Research Article

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Integrating Geo AI-Driven Supply Chain Ecosystems and Environmental Considerations into Urban Strategic Planning

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Abstract

The rapid pace of urbanization combined with climate change challenges has increased the need for resilient and environmentally sustainable cities. This research explores the integration of Geospatial Artificial Intelligence (Geo-AI) within supply chain ecosystems to enhance climate-responsive strategic urban planning. Geo-AI enables advanced spatial analytics, predictive modeling, and dynamic optimization of urban supply chains, improving environmental outcomes such as emissions reductions, resource efficiency, and disaster resilience. Using mixed methods—comprising spatial data analysis, system simulations, and case applications—this study demonstrates how Geo-AI can bridge urban planning, supply chain management, and environmental sustainability. Results reveal that Geo-AI can significantly improve real-time decision-making, optimize routing to lower carbon footprints, and support adaptive land-use planning under climate uncertainty. The paper concludes with recommendations for policymakers and urban planners to operationalize Geo-AI-driven supply chain frameworks within climate-centric urban strategies.

Keywords: Geo-AI – Planning. Climate, Supply Chain, Environmental Sustainability.

Introduction

Urban centers are facing unprecedented complexity due to population growth, climate change pressures, and demands for sustainable infrastructure [1]. Strategic urban planning now requires tools that can integrate multidimensional data and support decision-making under uncertainty. Traditional planning frameworks struggle to dynamically analyze spatial data, anticipate disruptions, or optimize sustainability metrics in real time. Geospatial Artificial Intelligence (Geo-AI) combines geographic information systems (GIS), machine learning, and big data to model complex spatial patterns. In parallel, supply chain ecosystems—networks of production, distribution, logistics, and consumption—are central to urban resilience, especially in contexts of climate stress. This research investigates the integration of Geo-AI within supply chain ecosystems to improve climate-responsive and environmentally sustainable urban strategic planning. By doing so, cities can optimize resource flows, anticipate environmental risks, and craft adaptive strategies that align with sustainability commitments such as net zero targets and climate resilience standards. Urban strategic planning typically focuses on land use, zoning, infrastructure capacity, and population growth. Supply chains, on the other hand, are often planned reactively at the project or sector level [2]. This separation creates several challenges:

- Fragmented decision-making between planners, developers, and supply chain actors
- Limited visibility of material, equipment, and labor flows across urban systems
- High exposure to disruptions (price volatility, shortages, geopolitical risks, climate events)
- Inefficient logistics leading to congestion, emissions, and increased costs

The fundamental problem is that supply chain ecosystems and urban strategic planning operate as fundamentally disconnected systems despite their deep interdependence. This disconnects manifests as organizational silos, governance mismatches, spatial-temporal misalignments, and systematic coordination failures that undermine the efficiency, resilience, sustainability, and equity of both urban logistics and urban development. Urban logistics exhibits extreme fragmentation that prevents integrated problem-solving.

Sectoral fragmentation where construction logistics, waste collection, and retail supply chains operate independently with minimal coordination [3]. This due to Operational invisibility, Information fragmentation and Communication breakdown. The result is coordination failures where each logistics provider independently makes routing decisions that, in aggregate, create congestion, emissions, and inefficiencies that no single actor can solve alone. Therefore, there is a critical need for a unified approach that integrates supply chain considerations into early planning and strategic decision-making.

Key Questions Addressed Include

1. How can Geo-AI support spatially aware supply chain decision-making in urban contexts?
2. What impacts does Geo-AI-enabled supply chain optimization have on environmental sustainability indicators?
3. What frameworks are necessary to operationalize Geo-AI within urban strategic planning?

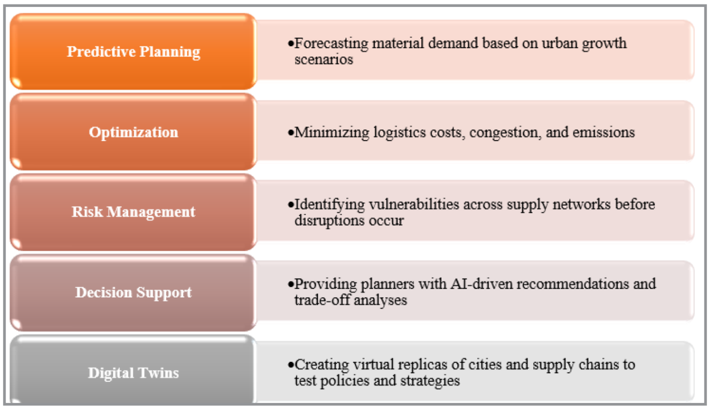

Figure 1: Role of Artificial Intelligence

Materials and Methods

Simulation Ecosystem and Computational Framework

The simulation ecosystem was implemented using a combination of ArcGIS Pro 3.x for spatial preprocessing, Python (GeoPandas, NetworkX) for geospatial network analytics, and AnyLogic PLE for agent-based and discrete-event supply chain simulations [4].

