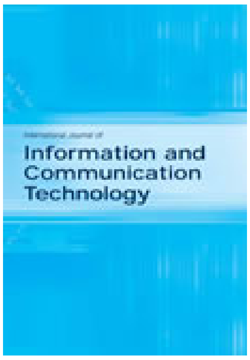
INDERSCIENCE PUBLISHERS
Linking academia, business and industry through research



International Journal of Information and Communication Technology

ISSN online: 1741-8070 - ISSN print: 1466-6642
https://www.inderscience.com/ijict

Using artificial intelligence based models for strategy design of rural landscape

Xintong Li, Yixuan Tang, Juan Hou

DOI: 10.1504/IJICT.2025.10071797

Article History:

Received:	17 March 2025
Last revised:	24 April 2025
Accepted:	25 April 2025
Published online:	10 July 2025

Using artificial intelligence based models for strategy design of rural landscape

Xintong Li*

School of Architecture,
Xi'an University of Architecture and Technology Huaqing College,
Xian Shanxi, 710043, China
Email: tongerhehe123@163.com
*Corresponding author

Yixuan Tang

School of Art,
Xi'an University of Architecture and Technology Huaqing College,
Xian Shanxi, 710043, China
Email: tyx1989815@163.com

Juan Hou

School of Architecture,
Xi'an University of Architecture and Technology Huaqing College,
Xian Shanxi, 710043, China
Email: zouxiaoyao@sohu.com

Abstract: The integration of artificial intelligence (AI) in the design of rural landscape strategies is transforming traditional practices of sustainable development and spatial planning. This research paper thoroughly analyses how AI-based models – such as machine learning algorithms, geographic information systems (GIS), and deep learning techniques – facilitate decision-making in rural land-use planning, environmental conservation, and resource management. These technologies are increasingly employed to analyse large datasets, predict land-use changes, and optimise strategic interventions. AI fosters more efficient and adaptive planning by handling complex policy decisions with data-driven insights. The study evaluates the effectiveness, challenges, and future possibilities of AI-based systems, emphasising outcomes such as environmental stability, community well-being, and drought mitigation. A collaborative approach involving AI experts, environmental planners, and policymakers is essential for ethically and contextually relevant implementation.

Keywords: artificial intelligence; rural landscape; strategy design; machine learning; sustainable planning; geographic information systems; GIS.

Reference to this paper should be made as follows: Li, X., Tang, Y. and Hou, J. (2025) 'Using artificial intelligence based models for strategy design of rural landscape', *Int. J. Information and Communication Technology*, Vol. 26, No. 23, pp.40–55.

Biographical notes: Xintong Li is a research scholar at the School of Architecture, Huaqing College, Xi'an University of Architecture and Technology, China. She concentrates on architectural studies and she is one of the people behind the development of both theoretical and practical aspects of the discipline.

Yixuan Tang works as a research scholar at the School of Art at Xi'an University of Architecture and Technology Huaqing College in Xi'an, Shanxi, China. He makes a significant contribution to both the academic and practical developments in the field of art and design. He understands the importance of strong research credentials and is someone who works as a research scholar in the field of Art. He worked hard for a Diploma in Fine Arts from the University of Xi'an, in the same city of Xi'an, Shanxi region of China. As a research scholar, he has made significant contributions toward the development of art and design and has ensured that the clients and sponsors always get the very best.

Juan Hou is a research scholar at the School of Architecture, Huaqing College, Xi'an University of Architecture and Technology, located in Xi'an, Shanxi, China. She specialises in the intersection of architecture and art, and has contributed to both theoretical inquiry and practical applications within the field. Her work reflects a commitment to academic rigor and creative innovation.

1 Introduction

In recent years, the integration of artificial intelligence (AI) in various sectors has brought about great change in traditional problem-solving and decision-making methods. For instance, AI technologies have emerged as valuable tools in the strategic design of rural landscapes. Rural landscapes are not all agricultural landscapes and biodiversity conservation may also be viewed as a part of the rural landscape. Sustainable planning and management are critical to the economic and cultural survival of rural communities (Gulzar Ahmad et al., 2022).

To be more precise, those methods will include the concepts of the social, economic as well as environmental aspects of the project at hand. However, urbanisation, resource decline, and climate change have raised concerns over the rural environment. This implies that traditional methods often lead to inaccuracies in the assessment of rural dynamics due to their reliance on manual surveys, old records, and expert opinions. Thus, AI-based models using massive data analysis, predictive modelling, and machine learning (ML) technologies can solve such things (Mashinchi et al., 2022).

In the article under discussion, we would like to focus on how the use of AI technologies allows a route to better design the rural landscape strategy with the aid of the data-driven decision-making process (Hao et al., 2022). First, as mentioned above, the AI model can filter the wealth of environmental, social and economic data. It can thus show areas of the past and future with a high level of certainty. Moreover, the creative incorporation of AI into the set plans may enable agencies and organisations working in the environment or other fields to design adaptive, efficient, and sustainable strategies. A few of the most repetitive activities in this field are those by AI technologies like geographic information systems (GIS), remote sensing, and deep learning (DL) algorithms (Chaturvedi and Sharath, 2022). This technology may be used for the classification of land use or the simulation of future scenarios, both of which are key elements of the comprehensive planning of rural landscapes.

