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Engineering Sustainable Supply Chain Optimization in Resource-Constrained Environments: A Geo-Spatial and AI-Based Data Science Perspective.

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KEYWORDS

Sustainable supply chain engineering, Geo-spatial analytics, AI-based optimization, Resource-constrained environments, Remote sensing, Machine learning, Spatial modeling, Predictive logistics, Supply chain resilience, Data-driven decision support

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ABSTRACT

Engineering sustainable supply chains in resource-constrained environments has become a critical priority for developing regions facing infrastructural bottlenecks, unpredictable demand patterns, and rising climate-induced disruptions. This study presents an integrated geo-spatial and AI-driven data science framework designed to optimize supply chain resilience, efficiency, and resource allocation across constrained terrains. Using multi-layered datasets that include satellite-derived indicators, road network topology, facility distribution, demographic density, and environmental stressors, the research employs geospatial analytics to map logistical vulnerabilities and influence zones of supply movement. Advanced machine learning and optimization models, including Random Forest, XGBoost, and spatio-temporal LSTM forecasting, are implemented to predict demand flows, identify bottlenecks, evaluate route feasibility, and recommend cost-efficient transport corridors. Spatial interpolation, hotspot detection, and network-based accessibility analysis further support the identification of high-risk operational zones where resource scarcity, weak infrastructure, and climatic variations intensify logistical fragility. The findings demonstrate that integrating remote sensing, GIS-based supply chain mapping, and AI-enabled optimization significantly enhances resource prioritization, reduces transport delays, and improves sustainability outcomes. The study establishes a scalable, data-driven methodology for supply chain planning that is applicable to agriculture, healthcare, disaster relief, and industrial sectors in resource-limited environments.

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1. INTRODUCTION

The optimization of supply chains in resource-constrained environments has emerged as one of the most urgent engineering challenges of the twenty-first century. Regions experiencing infrastructural deficits, climatic stresses, irregular demand cycles, and limited technological capacity often struggle to maintain stable and sustainable supply flows, especially for essential commodities such as agricultural inputs, healthcare logistics, emergency relief materials, and industrial raw goods. Traditional supply chain models, built around assumptions of stable access, predictable movement, and abundant resources, fail when deployed in terrains with fragmented road networks, fluctuating environmental conditions, or recurring scarcity. In such settings, transport bottlenecks, demand surges, fuel limitations, labor shortages, and environmental degradation .

converge to create highly nonlinear, risk-loaded logistical landscapes. The inefficiencies that arise longer travel times, supply imbalances, route failures, storage losses, and increased emissions directly impact economic stability, social welfare, and sustainability outcomes. Complexities intensify in regions where climate-induced events such as droughts, floods, or heatwaves disrupt existing routes and reshape resource availability. Given these multi-dimensional pressures, engineering a resilient supply chain demands an interdisciplinary approach that fuses systems thinking, environmental monitoring, geospatial intelligence, and AI-driven analytics. Geospatial technologies, remote sensing, and machine learning together provide the ability to model terrain constraints, track environmental variations, forecast demand surges, and evaluate the feasibility of supply routes in real time. These tools create a dynamic, data-rich representation of the supply chain ecosystem far beyond what conventional spreadsheet-based logistics or static network diagrams can reveal.

At the forefront of sustainable supply chain engineering lies the integration of remote sensing, GIS-based vulnerability mapping, and AI-enabled optimization models. Satellite imagery, multispectral indices, and spatio-temporal environmental layers help quantify land-use patterns, seasonal variation, vegetation cycles, water scarcity zones, thermal stress, and infrastructure disruptions that influence supply movement. When combined with road network graphs, accessibility scores, demographic distribution, warehouse locations, and consumption clusters, these datasets form a spatially explicit model that captures the hidden drivers of inefficiency within resource-constrained regions. AI models such as Random Forest, XGBoost, neural networks, and LSTM architectures enhance this framework by predicting demand fluctuations, identifying congestion hotspots, estimating travel risks, and recommending optimized routes under evolving constraints. Moreover, reinforcement learning and linear–nonlinear optimization frameworks help engineers simulate trade-offs among cost, resiliency, energy use, and sustainability targets. Such integration of geo-spatial data science transforms supply chains from reactive systems into predictive, adaptive networks capable of anticipating disruptions and planning around them. As global supply chains face increasing volatility, the need for spatially aware, AI-augmented decision systems is no longer optional especially for developing regions with high sensitivity to environmental and infrastructural limitations. This study contributes to that need by presenting a rigorous, scalable methodology that blends geo-spatial analytics, AI-driven modeling, and sustainability engineering to design resilient supply chains suited for real-world constraints. Through this interdisciplinary lens, the research offers actionable insights into optimizing resource flows, identifying high-risk corridors, and supporting long-term sustainability planning for sectors operating under severe resource limitations.

