GIS-Assisted Land Suitability Analysis for Sustainable Pulse Crop Production

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ABSTRACT

Background: Pulse crops are important for global and nutrition security and for effective agricultural systems, but soil heterogeneity, climate variability, and inefficient land allocation hinder their productivity.

Objective: This research creates a Geographic Information System (GIS) - based multi-criteria method for discovering agro-ecological zones for pulse crops.

Methods: The data used for the analysis included Digital Elevation Models, soil surveys, Land Use/Land Cover maps, rainfall and temperature data, NDVI, groundwater data. The data was later standardized and analyzed in GIS, using Analytical Hierarchy Processing method.

Results: The resulting model classified the analyzed area into four groups of suitability, where the quality of soil and precipitation were identified as key factors.

Conclusion: The GIS-AHP system presented in this research is a decision-making tool, which can be applied in agricultural land-use policy.

Keywords: Pulse crops; Geographic Information System (GIS); Analytical Hierarchy Process (AHP); Multi-Criteria Decision Analysis (MCDA)

1. Introduction

Pulse crops such as lentils, chickpeas, pigeon peas, and mung beans are vital in ensuring food security worldwide due to their richness in protein, very capable of fixing nitrogen, and adapting well to farming under low input systems. Unfortunately, inadequate agricultural practices have limited the growth of pulses by making soils depleted, affecting rainfall patterns, and leading to poor land use planning, while climate change continues worsening the situation. In sustainable agriculture, one of the land-use decisions must be made based on informed decision-making, where soil, terrain, climate, and other parameters must be evaluated through data collected through high-resolution GIS and remote sensing technologies. MCDA methods such as AHP support objective criteria weightings to allow transparent suitability mapping. Therefore, this study aims at designing a systematic GIS-aided land suitability framework such as this for isolating the areas suitable for pulse crop production based on soil, topography, climate, and vegetation with the use of a high-resolution GIS and remote sensing technologies.

2. GIS-Assisted Land Suitability Framework

The proposed framework (Figure 1) proceeds through spatial database preparation, environmental factor selection, criteria standardization, AHP-based weighting, weighted overlay analysis, and final suitability classification. Soil properties (texture, pH, organic carbon, drainage class), topographic attributes (slope, elevation derived from DEM), climatic variables (rainfall, temperature), and vegetation vigor (NDVI) were selected as primary criteria based on their agronomic relevance to pulse crops [11, 12]. Remote sensing imagery was used both for land cover classification and for deriving NDVI as a proxy of vegetation health and moisture availability [13].

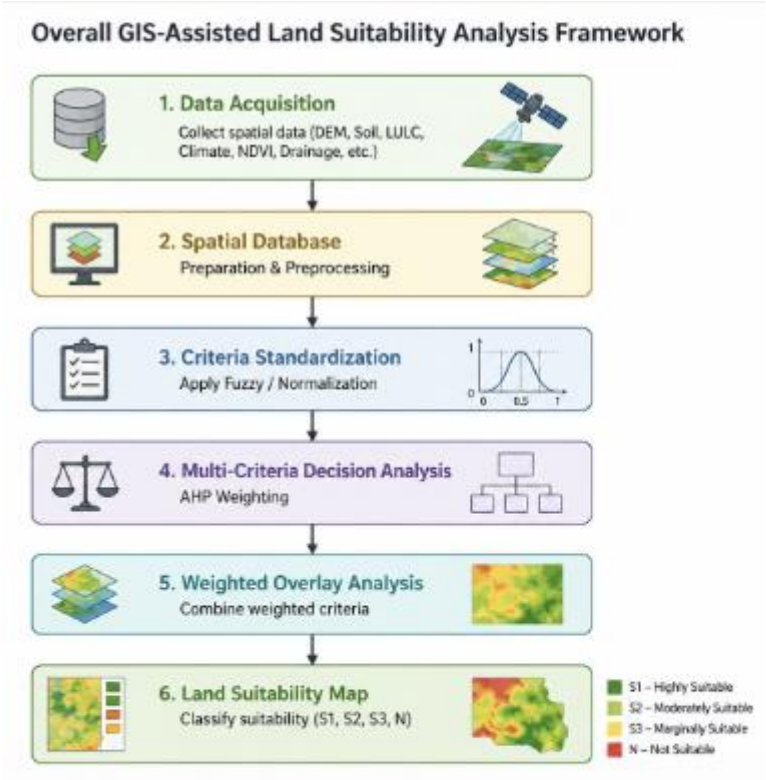

Fig 1: Overall GIS-assisted land suitability analysis framework.