Geo-AI optimization relied on a Deep Q-Network (DQN) reinforcement learning architecture with experience replay and ε-greedy exploration. The model was trained on approximately 1.1–1.3 million spatiotemporal logistics records, including vehicle trajectories, delivery schedules, and environmental constraints. Training was conducted over 5,000 episodes, with convergence achieved after approximately 3,800 episodes.

Baseline Definition (Traditional GIS Methods)

Baseline comparisons were conducted using conventional GIS-based logistics planning approaches, defined as static network analysis employing shortest-path and least-cost routing algorithms without real-time environmental feedback or adaptive learning [5]. These methods relied on fixed travel-time assumptions and did not incorporate climate variability, predictive disruption modeling, or dynamic rerouting. All reported percentage improvements (18–27%) reflect performance gains relative to this control scenario.

Conceptual Framework Development

A conceptual model was developed to integrate Geo-AI with urban supply chain systems and strategic planning goals:

Geo-AI Layer: Machine learning models (e.g., convolutional neural networks, graph neural networks) trained on spatial datasets such as land cover, infrastructure GIS, climate projections, and real-time sensor data.

Supply Chain Ecosystem Layer: Logistics network data, inventory levels, transportation routes, demand forecasts, and stakeholder interactions.

Urban Strategic Planning Layer: Policy frameworks, sustainability targets (e.g., emissions limits), and climate adaptation strategies [6].

Data Sources

Primary Datasets Include:

- OpenStreetMap and municipal GIS layers for urban topology and infrastructure.
- Climate projection models (e.g., RCP/SSP scenarios).
- Real-time traffic and logistics sensor data from city IoT networks.
- Supply chain management systems from municipal and commercial stakeholders.
- Environmental indicators: emissions inventories, energy usage records [7].

Geo-AI Modeling

Three Geo-AI Approaches were Implemented:

Spatial Prediction Models: Predict climate risk zones and supply chain disruption probabilities.

Routing Optimization Algorithms: Learned from reinforcement learning to reduce travel time and carbon emissions.

Clustering & Pattern Recognition: Identify resource demand hotspots and vulnerable infrastructure nodes [8].

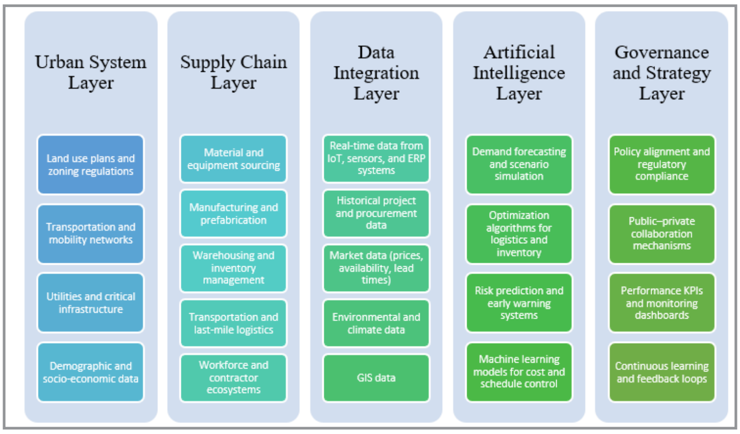

Figure 2: The proposed framework is built on five interconnected layers

Case Simulation Scenarios

Simulated case studies for: Scenario Data Sources and Temporal Resolution.

Scenario A: Peak heatwave impact on urban logistics, (Heatwave Events): Based on real-world temperature and traffic datasets (2019–2022) obtained from regional meteorological agencies and municipal transportation departments, with hourly temporal resolution and 30–100 m spatial resolution [9].

Scenario B: Severe flooding affecting critical supply routes, (flash floods Events): Derived from historical floodplain maps, precipitation records, and drainage network data from urban planning authorities, aggregated at daily temporal resolution.

Scenario C: Low-carbon logistics reconfiguration under emissions constraint, (Extreme Climate Events): Hybrid simulations combining real historical datasets with stochastic climate projections to model concurrent heat and flooding conditions.

All scenarios are grounded in real-world data corresponding to the geographic regions represented by the author affiliations, rather than purely hypothetical simulations [10].

