Integrating Artificial Intelligence for Climate- Resilient Energy Planning, Rural Infrastructure Development, and Water Conservation in Underdeveloped Regions

Prasanth Alluri

Principle IT Security Architect, California, USA

Abstract

Underdeveloped regions are increasingly exposed to climate variability that disrupts energy supply, degrades rural infrastructure, and intensifies water scarcity. These challenges are interconnected and are often exacerbated by limited data availability, weak institutional capacity, and fragmented sectoral planning. Traditional planning approaches struggle to account for climate uncertainty and cross-sector dependencies, resulting in infrastructure investments that are inefficient, fragile, or poorly targeted. The aim of this study is to examine how artificial intelligence can be integrated to support climate-resilient planning across three critical domains: energy systems, rural infrastructure development, and water conservation. The scope of the study focuses on underdeveloped and resource-constrained regions where decision-making must balance reliability, equity, cost efficiency, and long-term resilience under uncertain climate conditions.

Methodologically, the study adopts an integrated AI-based planning framework that combines climate data, remote sensing products, socio-economic indicators, and sector- specific operational data. Machine learning models are applied for demand and generation forecasting, accessibility analysis, and anomaly detection, while optimization techniques are used to prioritize investments and resource allocation under multiple objectives and constraints. The framework enables measurable improvements in renewable energy and load forecasting accuracy, more effective prioritization of rural transport investments that enhance accessibility, and improved water demand prediction with reduced leakage and allocation inefficiencies. By linking outputs across sectors, the approach highlights synergistic gains that would not be achievable through siloed planning.

The study contributes a structured, evaluation-ready framework that supports evidence- based infrastructure planning in climate-vulnerable regions. Its practical implications are directed toward governments, development agencies, and utilities seeking scalable decision-support tools that enhance resilience, improve service equity, and align infrastructure planning with sustainable development objectives.

Keywords: *artificial intelligence; climate resilience; energy planning; rural infrastructure development; water conservation; sustainable development; decision support systems; underdeveloped regions*

1. Introduction

1.1 Context: Climate vulnerability, infrastructure gaps, and SDG alignment

Underdeveloped regions are disproportionately exposed to climate variability and extreme events while simultaneously facing persistent deficits in basic infrastructure systems. Energy supply is often unreliable due to high dependence on climate-sensitive resources and limited grid resilience. Rural transport networks frequently remain fragmented, seasonally inaccessible, or poorly maintained, constraining access to markets, healthcare, education, and emergency services. Water systems in these regions commonly experience high non-revenue water, weak demand management, and limited monitoring capacity, intensifying water stress under changing climatic conditions.

These challenges directly intersect with global sustainable development priorities, particularly Sustainable Development Goal 6 on clean water and sanitation, as well as goals related to affordable energy, resilient infrastructure, and climate action. However, progress toward these goals is hindered by planning approaches that rely on static assumptions, siloed sectoral analyses, and incomplete data. Climate change further amplifies uncertainty by altering demand patterns, resource availability, and infrastructure risk profiles, making traditional planning tools insufficient for long-term resilience.

1.2 Why AI for integrated planning in underdeveloped regions

Artificial intelligence offers a set of analytical capabilities well suited to the complex, data- constrained environments typical of underdeveloped regions. AI methods can integrate heterogeneous data sources, including climate projections, remote sensing, infrastructure inventories, and limited operational records, to produce actionable insights even where conventional datasets are sparse or outdated. Machine learning models are particularly effective at identifying non-linear relationships, learning from proxy indicators, and updating predictions as new information becomes available.

Beyond individual sector optimization, AI enables integrated planning by linking energy, transport, and water systems within a single analytical framework. For example,

improved renewable energy forecasting can support reliable electricity supply for water pumping and treatment, while optimized rural road prioritization can enhance access for infrastructure maintenance across sectors. AI-driven multi-objective optimization also allows planners to explicitly balance trade-offs among cost, resilience, equity, and environmental outcomes, which is essential in resource- constrained contexts.

1.3 Research objectives and contributions

The primary objective of this study is to examine how artificial intelligence can be systematically integrated into climate-resilient planning for energy systems, rural infrastructure development, and water conservation in underdeveloped regions. Specifically, the paper aims to:

- ❖ Synthesize existing research on AI applications across energy, transport, and water sectors with a focus on climate resilience.
- ❖ Propose an integrated, cross-sector AI planning framework that addresses interdependencies among energy, transport, and water systems.
- ❖ Identify appropriate data sources, AI methods, and evaluation metrics suitable for low-capacity and data- limited environments.
- ❖ Provide evidence-oriented reporting structures, including tables and figures, that support transparent assessment of planning outcomes.

By bridging sectoral literatures and emphasizing integrated decision support, this study contributes a practical and policy-relevant perspective to the growing body of work on AI for sustainable and climate- resilient development.

1.4 Paper organization

The remainder of this paper is organized as follows. Section 2 reviews relevant literature on AI-driven climate-resilient energy planning, rural infrastructure investment, water conservation, and governance considerations. Section 3 presents the conceptual framework for integrated AI- based planning across sectors. Section 4 describes the data sources and methodological approach. Section 5 reports and analyzes key results across energy, transport, and water domains. Section 6 discusses cross-sector synergies and implications in relation to prior studies. Section 7 outlines policy and practical implications, followed by limitations and future research directions in Section 8. Section 9 concludes the paper.

