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Research Article

Assessing Agricultural Potential Through Combined Land Suitability and Machinery Management: A GIS-Based Approach

Olsid Mema[1,2*], Etleva Jojic[1], Përparim Laze[1], Valdete Vorpsi[1], Ndoc Vata[1], Ilir Salillari[3], Altin Dorri[4]

[1]Faculty of Agriculture and Environment, Agricultural University of Tirana, Tirana, Albania
[2]Geoinformation Centre for the Western Balkans, Agricultural University of Tirana, Tirana, Albania
[3]Agricultural Technology Transfer Center-Fushë Krujë, Ministry of Agriculture and Rural Development, Tirana, Albania
[4]Energy Department, Polytechnic University of Tirana, Tirana, Albania
***omema@ubt.edu.al**

Abstract

The evaluation of agricultural potential requires the simultaneous consideration of land biophysical capacity and mechanization feasibility, two interrelated components that are rarely integrated within conventional agricultural assessment approaches. This study addresses this gap through the development of a GIS-based multi-criteria assessment framework applied to the "Frakulla" administrative unit in southwestern Albania. The framework integrates land suitability analysis for cereal production based on soil properties, climatic conditions, slope, aspect and accessibility, together with machinery operation suitability analysis considering slope, elevation, accessibility and land characteristics. Both components were evaluated using Analytic Hierarchy Process (AHP)-based weighted overlay analysis within a GIS environment and subsequently combined through spatial overlay techniques to generate complementary agricultural potential outputs. These outputs consist of an Agricultural Potential (AP) classification matrix that cross-tabulates cereal production suitability and mechanization feasibility classes, and a spatial AP map representing the geographic distribution of these combined conditions across the study area. The proposed framework is intended as a diagnostic and planning-oriented classification system describing existing biophysical and operational land conditions, without predictive implications regarding crop yields, future agronomic performance or land use change. Statistical validation procedures, including contingency, correlation and sensitivity analyses, were conducted to evaluate the internal consistency and robustness of the classification results. Where applied, ROC analysis was used exclusively to examine the discriminatory coherence of classification thresholds. The resulting AP map provides a practical decision-support tool for land-use planning, mechanization management and investment prioritization in Mediterranean and other heterogeneous agricultural landscapes.

Keywords: Agricultural Mechanization; Agricultural Potential Mapping; GIS-Based Multi-Criteria Decision Analysis; Land Suitability Analysis; Raster-Based Analysis; Sustainable Land Management.

INTRODUCTION

Agriculture still represents to a large extent the base of socioeconomic development in various localities in the world, but the intensity of its sustainable and efficient use is coupled by several factors including biophysical, infrastructural and operational ones, that influence land use policies and choices [1]. In the context of increased world food demand, decreased expansion of available areas for agriculture and the need to operate land in a resource efficient way [2], the delineation of the agricultural potential is prerequisite for policy makers and scientists for land use policies [3]. Agricultural potential is a broad concept, which in essence include both land capacity to support crops production, as well as the capacity to operate or utilize that land with the existing technological/mechanical options [4], but traditional evaluation of that has always been carried out through ad hoc, single-criterion approaches.

GIS systems are now and will remain, an integral tool in the provision of spatial analysis and decision support in agriculture. They provide the ability to overlay, visualise and analyse a plethora of different types of spatial data within a uniform analytical environment [5]. When used in combination with MCDA methodologies they also provide a comprehensive analytical framework capable of addressing the multi-dimensionality and multi-faceted nature of land evaluation issues [6]. Many applications of GIS-MCDA techniques have been demonstrated within the application of agricultural planning, for example crop suitability mapping, and site selection for agriculture-related infrastructure, and have been shown to provide the flexibility to address a wide range of land evaluation issues [7, 8].

Land suitability analysis is a common land evaluation method based on the systematic consideration of the relation between land characteristics and land requirements for a particular land use type [9]. Many researchers used this approach for crop suitability evaluation by combining different land characteristics, such as soil physical and chemical properties (texture, depth, pH, organic matter status, drainage), topographic attributes (slope, elevation, aspect), climatic conditions (precipitation, temperature), proximity to infrastructure (roads, water source, markets) as criteria [10,11]. For example, one researcher used GIS and MCDA (AHP method with Weighted Overlay in ArcGIS) to evaluate rainfed cropping land suitability by taking soil attributes (salinity, organic matter, erosion, soil texture), climate (average rainfall, air temperature, sunlight, seasonal rainfall) and topographic factor (slope) [12]. In the same way, another researcher used the combination of GIS and AHP-based weighted sum overlay to evaluate the soil suitability for sustainable intensive agriculture by taking into consideration six indicators (p H, organic carbon, cation exchange capacity, texture, salinity and slope) to classify soil for good, medium, poor and excellent potential for cropping land utilization [13].

Similarly, agricultural mechanization, i.e. the application of machinery for tillage, planting, harvesting, and hauling activities, is another fundamental factor affecting farm efficiency, labor utilization and farm profitability [14]. Machinery suitability is determined by its own unique set of spatial factors, such as access to terrain, slope steepness and orientation, elevation limitations, physical soil characteristics, such as depth and texture, and relationships between the spatial configuration of field parcels and road accessibility [15]. Heavy, rocky, or very shallow soils combined with poorly connected parcel geometries and inaccessible road networks can inhibit the ability of standard machinery to be used even if the land is highly productive and well suited to crop production [16]. Several studies examined machinery management and viability through spatial approaches. One report considered the effect of terrain and soil characteristics on machinery operation and fuel efficiency and found that steep slopes and soil characteristics severely influence plant cultivation practicability [17], while another proposed a framework for agricultural fleet management with operations research and spatial modeling [18].

Although substantial literature exists on land suitability and machinery management as separate topics, very few studies combine both aspects into a unified assessment of agricultural potential [19, 20]. Three key gaps remain unaddressed: (i) ML-based approaches, while promising, are constrained by data scarcity in smallholder landscapes, limiting their reliability for policy-grade classification; (ii) fuzzy multi-criteria methods blur the discrete suitability thresholds that planners require for actionable land use decisions; and (iii) no established framework maintains CSS and MSS as separate analytical dimensions, existing studies either collapse them into a single index, masking trade-offs, or treat them sequentially rather than jointly. Preserving this separation is essential, as a parcel may be agronomically suitable yet mechanically inaccessible, or vice versa. These gaps justify the transparent, deterministic, two-axis GIS framework developed in this study. Throughout this study, the resulting AP index is treated strictly as a diagnostic planning construct, not a performance model: it characterizes current land conditions along two independent axes but does not project yields or agronomic outcomes.

The consequence of these methodological shortcomings is that existing approaches, whether treating land quality and mechanization separately or collapsing them into a single composite index, do not allow planners to differentiate between agricultural land that is suitable for crop production but inaccessible to machinery and land that is mechanically operable but biophysically marginal. Each condition warrants a distinct intervention strategy. Existing integration attempts remain insufficient because they treat mechanization as a secondary parameter of crop suitability rather than as an independent analytical dimension, thereby obscuring critical trade-offs and encouraging ill-conceived land allocation decisions. The two-axis framework proposed here, preserving CSS and MSS as separate, independent dimensions, resolves this shortcoming and enables transparent, two-dimensional, diagnostic-based prioritization of planning interventions.

In this respect, this research overcomes these deficiencies by providing an integrated GIS-based methodology for land evaluation for food crops production in an agricultural administrative unit of southwestern Albania. The selected unit of study (Frakulla) exhibits a mosaic of biophysical and socioeconomic conditions (coastal plain, rolling and hilly areas, diverse soils and land tenure and access to markets), but still functionally integrated within the agricultural system and thus providing a manageable study area under the scope of application of the proposed integrated evaluation approach. The innovative approach applied here for assessing the land suitability for cereal crops production (winter wheat, oats, barley and rye), as well as for the evaluation of land suitability for farm mechanization, integrates the (i) GIS-based multi criteria land suitability evaluation for cereal crops under various constraints (soil attributes, elevation and slope, rainfall and temperature regimes, proximity to roads and water bodies) and (ii) the GIS-based multi criteria evaluation of farm mechanization characteristics of land (closeness to roads, slope, elevation, soil texture and depth). Importantly, each of the proposed evaluation components here is described in terms of methodology, but neither has been given special emphasis in the presented study as an individual evaluation methodology; the novelty and focus of this research are the combined application of the aforementioned evaluation components into an agricultural potential matrix and an agricultural potential map.

This integration is implemented using a spatial overlay and matrix classification procedure in GIS, where each spatial unit in the study area is simultaneously classified in terms of its cereal production suitability and mechanization feasibility, producing a two-axis classification of agricultural potential. The two input categories resulting from this classification are then subjected to contingency analysis, correlation analysis and sensitivity testing [21] to assess the internal coherence and classification consistency of the AP map. It is important to emphasize that the Agricultural Potential (AP) framework presented here is explicitly a diagnostic and planning-oriented classification system: it is designed to characterize the current biophysical and operational conditions of land units for planning purposes and does not claim predictive capacity with respect to actual crop yields or future agricultural productivity outcomes. Accordingly, any receiver operating characteristic (ROC) analysis applied within this study serves exclusively to validate the internal coherence of the classification boundaries, that is, to assess how consistently the AP classes discriminate between defined land condition categories, and must not be interpreted as a validation of yield prediction or agronomic output forecasting. Together, the spatially explicit agricultural potential maps and statistical analyses constitute a conceptual, spatially explicit, decision-support tool that more effectively captures the spatial heterogeneity of actual agricultural land use planning considerations than is possible through the separate category analysis procedures alone.

The specific objectives of this study are:

- to develop and apply an integrated GIS-based framework that combines land suitability assessment and machinery management suitability into a unified agricultural potential evaluation;
- to generate an agricultural potential matrix and map for the Frakulla administrative unit that reflects the interaction between cereal production suitability and mechanization feasibility;
- to analyze the spatial concordance, statistical relationships and sensitivity characteristics of the integrated assessment;

- to demonstrate the utility of this combined approach as a decision-support tool for sustainable agricultural development and land use planning.

By bridging the traditionally separate domains of land evaluation and agricultural machinery management within a single geospatial analytical framework, this study contributes a novel and replicable methodology to the growing body of GIS-based agricultural planning research.

