

Article

System Model for Spatial Data Collection in Post-War Transport Infrastructure Planning

Anatoliy Tryhuba ^{1,2}, Szymon Glowacki ³, Oleg Zachko ⁴, Inna Tryhuba ¹, Sergii Slobodian ⁵,
Vasyl Demchyna ⁴, Iryna Horetska ⁶ and Taras Hutsol ^{6,7,*}

- ¹ Department of Information Technologies, Lviv National Environmental University, 80-381 Dublyany, Ukraine; trianamik@gmail.com (A.T.); tringle@ukr.net (I.T.)
 - ² Ukrainian University in Europe-Foundation, Balicka 116, 30-149 Krakow, Poland
 - ³ Department of Fundamentals of Engineering and Power Engineering, Institute of Mechanical Engineering, Warsaw University of Life Sciences (SGGW), 02-787 Warsaw, Poland; szymon_glowacki@sggw.edu.pl
 - ⁴ Department of Information Technologies and Electronic Communications Systems, Lviv State University of Life Safety, 79-000 Lviv, Ukraine; zachko@ukr.net (O.Z.); demchynavasy@gmail.com (V.D.)
 - ⁵ Institute of Energy, Higher Educational Institution “Podillia State University”, 32-316 Kamianets-Podilskyi, Ukraine; sergessb75@gmail.com
 - ⁶ Department of Agricultural Engineering, Odesa State Agrarian University, 65-012 Odesa, Ukraine; goreckaya.ira@gmail.com
 - ⁷ Department of Machine Operation, Ergonomics and Production Processes, Faculty of Production and Power Engineering, University of Agriculture in Krakow, Balicka 116B, 30-149 Krakow, Poland
- * Correspondence: taras.hutsol@urk.edu.pl or wte.inter@gmail.com

Abstract

This study presents a system model developed for collecting and analyzing spatial data on the project environment of transport infrastructure development in the post-war context, with a focus on supporting sustainable management and recovery planning. The model utilizes the OpenStreetMap Overpass Application Programming Interface (Overpass API) to extract structured geospatial information from OpenStreetMap (OSM), enabling efficient and accurate assessments of settlements affected by armed conflict. Python 3.11-based software modules were created to process OSM data, evaluate 17 relevant attributes of transport infrastructure objects, and visualize key characteristics for decision-makers. A case study was conducted on 23 Ukrainian settlements with partially damaged infrastructure, demonstrating how the proposed model facilitates timely and informed decisions for infrastructure redevelopment. By improving the accessibility and quality of spatial data, the model enhances the capacity for sustainable management of post-war transport infrastructure projects. To ensure the quality of spatial data obtained from OSM, a verification procedure was carried out by cross-checking with satellite images and official national geospatial data. The results showed an average deviation of $\pm 4.4\%$ in the length of road sections, confirming the reliability and accuracy of spatial objects obtained from OSM for use in transport infrastructure planning. The findings offer valuable insights for regional planners, public administrators, and policymakers involved in sustainable reconstruction and digital governance. Future research will focus on developing a comprehensive information system for identifying and prioritizing infrastructure development projects within defined administrative units such as municipalities and local communities.

Keywords: sustainable management; transport infrastructure; post-war recovery; spatial data; OpenStreetMap; project environment; system modeling



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1. Introduction

In recent decades, rapid advancements in information technology have fundamentally reshaped the way societies address complex tasks, including those involving planning, coordination, and decision-making. These technologies now play a central role in project management by providing more precise insights into the conditions under which projects are implemented [1–3]. Consequently, there is an increasing expectation that decisions, particularly those concerning infrastructure, will be guided not only by technical feasibility but also by a thorough understanding of the broader context and by sustainability considerations.

The post-war context represents one of the most challenging environments for project implementation. In regions where critical infrastructure has been partially or completely destroyed, the need for structured, transparent, and efficient recovery efforts becomes urgent. In such settings, transport infrastructure projects are of particular significance—not only for restoring mobility and supply chains, but also for driving long-term economic recovery and fostering social reintegration. When planned and executed with sustainability and contextual awareness, these projects can contribute directly to multiple Sustainable Development Goals (SDGs), including SDG 9 (Industry, Innovation, and Infrastructure), SDG 11 (Sustainable Cities and Communities), and SDG 13 (Climate Action) [4–6].

Managing transport infrastructure in post-conflict settings requires tools that are both responsive to local needs and aligned with long-term development strategies. Sustainable development principles emphasize the integration of environmental, economic, and social dimensions into infrastructure planning, which in turn depends on the availability of timely, accurate, and context-specific data on the project environment. Traditional planning instruments often fall short in such rapidly changing conditions, particularly when the spatial and physical characteristics of the area have been altered by damage or population displacement. As a result, achieving sustainability in infrastructure recovery demands digital solutions capable of adapting to complex, evolving, real-world conditions.

The model proposed in this study offers such a solution. It is designed to support the sustainable management of transport infrastructure development projects in post-war regions by enabling the structured collection, processing, and analysis of spatial data. By using open-source platforms such as OpenStreetMap and the OpenStreetMap Overpass Application Programming Interface (Overpass API), and integrating them with Python-based tools, the model facilitates real-time assessment of the project environment. This includes identifying existing road networks, nearby public facilities, and critical gaps in infrastructure coverage—all of which are essential for sustainable decision-making in reconstruction scenarios [7–9].

This article focuses on the practical implementation of this model in several war-affected Ukrainian settlements. The approach emphasizes transparency, accessibility of data, and reproducibility, making it suitable for broader application in infrastructure planning across regions undergoing recovery. By aligning data-driven project management with the values of sustainable development, the model contributes to a more resilient and informed approach to rebuilding transport systems in the post-war period.

The novelty of this study lies in the creation of a spatial data collection system model specifically designed to address the unique challenges of post-war transport infrastructure recovery. In contrast to existing approaches, often developed for stable environments and dependent on static or proprietary datasets, the proposed model leverages open geospatial data from OSM in combination with the Overpass API, enabling complex, parameterized queries and automated data processing through Python-based modules. This integration ensures adaptability to rapidly changing post-conflict conditions, where available information is frequently fragmented, outdated, or incomplete. By delivering timely, structured, and visually interpretable spatial information on critical infrastructure

characteristics, the model directly responds to the urgent need for reliable decision-support tools in war-affected regions. Furthermore, its architecture supports both replicability in other areas with sufficient open mapping coverage and scalability for integration into comprehensive post-war infrastructure planning frameworks.

2. Analysis of Literature Data and Problem Statement

The sustainable restoration of transport infrastructure in post-war conditions requires a well-structured and logically organized foundation of contextual and spatial data to ensure that planning and implementation processes are both responsive and resilient. Transport systems serve as critical enablers of social and economic recovery, and their redevelopment must align with broader principles of sustainability, including inclusivity, adaptability, and environmental responsibility [10–13]. A number of recent studies emphasize that, in addition to general sustainability principles, post-war reconstruction requires integrating geospatial intelligence into decision-making to address highly dynamic conditions. The collection of data on the characteristics of the project environment—such as the current condition of transport infrastructure, settlement topology, demographic dynamics, and ecological sensitivity—is essential for effective infrastructure planning and governance in war-affected regions [14–18].

The existing literature on sustainable infrastructure management increasingly focuses on the use of structured and science-based models for preparing and analyzing project-relevant data. Many works highlight how digital tools and modern information technologies can enhance project decision-making by supporting the transition from reactive planning to proactive, sustainability-oriented management [19–22]. In particular, researchers have explored big data analytics, project portfolio management frameworks, and customized tools for complex infrastructure scenarios [23–25]. However, despite their relevance, these tools are often developed for stable environments and lack adaptability to post-conflict contexts, where data are frequently fragmented, outdated, or incomplete. Traditional project management models may fall short due to their limited capacity to account for rapidly changing environmental and social variables.

A variety of methodological frameworks have been proposed to structure data collection efforts. For instance, the SMART (Specific, Measurable, Achievable, Relevant, Time-bound) model emphasizes measurable and time-bound indicators to guide project design and evaluation [26], while the ABCD (Advantages, Benefits, Constraints, Disadvantages) model organizes data around four key pillars—Assets, Buildings, Capabilities, and Deployment—to frame local development initiatives [27]. While conceptually valuable, both approaches lack direct integration with spatial data processing tools, which limits their applicability in transport infrastructure planning and recovery operations.

