

# Agroforestry potential of Kanchanpur District, Nepal using remote sensing and Geographic Information System

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**Abstract.** Subedi PB, Mahara S, Paudel S, Bhandari J, Thagunna RS. 2023. Agroforestry potential of Kanchanpur District, Nepal using remote sensing and Geographic Information System. *Asian J Agric* 7: 65-74. Researchers are interested in agroforestry because it can reduce poverty and land degradation, mitigate climate change, and improve food security. This study aimed to determine the land potential for agroforestry in Kanchanpur District, Nepal, using Geographic Information System modeling concepts and a variety of ancillary (soil fertility) and satellite data (Digital Elevation Model, wetness, Normalized Difference Vegetation Index, and Land Use Land Cover) sets. It was accomplished by logically integrating various thematic layers in the GIS domain. For Kanchanpur District of Nepal's Sudurpaschim Province, agroforestry suitability maps showed that 76.14 percent was very high suitable, 3.12 percent was highly suitable, 13.89 percent was medium, 5.67 percent was low suitable, and 1.15 percent was very low suitable. The use of remote sensing and GIS to find suitable land for agroforestry have significant impacts, which will significantly aid in the study of agroforestry practices and the estimation of crucial factors for optimal productivity. Such analyses and results will undoubtedly assist agroforestry policymakers, and planners put it into practice and expanding in new areas. GIS modeling has enormous potential for land resource mapping, eventually contributing to the benefit of poor rural people, especially farmers, and helping ensure food and environmental security and a sustainable livelihood.

**Keywords:** Agroforestry, ancillary data, GIS modeling, soil fertility, thematic layers

## INTRODUCTION

The term "agroforestry" was coined in response to a surge in global interest in tree management and planting (Munsell et al., 2022). Agroforestry is a dynamic discipline of natural resource management that combine crops and trees on farmlands to sustain, diversify, and increase environmental, social, and economic benefits for user groups at all levels (Wanjira and Muriuki 2020). This definition encompasses both non-woody and woody agroforestry components and their ecological and economic aspects. Simply put, agroforestry links forestry and agriculture, ensuring the long-term use of land resources (Tiwari et al., 2017).

Trees play a more significant role in biodiversity conservation and environmental protection (Gustafsson et al., 2020). Domestication of trees on farmland not only improves soil fertility but also improves microclimate, acts as a windbreak, and serves as a fence; on a larger scale, trees aid in enhancing the region's hydrological cycles and increasing wildlife diversity (Raj et al., 2019). Similarly, agroforestry trees provide a diverse range of domestic goods in addition to food, medicine, and timber. Farmers have begun to consider trees as part of their livelihood rather than just a forest resource, providing fuelwood and other goods (Khadka et al., 2021). In Nepal, the land is the most valuable natural resource, providing 90 percent of the

population with food, fiber, fodder, and timber. Agroforestry practices can increase land productivity, thereby contributing to the communal welfare of rural areas (Shrestha et al. 2020) and providing stable green employment opportunities. The Nepalese government is currently focusing on launching agroforestry programs in rural areas to improve rural livelihoods (Puri 2020).

Farmers in Nepal have been using their experiences to grow trees combined with crops and livestock for centuries (Paudel et al., 2021). Agroforestry practices in Nepal can be classified as (i) farm-based, which include home gardens and trees grown on agricultural fields, and (ii) forest-based, which includes agricultural activities linked to forests (Khadka et al., 2021). Nepal's forest area is dwindling, as are forest-related products that significantly impact the population relying on forest resources for a living. Agricultural activities provide a living for more than two-thirds of Nepalese households (Hernández et al., 2018). However, according to CBS 2012 statistics, at least one member of more than half of Nepalese households is employed abroad; while this may have remittance advantages, agriculture production is diminished as many families abandon agricultural methods (Cedamon et al. 2017). Land production has also been impacted by sedimentation and floods in the terai, as well as soil erosion and landslides in the highlands. The adoption of agroforestry has been advocated as a primary alternative in

Nepal for overcoming the demand and supply gap for forest-based goods (Bhattarai et al. 2020), along with other sustainable methods of boosting land potential and productivity (Kidd and Pimentel 1992). Dhakal et al. (2012) stated that infrastructure improvement, along with efficient institutional assistance, has a favorable impact on agricultural adoption in Nepal's terai areas. Many studies have assessed agroforestry adoption in tropics households (Mercer 2004; Meijer et al. 2015). While traditional studies of agroforestry potential have focused on agroforestry and forestry trends and practices, GIS is a relatively new data collection approach with great promise in the Nepalese context. Compared to traditional approaches, using scientific assessment tools to evaluate land resources not only aids in better planning and management but is also less costly and time-consuming (Ahmad et al., 2017). Kihoro, in Kenya, used a multi-criteria evaluation and GIS application to investigate land suitability for rice growing sites (Raza et al. 2018). Ritung et al. (2007) used remote sensing and GIS to examine land suitability for various agroforestry species in Aceh Barat, Indonesia, following FAO guidelines. Dengiz (2013) used GIS to investigate land suitability for rice cultivation in Cankiri-Kizilirmak, Turkey. In the present scenario, research carried out in the study area followed the conventional method and faced time and budget limitations. Thus, the objective of this study is to operate on remote sensing and GIS models to assess the agroforestry potential and status of the Kanchanpur District, Nepal. Policy developers or government agencies working in agroforestry and rural development need such data to understand and implement at a different level of project execution within the limited budget and time.

