IJCRT.ORG ISSN : 2320-2882
INTERNATIONAL JOURNAL OF CREATIVE RESEARCH THOUGHTS (IJCRT)
An International Open Access, Peer-reviewed, Refereed Journal

Ecosmart Routing: Intelligent Route Planning With Environment Integrity

Ms. Mythri S
Asst. Professor, dept of computer science engineering
(Data Science)
R N S Institute of Technology
Bengaluru, India

Rachana S
dept. of computer science engineering
(Data Science)
R N S Institute of Technology
Bengaluru, India

Sanjana BC
dept. of computer science engineering
(Data Science)
R N S Institute of Technology
Bengaluru, India

Shrujan Hadimani
dept. of computer science engineering
(Data Science)
R N S Institute of Technology
Bengaluru, India

Sushmitha
dept. of computer science engineering
(Data Science)
R N S Institute of Technology
Bengaluru, India

***Abstract*—Efficient highway route planning requires minimizing construction cost, reducing environmental disturbance, and adapting to complex terrain conditions—tasks that traditional GIS-based and manual planning methods often struggle to accomplish. This study presents a comprehensive review of satellite image–driven techniques for highway route optimization using high-resolution imagery collected from Google Earth. A set of 25 peer-reviewed studies published between 2019 and 2024 are analysed to examine advancements in deep learning–based semantic segmentation, terrain analysis, and multi-objective optimization algorithms. The survey highlights modern approaches such as U-Net-based land cover classification, graph-based shortest-path algorithms, and multi-criteria decision-making frameworks that enable the identification of eco-friendly and cost-efficient highway alignments. Key challenges—including data preprocessing complexity, regulatory constraints, and the lack of real-time adaptability—are discussed in detail. The findings also outline promising future directions in AI-driven geospatial modelling, automated environmental impact assessment, and sustainable route planning. This review serves as a valuable reference for researchers and policymakers seeking environmentally conscious and technically reliable highway route optimization solutions using satellite imagery from platforms like Google Earth.**

***Index Terms*—Highway Route Optimization, Google Earth, Satellite Imagery, Remote Sensing, Environmental Constraints, Deep Learning, GIS-Based Planning.**

I. Introduction

Highway construction is a fundamental component of national infrastructure development, supporting economic growth, regional connectivity, and urban expansion. However, identifying an optimal highway alignment remains a complex task due to environmental constraints, terrain variations, and the challenges of modern urban planning. Traditional route selection approaches—often dependent on manual surveys, outdated maps, and subjective decision-making—frequently result in suboptimal alignments that increase environmental damage, construction cost, and long-term ecological impact. With the advancement of computer vision, remote sensing, and artificial intelligence (AI), satellite imagery has become a powerful tool for data-driven highway route planning. High-resolution images from platforms such as Google Earth provide detailed information on land cover, terrain features, vegetation density, water bodies, and expanding urban zones. When integrated with geospatial analysis techniques, these datasets allow planners to evaluate natural and man-made constraints more systematically. Recent studies highlight how deep learning models—such as Convolutional Neural Networks (CNNs), U-Net architectures, and Vision Transformers—automate land-feature extraction and improve the accuracy of route evaluation. For example, Zhang et al. demonstrate how AI-based segmentation and terrain modelling can reduce ecological disturbances and enhance route feasibility by analyzing environmental features such as forests, wildlife corridors, wetlands, and flood-prone regions. Urban restrictions, including land- use patterns, population density, and existing infrastructure, also influence highway design. Multi-objective optimization techniques like NSGA-II have been widely applied to balance conflicting goals, such as minimizing cost while preserving environmentally sensitive regions. Similarly, genetic algorithms and heuristic search methods have shown significant potential in refining highway alignment decisions based on both environmental and urban constraints. The integration of AI, deep learning, and Geographic Information Systems (GIS) offers a transformative framework for sustainable highway planning. By combining satellite imagery with optimization algorithms and automated feature extraction, planners can determine routes that minimize ecological disruption while ensuring structural feasibility. The purpose of this paper is to provide a comprehensive examination of recent advancements in satellite image–based highway route optimization. Through a detailed analysis of AI-based, GIS-supported, and multi-objective optimization techniques, this study emphasizes the importance of environmentally conscious and urban-aware highway routing. The insights gathered aim to support the development of intelligent decision-support systems that enable more accurate, sustainable, and cost-effective highway route selection.

