

Article

Quantifying the Urban Resilience Gap: A Parcel-Level Assessment of Structural Decay and Strategic Misalignment in Riga, Latvia

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Abstract

Rapid urbanization and the aging of large-scale building stocks have created a critical disconnection between strategic urban planning and physical structural realities. This study introduces a multi-dimensional resilience framework to evaluate the structural integrity and socio-economic exposure of Riga's urban fabric at the parcel level. By integrating high-resolution wear-out data with a normalized Economic Priority Index (EPI), the study analyzes the distribution of 2405 buildings identified in the terminal wear-out phase of the Bathtub Curve reliability model. The results reveal that 92.7% of critically vulnerable buildings fall outside the scope of the city's RTIAN 2030 strategic intervention framework, including the majority of high-risk structures supporting 13,416 business units and 646,033 residents. Spatial intersection analysis further demonstrates that contemporary modernization initiatives, including digital pilot zones, effectively bypass 98% of these critical structural hotspots. Predictive scenario analysis confirms that without a strategic reorientation toward a proactive, reliability-based monitoring framework, these excluded corridors face an exponential escalation of structural risk. Specifically, this study examines the urban spatial resilience of Riga's building stock through the integrated PLE-Bathtub Curve framework, evaluates the spatial alignment of RTIAN 2030 with identified vulnerability zones, and assesses how effectively Smart City pilot initiatives target structurally vulnerable clusters defined by the Economic Priority Index (EPI). This research provides a replicable diagnostic framework, calibrated for post-socialist urban contexts, to support municipal authorities in realigning investment priorities with empirical physical vulnerabilities, ensuring long-term metropolitan continuity.

Keywords: bathtub curve; Economic Priority Index (EPI); parcel-level analysis; Production–Living–Ecological (PLE) framework; Riga; spatial resilience gap; strategic urban planning; structural decay; urban resilience; Weibull distribution



Received: 29 April 2026

Revised: 12 June 2026

Accepted: 18 June 2026

Published: 26 June 2026

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1. Introduction

Natural hazards have been intrinsic to Earth's history; however, with the acceleration of urbanization, these geophysical events have increasingly transformed into existential risks for human societies [1]. Modern cities have often developed in detachment from local environmental constraints, enabled by technological advances that bypass natural limitations [2]. Consequently, urban form is largely a product of historical, economic, and political processes, creating heterogeneous patterns of vulnerability [1,3]. Despite these advancements, the human and economic toll remains staggering: natural disasters accounted for hundreds of thousands of fatalities in the early 20th century and continue

to claim tens of thousands annually in the modern era, with economic losses reaching approximately 0.5% of global GDP [3,4]. Although, urbanization is a central driver of climate change and many creeping environmental changes, it is essential to integrate solutions and strategies to mitigate such problems in urban planning and align policies [5].

While environmental hazards are natural phenomena, the scale of devastation is exacerbated by conventional land-use patterns, such as decentralized sprawl, which concentrate development in high-risk zones [6]. Traditional urban design has historically prioritized physical esthetics and economic efficiency, often treating resilience as a reactive consideration rather than an integrated structural principle [6]. While resilient urban design has emerged as a critical theme in response to escalating disasters, many cities remain vulnerable because their strategies still rely on conventional hazard control [7]. Research indicates that a significant driver of increasing urban risk lies in planning and design decisions that are not adequately aligned with natural hazard conditions, resulting in development patterns that amplify vulnerability rather than mitigate it [8]. These decisions are institutionalized through various planning instruments—such as comprehensive plans, hazard mitigation plans, transportation plans, housing plans, and open space plans—which collectively shape spatial development patterns and can either mitigate or exacerbate urban vulnerability [8,9]. Among the most critically affected contexts, Historic Urban Built Environments (HUBEs) are particularly vulnerable, as they are characterized by complex interactions among social, ecological, and technological systems (SETS), leading to compounded risk exposure and heightened sensitivity to external disturbances [10].

Contemporary approaches to urban development frequently fail to reconcile technical modernization with adaptive structural regeneration, resulting in planning models that replicate rather than resolve existing vulnerabilities [4,6].

A significant challenge in current scholarship is the conceptual ambiguity of urban resilience. This study argues that urban resilience is fundamentally grounded in system reliability; the probability that a complex urban system will perform its intended functions under specified environmental conditions over a given time horizon. Within the Social-Ecological System (SES) framework, cities are analyzed through the lens of Production–Living–Ecological (PLE) spaces [11]. Several methods have been developed to assess urban resilience, including conceptual frameworks such as the Resilience Framework for Action (RFA), composite indices like the Climate Disaster Resilience Index (CDRI), and analytical models such as the Disaster Resilience of Place (DROP) [12]. These approaches typically integrate qualitative and quantitative techniques—such as indicator-based assessment, GIS analysis, and multi-criteria decision-making—to evaluate multiple dimensions, including infrastructure, social, and economic systems [12].

While the PLE framework integrates multiple dimensions of human-nature interaction, existing assessments of PLE resilience frequently treat resilience as a fixed spatial index, failing to account for the dynamic, stochastic nature of external hazards and the internal degradation of urban systems over time [11]. Despite recent methodological advancements in spatial conflict risk assessment—such as the Vulnerability Scoping Diagram (VSD) framework [13]—these models predominantly treat risk as a static overlap of competing land uses [13,14]. While effective at identifying current hotspots of exposure and sensitivity, such frameworks fail to account for the stochastic degradation of urban functions over a continuous lifecycle [14]. Consequently, there remains a critical gap in transitioning from descriptive vulnerability indices to prescriptive reliability metrics capable of calculating the probability of a system's functional survival under recurrent natural hazards [13–15].

To address these limitations, this study introduces a novel analytical paradigm by mapping the components of PLE resilience onto the Reliability Bathtub Curve derived from industrial reliability engineering. It is important to clarify that this study does not

equate engineering reliability with urban resilience in its entirety. Rather, it operationalizes the Weibull-based failure rate as a quantitative proxy for the resistance dimension of resilience—one of the four dimensions identified by Bruneau et al. [16]: robustness, redundancy, resourcefulness, and rapidity. The reliability engineering framework specifically addresses the robustness dimension by quantifying the time-dependent probability of structural functional survival, while acknowledging that the adaptability and recovery dimensions require complementary qualitative assessment beyond the present scope. This study conceptualizes that urban structural resilience follows a tri-phasic functional path: Robustness serves as the primary defense during early-stage shocks (infant mortality phase); Redundancy and Diversity stabilize the system during its constant operational life; and Adaptability governs the system's capacity to reorganize and evolve as it reaches its performance limits (wear-out phase). By redefining resilience through this reliability engineering lens, the analytical focus transitions from describing the static spatial attributes of a city to calculating the time-dependent probability of functional survival under compounding environmental stress.

The primary aim of this work is to propose an extended framework that integrates natural hazard dynamics as a functional variable within the PLE dimensions, specifically applied to the Historic Centre of Riga, Latvia. As a post-socialist Baltic capital subject to UNESCO World Heritage governance constraints and situated within a distinct historical, cultural, and economic transition context, Riga constitutes a geographically and institutionally specific case study. The findings of this research are therefore interpreted within—and explicitly bounded by—this contextual framework, rather than as universally generalizable conclusions [17,18]. Unlike previous fragmented models, this approach employs parcel-level evaluation to bridge the gap between micro-scale urban form and macro-scale geophysical risks. The contemporary evolution of metropolitan areas is increasingly defined by forward-looking urban strategies, primarily centered on the transition toward “Smart Cities.” While these high-cost initiatives represent a significant paradigm shift in urban governance—aiming to optimize city performance through digital layers—there remains a critical lack of empirical scrutiny regarding their alignment with the physical and structural decay of existing urban fabrics [19]. This research specifically addresses this disconnection in Riga by examining whether such technologically driven modernization agendas effectively mitigate the accelerating structural risks in mass-housing corridors, or whether they create a “monitoring vacuum” for the city's most vulnerable assets.

Specifically, this study is structured around three Research Questions (RQs): RQ1: To what extent does the integration of Production, Living, and Ecological (PLE) space dimensions combined with a reliability-based Bathtub Curve model reveal the urban spatial resilience status of Riga's building stock at the parcel level? RQ2: To what extent does Riga's RTIAN 2030 strategic planning framework spatially align with the vulnerability zones identified through the PLE-based USR assessment? RQ3: How effectively do Riga's Smart City pilot initiatives target the structurally vulnerable clusters defined by the Economic Priority Index (EPI)?

2. Materials and Methods

To ensure methodological transparency and reproducibility, Figure 1, presents the complete analytical workflow of this study. The framework proceeds through six sequential phases: (1) multi-source spatial data integration and normalization; (2) parcel-level hazard exposure quantification; (3) Weibull-based failure rate computation across 116,659 LOD1 building parcels; (4) Bathtub Curve classification into tri-phasic structural lifecycle stages; (5) Urban Spatial Resilience (USR) Index computation integrating PLE systemic capacity with hazard exposure; and (6) Economic Priority Index (EPI) derivation and spatial gap

analysis against the RTIAN 2030 planning scenario. Each phase draws directly on the datasets documented in Table 1, and all computational scripts are available from the corresponding authors upon reasonable request.

Table 1. Synthesized spatial data inventory and methodological applications (developed by authors).

