

# COMPARING TWO DIFFERENT RADIOMETRIC CORRECTIONS IN A VEGETATION MAPPING OF MOUNTAINOUS AREA USING FOREST COVER DENSITY TRANSFORMATION

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ABSTRACT: Vegetation mapping has been mostly carried out using remote sensing imagery. Vegetation index and forest cover density (FCD) transformation were frequently used for this purpose. The FCD transformation assumes that the vegetation index is less able to distinguish structural composition-related density, so that new approach involving several indices at once has been introduced. Meanwhile, radiometric correction is also strongly required for any spectral transformation including FCD. This study aimed to compare the effect of two kinds of radiometric correction on the vegetation structural composition in Arjuno-Welirang volcanic areas. East Java, Indonesia. Landsat 8 OLI image dataset which includes blue to mid-infrared and thermal bands were used to generate the FCD models. The Landsat dataset was treated with two kinds of radiometric correction, namely atmospheric correction with FLAASH and additional topographic correction using SCS+C. To derive FCD map, we transformed the original image dataset into Advanced Vegetation Index (AVI), Soil Brightness Index (BI), Shadow Index (SI), and Thermal Index (TI) images. We also added NDVI for a comparison. All indices were combined in three stages to derive the FCD models. All inputs made use of atmospheric corrected images in one treatment, and additional topographic correction in another one. Field surveys were carried out to produce two independent types of vegetation density and structural composition data for classification reference and for of FCD estimate accuracy assessment. This study found that in very rough mountainous terrain conditions such as in the study area, the FCD transformation was less able to produce maps of structural vegetation composition, since the accuracies obtained were only about 30%. However, the use of topographic correction was able to increase the accuracy from 29.92% (with atmospheric correction only) to 32.53%. The less accurate estimates of the vegetation density and structural composition mainly occurred on the slopes with 40-56% steepness.

#### 1. INTRODUCTION

Remote sensing is able to extract the characteristics of biophysical parameters in land-cover/land-use and vegetation studies to build new information in the scope of ecology (Jensen, 2015, Hidayati *et al.*, 2018; Danoedoro, 2019; Tesfaye and Awoke, 2021). Many studies of vegetation by mapping have used remote sensing as a data source, including mapping the density of the vegetation canopy. (Xue and Su, 2017; Bera *et al.*, 2020). The information extraction process can be carried out using digital interpretation and analysis, both with multispectral classification (Dimyati *et al.*, 2018) and spectral transformations such as vegetation index and Forest Canopy Density (FCD) (Sukarna, 2008; Hartoyo *et al.*, 2019; Abdollahnejad *et al.*, 2020). The FCD transformation was built in the late 1990s (Rikimaru *et al.*, 2002) with the assumption that the vegetation index is less able to distinguish structural composition with respect to the density of the vegetation canopy, such as paddy fields with mature or mature rice can have a higher index value than high density forest (Himayah *et al.*, 2016). FCD uses four biophysical indices and then combines them to obtain information on canopy structure and density.

Radiometric correction of remotely sensed images is very important for analyzes that utilize spectral transformations (Chavez, 1996; Jensen, 2015) such as FCD and vegetation indices, because mathematical transformations using either uncorrected or corrected input data can give different possible results (Danoedoro *et al.*, 2015; Dewa and Danoedoro, 2017; Umarhadi *et al.*, 2018). Radiometric correction in general includes simple corrections that rely on information from within the image only (Mather and Koch, 2011), or calibration to spectral radiance, atmospheric correction to at surface reflectance, and even correction of the influence of topographic position (Mather and Koch, 2011; Jensen, 2015; Umarhadi and Danoedoro, 2019). By considering the aforementioned studies, this study aimed to compare the effect of two kinds of radiometric corrections, *i.e.* atmospheric correction to at surface reflectance and topographic correction, on the results of vegetation structural composition mapping using FCD transformation in area with mountainous topography.