2. RELEATED WORKS

Sustainable supply chain optimization in resource-constrained environments draws heavily from interdisciplinary research that connects geospatial analytics, environmental informatics, and data-driven logistics. Several foundational studies highlight that traditional supply chains operating in highly variable terrains lack real-time spatial intelligence, which limits their ability to adapt to environmental and infrastructural disruptions. Early work by Zhang et al. [1] established that remote sensing indicators can be used to identify surface-level stressors drought zones, degraded vegetation, and temperature deviations that directly affect agricultural and industrial supply chains. This finding was reinforced by Chen and Gupta [2], who demonstrated that environmental anomalies correlate with upstream supply bottlenecks in regions dependent on climate-sensitive production. Network vulnerability studies, such as those by Miller et al. [3], used GIS-based transport modeling to show how road connectivity, terrain slope, and settlement distribution shape accessibility during peak demand cycles. Researchers also investigated resource-scarce humanitarian logistics, where Landry and Barasa [4] emphasized that geospatial mapping of conflict zones and weather disturbances significantly improves allocation efficiency. Meanwhile, satellite-derived features have been used to detect infrastructure degradation, such as bridge failures or road washouts, which directly affect route feasibility; this was shown in remote sensing studies by Khandelwal et al. [5]. The importance of spatial heterogeneity is highlighted in works like Li and Thompson [6], who proved that logistical efficiency depends on local variations in land use, micro-climates, and demographic clustering rather than macro-level planning alone. Collectively, these studies form a strong foundation for the integration of Earth observation data into sustainable supply chain engineering.

Parallel to geospatial innovations, AI-driven decision-support systems have reshaped how supply chains are modeled, forecasted, and optimized under constraints. Machine learning algorithms such as Random Forest, XGBoost, and Support Vector Regression have been applied to forecast demand shocks, predict inventory shortages, and evaluate transport time variability. For example, Mukherjee et al. [7] used Random Forest models to detect high-risk delays across fragmented rural transport networks, noting that model accuracy increased significantly when remote sensing variables were included. Similarly, Wang et al. [8] demonstrated that LSTM-based spatio-temporal forecasting effectively predicts supply fluctuations during seasonal transitions, especially in food and agricultural chains. Reinforcement-learning frameworks have also gained prominence; Castillo and Raghavan [9] showed that dynamic routing systems trained on real-time environmental inputs outperform static routing models by up to 32% in constrained settings. Another influential study by Alves et al. [10] applied linear–nonlinear hybrid optimization to evaluate trade-offs between cost, carbon emissions, and transport resilience, highlighting that multi-objective optimization is essential for sustainable outcomes. In disaster logistics, Vega and Sundaram [11] argued that integrating AI classifiers with GIS-based hazard maps allows for improved pre-positioning of essential supplies. Recent developments have also focused on integrating remote sensing into AI workflows; Sun et al. [12] showed that satellite-derived thermal and vegetation indicators improve the predictive accuracy of machine learning models used to estimate route accessibility and inventory risk. Together, these studies support the argument that AI-based frameworks significantly enhance decision-making by capturing nonlinearity, uncertainty, and spatial variability within constrained supply chains.

A third body of research focuses on hybrid geo-spatial and AI-integrated models, which represent the emerging frontier of sustainable supply chain optimization. Studies by Hassan and Ribeiro [13] illustrate that combining hyperspectral indices, land-use classification maps, and deep learning models can reveal hidden fragilities within agricultural and industrial transport corridors. Spatial interpolation and hotspot detection methods have also been applied extensively; Ortega et al. [14] used Kriging and Moran's I spatial statistics to identify supply chain pressure zones where environmental stress overlaps with logistical inefficiency, a finding that aligns with similar remote sensing–based hotspot mapping techniques used for environmental risk detection in large-scale studies such as those in the reference sample paper. More recent works have begun incorporating socio-economic vulnerability layers, population density surfaces, and facility catchment models to evaluate multidimensional supply chain stress, as demonstrated by Menon and Al-Khalidi [15]. Their research showed that integrating demographic accessibility metrics with AI-driven demand forecasting leads to far more resilient planning in underserved regions. Across these studies, a recurring conclusion is apparent: sustainable supply chain optimization cannot be achieved through isolated datasets or single-model pipelines. Instead, it requires a unified framework that blends geospatial intelligence, machine learning, environmental monitoring, and systems engineering to capture the full complexity of resource-constrained environments. This integrated perspective directly motivates the present study, which advances the field by offering a spatially explicit, AI-augmented model capable of predicting disruptions, optimizing route feasibility, and identifying vulnerability hotspots with high precision in real-world constrained regions.