II. BACKGROUND AND FUNDAMENTAL CONCEPTS

Satellite imagery–based highway route planning is an emerging interdisciplinary field integrating remote sensing, artificial intelligence (AI), multi-objective optimization, and geospatial analysis. This section introduces the essential technical background, key terminologies, and foundational theories that support modern data-driven route optimization.

A. Key Terminologies

• Satellite Imaging: The process of capturing high-resolution images of the Earth's surface using platforms such as Google Earth, Sentinel-2, and Landsat. These datasets provide essential geospatial information for analyzing terrain, vegetation, and land-use patterns.

• Remote Sensing: The acquisition and interpretation of Earth-surface data from a distance. It plays a major role in environmental monitoring, terrain assessment, and preliminary highway feasibility studies.

• Geographic Information System (GIS): A framework used to collect, store, analyze, and visualize spatial data. GIS enables the integration of satellite imagery with environmental, urban, and terrain layers for route analysis.

• Terrain Analysis: The study of landform characteristics—such as elevation, slope, aspect, and surface roughness—that influence highway alignment, construction feasibility, and cost.

• Urban Constraints: Restrictions arising from land-use regulations, built-up areas, transportation networks, and population density that guide or limit possible route alignments.

• Environmental Constraints: Ecologically sensitive regions including protected forests, wildlife corridors, rivers, wetlands, and vegetation zones that must be preserved in sustainable route planning.

• Multi-Objective Optimization: A computational method that evaluates multiple conflicting objectives (e.g., minimizing environmental impact, reducing construction cost, avoiding urban disturbance) to generate an optimal highway route.

B. Fundamental Theories and Models

• Remote Sensing and Satellite Data Processing Satellite imagery provides the foundational data needed for terrain evaluation and land-use classification. Platforms such as Google Earth and Sentinel offer multispectral imagery suitable for detecting vegetation, urban density, water bodies, and elevation changes. Tools like the Normalized Difference Vegetation Index (NDVI) and Digital Elevation Models (DEMs) help identify sensitive ecological zones and terrain complexity. Studies such as [3] and [5] highlight the importance of satellite-based environmental monitoring in sustainable infrastructure planning.

• Geospatial Analysis for Route Optimization GIS enables spatial integration of satellite data with environmental and urban constraints. Using techniques like spatial overlay analysis, buffering, and cost-surface modeling, GIS helps planners evaluate alternative alignments while maintaining a balance between ecological preservation and urban accessibility. As demonstrated in study [12], GIS-integrated decision-support systems are highly effective for analyzing topography, vegetation cover, and population density during initial route planning.

• Machine Learning and AI in Route Selection Machine learning models—particularly Convolutional Neural Networks (CNNs), U-Net, and Vision Transformers—are widely adopted for extracting land-cover information from satellite imagery. Paper [4] demonstrates how AI automates land-use detection, while Feng et al. (2022) use Graph Neural Networks (GNNs) to model road connectivity. These methods significantly enhance route selection by producing accurate land-classification maps and enabling data-driven decision-making. • Optimization Algorithms for Highway Planning Optimization techniques such as Genetic Algorithms (GAs) and the Non-Dominated Sorting Genetic Algorithm-II (NSGA-II) are used to evaluate multiple route alternatives and identify optimal alignments. Xu et al. (2020) applied GAs to improve terrain adaptability, while Kim and Park (2022) utilized NSGA-II to minimize ecological disturbance. These algorithms provide a structured approach for resolving trade-offs among cost, environmental preservation, and engineering feasibility.

This background establishes a strong technical foundation for understanding satellite-image-based highway route optimization. The following sections explore how these techniques are applied in practice and evaluate their effectiveness in developing environmentally and urban-conscious roadway designs.

