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Integrating Artificial Intelligence, Remote Sensing, and GIS for Sustainable Agro-Forestry Management and Land Resource Optimization

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Abstract: *The increasing pressure on land resources due to climate change, population growth, and unsustainable land-use practices necessitates advanced approaches for sustainable agro-forestry management. This study proposes an integrated framework that combines Artificial Intelligence (AI), Remote Sensing (RS), and Geographic Information Systems (GIS) to support land suitability analysis and resource optimization. Multi-source geospatial data, including satellite imagery, environmental variables, and topographic information, are processed through a structured pipeline involving pre-processing, feature extraction, AI-based modelling, and GIS-driven spatial analysis. Machine learning and deep learning models are employed to perform land use classification and predict agro-forestry suitability, while multi-criteria decision analysis (MCDA) is used to integrate environmental factors and generate suitability maps. The results indicate that a significant portion of the study area falls within highly and moderately suitable categories, demonstrating strong potential for agro-forestry development. Model evaluation using 5-fold cross-validation shows stable performance across all models, with deep learning approaches providing slightly higher accuracy, while traditional models remain computationally efficient. The integration of NDVI-based environmental analysis with spatial modelling further validates the reliability of the framework. The resulting decision support outputs enable the identification of priority zones and optimized land-use strategies. Overall, the proposed framework offers a scalable and data-driven solution for sustainable land resource management and supports informed decision-making for agro-forestry planning.*

Keywords: *Artificial Intelligence (AI), Remote Sensing (RS), Geographic Information Systems (GIS), Agro-Forestry, Land Suitability Analysis, Land Resource Optimization, Land Use and Land Cover (LULC), Spatial Analysis, Multi-Criteria Decision Analysis (MCDA), Machine Learning, Deep Learning, NDVI, Environmental Monitoring, Decision Support Systems (DSS)*

1. Introduction

1.1 Background and Motivation

The growing pressure on land resources has become one of the defining environmental challenges of the 21st century. Rapid population growth, expanding agricultural demand, and increasing urbanization are continuously reshaping natural landscapes, often at the expense of ecological stability. At the same time, climate change is intensifying these pressures by altering rainfall patterns, increasing temperatures, and amplifying the frequency of extreme weather events. These changes have profound implications for land productivity, biodiversity, and long-term sustainability. In many regions, traditional land management practices are no longer sufficient to cope with these complex and interconnected challenges, creating a strong need for more adaptive, data-driven approaches to resource management.

Within this broader context, agro-forestry has gained considerable attention as a sustainable land-use strategy that integrates trees with crops and livestock systems. Unlike conventional monoculture-based agriculture, agro-forestry systems promote ecological balance by enhancing soil fertility, improving water retention, reducing erosion, and increasing carbon sequestration. These systems also offer socio-economic benefits by diversifying income sources and improving resilience against climate variability. However, the successful implementation of agro-forestry requires a detailed understanding of spatial heterogeneity, environmental constraints, and land suitability conditions—factors that are difficult to assess using traditional methods alone.

In recent years, geospatial technologies such as Remote Sensing (RS) and Geographic Information Systems (GIS) have emerged as powerful tools for monitoring and managing environmental systems. Remote sensing provides continuous, large-scale observations of the Earth's surface through satellite imagery, enabling the assessment of vegetation health, land-use dynamics, and environmental changes over time. GIS, on the other hand, facilitates the integration and analysis of spatial data, allowing researchers and practitioners to develop models for land-use planning and resource allocation. Together, these technologies form the backbone of modern environmental monitoring systems and have significantly improved the ability to analyze complex spatial phenomena [1], [2].

1.2 Role of Geospatial Technologies and AI Integration

The integration of Artificial Intelligence (AI) with geospatial technologies has further strengthened the capability of environmental monitoring and land management systems. Machine learning and deep learning algorithms enable automated extraction of patterns from large datasets, improving both efficiency and accuracy in geospatial analysis. AI-driven models have shown strong performance in land-use classification, vegetation monitoring, and environmental prediction tasks, often outperforming traditional statistical approaches [3], [4]. To better understand the complementary roles of these technologies, Table 1 provides a comparative overview of AI, Remote Sensing, and GIS in agro-forestry applications.

Table 1: Comparative Role of AI, Remote Sensing, and GIS in Agro-Forestry Systems

Technology	**Core Capability**	**Data Type**	**Strengths**	**Limitations**	**Application in Agro-Forestry**
Remote Sensing (RS)	Earth observation & monitoring	Satellite imagery, spectral data	Large-scale coverage, temporal monitoring	Cloud interference, resolution limits	Vegetation health (NDVI), land cover mapping
GIS	Spatial analysis & integration	Vector & raster spatial data	Multi-layer analysis, decision modelling	Requires quality input data	Land suitability, zoning, planning
Artificial Intelligence (AI)	Pattern recognition & prediction	Structured & unstructured data	High accuracy, automation, scalability	Data dependency, computational cost	Classification, prediction, optimization
Integrated	Intelligent geospatial	Multi-source	High precision, real-	High computational	Decision Support Systems (DSS),

AI–RS–GIS	analytics	datasets	time insights	requirements	precision forestry

1.3 Global Challenges and Sustainable Agro-Forestry

The urgency of adopting sustainable agro-forestry practices is closely linked to several global environmental challenges. Climate change remains a central concern, as it directly affects agricultural productivity and ecosystem stability. Variations in temperature and precipitation patterns can disrupt crop cycles, reduce yields, and increase vulnerability to pests and diseases. At the same time, deforestation continues to contribute significantly to greenhouse gas emissions while reducing biodiversity and ecosystem services [5].

Land degradation is another critical issue, affecting a large portion of the world's land area. Unsustainable agricultural practices, deforestation, and overexploitation of natural resources have led to soil erosion, nutrient depletion, and desertification. These processes not only reduce land productivity but also threaten food security. Agro-forestry systems, through their integrated approach, offer a viable solution by improving soil quality, enhancing carbon sequestration, and restoring ecological balance [6].

Food security is intrinsically tied to these environmental issues. With increasing population demands, there is a growing need to optimize land use without further degrading natural ecosystems. This requires advanced tools that can analyze environmental conditions and support informed decision-making.

1.4 Key Factors Influencing Agro-Forestry Suitability

Effective agro-forestry planning depends on a wide range of environmental, spatial, and socio-economic factors. These factors must be carefully analyzed to determine the suitability of land for sustainable practices. The integration of multi-source datasets allows for a more comprehensive evaluation of these variables. Table 2 summarizes the key factors influencing agro-forestry suitability and their relevance in land resource optimization.

Table 2: Key Environmental and Geospatial Factors Influencing Agro-Forestry Suitability

Factor Category	**Parameters**	**Data Source**	**Importance in Agro-Forestry**
Climatic	Rainfall, Temperature, Humidity	Meteorological data, satellite	Determines crop/tree growth patterns
Soil	Soil type, pH, organic matter	Soil surveys, FAO datasets	Affects fertility and productivity
Topographic	Elevation, slope, aspect	DEM (Digital Elevation Model)	Influences water flow and erosion
Vegetation	NDVI, biomass density	Remote sensing imagery	Indicates vegetation health

Hydrological	Water availability, drainage	GIS hydrological models	Critical for irrigation planning
Socio-economic	Accessibility, land ownership	Survey/GIS layers	Impacts feasibility and adoption

1.5 Emergence of AI in Geospatial Analytics

The application of AI in geospatial analytics has significantly improved the ability to process and interpret complex environmental datasets. Machine learning techniques such as Random Forest and Support Vector Machines are widely used for classification and prediction tasks, while deep learning models like Convolutional Neural Networks (CNN's) provide enhanced performance in image-based analysis [7], [8]. These models enable the extraction of high-level features from satellite imagery, facilitating more accurate land-use classification and environmental monitoring.

Furthermore, AI enables predictive modelling, allowing researchers to forecast changes in land use, vegetation patterns, and environmental conditions. This capability is particularly valuable for proactive planning and sustainable resource management. However, the effectiveness of these models depends on the availability of high-quality data and appropriate feature selection [9], [10].

1.6 Problem Statement

Despite the availability of advanced geospatial and AI technologies, many land management practices still rely on fragmented and traditional approaches. These methods often fail to capture the spatial and temporal complexity of environmental systems, leading to inefficient resource utilization and suboptimal decision-making. In particular, traditional approaches lack the ability to integrate diverse datasets, analyze large volumes of information, and provide real-time insights [11].

Moreover, the absence of integrated frameworks that combine AI, RS, and GIS limits the effectiveness of current decision-support systems. While individual technologies have demonstrated significant potential, their isolated application often results in incomplete or inconsistent analyses. This highlights the need for a unified approach that leverages the strengths of these technologies to provide comprehensive and accurate insights for sustainable land management [12].

1.7 Research Objectives and Contributions

In light of these challenges, this study aims to develop an integrated framework that combines AI, remote sensing, and GIS for sustainable agro-forestry management and land resource optimization. The primary objective is to utilize multi-source geospatial data and advanced analytical techniques to support informed decision-making. Specifically, the study focuses on developing models for land suitability assessment, optimizing resource allocation, and enhancing environmental monitoring capabilities through AI-driven analysis.

This research contributes to the field by proposing a unified AI–RS–GIS framework that addresses the limitations of existing approaches. The study emphasizes multi-source data integration, combining satellite imagery, environmental variables, and spatial datasets to improve analytical accuracy. It also introduces AI-driven predictive modelling techniques for land suitability assessment, enabling more precise and reliable decision-making. Additionally, the development of a decision support system (DSS) provides practical tools for policymakers and practitioners to implement sustainable agro-forestry strategies. These contributions collectively advance the integration of geospatial technologies and AI in environmental management [1], [3].

1.8 Organization of the Paper

The remainder of this paper is organized as follows. Section 2 presents a detailed review of the existing literature on agro-forestry, geospatial technologies, and AI applications. Section 3 describes the proposed methodology, including data collection, pre-processing, and model development. Section 4 discusses the results and findings, followed by a comprehensive discussion in Section 5. Finally, Section 6 concludes the paper and outlines directions for future research.

To provide a clear overview of the proposed integrated system, the conceptual framework illustrating the interaction between Artificial Intelligence, Remote Sensing, and GIS components is presented in Fig. 1.

