

## CAUSAL GEOSPATIAL MODELING OF MULTIMODAL TRANSPORT NETWORKS UNDER DEMAND SHOCKS, LAND-USE CHANGE, AND INFRASTRUCTURE CONSTRAINTS

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### ABSTRACT

Multimodal transport systems form the backbone of contemporary urban mobility, linking road, rail, bus, and active transport infrastructures into interconnected spatial networks that support economic activity and regional accessibility. However, these systems are increasingly exposed to structural pressures arising from sudden demand shocks, dynamic land-use transformations, and persistent infrastructure constraints. Demand shocks such as rapid population redistribution, fuel price fluctuations, extreme weather disruptions, or policy-driven mobility restrictions can abruptly alter travel patterns and strain existing transport capacity. Concurrently, long-term land-use changes driven by urban expansion, zoning decisions, and commercial redevelopment reshape trip generation patterns and modify spatial accessibility across metropolitan regions. When these factors interact with infrastructure bottlenecks, capacity limitations, and uneven network investment, they can produce cascading disruptions across multimodal transport systems, reducing network efficiency and increasing spatial inequalities in mobility access. Traditional transport modeling approaches frequently rely on equilibrium-based demand forecasting or descriptive spatial analysis, which often fail to capture the causal mechanisms linking land-use dynamics, infrastructure capacity, and travel demand fluctuations. In contrast, causal geospatial modeling integrates spatial network analytics with causal inference techniques to identify structural relationships that govern how transport disruptions propagate across interconnected modes. By combining geospatial network topology, land-use spatial data, and mobility flow patterns, causal frameworks allow researchers to evaluate counterfactual scenarios and quantify the direct and indirect effects of demand shocks on network performance and accessibility outcomes. This study develops a causal geospatial modeling framework that evaluates multimodal transport network responses to simultaneous demand shocks, land-use changes, and infrastructure constraints. Using spatial causal graphs and network-based impact propagation models, the framework identifies critical nodes, vulnerable corridors, and spatial spillover effects across transport modes. The approach advances transportation planning by enabling policymakers to anticipate system vulnerabilities, prioritize infrastructure investments, and design adaptive mobility strategies that enhance resilience and spatial accessibility within rapidly evolving urban environments.

### Keywords:

Causal geospatial modeling; multimodal transport networks; demand shocks; land-use dynamics; infrastructure capacity constraints; spatial network resilience

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## 1. INTRODUCTION

### 1.1 Multimodal Transport Networks in Urban Systems

Multimodal transportation networks form the structural backbone of modern urban mobility systems, integrating multiple transport modes such as road infrastructure, rail systems, bus networks, metro transit, and active mobility options including cycling and walking [1]. These interconnected mobility systems enable the movement of people and goods across metropolitan regions and play a critical role in supporting economic productivity, social interaction, and regional development. Efficient multimodal networks facilitate access to employment opportunities, education institutions, healthcare facilities, and commercial activities, thereby improving overall urban accessibility and economic performance [2].

As metropolitan areas continue to expand, the complexity of urban mobility systems has increased significantly. Rapid population growth, suburban expansion, and evolving travel behavior patterns have intensified demand for flexible and integrated transport services across multiple mobility modes [3]. However, integrating these modes within a unified transportation system presents considerable planning and operational challenges. Differences in infrastructure capacity, scheduling coordination, and modal connectivity often create inefficiencies in travel routes and transfer points across transport networks [4].

Urban transportation networks are also characterized by strong dependency structures in which disruptions within one mode can propagate across other connected modes. For example, road congestion may affect bus transit reliability, while rail system delays may increase road traffic volumes as commuters seek alternative travel routes [5]. These interconnected dependencies influence spatial connectivity patterns and determine how effectively residents can move across different parts of the city.

Understanding these complex interactions requires advanced analytical frameworks capable of capturing dynamic transport network behavior and spatial connectivity patterns within rapidly evolving urban environments [6].

### **1.2 Impact of Demand Shocks and Land-Use Change**

Urban transportation networks operate within highly dynamic socioeconomic environments where travel demand patterns can change rapidly due to external shocks and structural transformations. Demand shocks may emerge from various sources, including population redistribution, economic fluctuations, infrastructure disruptions, policy interventions, and extreme weather events that alter travel behavior and mobility needs across metropolitan regions [7]. For example, economic downturns or sudden employment shifts can modify commuting patterns, while natural disasters or infrastructure failures may disrupt key transport corridors and require rapid adjustments within mobility systems.

Population redistribution associated with urbanization and migration patterns can significantly influence transport demand distribution across cities. As residential areas expand into suburban zones or new urban developments emerge, transport networks must accommodate evolving commuting flows and increased travel distances between residential areas and employment centers [8].

Land-use change also plays a central role in shaping transport demand patterns. Changes in land development, such as the construction of commercial districts, residential complexes, or industrial zones, influence trip generation rates and alter spatial demand distribution across transport networks [2]. These transformations often affect traffic congestion patterns by increasing travel volumes along specific corridors or creating new travel routes between emerging activity centers.

These dynamic interactions highlight the importance of transport network resilience, which refers to the capacity of transportation systems to absorb disruptions, adapt to changing demand conditions, and maintain operational performance under uncertain environmental and socioeconomic conditions [3].

### **1.3 Limitations of Traditional Transport Modeling**

Traditional transport modeling approaches have historically relied on equilibrium-based demand forecasting models and static network analysis frameworks to evaluate travel behavior and infrastructure performance. While these models have contributed significantly to transportation planning, they often assume stable demand conditions and predictable travel patterns [4]. In reality, urban mobility systems are influenced by complex interactions among socioeconomic dynamics, infrastructure constraints, and spatial development patterns that evolve continuously over time.

Conventional models also struggle to capture nonlinear relationships among variables such as land-use change, travel demand fluctuations, and infrastructure capacity constraints [5]. As a result, traditional modeling techniques frequently fail to accurately represent dynamic spatial interactions within multimodal transport networks.

These limitations have encouraged growing interest in machine learning–driven causal modeling approaches capable of identifying complex patterns within large-scale transport datasets [6].