Particularly relevant is the SCAT (Stepwise Cluster Analysis Technique) model, applied in post-disaster recovery to assess existing infrastructure conditions [28]. It offers a structured framework for evaluating the state of transport and utility networks, supporting repair and modernization decisions. Nonetheless, SCAT does not incorporate mechanisms for processing dynamic geospatial datasets or integrating real-time data from open digital platforms—capabilities that are critical for sustainable management in volatile environments.

Although the SMART, ABCD and SCAT models have each proved useful in different planning contexts, their direct application to the realities of post-war transport infrastructure recovery is far from straightforward. The SMART approach helps define measurable objectives, yet it offers no tools for working with spatial information or for adapting to the rapidly changing conditions that follow armed conflict, when the state of infrastructure can shift within weeks. The ABCD framework is well suited for identifying and mobilising

local assets, but it does not incorporate a geographic perspective, which makes it difficult to assess whether facilities are evenly distributed or accessible to affected communities. The SCAT model, while relevant for post-disaster evaluations, is built around static assessments and cannot directly draw on open, real-time mapping data or update results automatically via API (Application Programming Interface) connections. These shortcomings point to a clear need for a method that not only structures the assessment process but also brings in openly available geospatial information and allows for its regular updating. Such an approach would make it possible to obtain timely, location-specific insights that are essential for planning the recovery of transport networks in areas emerging from conflict.

Recent advancements in geographic information systems (GIS) have introduced powerful visualization and analytical tools for spatial planning [29]. These systems are widely used in transport-related projects for mapping, route analysis, and demand modeling. However, their application in post-war reconstruction faces specific constraints: datasets may be outdated due to wartime disruptions, integration can be hindered by incompatibilities in data formats or coordinate systems, and effective use often requires significant technical expertise and resources.

Recent studies emphasize the importance of detailed traffic behavior modeling and the integration of sensing data into predictive frameworks. For instance, Chen et al. analyzed differences in highway lane-changing behavior using vehicle trajectory data, highlighting the need for microscopic-level modeling of traffic flows and the decision-making processes of drivers [30]. In parallel, research by Chen et al. in the IEEE Sensors Journal demonstrated how traffic flow prediction can be enhanced through denoising schemes combined with artificial neural networks (ANN), providing robust comparative evidence on the effectiveness of different data preprocessing strategies for sensor-based traffic monitoring [31,32]. Together, these works show that both behavioral insights and advanced data-driven methods are critical for improving the reliability of transport infrastructure planning models, especially under conditions of uncertainty.

In summary, the literature reveals that while numerous models and tools exist for data collection and project environment analysis, none fully address the requirements of sustainable transport infrastructure development in war-affected settlements. There is a clear gap for a flexible, transparent, and spatially oriented model that can operate under volatile conditions and utilize open geospatial data. This study responds to that gap by proposing a practical system model based on the Overpass API and the OSM platform, enabling the structured retrieval of spatial data through customizable queries. The model is designed for replicability, scalability, and local relevance, supporting sustainability and efficiency in post-war infrastructure recovery.

The empirical component of the study focuses on 23 Ukrainian settlements whose transport infrastructure facilities were significantly affected by Russia's military aggression. The selection of these settlements was based on three main criteria:

- (1) verified evidence of partial or complete damage to transport infrastructure facilities as recorded in official damage assessment reports and open-source geospatial datasets;
- (2) availability of baseline spatial data in OSM sufficient for applying the proposed model;
- (3) representation of different administrative types and geographic locations to ensure diversity in settlement size, infrastructure complexity, and accessibility conditions.

This approach ensured that the case study set reflects both urban and rural contexts, enabling a comprehensive evaluation of the model's applicability in varied real-world recovery scenarios. These locations serve as case studies for evaluating the model's applicability and demonstrating its potential to support recovery planning in real-world settings.

To achieve the overall goal of the study, the following research objectives have been defined:

- to develop a system model for collecting and processing spatial data on the characteristics of the project environment for transport infrastructure development in the post-war period;
- to demonstrate the practical implementation of the model through the collection and analysis of spatial data in selected war-affected settlements and to justify the relevance of these data for the planning and execution of sustainable infrastructure development projects.

3. Development of a Data Collection Model to Support Sustainable Management of Post-War Transport Infrastructure Projects

The collection of data on the characteristics of the project environment constitutes a fundamental step in the sustainable planning and implementation of transport infrastructure development projects in post-war territories. Effective management in this context depends on a clear understanding of the spatial distribution, physical condition, and operational parameters of transport infrastructure assets within defined administrative boundaries—whether at the scale of individual settlements, districts, or municipalities. For each identified asset, a structured database should be created, incorporating both geometric and semantic attributes. These attributes encompass numerical and symbolic information that describe essential features of transport infrastructure components, including road segments, bridges, intersections, and public transport nodes.

A critical component of this process involves the formation of spatial databases capable of capturing the geolocation and spatial relationships of infrastructure objects. Spatial data, by definition, are multidimensional and include coordinates, lines, and polygons that describe the physical placement of infrastructure elements within a defined coordinate reference system [33]. The processing of such data necessitates specialized software capable of managing geospatial information in an efficient and scalable manner [34].

To support data collection activities within war-affected areas, a database management system (DBMS) with geospatial capabilities must be integrated into the model. A range of DBMS platforms is currently available, including Oracle (Oracle Database, Oracle Corporation, Austin, TX, USA), MySQL (My Structured Query Language, Oracle Corporation, Austin, TX, USA), NoSQL NoSQL (Not Only Structured Query Language, MongoDB Inc., New York, NY, USA) variants, and PostgreSQL (Postgres Structured Query Language, PostgreSQL Global Development Group, Berkeley, CA, USA). In this study, the object-relational DBMS PostgreSQL (PostgreSQL Global Development Group, Berkeley, CA, USA) was selected due to its open-source nature and extensive support for spatial data operations through the PostgreSQL Geographical Information System (PostGIS) (Refractons Research Inc., Victoria, BC, Canada) extension. This platform enables the structured storage and analysis of spatial datasets derived from the OSM framework, which provides free and open access to mapping data relevant to transport infrastructure across administrative regions [30].

To accelerate the identification and management of transport infrastructure projects, the proposed system model also supports the use of web-based and mobile applications. These tools empower project managers and local planners to interactively collect, validate, and visualize data on infrastructure characteristics in real time. Figure 1 illustrates the conceptual architecture of the proposed data collection system, highlighting its functional components, data flows, and integration points with external sources such as OSM.

The spatial data obtained from the OSM framework is stored in the PostgreSQL database with the ability to record multi-line geometric data. Multi-row data type refers to geometric data represented as a data frame DF_c with a set of vectors:

$$DF_c = \left[[D_{O_{Tli}}], [D_{O_{ri}}], [D_{O_{bi}}], [D_{O_{ji}}] \right], \quad (1)$$

where DF_c —is a data frame with a set of vectors, each of which contains data on the characteristics of transport infrastructure objects; $D_{O_{Tli}}$ —a vector with data on the characteristics of the transport infrastructure of O_{Tli} i -th settlements; $D_{O_{ri}}$ —a vector with data on the characteristics of i -th roads O_{ri} of the transport infrastructure; $D_{O_{bi}}$ —a vector with data on the characteristics of i -th bridges O_{bi} of the transport infrastructure; and $D_{O_{ji}}$ —a vector with data on the characteristics of i -th road junctions O_{ji} of the transport infrastructure.

