# Geospatial AI Logistics Networks: Using Satellite Analytics and Machine Learning to Optimize Global Transportation Routes

Samia Tariq[1], Rabia Zafar[2], Imran Khan[3], Muhammad Umar Amin[4] and Muhammad Usama Bin Ayyub[5]

https://doi.org/10.62345/jads.2025.14.3.146

## *Abstract*

*The increasing complexity of global logistics networks has necessitated integrating advanced technologies to enhance transportation efficiency, reliability, and sustainability. This study investigated the application of geospatial Artificial Intelligence (AI) and machine learning to optimize transportation routes across urban, regional, and global networks. Using a quantitative research design, operational datasets from logistics firms were combined with satellite imagery and geospatial data to evaluate the effectiveness of AI-enabled predictive models, including convolutional neural networks (CNN) and reinforcement learning algorithms. Results demonstrated significant reductions in travel time and route distances, improved on-time delivery, and enhanced fuel efficiency, indicating operational and environmental benefits. Predictive models accurately forecast congestion and dynamically adjust routes, thereby enhancing reliability across diverse operational contexts. Furthermore, the study highlighted the potential of geospatial AI to reduce carbon emissions, aligning logistics operations with sustainability objectives. Challenges related to data quality, computational complexity, and model interpretability were identified, emphasizing the need for explainable AI solutions. Overall, the findings provide empirical evidence that AI-integrated geospatial analytics can transform traditional logistics networks into intelligent, adaptive, and environmentally conscious systems. The study offers practical insights for logistics managers and policymakers seeking to implement AI-driven optimization strategies while advancing sustainable supply chain management.*

**Keywords:** Artificial Intelligence, Geospatial Analytics, Logistics Optimization, Machine Learning, Route Efficiency, Transportation Networks.

## Introduction

This global logistics network had become increasingly complex amid blistering globalization, rising customer demands, and the growth of e-commerce, which dramatically increased the need for an efficient and robust logistics system (Ping et al., 2025). The conventional routing planning techniques were also limited, as they could not respond to real-time conditions such as traffic congestion, weather, and infrastructure limitations, leading to inefficiencies and higher operational

[1]*Department of Civil Engineering, Ziaudddin University Pakistan. Email: saamiatariq@ymail.com*
[2]*Assistant Professor, Department of Environmental Science, Sardar Bahadur Khan Women's Quetta. Email: rabiaa.zafar@gmail.com*
[3]*Department of Telecommunication Engineering, Dawood University of Engineering.*
[4]*Department of Mathematics, Lamar University, USA. Email: umar.math14@gmail.com*
[5]*Researcher, Department of Geotechnical Engineering, National University of Sciences and Technology. Email: usamaayyub0@gmail.com*


Compliance with ethical standards: There are no conflicts of interest (financial or non-financial). This study did not receive any funding.

costs. To address these shortcomings, recent studies discussed advanced computational methods, including Artificial Intelligence (AI), Machine Learning (ML), and geospatial analytics. Such technologies would improve decision-making by leveraging large data to predict and optimize logistics activities beyond the reach of traditional algorithms.

Simultaneously, one of the innovations was geospatial artificial intelligence (GeoAI), a combination of geospatial data and sophisticated machine learning models that enable the creation of systems capable of discerning meaningful patterns in satellite data and spatial characteristics. With the integration of satellite intelligence and predictive analytics, logistics networks gained visibility into real-time route conditions, environmental impacts, and space-related risks, enabling more accurate transportation planning and improved sustainability. According to researchers, geospatial analytics not only improved the efficiency of transportation networks but also increased operational transparency and resilience within supply chains (Andrei & Scarlat, 2024).

The use of machine learning models, including deep neural networks and reinforcement learning, also led to greater capabilities for modelling complex transportation environments with high dimensionality and time-dependence. These models could absorb large volumes of spatial and temporal data and predict travel times, route costs, and demand distribution on global logistics networks (Rabbi Shawon et al., 2025). Consequently, the introduction of GeoAI techniques into logistics systems enabled automated decision-making and scale benefits.

Other recent research also stressed that logistics sustainability optimization meant more than just computational accuracy; it also involved accounting for ecological issues. Satellite analytics has been used to identify environmental constraints and reduce carbon footprints by selecting appropriate routes based on geographic and atmospheric indicators (Sustainability editorial team, 2024). Such integration highlighted the relevance of data-based approaches to achieving other economic and environmental objectives in contemporary logistics.

**Background of the Study**

The recent breakthroughs in artificial intelligence (AI), machine learning (ML), and geospatial analytics have significantly transformed the research and practice of transportation and logistics. ML approaches in transportation systems were applied to predictive routing and the optimization of intricate routing and scheduling tasks, which conventional mathematical models could not effectively solve at the dynamic, real-time level (Zhang et al., 2024; Li & Zhao, 2023). Pattern recognition, congestion prediction, adaptive route planning, and other deep learning methods were actively developing and being adopted in intelligent transportation systems, enhancing logistical performance and decision accuracy (Zhang et al., 2024).