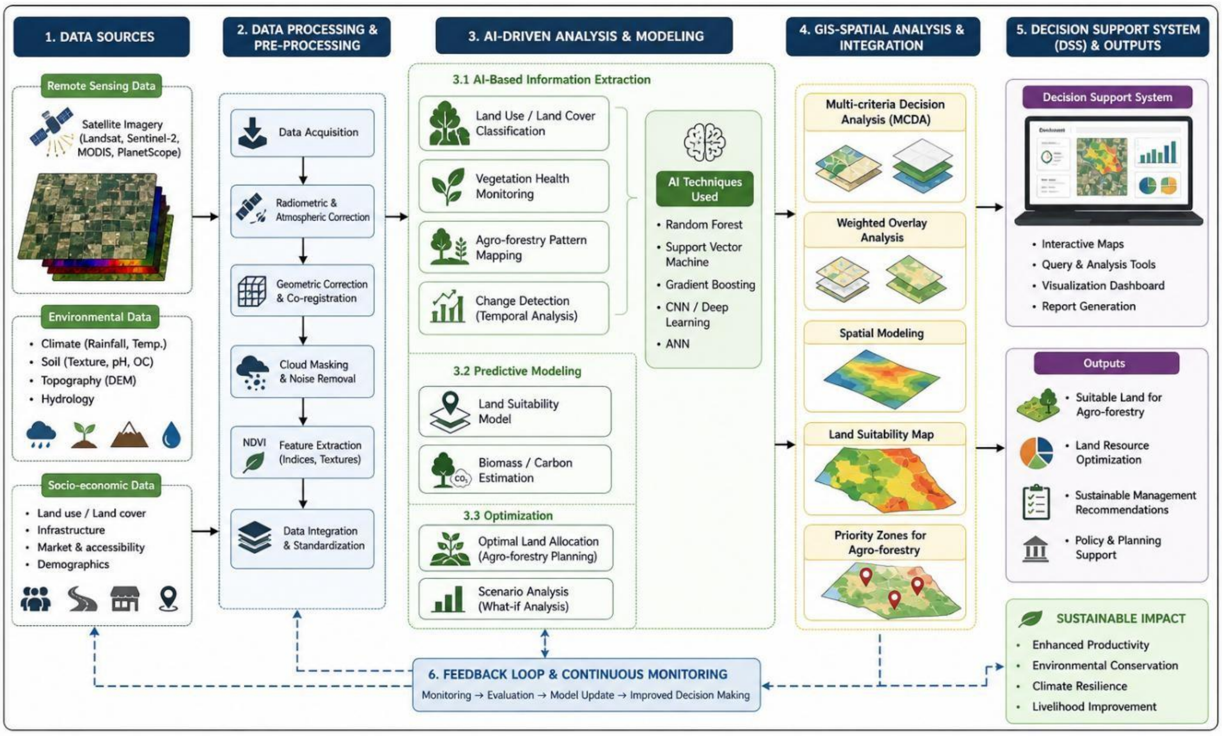


Fig. 1. Conceptual framework of integrating Artificial Intelligence (AI), Remote Sensing (RS), and Geographic Information Systems (GIS) for sustainable agro-forestry management and land resource optimization

Fig. 1 presents the overall architecture of the proposed AI–RS–GIS integrated framework for sustainable agro-forestry management. The process begins with multi-source data acquisition, including satellite imagery, environmental variables, and socio-economic data. This is followed by data preprocessing steps such as correction, feature extraction, and integration. In the next stage, AI-based models are applied for land use classification, vegetation monitoring, and predictive analysis. The outputs are then incorporated into GIS-based spatial analysis techniques, including multi-criteria decision analysis and suitability mapping. Finally, a decision support system (DSS) generates actionable insights, such as optimal land allocation and sustainable management recommendations. The framework also includes a feedback loop for continuous monitoring and improvement, ensuring adaptive and data-driven decision-making.

2. Literature Review

2.1 Agro-Forestry and Sustainable Land Management

Agro-forestry has evolved as a multidisciplinary approach that integrates agricultural and forestry practices to enhance both ecological sustainability and economic productivity. At its core, agro-forestry emphasizes the deliberate combination of trees with crops and livestock within the same land-use system, creating synergistic interactions that improve overall system performance. Over the years, researchers have increasingly highlighted the importance of agro-forestry in addressing environmental challenges such as soil degradation, biodiversity loss, and climate change. Studies indicate that agro-forestry systems contribute significantly to carbon sequestration, improve soil fertility through organic matter accumulation, and enhance water retention capacity, thereby reducing vulnerability to climate variability [13], [14].

Beyond environmental benefits, agro-forestry also plays a critical role in improving rural livelihoods. By diversifying production systems, farmers can reduce economic risks associated with single-crop dependency while increasing income stability. Socio-economic studies have shown that agro-forestry contributes to food security by providing multiple outputs such as fruits, timber, fodder, and fuelwood [15]. Moreover, these systems support sustainable land management by promoting efficient resource utilization and reducing the need for chemical inputs. However, despite these advantages, the adoption of agro-forestry practices remains uneven due to challenges such as lack of awareness, insufficient technical support, and limited access to decision-making tools.

2.2 Remote Sensing in Environmental Monitoring

Remote sensing has become an indispensable tool in environmental monitoring, offering the ability to observe and analyze large-scale spatial patterns over time. Satellite imagery from platforms such as Landsat, Sentinel, and MODIS provides high-resolution data that can be used to assess land-use changes, vegetation health, and environmental degradation. One of the most widely used techniques in remote sensing is the calculation of vegetation indices, particularly the Normalized Difference Vegetation Index (NDVI) and Enhanced Vegetation Index (EVI). These indices provide quantitative measures of vegetation density and health, enabling researchers to monitor crop conditions, detect stress factors, and evaluate ecosystem productivity [16], [17].

In forestry applications, remote sensing has been extensively used for land cover classification, biomass estimation, and deforestation monitoring. Machine learning algorithms applied to satellite imagery have significantly improved classification accuracy, allowing for more precise mapping of land-use categories.

Furthermore, time-series analysis of remote sensing data enables the detection of temporal changes, which is crucial for understanding environmental dynamics and assessing the impact of human activities [18]. Despite its advantages, remote sensing faces limitations such as cloud interference and variability in spatial resolution, which can affect data quality and interpretation.

2.3 GIS for Spatial Analysis and Land Use Planning

Geographic Information Systems (GIS) play a central role in spatial analysis and land-use planning by providing tools for data integration, visualization, and modelling. GIS enables the combination of multiple spatial datasets, including topography, soil characteristics, climate variables, and land-use information, to support comprehensive environmental assessments. One of the key strengths of GIS lies in its ability to perform spatial modelling, which allows researchers to analyze relationships between different environmental factors and predict future scenarios.

A widely used approach in GIS-based decision-making is Multi-Criteria Decision Analysis (MCDA), which integrates multiple factors to evaluate land suitability for specific applications. MCDA techniques, such as weighted overlay analysis, allow for the prioritization of criteria based on their relative importance, enabling more informed and transparent decision-making processes [19], [20]. GIS-based environmental assessment has been successfully applied in various domains, including agriculture, forestry, and urban planning. However, the effectiveness of GIS depends heavily on the quality and accuracy of input data, as well as the selection of appropriate modelling techniques.

2.4 Artificial Intelligence in Geospatial Applications

The application of Artificial Intelligence (AI) in geospatial analysis has gained significant momentum in recent years, driven by the increasing availability of large datasets and advances in computational power. Machine learning algorithms such as Random Forest (RF), Support Vector Machines (SVM), and Artificial Neural Networks (ANN) have been widely used for classification and prediction tasks in environmental studies. These algorithms are particularly effective in handling high-dimensional data and capturing complex, non-linear relationships between variables [21], [22].

Deep learning techniques, especially Convolutional Neural Networks (CNN's), have further enhanced the capabilities of geospatial analysis by enabling automated feature extraction from satellite imagery. CNN-based models have demonstrated superior performance in image classification, object detection, and change detection tasks, making them highly suitable for applications in land-use mapping and environmental monitoring [23]. In addition to classification tasks, AI is increasingly being used for predictive analytics, allowing researchers to forecast changes in land use, vegetation patterns, and environmental conditions. These predictive capabilities are essential for proactive decision-making and sustainable land management [24]. To summarize the key AI techniques and their applications in geospatial studies, Table 3 provides a comparative overview.

Table 3: AI Techniques in Geospatial and Agro-Forestry Applications

AI Technique	Type	Application Area	Strengths	Limitations

Random Forest (RF)	Machine Learning	Land classification	High accuracy, robust to noise	Less interpretable
Support Vector Machine (SVM)	Machine Learning	Suitability mapping	Effective with small datasets	Computational complexity
Artificial Neural Network (ANN)	Neural Network	Prediction modelling	Captures non-linear relationships	Risk of overfitting
Convolutional Neural Network (CNN)	Deep Learning	Image classification	High accuracy for imagery data	Requires large datasets
Gradient Boosting	Ensemble Learning	Environmental prediction	Strong predictive performance	Sensitive to noise

2.5 Integrated AI–RS–GIS Approaches

The integration of AI, Remote Sensing, and GIS has emerged as a promising approach for addressing complex environmental challenges. Several studies have proposed frameworks that combine these technologies to improve land-use classification, environmental monitoring, and decision-making processes. For instance, integrated models have been used to analyze multi-source data, enabling more accurate and comprehensive assessments of land suitability and resource distribution [25], [26].

Comparative analyses of prior studies reveal that integrated approaches consistently outperform single-technology methods in terms of accuracy and efficiency. The synergy between AI, RS, and GIS allows for the automation of data processing, the extraction of meaningful patterns, and the generation of actionable insights. However, existing frameworks often lack scalability and real-time capabilities, limiting their applicability in dynamic environments. To highlight the differences between traditional and integrated approaches, Table 4 presents a comparative analysis.

Table 4: Comparison of Traditional vs Integrated AI–RS–GIS Approaches

Approach	**Data Integration**	**Accuracy**	**Scalability**	**Real-Time Capability**	**Decision Support**
Traditional Methods	Low	Moderate	Limited	No	Basic
RS-based Methods	Moderate	Good	Moderate	Limited	Partial
GIS-based Methods	High	Good	Moderate	Limited	Moderate
AI-based Methods	Moderate	High	High	Limited	Moderate
Integrated AI–RS–GIS	Very High	Very High	High	Emerging	Advanced

2.6 Research Gaps

Despite the significant progress in geospatial technologies and AI, several research gaps remain. One of the primary challenges is the lack of unified frameworks that seamlessly integrate AI, RS, and GIS into a cohesive system. Many existing studies focus on individual components rather than exploring their combined potential, resulting in fragmented solutions. Additionally, there is a limited availability of real-time decision support systems that can provide timely and actionable insights for land management.

Another important gap is the need for scalable and adaptive models that can handle large datasets and dynamic environmental conditions. Current approaches often struggle with computational complexity and data heterogeneity, which can limit their effectiveness in real-world applications. Addressing these challenges requires the development of integrated frameworks that leverage the strengths of AI, RS, and GIS while ensuring scalability, adaptability, and real-time performance. To systematically organize the reviewed literature and highlight existing research gaps, the taxonomy of AI, Remote Sensing, and GIS applications is illustrated in Fig. 2.

