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Identification of Land Fire Risk Areas with Random Forest Using Landsat Image Data 8 OLI

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Abstrak

Kebakaran lahan merupakan masalah kompleks dan serius yang berdampak pada beberapa sektor kehidupan manusia. Memacu terjadinya kebakaran lahan, disebabkan kemarau panjang dan musim hujan yang tak menentu, menyebabkan tumbuhan kekeringan dan mati. Pembakaran liar lahan oleh oknum yang tidak bertanggungjawab, demi memperluas dan kepentingan lainnya yang dilakukan. Penelitian ini menggunakan metode kuantitatif, variabel yang digunakan nilai indeks vegetasi yang diperoleh dari citra landsat 8 OLI. Hasil dari penelitian ini adalah data diklasifikasikan menggunakan algoritma random forest pada rstudio menghasilkan jumlah pohon default 500 dan jumlah variabel yang dicoba pada setiap split adalah 2. Sehingga tingkat estimasi kesalahan 2 out of bag adalah 0.47 %. Prediksi dan confusion matrix – train terdapat 403 data yang kurang berisiko "0" (middle risk) terjadi kebakaran dan terdapat 22 data berisiko tinggi "1" (high risk) terjadinya kebakaran, dengan nilai accuracy : 0,9914, 1. Sedangkan prediksi kedua confusion matrix – test data terdapat 167 data kurang berisiko "0" (middle risk) terjadinya kebakaran. Terdapat 1 data berisiko tinggi "1" (high risk) terjadinya kebakaran. Terdapat 7 data berisiko tinggi "1" (high risk) terjadinya kebakaran, dengan nilai accuracy 0,9943 menunjukkan penilaian akurasi model yang lebih akurat dan kisarannya masih bagus sekitar 96% hingga 99%. Terdapat beberapa klasifikasi yang salah pada prediksi dan confusion matrix – train yang sedikit lebih tinggi dari prediksi kedua confusion matrix – test, serta sensitivitas : 1.0000 yang sama baik pada prediksi dan confusion matrix – train & test.

Kata kunci: *Identifikasi, Citra Landsat 8 OLI, Random Forest*

Abstract

Land fire is a complex and serious problem affecting several human life sectors. Stimulating the occurrence of land fires caused by long dry seasons and erratic rainy seasons causes plants to dry up and die. Illegal land burning by irresponsible people for expansion and other interests. This study uses quantitative methods. The variables used are vegetation index values obtained from Landsat 8 OLI images. The result of this research is that data classified using the random forest algorithm at RStudio produces a default number of 500 trees, and the number of variables tested in each split is 2. So, the estimated error rate of 2 out of the bag is 0.47%. Prediction and confusion matrix - train 403 data are less risky "0" (middle risk) of a fire, and there are 22 data of high risk of "1" (high risk) of a fire, with an accuracy value of 0.9914, 1. While the second prediction of the confusion matrix - test data, there are 167 data less risky "0" (middle risk) of fire. There is 1 data with a high risk of "1" (high risk) of a fire. There are seven high-risk data "1" (high risk) of fire, with an accuracy value of 0.9943, indicating a more accurate assessment of model accuracy, and the range is still good, around 96% to 99%. There are several incorrect classifications in the prediction and confusion matrix – train, which is slightly higher than the predictions of the two-confusion matrix – test, and sensitivity: 1.0000, which is the same in both prediction and confusion matrix – train & tes.

Keywords: Identification, Citra Landsat 8 OLI, Random Forest

1. INTRODUCTION

Indonesia is a country that is famous for its rich natural resources. Indonesia has vast and fertile forests and land. Forests and land are natural resources that are very important in human life. Forests and land bring many benefits to human life (Deslita, Hartiwiningsih, & Ginting, 2020; Saputro, Widodo, & Santosa, 2022). Forests in Indonesia are known as the world's lungs, and many plants and animals live in them. At the same time, land is a resource closely related to development. The land is widely used in almost all development fields, in the agricultural, housing, industrial, mining, and transportation sectors. Therefore, humans must be able to maintain and maintain the existence and beauty of forests and land.