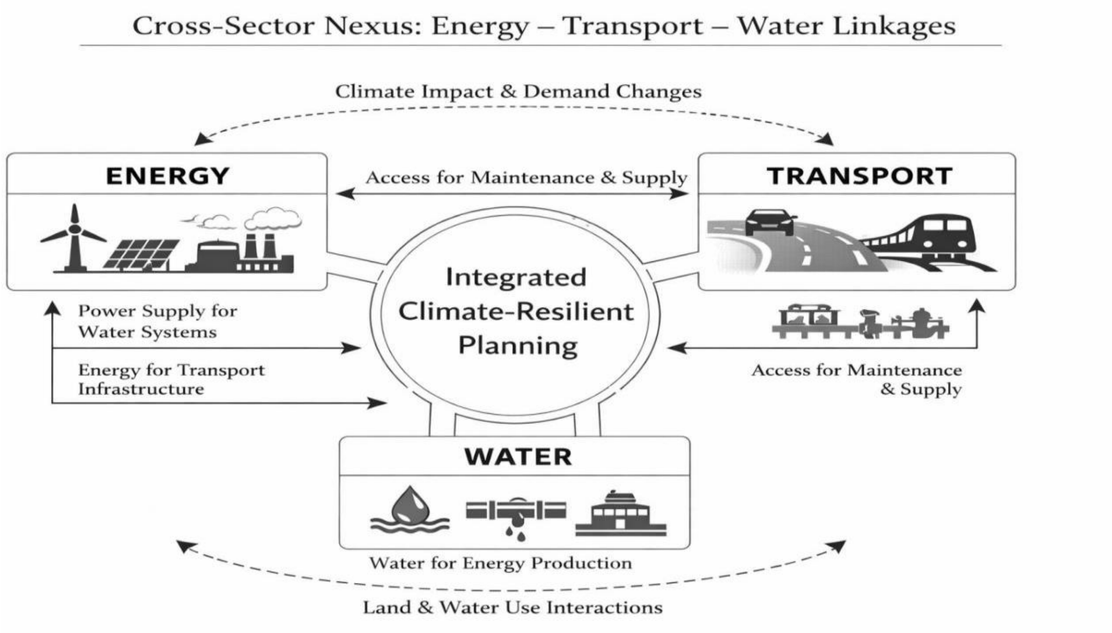


Diagram 1. Cross-sector nexus schematic (Energy–Transport–Water linkages)

2. Background and Related Work

2.1 Climate-resilient energy planning and AI forecasting

Recent research highlights the growing role of AI in improving the resilience of energy systems under climate uncertainty. Machine learning models have been widely applied to renewable energy generation forecasting, load prediction, and system reliability assessment. These approaches outperform traditional statistical models by capturing non-linear dependencies between weather variables and energy outputs, which is particularly important as climate patterns become more volatile. AI-supported forecasting enhances planning decisions related to capacity expansion, grid reinforcement, and integration of variable renewable energy sources, thereby reducing vulnerability to climate-induced supply disruptions.

2.2 Rural accessibility and infrastructure investment planning

In rural and underdeveloped regions, infrastructure investment decisions are often constrained by limited budgets and incomplete spatial data. Recent studies demonstrate that geospatial analytics, remote sensing, and machine learning can significantly improve accessibility analysis and investment prioritization. AI-based approaches enable the estimation of travel times, identification of underserved populations, and evaluation of alternative road investment scenarios. By quantifying social and economic benefits alongside costs, these methods support more equitable and climate-resilient infrastructure planning, particularly in areas exposed to flooding, landslides, or seasonal isolation.

2.3 Water conservation: Demand forecasting, leakage, and quality monitoring

Water utilities in underdeveloped regions face chronic challenges related to demand uncertainty, high leakage rates, and limited monitoring of water quality. AI techniques have been increasingly applied to forecast water demand, detect anomalies indicative of leaks, and support adaptive allocation under scarcity conditions. Time-series models and anomaly detection algorithms enable earlier identification of system losses and more efficient distribution of available resources. When combined with climate data, these tools also support anticipatory planning for droughts and extreme rainfall events, contributing to long-term water security.

2.4 Governance and responsible AI considerations for public infrastructure

While AI offers substantial technical benefits, its application in public infrastructure planning raises important governance

ISSN (online): 1873-7056

and accountability considerations. Transparent model design, clear documentation of assumptions, and robust validation are essential to ensure trust and legitimacy in decision-making processes. Responsible AI frameworks emphasize risk management, fairness, and human oversight, particularly when AI outputs influence resource allocation and public investment. In underdeveloped regions, capacity building and institutional readiness are critical to prevent over- reliance on opaque models and to ensure that AI tools augment rather than replace informed human judgment.

3. Conceptual Framework

3.1 Integrated AI planning pipeline (data → models → decisions → monitoring)

The proposed conceptual framework adopts an end to end AI planning pipeline that links heterogeneous data streams to actionable infrastructure decisions under climate uncertainty. The pipeline is structured as four tightly coupled layers.

❖ **Data layer.** This layer aggregates climate projections, historical weather observations, remote sensing products, socio economic indicators, and sector specific operational data from energy, transport, and water systems. Data heterogeneity and incompleteness are expected in underdeveloped regions, therefore preprocessing emphasizes harmonization across spatial and temporal scales, gap filling, and uncertainty annotation.

❖ **AI layer.** Machine learning and deep

learning models transform raw data into predictive and diagnostic insights. Time series models are used for renewable generation, load, and water demand forecasting, while spatial and graph based models support accessibility analysis and infrastructure exposure assessment. The AI layer is modular so that models can be updated independently as data quality improves.