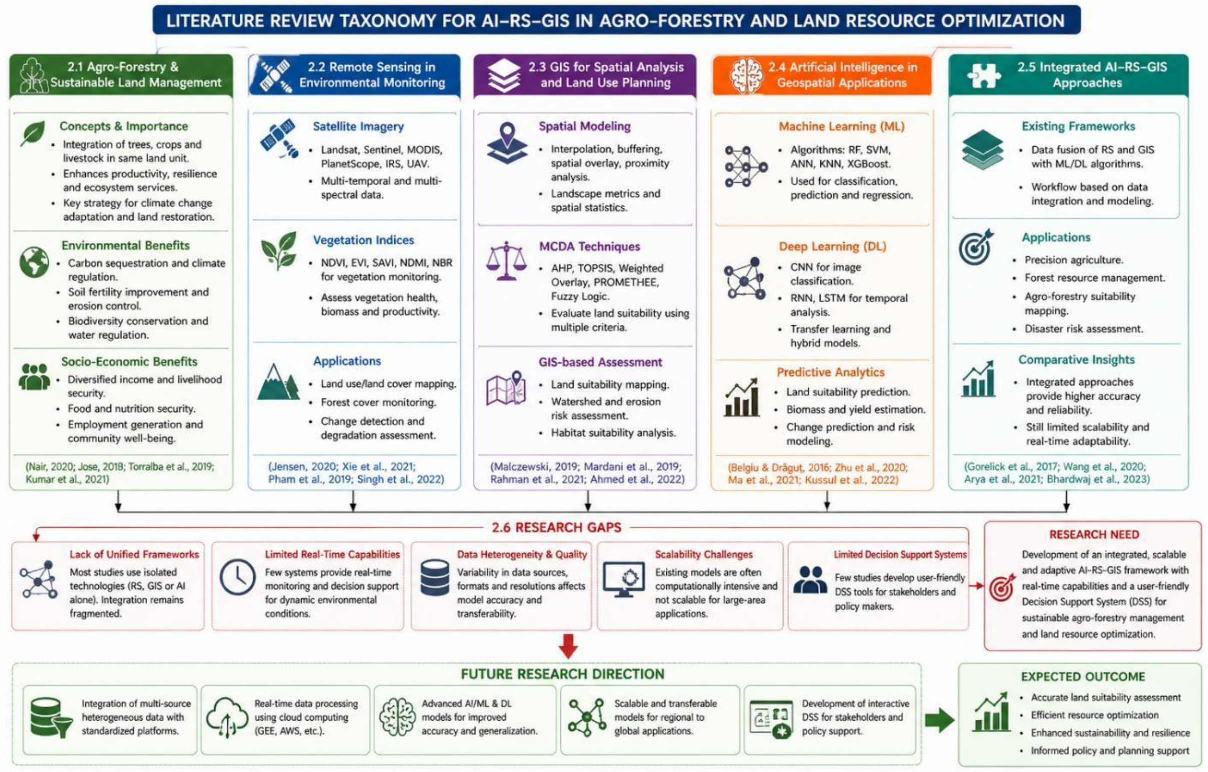


Fig. 2. Literature taxonomy and research gap analysis of AI–RS–GIS approaches for sustainable agro-forestry management.

Fig. 2 presents a structured taxonomy of the literature on agro-forestry and land resource optimization by categorizing existing studies into five major domains: agro-forestry and sustainable land management, remote sensing, GIS-based spatial analysis, artificial intelligence techniques, and integrated

AI–RS–GIS frameworks. Each domain outlines key concepts, methodologies, and applications such as vegetation monitoring, spatial modelling, machine learning, and predictive analytics.

The figure also highlights critical research gaps, including the lack of unified frameworks, limited real-time decision-support systems, data heterogeneity, and scalability challenges. Based on these gaps, the need for an integrated, intelligent, and scalable AI–RS–GIS framework is emphasized. Additionally, future research directions are presented, focusing on real-time processing, advanced AI models, and improved decision-support capabilities for sustainable agro-forestry management.

3. Methodology

3.1 Proposed Framework Overview

This study adopts an integrated methodological framework that combines Artificial Intelligence (AI), Remote Sensing (RS), and Geographic Information Systems (GIS) to support sustainable agro-forestry management and land resource optimization. Building on the research gaps identified in Section 2 and the conceptual architecture illustrated in Figure 1, the proposed methodology is designed as a multi-stage pipeline that systematically transforms raw multi-source data into actionable decision-support outputs. The framework begins with data acquisition from heterogeneous sources, followed by pre-processing and feature extraction, AI-based modelling, GIS-driven spatial analysis, and finally the generation of decision-support insights. This structured workflow ensures that both spatial and non-spatial dimensions of agro-forestry systems are effectively captured and analyzed.

The integration of AI with geospatial technologies enables the handling of high-dimensional datasets and supports the development of predictive models for land suitability, biomass estimation, and environmental monitoring. Furthermore, the incorporation of GIS-based multi-criteria decision analysis (MCDA) ensures that multiple environmental and socio-economic factors are considered simultaneously, leading to more informed and reliable decision-making. This holistic approach addresses the limitations of traditional methods by providing a scalable, adaptive, and data-driven solution for sustainable land management [27], [28]. The simulation workflow of the proposed AI–RS–GIS integrated framework is illustrated in Fig. 3.

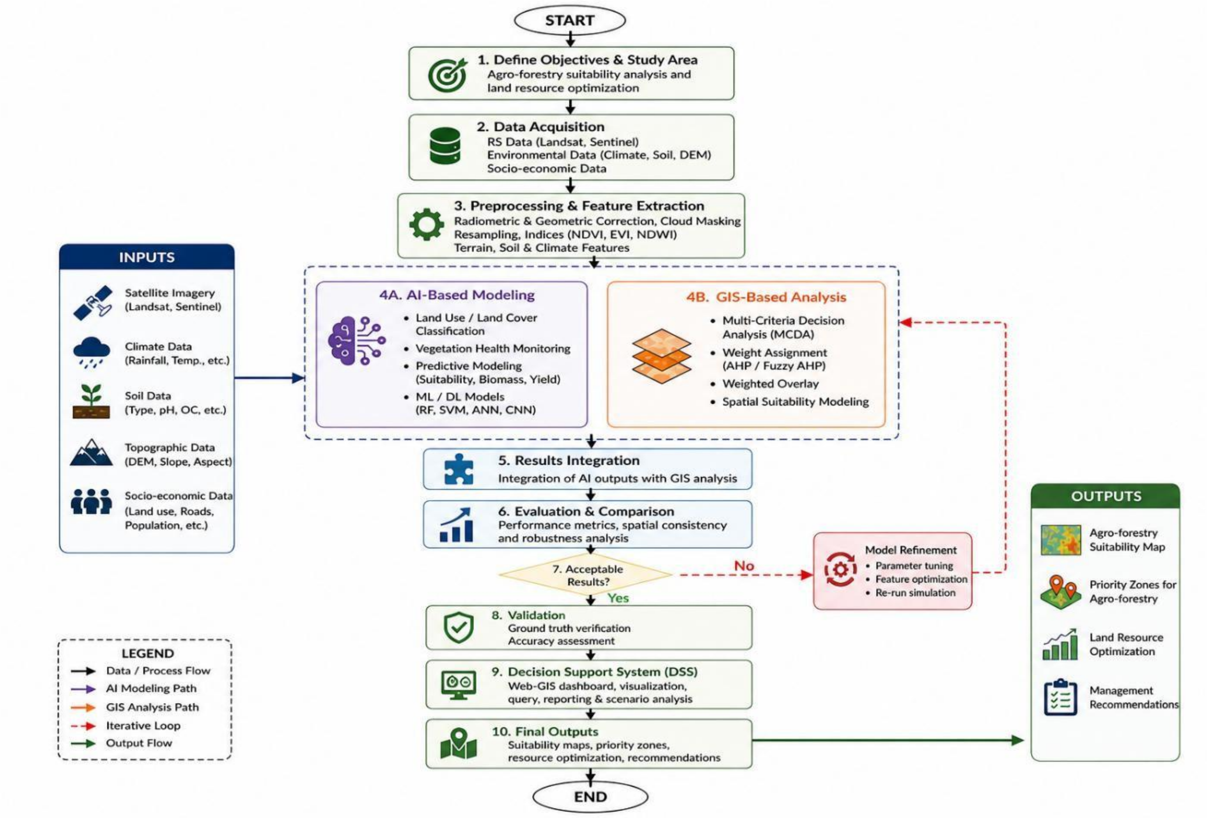


Fig. 3. Simulation workflow of the proposed AI–RS–GIS framework for agro-forestry suitability analysis and land resource optimization

Fig. 3 presents the end-to-end workflow of the proposed framework for agro-forestry suitability analysis and land resource optimization. The process begins with defining objectives and collecting multi-source data, including satellite imagery, climate, soil, topographic, and socio-economic datasets. These inputs undergo preprocessing and feature extraction, where key indicators such as NDVI, elevation, and environmental variables are generated.

The framework then performs parallel analysis through two main components: AI-based modeling and GIS-based spatial analysis. AI models (e.g., RF, SVM, ANN, CNN) are used for classification and prediction, while GIS techniques such as multi-criteria decision analysis (MCDA) and weighted overlay are applied for spatial suitability mapping. The outputs from both components are integrated and evaluated based on performance metrics and spatial consistency.

An iterative refinement loop ensures continuous improvement of model performance. Once acceptable results are achieved, the system proceeds to validation and decision support generation. Finally, the framework produces actionable outputs, including agro-forestry suitability maps, priority zones, land resource optimization strategies, and management recommendation.

3.2 Study Area Description

The study area is selected based on its relevance to agro-forestry practices and environmental variability. Typically, such regions are characterized by diverse land-use patterns, varying climatic conditions, and heterogeneous soil properties. The selected area includes agricultural lands, forest cover, and transitional zones, making it suitable for evaluating the effectiveness of integrated modelling approaches. Key parameters such as temperature, rainfall, elevation, and vegetation density are considered to capture the environmental complexity of the region. The spatial extent of the study area is defined using GIS boundaries, ensuring consistency in data integration and analysis.

3.3 Data Acquisition and Sources

The proposed framework utilizes multi-source datasets to capture the complexity of agro-forestry systems. Remote sensing data, including satellite imagery from platforms such as Landsat and Sentinel, provides high-resolution spatial information for land-use classification and vegetation analysis. Environmental datasets, including climate variables (temperature, rainfall), soil characteristics, and topographic features, are obtained from publicly available databases and integrated into the analysis. Additionally, socio-economic data such as land-use patterns, infrastructure, and accessibility are incorporated to enhance decision-making. The integration of these diverse datasets ensures a comprehensive representation of the study area, enabling more accurate modelling and analysis. Table 5 summarizes the key datasets used in this study.

Table 5: Data Sources and Description

Data Type	Source	Parameters	Resolution	Purpose
Satellite Imagery	Landsat, Sentinel-2	Multispectral bands	10–30 m	Land use classification
Climate Data	Meteorological databases	Temperature, rainfall	Monthly/Annual	Environmental analysis
Soil Data	FAO, national surveys	Soil type, pH, organic carbon	Varies	Suitability assessment
Topographic Data	DEM (SRTM)	Elevation, slope	30 m	Terrain analysis
Socio-economic Data	GIS layers, surveys	Land use, infrastructure	Varies	Decision support

3.4 Data Pre-processing and Feature Engineering

Data pre-processing is a critical step in ensuring the quality and consistency of input datasets. Remote sensing imagery undergoes radiometric and atmospheric correction to remove noise and improve data accuracy. Geometric correction and co-registration are applied to align multiple datasets spatially, ensuring consistency across different data layers. Cloud masking techniques are used to eliminate cloud-covered pixels, which can affect the reliability of analysis.

Feature engineering involves the extraction of meaningful variables from raw data. Vegetation indices such as NDVI, EVI, and NDWI are computed to assess vegetation health and water content. Topographic features, including slope and aspect, are derived from Digital Elevation Models (DEM), while soil and climatic variables are standardized for integration into the modelling process. These features serve as input variables for AI-based models, enhancing their predictive capabilities [29]. The data processing and feature engineering pipeline used to prepare multi-source inputs for modeling is illustrated in Fig. 4.