## 2. STUDY AREA:

The study area is located in the Arjuno-Welirang volcanic complex, East Java Province, Indonesia. The study area includes volcanic landforms located at the peak, upper slope, middle slope, and part of the footslopes. The slopes range from 0-140% and have elevations between 400-3393 m above sea level. The Arjuno-Welirang area has several forest ecosystems, namely hilly dipterocarp forest, upper dipterocarp forest, mountane forest, and ericaceous forest (Tahura Raden Soerjo, 2020). The research location also includes protected and production forest areas, as well as plantation forests. The predominant vegetation were in the form of tree stands, namely mountain pine (*Casuarina junghuniana*). The Arjuno-Welirang volcanic area has variations in the percentage of canopy cover and in the distribution of structural composition. Figure 1 shows the location of the study area.

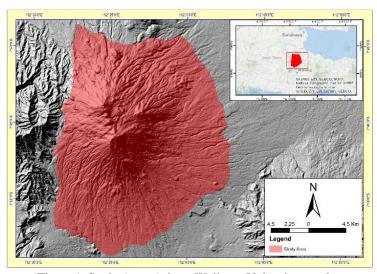


Figure 1. Study Area, Arjuno-Welirang Volcanic complex

# 3. METHODS

This study made use of Landsat 8 OLI image dataset which is the most suitable source of data for the FCD modeling, due to its complete spectral bands, ranging from blue up to thermal infrared (Rikimaru *et al*, 2002). The research stages included pre-processing in the form of radiometric correction, which consists of (a) atmospheric correction to at-surface reflectance and (b) correction of topographic influence. After that, each data at different level of correction was processed using FCD transformation to produce forest cover density map, which is related to variation in structural composition. Finally, accuracy comparison of the results was undertaken to see the difference in the effect of the two correction levels. We carried out the accuracy assessment by using independent data field observation and measurement.

# 3.1 Image Pre-Processing

We made use of Landsat 8 OLI/TIRS image dataset, which was recorded on June 13, 2020. This dataset includes all bands for FCD transformation processing, i.e. blue up to middle infrared and thermal channels. The image preprocessing stage was radiometric correction on Landsat 8 OLI images with two different treatments, namely atmospheric and topographic corrections. The atmospheric correction was applied using Fast Line-of-Sight Atmospheric Analysis of Spectral Hypercubes (FLAASH) algorithm. The algorithm was chosen because it suppresses atmospheric influences such as ozone, aerosols, water vapor in accordance with the study area (Guo and Zeng, 2012; Jensen, 2015; Prieto-Amparan *et al.*, 2018). For the topographic correction, we used the Sun-Canopy-Sensor+C (SCS+C) method, which considers various aspects of mountainous topography and canopy structure, and tends to have more stable results (Umarhadi and Danoedoro, 2020). Therefore, the input data used for topographic correction was the atmospherically corrected image as well as aspect and slope data generated from the ALOS-PALSAR DSM that was resampled to 30 meters pixel size. The aspect and slope were used to produce the illumination value, so that the coefficient C could be obtained, and then was applied to the following equation (Riano *et al.*, 2003):

$$\rho_H = \rho_T \left( \frac{\cos \alpha \cos \theta_Z + c}{IL + c} \right) \tag{1}$$

 $(\rho_H = \text{corrected at surface reflectance value}, \rho_T = \text{uncorrected at surface reflectance value}, \alpha = \text{slope angle}, \theta_Z = \text{solar zenith angle}, c = c \text{ coefficient}, IL = \text{illumination})$ 