### **1.4 Research Objectives and Contributions**

This study aims to develop a machine learning–based causal geospatial modeling framework for analyzing multimodal transport network dynamics under conditions of demand shocks, land-use change, and infrastructure constraints [7]. The research seeks to predict potential network disruptions, evaluate the influence of spatial development patterns on mobility flows, and assess transport network resilience using predictive performance metrics [8].

The proposed framework contributes an AI-driven transport risk modeling approach, a causal inference model for multimodal network analysis, and a policy-oriented evaluation system for infrastructure planning and urban mobility governance.

## **2. LITERATURE REVIEW**

### **2.1 Geospatial Modeling in Transportation Research**

Geospatial modeling has become a foundational approach for analyzing transportation systems and understanding spatial interactions within urban mobility networks. Geographic Information Systems (GIS) provide analytical capabilities for representing transportation infrastructure, mapping mobility patterns, and evaluating accessibility conditions across metropolitan regions [7]. GIS-based transport network analysis allows researchers to model road

networks, rail corridors, bus routes, and pedestrian pathways as interconnected spatial systems, enabling the examination of connectivity between origins and destinations across complex urban environments [8].

One of the key applications of GIS in transportation research is spatial accessibility modelling, which evaluates how efficiently individuals can reach employment centers, educational institutions, healthcare facilities, and other essential services [9]. Accessibility models often rely on spatial network analysis techniques that calculate travel time, travel distance, or generalized travel cost between different locations within a transportation network. These measures provide valuable insights into mobility inequalities and highlight geographic areas that experience limited connectivity to urban opportunities.

Urban mobility mapping techniques have also expanded the ability to visualize transportation flows and identify spatial patterns of travel behavior. By integrating geospatial datasets such as road network topology, population distribution, and traffic intensity data, researchers can generate detailed spatial maps illustrating congestion hotspots, commuter flow corridors, and areas with limited transport infrastructure coverage [10].

Network topology analysis plays an important role in this context by examining the structural configuration of transportation networks, including nodes, edges, and connectivity patterns among transport modes. Topological metrics such as node centrality, network density, and connectivity indices help identify critical infrastructure nodes and potential bottlenecks within urban transport systems [11].

Spatial flow modelling further enhances transport analysis by estimating how travelers move between locations across network structures. These models use origin–destination datasets and traffic flow information to simulate mobility patterns and evaluate how infrastructure constraints or spatial barriers influence travel routes and congestion patterns [12]. Such approaches provide valuable insights into how transportation networks operate as dynamic spatial systems influenced by both infrastructure design and human mobility behavior.

## **2.2 Machine Learning in Transport Systems Analysis**

Machine learning techniques have increasingly been applied to transportation systems analysis due to their ability to identify complex patterns within large-scale mobility datasets. Urban transport networks generate substantial volumes of data through traffic sensors, GPS tracking, smart transit cards, and mobile applications, creating opportunities for advanced analytical methods that can capture nonlinear relationships between travel demand, infrastructure capacity, and environmental conditions [13].

One prominent application of machine learning in transportation research is traffic prediction. Predictive models analyze historical traffic flow patterns and real-time sensor data to forecast future traffic conditions across road networks. These predictions allow transportation agencies to implement proactive traffic management strategies and mitigate congestion during peak travel periods [14]. Machine learning algorithms are also widely used for congestion forecasting by identifying recurring congestion patterns and predicting potential traffic bottlenecks within transportation networks.

Demand prediction represents another important area where machine learning techniques are applied. By analyzing travel behavior datasets, machine learning models can estimate future transport demand patterns based on factors such as population growth, land-use development, and seasonal travel variations [7]. These predictions support infrastructure planning decisions and enable transportation authorities to anticipate future capacity requirements within rapidly growing urban regions.

Route optimization is also enhanced through machine learning approaches that evaluate multiple travel routes simultaneously and identify the most efficient pathways based on traffic conditions, travel distance, and travel time variability. Algorithms such as Random Forest and Gradient Boosting have been applied to predict traffic conditions and classify congestion patterns, while Support Vector Machines are often used for pattern recognition within transportation datasets [8]. More recently, Graph Neural Networks have emerged as powerful tools for modelling spatial relationships within transport networks because they can capture dependencies among nodes and edges in complex network structures [9].

The primary advantage of machine learning in transport systems analysis lies in its ability to capture nonlinear spatial interactions that traditional statistical models often fail to represent accurately [10].

## **2.3 Causal Modeling in Infrastructure Networks**

While machine learning models are effective at identifying predictive relationships within transportation datasets, understanding the causal mechanisms underlying infrastructure network behavior requires additional analytical frameworks. Causal modelling approaches aim to identify cause-and-effect relationships between variables rather than simply detecting statistical correlations within observed data [11].

Causal inference models have therefore become increasingly relevant in transportation research, particularly for evaluating how policy interventions or infrastructure changes influence mobility patterns. Directed acyclic graphs (DAGs) are commonly used to represent causal relationships between variables by illustrating directional

dependencies among different components within a system [12]. In the context of transportation networks, DAGs can represent interactions between infrastructure capacity, travel demand, traffic congestion, and environmental factors.

Structural causal modelling extends this framework by incorporating mathematical representations of causal relationships, allowing researchers to estimate how changes in one variable may influence outcomes elsewhere within the network. These models can be used to evaluate hypothetical policy scenarios, such as the impact of congestion pricing policies or new transport infrastructure investments on travel demand patterns and network performance [13].

In transportation planning, causal modelling supports infrastructure decision-making by identifying the mechanisms through which infrastructure changes affect mobility behavior. This approach enables policymakers to evaluate the long-term effects of planning interventions and develop strategies for improving network resilience and operational efficiency under changing demand conditions [14].

#### **2.4 Research Gap**

Despite the growing use of GIS-based transport modelling and machine learning techniques in mobility analysis, relatively few studies integrate machine learning with causal geospatial modelling to examine multimodal transportation networks under dynamic demand conditions [15]. Existing research often models mobility patterns or infrastructure performance separately, without fully accounting for the combined effects of land-use change, demand shocks, and infrastructure constraints. Additionally, many studies focus primarily on single-mode transportation systems rather than integrated multimodal networks.

This study addresses these limitations by developing a machine learning-driven causal geospatial modelling framework capable of analyzing multimodal transport networks under evolving urban conditions.