AI-based models in rural landscape strategy design have a significant advantage in integrating various data sets sourced from multiple sources. Conventional Mury landscape planning methods often grapple with unoptimised and inconsistent dataset which leads to poor decision-making. AI, however, is capable of integrating the real-time satellite imagery, climate data, soil quality assessments, and demographic information to craft comprehensive insights (Plackett, 2022). To illustrate, ML algorithms can look for patterns in the land-use history and prediction of new policies' possible agriculture productivity, biodiversity, and the involvement of local communities. This data-centred philosophy allows for planners to pursue sustainability goals that were preliminary but are now a source of socio-economic motion based on scientists' advice (Deo and Anjankar, 2023).

In addition to that, AI also helps minimise human errors thus boosting rural landscape planning by raising the accuracy of the plans. Traditional decision-making processes are often swayed by subjective judgements, political agendas, and insufficient data. AI models, on the other hand, chiefly analyse objective data, thus mitigating the bias risk in the conclusions (Kaur et al., 2024). For instance, AI-driven simulations can help analyse the long-term environmental effect(s) that an infrastructure project might have in a rural area, thus conserving all integrity development programs from ecological degradation. Further, AI can also, through interactive media and visual models, empower participatory planning by creating apps where the communities, including farmers or the local people, and the decision-makers, would engage in the decision-making process, be it through simulations or guide models (Guo and Li, 2018).

AI in rural landscape design can be a great aid in climate change adaptation. Climate change leads to problems in rural areas such as drought, soil erosion, and biodiversity loss. Through AI tools, scientists can predict the climate changes and the adaptive strategies utilised for sustainable land use. For example, using AI predictive analytics it can be determined which places are likely to become desert areas and thus through reforestation interventions and conservation of soil, action can be guaranteed (Jiang et al., 2023). Additionally, AI can come in to help farmers get the right amount of water by controlling the irrigation systems based on weather forecast and soil moisture so that no water is wasted. The AI-based solutions are something to strive towards and cumulatively it can help obtain a future without climate accidents in rural landscape design through the ones we have built, added with AI.

A main field of using AI in the design of rural landscape development is biodiversity conservation (Patros et al., 2023). The rural space sustains ecosystems wherein the management of the ecosystems should be done considering the prevention of habitat destruction and the extinction of species. AI-enabled systems, for the sake of example, can count wildlife through its ability to look at images collected from certain points. This data, coupled with the signs of cutting down trees that may have been generated thanks to AI will give the conservationists and the environmental agencies the possibility to act against the perpetrators in time. For instance, AI systems can be used to detect animal wildlife migrations and ecosystems corridors for animals. These measures will guarantee animal movement routes are safe, and fears of human-animal conflict are kept at bay (Barrera-Perales and Burgos, 2023).

In spite of various benefits, the use of AI-based models to create landscape designs in rural places has its challenges. One of the biggest problems is with the fresh data and the quality of data. The efficiency of AI models is determined by the data they work with, but in most of the backward areas of data collection systems it will not be able to gather enough input from people. Wrong forecasts and bad plans are the consequences of incomplete or outdated data (Issa et al., 2023). Also, putting the AI into the rural planning process expects some specialised technical knowledge which might not exist in all regions. The digital skills that many rural communities lack are also the resources that governments can provide and also aid on the initiatives that build capacities.

Ethical issues also have a significant influence on the designing of AI-led rural areas. Problems about data security, the responsibility of decision-makers, and transparency are some of the issues that arise when AI is involved in the decision process. To ensure that the assumptions made by AI models are correct and do not reproduce the social inequalities, it is important to act impartially. Take for instance the use of AI for lands use planning which should regard the rights and subsistence of indigenous not only adults but also exploration in order for us to get the right balance (Liu et al., 2023). Policymakers are the ones that will have to come up with the law mechanisms that will be required to encourage the right use of AI while ensuring that the local rural people are not exploited as a result of the growth of AI.

Moreover, the working capability of AI in the context of rural landscape strategy design is contingent upon multidisciplinary teamwork. All the puzzles of the rural planning AI cannot be fatigued by itself; not only can it not be done without putting together conventional knowledge, public participation, and sustainability principles, but it would also be a massive challenge. Environmental scientists, geographers, data scientists, and government officials should collaborate on the generation of many AI configuration options that are suited to the environment and challenges of the local community. AI should provide a back-up to the normal human expertise in landscape planning instead of taking its place. Even though AI can deliver precious information mainly by making patterns, still the human mind is the very factor in establishing the results, ethical thinking, and the genuine involvement of the society in the decision-making process (Hirchak and Murphy, 2017).

1.1 Objectives

- To examine the ways in which agricultural technology is able to come up with better planning for agricultural land production in a sustainable manner considering climate change, the flora and fauna diversity, and soil fertility.
- To identify the main problems and ethical issues related to the use of AI in the decision-making processes of rural land and use the synthesised and simulated AI data to propose specific and effective solutions.