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However, what is currently happening is that land fires often occur. Land fire is a complex and serious problem affecting several human life sectors (Adam, Rindarjono, & Karyanto, 2020; Kusuma, Shodiq, Hazim, & Laksono, Puguh, 2021). Fires can occur in tropical countries, such as Indonesia in particular, due to two main factors, namely, natural and non-natural factors (made by humans). Natural factors in the form of long droughts cause plants to dry up and die, stimulating irresponsible human activities such as illegal burning to expand land (A. Humam et al., 2020; Supriyanto, Syarifudin, & Ardi, 2018). Based on data from the Ministry of Environment and Forestry, recapitulation of the area of forest and land fires (Ha) of East Nusa Tenggara Province from 2016: 8,968.09 Ha, 2017: 38,326.09 Ha, 2018: 57,428.79 Ha, 2019: 136,920.00 Ha, 2020: 114,719.00 Ha, 2021: 42.00 Ha. The data shows a decline in fires in 2020 and 2021 (Supriyanto et al., 2018). The decline in fires in the last two years shows the progress changes. However, it has not been able to demonstrate safety for five consecutive years. Economic, health, and even sustainable development planning are affected. Economic losses, the World Bank once revealed, the total losses borne by Indonesia throughout 2019 due to land and forest fires reached US$ 5.2 billion or equivalent to Rp. 72.95 trillion (at an exchange rate of Rp. 14,000/US dollar). 0.5% of Indonesia's gross domestic product (GDP) (Adam, 2020).

The government has made various efforts to prevent and repress forest fires. UU no. 32 of 2019 concerning Environmental Protection and Management, PP No. 60 of 2009 concerning Forest Protection, and Minister of Forestry Regulation No. 12/Menhut-II/2009 concerning Forest Fire Control (Prasetyo, Hartomo, Paseleng, Chandra, & E. Winarko, 2020). Based on the government's policies, it is necessary to re-evaluate to find the best solution to avoid land and forest fires. A good implementation strategy is needed to minimize land and forest fires so they do not happen again.

In Indonesia, so far in Riau and Jambi provinces, land and forest fires have been identified with NBR index, NDVI, and SPOT-4 data using Semi-Automatic Landsat Satellite Imagery analysis. The results show that NDVI or NBR's extraction value in pre-fire conditions is higher than in post-fire conditions, indicating a change from a high level of green vegetation to a low level. Proving that the NBR index is very sensitive in identifying burnt land that relies on the Shortwave Infrared (SWIR) radiation spectrum, which is sensitive to low water content in burnt land, and the NDVI index is more suitable for detecting land changes from vegetation to non-vegetation without burning. However, land fires have never been identified in East Sumba, which is still prone to fires. Seeing this, efforts to identify land fires in East Sumba must be carried out. One of them uses the random forest algorithm.

Random forest is an algorithm to classify large amounts of data using Landsat 8 OLI image data without direct contact with the area under study. A random forest is a combination of each good tree then combined into one model. The decision tree classifies a data sample whose class is not yet known into existing classes—the use of decision trees to avoid overfitting the data set when achieving maximum accuracy. Meanwhile, Landsat 8 Imagery is the eighth satellite of the Landsat program that collects and archives multispectral image data that includes seasonal global data of less than five years (Andianto & H. H. Handayani, 2014). Random Forest is one method that has a positive impact, so it is feasible. Several previous studies have shown that the random forest method can process data and has a high level of accuracy (Kusuma et al., 2021; Mursianto, Falih, Irfan, Sakinah, & Sandya, 2021; Suryoto & Prasetyo, 2020). Other studies analyze the area geospatially and make maps of forest and land fire susceptibility using parameters, air temperature, road access, river access, hotspot density, land use, rainfall, and land use (A. Humam et al., 2020). The purpose of this study is to present data and the process of land identification using the random forest algorithm. It is hoped that the process of analyzing Landsat image data with random forests will be a reference for predicting future land fires.

2. METHODS

This study uses quantitative methods. Quantitative research methods can be interpreted as research methods based on positivism, used to examine certain populations or samples, sampling techniques are generally carried out randomly, data collection uses research instruments, and data analysis is quantitative or statistical with the aim of testing hypotheses has been established (Sugiyono, 2016) The stages that are passed in this research are as follows: needs analysis, analyzing needs by conducting literature studies, and collecting data. The data used in this study is the value of the vegetation index variable obtained from Landsat 8 OLI image data from January 2018 to December 2019 and the shapefile format (SHP) of East Sumba. The data processing process from the Landsat 8 OLI satellite image begins with filtering, cutting, and processing the data using the vegetation index formula (NDVI, NDWI, NBR, SAVI) in QGIS tools and grouping and combining data using Microsoft Excel. The data that has been combined in a Microsoft Excel file is classified as data mining with predictions using the random forest algorithm on Rstudio.

