Integration of GIS and remote sensing for evaluating forest canopy density index in Kunar Province, Afghanistan

Intégration du SIG et de la télédétection pour évaluer l'indice de densité du couvert forestier dans la province de Kunar, Afghanistan

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ABSTRACT: Forests are an essential component of the natural environment and are essential to the advancement of sustainable development. But each year, natural forests are being destroyed by human endeavors. For this reason, forest management is essential to sustainable development. The forest canopy density (FCD) model is a valuable tool for assessing the condition of forests and their alterations over time. Three criteria are chosen to evaluate FCD: shadow index (SI), bare soil (BI), and advanced vegetation (AVI). Satellite images are used to calculate these characteristics. To compute the FCD, the Landsat 8 OLI image from 2023 is first normalized and then worked with in ArcGIS and ENVI software. When comparing the categorization result with the land cover map, the total accuracy is 86.6%. The distribution of forest canopy density in the study region is depicted in the final result, which includes non-forest, low, moderate and intense forest densities.
KEY WORDS: Forest canopy density, Remote Sensing and GIS, AVI, SI, BSI.

RÉSUMÉ: Les forêts sont une composante essentielle de l'environnement naturel et sont essentiels à la promotion du développement durable. Mais chaque année, les forêts naturelles sont détruites par les activités humaines. C'est pour cette raison que la gestion forestière est essentielle au développement durable. Le modèle de densité du couvert forestier (FCD) est un outil précieux pour évaluer l'état des forêts et leurs altérations au fil du temps. Trois critères sont choisis pour évaluer le FCD : l'indice d'ombre (SI), le sol nu (BI) et la végétation avancée (AVI). Des images satellites sont utilisées pour calculer ces caractéristiques. Pour calculer le FCD, l'image Landsat 8 OLI de 2023 est d'abord normalisée puis utilisée dans les logiciels ArcGIS et ENVI. En comparant le résultat de la catégorisation avec la carte de couverture terrestre, la précision totale est de 86,6 %. La répartition de la densité du couvert forestier dans la région d'étude est représentée dans le résultat final, qui comprend les densités forestières non forestières, faibles, modérées et intenses.
MOTS CLÉS : Densité du couvert forestier, Télédétection et SIG, AVI, SI, BSI.

1. Introduction

The percentage of the forest floor that is covered by the vertical projection of tree crowns is referred to as the forest canopy cover, canopy coverage, or crown cover (Jennings, Brown, & Sheil, 1999). Kunar's primary topography is made up of mountains and hills, which make up three-quarters of the country. Kunar thus boasts a varied forest ecology (Bader, Hanna, Douglas, & Fox, 2013). But over time, there has been a decline in the amount and quality of the forest. In study area forest types have been explored by (Bader et al., 2013; Reddy & Saranya, 2017) but there is lack of finding the density of forest cover in the study area. In order to preserve and safeguard the forest ecosystem, forest management becomes a pressing matter. A crucial instrument for the sustainable management of natural resources is the monitoring of forest canopy cover (Akike & Samanta, 2016). When designing and executing a restoration program, forest canopy density (FCD) is one of the most helpful indicators to take into account to measure ≥ 2m high tree cover (Saei Jamalabad & Abkar, 2000), (Kwon et al., 2012) and it plays a significant role in assessing the condition of the forest and management interventions (Azizi, Najafi, & Sohrabi, 2008). One of the most important factors to take into account when organizing and carrying out afforestation and reforestation projects is mapping the forest canopy density (Chandrashekhar, Saran, Raju, & Roy, 2005). Research is using satellite remote sensing more and more. Information regarding land usage and land cover is generated with the aid of multi-temporal satellite photos. Using classification techniques, remotely sensed photos are frequently used to obtain information about the land cover of forests (Mickelson, Civco, & Silander, 1998). The three factors that comprise the FCD model in this work are the canopy shadow index (SI), bare soil index (BSI), and advanced vegetation index (AVI) (Deka, Tripathi, & Khan, 2013; Loi, Chou, & Fang, 2017). The distribution of FCD in the research area is ascertained by processing Landsat images using ENVI and ArcGIS software (Azizi et al., 2008; Loi et al., 2017). The purpose of this research is to investigate the density of forest cover in the study area and how satellite imagery may be used to evaluate the FCD in order to support resource management.