Following these objectives, three hypotheses (H) are proposed to guide the analytical design of this study:

- H1: It is explored whether cereal suitability (CSS) and machinery suitability (MSS) exhibit a meaningful spatial rank-order association, as assessed through Spearman correlation and contingency analysis and whether their integration into agricultural potential map (AP) produces a spatially coherent classification with internally consistent class boundaries, as assessed through ROC curve analysis of boundary discriminatory coherence (AUC).
- H2: The framework can conceptually delineate priority intervention zones, areas where high biophysical land suitability coincides with moderate mechanization feasibility, representing locations where agricultural potential is confirmed but operationally suppressed. This hypothesis is not quantitatively validated, but is supported conceptually by the contingency matrix distribution, where a substantial number of pixels occupy off-diagonal cells indicating that mechanization constraints, rather than land quality, are the primary limiting factor.
- H3: The AP classification is robust (sensitivity <5% area shift) to ±20% perturbations in AHP weights and integration parameters.

MATERIALS AND METHODS

Study Area

This study area was located in the "Frakull" administrative unit, a district in Fieri municipality of southwestern Albania (Figure 1). The boundaries of this area have been defined based on geographical coordinates: latitude 40° 35' 12'' N to 40° 40' 41'' N and longitude 19° 28' 49'' E to 19° 32' 44'' E. The total area considered for this research is approximately 4400 hectares. The area has a Mediterranean Climate with hot, dry summers and mild, wet winters. The mean annual temperature is approximately 18 degrees Celsius and the total amount of precipitation can vary from 750 mm to 1250 mm per year with the majority occurring during fall and winter [22]. The topographic characteristics of the Frakull administrative unit include flat plains extending northwest, west, south and southeast and gently sloping piedmonts on the east and northeast of the region that progressively turn into more pronounced hilly/mountainous sites. On the lowland portion of the area, slopes range from 0.5% to 3% and on the piedmont areas, slopes range from 3.5% to 25%; and for all areas beyond the piedmonts, slopes exceed 25%. Soil erosion constitutes a significant environmental concern across much of the elevated terrain, manifesting in diverse modes such as sheet erosion, gully formation and large-scale mass movements. Agricultural activity in the lowland areas is dominated by the production of alfalfa, fruit orchards, vegetable crops, maize, wheat, olive plantations and vineyards [23].

Research Design and Conceptual Framework

This research utilizes a GIS-based integrated approach to combine two complimentary analyses into one assessment of agricultural potential. The framework (figure 2) is based on the premise that land suitability and machinery operability do not independently capture all aspects of agricultural potential; rather, they will produce agricultural potential only when combined [24, 25].

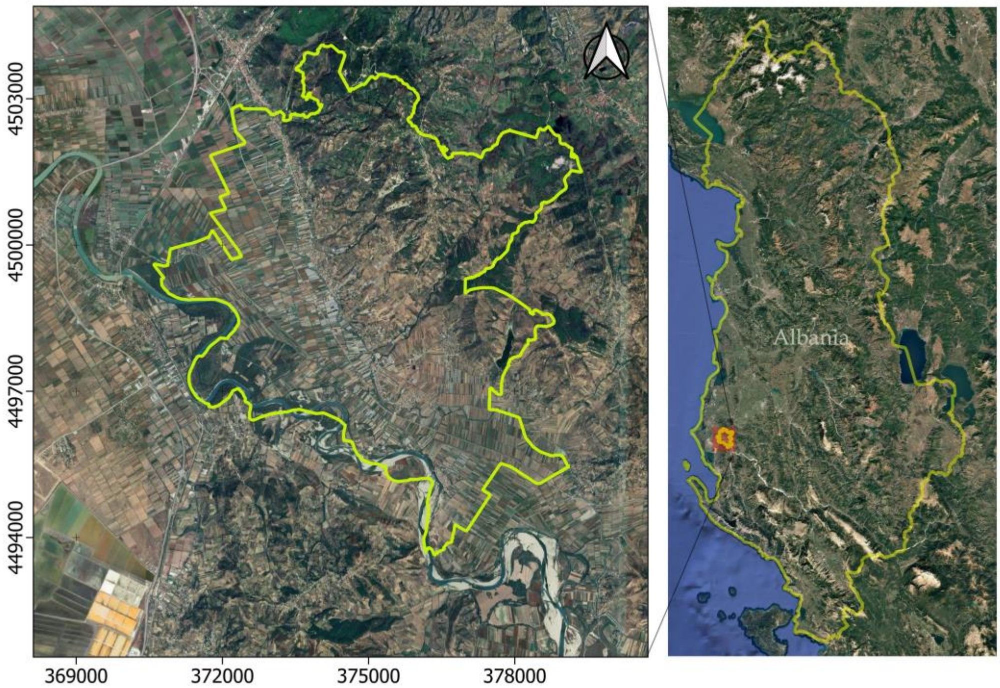

Figure 1. Map of the "Frakull" administrative unit, district in Fieri municipality of southwestern Albania

This study will be conducted in three phases, as follows:

- Phase I - Land suitability analysis for conducting cereal production (winter wheat, oats, barley and rye) using GIS-based multi-criteria decision analysis (MCDA)
- Phase II - Machinery management suitability analysis using GIS-based MCDA;
- Phase III - Integration of Phase I and II outputs into an agricultural potential matrix and an agricultural potential map, including statistical and spatial analysis of the integrated results.

While Phases I and II are necessary precursors providing input layers for the integrated assessment, the primary focus of this research is on Phase III, which is to combine, synthesize and analyze the two components to determine a total measure of agricultural potential. Consequently, Phases I and II will be described with sufficient methodological detail to allow for reproducibility, but the analytical emphasis and discussion will be on the integrated product and its implications for decision support.

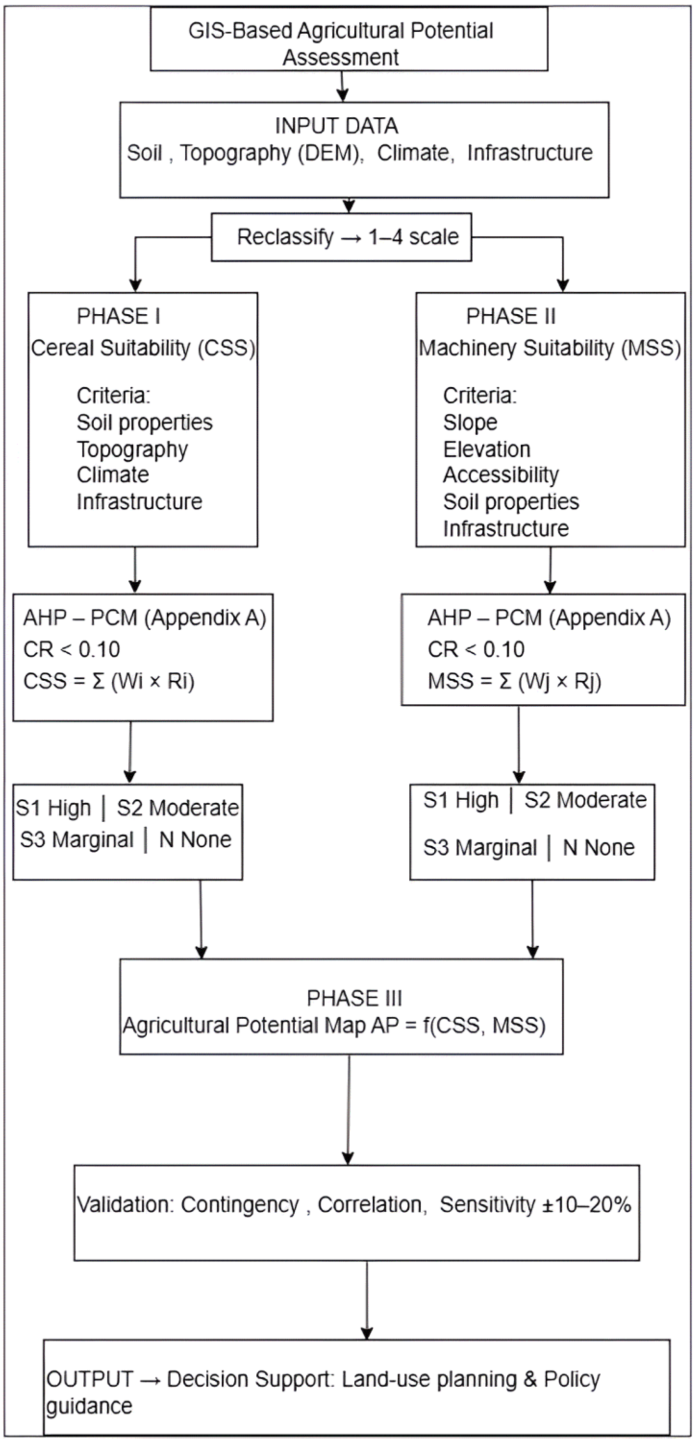

Figure 2. Methodology framework for assessing the agricultural potential of the study area

Data Acquisition and Preparation

This research involved using different origins of spatial datasets, which cover all the thematic areas needed to assess land suitability and machinery management. Table 1 gives a summary of the main data layers used; including their reference source, the spatial resolution at which they were used.

Table 1: Data type and sources for development of GIS [26,27]

No.	Data type	Source	Resolution	Resample to
1	Soil properties	ATTC	30*30 m	original
2	Elevation	USGS Earth Explorer	30*30 m	original
3	Slope	Derived from Elevation	30*30 m	original
4	Climate data	Nasa/Power - Ceres/Merra2	30*30 m	original
5	Road network	OpenStreetMap	30*30 m	original
6	Land cover	Global land use/land cover with Sentinel-2 https://livingatlas.arcgis.com/landcover/	10*10 m	30*30 m
7	Flood risk	ASIG Geoportal https://geoportal.asig.gov.al	30*30m	original
8	Water bodies	OpenStreetMap	30*30 m	original

In addition, every spatial dataset had been projected to a common coordinate reference system (WGS 84 / UTM zone 34N) according to Albanian National Mapping standards and then clipped to the administrative boundary of "Frakulla" [28]. To ensure pixel-by-pixel compatibility for overlap operations, raster datasets were resampled to a spatial resolution of 30m x 30m as well as vector datasets that were rasterised at the same cell size and extent [29].