### **3. CONCEPTUAL FRAMEWORK**

#### **3.1 Multimodal Network Causal Structure**

Understanding the dynamics of multimodal transportation systems requires identifying the causal relationships among the primary factors that influence network performance. In urban mobility systems, transport demand, infrastructure capacity, and spatial land-use patterns interact continuously to shape how efficiently people and goods move across metropolitan regions [14]. Demand shocks—such as population migration, economic fluctuations, infrastructure disruptions, or policy interventions—can alter travel demand patterns and create sudden pressure on existing transport networks [15]. These shocks often lead to changes in traffic volumes, modal shifts, and congestion levels that directly affect overall network performance.

Land-use change represents another key causal driver within urban transport systems. Changes in residential development, commercial expansion, or industrial land use influence where travel demand originates and how trips are distributed across transport corridors [16]. As land-use intensity increases within particular districts, trip generation rates rise and new mobility flows emerge between residential areas, employment centers, and commercial zones. These spatial transformations can reshape accessibility patterns and alter the load placed on different parts of the transportation network.

Infrastructure capacity forms the structural constraint that determines how well transport systems can accommodate changes in demand. Limitations in road capacity, transit service frequency, or modal integration can amplify the effects of demand shocks and land-use changes, leading to congestion and reduced network efficiency [17].

Together, these interactions create a causal structure in which demand shocks influence transport demand, land-use change shapes accessibility patterns, and infrastructure capacity determines overall network performance [18].

Figure 1. Causal Geospatial Modeling Framework

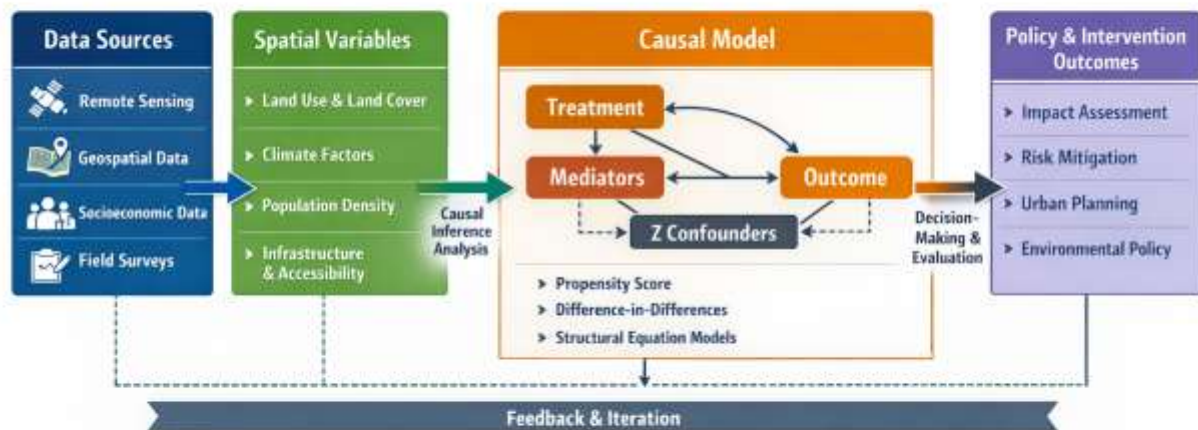


Figure 1. Causal Geospatial Modeling Framework

### 3.2 Network Flow Representation

To analyze multimodal transportation systems within a computational framework, transport networks are commonly represented using graph theory. In this representation, the transport system is modeled as a graph consisting of nodes and edges that describe the connectivity structure of the network [19]. Nodes represent locations such as intersections, transit stations, or transfer hubs, while edges represent the physical links connecting these nodes, including road segments, rail tracks, or pedestrian pathways.

The general representation of a transportation network can be expressed as:

$$G = (V, E)$$

Where:

$V$  represents the set of transport nodes within the network, and

$E$  represents the set of edges connecting those nodes.

This graph-based representation allows transportation networks to be analyzed using network flow algorithms that simulate how traffic or passenger flows move across interconnected infrastructure systems [20]. Network analysis techniques can evaluate shortest paths, network connectivity, and congestion propagation across transport corridors.

In multimodal systems, edges may represent different transport modes such as bus routes, rail services, or cycling lanes, each with different travel speeds and capacity characteristics. Incorporating these modal attributes allows researchers to model realistic travel behavior and estimate how users move between modes during multimodal trips.

Graph-based network representations therefore provide a powerful foundation for analyzing spatial connectivity and identifying critical nodes or links that influence the overall performance and resilience of transport systems [21].

### 3.3 Travel Demand Function

Travel demand within transportation systems is influenced by several spatial and socioeconomic variables, including population distribution, land-use patterns, and travel costs between different locations. A common formulation used to represent travel demand relationships is expressed as:

$$D_{ij} = f(P_i, L_j, C_{ij})$$

Where:

$D_{ij}$  represents the travel demand between origin location  $i$  and destination location  $j$ ,

$P_i$  represents the population density at the origin location,

$L_j$  represents the land-use intensity or activity level at the destination location, and

$C_{ij}$  represents the travel cost between the two locations.

Population density plays a fundamental role in determining the volume of trips generated from a particular area. Locations with higher population concentrations typically generate greater travel demand because more individuals require access to employment, services, and social activities [22]. Land-use intensity at destination locations represents the number of opportunities available within those areas, such as employment centers, commercial districts, or educational institutions. Areas with high activity density tend to attract more travel demand due to the concentration of opportunities they provide.

Travel cost represents the impedance between origin and destination locations and may include travel time, travel distance, or generalized travel expenses associated with transportation modes [23]. Higher travel costs typically reduce travel demand, while improved connectivity and reduced travel time increase the likelihood of travel between locations.

This functional relationship forms the basis for modelling travel demand patterns within multimodal transportation systems and supports predictive analysis of how spatial and infrastructure changes influence mobility flows.

#### 4. DATA ACQUISITION AND PRE-PROCESSING

##### 4.1 Data Acquisition

Developing a machine learning-driven causal geospatial model for multimodal transportation networks requires the integration of multiple spatial datasets representing transport infrastructure, land-use patterns, and population distribution across urban environments [23]. These datasets provide the foundational inputs for analyzing how transport demand, spatial development patterns, and infrastructure capacity interact within complex mobility systems.