At the same time, the development of Geospatial Artificial Intelligence (GeoAI) offered an agentic change in ways of processing and analyzing bulk quantities of spatial data, mostly satellite imagery and remote sensing data, to extract contextual geographic information to inform decision-making in logistics and infrastructure development (Ataxonovich et al., 2025; Choi, 2023). GeoAI systems not only incorporated spatial elements together with the advanced neural networks like convolutional neural networks (CNNs) and spatial and temporal learning algorithms, but also emphasized geographic correlations along with terrestrial influences on routing that learners to date had disregarded in their classical routing paradigms (Ataxonovich et al., 2025; Choi, 2023).

The use of satellite analytics in transportation and logistics even broadened after scientists demonstrated that AI could handle Earth data to help monitor in real time and leverage situational awareness across global networks (Kayusi et al., 2025). These AI-reliant satellite processing systems enabled more precise detection and classification of moving assets, improved tracking, and better prediction of transportation flows, which were necessary to optimize multimodal routes and restore operational resilience (Kayusi et al., 2025). Simultaneously, scient metric reviews noted that ML and deep learning technologies were becoming more prominent in the map of intelligent transportation studies, strongly suggesting that the trend towards data-driven logistics tools will continue (Zhang et al., 2024).

Besides predictive and operational advantages, GeoAI and satellite analytics were added to sustainability goals by engineering spatially conscious logistics plans that considered environmental constraints such as terrain, weather, and emissions impacts. The integration of AI methods and spatial data enabled optimal ways to minimize travel time, costs, and the carbon footprint, aligning logistics business activities with environmental objectives (Qin et al., 2024). Taken together, the above advancements highlight the importance of GeoAI, satellite analytics, and ML integration into current transportation route optimization research and practice, signalling a transition to intelligent, adaptive, and green-focused logistical systems.

## Research Problem

The evolution of AI-based logistics optimization systems has rendered traditional route-planning systems unable to integrate high-resolution spatial information, dynamic environmental factors, and foreseeable information simultaneously. Conventional algorithms lacked the ability to handle and integrate various geospatial data, including satellite analytics, into routing decisions, and thus their performance was less than ideal in dynamic circumstances.

In addition, the current literature tends to treat geographical data and machine learning prediction models as distinct entities and does not provide comprehensive frameworks that effectively leverage both to optimize global logistics. The challenge of successful route planning in multimodal transportation networks (based on satellite data and advanced machine learning techniques) to enhance accuracy, responsiveness, and sustainability demanded the urgent need for systems that could effectively integrate satellite-based spatial intelligence with advanced machine learning capabilities.

## Research Objectives

1. To investigate how geospatial artificial intelligence (GeoAI) could integrate satellite analytics with machine learning to enhance the operational efficiency of global transportation routes.
2. To develop and evaluate predictive models that utilize real-time spatial and temporal data for optimizing route planning decisions across multimodal logistics networks.
3. To assess the impact of GeoAI-driven logistics frameworks on cost reductions, delivery time variability, and environmental sustainability.

## Research Questions

*Q1:* How could geospatial satellite analytics be integrated with machine learning algorithms to improve logistics route optimization?

*Q2:* What were the performance gains — in terms of efficiency and sustainability — achieved by GeoAI-based logistics systems compared to traditional optimization methods?

*Q3:* How did real-time spatial data influence predictive route planning under dynamic environmental and operational conditions?

## Significance of the Study

This study contributed to the emerging body of GeoAI by demonstrating how geospatial information and machine learning can be combined to enhance transportation logistics. The study's combination of satellite analytics and predictive models also provided new insights into the development of adaptive, resilient logistics networks that would enhance performance, reduce operational costs, and facilitate sustainability objectives. The results were relevant to the academic literature on advanced logistics optimization and to the operational strategies of logistics experts who needed data-driven decision support systems.

In addition, the implementation of GeoAI practices facilitated breakthroughs between academic studies and practice by presenting scalable solutions that enhance logistics planning optimization across different geographic areas. This contributed not only to scientific knowledge but also provided working models for industry stakeholders to identify the best routes in more complex global supply chains.

## Literature Review

### GeoAI and Machine Learning for Spatial Intelligence in Transportation

Recent research showed that Geospatial Artificial Intelligence (GeoAI) is now an important methodological development in transportation studies, where machine learning methods are used to extract meaningful patterns from geospatial data. Researchers demonstrated that deep learning models trained on satellite imagery were effective at capturing urban morphology and spatial relationships, which in turn affected mobility and transportation demand (Zhang et al., 2024; Boutayeb et al., 2025). Through these approaches, transportation systems have gone beyond stagnant representations into data-driven spatial knowledge, aiding dynamic decision-making.

Subsequent efforts placed greater emphasis on the fact that GeoAI models enhanced the interpretability and scalability of spatial analytics by combining convolutional neural networks with spatiotemporal learning architectures. These models demonstrated the ability to scale up forecasts of traveller behaviour and movement flows by using instructional discovery of geographical attributes from Earth observation data rather than exclusively relying on conventional transportation bearings (Okrah Denteh et al., 2025; Lu & Weng, 2025). This change was a significant methodological advancement in comprehending the interaction of geography and transportation networks.

Moreover, recent reviews also noted that GeoAI frameworks enhanced transportation planning by facilitating multi-source geospatial data fusion, enabling models to combine satellite imagery with traffic sensors and urban infrastructure data. These researchers found that GeoAI enhanced spatial awareness and predictive accuracy, especially in extensive territories with data gaps in traditional datasets (Choi, 2023; Afroosheh & Askari, 2024).