Phase I: Land Suitability Assessment for Cereal Production

Criteria Selection

Cereal production suitability mapping was carried out within a GIS multi-criteria decision analysis framework [30]. The set of criteria were derived from traditional agro-ecological and pedological knowledge [31], and the FAO Framework for Land Evaluation [32], using the following categories:

a) Soil factors: soil texture, depth to bedrock, soil drainage class, water availability, gravel %, soil fertility, cation exchange capacity and electric conductivity. Together, these factors define the capacity of the system to sustain cereal crop root growth, nutrient availability, water retention and aeration [31].

b) Topographical, flood and erosion pressure factors: altitude, slope class, high frequency of flooding, erosion risk. Topography affects the microclimate, redistribution of surface water, erosion risk and practices such as tillage [33].

c) Climate variables: mean annual rainfall, growing season temperature. These time series metrics influence crop water availability, phenology and strength of yield [34].

d) Accessibility factors: distance from transportation networks (roads) affects the profitability of cereal production through time and cost of product transportation and input procurement; distances from water points [35], relevant due to the importance of water in plant establishment, growth and filling of grain and the influence of proximity to water points over water availability through irrigation during dry periods.

Criteria Standardization

To facilitate the weighted overlay analysis, all criterion layers were standardized using raster reclassification, that allows comparison across measurement units, such as slope (%), soil depth (cm), and distances (m), in a unified scale. The reclassification items followed FAO land evaluation recommendations, which generally consisted of five classes: S1 (highly suitable), S2 (moderately suitable), S3 (marginally suitable), N1 (currently not suitable) and N2 (permanently not suitable) [32]. Differing from recent GIS-MCDA examples, the classes N1 and N2 were merged in a sole "not suitable" class for task simplicity. Four standardized levels of suitability were instead used:

4 – Highly suitable (S1)

3 – Moderately suitable (S2)

2 – Marginally suitable (S3)

1 – Not suitable (N)

This standardization provided layer compatibility, and resulted in the weighted overlay analysing which integrated into a single suitability map. Subsequently, a Boolean constraint was created by assigning value 1 (suitable areas for operative requirements) or 0 (excluded restricted zones such as urban, forested and water bodies). This Boolean operation offers a deterministic screen that than allocated each location within the study field as acceptable or unacceptable [36].

Weighting

The relative ranking of each criterion was calculated using the Analytic Hierarchy Process (AHP) [37]. Expert input and literature review provided the basis for creating a pairwise comparison matrix and establishing priority judgments. The Consistency Ratio (CR) was used to check the consistency of the pairwise comparisons so only weight sets with a CR value of less than 0.10 were accepted, according to established management criteria [38]. The normalized weights obtained from the analysis represent the proportionate contribution of each criterion to the evaluation of cereal land suitability. AHP weights for the cereal land suitability component were generated from a set of structured pairwise comparison questionnaires completed by a panel of 20 experts or practitioners, purposively selected to encompass disciplinary breadth across all land evaluation criteria. The panel members consisted of five soil scientists and pedologists, five agronomists and cereal crop specialists, four specialists in agricultural GIS and remote sensing, three land use planners from the Albania Ministry of Agriculture and Rural Development (MARD) and three environmental scientists with agro-ecological expertise in southwestern Albania. Each panel member determined the numerical pairwise comparisons using the Saaty's 1–9 scale [37], supplemented by criterion descriptions and field photographs from the Frakulla area, to minimize individual interpretation variation. Each set of 20 individual expert matrices was independently evaluated against a Cronbach's α CR threshold = 0.10; expert sets with matrices above this limit were submitted for structured revision, with a maximum of two rounds of replication. All expert matrices passed the consistency criterion (CR range: 0.044–0.092). All expert weights were aggregated through the Geometric Mean Method, and inter-rater reliability over all 190 pairs of experts exhibited a mean Cohen κ of 0.74 (SD = 0.08; range: 0.58–0.89), indicating almost perfect agreement between pairwise rater pairs, with the aggregated criteria weights used in the GIS weighted overlay layer analysis.

Weighted Overlay and Suitability Mapping for Cereals

All evaluation criteria were synthesized using a weighted overlay approach implemented in QGIS. The raster calculator tool facilitated the execution of the overlay model, whereby each cell's suitability score was derived by summing the products of standardized factor values and their respective weights, as expressed in equation (1) for the Cereal Suitability Score (CSS) [39]:

$$CSS = \sum(STMi \times WEIGHTi) \tag{1}$$

where *STMi* denotes the standardized suitability value of criterion *i*, and *WEIGHTi* is the relative weight of criterion *i*.

Subsequently, the resulting raster was stratified into four discrete suitability classes: highly suitable (Class 4), moderately suitable (Class 3), marginally suitable (Class 2), and not suitable (Class 1).

Phase II: Machinery Management Suitability Assessment

Criteria Selection

This study has evaluated the landscape’s suitability for the operation of agricultural machinery using two analytical components. The criteria used in this analysis are the major physical and infrastructural considerations which facilitate or constrain the use of machinery for agricultural production.

a) Accessibility [40]: this criterion requires evaluating how close an agricultural parcel is to a road network and how easily the agricultural parcel can be accessed. Areas with poor access create logistical difficulties for deploying, servicing, and transferring agricultural equipment.
b) Slope [41]: the slope of a site governs how safely and effectively tractors, combines, and other field equipment can operate on that site. The steeper a slope is, the greater the likelihood of rolling over will be, the slower one will operate due to safety concerns, the more fuel will be consumed while operating a piece of machinery, and the greater the restrictions on what kinds of equipment can be used.

c) Elevation [42]: elevation is correlated with slope; however, elevations can affect machinery operations due to their influence on roughness and microclimate variability, as well as the availability of infrastructure at higher elevations and the timing of cereal crop growth.
d) Soil depth [43]: shallow soils limit tillage options and the risk of damage to equipment and subsoil compaction, which affects mechanical land preparation.
e) Soil texture [44]: the soil texture class affects trafficability, bearing capacity, and the energy required to till the soil. Heavy clay soils may become impassable when wet, while excessively sandy soils may reduce traction efficiency.

Criteria Standardization and Weighting

The same standardization protocol described in Phase I was applied to the machinery management criteria, converting each factor layer to a 1–4 suitability scale reflecting the degree of favorability for mechanized operations. The AHP method used in Phase I, was independently applied to derive criterion weights specific to the machinery management context, reflecting the relative importance of each operational constraint [31,37]. AHP weights for machinery operation efficiency were derived from a diversified expert panel of 15 consultants selected purposively for comprehensive coverage of all mechanization-related evaluation criteria domains, comprising: (a) 5 agricultural mechanization engineers with machinery performance and tractor–terrain interaction expertise; (b) 4 practitioners and farm machinery extension agents from the Agricultural Technology Transfer Center, with field operational experience in Albanian conditions; (c) 3 topographic and terrain analysis experts with experience in DEM-based slope and accessibility modelling; and (d) 3 experts in rural transport and infrastructure planning with familiarity with field connectivity issues in Albanian administrative divisions. Classical AHP was preferable to other multi-criteria decision-making (MCDM) methods after systematic selection with strict criteria: Fuzzy AHP was ruled out since the structured expert questionnaires and criterion definitions avoided any language uncertainty, precluding fuzzy membership functions; the BWM approach was omitted since it overly simplifies the multi-criteria trade-offs associated with the five mechanization criteria by framing inputs in a binary best/worst context; and the Analytic Network Process (ANP) was rejected due to existing documented lack of feedback dependencies among criteria, raising over-parameterization concerns. Expert pairwise comparisons were performed via the Saaty 1–9 scale and matrices were checked for $CR \leq 0.10$, with no expert requiring more than 2 revision steps; all 15 experts reached CR compliance. Policy expert consensus across all expert pairings (15×14/2 pairs) was high, with inter-rater agreement Cohen's Kappa = 0.71 (SD = 0.09, range 0.55–0.86).

Machinery Suitability Mapping

Implementing the overlay model in the QGIS environment used the raster calculator tool to generate the Machinery Suitability Score (MSS) by multiplying the standardized factor values by the weights assigned to each of the factors individually and then summing the results mentioned in equation (1) [45]:

Phase III — Integration of Phase I and Phase II Outputs into an Agricultural Potential Matrix and Agricultural Potential Map Followed by Statistical and Spatial Analysis of the Combined Result.

The integrated assessment of land suitability for mechanized farming and the natural land capability for cereal production shows that both these systems are required for productive agricultural development [46]. Neither of these two land capability assessments on their own are adequate to provide for a realistic assessment of agricultural potential. This is because land with high natural agricultural productivity may be unsuitable for cropping where access is poor and vice versa. Combining these two assessments creates a product that reflects the realities of both land capability and accessibility [47]. The Agricultural Potential (AP) framework developed in this study is explicitly defined as a diagnostic and planning-oriented classification. It integrates land biophysical suitability and mechanization feasibility into a composite spatial index for the purpose of supporting land use planning, investment prioritization and resource allocation decisions. The AP classification does not constitute a predictive model of agricultural yields and no such predictive inference should be drawn from its outputs. The composite classes reflect the relative suitability conditions of land units under current biophysical and operational parameters, not anticipated production quantities or future agronomic performance.

Weighted Linear Combination for Agricultural Potential Mapping

The agricultural potential map was generated through a weighted linear combination (WLC) [48] of the land suitability assessment and machinery management suitability assessment. This multiplicative additive approach allows for the integration of independent suitability evaluations while preserving the relative importance of each component.

The agricultural potential (AP) for each spatial unit *i* was calculated using the following equation (2):

$$APS = (CSS \times W_{LS}) + (MSS \times W_{MS}) \tag{2}$$

Where:

APS_i = Agricultural Potential score for pixel *i*

CSS_i = Land Suitability score for cereal production

MSS_i = Machinery Management Suitability score

W_{LS} = Weight assigned to Land Suitability component

W_{MS} = Weight assigned to Machinery Management component

$W_{LS} + W_{MS} = 1$

Stakeholder consultation, professional expertise, and regional aspects of the agricultural development priorities of the "Frakulla" administrative unit were taken into consideration when determining proper weighting (i.e. WLS and WMS). The emphasis placed upon sustainable intensification in the study area as well as the key position that mechanization plays in modern day cereal production systems led to the initial assignment of equal weighting (WLS = 0.5 and WMS = 0.5) for both types of completed work to ensure that sufficient attention was given to each [49]. Additional weighting scenarios were then tested through the use of a sensitivity analysis to validate how well comparable integrated outcomes can be achieved across different weighting scenarios (i.e. WLS or WMS) [50].