2. Study area

Kunar's is one of the 34 provinces of Afghanistan, located in the northeastern part of the country. Its Capital is Asadabad. Geographic coordinated of the study area is 35◦0' 0" N, 71◦ 12' 0"E. Kunar borders the following three provinces: Nangarhar, Nuristan, and Laghman. The Study covers an area of 4339 km2. 86% of the study area is mountains terrain (Bader et al., 2013). The primary geographic features of the study area are the lower Hindu Kush mountains which are cut by the Kunar River to form the forested Kunar Valley. Administratively, the province of Kunar Province is divided into sixteen districts (Asadabad, Bar Kunar, Chapa Dara, Chawkay, Dangam, Dara-I-Pech, Ghaziabad, Khas Kunar, Marawara, Narang Aw Badil, Nari, Nurgal, Shaigal, Shultan, Sirkani, and Wata Pur (Figure 1). Kunar is regarded as the primary source of timber extraction in the Northeast Region of the country (Bader et al., 2013).

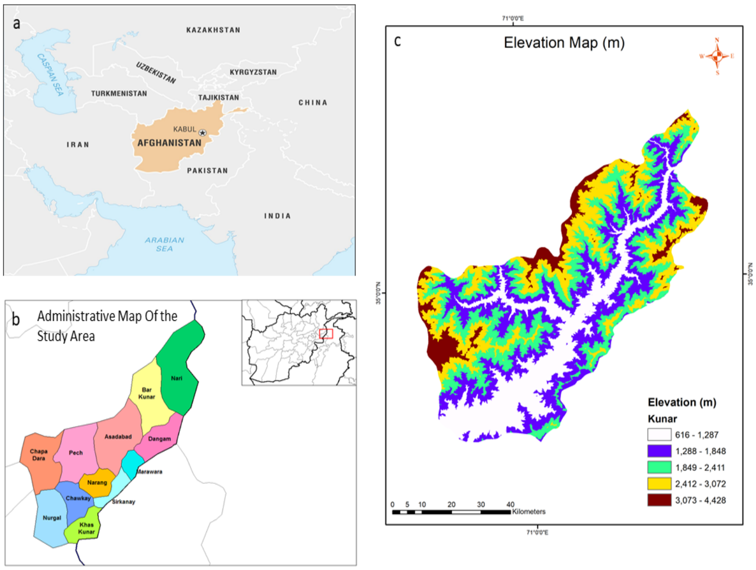

Figure 1 Location of the study area, (a) showing the geographic extent of the region, (b) administrative map of the area under study, (c) study Area Map of Kunar Province, highlighting the geographic extent under investigation.

3. Methods

This study made use of a Landsat 8 Operational Land Imager (OLI) satellite image that the U.S. Geological Survey (USGS) https://earthexplorer.usgs.gov/ provided in July 2023. Its 64-bit data size is made up of one panchromatic band with a greater spatial resolution of 15 meters and several pleasant spectral bands with a spatial resolution of 30 meters. The density of the forest canopy has been examined in this study. The density of the forest canopy is a crucial metric used by the Forest Canopy Density model to characterize the conditions of the forest.

This model uses information from tree indices to model and analyze bio-spectral phenomena.

- The Index of Advance Vegetation (AVI).
- Index of Bare Soil (BSI).
- Scaled Shadow Index (SI, SSI) or Shadow Index.

The methods in details are displayed in (Figure 2) below:

A. Conversion to Top of Atmosphere (TOA) Radiance

Digital numbers (DN) that have been scaled and quantized make up Landsat 8, which was utilized in this investigation. The range of values in this 64-bit format is 0 to 28 = 65536 (Azizi et al., 2008; Loi et al., 2017; Pandian & Nandhini, 2016). In order to calculate the vegetation indices, it must be converted into a radiance value. Equation (1) has been utilized in this approach.

$$L\lambda = MLQcal + AL \qquad (1)$$

where, $L\lambda$ = TOA spectral radiance (Watts/(m^2* srad *µm)).
ML = Multiplicative rescaling factor from the metadata that is specific to a band.
AL = is the metadata-derived band-specific additive rescaling factor.
Qcal = refers to standard product pixel values (DN) that have been quantized and calibrated.

B. Forest Canopy Density Index Calculation

The Advanced Vegetation Index (AVI), Bare Soil Index (BI), and Shadow Index (SI), sometimes known as Scaled Shadow Index (SSI), are the three parameters used to construct the Forest Canopy Density Index (FCDI) (Azizi et al., 2008; Loi et al., 2017). The value of the forest canopy density was computed as a percentage of each pixel using a range of 0 to 100.

