JURNAL geografi

https://jurnal.unimed.ac.id/2012/index.php/geo/article/view/29036
https://doi.org/10.24114/jg.v14i1.29036 - (Vol 14, No 1 - 2022)
available at http://jurnal.unimed.ac.id/2012/index.php/geo
e-issn (2549-7057) & p-issn (2085-8167)

Application of SPOT 6/7 Satellite Imagery for Rice Field Mapping Based on Transformative Vegetation Indices

Nirmawana Simarmata[1,2], Zulfikar Adlan Nadzir[1,2], Lea Kristi Agustina[1,2]

[1]*Geomatics Engineering, Infrastructure Technology and Planning Department, Institut Teknologi Sumatera, Lampung, Indonesia*
[2]*Research and Innovation Center of Geospatial Information Science, Institut Teknologi Sumatera, Lampung, Indonesia*

ARTICLE INFO

Article History:
Received: July 07, 2021
Revision: January 14, 2022
Accepted: January 17, 2022

Keywords:
Agricultural Land
SPOT 6/7
SAVI
TSAVI

Corresponding Author
E-mail:
nirmawana.simarmata@gt.itera.ac.id

ABSTRACT

Agriculture plays an essential role in national economic development. This fact made agricultural land one of the main unique production factors irreplaceable due to its importance in the agricultural business processes. However, a persistent problem of arable land conversion and land degradation have become more massive throughout the years. Meanwhile, the continuation of existing agricultural land and transformation into new agricultural land is inherently small. This research aimed to map agricultural land in sustainable agricultural development. Several transformative vegetation indices: NDVI, SAVI, and TSAVI, applied SPOT 6/7 satellite imagery in Lampung Province. Results show that the TSAVI value is the highest, with a 1.80 value, which indicates that this index value is very dense vegetation. Meanwhile, the NDVI index, which has a minimum value of -1.02, suggests that this index value is a non-vegetation object. However, high or low value does not indicate the rigorousness and Accuracy of an index. All three indices' results are then overlaid with the satellite imagery classification process result. The accuracy result shows that the agricultural land has a maximum of 100% producer accuracy while the user accuracy value is 87.87%. Overall, for NDVI, the Accuracy was valued at 90.25%, which could be classified as a reasonable classification result. SAVI has a PA value of 97.85%, UA 85.20% and OA 86.63%, while the TSAVI Index has a PA value of 98.23%, UA 86.16% and OA 87.63%. This accuracy value indicates that the map has good results but judging from the magnitude of the highest accuracy value obtained from NDVI, it can be concluded that NDVI is the best index to determine paddy fields.

INTRODUCTION

The agricultural sector, especially food crops such as rice, which has become a national strategic commodity, is one of the most important fields in meeting people's livelihoods and supporting the Indonesian economy. Globally, rice is counting on 720 million tons, of which 90% of it comes from the Asia region (Kuenzer & Knauer, 2013). One proof of the importance of agricultural in Indonesia is the inclusion of agricultural in the 2015-2019 RPJMN (National Medium-Term Government Plan) and the Indonesian Government's Nawa Cita Agenda and Law Number 41 of 2009 concerning the protection of sustainable food agricultural land (UU PLP2B). According to Law

Number 41 of 2009, Sustainable Food Agricultural Land is a plot of agricultural land that is determined to be protected and developed consistently to produce staple food for national self-reliance, security and sovereignty of foodstuff (Sadali, 2018).

The mandate of this law is to protect food crops from the trend of land conversion and land fragmentation. Looking at the condition of Lampung Province as one of Indonesia's rice granaries, it is experiencing a rapid flow of conversion of agricultural land into non-agricultural land. The Law has not been implemented properly in Lampung Province. The area of land will not increase but the quality of the land may decrease due to human exploitative actions, and the population and their needs will continue to grow. This awakens the related parties to carry out transparent, effective, and participatory spatial planning to create a safe, comfortable, productive, and sustainable living space (Marinda et al., 2020).

Therefore, systematic, and strategic steps are needed to implement Law 41 of 2009. It all starts with the identification and mapping process of raw rice fields followed by the issuance of Regional Regulations that regulate technical matters relating to the protection of agricultural land. One method in the process of mapping and identifying raw rice fields is to use geospatial information as the main source of information.

It is important to conduct a study on the preparation of spatial information and agricultural land resource management systems to support sustainable production. One realization of the preparation of spatial information and agricultural land resource management systems is the activity of making sustainable food agricultural land mapping in Lampung Province which aims to make a better food production system in Lampung Province.

Information about the agricultural area that is accurate is needed in supporting agricultural development policies. Food and energy agricultural includes: (1) improvement of rice production estimation, from the frame list for the frame area, (2) mapping of raw rice fields, and (3) the rate of extension of oil palm plantations related to climate change (deforestation) which can in turn, threaten agricultural land (Raimadoya, et. al. 2011).

The process of mapping raw rice fields can be used as a stepping-stone for the implementation of the frame area. The frame area approach not only requires a strong foundation in the mapping aspect but also requires a relatively high cost in the early stages. The cost in the early stages will be much cheaper if the sampling design is successfully imposed so that it can be used for the next 15-20 years. Moreover, if the mapping activity is considering to a topographical map for rural areas.

Therefore, the identification and mapping of raw rice fields are carried out using satellite imagery aims to obtain the geographical distribution and area of raw rice fields in Lampung Province as the first step in the realization of Law No. 41 of 2009.

One alternative to overcome the processing of maps is to utilize the results of remote sensing technology, namely satellite imagery, because imagery can be interpreted visually to obtain the most up-to-date information about forest cover, forest conditions, forest vegetation types, information on landforms, land use and potential, and others, which cannot be obtained from other data sources specifically (Berutu, 2013). The utilization of remote sensing imagery can be used to identify land cover using the vegetation index. The vegetation index is one of the parameters used to analyze the state of vegetation by measuring the greenness of the vegetation canopy, composite properties of leaf chlorophyll, leaf area, structure and canopy cover of vegetation in an area (Huete et al., 2010).