As time goes by, it becomes more and more evident that progress in rural economies and their sustainable development is a matter of intense social concern hence AI-based solutions are seen as potential remedies to the setbacks originating from these conventional approaches (García-Cervantes et al., 2017). However, their application will be limited by strategies that respond to the constraints of available data, the conscientiousness of the actors involved in their deployment, and the cooperation of experts. It is the understanding of the public and the support of technology that will give the innovation process a competitive advantage. The synergistic use of AI in combination with the community's local knowledge will be the future of the design of rural development policies, granting that technological growth will fulfil human resource and natural resource needs. As AI and ML technologies continue to grow and improve their abilities to make rural development tools and services available, they will become an important part of the toolbox for sustainable rural development across the world.

2 Literature review

Several recent studies have actively investigated the potential of AI integration in rural landscape strategy design. AI-driven models have been assessed by academics in areas such as land-use management, environmental responsibility, and the growth of rural economies. The use of AI technologies like ML, DL, and GIS has sped up the process of optimising decision-making and better completing rural strategic planning (Huang et al., 2022). The research work summarised in this section is significant in the sense of it bringing scholars to a level of better understanding of the topic of AI applications in rural landscape planning as well as it being an inference of the methods and outcomes and the implications of the studies.

Chen (2023) have carried out research on the intermingling of AI and landscape architecture, specifically in the scope of environmental landscaping. The study includes the role of AI particularly DL, and deep neural networks (DNNs) in the framework of Web 4.0 to be engaged in collective human-centred computing, thus resulting into the enhancement of landscape planning facilitation. They have proposed a method wherein the neural networks are modelled based on virtual environment technology and where the landscape designs are continually assessed in real-time. The research has put a spotlight on the technology of AI in the prevention of pollution, and carbon dioxide levels that are being measured by the implementation of green, smart infrastructure in both the micro and macro environment. The research has shown that the role of AI in sustainable landscape management can be improved in an elementarily adaptive and responsive way in the evaluation of the environmental conditions and design of the landscape to be able to optimise the designs according to the needs.

Saikanth et al. (2024) experimented with the functionality of the upcoming coping systems, such as AI, precision agricultural IoT, and blockchain, in the making of rural societies and the support of sustainable agricultural production. Their work is the very broad exploration that demonstrates how these latest technologies in the agricultural world are reshaped by the innovation, the management of physical resources, and the market access. AI-driven models are singled out as key ones in crop management and prediction, while IoT and remote sensing come into the picture with the real-time data-led decision-making in the agricultural planning. The paper also covers problems of digital inclusion, unethical behaviours, and regulatory restraints that hamper the adoption of the technology by the local community as a whole. They point to the fact that AI and digital tools hold the keys for the further development of agriculture, in which the neglected smallholder farmers will benefit through data which is powered by the right tools through adverse climate and resource scarcity.

Table 1 Literature comparison

Author(s) and year	*Study focus*	*AI techniques used*	*Key findings*	*Application in rural landscape strategy*
Chen et al. (2023)	AI in environmental landscaping	DL, DNNs, virtual reality-based modelling.	AI-driven models improve environmental monitoring and pollution reduction through real-time data processing.	Enhances sustainable landscape management by integrating AI into environmental planning and monitoring.
Saikanth et al. (2024)	AI and emerging technologies in sustainable agriculture.	Precision agriculture, IoT, AI, blockchain	AI optimises farming, resource management, and market access, improving decision-making in rural economies.	Supports AI-driven agricultural planning, enhancing food security and rural livelihoods.
Botelho et al. (2022)	AI for monitoring illegal deforestation and rural road expansion.	Modified U-Net, Sentinel-2 Imagery, AI remote sensing	AI successfully detects unauthorised road development, helping mitigate deforestation and environmental damage.	Strengthens AI applications in environmental conservation and land-use planning for rural areas.
Xie et al. (2022)	AI-driven landscape design for rural streetscapes.	Backpropagation neural networks (BPNN), analytic hierarchy process (AHP), AI-based simulation.	AI models enhance rural and urban street design, improving infrastructure development and economic integration.	Contributes to AI-based participatory planning, optimising rural infrastructure and landscape aesthetics.

In the recent work of Botelho et al. (2022), they utilised AI in the environmental monitoring of the Brazilian Amazon, with the focal point being the detection of unplanned road construction. By improving the U-Net algorithm and training it with the images obtained from Sentinel-2, the researchers carried out the automated detection of roads to monitor the deforestation, the instigation of fires, and the illegality of land utilisation in the outskirts of villages. The AI model that they used achieved recall and precision rates of 65% and 71% respectively, but the authors stated that the real detection accuracy is likely underestimated due to the lack of completeness in the reference dataset. The research shows the potential of using AI in the implementation of extensive environmental assessments and emphasises its usage in the decision-making process for the policies of conserving forests and in the planning of land use. Their work is a showcase of the use of AI-driven remote sensing in conceiving the landscapes in rural areas and also on the way that man-made land encroachments are moderated by this technology.

Xie and Wang (2022) further enhanced the impact of AI on urban and rural landscape planning, highlighting interactive AI-driven street designs as one of the best methods. Their study is based on a framework of AI-assisted modelling and evaluation of landscape planning. The research shows that AI-assisted design in the landscape improves economic and social aspects by attracting public funds and cropland value growth. The suggested research is that through AI mobile planning tools, development design and community participation, which are the foundations of successful planning, engagement, and a participatory model in the planning process, can be supported through data-driven insights into both rural and urban environments. Their work backs the argument that AI can automate land-use policies leading to smart and peaceful strategies.