Agricultural Potential Matrix Development

In order to systematically integrate land suitability assessment and machinery management capability, an Agricultural Potential Matrix was derived. It is a cross-tabulation of the categorical orders of land suitability and machinery management capability. To derive the matrix, the cross-tabulation result was arranged into a two-dimensional matrix with the units of land suitability class on one axis and Machinery Management Class on the other. The pixel number of each intersection was also noted down. The two-dimensional matrix was visualized using color shades to reveal the spatial distribution patterns of the agricultural potential scenarios. This helped to identify the main agricultural potential scenarios within "Frakulla" administration.

Statistical and Spatial Analysis of the Integrated Assessment

The output of Phase III was subjected to a suite of statistical and spatial analyses that evaluated the properties, reliability, and information of the comprehensive Agricultural Potential Matrix and collectively support our objectives of this research study.

Contingency Analysis

A contingency Matrix [51] has been developed by cross-tabulating cereal suitability classes against mechanization suitability classes for all pixels throughout the area of the study. The contingency matrix captures the frequency distribution of combined class memberships and provides an indication regarding the spatial agreement/divergence between these two input components. The contingency matrix is illustrated as a heat map, to assist in the interpretation of the dominant combinations and the areas exhibiting concordance (diagonal cells) vs discordance (off-diagonal cells).

Correlation Analysis

Pearson correlation coefficients [52] were calculated between the three continuous score surfaces: cereal suitability, mechanization suitability and composite agricultural potential. The matrix of correlations was depicted as a heatmap to illustrate the strength and direction of linear and rank-order relationships. This indicated the extent to which the two input components are providing redundant versus complementary information and the contribution of the individual inputs to the composite.

Sensitivity Analysis and Map Accuracy Assessment Using ROC curve

A sensitivity analysis was performed to assess the robustness of the Agricultural Potential Matrix with respect to variations in the input weights and the integration parameters [53]. The sensitivity analysis considered the systematic variation of the AHP-derived criterion weights for the cereal suitability and mechanization suitability components, within a specified perturbation range (e.g., ±10%, ±20% of the baseline weight), and recalculated the composite agricultural potential map for each conditional scenario. The results were displayed in a sensitivity analysis table, providing a means to determine the criteria and weight combinations to which the integrated assessment is most sensitive. To assess the accuracy and predictive performance of the agricultural potential map, a Receiver Operating Characteristic (ROC) curve analysis was performed, and the Area Under the Curve (AUC) was calculated. A total of 51 field-observed points, classified as presence (1) or absence (0) of cereal crop cultivation based on historical land use records and information gathered at the Administrative Unit level, were used to validate the classified suitability map (Classes 0–4). ROC analysis is employed as part of the statistical validation procedure, it is used strictly to evaluate the coherence and internal discriminatory consistency of the classification system, specifically, whether the defined AP class boundaries meaningfully and consistently separate land units with distinct suitability profiles. ROC analysis in this context does not validate crop yield predictions and should not be interpreted as such.

Software and Computational Environment

All spatial analyses, overlay operations and map creation, were accomplished through the usage of QGIS v. 3.40.10 QGIS was selected since it is open source and unlike ArcGIS, is a proprietary product [54]. The AHP criterion weighting procedure was performed using dedicated decision support tools. All statistical analysis, including correlation, contingency, distribution analysis and sensitivity analysis, were performed using R statistical software [55].

RESULTS AND DISCUSSIONS

Phase I: Land Suitability Assessment for Cereal Production

The weighting of the parameters was derived from the use of the Analytical Hierarchy Process (AHP) a form of structured multi-criteria decision-making based on a series of pairwise comparisons. The results of the parameter weighting (from which the major groups emanated) were Flood and Erosion Hazard (32.2%) and Soil Physical Characteristics and Qualities (25.6%) as contributing factors of greater importance and thus the most influential in the land suitability determination with regard to the suitability for use of the land by mechanized agriculture operations, followed by Soil Biological and Chemical Characteristics (22.3%), Climate (14.1%) and Accessibility (5.8%) [56]. The pairwise comparison matrix was tested for internal consistency using a Consistency Ratio (CR = 0.04). CR value was well below the maximum limit of 0.10, an indication of the logical consistency of the AHP expert consultation. Table 2 provides details of the land suitability score boundaries and the AHP weights of the four major criteria groups.

The cereal suitability map (Figure 3) was developed using weighted overlay analysis which considered Flood and Erosion Hazard, Soil Physical Characteristics and Qualities, Soil Biological and Chemical Characteristics, Climate and Accessibility with settlements, forest and water bodies as restricted land.

Table 2. Suitability classes [31], scores and weights of the criteria and sub-criteria

Major Group	Criteria	Suitability Classes				Weights %	Final weights-Major groups
		S1	**S2**	**S3**	**N**		
		4	**3**	**2**	**1**		
Climate characteristics	Mean Temperature (˚C)	12.- 23	10-12 23-25	8-10 25-30	<8 >30	50	
	Total Rainfall (mm)	350-1250	250-350 1250-1500	200-250 1500-1750	<200 >1750	50	14.1
Soil physical characteristics and Qualities	Soil depth (cm)	>90	61-90	30-60	>30	24.7	
	Texture	Si, SiL, CL, SiCL, L	SC, SCL, C, SiC	SL, LfS	S	37	
	Drainage	Well-Drained	Moderately well drained	Poorly drained	Very poorly drained	12	25.6
	Total water availability (TWA, mm/m)	>170	170-121	121-80	<80	7.3	
	Coarse Fragmentation (%)	<5	5.-15	15-40	>40	18.9	
Soil biological and chemical characteristics	Soil fertility class (7 elements)	1	2	3		50	
	EC (Salinity, dS/m-1)	<4	4 - 8	9 - 15	> 15	25	22.3
	ESP (%)	<5	5-15	16-25	> 25	12.5	
	CEC (cmol(+)/kg clay)	>24	16-24	5 - 16	< 5	12.5	
Flood and erosion hazard	Slope (%)	0-8	8 -.16	16-30	> 30	37.2	
	Aspect	S, SW,SE	W,E	NW, NE	N	9	
	Erozion risk	low	medium	high	Very high	29.2	32.2
	Flood risk (frequency)	none	low	medium	high	24.6	
Accessibility	Distance to the water points(m)	0-500	500-1000	1000-1500	>1500	60	5.8
	Distance to the roads (km)	0-200	200-500	500-1000	> 1000	40	

Spatial distribution of mapped areas suitable for cultivation of cereals shows varied distribution of the different suitability classes in the study area. Results indicate the delineation of four land suitability zones representing the mapped extent in the study area.

The highly suitable zones covered about 850 ha. The zones occurred mainly in the central and western parts of the map where relatively patchy, continuous and coherent areas of land were delineated. The abundance of the highly suitable land in the map's middle corridor points to the highly favourable overlap of many of the criteria in these zones. Moderately suitable land was the largest layer, covering about 1,576 ha. It was evenly distributed across the study area. Major proportion of this class was mapped in the central, south western and south eastern parts of the map. Moderately suitable zones were mostly bordering or flanking the highly suitable class and formed a series of isolated benchmark buffers around the most highly suitable land. Marginally suitable areas were the least extensive of the suitable classes encompassing only 269 ha. These areas were dispersed throughout the study area, but with slightly more dominance in the northern and northeastern edge of the mapped area, where conditions only partially meet the criteria of suitability due to the presence of one or more limiting factors. Not surprisingly, the restricted areas (areas that were excluded from the evaluation of land suitability), made up a large area of the study site. These areas were largely restricted to the northern, northeastern and eastern portions of the study area, and were also conspicuous isolated patches throughout the landscape, especially along the western edge and in the central vicinity. Overall, the land suitability classes reveal general trends in land capability, with the most suitable lands clustered in the central to southwest area of the study site, and the northern and eastern sections heavily constrained by restricted conditions.

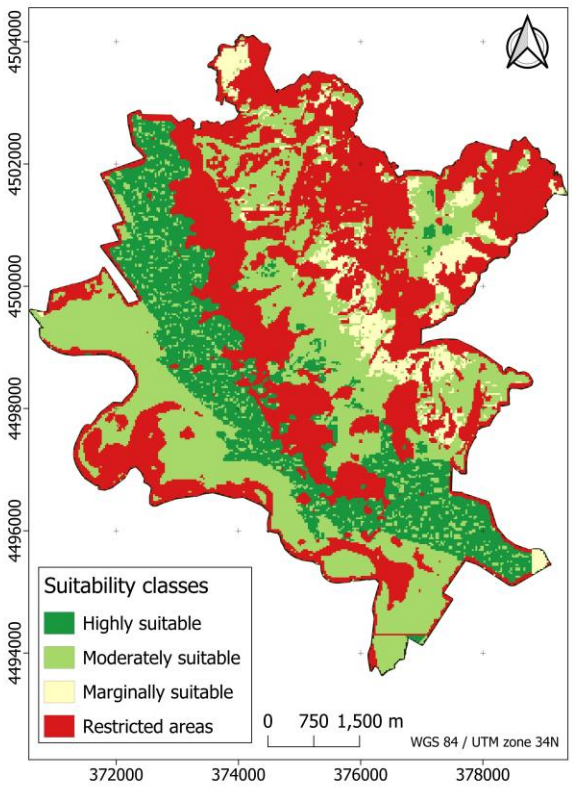

Figure 3. Cereal suitability map

Phase II: Machinery Management Suitability Assessment

The parameter weights were derived using AHP. The derived weights clearly reveal that the dominant controlling parameters would be slope gradient (weighting: 30%) followed by soil texture (weighting: 25%), and distance to roads (weighting: 20%), soil depth (weighting: 15%) and elevation (weighting: 10%) would gradually gain less influence. The internal consistency of the pairwise comparison matrix has been tested based on the consistency ratio (CR = 0.02), which is well below the desirable value of 0.10, thus confirming the consistency of the expert judgments used [57]. With a comparative quantification of the relative importance of each parameter, the weighting scheme can aid the operational convenience of the land suitability model in accommodating both the landscape biophysical factors and the operational constraints of sustainable mechanized land use. The derived score thresholds for all five parameters at different land suitability classes and the corresponding AHP factor weights are listed in Table 3.