Previous research related to the use of remote sensing imagery for rice fields mapping has been carried out using many vegetation indices. Several examples are

Rice field identification using NDVI and PCA with Landsat image (Subiyanto & Sukmono, 2015), utilization of SR (Simple Ratio) index, NDVI (Normalized Difference Vegetation index), TNDVI (Transformed Normalized Difference Vegetation Index), SAVI (Soil-Adjusted Vegetation Index) and TVI (Triangular Vegetation Index) for plant health monitoring (Vibhute & Gawali, 2013). The application of NDVI and EVI indices on MODIS imagery for rice-fields monitoring (Kuenzer & Knauer, 2013), another MODIS imagery utilization using NDVI index (Guan et al., 2016), deep learning method application for rice fields mapping (Wang et al., 2020) are another example of previous related research. Additional previous research are multi-season rice fields monitoring using NDVI index for Landsat-8 and Sentinel-1A data (Tian et al., 2018), Combination of Landsat and SAR imagery using NDVI, Enhanced Vegetation Index (EVI), and Land Surface Water Index (LSWI) (Park et al., 2018), Usage of EVI and LZWI for MODIS imagery (Dou et al., 2020). Moreover, one such example is rice fields mapping by means of NDVI, RDVI, OSAVI and MTVI indices. (Yeom et al., 2021).

The Vegetation Index used in this study is the Normalized Difference Vegetation Index (NDVI), Soil Adjusted Vegetation Index (SAVI) and Transformed Soil Adjusted Vegetation Index (TSAVI). The expected result of this research is to be able to identify raw rice fields with a good level of Accuracy.

RESEARCH METHODS

This research was conducted in Lampung Province which is the southernmost province on the island of Sumatra. Geographically, Lampung Province is located at 103° 40' - 105° 50' East Longitude and 6° 45' - 3° 45' South Latitude. Precisely, the location of the research is presented in the following image.

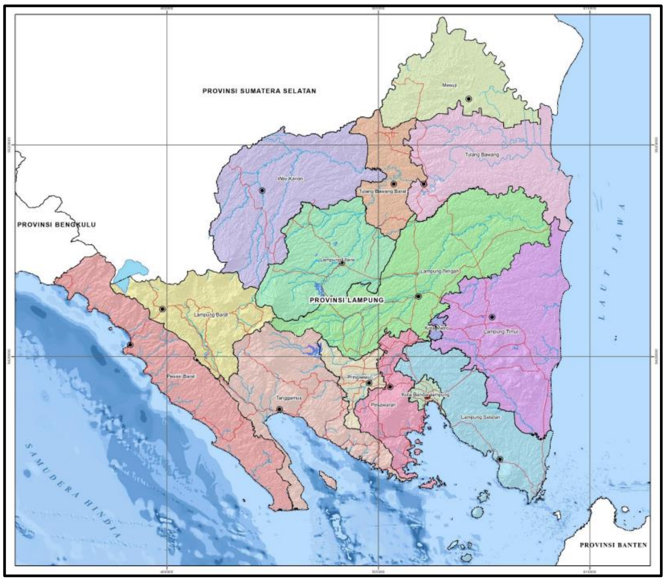


Figure 1. Location of research

The mapping process of raw rice fields was made according to image processing and field validation for the accuracy test. This mapping starts from data collection, processing, analysis, to field validation. In detail, the research flow is described in the following figure.

This study begins by collecting all the required data, namely, SPOT 6 and 7 high-resolution Satellite Imagery from the 2018 captures campaign. SPOT 6 and 7 satellites have a resolution of 6 meters for multispectral and 1.5 meters for panchromatic, respectively. These sets of imagery were obtained from the National Institute of Aeronautics and Space (LAPAN) which was downloaded via https://inderaja-catalog.lapan.go.id/ free of charge. The usage of satellite imagery in this research because of the characteristics of the image that has blue, green, red, and near-infrared wavelengths which are useful in formulating algorithms for identifying rice fields. Furthermore, SPOT6 and 7 are used in this study due to their high-resolution nature, which become an advantage when analyzing rice fields that usually is less than 1 hectare in urban areas. Additionally, this study also uses the Map of Raw Rice Fields in 2018 obtained from BIG and the Ministry of ATR/BPN. The SPOT image is then being carried out in a geometric correction process using the existing Ground Control Point.

The purpose of geometric correction is to equate the position of each pixel in the image to the same object on the Earth's surface.

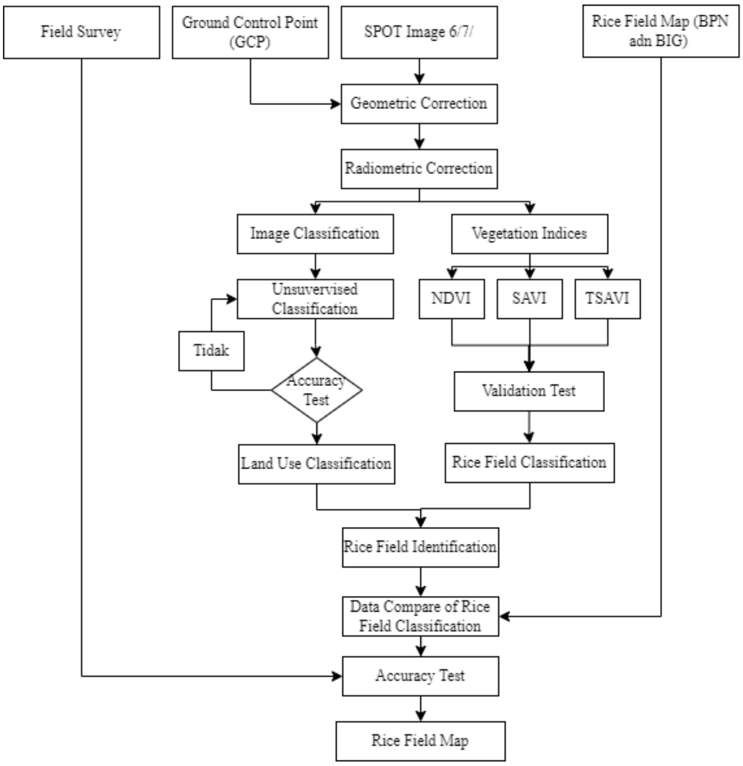


Figure 2. Research flowchart

The geometrically corrected image is then converted from a digital number value to a reflectance value that will be used in the vegetation index transformation stage. The stages of implementing the mapping processes of raw rice fields are divided into several stages, namely (i) initial identification of the location of rice fields using data from the transformation of the vegetation index (NDVI, TSAVI or SAVI). (ii) Conducting a digital classification process as a source of land cover data. This stage is followed by (iii) the field validation process to confirm the data on the location of the rice fields considering to the NDVI, TSAVI and SAVI algorithms and confirm the land cover data from the digital classification results. The next stage is (iv) comparing the classification results obtained with the Raw Rice Land map data from the Ministry of ATR/BPN, BIG and the Ministry of Agriculture in the year 2018. Lastly is (v) calculate the Accuracy of the data classification results in the image with the field using a confusion matrix.