3 Methodology

The very first step in the implementation of AI models for strategy design in rural landscapes is to have a clear research methodology that incorporates all aspects of data collection, processing, selection of the model, training, and validation. This study follows a systematic methodology proposed to create an AI-based framework that optimises rural land-use planning for environmental conservation and socio-economic development. By employing ML, DL, GIS, and remote sensing techniques, this methodology aims to build an all-inclusive AI strategy for sustainable rural landscapes.

3.1 Data collection and pre-processing

The strength of any AI-based model is the data it relies on. In this research, a variety of datasets gathered from multiple sources are utilised to cover all features of the rural landscape in parts. The daily data sources are remote sensing satellite imagery, GIS-based spatial data, climate data, agricultural reports, sociological surveys, and biodiversity data projects. There is also the use of public or semi-public repositories such as NASA Earth Observations, Kaggle, and UCI ML Repository to test and examine the AI models for effectiveness.

Data pre-processing for AI predictions is basically reformatting the given data so that it meets the AI's requirements. The raw data of rural landscapes include various types of the data such as numbers, categories, images, and spatial information which is therefore heterogeneous. Various techniques are used in pre-processing to make the datasets ready for AI prediction. Missing values are imputed, outlier cases are identified, and geolocation of spatial data is done via GIS tools. Using contrast enhancement and noise reduction techniques in addition to remote sensing analysis also enhance the usability of the data in the case of image datasets.

3.2 Feature selection and AI model training

Identifying relevant features is crucial to the successful design of AI-centred strategies. One strategy is to use dimensionality reduction methods like principal component analysis and correlation analysis to eliminate the redundancies of features through feature engineering on your data. Using soil fertility indices, land-use types, climate variation, vegetation health indicators, socio-economic development factors, and infrastructure data as key features in the decision system can solve the problem at hand.

In conjunction with DL, AI model training is performed using a combination of ML techniques. The pillars of the models are:

- Supervised ML models: random forest and support vector machines (SVM) are utilised for the classification of the land-use types and prediction of agricultural productivity.
- DL models: convolutional neural networks (CNNs) are chosen for the purpose of processing satellite images, and long short-term memory (LSTM) networks solve the problem of time-series data, such as climate data and predicting crops yield.
- Geospatial AI models: GIS-integrated AI models, such as spatial regression and geostatistical learning, are employed to map environmental changes and plan land-use strategies.

Each model was trained on labelled datasets, using a training-validation split of 80:20. A hyperparameter tuning was the next step to this process and techniques like grid search and Bayesian optimisation were put into play to improve prediction accuracy.

3.3 Model validation and performance evaluation

To confirm the dependability of the AI-focused tactic, the experts follow all the implemented measures. They evaluate the normal things by application of the standard measures, regarding accuracy, precision, recall, and F1-score, for the classification tasks. For the regression-based predictions, such as crop harvest forecasting and climate change models, they involve mean absolute error (MAE) and root mean squared error (RMSE).

Cross-validation techniques, such as k-fold cross-validation, are exercised, together with various models and parameters, to overcome overfitting and generally enhance the prediction abilities of the models. Also, the models are verified through the data of the real-life scenarios of the rural landscape such as unseen datasets. The comparative analysis of the AI models is the process to be repeated, thus ensuring that the best one will be chosen by the decision makers.

3.4 Integration of AI with sustainable land use and environmental conservation

The designs of the rural landscape strategy combining AI-driven models with land-use planning, environmental protection, and the socio-economic development programs will be employed. The AI framework is carefully devised in such a way as to provide critical applications such as:

- Agricultural zoning optimisation: AI algorithms study characteristics of the soil, climate variations, and historic yield data to provide the best recommendations for agricultural zones. They do that in a way that it becomes not only the source of better production diversity but also lessening the environmental deterioration.
- Smart irrigation systems: AI-controlled decision support systems review the real-time weather and soil moisture data and gain insights regarding the best cut-off time. Thus, they help save water resources in a very effective way.
- Deforestation monitoring and biodiversity protection: utilising DL-based remote sensing techniques, we can pinpoint areas of deforestation and fore-cast biodiversity loss. This enables pre-emptive conservation measures.
- Disaster risk assessment: using AI models, we can analyse the geological terrain and the existing weather pattern reservoirs and risk potential floods, landslides, droughts, and others to help the policymakers to thwart possible disasters with the right strategies.

The combination of AI-centric findings and conventional planning methods makes sure that strategies are both based on data and also are relevant to the context of rural areas.