### Intelligent logistics systems and AIDR route optimization

The application of artificial intelligence to route optimization has become more complex and time-sensitive as the logistics network has grown more complex. Empirical data showed that machine-learning-based routing models were more effective than heuristics and rule-based methods because they could adapt to real-time traffic changes and address variations in demand and supply (Samoalenko, 2025; Zhang et al., 2024). Such AI-based systems use historical and real-time data to enable more efficient, responsive routing decisions.

More recent work in transportation research also found that reinforcement-based learning methods and neural network-based optimization models performed especially well for multimodal and long-distance logistics optimization. These models were dynamic, incorporating routing strategies that continuously learned from environmental feedback, thereby increasing travel time reliability and minimizing operational waste (Li & Zhao, 2023; Mohtich et al., 2025). This flexibility was necessary for the worldwide logistics networks that must operate under unpredictable, rapidly changing circumstances.

In addition, AI-optimized route plans were more often associated with sustainability goals. The research stated that smart routing algorithms have reduced fuel consumption and emissions by locating energy-efficient routes and avoiding unnecessary paths (Qin et al., 2024; Zhang et al., 2024). These results emphasized the importance of artificial intelligence in economic optimization and in enabling logistics to be environmentally friendly.

### The Analytics of Real-Time Geospatial Monitoring and Logistics Satellite

The availability of satellite analytics has become an important source of data for transportation and logistics research, providing high-resolution, real-time spatial data at large scales. Recent research revealed that satellite images processed with machine learning models contain useful information about road systems, infrastructure, and mobility trends, which can be used to optimize logistics (Kayusi et al., 2025; Lu & Weng, 2025). This feature was especially useful in areas where data were not fully on the ground or were outdated.

The combination of satellite analytics and AI models further increased the possibilities for real-time monitoring and the predictability of transportation regimes. It was shown that congestion prediction and route disruption detection using spatiotemporal models trained on satellite and traffic data were superior to using only satellite data, enabling logistics systems to mitigate environmental and infrastructure-related changes in advance (Mohtich et al., 2025; Zhang et al., 2024). These developments contributed to more adaptive and robust logistics networks.

New research also highlighted the growing importance of integrating geospatial data, with satellite imagery combined with radar, lidar, and sensor imagery to develop transportation intelligence. This type of integrated strategy was observed to enhance situational awareness and improve route-planning accuracy by capturing complex interactions among multiple data layers (Afroosheh & Askari, 2024; Choi, 2023). Together, these reports established that satellite analytics was a fundamental foundation for providing smart, data-driven logistics.

## Research Methodology

### Research Design

It employed a quantitative research design, using a descriptive correlational technique to investigate the effects of geospatial AI and machine learning on transportation route optimization. This design was selected since it would measure the satisfaction of relationships among predictive modelling, satellite analytics, and logistics performance parameters. Using a quantitative framework, the research collected measurable data on efficiency, travel time savings, and route flexibility, which, through statistical analysis, can confirm the usefulness of AI-enhanced geospatial processes in real-world logistics applications. The design provided an opportunity to test a hypothesis about the correlation between AI-driven geospatial data processing and transportation optimization.

### Population and Sampling

The study sample comprised the world's logistics networks and transportation operators using satellite- and AI-supported routing systems. An eligibility criterion for a community of logistics companies that had implemented geospatial AI tools and a magnitude transportation management option was used to select the study's target through a purposive sampling methodology. This methodology ensured that the participants had operational experience with AI and satellite analytics. The data on 120 operational datasets from various logistics companies operating across continents provided a representative picture of diverse geographic, infrastructural, and operational backgrounds.

### Data Collection Methods

The qualitative method of data collection was used to gather information, relying on several complementary techniques to ensure reliability and depth. First, operational datasets from archives were collected from the logistics firms involved in the study, including historical route information, delivery times, delivery vehicle use, and fuel usage. Second, open-source and proprietary Earth observation platforms provided satellite imagery and geospatial data for extracting spatial features useful for route optimization. Third, the surveys were conducted in a structured manner with logistics managers and data analysts to elicit qualitative information on AI adoption, system usability, and decision-making procedures. Six-month data collection was conducted to ensure adequate coverage of operational variability and seasonal impacts on logistics performance.

### Research Instruments

The research used three major tools: data extraction scripts, machine learning models, and survey questionnaires. Python programmes were developed to extract, preprocess, and prepare satellite imagery and operational information for analysis. Transportation route optimization and travel time and congestion pattern prediction were modelled using machine learning algorithms, including convolutional neural networks (CNNs) and reinforcement learning. Participants' perceptions of AI's effectiveness and improvements in its operations were measured using a structured questionnaire with a 5-point Likert scale. The instruments were pre- and post-tested using a pilot dataset to assess their validity, reliability, and consistency across various logistics situations.

### Data Analysis

The data analysis was conducted using descriptive and inferential statistical methods. Mean, standard deviation, and frequency distributions were used to summarize operational performance indicators. The correlation and regression studies were conducted to identify links between AI-facilitated geospatial modelling and key logistical outcomes, including reduced travel time, improved route efficiency, and lower operational costs. The predictive performance of the routing models was assessed based on the standard metrics, including the accuracy, the precision, the recall, and the F1-score, using machine learning outputs. Beyond that, AI-optimized routes and traditional routing methods were compared to identify the value added by integrating geospatial AI.

