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Urban Resilience Index for Critical Infrastructure: A Scenario-Based Approach to Disaster Risk Reduction in Road Networks

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Abstract: Floods pose a significant threat to road networks globally, disrupting transportation, isolating communities, and causing economic losses. This study proposes a four-stage methodology (avoidance, endurance, recovery, and adaptability) to enhance the resilience of road networks. We combine analysis of constructed assets and asset system performance with multiple disaster scenarios (Reactive Flood Response, Proactive Resilience Planning, and Early Warning Systems). Advanced flood Geospatial-AI models and open data sources pinpoint high-risk zones affecting crucial routes. The study investigates how resilient assets and infrastructure scenarios improve outcomes within Urban Resilience Index (CRI) planning, integrating performance metrics with cost–benefit analysis to identify effective and economically viable solutions. A case study on the Lisbon Road network subjected to flood risk analyzes the effectiveness and efficiency of these scenarios, through loss and gain cost analysis. Scenario 2, Proactive Resilience Planning, demonstrates a 7.6% increase compared to Scenario 1, Reactive Flood Response, and a 3.5% increase compared to Scenario 3, Early Warning Systems Implementation. By considering asset performance, risk optimization, and cost, the study supports resilient infrastructure strategies that minimize economic impacts, while enabling communities to withstand and recover from flood events. Integrating performance and cost–benefit analysis ensures the sustainability and feasibility of risk reduction measures.

Keywords: urban resilience; critical infrastructure; disaster risk; road network; flood; cost–risk performance optimization

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1. Introduction

According to Ginkel et al. in *Natural Hazards and Earth System Sciences* [1], the European road networks face an estimated annual direct damage of approximately EUR 230 million from large river floods, with additional economic losses and emergency repair costs [1,2]. The pervasive impact of flooding poses a significant challenge to transportation networks worldwide [3]. Climate change and urban expansion exacerbate this challenge, resulting in infrastructure strain, road closures, traffic congestion, community isolation, and substantial economic ramifications [4]. Enhancing the resilience of road networks is imperative for societal well-being and economic stability in the face of escalating flood risks [5–7].

Portugal's mountainous terrain and extensive river systems contribute to the vulnerability of its road network during flood events. The rugged mountain ranges often funnel heavy rainfall into narrow valleys, leading to rapid runoff and increased flood risk. Roads winding through these regions are susceptible to landslides, rockfalls, and washouts. Additionally, the road network's intersection with numerous rivers, such as the Tagus, Douro, and Guadiana, increases the risk of inundation during heavy rainfall. Coastal highways are also vulnerable to storm surges, especially during extreme weather events.

The Portuguese road network is critical for the country's economy and community resilience. It facilitates the movement of goods, connects production centers to markets, and supports trade, enhancing productivity and promoting economic growth. During emergencies, roads play a crucial role in disaster response and recovery, providing access to essential services and supplies. Portugal's tourism industry also relies on the accessibility of scenic routes and historical sites across the country, fostering regional development and cultural exchange.

The urban resilience framework offers a comprehensive approach addressing this challenge, encompassing anticipation of risks, enduring disruptive events, swift restoration, and adaptive strategies to navigate dynamic hazard landscapes [8,9]. Strengthening physical assets, integrating predictive early warning systems, introducing network redundancy, and implementing flexible response protocols are essential components of resilience for the Portuguese Road Network.

Advancements in Geographic Artificial Intelligence (GeoAI) play a pivotal role in this research endeavor [9,10]. GeoAI leverages historical data, environmental factors, and sophisticated machine learning algorithms to map current flood risks and to accurately predict future vulnerabilities within the Portugal Road Network. This data-driven approach, combined with comprehensive physical evaluations of constructed assets such as bridges, culverts, embankments, and roadway materials identifies critical infrastructure weaknesses and informs targeted flood resilience interventions.

This study endeavors to comprehensively assess and enhance the resilience of road infrastructure in the face of flood hazards, with a particular focus on the Portugal Road Network. Our objectives encompass a multifaceted approach, ranging from data-driven analysis to cost optimization strategies. Firstly, we aim to extract critical road infrastructure from OpenStreetMap (OSM) data, prioritizing key road types based on their strategic significance. Subsequently, we seek to identify high-risk areas prone to flooding, through an analysis of concession scores, utilizing the flood and disaster database and evaluating the repetitiveness of flood occurrences against real data. We then simulate flood events using a stochastic approach, attributing probabilities of occurrence during rainy seasons, and validate our flood model using historical data on floods and landslides in Portugal. Additionally, we compile construction and maintenance costs for various road types, ensuring their ongoing sustainability through rigorous validation processes. Finally, we establish benchmarks for assessing road performance levels across diverse socioeconomic contexts, providing a framework for informed decision-making in road infrastructure enhancement and management. Through these objectives, our study aims to contribute to the development of effective flood resilience strategies for road networks, ultimately enhancing societal well-being and economic vitality.

This research pursues the following core objectives:

- Clean OpenStreetMap (OSM) data to extract critical road infrastructure, including motorways, primary roads, secondary roads, tertiary roads, and trunk roads, prioritizing extraction based on strategic significance;
- Identify high-risk areas with elevated concession scores, using the Zezere database, and analyze the occurrence repetitiveness versus real data, to enhance flood risk assessments for road infrastructure;
- Simulate flood events using a stochastic approach, attributing a probability of occurrence during rainy seasons, and validate the flood model using historical data on floods and landslides in Portugal, to improve flood risk assessments for road infrastructure;
- Compile Capital Expenditure (CAPEX) and Operating Expenditure (OPEX) for different road types, including motorways, primary roads, and secondary roads, and validate these expenditures or costs, by estimating them at five times the initial cost over a five-year period to ensure ongoing sustainability;
- Establish benchmarks for assessing road performance levels across diverse socioeconomic contexts, guiding strategic decision-making processes for road infrastructure resilience enhancement and management;

- Develop scenarios to explore various resilience strategies and their impacts on road network performance and cost optimization.

2. Literature Review

2.1. Urban Resilience Stages

The concept of resilience has permeated fields ranging from ecology and psychology to urban planning and disaster management. Urban resilience specifically addresses a city's capacity to function and thrive, even when confronted by severe shocks and chronic stresses [11,12]. Resilience frameworks often incorporate stages or phases, which categorize actions, strategies, and desired outcomes over time [13].

The early stage-based models: Resist–Recover–Adapt corresponds to the initial conceptualizations of resilience. It often follows a three-stage model inspired by ecological systems, as follows: (i) Resist. The city's ability to withstand a disruptive event and maintain core functions; (ii) Recover. The speed and efficiency with which a city bounces back to pre-disaster levels of activity; and (iii) Adapt. The willingness and capacity to make proactive adjustments to mitigate future risks and learn from past events.

The following stage, evolving and expanding Frameworks, determines the more nuanced models of urban resilience that have emerged, namely (i) The '4Rs' of Resilience—Robustness, Redundancy, Resourcefulness, and Rapidity—form a model, prioritizing preparedness, system flexibility, and responsive capabilities [14]; (ii) Resilience as a Continuum—this views resilience not as a distinct end-state, but as a continuous process of preparing for, managing, and learning from disturbances. This acknowledges resilience-building as an ongoing endeavor; (iii) Integrated Social–Ecological–Technical Resilience—some models explicitly link aspects of the urban environment (built infrastructure and ecosystem services) with social factors (community preparedness and governance capacity) to offer a more holistic vision of resilience [15]; and (iv) Making Cities Resilient (MCR) Campaign and Disaster Resilience Scorecard—the framework used by the UN Office for Disaster Risk Reduction outlines stages "Know Better," "Plan Better," and "Implement Better," aligning risk assessment, planning, and action for comprehensive urban resilience building [16,17].

Operationalizing of the application of resilience stages involves the following: (i) Vulnerability Assessments—specific hazards are studied, exposing weakness points (infrastructure, services, and population groups) for each resilience stage; (ii) Strategy Development—actions fit within stages (Avoid—land-use zoning; Endure—structural hardening; Recover—emergency plans; and Adapt—monitoring systems.); and (iii) Evaluation and Metrics—indicators for each stage track progress (reduced damage in resist phases, quick restoration times in recover stages, etc.)

The critique and considerations comprise (i) Simplicity vs. Complexity—stages simplify complex, interwoven resilient attributes. More sophisticated models may be harder to apply practically; (ii) Linearity—resilience may not be strictly linear, for example, a city could have high adaptive capacity, but need bolstering in the 'endure' stage; and (iii) Governance and Social Equity—models focused purely on technical infrastructure miss vital factors of equitable planning and decision-making in resilience.

Based on reviewing previous studies, this section provides a review of the literature on urban resilience. The most used stages are shown in Figure 1, including avoidance, endurance, recovery, and adaptability.

The avoidance stage of urban resilience involves proactive measures to minimize exposure to hazards and reduce vulnerability to potential risks. This may include land use planning, zoning regulations, and infrastructure design, aimed at avoiding high-risk areas or mitigating potential hazards. Research suggests that the early identification of risk-prone areas and strategic spatial planning can significantly reduce the likelihood of disasters and enhance overall urban resilience [18,19].

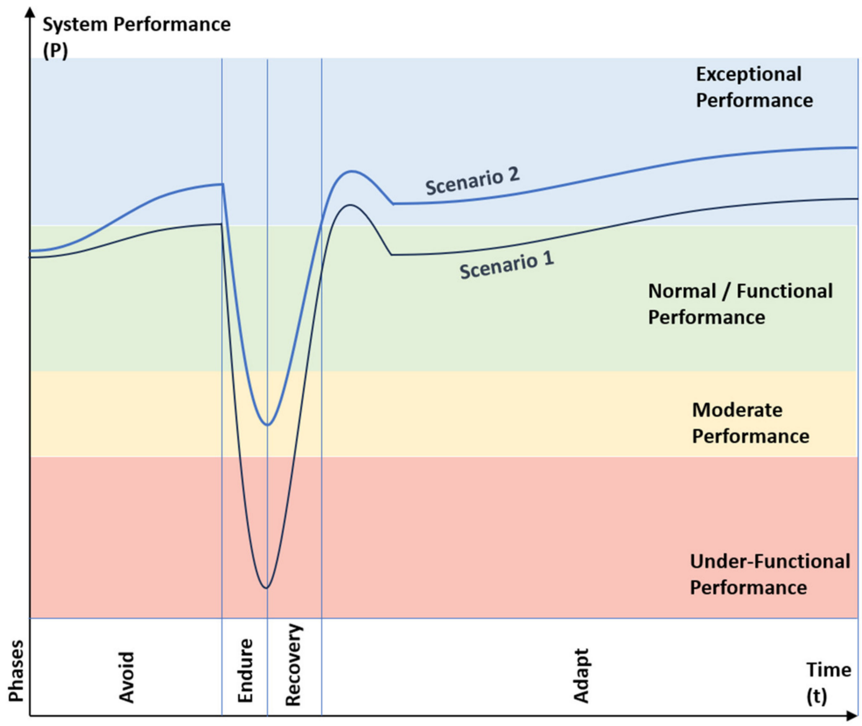

Figure 1. Resilience stages and demonstrative scenarios of system performance in the face of disruptive events.

The endurance stage focuses on enhancing the capacity of urban systems to withstand and absorb shocks and stresses, without experiencing significant disruptions or damages. This involves designing and maintaining infrastructures and the built environment to meet certain performance standards and withstand various hazards, such as floods, fire, earthquakes, and extreme weather events [20]. Studies have highlighted the importance of resilient infrastructure design, including flexible building materials, redundant systems, and adaptive infrastructure, in improving the endurance and performance of urban systems [21].

The recovery stage involves the ability of cities to bounce back and restore essential functions and services after a disruptive event. This includes emergency response, disaster recovery, and post-disaster reconstruction efforts, aimed at rebuilding damaged infrastructure, restoring livelihoods, and revitalizing communities. Research has emphasized the importance of effective coordination, communication, and collaboration among stakeholders during the recovery phase, to facilitate a swift and efficient recovery process [22].

The adaptability stage focuses on building long-term resilience by fostering adaptive capacity and promoting transformative changes within urban systems. This involves integrating lessons learned from past experiences, anticipating future challenges, and implementing adaptive measures to enhance the resilience of cities to changing conditions and emerging risks. Studies have highlighted the role of governance mechanisms, policy frameworks, and community engagement in fostering adaptive capacity and promoting sustainable urban development [23].

In summary, the literature on urban resilience stages underscores the importance of adopting a holistic and integrated approach to resilience-building, encompassing proactive risk reduction, robust infrastructure design, effective emergency response, and adaptive governance. By understanding and addressing the various stages of urban resilience, cities can better prepare for and respond to shocks and stresses, ultimately enhancing their capacity to thrive in an uncertain and rapidly changing world.

Urban resilience stage models offer frameworks to organize, assess, and develop actions, aimed at creating cities more capable of surviving and adapting to future disruptions.

Understanding the different phases of resilience allows for strategic and targeted investment in measures that strengthen overall urban preparedness, reduce losses, and ensure a swifter return to functionality. While the most applicable model depends on a city's unique challenges, utilizing stage-based thinking is a valuable starting point for developing comprehensive resilience planning.

2.2. Critical Infrastructure

The infrastructure that underpins modern societies is vast and diverse, comprising transportation networks, energy systems, water and wastewater infrastructure, telecommunications, buildings, and other critical assets [24]. According to the America Cyber Defense Agency, energy, communications, water, and transportation are four of the most critical infrastructure systems in the United States [25]. Within each sector, various components play essential roles in supporting economic activities, societal functions, and public services [26]. From roads and railways facilitating mobility to power plants generating electricity and water treatment plants ensuring clean water supply, these infrastructural elements form the foundation of our interconnected world [27]. Understanding the significance of each asset and its interdependencies is essential for effective planning, management, and resilience against disruptions.

In this section, we explore key components of critical infrastructure, factors influencing their criticality, and the importance of dynamic risk assessment in adapting to evolving challenges and opportunities (See Figure 2).

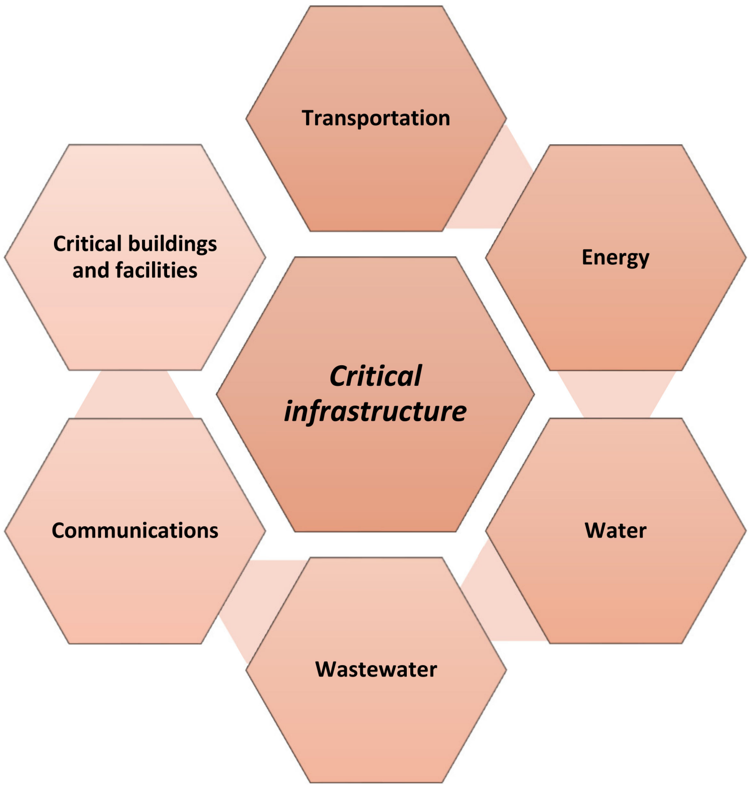

Figure 2. Critical infrastructure categories.