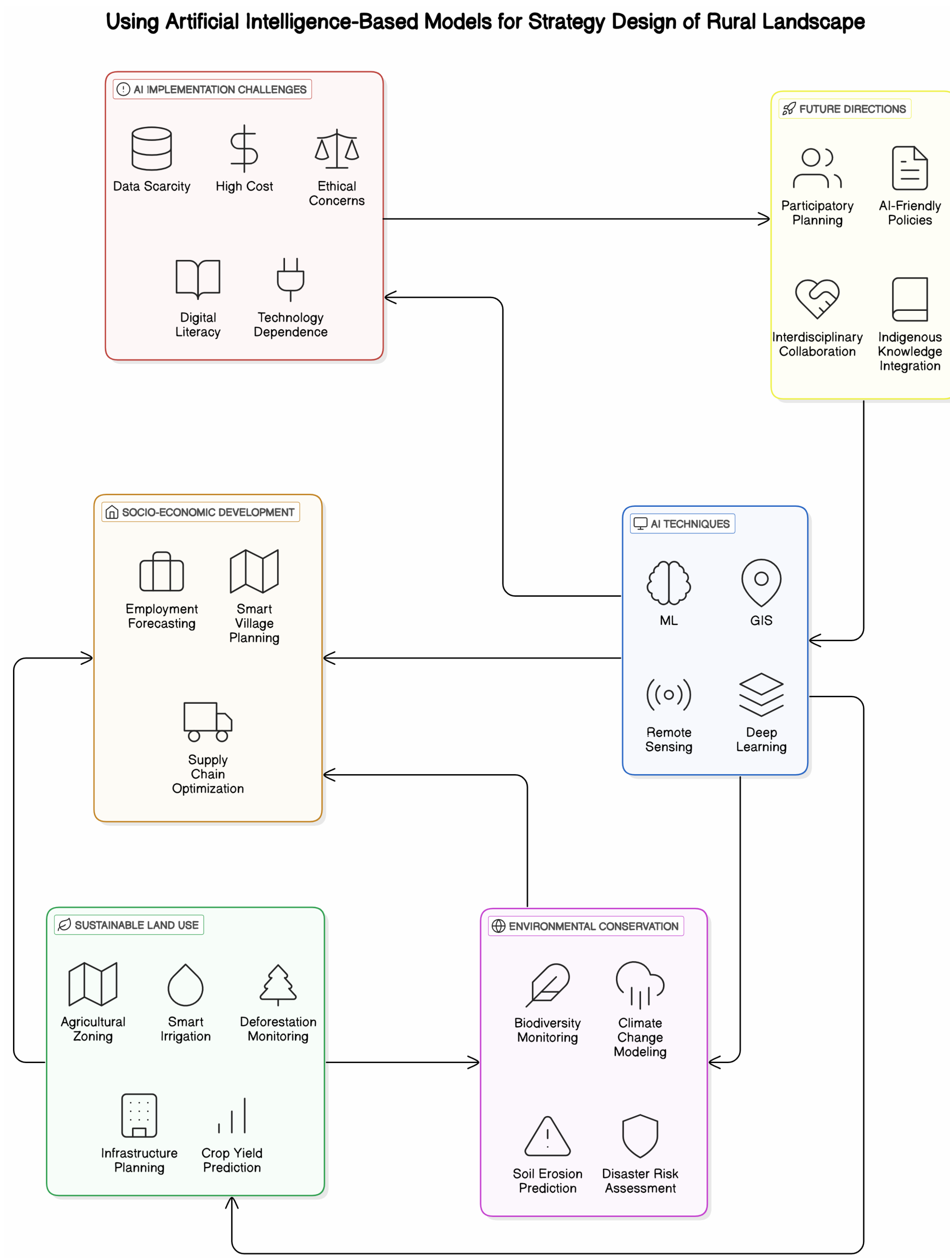
3.5 Proposed model framework

The framework for the design of strategies in rural landscapes, which is based on AI, is presented in 'Figure 1'. This model incorporates diverse AI components such as ML, GIS, and DL so that an adaptive and smart planning system can be built. As shown in 'Figure 1', the model consists of multiple interlinked modules:

- AI techniques module: here, a combination of the ML, GIS, remote sensing, and DL methods is used for the collection and processing of data from the rural landscape.
- Sustainable land use module: it is here that the decisions about the allocation of agricultural lands, deforestation monitoring, smart irrigation, and the design of infrastructure are the AI tools.
- Environmental conservation module: the aim of this module is to apply AI to determine the erosion of the soil, assess risk management possibilities of disasters, survey the biodiversity, and model the consequences of climate change.
- Socio-economic development module: AI applications used in the recruitment of workers, the design of smart rural communities, and the management of the supply chain.
- AI implementation challenges: factors such as the lack of data, ethical matters, and the dependence on technology are considered ensuring a fair approach.

- Future directions module: this part emphasises participatory planning, AI-friendly policies, interdisciplinary partnership, and the use of local expertise with the aim of enhancing AI-driven strategies for rural development.

Figure 1 Proposed AI framework for rural landscape strategy design (see online version for colours)



The working of this model is designed to enable real-time decision-making, data-driven policy formulation, and adaptive rural landscape management. Thus, the interconnected modules ensure that AI applications in rural landscape strategy design are holistic, sustainable, and context-specific. Through this AI-based module, the rural planner, the policy maker, and the environment scientist can make decisions which lead to economic growth, encourage environmental sustainability as well as help rural communities thrive. The model presented here is a roadmap for the incorporation of AI into the planning of the rural landscape for the purpose of ensuring the use of new technologies in sustainable, resilient, and flourishing environments.