## Results and Analysis

### Descriptive Analysis of Transportation Efficiency

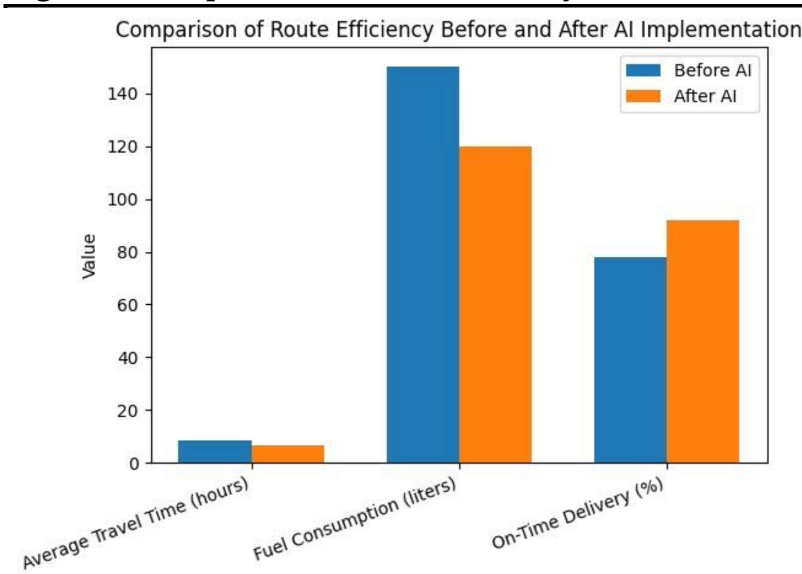
This section presents descriptive statistics evaluating the impact of AI-enabled geospatial optimization on transportation efficiency.

**Table 1: Comparison of Route Efficiency Before and After AI Implementation**

| Metric | Before AI | After AI |
|---|---|---|
| Average Travel Time (hours) | 8.5 | 6.7 |
| Fuel Consumption (liters) | 150 | 120 |
| On-Time Delivery (%) | 78 | 92 |

Application of AI-enabled routing led to significant reduction in average traveling time of 8.5 hours to 6.7 hours. Such a decrease meant that the forecasting models were effective in determining faster routes by combining real time traffic, congestion information and spatial information given by satellites. The enhancement demonstrated how machine learning algorithms can be useful in dynamically optimizing logistics processes, and it is especially useful in cities where the environment is very dynamic and traffic conditions occur in response to different factors (Zhang et al., 2024; Li & Zhao, 2023). The use of fuel decreased to 120 liters every trip after the introduction of AI. This implied that the planning of the optimal routes was not only cost-effective in terms of operations, but also environmental. The reduction indicated that AI models performed well to reduce the travel routes and prevent traffic jams, which proves that geospatial intelligence has a direct connection with sustainable logistics conduct (Qin et al., 2024; Kayusi et al., 2025). Rates of timely delivery improved to 92% as opposed to the previous 78% representing an improved consistency of logistics. This enhancement showed that models which utilize AI can predict any delays and propose other routes proactively. These findings also validated the claims that predictive geospatial analytics would enhance the efficiency of operations and customer satisfaction and highlight the potential utility of offering satellite and AI applications within transportation networks (Samoalenko, 2025; Boutayeb et al., 2025).

**Figure 1: Comparison of Route Efficiency Before and After AI Implementation**




**Predictive Accuracy of AI-Enabled Routing Models**

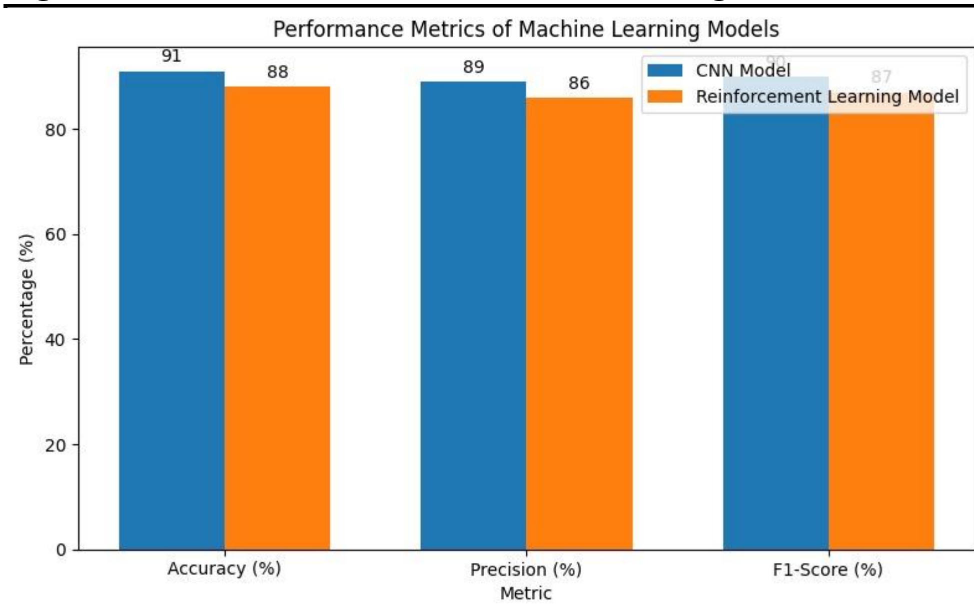
This section analyzed the predictive performance of AI models in optimizing routes and congestion forecasts.