Transportation networks encompass various modes of travel and infrastructure crucial for societal and economic activities. Within this domain, roads and highways serve as lifelines for mobility, connecting communities and facilitating commerce. Railway systems, comprising rail tracks, stations, and passenger facilities, play a pivotal role in long-distance travel and freight transportation. Ports and waterways constitute vital nodes in global trade networks, featuring infrastructure such as breakwaters, piers, cargo handling facilities, and docks. Similarly, airports serve as gateways to the skies, encompassing runways, terminals, and ancillary facilities essential for air travel.

Energy systems form the backbone of modern societies, encompassing power generation and transmission infrastructure. Power generation facilities, including thermal, hydro, nuclear, and renewable plants, produce electricity, while dams and substations regulate and distribute power across transmission lines. Transmission and distribution infrastructure, comprising high-voltage lines, distribution networks, and pipelines for various fuels, ensure the efficient delivery of energy to end-users [28].

Water and wastewater infrastructure are essential for public health and environmental sustainability. Water supply systems feature reservoirs, treatment plants, and distribution networks, ensuring access to clean water. Wastewater infrastructure, including treatment plants, sewer networks, and overflow outfalls, manage wastewater disposal and treatment [29,30].

Telecommunications infrastructure enables global connectivity and information exchange. Cell towers, wired networks, and data centers facilitate communication through wireless and wired technologies, supporting businesses, governments, and individuals [31].

Critical buildings and facilities provide essential services and support societal functions. These include hospitals, emergency services, government buildings, military installations, manufacturing plants, warehouses, shopping centers, and residential complexes [32,33].

Other critical assets include dams, landfills, and hazardous material storage sites, which require careful management to mitigate risks and ensure public safety [34–36].

Several factors influence the criticality of infrastructure assets, including vulnerability to disruption, impact on essential services, economic significance, and interdependencies with other systems. Regular dynamic risk assessment is essential to adapt to changing environmental, societal, and technological conditions [37].

The existing literature has explored the use of critical infrastructure data and models in various contexts. Several studies have utilized transportation network data, such as road and rail infrastructure, to analyze mobility patterns, travel time, and accessibility in specific regions [38]. Energy system models have been developed to simulate the production, transmission, and distribution of electricity, gas, and other forms of energy, with a focus on resilience and sustainability [29]. Water and wastewater infrastructure has been incorporated into hydrological models to assess water availability, quality, and treatment needs [39,40]. Telecommunication networks have been analyzed to understand information flow, network vulnerabilities, and the impact of disruptions on critical services [31]. Furthermore, the interdependencies between these different infrastructure systems have been investigated to capture the complex, interconnected nature of modern societies [41–43].

2.3. Constructed Assets and Assets Systems Performance: Road Networks

Modern road networks comprise a complex array of constructed assets, including pavements, bridges, tunnels, culverts, retaining walls, noise barriers, and traffic management systems. The overall performance of these assets—their ability to fulfil their intended function, while withstanding various stresses—has significant implications for road safety, traffic flow, maintenance costs, and the lifespan of the network. A growing body of research explores the diverse factors impacting constructed asset performance within road networks, informing decision-making regarding design, construction, and maintenance [44].

The key asset types and their performance aspects correspond to (i) Pavements—flexible (asphalt) and rigid (concrete) pavements must resist factors like traffic loads, thermal expansion, and moisture penetration [45]. Key performance measures include cracking resistance, smoothness, deflection, and skid resistance; (ii) Bridges—performance measures focus on structural health, deflection under load, corrosion resistance, and seismic resilience. Regular inspection and condition rating systems are vital for assessing bridge performance over time; (iii) Drainage Systems—culverts, pipes, and ditches play a critical role in preventing road inundation. Capacity, blockage avoidance, and resistance to scour are essential performance characteristics [46,47]; and (iv) Traffic Management Systems—signals, variable message signs, and other intelligent systems rely on technical reliability, energy efficiency, and the ability to manage traffic flows under changing conditions.

Regarding the factors influencing asset performance, we might consider (i) Design and Material Selection—initial design specifications, materials choices, and adherence to construction standards play a fundamental role in long-term asset performance [48,49]; (ii) Environmental Conditions—extreme temperatures, moisture levels, freeze–thaw cycles, soil properties, and seismic activity impose constant stresses on asset materials and structures [50]; (iii) Traffic Loading—intensity, frequency, and weight of vehicles generate cumulative wear and tear on pavements, bridges, and support structures; (iv) Maintenance Practices—regular preventative maintenance, rapid repair of emerging issues, and timely resurfacing extend asset lifespan and minimize major disruptions [51,52]; and (v) Technological Advancements—innovative materials (like recycled or self-healing asphalt), structural health monitoring, and asset management software can enhance performance and predict failures [53,54].

The performance evaluation methodologies include (i) Visual Inspections—routine visual assessment remains vital for detecting surface-level issues (cracks and deformations) and prompting repair; (ii) Non-Destructive Testing (NDT)—techniques like ground-penetrating radar, ultrasonic testing, and thermography assess sub-surface condition and reveal internal asset issues. (iii) Structural Health Monitoring (SHM)—networks of embedded sensors provide real-time data on bridge stress, vibration, and material deformation, facilitating the early detection of degradation; and (iv) Asset Management Systems—centralized databases of asset inventory, condition data, historical maintenance, and geospatial information support performance tracking and resource allocation decisions [55].

Finally, the challenges and future directions comprise (i) Limited Funding—competing budget priorities can put the maintenance of existing infrastructure at a disadvantage, leading to a backlog of needed repairs and accelerated asset degradation; (ii) Climate Change Impacts—increased frequency and intensity of extreme weather events strain existing assets, highlighting the need for climate-adaptive design and material innovations; and (iii) Data Integration—the effective use of sensor networks and diverse asset data necessitates advanced data analysis tools and predictive modeling for timely decision-making.

The long-term sustainability of road networks relies directly on the robust performance of constructed assets. Research focused on asset performance helps address engineering, material science, traffic management, and budgetary considerations. Optimizing the performance of these assets delivers a safer, more reliable, and cost-effective network that adapts to future transportation needs [56].

2.4. Flood Risk Reduction Strategies and Cost Optimization in Road Networks

Inundation poses a major threat to road networks globally, resulting in damage, closures, and economic disruption. A wide spectrum of flood risk reduction strategies exist, from engineering interventions to nature-based solutions and policy measures. Optimizing cost-effectiveness is essential to balance investment against tangible risk reduction, especially in a budgetary climate where competing priorities are common.

Considering the categories of flood risk reduction strategies, we may identify (i) Structural and Hard Engineering (levees, floodwalls, or seawalls physically bar water from roads; elevated roadways or causeways create 'above-flood' routes; pumping systems and retention basins aim to control water levels, as well as bridges; and culvert design is key for maximizing capacity in flood events); (ii) Nature-Based Solutions (NBSs) (coastal wetland and mangrove restoration buffer wave impact and absorb run-off; upstream reforestation or land-use planning slows run-off and relieves strain; and permeable pavements or bioswales within the road network reduce surges); and (iii) Non-Structural Strategies (flood forecasting/early warning systems allow road closures or detours [57]; adaptive traffic management adjusts routes or traffic flows in real time; land-use planning zones limit development in high-risk areas; and insurance-based schemes can help spread risk and fund recovery) [58,59].

Regarding the cost optimization of frameworks, it is important to refer to (i) Cost–benefit Analysis (CBA)—quantifies costs of a flood risk reduction strategy against anticipated avoided losses (property damage, productivity costs, etc.) and might be used in project-level decisions and prioritizing resource allocation; (ii) Life-cycle Costing—considers not just initial construction, but long-term maintenance and potential replacement costs over the asset's life. This aids in selecting durable, low-maintenance options, even if the initial cost is higher; (iii) Multi-Criteria Analysis (MCA)—factors in environmental impact, social disruption, or resilience of a solution beyond purely economic measures can aid comparison when a project has far-reaching effects beyond quantifiable monetary figures; and (iv) Risk-Based Prioritization—focuses on the most vulnerable, heavily impacted road segments first, where even moderate investments could significantly minimize consequences [60,61].

The factors influencing cost-effectiveness are (i) Site-Specific Conditions—geographic factors, intensity of flood hazard, and local regulatory standards all shape what interventions are feasible and their associated costs; (ii) Scale of Intervention—large-scale, structural defenses tend to have a higher initial investment, but might protect extensive lengths of the road network compared to localized measures; and (iii) Time Scale—strategies impacting long-term risk (like upstream land use changes) are harder to assess with traditional CBA, as costs are incurred sooner than the benefits are fully achieved [62,63].

The identified challenges for this area of study comprise (i) Uncertainty in Climate Projections—the scale and frequency of future extreme weather events make long-term cost optimization hard; robust strategies often need 'over-building', to cope with projected increases in severity; (ii) Funding Limitations—even seemingly optimal plans may be unfeasible due to budget constraints, leading to staged projects or lower-ambition plans; and (iii) Residual Risk—even with defenses, the risk is never zero. Cost optimization must integrate plans for response and recovery during events larger than the design parameters [64].

Successfully deploying flood risk reduction strategies with cost-efficiency in mind is a multi-layered challenge. Balancing flood resistance with adaptability is important, as hard engineering can sometimes create unintended effects downstream or leave little flexibility for change. Combining targeted structural protection with non-structural and nature-based solutions often delivers a more optimized outcome for risk reduction, in conjunction with broader environmental and social benefits [65,66].

2.5. Geospatial AI Technologies for Flood Prediction

The ability to accurately predict floods is essential for proactive disaster management and safeguarding lives, property, and critical infrastructure such as road networks. Geospatial Artificial Intelligence (GeoAI) is revolutionizing flood prediction by integrating vast amounts of spatial data with powerful machine learning and deep learning techniques. This review explores cutting-edge GeoAI methods, their applications, and the ongoing evolution of this dynamic field.

The core GeoAI technologies and data sources correspond to (i) Remote Sensing—satellite imagery (optical and radar) provides data on land cover, terrain elevation, soil moisture, and precipitation patterns, feeding into hydrological modeling; (ii) Geographic Information Systems (GISs)—GISs layer on historical flood data, infrastructure locations, population density, and other variables, allowing for vulnerability and risk assessment; (iii) Machine Learning (ML)—algorithms such as Support Vector Machines (SVMs), Random Forests, and Artificial Neural Networks (ANNs) can learn patterns from complex, multi-source data to predict flood occurrences and spatial extents; and (iv) Deep Learning (DL)—Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) excel at handling big data, uncovering subtle spatial–temporal relationships, and improving real-time predictions [67,68].

The key applications of GeoAI for flood prediction [69–71] (Figure 3) are (i) Flood Hazard Mapping—GeoAI models are employed to predict areas susceptible to flooding and to identify the zones likely to be inundated, providing critical information for preparedness, evacuation, and infrastructure protection; (ii) Flood Extent Forecasting—these models predict the geographic spread and depth of inundation in near-real time. This facilitates targeted emergency response and damage assessment; (iii) Early Warning Systems—the integration of AI with weather forecasting can lead to timely and accurate flood alerts, allowing for pre-emptive measures and saving lives [72]; and (iv) Scenario-Based Modeling—researchers employ GeoAI to simulate potential flooding under different climate change scenarios, informing long-term land-use planning, infrastructure hardening, and protective measures [73].

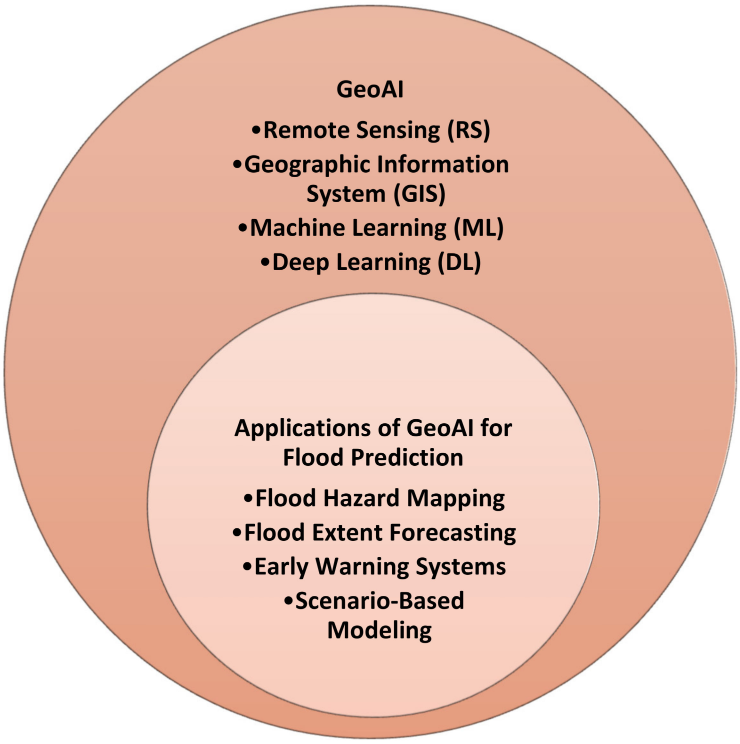

Figure 3. Core GeoAI technologies and applications for flood prediction.

The advantages of GeoAI in flood prediction include (i) Handling Diverse Data—GeoAI thrives on heterogeneous datasets, combining static terrain features with dynamic weather data, making for more robust predictions; (ii) Uncovering Non-Linear Relationships—neural networks excel at modeling the complex, non-linear systems typical in flood generation, enhancing predictive accuracy; (iii) Enhanced Accuracy and Speed—advances in deep learning enable the rapid generation of highly detailed and reliable flood risk predictions; and (iv) Scalability—cloud-based computing and remote sensing data allow GeoAI models to be utilized and adapted in vast and data-rich regions.

The challenges identified for Geospatial AI technologies for flood prediction are (i) Data Quality and Availability—the performance of GeoAI models hinges on reliable data that may be lacking in certain regions. Ongoing efforts in ground-based sensor networks and citizen science projects can contribute to improved data quality; (ii) Computational Requirements—powerful hardware and processing capabilities are often needed for advanced model training and execution, raising cost considerations; and (iii) Interpretation and Uncertainty—AI predictions remain 'black box' to some extent. Efforts are ongoing to increase interpretability and effectively communicate uncertainty to the broader end-user communities.

In conclusion, Geospatial AI offers significant breakthroughs in our ability to predict floods, moving from reactive to anticipatory disaster management approaches. The ability to fuse satellite-based spatial data, historical records, and real-time sensor inputs opens possibilities for increasingly precise, actionable flood warnings. The ongoing development of new AI algorithms, more comprehensive data sources, and increased computational capacity are set to further accelerate progress in this field.

3. Methodology

3.1. Framework

The present study employs a comprehensive framework methodology as a continuation of the Risk-Informed Asset-Centric (RIACT) Urban Resilience Enhancement Process [74], to address key aspects of road infrastructure management, including the extraction of critical road data from OpenStreetMap (OSM), performance evaluation using socioeconomic indicators, assessment of flood risk exposure, and analysis of construction and maintenance costs. The methodology comprises distinct stages designed to ensure rigor, accuracy, and applicability in addressing the research objectives (see Figure 4), namely (i) Data Collection and Preprocessing; (ii) Extraction of Critical Road Infrastructure; (iii) Performance Metrics Evaluation; (iv) Assessment of Flood Risk Exposure; (v) Analysis of Construction and Maintenance Costs; and (vi) Scenarios: Sensitivity Analysis and Robustness Evaluation.

