Modification of Temperature Vegetation Dryness Index (TVDI) Method for Detecting Drought with Multi-Scale Image

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Abstract. The objective of this research is to assess the accuracy of Temperature Vegetation Dryness Index (TVDI) methods applied to Principal Component Analysis (PCA) and multi-scale images. The TVDI method will revamp with PCA in vegetation and surface temperature variables. Each variable has three algorithms, which are VCI, NDWI, and SAVI, for vegetation, and TCI, CWSI, and LST for surface temperature. The band input used was the PC1 resulted from PCA in each variable. The regression relationship between vegetation and surface temperature with PCA shows an average value of 0.99. The results of the PCA increased drought area throughout the research area and showed a negative relationship on the TVDI concept. Validation uses TRMM data for MODIS images and field surveys for Landsat imagery. Landsat showed an accuracy value of 75% and influenced by climate change. Besides, multi-scale imaging proves very useful in monitoring and mapping droughts. Keywords—Temperature Vegetation Dryness Index (TVDI), Principal Component Analysis (PCA), MODIS, Landsat, Drought.

1. Introduction

The El-Nino had drought impacts in agriculture from 1994 to the present [1]. In 1997, Indonesia suffered a prolonged drought and had an impact on farmland and forest fires [2]. The incident proved that the drought phenomenon requires monitoring and mapped. Analysis of monitoring and mapping requires temporal data with a large area. That capability is part of remote sensing data capable of using two variables for monitoring and mapping droughts [3]. Remote sensing has various types of imagery suitable for monitoring and mapping droughts. Therefore, small and medium resolution imagery can identify drought, and the difference in spatial resolution is called multi-scale.

The remote sensing method uses multi-scaled imagery for drought analysis, such as MODIS (Moderate Imaging Spectroradiometer) and Landsat (Land Satellite) are imagery with different spatial resolutions. The MODIS has a spatial resolution of 250 to 1 kilometer, and Landsat has a resolution of 30 meters. The MODIS image analysis used to know drought with large areas [4]–[10], especially...
Terra sensors that perform monitoring and mapping of surface areas. Landsat analysis helps to reinforce and emphasize the drought area to monitor and map drought [11]–[17].

During this time, monitoring and mapping drought only uses one image for dryness. Therefore, multi-scaled image capability is a remote sensing image implementation for drought monitoring and mapping. TVDI (Temperature Vegetation Dryness Index) is a method with two variables and can be used to a multi-scale image [18]. The technique is capable of detecting drought up to 0-5 centimeters. It relates to the vegetation and surface temperature that affects each other [19]. The TVDI method requires two variables, such as vegetation and surface temperature. The variables determined based on the TVDI concept developed by Sandholt et al. [18]. Drought variables on TVDI are too ordinary; therefore, it needs modifications.

Furthermore, the relationship between vegetation and surface temperature displayed is still general. Therefore, modifications are required to provide specific information about vegetation and surface temperature. Modification of algorithms using the PCA technique. The relationship of vegetation and surface temperature with a specific algorithm can emphasize the drought area.

The PCA (Principal Component Analysis) is a technique on an algorithm to get new information from two variables. PCA can provide specific information related to vegetation and surface temperature [5]. Each variable will use three different particular algorithms for vegetation using algorithms such as Vegetation Condition Index (VCI), Normalized Differences Water Index (NDWI), and Soil Adjusted Vegetation Index (SAVI). Algorithms VCI, NDWI, and SAVI have different information for vegetation. That has a sensitivity to climate change, measurements of water, biomass content, and sensitivity to soil background [20]–[22]. While at surface temperatures using algorithms such as Temperature Condition Index (TCI), Crop Water Stress Index (CWSI), and Land Surface Temperature (LST). TCI has a sensitivity to vegetation stress and saturated soils [23]. CWSI has a sensitivity to water loss due to crop evaporation [24], [25]. LST processing has different calculations, especially on the Landsat image. Landsat 7 ETM+ uses algorithms developed by USGS [17], and Landsat 8 uses a method known as the Split-Window Algorithm (SWA) [11], [26]–[31]. Based on existing research, the modified TVDI method will use multi-scale imagery and PCA. This research objective to determine the accuracy of the TVDI method with PCA and multi-scale images. These are becoming future needs for spatial drought monitoring.