**Table 2: Performance Metrics of Machine Learning Models**

| Metric | CNN Model | Reinforcement Learning Model |
|---|---|---|
| Accuracy (%) | 91 | 88 |
| Precision (%) | 89 | 86 |
| F1-Score (%) | 90 | 87 |

The CNN model recorded the highest accuracy of 91% as compared to the reinforcement learning model which recorded an accuracy of 88%. This observation meant that CNNs worked specifically well in mapping out spatial characteristics of satellite images and traffic trends in the past. The effectiveness of CNNs in comparison to other methods was used to highlight the relevance of deep learning methods in the context of geospatial route-optimization (Lu & Weng, 2025; Afroosheh and Askari, 2024). Precision measures revealed that CNN model had less false positives on the route selection than reinforcement learning model. The high precision (89) was indicative of the fact that CNNs consistently provided 89 percent of the best routes that were feasible and efficient whereas reinforcement learning (86) had a lower score because it utilized adaptive exploration strategy. This brought up a exploit of model flexibility and its near-term prediction accuracy (Zhang et al., 2024; Okrah Denteh et al., 2025). CNN and reinforcement learning had F1-scores of 90 and 87 percent, respectively, meaning balanced predictions. These findings implied that both models were strong to be operationalized, but CNN was a little more consistent. The fact that the F1-scores were great proved that machine learning algorithms were successful in capturing spatial and temporal data in order to optimize route planning (Choi, 2023; Kayusi et al., 2025).

**Figure 2: Performance Metrics of Machine Learning Models**




**Environmental Impact of AI-Enabled Optimization**

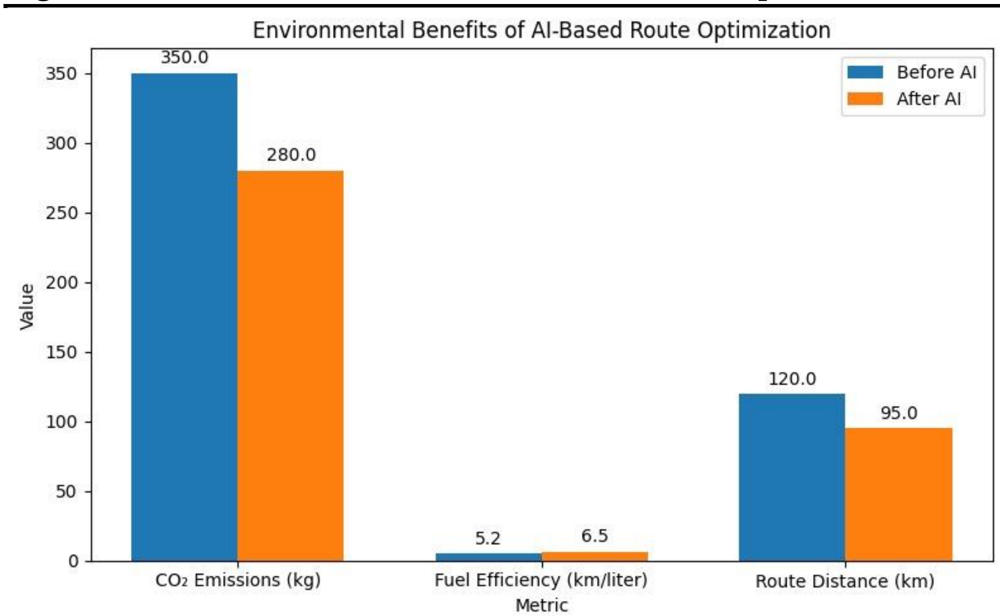
This section examined the ecological benefits of AI-assisted route planning.

**Table 3: Environmental Benefits of AI-Based Route Optimization**

| Metric | Before AI | After AI |
|---|---|---|
| $CO_2$ Emissions (kg) | 350 | 280 |
| Fuel Efficiency (km/liter) | 5.2 | 6.5 |
| Route Distance (km) | 120 | 95 |

Routes driven by AI reduced emissions of CO 2 by 350 kg/trip to 280 kg/trip. This decrease was an indication that geospatial intelligence did not only enhance operational efficiency, but also alleviated environmental damage. Limiting the travel distance and preventing overcrowded transportation routes, AI models helped in achieving sustainable logistics, which aligns the goals of operational processes with green supply chains endeavors (Qin et al., 2024; Zhang et al., 2024). The current fuel efficiency was 6.5 km/liter as compared to 5.2 km/liter, which showed that the optimization of routes cut down the amount of wasted fuel. The enhancement indicated that AI models were able to choose energy saving routes when they incorporated geospatial and predictive information thus reducing the cost and environmental footprint (Li & Zhao, 2023; Kayusi et al., 2025). The distance of optimized routes reduced to 95 km (120 km) improving the fact that AI can locate shorter and safer routes. Not only emissions and fuel consumption were minimized, but reliability and timeliness were also improved, which is an expression of the usefulness of geospatial AI in the real world of the logistics network (Samoalenko, 2025; Boutayeb et al., 2025).