## MATERIAL AND METHODS

### Study area

The total geographic area of the study area is 1,610 square kilometers, and its elevation range confines from 176 meters to 1,528 meters above sea level (asl) (<https://knoema.com/atlas/Nepal/Land-area>). The district is located in a humid subtropical climate. The district's average temperature ranges from 10°C (winter) to 30 °C (summer) (<https://www.worldweatheronline.com/kanchanpur-weather/np.aspx>). The district receives 1,500 mm of annual rainfall (<http://mecometer.com/whats/nepal/average-yearly-precipitation>). The forest in this area is described as a low tropical *Shorea robusta* Gaertn. (Sal) and mixed hardwood forest (Sudhakar et al. 2018) with excellent natural regeneration and composition of trees that vary moisture accordingly due to aspect and slope variation. The soil is clay loam, light to medium textured, and supports rice, maize, and wheat, as well as horticulture crops like mango (*Mangifera indica* L.), banana (*Musa* genus), lemon (*Citrus ×limon* (L.) Burm.fil.), and litchi (*Litchi chinensis* Sonn.). Tree species characterized as fast-growing such as Shisham (*Dalbergia sissoo* Roxb. ex DC.), Semal (*Bombax ceiba* L.), and Masala (*Eucalyptus camaldulensis* Dehnh.), support the area (*Tectona grandis* L.f.). The rearing of

cattle, such as buffaloes, goats, sheep, and pigs, is quite common, whereas poultry is greatly aided by integrating farming (Paudyal 2011).

### Data collection

The data used in determining agroforestry potential were soil fertility, slope, rainfall, NDVI, wetness index, and elevation.

**Soil fertility:** The dominant presence of nitrogen (N), phosphorus (P), and potassium (K) in the soil results in high soil fertility, which the plants require in large amounts for their growth. Furthermore, the availability of nutrients to plants/crops is affected by the pH range of the soil. In contrast, an adequate soil organic carbon percent helps to improve the soil structure resulting in a higher release of nutrients available to plants for growth. The National Agriculture Research Council's (<https://soil.narc.gov.np/soil/soilmap>) soil maps of nitrogen, phosphorus, potassium, organic carbon, and pH status of the Kanchanpur District were used in this study to determine the soil fertility status.

**Slope:** The rate at which the elevation of the land changes per unit distance is known as slope. Water flows faster down steeper slopes. Flowing water has higher kinetic energy than still water, affecting aquatic habitats' stability. Plants thrive on gentle slopes because the water stays there for a long time and provides sufficient moisture required. As a result, gentle slopes are preferred for agroforestry over steep slopes. The aster DEM (<https://www.usgs.gov/centers/eros/science/aster-global-digital-elevation-model>) from the USGS portal was used to calculate the slope.

**Rainfall:** Rainfall serves as an essential parameter; its spatial variation positively correlates with the FAO's plant growth metric for land resource assessment. Spatial rainfall patterns (continuous surface) were generated in ArcGIS for average rainfall of 15 years using the Kriging interpolation method. Rainfall data from 2000 to 2015 was downloaded from Climatic Research Unit (<https://crudata.uea.ac.uk/cru/data/hrg>).

**Normalized Difference Vegetation Index:** The Normalized Difference Vegetation Index (NDVI) is a widely preferred vegetation index that accurately reflects vegetation health and vigor from remote sensing data (Gomes et al. 2017) and can be used to map agroforestry suitability successfully. It's also used to determine the relationship between NDVI and vegetation density. The lower the extent of erosion due to high vegetation vigor, the higher the NDVI value (Stanton et al., 2017). It can be found at <https://www.usgs.gov/centers/eros/science/aster-global-digital-elevation-model>.

**Wetness Index:** Crop growth and agricultural production require moisture in the soil. As a result, it creates an ideal environment for agroforestry. Landsat-8 satellite data, with an acquisition date of 1 December 2019, was used to prepare the wetness map of the study area. In addition, data on rainfall from 2000 to 2015 AD was downloaded.

**Elevation:** Elevation is a significant factor that affects plant growth. As the elevation rises, the temperature and vegetation decrease, resulting in the concept of a tree line.

The temperature of the air has a significant impact on the growth rates of trees. It is directly associated with photosynthesis and the respiration process, as well as influencing plant tissue temperature. The aster DEM calculated the slope (https://www.usgs.gov/centers/eros/science/aster-global-digital-elevation-model) from the USGS portal.

## Data analysis

### Soil fertility mapping parameters

The different soil-related maps were first rectified, and all soil polygon categories were fed into the GIS domain (Ahmad et al., 2017). Then, the soil fertility status map (Figure 3) was created by combining the nitrogen, phosphorus, potassium, organic carbon, soil pH, and sulfur availability map in a GIS modeling concept assigning equal weight and various ranks to each theme.

$$SF = 16.67\% N + 16.67\% P + 16.67\% K + 16.67\% Oc + 16.67\% pH + 16.67\% S$$

Where, SF: Soil fertility, N: Nitrogen, P: Phosphorus, K: Potassium, Oc: Organic carbon content, pH: Soil pH, and S: sulfur.

### Agroforestry potential mapping

The agroforestry potential map was generated by integrating soil fertility, slope, rainfall, NDVI, soil wetness, and elevation maps in the GIS modeling concept, assigning various weights and ranks to each theme.

$$Ap = 30\% Sf + 30\% S + 10\% R + 10\% NDVI + 10\% Sw + 10\% E$$

Where: Ap: Agroforestry potential, S: slope, R: Rainfall, NDVI: Normalized Difference Vegetation Index, Sw: Soil wetness, and E: Elevation

The overall flow chart of the soil fertility analysis is shown in Figure 2.