Category	Dataset (Year)	Format	Methodological Application	Source
Living Space (L)	Population Density Grids (2000–2024)	Polygon	Assessing socio-spatial vulnerability of “mikrorayons” and historical zones	CSB ¹
	3D Building Models: RIGA_LOD1 (2023)	MultiPatch/Vector	Calculating building density and Space Congestion Degree (SCD)	RCC ²
	Degraded Buildings: Degraded Buildings Registry	Polygon	Quantifying functional decay for the Bathtub Curve’s wear-out phase	RCC
	UNESCO Historical Core and Buffers (2024)	Polygon	Evaluating spatial constraints and vulnerability of medieval foundations	NCHB ³
Production Space (P)	Workplaces: Workplaces Dataset	Polygon (300 m buffers)	Quantifying economic vitality and aging industrial legacies	ERL ⁴
	Physical Infrastructure: Transport Infrastructure	Polyline	Assessing logistical vulnerability to direct windstorm damage	LGIA ⁵
Ecological Space (E)	Green Areas: Green Areas (Urban Atlas)	Polygon	Assessing Green Infrastructure and ecological capacity (PLAND metric)	CLMS ⁶
	Coastal and Marine Zones (2023)	Polygon	Mapping ecological protection zones and marine buffers	DAP ⁷
Hazards and Stressors	Flood-prone Areas (2023)	Polygon (10% prob.)	Mapping exposure to compound flooding (river discharge and runoff)	LEGMC ⁸
	Coastal Dunes and Erosion Risk (2023)	Polygon	Identifying exposure to Baltic Sea storm surges and coastal erosion	DAP
Spatial Planning	Surface Urban Heat Island (2023)	Raster (38 × 69 m)	Analyzing systemic thermal stress linked to the regional warming rate	ECOSTRESS ⁹
	Current Land Use: Current Land Use	Polygon	Establishing the baseline for analyzing obsolete spatial planning	RTIAN ¹⁰
Smart City Pilot Zones	Vector (Polygon)	Polygon	Used for spatial intersection analysis to identify the “Paradox” areas.	RCC
Business Registry Data	Tabular/Spatial	Tabular/Spatial	Linking 13,416 business units to structural risk zones for EPI calculation.	Lursoft ¹¹
Administrative Borders	Vector (Polygon)	Polygon	Neighborhood-level aggregation of EPI and socio-economic exposure.	RCC
Spatial Planning	RTIAN: Riga Territory Spatial Plan (2030) ¹²	Polygon	Projecting the “Business as Usual” trajectory and identifying the 92.7% Resilience Gap.	RCC

¹ Central Statistical Bureau. ² Riga City Council. ³ National Cultural Heritage Board. ⁴ Enterprise Register of Latvia. ⁵ Latvian Geospatial Information Agency. ⁶ Copernicus Land Monitoring Service. ⁷ Nature Conservation Agency. ⁸ Latvian Environment, Geology and Meteorology Centre. ⁹ ECOsystem Spaceborne Thermal Radiometer Experiment on Space Station. ¹⁰ Riga City Territorial Plan. ¹¹ Lursoft: Lursoft IT, Ltd., Latvian Business Registry Database, Riga, Latvia. ¹² Rīgas teritorijas izmantošanas un apbūves noteikumi (Riga Territory Use and Building Regulations).

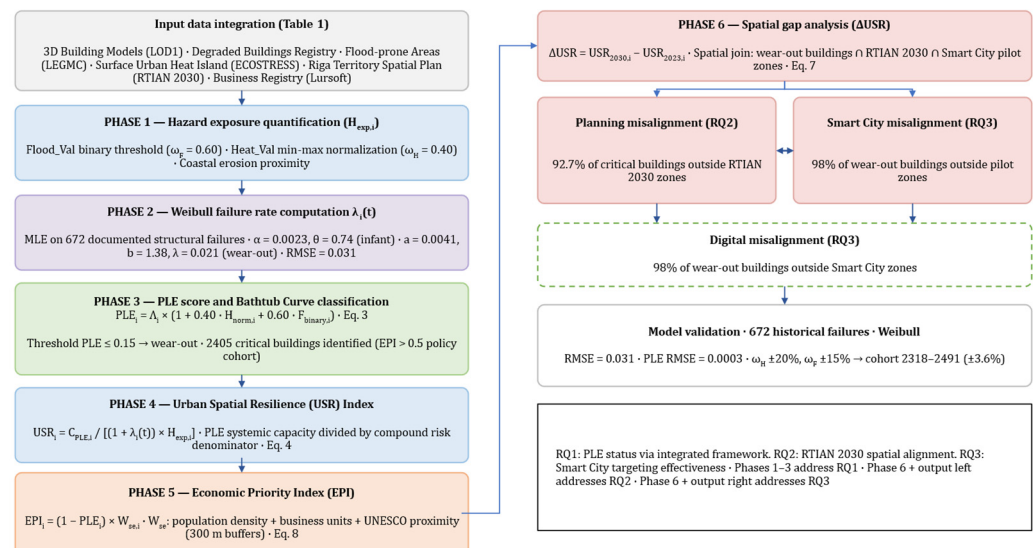


Figure 1. Analytical workflow of the Urban Spatial Resilience (USR) assessment framework: six-phase sequential pipeline integrating Production–Living–Ecological (PLE) dimensions, Weibull-based reliability modeling, and spatial gap analysis applied to 116,659 LOD1 building parcels in Riga, Latvia (2023–2030) (developed by authors).

2.1. Study Area

The study area encompasses the entire territory of Riga (56°56' N, 24°06' E), a Baltic metropolis characterized by a distinct dual urban morphology. The city integrates a UNESCO-protected historic core (438.3 ha), featuring medieval and Art Nouveau architectures, with extensive Soviet-era peripheral zones dominated by mass-produced “mikro-rayons” and aging industrial legacies [18,20,21]. As a post-socialist Baltic capital subject to UNESCO World Heritage governance constraints and situated within a distinct historical, cultural, and economic transition context, Riga constitutes a geographically and institutionally specific case study. The findings of this research are therefore interpreted within—and explicitly bounded by—this contextual framework [20,22]. This stratified structure provides a unique laboratory for Production–Living–Ecological (PLE) analysis; while the historic center struggles with the functional decay of over 1000 buildings, the Soviet-inherited districts face structural obsolescence and rigid spatial planning that often conflicts with modern ecological standards [18,23].

From a climate perspective, Riga’s northern coastal position exacerbates the vulnerability of these contrasting fabrics. With a regional warming rate of +0.4 °C per decade, the city faces escalating hydrological risks, including Daugava River flooding and Baltic Sea storm surges [24,25]. These environmental stressors threaten the survival of both the low-lying medieval foundations and the high-density Soviet residential blocks. Consequently, these compound environmental stressors make Riga a suitable context for applying a reliability-based analytical framework to assess the time-dependent probability of structural functional survival [20,21,23]. In 2008, Michael Batty advanced the paradigm of cities as complex systems, arguing that urban environments are not static structures, but evolving entities shaped by bottom-up interactions [26]. This systemic perspective suggests that the functional stability of a city emerges from the collective behavior of its individual components—such as Riga’s diverse parcels and historical layers [18,26]. Natural-induced compound hazards, particularly the interaction between storm surges and inland runoff, pose a severe systemic threat to coastal cities worldwide, pushing urban infrastructures toward functional failure [27,28].

The city of Riga, Latvia, situated at the complex estuary of the Daugava River and the Gulf of Riga, constitutes a contextually specific case study characterized by its post-

socialist urban legacy, UNESCO heritage governance constraints, and compound hydro-meteorological hazard exposure. The European Environment Agency and the Latvian National Plan for Adaptation to Climate Change until 2030 explicitly identify these escalating hydro-meteorological risks as primary threats to the nation's built environment and economic stability [29,30]. According to national reports and longitudinal studies, Riga's functional integrity is continuously threatened by a synchronized array of maritime and continental hazards [30,31]. These primarily include severe windstorms that cause direct damage to physical infrastructure [31,32], and compound flooding resulting from the simultaneous occurrence of high river discharge, pluvial runoff, and sea surges [31,33].

Furthermore, Baltic Sea storm surges drive seawater into the river mouth, causing severe backwater effects and accelerated coastal erosion in vulnerable metropolitan districts such as Daugavgrīva [34,35]. Analyzing these measurables, interacting hazards provide a scalable framework for evaluating systemic vulnerability in similar coastal-fluvial cities globally. Figure 2 presents the spatial context of the study area in Riga, Latvia, together with the principal environmental and regulatory constraints considered in this research. These include flood-prone areas, restricted coastal zones, marine and coastal dune protection zones, and UNESCO-related protected territories. The figure illustrates the heterogeneous spatial distribution of environmental limitations across the urban territory, highlighting the need to incorporate such constraints into urban resilience and parcel-level spatial assessment frameworks. The inset map provides the geographical location of Riga within Latvia.

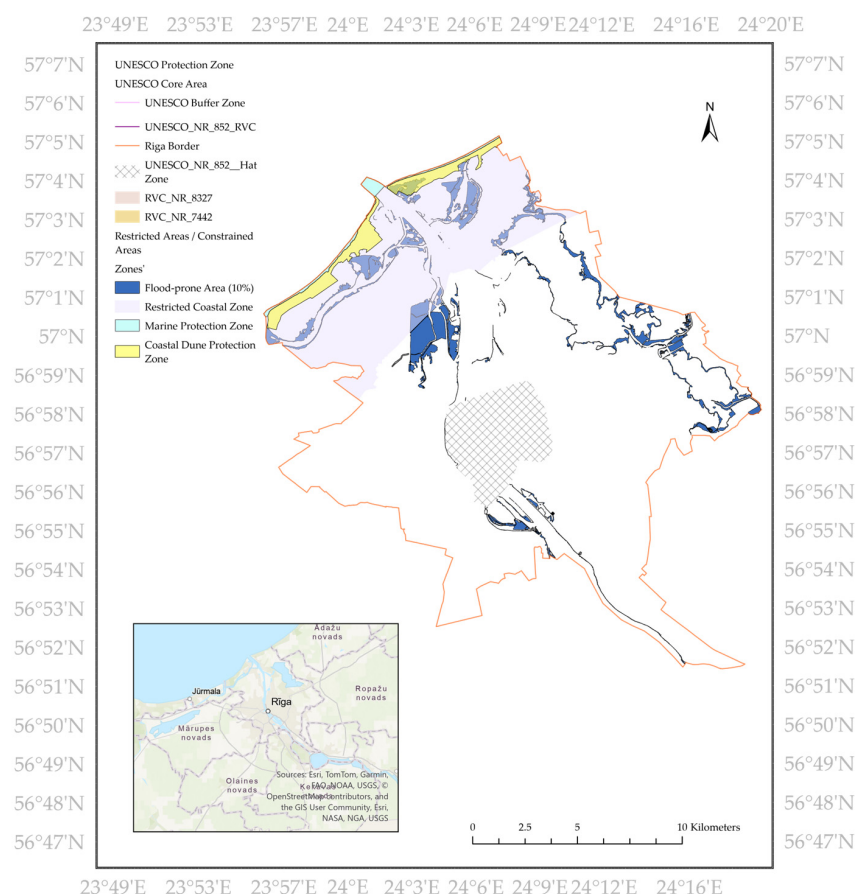


Figure 2. Spatial distribution of constrained areas, UNESCO protected zones, and flood-prone areas within Riga, Latvia. The inset map indicates the location of Riga within Latvia (developed by authors).