III. CLASSIFICATION OF EXISTING RESEARCH

Existing research on satellite-image-based highway route optimization can be broadly categorized into three groups: (1) image-based analysis methods, (2) optimization-driven techniques, and (3) GIS-integrated hybrid approaches. Each category focuses on addressing terrain suitability, environmental sensitivity, and urban restrictions using satellite-derived data.

• Image-Based Analysis Computer vision and deep learning techniques have been widely applied to extract valuable information from satellite imagery. Models such as Convolutional Neural Networks (CNNs) and Vision Transformers (ViTs) are used to classify land cover, detect vegetation, and analyze expansion. Several studies demonstrate the use of ViTs for large-scale remote-sensing feature extraction, while CNNs have shown strong performance in identifying feasible routes across challenging terrain. The primary limitation of these methods is their reliance on high-resolution, labeled datasets, which are not readily available for many regions.

• Optimization Methods Optimization algorithms are frequently used to determine the most suitable highway alignment while satisfying multiple constraints such as cost, environmental impact, and urban interference. Multi-objective evolutionary algorithms—including NSGA-II [10], Particle Swarm Optimization (PSO) [1], and Genetic Algorithms (GAs)—are commonly adopted. These methods can effectively explore large search spaces and produce diverse optimal solutions. However, large-scale roadway planning often requires high computational resources due to the complexity of evaluating multiple terrain and environmental constraints.

• Integrated GIS Techniques The integration of satellite imagery with GIS tools enables advanced spatial analysis for route selection. GIS-based reinforcement learning has been used, as demonstrated by Garcia and Martinez (2023), to identify routes with minimal ecological disturbance. Some researchers have also explored Graph Neural Networks (GNNs) embedded within GIS platforms to model road networks and connectivity patterns.

While GIS-integrated methods provide strong spatial reasoning, their effectiveness depends heavily on the availability of accurate and up-to-date geospatial datasets, which vary significantly by region.

A. *Comparison of AI and Optimization Techniques for Highway Route Optimization*

TABLE I
COMPARISON OF AI TECHNIQUES FOR ECO-FRIENDLY ROUTING

Technique	Advantages	Limitations
Convolutional Neural Networks (CNNs)	High accuracy in extracting terrain features	Requires large labeled datasets
Vision Transformers (ViTs)	Effective for large-scale image analysis	High computational cost
Reinforcement Learning (RL)	Learns adaptive, dynamic routing strategies	Requires extensive training data
Graph Neural Networks (GNNs)	Efficient for modeling road networks	Needs structured graph data and long training time
Genetic Algorithms (GAs)	Finds diverse optimal solutions	Slow convergence
Particle Swarm Optimization (PSO)	Fast convergence for optimization tasks	Prone to local optima
Multi-Objective Evolutionary Algorithms (NSGA-II, NSGA-III)	Balances multiple environmental and urban constraints	Computationally expensive
Federated Learning (FL)	Enables privacy-preserving collaborative model training	High communication and synchronization costs
GIS-Integrated Methods	Strong spatial analysis and visualization	Dependent on accurate geospatial datasets

B. *Trends in Research*

Recent work shows a significant shift toward AI-based feature extraction, including CNNs, ViTs, and reinforcement learning for dynamic route selection. Multi-objective optimization techniques—especially NSGA-II—remain dominant due to their ability to balance conflicting constraints. GIS-integrated approaches continue to be essential for spatial reasoning, though their performance depends on reliable satellite data sources.

C. *Comparative Analysis*

CNNs and ViTs provide high accuracy in land classification but require high-quality training datasets. Optimization algorithms such as NSGA-II perform well for balancing costs and environmental impact but incur high computational overhead. GNNs and RL methods offer improved modelling of spatial relationships and adaptation but suffer from long training times and data requirements.

D. *Research Gaps*

Despite substantial progress, several gaps remain: • Limited availability of high-resolution, annotated satellite datasets for many geographic regions.

