Land Use Suitability Analysis for Agriculture Crops Farming in Kaski District, Nepal: A Conjunction Study of Analytical Hierarchy Process, Random Forest and Support Vector Machine

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Abstract

A mix of machine learning algorithms and expert-based Analytical Hierarchy Process was applied to estimate land suitability for agricultural crop production in Kaski District, Nepal. For land parcels such as Kaski, in which cases urbanization and land fragmentation exert further pressures on agricultural land, a scientific analysis of land appraisal is needful to ensure support for sustainable agricultural practices in a country like Nepal, which has a strong agricultural-centric economy and differing physiographic conditions. Three methods were adopted for suitability mapping: Support Vector Machine classification with robust classification performance, Random Forest classification in which intricate relationships among environment-driven factors are easily managed, and Analytical Hierarchy Process, which favors expert knowledge using pairwise comparison matrices. By adopting GIS-based weighted analysis, all eighteen criteria such as weather conditions, soil qualities, topographic factors, and infrastructure accessibility were analyzed together through land appraisal analysis. Both confusion matrices and classification reports were adopted to ensure correct functioning of this model, and analysis revealed superiority of machine learning algorithms over AHP alone as supporting analysis methods. Climatic conditions and soil productivity emerged as important factors, with Southern and Southeastern sections being most favorable, which covered about 9.68% of this land parcel. Difficult topographic and environmental conditions made north sections most prone to low to moderate adaptability conditions only. As far as land planning decisions and agricultural extension support systems in Kaski District of Nepal are concerned, this combined analysis helps to provide support systems with spatiality, and this has very useful practical applications in mountainous sections interested in prioritizing agricultural land allocation through expert knowledge and latest computer technology-based interventions.

Keywords: AHP, Kaski, Land Use Suitability, RF, SVM,

1. Introduction

Assessing land appropriateness for use is a crucial factor in attaining sustainable agricultural growth, particularly in areas characterized by challenging topography and little resources (Hussain et al., 2026). The growing demand driven by urbanization and climate change, among other factors, makes land suitability and mapping a key concern in agriculture and land degradation has also made it an imperative to ensure the use of systematic approaches in assessing, monitoring, and effectively managing agricultural land use through use of tools such as geographic information systems and remote sensing (G. Anuber et al., 2025). Geographic Information Systems GIS, coupled with techniques of multi-criteria decision analysis, offers a strong basis for the treatment of various biophysical variables such as topographic, soil, and climate measures to derive suitability landscapes for optimal land allocation choices (Malczewski, 2006).

Managing land resources is a huge problem in Nepal since approximately 66% of the people there rely on farming for their living (Forzini et al., 2022). The diverse geography of Nepal, ranging from the highlands of the Himalayas to the flat lands of the Terai region, requires sectorial suitability analysis. The mid-hill region of Kaski District in the Gandaki Province of Nepal is an example of the challenges imposed by varied terrain conditions and the consequences of increased urbanization and fragmentation patterns (Karna et al., 2021). The farming techniques in the Kaski district typically lag behind the analytical approach of resource targeting and utilize the land unscientifically. Crop-land suitability remains inappropriate in spite of the existence of suitable arable lands because there is no combined analytical approach that combines expert opinions with predictive assessments.

In several prior studies conducted in Nepal, a single approach was largely employed in land suitability evaluation. In fact, (Karna et al., 2021) adopted an AHP-based GIS-MCDA approach to evaluate land suitability for an agricultural purpose. The applicability of GIS-based multi-criteria assessment was proved to be effective, where it was emphasized that dependency on personal judgment, along with precise non-linear relationships among environmental attributes, was unaccounted for in such processes. In a similar context, (Chiranjit Singha et al., 2019) adopted an AHP technique in determining crop suitability of potatoes. Notably, (Ozfidan-Konakci & Kabakci, 2020) emphasized wheat production in a similar environment. However, in such classical MCDA methods, complex relationships among criteria of appropriateness are largely neglected, where personal weightage assignments may dominate, ultimately creating threats to accuracy.

Through facilitating automatic recognition of patterns and effective predictive analyses based on multi-dimensional data, the applications of modern algorithms in the discipline of machine learning (ML) have radically altered not only the indices used in land suitability assessment but overall, the entire landscape of agricultural research. Random Forest (RF) and Support Vector Machine (SVM) are highly effective for suitability analysis because of their capacity of identifying complex patterns as well as works with non-linear data topologies, thus outperforms the rival algorithms with more sensitive classification analyses (Das et al., 2023). Through enabling more powerful data processing and recognition compared with conventional means, incorporation of artificial intelligence within geospatial analyses has thus proved that agricultural land assessment procedures could significantly benefit from greater operational efficiency coupled with greater accuracy (Karmaoui et al., 2023). However, expertise that is recognized as being essential in agricultural decision-making processes may not receive emphasis within purely ML-managed procedures, including in data-deprived regions like rural Nepal.

With the design of this research, the gaps within these methodologies would eventually be solved by constructing a hybrid modeling framework that integrates not only the structured expert judgment of AHP but also employs the predictive abilities of RF & SVM techniques. This research would aim specifically at:

- Estimating the relevant biophysical variables that influence crop suitability within Kaski District,
- Mapping land suitability using individual AHP, RF, & SVM models,
- Model validations with recommendations on sustainable agricultural land-use plans based on comparisons of modeling performances.

2. Materials and Methods

2.1 Study Area

Kaski District is in the Gandaki Province of Nepal, which is where the research area is located. Worth mentioning here is that Kaski is identified as a super zone for vegetable production under the Prime Minister Agriculture Modernization Project (PMAMP), and it remains the only district out of the 11 super zones identified under the PMAMP that was established for the purpose of vegetable production. The district embraces a vast elevation range with Pokhara acting as the administrative and business hub of the district. Kaski has a vast elevation range from 450 meters above sea level in the sub-tropical valleys to 8,091 meters in the Annapurna massif. Thus, the district embraces a diverse range of agro-ecological zones (Gaire et al., 2025). The district's agricultural potential is greatly affected by the different climate zones, which range from the sub-tropics in the lower elevation zones to the temperate and Alpine zones in the higher elevation zones. The physiography is characterized by deeply dissected hills, river valleys, and mountain slopes shaped by major river systems including the Seti, Madi, and Modi (Karna et al., 2021). Soil formation varies from fertile alluvial deposits in river basins to residual soils on hill slopes, with agricultural suitability closely tied to slope gradients, which frequently exceed 25° in the northern regions. Slope emerges as the dominant factor in land evaluation, carrying a weight of 60.57% in multi-criteria assessments (Gaire et al., 2025). Here agriculture is the major source of income as well as livelihood for around 60% of the inhabitants of the Kaski district, however agriculture is severely affected by acute land fragmentation and urbanization, with average plot sizes frequently below one hectare (LMTC, 2023).