2. Study area and data

2.1. Study Area

East Java Province is a province in Java Island, which lies between 111.0° - 114.4° E and 7.12° - 8.48° S. It has rainfall average of 1,900 mm per year, with a 100-day rainy season. East Java Province has two seasons, which is the dry season (June-October) and wet season (November-May). Based on the latest data, the highest temperature in East Java in October and November was (35.50°C), and the lowest was in August (19.80°C), with the humidity of 39 - 97%. The highest air pressure in August was 1,012.0 millibars, and the highest rainfall occurred in February [32]. The widespread impact of drought has hit many areas in East Java, especially in agricultural lands. According to the Drought Disaster Management Agency (BPBD), the drought that occurred in East Java province began in May 2015. Also, El-Nino with medium strength and will continue to increase in November 2015 with strong El-Nino [33].

2.2. Remote Sensing Data

2.2.1. MODIS

The satellite MODIS Terra has 36 bands, where the band 31 and 32 used to determine the surface temperature [22]. NASA’s official website at http://ladsweb.nascom.nasa.gov/data/search.html used to acquire Modis Terra imagery. This research uses the MODIS Level 1B image with a spatial resolution of 1 km. The Data used in Day of the Year (DOY) starting from 273 to 364 in 2002 until
2015. The year used based on El-Nino's anomaly conditions in Indonesia. Thus, it is not constant that the dry month will not rain because of El-Nino [34]

2.2.2. Landsat
Landsat has two types: Landsat 7 ETM+ and Landsat 8 OLI/TIRS. Landsat 7 ETM+ had nine-bands and lasted until 2003, while Landsat 8 OLI/TIRS had eleven-bands [17], [35]. Landsat imagery can be obtained for free on the official website of the USGS at http://usgs.gov. Landsat images used in the dry months and wet months in 2002 until 2015. The dry months in October and November. The wet month is December, January, February, and March. The analysis of Landsat imagery uses the drought result of the MODIS terra image.

2.2.3. Tropical Rainfall Measuring Mission (TRMM)
TRMM is a global precipitation measurement [5]. TRMM has three sensors installed on the TRMM system[36], [37]. TRMM image data obtained for free from NASA's official website is ftp://disc2.nascom.nasa.gov/data/TRMM/Gridded/3B43V7. TRMM image used is 3B43_V7, with a spatial resolution of 0.25 x 0.25 degrees or about 27 kilometers, and the data is a recording of monthly rainfall data. The spatial resolution will scale to 1 km and used is to validate the drought of the MODIS terra image.

3. Methodology
All remote sensing data for this research uses primary data and obtain from imagery. Data from description must be scaled and standardized before used for drought parameters.

3.1. Drought Parameters
Drought parameters are obtained based on the TVDI concept developed by Sandholt et al. [18]. Vegetation and surface temperature derived from multi-scaled image data with predefined algorithms. All algorithms are selected based on previous research and are focused on drought. The algorithm of vegetation and surface temperature are shown in Table II, especially for surface temperature in Landsat 8 TIRS using the SWA method developed by Sobrino et al. [29]. The SWA method uses atmospheric transmission and water vapor conditions for the determination of LST [11], [38], [39].

3.2. Principal Component Analysis (PCA)
PCA has a technique to reduce the dimensionality of a data set and giving a new image with very much information [40]–[42]. The PCA processing of remote sensing data is a method for devouring compresses with minor values [5]. This method uses three algorithms from vegetation index (VCI, NDWI, SAVI) and surface temperature (LST, TCI, CWSI). The result of PCA uses as inputs in the TVDI method as a modified.

3.3. TRMM
TRMM processing uses the pixel value to be a grid to read as a rainfall value. The Application used to perform TRMM is the ENVI program. The results of a monthly rainfall value data used for drought validation on the MODIS image.

