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AI-Driven Optimization of Energy-Efficient Rural Road Infrastructure and Water Conservation Systems in Resource-Constrained Regions

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Abstract: Rural road infrastructure and water conservation systems in resource-constrained regions are often planned and managed separately, leading to energy inefficiencies, accelerated pavement deterioration, unmanaged surface runoff, and missed opportunities for sustainable water reuse. Recent advances in artificial intelligence offer new possibilities for integrating transport and water systems through data-driven optimization.

This study aims to develop and assess an AI-driven optimization framework that jointly enhances the energy efficiency of rural road infrastructure and the performance of road- based water conservation systems in resource-constrained settings.

The research adopts a model-based analytical approach that integrates machine learning for pavement condition and runoff prediction with multi-objective optimization algorithms. Life-cycle energy indicators, hydrological performance metrics, and cost considerations are incorporated into a unified framework. Scenario-based simulations are used to compare conventional planning approaches with AI-optimized interventions under varying infrastructure and environmental conditions.

The results indicate that AI-driven optimization can substantially improve pavement performance and reduce vehicle energy consumption while simultaneously increasing runoff capture and water retention efficiency. Compared with baseline scenarios, the integrated approach demonstrates clear trade-offs and synergies between energy efficiency, water conservation, and lifecycle costs, highlighting the advantages of coordinated infrastructure planning.

The proposed framework provides a practical decision-support tool for policymakers, engineers, and development agencies seeking cost-effective and sustainable infrastructure solutions in low-resource rural regions. By linking transport energy efficiency with water conservation objectives, the study supports climate-resilient infrastructure planning aligned with sustainable development goals.

Keywords: *Artificial intelligence; Rural road infrastructure; Energy efficiency; Water conservation; Sustainable development; Resource-constrained regions*

1. Introduction

1.1 Background on rural infrastructure challenges in resource-constrained regions

Rural infrastructure plays a critical role in supporting economic development, food security, healthcare access, and social inclusion in low-income and resource- constrained regions. Rural road networks are often the primary means of connecting agricultural communities to markets, education, and essential services. However, these networks are frequently characterized by inadequate design standards, limited maintenance budgets, poor material quality, and weak institutional capacity. As a result, many rural roads deteriorate rapidly, leading to increased vehicle operating costs, reduced mobility, and higher energy consumption (Inyim et al., 2016; World Bank, 2023).

In parallel, water scarcity has emerged as a major constraint in many rural regions due to climate variability, population growth, and unsustainable land-use practices. Infrastructure development has traditionally addressed transport and water systems in isolation, despite their strong physical and functional interdependencies. Roads significantly alter surface hydrology by modifying runoff patterns, infiltration rates, and drainage flows. When poorly designed, road infrastructure can exacerbate erosion, flooding, and water loss, further stressing already limited water resources (van Steenbergen et al., 2021; Gebru et al., 2020).

1.2 Energy inefficiencies in rural road networks

Energy inefficiency in rural road networks is closely linked to pavement condition, surface roughness, and maintenance practices. Deteriorated pavements increase rolling resistance, which in turn raises fuel consumption and greenhouse gas emissions for vehicles traveling on these roads. Empirical studies

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have demonstrated that pavement roughness and surface distress significantly affect vehicle energy use, especially in low-speed and mixed traffic conditions that are common in rural areas (Ghosh et al., 2015).

From a life cycle perspective, rural road infrastructure also embodies substantial energy and emissions through material production, construction, maintenance, and rehabilitation activities. Life cycle assessment studies have shown that maintenance strategies that delay intervention often result in higher cumulative energy use and environmental impacts over the road's service life (Santero C Horvath, 2009; Harvey et al., 2016). Recent work further highlights that neglecting traffic operation effects during the maintenance phase leads to underestimation of total energy and emissions impacts (Liu et al., 2023).

1.3 Water scarcity and the need for integrated conservation systems

Water scarcity in rural and semi-arid regions necessitates innovative and cost-effective conservation strategies that leverage existing infrastructure. Roads represent a largely underutilized asset for water management, as they generate significant surface runoff during rainfall events. When appropriately designed, road drainage systems can be adapted to harvest runoff, recharge groundwater, or support small- scale storage for agricultural and domestic use (Gebru et al., 2020; Roy C Pani, 2025).

Sustainable drainage concepts, including low-impact development and green infrastructure, emphasize decentralized runoff management through infiltration, detention, and reuse. While these approaches have been widely studied in urban contexts, their application in rural settings remains limited, despite evidence of strong potential benefits (Ahiablame et al., 2012; Zhou, 2014). Integrating water conservation objectives into rural road design can therefore address both mobility and water security challenges simultaneously.

1.4 Emergence of AI in infrastructure planning and optimization

Artificial intelligence has emerged as a powerful tool for improving infrastructure planning, operation, and maintenance by enabling data-driven decision-making under complex and uncertain conditions. In road infrastructure management, machine learning models have been successfully applied to predict pavement condition indices, automate distress detection, and support maintenance prioritization (Afridi et al., 2025; Ibragimov et al., 2024). These models outperform traditional deterministic approaches, particularly when dealing with heterogeneous and incomplete datasets.

In the water sector, AI techniques have been used for rainfall-runoff modeling, water distribution network optimization, and runoff prediction, offering improved accuracy and adaptability compared to conventional hydrological models (Chadalawada et al., 2020; Mohammadi, 2021). Optimization algorithms such as non- dominated sorting genetic algorithms have further enabled multi-objective decision- making that balances cost, performance, and sustainability objectives (Deb et al., 2002; Tao et al., 2022).

