connectivity between roads). The statistic is defined as

$$g_{b1twostarb2network}(Y, X) = \sum_{i \in P} \sum_{j<k \in R} Y_{ij} Y_{ik} X_{jk} \tag{3}$$

This statistic counts the number of two-star configurations centered at nodes in P where the two neighboring nodes j and k in R are connected in the auxiliary network, X. In other words, the statistic measures the tendency of a place to connect to multiple roads that are themselves connected through the road network. A positive coefficient associated with this term indicates that places are more likely to be linked to groups of roads that are structurally related, capturing cross-layer structural patterns and reflecting the influence of the underlying road network topology on place-road connectivity.

As for *b2twostarb1network*, place-adjacency is represented in the auxiliary network, and a positive coefficient indicates that roads are more likely to link groups of spatially related places.

4. RESULTS AND DISCUSSION

Adopting the network configurations discussed, we report the ERGM results from the place-road network analysis of Texas in 2010 in this section.

4.1. ERGM Estimation Results

Building upon the settings discussed in Sec. 3, we define and explore four ERGMs with different specifications. The base model assumes dyadic independence, meaning that link formation depends only on node attributes while excluding network configuration terms. The bipartite model incorporates the network configurations between the two modes including $gwb1degree$, representing the popularity effect of a place, and $gwb2degree$, representing the popularity effect of a road. To further incorporate structural information from other network layers, we introduce multidimensional models that account for in-layer connectivity patterns, incorporating additional information from the place-place and road-road networks. Specifically, we consider three cases: **Case I**, which incorporates the place adjacency information (*b2twostarb1network*); **Case II**, which incorporates the road intersection information (*b1twostarb2network*); and **Case III**, which incorporates both in-layer networks simultaneously.

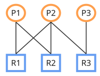
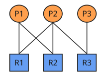
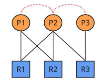
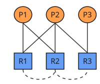
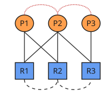
These extensions capture the intuition that place-road connectivity may be influenced by structural relationships within each individual layer. For example, places that share geographic boundaries may exhibit similar connections to nearby roads, while roads that intersect or form continuous transportation corridors may be more likely to connect to the same places. The multidimensional ERGMs enable the model to capture cross-layer dependencies that cannot be represented in a purely bipartite network formulation and provide a framework for capturing the co-structural relationships between settlements and transportation infrastructure across multiple network layers. Table 2 summarizes the model parameter estimates, their standard errors, and performance indicators calculated via the R programming language's *statnet* package [39].

The continuous place attributes, area and population, are log-transformed and z-standardized prior to estimation to reduce skewness and position the variables on a comparable scale [42]. As a result, the coefficients represent the change in the log-odds of forming a place-road connection associated with a one-standard deviation increase in the log-transformed variable. Across all model specifications, the coefficient for log(Area) is positive and statistically significant, indicating that larger places are more likely to connect to roads in the network. This effect remains robust across the base, bipartite, and multidimensional models, suggesting that the spatial extent of a place consistently increases the likelihood of forming place-road links. Similarly, the coefficient for log(Population) is positive and significant in all models, indicating that places with larger populations tend to exhibit a higher probability of connecting to roads. However, the magnitude of the population coefficient decreases substantially in the multidimensional models (Case I and Case III), implying that part of the apparent influence of population in simpler models may be explained by structural dependencies captured by the additional network configuration terms. In other words, once place-adjacency relationships are accounted for, the direct effect of population on link formation becomes weaker.

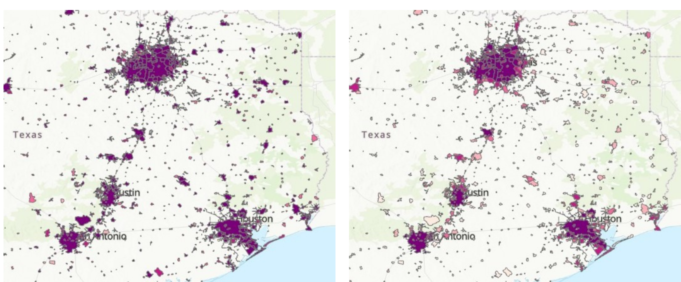
To further examine this finding, we construct spatial gradients of population and place-adjacency (node degree) using a log-quantile classification scheme, shown in Fig. 3. Both variables are categorized into quantile-based classes after log-transformation and standardization to ensure consistent rank-based comparability, allowing relative positioning comparison (i.e., high-degree places systematically align with high-population areas). The resulting figures show that place-adjacency degree reproduces the spatial pattern of population concentration to a certain extent, particularly in major metropolitan areas, indicating that the network structure implicitly captures aspects of urban scale. This overlap suggests that degree centrality encodes information that is correlated with population. Consequently, when place-adjacency is incorporated into the ERGM specification, the marginal contribution of population is reduced, as part of its explanatory power is already absorbed by structural connectivity patterns of places.