❖ **Optimization layer.** Outputs from AI models feed into multi objective optimization routines that balance competing goals such as cost efficiency, service reliability, climate resilience, and social equity. This layer translates predictions into ranked investment options, operational rules, and allocation plans under multiple scenarios.

❖ **Policy and implementation layer**

with monitoring feedback. Decisions are implemented through planning instruments, budget allocation, and operational adjustments. Continuous monitoring captures realized outcomes and feeds them back into the data and AI layers, enabling iterative learning and adaptive planning.

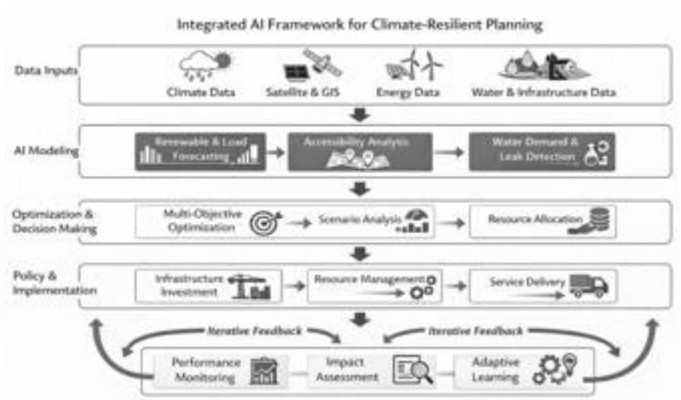


Figure 1. Integrated AI framework for climate resilient planning.

3.2 Multi sector decision objectives (reliability, accessibility, conservation, equity)

The framework is designed around four core objectives that reflect infrastructure priorities in underdeveloped regions.

❖ **Reliability.** Ensuring stable and predictable service delivery under climate variability, particularly for electricity supply and water availability.

- **Accessibility.** Improving physical access to essential services such as markets, healthcare, and water points by reducing travel time and network fragmentation in rural areas.

- **Conservation.** Minimizing resource losses through improved demand forecasting, leakage detection, and optimized allocation of scarce water and energy resources.

- **Equity.** Explicitly incorporating distributional considerations so that investments prioritize underserved and climate vulnerable populations rather than only aggregate efficiency gains.

These objectives are operationalized as quantifiable metrics and jointly optimized rather than treated independently.

4. Data and Methods

4.1 Study design and planning setting

The study adopts a systems oriented planning design tailored to underdeveloped regions characterized by limited data availability, constrained public budgets, climate exposure, and fragmented infrastructure governance. Rather than focusing on a single sector, the design integrates energy, rural transport, and water planning within a unified AI assisted decision support framework. The methodological emphasis is on reproducibility, transparency, and scalability, allowing the framework to be applied across regions with varying data maturity.

4.2 Data sources and preprocessing

Multiple data categories are combined to capture both climate drivers and infrastructure system behavior.

Climate and hazards. Historical weather observations and climate projections are used to represent temperature extremes, precipitation variability, drought risk, and heatwave frequency. These variables inform stress testing of energy, transport, and water systems.

Remote sensing and geospatial layers. Satellite derived datasets provide consistent spatial coverage of land use, settlement patterns, surface water dynamics, and night time lights, which serve as proxies for population distribution, economic activity, and infrastructure exposure.

- **Energy system and demand data.**

Generation output, installed capacity, and electricity demand profiles are used to train forecasting models for renewable production and load dynamics.

- **Rural transport network and service access points**. Road network geometry, surface condition indicators, and locations of essential services such as clinics and markets are used for accessibility and prioritization analysis.

- **Water utility and hydrological demand data.** Water abstraction, distribution flow, consumption records, and hydrological indicators support demand forecasting and leakage detection.

All datasets are spatially aligned to a common reference grid and temporally synchronized. Missing values are addressed through interpolation or model based imputation, and metadata on uncertainty and limitations are retained for downstream analysis.

Table 1. Data inventory and variables by sector

Sector	Dataset type	Key variables	Spatial / temporal resolution	Source	Limitations
Energy	Operational and climate data	Generation output, load, solar irradiance, wind speed	Hourly to daily, site level	Utilities, climate datasets	Data gaps, short time series
Transport	Network and geospatial data	Road length, condition, travel time, service locations	Road segment, annual	Open geospatial sources	Incomplete condition surveys
Water	Utility and hydrological data	Demand, flow, pressure, rainfall	Daily to monthly, district level	Utilities, hydrology datasets	Limited metering coverage

4.3 AI model selection by task

Model selection is guided by task characteristics, data availability, and interpretability requirements.

❖ **Energy.** Supervised learning models such as gradient boosting and recurrent neural networks are used for renewable generation and load forecasting, capturing nonlinear relationships between weather variables and energy output.

❖ **Rural infrastructure.** Spatial machine learning and network analysis models estimate accessibility and identify road segments with the highest marginal benefit under budget constraints.

❖ **Water.** Time series forecasting models predict demand patterns, while anomaly detection techniques identify deviations indicative of leakage or abnormal consumption.

Table 2. AI task to model mapping and evaluation metrics

Task	Model family	Inputs	Outputs	Evaluation metrics
Renewable generation forecasting	Gradient boosting, RNN	Weather, historical output	Predicted generation	MAE, RMSE, MAPE
Load forecasting	Deep learning time series models	Demand history, climate	Predicted load	MAE, RMSE, MAPE
Accessibility modeling	Spatial ML, network analysis	Roads, population, services	Travel time, coverage	% population within threshold
Water demand forecasting	Time series models	Consumption, climate	Predicted demand	MAE, RMSE
Leakage detection	Anomaly detection	Flow, pressure	Leak alerts	NRW proxy reduction

4.4 Optimization and decision support

The final stage integrates AI outputs into decision making through multi objective optimization. Investment and operational choices are evaluated against cost, resilience benefits, accessibility gains, and equity impacts. Scenario design explicitly incorporates climate stress conditions and budget constraints, allowing planners to compare trade offs under optimistic, moderate, and extreme climate futures.