Transport datasets form the core component of the analysis because they describe the physical structure and operational characteristics of urban transportation networks. One of the primary sources of transport network data is the OpenStreetMap platform, which provides detailed geospatial information on road networks, intersections, and transportation corridors across metropolitan regions [24]. These datasets allow researchers to reconstruct transport network topology, identify connectivity between nodes, and evaluate travel routes across different parts of a city. Additional transport data can be obtained from transit authority databases that provide information on bus routes, rail lines, metro networks, and service schedules. These datasets are essential for modeling multimodal connectivity and understanding how different transport modes interact within urban mobility systems [25].

Mobility datasets derived from GPS tracking and mobile device data provide valuable insights into real-world travel behavior patterns. These datasets capture vehicle movements, travel speeds, route choices, and commuting flows across transportation networks. Integrating GPS mobility data into spatial analysis allows researchers to examine dynamic transport demand patterns and evaluate how mobility flows respond to infrastructure constraints or demand shocks [26].

Land-use datasets represent another important component of the analytical framework. Satellite imagery and remote sensing data provide spatial information on urban development patterns, including residential areas, commercial districts, industrial zones, and transportation infrastructure [27]. Urban zoning databases further classify land-use categories and provide information on development intensity, allowing researchers to estimate activity levels and trip generation potential across different locations.

Population datasets are used to represent the spatial distribution of residents and potential travel demand sources. Census demographic data provide detailed information on population density, household characteristics, and socioeconomic attributes at neighborhood scales. Mobility surveys complement these datasets by capturing travel behavior patterns such as trip frequency, travel purpose, and preferred transport modes [28].

Figure 2. Transport Network Data Acquisition Pipeline

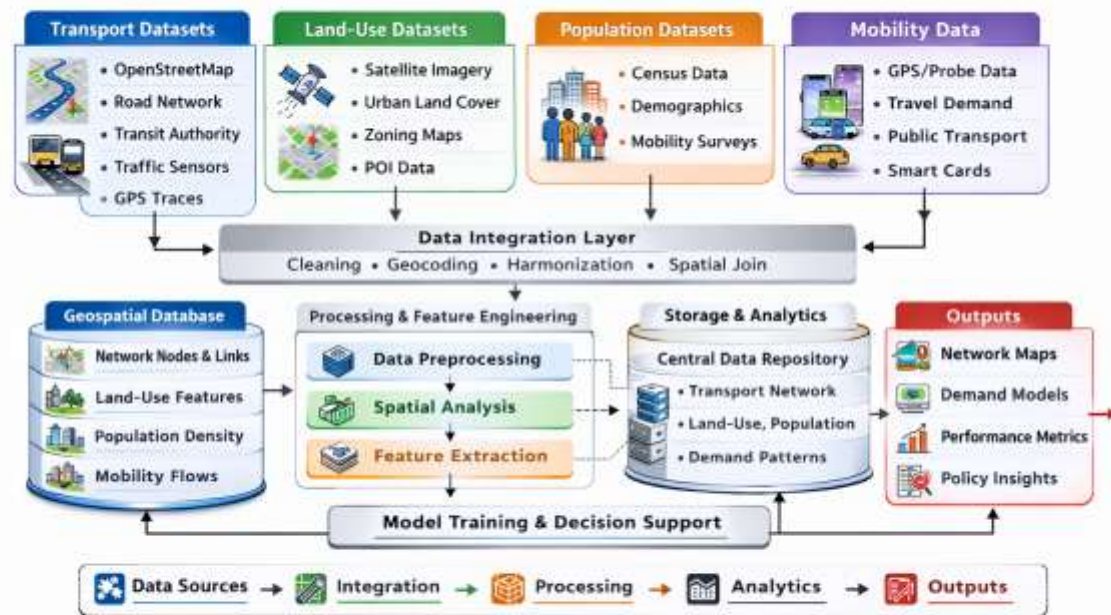


Figure 2. Transport Network Data Acquisition Pipeline

#### 4.2 Dataset Variables

Once spatial datasets are collected from various sources, the next step involves defining the variables used in the analytical framework. These variables represent key characteristics of the transportation system, land-use patterns, and travel demand conditions within the study area. Proper variable selection is essential for capturing the interactions among transport infrastructure, spatial development, and mobility demand that influence network performance [29].

Transport variables describe the operational conditions of the transportation network. These variables typically include traffic flow intensity, average travel time along road segments, and travel speed measurements derived from mobility data. Such variables provide insights into congestion levels and network efficiency across different transport corridors.

Land-use variables represent spatial development patterns that influence travel demand generation. Population density is commonly used as an indicator of residential activity levels and trip generation potential. Higher population density areas generally produce greater travel demand because more residents require access to employment and services.

Infrastructure variables capture the capacity characteristics of transportation networks. Road capacity indicators measure the ability of infrastructure to accommodate traffic flows without causing excessive congestion. Infrastructure capacity constraints often play a critical role in determining network resilience under high demand conditions.

Demand variables represent travel behavior patterns observed within mobility datasets. Trip frequency measures how often individuals travel between locations and reflects the intensity of mobility activity within the transport system [30].

**Table 1. Dataset Description**

Category	Variables
Transport	traffic flow, travel time
Land-use	population density
Infrastructure	road capacity
Demand	trip frequency

### 4.3 Data Preprocessing

Before the collected datasets can be used for machine learning and spatial modeling, several preprocessing steps must be performed to ensure data consistency and analytical reliability. Data preprocessing involves cleaning, transforming, and standardizing datasets obtained from different sources so that they can be integrated within a unified analytical framework [23].

The first step in the preprocessing pipeline is missing value treatment. In many real-world datasets, certain observations may contain incomplete information due to sensor failures, reporting errors, or inconsistent data collection procedures. Missing values are typically addressed through interpolation methods, statistical imputation techniques, or removal of unreliable records.

Spatial normalization is another important preprocessing step because variables collected from different sources may have different numerical scales. Without normalization, variables with larger magnitudes could dominate the learning process within machine learning algorithms. Normalization transforms variables into standardized ranges so that they contribute proportionally to the analytical model.