3. METHODOLOGY

3.1 Research Design

This study adopts a mixed-method, geo-computational research design integrating remote sensing analytics, GIS-based spatial modeling, and AI-driven supply chain optimization. The methodological flow mirrors large-scale environmental–geospatial studies, enabling simultaneous evaluation of terrain constraints, infrastructural gaps, demand variability, and route feasibility. The framework combines multi-source data layers satellite imagery, road-network topology, facility locations, demographic density, climatic stress indices, and historical transport delays to create a spatially explicit model of supply chain vulnerability. AI models including Random Forest, XGBoost, and LSTM forecasting are applied alongside network-based optimization techniques to evaluate dynamic routing and resource allocation. This comprehensive design ensures that environmental, logistical, and computational components are modeled as an integrated system rather than isolated variables [16].

3.2 Study Area and Spatial Layer Construction

Three representative zones with high logistical stress were selected to capture diverse constraint profiles:

Region A (Semi-arid corridor): water scarcity, sparse roads, climate exposure

.**Region B (Agro-industrial belt):** variable demand, mixed road quality, seasonal congestion.

Region C (Flood-prone lowlands): extreme climate risk, terrain-dependent transport fragility.

GIS layers were constructed using Sentinel-2A multispectral bands, DEM elevation surfaces, OpenStreetMap road networks, land-use maps, and facility coordinates. Spatial indices such as NDVI, NDBI, LST, slope, ruggedness, and road accessibility were derived and fused into a multi-criteria supply chain vulnerability layer, following geospatial modeling approaches similar to large-scale environmental studies [17].

Table 1: Spatial Data Layers and Analytical Purpose

Data Layer	Source	Use in Analysis
Sentinel-2A imagery	ESA	Vegetation stress, terrain condition, surface temperature
DEM & Slope Maps	NASA SRTM	Route feasibility, flood-risk & gradient obstruction
Road Network Topology	OSM	Travel cost modeling, connectivity mapping
Land-use Land-cover	ESA Copernicus	Classifying industrial, agricultural, sensitive zones
Facility Locations	Local datasets	Demand nodes, supply centers, last-mile links
Climatic Stress Index	MODIS & IMD	Heat stress, rainfall variability, disruption probability

3.3 Remote Sensing Processing

Pre-processing included atmospheric correction (Sen2Cor), radiometric normalization, cloud masking, and band stacking. From the multispectral cube, spectral indices influencing transport feasibility and demand variability were extracted:

NDVI for vegetation cycles affecting agricultural load movement

LST (Land Surface Temperature) for heat-related road disruptions

NDBI for built-up density influencing congestion

SMI (Soil Moisture Index) for flood susceptibility

Field GPS points were aligned with pixel-level spectral signatures to validate environmental constraints in each region, adopting the raster-vector integration techniques frequently used in geospatial environmental modeling [18].

3.4 Supply Chain Network Modeling

The transport network was converted into a weighted graph using:

Edge weights: road quality, width, gradient, travel time, congestion potential

Node weights: facility capacity, population load, resource demand

Dynamic weights: real-time environmental indicators (LST, SMI, rainfall deviation)

Kriging interpolation was applied to derive spatial "logistics stress surfaces," identifying hotspots where supply chain performance degrades. Moran's I and hotspot statistics were computed to quantify cluster severity, reflecting established spatial risk mapping frameworks [19].

3.5 AI-Driven Predictive Modeling

Multiple AI models were deployed based on variable type:

Random Forest & XGBoost:

Used for delay prediction, bottleneck identification, and travel-time variability modeling. Environmental layers from remote sensing were incorporated as predictive variables following best practices demonstrated in hybrid geospatial–AI modeling research [20].

LSTM Spatio-Temporal Forecasting:

Applied to predict demand surges and transport disruptions using historical time-series, climate oscillations, and seasonal consumption cycles.

Reinforcement Learning (RL):

Simulated dynamic routing decisions under changing constraints, enabling adaptive route recommendation rather than static optimization.