# 3.2 Forest Canopy Density Transformation

The atmospherically- and topographically-corrected images were saved in 8-bit format and then converted to TIFF format. FCD transformation utilizes four biophysical indices (Rikimaru et al., 2002), namely Advanced Vegetation Index (AVI), Bare Soil Index (BI), Shadow Index (SI), and Thermal Index (TI). The four indices were derived to produce the FCD model using several steps. First, the AVI and BI produced Vegetation Density (VD); while second the SI and TI derived Scaled Shadow Index (SSI). The process of generating the VD dan SSI made use of Principal Component Analysis (PCA) and took the PC1s from the two separate processes as VD and SSI respectively. The combination of the results of VD and SSI generated the FCD model with a value range of 0-100%. Based on Rikimaru *et al.* (2002), the indices involved in the FCD transformation were developed using the following equations, where Red, Green, Blue, NIR, and SWIR are the blue, green, red, near-infrared and middle infrared spectral bands of the Landsat 8 OLI respectively:

$$AVI = \sqrt[3]{(NIR \times (256 - Red) \times (NIR - Red) + 1)}$$
 (2)

$$BI = \frac{((SWIR + Red) - (Blue + NIR))}{((SWIR + Red) + (Blue + NIR))}$$
(3)

$$SI = \sqrt[3]{((256 - Blue) \times (256 - Green) \times (256 - Red))}$$
 (4)

According to Rikimaru et al. (2002), whose work had been adopted by Himayah *et al.* (2016) and Ismail, *et. al.* (2017) the thermal index for FCD transformation was obtained from the thermal band, which was converted to spectral radiance  $L_{\lambda}$  first and then generated to radiant temperature TI:

$$L_{\lambda} = (\text{Gain} \times \text{DN}) + \text{Bias}$$
 (5)

$$TI = \frac{\kappa_2}{\ln} \left( \left( \frac{\kappa_1}{L\lambda} \right) + 1 \right) K2/\ln \left( (K1/L_{\lambda}) + 1 \right)$$
 (6)

 $(L_{\lambda} = radiance, Gain = Lmax - Lmin / DNmax - DNmin, DN = Digital Number, Bias = Lmin, T = Land surface temperature (°C), K1 = Thermal band 1 constant value K2 = Thermal band 2 constant value)$ 

## 3.3 Accuracy and Structural Composition Assessment

Field work activities consisted of obtaining information on both vegetation canopy density and structural composition, which would be used as the basis for FCD classification and accuracy assessment. The vegetation canopy density information was obtained using bottom-up photography (Umarhadi *et al.*, 2018; Danoedoro *et al.*, 2020) to distinguish the percentage of vegetation and non-vegetation objects. In addition to the bottom-up photography of the canopy density, the data collection was also assisted with interpretation using Google Earth imagery. The accuracy assessment made use of 32 samples that were taken independently. We used Standard Error of Estimate (SEE) based on the 95% confidence level for estimating the accuracy of the FCD model, as shown in equation (7).

$$SEE = \sqrt{\frac{\sum_{i}^{n} (y' - y)^{2}}{n - 2}} \tag{7}$$

(y' = pixel value of vegetation index, y = field data, n = number of samples, i = i-th sample)

# 4. RESULTS AND DISCUSSION

## 4.1. Atmospheric and Topographic Corrections

The results of atmospheric and topographic corrections showed differences in the distribution of spectral values that can be observed visually. Figure 2 shows that the atmospherically corrected image (Figure 2a) has a clearer three-dimensional impression which is seen in the difference in color and hue of the valley and hill lines. The shadow effect reinforces this impression. There was an influence from sunlight causing different hues on the same object for the west and east sides of the slopes. The topographically corrected image (Figure 2b) does not show a three-dimensional impression and is no longer affected by the sunlight. The same objects on the west and east sides, as well as hills and valleys, have hue and color that tend to be heterogeneous. The results of the topographic correction also clarify the difference between vegetation and open soil objects.