3. RESULTS AND DISCUSSION

Result

Data Processing With Vegetation Index

The process of processing data with the vegetation index can be seen in Figure 1.

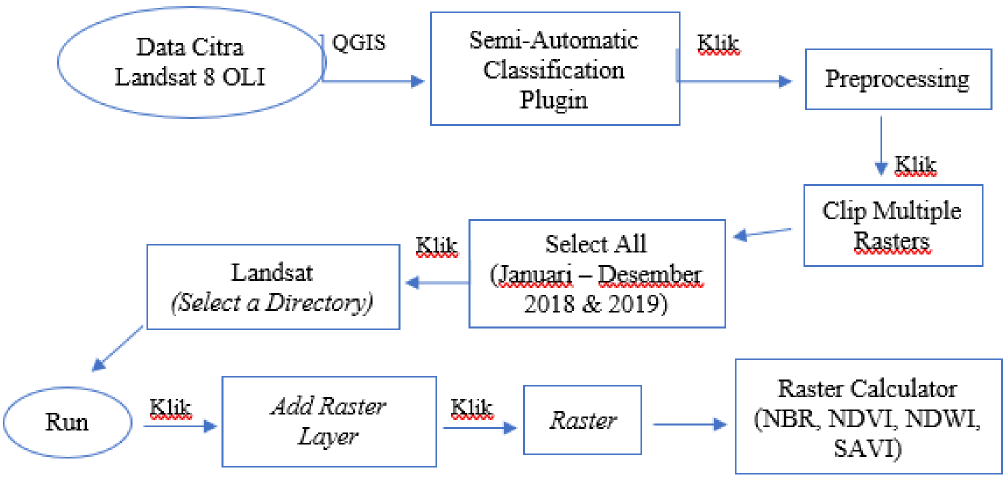


Figure 1. Flowchart of Data Processing with Veget Index

Landsat 8 OLI image data for the East Sumba Regency map that has been classified based on the calculation of the formula for each vegetation index can be described as follows:

Normalized Burn Ratio (NBR)

In the process, the NBR index is used to highlight burned areas and predict the severity of fires using the formula NBR = (Band5 – Band7) / (Band5 + Band7). The NBR Vegetation Index Map for January – December 2018 & 2019 can be seen in Figure 2.

2018

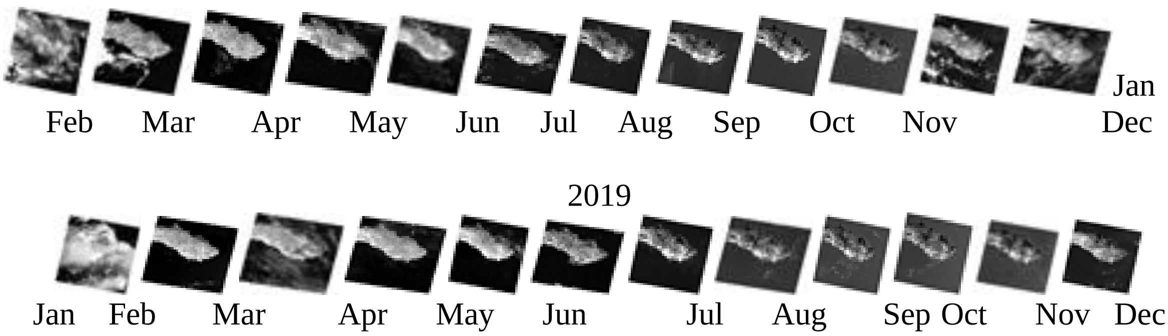


Figure 2. NBR Vegetation Index Map January – December 2018 & 2019

Figure 2 is data from Landsat 8 OLI East Sumba imagery from January to December 2018 and 2019, which has been processed using QGIS to map the raw data based on the vegetation index. This process is carried out to facilitate predicting land fires based on the vegetation index.

Normalized Difference Vegetation Index (NDVI)

Normalized Difference Vegetation Index (NDVI) is an index that describes a plant's greenness with calculations involving satellite imagery to obtain the vegetation index value. The NDVI index is used to measure the greenness of a plant by involving satellite images in the calculation, using the formula NDVI = (Band5 – Band4) / (Band5 + Band4). The NDVI Vegetation Index Map for January – December 2018 & 2019 can be seen in Figure 3.