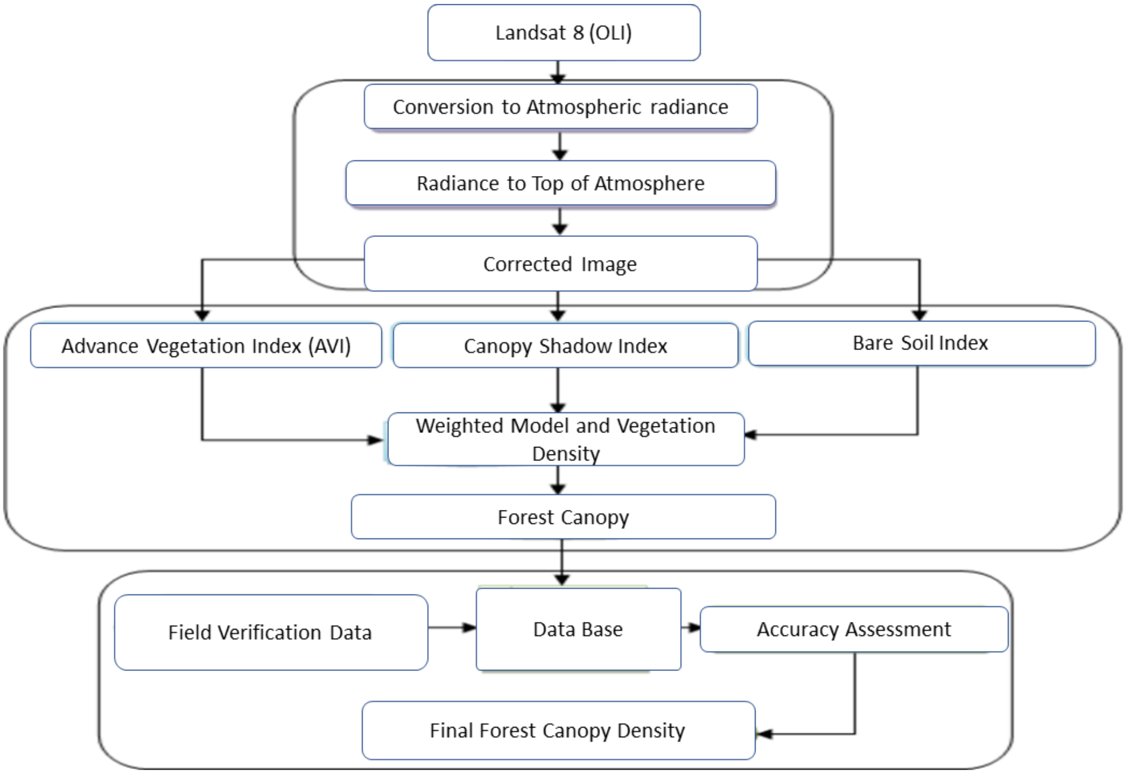

Figure 2 Research route of the methodology**.**

Index of Advanced Vegetation (AVI)

AVI is a crucial metric for identifying robust vegetation in the red and near-infrared regions of the spectrum. It is comparable to the oldest and most popular vegetation indicator in remote sensing, the Normalized Difference Vegetation indicator (NDVI) (Rikimaru, Roy, & Miyatake, 2002; Wang, Qi, & Cochrane, 2005). On the other hand, NDVI is widely used to categorize areas with high and low vegetation. Pointing out minute variations in the canopy density is illogical. Consequently, AVI was chosen for this investigation based on the infrared response's power degree. Equation (2) is used to calculate this index (Loi et al., 2017). The outcome is displayed in Figure 3.

$$AVI = [(B5+1)(65536-B3)(B5-B4)]^{1/3} \quad (2)$$

where B4 is the red band and B5 is the near-infrared band.

Index of Bare Soil (BSI)

To capture soil differences, blue, red, near infrared, and short wave infrared spectral bands are merged to create BSI. (Azizi et al., 2008; Loi et al., 2017)The blue and near infrared spectrum bands are utilized to increase the presence of plants, while the short wavelength infrared and the red band are used to assess the mineral makeup of the soil. Equation (3) is used to generate this index. The outcome is shown in Figure 4.

$$BI = (B6+B4)-(B5+B2)/(B6+B4)+(B5+B2)*100+100 \qquad (3)$$

where B5 is the near infrared band, B6 is the shortwave infrared band, B2 is the green band, and B4 is the red band.

Density of vegetation (VD)

In the analysis of forest canopy density, vegetation density (VD) is a crucial statistic that provides information about the density and spatial distribution of forest cover (Azizi et al., 2008; Loi et al., 2017). VD aids in the evaluation of the size and condition of forest ecosystems by measuring the amount of vegetation found in a particular area. While lower numbers may indicate sparse or degraded forest regions, higher values usually indicate dense, healthy woods (Azizi et al., 2008; Loi et al., 2017). Monitoring the health of forests, efficiently managing natural resources, and putting conservation measures into practice all depend on this analysis. Principal component analysis, which is based on the two input parameters AVI and BI, is used to perform VD (Azizi et al., 2008; Loi et al., 2017). In Figure 5, the value of VD is expressed and ranges from 0 to 100 percent.