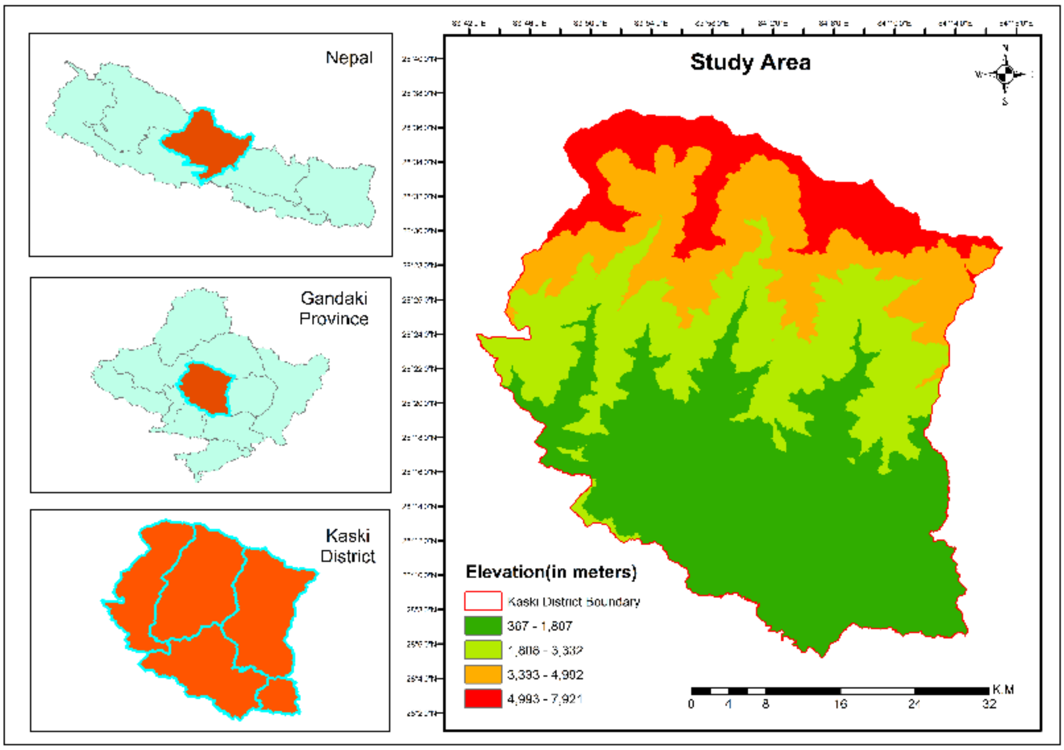


Fig. 1: Study area map

2.2 Dataset and software used

2.2.1 Dataset

Table 1: Dataset used in study

S. N	Data Category	Data Products	Data Source
1.	Meteorological Data	I. Rainfall II. Temperature	Department of Hydrology and Meteorology (DHM)
2.	Soil Data	I. Nitrogen II. Potassium III. Phosphorous IV. pH	National Soil Science Research Centre (NARC) (https://soil.narc.gov.np/soil/soilmap/)

		V. Organic matter VI. Boron VII. Zinc VIII. Silt IX. Sand X. Clay	
3.	Digital Elevation Model (DEM)	I. Elevation II. Slope III. Aspect IV. Distance to water bodies	NASA Earth Data (https://www.earthdata.nasa.gov/)
4.	Land Use Land Cover (LULC)	I. Land Cover Map	International Centre for Integrated Mountain Development (ICIMOD) (https://www.icimod.org/)
5.	Economic Data	I. Distance from Road	Open Street Map (OSM) (https://www.openstreetmap.org/)

2.2.2 Software Used

Table 2: Software Used

Software	**Remarks**
QGIS	Spatial data processing, thematic mapping, suitability analysis, and visualization of results
Visual Studio Code (VS Code)	Development and execution of Python scripts for implementing Random Forest, and Support Vector Machine models
Google Colaboratory (Google Colab)	Cloud-based execution of Python scripts, model training, testing, and validation of Random Forest and Support Vector Machine algorithms
Google Earth Pro	Visual interpretation, ground verification, and extraction of reference information
Google Earth Engine (GEE)	Access, processing, and analysis of satellite imagery and large-scale geospatial datasets

