

Editorial

Data-Driven Urban Resilience: From Risk Maps to Service Readiness—Closing Editorial for the Special Issue “Advances in Urban Spatial Analysis, Modeling and Simulation”

Alfonso Annunziata ¹, Dario Esposito ²  and Lucia Saganeiti ^{3,*} 

¹ School of Engineering, University of Basilicata, 85100 Potenza, PZ, Italy

² Department of Civil, Environmental, Territorial, Construction and Chemical Engineering, Polytechnic University of Bari, 70126 Bari, BA, Italy

³ Institute of Methodologies for Environmental Analysis, National Research Council of Italy (IMAA-CNR), c.da S. Loja, 85050 Tito, PZ, Italy

* Correspondence: lucia.saganeiti@cnr.it

1. Introduction

This closing editorial synthesizes the contributions gathered in the Special Issue “Advances in Urban Spatial Analysis, Modeling and Simulation.” We (i) present an introductory framing on open data, methods, and research infrastructures; (ii) outline recent methodological developments reshaping urban analytics; (iii) identify key knowledge gaps that still hinder the transition from analysis to policy; (iv) show how the five papers in this collection address those gaps with multiscale, multi-data, and decision-ready approaches; and (v) propose a forward agenda centered on comparable indicators, open benchmarking, governance thresholds, and transferability in contexts with limited data availability. Our argument aligns with broader evolutions in geospatial science, open technologies, and FAIR (Findable, Accessible, Interoperable, and Reusable) data stewardship, while remaining grounded in the pragmatic needs of cities. The following unified framework emerges: geospatial technologies and multiscale approaches represent strategic tools for guiding cities toward a more sustainable and adaptive future. Ultimately, spatial analysis and modeling should act as bridges between scientific insight and context-sensitive action—linking climate risk, microclimate, emergency response, and the reliability of everyday services.

2. Bridging Maps and Policy Goals: Toward Decision-Ready Urban Analysis

Analysis, modeling and spatial simulation are fundamental tools of modern scientific research, indispensable for understanding the complexity of spatial phenomena across diverse domains such as geography, ecology, environmental sciences and urban planning [1–3]. The growing availability of geospatial data, together with advances in computational methodologies and the rapid evolution of artificial intelligence, has profoundly transformed our capacity to describe, model and simulate spatial relationships and processes with unprecedented precision and depth [4,5]. In recent years, the most significant advances have been driven by the integration of Machine Learning and high-performance computing techniques, enabling increasingly sophisticated spatial models capable of addressing multiscale and multi-temporal dynamics [6,7].

At the same time, the importance of open, interoperable and constantly updated data has emerged as a crucial factor for advancing spatial research and ensuring its reproducibility [8]. As highlighted by recent contributions, significant challenges remain in terms



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of data accessibility and quality, particularly in developing countries, where the lack of harmonized and reliable datasets continues to constrain the full potential of spatial analysis and modeling [9,10]. In this regard, research infrastructures operating in the environmental domain play a central role in promoting data sharing, standardization and integration across disciplines, helping to build a more equitable and coherent global framework.

This Special Issue brings together a selection of studies that exemplify the latest advances in spatial analysis, modeling and simulation, focusing both on methodological innovation and the development of robust data ecosystems aligned with FAIR (Findable, Accessible, Interoperable, and Reusable) principles. The collected papers address some of the most pressing challenges of the 21st century, from urbanization and climate change to natural risk management, environmental sustainability and large-scale natural disasters.

Despite their diverse geographical and socioeconomic contexts, spanning cities from Mexico to Japan and from India to Thailand, the studies reveal a set of common challenges: hydraulic risks, climate change, unplanned urban growth and demographic decline [11–15]. Through innovative methodologies based on GISs (Geographic Information Systems), remote sensing and predictive modeling, the studies demonstrate the potential of nature-based solutions, green infrastructure, and spatial analysis to enhance urban resilience, optimize services and strengthen social cohesion.

A unified framework emerges: geospatial technologies and multiscale approaches represent strategic tools for guiding cities toward a more sustainable and adaptive future.