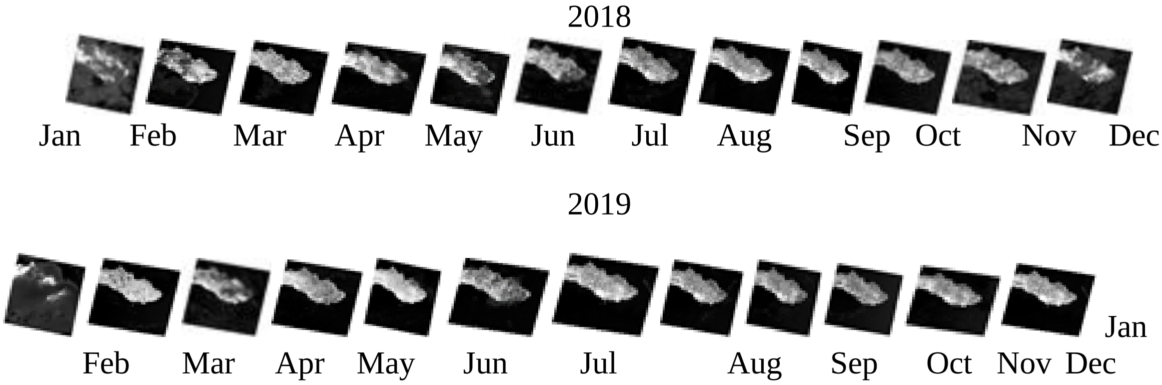


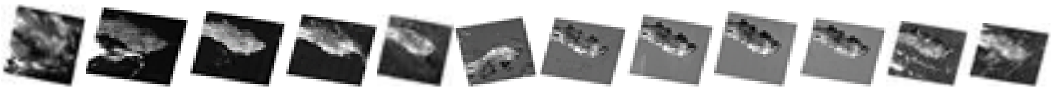
Figure 3. NDVI Vegetation Index Map January – December 2018 & 2019

Figure 3 is Landsat 8 OLI East Sumba image data from January to December 2018 and 2019, processed using QGIS to map the raw data based on the vegetation index. This process is carried out to facilitate predicting land fires based on the vegetation index.

Normalized Difference Wetness Index (NDWI)

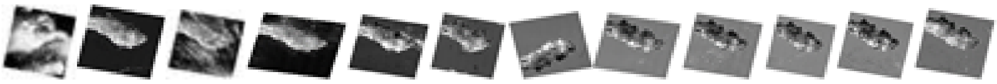
The NDWI index process is used to compare the level of wetness in satellite image data with the formula NDWI = (Band5 – Band6) / (Band5 + Band6) (Yudistira, Meha, & Prasetyo, 2019). The NDWI Vegetation Index Map for January – December 2018 & 2019 can be seen in Figure 4.

2018



Jan Feb Mar Apr May Jun Jul Agt Sep Oct Nov Dec

2019



Jan Feb Mar Apr May Jun Jul Agt Sep Oct Nov Dec

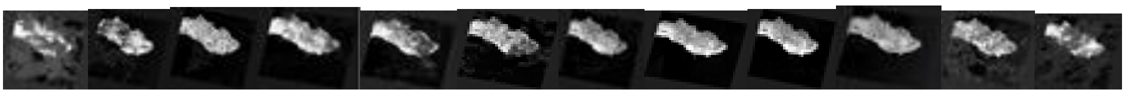
Figure 4. NDWI Vegetation Index Map January – December 2018 & 2019

Figure 4 is data from Landsat 8 OLI East Sumba imagery from January to December 2018 and 2019, which has been processed using QGIS to map the raw data based on the vegetation index. This process is carried out to facilitate predicting land fires based on the vegetation index.

Soil Adjusted Vegetation Index (SAVI)

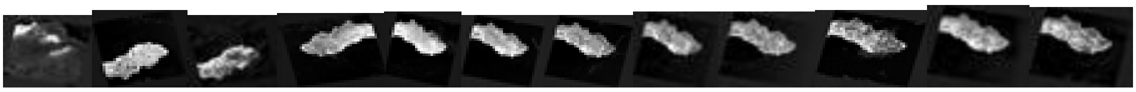
The SAVI index process is used to suppress the influence of the ground background on the brightness level using the formula SAVI = (Band5 – Band4) / (Band5 + Band4 + 0.5) * (1 + 0.5). The SAVI Vegetation Index Map for January – December 2018 & 2019 can be seen in Figure 5.