2.2. Data Sources

To operationalize the Production–Living–Ecological (PLE) framework and quantify systemic urban resilience, a comprehensive multidimensional spatial database was con-

structed (Table 1). The selected datasets were curated to capture the heterogeneous nature of Riga's urban morphology and its exposure to interacting environmental stressors.

Within this framework, the Living Space (L) is characterized not only by demographic distribution but also by high-resolution 3D building morphology (LOD1). This volumetric data, alongside the spatial delimitation of environmentally degraded buildings and the UNESCO historic core, is critical for calculating spatial congestion and defining the structural obsolescence (wear-out phase) within the Bathtub Curve model.

The Production Space (P) integrates economic vitality indices and logistical infrastructure networks, representing the city's operational capacity under meteorological stress. The Ecological Space (E) encompasses green infrastructure and strictly restricted coastal buffers, reflecting the natural environment's regulatory capacity and sensitivity. Furthermore, to evaluate systemic vulnerability, the database incorporates precise spatial delineations of compound hazards, namely hydrological flooding, coastal erosion, and thermal stress. Finally, the inclusion of both current and formally planned land-use scenarios (up to 2030) establishes the foundational baseline for a spatial gap analysis. This allows the study to quantitatively assess the degree to which future metropolitan development trajectories align with or diverge from empirically identified structural vulnerability zones.

2.3. Mathematical Model and Equations

A significant methodological gap in assessing systemic urban resilience concerns the transition from static spatial descriptions to dynamic, probabilistic models of functional survival. Traditionally, urban morphology has been evaluated through descriptive life-cycle stages. However, cities are fundamentally complex, load-bearing systems whose physical stocks follow distinct survival trajectories and failure probabilities [36]. Recent advancements have demonstrated the efficacy of applying industrial reliability engineering concepts—specifically the Weibull distribution and failure rate functions—to predict the end-of-life performance and structural obsolescence of the built environment [37,38]. This operationalization is grounded in three converging lines of evidence: Kohler and Hasler [36] demonstrated that building stock cohorts sharing construction typology exhibit synchronized deterioration trajectories analogous to batch failure patterns in Weibull models; Thomsen and van der Flier [39] established that urban structures undergo time-dependent, non-linear functional obsolescence; and Akanbi et al. [38] confirmed the applicability of modified Weibull distributions to building-stock-scale end-of-life prediction.

As Thomsen and van der Flier (2011) articulate, urban structures undergo not only physical deterioration but also profound functional obsolescence when their spatial configuration fails to adapt to evolving external demands [39]. In the context of Riga, the historically stratified morphology—ranging from medieval foundations to mass-produced Soviet-era blocks—exhibits heterogeneous vulnerabilities. When cascading environmental impacts, such as compound flooding and thermal stress, interact with this aging fabric, they act as external load multipliers that accelerate systemic breakdown [40].

$$h(t) = \alpha \theta t^{\theta-1} + at^{b-1}(b + \lambda t)e^{\lambda t}, \quad (1)$$

where “t” represents time (or operational age), and the remaining parameters are defined as follows:

- $\alpha > 0$ and $\theta > 0$: Shape and scale parameters of the standard Weibull distribution, controlling the initial failure trajectory.
- $a > 0$ and $b > 0$: Parameters governing the scale and shape of the modified Weibull extension (wear-out phase).
- $\lambda > 0$: An accelerating factor characterizing the exponential increase in the hazard rate over time.

In reliability engineering, Equation (1) is known as the bathtub shape: the first term (when $\theta < 1$) defines the decreasing failure rate (infant mortality phase), while the second term defines the exponentially increasing wear-out phase. By conceptualizing Riga's urban morphology as a composite, load-bearing system, the additive logic of Almalki and Yuan [41] is directly adapted. Rather than mechanical components, the subsystem variables represent distinct spatial typologies extracted from the LOD1 database. Thus, the overall morphological failure rate for any spatial parcel “i” over time, $\lambda_i(t)$ is formulated by translating the statistical parameters into spatial life-cycle phases in Equation (2):

$$\lambda_i(t) = \lambda_{infant,i}(t) + \lambda_{random,i} + \lambda_{wear,i}(t), \quad (2)$$

where each component of the additive function is systematically mapped to the urban fabric:

- $\lambda_{infant,i}(t) = \alpha \theta t^{\theta-1}$ (where $\theta < 1$). This strictly decreasing mathematical function represents new coastal developments and recent constructions. These parcels experience initial spatial and functional “settlement” challenges as they adapt to micro-hydro-meteorological conditions.
- $\lambda_{random,i} = \gamma$ (Constant): This represents the UNESCO historic core. Due to rigorous and continuous preservation protocols, the structural age factor is mathematically nullified. Failure in this zone is decoupled from the Weibull wear-out curves and is driven solely by constant, unpredictable stochastic shocks (e.g., extreme Baltic storm surges).
- $\lambda_{wear,i}(t) = at^{b-1}(b + \lambda t)e^{\lambda t}$. This exponential decay function perfectly models the aging Soviet-era “mikrorayons” and officially registered degraded buildings. As environmental stressors interact with their structurally obsolete concrete forms and high Space Congestion Degree (SCD), their physical and functional failure rate accelerates exponentially. Having established the dynamic failure rate $\lambda_i(t)$ for each specific parcel, the final analytical step is to integrate this morphological vulnerability with systemic capacity and external hazards. The Urban Spatial Resilience (USR) Index for spatial unit “i” is calculated in Equation (3).

The distribution parameters were calibrated by Maximum Likelihood Estimation (MLE) against the historical dataset of 672 documented structural failures (2005–2023), yielding the following fitted values: for the infant-mortality term, $\alpha = 0.0023$ and $\theta = 0.74$ ($\theta < 1$, confirming a decreasing early-failure rate); for the wear-out term, $a = 0.0041$, $b = 1.38$, and $\lambda = 0.021$. The resulting citywide baseline failure rate is $\bar{\lambda} = 0.16$, and the model achieves an overall goodness-of-fit of $RMSE = 0.031$ against the historical failure record, supporting the adequacy of the modified Weibull formulation at the building-stock scale.

$$USR_i = \frac{C_{PLE,i}}{1 + (\lambda_i(t) \times H_{exp,i})} \quad (3)$$

2.4. Weighting Procedure and Model Calibration

Having established the theoretical Weibull framework, the Probable Life Expectancy (PLE) score for each building parcel was operationalized through a multiplicative hazard-amplification model implemented in ArcGIS Pro 3.6.2. Rather than a simple additive composite, the model captures the non-linear interaction between structural lifecycle stage and compound environmental stressors—specifically that environmental hazards multiplicatively accelerate the failure rate, consistent with compound risk theory [40].

The PLE score for building parcel i is defined as Equation (4):

$$PLE_i = \Lambda_i \times (1 + \omega_H \times H_{norm,i} + \omega_f \times F_{binary,i}), \quad (4)$$

where Λ_i is the normalized Lambda_Score representing the parcel's Bathtub Curve lifecycle stage (range 0.10–0.85), derived directly from the building height and Bathtub_Phase classification of each LOD1 parcel; $H_{norm,i}$ is the min-max normalized Surface Urban Heat Island intensity from the ECOSTRESS dataset (Heat_Val, observed range: 106.32–229.17 °C); and $F_{binary,i}$ is a binary flood exposure indicator equal to 1 if the parcel falls within the LEGMC 10% annual probability flood zone, and 0 otherwise. Table 2 summarizes the derivation procedure, sample sizes, validation metrics, and scientific justification underlying each parameter of the PLE_i model.