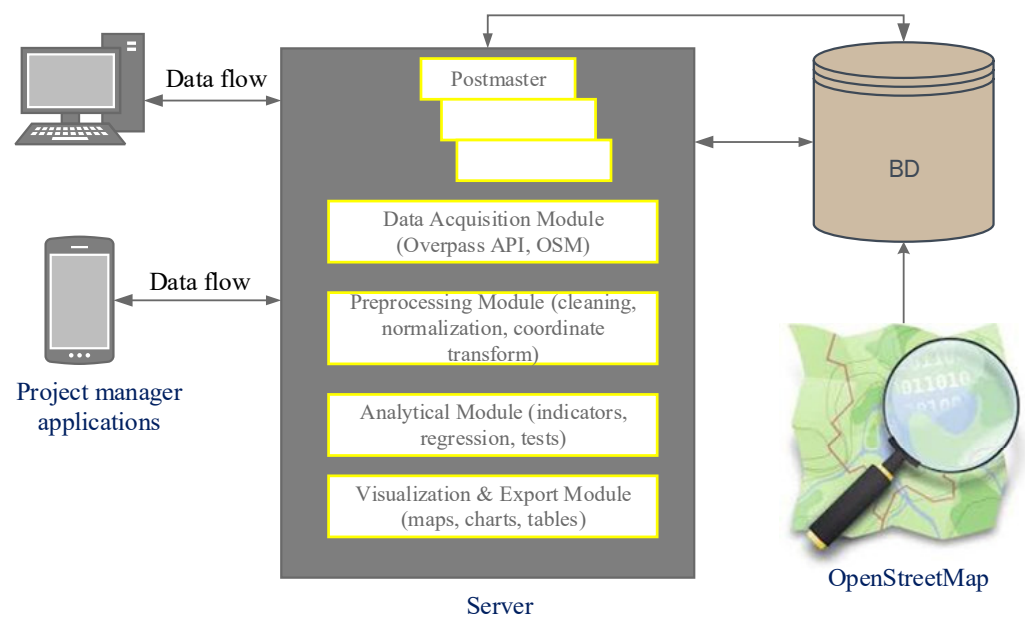


Figure 1. Architecture model of the system for collecting data on the characteristics of transport infrastructure objects.

The resulting data frame, composed of a structured set of spatial vectors, enables the visualization and analysis of key characteristics of transport infrastructure elements. These include road classifications, bridge locations, river crossings, pedestrian paths, and transportation routes, all of which are represented within detailed maps of the selected settlements. The stages involved in presenting and interpreting spatial data on road infrastructure are illustrated in Figure 2.



Figure 2. Stages of processing spatial data on transport infrastructure objects.

A fundamental operation in the proposed model is the acquisition and processing of publicly available spatial maps derived from OSM. These maps serve as the primary data source for assessing transport infrastructure in the administrative areas where development projects are to be implemented. OSM data are generated through a combination of community-driven GPS (Global Positioning System) mapping, satellite image digitization, and the aggregation of open geographic datasets. This crowdsourced approach makes

OSM a unique and valuable tool for project managers operating in data-scarce environments. Moreover, OSM's commitment to open access ensures that spatial data remain freely available to users worldwide, thereby promoting transparency, accessibility, and equity in infrastructure planning [35].

In addition to the quantitative evaluation of OSM data quality, the proposed system model integrates preprocessing procedures aimed at improving the reliability of the collected information. Data cleaning was applied to eliminate duplicate records, incomplete entries, and topological inconsistencies in the extracted spatial datasets. Outlier detection methods were used to identify and correct anomalous values, such as unrealistically short or long road segments, missing attributes, or incorrect coordinate references. These operations ensured the structural consistency of the dataset before further analysis.

Furthermore, exception handling mechanisms were implemented within the Python-based modules to automatically detect and flag errors generated during data extraction or attribute parsing. This prevents the propagation of inconsistencies into subsequent stages of spatial modeling.

To strengthen the robustness of the results, a cross-validation procedure was introduced, whereby spatial attributes derived from OSM were compared against subsets of external reference data (satellite imagery and national cadastral datasets) across multiple settlement samples. This form of cross-validation reduces the risk of over-reliance on a single data source and increases confidence in the model's outputs.

For the purposes of this study, we extracted spatial data from the OSM platform related to settlements in Ukraine that were affected by armed conflict and experienced damage to critical infrastructure. These data were imported into a PostgreSQL/PostGIS database, allowing for efficient spatial operations based on custom-designed functional blocks. The collected data were subsequently transformed into standard formats suitable for further computational processing, visualization, and integration into decision-support workflows.

To ensure that the spatial data extracted from OSM accurately reflected the actual condition of the transport infrastructure, a dedicated verification stage was conducted. For a selected sample of settlements, the datasets obtained from OSM were compared with official government records and the most recent high-resolution satellite imagery. The comparison focused on confirming the presence and classification of road segments, intersections, and bridges, as well as identifying any discrepancies in their geometry or attributes. When inconsistencies were detected, they were examined to determine whether they stemmed from outdated mapping, variations in classification standards, or gaps in the source data. This process not only enabled an assessment of the reliability of OSM-based data extraction but also provided insights into how the model could integrate corrective measures or additional data sources to enhance accuracy in future applications.

This approach not only reduces the barriers to entry for spatial analysis in post-war reconstruction but also promotes the use of reproducible and scalable digital tools for sustainable infrastructure management. By leveraging free and collaboratively generated data, the model aligns with sustainability principles such as resource efficiency, participatory governance, and the democratization of information access [36–41].

To operationalize the proposed model, a combination of open-source tools, geospatial data processing algorithms, and structured database-management approaches was employed [42–45]. The methodological framework is based on the integration of three key components: spatial data acquisition, database construction, and data transformation for analytical and decision-support purposes.

Let $S = \{s_1, s_2, \dots, s_n\}$ represent the set of settlements in which post-war transport infrastructure development projects are to be implemented. For each settlement $s_i \in S$, the goal is to construct a spatial dataset D_i , such that:

$$D_i = \{(x_j, y_j, t_j, a_j) \mid j = 1, \dots, m\}, \quad (2)$$

where x_j, y_j —are the geographic coordinates of transport infrastructure object j ; t_j —denotes its type (e.g., road, bridge, crossing); a_j —is a set of attributes characterizing its physical or operational condition.

Let $Q(s_i)$ represent a structured query to the OSM database via the Overpass API, targeting transport infrastructure elements within the administrative area, named s_i . The query can be formally expressed as follows:

$$Q(s_i) = \cup \left\{ \begin{array}{l} \text{way : ["highway"]} \in A(s_i), \\ \text{relation : ["route"]} \in A(s_i), \\ \text{node : ["bridge"]} \in A(s_i) \end{array} \right\}, \quad (3)$$

where $A(s_i)$ —denotes the set of geographic features within the boundary of settlement s_i ; “highway”—refers to all types of road segments (e.g., residential, primary, tertiary); “route”—refers to structured transport routes (e.g., bus lines, road networks); “bridge”—identifies the infrastructural nodes tagged as bridges in OSM.

To extract usable geospatial information, the raw results of the query are exported and transformed into structured vector formats suitable for database ingestion and spatial analysis:

$$\mathcal{E}(s_i) = \text{Transform}(\text{Export}(Q(s_i))), \quad (4)$$

where $\mathcal{E}(s_i)$ —is the processed geospatial dataset representing the infrastructure characteristics of settlement s_i .

The query $Q(s_i)$ retrieves all relevant elements from the OSM database within the boundary of settlement s_i , filtered by the tags relevant to transport infrastructure.

The extracted data were parsed and transformed using Python scripts built upon libraries such as OpenStreetMap NetworkX (OSMnx), geopandas, and shapely. These tools allowed for the conversion of raw OSM outputs into geospatial vector layers suitable for further analysis and visualization. The parsed objects were stored in a PostgreSQL/PostGIS database, enabling spatial indexing, querying, and computation.

Let $\Phi(s_i)$ represent the complete geospatial profile of a settlement s_i , which includes spatial layers L_k corresponding to different types of infrastructure objects:

$$\Phi(s_i) = \bigcup_{k=1}^K L_k(s_i), \quad \text{where } L_k(s_i) \subseteq D_i, \quad (5)$$

Each L_k is stored as a geometry-enabled table in the PostGIS database and linked to metadata describing source reliability, date of collection, and classification schema.

To ensure alignment with the Sustainable Development Goals, the collected data were assessed using indicators such as spatial accessibility, infrastructure density, and connectivity coefficients. For example, the road network density ρ for a settlement s_i is calculated as follows:

$$\rho(s_i) = \frac{L_{\text{total}}(s_i)}{A(s_i)}, \quad (6)$$

where $L_{\text{total}}(s_i)$ —is the total length of roads in kilometers; $A(s_i)$ —is the area of the settlement in square kilometers.