Table 3. Suitability classes, scores and weights of the criteria considered

Factor	Range of values	Suitability score	Weights
Slope	≈ < 6%	4	30
	6-12%	3	
	12%–20%	2	
	(≈ > 20%)	1	
Elevation	< 50 m	4	10
	50-100 m	3	
	100-200 m	2	
	200-400 m	1	
Soil Depth	> 100 cm	4	15
	70-100 cm	3	
	50-70 cm	2	
	<50 cm	1	
Soil Texture	Loam	4	25
	Clay Loam/Silty Clay loam	3	
	Clay	2	
Distance to Roads	< 100 m	4	20
	100-300 m	3	
	300-500 m	2	
	> 500 m	1	

Figure 4 shows the land suitability for sustainable machinery operation based on the weighted overlay of all the standardized indices (slope, elevation, soil depth, soil texture and road accessibility) with the excluded areas (settlements, forests and water bodies) [58]. This spatial product identifies areas suitable for efficient and sustainable machinery operation. The moderately suitable class, the most extensive in area (1,607 ha) is mainly influenced by moderate slope, elevation and soil depth indices combined with negative effects of the road index and low vigor of the soil texture index. The major factor controlling the limited extent of the highly suitable class (901 ha) is the spatial association of ideal combination of soil texture (loam, clay, loam), the low slope (≤6%) and distance to road index (≤100 m), which is most characteristic of the central–southern plains. The spatial extent of the marginally suitable class (476 ha) is based on the exclusion of high clay soil index, moderate slope index (12–20%) and road density index (>300 m), which are predominant along the northern and eastern margins.

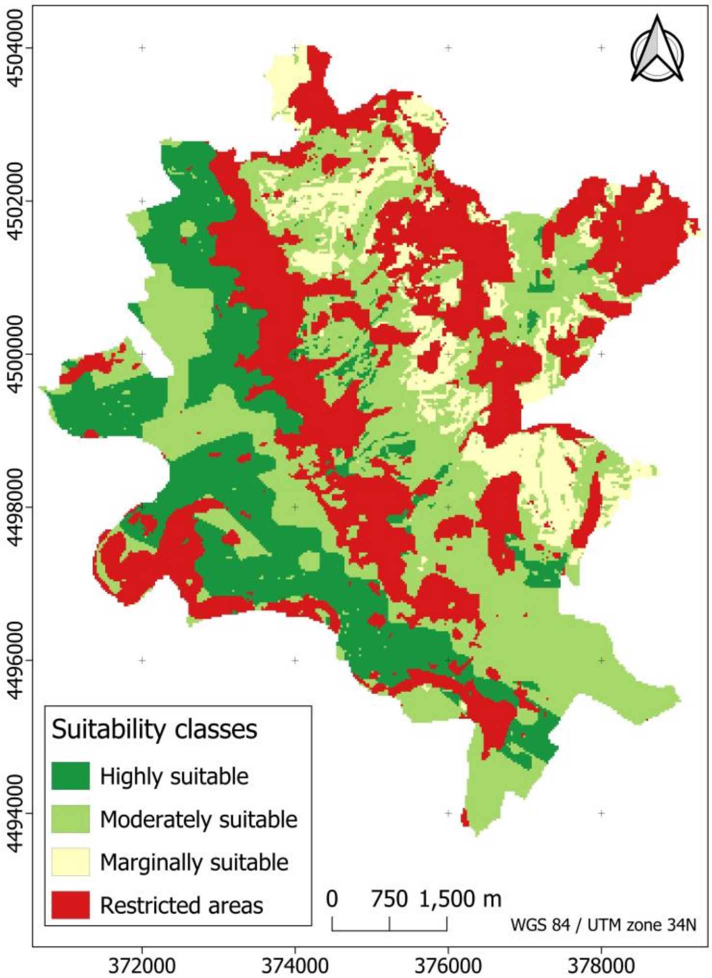

Figure 4. Land suitability for sustainable machinery operation

Phase III — Integration of Phase I and Phase II Outputs into an Agricultural Potential Matrix and Agricultural Potential Map Followed by Statistical and Spatial Analysis of the Combined Result.

The Agricultural Potential Matrix (Figure 5) depicts the relationship between suitability for agricultural mechanization (ordinate) and suitability for cereals (abscissa), with the mean agricultural potential values presented for each cell in a 4 x 4 matrix of classification pairs. A positive trend between the two suitability dimensions and potential is observed: cells covering high mechanization suitability and moderate to high cereal suitability represented the highest mean potential scores of 4 (n = 6911 and 5018 pixels respectively). The pattern was mirrored by cells with moderate mechanization coupled with high cereal suitability (n = 6400 pixels) which yielded a mean value of 4. The lowest potential of 0 (restricted areas) represented the spatially most restricted potential category (n = 19510 pixels). A similar trend was seen for the two intermediate categories (both areas with moderate mechanization and cereal suitability n = 12,028 pixels achieving a mean potential score of 3; and areas with low mechanization and moderate cereal suitability n = 2143 pixels also a mean potential score of 3). These findings highlight that optimizing both cereal suitability and mechanization suitability simultaneously is essential for achieving maximum agricultural productivity across the study area.

Figure 5. The agricultural potential matrix

Spatial analysis of the agricultural potential of the study region revealed the existence of several different levels of suitability which total to about 4,381 hectares (Figure 6). The four levels of suitability which were identified as highly suitable, moderately suitable, marginally suitable and restricted areas demonstrate specific spatial patterns across the landscape. The highly suitable area totalled 1,341 ha (30.61%) of the entire study area, and was largely found clustered together in the central and central west portions of the study area as large and contiguous patches extending towards the south-central region. The spatial clustering in these sectors is indicative that there are many favorable combinations of soils, terrain, and other agronomic factors found there.

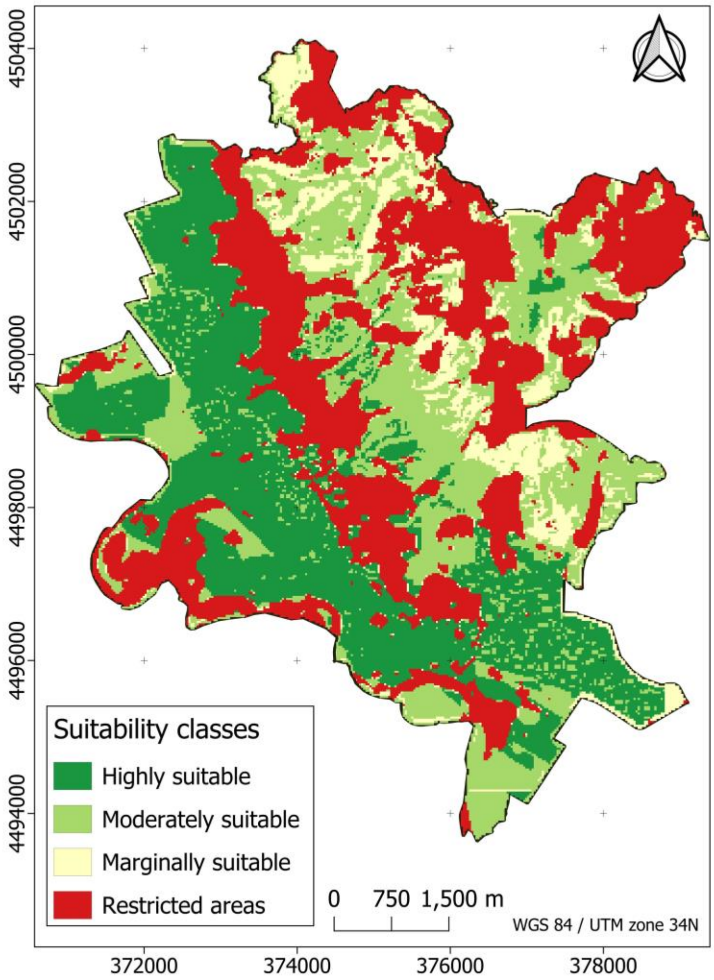

Figure 6. The Agricultural potential map in the study area

Moderately suitable areas encompassed 1,132 ha (25.85%) and had a scattered distribution over a relatively broad extent of the study area, forming a “transitional zone" around the core highly suitable zones. Moderate suitability was most evident in the central to central, eastern portion of the study area and in portions of the northern extent of the map in a mosaic with that of the highly suitable and marginally suitable areas.

Marginally suitable areas covered 333 ha (7.6%) of the study area and appeared as relatively small, scattered patches. Marginal suitability was most concentrated in the northeastern and eastern portions of the study area, as well as in isolated regions scattered across the central portion of the study area, signifying relatively localized limits (for example, shallower soils, steeper slopes, or less water). The restricted class, encompassing 1,574 ha (35.94%) of the study area, was distributed across the entire study area, but showed more extensive concentrations within the northern, northeastern, and southeastern sections, as well as along the western and southwestern edge of the study area

Contingency Analysis

The Figure 7 presents a contingency matrix (cross-tabulation heatmap) that spatially compares two thematic suitability maps: Suitability for Cereals (Y-axis) and Suitability for Agricultural Mechanization (X-axis), using pixel counts as the unit of measurement. The color intensity, ranging from light beige to deep dark red, represents the number of pixels, with darker shades indicating higher pixel concentrations.