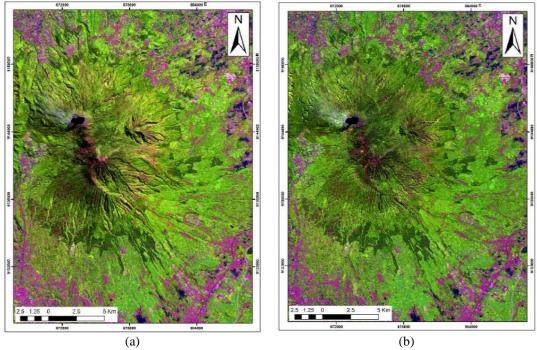


Figure 2. Landsat 8 OLI Imagery 654 composite in (a) atmospheric correction and (b) topographic correction

# 4.2. Forest Cover Density Modeling

The derivation of VD was controlled by the vegetation index selection, which was then correlated with soil brightness index BI. For atmospherically corrected images the correlation between NDVI and BI was 0.742 and for topographically corrected images it was 0.82. Therefore, the NDVI is used as input for making VD. All indices which were used to build the FCD models were presented in Figure 3, while the results of setting the minimum and maximum ranges for each object in FCD Mapper v2 produced FCD models as shown in Figure 4.

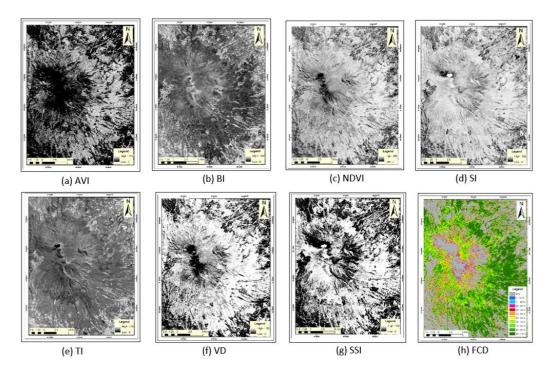


Figure 3. Example of Landsat 8 OLI-based indices that were used for deriving FCD model. In this picture, all indices were processed using atmospheric correction only.



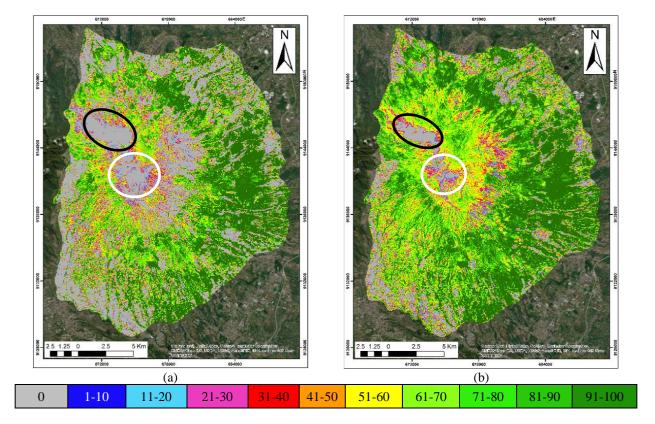


Figure 4. Comparison of FCD models using (a) atmospherically corrected and (b) topographically corrected images. The color bar in the bottom depicts the FCD classes related to vegetation canopy density and structural composition.

The ITTO/JOFCA (2003) classification has a range of 11 classes from 0 to 100% based on information on canopy density and vegetation structure composition. Figure 4 shows the results of the FCD transformation on both images with different levels of correction, with a white circle border indicating a savanna object and a black circle representing a cloud object. Based on the ITTO/JOFCA classification, there are differences in the classification results between atmospheric corrected images (Figure 4a) and topographically corrected images (Figure 4b). The effect of the correction in the form of different object hues between the east and west sides for vegetation objects is clearly visible in the classification results of the FCD model. Classification with a density value of 0% is more in atmospheric images than topographic images. The mountain peak in the form of a savanna is clearly visible in both images and has a classification with a density of 0%. However, in the topographically corrected image, the area of the savanna is narrower and has an edge with a classification of 1-40%. Classification with a density of 61-100% is also more varied in topographically corrected images. This is influenced by the effect of sunlight on the atmospheric corrected image. Before being corrected the topography of the west side has a darker hue, so that the vegetation and soil objects are less classified in the atmospheric image.