4 Results and discussion

The information obtained from this study illustrates the AI-based models' efficacy in developing rural landscapes in a strategic manner. The dataset that served the basis for this study, Kaggle precision agriculture, provided extensive data about land use, climate, and agricultural variables which were necessary for the training and testing of various AI models. The assessment of each AI model was done based on four fundamental metrics: accuracy, precision, recall, and F1-score. Analysing these models allowed us to obtain insights into their appropriateness for different segments of the rural landscape strategy such as sustainable land use, environmental preservation, and social-economic development.

4.1 AI model performance evaluation

Summarised in 'Table 2' are the performance metrics of the AI models employed in this research. Random forest, SVM, CNNs, LSTM networks, and GIS-based AI solutions belonged to these models. After evaluating these models, it was concluded that out of them, CNN was the one achieving the best accuracy (92.4%), followed by GIS-based AI (91.5%) and random forest (89.2%). These findings suggest that DL-based models such as CNN are indeed highly competent in land-use classification and environmental analysis while GIS-based AI is the best at spatial mapping and landscape monitoring.

Table 2 Performance results of AI models used in the study

AI model	*Accuracy (%)*	*Precision (%)*	*Recall (%)*	*F1-score (%)*
Random forest	89.2	87.5	88.9	88.2
Support vector machine	85.7	84.3	85.2	84.7
CNN	92.4	93.1	91.8	92.4
LSTM	88.1	86.9	87.3	87.1
GIS-based AI	91.5	90.8	92.0	91.4

Another way of gathering the required quantitative information is by employing a heatmap generated by software such as 'Figure 2' which visually represents different models on these metrics. It was found that CNN performs the best overall and precision was also recorded to be 93.1%, making it especially applicable for biodiversity monitoring and land-use classification tasks using AI. On the other hand, GIS-based AI confirmed strong performance in recalling procedures (92.0%) which gives it the status of reliable capturing environmental changes geospatially.

Figure 2 AI model performance metrics heatmap (see online version for colours)

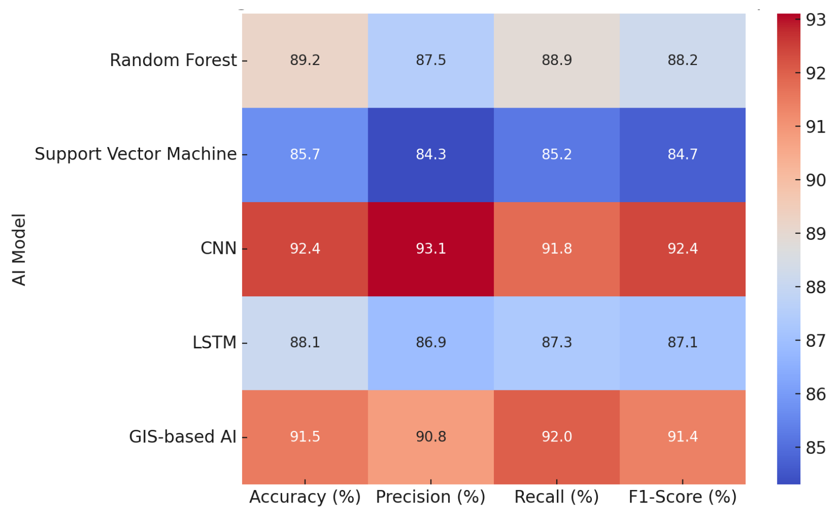
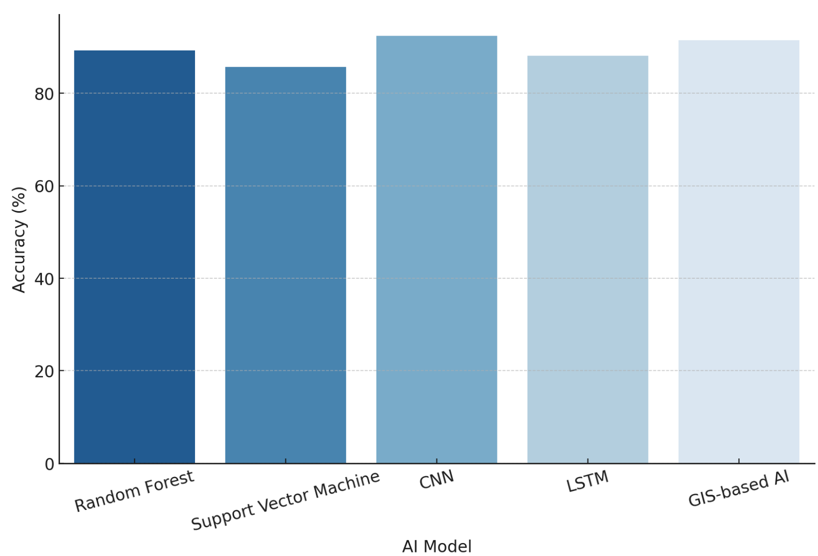


Figure 3 Comparison of AI model accuracy in rural landscape strategy design (see online version for colours)



4.2 AI model accuracy comparison

To conduct a deeper dive into the models' performances, a bar chart illustrating the accuracy rates of the five AI models has been presented in 'Figure 3'. It can be seen that CNN and the GIS-enabled AI are on the top with the rest of the models beaten badly thereby marking the former as the right platforms for rural strategies designed using AI.