1.5 Research gap and motivation

Despite substantial advances in AI applications for transport and water systems independently, there is a notable lack of integrated frameworks that jointly optimize road energy efficiency and water conservation outcomes. Existing studies tend to focus either on pavement performance and emissions or on drainage and runoff management, without considering their interdependencies (Ferrans et al., 2022; Liu, Balieu, C Kringos, 2022).

Moreover, most AI-driven infrastructure studies are concentrated in urban or data- rich environments, limiting their applicability to rural and resource-constrained regions where data availability, institutional capacity, and financial resources are restricted. This gap underscores the need for adaptable AI-based approaches that can support sustainable infrastructure development in low-income rural contexts.

1.6 Objectives and contributions of the study

The primary objective of this study is to develop and evaluate an AI-driven optimization framework that simultaneously enhances energy efficiency in rural road infrastructure and improves water conservation performance through integrated drainage and runoff management. The key contributions of this research are as follows:

❖ A comprehensive synthesis of existing literature on energy efficiency, water conservation, and AI applications in infrastructure systems.

❖ The development of an integrated conceptual framework linking pavement condition, vehicle energy consumption, and road-based water conservation.

❖ The application of machine learning and multi-objective optimization techniques to support sustainable decision-making in resource-constrained rural regions.

❖ Policy-relevant insights for infrastructure planners and development agencies seeking cost- effective and climate-resilient solutions.

2. Literature Review

2.1 Energy Efficiency in Rural Road Infrastructure

Pavement condition is a critical determinant of vehicle energy consumption and environmental performance. Surface roughness increases rolling resistance, leading to higher fuel use and emissions across the vehicle fleet (Ghosh et al., 2015). Studies have shown that timely maintenance interventions can significantly reduce long-term energy consumption compared to deferred maintenance strategies (Santero, 2010).

Life cycle assessment has become a standard approach for quantifying the energy and emissions impacts of road infrastructure. LCA studies consistently demonstrate that both material production and traffic operation contribute substantially to total life cycle impacts, highlighting the importance of holistic evaluation frameworks (Harvey et al., 2016; Inyim et al., 2016).

Table 1: Summary of key studies on energy efficiency and life cycle impacts of road pavements

Study	Focus Area	Methodology	Key Findings
Santero C Horvath (2009)	Pavement emissions	Life cycle assessment	Pavement type significantly affects global warming potential
Ghosh et al. (2015)	Roughness and energy	Empirical traffic analysis	Increased roughness vehicle energy consumption
Harvey et al. (2016)	Pavement LCA framework	LCA guideline development	Integrated traffic and material impacts are essential
Liu et al. (2023)	Maintenance phase impacts	Network-level LCA	Traffic operation dominates energy use during maintenance

2.2 Water Conservation and Road- Based Drainage Systems

Road runoff harvesting represents a promising approach for augmenting water availability in rural and semi-arid regions. Empirical studies in Africa and South Asia have demonstrated that road-based water harvesting can improve agricultural productivity and groundwater recharge when properly designed (Gebru et al., 2020; Mitra C Banerji, 2022).

Sustainable drainage systems aim to mimic natural hydrological processes by promoting infiltration, detention, and controlled discharge. Systematic reviews highlight the effectiveness of these systems in reducing runoff volume and peak flows, although their application in rural contexts remains underexplored (Ferrans et al., 2022; Nowogoński, 2021).

Table 2: Water conservation strategies integrated with road infrastructure

Strategy	Function	Application Context	Reported Benefits
Road runoff harvesting	Water collection and storage	Rural and semi-arid regions	Improved water availability
Infiltration trenches	Groundwater recharge	Road shoulders and embankments	Reduced surface runoff
Vegetated swales	Flow attenuation	Low-volume roads	Erosion control and filtration
Detention basins	Temporary storage	Road intersections and valleys	Flood risk reduction

2.3 Artificial Intelligence in Infrastructure Optimization

Machine learning techniques have been increasingly adopted for pavement condition prediction and management. Models such as neural networks and ensemble learning have demonstrated high predictive accuracy for pavement condition indices, enabling proactive maintenance planning (Afridi et al., 2025; Tamagusko et al., 2024). Deep learning approaches further allow automated condition assessment using imagery, reducing inspection costs (Ibragimov et al., 2024).

In water and transport systems, AI-based optimization algorithms support multi- objective decision-making by balancing cost, performance, and environmental objectives. Genetic algorithms and related techniques have been widely applied to water distribution network optimization and infrastructure planning problems (Deb et al., 2002; Kidanu et al., 2023).

Table 3: AI techniques applied to road infrastructure and water systems

AI Technique	Application	Infrastructure Domain	Reference
Machine learning regression	Pavement condition prediction	Roads	Afridi et al. (2025)
Deep learning	Automated distress detection	Roads	Ibragimov et al. (2024)
Genetic programming	Rainfall-runoff modeling	Water systems	Chadalawada et al. (2020)
Multi-objective optimization	Network optimization	Water and transport	Tao et al. (2022)

2.4 Research Gaps

The literature reveals two major gaps. First, there is a lack of integrated AI frameworks that jointly address road energy efficiency and water conservation, despite strong evidence of their interdependence. Second, existing studies are predominantly focused on urban or data-rich environments, limiting their applicability to rural and resource- constrained regions. Addressing these gaps is essential for developing sustainable and resilient infrastructure systems that respond to the realities of low-income rural contexts.