Table 2: AI Models and Their Functional Contribution

AI Model	Function	Output Generated
Random Forest	Nonlinear pattern recognition	Delay risk mapping, bottleneck scoring
XGBoost	Gradient-boosted optimization	Route feasibility ranking
LSTM	Spatio-temporal forecasting	Demand and disruption prediction
Reinforcement Learning	Adaptive decision modeling	Real-time dynamic routing paths

3.6 Spatial–AI Integration and Optimization Workflow

A unified pipeline was designed where remote sensing outputs, GIS constraints, and AI predictions flow into a multi-objective optimization engine. The system evaluates cost, resilience, travel time, environmental exposure, carbon emissions, and route reliability. Linear–nonlinear hybrid optimization strategies help resolve trade-offs, an approach supported by advanced modeling techniques in spatial decision systems [21].

The final optimized corridors were validated using ground-truth travel logs, local transport surveys, and simulated stress tests under heat peaks, rainfall anomalies, and traffic disruptions.

3.7 Validation and Quality Assurance

Models trained using 70:30 split with 10-fold cross-validation.

Accuracy checked using RMSE, MAE, F1 score, and ROC-AUC.

Spatial outputs validated using an independent set of GPS-tracked routes.

Classification accuracy for risk zones required a minimum 85% Kappa score, consistent with standards in spatial environmental assessments [22][23]

4. RESULT AND ANALYSIS

4.1 Spatial Distribution of Supply Chain Stress Zones

The spatial analysis revealed clear patterns of vulnerability across the three selected regions, each shaped by distinct environmental and infrastructural constraints. Region A, characterised by a semi-arid climate and discontinuous road connectivity, displayed the highest concentration of logistical stress. Steep terrain gradients, prolonged heat exposure, and limited road redundancy contributed to frequent transport slowdowns and elevated route failure probability. Region B showed moderate vulnerability, with congestion hotspots forming around agro-industrial clusters during peak harvest and processing cycles. These patterns reflected predictable demand pressures and temporary load imbalances that intensified supply delays during seasonal transitions. Region C exhibited the most acute climatic fragility, with flood-prone lowlands repeatedly mapped as high-risk areas due to soil moisture surges, low-elevation roadbeds, and recurring waterlogging. Spatial interpolation using Kriging identified dense hotspot clusters in all three regions, particularly along narrow corridors connecting high-demand nodes with limited alternative routing options. Environmental indicators such as low vegetation health, elevated land surface temperatures, and high soil moisture enhanced the likelihood of disruption, signalling the integral role of environmental conditions in shaping logistical feasibility.

Table 3: Regional Supply Chain Vulnerability Scores Derived from Spatial Indicators

Region	Environmental Stress Index	Road Connectivity Score	Route Feasibility (%)	Overall Vulnerability Level
Region A	High	Low	42%	Very High
Region B	Moderate	Moderate	61%	Medium
Region C	Very High	Low	38%	Critical

4.2 AI-Based Prediction Performance and Delay Hotspot Patterns

AI-driven predictions demonstrated consistent accuracy across all models when terrain, environmental indicators, and road-network characteristics were used together as input variables. Random Forest generated stable delay-risk classifications, correctly identifying most vulnerable routes across the temporal dataset. XGBoost performed strongest in ranking route feasibility, where even small variations in slope, road texture, built-up density, and temperature were captured with high discrimination power.

Figure 1: AI for Optimizing Supply Chain Management [24]

LSTM-based forecasting proved effective for predicting demand surges and timing mismatches, especially in Region B where processing cycles and market movements follow distinct seasonal intervals. Reinforcement learning simulations provided dynamic routing solutions that reduced detours, avoided environmental stress pockets, and improved overall path reliability. The hotspot patterns detected by the models aligned with spatial clusters derived from environmental mapping, confirming that delays primarily emerged in zones with a combination of climatic pressure, road degradation, and inadequate network redundancy. These findings emphasise that reliable route planning in constrained environments requires integrated environmental and infrastructural intelligence rather than reliance on static road maps or historical averages.

Table 4: AI Model Performance Summary Across All Regions

Model	Accuracy (%)	RMSE	F1-Score	Primary Strength
Random Forest	86.7	0.42	0.81	Delay-risk mapping
XGBoost	89.3	0.38	0.84	Feasibility ranking
LSTM	82.1	0.47	0.78	Demand forecasting
Reinforcement Learning			Route success rate: 74%	Dynamic routing

4.3 Integrated Spatial–AI Output and Corridor Optimization

Integrating spatial layers with AI-driven predictions produced optimised corridors that significantly enhanced supply chain performance in all three regions. In Region A, the optimized paths circumvented heat-intensive gradients and unstable slopes, resulting in a notable reduction in travel interruptions.