2018



Jan Feb Mar Apr May Jun Jul Agt Sep Oct Nov
Dec

2019



Jan Feb Mar Apr May Jun Jul Agt Sep Oct Nov
Dec

Figure 5. SAVI Vegetation Index Map January – December 2018 & 2019

Figure 5 is Landsat 8 OLI East Sumba image data from January to December 2018 and 2019, processed using QGIS to map the raw data based on the vegetation index. This process is carried out to facilitate predicting land fires based on the vegetation index.

Cutting *(CLIP)*

The Flowchart of the Cutting Process (CLIP) for each Vegetation Index for 2018 & 2019 from January – December can be seen in Figure 6.

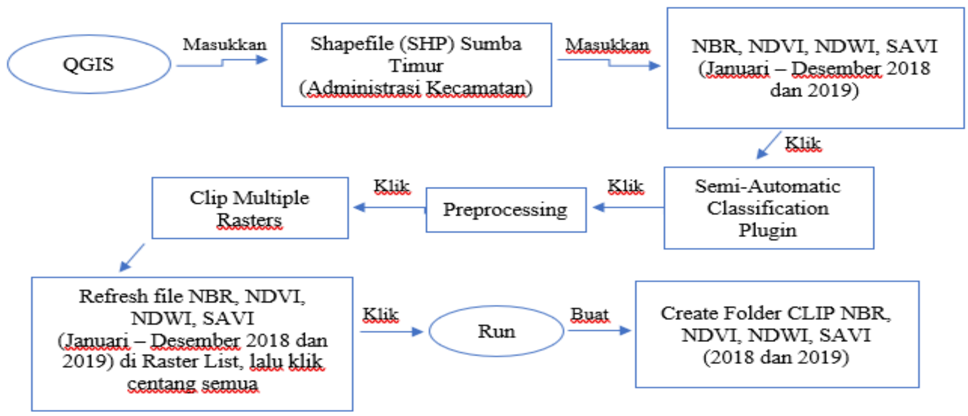


Figure 6. Flowchart of the Cutting Process (CLIP) for each Vegetation Index for 2018 & 2019 from January – December

Based on Figure 6, the author performs the cutting process (CLIP) using the QGIS application at this stage. The first step is to enter the shapefile file (SHP) of the East Sumba sub-district administration. shpfile, in QGIS. Then enter one of the annual vegetation indexes from 2018 and 2019, which will be processed alternately, then click Semi-Automatic Classification Plugin, select it and click Preprocessing -> Clip Multiple Rasters. File one of the vegetation index that is being processed appears monthly from January to December after clicking refresh. Check the entire file from January to December, then click run for processing. The author creates a clip folder according to the vegetation index file and the year that is being processed so that the processed data results are stored in a folder that has been created and determined. The clipping process is carried out to filter several spatial and non-spatial data parameters from the results of Landsat 8 image classification.

Normalized Burn Ratio (NBR)

Normalized Burn Ratio (NBR) highlights burned areas and estimates fire severity. NBR calculation formula = (Band5 – Band7) / (Band5 + Band7) (A. Parwati et al., 2012). A map of NBR Cutting Results from January – December 2018 & 2019 can be seen in Figure 7.