Scale Shadow Index (SSI)

By using a linear transformation, the canopy shadow index (SI) is used to calculate the SSI (Rikimaru et al., 2002). Moreover, the SSI value is scaled from 0% to 100%. Whereas 0% responds in the other way, 100% of SSI responds with the largest shadow conceivable (Joshi, De Leeuw, Skidmore, Van Duren, & Van Oosten, 2006), (Loi et al., 2017). Since the canopy shadow offers crucial information on the arrangement of trees and plants, SI is regarded as the primary application in forestry and crop monitoring. This index, which is determined using the visible bands of the spectrum as the equation (4), is frequently used in conjunction with AVI and BSI to represent the state of the vegetation(Azizi et al., 2008; Loi et al., 2017). The outcome is displayed in Figure 6.

$$SI = [(65536-B2)\,(65536-B3)\,(65536-B4)]^{1/3} \qquad (4)$$

where B3 is the blue band, B4 is the red band, and B2 is the green band.

Density of the forest canopy (FCD)

One index used to determine the quality of the forest is FCD. Transformation of the forest canopy density value is achieved through the integration of VD and SSI (Nandy, Joshi, & Das, 2003). Equation (5) is used to calculate FCD by combining VD and SSI. Figure 7 describes FCD on a scale from 0 to 100 percent (Loi et al., 2017).

$$FCD = [(VD)(SSI)]^{1/2} \qquad (5)$$

Table 2. Relationship in between FCD and its Parameters.

Index	High FCD	low FCD	Grassland	Bare land
Avi	high	mid	high	low
Bi	low	low	low	high
SI	high	mid	low	low
VD	high	mid	mid	low

4. Results and discussion

The results and discussion section of this research paper presents findings related to the categorization of forest canopy density in Kunar province, along with the assessment of the accuracy of the methodology used. Firstly, the researchers classified each pixel into one of four categories of forest canopy density based on a methodology outlined by (Loi et al., 2017). The researchers utilized this classification to generate a map depicting the distribution of forest resources across Tehran and ThaiNguyen province (Jamalabad, 2004; Loi et al., 2017). These categories include non-forest, low forest density, moderate forest density, and dense forest density see (Table 1) (Figure 8). Dense forests were characterized as areas occupying 85% to 100% of the pixel, while moderate, low, and non-forest categories corresponded to 50–85%, 15–50%, and less than 15% of the area, respectively. Dense forest were mainly found in areas with ample water supply and undulating terrain, promoting plant growth.

The research area's north and south have a number ofrivers, tiny lakes and ponds that have been seen. Thus, it can be said that the study region has a water supply, which supports the growth of plants. The presence of rivers, lakes, and ponds in the north and south of the study area indicates a significant water supply, which supports vegetation growth. The availability of water resources positively impacts the forest canopy density, contributing to higher densities in these regions. A number of tiny, undulating hillocks can be seen in the heart of the study area, which is also where the canopy cover density is located. However, the shadow effect of hills can cause classification errors overall, which is why the canopy shadow index was developed to remove the canopy cover's shadow effect. The bare soil index (Figure 4) has been computed to identify areas of non-forest or bare soil that are visible in the image. This index aids in distinguishing non-forest environments, contributing to more accurate classification of land cover. The classification of other non-forest environments can also be aided by this index. The purpose of these four parameters (VD, AVI, BSI, and SI) see (Figure 3-6) is to produce a classified canopy density map (Banerjee, Panda, Bandyopadhyay, & Jain, 2014) see (Figure 7).

Applying a same measurement scale of values to many and distinct inputs to produce an integrated analysis is known as weighted overlay. Every layer in the weighted model is given a weighted value based on how important they are for identifying the canopy cover (Banerjee et al., 2014). For example, the Advance Vegetation Index has a greater weighted value since it contributes more than the Canopy Shadow Index (Banerjee et al., 2014). Also included is the percentage of contributions in the weighted model for each class within each Index. The majority of Kunar province was found to be covered by moderate to low densities of forests. The accurate classification of forest canopy density has significant implications for landscape management and conservation efforts. Identifying areas with varying densities allows for targeted conservation strategies, resource allocation, and sustainable management practices. Understanding the distribution of forest density helps in planning infrastructure development, ensuring that projects do not adversely affect critical forest areas.