The interpretation of land use classification is carried out to help facilitate the interpretation of raw fields. The interpretation is carried out using supervised classification with an accuracy test of more than 85%. The results of land use processing can be mapped if the test accuracy is more than 85%, otherwise it must be reprocessed until it reaches an interpretation accuracy of more than 85%. The field validation survey for the processing results of the vegetation index transformation was carried out by looking at the vegetation density level of 30 x 30 meters. This was necessary because it took into account the reflectance of the background such as soil and water included in the satellite data (Oguro et.al., 2003 in Li, et.al., 2014) (Li et al, 2013).

The process is continued with matters related to the use of satellite imagery for calculating the algorithm and then determining the location of the rice fields in the various phases using the calculation algorithm described and mentioned in this work. The results of the classification were then being subjected to a random field validation test (field campaign to obtain ground truth data). The field validation survey was carried out by recording the land cover and calculating the accuracy level of the rice field classification.

This data collection process is carried out to obtain the average value of rice yields in Lampung Province, which will later be used to calculate the potential for rice harvests in Lampung Province.

SAVI Algorithm

SAVI (Soil Adjusted Vegetation Index) which was proposed (Ren et al, 2018) uses a vegetation isoline equation derived by approximating canopy reflectance with a first-order photon interaction model between the canopy and the soil layer. The SAVI model has used knowledge of the vegetation isoline equation, which is simple, to obtain a Vegetation Index that has been corrected for soil background effects (Rondeaux et al., 1996). Described below is the equation of SAVI:

$$SAVI = \left[\left(\frac{\rho_{NIR} - \rho_{RED}}{\rho_{NIR} - \rho_{RED} + L}\right)\right] x\ (1 + L) \ldots.(1)$$

Where L is the "global" soil "adjustment" factor. The L constraint is related to Beer's Law and calculates for the difference in the red canopy and NIR spectral extinction factors through the actively photosynthesized canopy. (Huete, 1988 in Mulla, 2013). The value of L in this research is assigned in 0.6.

TSAVI Algorithm

TSAVI (Marino & Alvino, 2018) is a further development of the SAVI concept. TSAVI is a vegetation index that used to minimize the brightness of the soil of which causes an error in the electromagnetic wavelength reflected from the vegetation (Rondeaux et al., 1996) (Xue & Su, 2017) which is defined as:

TSAVI = a(NIR - aR - b) / [R + a(NIR - b) + 0.08(1 + a2)]..(2)

Where a and b are the slope and intercept of the ground line, respectively (NIRsoil = aRs~l + b); and the 0.08 coefficient value was adjusted to minimize the soil effect.

NDVI Algorithm

NDVI is one of the most popular indices for identification of vegetated areas. This index is closely related to the amount of vegetation to saturation in dense canopy cover and the biophysical properties of the plant canopy, such as: absorption of photosynthetic active radiation, efficiency, and productivity. However, the NDVI index is very sensitive to the optical properties of the soil, and is difficult to interpret with low vegetation cover when the soil is unknown. (Rondeaux et al., 1996) (Gandhi et al., 2015).

The red band (Red) and near-infrared band (Near-IR) in Landsat satellite imagery are used to obtain NDVI values with the following calculations (Gandhi et al., 2015) (Robinson et al., 2017), for example Landsat 8.

$$NDVI = \frac{NIR - R}{NIR + R} \ldots\ldots\ldots\ldots\ldots (3)$$

Information:
Band 4: Red channel on Landsat 8
Band 5: Near infrared channel on Landsat 8

Field Surveys

Field surveys from the results of satellite image processing are used to see the level of errors that occur in the classification of the sample area so that the percentage of mapping accuracy can be determined. The Accuracy of land use mapping is done by making a contingency matrix or an error matrix. Accuracy tests of the results of mapping are carried out by sampling, the sampling technique used is Random Sampling based on sample size using 95% confidence level with a margin of error of 3.305%, calculated according to the z-score.

Sampling of field accuracy testers considering to this reference land use map was carried out using a point basis. The area of Lampung Province is divided by a field size 30x30, to obtain a total population of 8,842, so that by using the specifications as above, 800 sample points are obtained, covering 10% of the population.

Accuracy Test

The accuracy test was carried out to determine the Accuracy of the mapping of raw land cover for rice fields. The accuracy test was carried out using a reference of 70% of the field data. The accuracy test is carried out after conducting a survey or field work. The results of the classification need to be tested to produce acceptable data with a certain level of Accuracy (BIG, 2014).

The process of testing the Accuracy of the interpretation results starts from using all samples from the population to be tested on the data from the field checks. The question test is to make a comparison by compiling an error matrix (confusion matrix). Tests are carried out on samples that represent certain objects in an object polygon with the coordinates of the same location in the field. Samples that have been taken from the field are compared with the class of objects classified as a result (BIG, 2014).

Resulted in a matrix is composed of a confusion matrix, which shown in Table 1 below. From the table, to calculate the Overall Accuracy (overall Accuracy) is calculated built upon several equation below.

The overall accuracy value shows the number of pixels that are correctly classified in each class compared to the number of samples used for accuracy testing in all classes.

Table 1. Cross tabulation confusion matrix from accuracy test result

Data Image	Field Survey				
	A	B	C	Total	Producer Accuracy
A	AA	BA	CA	AA+BA+CA	AA/AA+ AB+AC
B	AB	BB	CB	AB+BB+CB	BB/BA+BB+BC
C	AC	BC	CC	AC+BC+CC	CC/CA+CB+CC
Total	AA+AB+AC	BA+BB+BC	CA+CB+CC	Total Number of Sample Point	
User Accuracy (%)	AA/AA+ BA+CA	BB/AB+ BB+CB	CC/AC+ BC+CC		Overal Accuracy (%)

Source: (Prayuda, 2014).