• Need for hybrid models combining AI, GIS, and optimization to improve accuracy and robustness.

• Requirement for computationally efficient optimization algorithms capable of handling large geospatial datasets.

• Lack of scalable systems leveraging distributed or parallel computing for accelerating route-planning computations.

IV. CRITICAL ANALYSIS AND DISCUSSION

Key trends, constraints, and gaps that need to be filled for future developments are shown by a study of the literature on highway route optimization using satellite images. The majority of studies use AI and optimization-based methods to enhance route selection; nonetheless, there are still significant issues with computational efficiency, model generalization, and data availability.

V. METHODOLOGY

The proposed methodology integrates satellite image analysis, deep learning–based land segmentation, and pathfinding algorithms to generate efficient and environmentally sensitive highway routes. The workflow consists of six major stages, as described below.

A. *Dataset Collection*

The first step involves gathering and organizing the raw data required for route planning. The dataset includes:

• RGB Satellite Images: High-resolution Google Earth images of the study area, containing visible-spectrum information (R, G, B). These images capture land features such as vegetation, water bodies, built-up areas, and open land.

• Segmentation Masks: Pixel-wise labeled images that classify each region into land-type categories (e.g., forest, water, urban, barren land, roads). These serve as ground truth for supervised model training.

B. Data Preprocessing

Prepare the satellite imagery for deep learning, several preprocessing operations are applied:

• Normalization: Pixel values are scaled to a uniform range (e.g., 0–1), improving network convergence and stability.

• Resizing and Tiling: Large satellite images are resized or divided into smaller patches (typically 256×256) to reduce computational load and enable efficient GPU processing.

• Mask Generation (if required): If ground-truth masks are unavailable, manual or semi-automated tools are used for annotation.

C. Deep Learning Segmentation

Segmentation is performed to classify each pixel into its corresponding land category.

- Model-selection U-Net:
  A U-Net architecture is used due to its encoder–decoder structure, which captures both high-level context and fine spatial details.
- Land-Type Classification:
  The model identifies and labels:
  - Roads
  - Vegetation / Forest
  - Water bodies
  - Buildings
  - Urban areas
  - Open or barren land
- Output:
  A segmentation map that highlights all land types within the satellite image. This map is used to estimate construction difficulty.

D. Feature Classification

After segmentation, the output is processed to obtain meaningful classes for analysis.

• Pixel-wise Translation: Segmented pixels are converted into discrete land-type labels.

• Integration of Terrain Data: Elevation and slope information are overlaid to refine land classification.

• For example: Flat roads are preferable, Dense forests or steep slopes increase construction difficulty. This ensures that both environmental and geographical factors are incorporated.

E. Cost Map Generation

The cost map transforms the segmented terrain into a numerical representation reflecting traversal difficulty.

- Assigning Weights: Each land type is assigned a cost value depending on construction difficulty or environmen- tal impact:
  - Roads → Low cost
  - Urban areas → Medium cost
  - Forests / Water bodies → High cost
- Terrain and Ecology Modifiers: Factors such as slope, elevation, and ecological sensitivity further adjust the cost. This cost map forms the primary input for the optimization algorithm.

F. Route Optimization

The final stage computes the optimal highway alignment using the cost map.

• Pathfinding Algorithm: The A* algorithm is used to compute the most efficient path, considering both distance and terrain cost.

• Evaluation of Alternatives: Multiple paths are compared based on Total distance, Environmental impact, Construction feasibility.

• Optimization Objective: To minimize distance, reduce ecological disturbance, and avoid high-cost terrain, resulting in a practical and sustainable highway route.

VI. SYSTEM ARCHITECTURE

The proposed system processes raw satellite imagery and generates an optimal highway route through a sequence of automated stages. First, the input satellite images are pre-processed through resizing, normalization, tiling, and noise reduction to ensure uniformity and suitability for analysis. A deep learning–based segmentation model, such as U-Net or DeepLab, is then applied to classify each pixel into specific land categories including roads, forests, water bodies, urban regions, and open land. The segmented output is transformed into a cost map, where each land type is assigned a numerical cost based on construction difficulty and environmental sensitivity. High-cost regions include forests, water bodies, and steep terrain, while low-cost areas such as plains and existing roads are preferred for route alignment.