The road classification variables capture differences in connectivity across primary road types. With state highways (*S*) serving as the reference category, Interstate highways (*I*) and U.S. highways (*U*) are compared against it. The positive and statistically significant coefficients for both Interstate and U.S. highways across all models indicate that these higher-level road classes are more likely to form connections with places compared to state highways. The ERGM framework allows this effect to be quantified while controlling for place attributes and network structural dependencies. For example, the odds of a place-road link involving an Interstate highway in the base model are approximately 2.4 (= $e^{0.876}$) times that of a state highway, holding other variables constant. This result not only confirms the hierarchical structure of the U.S. transportation system, but also

TABLE 2: ERGM parameter estimates of the five models.

			Multidimensional model		
Explanatory variables	Base model 	Bipartite model 	Case I 	Case II 	Case III 
Urban attributes					
z-standardized log(Area)	0.362*** (0.034)	0.326*** (0.042)	0.444*** (0.034)	0.301*** (0.034)	0.390*** (0.034)
z-standardized log(Population)	0.440*** (0.034)	0.397*** (0.033)	0.163*** (0.033)	0.374*** (0.034)	0.107** (0.033)
Road type *I*	0.876*** (0.060)	0.580*** (0.057)	0.514*** (0.069)	0.777*** (0.060)	0.424*** (0.069)
Road type *U*	0.880*** (0.036)	0.589*** (0.035)	0.844*** (0.038)	0.796*** (0.060)	0.765*** (0.039)
Network configurations					
edge	-6.997*** (0.026)	-6.496*** (0.042)	-7.095*** (0.028)	-6.996*** (0.026)	-7.104*** (0.027)
gwb1degree	-	-0.455*** (0.086)	-	-	-
gwb2degree	-	-1.721*** (0.092)	-	-	-
b2twostarb1network	-	-	3.178*** (0.038)	-	3.155*** (0.039)
b1twostarb2network	-	-	-	0.573*** (0.019)	0.546*** (0.022)
Model fit					
Null deviance	2,899,973	2,899,973	2,899,973	2,899,973	2,899,973
BIC	49,072	48,766	42,720	48,387	42,278

Notes: Standard errors are in parentheses.
Significance codes: $^{***}p < 0.001$, $^{**}p < 0.01$.



(a) ***Population gradient*** **(b)** ***Place-adjacency degree gradient***

FIGURE 3: Spatial comparison between population distribution and place-adjacency structure in Texas Triangle (2010).

provides a quantitative estimate of how much more likely major corridors are to connect with places relative to lower-level highways. The magnitude of these coefficients varies across model specifications, reflecting how the inclusion of additional network configurations alters the estimated contribution of road type to place-road connectivity.

Next, the edge term presents the baseline propensity for edge formation and functions similarly to an intercept in logistic regression. It is included in ERGM to control network density, ensuring that simulated networks match the link count of the observed network [43]. The consistently large and negative coefficients across all model specifications indicate that place-road connections are sparse, where the probability of a link between a place and a road is generally low in the absence of other effects.

In the bipartite model, the terms *gwb1degree* and *gwb2degree* are negative and significant coefficients (-0.455 and -1.721). In ERGM formulations, a negative coefficient for geometrically weighted degree statistics implies that links are more likely to form with nodes that already have higher degrees, reflecting a hub-like structure in which highly connected nodes attract additional connections [40]. This pattern is consistent with a preferential attachment mechanism, where a small number of places or roads accumulate a disproportionate share of connections in the network [44]. In the context of the place-road system, this suggests that certain places serve as major transportation hubs (e.g., Dallas (degree of 34), San Antonio (29), Houston (27)), while some major roads intersect with many places (e.g., U.S. Highway 83 (95), U.S. Highway 77 (63), U.S. Highway 59 (57)).