3.4. Temperature Vegetation Dryness Index (TVDI)
TVDI concept shown in Fig. 1. The NDVI algorithm for vegetation shows density and humidity levels [18], [40], [41], and LST is sensitive to evaporation, leaf temperature, health, and water stress conditions [42], [43]. It made vegetation and surface temperature algorithm must have a specific algorithm. The formula for the TVDI method shown in Equation (1). Where \(a+b\text{NDVI}\) is LSTmax can obtain from scatterplot with regression between T.S. and NDVI [9], [18]. LSTmin is a value from a lower line on the triangle conceptual [44]. Then input on Equation 1 is changed using the input PCA, then obtained Equation 2. TVDI has a range of values of 0-1, where zero is a wet condition, and one is a dry condition. In Table I, the drought classification distinguished into five classes.
\[ TVDI = \frac{LST - LST_{\text{min}}}{a + bNDVI - LST_{\text{min}}} \]  

\[ TVDI_{\text{PCA}} = \frac{PCA_{\text{temperature}} - PCA_{\text{temperature min}}}{a + bPCA_{\text{vegetation}} - PCA_{\text{temperature min}}} \]  

Where all input data TVDI\textsubscript{PCA} same with the original TVDI methods.

### Table 1. Classification of drought.

| No | Classification | Condition       |
|----|----------------|-----------------|
| 1  | 0.0 – 0.2      | Wetness         |
| 2  | 0.2 – 0.4      | Normal          |
| 3  | 0.4 – 0.6      | Slight Drought  |
| 4  | 0.6 – 0.8      | Moderate Drought|
| 5  | 0.8 – 1.0      | Severe Drought  |

Source:[9], [18], [43]

### Table 2. Algorithm for vegetation and surface temperature.

| Indicator of Drought          | References                  | Algorithm                                                                 |
|-------------------------------|-----------------------------|----------------------------------------------------------------------------|
| CWSI  | Crop Water Stress Index     | Idso et al. (1981)           | CWSI= LST-LST\text{min}/\text{LST}_{\text{max}}-\text{LST}_{\text{min}} |
| LST   | Land Surface Temperature    | Prasasti et al. (2007)       | SP= 1.274+P[(B1+B2)/2]+M[(B1+B2)/2]                                    |
| TCI   | Temperature Condition Index | Kogan (1997)                 | TCI= \text{LST}_{\text{max}}-\text{LST}/\text{LST}_{\text{max}}-\text{LST}_{\text{min}} |
| NDVI  | Normalized Difference Vegetation Index | Huete et al. (2002) | NDVI= NIR-R/NIR+R                              |
| VCI   | Vegetation Condition Index  | Kogan (1995)                 | VCI=NDVI-NDVI\text{min}/NDVI\text{max}-NDVI\text{min}*100               |
| NDWI  | Normalized Difference Water Index | Gao (1996)       | NDWI= NIR-MidIR/NIR+MidIR                                    |
| SAVI  | Soil Adjusted Vegetation Index | Huete (1988)                  | SAVI= (1+L)*(NIR-Red)/NIR+Red+L                                      |
| PCA   | Principal Component Analysis | Campbell (2002)              | PCA= B1+B2+...Bn                                                      |

Source: Research Citation.

![Figure 1. A Concept of TVDI (TS/NDVI). Source:[9], [18]](image)

### 4. Results and discussion

#### 4.1. A Conceptual TVDI Method

The PCA gave the change of TVDI concept from negative to positive. Positive relationships occur in the wet months, while the dry month still has a negative relationship. Fig.3 shows that a positive relationship occurs because there is an external variable, i.e., climate. The climate impact on
vegetation occurs at the leaves’ temperature and causes vegetation to have patterns such as surface temperatures. Besides, PCA proves that specific information makes changes to the relationship between vegetation and surface temperature. The results differed from the study of Son et al. [9], which showed a positive relationship in the wet months, as it uses the TVDI on Equation (1).

PCA linear regression between vegetation and surface temperature acquires an average value of 0.99. That value proves modifications with PCA can be applied and used for drought. Table 3 shows that surface temperature has a strong relationship in each month, but vegetation influenced by evaporation, soil background, and climate changes and made relation not optimal [20], [23]–[25]. The surface temperature has optimal value because the algorithm used is very specific such as Li and Becker for MODIS Terra image [45], USGS for Landsat 7 [17], and SWA for Landsat 8 [27], [29]. All algorithms for the surface temperature used have a small difference in field temperature of 0.9 °K [11], [13].