### 4.3. Accuracy Assessment

Based on the SEE calculation, this study found that the value of the atmospherically corrected FCD model is 29.16 while the topographically corrected FCD one reached 28.07. All values are in percent. These calculated SEE values indicated that the topographically corrected image has a smaller error than the topographically uncorrected one. As viewed from the maximum accuracy obtained by both models, we also found that the FCD maps could only reach relatively low accuracy, *i.e.* 29.92% for the atmospherically corrected model and 32.53% for the topographically corrected one. These findings were parallel with the results of the SEE calculation. Table 1 depicts the results.

Table 1. Result of SEE and accuracy assessment of the FCD models

Methods	Sum (y'-y) <sup>2</sup>	SE	Max Error	Min Error	Max Accuracy (%)
Atmospheric Correction	25509.06	29.16	134.48	70.08	29.92
Topographic Correction	23645.4	28.07	129.47	67.47	32.53



Table 2 provides information on the structural composition and range of percentage of canopy density in the field, as compared to the class range of the ITTO/JOFCA classification. This information is given for atmospherically- and topographically corrected FCD models. Class 1 in the FCD model explains that the canopy density is 0% with no canopy cover. If seen in the table, some conditions in the field with canopy cover have canopy percentage values, but most of the FCD results for atmospheric and topography give class ranges starting from 1. This was certainly not in accordance with conditions in the field. Besides, the structural composition, which is only in the form of canopy cover, reached the maximum value of 89.31%; but when it was classified in the FCD model, the category fell down into class 10. However, both atmospherically- and topographically corrected FCD models gave a class range from 1 up class 11, which was not in accordance with the reality in the field.

Mismatches also occurred in varying structural compositions without canopy cover, namely built-up area with grass. Conditions in the field gave a canopy density of 0% but the atmospherically corrected FCD model classified it as class 5, which means there were vegetation canopy with shrubs at 31-40% density; while the topographically corrected FCD model categorized it as class 3, or vegetation canopy with 11-20% density, although the pixel was still dominated by grass. Thus, in this case, the topographically corrected FCD model shows condition that was closer to the reality in the field.

Table 2. Comparison between field data (structural composition and canopy density) and the results of the FCD transformation, for both atmospherically- and topographically corrected images

FIELD REFEREN	FCD MODELING RESULTS USING:		
Field Data Structural	Field Data Canopy	atmospheric correction	topographic correction
Composition	Percentage	Class Range	Class Range
Herb	0	1	1
Built-up area	0	1	1 - 5
Built-up area and grassland	0	5	3
Built-up area and shrubs	0	1	1 - 4
Built-up area, herb, and shrubs	0	1	1
Tree canopy	23.69 - 89.31	1 – 11	1 – 11
Tree canopy and herb	8.4 - 82.67	1 – 11	1 – 11
Tree canopy and grassland	33.07	11	11
Tree canopy and shrubs	36.29 – 79.36	1 – 10	1 – 11
Tree canopy, herb, and grassland	21.47 - 68.56	1 – 11	1 – 11
Tree canopy, herb, grassland, and shrubs	30.75 – 35.76	1 – 3	6 – 8
Tree canopy, shrubs, and herb	23.95 - 68.38	1 – 11	1 – 9
Tree canopy, shrubs, and grassland	7. 94 – 51.83	1 – 11	1 – 6

The accuracy assessment of the atmospherically corrected FCD transformation showed that its accuracy was relatively low, which is less than 30%. The FCD model which provides information on canopy density and structural composition in this study was not able to accommodate the study area condition, which has a rugged mountainous topography. Atmospheric correction was less able to suppress the influence of topographic aspects so that the resultant accuracy was lower. After the topographic correction, the FCD model's accuracy only increased by 2.61% (to 32.53%). However, the topographic correction was able to accentuate the difference between vegetation and open soil objects in the image, so that the AVI and BI indices used in the FCD could work better.