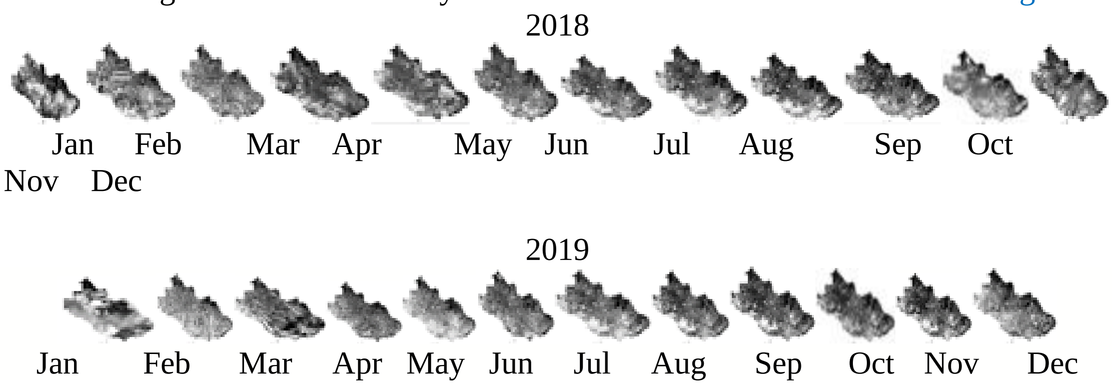


Figure 7. Map of NBR Withholding Results January – December 2018 & 2019

Figure 7 shows that the 2018 and 2019 NBR vegetation index data files from January to December have completed the cutting process.

Normalized Difference Vegetation Index (NDVI)

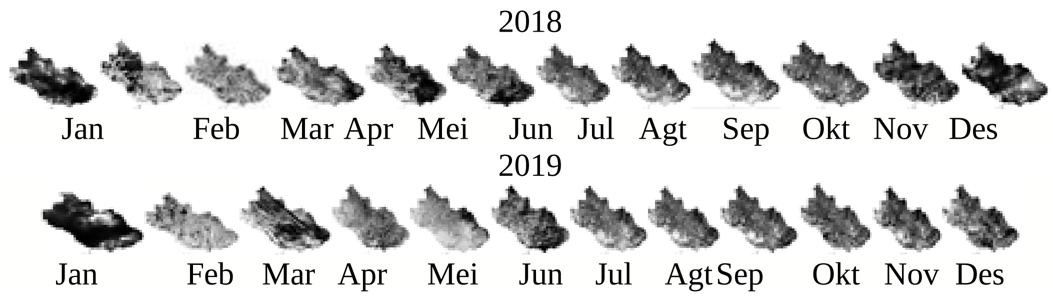


Figure 8. Map of NDVI Cutting Results January – December 2018 & 2019

Figure 8 is the 2018 and 2019 NDVI vegetation index data file from January to December, which has finished the cutting process.

Normalized Difference Wetness Index (NDWI)

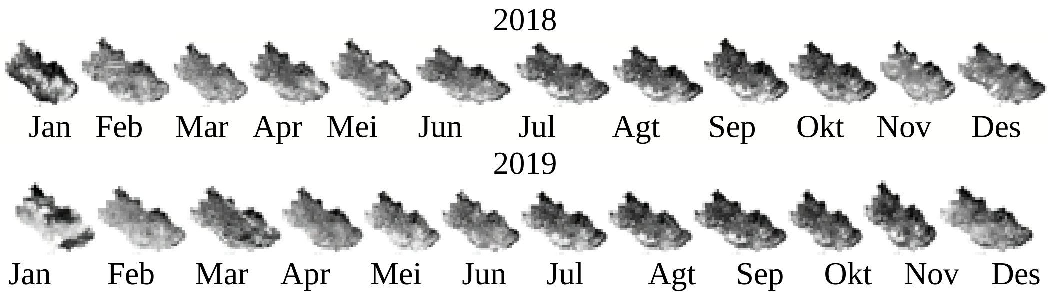


Figure 9. Map of NDWI Cutting Results January – December 2018 & 2019

Figure 9 is the 2018 and 2019 NDWI vegetation index data file from January to December, which has finished the cutting process.

Soil Adjusted Vegetation Index (SAVI)

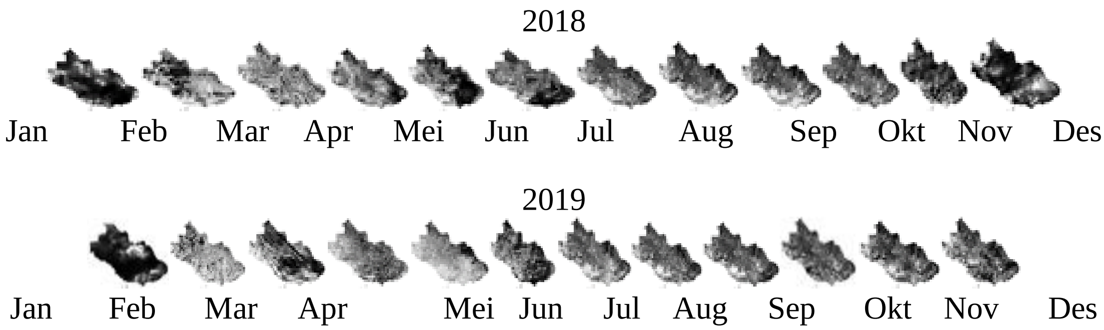


Figure 10. Map of SAVI Cutting Results January – December 2018 & 2019

Figure 10 is the 2018 and 2019 SAVI vegetation index data file from January to December, which has finished the cutting process