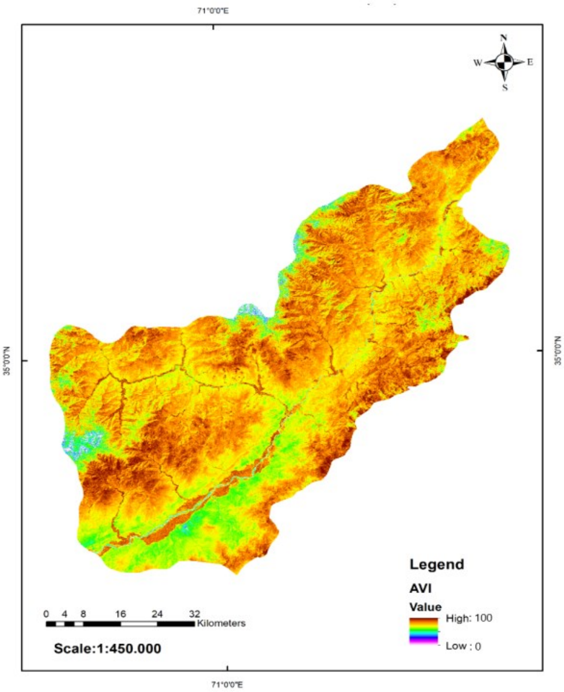

Figure 3 Advance Vegetation Index (AVI) representation of Kunar Province, depicting vegetation density from low to high index values. The AVI highlights areas of varying vegetation cover across the study area, providing valuable insights into vegetation distribution and density.

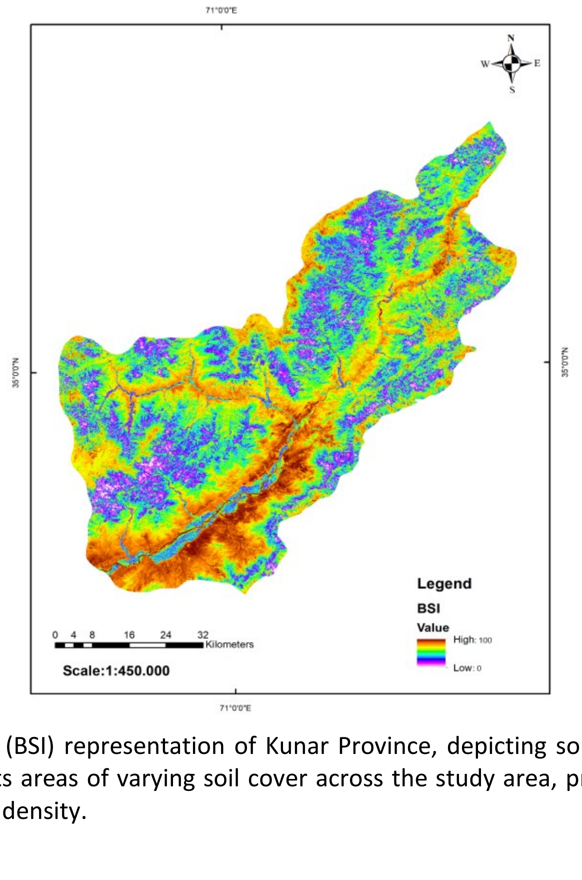

Figure 4 Bare Soil Index (BSI) representation of Kunar Province, depicting soil from low to high index values. The AVI highlights areas of varying soil cover across the study area, providing valuable insights into soil distribution and density.

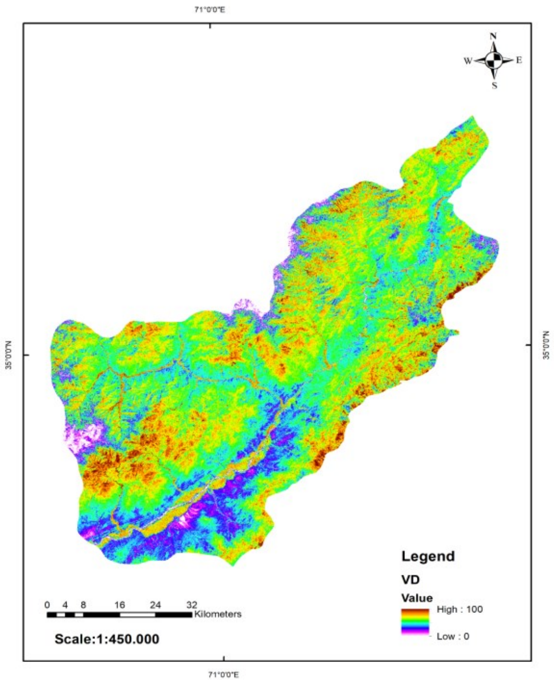

Figure 5 Vegetation Index (VI) representation of Kunar Province, depicting vegetation cover from low to high index values. The VI highlights areas of varying vegetation cover across the study area, providing valuable insights into vegetation distribution and density.