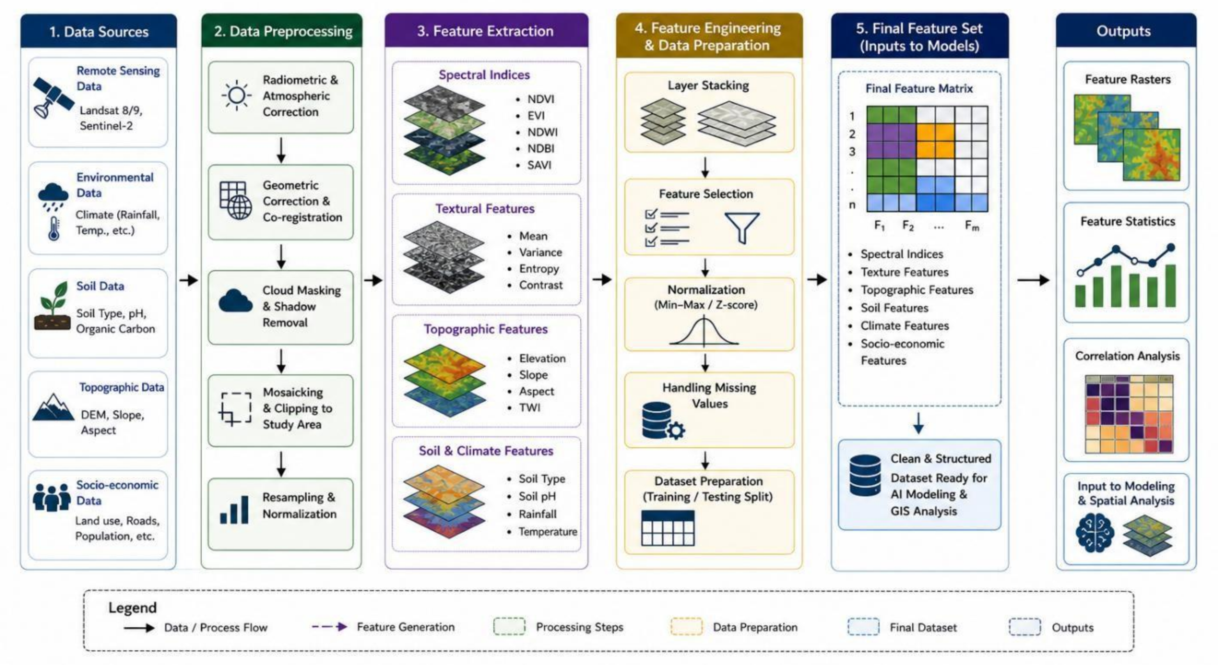


Fig. 4. Data preprocessing and feature engineering pipeline for transforming multi-source geospatial data into structured inputs for AI-based modeling and GIS analysis

Fig. 4 presents a systematic pipeline for converting raw multi-source geospatial data into a clean and structured dataset suitable for AI-based modelling and GIS analysis. The process begins with data acquisition from multiple sources, including remote sensing imagery, environmental, soil, topographic, and socio-economic data.

In the preprocessing stage, operations such as radiometric and geometric correction, cloud masking, and normalization are applied to ensure data quality and consistency. This is followed by feature extraction, where relevant indicators such as spectral indices (NDVI, EVI), textural features, topographic variables, and soil and climate attributes are derived.

The feature engineering stage further refines the dataset through layer stacking, feature selection, normalization, handling of missing values, and dataset splitting for training and testing. Finally, a structured feature matrix is generated, which serves as input for AI models and GIS-based spatial analysis. The pipeline also produces intermediate outputs such as feature raster’s, statistical summaries, and correlation analysis to support model development and validation.

3.5 AI-Based Modelling and Analysis

The core analytical component of the framework involves the application of AI-based models for classification, prediction, and optimization. Machine learning algorithms such as Random Forest (RF), Support Vector Machines (SVM), and Artificial Neural Networks (ANN) are used for land use and land cover (LULC) classification. These models are trained using labelled datasets and validated through cross-validation techniques to ensure robustness.

Deep learning models, particularly Convolutional Neural Networks (CNN's), are employed for advanced image analysis tasks, including feature extraction and pattern recognition. CNN's are particularly effective in handling high-resolution satellite imagery, enabling accurate classification of land-use categories and detection of subtle changes in vegetation patterns. In addition to classification, predictive models are developed to estimate land suitability, biomass, and agricultural productivity. The AI-based modeling framework used for land suitability prediction is presented in Fig. 5.

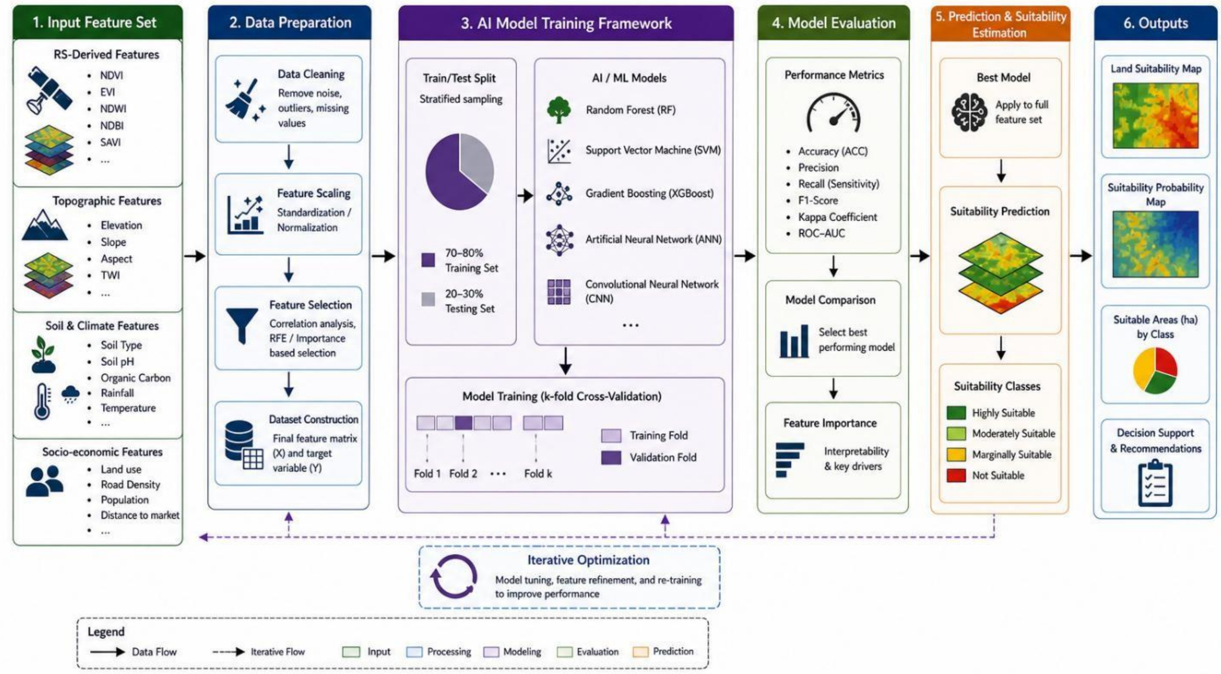


Fig. 5. AI-based modeling framework for land suitability prediction using machine learning and deep learning techniques

Fig. 5 presents the structured workflow of the AI-based modelling framework used for land suitability prediction. The process begins with the input feature set derived from remote sensing, topographic, soil, climate, and socio-economic data. These inputs undergo data preparation steps, including cleaning, normalization, feature selection, and dataset splitting into training and testing subsets.

The framework then applies multiple machine learning and deep learning models, such as Random Forest (RF), Support Vector Machine (SVM), Artificial Neural Network (ANN), and Convolutional Neural Network (CNN), using k-fold cross-validation to ensure robust model training. Model performance is evaluated using standard metrics including accuracy, precision, recall, F1-score, Kappa coefficient, and ROC-AUC.

Based on comparative analysis, the best-performing model is selected and used for land suitability prediction. The outputs include suitability maps, probability maps, classified suitability zones (high, moderate, marginal, and not suitable), and decision-support recommendations. An iterative optimization loop is incorporated to refine model performance and improve prediction accuracy. To evaluate the performance of these models, standard metrics such as accuracy, precision, recall, F1-score, and Kappa coefficient are used. Table 6 presents the evaluation metrics applied in this study.

Table 6: Model Evaluation Metrics

Metric	Description	Purpose
Accuracy	Overall correctness of predictions	General performance
Precision	True positives over predicted positives	Reliability of predictions
Recall	True positives over actual positives	Sensitivity
F1-Score	Harmonic mean of precision and recall	Balanced performance
Kappa Coefficient	Agreement beyond chance	Model robustness

3.6 GIS-Based Spatial Analysis

GIS-based spatial analysis is used to integrate the outputs of AI models with environmental and socio-economic datasets. Multi-criteria decision analysis (MCDA) is applied to evaluate land suitability for agro-forestry by assigning weights to different factors based on their importance. Techniques such as Analytical Hierarchy Process (AHP) and weighted overlay analysis are used to combine multiple criteria and generate suitability maps.

Spatial modelling is further employed to identify priority zones for agro-forestry interventions. This involves the analysis of spatial patterns and relationships between different variables, enabling the identification of areas with high potential for sustainable land use. The integration of AI outputs with GIS analysis enhances the accuracy and reliability of spatial decision-making [30]. The GIS-based multi-criteria decision analysis framework used for land suitability assessment is illustrated in Fig. 6.