This metric allows decision-makers to compare infrastructure provision across different regions and prioritize interventions in underserved areas.

The model also incorporates a time-sensitive component, enabling the assessment of changes in infrastructure conditions over time. By conducting repeated data extractions and updating the database, temporal trends in network degradation or recovery can be visualized and quantified [46–49].

In order for the proposed model to remain relevant to post-war recovery conditions, it is important to ensure not only the technical accuracy of calculations, but also their consistency with the priorities and knowledge of those directly involved in the processes of transport network development. The involvement of stakeholders, including local planners, representatives of local authorities, and residents of affected communities, ensures both the quality and accuracy of management decisions.

In practice, such engagement is implemented through structured working meetings or consultations, during which the preliminary outputs of the model, for example, the ranking of streets or settlements according to restoration priority, are presented for discussion. Participants contribute contextual knowledge that may not be fully captured by quantitative analysis, such as identifying roads that are critical for emergency services, providing access to key economic activity sites, or ensuring the delivery of essential public services. This feedback can be incorporated into the weighting coefficients of the model's attributes or used to validate and adjust the prioritization results.

Adopting such a participatory approach transforms the model from a purely technical analysis tool into a platform for joint planning. This not only increases local support for recovery strategies but also enhances the alignment of planned measures with the social, economic, and logistical realities of specific territories. Over time, repeated stakeholder engagement can serve as an effective feedback mechanism, enabling the model to evolve in response to changing community needs and the evolving condition of infrastructure.

The application of this model in 23 Ukrainian settlements allowed the structured retrieval of 17 unique indicators per location, including road classifications, intersection types, proximity to public facilities, and existing damage zones. These indicators support a comprehensive analysis of the project environment and enable more sustainable, data-driven decision-making in the reconstruction of post-war transport systems.

4. Results of Spatial Data Collection and Their Application in Sustainable Post-War Infrastructure Planning

The spatial data collection process concerning transport infrastructure characteristics in the context of post-war development projects was conducted in accordance with the system architecture model proposed in this study (see Figure 1). This architecture enables structured, scalable, and replicable data acquisition across various administrative territories and infrastructure types, ensuring consistency with sustainable infrastructure planning principles.

As a first step, we identified and selected the settlements for which spatial data on transport infrastructure would be collected. The selection criteria were guided by pre-war population levels and the relevance of transport infrastructure to community functioning, mobility, and access to essential services. Priority was given to settlements that experienced partial or complete damage to key transport infrastructure facilities due to Russia's military aggression.

In total, 23 settlements were selected for the study. Each represents a distinct case of infrastructure disruption requiring targeted data analysis for effective recovery planning. The list of selected settlements, along with their relevant demographic and administrative information, is presented in Table 1.

Table 1. Settlements of Ukraine affected by Russia’s military aggression (as of 14 November 2023).

Name of the Settlement	Administrative Region	Number of Inhabitants Before the War, Thousand People	Number of Residents After the Hostilities (Approximate), Thousand People
Mykolaiv	Mykolaiv	482.5	230
Mariupol	Donetsk	431.86	100
Sumy	Sumy	269.58	150
Kramatorsk	Donetsk	157.69	60
Sloviansk	Donetsk	114.66	40
Severodonetsk	Luhansk	102.21	30
Lysychansk	Luhansk	96.803	15
Bakhmut	Donetsk	72.324	20
Rubizhne	Luhansk	56.453	20
Okhtyrka	Sumy	49.527	30
Raisin	Kharkiv	45.433	15
Chuguev	Kharkiv	32.572	15
Toretsk	Donetsk	32.348	12
Avdiivka	Donetsk	31.94	10
Popasnaya	Luhansk	21.531	5
Starobelsk	Luhansk	16.344	5
Ugledar	Donetsk	14.945	5
Orikhiv	Zaporizhzhya	14.664	5
Belovodsk	Luhansk	14.437	5
Gulyaypole	Zaporizhzhya	14.357	5
Bashtanka	Mykolaiv	12.71	5
Beryslav	Kherson	12.306	5
Snihurivka	Mykolaiv	12.274	5

Following the cessation of active hostilities in the selected settlements, there will be an urgent need to initiate and coordinate projects aimed at the restoration and modernization of critical transport infrastructure. Ensuring that such recovery efforts align with the principles of sustainable development requires access to accurate, up-to-date, and open spatial data that can support evidence-based planning and equitable resource allocation.

To this end, data collection on the characteristics of transport infrastructure facilities was conducted using the OSM framework. As a globally accessible and collaboratively maintained geospatial platform, OSM offers detailed and freely available data layers that include roads, intersections, bridges, and other key elements of the transport network. Figure 3 presents an example of the spatial representation of transport infrastructure features as visualized through the OSM framework.

	geometry	bbox_north	bbox_south	bbox_east	bbox_west	place_id	osm_type	osm_id	lat	lon	class	type	place_rank	importance
0	POLYGON ((34.50901 48.44168, 34.53553 48.43989...	48.473065	48.268843	34.913960	34.509011	203318244	relation	12616004	48.371940	34.716495	boundary	administrative	14	0.400010
1	POLYGON ((36.42894 49.51988, 36.42898 49.51806...	49.598787	49.378436	36.825654	36.428939	203950295	relation	11815194	49.488041	36.614400	boundary	administrative	14	0.400010
2	MULTIPOLYGON (((34.69106 50.93782, 34.69191 50...	51.069862	50.836850	35.043795	34.691057	203412191	relation	10553891	50.952017	34.867512	boundary	administrative	14	0.400010
3	POLYGON ((36.42894 49.51988, 36.42898 49.51806...	49.598787	49.378436	36.825654	36.428939	203950295	relation	11815194	49.488041	36.614400	boundary	administrative	14	0.400010

Figure 3. A fragment of the data received from the OSM framework APIs.

In the course of the study, data were collected on 17 key attributes describing the transport infrastructure features of the 23 selected settlements. These attributes provide a comprehensive spatial and semantic profile of each locality, which is essential for understanding the configuration, extent, and hierarchical significance of transport networks in the context of post-war recovery and sustainable planning. The collected attributes include:

1. geometry—polygonal geometry defining the administrative boundary of the settlement;
2. bbox_north—northern boundary coordinate of the selected area;
3. bbox_south—southern boundary coordinate of the settlement territory;
4. bbox_east—eastern boundary coordinate;
5. bbox_west—western boundary coordinate;
6. place_id—unique identifier of the settlement within the geospatial database;
7. osm_type—classification of the object type according to the OSM data schema [30];
8. osm_id—unique identifier of the OSM object;
9. lat—latitude coordinate of the settlement’s central point;
10. lon—longitude coordinate of the settlement’s central point;
11. class—semantic class of the OSM object;
12. type—structural type of the object in OSM;
13. place_rank—hierarchical rank of the settlement in the geospatial dataset;
14. importance—relative importance of the location based on population and regional role;
15. addresstype—administrative type of the location (e.g., village, town, city);
16. name—official name of the community to which the settlement belongs;
17. display_name—composite displayed name, including region and administrative units.

To translate the collected attributes into practical decision-making inputs, it is not enough to treat them as a descriptive list. In recovery planning, different attributes vary in their relative importance. For example, importance, place_rank, and central location coordinates may have greater influence on accessibility planning than purely geometric boundary data. For this reason, the dataset can be integrated into a multicriteria evaluation framework, where each attribute is assigned a weight that reflects its strategic value for reconstruction priorities.

One of the methods suitable for this purpose is the Analytic Hierarchy Process (AHP). In AHP, expert judgments are used to perform pairwise comparisons of attributes, producing a set of normalized weights that sum to one. The overall priority score for a settlement can then be calculated as follows:

$$S_j = \sum_{i=1}^n w_i \cdot a_{ij}, \quad (7)$$

where S_j —is the composite score of j -th settlement; w_i —is the weight of i -th attribute; a_{ij} is the normalized value of i -th attribute for j -th settlement; n —is the number of attributes.

An illustrative example of preliminary weights (based on hypothetical expert scoring) is shown below (Table 2).