In addition, the FCD transformation classified the canopy density and structural composition into 11 different classes. Based on Table 2, it can be seen that the results of the FCD transformation were not always in accordance with the conditions in the field. Objects without vegetation canopy in the field as well as objects with structural compositions that have vegetation coverage in the form of grass, herbs, and shrubs often misclassified. This was because some vegetation objects such as plants in rice fields or horticulture were categorized as high density vegetation in the FCD model. This can be considered as a shortcoming of the FCD classification results.

Another problem was that the FCD classes tended to be overestimate as compared to the canopy cover measurement in the field, so that the canopy density was classified to the highest class or 11 or very dense. In fact, based on the results in the field, the densest canopy cover only reached class 10, which is in the range of 81-90%. This shows that FCD modeling using FCD Mapper requires knowledge of the real conditions in the field to determine the right model set (Mon *et. al.*, 2012). Comparison between the FCD modeling results different levels of correction, it can be seen



that the topographically corrected image has a more heterogeneous classification range than that with atmospheric correction. This also proved that the topographic correction process could provide without being affected by topographic aspects and the direction of sunlight. The topographically corrected FCD models also have classes that closer to the real conditions in the field, thus providing higher accuracy.

The finding previously mentioned was in accordance with the results obtained by Himayah (2016), whose found that the use of topographic corrections could increase the accuracy of FCD models from 73.5% to 85.57% and from 72.3% to 85.04% with two different dates of recording. However, the Himayah's work showed a big difference in accuracy as compared to this study's result. The difference in topographic roughness between two study areas might be one of the reasons. In addition, based on the error analysis of the slope steepness in the study area, the inaccuracies for canopy density and structure composition estimate were the most common when the objects are on slopes with a range of 40-56%. It is also important to note that the distribution of samples could not be ideally achieved due to the difficult access to the very rugged terrain.

#### 5. CONCLUSION

FCD transformation at different levels of radiometric correction gave different accuracy results. The Landsat 8 OLI dataset that was only corrected with respect to the atmospheric effect reached an accuracy of 29.92%, while the topographically corrected dataset performed a higher accuracy of 32.53%. The results of structural composition classification using those two correction levels were quite different as compared to the real conditions in the field, although the topographically corrected-based FCD model was better able to represent canopy density and structural composition in the study area with mountainous terrain. Inaccuracies of the classified pixels mostly found in vegetated areas at the steeper slopes.

## REFERENCES

Abdollahnejad, A., Panagiotidis, D., and Surovy, P., 2020. Forest canopy density assessment using different approaches – Review. Journal of Forest Science, (63) 3, pp. 106–115. <a href="https://doi.org/10.17221/110/2016-JFS">https://doi.org/10.17221/110/2016-JFS</a>

Bera, B., Saha, S., & Bhattacharjee, S., 2020. Estimation of Forest Canopy Cover and Forest Fragmentation Mapping Using Landsat Satellite Data of Silabati River Basin (India). KN - Journal of Cartography and Geographic Information, (70) 4, pp. 181–197. <a href="https://doi.org/10.1007/s42489-020-00060-1">https://doi.org/10.1007/s42489-020-00060-1</a>

Chavez, P. S., 1996. Image-Based Atmospheric Corrections Revisited and Improved. Photogrammetric Engineering and Remote Sensing, (62) 9, pp. 1025–1036. <a href="http://www.asprs.org/wp-content/uploads/pers/1996journal/sep/1996">http://www.asprs.org/wp-content/uploads/pers/1996journal/sep/1996</a> sep 1025-1036.pdf

Danoedoro, P., 2019. Multidimensional Land-use Information for Local Planning and Land Resources Assessment in Indonesia: Classification Scheme for Information Extraction from High-Spatial Resolution Imagery. Indonesian Journal of Geography, (51) 2, pp. 131-146.