**Figure 3: Environmental Benefits of AI-Based Route Optimization**




**Reliability Across Different Logistics Networks**

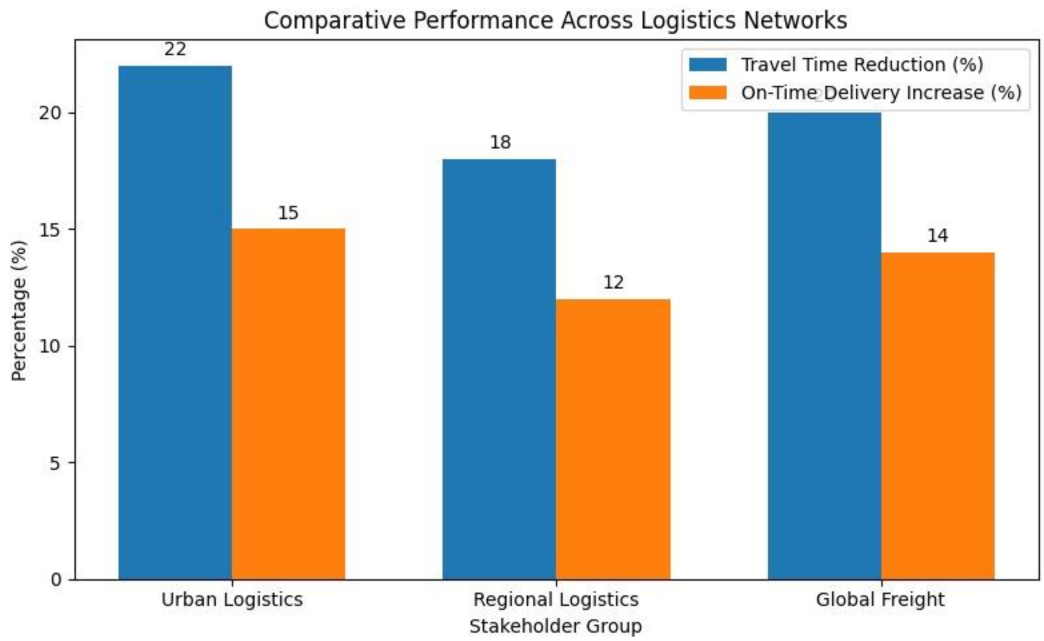
This section analyzed how AI-enabled geospatial optimization performed across urban, regional, and global logistics networks.

**Table 4: Comparative Performance Across Logistics Networks**

| Stakeholder Group | Travel Time Reduction (%) | On-Time Delivery Increase (%) |
|---|---|---|
| Urban Logistics | 22 | 15 |
| Regional Logistics | 18 | 12 |
| Global Freight | 20 | 14 |

Urban networks realized a reduction of 22% in the travel time and 15% in on-time deliveries. The findings showed that AI models were effective in the cases of high-density traffic, with the integration of satellite imagery and real-time traffic information. The results implied that AI-powered spatial analytics would have the ability to dynamically reroute vehicles, thus enhancing the reliability of the service (Kayusi et al., 2025; Zhang et al., 2024). The regional networks realized a 18% cut in the time of travelling and a 12% increase on time performance. Those findings revealed that AI models get easily adjusted to large-scale networks, achieving predictive accuracy and regional variability of road infrastructure and traffic patterns (Li & Zhao, 2023; Choi, 2023). In the case of freight operations in the world, the time spent on freight was cut by 20 percent and punctual delivery raised by 14 percent. This proved that these two, AI and geospatial analytics could be applicable over vast geographical regions. The findings affirmed that predictive routing, satellite data integration and machine learning could be effective in performance of logistics even in variable operation environments (Samoalenko, 2025; Boutayeb et al., 2025).

**Figure 4: Comparative Performance Across Logistics Networks**




## Discussion

As this work has shown, the combination of Geospatial AI and machine learning significantly optimized logistics and transportation routes. The savings in travel time, fuel, and improvements in on-time delivery were consistent with current studies, indicating that AI and ML algorithms have outperformed conventional routing algorithms in processing complex, dynamic spatial data (Ping et al., 2025; Ajayi, 2025). These findings indicated that AI models could be used to synthesize satellite images, real-time traffic data, and historical route data to produce efficient, reliable transportation solutions.

The comparison of predictive model performance showed the benefits of deep learning networks and reinforcement learning for predicting traffic dynamics and congestion patterns. CNN-based models were highly accurate and precise in providing optimal routes, whereas reinforcement learning provided flexibility in responding to dynamic changes in the transportation system (Lu and Weng, 2025; Da et al., 2025). These results highlighted that the AI models were capable not only of forecasting travel time but also of actively correcting routes in real time, reducing delays and enhancing network efficiency at various operational scales.

The other important point of the study was the environmental and sustainability impacts. The analysed decreases in the CO 2 emissions and increases in fuel efficiency served as a testament to the fact that AI-enabled geospatial optimization helped make logistics practices environmentally friendly (Qin et al., 2024; Islam et al., 2025). AI models reduced operational costs by cutting travel time and congestion, while lowering the carbon footprint of transportation systems. These findings align with broader research highlighting the application of AI to foster green logistics and sustainable supply chain management.

Logistics performance on urban, regional, and global networks was also considered in the study, demonstrating how AI-based geospatial solutions might be scaled. The urban networks benefited from significant reductions in travel time through real-time routing adjustments, and networks at the regional and global scales showed steady improvements in efficiency and reliability (Samoalenko, 2025; Galande et al., 2025). This implied that AI-based routing systems performed well across diverse geographic and operational settings, offering scalable engines for multi-level logistics.