Although the geometrically weighted degree statistics can uncover hub-like structures and capture heterogeneity in the place and road degree distributions, they are not included in the multidimensional models due to an overlap in structural effects. In particular, the statistics *b2twostarb1network* and *b1twostarb2network* capture the tendency of adjacent places to share roads and of connected roads to serve the same places. These configurations generate subsets of the star patterns summarized by the geometrically weighted degree statistics. Including both sets of terms would therefore introduce redundancy and make it difficult to distinguish the influence of degree-based popularity from the influence of cross-layer network structures.

The multidimensional models introduce cross-layer structural dependencies through the statistics *b1twostarb2network* and *b2twostarb1network*. The positive and highly significant coefficients for *b2twostarb1network* in Case I and Case III signify that places connected through the place-place adjacency network are substantially more likely to share connections with the same roads. This suggests that geographically adjacent places tend to rely on similar transportation infrastructure. The magnitude of these coefficients (at approximately 3) highlights the strong explanatory power of the place adjacency structure in shaping place–road connectivity. In contrast, the *b1twostarb2network* coefficients in Case II and Case III, while still positive and significant, are considerably smaller, suggesting that road–road connectivity contributes to explaining place–road links but plays a comparatively weaker role. The positive multidimensional configuration terms imply a tendency toward clique-like connectivity across layers [29], where groups of spatially related places share common road infrastructure. Such structures create centralization effects on network ties among the nodes involved, as multiple places become connected through a set of key transportation corridors, producing localized clusters of place–road interactions.

Among the four models, Multidimensional Model Case III exhibits the best overall fit with the lowest Bayesian Information Criterion (BIC) value of 42,278. BIC is defined as

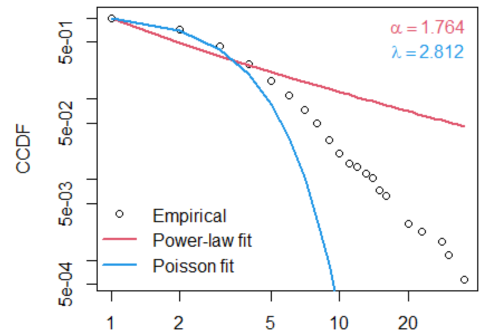
$$BIC = -2log(L) + klog(n), \tag{4}$$

where L is the log likelihood, k is the number of parameters in the model, and n is the sample size [45, 46]. Lower BIC values correspond to a better model fit by balancing model likelihood and model complexity. Compared with the base and bipartite models, the multidimensional models are shown to have a reduction in BIC, indicating that incorporating structural information from additional network layers improves the model's ability to explain place-road connectivity. In particular, the strong effects associated with the place-place adjacency network (Case I, III) suggest that the connectivity between places and transportation infrastructure is shaped not only by the characteristics of node-level attributes, but also by the spatial organization of Texas urban areas in 2010.

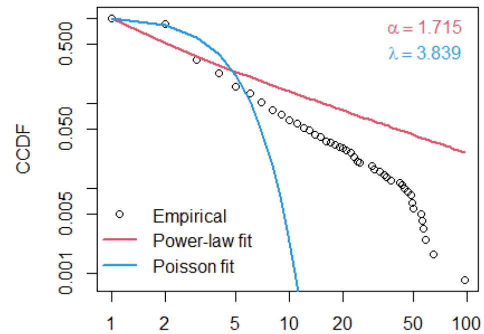
As ERGMs explicitly model the link formation processes of networks, the estimated coefficients in Table 2 can be used to predict link formation in future network realizations. Specifically, the learned parameters can be applied to compute the probability of place-road links in subsequent years (e.g., 2020), and conduct performance evaluations via typical accuracy metrics, such as precision-recall curves and F1 scores. This capability demonstrates how the proposed multidimensional ERGM framework can support predictive analysis and provide a quantitative basis for studying the co-evolution of coupled urban-infrastructure systems.

4.2. Degree Distribution Analysis Across Network Layers

To further interpret the structural mechanisms suggested by the ERGM results, we examine the degree distributions of place and road nodes. In particular, the popularity effects captured by the geometrically weighted degree statistics may indicate preferential attachment–like dynamics, which are commonly associated with heavy-tailed degree distributions. To investigate whether the observed connectivity patterns are consistent with such mechanisms, we compare the empirical degree distributions against two candidate models: a power-law distribution, representing heterogeneous hub-dominated structures, and a Poisson distribution, representing more homogeneous connectivity patterns [47]. The comparison is conducted using Vuong's likelihood ratio test, which evaluates the relative fit of two competing non-nested distributions [48, 49]. The hypotheses are defined as follows:
H_0 : Both distributions are equally far from the true distribution;
H_1 : One of the test distributions is closer to the true distribution.
The test statistic results are summarized in Table 3.