Yet, these contributions also underline a recurring theme—the critical need for reliable, up-to-date and open data. In developing countries in particular, data scarcity or fragmentation remains a major obstacle to both research and planning, limiting the capacity to implement evidence-based strategies. In this context, research infrastructures, especially in the environmental domain, play a pivotal role. Ensuring access to FAIR data means not only enhancing the quality of analyses and models but also enabling more effective and inclusive decision-making [16,17]. This, in turn, aligns with broader policy visions for open, interoperable and trustworthy data ecosystems [18,19].

This Special Issue, therefore, contributes to the ongoing scientific and political debate on how the integration of advanced methodologies and open data can foster more resilient cities, more cohesive societies and more sustainable management of natural resources.

The remainder of this editorial is organized as follows: Section 3 outlines recent developments in the field; Section 4 identifies the key knowledge gaps that still limit impact and transferability; Section 5 explains how the contributions in this Special Issue address those gaps with multiscale, multi-data and decision-ready approaches; Section 6 sketches future research directions and operational priorities; finally, the concluding remarks synthesize the main messages and policy implications of this issue.

3. Recent Developments in the Field

Urban spatial analysis has moved decisively into a data-rich, model-aware phase. The convergence of open geospatial ecosystems, multi-platform sensing, and advances in computational modeling has shortened the distance between observation, simulation, and policy use. In practice, this maturation is visible in three intertwined trajectories that now structure much of the field: (a) the multiscale integration of urban form, flows, and functions; (b) multi-platform remote sensing and data fusion that feed decision models in near-real time; and (c) benchmarking of modeling choices within open, web-distributed environments that make workflows auditable, reusable, and governance-ready.

(a) Multiscale integration of form, flows, and functions.

Toolchains increasingly connect street- and building-scale morphologies to neighborhood and city performance, combining Space/Place Syntax, accessibility analytics, and

decision frameworks with hydrologic and risk models. This enables a tighter loop between spatial diagnosis and operational prioritization, reflecting a decade of advances in open tooling for transport and spatial planning that have lowered entry barriers and improved reproducibility, in particular, through open-source transport planning toolchains [1,2,7,8].

(b) Multi-platform remote sensing and data fusion.

The coupling of VHRS (Very-High-Resolution Satellite) imagery, UAV photogrammetry (Unmanned Aerial Vehicle photogrammetry), and SAR data (Synthetic Aperture Radar data) is now mainstream in urban analytics, supporting UCP (Urban Canopy Parameters) for microclimate models, damage and hazard mapping, and land-use updates in near-real time. These pipelines embody the broader turn toward data-driven Earth system analysis, where ML (Machine Learning) complements, and does not replace, the understanding of processes [5–7]. In data-scarce settings, such fusion compensates for missing administrative datasets and aligns with long-standing efforts to build SDIs (Spatial Data Infrastructures) that are fit for public decision-making [9,10].

(c) Benchmarking of modeling choices and open, web-distributed simulation.

The field is moving from one-off demonstrations to explicit comparisons between deep learning and physics-based models, judged on shared datasets with transparent scorecards that balance accuracy, sensitivity to extremes, interpretability, compute costs, and involve data footprints. This shift echoes calls for open, web-distributed, integrated modeling, so workflows are auditable, reusable, and broadly participatory, and aligns with the reproducibility agenda in geospatial science [4,8]. It also converges with the concepts of open science, FAIR data stewardship and emerging data infrastructures that operationalize findability, accessibility, interoperability, and reusability at scale, including the FAIR emphasis on machine-actionability [15–18]. This maturation is accompanied by transformative governance frameworks that treat resilience as an evolutionary process rather than a state to optimize: a stance that helps connect technical benchmarking to institutional learning and policy uptake and resonates with the idea of light-weight governance and Rules of Engagement (RoE) for open, federated data/model ecosystem [4,8,15–18,20].

4. Key Knowledge Gaps

Despite clear progress, impact and transferability remain uneven. Cities often experience exceptional one-off studies that are hard to compare, replicate, or translate into procurement clauses and service levels. Four gaps, in particular, still limit the step from analysis to policy and operations: the absence of comparable cross-domain indicators, the scarcity of open benchmarks and reproducible pipelines for method selection, the under-representation of socio-spatial co-evolution in models, and the lack of operational thresholds and governance hooks that embed results into everyday decisions.