Overall Accuracy (OA)

The accuracy test value is the most widely used to test the Accuracy of an interpretation or a classification result. Overall Accuracy is calculated following the equation:

$$Overall\ Accuracy\ (\%) = \frac{Ji}{Tt} \times 100 \qquad (4)$$

Information:
OA = Overall Accuracy
Ji = Number of samples on the diagonal (correctly classified)
Tt = Total sample tested

Producer Accuracy (PA)

Accuracy producer to determine the level of Accuracy according to the facts obtained in the field.

$$Producer\ Accuracy\ (\%) = \frac{Cc}{Tt} \times 100 \qquad (5)$$

Information:
OA = Overall Accuracy
Cc = Number of samples on the row (correctly classified)
Tt = Total sample tested

User Accuracy (UA)

User accuracy to determine the level of Accuracy according to the results of image reading.

$$User\ Accuracy\ (\%) = \frac{Dd}{Tt} \times 100 \qquad (6)$$

Information:
OA = Overall Accuracy
Dd = Number of samples on the column (correctly classified)
Tt = Total sample tested

The value of user and producer accuracy is calculated for each class in the classification. Continuing from this matrix, the results of the mapping accuracy are obtained to determine the processed maps have good mapping results and are following the original conditions in the field, so that the maps can be used for further analysis.

RESULTS AND DISCUSSIONS

Data Analysis (NDVI, SAVI, TSAVI)

The processing of vegetation density index using the NDVI, SAVI and TSAVI algorithms are carried out to see the value of vegetation density in Lampung Province. The results of the processing will show the magnitude of the change in the value of the vegetation density in each algorithm. The processing of vegetation index density is carried out using the red band and the near-infrared band. A good range of wavelength values for NDVI is -1 to 1, the longer the wavelength is closer to 1, the vegetation density index indicates that the area has dense vegetation.

Comparison of the analysis results using these three indices could be seen in the distribution of rice fields in Lampung Province. First of all, all three indices have an overall accuracy which higher than 86%, indicating that all of three has good agreement with field result, as also mentioned in (Kimura dkk., 2004) and (Xue dkk., 2004). The distribution of rice fields according to the NDVI transformation vegetation index has a contrasting comparison with other vegetation objects which makes that easier to identify. The behavior of NDVI result is different with the SAVI and TSAVI indices results because of the influence of the soil which causes separation from other objects is quite difficult. This causes the results of rice field classification using NDVI is better than SAVI and TSAVI. This is also in line with previous research which stated that NDVI is more effectively used in mapping rice fields for a wider area (Guan dkk., 2016). The wavelength values obtained from the results of data processing are as follows.

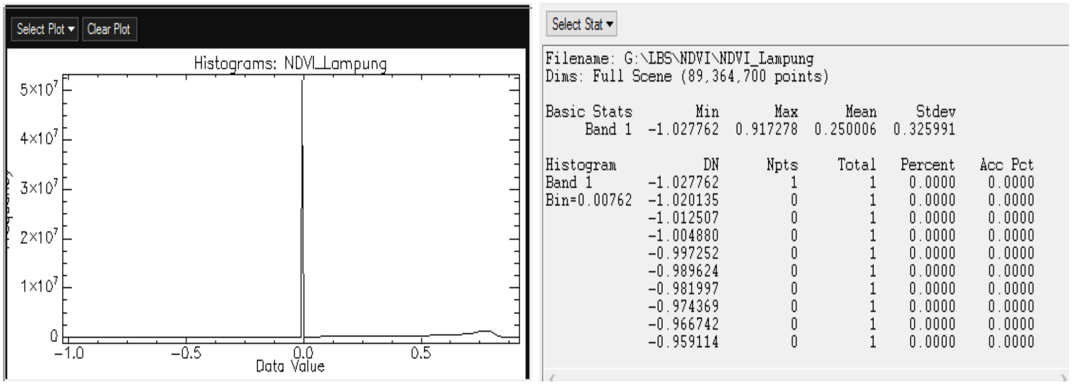
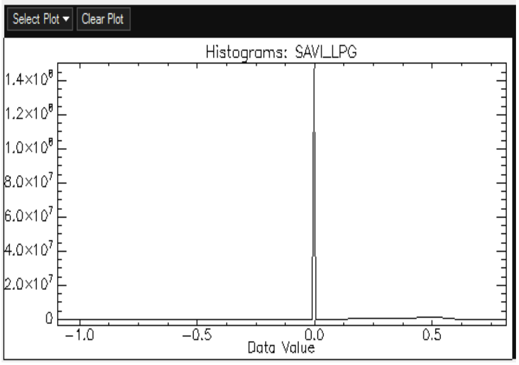


Figure 3. Wavelengths of NDVI results

The determination of the rice vegetation index was carried out to determine the pattern of the vegetation index for rice fields in Lampung Province. The Lampung Province NDVI index value has a minimum value range between -1.02 to a maximum value of 0.91 with an average value of 0.25, built upon the results of the analysis for the rice field object has a range between 0.1 - 0.8. The -1.02 value is deemed as outlier due to the nature of its existence (only 1 data with that value from more than 89 million data points). The index value is used as a reference for determining rice fields using the results of the transformation of the NDVI algorithm. According to the results SPOT 6/7 image processing using the NDVI algorithm, it is shown on the map in Figure 4 below.

Figure 4. Map of vegetation density in Lampung Province using NDVI

The determination of the rice vegetation index was carried out to determine the pattern of the vegetation index for rice fields in Lampung Province. The Lampung Province SAVI index value has a minimum value range between -1.09 to a maximum value of 0.81 with an average value of 0.09. Built upon the results of the analysis for rice fields objects have a range between 0.1 - 0.8 for the results of SPOT 6/7 image processing using the SAVI algorithm. The index value is used as a reference for determining rice fields according to the index value according to the algorithm. As shown from the results of processing the vegetation index transformation using the SAVI algorithm, the vegetation density is presented in Figure 4 below. The determination of the rice vegetation index was carried out to determine the pattern of the vegetation index for rice fields in Lampung Province using TSAVI transformation.

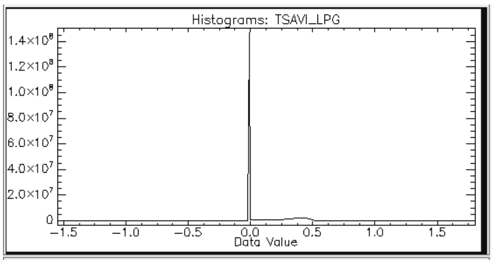



```
Select Stat
Filename: G:\LBS\Masking\SAVI_LPG
Dims: Full Scene (190,718,961 points)

Basic Stats       Min       Max      Mean     Stdev
     Band 1  -1.094912  0.813634  0.091196  0.180912

Histogram          DN       Npts      Total    Percent   Acc Pct
Band 1       -1.094912         1          1     0.0000    0.0000
Bin=0.00748  -1.087428         1          2     0.0000    0.0000
             -1.079943         0          2     0.0000    0.0000
             -1.072459         0          2     0.0000    0.0000
             -1.064974         0          2     0.0000    0.0000
             -1.057490         0          2     0.0000    0.0000
             -1.050005         0          2     0.0000    0.0000
             -1.042521         0          2     0.0000    0.0000
             -1.035036         1          3     0.0000    0.0000
             -1.027552         0          3     0.0000    0.0000
             -1.020067         0          3     0.0000    0.0000
```