In practical application, these weights would be refined through consultations with planners, engineers, and local authorities. The weighted sum scores allow settlements to be ranked in terms of reconstruction priority, ensuring that planning decisions consider both technical characteristics and strategic importance.

For cases where less expert input is available, simpler methods such as Simple Additive Weighting (SAW) can be applied. Here, all attributes are normalized to a common scale (e.g., 0 . . 1), multiplied by predefined weights, and summed. Although less rigorous than AHP, SAW is easier to implement and can be automated within the existing Python-based data processing pipeline.

Table 2. A clear example of preliminary weights (based on a hypothetical expert assessment).

Attribute	Weight, w_i	Rationale for Higher or Lower Weight
importance	0.18	Strongly linked to regional role and service coverage
place_rank	0.15	Reflects settlement hierarchy in national/regional network
lat/lon	0.10	Geographic position affects accessibility and logistics
geometry	0.08	Defines administrative scope for infrastructure planning
osm_type/osm_id	0.06	Identifiers essential for consistent spatial processing
addresstype	0.06	Determines governance and planning jurisdiction
bbox coordinates (north/south/east/west)	0.12 (combined)	Affect spatial extent and boundary interactions
class/type	0.10	Semantic classification useful for thematic analysis
name/display_name	0.05	Minimal influence on prioritization, mainly for identification

Integrating such a weighting framework into the model would allow decision-makers to move from raw spatial data toward transparent, evidence-based prioritization of settlements and infrastructure links, improving both efficiency and accountability in post-war recovery planning.

To process and analyze this dataset, a dedicated Python 3.11-based software module was developed. This module enables automated extraction, analysis, and visualization of geographic attributes for each settlement. It supports the assessment of spatial patterns and infrastructure coverage, thus contributing to data-informed and sustainable decision-making in reconstruction planning.

As an example, Figure 4 illustrates the visualized road network characteristics of the city of Bakhmut, located in the Donetsk region of Ukraine. This visualization reflects both the current geometric configuration and the status of the transport infrastructure as captured in the OSM database.

Based on the analysis of the geographical characteristics of the road network in the city of Bakhmut (Donetsk region, Ukraine), a distribution histogram was generated to illustrate the classification of roads according to their functional types, as defined within the OSM schema. This visual representation (Figure 5) provides insight into the structure and hierarchy of the local transport network, which is essential for prioritizing reconstruction measures and planning sustainable infrastructure interventions.

The analysis of the road network in Bakhmut revealed a heterogeneous distribution of road types, reflecting the functional structure and planning logic of the city prior to the war. The most prevalent category was “residential” roads, which comprised 40.04% of the entire network. These roads primarily serve residential areas and are typically characterized by limited traffic capacity and lower design speeds, underscoring their importance for neighborhood-level accessibility and pedestrian safety.

The second most common category was “service” roads, accounting for 26.77% of the network. These roads are usually designed to provide access to specific facilities such as industrial complexes, logistics centers, shopping areas, and other specialized infrastructure. Their presence indicates zones of economic activity that may require targeted attention in post-war recovery planning.

Footways, representing 11.24%, are non-motorized routes intended for pedestrians and cyclists. This category includes sidewalks, walking paths, and bicycle lanes, and highlights the relevance of maintaining soft mobility infrastructure in the context of inclusive and sustainable urban redevelopment.

Tertiary roads make up 6.57% of the network and generally function as connectors between local streets and higher-capacity roads. They provide essential links within the urban fabric and often serve mixed residential and commercial areas. Secondary roads, which constitute 4.60%, act as key intra-urban arteries that facilitate mobility across different neighborhoods.



Figure 4. Results of visualization of road network characteristics and types for the city of Bakhmut, Donetsk region (Ukraine).

A smaller share is held by primary roads (2.72%), which are major arterial routes that link the city to regional or national transport corridors. Their relatively low proportion suggests limited external connectivity, a factor to consider in reconstruction planning for regional integration.

The remaining share of the road network (less than 2%) includes specialized types such as pedestrian zones, minor streets, trails, and unclassified paths. Although numerically limited, these segments often play critical roles in local mobility, emergency access, and non-motorized transport systems.

To better understand the functional significance of road segments in Bakhmut's urban network, we conducted a network analysis to evaluate two key topological indicators:

betweenness centrality and closeness centrality. Figure 6 presents a scatterplot showing the relationship between these two measures for individual streets. Segments with higher centrality values are considered more structurally important in terms of traffic flow and accessibility, making them priority targets for sustainable rehabilitation efforts. This analysis supports evidence-based decision-making in the allocation of limited post-war reconstruction resources.

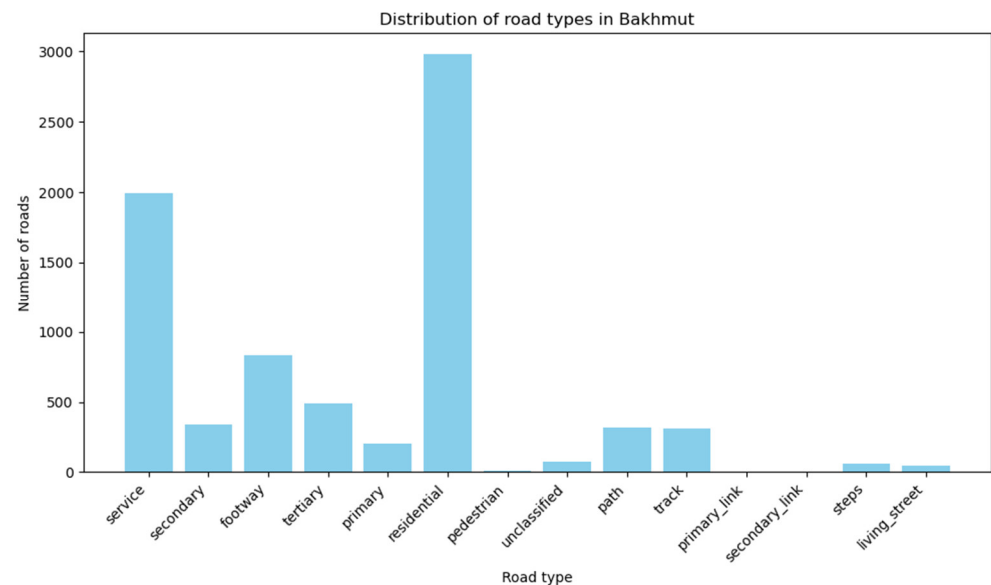


Figure 5. Histogram of road network distribution by road type in the city of Bakhmut (Donetsk region, Ukraine).

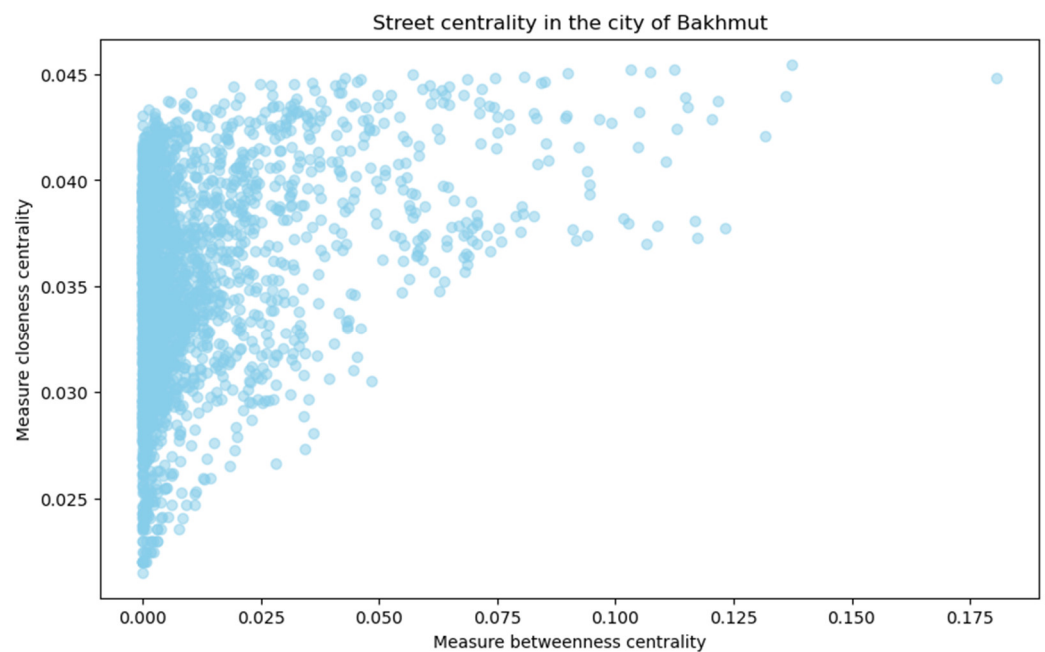


Figure 6. Diagram of the center of the streets of Bakhmut, Donetsk region (Ukraine).