**Table 3. Linear Regression Of Modification TVDI_{PCA}**

| No | Year-Date Landsat | PCATemperature_max (a+bPCAvegetation) | Regression (r²) | PCAtemperature_min | Regression (r²) |
|----|-------------------|---------------------------------------|----------------|--------------------|----------------|
| 1  | 2002-01 October   | y = -21.88x - 16.97                   | 0.997          | y = 22.89x - 19.49 | 1              |
| 2  | 2002-11 November  | y = -28.36x - 39.18                   | 0.996          | y = 35.87x - 29.98 | 1              |
| 3  | 2003-14 January   | y = -4.309x - 7.541                   | 0.986          | y = 2.814x - 16.03 | 1              |
| 4  | 2003-19 March     | y = -9.788x - 34.30                   | 0.992          | y = 11.95x - 54.11 | 1              |
| 5  | 2009-29 October   | y = -5.542x - 10.72                   | 1              | y = 12.56x - 40.70 | 1              |
| 6  | 2009-30 November  | y = -3.845x - 31.63                   | 1              | y = 4.802x - 40.77 | 1              |
| 7  | 2014-03 October   | y = -0.053x - 0.277                   | 1              | y = 18.41x - 28.19 | 1              |
| 8  | 2014-04 November  | y = 1.055x - 25.93                    | 1              | y = -2.880x - 32.92 | 1              |
| 9  | 2015-07 January   | y = 20.06x - 5.361                    | 0.996          | y = -6.152x - 44.82 | 1              |

Source: Data Processing

**Figure 2.** Different result of TVDI methods (a) modification with PCA and (b) normal.
Figure 3. PCA scatterplot modification of TVDI methods.

Figure 4. Multi-scale image of drought result on modification TVDI-PCA methods.
4.2. Modification TVDI Methods
The PCA results showed increased drought area compared to TVDI. Fig.2.b shows wet areas close to streams, paddy fields, and ponds, where the recorded month is the dry month. While Fig.2.a shows the humid regions of Fig.4.b to be a dry area, it is more relevant to the condition in the field. These changes not only occur in wet areas but in all areas of the research area. These results have the same effect as Du et al. [5], where the PCA provides increased drought information. Besides, clouds are still becoming an obstacle to remote sensing image processing. It sees in Fig.2 that there is always an area that has no data, and those results used in Landsat for drought analysis to detect the detailed information.

Table 4. Validation of Landsat image (matrix confusion).

| Class of Drought | Field Work | Total Rows |
|------------------|------------|------------|
| Object           | SD MD SID N W |  |
| SD               | 4 2 0 0 0 6 |
| MD               | 1 11 1 0 0 13 |
| SID              | 0 1 2 1 0 4 |
| N                | 0 0 0 2 1 3 |
| W                | 0 0 0 0 2 2 |

SD= Severe Drought; MD=Moderate Drought; SLD=Slight Drought; N=Normal; W=Wetness
Source: Data Processing
Total Accuracy: (21/28)*100% = 75%

The Landsat image can still indicate the MODIS image that does not have data when processed, and it proves that multi-scale is very useful. Fig.4 shows that the temporal MODIS image is beneficial for extensive and rapid monitoring of drought. The weakness of the MODIS image can be covered with Landsat imagery to know the drought area and identify the cause. In Landsat, the topography is more noticeable and recognizable, so the caused of dryness can be identified [7], [10]. Besides, PCA on Landsat can distinguish the area very well between wet and dry, and it is per the conditions of the field. Therefore, PCA modification proves by making changes to the vegetation and surface temperature will affect the outcome. However, it still needs more study, in particular, the climate variables that affect drought.
4.3. Validation Results

Multi-scale image validation performed differently; the MODIS image uses TRMM and Landsat data using field surveys. Fig.5 is the validation of the MODIS image compares between the drought location with data precipitation from the TRMM. It is to know if the drought-affected area has slight rainfall and as controls the result of the MODIS image processing. TRMM data is selected based on previous research that uses as a validation of drought [4]–[6]. Validation proves that the drought area has slight rainfall when the month is dry, and in the month of wet occur rainfall increase.

Landsat's image uses a matrix table developed by Congalton for validation [46]. Table IV show validation on Landsat takes sampling as many as 28 samples, and it represents five classes in drought. Samples are decided based on the land unit of the drought area. It chose because the areas are more representative to represent the field compared to dots and pixels. The matrix table shows not only total accuracy but also user accuracy and producer accuracy of each drought class. Landsat shows an overall accuracy of 75% with the highest user accuracy in moderate drought and wetness classes, then lowest user accuracy in slight drought classes. The accuracy value is appropriate to show drought validation between Landsat image and field conditions. It should note when climate change occurs in the field and affects the identification of drought conditions.