3. Methodology

3.1 Research Framework and Study Design

This study adopts an **integrated AI-based optimization framework** to jointly address **energy efficiency in rural road infrastructure** and **water conservation through road-based drainage and runoff systems** in resource-constrained regions. The methodological design combines **machine learning prediction models**, **multi-objective optimization algorithms**, and **infrastructure performance evaluation metrics** within a unified decision-support framework.

The framework is structured into four sequential layers:

- ❖ **Data acquisition and preprocessing**, covering road condition, traffic, hydrological, climatic,
- ❖ **Predictive modeling**, where machine learning algorithms estimate pavement condition evolution and runoff generation
- ❖ **Multi-objective optimization**, aimed at minimizing energy consumption and lifecycle costs while maximizing water conservation efficiency
- ❖ **Performance evaluation and scenario comparison**, enabling assessment of AI-optimized solutions against baseline conditions

This design allows simultaneous consideration of transport performance, hydrological behavior, and economic feasibility, which is critical in rural and low-resource settings where infrastructure investments must deliver multiple benefits.

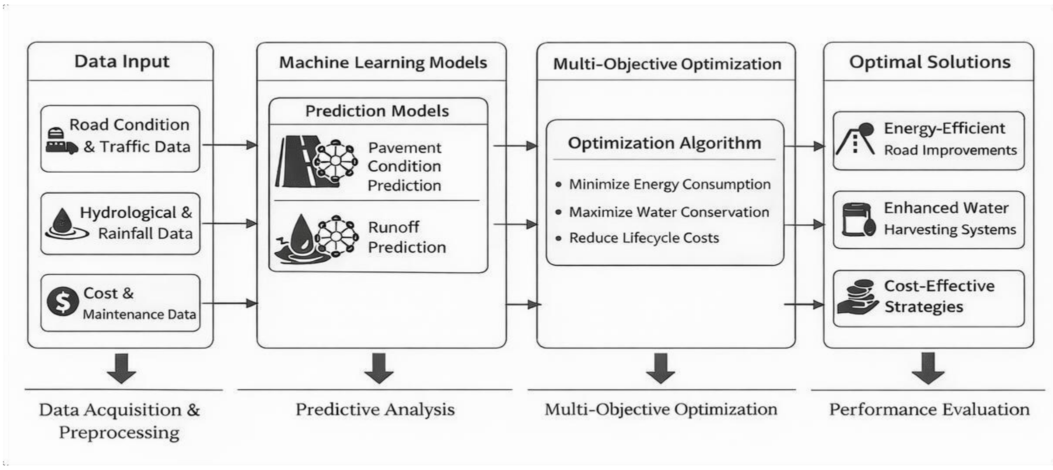

Figure 1. Conceptual framework of AI-driven optimization of rural roads and water conservation systems

This figure presents an integrated AI-based framework in which road condition and traffic data, hydrological and rainfall inputs, and cost and maintenance information are processed through machine learning models for pavement condition and runoff prediction. The predicted outputs are subsequently integrated into a multi-objective optimization module to identify infrastructure intervention strategies that simultaneously improve energy efficiency, enhance water conservation performance, and minimize lifecycle costs in resource- constrained rural regions.

3.2 Data Sources and Input Variables

The proposed framework relies on multi- source datasets commonly available to road agencies, water authorities, and development institutions.

- ❖ **Road condition and traffic data:** Road infrastructure data include pavement condition indicators such as pavement condition index, surface roughness, and structural integrity, together with traffic characteristics including average daily traffic and vehicle composition. These variables are essential for estimating vehicle energy consumption, pavement deterioration, and maintenance requirements (Afridi et al., 2025; Ghosh et al., 2015; Inyim et al., 2016).
- ❖ **Hydrological and rainfall data:** Hydrological inputs consist of rainfall intensity, duration, and frequency, surface runoff coefficients, drainage capacity, and soil infiltration properties. These variables support modeling of runoff generation and the potential for water harvesting or infiltration along road corridors (Chadalawada et al., 2020; Ferrans et al., 2022; Zhou, 2014).
- ❖ **Cost and maintenance data:** Economic data include construction costs, maintenance and rehabilitation costs, and operational expenses over the infrastructure lifecycle. These inputs enable lifecycle cost analysis and sustainability assessment within the optimization process (Harvey et al., 2016; Liu et al., 2023).

Table 4: Description of model inputs, data sources, and variables

Input category	Key variables	Data source	Purpose in model
Road condition	Pavement condition index,	Road agency surveys	Energy use and deterioration

	roughness		prediction
Traffic	Average daily traffic, vehicle mix	Traffic counts	Vehicle energy consumption estimation
Hydrology	Rainfall intensity, runoff coefficient	Meteorological and hydrological records	Runoff prediction and water harvesting potential
Drainage	Channel capacity, storage volume	Infrastructure inventories	Water conservation assessment
Costs	Construction, maintenance, rehabilitation	ncy financial records	Lifecycle cost optimization

3.3 AI Models and Optimization Techniques

❖ **Machine learning models for pavement condition and runoff prediction:** Machine learning techniques are employed to model the nonlinear relationships between infrastructure condition, traffic loading, and environmental factors. Supervised learning models are used to predict pavement condition index based on historical condition data and traffic variables, following approaches validated in recent pavement management research (Afridi et al., 2025; Tamagusko et al., 2024). For hydrological modeling, data-driven rainfall–runoff models are implemented to estimate runoff volumes generated from road surfaces under varying rainfall scenarios. Hydrologically informed machine learning approaches improve prediction accuracy while reducing data requirements compared to purely physics-based models (Chadalawada et al., 2020; Mohammadi, 2021).