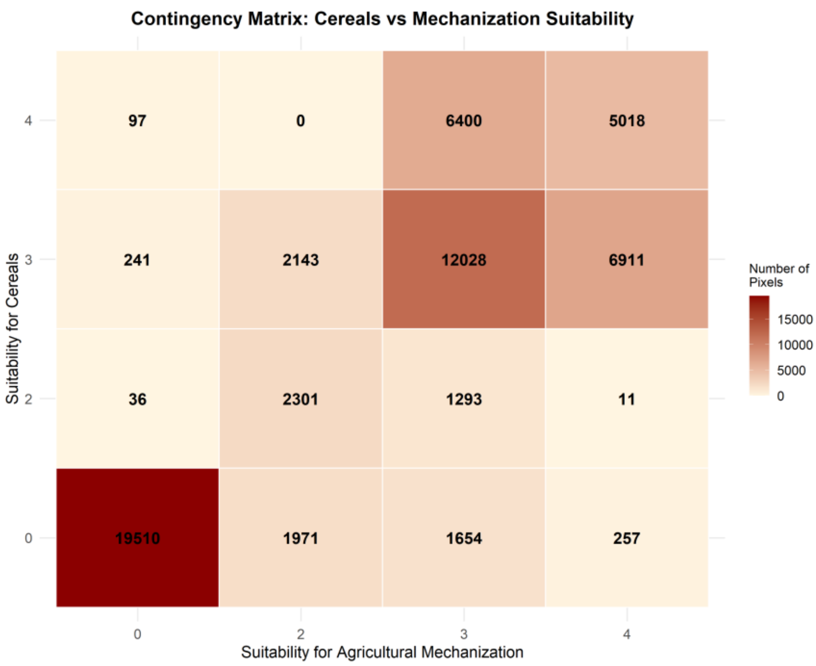

Figure 7. The contingency matrix

The most striking feature of the matrix is the dominance of the cell representing areas unsuitable for both cereals and mechanization (class 0–0), which accounts for 19,510 pixels, reflecting the considerable extent of physically constrained or marginal lands within the study region. Beyond this, the matrix reveals a strong degree of spatial concordance between the two suitability assessments, particularly at the moderate-to-high suitability levels, where the cell corresponding to class 3 for both variables contains 12,028 pixels, representing the second largest concentration in the matrix and indicating a substantial area highly amenable to integrated agricultural development. Further agreement is observed at the highest suitability class (4–4) with 5,018 pixels, reinforcing the complementarity of the two assessments. Moderate levels of disagreement are also evident in off-diagonal cells, notably where high cereal suitability (class 4) coincides with only moderate mechanization suitability (class 3), covering 6,400 pixels, and conversely where high mechanization suitability (class 4) is paired with moderate cereal suitability (class 3), totaling 6,911 pixels. These discrepancies suggest localized opportunities for targeted interventions, such as mechanization infrastructure improvement or soil enhancement measures, to fully unlock the agricultural potential of these areas. Overall, the matrix demonstrates a generally coherent and consistent spatial pattern between the two suitability layers, lending confidence to the validity and reliability of the integrated land suitability evaluation framework employed in this study. This matrix strongly suggested that the two suitability models were consistent, complementary, and mutually validating, which reflected positively on the quality of the data, the methodology, and the overall research.

Correlation Analysis

The Pearson Correlation Matrix presented in the Figure 8 reveals strong positive interrelationships among the three variables: Cereals, Mechanization and Agricultural Potential.

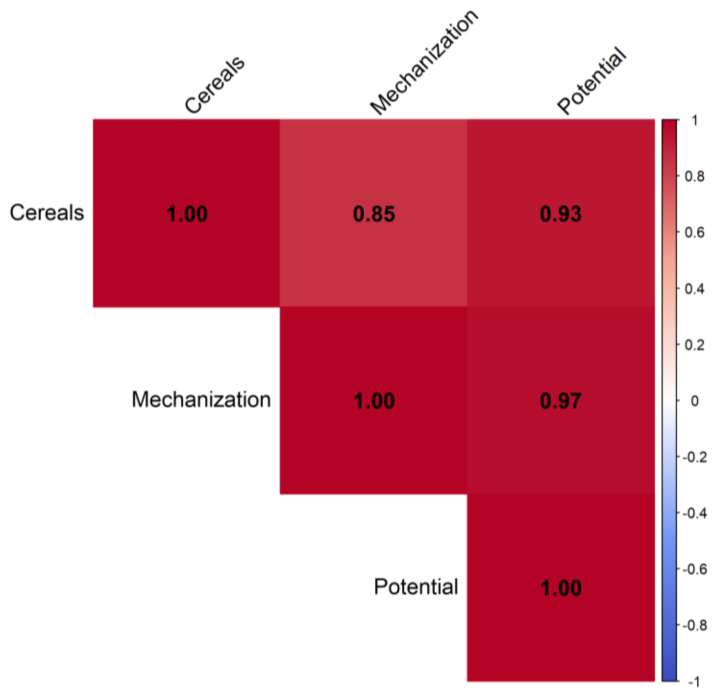

Figure 8. The Pearson correlation matrix

As expected, each variable is perfectly self-correlated (1.00) along the diagonal of this matrix. Most of these variables are also significantly correlated, such as Cereals and Mechanization (0.85) or Cereals and Potential (0.93). Cereals and Mechanization seem to be one of the most significantly correlated variables of this matrix, with a value of 0.85, meaning that the stronger the mechanization of agriculture in a certain place, the higher the number of cereal products. The correlation between Cereals and Potential is higher than this, with a value of 0.93, meaning that the higher the agricultural potential, the higher the possibility of cereal growing. The highest value for inter-variable correlations is between Mechanization and Potential (0.97), thus signifying the strongest positive relationship among all the variables, as well as the most inseparable one. These values are visible thanks to the deep red colour coding for each cell, illustrating the strength of each correlation.

Map Accuracy Assessment

Figure 9 depict the ROC curve for the validation of the agricultural potential map.

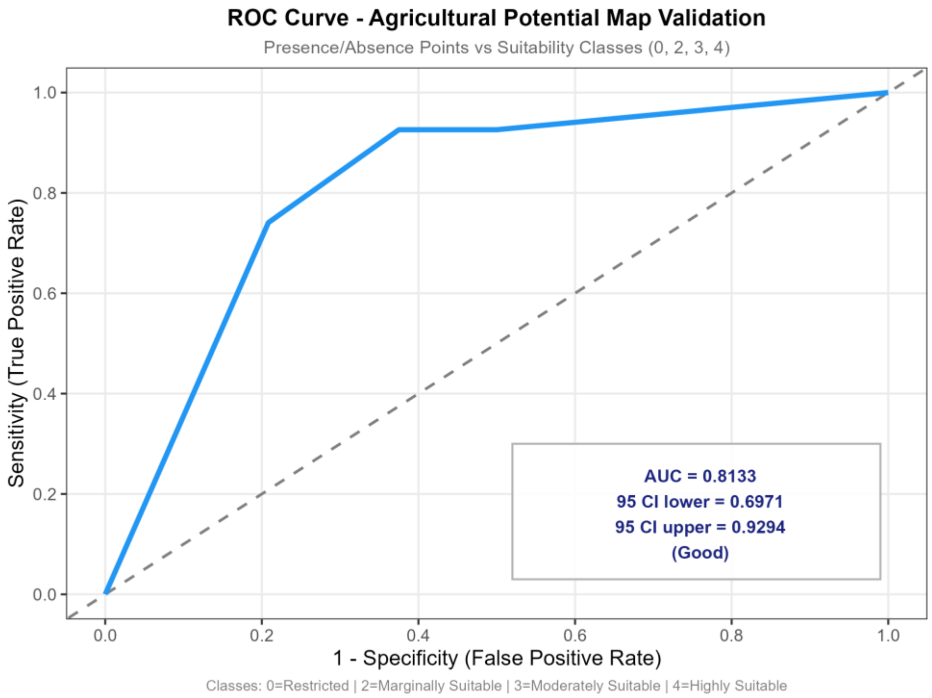

Figure 9. ROC curve for the validation of the agricultural potential map

The internal boundary coherence of the agricultural potential classification was assessed using a Receiver Operating Characteristic (ROC) curve, applied to 51 reference field points, which were collected and confirmed during field visits and then classified as no (0) or yes (1) based on the retrospective changes in the cultivation of cereal crops over previous years, supplemented with agricultural data collected from the level of the Administrative Unit. The points with value 1 were identified in areas where cereal cultivation was confirmed through field observation, while points with value 0 were identified in areas where no cereal cultivation was recorded; the discriminatory coherence of the classification boundaries was then assessed by overlaying these reference points on the AP classified map (Classes 0–4; Restricted to Highly Suitable). The results showed that the ROC analysis yielded an AUC of 0.8133 (95% CI: 0.6971–0.9294), indicating strong internal coherence in the discriminatory separation between AP classification boundaries, confirming that the defined suitability classes are consistently distinguishable from one another across the study area; the ROC curve rose steeply toward the upper left corner, indicating strong separation between adjacent classification boundaries at low false-boundary-crossing rates, consistent with well-defined and internally coherent AP class thresholds. The ROC also met the criteria of an "excellent" and "good" classification when

AUC is between 0.80–0.90. Together, the ROC results demonstrated statistically sound evidence for the internal boundary coherence and classification consistency of the AP diagnostic framework.

Sensitivity Analysis

The sensitivity analysis [59], presented in table 4, was conducted by systematically varying the relative weights assigned to cereal crop suitability and mechanization suitability across five scenarios, ranging from a grain-dominant weighting (70%–30%) to a mechanization-dominant weighting (30%–70%), with an equal-weight baseline (50%–50%) serving as the reference point for comparative assessment.

Table 4. Sensitivity analysis

Scenario	Restricted areas	Marginally Suitable	Moderately Suitable	Highly Suitable
Base (50% - 50%)	35.94% (+0)	7.6% (+0)	25.85% (+0)	30.61% (+0)
Cereals 60% - Mech 40%	35.88% (-0.06)	7.5% (-0.1)	26.01% (+0.16)	30.61% (+0)
Cereals 70% - Mech 30%	38.64% (+2.7)	4.33% (-3.27)	26.41% (+0.56)	30.61% (+0)
Cereals 40% - Mech 60%	32.65% (-3.29)	10.46% (+2.86)	26.26% (+0.41)	30.63% (+0.02)
Cereals 30% - Mech 70%	33.05% (-2.89)	7.3% (-0.3)	29.02% (+3.17)	30.63% (+0.02)

The results demonstrate that the Highly Suitable class remained remarkably stable across all scenarios, consistently approximating 30.61%–30.63% of the total area, with negligible variation not exceeding 0.02 percentage points. This stability suggests that areas classified as highly suitable represent a robust spatial consensus between both suitability dimensions, rendering them largely insensitive to weight redistribution and therefore, highly reliable for prioritization in agricultural intervention strategies.