A pathfinding algorithm—typically the A* algorithm—uses this cost map to compute the least-cost route between selected start and end points. The final optimal path is visualized on top of the segmented image and original satellite map, enabling clear interpretation of terrain suitability and the environmental impact of the proposed route.

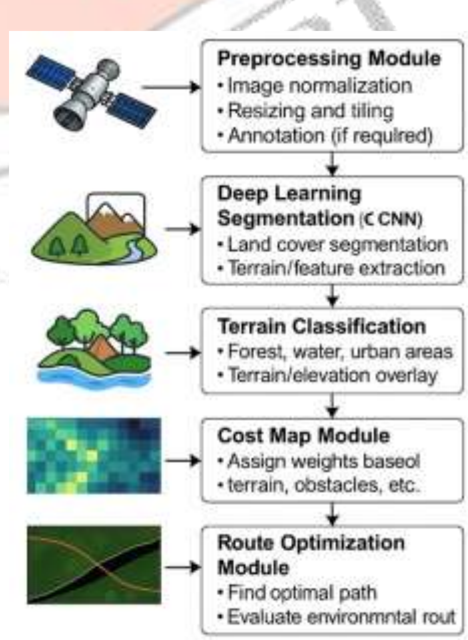

Fig. 1. System Architecture

VII. METRICS

This section describes the evaluation metrics used to assess the accuracy of the land-cover segmentation model and the efficiency of the computed highway route.

A. Segmentation Metrics

These metrics are used to evaluate the performance of the U-Net segmentation model, which classifies different land-cover types from satellite imagery.

- **Pixel Accuracy (PA):** Measures the ratio of correctly predicted pixels to total pixels:

$$PA = \frac{\sum_{i=1}^{N} \mathbf{1}(y_i = \hat{y}_i)}{N} \quad (1)$$

where y_i = ground truth label, $\hat{y}_i$ = predicted label, N = total number of pixels, $\mathbf{1}(\cdot)$ = indicator function.

- **Intersection over Union (IoU):** Evaluates the overlap between prediction and ground truth for each class:

$$IoU = \frac{|P \cap G|}{|P \cup G|} \quad (2)$$

where P = predicted region, G = ground truth region.

- **Dice Coefficient (F1-Score):** A similarity score emphasizing overlap:

$$Dice = \frac{2|P \cap G|}{|P| + |G|} \quad (3)$$

It may also be expressed using true positives (TP), false positives (FP), and false negatives (FN):

$$Dice = \frac{2TP}{2TP + FP + FN} \quad (4)$$

B. Route Optimization Metrics

These metrics evaluate how suitable and efficient the computed route is.

- **Total Route Distance** The total length of the computed path is:

$$D = \sum_{i=1}^{k-1} \sqrt{(x_{i+1} - x_i)^2 + (y_{i+1} - y_i)^2} \quad (5)$$

where k = number of points in the path, (x_i, y_i) = coordinates of each point, and distance may be measured in pixels or meters (if georeferenced).

- **Total Route Cost** The cumulative environmental and construction cost of the route:

$$C = \sum_{i=1}^{k} w(x_i, y_i) \quad (6)$$

where $w(x_i, y_i)$ is the cost assigned to pixel (x_i, y_i).

- **Ecological Impact Score** Measures ecological disturbance along the path:

where $e(x_i, y_i) \in [0, 1]$ is an ecological penalty value representing forests, wetlands, water bodies, or protected zones. Higher values indicate increased ecological impact.

- **Construction Feasibility Score** A slope-based penalty capturing terrain difficulty:

$$Feasibility = \sum_{i=1} f(\nabla h_i) \quad (8)$$

where $\nabla h_i = |h_{i+1} - h_i|$ is the elevation change between consecutive points. Higher slope → higher construction difficulty.