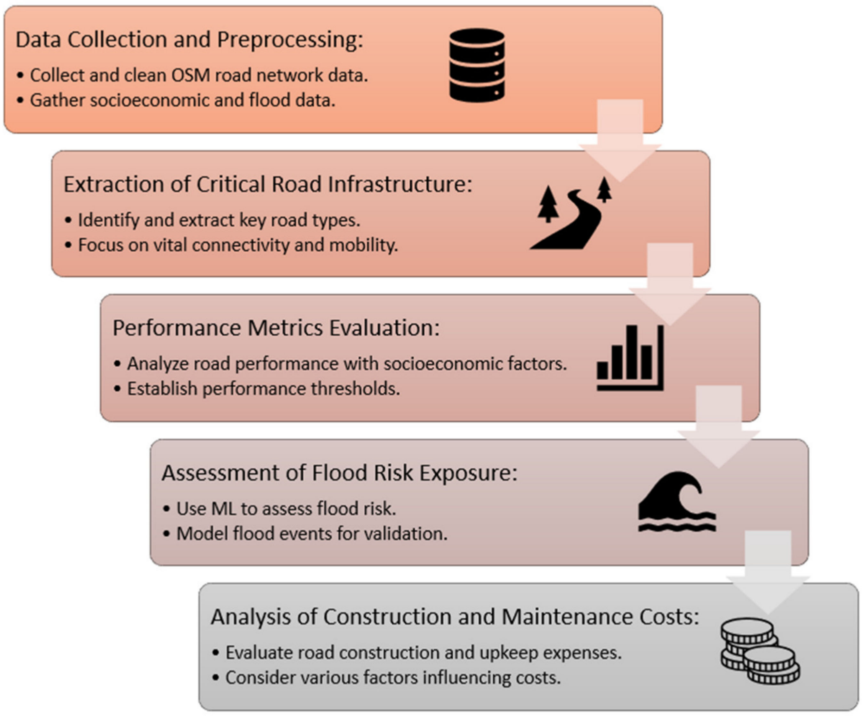

Figure 4. Proposed framework for assessing urban road infrastructure resilience.

The first stage (Data Collection and Preprocessing) comprises the following steps: (i) OpenStreetMap (OSM) data for road networks is collected and preprocessed to extract the relevant features, including motorways, primary roads, secondary roads, tertiary roads, and trunk roads, along with their associated links. This process involves data cleaning and validation to ensure accuracy and completeness; and (ii) Socioeconomic data, such as revenue of the municipality per inhabitant (RMI), are gathered from reliable sources to evaluate road performance metrics [56,75]. Historical flood data and geographical information are also acquired to assess flood risk exposure. Figure 5 presents a scatter plot illustrating the relationship between transportation efficiency, population density, and municipal revenue per inhabitant. On the x-axis, a composite metric is depicted, representing the efficiency of road transportation services relative to population density, calculated as the ratio of passengers carried by road per unit population, divided by the road length per unit area. Meanwhile, the y-axis displays the revenue generated by the municipality per inhabitant, serving as a measure of the financial performance and resource utilization efficiency of the local government [56,75].

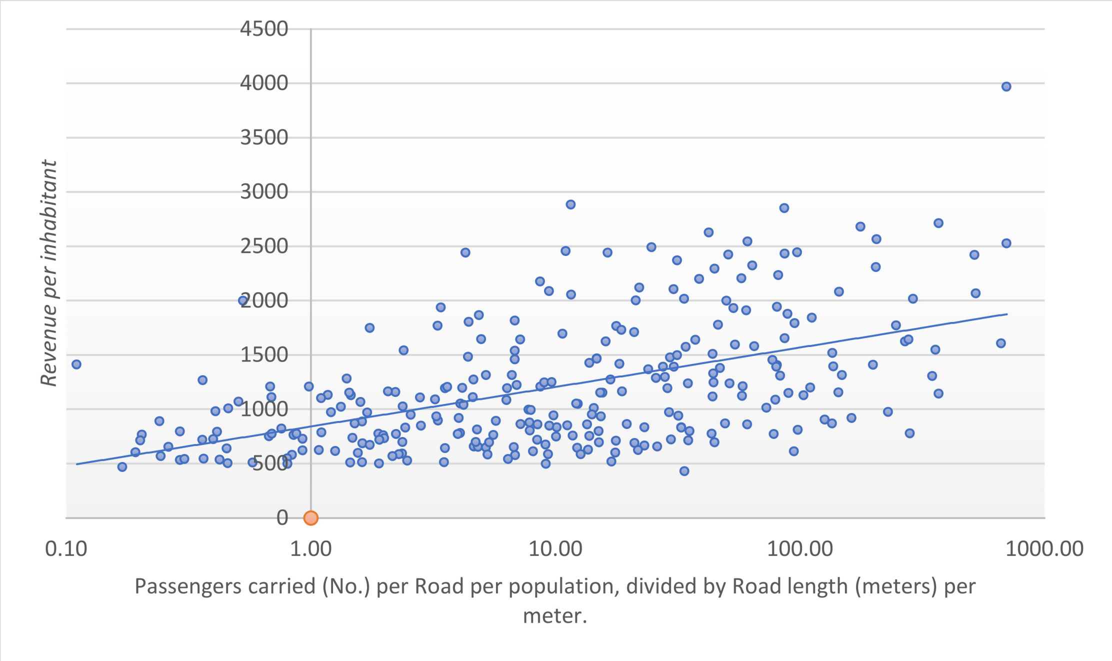

Figure 5. Correlation between transportation efficiency and municipal revenue per inhabitant, for all Portuguese municipalities.

In the second stage (Extraction of Critical Road Infrastructure) specific road construction types, including motorways, primary roads, secondary roads, tertiary roads, and trunk roads, are identified and extracted from the preprocessed OSM data. This extraction focuses on segments crucial for regional and national connectivity, urban mobility, and economic development.

The third stage (Performance Metrics Evaluation) comprises (i) the integration of socioeconomic indicators, particularly RMI, into road performance evaluations. A statistical analysis is conducted to explore the relationship between RMI and road infrastructure performance, considering factors such as traffic volumes, maintenance priorities, and investment patterns; and (ii) the establishment of performance metrics, including minimum, optimal, and maximum performance thresholds, based on RMI and other relevant indicators. Novel indicators, such as Economic power of districts, are introduced to assess road performance variability and functionality relative to RMI.

The scatter plot in Figure 4 provides insights into the relationship between transportation efficiency, population density, and municipal revenue per inhabitant across Portuguese municipalities. The observed distribution suggests that municipalities with higher levels of transportation efficiency, as indicated by the ratio of passengers carried by road per unit population to road length per unit area, tend to have higher levels of municipal revenue per inhabitant. This implies that more efficient road transportation infrastructure is associated with a greater financial performance and resource utilization efficiency of local governments. The scatter plot also demonstrates the variability in this relationship, with some municipalities exhibiting a higher transportation efficiency, but a lower municipal revenue per inhabitant, and vice versa. This suggests that other factors, such as socioeconomic characteristics, investment patterns, and governance structures, may also play a significant role in determining the overall financial performance of local governments.

In the fourth stage (Assessment of Flood Risk Exposure), (i) a Random Forest machine learning model is employed to quantify flood risk exposure along road networks. Concession scores, indicating susceptibility to flood hazards, are assigned to road sections, based on historical flood data and geographic features; and (ii) stochastic simulation techniques are used to model flood events, considering probabilities of occurrence during specific seasons and leveraging historical flood data for validation. The effectiveness of flood risk assessment methods is evaluated to enhance reliability and accuracy.

The fifth stage (Analysis of Construction and Maintenance Costs) analyzes (i) construction and maintenance costs for various road construction types, based on data from reliable sources and expert estimations. Factors influencing costs, such as road dimensions, terrain characteristics, drainage requirements, and environmental regulations, are considered; and (ii) cost assessment, which encompasses both initial construction expenses and long-term maintenance requirements [76]. Calibration of cost estimates is conducted to account for variations in slope steepness and terrain complexity, ensuring precision in financial planning and resource allocation.

Finally, in the sixth stage (Scenarios: Sensitivity Analysis and Robustness Evaluation), (i) multiple scenarios are defined, to assess the sensitivity and robustness of resilience strategies for road networks under varying conditions. These scenarios include reactive flood response, proactive resilience planning, implementation of early warning systems [77], multi-stakeholder collaboration, and adaptive management strategies; and (ii) sensitivity analysis involves evaluating the impact of key parameters and assumptions on outcomes, while robustness evaluation assesses the effectiveness and reliability of resilience strategies against uncertainties and disruptions. Insights gained from scenario analysis inform decision-making processes, aimed at enhancing road network resilience and promoting sustainable development.

By systematically following this framework methodology, the study aims to provide comprehensive insights into road infrastructure management, addressing critical issues related to performance evaluation, flood risk mitigation, cost optimization, and resilience enhancement.

3.2. Extracting Main Roads from OpenStreetMap Data

We have undertaken the task of cleaning up OpenStreetMap (OSM) data and specifically extracting critical infrastructure from the road network, focusing on the following construction types: motorways, motorway links, primary roads, primary road links, secondary roads, secondary road links, tertiary roads, tertiary road links, trunk roads, and trunk road links.

The rationale behind this focused extraction lies in the importance and strategic significance of these road types within the overall transportation network. Motorways serve as major arterial routes, facilitating high-speed and long-distance travel, making them vital for regional and national connectivity [78,79]. Motorway links provide essential connections between motorways and other roads, ensuring seamless transitions and efficient traffic flow. Primary roads represent key arteries within urban and rural areas, handling significant traffic volumes and serving as major thoroughfares for local and regional travel. Similarly, primary road links play a crucial role in connecting primary roads to other road networks, enhancing accessibility and connectivity (Figure 6). Secondary roads and their corresponding links serve as feeder routes, connecting smaller towns and communities to primary roads and motorways, thereby extending the reach of the transportation network, and supporting regional mobility [80]. Trunk roads, characterized by their importance for freight transport and long-distance travel, are critical components of the transportation network, supporting economic activity and regional development. Trunk road links ensure efficient connectivity between trunk roads and other key routes, optimizing the flow of goods and passengers. Tertiary roads, while of lower classification, are essential for local access and connectivity, providing crucial links to residential areas, commercial centers, and agricultural regions. Tertiary road links complement these routes by facilitating access to secondary and primary roads [81,82] (Figures 7 and 8).

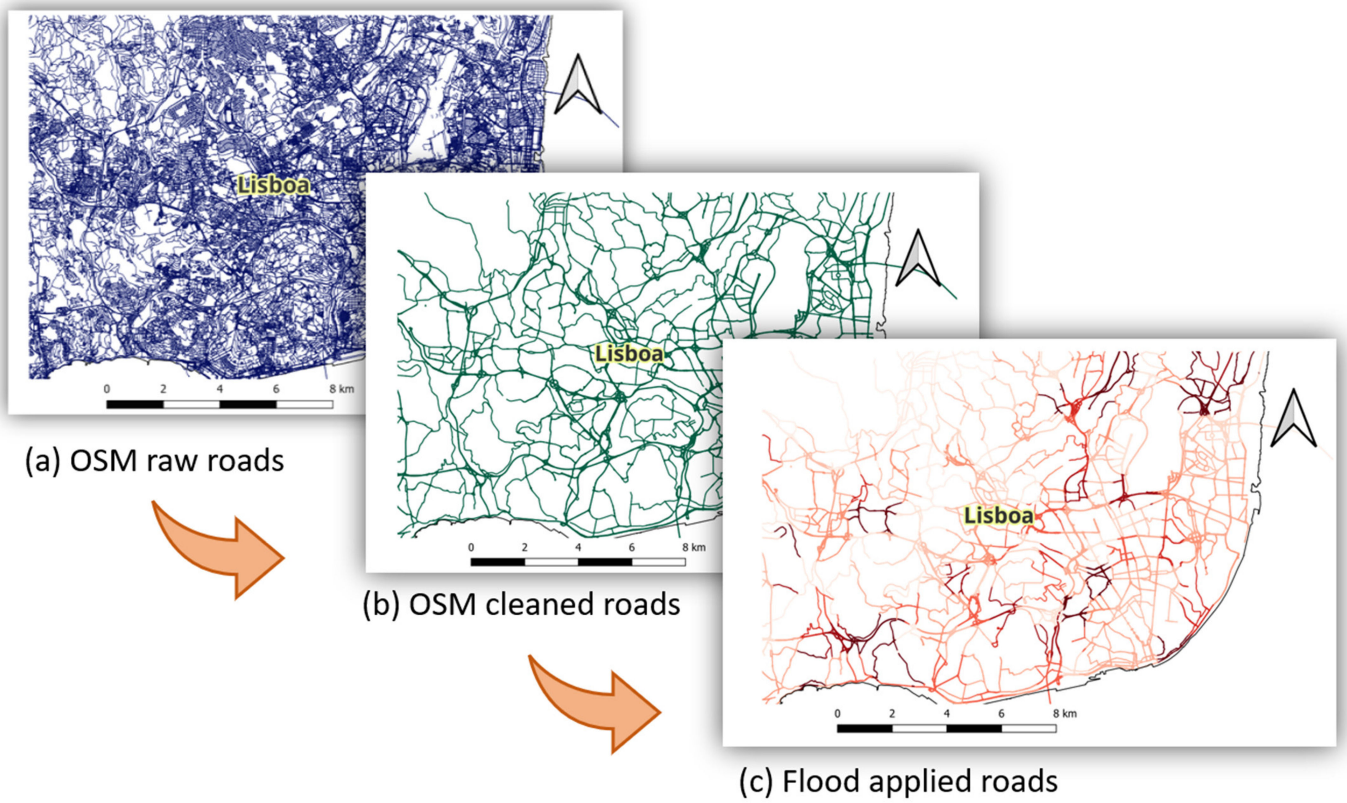

Figure 6. OpenStreetMap (OSM) map transformation methodology.

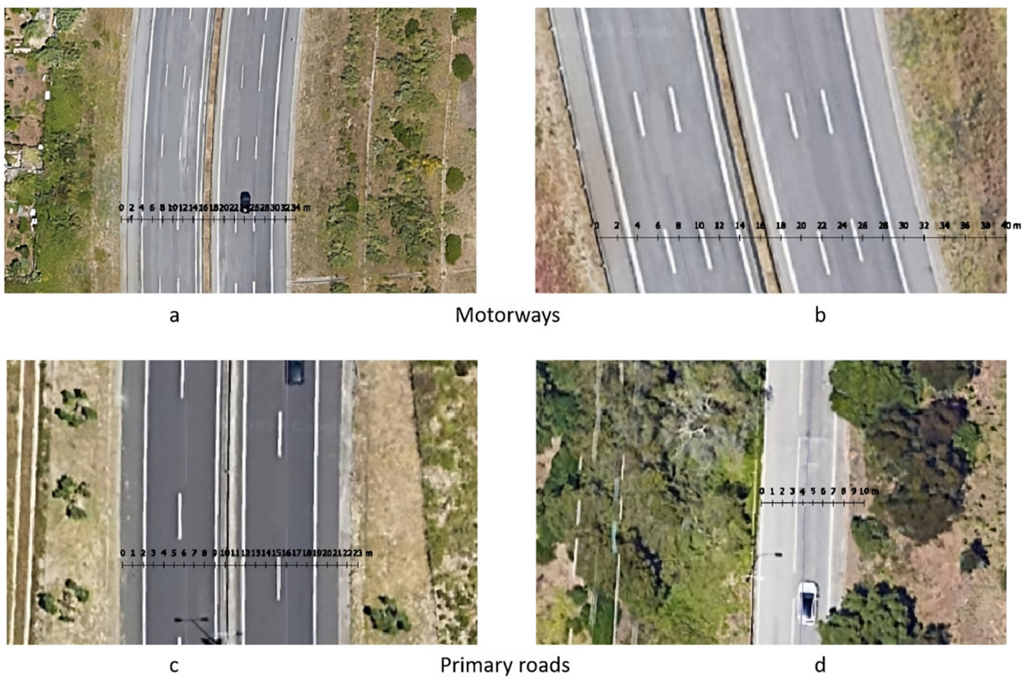

Figure 7. Scaled satellite view of Motorway (**a**,**b**) and Primary roads (**c**,**d**).