The overall flow chart of the potential agroforestry analysis is shown in Figure 3.

### Validation of result

Comparing classification against ground truth data to see how well the classification represents true geographical reference data is an accurate assessment. In assessing the classification accuracy, 50 ground truth positions were taken from the final agroforestry potential map by categorizing overall land into good (very high and high) and medium and bad (low and very low) potential agroforestry categories with the geographic coordinate of 30 and 20 respectively and applied it in the Google Earth images of 2021. The assessment was carried out using a confusion matrix, with the Kappa coefficient and overall accuracy calculated. The classification accuracy was calculated by dividing correctly categorized pixels by the total number of pixels. Furthermore, the accuracy of users and producers was determined to classify the accuracy of specific classes (Bharatkar and Patel 2013). Results are demonstrated using Table 4.

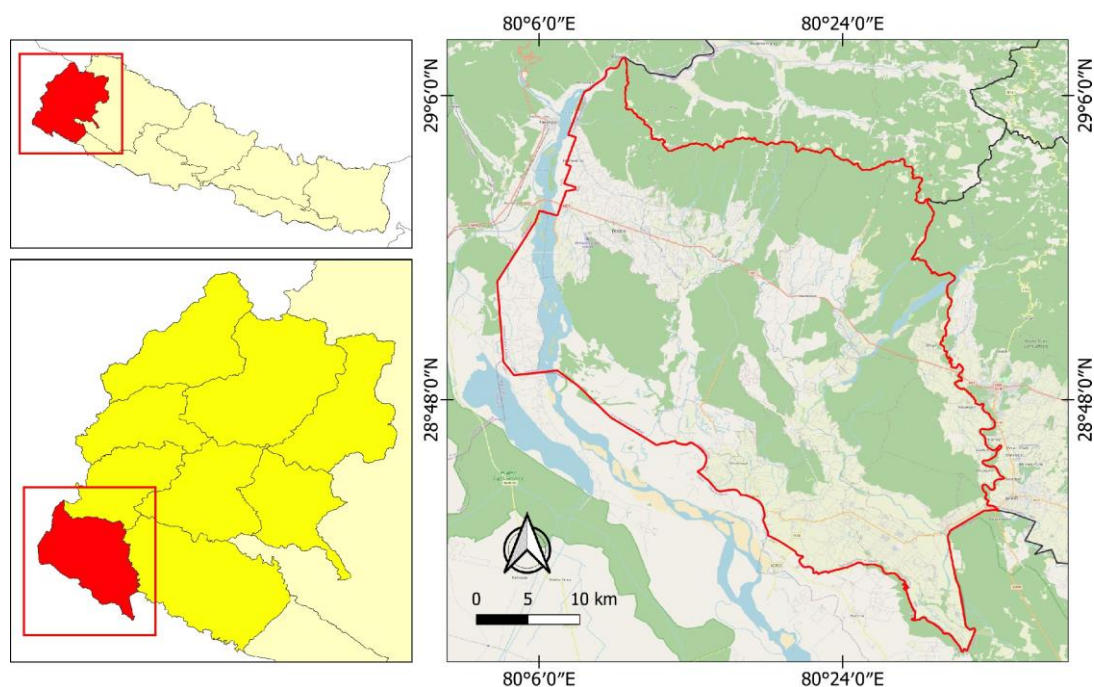
$$\text{Overall accuracy (\%)} = (\text{Number of correct pixels} / \text{Total number of pixels}) * 100$$

$$\text{Users' accuracy (\%)} = (\text{pixels classified correctly} / \text{Total classified pixels}) * 100$$

$$\text{Producers' accuracy (\%)} = (\text{pixels classified correctly} / \text{Total reference pixels}) * 100$$

$$\text{Kappa coefficient (K)} = (Po - Pe) / (1 - Pe)$$

Where: Po: Proportion of pixels classified correctly and Pe: Proportion of pixels classified correctly expected by chance.



**Figure 1.** Map of study area showing Kanchanpur District, Nepal

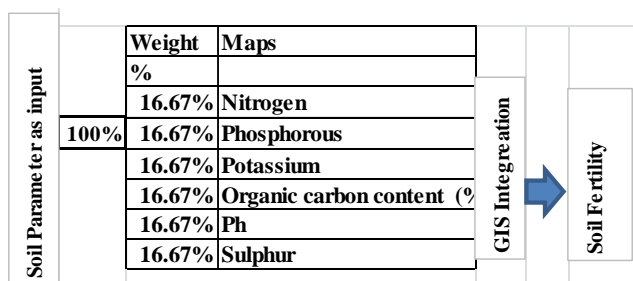
**Table 1.** Collected datasets in the study

Dataset	File type	Data type	Spatial resolution	Sources
Study area boundary	Shp	Polygon		Department of Land Management and achieve, Nepal
Soil Data (N, P, K, Ph, Organic carbon)	HDF	Raster	30 m	National Agriculture Research Council
ASTER DEM	Tiff	Raster	30 m	USGS Earth explorer
NDVI	Tiff	Raster	30 m	USGS Earth explorer
Soil Wetness	HDF	Raster	30 m	USGS Earth explorer
Rainfall data	NetCDF	Raster		Climatic Research Unit