Criteria layers were normalized to a common 1-9 suitability scale using fuzzy membership functions, then combined through Weighted Overlay Analysis (WOA), where AHP-derived weights reflect each criterion's relative agronomic importance (Figure 2) [14, 15]. This structured decision-support workflow ensures analytical transparency and allows sensitivity testing of weighting assumptions.

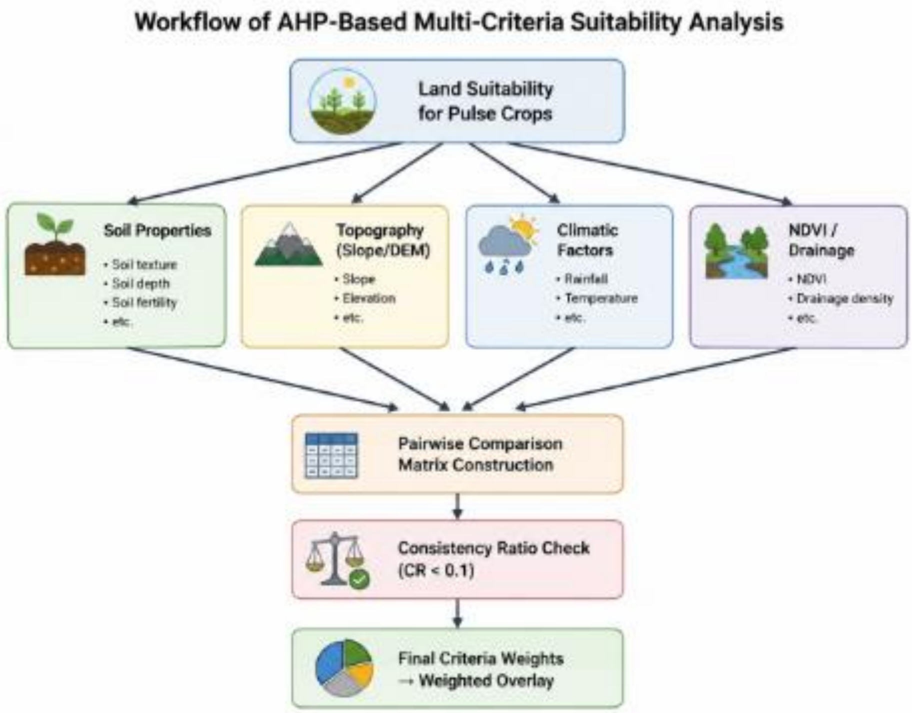

Fig 2: Workflow of AHP-based multi-criteria suitability analysis.

3. Materials and Methods

3.1. Study Area

The analysis was conducted for a semi-arid agricultural region characterized by mixed cropping systems, undulating terrain, and moderate seasonal rainfall, representative of typical pulse-growing landscapes.

3.2. Dataset Collection

Table 1 summarizes the environmental criteria used, and Table 2 lists dataset sources and spatial resolutions.

Table 1: Environmental criteria used for land suitability analysis.

Criterion	Category	Agronomic Relevance
Soil texture & pH	Soil	Root development, nutrient uptake
Slope	Topography	Erosion risk, drainage, mechanization
Rainfall	Climate	Moisture availability during growth stages
Temperature	Climate	Germination and flowering thresholds
NDVI	Vegetation	Vigor and moisture proxy
Drainage class	Hydrology	Waterlogging tolerance
LULC	Land use	Current land allocation constraints

Table 2: Dataset sources and spatial resolution.

Dataset	Source	Spatial Resolution
DEM	SRTM	30 m
Soil map	National soil survey	1:50,000
LULC	Sentinel-2 classification	10 m
Rainfall	IMD gridded data	0.25°
Temperature	IMD gridded data	0.25°
NDVI	Landsat-8/Sentinel-2	10-30 m
Groundwater depth	Central Ground Water Board	Station-based, interpolated

3.3. GIS Software and Data Processing

ArcGIS, QGIS, Google Earth Engine, and GRASS GIS were used for raster preparation, spatial interpolation (Inverse Distance Weighting for climatic surfaces), supervised image classification, buffer analysis, and overlay operations. All criteria rasters were resampled to a common 30 m grid and normalized to a 1-9 scale prior to overlay [16, 17].

3.4. Suitability Modeling

Pairwise comparisons among criteria were performed following Saaty's AHP procedure, with consistency ratios maintained below 0.10 to ensure judgment reliability [18, 19]. Resulting weights (Table 3) were applied through Weighted Linear Combination, and fuzzy membership functions handled continuous variables such as slope and rainfall. Output pixels were classified into four suitability classes: Highly Suitable (S1), Moderately Suitable (S2), Marginally Suitable (S3), and Unsuitable (N) [20].