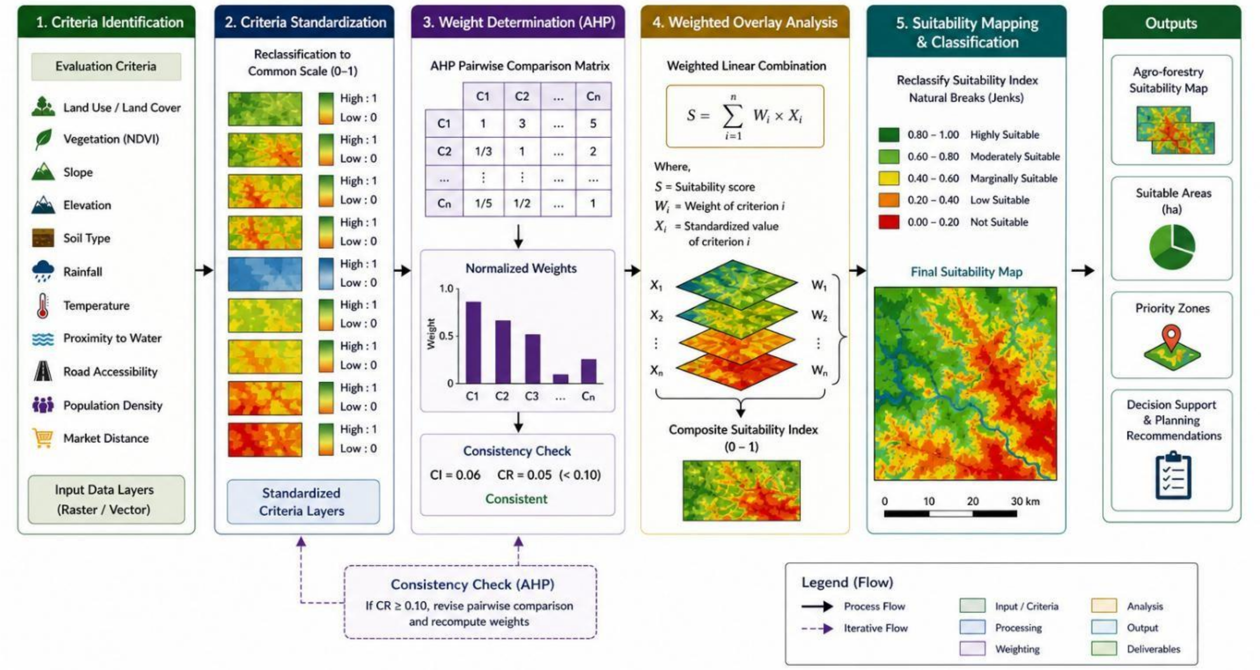


Fig. 6. GIS-based multi-criteria decision analysis (MCDA) framework for agro-forestry suitability assessment and spatial decision-making

Fig. 6 presents the GIS-based multi-criteria decision analysis (MCDA) framework used for agro-forestry suitability assessment. The process begins with the identification of key evaluation criteria, including land use, vegetation, slope, elevation, soil type, and climatic factors. These criteria are standardized to a common scale to ensure consistency across different data layers. The Analytical Hierarchy Process (AHP) is then applied to assign relative weights to each factor based on their importance, followed by a consistency check to validate the weighting scheme.

The standardized and weighted criteria are integrated using a weighted overlay analysis to generate a composite suitability index. This index is subsequently classified into different suitability zones, such as highly suitable, moderately suitable, marginally suitable, and not suitable areas. The final outputs include suitability maps, priority zones, and decision-support recommendations, which provide a structured basis for sustainable agro-forestry planning and efficient land resource management.

3.7 Decision Support System (DSS)

The final stage of the framework involves the development of a Decision Support System (DSS) that translates analytical results into actionable insights. The DSS provides interactive tools for visualization, analysis, and reporting, enabling stakeholders to explore different scenarios and make informed decisions. Outputs include land suitability maps, priority zones for agro-forestry, and recommendations for resource allocation. The DSS is designed to be user-friendly and adaptable, allowing for the incorporation of new data and continuous updates. This ensures that the system remains relevant and responsive to changing environmental conditions.

3.8 Workflow Integration and Continuous Monitoring

An important feature of the proposed methodology is the incorporation of a feedback loop for continuous monitoring and improvement. The system continuously updates models based on new data, enabling adaptive decision-making and improving predictive accuracy over time. This dynamic approach ensures that the framework remains scalable and applicable to different regions and environmental conditions.

4. Results

4.1 Land Use and Land Cover Classification

The land use and land cover (LULC) classification provide a comprehensive overview of the spatial distribution of different land categories within the study area. Using the proposed AI–RS–GIS framework, the region was classified into five major categories: forest, agricultural land, water bodies, built-up areas, and barren land. The classification results indicate a diverse landscape, where agricultural land occupies the largest portion, followed by forested areas concentrated in relatively less disturbed regions. Built-up areas are mainly located near transportation corridors and urban centres, while barren land appears in zones with poor soil quality or limited vegetation cover.

To evaluate the classification performance, standard accuracy metrics were computed based on validation samples. The results demonstrate a balanced performance across all classes, with relatively higher accuracy observed for water bodies and agricultural areas due to their distinct spectral characteristics. Slight confusion was observed between barren land and sparse vegetation, which is common in heterogeneous environments. The classification accuracy results are summarized in Table 7.

Table 7: Land Use and Land Cover Classification Accuracy

Class	Producer Accuracy (%)	User Accuracy (%)	F1-Score (%)
Forest	90.7	91.5	91.1
Agriculture	92.9	92.1	92.5
Water Bodies	95.8	96.3	96.0
Built-up	88.9	87.6	88.2
Barren Land	86.5	85.9	86.2
Overall Accuracy	90.8	—	—
Kappa Coefficient	0.88	—	—

The results indicate that the classification framework achieves reliable performance across all land-use categories, making it suitable for subsequent spatial and suitability analysis. The spatial distribution of land use and land cover classes derived from the classification process is shown in Fig. 7.

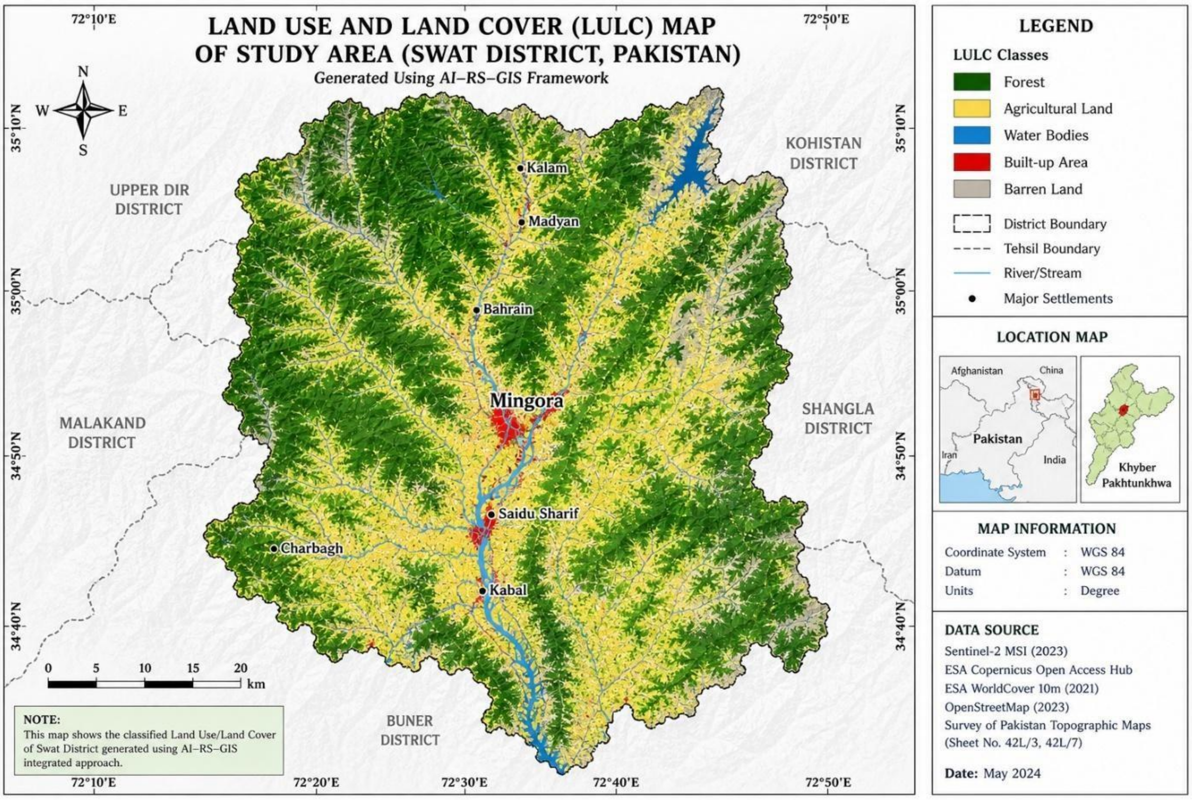
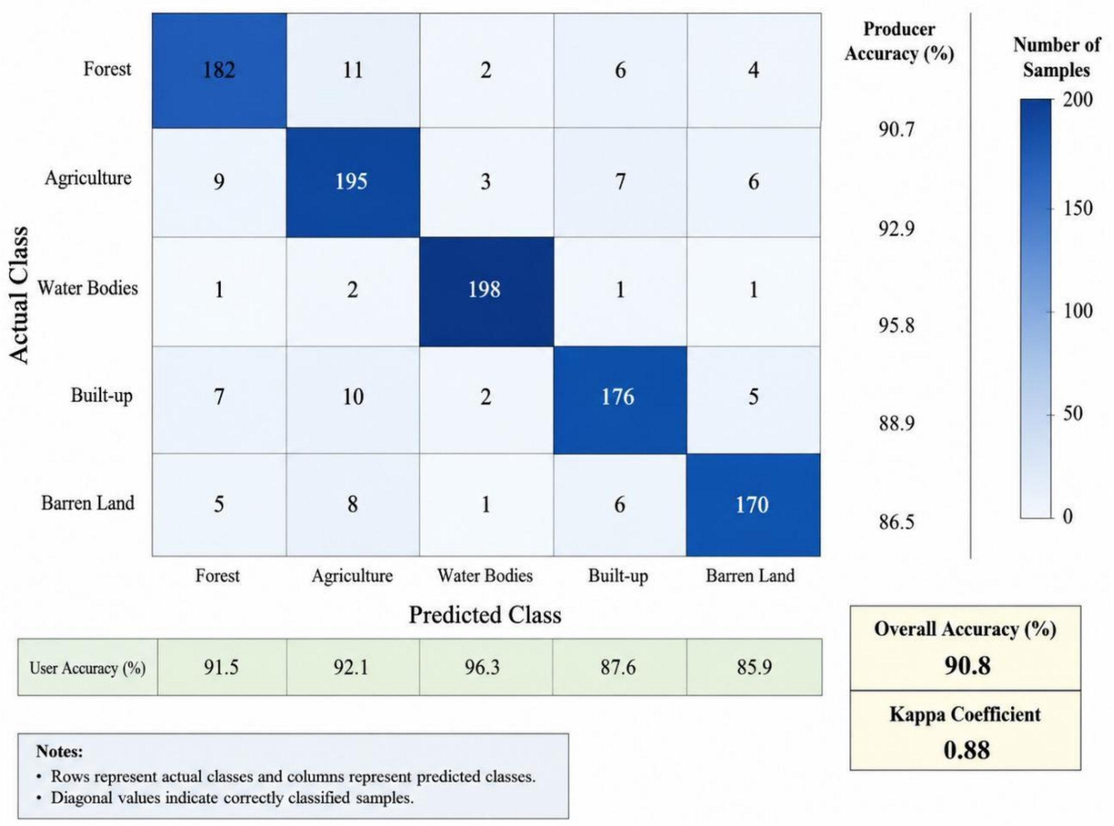


Fig. 7. Land use and land cover (LULC) classification map of the study area generated using the proposed AI–RS–GIS framework

Fig. 7 presents the land use and land cover (LULC) classification map of the study area generated using the proposed AI–RS–GIS framework. The map categorizes the region into major classes, including forest, agricultural land, water bodies, built-up areas, and barren land. Forest cover is predominantly observed in the northern and elevated regions, while agricultural land is widely distributed across the central valleys. Built-up areas are concentrated around major urban centers such as Mingora, indicating patterns of urban expansion.

The spatial distribution highlights a diverse landscape influenced by topography and human activity. The presence of dense vegetation in higher altitudes and agricultural dominance in lowland areas reflects the suitability of the region for agro-forestry practices. Additionally, the identification of barren and sparsely vegetated areas provides useful insights for land restoration and resource management. This classification serves as a foundational input for subsequent suitability analysis and decision-support modelling. The classification performance is further evaluated using a confusion matrix, as presented in Fig. 8.