Figure 5. Wavelengths of SAVI results

Figure 6. Map of vegetation density in Lampung Province using SAVI

The Lampung Province TSAVI index value has a minimum value range between -1.55 to a maximum value of 1.80 with an average value of 0.07. Refer to the results of the analysis for rice fields objects have a range between 0.1 - 0.8. The index value is used as a reference for determining rice fields based on the results of the transformation of the NDVI algorithm. Considering to the results of SPOT 6/7 image processing using the TSAVI algorithm, it is shown in the histogram table 6 below.




```
Select Stat
Filename: G:\LBS\Masking\TSAVI_LPG
Dims: Full Scene (190,718,961 points)

Basic Stats       Min       Max      Mean     Stdev
     Band 1  -1.551107  1.804436  0.072515  0.154232

Histogram          DN       Npts      Total    Percent   Acc Pct
Band 1       -1.551107         4          4     0.0000    0.0000
Bin=0.01315  -1.537948         2          6     0.0000    0.0000
             -1.524789         3          9     0.0000    0.0000
             -1.511630         0          9     0.0000    0.0000
             -1.498471         2         11     0.0000    0.0000
             -1.485312         0         11     0.0000    0.0000
             -1.472153         0         11     0.0000    0.0000
             -1.458994         0         11     0.0000    0.0000
             -1.445835         0         11     0.0000    0.0000
             -1.432676         0         11     0.0000    0.0000
```

Figure 7. Wavelengths of TSAVI results

The distribution of vegetation density values is grouped of the wavelength of each algorithm value to determine the condition of vegetation in Lampung Province. The vegetation density class according to the Regulation of the Minister of Forestry numbered P.12 of 2012 is divided into unvegetated land, very low density, low density, medium density, and high density. The following is the result of the vegetation density map of Lampung Province. Refer to the results of SPOT 6/7 image processing using the TSAVI algorithm, it is shown on the map in Figure 8 below.

Based on the results of image analysis using the three algorithms which include NDVI, SAVI and TSAVI, it is found that the index value of TSAVI has the highest index value with a maximum value of 1.80 while the index that has a minimum value of NDVI is around -1.02. The three index values obtained are overlaid with land use results from image classification.

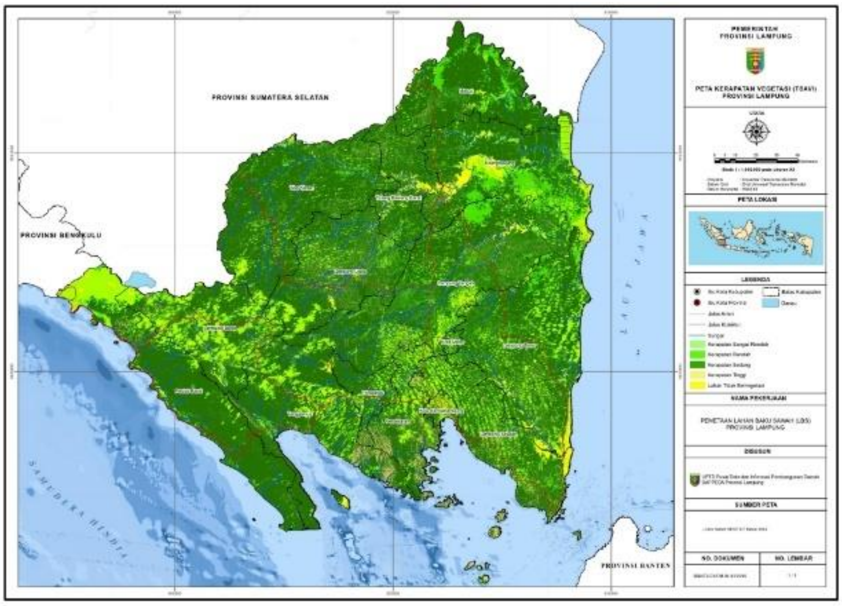


Figure 8. Map of vegetation density in Lampung Province using TSAVI

Mapping of raw rice fields is obtained by looking at the level of vegetation density and visual interpretation of the image. The digital interpretation of the image is carried out based on the recognition of the spatial characteristics of the object by looking at the shape, color, pattern, location, and texture. Determination of the training sample is carried out at points that are suspected to be rice fields as sample areas that represent the distribution of raw rice fields in Lampung Province. Based on the results of the interpretation and knowledge of the analysis of raw rice fields in Lampung Province, the area of raw rice fields in Lampung Province was obtained. The following is the area of raw rice fields in Lampung Province because of data processing that has been carried out. In more detail, the area of raw rice fields in Lampung Province is presented in the following table.

Table 2. Raw Rice Fields Area of Lampung Province

No	District/City	Area by Image (Ha)	Percentage (%)
1.	Bandar Lampung	501,17	0,19
2.	Lampung Barat	8053,41	3,02
3.	Lampung Selatan	40150,21	15,08

No	District/City	Area by Image (Ha)	Percentage (%)
4.	Lampung Tengah	66454,51	24,96
5.	Lampung Timur	55418,12	20,81
6.	Lampung Utara	9994,8	3,75
7.	Mesuji	5819,65	2,19
8.	Metro	2966,69	1,11
9.	Pesawaran	12668,18	4,76
10.	Pesisir Barat	6283,68	2,36
11.	Pringsewu	13633,8	5,12
12.	Tanggamus	13848,39	5,20
13.	Tulang Bawang	5816,41	2,18
14.	Tulang Bawang Barat	14884,06	5,59
15.	Way Kanan	9766,56	3,67
	Total	266.259,64	100

Source: (Data processing, 2019).