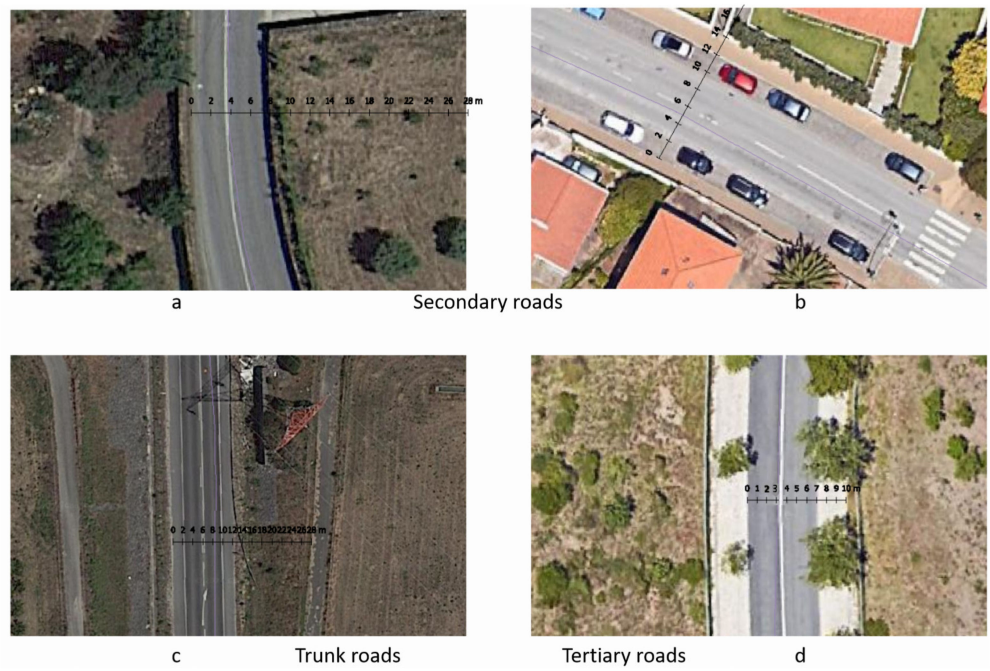

Figure 8. Scaled satellite view of Secondary roads (**a**,**b**), Trunk roads (**c**), and Tertiary roads (**d**).

By focusing on these specific construction types, we aim to capture the most vital segments of the road network, ensuring that our analysis and infrastructure planning efforts prioritize the enhancement and maintenance of critical transportation infrastructure, for the benefit of communities and economies.

3.3. Performance Metrics

In recent years, there has been a growing emphasis on incorporating socioeconomic indicators into the evaluation of road infrastructure performance. One such indicator gaining traction is the RMI, which serves as a proxy for the economic health and development level of a region. The consideration of RMI in assessing road section performance reflects a broader shift towards holistic and context-sensitive infrastructure management practices.

The rationale behind integrating RMI into road performance evaluations stems from its potential to capture the economic viability and importance of transportation infrastructure within a given locality. Higher levels of RMI often correlate with increased economic activity, investment capacity, and overall infrastructure development. As such, roads serving areas with a higher RMI may be subject to greater traffic volumes, commercial activities, and socioeconomic dependencies, necessitating closer scrutiny of their performance metrics.

Several studies have explored the relationship between RMI and road infrastructure performance, highlighting its utility as a predictor of transportation demand, investment priorities, and maintenance needs. For example, research by the authors of [83] demonstrated a positive correlation between RMI and road traffic volumes, indicating the significance of municipal RMI levels in shaping transportation patterns. Similarly, Espinet et al. [84] found that areas with higher RMI tend to allocate greater resources towards road maintenance and upgrades, leading to improved road conditions and safety outcomes.

In addition to its role in assessing transportation demand and infrastructure investment, RMI can also inform equitable resource allocation and policy decision-making processes. By considering the economic disparities across different regions within a municipality, policymakers can prioritize road projects based on their potential to enhance connectivity, stimulate economic growth, and improve accessibility for all residents. This approach aligns with the principles of sustainable development and social equity, ensuring that transportation infrastructure investments contribute to inclusive and balanced regional development.

However, it is essential to recognize the limitations and challenges associated with using RMI as a performance metric for road sections. Variations in RMI levels may not fully capture the diverse socioeconomic dynamics and infrastructure needs within a municipality. Moreover, external factors such as regional economic trends, government funding allocations, and population demographics can influence the relationship between RMI and road performance outcomes.

In conclusion, the consideration of RMI in assessing road section performance represents a valuable approach towards enhancing the effectiveness and relevance of infrastructure management strategies. By integrating socioeconomic indicators into the evaluation framework, policymakers and transportation planners can make more informed decisions, allocate resources efficiently, and promote sustainable development outcomes for communities across diverse regions. Further research is warranted to refine methodologies, address data gaps, and explore the broader implications of socioeconomic factors on road infrastructure performance in varying contexts.

3.4. Urban Resilience Index

The City Resilience Index (CRI) is a comprehensive framework developed by Arup, with the support of the Rockefeller Foundation, to help cities measure and monitor the factors that contribute to their resilience. The CRI is structured around four key dimensions, twelve goals, and fifty-two indicators that are critical for city resilience. These dimensions include aspects related to health and well-being, economy and society, infrastructure and environment, and leadership and strategy. The development of the CRI involved a thorough literature review, fieldwork in six cities, and consultation with experts, which helped to identify the key functions of a resilient city and the qualities that enable urban systems to withstand, respond, and adapt to shocks and stresses [85].

The CRI will be delivered as an online platform that allows cities to assess their current resilience, identify strengths and weaknesses, and track progress over time. It utilizes both quantitative metrics and qualitative scenarios to develop a comprehensive resilience profile for each city. The CRI is intended to serve as a common basis for measurement and assessment, enabling cities to learn from each other and share best practices in building resilience. The framework is designed to be globally applicable, while allowing for contextual differences between cities, as illustrated by the case studies from Surat, Concepción, New Orleans, Semarang, Cali, and Cape Town, which demonstrate how different cities are approaching the challenge of enhancing their resilience to a wide range of shocks and stresses [85].

Specifically, in this study, CRI is a comprehensive metric developed to assess the overall resilience of the road network against flood risks. CRI captures the multi-dimensional nature of resilience, accounting for the road network's ability to avoid, endure, recover, and adapt to flood-related disruptions.

CRI is constructed by integrating several key performance indicators across these four resilience dimensions [1,85,86]. The "avoidance" component evaluates the road network's capacity to prevent or mitigate the impacts of floods, through factors such as infrastructure design, flood protection measures, and risk mitigation strategies [87]. The "endurance" dimension assesses the structural integrity, flood-proofing, and operational continuity of the road assets, determining their ability to withstand the immediate impacts of flood events. The "recovery" aspect measures the speed and effectiveness of restoring full functionality after a flood, considering emergency response, repair capabilities, and restoration timelines. Finally, the "adaptability" component examines the road network's capacity to evolve and enhance its resilience over time, in response to changing flood risks and environmental conditions [13,88].

By synthesizing these diverse resilience aspects into a single index, the study provides a holistic evaluation of the road network's overall performance and preparedness in the face of flood-related disruptions. The CRI serves as a critical decision-support tool, enabling urban planners and infrastructure managers to prioritize interventions, allocate resources, and develop strategies that maximize the long-term resilience of the transportation system. This comprehensive approach ensures that the road network can withstand, respond to, and recover from flood events, while continually adapting to emerging challenges and enhancing its resilience over time [11].

3.5. Risk of Flood Exposure to Roads

For the assessment of road infrastructure vulnerability to flood events, this study builds upon previous research employing a Random Forest machine learning (ML) model consisting of 100 trees. Utilizing nearest neighbor techniques, the model associates concession scores, ranging from 0 to 100 (in increments of 10), with road sections. These concession scores serve as indicators of susceptibility to flood hazards, providing a basis for quantifying flood risk along road networks.

Drawing on the database of hydro-geomorphologic disasters in Portugal [88], which records the occurrence of forest floods, this study identifies areas with the highest concession scores, indicative of heightened flood risk. Analysis reveals that forest floods, characterized by the highest concession scores, occur approximately every five years. Leveraging this information, the study introduces a stochastic approach to simulate flood events, attributing a 20% probability of occurrence during rainy seasons, spanning from September to the end of March.

To validate the stochastic flood model, historical data on floods and landslides in Portugal are utilized [88]. By examining past occurrences of flood events and their associated impacts, the model's predictive capabilities are evaluated. Through this rigorous validation process, the study aims to enhance the reliability and accuracy of flood risk assessments for road infrastructure.

3.6. CAPEX and OPEX of Road Network

The cost of constructing a new road is a complex equation, with a multitude of factors at play. First and foremost, the physical dimensions of the road heavily influence expenses. Longer and wider roads naturally demand a greater investment in materials and labor [89]. The intended use of the road also dictates its cost. Simpler gravel roads are suitable for low-traffic zones, while busy urban areas might require durable (and pricier) asphalt or concrete surfaces.

Terrain and geography are significant cost determinants. Building a road across flat, stable land is much less expensive than navigating mountainous regions, swamps, or forests. Complex terrain may require expensive earthworks, bridges, tunnels, and specialized equipment to ensure the road's stability. Additionally, the underlying soil conditions impact the road's foundation requirements, with soft soils needing extra reinforcement, further increasing costs.

Drainage is essential to a road's longevity, and costs vary based on local precipitation patterns [90]. Areas with heavy rainfall necessitate elaborate culverts, ditches, and retention systems, to prevent flooding and erosion damage. These water management systems drive up construction expenses [91]. In addition to physical considerations, environmental regulations frequently influence infrastructure development. These regulations might mandate actions such as costly detours, specialized construction techniques, or other measures to safeguard sensitive habitats, minimize wildlife disruptions, or conserve historical sites. Additionally, flooding presents a significant threat to road networks, potentially causing performance degradation and incurring substantial economic burdens.

In the following, the main identified risks are presented: (i) Structural Damage—floodwaters can erode road foundations, wash away pavement, and damage bridges or culverts. This undermines the road's integrity, potentially leading to collapse; (ii) Safety Hazards—flooded roads pose a significant danger to motorists. Reduced visibility, debris, and swift-moving water increase accident risks. Roads might become impassable, isolating communities; and (iii) Disruption to Transportation—floods can cause road closures, detours, and delays.

This disrupts commutes, the flow of goods, and emergency services, impacting the local economy and hindering vital operations.

Regarding performance loss, the following might be considered: (i) Reduced Lifespan—flood damage accelerates the deterioration of roads. Potholes, cracking, and weakened foundations shorten a road's lifespan, necessitating more frequent repairs and potentially even earlier reconstruction; (ii) Traffic Congestion—flood-induced closures and detours force traffic onto alternate routes, often leading to congestion and extended travel times; and (iii) Increased Vehicle Wear and Tear—flooded roads can strain vehicle components and lead to premature wear on tires, brakes, and suspension systems.

As concerns cost, we should consider and include the following: (i) Emergency Repairs—urgent repairs to address flood damage are often costly, due to the immediate need and challenging conditions; (ii) Reconstruction—severely damaged roads may require full reconstruction, a major expense that can strain budgets; (iii) Maintenance Costs—the shortened lifespan of flood-damaged roads leads to increased maintenance costs over time; and (iv) Economic Losses—disrupted transportation networks due to flooding translate into economic losses for businesses, delayed goods, and lost productivity.

The cost analysis extracted from various sources from the Portugal Construction Market, Spain [92], and Australia Road Transport Report [93], as well as expert estimation, lies in the comprehensive analysis of construction costs and maintenance expenses across various types of roadways. Australia's inclusion is due to the comprehensiveness of its report and the reliable nature of its road construction and maintenance cost data. While geographically distant, Australia offers valuable insights due to the comprehensive nature of its report and potential similarities in road types and weather patterns relevant to the study.

Each construction type, delineated by factors such as lane count and width, exhibits distinct cost profiles, reflective of the complexity and scale of infrastructure development. For instance, high-capacity roadways like motorways typically entail higher construction costs per lane, compared to lower-capacity roads like tertiary or secondary routes. This variance is attributable to the intricate engineering requirements and material specifications necessary for accommodating heavy traffic volumes and ensuring long-term durability (see Table 1).

Table 1. Roadway construction and maintenance expenses comparison [92,93].

Construction Type	Number of Lanes	Lane Width (m)	Average Construction Price per Lane (EUR Million)	Maintenance Cost per Kilometer (EUR Thousand)	Five Times Maintenance Cost, as Percentage of Initial Construction Cost
Motorway	3.5	12.25	5.2	54.6	21%
Motorway Link	2	7	3	12.48	8%
Primary	2.5	8.75	3.33	21.06	13%
Primary Link	1	3.5	1.35	7.02	10%
Secondary	2	7	2.4	12.48	10%
Secondary Link	1	3.5	1.2	6.24	10%
Tertiary	2	6	1.75	9.345	11%
Tertiary Link	1	3	0.91	4.69	10%
Trunk	2	8	2.72	14.28	11%
Trunk Link	1	4	1.36	7.12	10%

Moreover, the validation of maintenance costs, aligned with industry norms, reinforces the economic rationale behind the initial construction expenditures. By estimating maintenance expenses at five times the initial cost over a five-year period, stakeholders validate the ongoing sustainability and operational viability of road infrastructure investments. This validation process not only ensures financial prudence, but also aligns with broader industry standards, thereby facilitating informed decision-making, regarding resource allocation and infrastructure planning. In essence, the justification for these prices rests on a thorough assessment of construction complexities, maintenance requirements, and adherence to established industry benchmarks.

Based on the diverse slope types identified across different road and highway segments, a calibrated cost assessment has been conducted for each section of the roadway, encompassing both construction and maintenance expenses. The categorization of slope steepness into five distinct ranges—ranging from 0 to 3 percent, 3 to 8 percent, 8 to 16 percent, 16 to 25 percent, and above 25 percent—facilitates a granular analysis of cost factors associated with varying terrain characteristics. By accounting for the unique challenges posed by different slope gradients, such as increased construction complexity and heightened maintenance requirements, this calibrated cost framework offers a more precise estimation of the financial resources needed for sustainable road infrastructure development and management.

3.7. Calibration of Road Performance Levels

The performance of each road depends on the data available from sources like the Institute of Statistical Data of Portugal (INE). We use this data to create performance metrics specific to road infrastructure. However, turning raw data into useful metrics requires careful processing. By using advanced methods, we simplify and organize the data, to understand how roads function and where improvements are needed. This approach helps us make better decisions about managing road networks and allocating resources effectively.

In our comprehensive analysis of road infrastructure, we have meticulously extracted various performance metrics essential for optimal functionality achievement. These metrics delineate the minimum, optimal, and maximum performance thresholds, crucial for ensuring efficient road operations, based on the RMI as a key determinant. Additionally, we introduce a novel indicator, denoted as PP_High_Eco_power, which serves as a positive performer in assessing road performance variability.

The calculation of PP_High_Eco_power is derived using a formula that divides the RMI by the maximum value, subsequently applying a power operator of 1/3 to normalize the range between zero and one, while reducing disparities between the highest and lowest values.