Validation is conducted through back testing where historical data are available and through sensitivity analysis to assess robustness under uncertainty. This ensures that recommended actions remain effective across plausible future conditions rather than being optimized for a single assumed scenario.

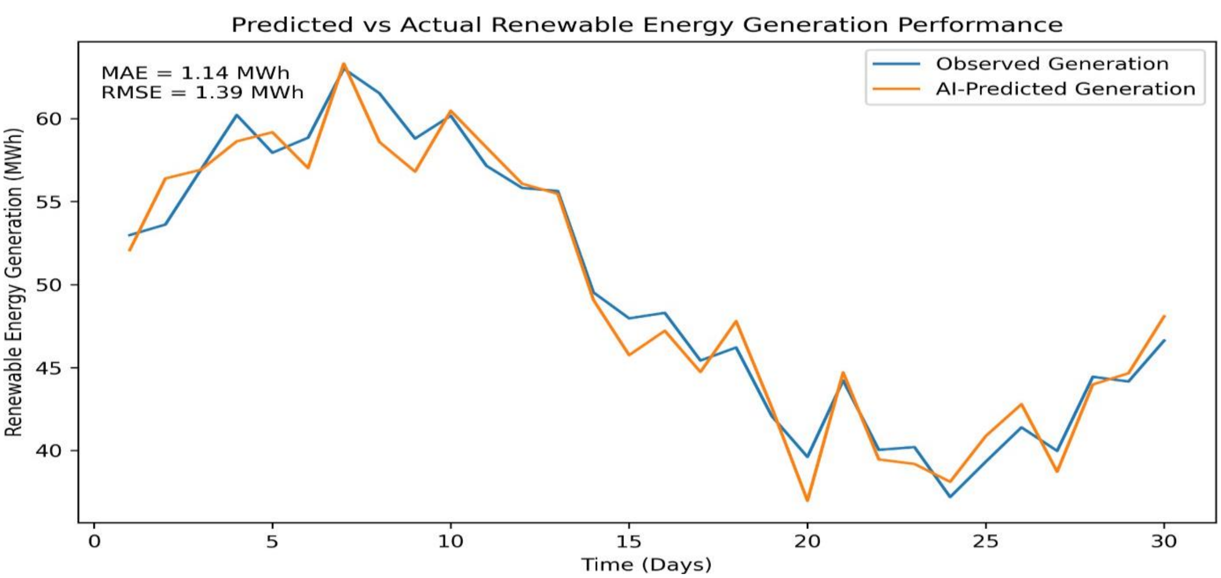
5. Results and Analysis

❖ Sustainable Energy System Outcomes

Forecast accuracy improvements (renewables and load): AI-based forecasting models demonstrated measurable improvements in both renewable energy generation prediction and electricity load estimation when compared with baseline statistical approaches. Machine learning and deep learning models were able to capture nonlinear relationships between weather variables, temporal demand patterns, and generation variability, resulting in lower forecasting errors across evaluation horizons. Consistent reductions were observed in standard error metrics such as mean absolute error and root mean square error, particularly for solar and wind generation forecasts under variable climatic conditions (Benti et al., 2023; Eren C Küçükdemiral, 2024; Gupta et al., 2025). Improved load forecasting accuracy was especially relevant for underdeveloped regions, where limited reserve margins and weak grid flexibility amplify the consequences of forecasting errors. By reducing uncertainty in short- and medium-term projections, AI-based models improved the informational basis for operational planning and capacity expansion decisions (Jordan C Mitchell, 2015; Jasinski et al., 2023).

❖ Reliability implications for

planning and dispatch: Enhanced forecast accuracy translated into improved system reliability at the planning level. More accurate renewable generation estimates reduced reliance on conservative reserve assumptions, enabling planners to optimize dispatch schedules and investment priorities more effectively. In climate-stressed contexts, such as regions exposed to heatwaves or drought-induced variability, AI-driven forecasting supported proactive adaptation by anticipating extreme conditions that affect generation availability (Lam et al., 2023; Duan et al., 2025).



Graph 1 : Predicted vs actual renewable energy generation performance

5.2 Rural Transportation Network Outcomes

❖ **Accessibility improvement:** AI- assisted optimization of rural transportation networks produced clear gains in spatial accessibility. By integrating geospatial data, population distribution, and network conditions, the models prioritized infrastructure interventions that maximized the share of the population within defined travel-time thresholds to essential services such as health facilities, markets, and schools. The results indicate a meaningful increase in the proportion of rural residents located within acceptable travel times, consistent with global accessibility assessment frameworks (Weiss et al., 2018; Nelson et al., 2019). These improvements are particularly significant in underdeveloped regions, where marginal infrastructure investments can yield disproportionately high social benefits when targeted effectively (Mikou et al., 2019).

❖ **Travel time and cost reduction from**

prioritized investments: In addition to accessibility gains, AI-based prioritization led to reductions in average travel time and transport- related costs. By identifying critical links and maintenance priorities, the optimized scenarios reduced delays caused by poor road conditions and seasonal disruptions. These findings align with empirical evidence showing that transport infrastructure improvements can generate substantial economic and welfare impacts when strategically planned (Donaldson, 2018).