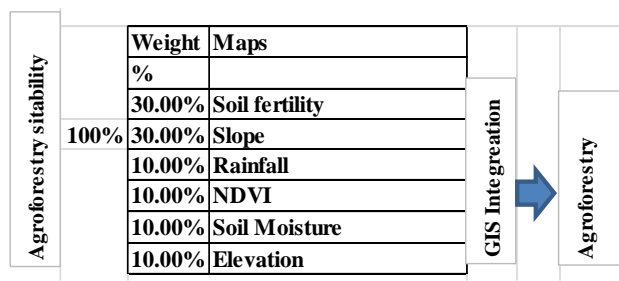
**Table 2.** Weight, value, and rating assigned to determine soil fertility

Soil map	Weights %	Value/Description	Ranks	Suitability
Nitrogen	16.67%	0.05 - 0.10 %	2	Low
		0.10 - 0.15 %	3	Medium
		0.15 - 0.20 %	4	High
Phosphorous	16.67%	<6 kg/ha	1	Very low
		6- 12 kg/ha	2	Low
		12-18 kg/ha	3	Medium
		18-24 kg/ha	4	High
		24-30 kg/ ha	5	Very high
Potassium	16.67%	< 200 kg/ha	1	Very low
		200- 250 kg/ha	2	Low
		250- 300 kg/ha	3	Medium
		300 - 350 kg/ha	4	High
		>350 kg/ha	5	Very high
Organic carbon content (%)	16.67%	1.5- 2 %	1	Very low
		2- 2.5 %	2	Low
		2.5 - 3 %	3	Medium
		3- 3.5%	4	High
		3.5 - 4%	5	Very high
pH	16.67%	6 to 7	3	Medium
		7 to 8	4	High
		8 to 9	3	Medium
Sulphur	16.67%	<5 mg/kg	1	Very low
		5- 10 mg/kg	2	Low
		10- 15 mg/kg	3	Medium
		15- 20 mg/kg	4	High
		>20 mg/kg	5	Very high

Source: Ahmad et al. (2017) and Ritung et al. (2007)



**Figure 2.** Flow chart of soil fertility analysis



**Figure 3.** Flow chart of potential agroforestry analysis

**Table 3.** Weight, value, and rating assigned to determine agroforestry potential

Agroforestry suitability mapping	Weights %	Value/description	Ranks	Suitability
Soil fertility	30%	Weighted average output based on three categories	1	Very low
			2	Low
			3	Medium
			4	High
			5	Very high
Slope	30%	<2 degrees 2-8 degrees 8 - 16 degrees 16 - 24 degrees > 24 degrees	5	Very high
			4	High
			3	Medium
			2	Low
			1	Very low
Rainfall	10%	< 1500 mm 1500 mm	3	Medium
			4	High
NDVI	10%	<0.4 0.4 - 0.5 0.5 - 0.6 0.6 - 0.7 >0.7	1	Very low
			2	Low
			3	Medium
			4	High
			5	Very high
Soil moisture	10%	Weighted average output based on three categories	2	Low
			3	Medium
			4	High
			5	Very high
Elevation	10%	<200 m 200 - 400 m 400 - 674 m 674 - 954 m 954 - 1489 m	5	Very high
			4	High
			3	Medium
			2	Low
			1	Very low

Source: Ahmad et al. (2017) and Ritung et al. (2007)

## RESULTS AND DISCUSSION

### Soil fertility status map

All the soil nutrient parameters were accredited with equal weights to create the fertility map, resulting in a map that was 100 percent. Parameters were chosen based on findings of various related nutrient suitability research works, which were FAO-certified and used widely for plant growth. In creating soil fertility maps, soil nitrogen (N), phosphorus (P), potassium (K), soil organic carbon content (C), pH, and sulfur (S) were used. These parameters signify soil fertility and, more importantly, help ensure food security. For mapping different thematic maps, weights and ranks were assigned.

### Agroforestry suitability mapping

#### Soil fertility map

All the parameters were assigned equal weights for preparing the nutrient availability map and then classified majorly into three groups: very high, high, medium, low, and very low.

#### Slope map

Aster DEM was used for slope extraction and then was reclassified into classes of <2°, 2-8°, 8-16°, 16-24°>24° with the use of standard reclassification technique and finally ranked as 5, 4, 3, 2, and 1 with very high, high, medium, low and very low description.

#### Rainfall

Further classification of the map into two classes (<1500, 1500 mm) was carried out based on agroforestry suitability; and were ranked as 3 and 4 and detailed as medium and high, respectively.

### Normalized Difference Vegetation Index (NDVI)

The high value of NDVI reflects the lesser erosion extent due to high vegetation vigor (Stanton et al., 2017). Therefore, the elevation was further reclassified into five subgroups Very Low (<0.4), Low (0.4-0.5), Medium (0.5-0.6), High (0.6-0.7), and Very High (>0.7).

### Wetness index

The wetness value is classified into three classes and described as low, medium, and high based on their agroforestry suitability.

### Elevation

The elevation was reclassified into five subgroups. First, the new values of our findings were assigned based on their agroforestry suitability, then ranked as 5, 4, 3, 2, and 1 accordingly, and finally described as very high, high, medium, low, and very low, respectively.

### Agroforestry potential map

Factors contributing toward the agroforestry potentiality are Soil fertility [30], slope [30], Rainfall [10], NDVI [10], Soil wetness [10], and elevation [10], whose weights were scientifically chosen and are based upon the empirical results of various findings. For example, agroforestry suitability mapping for the Kanchanpur District of Sudurpaschim province, Nepal, showed 76.14% as very high suitable, 3.12% as high suitable, 13.89% as medium suitable, 5.67% as low suitable, and 1.15% as very low suitable.