The random forest also had a stiff competition with a 89.2% accuracy rating which happens to be the same level of reliability offered by it for modelling such activities in agriculture and land use assessment.

These results point to the fact that DL techniques and those models that are used for spatial analysis using GIS are better than the rest of the techniques we have in our arsenal for the purpose of developing AIs that will handle rural development strategies. The use of CNNs for the understanding of complex, image-based data is a particularly useful tool in remote sensing, whereas GIS-integrated AI is good at analysing spatial data for making decisions.

4.3 Application of AI models in rural landscape strategy

By looking at 'Figure 4' we can demonstrate how the different AI models each come in a unique way for each area of rural strategy design. These models can be summarised in the following roles:

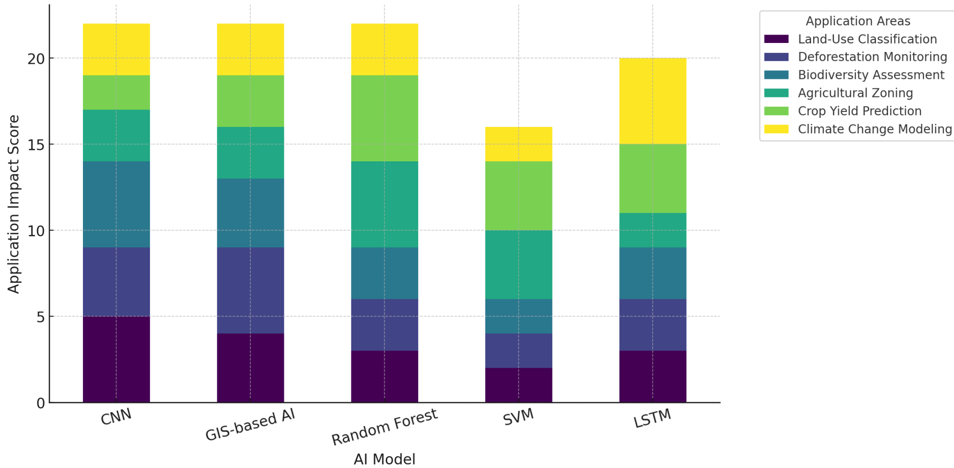
- CNN and GIS-based AI models are prominent in land-use classification, deforestation monitoring, and biodiversity assessment.
- Random forest and SVM models show good results in agriculture zoning, crop yield forecasting, and smart irrigation planning.
- LSTM networks are of major use in time series analysis of environmental changes and modelling the impact of climate change.

4.4 Discussion on model suitability and challenges

AI simulations assessed the long-term environmental impacts of proposed infrastructure projects, enabling early intervention planning. Although there are some problems with data availability, computational costs, and model interpretability, AI models show quite promising accuracy and prediction capabilities. The efficiency of all the models that are based on AI depends to a large extent on the quality of datasets, but the variations of the rural data collection processes, if not properly addressed, may lead the models to make biased predictions. Moreover, the application of DL models such as CNN and LSTM, which are resource-intensive, may not be possible in the real world, especially in low-resource rural scenarios.

Moreover, to fully address the ethical concerns associated with AI-based decision-making in rural communities, the matter needs to be properly addressed. More than just being dependent on AI models, community participation along with traditional ecological knowledge must be used so that the strategies created through AI could meet local needs and socio-economic situations. The results show that AI models can be powerful tools in modifying sustainable rural landscape planning. CNN and GIS-based AI are the models that provide the highest precision and offer strong predictive capabilities. On the other hand, traditional knowledge integration with participatory planning and AI advancements is crucial to achieving the fair and responsible implementation of AI in rural strategic design.

Figure 4 AI model applications in rural landscape strategy (see online version for colours)



5 Conclusions

The application of AI-driven models in the development of the rural landscape strategy has been recognised as a revolutionary procedure in optimising land use, environmental conservation, and socio-economic development. The outputs of this research using the Kaggle precision agriculture dataset show that CNN will be 92.4% accurate whereas GIS-based AI will result in a 91.5% accuracy. Land-use classification and biodiversity monitoring are accomplished best through CNN's DL capabilities while GIS-based AI improves spatial decision-making and environmental evaluation. Traditional ML models, like random forest (84.7% accuracy) and SVM (90% accuracy), are also innovative in their own right, supplying useful pointers to agricultural zoning, crop yield, and irrigation planning. Such results emphasise the great potential of AI to make situations better through data-driven strategies.

Nonetheless, the complexity of the model also stands out as a limitation for the research. The insufficiency and deficiencies of the rural data can be a source of great difficulty in the path of AI model accuracy. Another note of concern has to do with the case of AI adoption in rural areas, which are usually with limited technological infrastructure because of both computational complexity and resource conditions. There are some ethical, data privacy, and transparency considerations as well as exclusionary aspects of local knowledge that should be considered so that no one is left out in the AI-driven strategies. The future studies must enhance the interpretability of AI, integrate community involvement in the planning process, and be those cost-effective AI practices to make the rural development strategy by AI more accessible and member-friendly.

Declarations

The authors declared that they have no conflicts of interest regarding this work.