The table above explains that the Raw Rice Fields area of West Lampung Province is 8,053.41 Ha with a percentage of 3.02%, South Lampung has an area of 40,150.21 Ha with a percentage of 15.08%. The area that has the largest area of raw rice fields is Central Lampung Regency with an area of 66,454.51 Ha or 24.96% of the total area of raw rice fields in Lampung Province. The area of raw land for rice fields in East Lampung is 55,418.12 Ha with a percentage of 20.81%. North Lampung Regency has an area of 9,994.80 Ha with a percentage of 3.75%. Mesuji Regency has an area of 5819.65 hectares of raw rice fields with a percentage of 2.19%. The area of Metro City's raw rice fields is 2,966.69 Ha with a percentage of 1.11%. Pesawaran Regency has an area of 12,668.18 Ha with a percentage of 4.76%. The raw land of West Pesisir Regency is 6,283.68 Ha with a percentage of 2.36%. The area of raw rice fields in Pringsewu Regency is 13,633.80 Ha with a percentage of 5.12%. Tanggamus Regency has a land area of 13,848.39 Ha with a percentage of 5.20%. The area of raw rice fields in Tulang Bawang Regency has an area of 5,816.41 Ha with a percentage of 2.18%. Tulang Bawang Barat Regency has a rice field area of 14884.06 with a percentage of 5.59%. Way Kanan Regency has a land area of 9,766.56 hectares with a percentage of 3.67%. While the minimum raw land for rice fields is in Bandar Lampung City with an area of 501.17 hectares or 0.19% of the total area of raw rice fields in Lampung Province.

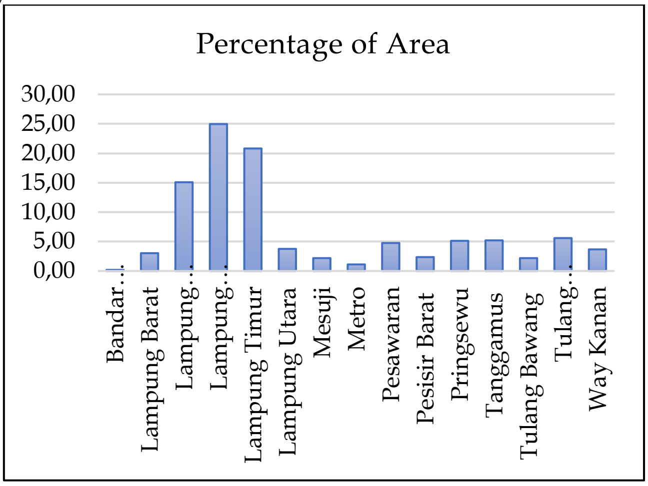


Figure 9. Raw Rice Fields Area of Lampung Province
Source: (Data processing, 2019).

In more detail, the distribution of raw land for rice fields in Lampung Province is presented in the following figure 10.

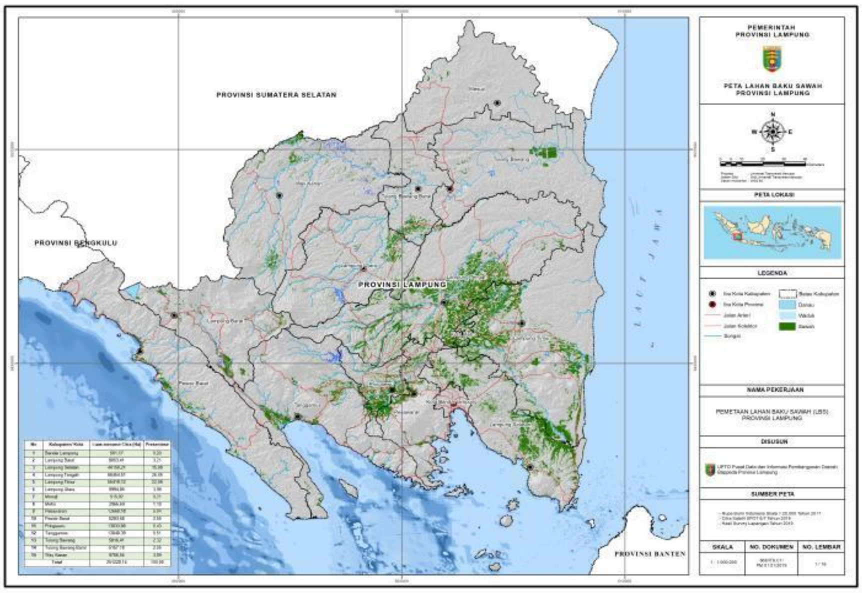


Figure 10. Map of raw rice fields in Lampung Province

Accuracy and Validation of Rice Fields Raw Land Map Result of Digital Classification with Field

The accuracy test for the results of the classification of raw rice fields is carried out to determine the level of Accuracy of the results of the classification of rice fields and non-rice fields to determine whether the results of this classification can be used to limit the study area to be further processed. Field validation is determined by measuring the coordinates of the observation locations in the field using a GPS (Global Positioning System) device following pre-determined sample points totaling 800 sample points.

The confusion matrix table is one way of testing accuracy. Shown in Table 3 is the result of NDVI index classification using confusion matrix. The accuracy test serves to measure the Accuracy in image interpretation. In this accuracy test, the classification results will be compared with the actual conditions in the field regarding the points taken in the field and are considered to represent all categories of percent of raw rice fields. The results of measuring Accuracy from processing are producer accuracy, user accuracy, overall Accuracy (OA) is presented in the following table. The results of the calculation accuracy using the confusion matrix are shown in Table 3. It produces an overall mapping accuracy of 90.25% which indicates that the map has good results. Table 4 and Table 5 indicates the confusion matrices of SAVI and TSAVI, respectively.

Table 3. Matrix of accuracy test for NDVI

NDVI	Field Survey			
	Rice Field	Non-Rice Field	Total	User Accuracy (%)
Rice Field	565	78	643	87,87
Non-Rice Field	0	157	157	100,00

Total	565	235	800	
Producer Accuracy (%)	100,00	66,81	166,81	
Overall Accuracy (%)		90,25		

Source: (Data Processing, 2019).

The total sample points in the field were 800 samples, with details of 565 points in the field that were correctly confirmed as rice fields, 78 points in the field were not confirmed as rice fields, and 157 were confirmed as non-rice fields, both in the image and in the field. If you look at the producer accuracy value, the rice field class has a value of 100%. This value indicates that an average of about 100% of the reference data of surveyed rice fields will always be correctly confirmed as rice fields in the image classification results. In the user accuracy value for the field class, the resulting value is 87.87%. This value indicates that an average of about 87.87% of the pixel data in the rice field category, the image classification results will be confirmed correctly in the field as rice fields. The overall accuracy value obtained is 90.25%, representing image accuracy in general.

Table 4. Matrix of accuracy test for SAVI

SAVI	Field Survey			
	Rice Field	Non-Rice Field	Total	User Accuracy (%)
Rice Field	547	95	642	85,20
Non-Rice Field	12	146	158	92,41
Total	559	241	800	
Producer Accuracy (%)	97,85	60,58		158,43
Overall Accuracy (%)		86,63		

Source: (Data Processing, 2019).