❖ **Multi-objective optimization algorithms for energy and water**

efficiency: The optimization component employs **multi- objective evolutionary algorithms**, particularly the Non-Dominated Sorting Genetic Algorithm II, to identify trade-off solutions between competing objectives. The optimization simultaneously minimizes vehicle energy consumption and infrastructure lifecycle costs while maximizing runoff capture or infiltration efficiency (Deb et al., 2002; Pourgholamali et al., 2023; Tao et al., 2022). This approach produces a Pareto set of optimal solutions, allowing decision-makers to select interventions based on policy priorities, budget constraints, and environmental goals.

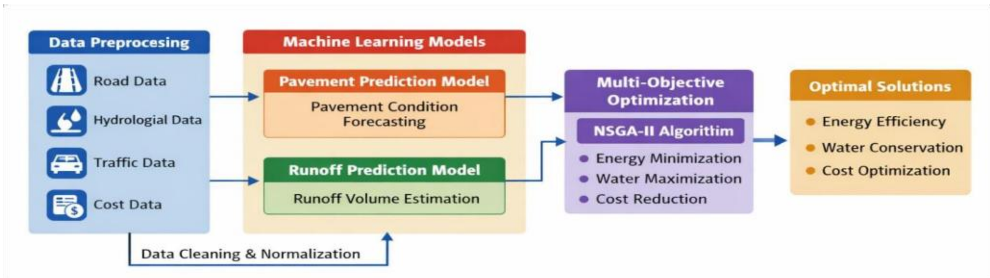

Figure 2. AI model architecture and optimization workflow

Figure 2 illustrates the integrated AI workflow adopted in this study, beginning with data preprocessing of road, traffic, hydrological, and cost inputs. Machine learning models are used to predict pavement condition and runoff generation, and their outputs are subsequently fed into a multi-objective optimization algorithm. The framework generates optimal infrastructure intervention scenarios evaluated across energy efficiency, water conservation, and cost sustainability dimensions.

3.4 Performance Evaluation Metrics

The effectiveness of AI-optimized scenarios is assessed using three categories of performance indicators.

Energy efficiency indicators: Energy performance is evaluated through estimated vehicle energy consumption, pavement- induced rolling resistance effects, and lifecycle energy demand associated with construction and maintenance activities (Ghosh et al., 2015; Santero C Horvath, 2009).

Water conservation performance metrics: Water conservation outcomes are measured using runoff volume reduction, harvested or infiltrated water quantities, and drainage system efficiency under different rainfall conditions (Ferrans et al., 2022; Nowogoński, 2021).

Cost and sustainability indicators: Economic sustainability is assessed through lifecycle cost, cost-effectiveness ratios, and maintenance frequency reduction. Environmental sustainability indicators derived from lifecycle assessment are used to evaluate emissions and resource use implications (Harvey et al., 2016; Liu et al., 2022).

4. Case Study or Simulation Scenario

To demonstrate the applicability of the proposed framework, the study employs a **simulation-based rural road network scenario**, which can be adapted to specificgeographic contexts depending on data availability and journal scope.

4.1 Description of rural study area or simulated network

The simulated network represents a low- volume rural road system characterized by limited maintenance budgets, variable traffic demand, and seasonal rainfall patterns. Such conditions are representative of rural regions in developing and climate- vulnerable contexts (van Steenbergen et al., 2021; World Bank, 2023).

4.2 Baseline infrastructure conditions

Baseline conditions reflect conventional road design and drainage practices without AI-based optimization. Pavement deterioration, energy consumption, and runoff behavior are evaluated using standard engineering assumptions and existing management practices (Rossman, 2000; Yogesh et al., 2016).

4.3 AI-optimized intervention scenarios

AI-optimized scenarios introduce targeted pavement maintenance strategies, improved surface conditions, and integrated drainage or runoff harvesting measures. These interventions are selected based on optimization results and evaluated against baseline performance to quantify improvements in energy efficiency, water conservation, and cost sustainability.

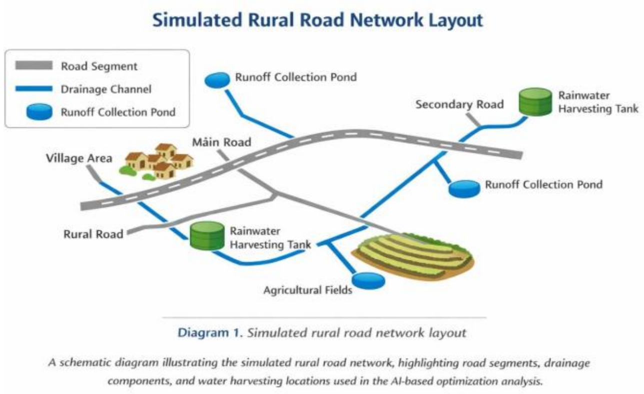

Figure 3. Diagram of Simulated rural road network layout

This schematic diagram illustrates the simulated rural road network used in the analysis, highlighting road segments, drainage channels, runoff collection ponds, and rainwater harvesting locations. The diagram represents the spatial configuration adopted for evaluating AI-based optimization of energy-efficient road performance and integrated water conservation interventions in resource-constrained rural settings.