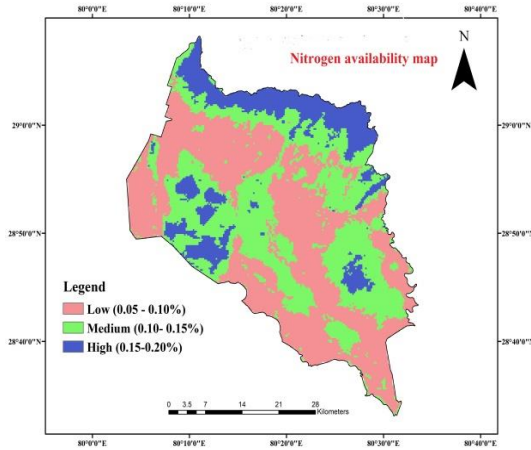


Figure 4. Nitrogen availability map

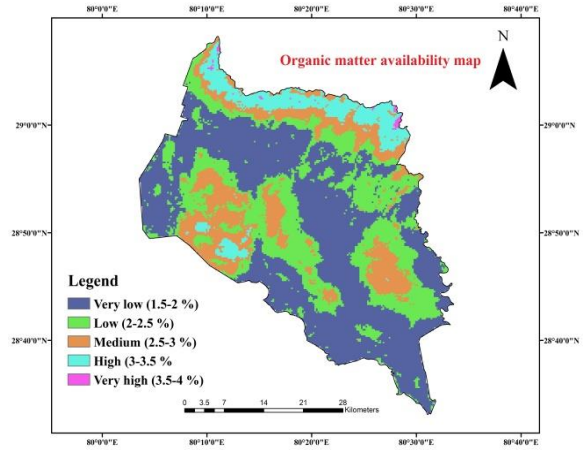


Figure 7. Organic matter availability map

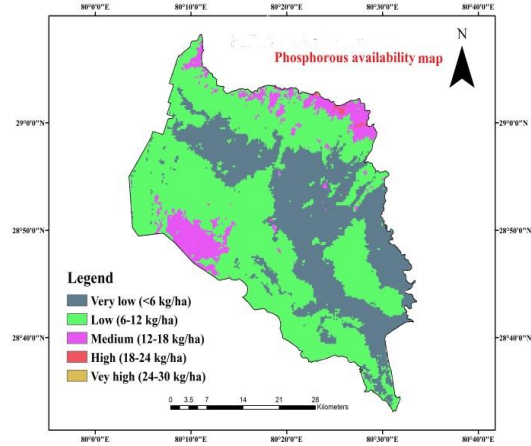


Figure 5. Phosphorous availability map

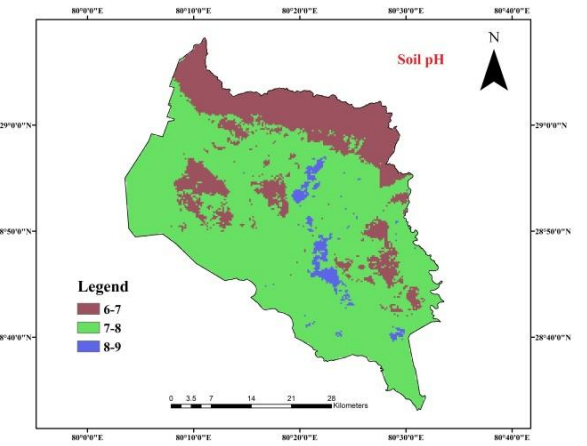


Figure 8. Soil pH level map

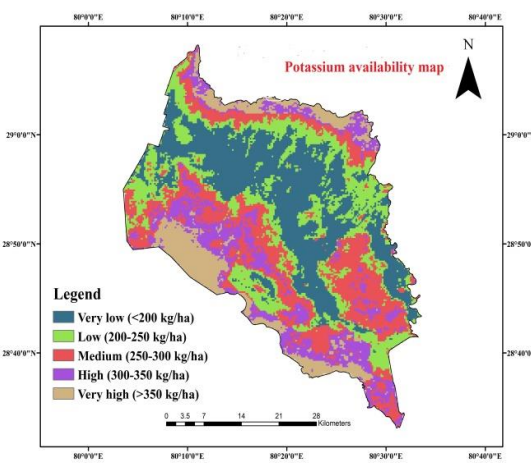


Figure 6. Potassium availability map

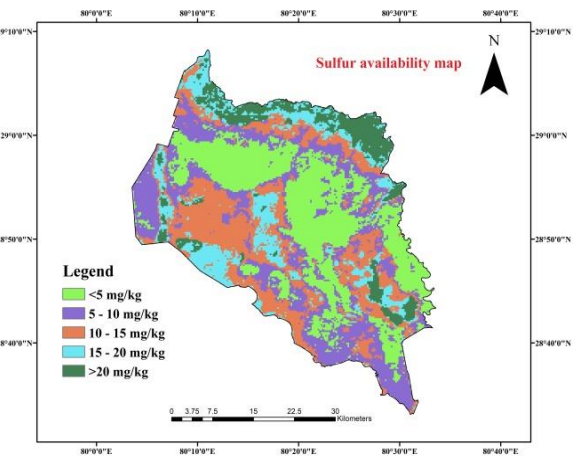


Figure 9. Sulfur availability map

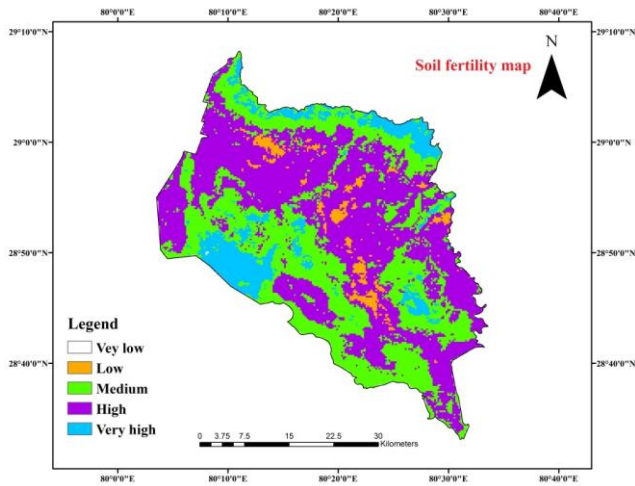


Figure 10. Soil fertility map

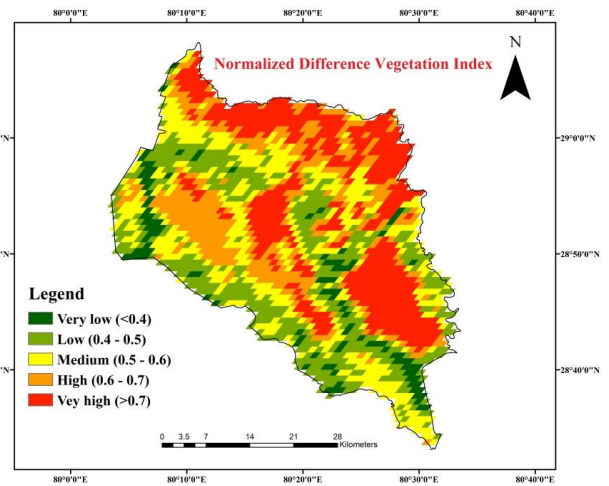


Figure 13. NDVI map

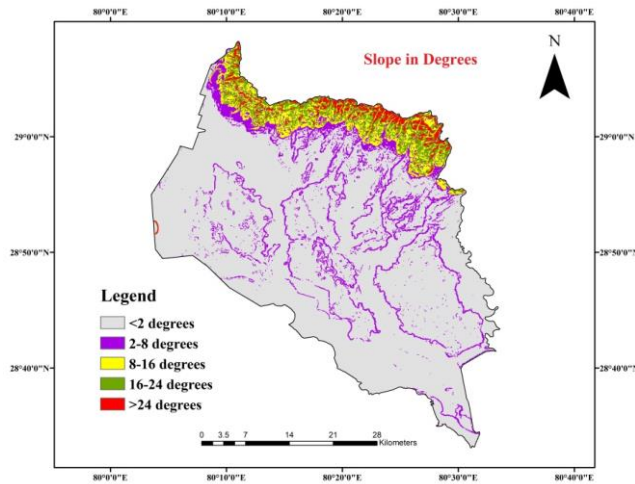


Figure 11. Slope map

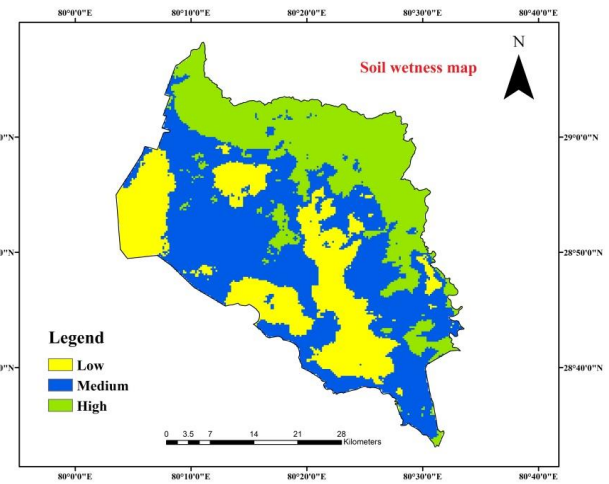


Figure 14. Wetness map

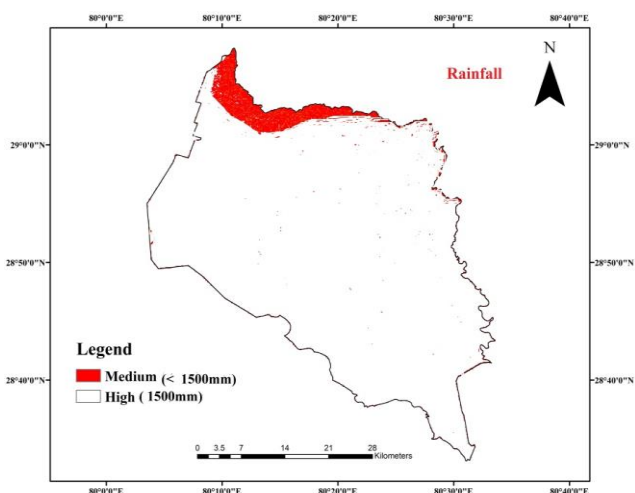


Figure 12. Rainfall map

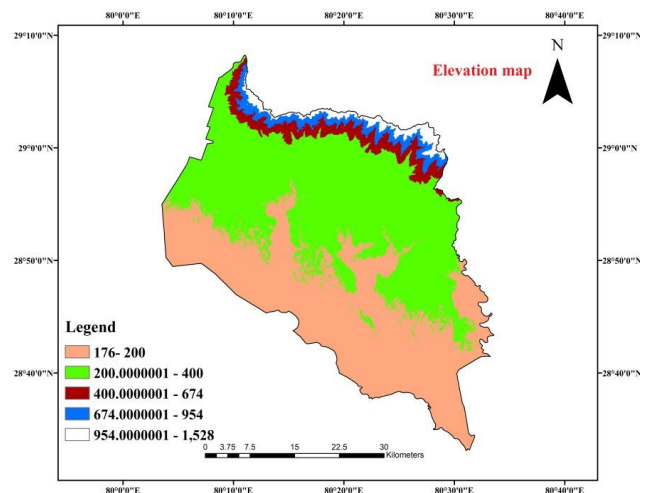


Figure 15. Elevation map

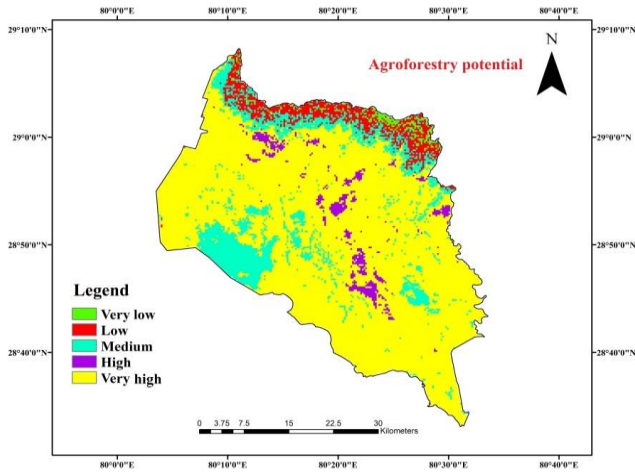