Danoedoro, P., Kristian, G., and Rahmi, K.N.I., 2015. Pengaruh metode koreksi radiometrik citra ALOS AVNIR-2 terhadap akurasi hasil estimasi karbon vegetasi tegakan di wilayah kota Semarang bagian timur. Prosiding PIT MAPIN XX, Institut Pertania Bogor, Bogor

Danoedoro, P., Ananda, I.N., Kartika, C.S.D., Umela, A.F., Indayani, A.B., 2020. Testing a detailed classification scheme for land-cover/ land-use mapping of typical Indonesian landscapes: Case study of Sarolangun, Jambi and Salatiga, Central Java. Indonesian Journal of Geography (52) 3, pp. 327 - 340

Deka, J., Tripathi, O.P., and Khan, M. L., 2013. Implementation of Forest Canopy Density Model to Monitor Tropical Deforestation. Journal of Indian Society of Remote Sensing, 41(2), pp. 469–475. <a href="https://link.springer.com/article/10.1007/s12524-012-0224-5">https://link.springer.com/article/10.1007/s12524-012-0224-5</a>

Dewa, R.P., and Danoedoro, P., 2018. The effect of image radiometric correction on the accuracy of vegetation canopy density estimate using several Landsat-8 OLI's vegetation indices: A case study of Wonosari area, Indonesia. IOP Conference Series: Earth and Environmental Science (54) 1.

Dimyati, R.D., Danoedoro, P., Hartono, and Kustiyo, 2018. A minimum cloud cover mosaic image model of the operational land imager landsat-8 multitemporal data using tile based. International Journal of Electrical and Computer Engineering, (8) 1, pp. 360-3



Guo, Y., and Zeng, F., 2012. Atmospheric Correction Comparison of SPOT-5 Image based on Model FLAASH and Model QUAC. International Archives of the Photogrammetry, Remote Sensing And Spatial Information Sciences, Volume Xxxix-B7, 2012 XXII ISPRS Congress, 25 August – 01 September, Melbourne, Australia

Hartoyo, A. P. P., Prasetyo, L.B., Siregar, I. Z., Supriyanto, Theilade, I., & Siregar, U. J., 2019. Carbon Stock Assessment Using Forest Canopy Density Mapper In Agroforestry Land In Berau, East Kalimantan, Indonesia. Biodiversitas, (20) 9, pp. 2661–2676. <a href="https://doi.org/10.13057/biodiv/d200931">https://doi.org/10.13057/biodiv/d200931</a>

Hidayati, I.N., Suharyadi, R., and Danoedoro, P. 2018, Exploring Spectral Index Band and Vegetation Indices for Estimating Vegetation Area. The Indonesian Journal of Geography (50) 2, pp. 211-221

Himayah, S. (2016). Pemanfaatan Citra Landsat 8 Multitemporal dan Model Forest Canopy Density (FCD) untuk Prioritas Reklamasi Hutan Di Kawasan Gunung Kelud, Jawa Timur. MSc Thesis. Remote Sensing Study Program, Faculty of Geography Universitas Gadjah Mada, Yogyakarta.

Himayah, S., Hartono, and Danoedoro, P., 2016. The utilization of Landsat 8 multitemporal imagery and forest canopy density (FCD) model for forest reclamation priority of natural disaster areas at Kelud Mountain, East Java. IOP Conference Series: Earth and Environmental Science (47) 1, pp. 012043

Ismail, M., Hartono, and Danoedoro, P., 2017. The Application of Forest Cover Density (FCD) Model for Structural Composition of Vegetation Changes in Part of Lore Lindu National Park, Central Sulawesi Province. IOP Conference Series: Earth and Environmental Science, (98) 1.

ITTO/JOFCA. 2003. FCD-Mapper Ver.2 Guide. International Tropical Timber Organization / Japan Overseas Forestry Consultants Association, Japan.