2.3 Methodology

2.3.1 Workflow

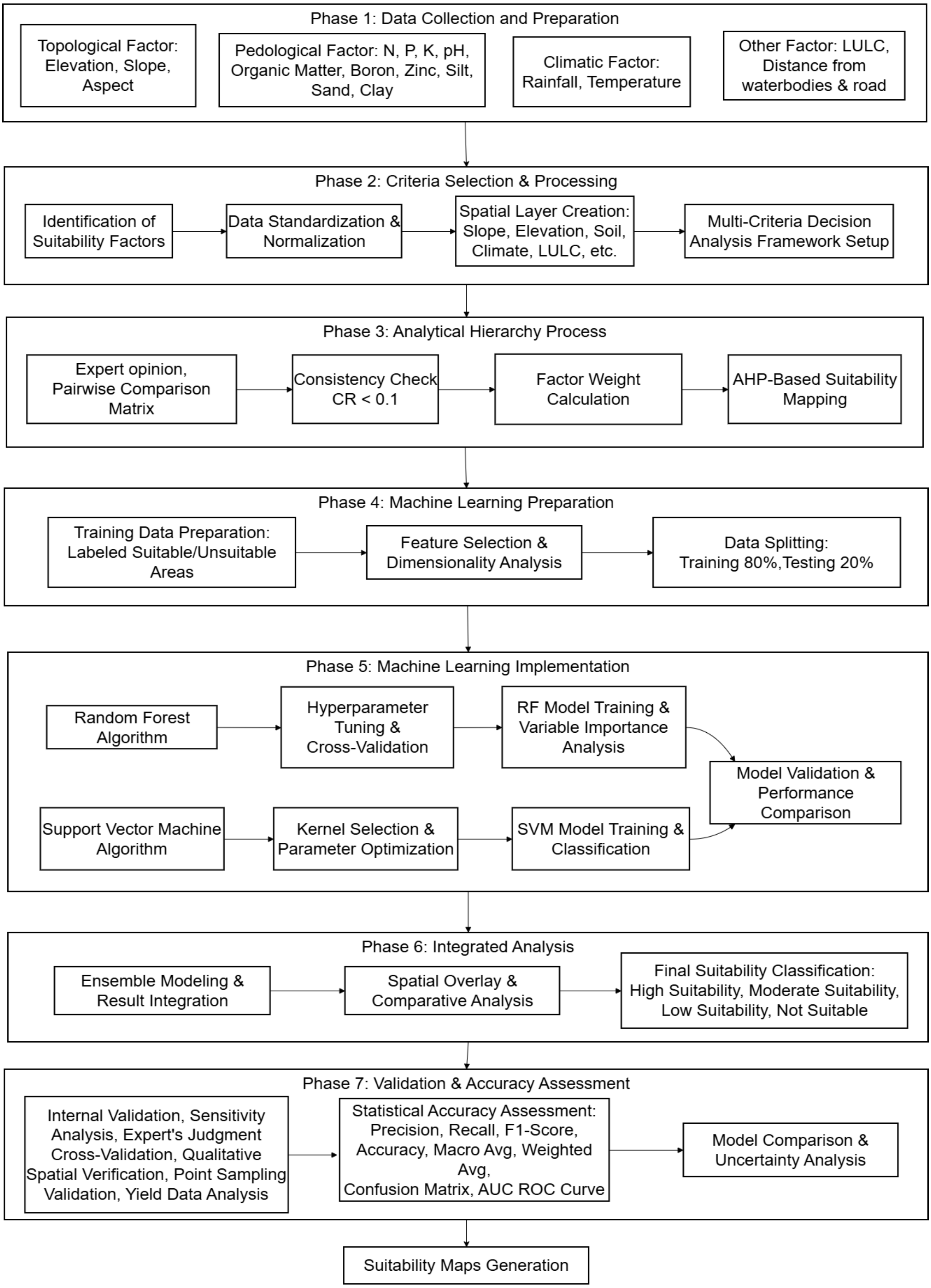


Fig. 2: Methodological flow chart

2.3.2 AHP

Developed by (Saaty, 1980) AHP is a structured multi-criteria decision analysis method that decomposes complex problems into hierarchical levels (goal, criteria, sub-criteria, and alternatives) and derives quantitative priority weights through systematic pairwise comparisons using a 1–9 fundamental scale (1 = equal importance, 9 = extreme importance). The process involves: (1) constructing the decision hierarchy; (2) creating reciprocal pairwise comparison matrices; (3) computing normalized priority weights and the principal eigenvector of matrix; (4) evaluating consistency using Consistency Ratio(CR), where CI is consistency index and RI is the random index, with CR ≤ 0.10 considered acceptable; and (5) aggregating weighted scores through summation to rank alternatives (Malczewski, 2006).

Key Equations:

Pairwise matrix: $a\_ij = 1/a\_ji$

Consistency Index: $CI = (\lambda\_max - n)/(n - 1)$

Consistency Ratio: $CR = CI/RI$

Final score: $S\_i = \Sigma(w\_j \times s\_ij)$

Where, a_ij means importance of criterion i compared to criterion j, a_ji means importance of criterion j compared to criterion I, λ_max means the largest eigenvalue of PCM, n means number of parameters, RI means Random Consistency Index, S_i means final suitability score of location, w_j means weight of criterion j and s_ij means standardized score of criterion j at location i.

Analytic Hierarchy Process (AHP), helps us for comprehensive integration of several parameters included in the study such as slope, elevation, aspect, rainfall, temperature, soil properties and economic data, with the capacity to include expert suggestions and weightage within a mathematical framework (Tashayo et al., 2020). In short Analytical Hierarchy Process (AHP) is an expert driven method which considers expert weightage to the parameters included in the study.

2.3.3 RF

To overcome AHP's shortcomings in capturing non-linear interactions and fluctuating importance rankings, Random Forest was added. RF, an ensemble learning method based on decision trees, excels in handling high-dimensional geospatial datasets and provides robust predictions even with correlated predictor variables (Breiman, 2001). Its superiority in land degradation vulnerability assessment has been demonstrated by (Das et al., 2023) who reported that AHP-RF hybrid models achieved the highest AUC (0.996) compared to standalone approaches. The procedure is as follows: (1) training data is used to generate [B] bootstrap samples; (2) each tree is grown by recursively splitting nodes using the best variable among m randomly selected predictors (usually $m = \sqrt{p}$ for classification); (3) each tree is built to maximum depth without pruning; and (4) predictions are aggregated across all trees. The ultimate prediction for classification is $\Psi^2 = mode\{h_1(x), h_2(x), \ldots, h\_B(x)\}$, where h_B are predictions from individual trees (Das et al., 2023). RF's ability to represent threshold effects and interactions between topographic and edaphic elements is very useful for agricultural suitability in Kaski's complicated topography. Internal estimations of variable relevance are produced by the algorithm, providing insights into important suitability factors that might not be obvious through human opinion alone. Furthermore, RF is perfect for areas with inconsistent data quality because to its resistance to overfitting and capacity to handle missing data.

2.3.4 SVM

In order to maximize the gap between classes and ensure robust generalization, the Support Vector Machine supervised classification algorithm builds an ideal hyperplane in a high-dimensional feature space (Cortes et al., 1995). The procedure entails: (1) using the kernel function $K(x\_i, x\_j)$ to map input vectors x into feature space; (2) solving the convex optimization problem to minimize $½||w||^2 + C\sum\xi\_i$ subject to $y\_i(w \cdot \varphi(x\_i) + b) \geq 1 - \xi\_i$ (where ξ_i are slack variables, C is the penalty parameter, and w is the weight vector); (3) finding support vectors that define the margin boundaries; and (4) classifying new data using $f(x) = sign({}_2\alpha\_i\, y\_i\, K(x\_i, x) + b)$, where α_i are Lagrange multipliers. The radial basis function (RBF) kernel $K(x\_i, x\_j) = exp(-\gamma||x\_i - x\_j||^2)$ is frequently used for complex environmental data, allowing non-linear separation without explicit transformation.

2.3.5 Conjunction Approach: Integration of AHP, RF, and SVM

The integration of AHP, RF and SVM makes it possible to: (1) incorporate both data-driven patterns and expert knowledge; (2) improve accuracy through ensemble forecasts; (3) quantify uncertainty by comparing method-specific outputs; and (4) create more dependable maps for policy-making. This combination guarantees that both globally-derived patterns and locally-specific expert knowledge are optimally employed for Kaski District's complex landscape, resulting in suitability assessments that are both sociocultural relevant and scientifically sound.

3. Results and Discussion

3.1 Generation of Land Requirements Criterions for Agriculture

Table 3: Land Characteristics and suitability class

Parameters	Highly Suitable (S1)	Moderately Suitable (S2)	Low Suitable (S3)	Not Suitable (N)
Annual Rainfall (mm/yr)	1200 - 2000	2000 - 2500	300 - 800 and 2500 - 3500	< 300 or > 3500
Temperature (^{0}C)	15 – 25	25 - 30	5 - 10 and 30 - 35	< 5 or > 35
Distance to water bodies (m)	0 – 400	400 – 1000	1000 - 2000	> 2000
Distance from road (m)	0 – 500	500 – 1500	1500 - 3000	> 3000
LULC	Cropland, Grassland	Bare soil, Forest	Other wooded land	Built-up, Water bodies, Snow
Aspect	Flat, E, SE, S	N, SW, NW, N	NE, W	Very steep shadowed aspects
Slope (^{0})	0 – 5	5 – 15	15 - 25	>25
Elevation (m)	600 – 1200	1200 – 1800	1800 - 2500	< 600 or > 2500
pH	6.0 – 6.8	5.5 – 6.0 & 6.8 – 7.0	5.0 – 5.5 & 7.0 – 7.5	< 5.0 or > 7.5