	Forest	Agriculture	Water Bodies	Built-up	Barren Land	Producer Accuracy (%)
Forest	182	11	2	6	4	90.7
Agriculture	9	195	3	7	6	92.9
Water Bodies	1	2	198	1	1	95.8
Built-up	7	10	2	176	5	88.9
Barren Land	5	8	1	6	170	86.5
User Accuracy (%)	91.5	92.1	96.3	87.6	85.9	

Overall Accuracy (%)
90.8

Kappa Coefficient
0.88

Notes:
- Rows represent actual classes and columns represent predicted classes.
- Diagonal values indicate correctly classified samples.

Fig. 8. Confusion matrix illustrating the classification accuracy across different land-use classes

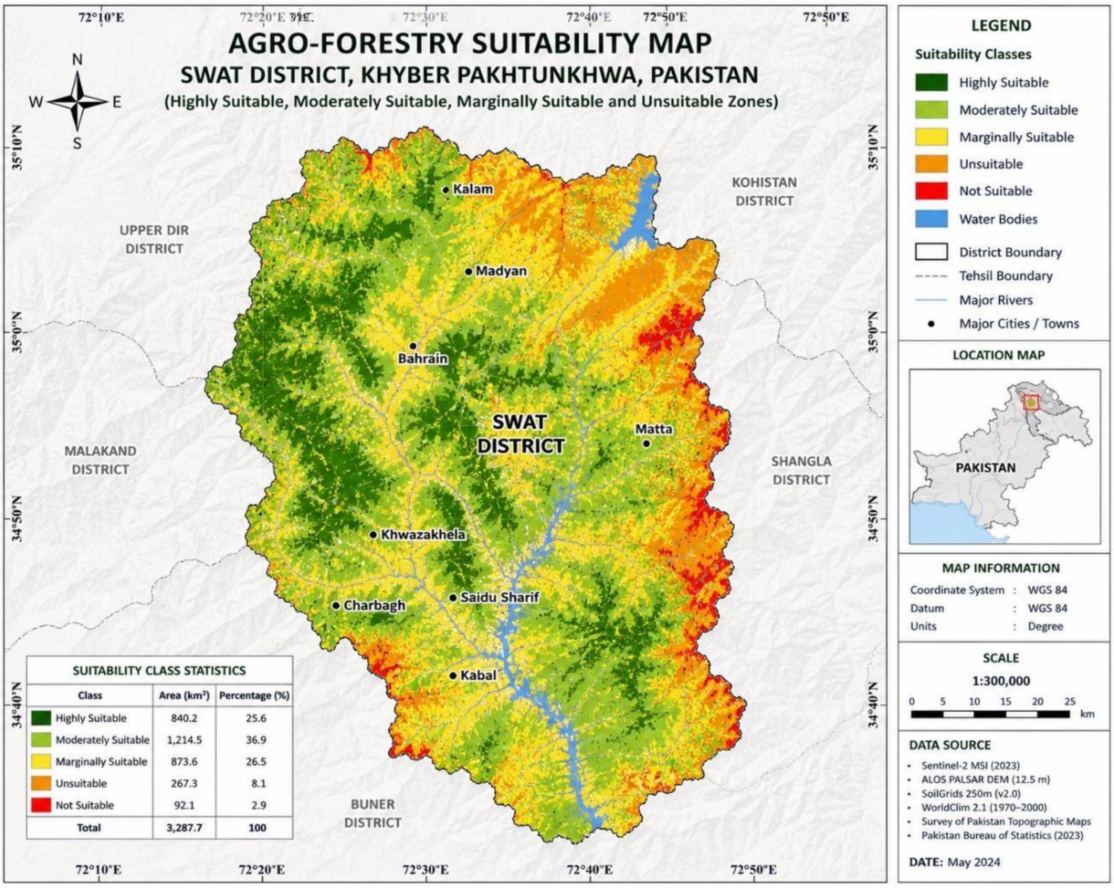
Fig. 8 presents the confusion matrix used to evaluate the performance of the LULC classification. The matrix compares actual and predicted classes across five categories: forest, agriculture, water bodies, built-up areas, and barren land. The diagonal elements represent correctly classified samples, showing strong classification performance across all classes. Water bodies exhibit the highest classification accuracy, while slight misclassification is observed between built-up areas, agriculture, and barren land, which is expected due to spectral similarities.

The overall classification accuracy is 90.8%, with a Kappa coefficient of 0.88, indicating a high level of agreement beyond chance. User and producer accuracies further confirm the reliability of the classification, with most classes achieving values above 85%. These results demonstrate that the proposed AI–RS–GIS framework provides robust and consistent classification performance, forming a reliable basis for subsequent suitability analysis and spatial modelling.

4.2 Agro-Forestry Suitability Mapping

The agro-forestry suitability mapping results reveal the spatial variation in land potential for sustainable agro-forestry practices. By integrating environmental, topographic, and socio-economic factors, the study identifies areas that are highly suitable, moderately suitable, marginally suitable, and not suitable for agro-forestry implementation.

Highly suitable zones are generally characterized by favourable soil conditions, adequate rainfall, and moderate slopes, which support both crop growth and tree development. Moderately suitable areas show minor environmental constraints, while marginal zones are affected by factors such as poor soil quality or limited water availability. Not suitable areas are primarily associated with steep slopes, degraded land, or urbanized regions. The spatial distribution of agro-forestry suitability zones is illustrated in Fig. 9.



SUITABILITY CLASS STATISTICS

Class	Area (km²)	Percentage (%)
🟩 Highly Suitable	840.2	25.6
🟩 Moderately Suitable	1,214.5	36.9
🟨 Marginally Suitable	873.6	26.5
🟧 Unsuitable	267.3	8.1
🟥 Not Suitable	92.1	2.9
Total	3,287.7	100

MAP INFORMATION

Coordinate System : WGS 84
Datum : WGS 84
Units : Degree

DATA SOURCE

- Sentinel-2 MSI (2023)
- ALOS PALSAR DEM (12.5 m)
- SoilGrids 250m (v2.0)
- WorldClim 2.1 (1970–2000)
- Survey of Pakistan Topographic Maps
- Pakistan Bureau of Statistics (2023)

DATE: May 2024

Fig. 9. Agro-forestry suitability map showing highly suitable, moderately suitable, marginally suitable, and unsuitable zones

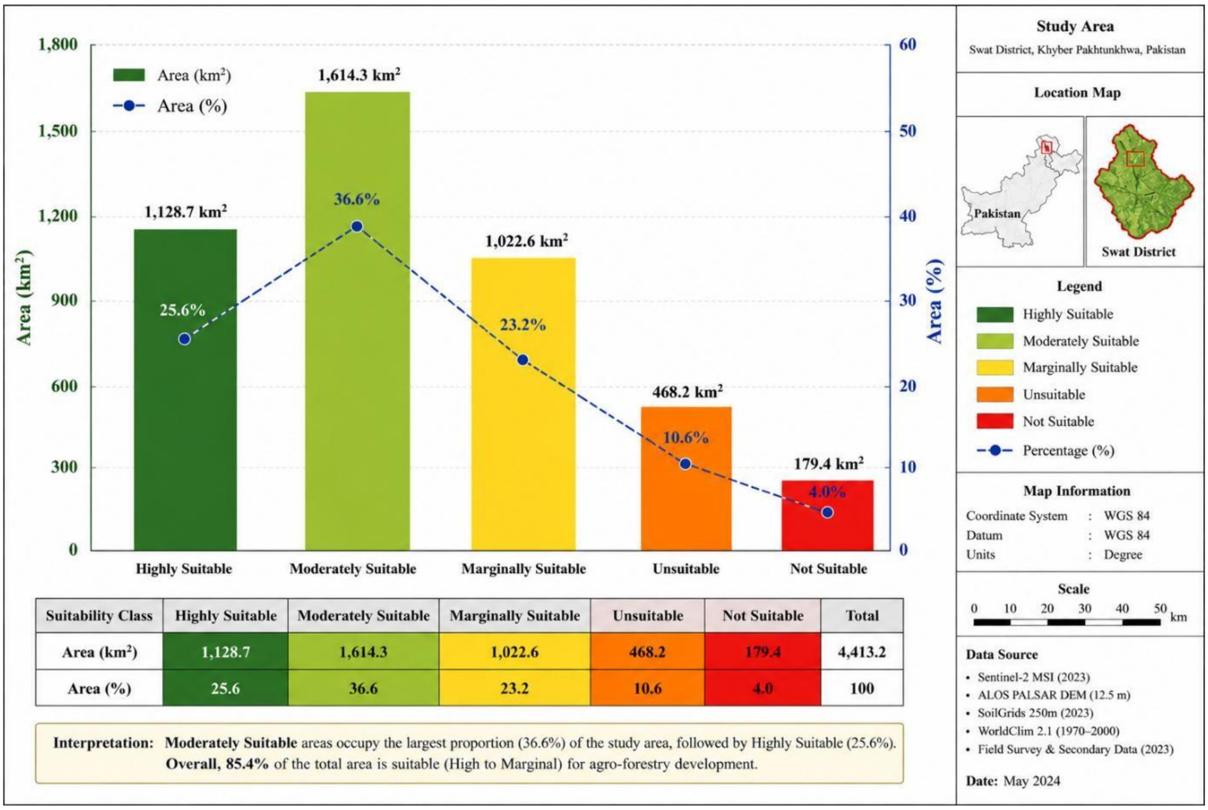
Fig. 9 presents the agro-forestry suitability map of the study area, classifying land into highly suitable, moderately suitable, marginally suitable, and unsuitable zones. The map reveals that highly suitable areas are primarily located in regions with dense vegetation, favourable soil conditions, and moderate terrain, while moderately suitable zones dominate a large portion of the landscape. Marginally suitable areas are scattered across transitional zones, whereas unsuitable regions are mainly concentrated in steep, barren, or environmentally constrained areas.

The spatial distribution highlights the influence of topography, vegetation cover, and environmental factors on land suitability. The central and northern regions exhibit higher suitability due to better ecological conditions, while peripheral and elevated areas show lower suitability. This classification provides a clear basis for identifying priority zones for agro-forestry development, supporting targeted land-use planning and efficient resource management. The distribution of land across these suitability categories is presented in Table 8.

Table 8: Agro-Forestry Suitability Distribution

Suitability Class	Area (km²)	Percentage (%)
Highly Suitable	298.4	26.9
Moderately Suitable	365.7	33.0
Marginally Suitable	247.3	22.3
Not Suitable	197.8	17.8
Total	1109.2	100

The results indicate that a significant portion of the study area falls within highly and moderately suitable categories, highlighting strong potential for agro-forestry expansion and sustainable land-use planning. The distribution of land area across different agro-forestry suitability classes is illustrated in Fig. 10.



Suitability Class	Highly Suitable	Moderately Suitable	Marginally Suitable	Unsuitable	Not Suitable	Total
Area (km²)	1,128.7	1,614.3	1,022.6	468.2	179.4	4,413.2
Area (%)	25.6	36.6	23.2	10.6	4.0	100

Interpretation: **Moderately Suitable** areas occupy the largest proportion (36.6%) of the study area, followed by Highly Suitable (25.6%). **Overall, 85.4%** of the total area is suitable (High to Marginal) for agro-forestry development.