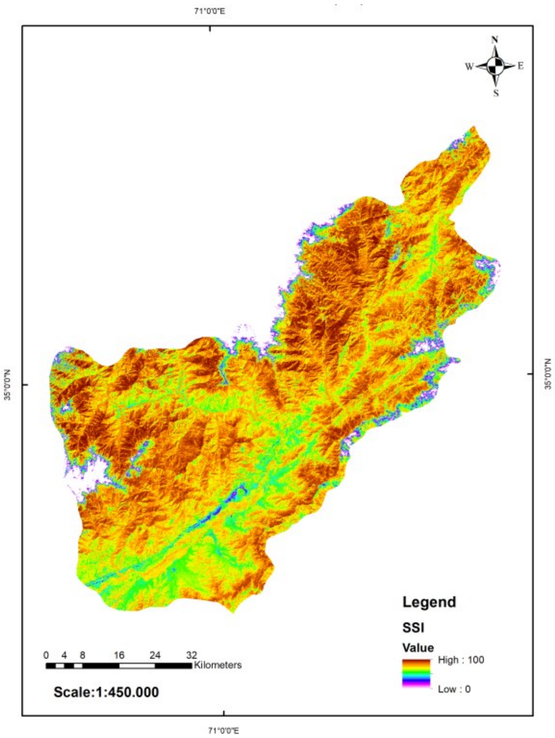

Figure 6 Scale Shadow Index (SSI) representation of Kunar Province, depicting shadow index from low to high index values. The SSI highlights areas of varying canopy cover across the study area, providing valuable insights into canopy distribution and density.

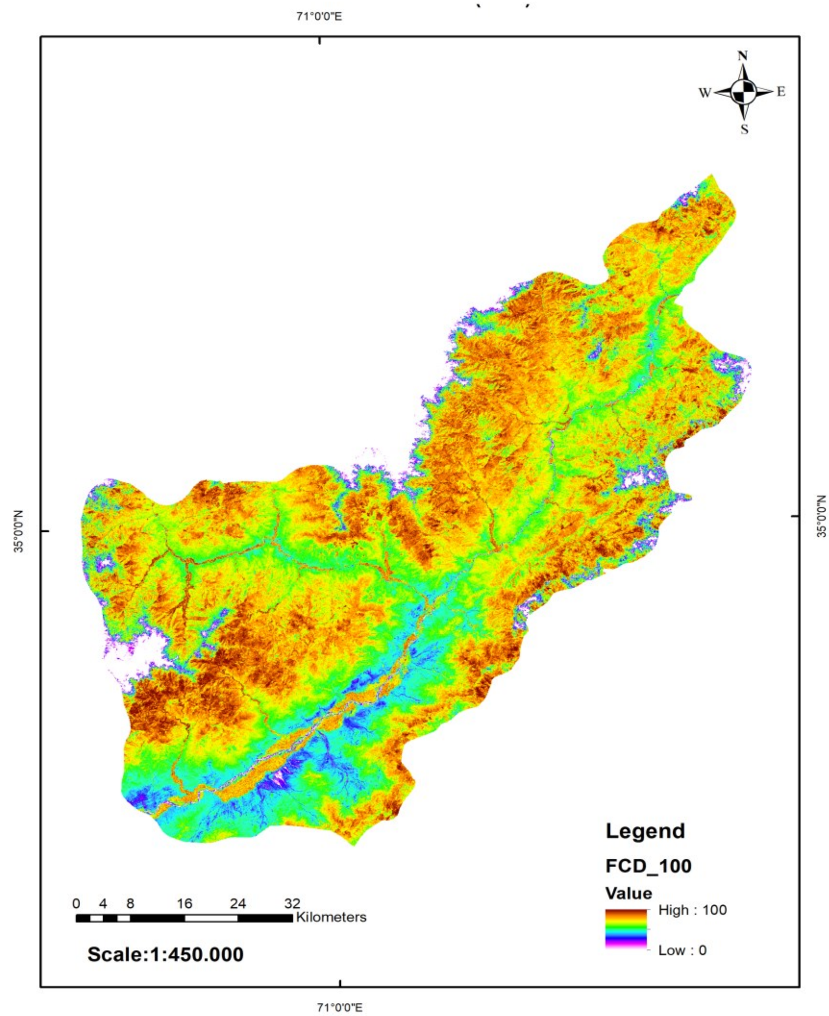

Figure 7 Forest Canopy Density (FCD), representation of Kunar Province, depicting canpy density of forest from low to high values. The AVI highlights areas of forest canopy cover across the study area, providing valuable insights into forest cover distribution and density.