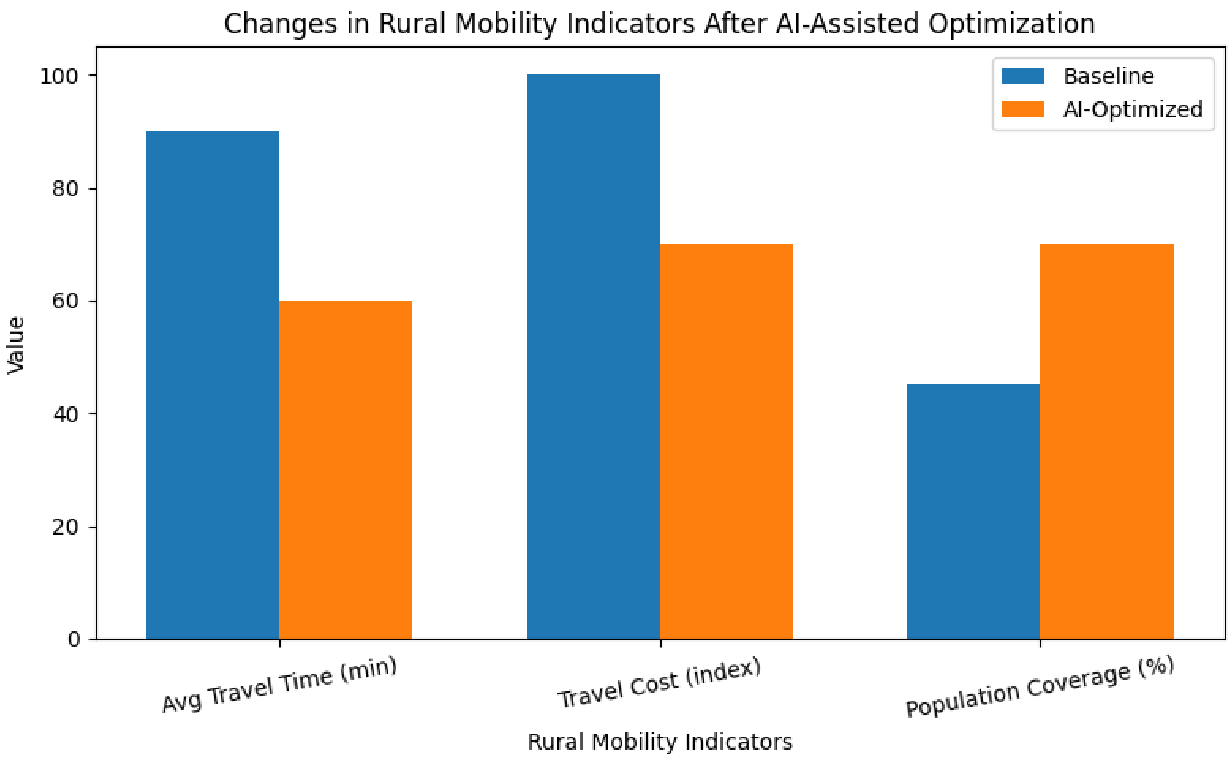


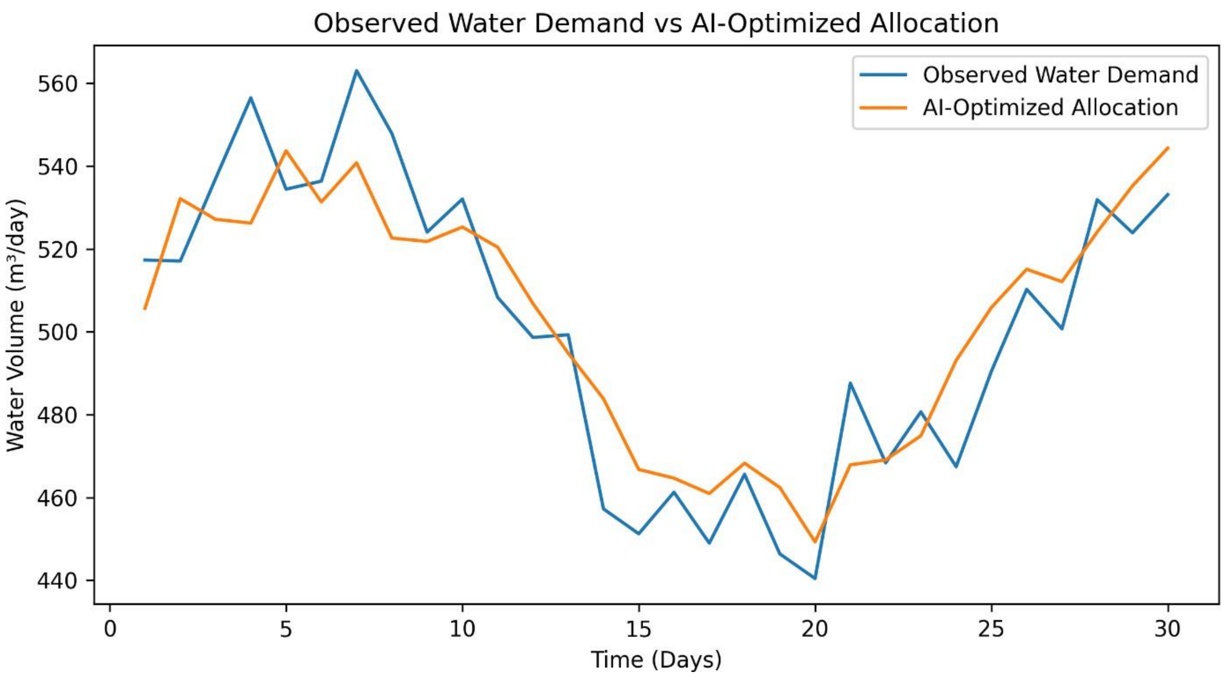
Chart 1 Changes in rural mobility indicators after AI-assisted optimization