This innovative approach enables a nuanced understanding of road performance dynamics, allowing stakeholders to gauge functional efficiency relative to RMI. The resulting metrics—min_functional_performance, opt_functional_performance, and max_functional_performance—establish clear benchmarks for assessing road performance levels across diverse socioeconomic contexts. Such calibrated performance thresholds are instrumental in guiding strategic decision-making processes, aimed at enhancing road infrastructure sustainability and operational effectiveness.

3.8. Urban Resilience Index Formulation

To formulate the concept of urban resilience index (URI) based on the performance system over time ($P(T)$), we can define the area under the performance curve as a measure of urban resilience. Let's consider two scenarios represented by performance lines $P_1(T)$ and $P_2(T)$ on a graph where P is the performance system and T is time. The area under each performance curve $P_1(T)$ and $P_2(T)$ over time T represents the urban resilience (UR) for each scenario (See Figure 15).

Define Urban Resilience (UR):

Urban Resilience for Scenario 1(UR1) is represented by the area under the performance curve $P_1(T)$ over the time interval T, denoted as:

$$\text{UR1} = \int_{T_0}^{T_1} P_1(T)dT$$

Urban Resilience for Scenario 2 (UR2) is represented by the area under the performance curve $P_2(T)$ over the same time interval T, denoted as:

$$\text{UR2} = \int_{T_0}^{T_1} P_2(T)dT$$

Define Urban Resilience Index (URI):

The Urban Resilience Index (URI) can be defined as the difference between the urban resilience of Scenario 2 (UR2) and Scenario 1 (UR1), calculated as:

$$\text{URI} = \text{UR2} - \text{UR1} = \int_{T_0}^{T_1} P_2(T)dT - \int_{T_0}^{T_1} P_1(T)dT$$

Therefore, the Urban Resilience Index (URI) quantifies the change in urban resilience over time between two scenarios $P_1(T)$ and $P_2(T)$ by comparing the areas under their respective performance curves. A positive URI indicates an improvement in urban resilience from Scenario 1 to Scenario 2, whereas a negative URI suggests a decline. This formulation provides a mathematical concept to assess and compare urban resilience based on performance system dynamics over a specified time period.

To evaluate the resilience of urban areas within the framework of road network infrastructure, a formulation for System Performance (SP) is introduced. The SP aims to standardize and quantify the resilience capacity of individual municipalities, thereby providing insights into their contributions to overall urban resilience. The SP is defined as:

$$\text{SP}_i = \left[\frac{RMI_i}{\max(RMI)}\right]^{k_1}$$

Revenue of the Municipality per Inhabitant for each municipality i, $\max(\text{RMI})$ signifies the maximum Revenue of the Municipality per Inhabitant across all municipalities, and k_1 is a parameter that controls the degree of influence of economic power on urban resilience, constrained within the range of 0 to 1. The parameter k_1 plays a crucial role in shaping the SP by adjusting the influence of economic power on urban resilience.

Building upon the concept of the SP, an advanced formulation of Functional Performance Classes (FPCs) is proposed to elucidate the interaction between economic factors and road network resilience. This formulation categorizes performance based on road class characteristics, defined as follows:

$$\begin{aligned} \gamma_{\min(F)} &= a_F + b_F \cdot \text{SP}_i \\ \gamma_{\text{opt }(F)} &= \left(\gamma_{\min(F)}\right)^{k_2} \\ \gamma_{\max(F)} &= \left(\gamma_{\min(F)}\right)^{k_3} \end{aligned}$$

where $\gamma_{\min(F)}$ represents the minimum functional performance for FPC F, $\gamma_{\text{opt}(F)}$ denotes the optimal functional performance for FPC F, $\gamma_{\max(F)}$ signifies the maximum functional performance for FPC F, a_F and b_F are FPC-specific coefficients, and k_2 and k_3 are parameters that control the degree of performance enhancement, constrained within the range of 0 to 1. These parameters serve as performance enhancers, proportionally increasing all values to a higher level within the model, while ensuring that adjustments remain within realistic bounds reflecting the practical constraints and objectives of road network resilience enhancement strategies.

Considering that k_2 and k_3 serve as performance enhancers, proportionally increasing all values to a higher level within the model. By restricting these parameters to values between 0 and 1, k_2 and k_3 ensure that performance adjustments remain within realistic bounds, reflecting the practical constraints and objectives of road network resilience enhancement strateqies: (i) Avoidance_Gain as the increment in performance due to the avoidance strategy; (ii) Avoidance_Loss as the decrement in performance if avoidance fails;

(iii) Recovery_Factor as the factor influencing performance recovery after a disaster event; and (iv) Adaptation_Factor as the factor influencing performance adaptation over time.

Avoidance_Gain and Avoidance_Loss are chosen to reflect the expected change in performance when the avoidance strategy succeeds or fails, respectively. Their values are determined through sensitivity analysis and empirical data to ensure a balanced response to external factors. Recovery_Factor and Adaptation_Factor represent the effectiveness of the recovery and adaptation processes in restoring and enhancing performance, respectively. Their values are determined based on historical data, expert knowledge, and optimization techniques to maximize resilience outcomes. Complementary, Time_Decay governs the rate of decay in performance adaptation over time. A value close to 1 indicates slower decay, allowing for a more gradual adjustment of performance. The choice of 0.99 reflects a modest decay rate, balancing the need for resilience with computational efficiency and model stability.

The refined mathematical representation of the functions is as follows: (i) simulate_avoid; (ii) simulate_disaster; (iii) simulate_recovery, and (iv) simulate_adapt.

Simulate_avoid, simulates the avoidance strategy to mitigate performance degradation due to external factors, in accordance with the following.

$$\begin{cases} \text{Performance } (t-1) + \text{ Avoidance\_Gain}, & \text{if scenario } = 1 \text{ and Performance } (t-1) < \text{T} \\ \text{Performance } (t-1) - \text{ Avoidance\_Loss}, & \text{otherwise} \end{cases}$$

Simulate_disaster, simulates the occurrence of a disaster event and its impact on road performance, in accordance with:

$$\begin{cases} \text{Performance } (t) - \text{ Disaster\_Loss}, & \text{with probability } \frac{\text{Disaster\_ChancexDisaster\_Weight}}{12} \\ \text{Performance } (t), & \text{otherwise} \end{cases}$$

Simulate_recovery simulates the recovery process after a disaster event, enhancing performance towards the optimal level, in accordance with the following

$$\text{Performance } (t) = \text{ Performance } (t) + \text{ Recovery\_Factor } \times \left(\gamma_{\text{opt}} - \text{ Performance } (t-1)\right),$$

Simulate_adapt simulates the adaptation process to improve resilience over time, in accordance with:

$$\text{Performance } (t) = \text{ Performance } (t) + \text{ Adaptation\_Factor } \times \frac{\gamma_{\text{opt}} - \text{ Performance } (t)}{(\text{Time\_Decay })^{t/12}},$$

where t represents time in months, and the values of parameters are derived based on empirical observations and model calibration.

These parameterized formulations offer flexibility and adaptability to various scenarios and contexts, enabling effective simulation and analysis of urban resilience strategies within the road network framework.

3.9. Scenarios Analysis

The assessment of urban resilience requires a comprehensive understanding of different strategies to enhance road networks' ability to withstand and recover from flood events. This study adopts a scenario-based approach, exploring three distinct resilience strategies and their potential impacts on Portuguese Road Networks. We also employ a scenario-based approach, delving into three distinct resilience strategies over a 25 year, 12 month analysis period, totaling 300 time frames, specifically tailored to the Portuguese Road Networks (see Figure 9).

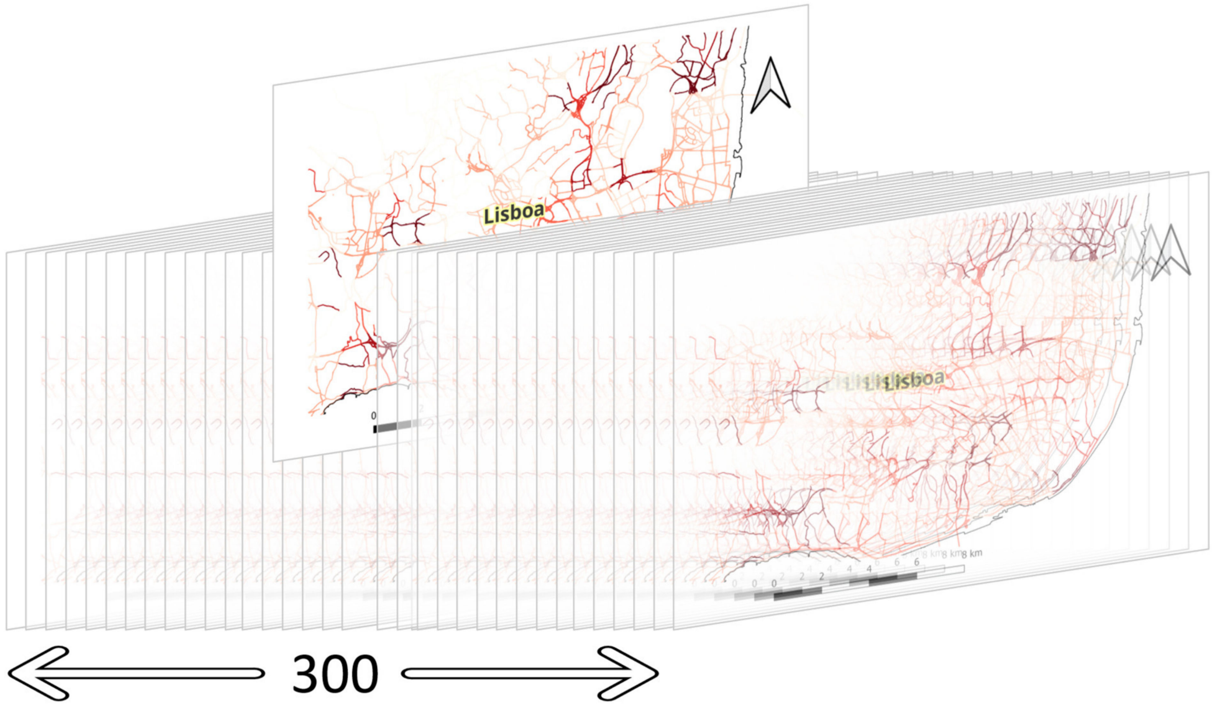

Figure 9. illustration of the timeseries analysis of scenarios.

The selected scenarios (Figure 10) capture the differences, as well as the trade-offs inherent in flood risk management, ranging from reactive measures to proactive planning and early warning systems. This multifaceted analysis informs evidence-based decision-making for strengthening the Portuguese Road Networks' resilience.

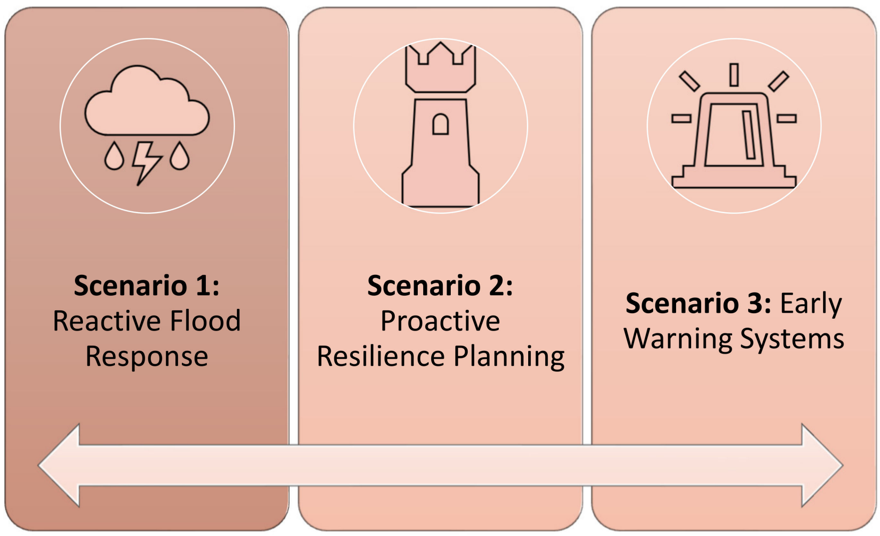

Figure 10. Selected Scenarios for the scenario based approach.

In the Reactive Flood Response Scenario (Scenario 1), the focus lies on reactive measures to address flood events as they occur. Road maintenance and repair efforts are initiated post-flooding, aiming to restore functionality and mitigate immediate risks. While reactive strategies are necessary for managing crisis situations, they often entail higher costs and may lead to disruptions in transportation networks and economic activities. Sensitivity analysis in this scenario involves assessing the effectiveness of response measures in minimizing flood impacts and optimizing resource allocation for emergency repairs.

The Proactive Resilience Planning Scenario (Scenario 2) emphasizes proactive measures aimed at enhancing road network resilience before flood events occur. Investments in flood-resistant infrastructure, such as raised embankments, improved drainage systems, and resilient pavement materials, are prioritized to reduce vulnerability and minimize damage. Robustness evaluation in this scenario entails examining the long-term effectiveness of proactive resilience measures in mitigating flood risks and optimizing cost savings, through pre-emptive investments.

The Early Warning Systems Implementation Scenario (Scenario 3) focuses on leveraging advanced technologies and real-time data to forecast and alert relevant stakeholders about impending flood events. By providing timely information and enabling proactive response measures, early warning systems can significantly reduce flood impacts on road networks and enhance overall resilience. Sensitivity analysis involves assessing the accuracy and reliability of warning systems in predicting flood events, while robustness evaluation examines the effectiveness of response actions triggered by early warnings in minimizing damages and optimizing resource allocation.

Overall, sensitivity analysis and robustness evaluation within these scenarios provide valuable insights into the effectiveness, efficiency, and reliability of resilience strategies for road networks in mitigating flood risks and optimizing cost savings. By systematically exploring different scenarios and assessing their implications, researchers and decision-makers can make informed choices to enhance urban resilience and promote sustainable development outcomes.

4. Results

The provided framework for assessing urban resilience can be described as a multi-stage algorithm that simulates the performance of the road network under different resilience strategies. This algorithm encompasses the following four key stages: Avoid, Disaster, Recovery, and Adapt, each representing a distinct aspect of urban resilience.

In Stage 1 (Avoid), the algorithm simulates the performance of the road network, based on the given scenarios. The performance is adjusted according to the minimum, optimal, and maximum functional performance levels, as well as the specific scenario parameters. This stage can be represented using a mathematical function that determines the performance gain or loss, based on the scenario. Stage 2 (Disaster) models the impact of disruptive events, such as floods, on the road network performance. The probability and severity of these events are influenced by factors like the time of the year (rainy season) and the specified disaster parameters. This stage can be represented using a mathematical function that calculates the performance degradation due to the disaster event. Stage 3 (Recovery) simulates the process of restoring the road network's performance after a disaster event. The recovery rate is affected by factors such as the economic power and population density of the affected area. This stage can be represented using a mathematical function that determines the performance improvement during the recovery process. Finally, Stage 4 (Adapt) models the adaptation of the road network to changing conditions, such as infrastructure upgrades or policy changes. The adaptation rate is influenced by the time elapsed and the performance level, relative to the functional performance thresholds. This stage can be represented using a mathematical function that calculates the performance gain or loss due to the adaptation process.

The different resilience scenarios are generated by adjusting the parameters associated with each stage, such as the probabilities, performance thresholds, and recovery/adaptation rates. This allows for the exploration of different strategies and their impact on the overall performance of the road network over time. By conceptualizing the problem in this algorithmic framework, the analysis can focus on the high-level stages and the mathematical representations of the performance changes, without delving into the specific implementation details of the code. This approach facilitates a more general understanding of the urban resilience assessment process and the underlying principles governing the different resilience strategies.