- **Multi-Route Comparison Score** A composite decision metric combining all cost factors:

$$Score = \alpha D + \beta C + \gamma Impact + \delta Feasibility \quad (9)$$

where $\alpha, \beta, \gamma, \delta$ are user-defined weights representing environmental, economic, or practical priorities.

These metrics ensure that the segmentation model produces accurate land classification and that the route optimization selects practical, cost-effective, and environmentally sustainable paths.

VIII. RESULTS

The proposed framework combines satellite imagery, deep-learning segmentation, cost-map generation, and route optimization to create efficient and environmentally sustainable highway routes. It identifies key land features and applies terrain constraints to ensure practical, eco-friendly paths. The generated cost maps help compute optimal routes that balance distance, impact, and construction feasibility, demonstrating the effectiveness of the approach.

A. Original and Segmented Land Cover

The left image shows the raw satellite input, while the right image displays the segmented land cover, highlighting forest and non-forest areas used for further route planning. A filtered feature map is then extracted, highlighting only the key classes—Water, Forest, and Urban—which are essential for cost-map generation and route planning.

$$Impact = \sum_{i=1} e(x_i, y_i) \quad (7)$$

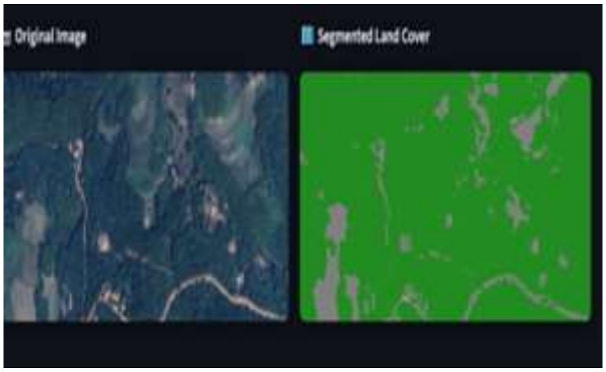

Fig. 2. Original Image and Segmented Land Cover

B. Segmented Terrain and Cost Heatmap

The left image shows the segmented terrain highlighting major land types. The right image presents the corresponding construction cost heatmap.

Fig. 3. Land-Cover Segmentation and Cost Map

C. Optimal Route on Cost Map and Satellite Image

The left image overlays the computed optimal path on the construction cost map, showing how the algorithm avoids high-cost regions. The right image visualizes the same route on the original satellite imagery, confirming that the path follows feasible terrain while minimizing environmental impact.

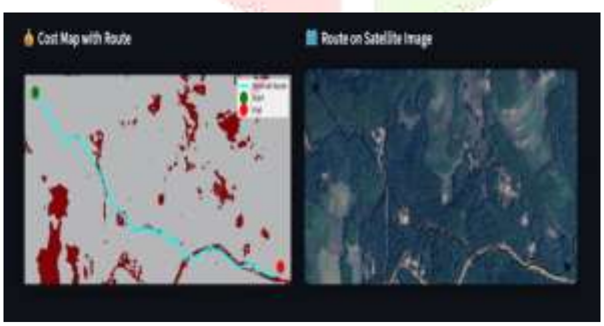

Fig. 4. Route Overlay on Cost Map and Satellite Terrain

IX. OPEN CHALLENGES AND FUTURE DIRECTIONS

Despite notable progress in AI-driven highway route optimization, several challenges must still be addressed to enhance the reliability and real-world applicability of current methods.

• Limited Access to High-Resolution Satellite Data: High-quality imagery is essential for accurate land classification and terrain analysis; however, many regions—especially in developing countries—lack detailed satellite coverage. Future research should focus on improving data accessibility through open-source geospatial platforms, collaborations with space agencies, and next-generation imaging technologies.

• Need for Multi-Source Data Integration: Most existing studies rely on a single dataset, which limits their ability to capture complex environmental, urban, and terrain conditions. Integrating multi-source geospatial data such as LiDAR, drone imagery, and SAR can significantly improve route accuracy and robustness.