The results of the accuracy calculation using the confusion matrix shown in Table 4 of the SAVI index. The processing resulted in an overall mapping accuracy of 86.63% which indicates that the map has good results, but this accuracy result is lower than the NDVI calculation of 90.25%. The total sample points in the field were 800 samples, which 547 points in the field that were correctly confirmed as rice fields, another 95 points in the field were not confirmed as rice fields, and last 146 were confirmed as non-rice fields, both in the image and in the field.

If we look at the producer accuracy value, the rice field class has a value of 97.85%. This value indicates that less than 3% of the reference data from the survey results will not be correctly confirmed as rice fields in the image classification results. In the user accuracy value for the field class, the resulting value is 85.20%. This value indicates that in an average 85 out of 100-pixel data in the rice field category, the results of the image classification will be confirmed correctly in the field as rice fields.

Table 5. Matrix of Accuracy Test for TSAVI

TSAVI	Field Survey			
	Rice Field	Non-Rice Field	Total	User Accuracy (%)
Rice Field	554	89	643	86,16
Non-Rice Field	10	147	157	93,63
Total	564	236	800	
Producer Accuracy (%)	98,23	62,29		160,52
Overall Accuracy (%)		87,63		

Source: (Data Processing, 2019).

Meanwhile, the results of the accuracy calculation using the confusion matrix shown in Table 5 of the TSAVI index, resulted in an overall mapping accuracy of 87.63% which indicates that the map has good results with an accuracy value above SAVI, but this accuracy result is still lower than NDVI calculation. The total sample points in the field were 800 samples, with details of 554 points in the field being correctly confirmed as rice fields, 89 points in the field not being confirmed as rice fields, and 147 confirmed not being rice fields, both in the image and in the field. If you look at the producer accuracy value, the rice field class has a value of 98.23%. This value indicates that an average of about 98 out of 100 data of the reference data from the survey results will always be correctly confirmed as rice fields in the image classification results. In the user accuracy value for the field class, the resulting value is 88.16%. This value indicates that an average of about 86.16% of the pixel data in the rice field category, the image classification results will be confirmed correctly in the field as rice fields.

CONCLUSION

According to the results of the analysis using high-resolution satellite imagery SPOT 6 and 7 and the vegetation index NDVI, SAVI and TSAVI with a range of pixel values for rice fields of 0.1 to 0.8 and divided into 5 classes of non-vegetated land, very low density, low density, medium density, and high density. It resulted in an area of rice fields in Lampung Province of 266259.64 Ha which covers 7.2% of the total area of Lampung Province. Central Lampung and East Lampung districts are the two districts with the largest area, reaching 66,454.51 Ha (24.96%) and 55,418.12 Ha (22.81%). Bandar Lampung is an area that has the least rice fields, having an area of 501.17 hectares which is 0.19% of the total area of Lampung Province, where there are two types of rice fields, namely irrigated rice fields and rain-fed rice fields. Based on findings of a field survey conducted with 800 samples spread across 15 regencies/cities in Lampung Province (according to the Random Sampling method with a 95% confidence level and a margin of error of 3.305%), 565 points were obtained which were rice fields and 235 points were not rice fields. (70.625% and 29.375%). The results of the accuracy test show that the highest Accuracy for determining paddy fields is obtained from the results of identification using NDVI. As a general suggestion, the results should then be compared with results of processing from another satellite imagery with different acquisition time to preliminary develop a refined raw rice field identification algorithm, as (Nadzir et. al, 2020) has started.

ACKNOWLEDGEMENT

We would like to thank LP3 Institut Teknologi Sumatera for providing support in carrying out this research activity.

REFERENCES LIST

Berutu, D. S. (2013). Aplikasi Penginderaan Jauh Dan Sistem Informasi Geografis Dalam Mengkaji Perubahan Luas Hutan Di Kabupaten Kuantan Singingi (Riau) Tahun 2000-2010. 10.

BIG. (2014). Pedoman Teknis Ketelitian Peta Dasar. Peraturan Kepala Badan Informasi Geospasial Nomor 15 Tahun 2014.

BPS. (2018). Luas Panen dan Produksi Padi di Provinsi Lampung. Lampung: Badan Pusat Statistik Provinsi Lampung.

BPS (2019). Lampung Dalam Angka. Dipetik 09 September 2019, dari https://lampung.bps.go.id/subject/53/lampung-dalam-angka.html

Dou, Y., Huang, R., Mansaray, L. R., & Huang, J. (2020). Mapping high temperature damaged area of rice rice along the Yangtze River using Moderate Resolution Imaging Spectroradiometer data. International Journal of Remote Sensing, 41(2), 471–486. https://doi.org/10.1080/01431161.2019.1643936

Gandhi, G. M., Parthiban, S., Thummalu, N., & Christy, A. (2015). Ndvi: Vegetation Change Detection Using Remote Sensing and Gis – A Case Study of Vellore District. Procedia Computer Science, 57, 1199–1210. https://doi.org/10.1016/j.procs.2015.07.415

Guan, X., Huang, C., Liu, G., Meng, X., & Liu, Q. (2016). Mapping Rice Cropping Systems in Vietnam Using an NDVI-Based Time-Series Similarity Measurement Based on DTW Distance. Remote Sensing, 8(1), 19. https://doi.org/10.3390/rs8010019

Huete, A., Didan, K., van Leeuwen, W., Miura, T., & Glenn, E. (2010). MODIS Vegetation Indices. Dalam B. Ramachandran, C. O. Justice, & M. J. Abrams (Ed.), Land Remote Sensing and Global Environmental Change (Vol. 11, hlm. 579–602). Springer New York. https://doi.org/10.1007/978-1-4419-6749-7_26

Kimura, R., Okada, S., Miura, H. & Kamichika, M. (2004). Relationships among the leaf area index, moisture availability, and spectral reflectance in an upland rice field. Agricultural Water Management, 69(2), 83-100. https://doi.org/10.1016/j.agwat.2004.04.009.

Kuenzer, C., & Knauer, K. (2013). Remote sensing of rice crop areas. International Journal of Remote Sensing, 34(6), 2101–2139. https://doi.org/10.1080/01431161.2012.738946

Lampung, B. P. (2015). Bandar Lampung dalam Angka Tahun 2015. Bandar Lampung: BPS Kota Bandar Lampung.

Lampung, B. P. (2018). Bandar Lampung dalam Angka Tahun 2015. Bandar Lampung: BPS Kota Bandar Lampung.