4.1. Individual Road Resilience Assessment Output

In this section, we present the outcomes of the individual road resilience assessment, focusing on the performance of specific road segments in the face of flood hazards, with samples shown in Figures 11 and 12. Through detailed analysis, we evaluate the resilience of each road segment based on factors such as elevation, construction materials, and proximity to flood-prone areas. By examining the vulnerability and adaptive capacity of individual roads, we provide insights into their potential susceptibility to flood events and highlight areas for targeted intervention and improvement.

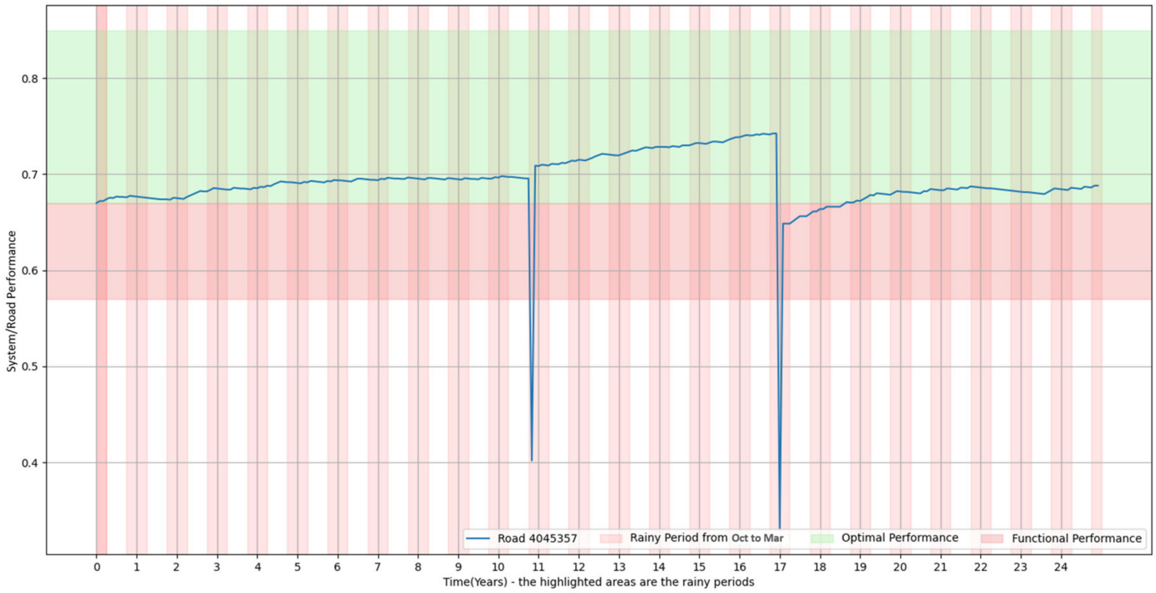

Figure 11. Example of a road resilience assessment output of two flood events.

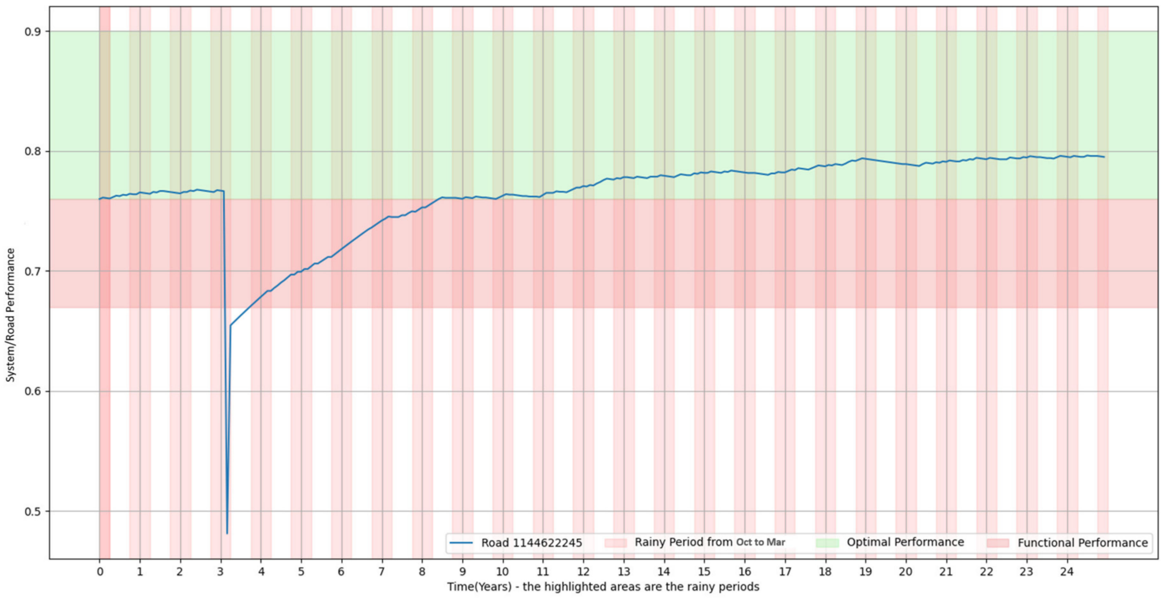

Figure 12. Example of a road resilience assessment output of one flood event.

In Figures 11 and 12, the occurrence of a flood event initiates immediate recovery efforts, aimed at restoring the functionality of the road network. These immediate recovery actions typically involve activities such as clearing debris, repairing damaged infrastructure, and ensuring safe passage for vehicles. However, despite these initial efforts, it is important to recognize that full recovery may not be achieved immediately. Some level of performance loss may persist, even after the initial restoration phase.

For instance, the flood may have caused damage beyond what is immediately visible, such as hidden structural weaknesses in bridges or subsurface erosion beneath the road. Additionally, the asphalt surface may develop potholes or cracks, due to prolonged exposure to floodwaters or the weakening of the underlying foundation. These residual damages may compromise the safety and efficiency of the road network, leading to ongoing performance loss, even after the immediate recovery phase.

Moreover, Figures 11 and 12 also illustrates the longer-term damages that may persist beyond the immediate aftermath of the flood event. These could include issues such as soil erosion along road shoulders, degradation of drainage systems, or the destabilization of embankments. Addressing these longer-term damages often requires more extensive efforts and resources, such as periodic maintenance and enhancement of the road section over an extended period of time.

The municipality or responsible authorities may implement measures such as regular inspection and maintenance routines, reinforcement of vulnerable infrastructure, or the implementation of new drainage systems to mitigate future flood risks. These longer-term actions are essential for ensuring the sustained resilience and functionality of the road network in the face of recurrent flood events. By addressing both immediate and longer-term damages, municipalities can enhance the overall resilience of their road infrastructure and minimize the disruptive impacts of floods on transportation systems and communities.

4.2. Comparative Analysis of Multiple Roads

Here, we conduct a comparative analysis of multiple roads within the study area to identify patterns and trends in road resilience, as shown in Figure 13. By examining different road types, locations, and characteristics, we assess the relative resilience of different segments and highlight disparities in vulnerability and adaptive capacity. Through this comparative approach, we aim to discern factors that contribute to resilience disparities among roads and inform prioritization strategies for resilience investments and interventions.

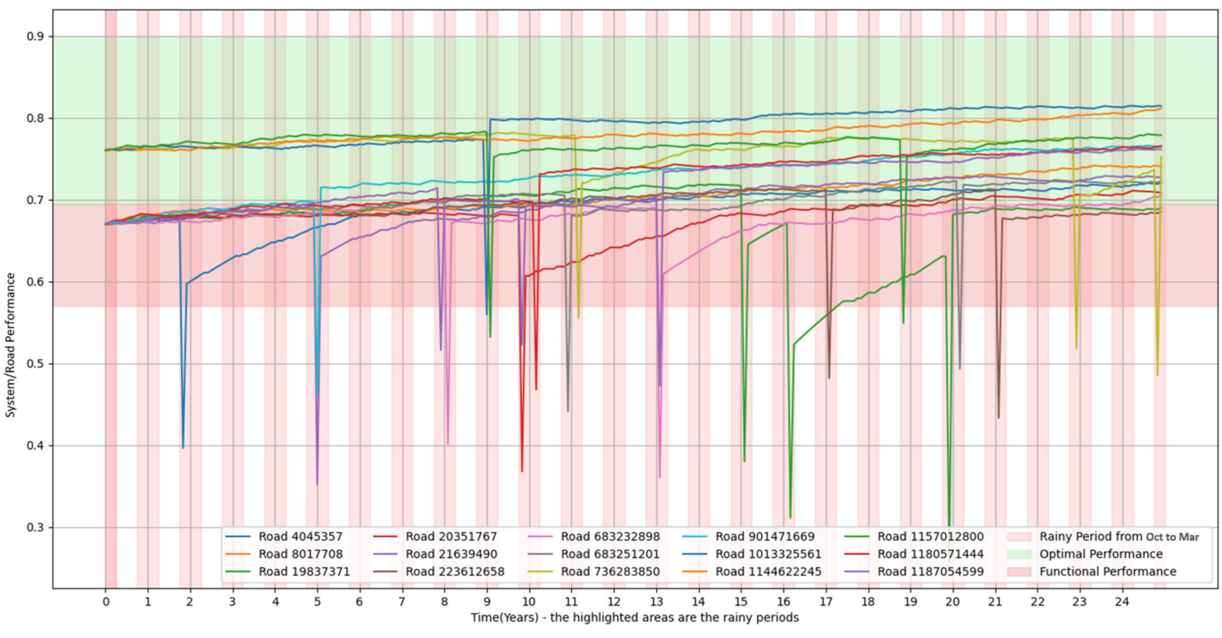

Figure 13. Sample of multiple road resilience assessment output.

In Figure 13, flood events trigger immediate recovery efforts across multiple road sections. Despite these efforts, some performance loss may persist due to hidden damages.

Longer-term challenges, such as ongoing infrastructure degradation, requiring sustained collective action, including periodic maintenance and resilience investments. Through stochastic analysis, municipalities can anticipate challenges and allocate resources effectively, to enhance road network resilience against floods.

4.3. Municipality-Level Resilience Analysis and Scenario Application

This section presents the results of the municipality-level resilience analysis and the application of various scenario simulations. By aggregating road resilience data at the municipality level, we assess the overall resilience of transportation networks and evaluate the potential impacts of different resilience strategies. Through scenario simulations, we explore alternative futures and assess the effectiveness of different intervention options in enhancing overall resilience. These findings provide valuable insights for policymakers and urban planners seeking to strengthen the resilience of entire municipalities to flood hazards. Figure 14 presents a longitudinal analysis of road network resilience in an urban setting, focusing on the Lisbon area. It compares the performance trajectories of three different resilience scenarios over time, as measured using a CRI, as explained in Section 3.4.

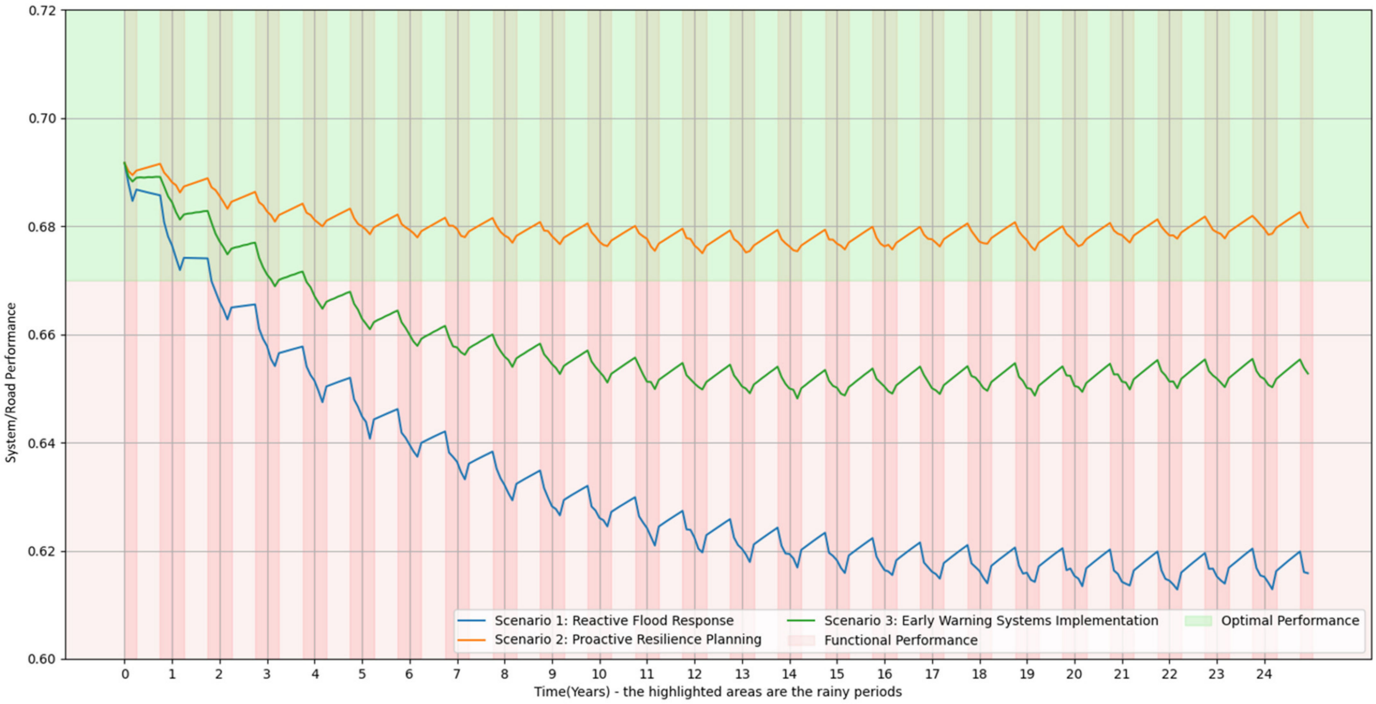

Figure 14. Urban resilience of road network resilience over time, of Lisbon roads of three various scenarios.

The Reactive Flood Response (Scenario 1) depicts the lowest overall performance throughout the analyzed period. This suggests that a reactive approach, where actions are taken only in response to a flood event, results in the least desirable resilience outcomes for the road network in Lisbon. In contrast, the Early Warning Systems Implementation (Scenario 3) demonstrates a higher and more stable performance trajectory, indicating that the implementation of early warning systems can enhance the overall resilience of the road network. The most effective approach appears to be Proactive Resilience Planning (Scenario 2), where pre-emptive measures are taken to enhance the road network's resilience. This proactive approach leads to the highest and most consistent performance over the analyzed time frame.

These findings highlight the importance of adopting a proactive approach to urban resilience planning, particularly in the context of climate-related threats such as flooding. By implementing early warning systems and engaging in proactive resilience planning, Lisbon can better prepare its road network to withstand and recover from potential flood events, ultimately enhancing the overall resilience and functionality of the urban transportation infrastructure.

4.4. Cost–Benefit Analysis of Flood Resilience Scenarios for the Lisbon Road Network

The loss and gain cost analysis of the performance of the Lisbon municipality provides crucial insights into the effectiveness and efficiency of the various resilience scenarios under consideration. This type of analysis is essential for understanding the trade-offs and potential impacts associated with different approaches to enhancing the road network's resilience, by adjusting the cost–benefit analysis. Figure 15 presents the loss and gain analysis for the following three scenarios: S1 is Reactive Flood Response (Scenario 1), S2 is Proactive Resilience Planning (Scenario 2), and S3 is Early Warning Systems Implementation (Scenario 3). A higher loss value indicates a more significant deterioration in the system's performance, while a higher gain value suggests that the system requires more resources to regain its functional performance.