The normalization process can be expressed as:

$$X_{norm} = \frac{X - X_{min}}{X_{max} - X_{min}}$$

where  $X$  represents the original variable value,  $X_{min}$  represents the minimum observed value, and  $X_{max}$  represents the maximum observed value within the dataset.

Geospatial coordinate transformation is also required to ensure that all spatial datasets share a consistent coordinate reference system. Finally, outlier removal techniques are applied to identify abnormal observations that could distort analytical results or produce misleading model predictions [24].

### 4.4 Spatial Feature Construction

After preprocessing, spatial feature construction is performed to derive additional variables that capture meaningful characteristics of the transportation network and urban environment. These derived features help machine learning models identify patterns associated with congestion dynamics, accessibility conditions, and infrastructure constraints within the transport system [25].

One important derived feature is the congestion index, which measures the level of traffic congestion along specific road segments or transport corridors. The congestion index can be computed by comparing observed travel speeds with free-flow travel speeds across the network. Higher index values indicate more severe congestion conditions and reduced transport efficiency.

Accessibility scores represent another critical spatial feature derived from network analysis. These scores measure how easily residents in a particular location can reach employment centers, healthcare facilities, or commercial areas within predefined travel time thresholds. Accessibility indicators are often computed using GIS network analysis techniques that evaluate connectivity between residential zones and opportunity locations.

Infrastructure capacity ratio is also an important feature used to evaluate whether existing transport infrastructure can accommodate current traffic demand levels. This ratio compares observed traffic flows with maximum road capacity to identify infrastructure bottlenecks within the network.

Finally, the land-use diversity index captures the variety of land-use types within a specific area. Areas with diverse land-use patterns often generate more complex travel behavior patterns because residential, commercial, and recreational activities coexist within close proximity. These spatial features collectively enhance the predictive capability of machine learning models analyzing multimodal transport network dynamics [26].

## 5. FEATURE ENGINEERING

### 5.1 Feature Vector Representation

Feature engineering plays a central role in transforming raw geospatial and transportation datasets into structured variables that can be processed by machine learning algorithms. In multimodal transportation analysis, large volumes of spatial and mobility data such as traffic flow measurements, travel times, infrastructure characteristics,

and land-use attributes must be organized into numerical representations that allow models to capture relationships among different transport variables [23]. This transformation process enables computational frameworks to analyze how spatial infrastructure conditions interact with travel demand patterns across urban transport networks [24].

A common representation used in machine learning is the feature vector, which aggregates multiple variables describing a specific spatial observation. The general formulation of a feature vector is expressed as:

$$F = [f_1, f_2, f_3, \dots, f_n]$$

where  $F$  represents the overall feature vector and  $f_i$  represents individual spatial network features derived from transportation datasets [25]. Each element of the feature vector corresponds to a measurable attribute of the transportation system or surrounding urban environment.

Transport variables are mapped into this representation through systematic transformation of raw datasets. Traffic flow values obtained from sensor networks or GPS mobility datasets can be converted into congestion indicators, while travel time measurements generated through GIS network analysis can represent accessibility conditions between different urban locations [26]. Infrastructure characteristics such as road capacity, intersection density, and modal connectivity are also incorporated as structural variables describing the topology of the transportation network [27].

Land-use indicators and population density measures further enrich the feature representation by capturing spatial demand conditions and urban activity intensity. Combining these variables within a unified feature vector enables machine learning models to analyze complex interactions among infrastructure capacity, spatial demand patterns, and mobility behavior across multimodal transport systems [28].

### 5.2 Statistical Feature Extraction

Statistical feature extraction is commonly used to summarize patterns within transportation datasets and identify variations in network performance across spatial and temporal dimensions. By computing statistical descriptors such as mean and variance, researchers can characterize traffic conditions, travel time reliability, and demand fluctuations within multimodal transport networks [29]. These statistical indicators allow machine learning models to detect abnormal mobility conditions and capture variability in traffic flows across different parts of a transportation system [30].

The mean value represents the central tendency of a dataset and provides an estimate of the average magnitude of a particular variable across observations. The mean is defined mathematically as:

$$\mu = \frac{1}{n} \sum_{i=1}^n x_i$$

where  $\mu$  represents the mean value,  $x_i$  represents individual observations, and  $n$  represents the number of observations within the dataset [23]. In transportation analysis, mean values may represent the average traffic volume on road segments, average travel times across specific routes, or average trip frequencies observed within mobility datasets [24]. Such measures help identify general traffic conditions and baseline travel patterns within the network.

Variance provides an estimate of the dispersion of observations around the mean and indicates how widely values vary across different observations. The variance formulation is expressed as:

$$\sigma^2 = \frac{1}{n} \sum (x_i - \mu)^2$$

where  $\sigma^2$  represents the variance of the dataset [25]. In transport systems, variance values are particularly useful for identifying instability in travel conditions. High variance may indicate significant fluctuations in traffic speeds or irregular congestion patterns along specific corridors [26]. Conversely, lower variance values suggest stable and predictable traffic flows within transport networks [27].

These statistical features therefore serve as critical indicators for detecting traffic variability and identifying network segments experiencing abnormal mobility conditions [28]. Incorporating statistical measures into feature engineering enhances the ability of machine learning models to identify congestion hotspots and temporal fluctuations within multimodal transportation systems [29].

### 5.3 Dimensionality Reduction

Transportation datasets frequently contain numerous variables derived from infrastructure attributes, travel demand patterns, environmental factors, and mobility conditions. While incorporating many features can improve

the descriptive capability of machine learning models, high-dimensional datasets may introduce redundancy and increase computational complexity during model training [30]. Dimensionality reduction techniques are therefore used to transform large feature spaces into smaller sets of informative variables that retain the most important patterns within the dataset [23].

Principal Component Analysis (PCA) is one of the most widely used dimensionality reduction techniques in transportation modelling and geospatial analytics. PCA transforms correlated features into a new set of orthogonal variables called principal components, which capture the maximum variance present in the original dataset. The transformation used in PCA can be expressed as:

$$Z = W^T X$$

where  $X$  represents the original feature matrix,  $W$  represents the eigenvector matrix derived from the covariance matrix of  $X$ , and  $Z$  represents the transformed dataset containing the principal components [24].