Gap 1—Comparable cross-domain indicators.

Cities need a compact dashboard to compare options across domains—minutes-to-coverage for emergency response; the volume of rainwater retained per hectare; UCP (Urban Canopy Parameters) completeness and derived thermal load indices for microclimate readiness; kg/inh/day and recycling sharing for waste services; and the amount of built-up areas that are exposed under given return periods (at TR X, i.e., at return period X). Without comparable metrics, prioritization across departments remains ad hoc, even when methods are advanced [1,2,7,8].

Gap 2—Open, benchmarked pipelines for method selection.

Choices between ML (Machine Learning), hybrids, and physics-based simulations are rarely tested on shared datasets with reproducible codes and agreed scorecards. The lack of open benchmarks slows institutional learning and undermines confidence in transferring

methods across contexts—precisely the challenges flagged in data-driven geospatial and Earth-system communities (including issues of bias and generalizability) [4–8].

Gap 3—Socio-spatial co-evolution.

Exposure and vulnerability are too often treated as static overlays. In reality, demographic changes, land-use dynamics, and service provision co-evolve, reshaping accessibility and risk profiles through feedback. Absent dynamics from these strategies risk maladaptation—a concern that becomes acute under shrinkage or rapid densification [2,6].

Gap 4—Operational thresholds and governance hooks.

Technical results underperform when they are not translated into SLAs (Service-Level Agreements), regulatory thresholds, procurement clauses, or monitoring routines. The “last mile” from analysis to policy requires codified targets and accountability, supported by FAIR-compliant data governance and interoperable SDI infrastructures, ideally implemented via light-weight governance and clear Rules of Engagement (RoE) for data and model sharing [8,15–18,20].

5. How This Special Issue Addresses These Gaps

The five papers assembled here close the loop between methods and policy goals by pairing technical advances with clear, decision-oriented outputs. Collectively, they operate a consistent toolkit: multiscale analyses that travel from building to city, multi-platform data fusion (VHRS/UAV/SAR) that feeds robust models, and comparable indicators that can be embedded in SLAs, plans, and procurement. Each contribution tackles a different part of the problem, benchmarking models, standardizing parameters, quantifying time-critical coverage, or scheduling everyday services so that, taken together, they directly address the four gaps identified above and make results transferable, auditable, and governance-ready.

(1) Green Infrastructure for reintegrating fragmented urban fabrics (Ciudad Juárez, Mexico).

Granados Aragonez et al. integrate Space/Place Syntax, MGWR (Multiscale Geographically Weighted Regression), fuzzy multi-criteria analysis, and hydrologic reasoning to identify high-leverage GI (Green Infrastructure) sites across city, local, and micro scales [11]. This approach operationalizes Gap 1 via trans-scalar indicators (e.g., infiltration capacity; pedestrian accessibility) and addresses Gap 4 through a planning-ready shortlist for investment phasing, echoing open-toolchain best practices in transport and spatial planning [1] and enabling dashboard-ready metrics.

(2) Urban Canopy Parameters from multi-platform remote sensing (India).

Gupta et al. fuse VHRS stereo imagery and UAV photogrammetry to derive building heights and footprints with sub-meter errors, producing a UCP that is directly consumable by microclimate models [13]. This advances Gap 2 with an open, replicable workflow and supports Gap 1 by standardizing parameter sets for district-scale thermal analysis. This is consistent with the call to pair ML with process understanding in Earth-system contexts [5–7].

(3) Flood hazard mapping and urban shrinkage (Japan).

Safabakhshpachehkenari et al. compare SAR-based deep learning segmentation with a physics-based flood simulator, intersecting outputs with building-level abandonment potential to assess evacuation site robustness [12]. This paper directly tackles Gap 2 (transparent benchmarking) and Gap 3 (socio-spatial co-evolution), and it showcases why method selection must be explicit with auditable principles at the heart of open, web-distributed modeling and reproducibility debates [4,8].

(4) Time-critical coverage for emergency response (Thailand).