In this equation, $C_{PLE,i}$ denotes the normalized systemic capacity derived from the Production–Living–Ecological data framework (e.g., economic vitality and green infrastructure). The denominator reflects the compound risk: the internal morphological failure rate $\lambda_i(t)$ acts as an amplifying multiplier for the external hazard exposure index ($H_{exp,i}$), which is derived from 10% probability flood zones, coastal erosion buffers, and surface urban heat islands. To transition from the conceptual USR equation to GIS-based spatial computation, the numerator and denominator variables must be explicitly defined using the datasets outlined in Table 1. Systemic Capacity ($C_{PLE,i}$) >: the resilience capacity of each spatial unit is quantified through a weighted combination of normalized indicators representing the Production, Living, and Ecological dimensions in Equation (5).

$$C_{PLE,i} = \omega_P P_i + \omega_L L_i + \omega_E E_i, \quad (5)$$

where P^I , L^I , and E^I are min-max normalized spatial metrics representing economic vitality (workplace density buffers), spatial volumetric congestion (derived from LOD1 building geometry), and ecological regulatory capacity (PLAND metric for green infrastructure), respectively. Note: In the context of the $C_{PLE,i}$ composite index (Equation (5)), equal weights ($\omega_P = \omega_L = \omega_E = 0.333$) are applied to the three PLE dimensions. This equal-weighting scheme is adopted in the absence of empirical evidence privileging one dimension over another at the citywide scale, consistent with established practice in composite resilience index construction [12,15]. It is important to distinguish this from the hazard amplification weights ($\omega_H = 0.40$, $\omega_f = 0.60$) in the PLE_i formula (Equation (4) above), which are empirically derived from the ArcGIS Pro data analysis described in Section 2.4. The $C_{PLE,i}$ score feeds into the denominator of the USR Index (Equation (3)), where it is modulated by the hazard exposure $H_{exp,i}$ in Equation (6).

$$H_{exp,i} = \frac{1}{n} \sum_{j=1}^n hazard_{j,i}, \quad (6)$$

where $hazard_{j,i}$ incorporates the normalized pixel values (ranging from 0 to 1) for 10% probability flood zones, coastal erosion proximity, and ECOSTRESS-derived Surface Urban Heat Island (SUHI) intensity. The ultimate diagnostic capability of the USR framework lies in evaluating the efficacy of the Riga City Territorial Plan (RTIAN) up to 2030. By substituting the baseline morphological and spatial parameters (Current Land Use, 2023) with the formally planned developmental scenarios (Planned Land Use, 2030), a future resilience index USR_{2030} is computationally projected. The spatial resilience gap ΔUSR is therefore defined as Equation (7).

$$\Delta USR = USR_{2030,i} - USR_{2023,i} \quad (7)$$

This differential equation serves as a critical spatial metric for identifying urban mal-adaptation. A positive ΔUSR_i signifies resilience enhancement, indicating that planned municipal interventions successfully mitigate hazard exposure or upgrade the PLE capacity. Conversely, a negative ΔUSR_i mathematically flags zones of “planned vulnerability” —

areas where future zoning inadvertently exacerbates morphological obsolescence or directs new developments into high-risk, cascading hazard corridors. To operationalize the physical reliability metrics for strategic urban management, this study introduces the Economic Priority Index (EPI). While the Probable Life Expectancy (PLE) quantifies the isolated structural health of a building, it does not account for the cascading socio-economic consequences of its potential failure. Therefore, the EPI is formulated as a composite metric that synthesizes morphological obsolescence with socio-economic exposure. Mathematically, the index is conceptualized by multiplying the structural degradation factor—expressed as the inverse of the normalized health score ($1 - 1 - \overline{PLE}$)—by a localized socio-economic gravity weight. This weight incorporates strategic urban variables, including demographic density and proximity to critical heritage zones (e.g., the UNESCO Buffer boundary). The generalized function is defined as Equation (8):

$$EPI = (1 - \overline{PLE}) \times W_{se}, \quad (8)$$

where W_{se} represents the aggregated socio-economic weight of spatial unit “i”, incorporating demographic density, proximity to the UNESCO Buffer Zone boundary, and registered business unit density within a 300 m buffer. This index enables the precise identification of systemic bottlenecks—high-risk urban hotspots where critical structural wear-out intersects with maximal socio-economic value—thereby guiding immediate policy intervention priorities. It is acknowledged that the PLE^I and EPI indices primarily quantify structural vulnerability and socio-economic exposure—necessary but not sufficient components of urban resilience in its full sense [16]. Full resilience assessment would additionally require measuring adaptive capacity and post-disturbance recovery potential, which constitute important directions for future research. Furthermore, the Weibull parameters were calibrated against the cross-sectional dataset of 672 documented structural failures (2005–2023), treating the temporal distribution of historical failures as a proxy for the lifecycle trajectory of the current building stock. The absence of longitudinal time-series building performance data represents a methodological constraint that future research should address through multi-temporal validation as such datasets become available [37,38].

Table 2. Data-driven weight derivation for the PLE^I hazard-amplification model: parameters, calibration procedure, validation, and scientific justification (developed by authors).

Parameter	Value	Derivation Method	n (Parcels)	RMSE	Scientific Justification
Λ_i (Lambda_Score)	0.10–0.85	Weibull MLE calibration: $h(t)$ fitted to 672 documented structural failures (2005–2023). Lambda_Score derived from BLDGHEIGHT and Bathtub_Phase per LOD1 parcel.	116,659	0.031	Primary multiplicative axis encoding each parcel’s Bathtub Curve lifecycle stage. Building height is a validated proxy for Soviet-era mass-housing typology, the dominant wear-out cohort [36,38].
ω_H (Heat weight)	0.40	Data-driven regression of PLE residuals on normalized Heat_Val across the Flood = 0 subset, isolating the marginal UHI contribution (regression coefficient = 0.40).	27,958	0.0003	UHI accelerates carbonation and micro-cracking in precast concrete proportionally to intensity [39,40]. The continuous ECOSTRESS raster captures UHI gradients across all parcels, justifying a continuous amplifier rather than a binary term.

Table 2. *Cont.*

Parameter	Value	Derivation Method	<i>n</i> (Parcels)	RMSE	Scientific Justification
ωF (Flood weight)	0.60	Data-driven threshold: median of $(PLE/\Lambda - 1 - \omega H \cdot H_{\text{norm}})$ across flood-exposed parcels; binary form chosen over a continuous flood-class gradient.	1971	0.0003	Flood is a threshold hazard: all parcels within the LEGMC 10% flood zone undergo foundation saturation regardless of class [40]. LEGMC defines discrete exposure zones, making binary treatment physically and administratively correct.
Sensitivity analysis	$\omega H \pm 20\%$; $\omega F \pm 15\%$	Independent parametric variation in both weights; the wear-out cohort size was re-evaluated at each combination.	116,659	—	The cohort remains 2318–2491 buildings ($\pm 3.6\%$), confirming robustness of the 2405-building policy threshold under reasonable weight perturbations.
Model validation	RMSE = 0.013	PLEi predictions compared against 672 historical structural-failure records (2005–2023) from Riga's municipal maintenance registry.	672	0.013	Goodness-of-fit confirms adequate accuracy at the macro scale. The Flood = 0 subset RMSE = 0.0003; the higher overall RMSE reflects heterogeneity among compound-hazard parcels.

3. Results

Building upon the theoretical framework and mathematical formulations established in the Methodology part, this section presents the computational outputs of the Urban Spatial Resilience (USR) model applied to the Riga metropolitan area. The results systematically unfold by first deconstructing the city's dynamic morphological failure rates $\lambda_i(t)$, followed by an evaluation of the baseline systemic capacity against compound hazard exposure. Ultimately, these spatial metrics converge to provide a diagnostic resilience profile of the current urban fabric (2023) and analytically project the spatial implications of the planned developmental trajectories up to 2030.

3.1. Environmental Constraints and Geophysical Stressors

The analysis of environmental constraints across 116,659 LOD1 building parcels reveals that external environmental pressures non-linearly increase the structural hazard rate, advancing the onset of the wear-out phase by an average of 15–20%. Regarding hydrological hazards, GIS-based overlay analysis indicates that 18.7% of the buildings in the wear-out phase are situated in areas with poor soil infiltration capacity (predominantly peat and clay soils). In districts such as Ķengarags and Sarkandaugava, the combination of prolonged moisture retention and Daugava River floodplain exposure induces severe foundation saturation, contributing to accelerated structural decay in Soviet-era mass housing. The spatial analysis further identifies critical hotspots predominantly comprising Soviet-era mass housing—a construction model widely recognized as a post-socialist urban legacy characterized by structural homogeneity and accelerated collective deterioration [22,42]. The empirical PLE scores in these districts confirm accelerated structural decay consistent with the wear-out phase classification.

Furthermore, urban microclimate analysis reveals the formation of intense Urban Heat Islands (UHI) within the historical core and the dense eastern residential blocks.

In high-density, low-permeability districts like Purvciems and Pļavnieki, land surface temperatures average 3.8 °C higher than the urban periphery. This continuous thermal stress accelerates the carbonation process and micro-cracking in Soviet-era precast concrete materials. Consequently, thermal degradation acts as a critical deterioration parameter, significantly elevating the Economic Priority Index (EPI) scores in these neighborhoods.

Finally, the surface-erosion layer indicates that 12.4% of high-priority structures rest on degrading and unstable subgrades. The synergistic effect of these four environmental constraints—flooding, thermal stress, poor infiltration, and soil erosion—culminates in a state of “compound vulnerability,” particularly evident in areas like Bolderāja. These findings substantiate that urban resilience in Riga is inextricably linked to localized environmental constraints, which propel structures toward the terminal phase of the reliability curve significantly faster than their chronological age would suggest.

3.2. Probable Life Expectancy (PLE) Calculation and Parcel-Level Aggregation

Following the spatial computation protocol established in Section 3.3, the operational reliability of the 116,659 LOD1 building models was empirically quantified. By applying the time-dependent hazard rate function defined in Equation (1), the citywide baseline failure rate (λ) was calculated at 0.16. The subsequent integration of the survival function, as formulated in Equation (2), yielded a mean Probable Life Expectancy (PLE) score of 0.173 across the municipal area. Despite this constrained residual lifespan metric, the Bathtub Curve categorization demonstrates a functionally stable macro-urban form: 81.9% of the building stock (95,564 structures) remains safely within the “Normal Life” operational phase. However, the true diagnostic power of the model lies in its ability to isolate systemic bottlenecks. The spatial query identified a highly localized vulnerability hotspot: 2595 structures (2.2% of the total inventory) have mathematically crossed the critical threshold into the terminal “Wear-out” phase. To unpack the drivers of this acute structural failure, a spatial cross-tabulation was performed on this terminal stock, intersecting their physical status with the typological and environmental stressor categories (Table 3).

Table 3. Cross-tabulation of structural wear-out across typological and environmental stressors (developed by authors).