N (%)	> 0.2	0.1 – 0.2	0.05 – 0.1	<0.05
P (kg/ha)	> 30	15 – 25	10 - 15	<10
K (kg/ha)	> 280	110 - 280	50 - 110	<50
Organic Matter (%)	> 4	2 – 4	1 - 2	<1
Boron (ppm)	0.5 – 1.0	0.35 – 0.5	0.2 – 0.35	< 0.2 or > 1.0
Zinc (%)	5.0 – 8	2.5 – 5.0	1.27 – 2.5	< 1.27 or > 8.0
Silt (%)	40 – 60	20 – 40	10 - 20	< 10 or > 60
Sand (%)	10 – 20	20 - 40	40 - 60	< 10 or > 60
Clay (%)	15 – 30	30 – 45	45 - 60	< 15 or > 60

3.2 Weight determination using AHP and Weighted Overlay

AHP is used to determine the weighting of various parameters. The criteria are weighted according to how important they are for agricultural crops. Highly important parameters are given more weight. The following are the computation results:

Table 4: Pairwise comparison matrix

P	**R**	**T**	**DW**	**DR**	**S**	**A**	**E**	**N**	**P**	**K**	**pH**	**B**	**OM**	**Z**	**Si**	**Sa**	**C**	**L**
R	1	3	5	7	6	8	4	2	3	4	5	6	3	4	5	6	7	4
T	1/3	1	4	6	5	7	3	2	2	3	4	5	2	3	4	5	6	3
DW	1/5	1/4	1	5	4	6	2	1	1	2	3	4	1	2	3	4	5	2
DR	1/7	1/6	1/5	1	2	4	1	1/2	1/2	1	2	3	1/2	1	2	3	4	1
S	1/6	1/5	1/4	1/2	1	3	1	1/3	1/3	1	2	3	1/3	1	2	3	4	1
A	1/8	1/7	1/6	1/4	1/3	1	1/2	1/4	1/4	1/2	1	2	1/4	1/2	1	2	3	1/2
E	1/4	1/3	1/2	1	1	2	1	1/2	1/2	1	2	3	1/2	1	2	3	4	1
N	1/2	1/2	1	2	3	4	2	1	1	2	3	4	1	2	3	4	5	2
P	1/3	1/2	1	2	3	4	2	1	1	2	3	4	1	2	3	4	5	2
K	1/4	1/3	1/2	1	1	2	1	1/2	1/2	1	2	3	1/2	1	2	3	4	1
Ph	1/5	1/4	1/3	1/2	1/2	1	1/2	1/3	1/3	1/2	1	2	1/3	1/2	1	2	3	1/2
B	1/6	1/5	1/4	1/3	1/3	1/2	1/3	1/4	1/4	1/3	1/2	1	1/4	1/3	1/2	1	2	1/3
OM	1/3	1/2	1	2	3	4	2	1	1	2	3	4	1	2	3	4	5	2
Z	1/4	1/3	1/2	1	1	2	1	1/2	1/2	1	2	3	1/2	1	2	3	4	1
Si	1/5	1/4	1/3	1/2	1/2	1	1/2	1/3	1/3	1/2	1	2	1/3	1/2	1	2	3	1/2
Sa	1/6	1/5	1/4	1/3	1/3	1/2	1/3	1/4	1/4	1/3	1/2	1	1/4	1/3	1/2	1	2	1/3
C	1/7	1/6	1/5	1/4	1/4	1/3	1/4	1/5	1/5	1/4	1/3	1/2	1/5	1/4	1/3	1/2	1	1/4
L	1/4	1/3	1/2	1	1	2	1	1/2	1/2	1	2	3	1/2	1	2	3	4	1

Table 5: Weight of parameters for agriculture crops

Parameters	Weight (%)
Rainfall	13.5
Temperature	11.0
Distance from Water Bodies	8.8
Distance form road	4.9
Slope	4.3
Aspect	2.0
Elevation	5.7
Nitrogen	9.2
Phosphorous	7.9

Potassium	6.9
pH	3.3
Boron	1.6
Organic matter	8.0
Zinc	4.1
Silt	2.3
Sand	1.0
Clay	0.4
LULC	5.1
Total	**100**

Here, Consistency Index (CI): 0.0579

Consistency Ratio (CR): 0.0358

As, CR < 0.1 (10%) indicates acceptable consistency. So AHP is valid.