Figure 16. Agroforestry potential map

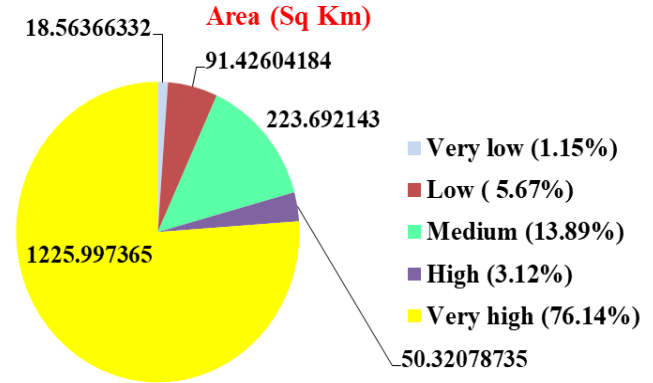


Figure 17. Agroforestry potential area

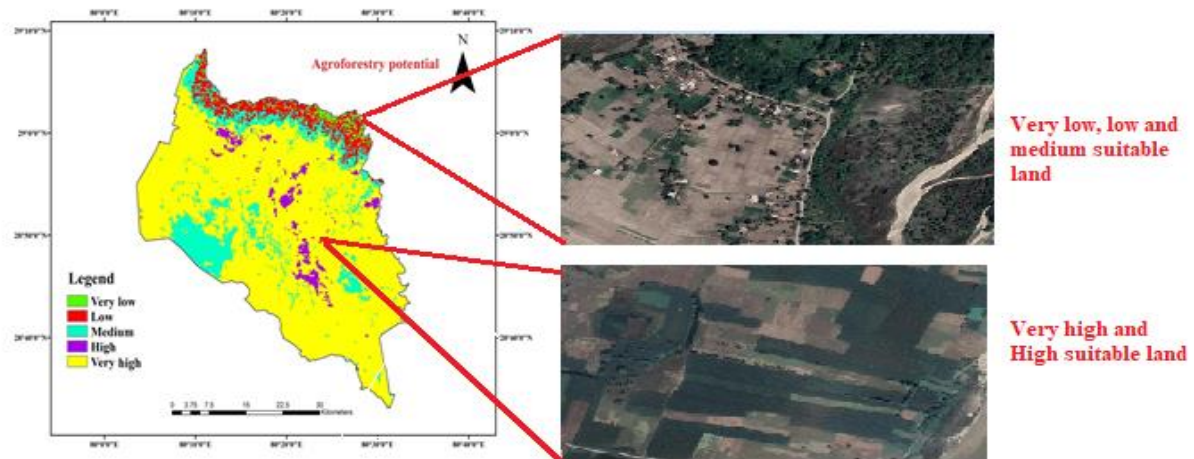


Figure 18. Accuracy assessment for agroforestry suitability map

Table 4. Ground truth data, accuracy, and Kappa coefficient

Ground truth	Good	Medium and bad	Undefined*	Total	User's accuracy(%)
Good	22	3	5	30	73.33333333
Medium and bad	1	13	6	20	65
Total	23	16	11	50	
Producers' accuracy (%)	95.65217391	81.25			
Kappa coefficient	0.67				Overall accuracy=70%

Note: \*land conditions that are unclear to distinguish. The overall accuracy was 70%, while the kappa coefficient was 0.67. Since the classified maps' Kappa value was within 0.61-0.8, they are substantial and meet the accuracy assessment. (Note: According to Landis et al., 1977 considers 0-0.20 as slight, 0.21-0.40 as fair, 0.41- 0.60 as moderate, 0.61-0.80 as substantial, and 0.81-1 as almost perfect. Fleiss considers kappa > 0.75 as excellent, 0.40-0.75 as fair to good, and < 0.40 as poor)

**Discussion**

Agroforestry planning in tree/crop harvesting is intricately associated with agro-climatic factors (Ekka et al., 2020) and can be defined by determining agroforestry suitability (Ahmad et al., 2021). Soil fertility, slope, elevation, annual rainfall pattern, wetness, NDVI, Organic matter, and pH all play a role in an area's agroforestry suitability. Nitrogen, phosphorus, sulfur, organic matter,

and pH affect soil fertility. Therefore, high agroforestry suitability is characterized by high soil fertility, high annual rainfall, high wetness, high NDVI, and low slope and elevation. Generally, hills have harsh slopes and terrain, so in terms of slope, agroforestry suitability is low compared to the area with moderate and low slopes. That is because hills have low water holding capacity and, as a result, the wetness level of the soil.