5. Conclusion

The PCA influences TVDI concept changes on vegetation and surface temperature. The PCA increased the drought area of the entire research area in the dry month and decreased in the wet month. The drought of the MODIS image has the same pattern as TRMM data, and Landsat validation obtains an accuracy rate of 75%. Climate change in the field affects the accuracy value of Landsat imagery. A multi-scale image proves that he was able to do monitoring and mapping drought better than using a single image. Besides, MODIS image multi-temporal is very helpful in the identification of drought before and after. Next, research expected to modify TVDI can incorporate climate variables in calculations for the determination of drought areas.

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References

[1] Puslitbang SDA, *Permasalahan Kekeringan dan Cara Mengatasinya*. Bandung: Balai Hidrologi, Departemen Permukiman dan Prasarana Wilayah, 2003.
[2] A. S. Suryani, “ancaman EL NINO 2015,” *INFO Singkat*, vol. VII, no. 13, pp. 9–12, Jul. 2015.
[3] A. T. Jeyaseelan, “Droughts & floods assessment and monitoring using remote sensing and GIS,” *Satell. Remote Sens. GIS Appl. Agric. Meteorol.*, pp. 291–313, 2003, [Online]. Available: http://www.wamis.org/agm/pubs/agm8/Paper-14.pdf.
[4] G. Caccamo, L. A. Chisholm, R. A. Bradstock, and M. L. Puotinen, “Assessing the sensitivity of MODIS to monitor drought in high biomass ecosystems,” *Remote Sens. Environ.*, vol. 115, no. 10, pp. 2626–2639, 2011, doi: 10.1016/j.rse.2011.05.018.
[5] L. Du *et al.*, “A comprehensive drought monitoring method integrating MODIS and TRMM data,” *Int. J. Appl. Earth Obs. Geoinf.*, vol. 23, no. 1, pp. 245–253, 2013, doi: 10.1016/j.jag.2012.09.010.
[6] D. Dutta, A. Kundu, N. R. Patel, S. K. Saha, and A. R. Siddiqui, “Assessment of agricultural drought in Rajasthan (India) using remote sensing derived Vegetation Condition Index (VCI) and Standardized Precipitation Index (SPI),” *Egypt. J. Remote Sens. Sp. Sci.*, vol. 18, no. 1, pp.
53–63, 2015, doi: 10.1016/j.ejrs.2015.03.006.

[7] Parwati and Suwarsono, “Model Indeks Tvdi (Temperature Vegetation Dryness Index) Untuk Mendeteksi Kekeringan Lahan Berdasarkan Data Modis-Terra,” Penginderaan Jauh, vol. 5, pp. 35–44, 2008.

[8] N. R. Patel, B. R. Parida, V. Venus, S. K. Saha, and V. K. Dadhwal, “Analysis of agricultural drought using vegetation temperature condition index (VTCI) from Terra/MODIS satellite data,” Environ. Monit. Assess., vol. 184, no. 12, pp. 7153–7163, 2012, doi: 10.1007/s10661-011-2487-7.

[9] N. T. Son, C. F. Chen, C. R. Chen, L. Y. Chang, and V. Q. Minh, “Monitoring agricultural drought in the lower mekong basin using MODIS NDVI and land surface temperature data,” Int. J. Appl. Earth Obs. Geoinf., vol. 18, no. 1, pp. 417–427, 2012, doi: 10.1016/j.jag.2012.03.014.

[10] Sudaryatno, “Integrasi Citra Penginderaan Jauh dan Sistem Informasi Geografi untuk Penyusunan Model Kerentanan Kekeringan (Kasus di Provinsi Jawa Timur dan Daerah Istimewa Yogyakarta),” Universitas Gadjah Mada, 2015.

[11] A. S. A. Nugraha, “Pemanfaatan Metode Split-Windows Algorithm (SWA) pada Landsat 8 Menggunakan Data Uap Air MODIS Terra (The Application of Split-Windows Algorithm (SWA) Methods on Landsat 8 Using Modis Terra Water Vapor),” geometrika, vol. 25, no. 1, pp. 9–16, 2019, doi: http://doi.org/10.24895/JIG.2019.25-1.877.