3.3 Generation of Criterion Maps and Suitability Maps

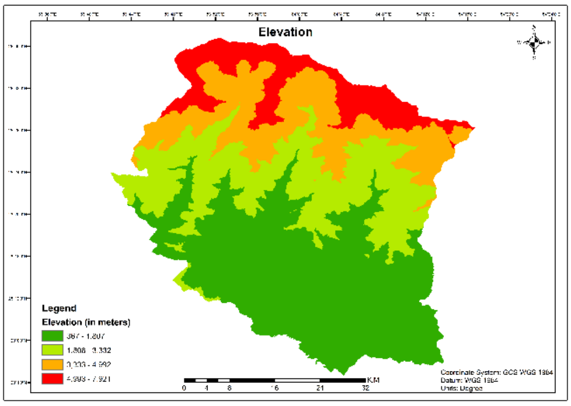


Figure 3: Elevation Map

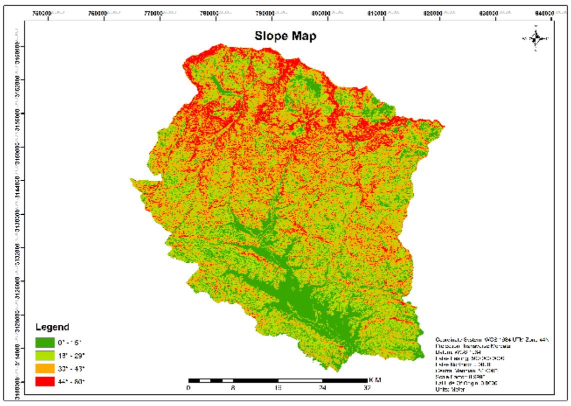


Figure 4: Slope Map

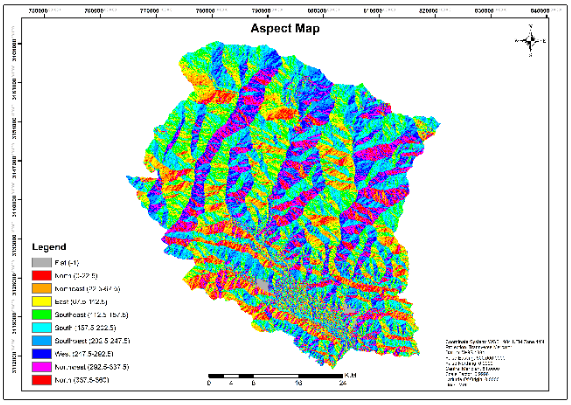


Figure 5: Aspect Map

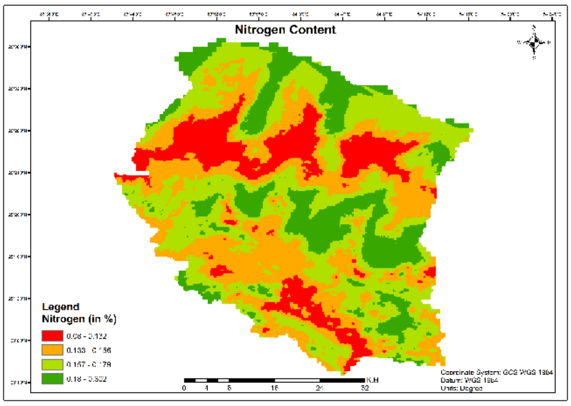


Figure 6: Nitrogen Content Map

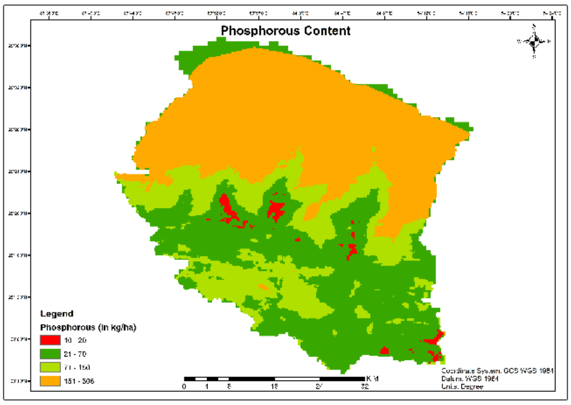


Figure 7: Phosphorous Content Map

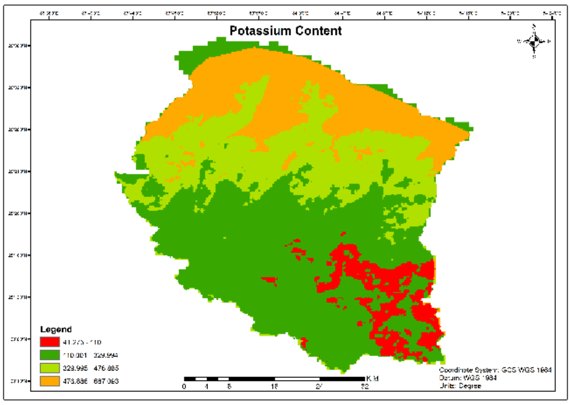


Figure 8: Potassium Content Map

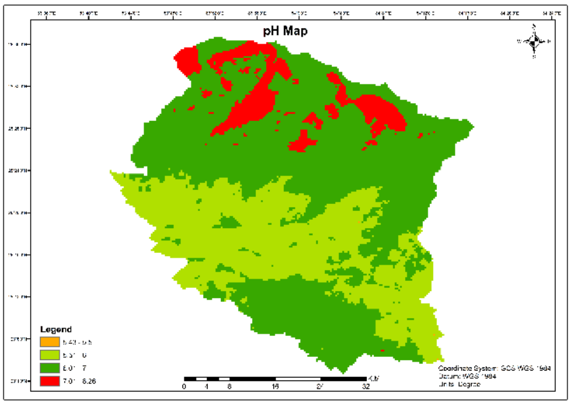


Figure 9: pH Map

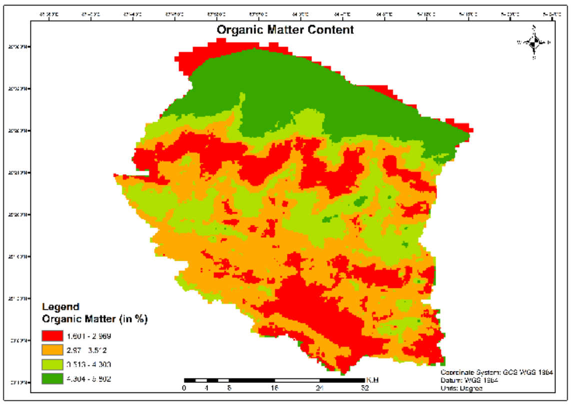


Figure 10: Organic Matter Map

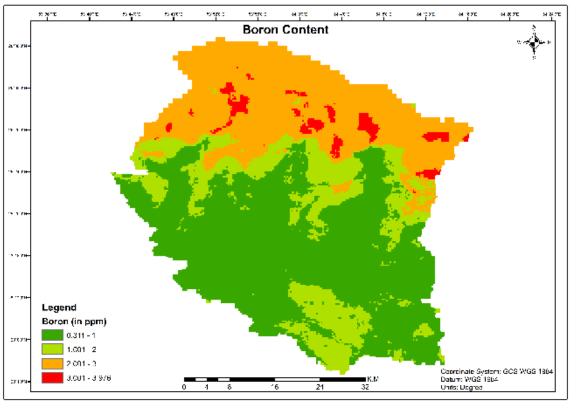


Figure 11: Boron Content Map

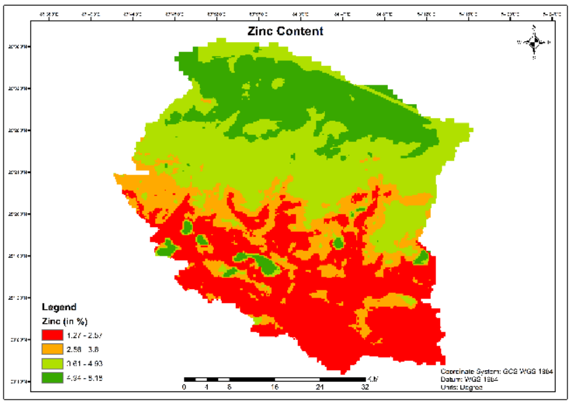


Figure 12: Zinc Content Map

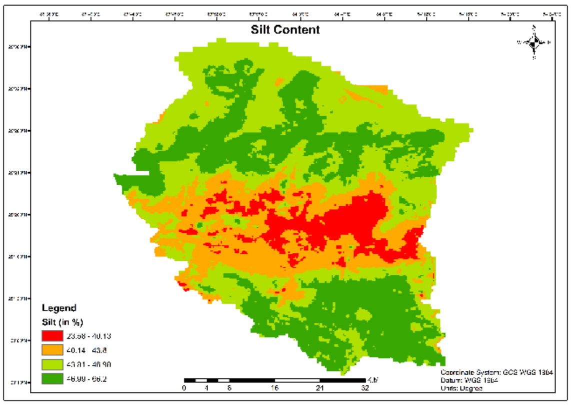


Figure 13: Silt Content Map

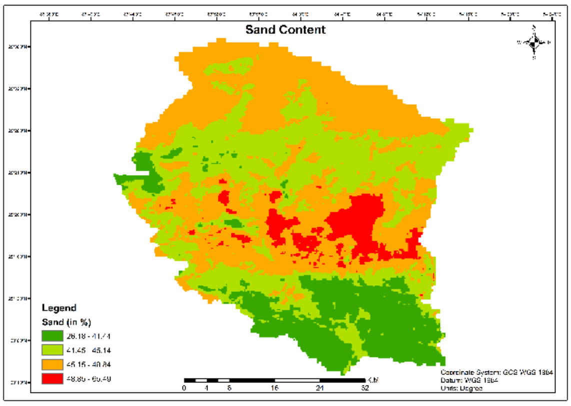


Figure 14: Sand Content Map

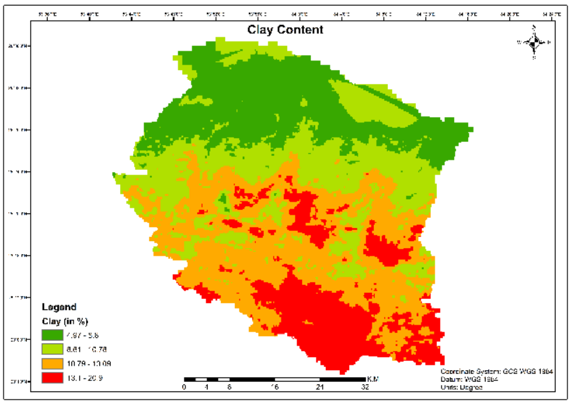


Figure 15: Clay Content Map

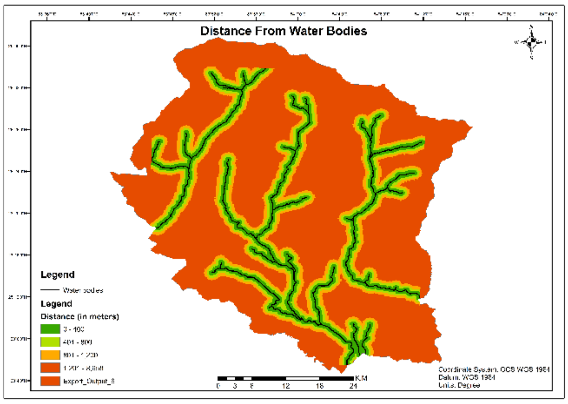


Figure 16: Distance from Water Bodies