• Computational Complexity and Scalability Issues: Deep learning models and multi-objective optimization algorithms often demand substantial processing power, making large-scale route planning computationally expensive.

• Insufficient Environmental and Socioeconomic Modelling: Current models mainly focus on technical optimization, often overlooking ecological sensitivity, carbon emissions, and community impact. Incorporating sustainability metrics and socio-environmental constraints will lead to more responsible route-planning solutions.

• Gap in Real-World Deployment and Validation: Many proposed frameworks are validated on limited or simulated datasets rather than actual field conditions. Future research should involve real-world case studies, collaboration with transportation authorities, and large-scale pilot implementations. Future works should explore light weight architectures, parallel computing, and more efficient optimization strategies.

By addressing these challenges and advancing the integration of AI, geospatial analytics, and environmental modelling, future highway route planning systems can become more accurate, sustainable, and practically deployable.

X. CONCLUSION

Highway route optimization has become an interdisciplinary field shaped by advances in satellite remote sensing, artificial intelligence, and geospatial information systems. This survey reviewed recent developments across deep learning–based image analysis, optimization algorithms, and GIS-integrated workflows, emphasizing how these technologies improve terrain interpretation, environmental assessment, and alignment feasibility compared to traditional planning approaches.

Modern high-resolution satellite imagery from platforms such as Sentinel-2, Landsat, Google Earth, and Bhoonidhi enables planners to extract detailed information on vegeta- tion, hydrology, terrain features, and built-up areas. Deep learning models—including U-Net, CNNs, Vision Transform- ers, DeepLabV3+, and GNNs—further enhance land-cover classification, supporting accurate cost-map generation and environmental sensitivity analysis. Optimization techniques such as GAs, PSO, ACO, SA, NSGA-II, and NSGA-III allow planners to balance multiple objectives, including construction cost, ecological preservation, and route length, while GIS frameworks integrate diverse datasets for comprehensive spatial evaluation.

Environmental sustainability and socio-economic considerations are increasingly incorporated into routing models, reflecting the need to avoid ecologically sensitive areas, reduce emissions, minimize displacement, and comply with policy constraints. Despite this progress, challenges persist, including limited availability of labeled datasets, high computational demands, lack of standardized evaluation benchmarks, and insufficient real-world validation.

Future research should focus on lightweight deep learning models, multi-source geospatial fusion, scalable optimization algorithms, and dynamic routing that adapts to real-time environmental changes. Standardized geospatial frameworks and policy-aware routing will also be essential for large-scale deployment.

In summary, the integration of satellite imagery, AI-driven segmentation, GIS analytics, and multi-objective optimization represents a transformative step toward sustainable and intelligent highway planning. As data accessibility and interdisciplinary collaboration continue to improve, these technologies will enable more efficient, environmentally responsible, and resilient transportation infrastructure.

References

[1] D. S. Tharun *et al.*, "Deforestation Detection from Remote Sensing Images using Machine Learning," Sep. 2024. [Online]. Available: https://ieeexplore.ieee.org/document/5980984

[2] V. Waikar, S. Sawant, and A. Joshi, "A Review Paper on Route Optimization Using Deep Learning," Sep. 2023. [Online]. Available: https://ieeexplore.ieee.org/document/10397919

[3] N. T. Chitra *et al.*, "Satellite Imagery for Deforestation Prediction using Deep Learning," 2021. [Online]. Available: https://ieeexplore.ieee.org/document/8258330

[4] H. A. H. Baca, F. L. P. Valdivia, J. I. O. Guizado, Y. P. Atencio, and F. T. Tadeo, "Vegetation Cover Estimation from High-Resolution Satellite Images Based on Chromatic Charac- teristics and Image Processing," Jun. 2020. [Online]. Available: https://ieeexplore.ieee.org/document/9281247/

[5] S. P. Gu¨vela, M. A. Akgu¨l, and H. Aksu, "Flood inundation maps using Sentinel-2: a case study in Berdan Plain," *Water Supply*, vol. 22, no. 4, pp. 4098–4113, 2022, doi: 10.2166/ws.2022.039.