Random Forest

At this stage, the author uses testing with rstudio tools to make predictions, a confusion matrix, and statistics on the random forest algorithm's identification. Library (random Forest) is used to classify the data that has been provided and will be processed. Require (caTools) is a caTools package used to share training and testing data in the machine learning process using rstudio tools. The library (caret) is used to predict and classify data and see the accuracy value using the random forest algorithm.

```
A tibble: 6 x 8
  Kode Bulan Tahun   NDVI   NBR  NDWI
 <dbl> <chr> <dbl>  <dbl> <dbl> <dbl>
     1 Jan    2018 0.0757 0.303 0.191
     2 Jan    2018 0.0425 0.285 0.186
     3 Jan    2018 0.0484 0.345 0.218
     4 Jan    2018 0.0963 0.236 0.140
     5 Jan    2018 0.0782 0.223 0.136
     6 Jan    2018 0.0816 0.253 0.158
... with 2 more variables: SAVI <dbl>,
  Fire_Rate <chr>
```

```
> data$Fire_Rate[data$Fire_Rate > 1] <- 1
> summary(data)
      Kode           Bulan          
 Min.   :  1.0   Length:600        
 1st Qu.:150.8   Class :character  
 Median :300.5   Mode  :character  
 Mean   :300.5                     
 3rd Qu.:450.2                     
 Max.   :600.0                     
     Tahun           NDVI          
 Min.   :2018   Min.   :-0.0002961  
 1st Qu.:2018   1st Qu.: 0.1761910  
 Median :2018   Median : 0.2312910  
 Mean   :2018   Mean   : 0.2318793  
 3rd Qu.:2019   3rd Qu.: 0.3010062  
 Max.   :2019   Max.   : 0.4580878  
      NBR              NDWI         
 Min.   :0.02298   Min.   :-0.10683  
 1st Qu.:0.17968   1st Qu.: 0.03758  
 Median :0.25643   Median : 0.12378  
 Mean   :0.25032   Mean   : 0.11736  
 3rd Qu.:0.32415   3rd Qu.: 0.18291  
 Max.   :0.52188   Max.   : 0.53615  
      SAVI             Fire_Rate        
 Min.   :-0.0004441   Length:600        
 1st Qu.: 0.2642816   Class :character  
 Median : 0.3469300   Mode  :character  
 Mean   : 0.3478124                     
 3rd Qu.: 0.4515009                     
 Max.   : 0.6871195                     
```

Gambar 11. *Output* Data Based on Variable and Vegetation Index

Figure 11 is data from OLI's Landsat 8 image, namely the East Sumba area map in 2018 and 2019 from January to December and the shapefile (SHP) of East Sumba. The following is a display of the data heads that have been called to see the results of the data grouping being processed and find out the mean and median values of each categorical variable.

```
Call:
 randomForest(formula = Fire_Rate ~ ., data = train)
               Type of random forest: classification
                     Number of trees: 500
No. of variables tried at each split: 2

        OOB estimate of  error rate: 0.47%
Confusion matrix:
    0  1 class.error
0 403  0  0.00000000
1   2 20  0.09090909
```