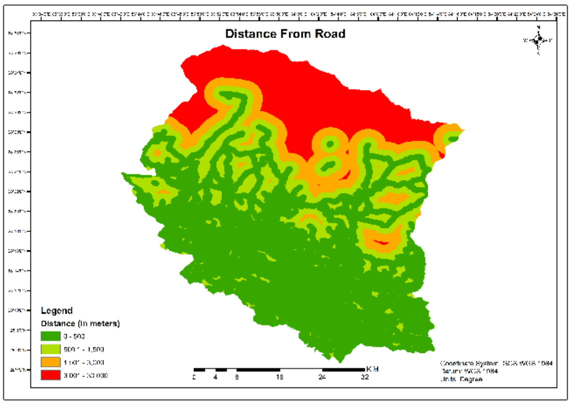


Figure 17: Distance from Road

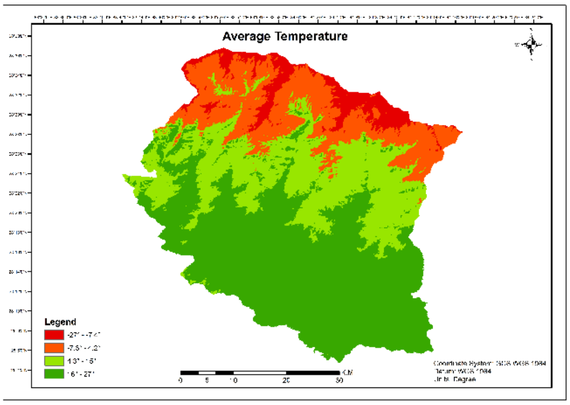


Figure 18: Average Temperature

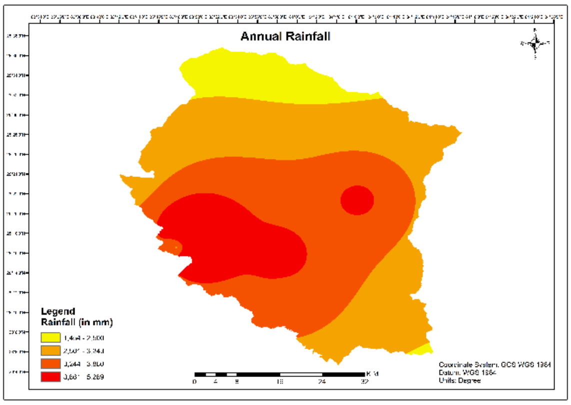


Figure 19: Annual Rainfall

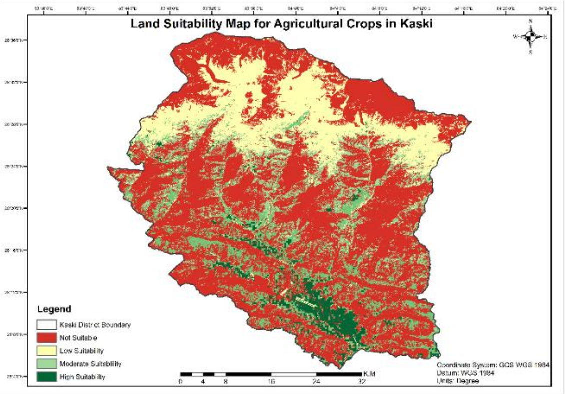


Figure 20: AHP Suitability Map

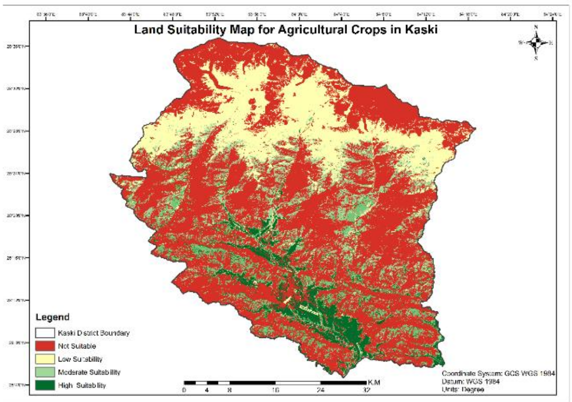


Figure 21: RF Suitability Map

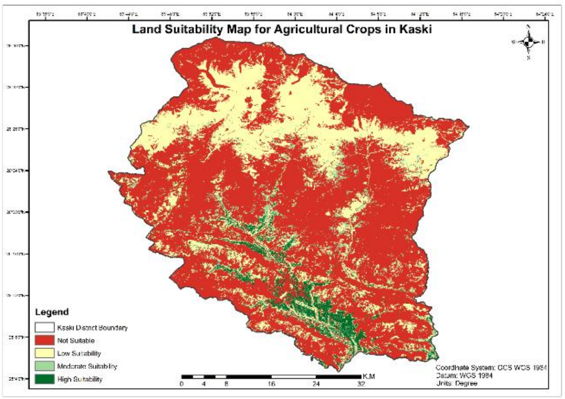


Figure 22: SVM Suitability Map

The Land Use Suitability map created from AHP, RF and SVM were categorized into four classes. The High suitability class covers 9.68% of the study area and covers 195.25 sq. km. of the total area. The second class created was Moderate suitability which covers 22.14% of the total study area and covers 446.56 sq. km. of the total area. The third class created was Low suitability which covers 28.79% of the total study area and covers 580.69 sq. km. of the total area. The final class created was Not suitable which covers 35.26% of the total study area and covers 711.19 sq. km. of the total area.