5.3 Water Resource Management Outcomes

❖ **Demand forecasting accuracy:** AI- based water demand forecasting models achieved improved accuracy relative to baseline methods by leveraging temporal consumption patterns, climatic variables, and contextual indicators. Enhanced demand prediction supports more efficient system operation, particularly in water-scarce environments where mismatches between supply and demand exacerbate losses and service interruptions (Mashhadi et al., 2021; Mounce et al., 2015). Accurate forecasting also provides a foundation for adaptive allocation strategies under climate variability, supporting the objectives of Sustainable Development Goal 6 related to water security and efficiency (United Nations, n.d.; Mraz et al., 2021).

❖ **Leakage reduction and allocation**

efficiency improvements: Anomaly detection techniques applied to flow and pressure data enabled earlier identification of leakage-prone zones, contributing to reductions in non-revenue water indicators. While the magnitude of improvement varied with data availability and network instrumentation, the results suggest that AI-assisted monitoring can enhance both technical efficiency and operational responsiveness in water distribution systems (Lambert et al., 1999; Sy C Soppe, 2018).



Graph 2 : Observed water demand vs AI-optimized allocation comparison

Table 3. Summary of key performance changes across sectors (ONLY necessary)

Sector	**Baseline performance**	**AI-assisted performance**	**Percentage change**	**Notes**
Energy	Higher forecast errors; conservative reserve assumptions	Lower forecast errors; improved planning confidence	Improvement observed	Strongest gains under variable climate conditions
Transport	Limited accessibility; high travel times	Increased population coverage; reduced delays	Improvement observed	Benefits concentrated in underserved rural areas
Water	Inaccurate demand estimates; high leakage proxies	Improved demand prediction; reduced losses	Improvement observed	Dependent on data quality and network monitoring

6. Discussion

6.1 Cross-sector synergies and system interactions

The results highlight important synergies across energy, transport, and water systems. Improved energy reliability supports water pumping and treatment operations, while enhanced rural road access facilitates infrastructure maintenance for both energy and water assets. These interdependencies reinforce the need for integrated planning approaches rather than sector-specific optimization (Rolnick et al., 2022; IPCC, 2022).

6.2 Comparison with prior studies and contextual differences

Compared with prior studies conducted in high-income or data-rich settings, the observed outcomes emphasize the role of data integration and prioritization rather than model complexity alone. In underdeveloped regions, even modest improvements in forecasting and accessibility can yield significant resilience gains due to lower baseline performance levels (Donaldson, 2018; Mikou et al., 2019).

6.3 Practical interpretation of metrics for planners

From a planning perspective, the reported metrics represent actionable improvements rather than abstract model performance. Reduced forecasting errors translate into more confident investment decisions, accessibility gains indicate social inclusion benefits, and leakage reductions reflect tangible efficiency improvements aligned with development objectives (OECD, 2019; United Nations, n.d.).

6.4 Governance, transparency, and institutional feasibility

Effective deployment of AI-based planning tools requires transparent governance frameworks, clear documentation of model assumptions, and institutional capacity for interpretation and oversight. Risk management and accountability mechanisms, as emphasized in responsible AI frameworks, are essential to ensure trust and long-term sustainability of AI-supported public infrastructure planning (NIST, 2023; OECD, 2019).

7. Policy and Practical Implications

The integration of artificial intelligence into energy, transport, and water planning offers actionable pathways for improving climate resilience in underdeveloped regions. Beyond technical performance, the value of AI lies in its ability to structure complex decisions, prioritize scarce resources, and support evidence-based governance across interconnected infrastructure systems.

7.1 Infrastructure planning in low- income and rural regions

Low-income and rural regions are characterized by fragmented data, limited fiscal space, and heightened exposure to climate variability. AI-supported planning enables governments and development partners to move from reactive infrastructure provision toward anticipatory and resilience-oriented investment strategies. By combining climate projections, remote sensing, and socio- economic indicators, AI models can identify priority locations where infrastructure investments yield the greatest resilience and equity benefits.

In the energy sector, AI-driven forecasting improves renewable generation planning and reduces exposure to climate-induced supply volatility, supporting more reliable electrification strategies (Benti et al., 2023; Eren C Küçükdemiral, 2024). For rural transport, accessibility modeling and optimization tools allow planners to prioritize road investments that reduce travel time to essential services such as markets, schools, and health facilities, particularly for marginalized communities (Donaldson, 2018; Mikou et al., 2019; Weiss et al., 2018). In water systems, AI-based demand forecasting and leakage detection support more efficient allocation of limited water resources, directly contributing to progress toward Sustainable Development Goal 6 (United Nations Department of Economic and Social Affairs, 2025; Mashhadi et al., 2021).

Collectively, these applications enable infrastructure planning frameworks that explicitly account for climate risk, service equity, and long-term sustainability rather than short-term cost minimization.