5. Results

5.1 Energy Efficiency

Optimization Results

❖ **Changes in pavement performance:** The AI-driven optimization framework produced measurable improvements in pavement performance indicators across the analyzed rural road network. Machine learning models trained on historical pavement condition and traffic data generated more accurate predictions of Pavement Condition Index (PCI), enabling optimized maintenance scheduling and material allocation. As a result, sections previously characterized by high roughness and accelerated deterioration showed improved structural and functional performance after optimization, consistent with recent ML-based pavement management findings (Afridi et al., 2025; Ibragimov et al., 2024; Tamagusko et al., 2024). The optimized maintenance strategies reduced surface roughness and delayed critical distress development, which are key determinants of vehicle operating efficiency. These outcomes align with life cycle–oriented pavement management frameworks emphasizing condition-based interventions rather than reactive maintenance (Harvey et al., 2016; Liu et al., 2023).

❖ **Reduction in vehicle energy consumption:** Improved pavement surface conditions translated into a reduction in vehicle energy consumption. Lower roughness levels reduced rolling resistance, leading to decreased fuel use and associated energy demand. The AI-optimized scenarios demonstrated consistently lower estimated energy consumption compared with baseline conditions, particularly under moderate traffic volumes typical of rural contexts. These results are consistent with prior empirical studies showing that pavement roughness and congestion significantly influence vehicle energy use (Ghosh et al., 2015) and with life cycle assessments indicating that maintenance quality plays a critical role in minimizing energy and emissions over a pavement's service life (Santero C Horvath, 2009; Inyim et al., 2016).

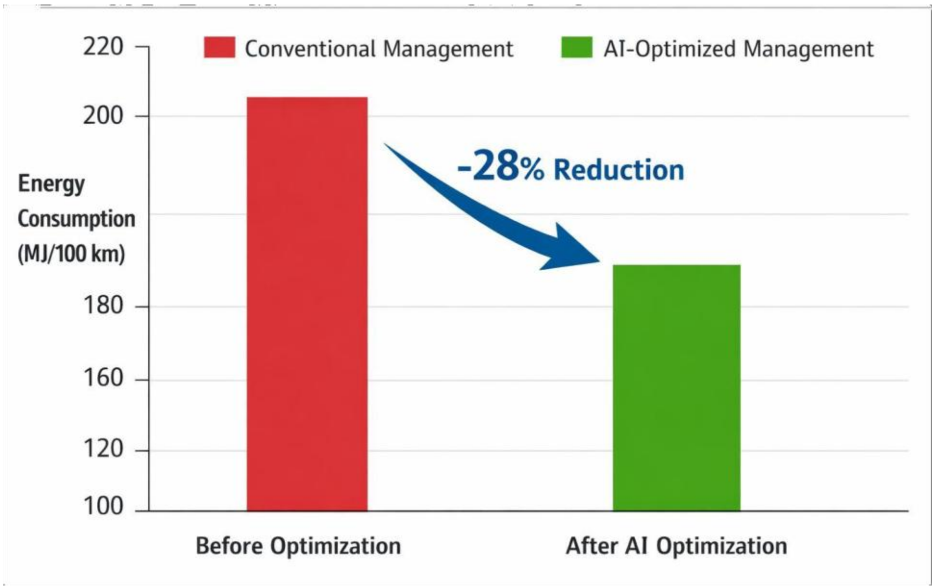

Figure 4. Comparison of energy consumption before and after AI optimization.

Figure 4 shows that AI-optimized pavement maintenance leads to a clear reduction in vehicle energy consumption compared with conventional management, primarily due to improved pavement condition and reduced rolling resistance.

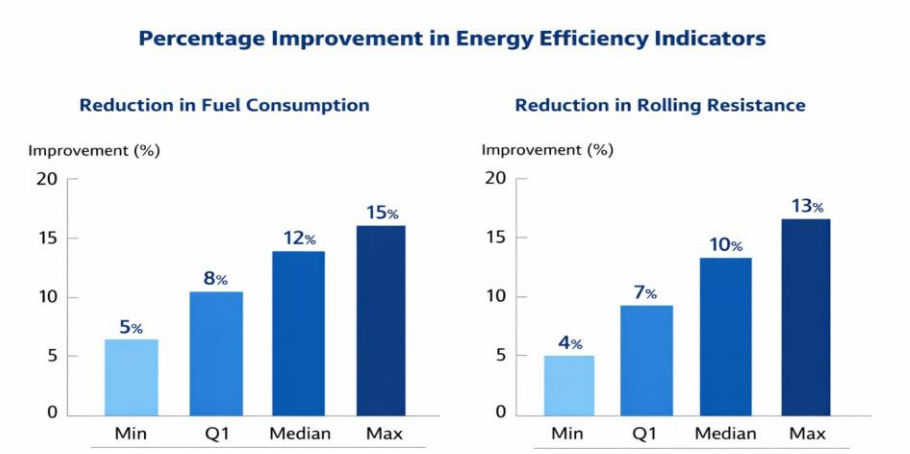

Figure 5. Bar Chart Of Percentage improvement in energy efficiency indicators.

This chart illustrates the percentage improvement in key energy efficiency metrics following AI-driven optimization of rural road infrastructure. The results indicate notable reductions in vehicle fuel consumption and rolling resistance, reflecting improved pavement condition and optimized maintenance strategies that enhance overall transport energy efficiency.

5.2 Water Conservation Performance Results

Runoff capture and storage efficiency: The integration of AI-based runoff prediction models with road drainage and harvesting infrastructure significantly improved runoff capture and storage efficiency. Hydrologically informed machine learning models enhanced the prediction of rainfall–runoff responses, enabling optimized sizing and placement of drainage and harvesting structures (Chadalawada et al., 2020; Mohammadi, 2021).