Reliable data on forest canopy density supports local communities by informing them about forest resources, which are crucial for their livelihoods, particularly in regions dependent on forestry. Accurate mapping and validation can aid in disaster management, such as planning for flood zones and understanding water catchment areas, thereby enhancing community resilience. To validate the accuracy of their findings, the researchers conducted fieldwork using a land cover map (Jamalabad, 2004; Loi et al., 2017) (Abdollahnejad, Panagiotidis, & Surový, 2017). The results of this validation process are presented in Table I, indicating a Kappa Coefficient of 0.80 and an Overall Accuracy of 86.6%. These metrics suggest a high level of agreement between the classified forest canopy density and the ground truth obtained through fieldwork (Abdollahnejad et al., 2017). Overall, the results suggest that the methodology employed effectively categorized forest canopy density in Kunar province, with the majority of the area characterized by moderate to low densities of forests. The validation process further confirmed the accuracy of the classification, providing confidence in the reliability of the study's findings.

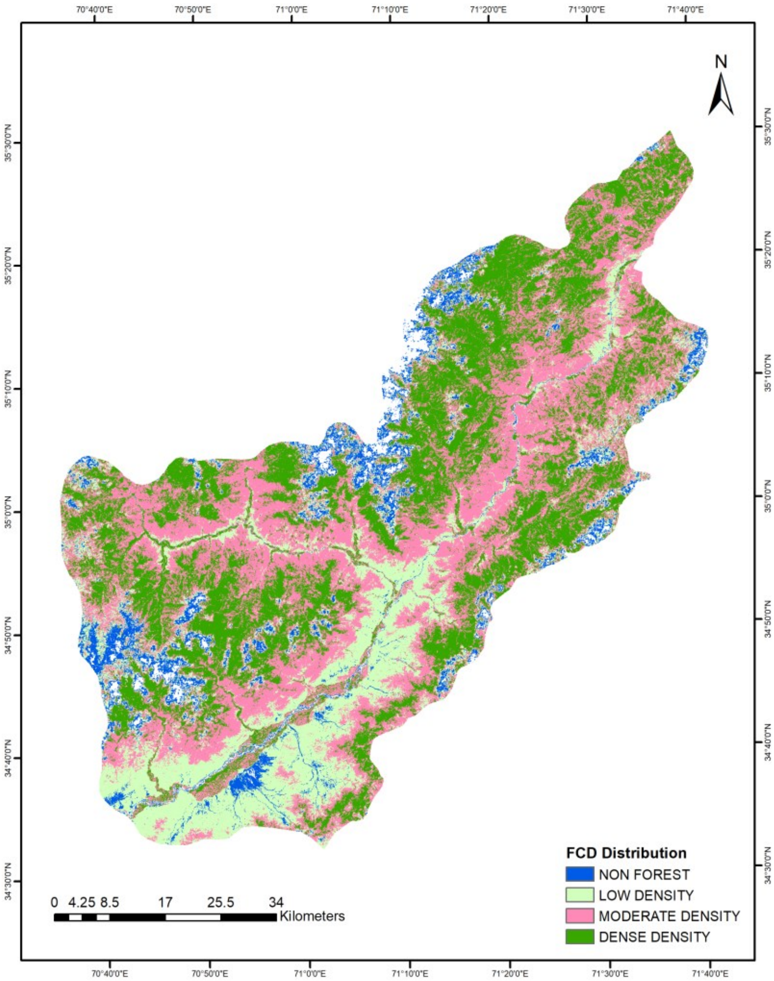

Figure 8 Distribution Map of Forest Canopy Density (FCD) in the study area.

Table 1 Confusion Matrix.

	Dense density Forest	Moderate density Forest	Low density Forest	Non-Forest	Total
Class 1	5251	302	15	33	5601
Class 2	250	3246	190	3	3689
Class 3	72	127	1000	806	2005
Class 4	83	20	20	1663	1786
Total	5656	3695	1225	2505	13081

Kappa Coefficient = 08.0, overall Accuracy = 86.6%

5. Conclusion

Numerous variables must frequently be evaluated when solving geographic challenges. For example, several parameters such as AVI, BSI, and SI are needed to delineate the canopy density map. Large-scale estimates of the thick forest fluctuations were made in this study using data from the Landsat 8 satellite. The degree of canopy density on the forest canopy density map represented the state of the forests in Kunar province. But this research can advance by utilizing a large number of satellite images from various eras. Accurate measurements of canopy density are achievable, but they require additional information on DEM, slope, soil type, and other variables specific to the research area. In order to meet these parameters' requirements, Advance Indexes have been taken into account. These indexes are the combined outcome of various factors, including slope, DEM, and so forth. This aids in evaluating how the density of the forest canopy varies across space and time. This is a crucial criterion for assessing the quality of the forest and providing data for forest management.