The derivation of PCA begins with the computation of the covariance matrix of the original dataset to measure relationships among variables. Eigenvalue decomposition is then applied to this covariance matrix to determine eigenvectors and eigenvalues representing the directions and magnitude of maximum variance in the data [25]. Eigenvectors associated with the largest eigenvalues capture the most significant variability patterns and form the principal components used in dimensionality reduction [26].

By projecting the original dataset onto these principal components, PCA reduces redundancy among correlated variables such as traffic flow, congestion index, and travel speed while preserving the essential structure of the dataset [27]. This process improves computational efficiency and enhances the predictive performance of machine learning models analyzing multimodal transportation network dynamics [28].

## 6. MACHINE LEARNING MODEL DEVELOPMENT

### 6.1 Data Splitting Strategy

In machine learning-based transportation modeling, the reliability of predictive outcomes depends strongly on how datasets are partitioned during model development. Proper dataset splitting ensures that the model learns meaningful patterns from historical data while maintaining the ability to generalize to unseen network conditions [28]. In geospatial transport analytics, datasets often contain thousands of spatial observations derived from road networks, mobility traces, land-use attributes, and population distributions, making systematic partitioning essential for robust model validation [29].

The dataset used for training predictive models is typically divided into three subsets: training, validation, and testing datasets. The training dataset contains the majority of observations and is used to learn model parameters and feature relationships. The validation dataset is used to tune model configurations and optimize hyperparameters without exposing the model to final evaluation data [30]. The testing dataset is reserved for independent evaluation and measures the predictive performance of the trained model on previously unseen data [31].

A typical dataset partitioning configuration is:

Training set = 70%

Validation set = 15%

Testing set = 15%

The dataset partition can be expressed mathematically as:

$$D = D_{train} + D_{test}$$

where  $D$  represents the full dataset,  $D_{train}$  represents the training portion, and  $D_{test}$  represents the independent testing dataset [32].

A critical consideration in this process is the prevention of data leakage. Data leakage occurs when information from the testing dataset inadvertently influences model training, leading to overly optimistic performance estimates [33]. By maintaining strict separation between training, validation, and testing datasets, the modeling framework ensures unbiased evaluation and improves the reliability of predictive transport network analysis [34].

### 6.2 Model Training Phase

The model training phase represents the stage where machine learning algorithms learn relationships between spatial network features and transport system outcomes. During this stage, the prepared feature vectors derived from transport infrastructure, land-use variables, and mobility patterns are used to train predictive models capable of capturing complex nonlinear relationships within multimodal transportation systems [35].

The training pipeline begins with feature transformation, where engineered spatial features are standardized or normalized to ensure consistent numerical scales across variables. Normalization is particularly important when integrating heterogeneous datasets such as traffic flow measurements, infrastructure attributes, and demographic indicators [28]. Once feature transformation is completed, the training dataset is fed into machine learning algorithms to estimate predictive model parameters.

Several machine learning algorithms are commonly used for geospatial transport modeling due to their ability to capture nonlinear spatial relationships and complex network interactions. Random Forest models are widely applied because they combine multiple decision trees to improve predictive accuracy while reducing overfitting risks [29]. Gradient boosting algorithms such as XGBoost iteratively improve model predictions by minimizing error functions through sequential tree learning [30].

Graph Neural Networks (GNNs) have also emerged as powerful tools for analyzing transportation networks because they explicitly model relationships between nodes and edges in network structures. By leveraging graph topology, GNNs can capture spatial dependencies across road segments and transport nodes more effectively than traditional machine learning methods [31].

Figure 3. Machine Learning Training Pipeline

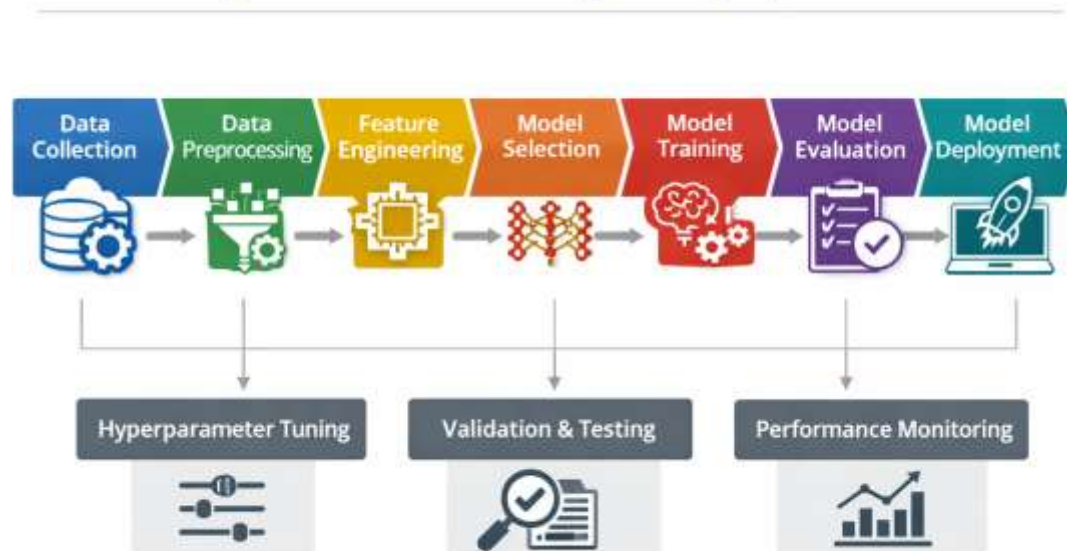


Figure 3. Machine Learning Training Pipeline

This training architecture ensures that transport network features are systematically processed and integrated into predictive modelling workflows capable of identifying congestion patterns and infrastructure constraints across urban mobility systems [32].

### 6.3 Model Testing Phase

After model training and validation are completed, the final stage of the predictive modelling process involves evaluating model performance using the testing dataset. The testing dataset contains observations that were not used during the training or validation phases, ensuring that model evaluation reflects genuine predictive capability rather than memorization of training data [33].