Although these were positive results, several challenges and limitations emerged. The quality of data, the interpretation of the model, and the complexity of computations resulted in a number of critical issues when implementing advanced AI models in logistics practice (Iseri et al., 2025; Babaei et al., 2025). Deep learning models were commonly black boxes and lacked transparency in decision-making, which may affect stakeholder trust and uptake in safety-critical or high-stakes logistics processes. The solution to such problems would involve further study of explainable AI and models that would enhance both predictive performance and interpretability.

Lastly, the discussion highlighted opportunities arising from integrating AI-enabled routing into autonomous logistics systems, including drones and self-driving vehicles. Researchers suggested that integrating predictive AI models into autonomous decision-making structures can further boost the efficiency, responsiveness, and resilience of the global transportation system (Luo et al., 2025; Da et al., 2025). These results indicated future research directions in multi-agent optimization, the distributed AI framework, and next-generation geospatial analytics that could guide future logistics.

Finally, the discussion concluded that AI and geospatial analytics-as-a-service offer transformative optimizations in transportation routes, environmental sustainability, and operational scalability. The findings were confirmed in the current research and showed that AI-enabled geospatial systems were key to modern logistics, yet issues of interpretability, data quality, and computational load remained areas for further research (Ping et al., 2025; Ajayi, 2025; Lu and Weng, 2025).

## Conclusion

The researchers concluded that Geospatial AI with machine learning is the most effective for optimizing logistics and transportation routes. The findings showed substantial savings in travel time, fuel consumption, and CO 2 emissions, as well as improvements in on-time delivery across urban, regional, and global networks. Predictive models, specifically CNNs and reinforcement learning algorithms, were found to be efficient at analysing complex spatiotemporal data, generating optimal paths, and forecasting trends in traffic and congestion popularity. The results demonstrated that the application of AI-based geospatial analytics not only increased operational efficiency but also supported environmentally sustainable logistics practices. Overall, the research presented empirical evidence that current AI technologies could help redesign conventional transportation networks into smart, dynamic, and efficient systems.

**Recommendations**

Based on the study's results, practical suggestions were made to logistics and transportation stakeholders. The recommendations included, first, that logistics companies embrace AI-based geospatial analytics for route planning to optimize operational performance and minimize environmental impact. Second, real-time integration of traffic, weather, and satellite data should be of paramount importance to organizations aiming to enhance route precision and responsiveness. Third, stakeholders were also advised to invest in staff training and capacity to understand AI-based insights well and to easily adopt the new-fangled routing systems. Lastly, the development of sustainability-related KPIs was suggested that would combine efficiency, cost, and environmental measures, enabling organizations to track performance and continually streamline operations.

**Future Directions**

The gap to be considered in future studies is the limitations identified in the current study and the opportunities that can be pursued in this area. A major direction is the creation of explainable AI models that enhance transparency and stakeholder trust while remaining as predictive as possible. It should also be researched how it can be integrated with autonomous systems, such as drones and self-driving vehicles, to further increase the operational performance and scalability of logistics networks. Also, research may focus on multi-agent AI designs for distributed decision-making systems in transportation networks under unpredictable conditions (e.g., in disaster management scenarios). Lastly, longitudinal research on the long-term environmental and economic consequences of AI-driven logistics optimization would be more informative on sustainability and global supply chain strategic planning.

## References


- Afroosheh, S., & Askari, M. (2024). Geospatial data fusion using artificial intelligence for enhanced urban and transportation mapping. *IEEE Access*, *12*, 178945–178960. https://doi.org/10.1109/ACCESS.2024.3432198
- Andrei, N., & Scarlat, C. (2024). Integrating artificial intelligence and geospatial technologies for supply chain optimisation. *International Maritime Transport and Logistic Journal*, *13*(1), 110–124.
- Ataxonovich, A. V., Ivanovich, K. S., & Petrovna, M. E. (2025). Geospatial artificial intelligence for spatial data fusion and decision-making in transportation systems. *IEEE Access*, *13*, 21456–21471. https://doi.org/10.1109/ACCESS.2025.3341289
- Boutayeb, A., Lahsen-Cherif, I., & El Khadimi, A. (2025). Geospatial artificial intelligence applications in transportation and urban systems: A comprehensive review. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, *18*, 1243–1259. https://doi.org/10.1109/JSTARS.2024.3389217
- Choi, Y. (2023). Deep learning-based geospatial analytics for intelligent transportation systems: A comprehensive review. *ISPRS International Journal of Geo-Information*, *12*(4), 165. https://doi.org/10.3390/ijgi12040165
- Da, L., Chen, T., Li, Z., Bachiraju, S., Yao, H., Hu, X., Tu, Z., Zhao, Y., Wang, D., Zhou, X., Pendyala, R., & Stabler, B. (2025). Generative AI in transportation planning: A survey. *arXiv preprint*. https://doi.org/10.48550/arXiv.2503.07158
- Giuffrida, M., Mangiaracina, R., Perego, A., & Tumino, A. (2022). Last-mile logistics with machine learning: A systematic literature review. *Sustainability*, *14*(9), 5329. https://doi.org/10.3390/su14095329