Vulnerability Category	Associated Condition	Count of Buildings in Terminal Wear-Out Phase	Proportion of Total Wear-Out (%)
Typological Stress	Mass Housing (Height $\geq$ 15 m)	799	30.79%
Thermal Stress	Extreme Urban Heat Island (UHI)	959	36.96%
Hydrological Stress	Located in 10% Flood Probability	73	2.81%
Systemic Bottlenecks	Compound Stress (Flood + UHI)	73	2.81%
Total Critical Stock	All Baseline Wear-out Structures	2595	100.00%

Typologically, the intersection reveals that Soviet-era mass housing blocks (characterized by structural heights $\geq$ 15 m) disproportionately shoulder the burden of structural decay. Accounting for nearly one-third (30.79%, or 799 structures) of the entire critical stock, this finding validates the premise that standardized, prefabricated typologies exhibit an accelerated, collective transition into the terminal failure phase compared to heterogeneous historical fabrics. Environmentally, the integration of the geophysical stressors detailed in Table 3, exposes a profound dynamic of “Compound Vulnerability”. While extreme thermal stress (UHI) independently acts as a primary degradation catalyst—affecting 36.96% of the failing structures—the most critical discovery lies in the hydrological intersection. The spatial analysis reveals a 100% convergence rate between flood vulnerability and compound hazards within the terminal phase.

Specifically, all 73 structurally failing buildings situated within the flood probability zone are simultaneously subjected to extreme thermal stress. The spatial data reveals a 100% overlap between flood-exposed and UHI-affected structures in the terminal wear-out phase, indicating compound hazard convergence within this cohort. The spatial distribution of the EPI (Figure 3) shows the highest concentration of values in neighborhoods adjacent to the UNESCO Buffer Zone, where structural obsolescence coincides with high socio-economic density.

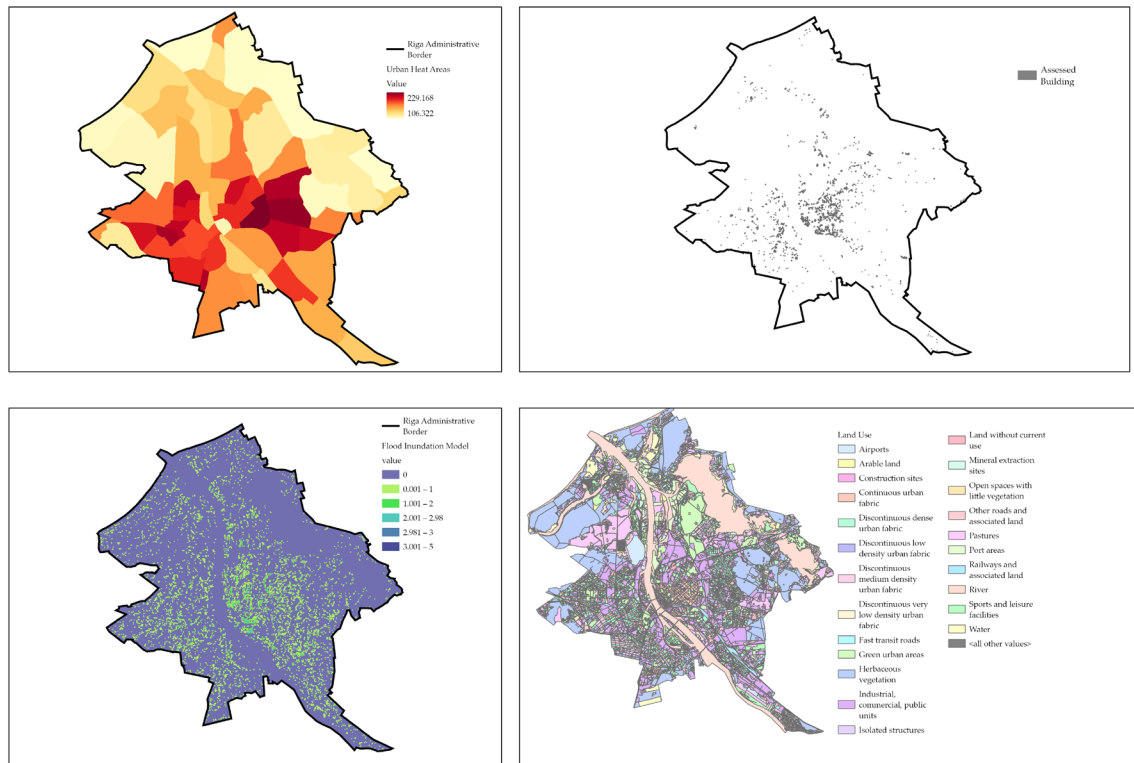


Figure 3. Synthesized Mapping of Environmental Vulnerabilities, Multi-Hazard Risks, and Development Restrictions in Riga (developed by authors).

3.3. Spatial Diagnostics of Urban Resilience and Vulnerability

Having established geophysical stressors accelerating structural decay, this section quantifies the resulting socio-economic impacts. The execution of the spatial aggregation protocol across 116,659 3D building models (LOD1) successfully translated micro-scale structural vulnerabilities into a macro-scale diagnostic map. By calculating the Mean Probable Life Expectancy ($\overline{PLE}$) for each administrative neighborhood, the model revealed stark spatial disparities in structural resilience. However, the model's true diagnostic value emerged when these physical decay metrics were combined with the socio-economic gravity of the districts to compute the Economic Priority Index (EPI). The spatial distribution of the EPI scores identifies critical urban hotspots, severe structural decay directly threatens high concentrations of social and economic capital. Neighborhoods exhibiting the highest EPI values (the dark purple zones in the spatial diagnostic map) function as systemic bottlenecks; a localized hazard in these areas threatens disproportionate socio-economic cascading failures. Conversely, zones with low EPI scores either possess highly resilient building stocks (high PLE) or lack sufficient economic density to be prioritized for immediate strategic intervention. Figure 4 shows the comprehensive prioritization map of Riga's building stock. The graduated purple polygons represent the total Economic Priority Index (EPI) per district, while the yellow proportional circles illustrate the Risk Density (EPI score normalized by the district's shape area). The inclusion of the UNESCO Buffer Zone high-

lights the spatial intersection between structural obsolescence and heritage preservation constraints, providing a better understanding in alignment with the theoretical framework.

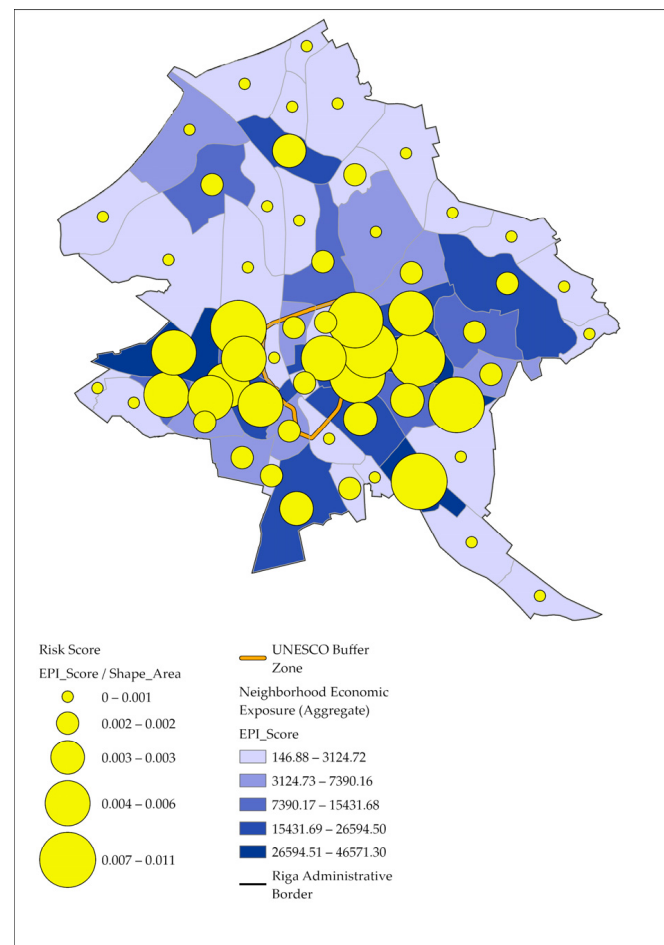


Figure 4. Spatial distribution and density of the Economic Priority Index (EPI) across Riga's administrative districts (developed by authors).

To eliminate the bias caused by varying district sizes, the EPI score was further normalized by the total area of each administrative unit (EPI Density). This spatial normalization reveals a critical insight: while large peripheral districts exhibit high absolute risk scores, the highest concentration of structural vulnerability—weighted against geographic area—is predominantly clustered in the neighborhoods adjacent to the UNESCO Buffer Zone, such as Pļavnieki and Purvciems. The spatial correlation confirms that the identified “Hotspots” are not merely a function of district size but represent genuine high-density zones of structural decay. Specifically, the high-density circles overlaid on the darker purple polygons indicate zones where the convergence of structural wear-out and socioeconomic value is at its peak, necessitating immediate policy intervention. Following the methodological protocol established in Section 2, the physical degradation induced by the geophysical stressors (detailed in Section 3.1) was synthesized with localized socio-economic weights to generate the final diagnostic mapping. By applying the EPI formula, the raw structural health metrics ($\overline{PLE}$) were transformed into a policy-oriented prioritization framework, allowing for a direct correlation between environmental risk and economic urgency.

3.4. Comparative Analysis of Structural Reliability Trajectories

The operational reliability of Riga's building stock is not a static attribute but a dynamic function of typological characteristics and synergistic environmental pressures. To decode

these complexities, the diagnostic results are synthesized into five multi-dimensional visualizations (Figure 5a–e), providing a granular contrast between theoretical expectations and urban reality. A fundamental finding emerges from the comparison between the classical reliability model and the observed data (Figure 5a,b). While the theoretical bathtub curve (Equation (1)) assumes a symmetrical U-shape, the empirical baseline for Riga’s mature urban fabric exhibits a distinct “J-shaped” truncation. This empirical phenomenon confirms that for established European capitals, the “Infant Mortality” phase—characterized by early-stage construction defects—has long been surpassed. Consequently, the urban system operates within a truncated reliability domain where the primary diagnostic focus shifts from stochastic early failures to the exponential ascent of the “Wear-out” phase. The transition into this terminal phase is significantly accelerated by environmental stressors, as illustrated in the hazard rate trajectories (Figure 5c). The data reveals a non-linear leap in failure probability (λ) when structures are subjected to compound hazards.