Testing the model on unseen data provides an assessment of how well the trained algorithm can generalize to new transportation scenarios. In multimodal transport systems, this capability is particularly important because network conditions frequently change due to demand fluctuations, infrastructure disruptions, or land-use changes [34]. A model that performs well on unseen data is therefore more likely to provide reliable predictions under dynamic urban mobility conditions.

During the testing phase, the trained machine learning model processes feature vectors from the testing dataset and generates predictions related to transport network outcomes such as traffic congestion, demand distribution,

or accessibility patterns. These predictions are then compared with actual observed values to evaluate model accuracy and reliability [35].

Performance evaluation typically involves calculating statistical performance metrics such as prediction accuracy, precision, recall, and F1 score. These metrics quantify how effectively the model identifies transport patterns and network disruptions across spatial datasets [28]. By evaluating predictive performance using independent testing data, researchers can ensure that the model maintains strong generalization capabilities when applied to real-world transportation systems.

#### 6.4 Hyperparameter Optimization

Hyperparameter optimization plays a crucial role in improving machine learning model performance by adjusting configuration parameters that control the learning process. Unlike model parameters that are learned directly from data, hyperparameters must be defined prior to training and can significantly influence predictive accuracy [29]. Common hyperparameters used in transport modelling algorithms include learning rate, tree depth, and training epochs. The learning rate controls how quickly the model updates its parameters during training, while tree depth determines the complexity of decision trees used in ensemble methods such as Random Forest and gradient boosting algorithms [30]. Training epochs represent the number of iterations used to update model weights during neural network learning processes.

Optimization techniques such as grid search and cross-validation are commonly used to identify the most effective hyperparameter configurations for a given dataset [31]. By systematically evaluating multiple parameter combinations, hyperparameter optimization improves model stability and enhances predictive performance when analyzing complex geospatial transportation networks [32].

## 7. MODEL EVALUATION AND NETWORK ANALYSIS

### 7.1 Performance Metrics

Evaluating the performance of machine learning models is essential to determine whether predictive systems can reliably analyze multimodal transport networks and identify patterns associated with demand fluctuations and infrastructure constraints. Performance metrics provide quantitative measures that assess how accurately a model predicts transport system behavior under different spatial and operational conditions [33]. In transportation modeling, reliable evaluation metrics ensure that predictive models can support policy analysis, congestion forecasting, and infrastructure planning decisions across complex urban mobility systems [34].

One commonly used evaluation metric is accuracy, which measures the proportion of correctly predicted observations relative to the total number of predictions. Accuracy can be mathematically expressed as:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

where TP represents true positives, TN represents true negatives, FP represents false positives, and FN represents false negatives [35]. Accuracy provides a general indicator of predictive performance but may be insufficient when datasets contain imbalanced class distributions commonly observed in transportation events such as rare network disruptions [36].

To address this limitation, the F1 score is often used because it combines precision and recall into a single metric. The F1 score is defined as:

$$F1 = \frac{2PR}{P + R}$$

where P represents precision and R represents recall [37]. Precision measures the proportion of correctly identified positive predictions, while recall evaluates the ability of the model to detect actual positive outcomes within the dataset [38]. The F1 score therefore provides a balanced evaluation metric for assessing predictive performance in complex transportation modeling scenarios where network disruptions or congestion events may occur infrequently [39].

### 7.2 Mean Deviation Network Stability Analysis

Mean deviation analysis is commonly used in transportation network modeling to measure variability in traffic flows, travel times, and congestion patterns across different nodes of a transport system. Variability metrics help researchers understand how stable or unstable mobility conditions are across the network and identify locations experiencing abnormal traffic fluctuations [40].

The mean deviation (MD) provides a measure of the average absolute deviation of observations from their mean value and is mathematically expressed as:

$$MD = \frac{1}{n} \sum |x_i - \mu|$$

where  $x_i$  represents individual observations,  $\mu$  represents the mean value of the dataset, and  $n$  represents the number of observations [33]. In the context of transportation analysis,  $x_i$  may represent traffic flow values, vehicle speed measurements, or travel time observations across different transport nodes.

Mean deviation is particularly useful for detecting irregular mobility patterns within urban transport networks. High deviation values indicate large fluctuations in traffic conditions, suggesting unstable network performance or congestion variability across certain road segments [34]. Conversely, lower deviation values indicate more consistent traffic patterns and stable infrastructure performance across the network [35].

Transport planners often use deviation metrics to evaluate the reliability of transport corridors and identify areas requiring infrastructure upgrades or operational improvements. When combined with machine learning predictions, mean deviation analysis can highlight network nodes experiencing abnormal congestion patterns that may require targeted policy interventions [36].

**Table 2. Mean Deviation Comparison Across Network Nodes**

Network Node	Mean Traffic Flow	Mean Deviation	Stability Indicator
Node A	Moderate	Low	Stable
Node B	High	High	Congestion-prone
Node C	Moderate	Moderate	Variable
Node D	Low	Low	Stable

This comparison provides insight into how traffic stability differs across network locations and helps identify critical transport corridors requiring infrastructure improvements or operational adjustments [37].

### 7.3 Transport Network Resilience Analysis

Transport network resilience refers to the ability of urban mobility systems to maintain operational performance when subjected to disruptions such as demand shocks, infrastructure failures, or environmental events. Evaluating resilience is essential for ensuring that multimodal transport networks remain functional under varying urban mobility conditions [38].

Predictive modelling techniques allow researchers to simulate network responses under different demand scenarios and compare predicted outcomes with established transport planning benchmarks. These benchmarks include international mobility resilience guidelines, sustainable urban transport indicators, and congestion threshold standards used in urban mobility planning frameworks [39].

For example, congestion thresholds are often defined in terms of travel time reliability and traffic density indicators. If predicted network conditions exceed these thresholds, transport planners may interpret the results as evidence of infrastructure limitations or insufficient transport capacity within certain corridors [40]. Similarly, sustainable mobility indicators evaluate accessibility levels, modal balance, and network connectivity to determine whether transport systems support efficient and equitable mobility outcomes [33].

Machine learning predictions can therefore be used to evaluate how infrastructure capacity, travel demand patterns, and land-use changes affect network resilience across urban regions. By comparing predicted outcomes with planning standards, researchers can identify areas where transport infrastructure may require capacity expansion or operational improvements [34].