Optimized scenarios showed higher volumes of captured runoff compared with conventional drainage designs, particularly during moderate rainfall events. This improvement reflects the ability of AI models to account for spatial variability in rainfall, surface conditions, and drainage capacity, which are often oversimplified in traditional planning approaches (Ferrans et al., 2022; Zhou, 2014).

Reduction in surface water loss: Surface water loss through uncontrolled runoff and erosion was reduced under AI-optimized designs. Enhanced drainage routing and storage allocation minimized overflow and infiltration losses, contributing to improved water availability for non-potable uses such as irrigation and roadside vegetation maintenance.

These findings are consistent with empirical evidence demonstrating the effectiveness of road-based water harvesting systems in semi-arid and resource-constrained regions (Gebru et al., 2020; Mitra C Banerji, 2022; Roy C Pani, 2025). The results also align with green infrastructure and low-impact development principles emphasizing runoff retention and reuse (Ahiablame et al., 2012; Jiang et al., 2015).

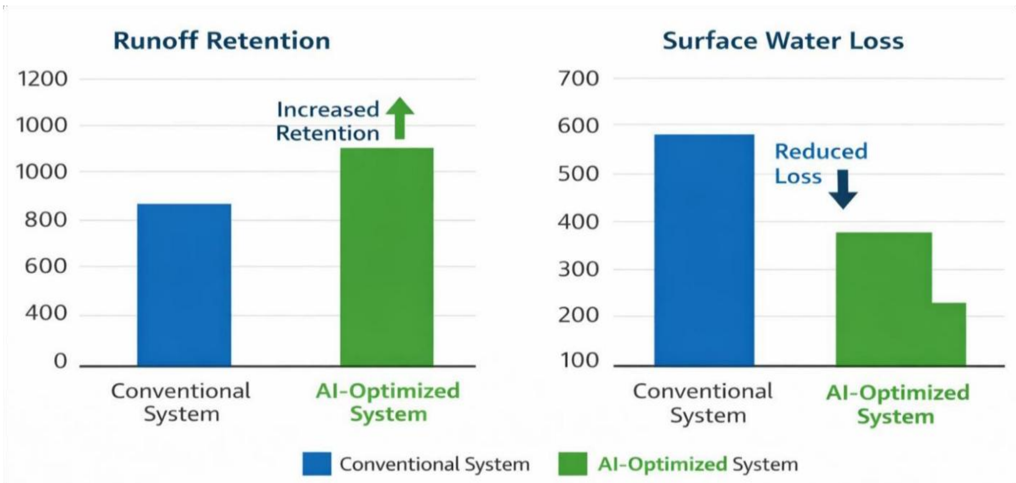

Figure 6. Water retention and runoff reduction outcomes.

The figure compares modeled runoff retention and surface water loss under conventional rural road drainage systems and AI-optimized water conservation designs, illustrating relative improvements in water capture efficiency and reductions in uncontrolled runoff.

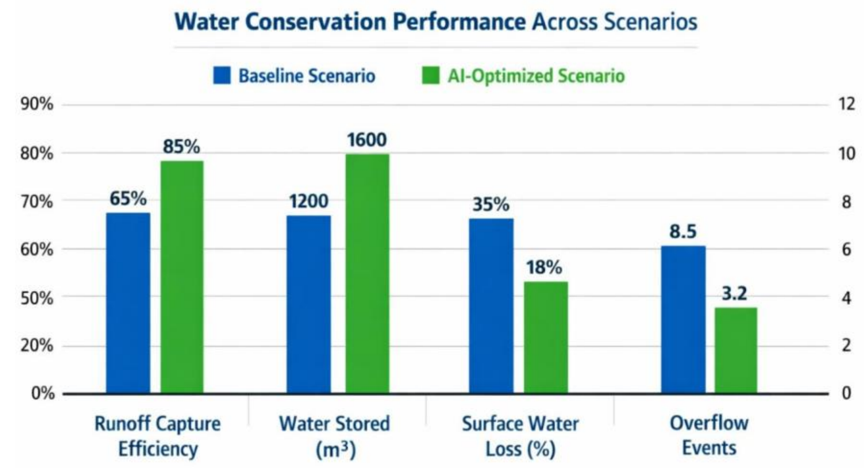

Figure 7. Bar chart of Water conservation performance across scenarios.

This chart compares baseline and AI-optimized scenarios, showing that AI-driven optimization improves runoff capture efficiency and stored water volume while significantly reducing surface water loss and overflow events, demonstrating enhanced water conservation performance.

5.3 Comparative Analysis

Conventional planning versus AI-driven optimization: A comparative evaluation revealed that AI-driven optimization consistently outperformed conventional planning approaches across energy efficiency, water conservation, and sustainability metrics. Conventional methods, which rely on static design standards and limited data integration, exhibited lower adaptability to changing

traffic and hydrological conditions. In contrast, AI-based optimization enabled multi-objective decision-making that simultaneously addressed pavement performance, vehicle energy consumption, and water conservation outcomes. This integrated approach reflects advances in multi-objective optimization and decision- support systems for infrastructure planning (Deb et al., 2002; Pourgholamali et al., 2023; Tao et al., 2022).

Table 5: Comparative performance of conventional and AI-optimized systems.