The results presented in Figure 5, which show the distribution of road types in the city of Bakhmut, serve as a foundation for the analysis and planning of transport infrastructure development projects in the post-war period. This classification supports sustainable urban planning by allowing decision-makers to identify imbalances in the structure of the road

network, prioritize investments in critical segments, and develop targeted responses to pressing transportation challenges.

To complement this, a network analysis of street centrality was performed using geospatial data on individual road segments within the settlement (Figure 6). The resulting centrality graph provides insights into the functional importance of each street and intersection within the urban network. Streets with high centrality values can be identified as key mobility corridors, which should be prioritized for restoration, expansion, or traffic optimization measures as part of a sustainable transport recovery strategy.

This analysis supports the strategic allocation of limited financial and technical resources by highlighting the segments most crucial for mobility, accessibility, and connectivity. In practical terms, centrality data can inform decisions such as which routes to widen, where to install traffic regulation systems, or which intersections require improved signage or redesign. This contributes not only to efficiency but also to safety, inclusivity, and the long-term resilience of the transport system.

Moreover, the use of street centrality metrics enhances the transparency of decision-making processes by providing clear visual and quantitative justifications for planned interventions. Sharing such data with stakeholders, including municipal authorities, civil society, and residents, promotes trust and fosters informed public participation in the design of post-war urban environments.

In Bakhmut, almost 40% of all street and road lines are classified as residential. This means that a significant part of the transport network mainly provides intra-neighborhood and inter-neighborhood transportation for residents, rather than being used for transit transport. In the post-war period, this structure directly affects the order of restoration work. Repairing residential streets allows for the restoration of residents' daily mobility, ensuring access to housing, educational institutions, healthcare, and commercial facilities, as well as restoring the normal operation of emergency services. In addition, such roads usually require less complex engineering work than main roads, making their restoration faster and less costly.

Centrality indicators make it possible to determine which sections of the network should be repaired first. Junctions or sections with a high centrality index are a priority for restoration, as they serve as basic connecting links. Their restoration significantly improves overall accessibility to the transport network. Similarly, elements with high proximity contribute to reducing average distances and travel times after commissioning. Combining road type analysis with centrality indicators provides the basis for developing a coherent transport network restoration project plan that takes into account both accessibility for residents and the timely renewal of the most strategic elements of the transport system.

Based on the developed Python-based spatial data processing module, a set of dependencies and spatial relationships was established to describe the project environment of the selected settlements (Figure 7). These analytical results serve as a baseline for initiating and planning recovery-oriented transport infrastructure development projects, helping to ensure that they are grounded in evidence, spatial logic, and the broader goals of sustainable urban development.

The dependencies obtained from the analysis of the project environment characteristics of transport infrastructure in post-war settlements are presented in Figure 7 and are described by the following linear regression equations:

Road count

$$R_c = 191.32 \cdot P_{bw} - 2784.69, R = 0.98, \quad (8)$$

Intersection count

$$I_c = 52.44 \cdot P_{bw} - 747.58, R = 0.98, \quad (9)$$

Road network density

$$R_{nd} = 0.03 \cdot P_{bw} + 2.78, R = 0.2, \quad (10)$$

Bridge count

$$B_c = 0.41 \cdot P_{bw} + 3.64, R = 0.84, \quad (11)$$

where P_{bw} —is the pre-war population of the settlement (in thousands of people).

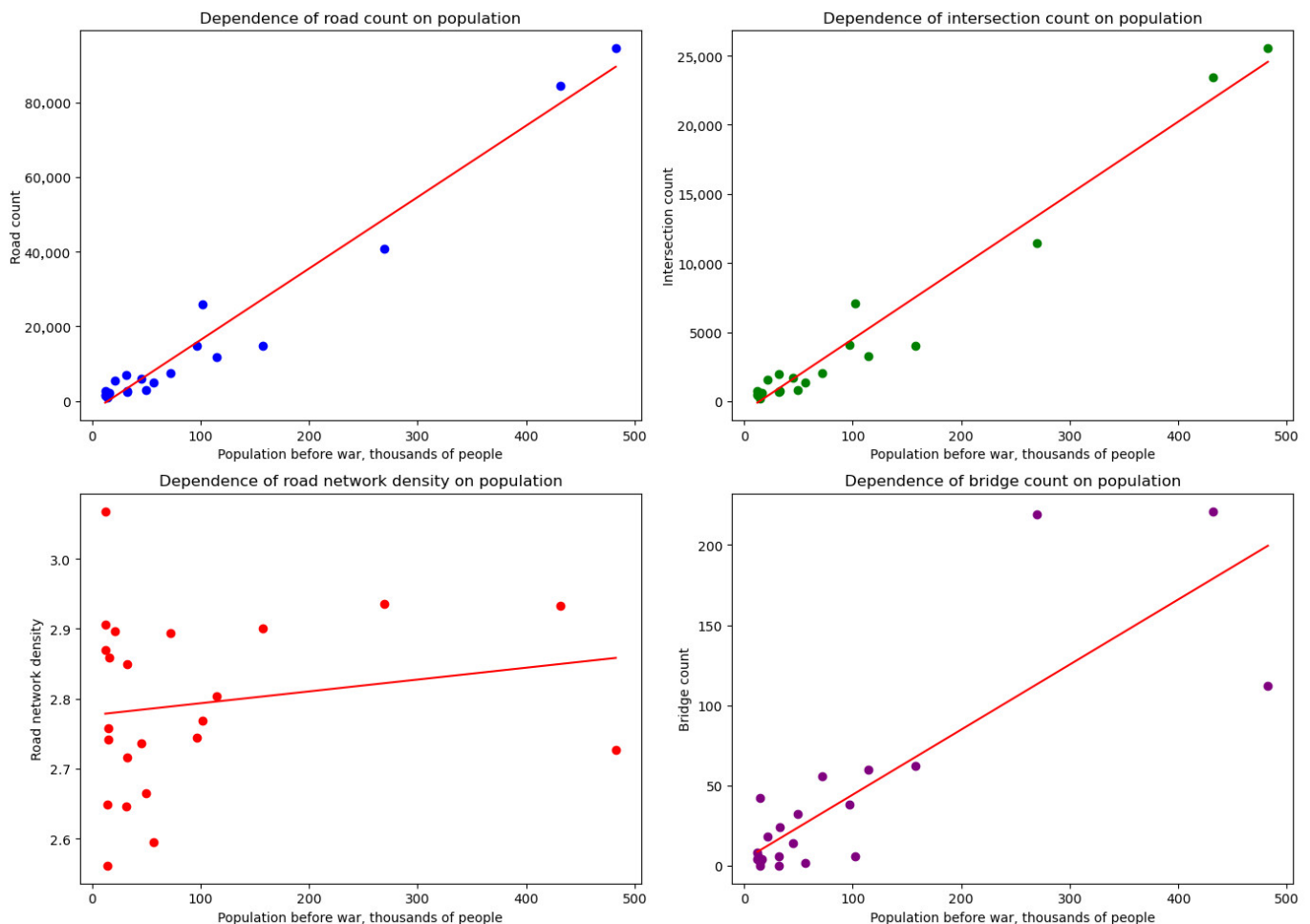


Figure 7. Relationships between population size and selected characteristics of the transport infrastructure project environment in post-war Ukrainian settlements.

We present Table 3, which summarizes the key results of the regression analysis, their interpretation, and practical implications for recovery. This allows for a deeper analysis and consideration of the impact of each indicator on planning priorities.