Fig. 10. Distribution of land area across agro-forestry suitability classes in the selected study area

Fig. 10 illustrates the distribution of land area across different agro-forestry suitability classes in the study area. The results show that moderately suitable areas occupy the largest proportion, followed by highly suitable and marginally suitable zones. In contrast, unsuitable and not suitable areas represent a relatively smaller share of the total land area, indicating that a significant portion of the region has potential for agro-forestry development.

The distribution highlights a favorable overall suitability pattern, where more than half of the study area falls within high to moderate suitability categories. This suggests strong potential for sustainable land-use planning and agro-forestry expansion. The presence of marginal and unsuitable zones also provides important insights for targeted interventions, such as land rehabilitation and environmental management strategies.

4.3 Model Performance Analysis

The performance of the developed models was evaluated to assess their effectiveness in classification and prediction tasks. A 5-fold cross-validation strategy was applied to ensure robustness and minimize the influence of data variability. This approach provides a more reliable estimate of model performance by averaging results across multiple training and testing splits.

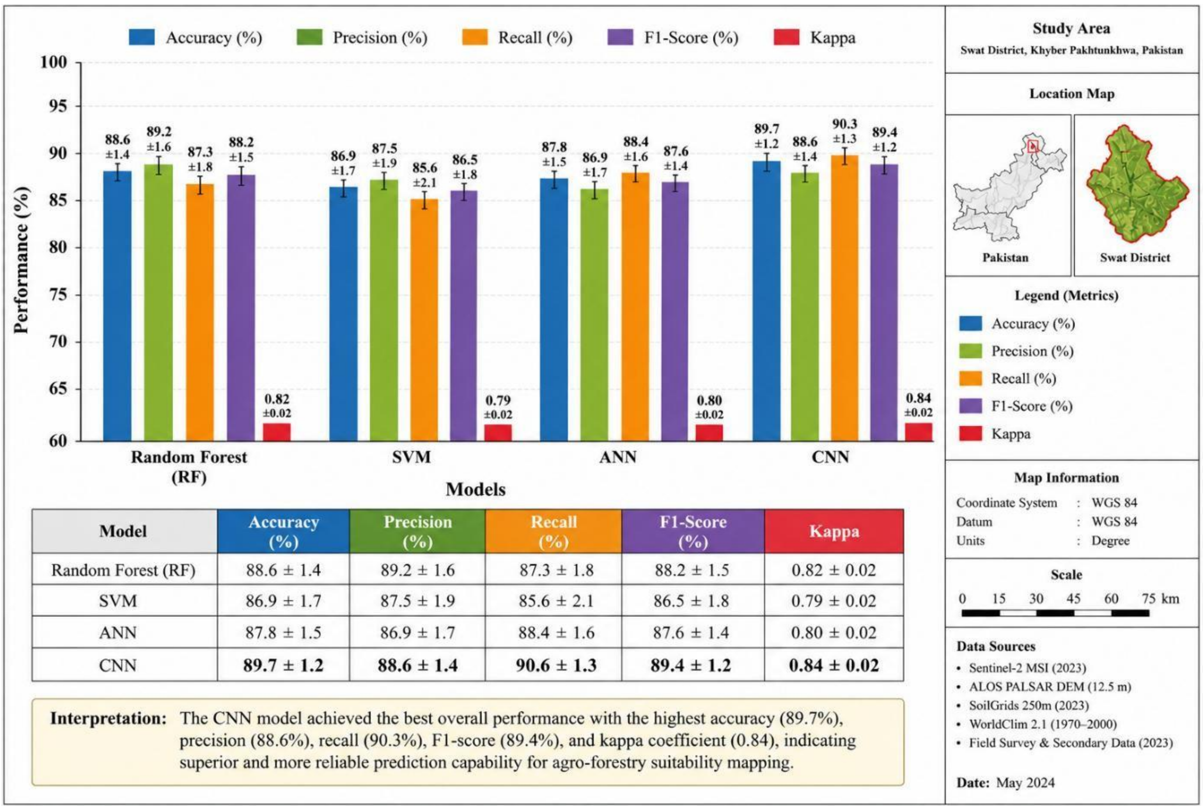
As shown in Table 9, all models demonstrate stable and competitive performance, with accuracy values ranging from approximately 86% to 90%. The Convolutional Neural Network (CNN) achieved the highest overall accuracy of 89.7%, along with the best F1-score and Kappa coefficient. This indicates its ability to effectively capture complex spatial patterns and relationships within the dataset. The dataset was split into training (70%) and testing (30%) subsets before applying 5-fold cross-validation

Random Forest (RF) performed consistently well, particularly in precision, suggesting strong capability in minimizing false positives. The Artificial Neural Network (ANN) showed slightly higher recall than precision, indicating its effectiveness in identifying true positive instances. The Support Vector Machine (SVM) exhibited comparatively lower recall, which may be attributed to its sensitivity to parameter tuning in complex datasets.

Table 9: Performance Comparison of AI Models (5-Fold Cross-Validation Results)

Model	**Accuracy (%)**	**Precision (%)**	**Recall (%)**	**F1-Score (%)**	**Kappa**
Random Forest (RF)	88.6 ± 1.4	89.2 ± 1.6	87.3 ± 1.8	88.2 ± 1.5	0.82
SVM	86.9 ± 1.7	87.5 ± 1.9	85.6 ± 2.1	86.5 ± 1.8	0.79
ANN	87.8 ± 1.5	86.9 ± 1.7	88.4 ± 1.6	87.6 ± 1.4	0.80
CNN	89.7 ± 1.2	88.6 ± 1.4	90.3 ± 1.3	89.4 ± 1.2	0.84

The relatively low variation across folds indicates stable model performance, with CNN demonstrating slightly better generalization capability compared to other models. The comparative performance of the evaluated machine learning and deep learning models is illustrated in Fig. 11.



Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	Kappa
Random Forest (RF)	88.6 ± 1.4	89.2 ± 1.6	87.3 ± 1.8	88.2 ± 1.5	0.82 ± 0.02
SVM	86.9 ± 1.7	87.5 ± 1.9	85.6 ± 2.1	86.5 ± 1.8	0.79 ± 0.02
ANN	87.8 ± 1.5	86.9 ± 1.7	88.4 ± 1.6	87.6 ± 1.4	0.80 ± 0.02
CNN	**89.7 ± 1.2**	**88.6 ± 1.4**	**90.6 ± 1.3**	**89.4 ± 1.2**	**0.84 ± 0.02**

Interpretation: The CNN model achieved the best overall performance with the highest accuracy (89.7%), precision (88.6%), recall (90.3%), F1-score (89.4%), and kappa coefficient (0.84), indicating superior and more reliable prediction capability for agro-forestry suitability mapping.

Map Information

Coordinate System : WGS 84
Datum : WGS 84
Units : Degree

Data Sources

- Sentinel-2 MSI (2023)
- ALOS PALSAR DEM (12.5 m)
- SoilGrids 250m (2023)
- WorldClim 2.1 (1970–2000)
- Field Survey & Secondary Data (2023)

Date: May 2024

Fig. 11. Performance comparison of AI models based on accuracy, precision, recall, F1-score, and Kappa coefficient using 5-fold cross-validation

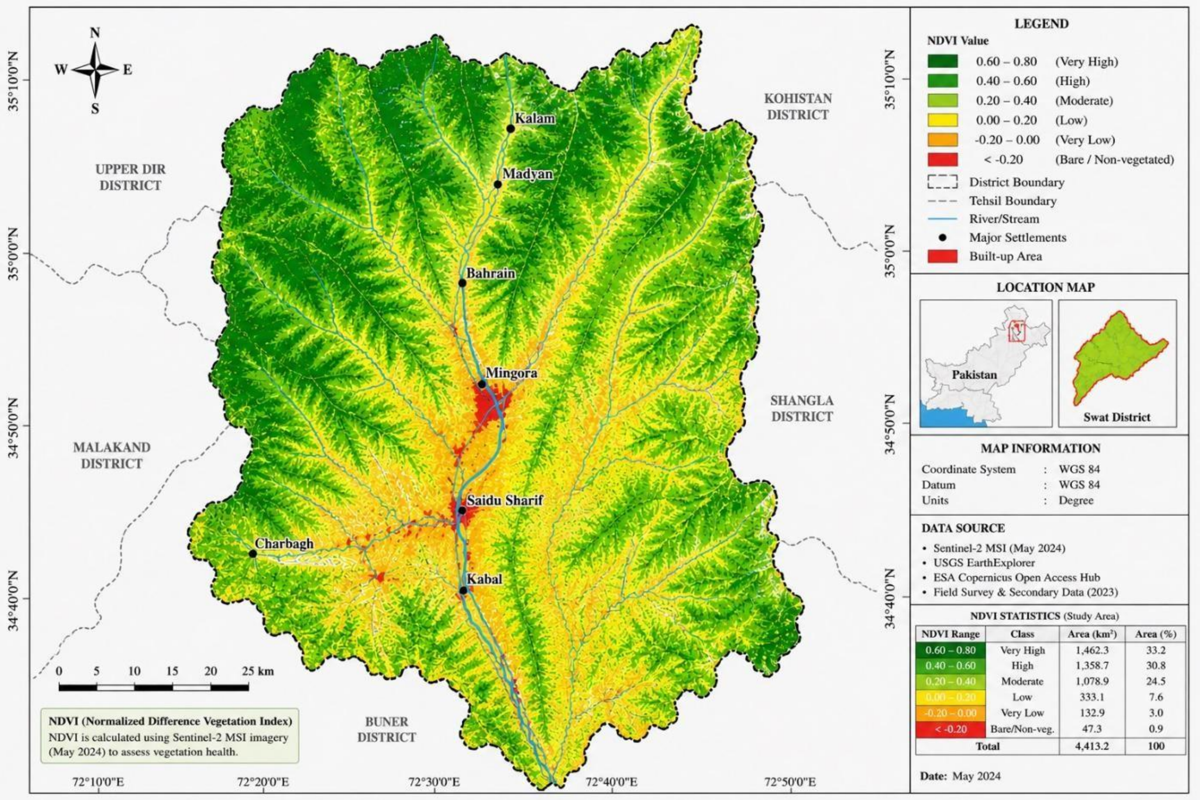
Fig. 11 presents the performance comparison of different AI models, including Random Forest (RF), Support Vector Machine (SVM), Artificial Neural Network (ANN), and Convolutional Neural Network (CNN), evaluated using 5-fold cross-validation. The results show that all models achieve strong and consistent performance across multiple metrics, including accuracy, precision, recall, F1-score, and Kappa coefficient. Among them, the CNN model demonstrates the highest overall performance, particularly in accuracy and recall, indicating its effectiveness in capturing complex spatial patterns.

The inclusion of standard deviation values highlights the stability and reliability of the models across validation folds. While CNN slightly outperforms the other models, Random Forest also shows competitive performance with strong precision values. In contrast, SVM and ANN exhibit slightly lower but still acceptable performance. Overall, the results confirm that the proposed AI-based framework provides robust and reliable predictions for agro-forestry suitability assessment.