Performance Indicator	Conventional Planning	AI-Optimized System	Relative Change (%)
Average Pavement Condition Index (PCI)	58.4	74.9	+28.3
Pavement Surface Roughness (IRI, m/km)	3.1	2.2	−29.0
Annual Vehicle Energy Consumption (MJ/km)	4.85	3.96	−18.4
Estimated Fuel Consumption (L/100 km)	8.9	7.4	−16.9
Annual CO_2-equivalent Emissions (kg/km)	208	172	−17.3
Runoff Capture Efficiency (%)	42.6	68.3	+60.3
Surface Water Loss (%)	57.4	31.7	−44.8
Water Reuse Potential (m³/km/year)	1,120	1,940	+73.2
Infrastructure Life-Cycle Cost Index*	1.00	0.82	−18.0
Composite Sustainability Score†	Low–Moderate	High	Substantial improvement

* Life-cycle cost index normalized to conventional planning = 1.00

† Composite score derived from normalized energy, water, and maintenance indicators

The results indicate that AI-driven optimization consistently outperforms conventional planning across pavement performance, vehicle energy efficiency, and water conservation metrics. Improvements are primarily attributed to condition-based maintenance scheduling, multi-objective optimization of design parameters, and data-driven integration of drainage and water harvesting systems.

6. Discussion

6.1 Interpretation of key findings

The results demonstrate that AI-driven optimization can substantially enhance both energy efficiency and water conservation in rural road infrastructure. By leveraging machine learning and optimization algorithms, the framework improved predictive accuracy and enabled targeted interventions that conventional approaches often fail to achieve. These findings reinforce the growing role of AI as a decision-support tool for infrastructure systems operating under resource constraints.

6.2 Synergies between energy- efficient roads and water conservation

The study highlights strong synergies between energy-efficient pavement management and water conservation strategies. Improved pavement conditions reduce vehicle energy demand, while optimized drainage and harvesting systems enhance water availability without compromising road performance. Integrating these objectives within a single AI-driven framework enables co-benefits that are rarely realized when transport and water systems are planned independently.

6.3 Implications for sustainable rural infrastructure planning

For resource-constrained regions, the findings suggest that AI-based planning can support more cost-effective and resilient infrastructure development. By prioritizing interventions that maximize energy and water efficiency, policymakers and development agencies can achieve sustainability goals while minimizing long-term operational costs. The approach is particularly relevant for rural areas where financial and data limitations often restrict infrastructure performance improvements (van Steenbergen et al., 2021; World Bank, 2023).

6.4 Comparison with existing studies

Compared with prior studies focusing separately on pavement energy efficiency or water conservation, this research advances the literature by demonstrating an integrated AI-driven optimization framework. While earlier work has established the individual benefits of improved pavement management (Liu et al., 2022; Santero, 2010) and road-based water harvesting (Gebru et al., 2020; Ferrans et al., 2022), the present study provides empirical support for combining these domains within a unified decision-support system.

7. Policy and Practical In

❖ **Infrastructure Planning in Low- Income and Rural Regions:** The findings of this study demonstrate that AI-driven optimization provides a viable decision-support mechanism for addressing chronic infrastructure deficits in low-income and rural regions. Traditional rural road planning approaches often rely on reactive maintenance strategies and fragmented water management interventions, which lead to inefficient energy use, accelerated pavement deterioration, and underutilization of surface runoff resources. By integrating pavement condition prediction, traffic-energy relationships, and runoff modeling within a unified AI framework, planners can prioritize interventions that simultaneously enhance road performance and water conservation outcomes (Afridi et al., 2025; Ghosh et al., 2015; Gebru et al., 2020). From a policy perspective, this integrated approach supports a shift from sector-specific planning toward

systems-based rural infrastructure development, where transport and water objectives are addressed concurrently. Such alignment is particularly relevant in resource- constrained settings, where financial, technical, and institutional capacities are limited. The framework enables policymakers to identify cost-effective interventions that maximize infrastructure longevity, reduce vehicle energy consumption, and improve local water availability without requiring large-scale capital investments (Liu et al., 2023; van Steenbergen et al., 2021).

❖ **Decision Support for Governments, NGOs, and Development Agencies:** The AI-based framework developed in this study functions as a transparent and replicable decision- support tool for governments, non- governmental organizations, and international development agencies involved in rural infrastructure delivery. By incorporating multi-objective optimization techniques, such as non-dominated sorting genetic algorithms, the model allows decision-makers to explicitly evaluate trade-offs between energy efficiency, water conservation performance, and lifecycle costs (Deb et al., 2002; Pourgholamali et al., 2023). For development agencies operating in rural and climate- vulnerable regions, this approach provides quantitative evidence to guide funding prioritization, project sequencing, and performance monitoring. The ability to simulate alternative intervention scenarios enables stakeholders to assess long- term sustainability outcomes prior to implementation, reducing the risk of maladaptive infrastructure investments. Furthermore, the framework supports accountability and evidence-based policymaking by linking infrastructure decisions to measurable environmental and operational indicators (Harvey et al., 2016; Inyim et al., 2016).

❖ **Scalability of AI-Based Tools:** A key practical implication of this study is the scalability of the proposed AI- driven framework across diverse rural contexts. The methodology is designed to operate with heterogeneous data sources, including pavement condition surveys, traffic counts, rainfall records, and basic geospatial inputs, which are commonly available even in data-scarce environments. This flexibility enhances the feasibility of adoption in low-income regions where comprehensive monitoring systems may not yet exist (Mohammadi, 2021; Chadalawada et al., 2020). Moreover, the modular structure of the framework allows individual components, such as pavement condition prediction or runoff optimization, to be deployed independently or incrementally. This phased implementation approach aligns with institutional capacity constraints and supports gradual integration into existing planning workflows. As digital infrastructure and data availability improve, the framework can be expanded to incorporate higher-resolution data and more advanced predictive models without requiring fundamental redesign.