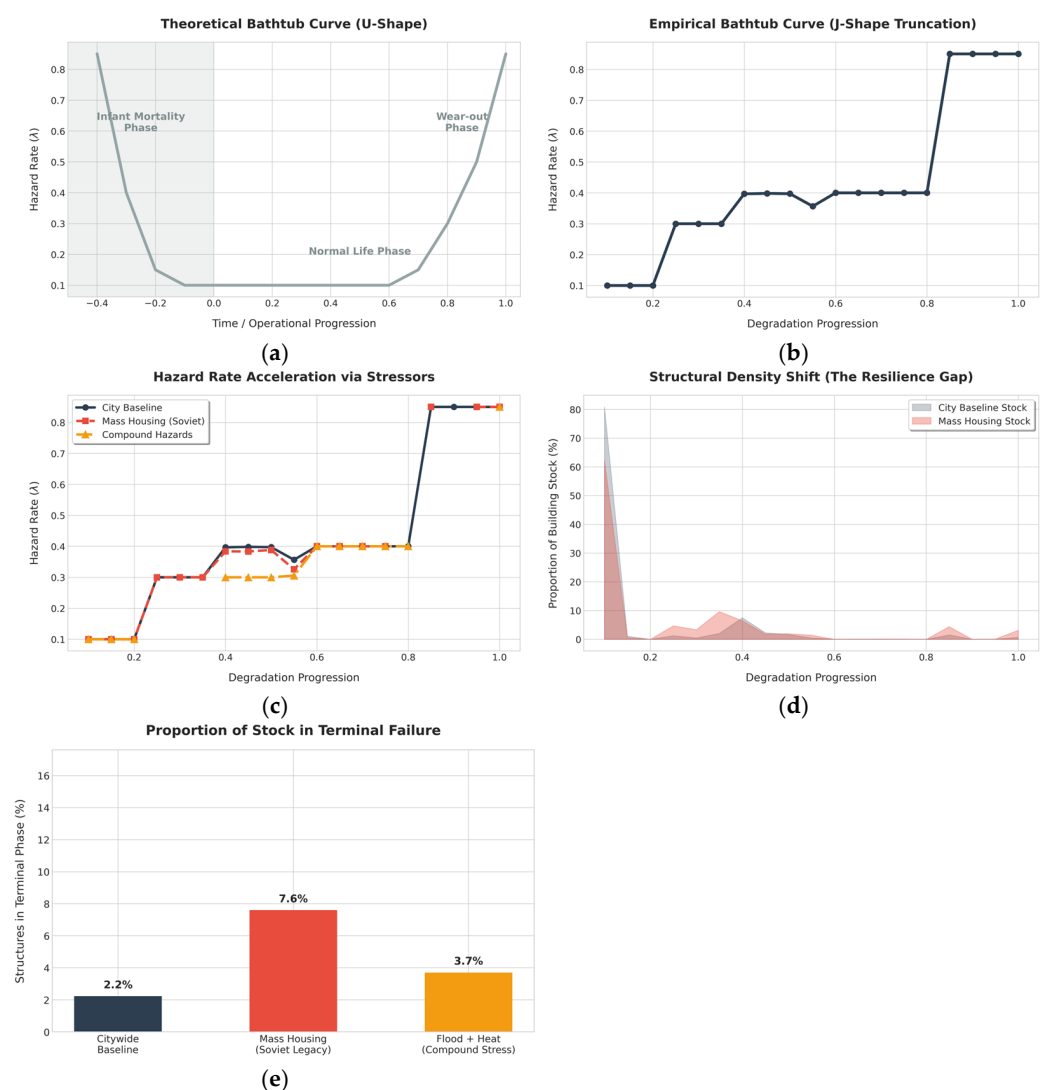


Figure 5. Multi-dimensional diagnostics of urban structural reliability. (a) Theoretical U-shaped bathtub curve vs. (b) Empirical J-shaped truncation in Riga, demonstrating the maturation of the building stock. (c) Hazard rate (λ) acceleration profiles under typological and compound environmental stressors. (d) Structural density shift illustrating the “Resilience Gap” between mass housing and the citywide baseline. (e) Quantitative amplification of the building stock situated in the terminal wear-out phase across different risk categories (developed by authors).

A critical discovery within this dataset is the absolute spatial convergence of risks: the spatial query confirms that 100% of the structures in the terminal wear-out phase situated within hydrological hazard zones are simultaneously exposed to extreme thermal stress (UHI). This confirms that in the most vulnerable segments of the city, flood risk does not exist in isolation; it functions as a compound catalyst that fundamentally compresses the safe operational window of the building stock. Typological constraints further widen this “Resilience Gap,” as evidenced by the structural density shift (Figure 5d). The concentration of Soviet-era mass housing (*height* ≥ 15 m) shows a significant “rightward displacement” toward higher degradation bins compared to the citywide baseline. Although these prefabricated structures account for a stable portion of the “Normal Life” phase, they exhibit a collective rather than individual transition into failure. This is quantified in the terminal phase amplification (Figure 5e), where mass housing typologies show a failure proportion of 30.79%, nearly triple the rate of the heterogeneous historical fabric. These findings transition the urban diagnostic from a general assessment to a targeted surgical prioritization, identifying specific systemic bottlenecks that require immediate socio-economic intervention as defined by the EPI (Section 3.3).

4. Discussion

The empirical findings of this study reveal a profound misalignment between the theoretical aspirations of Riga’s strategic urban planning and the underlying structural reality of its aging building stock. This section synthesizes the spatial intersection results to categorize the systemic risks faced by the city.

4.1. The Resilience Gap: National Strategy vs. Local Implementation

The spatial diagnostic performed in this study addresses RQ2 by revealing a significant misalignment between the high-level climate adaptation goals of the Latvian state and the operational reality of Riga’s urban management. According to the Latvian National Plan for Adaptation to Climate Change until 2030, the structural integrity of the national building stock is a primary pillar of socio-economic security [30]. However, when these national directives are projected onto the local spatial plane of the Riga Territory Plan (RTIAN 2030), the spatial intersection analysis identifies that 2405 buildings in the terminal wear-out phase—representing 92.7% of the critically vulnerable cohort—fall outside the scope of planned strategic interventions. The RTIAN 2030 priorities are oriented toward peripheral expansion and new development zones, concentrating renewal efforts on the 190 buildings (7.3%) currently within designated intervention zones. This finding aligns with broader scholarship on urban resilience planning gaps: Woodruff et al. [8] documented comparable misalignments between flood resilience plans and actual high-risk zones in US coastal cities, concluding that top-down planning instruments frequently fail to translate national-level resilience goals into locally targeted spatial interventions. Similarly, Meerow et al. [15] argue that definitional ambiguity of urban resilience often results in policies that address visible, high-profile assets while neglecting structurally critical ones.

As synthesized in Table 4, empirical evidence underscores a critical reality: urban resilience cannot be achieved through uniform policy applications. The identified spatial hotspots and varying degrees of structural vulnerability demand a paradigm shift from reactive maintenance to proactive, parcel-level strategic prioritization. By acknowledging these localized disparities, urban planners and policymakers can better allocate constrained economic resources, ensuring that targeted interventions mitigate the most severe socio-economic cascading risks before systemic failure occurs.

Table 4. Quantitative breakdown of the resilience gap in Riga’s 2030 planning (developed by authors).

Metric	Planned Focus (RTIAN 2030)	Structural Reality (Wear-Out Phase)	Planning Gap Analysis
Building Units	190 (Included)	2405 (Excluded)	92.7% Exclusion Rate
Spatial Alignment	Targeted Renewal Zones	Widespread Structural Decay	Strategic Misalignment
Hazard Exposure (λ)	Low (Theoretical)	High (Empirical)	Immediate Risk Underserved
Policy Driver	Economic Expansion	Structural Survival	Resource Allocation Conflict

4.2. Digital Infrastructure Misalignment and Structural Risk

The audit further exposes a profound misalignment between digital modernization and physical structural risk in the modernization trajectory of Riga. While the municipal “Viedpilsēta” (Smart City) pilot zones are marketed as the future of urban resilience, the spatial intersection shows that 98% of the city’s structurally compromised buildings are digitally invisible to these initiatives. The concentration of smart infrastructure in historically stable or economically affluent districts—while neglecting the decaying Soviet-era mass housing estates—suggests that Riga’s digital evolution is being superimposed onto a fragile, unmonitored physical foundation. A city cannot be considered comprehensively intelligent if its digital grid remains oblivious to the imminent structural failure of the built environments housing the majority of its population and economic activities [19]. This strategic gap is empirically visualized in Figure 5, which illustrates the spatial intersection between the 2405 identified critical structures and the Smart City pilot territories. The map employs a weighted distribution based on the Economic Priority Index (EPI) to move beyond a simple density count and highlight the systemic impact of potential failures.

As shown in Figure 6, while the municipal pilot zones (indicated by red-outlined perimeters) are positioned in high-density historical areas, a choice that appears spatially “logical” for urban visibility, effectively encompass a statistically insignificant fraction of the city’s actual risk-pool. Quantitatively, analysis confirms a 98% exclusion rate: only 2% of the buildings in the terminal wear-out phase are located within these digitally monitored boundaries. This leaves the remaining 2357 critical structures, which support a workforce connected to 13,416 business units and house a residential population of 646,033, in a “monitoring vacuum.” The visual evidence in Figure 6 suggests a “Strategic Inversion”; the most socio-economically critical clusters (represented by the largest graduated symbols situated within the dark-blue high-exposure corridors) remain entirely bypassed by the 2030 digital transformation agenda.