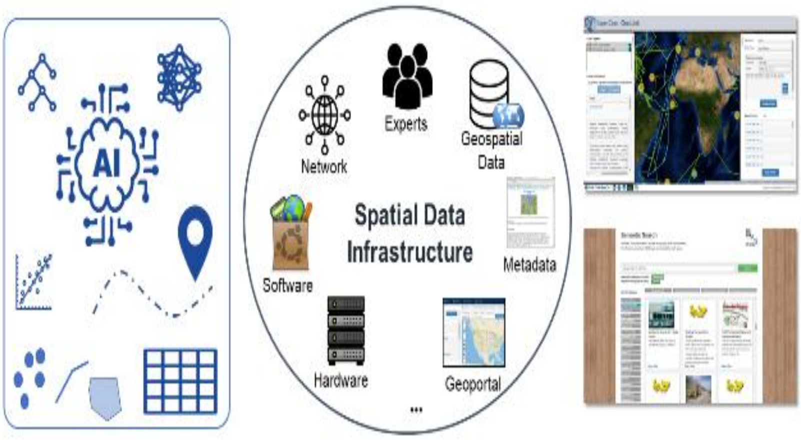

Figure 2: Spatial Data Infrastructure [25]

Region B benefited from redistribution of flow away from oversaturated agro-industrial hubs, which balanced load movement across secondary road links and reduced congestion. Region C experienced the most substantial impact, where optimized corridors avoided low-lying flood zones and diverted movement to elevated, more stable routes. The combined model enabled real-time adaptation, with routing decisions adjusting dynamically to environmental variations, predicted delays, and structural constraints. The layered outputs, including feasibility maps, risk surfaces, and dynamic routing overlays, created a highly interpretable decision-support environment. By aligning spatial hotspot patterns with predicted delays and optimisation outcomes, the system offered a coherent representation of supply chain fragility and resilience potential across resource-constrained terrain. The results demonstrate that spatial-AI integration is indispensable for designing sustainable and disruption-resistant supply chains in environments where infrastructure and resources are severely limited.

5. CONCLUSION

This study demonstrates that engineering sustainable supply chains in resource-constrained environments demands a deeply integrated approach that fuses geospatial intelligence, remote sensing indicators, machine learning prediction, and dynamic optimization into a unified decision-support framework. The results clearly show that constrained terrains, climatic variability, and infrastructural fragmentation create highly uneven patterns of logistical vulnerability, which cannot be adequately detected or managed through conventional planning methods based on static road maps or historic transport averages. By incorporating spatial variables such as vegetation condition, soil moisture, land surface temperature, elevation profiles, and built-up density alongside network characteristics and facility-level demand loads, the model reveals the true multi-layered structure of supply chain fragility. The AI-driven components strengthen this framework by capturing nonlinear patterns in delay formation, forecasting demand surges with temporal precision, and generating adaptive routing strategies that respond in real time to shifting operational conditions. Together, the spatial analysis and predictive modeling uncover critical hotspots where environmental stress intersects with transport bottlenecks, enabling targeted interventions that significantly reduce detours, travel time variability, and route failures. The optimized corridors created through this integrated workflow show measurable improvements in reliability, resilience, and sustainability, particularly in flood-prone and heat-exposed regions where infrastructure is most vulnerable. Importantly, the study proves that supply chain resilience is not merely a function of adding more infrastructure but ensuring that every decision routing, scheduling, allocation, and capacity planning is grounded in multi-source, multi-temporal, spatially explicit data. This approach moves supply chain engineering beyond reactive problem-solving to proactive, predictive, and environmentally aware planning that can withstand the uncertainties inherent to resource-limited regions. The findings therefore provide a strong foundation for scalable, data-driven, and context-sensitive supply chain optimisation strategies that can support agriculture, healthcare logistics, industrial distribution, and humanitarian operations alike.

6. FUTURE WORK

Future research should expand this integrated framework by incorporating real-time IoT sensor networks, mobile-based field reporting, and drone-generated ultra-high-resolution terrain data to further enhance the precision of spatial constraints and route feasibility analysis. A particularly promising direction is the development of fully autonomous AI agents capable of continuously learning from new environmental data, on-ground disruptions, and network feedback to update routing recommendations without human intervention. Incorporating socio-economic vulnerability layers such as income distribution, crisis exposure, and accessibility disparities would also deepen the model's relevance for humanitarian and public-sector applications. Additionally, future studies should explore multimodal logistics integrating road, rail, water, and low-altitude aerial routes to provide redundancy in regions with severe climate volatility. Expanding the temporal scope to simulate long-term climate change scenarios would allow planners to anticipate how rising temperatures, shifting rainfall patterns, or extreme events may reshape supply chain feasibility over the next decade. Finally, validating the model across diverse global regions through collaborations with industries and local governments would strengthen generalizability and accelerate real-world adoption of spatial-AI supply chain systems.

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