3.4 Validation of the models

The validation of the different models was performed differently. In case for AHP, we obtained the Consistency Ration (CR) which was 0.0358 which is less than 0.10, hence it validates the weights assigned in AHP. Also, for the case of AHP the suitability classes align well with the know agricultural areas of Kaski, particularly in the southern(central) and southeastern regions. For the validation of RF and SVM Classification report and Confusion matrix was generated. The independent test data through confusion matrices and classification reports suggested that RF achieved 80% accuracy, while SVM achieved the highest accuracy with 84%. The suitability classes of RF and SVM also align well with the know agricultural area of Kaski.

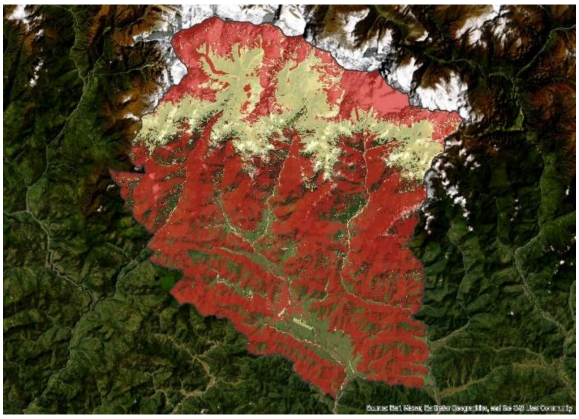
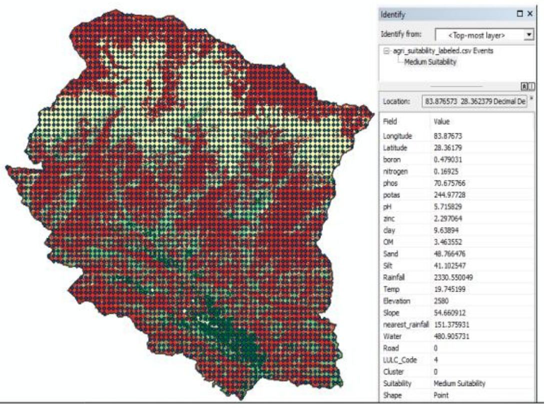


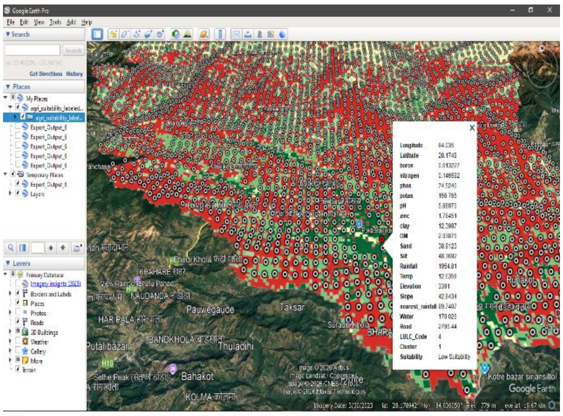
Figure 23: Comparison with satellite imagery



Location: 83.876573 28.362379 Decimal De

Field	Value
Longitude	83.87673
Latitude	28.36179
boron	0.479031
nitrogen	0.16925
phos	70.675766
potas	244.97728
pH	5.715829
zinc	2.297064
clay	9.63894
OM	3.463552
Sand	48.766476
Silt	41.102547
Rainfall	2330.550049
Temp	19.745199
Elevation	2580
Slope	54.660912
nearest_rainfall	151.375931
Water	480.905731
Road	0
LULC_Code	4
Cluster	0
Suitability	Medium Suitability
Shape	Point

Figure 24: Point Sampling Validation using GIS tool



Longitude	84.036
Latitude	28.1748
boron	0.613227
nitrogen	0.146592
phos	74.5246
potas	156.765
pH	5.86875
zinc	1.78451
clay	12.3987
OM	2.93875
Sand	38.9123
Silt	48.3692
Rainfall	1954.01
Temp	12.5369
Elevation	3391
Slope	42.8434
nearest_rainfall	89.7407
Water	170.025
Road	2795.44
LULC_Code	4
Cluster	1
Suitability	Low Suitability