Figure 4. Network Congestion and Resilience Visualization



Figure 4. Network Congestion and Resilience Visualization [27]

The visualization illustrates congestion intensity and network resilience patterns across transport corridors, highlighting areas experiencing high congestion risk and potential infrastructure stress [35]. These insights support evidence-based decision-making aimed at strengthening transport system reliability and resilience in rapidly evolving urban environments [36].

## 8. POLICY AND INFRASTRUCTURE PLANNING IMPLICATIONS

### 8.1 Infrastructure Investment Planning

Predictive modelling frameworks based on machine learning and geospatial analytics provide valuable insights for transportation infrastructure investment planning. By identifying spatial patterns of congestion, accessibility gaps, and infrastructure constraints, predictive models enable planners to prioritize infrastructure investments in areas where mobility demand is growing most rapidly [37].

Traditional transport planning approaches often rely on historical traffic statistics and simplified forecasting techniques that may not capture the dynamic interactions between land-use change, travel demand, and infrastructure capacity. Machine learning-driven transport models, however, can analyze large volumes of geospatial data to detect emerging mobility patterns and forecast potential infrastructure stress points before they become critical bottlenecks [38].

For example, predictive congestion modelling can identify transport corridors expected to experience significant demand growth due to urban expansion or economic development. These insights allow policymakers to evaluate alternative infrastructure investment strategies, including road network expansion, public transport improvements, and multimodal connectivity enhancements [39].

Infrastructure planning decisions may also involve evaluating cost-benefit trade-offs associated with different transport interventions. Predictive models can simulate network conditions under multiple infrastructure scenarios, allowing planners to assess how different investment options affect accessibility, congestion levels, and travel efficiency across urban regions [40].

By integrating machine learning predictions into infrastructure planning processes, transportation agencies can improve long-term investment strategies and allocate resources more effectively. This approach supports proactive infrastructure development that anticipates future mobility demand rather than reacting to congestion problems after they emerge [41].

### 8.2 Smart City Mobility Governance

The integration of predictive analytics into transportation planning also supports the development of intelligent mobility governance frameworks within smart city environments. Modern urban mobility systems increasingly

rely on digital technologies such as traffic sensors, connected vehicles, and real-time mobility data platforms to monitor and manage transportation networks dynamically [33].

Machine learning models can process these large-scale mobility datasets to generate real-time insights into traffic conditions, enabling city authorities to implement adaptive traffic management strategies. For example, predictive models can inform dynamic traffic signal control systems that adjust signal timing based on real-time congestion patterns, thereby improving traffic flow efficiency across urban corridors [34].

Smart city governance frameworks also incorporate multimodal mobility strategies designed to reduce reliance on private vehicles and encourage sustainable transport alternatives such as public transit, cycling, and shared mobility services. Predictive transport analytics can help evaluate how these policy interventions affect accessibility, travel demand distribution, and environmental impacts across urban areas [35].

Furthermore, integrating predictive modelling with urban planning frameworks allows policymakers to align transport investments with broader sustainability objectives. For example, transport planning strategies may prioritize infrastructure improvements that reduce emissions, improve accessibility for vulnerable populations, and promote equitable mobility outcomes across different neighborhoods [36].

Through these governance mechanisms, machine learning-driven transport analysis can support more adaptive and evidence-based urban mobility policies. By combining predictive analytics with smart city technologies, transportation authorities can improve network performance, enhance infrastructure resilience, and create more sustainable and inclusive urban mobility systems [37].

## 9. CONCLUSION

The growing complexity of modern urban mobility systems has created new analytical challenges for transportation planning and infrastructure management. Multimodal transport networks operate within dynamic environments influenced by population growth, land-use transformation, economic activity, and changing travel behavior. Traditional transport modeling approaches have often relied on static assumptions and equilibrium-based frameworks, which limit their ability to capture nonlinear interactions between infrastructure capacity, spatial demand distribution, and evolving mobility patterns. The integration of machine learning techniques with geospatial analysis offers a more adaptive framework capable of addressing these limitations and improving transport system understanding.

This study demonstrated how machine learning methods can enhance causal geospatial modeling of multimodal transport networks by incorporating spatial datasets, infrastructure indicators, and demand variables within a unified analytical framework. Through feature engineering, statistical extraction, and dimensionality reduction techniques, large-scale transport datasets can be transformed into structured inputs suitable for predictive modeling. Machine learning algorithms are then able to identify complex relationships among demand shocks, land-use changes, and infrastructure constraints that influence transport network performance. Such analytical capability allows planners to move beyond purely descriptive mobility analysis toward predictive and explanatory modeling of urban transport dynamics.

Another important contribution of machine learning-based transport modeling is its potential to support evidence-based infrastructure planning. Predictive analysis enables transportation agencies to anticipate congestion patterns, identify infrastructure bottlenecks, and evaluate how future land-use developments may affect travel demand. By simulating different demand scenarios, planners can assess the resilience of multimodal networks under varying conditions and prioritize infrastructure investments that improve connectivity, accessibility, and network reliability. This approach strengthens the capacity of urban transport systems to respond to disruptions while maintaining stable mobility services for growing metropolitan populations.

Beyond infrastructure planning, the integration of predictive analytics with transportation governance frameworks can contribute to more resilient multimodal mobility systems. Data-driven insights allow policymakers to design adaptive mobility strategies that balance road capacity, public transport services, and emerging transport technologies. The use of machine learning models can also improve monitoring of transport system performance by identifying early signals of congestion risk or infrastructure stress within complex urban networks.

Future research should expand this analytical framework by incorporating real-time mobility analytics derived from connected sensors, traffic monitoring systems, and mobile data platforms. Integrating such data streams would allow predictive models to update dynamically as mobility conditions change. Another promising direction involves the development of digital twin transport systems that simulate physical transport infrastructure in virtual environments, enabling planners to evaluate policy interventions and infrastructure modifications before implementation. Finally, advances in autonomous transport technologies and intelligent mobility systems will

require new modeling approaches capable of capturing interactions between automated vehicles, traditional transport modes, and evolving urban mobility ecosystems.

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