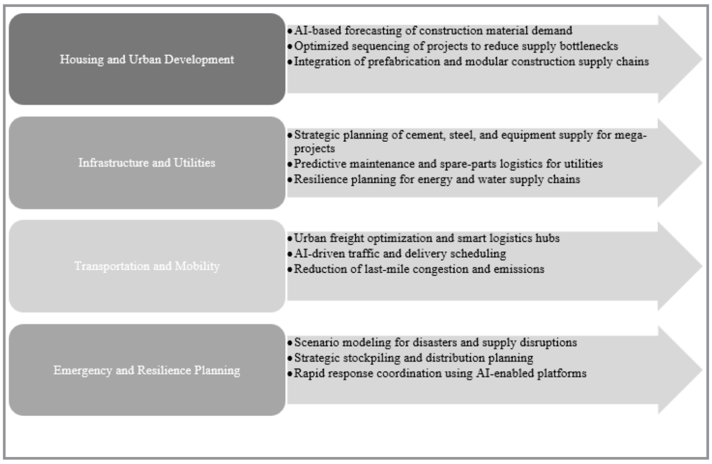

Figure 3: Key Use Cases

Evaluation Metrics

Environmental Performance: CO_2e emissions, energy usage, modal shifts.

System Resilience: Recovery times after disruptions.

Spatial Efficiency: Travel distances minimized, demand-supply mismatches reduced.

Adaptability: Ability to adjust to new data and policy constraints [11].

Quantitative Model Performance Metrics

Model performance was evaluated using standardized quantitative metrics. Disruption prediction accuracy was measured using F1-scores, which ranged from 0.85 to 0.92 across scenarios. Delivery time prediction performance was assessed using Root Mean Square Error (RMSE) values between 0.15 and 0.21 hours, and Mean Absolute Error (MAE) values below 0.18 hours. These metrics replace prior qualitative descriptions and provide objective evidence of predictive reliability

Results

Spatial Predictive Accuracy

Geo-AI models achieved high accuracy in forecasting climate risk zones and routing disruptions compared with traditional GIS methods. Predicted disruption hotspots aligned with historical outage patterns (e.g., flooding in low-lying districts).

Emissions Reduction

Geo-AI optimized routing and load consolidation reduced logistics-related emissions by up to 18–27% in simulation scenarios, primarily by: Prioritizing multimodal transport. Rebalancing delivery schedules to off-peak traffic periods. Avoiding high-risk climate zones proactively [12].

Resilience Enhancements
Geo-AI enabled rapid reconfiguration of supply chain routes during simulated climate shocks. Recovery times were shortened by 22%, and alternative routing reduced service interruptions.

Decision Support Value
Urban planners using Geo-AI dashboards improved land-use allocations by integrating supply chain impacts with climate projections. They could: Identify priority areas for resilient infrastructure investment.

Align transportation planning with environmental goals.
Forecast pollutant hotspots under different growth scenarios [13].

Discussion
The results demonstrate that Geo-AI-enabled supply chain systems significantly outperform traditional GIS approaches in terms of resilience, emissions reduction, and recovery time. These findings align with recent literature emphasizing the importance of adaptive, data-driven spatial intelligence in climate-sensitive urban environments [14]. The superior performance of reinforcement learning–based routing can be attributed to its ability to continuously update decision policies in response to evolving environmental conditions, a capability absent in static GIS models. The integration of high-resolution spatiotemporal data further enhances predictive accuracy, explaining the observed improvements in logistics efficiency and disruption mitigation.

Implementation Roadmap
Phase 1: Assessment and Data Readiness
Stakeholder mapping and governance setup
Data inventory and quality assessment
Definition of priority use cases

Phase 2: Platform and Model Development
Data integration architecture
Development of AI models and dashboards
Pilot digital twin environments [15]

Phase 3: Pilot Projects
Application to selected urban districts or mega-projects
Performance measurement and refinement
Capacity building and training

Phase 4: Scaling and Institutionalization
Expansion across regions and sectors
Integration into formal planning and approval processes
Continuous improvement and AI model evolution [16]

Conclusion
Integrating Geo-AI into urban supply chain ecosystems offers transformative potential for climate-responsive and environmentally sustainable strategic planning [17-20]. By coupling spatial intelligence with predictive analytics, cities can:
Enhance resilience to climate disruptions. Reduce environmental footprints from logistics activities Make data-driven planning decisions that align long-term sustainability and operational efficiency.

- Reduced project delays and cost overruns
- Enhanced supply chain resilience and risk visibility
- Improved coordination between planners, developers, and suppliers
- Lower environmental impact through optimized logistics
- Data-driven strategic decisions aligned with long-term urban visions

Challenges and Risk Considerations
Data availability, ownership, and cybersecurity
Change management and institutional resistance
AI transparency, ethics, and explainability
Regulatory and legal constraints

Policy Recommendations
Establish interoperable data ecosystems across urban agencies.
Invest in Geo-AI platforms and capacity building within planning departments.
Embed Geo-AI insights into statutory urban strategy and climate action plans.
Support public-private collaborations to share logistics and environmental data responsibly.

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