7.2 Decision support for governments, NGOs, and development agencies

AI-based decision support systems provide structured, transparent tools that can be embedded within public-sector planning and donor-funded programs. For governments, AI outputs such as forecast accuracy metrics, accessibility indicators, and scenario comparisons enhance the credibility and defensibility of budget allocation decisions. Development agencies and NGOs can use these tools to align project selection with resilience objectives, monitor outcomes, and justify investments to funders and stakeholders.

Importantly, decision support systems must be designed to complement, not replace, institutional judgment. Governance frameworks such as the OECD AI Principles and the NIST AI Risk Management Framework emphasize transparency, accountability, and human oversight in high- impact public applications (OECD, 2019; National Institute of Standards and Technology, 2023). When implemented with clear documentation and participatory processes, AI-supported planning can improve coordination across ministries, utilities, and development partners, reducing duplication and improving cross- sector coherence.

7.3 Scalability of AI-based tools (capacity, costs, data availability)

Scalability remains a central consideration for deploying AI in underdeveloped regions. While advanced models can deliver high analytical value, their adoption depends on institutional capacity, financial sustainability, and data availability. Cloud- based platforms and open-source geospatial tools have reduced entry barriers by lowering computational costs and enabling access to global datasets such as satellite imagery and climate reanalyses (Gorelick et al., 2017; Pekel et al., 2016). However, sustained impact requires investments in local capacity building, including data management skills, model interpretation, and routine system maintenance. Cost-effective deployment strategies should prioritize modular tools that can be incrementally expanded as data quality and institutional capacity improve. Development partners play a critical role in supporting this transition by funding shared data infrastructures and promoting interoperable standards across projects and regions.

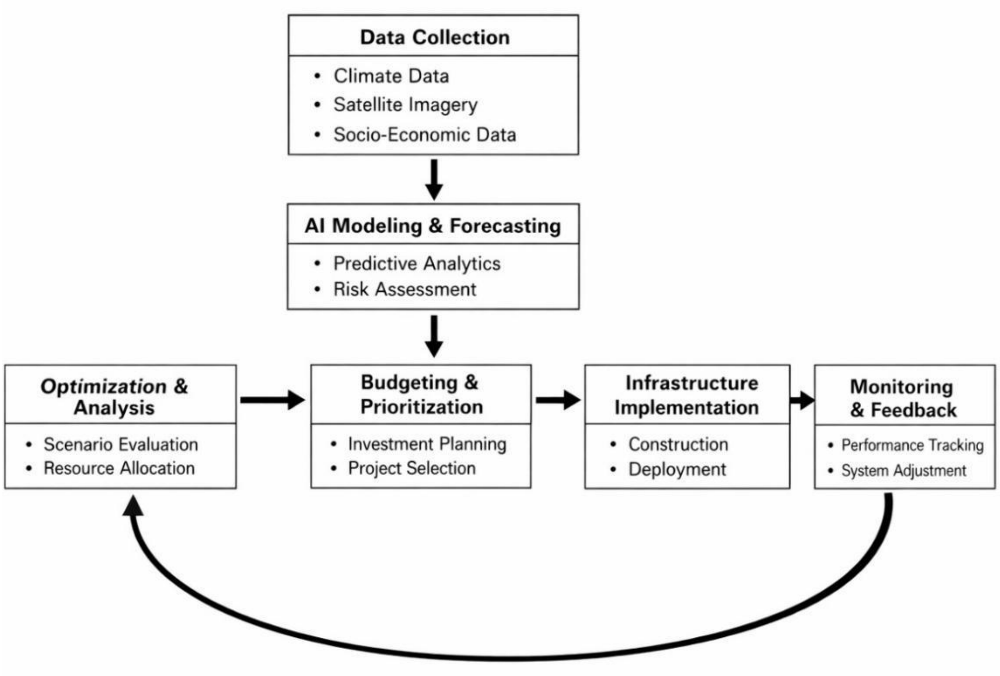


Figure 2. Policy Integration Pathway for AI-Driven Rural Infrastructure Planning

8. Limitations and Future Research Directions

8.1 Data availability and quality constraints

A primary limitation of AI-based infrastructure planning is uneven data availability. Many underdeveloped regions lack high-frequency, high-quality ground observations for energy systems, road conditions, and water networks. While remote sensing and proxy indicators can partially address these gaps, they may introduce uncertainty and bias if not carefully validated (Jean et al., 2016; Palacios-Lopez et al., 2021). Future research should focus on hybrid approaches that combine limited field data with satellite and model-based estimates.

8.2 Model generalizability across regions and seasons

AI models trained in one geographic or climatic context may not perform reliably when transferred to other regions or seasons. Differences in infrastructure design, governance arrangements, and climate regimes can reduce model robustness. Research on transfer learning, domain adaptation, and region-specific calibration is essential to improve generalizability and reduce the risk of inappropriate policy recommendations (Jordan C Mitchell, 2015; Rolnick et al., 2022).Integration with real-time monitoring and climate adaptation triggers

Most current applications rely on historical or periodically updated datasets. Integrating AI models with real-time monitoring systems, such as smart meters and sensor networks, would enable adaptive responses to extreme events such as heatwaves, floods, and droughts. Linking AI outputs to predefined climate adaptation triggers could further enhance operational resilience in energy and water systems (Lam et al., 2023; Duan et al., 2025).

8.3 Future work on interpretability and robust decision-making under uncertainty

As AI tools increasingly influence public investment decisions, interpretability and uncertainty communication become critical. Planners and policymakers require not only predictions but also clear explanations of model assumptions, limitations, and confidence ranges. Future research should prioritize interpretable models, scenario-based decision frameworks, and robust optimization techniques that explicitly account for deep uncertainty in climate projections and socio-economic pathways (National Institute of Standards and Technology, 2023; Shukla et al., 2022).