The dependencies obtained demonstrate that demographic indicators can be an effective indicator for predicting the scale and complexity of restoration work, especially for the number of roads and intersections, where the correlation is extremely high ($R = 0.98$). This allows preliminary estimates of needs to be made even in conditions of incomplete data. At the same time, the network density indicator has a low correlation with population size, which requires a more in-depth contextual analysis. For bridges, there is a moderate correlation, which complements the overall picture but also requires consideration of engineering factors.

Table 3. Interpretation of regression analysis results and their practical implications for transport infrastructure restoration.

Indicator (Equation)	Slope Coefficient	R	Interpretation of Result	Potential Impact on Recovery Priorities
Road count (Equation (8))	191.32	0.98	For every additional 1000 residents, there are on average ~191 additional road segments. Very strong relationship between population size and the scale of the road network.	Enables quick estimation of the volume of reconstruction works in communities without complete mapping data; can be used for resource planning.
Intersection count (Equation (9))	52.44	0.98	High intersection density correlates with population size.	Allows forecasting of work complexity in central areas; may influence prioritization of network node restoration.
Network density (Equation (10))	0.03	0.20	Weak dependence on population size; more influenced by historical planning and geography.	Requires additional variables (topography, zoning) for accurate forecasting; should not be used as the sole criterion for prioritization.
Bridge count (Equation (11))	0.41	0.84	Moderately strong relationship; larger settlements have more bridge structures.	Can help assess the scope of work for restoring critical infrastructure; important to consider engineering complexity and the strategic role of bridges.

The relationship described by Equation (8) suggests that, on average, an increase of 1000 residents corresponds to an increase of approximately 191.32 road segments. The correlation coefficient of 0.98 indicates a very strong positive linear relationship. However, correlation alone does not prove causation; therefore, statistical significance tests were conducted to confirm the robustness of the observed relationships. For each regression equation, *t*-tests for the slope coefficients showed *p*-values < 0.001, indicating that the relationships are statistically significant at the 99% confidence level. In addition, ANOVA *F*-tests confirmed that the models explain a substantial proportion of the variance in the dependent variables (e.g., for Equation (7), $F = 512.3$, $p < 0.001$), which supports their predictive validity. The 95% confidence intervals for the slope coefficients were calculated, further reinforcing the stability of the estimates.

These results make the road count metric a reliable basis for planning road network expansion in line with demographic recovery, while also acknowledging that additional factors, such as terrain and historical road development patterns, may influence infrastructure needs.

Similarly, the number of intersections increases by an average of 52.44 per 1000 residents (Equation (9)), with an equally high correlation coefficient of 0.98. This supports the conclusion that the urban street grid complexity scales proportionally with population growth and should be considered when designing post-war urban mobility systems.

In contrast, the correlation between road network density and population (Equation (10)) is weak, with a coefficient of only 0.20. This suggests that road density is influenced more by spatial, economic, or historical factors than by population size alone. It reflects

the importance of considering land use patterns, pre-existing planning frameworks, and regional development policies when assessing road network sufficiency.

The analysis of bridge count (Equation (11)) demonstrates a moderate linear relationship with population (correlation coefficient: 0.84). While a larger population is generally associated with more bridges, indicating a need to facilitate cross-city mobility, other non-demographic variables such as topography, water features (rivers, canals), and historical urban morphology also play a key role in shaping bridge distribution.

Taken together, these regression models provide a data-driven foundation for prioritizing reconstruction efforts in a manner consistent with the principles of sustainable development. They enable targeted planning of road infrastructure that reflects both demographic realities and spatial-functional constraints in war-affected regions.

The findings of this study can inform the planning and prioritization of post-war transport infrastructure projects; however, it is important to recognize that population is only one of many factors influencing infrastructure development. Other critical variables—such as land use, urban morphology, environmental constraints, and socio-economic conditions—must also be considered to ensure that interventions align with long-term sustainability goals.

Spatial knowledge of the number and location of road intersections allows planners to identify zones requiring modernization or reconstruction. This may involve the installation of new traffic lights, the improvement of pedestrian safety infrastructure (e.g., crosswalks, pedestrian zones), or the redesign of intersections to accommodate evolving mobility needs. Similarly, the analysis of street centrality provides insight into the structural importance of specific routes, enabling the identification of segments that should be widened, upgraded, or redesigned to improve traffic circulation and system resilience. Such insights form a critical basis for initiating targeted infrastructure projects under post-war resource constraints, ensuring that limited funds are allocated where they yield the greatest social and functional impact.

The research confirms that the proposed model for collecting data on transport infrastructure characteristics—based on automated queries through OSM's Overpass API—is a viable tool for supporting spatial analysis in war-affected regions. This model facilitates the assessment of road network accessibility, current infrastructural conditions, and the feasibility of development-oriented interventions. The use of OSM as a data source promotes transparency, replicability, and cost-efficiency, which are essential attributes of sustainable infrastructure management.

To extend the practical applicability of the proposed model, further research should focus on the development of an integrated information system for identifying and prioritizing transport infrastructure development projects at the level of specific administrative units (e.g., settlements, municipal districts, or communities). Such a system, built upon the spatial data collection architecture presented in this study, will enhance the capacity of local authorities and stakeholders to assess project environments and accelerate evidence-based decision-making in infrastructure reconstruction.

The presented results confirm the successful implementation of the defined research objectives. Firstly, a system model was developed that enables the collection and processing of spatial data on the characteristics of the project environment in the context of post-war transport infrastructure development. The model integrates open geospatial data from the OSM platform with spatial database structures and analytical modules, allowing for flexible application across various territorial units. Its architecture supports transparency, replicability, and adaptability—key requirements for modern sustainable infrastructure planning.

Secondly, the model was practically tested on a sample of 23 settlements in Ukraine that experienced significant infrastructural damage as a result of military aggression. Through this application, relevant spatial attributes were extracted, analyzed, and visualized to support evidence-based decision-making. The structured data generated within the model are directly applicable for the planning, prioritization, and justification of infrastructure interventions and enable stakeholders to operate within a unified spatial framework.

From a scientific standpoint, the proposed approach contributes to the methodological basis for spatially grounded transport infrastructure planning in crisis-affected regions. While existing research offers general principles of data collection or GIS application, this study integrates open-source geospatial technologies into a replicable system specifically tailored to the challenges of post-war reconstruction. This constitutes the core element of the study's novelty.

Importantly, the model is not limited to technical data management; it directly supports the principles of sustainable development by facilitating equitable access to infrastructure, promoting cost-effective solutions, and enabling long-term spatial coherence in planning. The approach aligns with the Sustainable Development Goals—particularly SDG 9 (Industry, Innovation and Infrastructure) and SDG 11 (Sustainable Cities and Communities) by ensuring that infrastructure recovery is not only rapid but also inclusive, data-informed, and future-oriented.

The outcomes presented in this section confirm that the developed model meets both theoretical and practical expectations. It offers a robust foundation for initiating further research aimed at creating a comprehensive information system for infrastructure needs assessment and project identification across post-conflict regions. In terms of replicability, the model is built entirely on open geospatial data (OSM) and publicly accessible tools (Overpass API, Python-based processing modules), which allows its application in other geographic contexts without dependence on proprietary datasets or region-specific software. The main requirement for replication is the availability of sufficiently detailed OSM coverage and basic technical capacity for geospatial data processing.

Regarding feasibility, the model's methodology is adaptable to varying infrastructural, demographic, and environmental conditions by adjusting attribute selection, query parameters, and analytical thresholds. However, its performance may differ depending on data completeness, the quality of local mapping efforts, and the complexity of the transport network. In sparsely mapped areas, preliminary data enrichment, through field surveys or integration with alternative open datasets, may be required to achieve results comparable to those obtained in this study.

The outcomes presented in this section confirm that the developed model meets both theoretical and practical expectations. It offers a robust foundation for initiating further research aimed at creating a comprehensive information system for infrastructure needs assessment and project identification across post-conflict regions. This direction represents a logical continuation of the current study and a meaningful contribution to the field of sustainable reconstruction planning.