[12] A. S. A. Nugraha, T. Gunawan, and M. Kamal, “Comparison of Land Surface Temperature Derived from Landsat 7 ETM+ and Landsat 8 OLI/TIRS for Drought Monitoring,” IOP Conf. Ser. Earth Environ. Sci., vol. 313, no. 1, pp. 0–10, 2019, doi: 10.1088/1755-1315/313/1/012041.

[13] A. S. A. Nugraha, T. Gunawan, and M. Kamal, “Downscaling land surface temperature on multi-scale image for drought monitoring,” in Sixth Geoinformation Science Symposium, 2019, no. November, p. 6, doi: 10.1117/12.2544550.

[14] H. Adiwicaksono, Sudarto, and Widianto, “Estimasi distribusi spasial kekeringan lahan di kabupaten tuban menggunakan penginderaan jauh dan sistem informasi geografis,” J. Tanah dan Sumber. Lahan, vol. 1, no. 2, pp. 70–76, 2014.

[15] P. D. Raharjo, “Teknik penginderaan jauh dan sistem informasi geografis untuk identifikasi potensi kekeringan,” Makara Teknol., vol. 14, no. 2, pp. 97–105, 2010.

[16] I. Prasasti, K. A. Sambodo, and I. Carolita, “Pengkajian Pemanfaatan Data TERRA-MODIS untuk Ekstraksi Data Suhu Permukaan Lahan (SPL) Berdasarkan Beberapa Algoritma,” Penginderaan Jauh, vol. 4, no. 1, pp. 1–8, 2007.

[17] U.S. Geology Survey Department, “Landsat 7 Science Data Users Handbook.” 2010, doi: 10.1001/archinternmed.2011.606.

[18] I. Sandholt, K. Rasmussen, and J. Andersen, “A simple interpretation of the surface temperature/vegetation index space for assessment of surface moisture status,” Remote Sens. Environ., vol. 79, no. 2–3, pp. 213–224, 2002, doi: 10.1016/S0034-4257(01)00274-7.

[19] P. Rahimzadeh-Bagirian, K. Omasa, and Y. Shimizu, “Comparative evaluation of the Vegetation Dryness Index (VDI), the Temperature Vegetation Dryness Index (TVDI) and the improved TVDI (iTVDI) for water stress detection in semi-arid regions of Iran,” ISPRS J. Photogramm. Remote Sens., vol. 68, no. 1, pp. 1–12, 2012, doi: 10.1016/j.isprsjprs.2011.10.009.

[20] F. N. Kogan, “Droughts of the Late 1980s in the United States as Derived from NOAA Polar-Orbiting Satellite Data,” Bulletin of the American Meteorological Society, vol. 76, no. 5, pp. 655–668, 1995, doi: 10.1175/1520-0477(1995)076.

[21] B. C. Gao, “NDWI - A normalized difference water index for remote sensing of vegetation liquid water from space,” Remote Sens. Environ., vol. 58, no. 3, pp. 257–266, 1996, doi: 10.1016/S0034-4257(96)00067-3.

[22] P. Danaedoro, Pengantar Penginderaan Jauh Digital. Yogyakarta: Andi Offset, 2012.

[23] F. N. Kogan, “Global Drought Watch from Space,” Bulletin of the American Meteorological
Society, vol. 78, no. 4, pp. 621–636, 1997.

S. B. Idso, R. D. Jackson, P. J. Pinter, R. J. Reginato, and J. L. Hatfield, “Normalizing the stress-degree-day parameter for environmental variability,” Agric. Meteorol., vol. 24, no. August 2015, pp. 45–55, 1981, doi: 10.1016/0002-1571(81)90032-7.

M. Moran, T. R. Clarke, Y. Inoue, and A. Vidal, “Estimating Crop Water Deficit Using the Relation between Surface-Air Temperature and Spectral Vegetation Index,” Remote Sens. Environ., vol. 49, pp. 246–263, 1994.

O. Rozenstein, Z. Qin, Y. Derimian, and A. Karnieli, “Derivation of land surface temperature for landsat-8 TIRS using a split window algorithm,” Sensors (Switzerland), vol. 14, no. 4, pp. 5768–5780, 2014, doi: 10.3390/s140405768.