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Bilal Jan HAJI MUHAMMAD and Wang PING contributed equally to this work.

References

Abdollahnejad, A., Panagiotidis, D., & Surový, P. (2017). Forest canopy density assessment using different approaches-review. *Journal of Forest Science, 63*(3), 107-116.

Akike, S., & Samanta, S. (2016). Land use/land cover and forest canopy density monitoring of Wafi-Golpu project area, Papua New Guinea. *Journal of Geoscience and Environment Protection, 4*(08), 1.

Azizi, Z., Najafi, A., & Sohrabi, H. (2008). Forest canopy density estimating, using satellite images. Commission VIII, WG VIII/11. *Proceedings of ISPRS, Beijing (China)*, 4.

Bader, H. R., Hanna, C., Douglas, C., & Fox, J. D. (2013). Illegal timber exploitation and counterinsurgency operations in Kunar Province of Afghanistan: A case study describing the nexus among insurgents, criminal cartels, and communities within the forest sector. *Journal of sustainable forestry, 32*(4), 329-353.

Banerjee, K., Panda, S., Bandyopadhyay, J., & Jain, M. K. (2014). Forest canopy density mapping using advance geospatial technique. *international Journal of innovative science, engineering & technology, 1*(7), 358-363.

Chandrashekhar, M. B., Saran, S., Raju, P., & Roy, P. (2005). Forest canopy density stratification: How relevant is biophysical spectral response modelling approach? *Geocarto International, 20*(1), 15-21.

Deka, J., Tripathi, O. P., & Khan, M. L. (2013). Implementation of forest canopy density model to monitor tropical deforestation. *Journal of the indian society of remote sensing, 41*, 469-475.

Jamalabad, M. (2004). *Forest canopy density monitoring using satellite images.* Paper presented at the Geo-Imagery Bridging Continents XXth ISPRS Congress, Istanbul, Turkey, 2004.

Jennings, S., Brown, N., & Sheil, D. (1999). Assessing forest canopies and understorey illumination: canopy closure, canopy cover and other measures. *Forestry, 72*(1), 59-74.

Joshi, C., De Leeuw, J., Skidmore, A. K., Van Duren, I. C., & Van Oosten, H. (2006). Remotely sensed estimation of forest canopy density: A comparison of the performance of four methods. *International Journal of Applied Earth Observation and Geoinformation, 8*(2), 84-95.

Kwon, T.-H., Lee, W.-K., Kwak, D.-A., Park, T.-J., Lee, J.-Y., Hong, S.-Y., . . . Kim, S.-R. (2012). Forest canopy density estimation using airborne hyperspectral data. *Korean Journal of remote sensing, 28*(3), 297-305.

Loi, D. T., Chou, T.-Y., & Fang, Y.-M. (2017). Integration of GIS and remote sensing for evaluating forest canopy density index in Thai Nguyen Province, Vietnam. *International journal of environmental science and development, 8*(8), 539-542.

Mickelson, J. G., Civco, D. L., & Silander, J. (1998). Delineating forest canopy species in the northeastern United States using multi-temporal TM imagery. *Photogrammetric engineering and remote sensing, 64*, 891-904.

Nandy, S., Joshi, P., & Das, K. (2003). Forest canopy density stratification using biophysical modeling. *Journal of the indian society of remote sensing, 31*, 291-297.

Pandian, M., & Nandhini, R. (2016). Forest canopy density and ASTER DEM based study for dense forest investigation using remote sensing and GIS techniques. *International Journal of Research in Environmental Science and Technology, 6*(1), 1-4.

Reddy, C. S., & Saranya, K. (2017). Earth observation data for assessment of nationwide land cover and long-term deforestation in Afghanistan. *Global and Planetary Change, 155*, 155-164.

Rikimaru, A., Roy, P., & Miyatake, S. (2002). Tropical forest cover density mapping. *Tropical ecology, 43*(1), 39-47.

Saei Jamalabad, M., & Abkar, A. (2000). Vegetation coverage canopy density monitoring, using satellite images. *ISPRS commission VII, 17*.

Wang, C., Qi, J., & Cochrane, M. (2005). Assessment of tropical forest degradation with canopy fractional cover from Landsat ETM+ and IKONOS imagery. *Earth Interactions, 9*(22), 1-18.