Jensen, J. R. 2015. Remote Sensing of the Environment an Earth Resource Perspective (4<sup>th</sup> ed.). Prentice Hall, Englewood Cliffs, NJ.

Mather, P.M., and Koch, M., 2011. Computer Processing of Remotely-Sensed Images: An Introduction, 4th Edition. John Wiley and Sons, London.

Mon, M.S., Mizoue, N., Htun, N.Z., Kajisa, T., & Yoshida, S., 2012. Estimating forest canopy density of tropical mixed deciduous vegetation using Landsat data: a comparison of three classification approaches. International Journal of Remote Sensing, (33) 4, pp. 1042-1057.

Prieto-Amparan, J.A., Villarreal-Guerrero, F., Martin Martinez-Salvador, M., Manjarrez-Domínguez, C., Santellano-Estrada, E., and Pinedo-Alvarez, A., 2018 Atmospheric and Radiometric Correction Algorithms for the Multitemporal Assessment of Grasslands Productivity. Remote Sens. 2018, (10) 2, pp. 219-234. <a href="https://doi.org/10.3390/rs10020219">https://doi.org/10.3390/rs10020219</a>

Riano, D., Chuvieco, C., Salas, S., and Aguado, I., 2003. Assessment of Different Topographic Corrections in Landsat-TM Data for Mapping Vegetation Types. IEEE Transactions on Geoscience and Remote Sensing, (41) 5.

Rikimaru, A., Roy, P.S., and Miyatake, S., 2002. Tropical forest cover density mapping. Tropical Ecology, (43) 1, pp. 39–47. http://tropecol.com/pdf/open/PDF 43 1/43104.pdfhttp://tropecol.com/pdf/open/PDF 43 1/43104.pdf

Sukarna, R. M. (2008). Aplikasi Model Forest Canopy Density Citra Landsat 7 ETM untuk Menentukan Indeks Luas Tajuk (Crown Area Index) Dan Kerapatan Tegakan (Stand Density) Hutan Rawa Gambut Di DAS Sebangau Provinsi Kalimantan Tengah. Majalah Geografi Indonesia, (22) 1, pp. 1–21.

Tahura Raden Soerjo. 2020. Gunung Arjuno Welirang. Retrieved November 2, 2020, from <a href="https://tahuraradensoerjo.or.id/sub/owa/arjuno.php?via=arjuno">https://tahuraradensoerjo.or.id/sub/owa/arjuno.php?via=arjuno</a>

Tesfaye, A.A., and Awoke, B. G., 2021. Evaluation of the saturation property of vegetation indices derived from sentinel-2 in mixed crop-forest ecosystem. Spatial Information Research, (29) 1, 109–121. https://doi.org/10.1007/s41324-020-00339-5

Umarhadi, D.A., Danoedoro, P., Wicaksono, P., Widayani, P., Nurbandi, W., and Juniasyah, A., 2018. The Comparison of Canopy Density Measurement Using UAV and Hemispherical Photography for Remote Sensing based Mapping. International Conference on Science and Technology-Computer (ICST), pp. 8528670.



Umarhadi, D.A., and Danoedoro, P., 2019. Correcting topographic effect on Landsat-8 images: An evaluation of using different DEMs in Indonesia. Proceedings of SPIE - The International Society for Optical Engineering 11311, 113110

Umarhadi, D. A., & Danoedoro, P., 2020. The Effect of Topographic Correction on Canopy Density Mapping Using Satellite Imagery in Mountainous Area. International Journal on Advanced Science, Engineering and Information Technology, (10) 3, pp. 1317–1325.

Xue, J., & Su, B. (2017). Significant Remote Sensing Vegetation Indices: A Review of Developments and Applications. Journal of Sensors, 2017, pp. 1–17. <a href="https://doi.org/10.1155/2017/1353691">https://doi.org/10.1155/2017/1353691</a>