Table 3: AHP weighting values for suitability factors.

Criterion	AHP Weight (%)
Soil properties	28
Rainfall	22
Slope	16
Temperature	14
NDVI	10
Drainage	10

3.5. Validation and Evaluation Metrics

Model outputs were validated against 240 ground-truth points and existing cultivation maps using overall accuracy, Kappa coefficient, precision, recall, and F1-score to assess spatial agreement and prediction reliability [21, 22].

Table 4: Experimental parameters and GIS processing workflow.

Parameter	Value / Description
Grid resolution	30 m
Normalization method	Fuzzy linear + min-max
Overlay method	Weighted Linear Combination
Consistency ratio (AHP)	< 0.10
Ground-truth samples	240 points

4. Results and Performance Evaluation

The final suitability map (Figure 3) delineated distinct zones of cultivation potential, with highly suitable (S1) areas concentrated in regions with deep loamy soils, gentle slopes (<5%), and adequate seasonal rainfall. Moderately suitable (S2) zones were associated with steeper terrain or moderate moisture deficits, while marginal and unsuitable zones coincided with poor drainage, shallow soils, or high slope gradients.

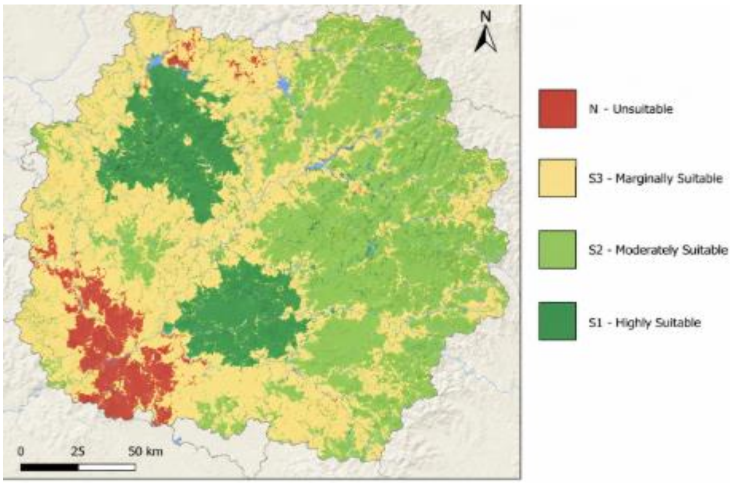

Fig 3: Final land suitability map for sustainable pulse crop production (illustrative).

Validation indicated strong spatial agreement between predicted suitability classes and existing cultivation patterns (Table 5). Sensitivity analysis showed that suitability outcomes were most responsive to variation in soil and rainfall weights, confirming their dominant agronomic influence [23]. Limitations included coarse-resolution climatic interpolation and temporal mismatches between satellite acquisition dates and ground survey periods.

Table 5: Suitability classification results and validation metrics.

Metric	Value
Overall Accuracy	87.4%
Kappa Coefficient	0.81
Precision	0.85
Recall	0.83
F1-score	0.84

5. Discussion

The results confirm that soil quality and rainfall distribution are the principal drivers of pulse crop suitability, consistent with prior GIS-based agricultural suitability studies [24]. The AHP-weighted overlay approach proved effective in translating expert agronomic judgment into a reproducible spatial model, and the close correspondence between predicted suitability and observed cultivation patterns supports its practical validity [25]. Compared with conventional site-selection methods, GIS-assisted MCDA offers superior spatial precision, transparency in criteria weighting, and scalability across regions.

Nonetheless, spatial data quality, temporal variability in climatic inputs, and inherent uncertainty in expert-derived weights remain challenges. Climate change is expected to shift suitability boundaries, particularly through altered rainfall patterns, underscoring the need for periodic model updates. The framework is readily scalable to regional or national planning and can be enhanced through integration with precision agriculture tools, including UAV-based field monitoring, IoT soil sensors, and AI/machine-learning models capable of learning nonlinear relationships between environmental variables and crop performance, offering a promising direction for future suitability modeling.

6. Conclusion

The research showed that a framework utilizing GIS and AHP can effectively identify areas suitable for pulse crop cultivation. The factors determined to be the most influential for determining suitability include soil properties and precipitation. The findings can assist in implementing smart agriculture initiatives and evidence-based land-use planning. Future studies should focus on field-scale testing as well as timely integration into GIS systems improved with machine learning, devices for remote sensing, and IoT monitoring methods in order to make models adaptable to changes in climatic conditions.

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