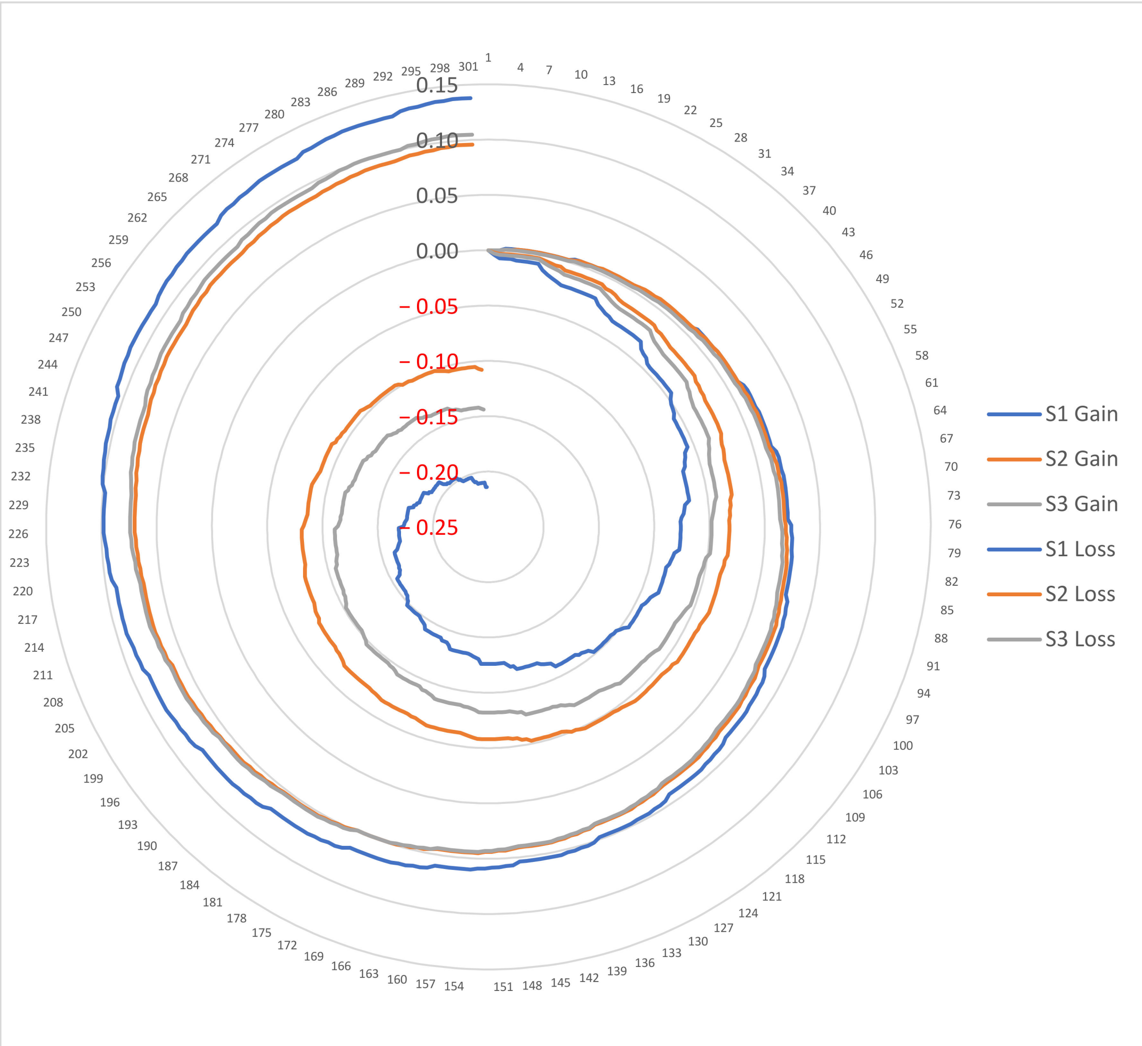

Figure 15. Loss and gain analysis of Lisbon municipality's performance (25 years−300 months).

In the case of the Lisbon municipality, the Reactive Flood Response scenario (Scenario 1) exhibits the highest loss at −0.214, indicating that this approach results in the most significant decline in performance during flood events. On the other hand, the Proactive Resilience Planning scenario (Scenario 2) demonstrates the lowest loss at −0.108, suggesting that pre-emptive measures can effectively mitigate the impact of floods on the road network. The Early Warning Systems Implementation scenario (Scenario 3) falls in the middle, with a loss of −0.144, highlighting the potential of early warning systems to reduce, but not completely eliminate, performance degradation [52].

Regarding the gain analysis, the Reactive Flood Response scenario (Scenario 1) shows the highest gain, at 0.138, implying that this approach requires the most resources to restore the system's functionality after a flood event. The Proactive Resilience Planning scenario (Scenario 2), at 0.096, has the lowest gain, suggesting that this approach is less resource-intensive, in terms of the preparedness, recovery, and adapt phases. The Early Warning Systems Implementation scenario (Scenario 3) lies in between, with a gain of 0.105, indicating that the implementation of early warning systems can strike a balance between performance preservation and resource requirements.

These findings underscore the importance of carefully evaluating the trade-offs between the different resilience strategies and their implications for the overall performance and cost-effectiveness of the road network. By considering both the loss and gain metrics, decision-makers can make informed choices that optimize the resilience of the Lisbon municipality's transportation infrastructure, while ensuring the efficient allocation of resources.

4.5. The Numerical Comparison between Scenarios

Figure 16 shows a comparison of the area below the performance curves for the three scenarios and provides further insights into the relative effectiveness of each approach. Scenario 2, Proactive Resilience Planning, has the highest area of 203.5, which represents a 7.6% increase compared to Scenario 1 (Reactive Flood Response) and a 3.5% increase compared to Scenario 3 (Early Warning Systems Implementation). This suggests that the proactive approach, with pre-emptive measures to enhance the road network's resilience, is the most efective in maintaining a higher overall performance level over time.

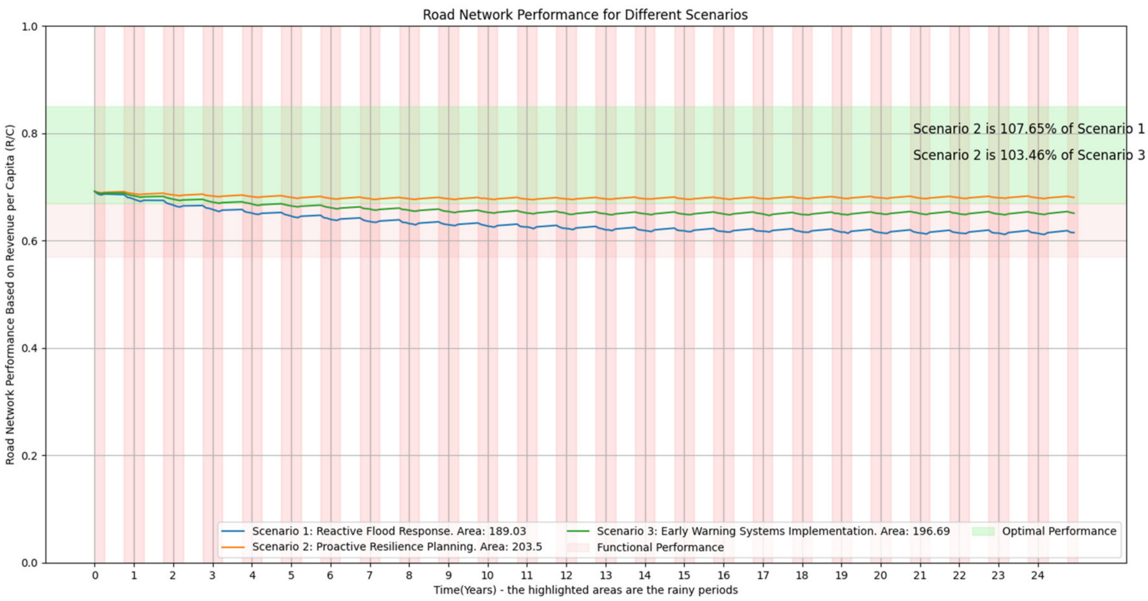

Figure 16. Scenarios in full spectrum height, with comparisons.

The area under each performance curve $P_i(T)$ (where $i = 1, 2, 3$) represents the urban resilience (UR) for the corresponding scenario. Therefore, we have:

Urban Resilience for Scenario 1 (UR1):

$$\text{UR1} = \int_{T_0}^{T_1} P_1(T)dT = 189.03$$

Urban Resilience for Scenario 2 (UR2):

$$\text{UR2} = \int_{T_0}^{T_1} P_2(T)dT = 203.5$$

Urban Resilience for Scenario 3 (UR3):

$$\text{UR3} = \int_{T_0}^{T_1} P_3(T)dT = 196.69$$

Now, applying the Urban Resilience Index (URI) formula to compare these scenarios:

$$\begin{aligned} \text{URI}_{2-1} &= \text{UR2} - \text{UR1} = 203.5 - 189.03 = 14.47 \\ \text{URI}_{3-2} &= \text{UR3} - \text{UR2} = 196.69 - 203.5 = -6.81 \end{aligned}$$

On the other hand, Scenario 1 (Reactive Flood Response) has the lowest area of 189.03, indicating a 7.6% decrease compared to Scenario 2 and a 3.9% decrease compared to Scenario 3. This underscores the limitations of a reactive approach, where actions are taken only in response to a flood event, in terms of preserving the road network's resilience and functionality. Early Warning Systems Implementation (Scenario 3) falls in the middle, with an area of 196.69, which is a 3.5% decrease from Scenario 2, but a 3.9% increase from Scenario 1. This suggests that, while early warning systems can enhance resilience, a proactive approach with pre-emptive measures remains the most effective option for the Lisbon municipality's road network.

5. Discussion

5.1. Significance for the Portuguese Road Networks

The findings of this study hold significant implications for the resilience of the Portuguese Road Networks, particularly in the context of flood risk management. The scenario analyses comparing different resilience strategies provide valuable insights for optimizing the evaluation and enhancement of urban resilience, ultimately improving the network's performance and cost-effectiveness [94,95].

The most effective strategy appears to be the Proactive Resilience Planning scenario, where pre-emptive investments are made to enhance the flood-resistance of the road infrastructure [96]. This includes measures such as constructing raised embankments, improving drainage systems, and utilizing resilient pavement materials [79,97]. The long-term effectiveness and cost-savings of these proactive resilience interventions are critical considerations for decision-makers and urban planners tasked with prioritizing infrastructure investments. The first scenario, Reactive Flood Response, highlights the limitations of a reactive approach, where actions are taken solely in response to flood events [98]. This strategy results in the lowest overall performance, as it often involves higher costs and leads to more disruptions in the transportation network and economic activities. In contrast, the Early Warning Systems Implementation scenario demonstrates the benefits of proactive measures, such as leveraging advanced technologies and real-time data to forecast and alert stakeholders about impending flood events [57]. By enabling timely response actions, this approach can significantly reduce flood impacts and enhance the overall resilience of the road network.

The proposed resilience strategies are particularly relevant for coastal areas prone to flooding and mountainous regions at risk of landslides, as these regions are likely to experience heightened vulnerability to climate-related hazards. Coastal areas, for instance, may benefit from the implementation of Proactive Resilience Planning strategies, including the construction of raised embankments and the use of resilient pavement materials to mitigate the impacts of storm surges and coastal flooding. Similarly, mountainous regions at risk of landslides could prioritize the implementation of early warning systems and the reinforcement of critical road infrastructure, to enhance their resilience to extreme weather events. By targeting these specific regions and road types, the resilience strategies outlined in this study can be tailored to address the unique challenges faced by different parts of the Portuguese Road Network, leading to more effective and context-specific solutions.

These findings highlight the importance of adopting a proactive and holistic approach to urban resilience planning, particularly in the face of climate-related threats like flooding. By implementing early warning systems and engaging in comprehensive resilience planning, the Portuguese Road Networks can be better prepared to withstand and recover from potential flood events, ultimately enhancing the overall resilience and functionality of the transportation infrastructure.

5.2. Implications for Urban Resilience Policy and Planning

The insights generated by this study have significant implications for urban resilience policy and planning, in the context of Portugal's road network. The identification of high-risk areas prone to flooding and the simulation of flood events provide policymakers with valuable information to inform the development of targeted resilience strategies [99,100].

Policymakers can leverage this knowledge to prioritize infrastructure upgrades, such as constructing flood-resistant roads, implementing early warning systems, and establishing emergency response protocols [101]. The compilation of construction and maintenance costs for different road types further enables informed resource allocation decisions, ensuring that resilience interventions are cost-effective and maximize the resilience of the road network, within budget constraints [102,103].

Moreover, the establishment of performance benchmarks across diverse socioeconomic contexts allows policymakers to evaluate the effectiveness of resilience interventions over time and adjust them, as needed. By integrating resilience considerations into urban planning processes, policymakers can foster more resilient communities and economies capable of withstanding and recovering from the impacts of flooding.

To further support urban resilience, policymakers should consider integrating resilience planning into existing urban development policies or introducing new legislative initiatives. This could involve the following steps:

1. Mandating the incorporation of resilience assessments into urban planning processes, requiring the evaluation of flood risks and the implementation of appropriate mitigation strategies.
2. Establishing guidelines or regulations for the construction and maintenance of critical infrastructure, such as roads, to ensure they meet robust resilience standards.
3. Incentivizing the adoption of nature-based solutions, such as the use of permeable surfaces and green infrastructure, to enhance urban flood management.
4. Allocating dedicated funding streams for resilience-focused interventions, ensuring the availability of resources for high-impact projects.
5. Promoting cross-sectoral collaboration between urban planning, emergency management, and environmental agencies, to foster a comprehensive approach to resilience.

By addressing these policy and legislative aspects, policymakers can create an enabling environment that supports the long-term resilience of urban areas and their critical infrastructure, such as road networks.

5.3. Mitigation Strategies

The findings of this study underscore the critical importance of implementing flood mitigation strategies to minimize the risks and costs associated with flood events on road infrastructure. Investing in proactive measures, such as constructing flood-resistant roads, enhancing drainage systems, and deploying early warning systems, can significantly reduce the vulnerability of the Portuguese Road Network and enhance its resilience to flood hazards [104].

The urgent need for repairs to restore flooded roads incurs substantial expenses, driven by factors like overtime labor costs, the deployment of specialized equipment, and the logistical challenges of operating in flooded areas. In severe cases, complete road reconstruction may be necessary, entailing major expenditures. Furthermore, flood damage can shorten the lifespan of roads, leading to more frequent maintenance interventions and escalating long-term costs [105].

Beyond the direct repair and maintenance costs, floods can also inflict indirect economic losses on communities, including disruptions to businesses, increased fuel costs for commuters, and lost productivity due to detours and delays. These broader economic impacts underscore the importance of investing in flood mitigation measures, which not only reduce direct costs, but also mitigate indirect losses, contributing to the overall resilience and sustainability of the road network and the communities it serves.

While the implementation of flood mitigation strategies is crucial, it is essential to acknowledge the potential barriers that may hinder their effective deployment. These barriers can include political resistance, funding limitations, and technological constraints.

Political resistance can arise from competing priorities, budget constraints, or divergent stakeholder interests. Securing the necessary political support and coordinating efforts across various government agencies and jurisdictions can be a significant challenge. Overcoming this resistance may require effective stakeholder engagement, strategic policy advocacy, and a clear demonstration of the long-term benefits of flood mitigation investments.