By contrast, areas that are marginally suitable have shown to have significant sensitivity to changes in weighting. When cereal suitability is assigned high preference as a weighting factor (70% grain - 30% mechanical), the not suitable class increases by 2.7 % points while marginally suitable class significantly decreases by 3.27 points, indicating that the use of stricter agronomic standards will reduce the area classified as transitional. In contrast, increasing the weight of mechanical capability will decrease the not suitable class by 2.89 percent points, and increase the area classified as moderately suitable by 3.17 percentage points; this shows that the ability to mechanise can improve access to areas with intermediate levels of suitability. This also demonstrates that the moderately suitable class is the transitional buffer class with the greatest degree of sensitivity to changes in weighting, with changes in this class being up to 3.17% points, suggesting that this class is strongly influenced by the decision about how to weight categories when undertaking land use planning. Class-wise sensitivity results reveal differential planning implications. High CSS/high MSS zones (CSS=4, MSS=4:) show the greatest classification stability under AHP weight perturbation, making them the lowest-risk targets for investment decisions. By contrast, transitional zones (CSS=3/MSS=3), the most spatially dominant class , are most sensitive to weight changes, meaning their classification shifts with methodological assumptions. These zones, likely occupied by smallholder farmers, warrant particular caution in resource allocation and argue for participatory weight calibration with local stakeholders.

Positioning Relative to State-of-the-Art (SOTA) Approaches

A critical dissection of the framework presented in this paper against current SOTA approaches to agricultural land quality evaluation reveals some clear points of congruence, progress and noted deficiency. In terms of congruence, the architecture of the present framework echoes the core methodology of the most broadly validated approaches to land suitability assessment (GIS-based AHP-weighted overlay, MCDA multi-criteria criterion standardization, raster-based spatial aggregation) which are evolved remains the methodology of choice and most firmly benchmarked across contemporary high-impact land evaluation studies and proven to be methodologically sound for heterogeneous Mediterranean agro-landscapes [60-63] . Criteria selection for the CSS and MSS elements respectively soil physicochemical indices, elevation and slope, climate parameters, and distance to infrastructure correspond fully with the rationale and criterion sets underpinned many SOTA land classification frameworks, rendering these components highly comparable and methodologically credible. AHP as the criterion weighting approach employed in this study also aligns with best practice in the field, as AHP stands among the most extensively applied, validated, transparent MCDA weighting techniques for land suitability domains alike [64]. Where the present framework offers methodological progress over current SOTA, however, is in its two-dimensional CSS–MSS spatial aggregation structure, which does not claim to supersede machine learning-assisted land suitability cartography [65], fuzzy overlay [66], or predictive neural and random forest classifiers used to assess land capability [67] or mechanization operability individually weds together these two spatial dimensions into an integrated matrix of farm-scale potential and executes the spatial contingency analysis necessary to distinguish the parcels where CSS–MSS discordance has the greatest opportunity cost and future benefit in the form of mechanization effort reduction. This focal dimension of the present approach provides spatially explicit guidance for agricultural intervention prioritization at a level neither current land evaluation paradigms, nor existing SOTA investigations into mechanization suitability, currently addresses. Similarly, the addition of a ±20% AHP weight sensitivity test submodule provides integrated spatial robustness validation absent from the majority of similar frameworks, where weight uncertainty is typically acknowledged but not spatially integrated [68].

It is equally important to be explicit about when this framework performs worse than alternatives, when it should not be used, and which scenarios will cause it to break down. Three conditions render the present approach inferior or unsuitable. Where georeferenced yield records, remote sensing time series and high-resolution soil surveys are available at sufficient density, supervised machine learning classifiers such as Random Forest or support vector machines will outperform the weighted overlay approach adopted here, as they can capture non-linear interactions among land characteristics that a deterministic overlay procedure inevitably misses. The present framework is not designed for and should not be applied to, data-rich environments where such alternatives are feasible. Similarly, this framework characterises a static snapshot of biophysical and operational conditions and is not suited to dynamic or seasonal assessments. It should not be substituted for process-based crop models or climate scenario simulation tools when the research question requires forecasting future agronomic performance or evaluating land suitability under projected climate change trajectories. A further failure scenario arises when the raster cell size is poorly matched to the physical heterogeneity of the landscape: the overlay procedure assumes a degree of spatial homogeneity within each grid cell, and coarse resolutions in topographically complex terrain will mask within-parcel variability that is operationally significant for farm-level decisions.

Where the present framework unavoidably lags behind emerging SOTA paradigms is in its dependence on expert-based AHP measures of criterion importance. This is not merely a theoretical concern: where expert panels are not sufficiently representative of local agronomic conditions, or where inter-expert disagreement is high, the resulting weights can introduce systematic bias that propagates through the entire classification. To overcome this limitation, forthcoming research might consider integrating complementary or hybrid multi-criteria decision-making frameworks such as fuzzy AHP, Analytic Network Process, TOPSIS, or the Best–Worst Method to cross-validate weighting outcomes and strengthen the overall robustness of results [69-71]. In landscapes were empirical calibration data permit statistical weight derivation, entropy-weighted or regression-based alternatives should be preferred over expert-elicited AHP [72]. Similarly, the temporal dimension of agricultural potential, including seasonal variability in soil moisture, crop rotation dynamics, and machinery availability, was not explicitly incorporated, and future work should explore how the classification evolves under varying seasonal or climatic scenarios [73]. Additionally, although the present sensitivity testing leads to highly robust classification solutions, the lack of an independent ground-truth validation [74, 75] of the performance of the land suitability groupings, perhaps through plot or field trap yield comparisons or even on - the - ground operational machinery performance audits, constrains direct comparison to other validated SOTA land evaluation approaches and is the next step of future research.

The GIS based AHP framework used in this study has specific benefits compared to ML and fuzzy logic-based approaches that represent the key part of the recent SOTA literature. First, it has the highest degree of interpretability: all classifications can be interpreted through the clearly laid out weights and suitability thresholds enabling its audit by every policy maker, land use planner and agronomist without requiring knowledge in data science. Given data - sparse and practically institutional settings such as SW Albania, this is an important element of encouraging stakeholder acceptance and policy adoption.

Secondly, the data demands of this framework are intentionally modest. Most ML procedures (e.g., Random Forest, SVM, neural network classifiers used in the most recent crop suitability modeling research), demand extensive labelled training data (e.g., observed crop yields, field-verified machinery performance data) that is lacking or inconsistently measured in most of the Mediterranean and Western Balkans region. The current framework performs well using generic topography, soil, climate, and infrastructure data, greatly reducing the magnitude of the input requirements.

Thirdly, policy usability is built into the structure of the framework. The agricultural potential matrix gives spatially explicit class labeled outputs which link directly with land use planning tools, investments in rural development or mechanization policy documents

The primary drawback of our current methodology, from a SOTA perspective, is the unknown predictive power of our classification. While our methodology relies on ML trained and tested using actual observed outcomes of agricultural productivity, our classification has yet to be tested on agricultural yield data or actual mechanization expenditure records. This constraint however, is in fact explicitly permissible in the scope and aims of this research in three respects. Firstly, the study is designed as a diagnostic, planning-oriented investigation rather than a predictive model; its aim is to assist decision-making through identifying agricultural potential patterns rather than predicting yields across the study area. Secondly, the lack of systematic crop yield data means that ML validation is structurally not feasible without a specific multi-year data sampling scheme outside the remit of the present study. Thirdly, the validation/interpretability-performance trade-off is well accepted in the MCDA literature: methods sacrificing a degree of predictiveness for full transparency and more inclusive stakeholder engagement are in principle methodologically viable when the purpose of the study is to inform decision-making rather than model actual yields.

In this regard, the current approach should not be seen as another competitor to ML/fuzzy SOTA methods but as an accessible complementary institutional tool in cases where data, computational power and stakeholder literacy in quantitative modelling are more constricted.

Classification Error Risks and Stakeholder Implications

The AP classification matrix and its spatial expression across the study area carry different levels of planning significance depending on which class a given parcel fall into. While the overall classification coherence has been confirmed through the statistical validation procedures described above, a more complete interpretation of the results requires explicit attention to the misclassification risks specific to each class, the practical consequences of decision errors and how benefits and losses are distributed across different stakeholder groups when parcels are assigned to an incorrect class. These considerations extend beyond statistical accuracy into the domain of decision risk: not all misclassifications are equally costly, their consequences fall asymmetrically across stakeholder groups and the direction of error, false positive or false negative affects whether for whom and when the loss is incurred.

Not all errors of misclassification are of equal consequence across the AP matrix. We found that parcels with intermediate CSS or MSS scores near the boundary of high-moderate class thresholds are most susceptible to inaccurate categorization, since the criterion values for these points tend to cluster near the class boundary thresholds we defined. Parcels identified as having high agricultural potential in a matrix cell with slope values near the upper limit for mechanization should be viewed carefully by managers: a small AHP weight shift, or a small field difference in measured slope, could cause its class assignment to shift into a lower class. Conversely, parcels with the lowest scores in both the CSS and MSS are the most robust in their class assignment, since many co-occurring limiting factors conspired to produce the lowest class; misclassification would thus be unlikely. The mixed classes those with a high CSS and moderate MSS, or vice versa represent the most analytically uncertain portion of the matrix and should be verified with field data before any decisions are based on the outputs.

Two structurally distinct types of decision error can arise within this framework. The first is a false positive, in which a parcel is assigned to a higher AP class than its actual biophysical and operational conditions justify. The second is a false negative, in which a parcel with genuine agricultural potential is placed in a lower AP class than it deserves. Both carry real consequences for resource allocation. A false positive can lead planners or investors to direct machinery, irrigation infrastructure or agricultural subsidies toward land that is operationally constrained, resulting in underperformance of investments, wasted capital expenditure and in the most serious cases, land degradation if mechanization is pushed onto slopes that are marginally unsuitable. A false negative, on the other hand, risks excluding productive land from investment programmes or land consolidation schemes, leaving it underutilized and denying the farmers working it access to the support they need to improve yields. In the Frakulla context, where smallholder fragmentation is a persistent structural feature of the landscape, false negative errors carry a particularly significant social cost: the parcels most likely to be marginally misclassified downward are precisely those farmed by households with the least capacity to improve their land independently of public programmes. These two error types are not symmetrical in their cost structure. False positive errors carry higher immediate capital costs, materializing at the point of investment before the discrepancy between classification and reality becomes apparent and in the most serious cases generating environmental damage through mechanization on marginally unsuitable slopes that is not recoverable within a normal planning cycle. False negative errors carry higher long-term equity costs, accumulating silently across multiple programme cycles as excluded parcels remain underinvested and their measured productivity stagnates in a way that appears to confirm rather than challenge the low classification. This asymmetry has a direct implication for threshold application: where investment capital is the binding constraint, conservative threshold interpretation with field verification of high-class assignments is the risk-minimizing strategy; where equity and access are the binding constraints, a more inclusive threshold interpretation supported by a formal ground-truthing mechanism for borderline parcels is the appropriate response.