Lampung, B. P. (2018). Luas Panen dan Produksi Padi di Provinsi Lampung 2018 (Perbaikan Metodologi Perhitungan Data Produksi Beras dengan Metode Kerangka Sampel Area). Bandar Lampung: BPS Provinsi Lampung.

Li, P., Jiang, L., & Feng, Z. (2013). Cross-Comparison of Vegetation Indices Derived from Landsat-7 Enhanced Thematic Mapper Plus (ETM+) and Landsat-8 Operational Land Imager (OLI) Sensors. Remote Sensing, 6(1), 310–329. https://doi.org/10.3390/rs6010310

Li, Peng, Luguang Jiang, and Zhiming Feng. 2014. "Cross-Comparison of Vegetation Indices Derived from Landsat-7 Enhanced Thematic Mapper Plus (ETM+) and Landsat-8 Operational Land Imager (OLI) Sensors" *Remote Sensing* 6, no. 1: 310-

329. https://doi.org/10.3390/rs6010310

Marinda, R., R.P. Sitorus, S., & Pribadi, D. O. (2020). Analisis Pola Spasial Persebaran Kawasan Lahan Pertanian Pangan Berkelanjutan Di Kabupaten Karawang. Jurnal Geografi, 12(02), 161. https://doi.org/10.24114/jg.v12i02.17646

Marino, Stefano; Alvino, Arturo. (2018) Detection of homogeneous wheat areas using multi-temporal UAS images and ground truth data analyzed by cluster analysis. European Journal of Remote Sensing 51:1, pages 266-275.

Mulla, D. J. (2013). Twenty-five years of remote sensing in precision agriculture: Key advances and remaining knowledge gaps. Biosystems Engineering, 114(4), 358–371. https://doi.org/10.1016/j.biosystemseng.2012.08.009

Nadzir, Z. A., Simarmata, N., & Aliffia, A. (2020). Pengembangan Algoritma Identifikasi Sawah Padi Berdasarkan Spektra Fase Padi (Studi Kasus: Lampung Selatan) (Rice Field Identification Algorithm Development Using Spectral Value of Rice Field (Case Study: South Lampung)). JURNAL SAINS INFORMASI GEOGRAFIS, 3(1), 23. https://doi.org/10.31314/jsig.v3i1.537

Oguro, Y., Suga, Y., Takeuchi, S., Ogawa, H., & Tsuchiya, K. (2003). Monitoring of a rice field using landsat-5 TM and landsat-7 ETM+ data. Advances in Space Research, 32(11), 2223–2228. https://doi.org/10.1016/S0273-1177(03)90546-1

Park, S., Im, J., Park, S., Yoo, C., Han, H., & Rhee, J. (2018). Classification and Mapping of Rice Rice by Combining Landsat and SAR Time Series Data. Remote Sensing, 10(3), 447. https://doi.org/10.3390/rs10030447

Pertanian, K. (2018). Luas Sawah pada Fase Pertanaman Padi Data Satelit Landsat-8 Edisi 59 Periode 20 Juli-4 Agustus 2018. Bandar Lampung: BPS Lampung.

Pertanian, P. D. (2019, Juli). Diambil kembali dari Buku Statistik Data Lahan Tahun2012-2016: http://epublikasi.setjen.pertanian.go.id/epublikasi/statistik%20data%20lahan/Buku%20Statistik%20Data%20Lahan%20Tahun%202012-2016/files/assets/basic-html/page71.html

Prayuda, B. (t.t.). Panduan Teknis Pemetaan Habitat Dasar Perairan Laut Dangkal. 29.

Raimadoya, M. A., Trisasongko, B. H., Zain, A., Hasbi, W., & Tahir, A. (t.t.). Analisis Misi Dan Rancangan Lapan-Ipb Satellite (Lisat) Untuk Pemantauan Kemandirian Pangan. 16(3), 6.

Ren, H., Zhou, G., & Zhang, F. (2018). Using negative soil adjustment factor in soil-adjusted vegetation index (SAVI) for aboveground living biomass estimation in arid grasslands. Remote Sensing of Environment, 209, 439–445. https://doi.org/10.1016/j.rse.2018.02.068

Robinson, N., Allred, B., Jones, M., Moreno, A., Kimball, J., Naugle, D., Erickson, T., & Richardson, A. (2017). A Dynamic Landsat Derived Normalized Difference Vegetation Index (NDVI) Product for the Conterminous United States. Remote Sensing, 9(8), 863. https://doi.org/10.3390/rs9080863

Rondeaux, G., Steven, M., & Baret, F. (1996). Optimization of soil-adjusted vegetation indices. Remote Sensing of Environment, 55(2), 95–107. https://doi.org/10.1016/0034-4257(95)00186-7

Sadali, M. I. (2018). Ketahanan Pangan Berkelanjutan Di Kabupaten Sukoharjo. 12.

Subiyanto, S., & Sukmono, A. (2015). Identifikasi Lahan Sawah

Menggunakan Ndvi Dan Pca Pada Citra Landsat 8. 4, 9.

Tian, H., Wu, M., Wang, L., & Niu, Z. (2018). Mapping Early, Middle and Late Rice Extent Using Sentinel-1A and Landsat-8 Data in the Poyang Lake Plain, China. Sensors, 18(2), 185. https://doi.org/10.3390/s18010185

Vibhute, A. D., & Gawali, D. B. W. (2013). Analysis and Modeling of Agricultural Land use using Remote Sensing and Geographic Information System: A Review. International Journal of Engineering Research And, 3(3), 12.

Wang, S., Di Tommaso, S., Faulkner, J., Friedel, T., Kennepohl, A., Strey, R., & Lobell, D. B. (2020). Mapping Crop Types in Southeast India with Smartphone Crowdsourcing and Deep Learning. Remote Sensing, 12(18), 2957. https://doi.org/10.3390/rs12182957

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

Xue, Li-Hong., Cao, Wei-Xing., Luo, Wei-Hong., Wang, Shao-Hua. (2004). Relationship Between Spectral Vegetation Indices and LAI in Rice. Chinese Journal of Plant Ecology, 28(1): 47-52. https://www.plant-ecology.com/EN/10.17521/cjpe.2004.0007

Yeom, J.-M., Jeong, S., Deo, R. C., & Ko, J. (2021). Mapping rice area and yield in northeastern asia by incorporating a crop model with dense vegetation index profiles from a geostationary satellite. GIScience & Remote Sensing, 58(1), 1–27. https://doi.org/10.1080/15481603.2020.1853352