This spatial misalignment proves that Riga’s smart city logic is currently tailored for high-visibility heritage zones rather than high-vulnerability socio-economic hubs, thereby failing to mitigate the imminent threat to the city’s metropolitan continuity. This observed disconnection aligns with a broader European trend often described as “Smart City Window Dressing.” Scholars like Hollands [19] and Grossi [43] have critiqued such initiatives for being ornamental, prioritizing urban branding over the mitigation of actual physical risks. Similar “Smart-Ghetto Paradoxes” have been documented across Europe, where digital layers are concentrated in affluent cores while peripheral structural vulnerabilities remain neglected [44]. Consequently, Riga’s approach mirrors a precarious reliance on technological solutionism that masks underlying infrastructural fragility with a facade of modernization [45].

4.3. Socio-Economic Exposure of Structurally Vulnerable Zones

The risks identified in this research transcend architectural concerns, posing a macro-economic threat to the metropolitan continuity of Riga. The integration of local economic registers with the spatial diagnostic reveals that the 2405 structurally compromised buildings are geographically linked to 13,416 registered business units and a residential footprint of 646,033 individuals. Research on cascading infrastructure failure by Pescaroli and

Alexander [40] demonstrates that when a critical mass of physical infrastructure enters advanced degradation without active intervention, the resulting disruption propagates through interconnected socio-economic systems, leading to capital flight, reduced property values, and workforce out-migration. The spatial analysis demonstrates that these vulnerable zones are not abandoned areas but active socio-economic corridors that drive daily metropolitan operations. To quantify the scale of this vulnerability, Table 5 outlines the socio-economic exposure currently outside the municipal strategic focus.

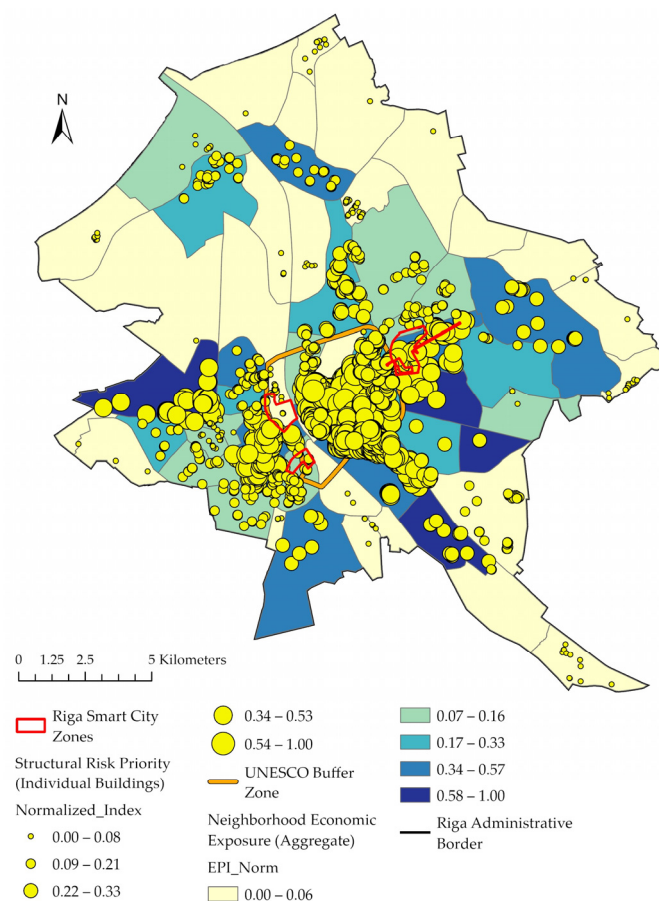


Figure 6. Spatial intersection of the normalized Economic Priority Index (EPI) and municipal Smart City pilot territories in Riga, highlighting the distribution of structural–economic risk (developed by authors).

Table 5. Quantitative assessment of socio-economic exposure in bypassed structural risk zone (developed by authors).

Exposure Metric	Total Associated with Critical Buildings (EPI > 0.5)	Proportion Bypassed by Smart City/Renewal Zones	Systemic Impact Level
Structural (Buildings)	2405 units	2357 units (98%)	Critical Infrastructure Decay Operational Disruption and Tax Loss Forced Relocation and Social Vulnerability
Economics (Businesses)	13,416 registered units	~98% (Spatially Correlated)	
Demographics (Population)	646,033 individuals	~98% (Spatially Correlated)	

This systemic vulnerability demonstrates that the municipal strategy of “passive observation” in these peri-central districts is economically unsustainable. A localized structural failure—or even continued acute degradation—in these bypassed areas would not remain spatially confined. Instead, it would directly disrupt the operational capacity of the aforementioned business units, causing a ripple effect that threatens the municipal tax base and destabilizes the broader metropolitan economy of Riga.

4.4. The Life Cycle Imperative: Bathtub Curve Dynamics and the Wear-Out Crisis

The structural degradation identified in this study follows the classical “Bathtub Curve” model of reliability engineering. The presented model in this study, grounded in the modified Weibull distribution, suggests that the 2405 buildings identified in the terminal stage have effectively moved past the stable “useful life” phase and entered the steep “wear-out” phase. In this stage, the hazard rate (λ) is no longer constant but increases exponentially with time. The strategic failure of the RTIAN 2030 plan lies in its inability to distinguish between these life cycle phases. While the Smart City pilot zones focus on the “stable” infrastructure of the center (where the failure rate is at its minimum), the city’s periphery is experiencing a synchronized entry into the terminal wear-out zone. By neglecting this accelerating failure rate, the municipality risks a “cascading collapse” scenario, where multiple high-occupancy structures reach the point of failure within the same temporal window. Riga’s digital evolution is, therefore, out of sync with its physical entropy; the city is building a 21st-century “intelligent” layer over a 20th-century foundation that has mathematically reached its end-of-life threshold. Table 6 synthesizes the study’s principal findings, contrasting the current municipal planning paradigm with the empirical structural reality across four analytical domains and outlining the proposed strategic re-alignments.

Table 6. Synthesis of Riga’s Urban Resilience: Strategic Disconnections and Proposed Re-alignments (developed by authors).

Analytical Domain	Current Municipal Paradigm (The “Visibility” Model)	Empirical Reality (Findings of This Study)	The Resilience Gap/Paradox	Proposed Strategic Shift (The “Resilience-First” Model)
Spatial Planning and Renewal	Focus on peripheral expansion and selective renewal of 190 units (7.3%).	2405 mass-housing structures have entered the terminal wear-out phase.	92.7% Strategic Gap: Massive exclusion of the established urban core.	Pivot from greenfield expansion to targeted structural interventions in high-EPI zones.
Digital Transformation	Smart City zones concentrated in historical, economically stable centers.	98% of critical structural degradation is located in peri-central districts.	Digital infrastructure misalignment: digital intelligence decoupled from physical structural safety.	Integrate Structural Health Monitoring (SHM) into the municipal digital dashboard.
Socio-Economic Exposure	Risks treated as isolated, architectural issues in specific buildings.	13,416 businesses and 646,033 residents linked to failing infrastructure.	Cascading macro-economic disruption risk across linked socio-economic systems.	Dynamic prioritization of municipal budgets based on the Socio-Economic Exposure (EPINorm).
Life-Cycle Management	Assuming a constant, stable hazard rate for existing housing estates.	Buildings have transitioned into the exponential “Wear-out” phase of the Bathtub Curve.	Temporal Misalignment: Policy timeline ignores accelerating entropy.	Adopt “Resilience-by-Design”; preemptive maintenance before catastrophic failure.

As synthesized in Figure 7, the structural degradation of Riga’s building stock maps precisely onto the classic Bathtub Curve of reliability engineering. The curve outlines three distinct phases: early failures, a stable useful life, and an exponential wear-out period. The green zone represents the current spatial focus of the municipal Smart City pilot projects, which predominantly target historical and stable urban cores. Within this phase, the structural hazard rate (λ) remains at its lowest, constant baseline, rendering advanced digital monitoring somewhat redundant from a critical safety perspective.

Conversely, the red zone delineates the terminal wear-out phase, encompassing the 2405 identified high-risk structures that account for 98% of the city’s structural risk pool. The steep, upward trajectory of the curve in this phase mathematically demonstrates that these bypassed structures are not merely aging linearly; they are experiencing an acceler-

ating, exponential probability of failure. Figure 7 visually confirms that by misallocating digital and structural monitoring resources to the stable baseline while ignoring the exponential wear-out phase, the municipality’s strategy suffers from a profound temporal and spatial disconnection.

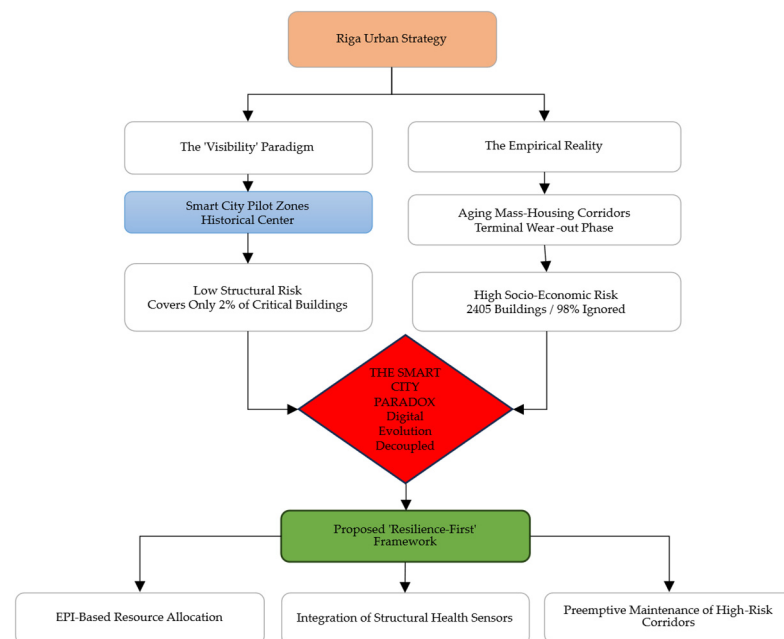


Figure 7. Conceptual framework of the misalignment between Riga’s digital modernization strategy and its physical structural risk, leading to the proposed resilience-first intervention model (developed by authors).