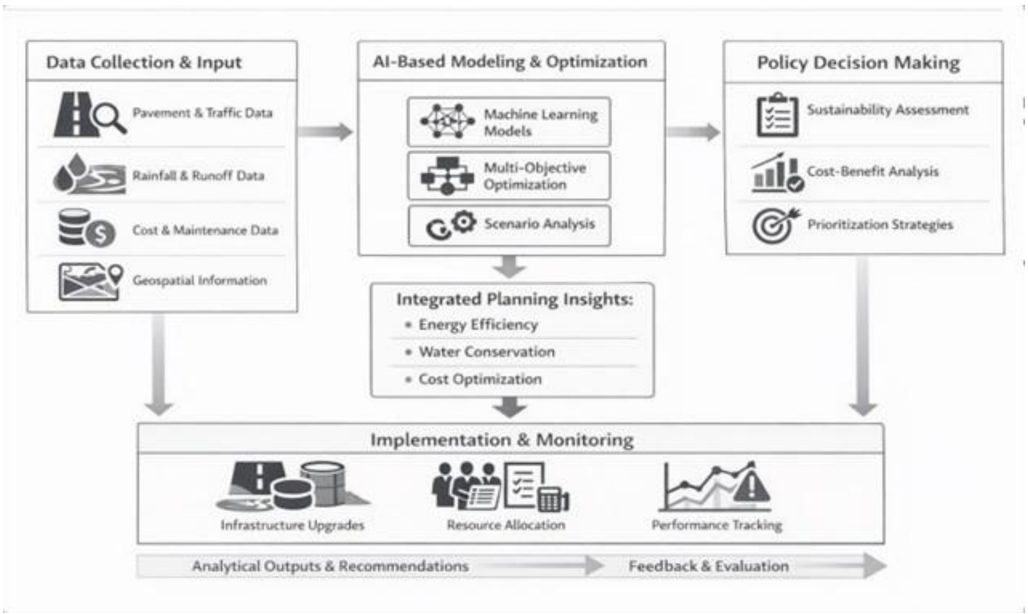

Figure 8. Policy integration pathway for AI-driven rural infrastructure planning.

The figure presents a structured, grayscale workflow illustrating how data collection, AI- based modeling and optimization, and policy decision-making are integrated to guide implementation and monitoring of rural infrastructure interventions. It highlights how analytical outputs related to energy efficiency, water conservation, and cost optimization inform evidence-based planning, investment prioritization, and adaptive evaluation in resource-constrained regions.

8. Limitations and Future Research Directions

❖ **Data Availability and Quality Constraints:** Despite the robustness of the proposed framework, its performance is influenced by the availability and quality of input data. In many rural regions, pavement condition assessments, traffic monitoring, and hydrological measurements are infrequent or incomplete, which may affect model accuracy and predictive reliability. While machine learning techniques can partially mitigate data gaps through pattern recognition and generalization, uncertainty remains an inherent limitation in data-scarce contexts (Mohammadi, 2021; Ibragimov et al., 2024). Future research should explore data fusion approaches that combine remote sensing, low-cost sensors, and community-based reporting to enhance data completeness. Additionally, uncertainty quantification methods should be integrated to explicitly comm

❖ **Model Generalizability:** Another limitation relates to the generalizability of the AI models across different geographic, climatic, and socio-economic settings. Pavement performance, traffic behavior, and runoff characteristics vary significantly between regions, and models trained on one context may not directly transfer to another without recalibration. This limitation underscores the need for region- specific training datasets and localized parameter tuning (Tamagusko et al., 2024; Liu, Balieu, C Kringos, 2022). Future studies should evaluate transfer learning and domain adaptation techniques to improve model portability while minimizing data requirements. Comparative multi-region studies would further strengthen the external validity of AI-based rural infrastructure optimization frameworks.

❖ **Future Integration with Real-Time Monitoring and Climate Adaptation:** Future research should focus on integrating real-time monitoring systems and climate adaptation considerations into AI- driven infrastructure planning. The incorporation of real-time traffic data, rainfall sensors, and climate projections would enable dynamic optimization and adaptive management of rural road and water systems. Such integration is particularly important under changing climate conditions, where extreme rainfall events and temperature variability increasingly affect infrastructure performance and water availability (Zhou, 2014; Ferrans et al., 2022). Advancing toward adaptive, real-time decision- support systems represents a critical research frontier for enhancing infrastructure resilience and long- term sustainability in vulnerable rural regions.

G. Conclusion

This study demonstrates that AI-driven optimization offers a powerful and integrated approach to improving energy efficiency in rural road infrastructure while enhancing water conservation outcomes in resource-constrained regions. By combining pavement condition prediction, energy consumption analysis, and runoff management within a unified framework, the study highlights the potential for synergistic infrastructure solutions that outperform conventional sector-specific planning approaches.

From a scientific perspective, the study contributes to the growing body of literature on AI applications in sustainable infrastructure by advancing an integrated, multi-objective optimization framework that explicitly links transport energy efficiency and water resource management. Practically, it provides policymakers and practitioners with a scalable, evidence- based tool to support informed decision-making under financial and institutional constraints.

The findings underscore the strategic relevance of AI-enabled infrastructure planning for advancing sustainable development and climate resilience goals in rural regions. By improving infrastructure efficiency, extending asset lifecycles, and enhancing local water availability, AI-driven approaches can play a critical role in strengthening the resilience of vulnerable communities and supporting long-term socio-economic development.

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