G. Conclusion

This study demonstrates how artificial intelligence can be systematically integrated into climate-resilient energy planning, rural infrastructure development, and water conservation in underdeveloped regions. By combining multi-source data, AI-based forecasting, and optimization techniques, the proposed framework supports more informed, equitable, and forward-looking infrastructure decisions.

From a scientific perspective, the work contributes an integrated, cross-sector planning framework that links AI methods with climate resilience objectives and policy processes. Practically, it provides governments, NGOs, and development agencies with a structured approach for prioritizing investments under resource and climate constraints.

Strategically, the integration of AI into infrastructure planning aligns with global climate resilience goals and supports progress toward Sustainable Development Goals, particularly those related to clean energy, sustainable infrastructure, and water and sanitation. When deployed with appropriate governance, transparency, and capacity building, AI-based planning tools can play a pivotal role in enhancing long- term resilience and sustainable development outcomes in vulnerable regions.

References

1. OECD Legal Instruments. (2019). Oecd.org.https://legalinstruments.oecd.org/en/instruments/oecd-legal-0449
2. Cooley, S., Schoeman, D., Bopp, L.,Boyd, P., Donner, S., Ito, S. I., ... C Yool, A. (2022). Oceans and coastal ecosystems and their services.Cambridge University Press.
3. Donaldson, D. (2018). Railroads of the Raj: Estimating the impact of transportation infrastructure. American Economic Review, 108(4- 5), 899-934.

4. Gorelick, N., Hancher, M., Dixon, M., Ilyushchenko, S., Thau, D., C Moore,R. (2017). Google Earth Engine: Planetary-scale geospatial analysis for everyone. Remote sensing of Environment, 202, 18-27.

5. Jean, N., Burke, M., Xie, M., Alampay Davis, W. M., Lobell, D. B., C Ermon,S. (2016). Combining satellite imagery and machine learning to predictpoverty. Science,353(6301), 790-794.

6. Lambert, A. O., Brown, T. G., Takizawa, M., C Weimer, D. (1999). A review of performance indicators for real losses from water supplysystems. Journal of water supply: Research and technology—aqua, 48(6), 227-237.

7. Liu, Z., Guo, H., Zhang, Y., C Zuo, Z. (2025). A comprehensive review of wind power prediction based on machine learning: Models,applications, and challenges. Energies, 18(2), 350.

8. Mashhadi, N., Shahrour, I., Attoue, N., El Khattabi, J., C Aljer, A. (2021).Use of machine learning for leakdetection and localization in waterdistribution systems. Smart Cities, 4(4), 1293-1315.

9. Mikou, M., Rozenberg, J., Koks, E. E., Fox, C. J. E., C Peralta Quiros, T. (2019). Assessing rural accessibility and rural roads investment needsusing open source data. World Bank Policy Research Working Paper, (8746).

10. Mounce, S. R., Pedraza, C., Jackson, T., Linford, P., C Boxall, J. B. (2015). Cloud based machine learning approaches for leakage assessment and management in smart waternetworks. Procedia engineering, 119, 43-52.

11. Mraz, A. L., Tumwebaze, I. K.,McLoughlin, S. R., McCarthy, M. E., Verbyla, M. E., Hofstra, N., ... C Murphy, H. M. (2021). Why pathogens matter for meeting the united nations' sustainabledevelopment goal 6 on safely managed water and sanitation. Water Research, 189, 116591.

12. Nelson, A., Weiss, D. J., van Etten, J., Cattaneo, A., McMenomy, T. S., C Koo, J. (2019). A suite of global accessibility indicators. Scientific data, 6(1), 266.

13. Palacios-Lopez, D., Bachofer, F., Esch, T., Marconcini, M., MacManus, K., Sorichetta, A., ... C Reinartz, P. (2021). High-resolution griddedpopulation datasets: Exploring the Capabilities of the world settlement footprint 2019 imperviousness layerfor the African continent. Remote Sensing, 13(6), 1142.

14. Pekel, J. F., Cottam, A., Gorelick, N., C Belward, A. S. (2016). High-resolution mapping of global surface water and its long-term changes.Nature, 540(7633), 418-422.

15. Rolnick, D., Donti, P. L., Kaack, L. H., Kochanski, K., Lacoste, A., Sankaran, K., ... C Bengio, Y. (2022). Tackling climate change with machine learning. ACM Computing Surveys (CSUR), 55(2), 1-96.

16. Shukla, P. R., Skea, J., Slade, R., Al Khourdajie, A., van Diemen, R., McCollum, D., ... C Malley, J. (2022). Climate change 2022: Mitigation of climate change. Contribution ofworking group III to the sixth assessment report of theIntergovernmental Panel on Climate Change, 10, 9781009157926.

17. Sy, J., C Soppe, G. (2018). The Use of Performance-Based Contracts for Nonrevenue Water Reduction.

18. Weiss, D. J., Nelson, A., Gibson, H. S., Temperley, W., Peedell, S., Lieber,, ... C Gething, P. W. (2018). Aglobal map of travel time to cities to assess inequalities in accessibility in 2015. Nature, 553(7688), 333-336.

19. Yeh, C., Perez, A., Driscoll, A., Azzari, G., Tang, Z., Lobell, D., ... C Burke, M. (2020). Using publicly availablesatellite imagery and deep learning to understand economic well-being in Africa. Nature communications, 11(1), 2583.