(a) Place degree distribution.



(b) Road degree distribution.

FIGURE 4: Empirical complementary cumulative distribution functions (CCDFs) with fitted power-law and Poisson models.

TABLE 3: Summary statistics of Vuong's test.

	p (two-sided)	*p (one-sided)* (Power-law, Poisson)
Place	0.443	0.779
Road	1.508×10^{-6}	7.539×10^{-7}

For place nodes (see Fig. 4a), the Vuong test yields inconclusive results. The two-sided statistic of 0.443 does not indicate a significant difference between the power-law and Poisson models, and the one-sided statistic of 0.779 similarly fails to provide strong evidence that the power-law distribution offers a significantly better fit than the Poisson model. This outcome is not unusual, as real-world networks rarely conform to a perfect power-law distribution. In practice, identifying heavy-tailed behavior often requires estimating an appropriate lower bound for power-law fitting [50].

In contrast, the road nodes show strong evidence favoring the power-law model (see Fig. 4b). Both Vuong test statistics indicate that the power-law distribution provides a substantially better fit than the Poisson distribution. This finding suggests that the road layer exhibits a heterogeneous connectivity structure characterized by a small number of highly connected roads serving many places, primarily among higher-class transportation corridors such as Interstate and U.S. highways.

Taken together, these results highlight the limitations of relying solely on degree distributions to characterize network structure. While the degree distribution analysis provides evidence of heterogeneous connectivity in the road layer, it remains inconclusive for the place layer. In comparison, the ERGM framework offers deeper insight into the mechanisms governing link formation. The significant geometrically weighted degree terms indicate popularity effects in the network, suggesting that nodes with higher degrees have an increased likelihood of attracting additional connections even when the overall degree distribution does not clearly reveal such patterns.

5. CONCLUSION AND FUTURE WORK

By modeling place adjacency, road connectivity, and cross-layer place–road interactions within a unified statistical network model (Case III), the ERGM configurations quantify how node attributes and spatial network structures jointly influence the formation of regional connectivity patterns. The ERGM results provide the following policy implications for state of Texas:

- Larger and more populated places are more likely to connect to primary roads, suggesting that transportation infrastructure naturally concentrates around areas with greater spatial and demographic scale. A one-standard deviation increase in the log-transformed area of a place increases the odds of forming a place-road link by approximately 48% (= $e^{0.390}$), and 11% (= $e^{0.107}$) for the increase in population. These results suggest that planners may prioritize infrastructure investments in rapidly growing jurisdictions where future connectivity demand is likely to increase.
- Interstate and U.S. highways are significantly more likely to form connections with places than state highways (1.53 (= $e^{0.424}$) and 2.15 (= $e^{0.765}$) times, respectively), highlighting their central role in structuring regional accessibility. Transportation agencies may consider these higher-order corridors as critical infrastructure when planning regional mobility and allocating maintenance resources.
- The place–road network exhibits hub-like connectivity patterns. Geographically adjacent places are substantially more likely to share connections to the same roads, with the cross-layer configuration associated with place adjacency increasing the odds that adjacent places connect to the same road by more than 23 times (= $e^{3.155}$). Meanwhile, intersecting roads are approximately 1.73 times (= $e^{0.546}$) more likely to connect to the same places.These patterns suggest that Texas's transportation infrastructure in 2010 serves clusters of neighboring jurisdictions through a limited number of key corridors. Because disruptions at these hubs could significantly affect regional connectivity, policymakers may consider strengthening network resilience by developing alternative routes near highly connected corridors and by coordinating infrastructure planning across adjacent municipalities to improve regional accessibility.

This study has limitations that suggest directions for future research. First, the analysis incorporates a limited set of place and road attributes. Inclusion of additional variables (e.g., economic activity, land-use characteristics, road capacity), once data become available, may provide further insight into the mechanisms shaping place-road connectivity. Second, ERGM specification involves an exploratory process of network configurations selection, as they are iteratively evaluated to avoid degeneracy. Other structural configurations may also contribute to explaining the observed network patterns. Finally, the present study analyzes a single network snapshot for 2010. This baseline analysis provides a foundation for developing predictive capabilities to study the co-evolution of urban settlements and transportation infrastructure, particularly by extending the analysis to later years such as 2020. Extending the framework to nation-wide data would also enable a generalizability assessment across diverse urban contexts.

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