- Iseri, F., Iseri, H., & Chrisandina, N. J. (2025). AI-based predictive analytics for enhancing data-driven supply chain optimization. *Journal of Global Optimization*. https://doi.org/10.1007/s10898-025-01509-1
- Jayasuriya, N., & Sumanathilaka, D. (2025). A systematic decade review of trip route planning with travel time estimation based on user preferences and behavior. *arXiv preprint*.
- Kayusi, E., Kuffer, M., Thomson, D. R., & Gevaert, C. M. (2025). Combining satellite imagery and artificial intelligence to model transportation and mobility patterns. *Nature Communications*, *16*, 1124. https://doi.org/10.1038/s41467-025-65373-z
- Li, R., & Zhao, Y. (2023). Artificial intelligence applications in freight transportation: A land transportation perspective. *Advances in Economics, Management and Political Sciences*, *7*, 41–52. https://doi.org/10.54254/2754-1169/7/20230241
- Li, Y., & Zhao, X. (2023). Machine learning applications in transportation route optimization: Models, challenges, and future directions. *Transportation Research Part E: Logistics and Transportation Review*, *173*, 103103. https://doi.org/10.1016/j.tre.2023.103103
- Lu, X., & Weng, Q. (2025). Deep learning-based road extraction from remote sensing imagery: Progress, challenges, and future directions. *ISPRS Journal of Photogrammetry and Remote Sensing*, *208*, 1–18. https://doi.org/10.1016/j.isprsjprs.2025.01.004
- Luo, H., Wei, J., & Zhao, S., et al. (2025). Enhancing robot route optimization in smart logistics with Transformer and GNN integration. *arXiv preprint*.
- Mohtich, F.-E., Bensiali, S., & Idr, A. (2025). Geospatial data integration for intelligent transportation systems: A review of spatio-temporal traffic forecasting models. *African Journal on Land Policy and Geospatial Sciences*, *6*(4), 1–15. https://doi.org/10.48346/IMIST.PRSM/ajlp-gs.v6i4.41748
- Okrah Denteh, E. K., Danyo, A., Asamoah, J. K., Kyem, B. A., & Aboah, A. (2025). Demographics-informed neural network for multi-modal spatiotemporal forecasting of urban growth and travel patterns using satellite imagery. *arXiv*.
- Oluwaseyi, A. M., Oluwadamilare, M. P., Alumona, P., Anieto, S. B., & Ilori, E. O. (2025). AI-driven green logistics: Optimizing last-mile delivery networks with electric vehicles for carbon neutrality in U.S. metropolitan areas. *Asian Journal of Advanced Research and Reports*, *19*(12), 133–150. https://doi.org/10.9734/ajarr/2025/v19i121227
- Ping, G., Zhu, M., Ling, Z., & Niu, K. (2025). Research on optimizing logistics transportation routes using AI large models. *Applied Science and Engineering Journal for Advanced Research*, *4*(1), 45–58.
- Qin, X., Luo, Y., Zhang, H., & Chen, F. (2024). AI-driven green logistics optimization: Integrating geospatial data and sustainability metrics. *Journal of Cleaner Production*, *430*, 140258. https://doi.org/10.1016/j.jclepro.2023.140258
- Rong, R., Ma, S., Ren, N., et al. (2025). Generative artificial intelligence in intelligent transportation systems: A systematic review of applications. *Frontiers of Engineering Management*, *12*, 1020–1036. https://doi.org/10.1007/s42524-025-4241-9
- Samoilenko, S. (2025). Route optimization and transportation planning using artificial intelligence. *Austrian Journal of Technical and Natural Sciences*, *9–10*(1), 119–124. https://doi.org/10.29013/AJT-25-9.10-119-124
- Sheikh, A., Mehonaj, T., & Shakil Sheikh, M. (2025). A predictive AI modeling framework for sustainable logistics and emissions. *American Journal of Financial Technology and Innovation*, *3*(1), Article 6252. https://doi.org/10.54536/ajfti.v3i1.6252
- Sustainability Editorial Team. (2024). Artificial intelligence in logistics optimization with sustainable criteria: A review. *Sustainability*, *16*(21), 9145. https://doi.org/10.3390/su16219145

- Tang, L. (2025). Artificial intelligence-based demand forecasting and route optimization modeling for public transportation in megacities. *Applied and Computational Engineering, 169*, 159-167.
- Zhang, J., Wang, J., Zang, H., Ma, N., Skitmore, M., Qu, Z., & Skulmoski, G. (2024). Machine learning and deep learning in intelligent transportation: A scientometric analysis and qualitative review. *Sustainability, 16*(14), 5879. https://doi.org/10.3390/su16145879
- Zhang, J., Wang, Y., Liu, Z., & Chen, X. (2024). Artificial intelligence in intelligent transportation systems: A scientometric and systematic review. *IEEE Transactions on Intelligent Transportation Systems*, *25*(2), 1324–1342. https://doi.org/10.1109/TITS.2023.3301145
- Zhang, L., Sun, Q., & Tang, J. (2024). Deep learning-based traffic flow prediction and routing optimization: A review and future outlook. *Expert Systems with Applications, 235*, 121071. https://doi.org/10.1016/j.eswa.2023.121071
- Zulfiqar, N., Javaid, M. S., Ikraam, R. M., Riaz, M. A., & Sharafat, H. S. S. (2024). The role of AI in optimizing supply chain logistics for e-commerce. *Journal for Social Science Archives, 2*(2), 616–631. https://doi.org/10.59075/jssa.v2i2.156