[6] J. Liu *et al.*, "Solving A Multi-objective Mission Planning Problem for UAV Swarms with An Improved NSGA-III Algorithm," *Int. J. Comput. Intell. Syst.*, vol. 11, no. 1, pp. 1067–1081, 2018, doi: 10.2991/ijcis.11.1.81.

[7] J. Zhang, "Optimization design of highway route based on deep learning," *Front. Future Transp.*, vol. 5, 1430509, 2024, doi: 10.3389/ffutr.2024.1430509.

[8] H. Zhang, Z. Jiang, G. Zheng, and X. Yao, "Semantic Segmentation of High-Resolution Remote Sensing Images with Improved U-Net Based on Transfer Learning," *Int. J. Comput. Intell. Syst.*, vol. 16, p. 181, 2023, doi: 10.1007/s44196-023-00364-w.

[9] A. Ruiz-Ve´lez, J. Garc´ıa, J. Alcala´, and V. Yepes, "Sustainable Road Infrastructure Decision-Making: Custom NSGA-II with Repair Operators for Multi-Objective Optimization," *Mathematics*, vol. 12, p. 730, 2024, doi: 10.3390/math12050730.

[10] X. Jin and Z. Wang, "Proximal policy optimization based dynamic path planning algorithm for mobile robots," *Electronics Letters*, accepted Sep. 2021, doi: 10.1049/ell2.12342.

[11] Y. Zheng *et al.*, "Spatial planning of urban communities via deep reinforcement learning," *npj Urban Sustain.*, Jul. 2023, doi: 10.1038/s43588-023-00503-5.

[12] D. Chen *et al.*, "Highway-Graph: Modelling Long-distance Node Relations for Improving General-Graph Neural Network," *arXiv preprint* arXiv:1911.03904, 2020, doi: 10.48550/arXiv.1911.03904.

[13] "Semi-automatic optimal route location using high resolution satellite images, GIS, linear programming and active contours optimization techniques." [Online]. Available: https://ieeexplore.ieee.org/document/8900322/

[14] A. Keselman, S. Ten, A. Ghazali, and M. Jubeh, "Reinforcement Learning with A* and a Deep Heuristic," *arXiv preprint* arXiv:1811.07745, 2018, doi: 10.48550/arXiv.1811.07745.

[15] "Classification of Satellite Images and Predicting Field Areas after Fine-Tuning Using Sequential CNN Model," in *Proc. 2023 2nd Int. Conf. on Futuristic Technologies (INCOFT)*, Nov. 2023, doi: 10.1109/INCOFT60753.2023.10425312.

[16] A. I. Hassabo, *Semi-Automatic Route Location Using High Resolution Satellite Images, GIS, and Active Contours Optimization Technique*. Dar-es-Salaam, Tanzania: Ardhi University, 2010.

[17] "Identifying Land Patterns from Satellite Imagery in Amazon Rainforest using Deep Learning," *arXiv preprint* arXiv:1809.00340, Sep. 2018, doi: 10.48550/arXiv.1809.00340.

[18] A. D. Vibhute, K. V. Kale *et al.*, "Classification of complex environments using pixel level fusion of satellite data," *Multimedia Tools and Applications*, vol. 79, no. 47–48, pp. 34737–34769, Dec. 2020, doi: 10.1007/s11042-020-08978-4.

[19] J. Babbargive and N. Rathee, "Satellite Image Analysis: A Review," in *Proc. 2019 IEEE Int. Conf. on Electrical, Computer and Communication Technologies (ICECCT)*, Coimbatore, India, Feb. 2019, doi: 10.1109/ICECCT.2019.8869481.

[20] A. Pn and N. Subramanyam, "A Novel Approach Using Active Con- tour Model for Semi-Automatic Road Extraction from High Res- olution Satellite Imagery," in *Proc. 2010 Int. Conf. on Machine Learning and Computing (ICMLC)*, Bangalore, India, Feb. 2010, doi: 10.1109/ICMLC.2010.36.