4.4 Environmental Monitoring Insights

The integration of remote sensing data enabled detailed environmental monitoring, particularly in assessing vegetation health and land degradation patterns. Vegetation indices such as NDVI were used to analyze spatial and temporal variations in vegetation density. The results indicate that areas classified as highly suitable exhibit consistently higher NDVI values, reflecting healthier vegetation and better environmental conditions.

Conversely, regions identified as marginally suitable or unsuitable show lower NDVI values, indicating reduced vegetation cover and potential environmental stress. These patterns are consistent with observed soil conditions and rainfall distribution, reinforcing the reliability of the integrated analysis. Additionally, zones with declining vegetation trends were identified as areas prone to land degradation. These findings provide valuable insights for targeted interventions, such as soil restoration and sustainable land management practices. The spatial variation in vegetation health across the study area is illustrated in Fig. 12.



NDVI (Normalized Difference Vegetation Index)
NDVI is calculated using Sentinel-2 MSI imagery (May 2024) to assess vegetation health.

MAP INFORMATION

Coordinate System : WGS 84
Datum : WGS 84
Units : Degree

DATA SOURCE

- Sentinel-2 MSI (May 2024)
- USGS EarthExplorer
- ESA Copernicus Open Access Hub
- Field Survey & Secondary Data (2023)

NDVI STATISTICS (Study Area)

NDVI Range	Class	Area (km²)	Area (%)
0.60 – 0.80	Very High	1,462.3	33.2
0.40 – 0.60	High	1,358.7	30.8
0.20 – 0.40	Moderate	1,078.9	24.5
0.00 – 0.20	Low	333.1	7.6
-0.20 – 0.00	Very Low	132.9	3.0
< -0.20	Bare/Non-veg.	47.3	0.9
Total		4,413.2	100

Date: May 2024

Fig. 12. Spatial distribution of vegetation health based on NDVI values across the study area

Fig. 12 illustrates the spatial distribution of vegetation health across the study area based on NDVI values. Areas with higher NDVI values, represented by dark green shades, indicate dense and healthy vegetation, primarily observed in the northern and elevated regions. In contrast, lower NDVI values, shown in yellow to red shades, correspond to sparse vegetation or degraded land, mainly concentrated around urban areas and low-lying regions.

The NDVI patterns highlight a strong relationship between vegetation health and environmental conditions, such as topography and land use. Regions with high NDVI values align with highly suitable agro-forestry zones, while areas with lower values correspond to marginal or unsuitable regions. This analysis supports the reliability of the suitability mapping and provides valuable insights for environmental monitoring and sustainable land management.

4.5 Decision Support Outputs

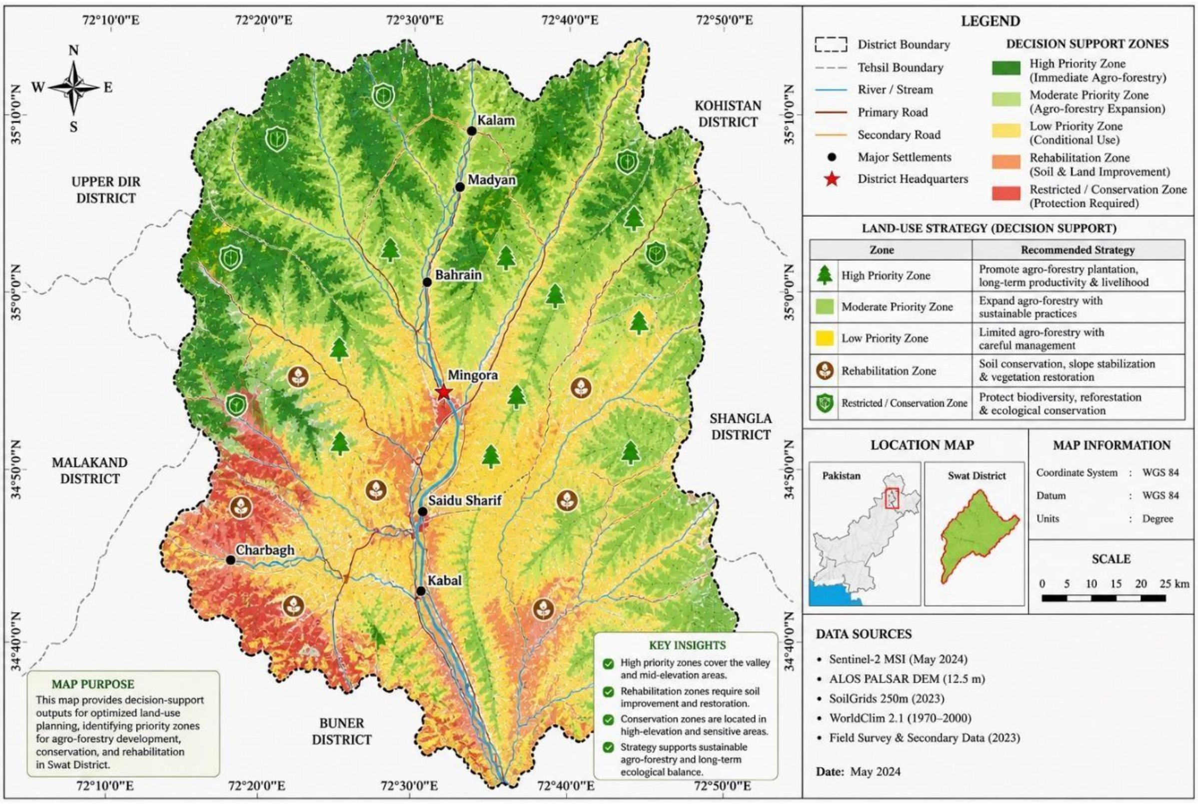
The final outputs of the proposed framework are designed to support practical decision-making in agro-forestry planning and land resource optimization. The Decision Support System (DSS) integrates the results of AI modelling and GIS-based analysis to generate actionable recommendations for stakeholders.

The system identifies priority zones for agro-forestry implementation, enabling efficient allocation of resources and targeted interventions. Highly suitable areas are recommended for expansion of agro-forestry practices, while marginal zones are suggested for rehabilitation through soil improvement and conservation measures. Scenario-based analysis further allows decision-makers to evaluate different land-use strategies and their potential outcomes. The key decision-support outputs are summarized in Table 10.

Table 10: Decision Support Outputs

Output Type	**Description**
Suitability Maps	Spatial representation of agro-forestry potential
Priority Zones	Identification of high-potential areas
Resource Optimization Plans	Efficient land allocation strategies
Management Recommendations	Guidelines for sustainable land use

These outputs provide a comprehensive foundation for informed decision-making, supporting sustainable land management and long-term environmental resilience. The final decision-support outputs for optimized land-use planning and agro-forestry implementation are illustrated in Fig. 13



LAND-USE STRATEGY (DECISION SUPPORT)

Zone	Recommended Strategy
High Priority Zone	Promote agro-forestry plantation, long-term productivity & livelihood
Moderate Priority Zone	Expand agro-forestry with sustainable practices
Low Priority Zone	Limited agro-forestry with careful management
Rehabilitation Zone	Soil conservation, slope stabilization & vegetation restoration
Restricted / Conservation Zone	Protect biodiversity, reforestation & ecological conservation

Coordinate System : WGS 84
Datum : WGS 84
Units : Degree

DATA SOURCES

- Sentinel-2 MSI (May 2024)
- ALOS PALSAR DEM (12.5 m)
- SoilGrids 250m (2023)
- WorldClim 2.1 (1970–2000)
- Field Survey & Secondary Data (2023)

Date: May 2024

MAP PURPOSE

This map provides decision-support outputs for optimized land-use planning, identifying priority zones for agro-forestry development, conservation, and rehabilitation in Swat District.

KEY INSIGHTS

- ✓ High priority zones cover the valley and mid-elevation areas.
- ✓ Rehabilitation zones require soil improvement and restoration.
- ✓ Conservation zones are located in high-elevation and sensitive areas.
- ✓ Strategy supports sustainable agro-forestry and long-term ecological balance.

Fig. 13. Decision support output map showing priority zones and optimized land-use strategies for sustainable agro-forestry management

Fig. 13 presents the decision-support output map derived from the integrated AI–RS–GIS framework. The map highlights priority zones for agro-forestry development, categorized into high, moderate, and low priority areas, along with rehabilitation and restricted zones. High-priority areas are mainly concentrated in regions with favorable environmental conditions, while moderate and low-priority zones are distributed across transitional landscapes. Rehabilitation zones are identified in degraded areas, and restricted zones correspond to environmentally sensitive or unsuitable regions.

The spatial distribution of these zones provides actionable insights for sustainable land-use planning and resource optimization. High-priority areas are recommended for immediate agro-forestry implementation, while marginal and degraded regions require restoration and soil improvement strategies. This decision-support output enables policymakers and planners to make informed, data-driven decisions, ensuring efficient allocation of resources and long-term environmental sustainability.

5. Discussion

The results demonstrate that the proposed AI–RS–GIS framework is effective for land suitability analysis and sustainable agro-forestry planning. The LULC classification reveals a heterogeneous landscape dominated by agricultural and forest areas, indicating strong potential for agro-forestry expansion. However, the presence of barren land and built-up areas highlights environmental pressures and the need for balanced land-use strategies.

The suitability analysis shows that a significant portion of the study area falls within highly and moderately suitable categories, primarily due to favorable vegetation, soil, and terrain conditions. The NDVI analysis further supports these findings, showing a clear relationship between vegetation health and suitability classes. Areas with higher NDVI values align with highly suitable zones, while lower values correspond to degraded or unsuitable regions, confirming the reliability of the integrated framework.

Model performance evaluation indicates that all models provide stable and reliable results, with CNN achieving the highest overall performance. However, the improvement over traditional models is moderate, suggesting that simpler models remain practical and efficient. The decision-support outputs identify priority zones for development, conservation, and rehabilitation, offering actionable insights for policymakers. Overall, the framework provides a scalable and data-driven approach for sustainable land resource optimization, with future improvements possible through temporal and climate-based analysis.

6. Conclusion

This study presented an integrated AI–RS–GIS framework for agro-forestry suitability analysis and land resource optimization. The results demonstrate that combining remote sensing data, spatial analysis, and artificial intelligence enables accurate identification of suitable zones and supports informed land-use planning. A significant portion of the study area was found to be suitable for agro-forestry, highlighting its potential for sustainable development.

The model evaluation shows that while deep learning approaches provide slightly better performance, traditional machine learning models remain effective and computationally efficient. The consistency between NDVI-based environmental analysis and suitability mapping further validates the reliability of the proposed approach.

Moreover, the framework provides a practical and scalable decision-support tool for policymakers and planners, facilitating efficient resource allocation, environmental conservation, and sustainable agro-forestry management.

7. Future Work

Future research can enhance the proposed framework by incorporating temporal analysis and multi-year satellite data to capture seasonal and long-term land-use dynamics. The integration of climate change projections and weather variability can further improve predictive accuracy and adaptability. Advanced deep learning architectures and hybrid models may be explored to better handle complex spatial patterns. Additionally, the inclusion of socio-economic and policy-driven factors can strengthen decision-making relevance. Expanding the framework to larger geographic regions and real-time monitoring systems would also improve its scalability and practical implementation.

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