The agroforestry suitability mapping for the Kanchanpur District of Sudurpaschim province, Nepal, showed 1225 sq km (76.14%) area with very high suitability, 50.32 sq km (3.12%) area with high suitability, 223.69 sq. km (13.89%) area, with medium suitability, 91.42 sq km (5.67%) with low suitability and 18.56 sq km (1.15%) with very low suitability. The high-priority regions were discovered in open areas with abundant soil nutrients and adequate wetness, high rainfall, a moderate or low slope, and elevation, which all contribute to ideal plant growth conditions. They are primarily found in the southeast part of the study area. They are best suited for paddy crop cultivation due to suitable water and moisture availability during the rainy season. Medium agroforestry adaptability areas were common in moderate soil nutrients; high to moderate wetness, high to average rainfall, low to moderate slope, and low to medium elevation provided moderately favorable conditions for plant growth, accounting for about 13.89 percent of the entire research area. These areas are highly suitable for silvi-pastoral practices; soil binder grasses are likely to produce the desired results, as Ahmad et al. (2017) mentioned. The northwestern part exhibits harsh slope conditions, resulting in low agroforestry suitability. According to Ahmad et al. (2017), the lands suitable for agroforestry are found closer to rivers/lowland areas because of their high soil fertility and abundant soil wetness. In contrast, the soil in the southwestern part of the study areas is less suitable for agroforestry because of its low to medium soil fertility and low wetness, which contradicts our findings. Considering the site condition of the study region, several agroforestry systems such as Agri-Horti silviculture, Agri-silviculture, Silvi-pastoral, and agro-Silvi-pastoral can be effectively utilized. Waterlogged tree species such as *Albizia procera* (Roxb.) Benth. (white siris), *Butea monosperma* (Lam.) Kuntze (Palash), *Syzygium cumini* (L.) Skeels, *Terminalia arjuna* (Roxb.) Wight & Arn., and *Anthocephalus cadamba* (Roxb.) Miq. can be grown, whereas unfertile land tree species such as *D. sissoo*, *Gmelina arborea* Roxb. ex Sm., *Madhuca indica* J.F.Gmel., *Albizia lebeck* (L.) Benth., *Ziziphus jujuba* Mill., and *Acacia catechu* (L.f.) Willd. can be grown. In addition, tree species such as *Azadirachta indica* A.Juss., *Pongamia pinnata* (L.) Pierre, *T. arjuna*, *A. procera*, *A. lebeck*, and *Acacia auriculiformis* A.Cunn. ex Benth. can be grown in alkaline soil (Ahmad et al., 2021). The multipurpose leguminous tree species can be raised in field bunds to enhance the soil fertility of the land (Jhariya et al., 2018). A highly suitable landscape can be planned for the Agri-Silvi horticulture system based on the farmer's socio-economic needs with vegetables such as brinjal (*Solanum melongena* L.), cabbage (*Brassica oleracea* var. *capitata*), cauliflower (*Brassica oleracea* var. *botrytis*), okra (*Abelmoschus esculentus*), potato (*Solanum tuberosum* L.), tomato (*Solanum lycopersicum* L.) (Pandit et al. 2014). Medium areas can be preferred for an agri-silviculture practice, provided with an adequate irrigational facility during the off-monsoon season to ensure suitable soil moisture for trees and crops (Ahmad et al., 2021).

In conclusion, this study drew on various themes from numerous sources of information connected to multiple

agroforestry systems. Computer-based varied datasets and their logical analysis utilizing geospatial tools such as rs and gis have substantially improved the decision-making process for users such as landowners, foresters, and farmers to meet the aims of agroforestry suitability mapping. The government has launched several programs for the impoverished and tribal people/farmers to implement integrated land management plans to maximize agroforestry potential. It is necessary to identify potentially suitable land for agroforestry and develop or redirect existing programs to utilize it considerably, improving livelihood. Agroforestry is similar to hanging fruits that must be harvested scientifically.

Agroforestry is regarded as the backbone of marginal farming for self-sufficiency and sustainability. It can tackle the most severe food security concerns, while environmental security is a crucial advantage of agroforestry systems. The results show that three-fourths of the total land in the research region has a high potential for agroforestry practice because it falls in the very high appropriate category (s1), provided restrictions such as soil moisture, enough funding, and proper technical assistance are addressed. The findings and suitability map may be implemented into many existing and future land-based management programs, resulting in long-term advantages to rural and tribal people in poverty alleviation through increased livelihood choices. Assessing the land's capability and potential for appropriateness for various crop/tree productivity is necessary. Policymakers must incorporate such data into future land planning and management to ensure crop and tree appropriateness. Even though topographic shadows in satellite images, like layover and forecasting effect, were a significant hindrance in image classification, this research describes the tremendous ability of remote sensing (coarse resolution data) as well as spatial dimensions of land, soil, climate, and topographical data integration under gis domain, demonstrating its enormous potential for evaluating land capability and economic output.

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