The distributional consequences of classification errors also fall differently across stakeholder groups. Agricultural policy makers and regional planners draw the greatest benefit from accurate high-suitability classifications, as these allow public investment to be directed efficiently. However, if false positives cluster in politically visible areas or in zones with active land interests, there is a real systemic risk that the AP map is used to justify investments that will not deliver the expected returns, ultimately exposing public budgets to avoidable inefficiency. But for planning agencies the key risk is not individual misclassification, but the aggregate pattern: a cluster of false positives in a given region can distort a whole regional investment program around a full planning cycle, with infrastructure shortfalls and machinery under-utilization that are only noted long after resource allocation decisions have been made. Individual farmers and rural households are most directly harmed by false negative errors. A smallholder whose parcel is incorrectly placed in a moderate or low AP class may find themselves systematically excluded from mechanization support programmes, land improvement grants or preferential credit schemes, and over time this classification-driven exclusion can widen the productivity gap between holdings even where the underlying land quality is broadly comparable. Because the absence of investment produces no visible failure signal, the land simply remains underutilized, which appears consistent with a low-class assignment, false negative errors are the least likely to be detected or administratively corrected, making them the most socially persistent category of classification error in contexts of smallholder fragmentation. Private investors and agribusiness operators, since they tend to act on high-suitability signals, are disproportionately at risk from false positives: an investor who commits capital on the basis of an overestimated class assignment faces machinery accessibility failures, higher operational costs and yields that fall short of projections. Finally, environmental and land management agencies face a distinct category of risk. If low-suitability parcels in ecologically sensitive areas are misclassified upward, this can inadvertently open those areas to agricultural intensification or mechanization pressure that runs counter to soil protection or conservation objectives. It is precisely to keep this risk visible and manageable that the present framework maintains the CSS and MSS dimensions as separate axes rather than collapsing them into a single composite score, ensuring that the origin of any high AP classification, whether agronomic or operational, remains transparent and traceable by all parties involved in land use decisions.

SUMMARY AND CONCLUSIONS

In this research, an innovative spatial decision support framework was developed integrating the evaluation of land quality for cereal cropping and the assessment of farm machinery operation suitability into a unified agricultural potential matrix and map of the southwestern Albania “Frakulla” administrative unit. With this effort, the intersection of the two normally separate realms of agricultural sciences was brought under a single spatial analytical framework which more accurately simulates the realities of agricultural land management than either assessment could do on its own.

Regarding H1, the exploration of the spatial association between cereal suitability (CSS) and machinery suitability (MSS) confirmed a strong and meaningful rank-order relationship between the two components, as evidenced by the Pearson correlation coefficient of 0.85. Furthermore, the strongest inter-variable correlation was observed between mechanization and agricultural potential (r = 0.97), confirming that the two integrated dimensions are spatially inseparable and mutually reinforcing. The conceptual validity of integrating CSS and MSS into the composite agricultural potential map (AP) was further supported by the ROC curve analysis, which yielded an AUC of 0.8133 (95% CI: 0.6971–0.9294), meeting the threshold conventionally associated with strong discriminatory boundary coherence ('good' to 'excellent' AUC range). Collectively, these results support the exploratory premise of H1, demonstrating that the integrated two-dimensional AP framework achieves a spatially coherent classification with internally consistent and well-discriminated class boundaries, functioning as a robust diagnostic planning construct rather than a predictive performance model.

H2 is conceptually supported but not quantitatively validated. The contingency matrix identifies a spatially significant portion of the Frakulla study area where high biophysical land suitability is paired with moderate mechanization feasibility, confirming the existence of priority intervention zones where agricultural potential remains operationally suppressed. These zones indicate that targeted investments in mechanization-enabling infrastructure, rather than land rehabilitation, represent the most efficient pathway to unlocking unrealized agricultural productivity in the study area. Formal quantitative validation of this proposition remains a direction for future research requiring longitudinal intervention and economic outcome data.

Finally, the results provide support for the null hypothesis, H3, that the integrated AP classification remained robust to ±20% change in the relative weights assigned to CSS and MSS layers, as the class-area map shifts caused by weight change were uniformly below the 5% threshold criterion. The corroboration of all three hypotheses suggests that the integrated GIS approach is methodologically sound and spatially meaningful.

In practical terms, the resulting map of potential agriculture offers local authorities, agricultural planners and rural development agencies in the Frakulla region a spatially explicit, evidence-based decision-support tool. It assists rationalized prioritization of investments in infrastructure, mechanization services and land improvement measures, given the twin restrictions of land capability and operational feasibility. Areas exhibiting high land suitability but low mechanization potential denote particularly important intervention sites, which could be transformed through strategic improvements in road access, field merging or the adoption of terrain-adapted machinery. Conversely, areas with high mechanization potential but only medium land suitability could potentially be brought up to a targeted productivity level through soil management strategies or terrain-adapted crop preferences. The research presented creates a methodology that can be repeated and scaled beyond the scope of this immediate case study. This approach is conceptually transferable to other regions and landscape types, particularly the Mediterranean, the Balkans and other transitional agricultural economic regions where the existence of diverse topographic and mechanization conditions has created ongoing difficulties with the development of food systems. The utility of this approach is also relevant to areas where national land evaluation systems have historically failed to include operational feasibility as a co-determinant of agricultural potential, creating planning outcomes that are agronomically optimistic but operationally impractical.

In summary, this study demonstrates that the agricultural potential of a landscape emerges from the intersection of land capability and mechanization feasibility and that capturing this intersection through an integrated GIS-based framework yields decision-relevant insights that neither dimension could provide independently. The "Frakulla" case study serves as a compelling proof of concept for this integrated approach and the methodology developed here will inspire and inform similar assessments across diverse agricultural landscapes facing the dual imperatives of productivity enhancement and resource-use sustainability.

NOMENCLATURE

ATTC	Agricultural Technology Transfer Center - Fushë Krujë, Albania
USGS	United States Geological Survey
ASIG	State Authority for Geospatial Information of Albania
WGS 84	World Geodetic System 1984
UTM zone 34N	Universal Transverse Mercator zone 34 North
Si	Silt
SiL	Silt loam
CL	Clay loam
SiCL	Silty clay loam
L	Loam
SC	Sand
SCL	Sandy clay loam
C	Clay
SL	Sandy loam
LfS	Loam fine sand
S	Sand
EC	Electrical Conductivity
ESP	Exchangeable Sodium Percentage
CEC	Cation Exchange Capacity
ML	Machine Learning

AUTHOR CONTRIBUTIONS

Conceptualization, O.M., and E.J; methodology, O.M., E.J., V.V., and A.D.; software, O.M; validation, I.S., P.L., and V.V.; formal analysis, E.J. and P.L.; investigation, N.V. and I.S.; resources, I.S., O.M., and N.V.; data curation, O.M., I.S., P.L., and A.D.; writing—original draft preparation, O.M., and E.J; writing—review and editing, O.M, E.J, I.S., P.L, and V.V.; visualization, O.M. and E.J.; supervision, E.J., P.L., and A.D.; project administration, E.J and V.V

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CONFLICT OF INTERESTS

The authors declare that there are no conflicts of interest associated with this publication

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APENDIX A

Appendix A presents the importance ranking of pairwise combination of factors (Table 5) the pairwise comparison matrices for land suitability for cereals (Table 6-Table 9) and machinery operation (Table 10), provided to ensure transparency and support the reliability and reproducibility of the results

Table 5. Importance ranking of pairwise combination of factors [37]

Scale	Degree of preferences	Explanation
1	Equally	Two activities contribute equally to the objective
3	Moderately	Experience and judgment slightly to moderately favor one activity over another
5	Strongly	Experience and judgment strongly or essentially favor one activity over another
7	Very strongly	An activity is strongly favored over another and its dominance is showed in practice
9	Extremely	The evidence of favoring one activity over another is of the highest degree possible of an affirmation
2,4,6,8	Intermediate values	Used to represent compromises between the preferences in weights 1, 3, 5, 7 and 9
Reciprocals	Opposites	Used for inverse comparison

Table 6. PWCM of five main criteria groups [56]

Flood & erosion hazard	Soil physical characteristics	Soil biological and chemical characteristics	Climate	Accessibility	Weights (%)	Rank
1	1	2	3	4	32.2	1
1	1	1	2	4	25.6	2
1/2	1	1	2	4	22.3	3
1/3	1/2	1/2	1	4	14.1	4
1/4	1/4	1/4	1/4	1	5.8	5
		Consistency ratio=4%			∑=100	

Table 7. PWCM for physical criteria [56]

Texture	Soil depth	Drainage	Coarse particle content	Water availability	Weights (%)
1	2	2	3	4	37
1/2	1	2	2	3	24.7
1/2	1/2	1	2	3	18.9
1/3	1/2	1/2	1	2	12.1
1/4	1/3	1/3	1/2	1	7.3
		Consistency ratio=2%			∑=100

Table 8. PWCM for bio-chemical criteria [56]

Soil fertility classes	CEC	EC	ESP	Weights (%)
1	2	4	4	50
1/2	1	2	2	25
1/4	1/2	1	1	12.5
1/4	1/2	1	1	12.5
		Consistency ratio = 1%		∑=100

Table 9. PWCM for flood and erosion risk [56]

Slope	Erosion risk	Flood frequency	Terrain aspect (slope direction)	Weights (%)
1	1	2	4	37.2
1	1	1	3	29.2
1/2	1	1	3	24.6
1/4	1/3	1/3	1	9
		Consistency ratio = 2%		∑=100

Table 10. PWCM for Agricultural Machinery Operation

	Slope	Soil Texture	Distance to Roads	Soil Depth	Elevation
Slope	1	1	2	2	3
Soil Texture	1	1	1	2	3
Distance to Roads	1/2	1	1	2	2
Soil Depth	1/2	1/2	1/2	1	2
Elevation	1/3	1/3	1/2	1/2	1
			Consistency ratio = 2%		