Figure 25: Point Sampling Validation using Google Earth

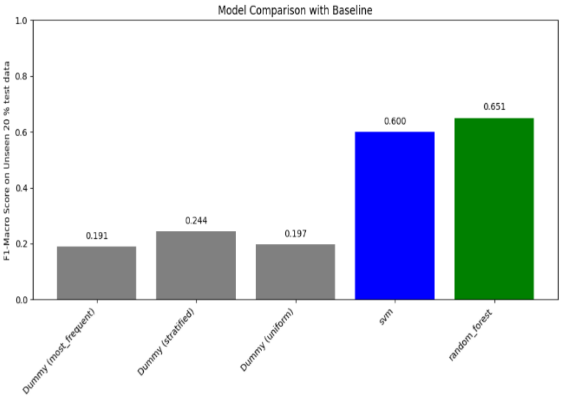


Figure 26: Model Comparison with Baseline

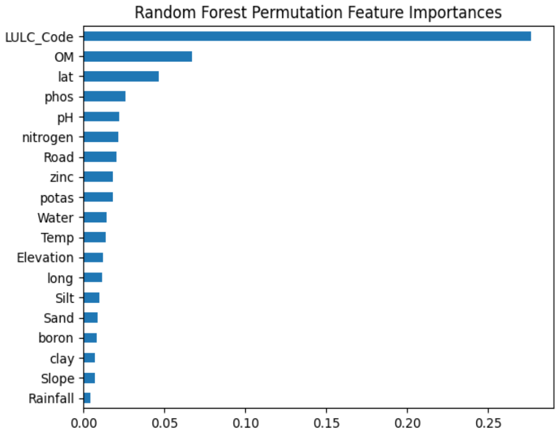


Figure 27: RF Permutation Feature Importances

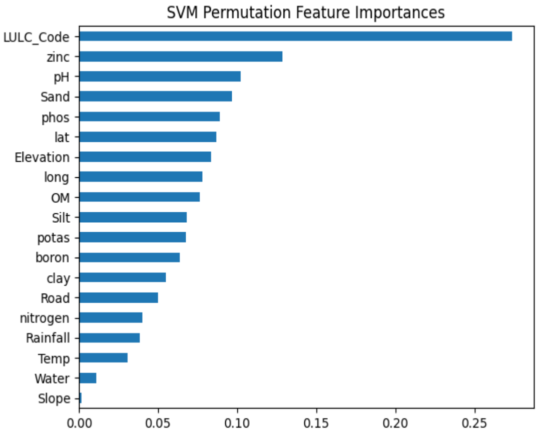


Figure 28: SVM Permutation Feature Importance

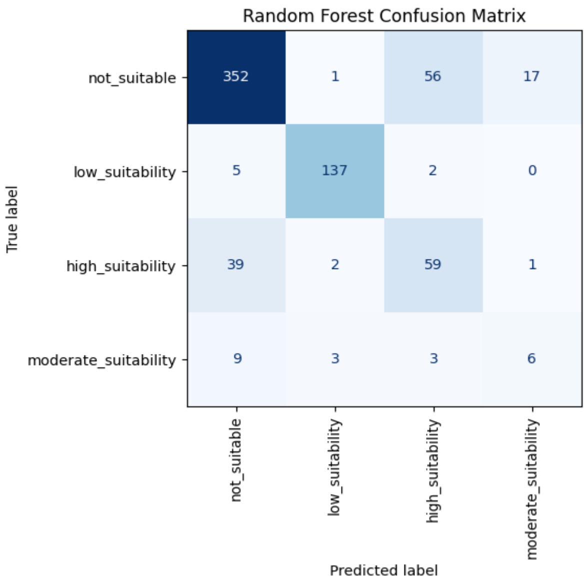


Figure 29: Random Forest Confusion Matrix

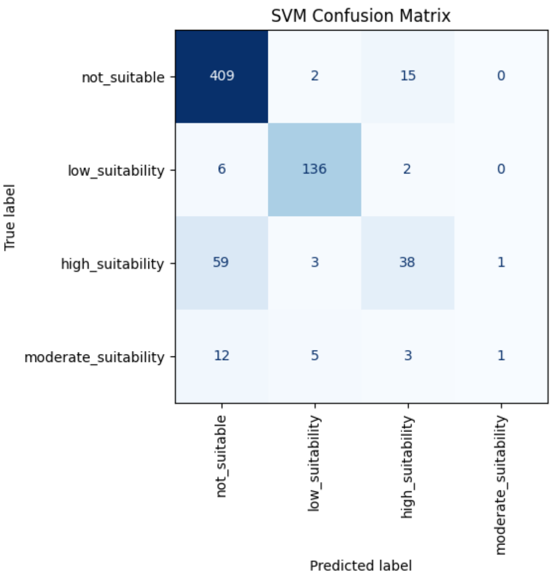


Figure 30: SVM Confusion Matrix

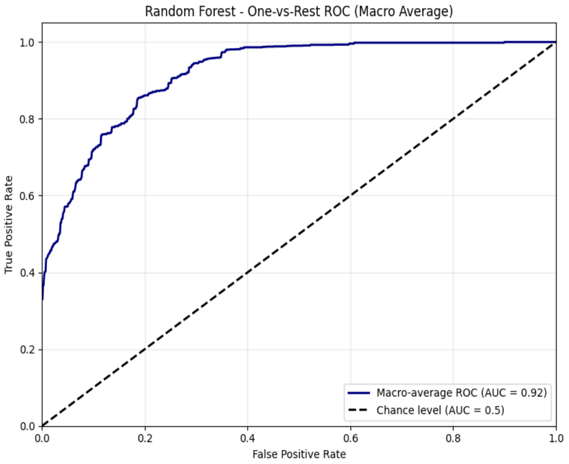


Figure 31: Random Forest-One-vs-rest ROC

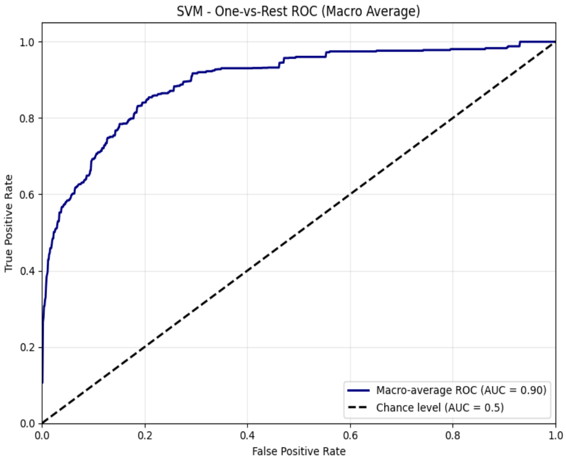


Figure 32: SVM-One-vs-Rest ROC

Table 6: Classification Report of RF

RF	P	R	F1	S
S1	0.49	0.58	0.53	101
S2	0.25	0.29	0.27	21
S3	0.96	0.95	0.95	144
N	0.87	0.83	0.85	426
Acc			0.80	692
MA	0.64	0.66	0.65	692
WA	0.81	0.80	0.81	692

Table 7:Classification Report of SVM

SVM	P	R	F1	S
S1	0.66	0.38	0.48	101
S2	0.50	0.05	0.09	21
S3	0.93	0.94	0.94	144
N	0.84	0.96	0.90	426
Acc			0.84	692
MA	0.73	0.58	0.60	692
WA	0.82	0.84	0.82	692

3.5 Discussion

By combining the Analytical Hierarchy Process (AHP), Random Forest (RF), and Support Vector Machine (SVM) methods, the current study sought to evaluate land use suitability for agricultural crop growing in Kaski District, Nepal. As we know Analytical Hierarchy Process (AHP) is expert driven method, so on the basis of expertise the AHP tool was successful in identifying the level of importance of the criteria used in the study. It identified that the top factors affecting suitability are pedological factors, climatic factors, water and road access, topographic factors, elevation, and LULC. Whereas Random Forest (RF) and Support Vector Machine (SVM) rely on feature importance in identifying the level of importance of the criteria used in the study. It identified that the top factors affecting suitability are Land Use Land Classifications (LULC), pedological factors, water and road access, climatic factors and topographic factors.

In addition, the utilization of huge datasets and the capacity to discern complicated non-linear patterns among variables using machine learning techniques, notably supervised classifiers like Random Forest and Support Vector Machines, helped to the creation of land suitability maps (Rodriguez-Galiano et al., 2012). In terms of agriculture land suitability classification performed, the machine learning approaches provided us better results and is far more reliable than the traditional approaches like Analytical Hierarchy Process (AHP) and can be considered for future agricultural planning and development efforts.

4. Conclusion

The southern and southeastern regions (i.e., the plains of Pokhara Valley) exhibit high to moderate suitability. This area is best for agricultural crop production due to its flat and low elevation lands, humid subtropical climate with plenty of rainfall, highly fertile soil, irrigation facility, and easy access to the road and market. The northern part of Kaski District, where the slope is steep with limited access to the road and irrigation facility, along with low soil fertility and adverse climatic conditions, exhibits low to no suitability for agricultural crop production.

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