5. Discussion of Research Results

Interpretation of Core Findings. This study presents a novel spatial-data-driven model for planning post-war transport infrastructure underpinned by sustainability principles. The linear relationships identified, such as the rise in road and intersection counts per 1000 residents, provide quantitative benchmarks that enhance recovery planning. For example, Equation (8) shows an average of 191 new road segments per additional 1000 inhabitants, while Equation (9) suggests approximately 52 additional intersections.

These findings enable precise estimations of recovery needs and support efficient resource allocation in data-scarce, war-affected regions.

Comparison with Related Studies. Our results align with and extend existing OSM-based research. For instance, Kunkler and Kellner [50] evaluated German road network performance using OSM, emphasizing the utility of spatial indicators for sustainable city planning. Their methodology mirrors ours in leveraging open-source data and geospatial modeling to examine infrastructure resilience.

Similarly, studies by Pavlovic et al. [51] employing remote sensing and OSM for environmental impact assessments highlight how spatial analysis frameworks can inform infrastructure restoration while considering environmental implications. Our work complements theirs by focusing on post-conflict settings and developing actionable metrics for intersection and road density.

Importantly, Rosa and Thomas [52] demonstrated the use of OSM for assessing territorial innovation potential, noting that open, granular spatial data better informs regional development strategies. Our model builds on this by targeting recovery contexts where long-term sustainability and inclusivity are priorities. The integration of centrality analysis echoes the approach of Gao et al. [53], who used spatial-autocorrelation methods to optimize transport-tourism connectivity, demonstrating broader applicability in both urban and crisis contexts.

Scientific Significance. The methodological novelty of this research lies in its integration of open geographic data from OSM via the Overpass API, scalable database processing (PostgreSQL/PostGIS), and spatial network analytics (centrality measures). While GIS-based approaches have been widely used [50–54], they often rely on commercial software and do not provide population-based regression models tailored for post-crisis reconstruction. The developed model fills this gap, offering an accessible, replicable framework that bridges demographic data and geospatial infrastructure metrics.

Practical Implications and Recommendations. The findings are directly actionable. Interventions should first prioritize streets with high intersection density or centrality—particularly those identified as primary or secondary in centrality analysis. Such priorities align with SDG 9 and SDG 11, which emphasize resilient, inclusive infrastructure and cities. Moreover, the regression models (e.g., Equations (8) and (9)) enable rapid estimation of infrastructure needs in settlements with limited data, improving decision-making at early stages of recovery. However, when using these models for prioritization, it is important to recognise that the predicted values reflect average tendencies and may not always match local realities. Over-reliance on population-based estimates without considering other contextual factors could lead to misallocation of resources, for example by overestimating needs in compact settlements or underestimating them in geographically dispersed ones. Therefore, regression outputs should be treated as an initial screening tool and supplemented with detailed spatial and field assessments before final decisions are made.

To enhance its practical value, the model can be integrated into a decision-support tool for local planners, combining demographic, spatial, and economic data layers. Such a tool could support scalable, participatory planning processes and foster transparency and accountability.

Limitations and Future Research. Although the population-based regressions serve as strong baseline indicators, they do not capture the full range of influences such as topography, policy, or economy—all of which may affect infrastructure development. For example, weak correlation in network density (Equation (10), $r = 0.20$) suggests that other variables such as historical layout or land-use constraints should be factored in. This limitation has direct implications for recovery prioritization: if regression results are applied without adjustment, there is a risk of directing resources toward areas with

statistically higher predicted needs while overlooking links that are critical for connectivity or emergency access but fall outside the model's projections. In settlements with unique geographical constraints, war-related damage patterns, or atypical spatial layouts, this could lead to a mismatch between actual recovery needs and allocated resources. In practical terms, regression outputs should therefore be treated as an initial screening tool, followed by validation through detailed spatial analysis and local field assessments.

Future research should incorporate environmental variables and terrain data, possibly from satellite sources, to refine these models. Integrating Copernicus imagery with OSM could allow for the dynamic monitoring of road conditions and resilience, enabling prioritization to reflect both structural importance and current usability. Similarly, analyzing other post-conflict contexts, through cross-validation in different regions, would provide insight into the model's generalizability and adaptability.

One of the main advantages of the proposed tool is its ability to support the principles of sustainable transport infrastructure recovery in the context of post-war development. The use of OSM open data and free APIs avoids dependence on commercial sources and ensures long-term availability of the information base for local authorities and communities. This promotes transparency in planning processes and ensures equal access to spatial information for different stakeholder groups.

The model also prioritizes the efficient use of resources. Its ability to rapidly generate spatial profiles of settlements and evaluate the fundamental characteristics of the transport network enables planners to avoid redundant work and allocate funding to areas where the anticipated socio-economic impact will be highest. This targeted approach minimizes the unnecessary use of materials, equipment, and labor—factors that are essential for both environmental and economic sustainability.

Equally important, the tool supports inclusiveness, an integral principle of sustainable development. The data produced by the model can be applied to address the needs of diverse population groups, including vulnerable segments most affected by limitations in transport accessibility. In doing so, it facilitates the design of interventions aimed not only at restoring physical infrastructure but also at enhancing overall quality of life within communities.

Thus, the proposed model and software modules combine technological efficiency, environmental sustainability, and social justice. This makes the proposed tool not just a technical solution for collecting and analyzing spatial data, but a component of a broader recovery management system that meets the main goals of sustainable development (SDG 9 and SDG 11) and promotes long-term reconstruction of territories based on sustainability.

The main contributions of this study can be summarized as follows. First, a system model for collecting and processing spatial data from OSM was developed, enabling the extraction of 17 critical attributes of transport infrastructure objects in post-war contexts. Second, a structured validation framework was proposed, combining data quality assessment with cleaning procedures, exception handling, and cross-validation against satellite and cadastral datasets. Third, a case study across 23 Ukrainian settlements demonstrated the feasibility of the model in identifying infrastructure characteristics under conditions of limited data availability.

In terms of practical application, the research findings provide a methodological basis for integrating open geospatial data into decision-support systems for regional and municipal infrastructure planning. The model can be applied by public administrators and policymakers to prioritize reconstruction projects, optimize resource allocation, and monitor progress toward the Sustainable Development Goals (SDGs). Moreover, its modular Python-

based architecture allows for adaptation to other regions affected by conflict or disaster, ensuring scalability and transferability of the approach.

6. Conclusions

This research presents the development and practical application of a spatial data-driven system model aimed at supporting the planning of transport infrastructure projects in the post-war context. The model is designed to collect, process, and visualize key characteristics of the project environment using openly accessible data from OSM. By integrating the Overpass API for targeted data extraction and custom Python-based modules for data analysis, the system enables the efficient evaluation of settlement-specific infrastructure features critical for informed project planning.

The system was tested using data from 23 Ukrainian settlements that experienced damage to transport infrastructure due to military conflict. Selection criteria were based on pre-war population size and strategic relevance. For each settlement, 17 transport-related spatial attributes were extracted and analyzed, allowing for detailed mapping and typological classification of road networks. For example, in Bakhmut (Donetsk region), the analysis revealed the structural composition of the road system, which can inform prioritization in reconstruction and urban mobility planning.

A quantitative assessment of the model's effectiveness demonstrated its significant advantages. In the example under consideration, involving 23 settlements, automated data extraction and processing reduced the average time required to compile an initial infrastructure profile from several working days (when performed manually) to less than 30 min per settlement. A comparative check with official data sets showed that the model's results achieved an accuracy level of approximately 92% in identifying road network features and filled in up to 15...20% of previously unregistered small road segments in missing areas. These improvements not only speed up the planning process, but also reduce data gaps that can hinder priority setting and resource allocation.

Furthermore, the project generated a range of derived analytical outputs, including graphs and distributions of environmental characteristics, which capture both the current state and the recovery potential of transport infrastructure. These outputs are designed to support stakeholders in developing resilient development strategies and in pinpointing priority areas for investment. The findings highlight the important role of spatial data analytics in improving the assessment of the project environment, particularly in regions undergoing post-conflict recovery.

In future work, the model will be expanded into a full-scale decision-support system capable of recommending priority infrastructure projects across different administrative units. Such a system would automate the identification of development scenarios and support faster, evidence-based decision-making in complex and dynamic post-war environments.

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