Arreeras et al. quantify 3–5–10 min coverage for firefighting, police, and medical services via network-based accessibility, revealing gaps and redundancies [14]. By translating

configuration into temporal SLAs, this study provides a template for Gap 1 and Gap 4: indicators that cities can adopt in preparedness plans, facility siting, and shift scheduling aligned with public-health-relevant SDIs and data-ecosystem governance for emergency planning [9,10].

(5) Spatial analytics for solid-waste collection (Chiapas, Mexico).

Araiza-Aguilar et al. use composition, density, and generation rates to cluster collection sectors and design operational calendars, extending the resilience agenda to everyday service reliability [16]. This addresses Gap 4 with monitorable KPIs (e.g., missed pickups per 1000 households and recycling sharing), and complements hazard-centric studies with a service-performance lens, reinforcing the need for interoperable, FAIR-aware municipal data cycles [15–20].

6. Future Research Directions

Building on these contributions, and in continuity with open/FAIR practices, we highlight five priorities that will transition this field from promising prototypes to institutional routines. The emphasis should shift from inventing new models to standardizing metrics, establishing open, comparable benchmarks, linking maps to operational thresholds (SLAs), and modeling the co-evolution between risk, services, and urban transformations. Finally, we call for transferable playbooks and capacity-building pathways for data-scarce administrations, so that analyses and simulations become truly decision-ready at the urban scale.

Direction 1—A minimal cross-domain dashboard.

Co-design should be conducted with city departments with a small, stable set of comparable metrics: coverage ≤ 5 min; runoff retained m^3/ha ; UCP completeness/thermal load index; exposed built-up area (km^2) at TR X; waste reliability (missed pickups/1000 hh; recycling %). Clear definitions, data needs, and target ranges should be published, leveraging open geospatial tooling to standardize computation and sharing [1,8,15–20].

Direction 2—Open benchmarks for method selection.

Shared datasets and scorecards should be established to compare ML, hybrid, and physics-based approaches for flood mapping, microclimate readiness, and accessibility under disruption, reporting accuracy, sensitivity to extremes, interpretability, compute cost, and data footprints. Web-distributed and integrated environments can make such benchmarks living resources for cities and researchers alike [4–7].

Direction 3—Co-evolutionary models of risk and services.

Models should be developed that explicitly capture feedback loops among demographics, land-use, accessibility, and service provision (e.g., service cuts $\rightarrow$ perceived decline $\rightarrow$ out-migration $\rightarrow$ degraded coverage). This reduces maladaptation risks under shrinkage or rapid densification, and answers calls for more robust, data-driven environmental modeling practices [2,6,21].

Direction 4—From maps to thresholds: SLAs and governance hooks.

Spatial outputs should be translated into SLAs (Service-Level Agreements) and thresholds that can be encoded in regulations and procurement (e.g., $\geq 95\%$ of at-risk facilities within 5 min for firefighting and GI portfolios (Green Infrastructure portfolios sized to retain the first 25 mm event). Threshold sensitivity should be tested and monitoring routines compatible with municipal capacities proposed, grounded in reproducibility and FAIR stewardship [8,15–20].

Direction 5—Transferability playbooks for data-scarce cities.

There is a need for package methods as stepwise recipes with required vs. optional data, default parameters, validation shortcuts, and good-enough variants, supported by open-source code/notebooks and training modules for municipal staff. This will opera-

tionalize lessons from open geospatial ecosystems while aligning with SDI governance for public health and environmental services [1,9,10,15–20].

7. Concluding Remarks

“Resilience” is not only about rare extremes; it also hinges on the reliability of everyday services [22,23]. The five papers in this Special Issue show how to connect hazard mapping, microclimate readiness, emergency coverage, and waste operations through comparable indicators and benchmarked pipelines. The next step is to standardize metrics, open benchmarks, and codify thresholds, underpinned by FAIR-compliant data governance, so that cities can act with confidence, turning spatial analysis into a durable decision infrastructure [1–8,15–20]. From this perspective, urban resilience becomes an evolutionary governance project that shifts from control to co-creation and is well captured by ladder-based approaches for chronic crises [21].

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

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