Funding limitations can also pose a significant obstacle to the implementation of comprehensive flood mitigation strategies. The upfront costs associated with constructing flood-resistant infrastructure, upgrading drainage systems, or deploying early warning technologies can be substantial, particularly in the context of limited public resources. Exploring alternative funding mechanisms, such as public–private partnerships, innovative financing schemes, or securing external grants and subsidies, may be necessary to overcome these financial constraints.

Additionally, technological constraints, such as the availability of advanced flood modeling and monitoring tools, or the capacity to integrate these technologies into existing infrastructure, can pose challenges to the effective implementation of mitigation strategies. Investing in research and development, enhancing technological capabilities, and fostering cross-sectoral collaboration can help address these constraints and ensure the successful deployment of flood mitigation measures.

5.4. Broader Applicability of the Methodology

The comprehensive methodology developed and applied in this study holds a broader applicability beyond the specific context of the Portuguese Road Networks, offering valuable insights for enhancing the resilience of road infrastructure in diverse geographical settings.

By leveraging advanced techniques like Geographic Artificial Intelligence (GeoAI) and machine learning algorithms, the approach can be adapted to assess flood risk and optimize resilience strategies for road networks in various regions worldwide [106]. The systematic framework for identifying high-risk areas and simulating flood events can inform decision-making processes for policymakers and urban planners seeking to mitigate the impact of floods on transportation infrastructure [107].

Furthermore, the integration of cost–benefit analysis and validation processes for construction and maintenance costs enhances the methodological robustness, ensuring its relevance across different economic contexts [105]. This comprehensive approach provides a practical toolkit for assessing the economic feasibility of resilience interventions and optimizing resource allocation strategies to maximize the effectiveness of flood mitigation measures [105].

The establishment of performance benchmarks across diverse socioeconomic contexts offers a valuable framework for comparative analysis and benchmarking exercises, enabling policymakers to identify areas for improvement and prioritize interventions to enhance the functionality and resilience of transportation networks [108]. The scalability and adaptability of the methodology make it a valuable tool for supporting evidence-based decision-making in infrastructure planning and management, ultimately contributing to the development of more resilient and sustainable communities worldwide [109].

6. Conclusions

The present study offers a multifaceted approach to enhancing the resilience of the Portuguese Road Network against flood hazards, with several key takeaways and contributions. The scenario-based analysis provides valuable insights into the effectiveness of different resilience strategies, highlighting the limitations of a reactive approach and the benefits of proactive measures.

The Reactive Flood Response scenario underscores the higher costs and disruptions associated with post-event repair efforts, emphasizing the need for a more proactive approach. In contrast, the Early Warning Systems Implementation scenario demonstrates how leveraging advanced technologies can significantly reduce flood impacts by enabling timely response actions. The most effective strategy, as evidenced by the Proactive Resilience Planning scenario, involves pre-emptive investments in flood-resistant infrastructure, such as raised embankments, improved drainage systems, and resilient pavement materials.

These findings offer practical recommendations for policymakers and urban planners to enhance the resilience of the Portuguese Road Network. By prioritizing proactive resilience planning and the deployment of early warning systems, decision-makers can better prepare the transportation infrastructure to withstand and recover from flood events, minimizing disruptions and optimizing resource allocation.

Furthermore, the study's systematic approach to extracting critical road infrastructure from OpenStreetMap data and integrating historical flood and landslide databases enhances the accuracy of risk assessments. The compilation of construction and maintenance costs, along with the validation of these figures, provides a robust framework for evaluating the economic feasibility of resilience interventions and guiding investment decisions.

The establishment of performance benchmarks across diverse socioeconomic contexts serves as a valuable tool for policymakers, enabling them to evaluate the effectiveness of resilience strategies and make data-driven decisions to optimize the resilience and functionality of the road network. By adopting a holistic and evidence-based approach, this study contributes to the development of more resilient and sustainable transportation systems in Portugal and beyond.

Building upon the methodologies and insights of this study, future research can explore several promising avenues to further enhance the resilience of road infrastructure to flood hazards. Integrating GeoAI models with time series data from previous disaster events can improve predictive capabilities, enabling the identification of recurring flood patterns and informing more targeted mitigation planning.

Incorporating current and future weather patterns, as well as precipitation maps, into the flood model can enhance the realism and accuracy of risk assessments, providing stakeholders with a more dynamic understanding of evolving flood risks. Extending the application of GeoAI to other critical assets, such as hospitals and schools, can offer a holistic perspective on flood impacts and guide prioritization strategies for resilience investments.

Additionally, exploring the cascading effects of asset failures on other infrastructure elements using agent-based modeling and Petri nets can elucidate the interconnected nature of resilience challenges, informing integrated risk management approaches. Incorporating cost–benefit analyses of flood-reactive actions from practitioners and developing ready-to-launch repair execution packages can further streamline response efforts and minimize post-flood disruptions.

By pursuing these future research directions, stakeholders can develop more robust and adaptive strategies for enhancing the resilience of road infrastructure to flood hazards, ultimately fostering safer and more sustainable communities in Portugal and beyond.

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Data Availability Statement: The data supporting the findings of this study will be made available on the Netobra platform (https://www.netobra.com/, accessed on 1 April 2024) following the publication of this article. Interested researchers and practitioners will be able to access the complete dataset, which includes detailed information, as well as the associated Geographic Information System (GIS) mapping data.

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Conflicts of Interest: The authors declare no conflicts of interest.

Annex

```
Code snippet:
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import multiprocessing as mp

df = pd.read_csv('Road network analysis/RoadData.csv')

def simulate_avoid(performance, min_functional_performance, opt_functional_performance, max_functional_performance, scenario):
if scenario = 1:
if performance < np.random.choice([min_functional_performance, opt_functional_performance, max_functional_performance], p = [0.8, 0.1, 0.1]):
performance = performance + 0.0004
else:
performance = performance − 0.0003
elif scenario == 2:
if performance < np.random.choice([min_functional_performance, opt_functional_performance, max_functional_performance], p = [0.1, 0.1, 0.8]):
performance = performance + 0.0005
else:
performance = performance − 0.0003
else:
if performance < np.random.choice([min_functional_performance, opt_functional_performance, max_functional_performance], p = [0.1, 0.8, 0.1]):
performance = performance + 0.0003
else:
```

```
performance = performance − 0.0003
return performance

def simulate_disaster(performance, count_disaster, disaster_chance, Disaster_performance_loss_lower, Disaster_performance_loss_upper, min_functional_performance, opt_functional_performance, max_functional_performance, t, scenario):
month_of_year = −t − np.floor(t/12)*12
if scenario == 1:
# Increase the probability of disasters during the rainy season (months 3–9)
if month_of_year < 3 or month_of_year > 9:
if np.random.rand() < (disaster_chance*0.2)/12:
disaster = np.random.uniform(
Disaster_performance_loss_lower, Disaster_performance_loss_upper)
count_disaster += 1
performance = performance − (disaster/100)*1.3
if performance < 0.25:
performance = 0.25
elif scenario == 2:
if month_of_year < 3 or month_of_year > 9:
if np.random.rand() < (disaster_chance*0.10)/12:
disaster = np.random.uniform(
Disaster_performance_loss_lower, Disaster_performance_loss_upper)
count_disaster += 1
performance = performance − (disaster/100)*1.15
if performance < 0.25:
performance = 0.25
else:
if month_of_year < 3 or month_of_year > 9:
if np.random.rand() < (disaster_chance*0.15)/12:
disaster = np.random.uniform(
Disaster_performance_loss_lower, Disaster_performance_loss_upper)
count_disaster += 1
performance = performance − (disaster/100)
if performance < 0.25:
performance = 0.25
return performance, count_disaster

def simulate_recovery(performance, min_functional_performance, opt_functional_performance, max_functional_performance, PP_High_Eco_power, NP_Low_Eco_power, NPHigh_pop_density, scenario):
if performance < max_functional_performance:
if scenario == 1:
performance = performance + (np.random.uniform(PP_High_Eco_power*0.9,
PP_High_Eco_power*1)**(0.9))*(min_functional_performance-performance)
elif scenario == 2:
performance = performance + (np.random.uniform(PP_High_Eco_power*0.5,
PP_High_Eco_power*1)**(0.9))*(min_functional_performance-performance)
else:
performance = performance + (np.random.uniform(PP_High_Eco_power*0.5,
PP_High_Eco_power*1)**(0.9))*(min_functional_performance-performance)
return performance
```

```
def simulate_adapt(performance, min_functional_performance, opt_functional_performance, max_functional_performance, PP_High_Eco_power, NP_Low_Eco_power, NPHigh_pop_density, t, scenario):
if scenario == 1:
if performance < np.random.choice([min_functional_performance, opt_functional_performance, max_functional_performance], p = [0.4, 0.4, 0.2]):
performance = performance + \
((opt_functional_performance-performance)/(0.99 ** (t/12)))/100
else:
performance = performance − 0.0002
elif scenario == 2:
if performance < np.random.choice([min_functional_performance, opt_functional_performance, max_functional_performance], p = [0.5, 0.3, 0.2]):
performance = performance + \
((opt_functional_performance-performance)/(0.99 ** (t/12)))/100
else:
performance = performance − 0.0002
else:
if performance < np.random.choice([min_functional_performance, opt_functional_performance, max_functional_performance], p = [0.1, 0.7, 0.2]):
performance = performance + \
((opt_functional_performance-performance)/(0.99 ** (t/12)))/100
else:
performance = performance − 0.0002
return performance

def simulate_urban_resilience(time_steps, Disaster_performance_loss_upper, Disaster_performance_loss_lower, min_functional_performance, opt_functional_performance, max_functional_performance, Usage, Capex_tot, PP_High_Eco_power, NP_Low_Eco_power, NPHigh_pop_density, disaster_chance, scenario):
time = np.arange(0, time_steps)
performance = np.zeros_like(time, dtype = float)
performance [0] = opt_functional_performance
count_disaster = np.zeros_like(time, dtype = int)
count_disaster [0] = 0
for t in range(1, time_steps):
performance[t] = simulate_avoid(performance[t − 1], min_functional_performance,
opt_functional_performance, max_functional_performance, scenario)
performance[t], count_disaster[t] = simulate_disaster(performance[t], count_disaster[t − 1], disaster_chance, Disaster_performance_loss_lower,
Disaster_performance_loss_upper, min_functional_performance, opt_functional_performance, max_functional_performance, t, scenario)
if count_disaster[t − 1] > count_disaster[t − 2]:
performance[t] = simulate_recovery(performance[t], min_functional_performance, opt_functional_performance,
max_functional_performance, PP_High_Eco_power, NP_Low_Eco_power, NPHigh_pop_density, scenario)
performance[t] = simulate_adapt(performance[t], min_functional_performance, opt_functional_performance,
max_functional_performance, PP_High_Eco_power, NP_Low_Eco_power, NPHigh_pop_density, t, scenario)
return time, np.round(performance,4), count_disaster
```

```
years = 25
time_steps = 12*years

# Run the simulation for each scenario
performance_scenario1 = {}
performance_scenario2 = {}
performance_scenario3 = {}

# Iterate over the unique road IDs in the dataframe
for road_id in df['osm_id'].unique():
# Filter the dataframe for the current road ID
road_data = df[df['osm_id'] = road_id]

# Extract the required parameters for simulation
disaster_performance_loss_upper = road_data['Disaster_performance_loss_upper'].
values [0]
disaster_performance_loss_lower = road_data['Disaster_performance_loss_lower'].
values [0]
min_functional_performance = road_data['min_functional_performance'].values [0]
opt_functional_performance = road_data['opt_functional_performance'].values [0]
max_functional_performance = road_data['max_functional_performance'].values [0]
usage = road_data['Usage'].values [0]
capex_tot = road_data['Capex_tot'].values [0]
pp_high_eco_power = road_data['PP_High_Eco_power'].values [0]
np_low_eco_power = road_data['NP_Low_Eco_power'].values [0]
np_high_pop_density = road_data['NPHigh_pop_density'].values [0]
disaster_chance = road_data['disaster_chance'].values [0]
# print percentage of completion by %
print(np.round((road_id − df['osm_id'].unique()[0])/
(df['osm_id'].unique()[−1] − df['osm_id'].unique()[0]) * 100,1), '%')

# Simulate urban resilience for each scenario
time, performance_scenario1[road_id], _ = simulate_urban_resilience(time_steps, dis-
aster_performance_loss_upper, disaster_performance_loss_lower, min_functional_
performance,
opt_functional_performance, max_functional_performance, usage, capex_tot, pp_
high_eco_power, np_low_eco_power, np_high_pop_density, disaster_chance, 1)
time, performance_scenario2[road_id], _ = simulate_urban_resilience(time_steps, dis-
aster_performance_loss_upper, disaster_performance_loss_lower, min_functional_
performance,
opt_functional_performance, max_functional_performance, usage, capex_tot, pp_
high_eco_power, np_low_eco_power, np_high_pop_density, disaster_chance, 2)
time, performance_scenario3[road_id], _ = simulate_urban_resilience(time_steps, dis-
aster_performance_loss_upper, disaster_performance_loss_lower, min_functional_
performance,
opt_functional_performance, max_functional_performance, usage, capex_tot, pp_
high_eco_power, np_low_eco_power, np_high_pop_density, disaster_chance, 3)
# save the results to a csv file
pd.DataFrame(performance_scenario1).to_csv('performance_scenario1_lisbon.csv')
pd.DataFrame(performance_scenario2).to_csv('performance_scenario2_lisbon.csv')
pd.DataFrame(performance_scenario3).to_csv('performance_scenario3_lisbon.csv')
```

```
min_functional_performance_avg = np.mean([np.mean(list(performance_scenario1.values()), axis = 0), np.mean(list(performance_scenario2.values()), axis = 0), np.mean(list(performance_scenario3.values()), axis = 0)], axis = 0)
opt_functional_performance_avg = np.mean([np.mean(list(performance_scenario1.values()), axis = 0), np.mean(list(performance_scenario2.values()), axis = 0), np.mean(list(performance_scenario3.values()), axis = 0)], axis = 0)
max_functional_performance_avg = np.mean([np.mean(list(performance_scenario1.values()), axis = 0), np.mean(list(performance_scenario2.values()), axis = 0), np.mean(list(performance_scenario3.values()), axis = 0)], axis = 0)

# Plot the performance for each scenario
plt.figure(figsize = (18, 9))
plt.plot(time, np.mean(list(performance_scenario1.values()), axis = 0),
label = 'Scenario 1: Reactive Flood Response')
plt.plot(time, np.mean(list(performance_scenario2.values()), axis = 0),
label = 'Scenario 2: Proactive Resilience Planning')
plt.plot(time, np.mean(list(performance_scenario3.values()), axis = 0),
label = 'Scenario 3: Early Warning Systems Implementation')

plt.xlabel('Time(Years) − the highlighted areas are the rainy periods')
plt.ylabel('Urban Resilience Performance Index')
plt.title('Urban Resilience Performance Trajectory: A Longitudinal Analysis of Road Network Resilience Over Time')
plt.grid(True)
plt.xticks(np.arange(0, time_steps, 12), np.arange(0, years))

for i in range(0, time_steps, 12):
plt.axvspan(i, i + 3, color = 'red', alpha = 0.1)
plt.axvspan(i + 9, i + 12, color = 'red', alpha = 0.1)

plt.axhspan(float(min_functional_performance), float(opt_functional_performance),
color = 'lightcoral', alpha = 0.1, label = 'Functional Performance')
plt.axhspan(float(opt_functional_performance), float(max_functional_performance),
color = 'lightgreen', alpha = 0.3, label = 'Optimal Performance')

# the y-axis min and max values are fixed to ensure the plot is consistent
plt.ylim(0.6, 0.75)

plt.legend(loc = 'lower right', ncol = 3)
plt.show()
```

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