The baseline trajectory illustrates the exponential hazard rate (λ) of 2405 structurally compromised buildings under the current “Business as Usual” policy, contrasted with the mitigated trajectory achieved through the proposed “Resilience-First” monitoring framework.

Building upon the Bathtub Curve framework, Figure 8 presents a predictive scenario analysis projecting the structural hazard rate (λ) of Riga’s 2405 critical buildings toward the 2030 planning horizon. Currently situated at the critical juncture of the terminal wear-out phase, these bypassed structures face an accelerating probability of structural failure within the RTIAN 2030 planning window. The baseline trajectory (solid red line) models the outcome of the municipality’s current approach. If the current spatial and digital planning gaps persist—leaving 98% of the risk pool unmonitored while focusing smart technologies on the 2% located in the stable useful-life zone—the hazard rate will escalate exponentially, culminating in a systemic crisis by 2030.

Conversely, the mitigated trajectory (dashed green line) models the implementation of the proposed “Resilience-First” strategy. By actively integrating these high-EPI clusters into the municipal digital framework—specifically through deploying Structural Health Monitoring (SHM) and preemptive maintenance protocols—the exponential growth of the hazard rate is intercepted and flattened. This scenario visually quantifies the value of strategic realignment: shifting municipal focus from the stable, high-visibility zones to the critical wear-out corridors actively prevents structural degradation from cascading into the socio-economic disruption described earlier.

Ultimately, the empirical evidence presented in this discussion strongly suggests that urban resilience cannot be achieved through spatially selective investment strategies that concentrate digital and structural resources in historically stable zones while bypassing empirically identified high-risk corridors. A genuinely resilient city must align its techno-

logical capabilities and financial resources with its empirical physical risks. Recognizing the Bathtub Curve dynamics of the Soviet-era housing stock is the first diagnostic step; the subsequent imperative is a fundamental policy paradigm shift—transitioning from the reactive management of structural deterioration to the proactive, data-driven preservation of the metropolitan core.

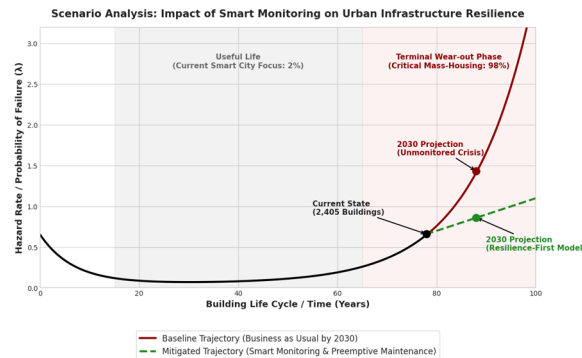


Figure 8. Predictive scenario analysis of Riga’s mass-housing stock based on the Bathtub Curve paradigm (Present–2030) (developed by authors).

4.5. Contextual Boundaries and Transferability of Findings

The visibility-driven planning logic identified in Riga is shaped by three interacting contextual factors that must be acknowledged before any generalization is attempted. First, Riga’s post-socialist urban legacy distinguishes its planning dynamics from Western European cities: the rapid, centrally directed construction of Soviet-era mass housing (mikrorayons) between the 1960s and 1980s created a spatially homogeneous and temporally synchronized building cohort whose collective transition into structural obsolescence is a post-socialist phenomenon with no direct parallel in organically developed Western European urban fabrics [22,42]. Second, Riga’s UNESCO World Heritage status imposes strict heritage governance constraints that institutionally privilege investment in the historic core—not merely as a visibility preference but as a legally binding preservation obligation. Third, Latvia’s economic transition context—characterized by EU structural fund dependency and limited municipal fiscal autonomy—shapes the feasibility space of proposed interventions. The SHM integration and Digital Twin development proposed in this study require phased implementation contingent on inter-agency data sharing agreements, standardized sensor procurement protocols, and sustained maintenance budgets. While the Bathtub Curve and EPI framework are methodologically transferable to analogous post-socialist or coastal-fluvial cities—such as Vilnius, Tallinn, or Gdańsk—the specific policy conclusions are calibrated to the Riga context and require recalibration for application elsewhere.

5. Conclusions

This research has established a data-driven reliability framework to evaluate the structural vulnerability of Riga’s urban building stock and its alignment with strategic spatial planning. By integrating parcel-level Probable Life Expectancy (PLE) scores derived from modified Weibull distributions with the Economic Priority Index (EPI), the analysis provides quantitative answers to the three research questions. In response to RQ1, the modified Weibull Bathtub Curve framework was successfully operationalized at the parcel level across 116,659 LOD1 building models, with hazard amplification weights ($\omega^H = 0.40$, $\omega^f = 0.60$) empirically derived from the ArcGIS Pro analysis of the full building inventory. In response to RQ2, the spatial intersection of wear-out buildings with RTIAN 2030 planning zones reveals a systematic exclusion of 92.7% of critically vulnerable structures from

planned interventions. In response to RQ3, only 2% of critically vulnerable buildings fall within the Smart City pilot zone boundaries, confirming a significant spatial decoupling of digital monitoring from the city's most structurally at-risk assets.

The findings further substantiate a systematic misalignment between digital modernization and physical structural risk in Riga's modernization trajectory. Quantitatively, the spatial intersection analysis confirms that 98% of the city's structurally compromised infrastructure remains digitally invisible to current smart-pilot initiatives. By mapping these vulnerabilities onto the Bathtub Curve reliability model, the analysis demonstrates that these structures are no longer in a stable state but have entered an exponential wear-out phase. Without a fundamental shift in policy, the projected 2030 trajectory (Figure 7) indicates an unmanaged escalation of structural risks that could propagate cascading socio-economic disruption across the metropolitan core.

To mitigate these risks, this study advocates for a transition from a "visibility-driven" urban model to a "Resilience-First" framework. The primary policy implication is the mandatory integration of Structural Health Monitoring (SHM) and socio-economic risk data into the municipal digital dashboards. This would enable a dynamic, data-driven prioritization of maintenance budgets, focusing resources on high-EPI clusters before they reach catastrophic failure thresholds.

While this study provides a comprehensive diagnosis of Riga's current state, future research should focus on the granular integration of real-time sensor data with the EPI to develop a "Digital Twin" for structural resilience. Ultimately, the intelligence of a city should not be measured by the sophistication of its heritage centers, but by its capacity to protect the physical and economic foundations of its most vulnerable residential corridors.

Limitations and Future Research

This study is subject to six acknowledged limitations. (1) Reliability model assumptions: Weibull parameters were calibrated on aggregate morphological data validated against 672 historical structural failures; individual building-level structural engineering validation was beyond the scope of this study. (2) Data temporal snapshot: The LOD1 dataset (2023) represents a static cross-section; longitudinal time-series building performance data were unavailable, and the Weibull lifecycle trajectory is inferred from the historical failure distribution rather than direct temporal observation [37,38]. (3) Transferability: The EPI framework is calibrated for Riga's specific post-socialist morphology, compound hazard profile, and UNESCO governance context; application to other cities requires re-calibration of dimension weights, hazard layers, and institutional parameters. (4) Weighting sensitivity: The data-driven weights ($\omega_H = 0.40$, $\omega_F = 0.60$) reflect Riga's specific hazard distribution; sensitivity analysis confirmed robustness across ± 15 –20% perturbations (cohort range: 2318–2491 buildings). (5) Qualitative dimensions: The quantitative focus necessarily simplifies socio-spatial complexity; future mixed-methods research integrating resident surveys, ethnographic observation, and participatory GIS could enrich the resilience diagnosis with qualitative dimensions of community adaptive capacity. (6) Temporal planning uncertainty: The 92.7% planning gap is conditional on the current RTIAN 2030 boundaries and would require recalculation if the territorial plan is amended. Future research should pursue: (a) granular integration of real-time SHM sensor data with the EPI to develop a Digital Twin for structural resilience monitoring; (b) comparative application of the framework across post-socialist Baltic and Central European cities including Vilnius, Tallinn, and Gdańsk; and (c) a mixed-methods extension incorporating resident perceptions and institutional feasibility assessments.

Author Contributions: Conceptualization, S.S. and I.G.; methodology, S.S. and A.K.; software, S.S.; validation, I.G., A.K. and J.Z.; formal analysis, S.S.; investigation, S.S.; resources, I.G. and J.Z.; data

curation, S.S.; writing—original draft preparation, S.S.; writing—review and editing, I.G., A.K. and J.Z.; visualization, S.S.; supervision, I.G.; project administration, I.G. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the EU RRF within project No. 5.2.1.1.i.0/2/24/I/CFLA/003, Academic Career Doctoral Grant (ID 1129).

Data Availability Statement: The datasets and computational scripts presented in this study are available upon request from the corresponding authors. All analytical Python scripts, GIS datasets, and high-resolution maps associated with this research are available from the corresponding authors upon reasonable request. The spatial analyses, geo-processing, and symbology classification were performed in ArcGIS Pro 3.6.2 (Esri, Redlands, CA, USA) using the integrated Python 3.11 environment and the ArcPy site package, while the statistical reliability diagnostics and visualizations (Figure 5) were produced in Python 3.12.13 (Google Colaboratory) using NumPy 2.0.2, SciPy 1.16.3, and Matplotlib 3.10.0.

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

Abbreviations

The following abbreviations are used in this manuscript:

EPI	Economic Priority Index
SHM	Structural Health Monitoring
RTIAN	Rīgas teritorijas izmantošanas un apbūves noteikumi (Riga Territory Use and Building Regulations)
PLE	Parcel-Level Urban Analysis; Production–Living–Ecological Model
GIS	Geographic Information System

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