Funding

2024 Shaanxi Provincial Department of Education Scientific Research Plan Project-General Special Project, Project Name: Research on the Path and Method of Renewal and Reuse of Remaining Space in Xi'an Urban Area, No.24JK0136.

References

Barrera-Perales, O.T. and Burgos, A.L. (2023) 'Conceptual distinction between agricultural innovation and rural innovation: implications for scientific research and public policy', *Innovation and Development*, Vol. 13, No. 3, DOI: 10.1080/2157930X.2022.2049534.

Botelho, J., Costa, S.C.P., Ribeiro, J.G. and Souza, C.M. (2022) 'Mapping roads in the Brazilian Amazon with artificial intelligence and Sentinel-2', *Remote Sens. (Basel)*, Vol. 14, No. 15, DOI: 10.3390/rs14153625.

Chaturvedi, V. and Sharath, K. (2022) 'Artificial intelligence in healthcare – a revolution to social healthcare system', *J. Evol. Med. Dent. Sci.*, Vol. 11, No. 1, DOI: 10.14260/jemds/2022/54.

Chen, X. (2023) 'Environmental landscape design and planning system based on computer vision and deep learning', *Journal of Intelligent Systems*, Vol. 32, No. 1, DOI: 10.1515/jisys-2022-0092.

Deo, N. and Anjankar, A. (2023) 'Artificial intelligence with robotics in healthcare: a narrative review of its viability in India', *Cureus*, DOI: 10.7759/cureus.39416.

García-Cervantes, P.C. et al. (2017) 'Giardia duodenalis genotypes among schoolchildren and their families and pets in urban and rural areas of sinaloa, Mexico', *J. Infect. Dev. Ctries*, Vol. 11, No. 2, DOI: 10.3855/jidc.8223.

Gulzar Ahmad, S. et al. (2022) 'Sensing and artificial intelligent maternal-infant health care systems: a review', *Sensors*, DOI: 10.3390/s22124362.

Guo, J. and Li, B. (2018) 'The application of medical artificial intelligence technology in rural areas of developing countries', *Health Equity*, DOI: 10.1089/heq.2018.0037.

Hao, S. et al. (2022) 'Clinical evaluation of AI-assisted screening for diabetic retinopathy in rural areas of midwest China', *PLoS One*, October, Vol. 17, No. 10, DOI: 10.1371/journal.pone.0275983.

Hirchak, K.A. and Murphy, S.M. (2017) 'Assessing differences in the availability of opioid addiction therapy options: rural versus urban and American Indian reservation versus non-reservation', *Journal of Rural Health*, Vol. 33, No. 1, DOI: 10.1111/jrh.12178.

Huang, X.M. et al. (2022) 'Cost-effectiveness of artificial intelligence screening for diabetic retinopathy in rural China', *BMC Health Serv. Res.*, Vol. 22, No. 1, DOI: 10.1186/s12913-022-07655-6.

Issa, C.J., Reimer-Taschenbrecker, A. and Paller, A.S. (2023) 'A call for implementing augmented intelligence in pediatric dermatology', *Pediatr. Dermatol.*, Vol. 40, No. 3, DOI: 10.1111/pde.15298.

Jiang, G., Gao, W., Xu, M., Tong, M. and Liu, Z. (2023) 'Geographic information visualization and sustainable development of low-carbon rural slow tourism under artificial intelligence', *Sustainability (Switzerland)*, Vol. 15, No. 4, DOI: 10.3390/su15043846.

Kaur, R., Dharmadhikari, S.P. and Khurjekar, S. (2024) 'Assessing the customer adoption and perceptions for AI-driven sustainable initiatives in Indian banking sector', *Environment and Social Psychology*, Vol. 9, No. 5, DOI: 10.54517/esp.v9i5.1934.

Liu, H. et al. (2023) 'Economic evaluation of combined population-based screening for multiple blindness-causing eye diseases in China: a cost-effectiveness analysis', *Lancet Glob. Health*, Vol. 11, No. 3, DOI: 10.1016/S2214-109X(22)00554-X.

Mashinchi, G.M., Hicks, E.C., Leopold, A.J., Greiman, L. and Ipsen, C. (2022) 'The intersection of disability status and rurality in American Indian/Alaskan native communities', *Frontiers in Rehabilitation Sciences*, Vol. 3, DOI: 10.3389/fresc.2022.875979.

Patros, P. et al. (2023) 'Rural AI: serverless-powered federated learning for remote applications', *IEEE Internet Comput*., Vol. 27, No. 2, DOI: 10.1109/MIC.2022.3202764.

Plackett, B. (2022) 'The rural areas missing out on AI opportunities', *Nature*, Vol. 610, No. 7931, DOI: 10.1038/d41586-022-03212-7.

Saikanth, D.R.K. et al. (2024) 'The impact of emerging technologies on sustainable agriculture and rural development', *International Journal of Environment and Climate Change*, Vol. 14, No. 1, DOI: 10.9734/ijecc/2024/v14i13830.

Xie, J. and Wang, D. (2022) 'Street landscape planning and design guided by artificial intelligence interactive experience', *Comput. Intell. Neurosci.*, Vol. 2022, DOI: 10.1155/2022/3146637.