Figure 12. *Classification Random Forest*

Figure 12 is the output classification random forest. Total tree 500 processed data and variables (mtry) 2. Classification of processed data trains using the Fire_Rate formula. Fire_Rate is a variable that classifies as less risk of “0” (middle risk) of fire occurrence and a high risk of “1” (high risk) of fire.

```
Confusion Matrix and Statistics

          Reference
Prediction   0   1
         0 403   0
         1   0  22

               Accuracy : 1
                 95% CI : (0.9914, 1)
    No Information Rate : 0.9482
    P-Value [Acc > NIR] : 1.546e-10

                  Kappa : 1

 Mcnemar's Test P-Value : NA

            Sensitivity : 1.0000
            Specificity : 1.0000
         Pos Pred Value : 1.0000
         Neg Pred Value : 1.0000
             Prevalence : 0.9482
         Detection Rate : 0.9482
   Detection Prevalence : 0.9482
      Balanced Accuracy : 1.0000

       'Positive' Class : 0
```

```
Confusion Matrix and Statistics

          Reference
Prediction   0   1
         0 167   1
         1   0   7

               Accuracy : 0.9943
                 95% CI : (0.9686, 0.9999)
    No Information Rate : 0.9543
    P-Value [Acc > NIR] : 0.002607

                  Kappa : 0.9304

 Mcnemar's Test P-Value : 1.000000

            Sensitivity : 1.0000
            Specificity : 0.8750
         Pos Pred Value : 0.9940
         Neg Pred Value : 1.0000
             Prevalence : 0.9543
         Detection Rate : 0.9543
   Detection Prevalence : 0.9600
      Balanced Accuracy : 0.9375

       'Positive' Class : 0
```

Figure 13. *Output Prediction and Confusion Matrix train – test data*

Figure 13 shows the confusion matrix and statistics train–test data. Prediction and Confusion Matrix train data identified that new data contained 403 data with a low risk of “0” of fire occurrence, which was identified as low-risk data of fire occurrence, and 22 data with a high risk of “1” (high risk)—the occurrence of fires identified as high-risk data of fire. While the Prediction and Confusion Matrix test data identified new data, there were 167 data with less risk of “0” (middle risk) of fire occurrence, which was identified as low-risk data (middle risk). There is 1 data with a high risk of “1” (high risk) of the fire identified as high risk of fire. There are 7 data with a high risk of “1” (high risk) of fire occurrence, which is identified as data of high risk of “1” (high risk) of fire. From the results of the Prediction and Confusion Matrix train–test data, it can be concluded that areas with less fire risk are more likely than areas with high fire risk.

Discussion

The study's results showed that the random forest method used Landsat 8 OLI Image Data to identify the risk of land fires to obtain accurate results. Random forest combines each good tree into one model (Kusuma et al., 2021; Mursianto et al., 2021). Random forest is one of the methods in the Decision Tree. A decision tree is a flow diagram shaped like a tree with a root node used to collect data. The inner node located at the root node contains questions about data, and the leaf node is used to solve problems and make decisions (Risdiyanto & Wahid, 2017). The decision tree classifies a data sample whose class is not yet known into existing classes. The use of decision trees to avoid overfitting the data set when achieving maximum accuracy (Jawa, Matatula, & Rehatta, 2020).

While the Landsat 8 imagery was first recognized on February 11, 2013, by the Vandeberg Air Base, California, it is the eighth satellite of the Landsat program whose function is to collect and archive multispectral image data covering seasonal global data of less than five years (Andianto & H. H. Handayani, 2014; Derajat, 2020; Suryoto & Prasetyo, 2020). One of the satellites has an unequal band of frequencies along the electromagnetic spectrum of color, although the color is not always visible to the human eye. The Operational Land Manager (OLI) sensor uses 9 bands (Febriani, Yunidar, Hidayat, Amor, & Indrayani, 2022; Husen, Sandi, Bumbungan, Kusrini, & Kusnawi, 2022). Landsat 8 OLI imagery is used to obtain data without direct contact with the studied area. The random forest method using Landsat 8 imagery has a good impact, making it feasible. Several previous studies have shown that the random forest method can process data and has a high level of accuracy (Kusuma et al., 2021; Mursianto et al., 2021; Suryoto & Prasetyo, 2020). Other studies analyze the area geospatially and make maps of forest and land fire susceptibility using parameters, air temperature, road access, river access, hotspot density, land use, rainfall, and land use (A. Humam et al., 2020). It is hoped that the process of analyzing Landsat image data with random forests will be a reference for predicting future land fires.

4. CONCLUSION

Based on the Land Fire Risk Identification study using the random forest method using Landsat 8 OLI Image Data in East Sumba, it can be concluded that identification using the random forest method shows a more accurate assessment of the model's accuracy with a good range of around 96% to 99%. The results of the first and second predictions show the confusion matrix train & test data so that it represents land that is less at risk (middle risk 0) of fires more than land that is at high risk (high risk 1) of fires, 570 data that are less at risk of fire and there are 8 data on high risk of fire. Identification of land fires using the NBR, NDWI, NDVI, and SAVI vegetation index with the random forest method is optimal and maximum, with a low error estimate rate of 0.47% out of the bag.

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