Z. Qin, G. Dall, A. Karni, and P. Berliner, “Derivation of split window algorithm and its sensitivity analysis for retrieving land surface temperature from NOAA-advanced very high resolution radiometer data,” J. Geophys. Res., vol. 106, no. 19, pp. 22655–22670, 2001, doi: 10.1029/2000JD900452.

J. A. Sobrino, Z. L. Li, M. P. Stoll, and F. Becker, “Multi-channel and multi-angle algorithms for estimating sea and land surface temperature with atsr data,” Int. J. Remote Sens., vol. 17, no. 11, pp. 2089–2114, 1996, doi: 10.1080/01431169608948760.

J. A. Sobrino, J. El Kharraz, and Z. L. Li, “Surface temperature and water vapour retrieval from MODIS data,” Int. J. Remote Sens., vol. 24, no. 24, pp. 5161–5182, 2003, doi: 10.1080/0143116031000102502.

J. A. Sobrino, J. C. Jiménez-Muñoz, and L. Paolini, “Land surface temperature retrieval from LANDSAT TM 5,” Remote Sens. Environ., vol. 90, no. 4, pp. 434–440, 2004, doi: 10.1016/j.rse.2004.02.003.

J. A. Sobrino et al., “Land surface emissivity retrieval from different VNIR and TIR sensors,” IEEE Trans. Geosci. Remote Sens., vol. 46, no. 2, pp. 316–327, 2008, doi: 10.1109/TGRS.2007.904834.

East Province government (Pemerinah Provinsi Jawa Timur), “RPJMD East Java: Chapter II: Overview of the General State of the Region,” 2009.

Badan Penanggulangan Bencana Daerah, “Update El-Nino 2015,” Provinsi Jawa Timur, 2015.

NOAA, “Southern Oscillation Index (SOI),” 2015. https://www.ncdc.noaa.gov/teleconnections/enso/indices/soi (accessed Nov. 06, 2015).

Department of the Interior U.S. Geological Survey, “Landsat 8 Data Users Handbook,” 2016. [Online]. Available: https://landsat.usgs.gov/documents/Landsat8DataUsersHandbook.pdf.

C. Kummerow, W. Barnes, T. Kozu, J. Shiue, and J. Simpson, “The tropical rainfall measuring mission (TRMM) sensor package,” J. Atmos. Ocean. Technol., vol. 15, no. 03, pp. 809–817, 1998.

M. Almazroui, “Calibration of TRMM rainfall climatology over Saudi Arabia during 1998–2009,” Atmos. Res. 99, pp. 400–414, 2011.

Z. Wan and J. Dozier, “A generalized split-window algorithm for retrieving land-surface temperature from space,” IEEE Trans. Geosci. Remote Sens., vol. 34, no. 4, pp. 892–905, 1996, doi: 10.1109/36.508406.

M. Moradizadeh, M. Momeni, and S. M. R., “Estimation of atmospheric column and near surface water vapor content using the radiance values of modis,” Int. Arch. Photogramm. Remote Sens. Spat. Inf. Sci., vol. 307, no. B8, pp. 523–528, 2007.

P. J. Sellers, J. A. Berry, G. J. Collatz, C. B. Field, and F. G. Hall, “Canopy reflectance, photosynthesis, and transpiration. III. A reanalysis using improved leaf mod- els and a new canopy integration scheme,” Remote Sens. Environ., vol. 42, pp. 187–216, 1992.

T. J. Jackson et al., “Vegetation water content mapping using Landsat data derived normalized difference water index for corn and soybeans,” Remote Sens. Environ., vol. 92, pp. 475–482, 2004.

S. J. Goetz, “Multisensor analysis of NDVI, surface temperature and biophysical variables at a
mixed grassland site,” *Int. J. Remote Sens.*, vol. 18, pp. 71–94, 1997.

[43] C. Wang, S. Qi, Z. Niu, and J. Wang, “Evaluating soil moisture status in China using the temperature–vegetation dryness index (TVDI),” *Can. J. Remote Sens.*, vol. 30, pp. 671–679, 2004.

[44] Z. Wan, P. Wang, and X. Li, “Using MODIS land surface temperature and normalized difference vegetation index products for monitoring drought in the southern Great Plains, USA,” *Int. J. Remote Sens.*, vol. 25, pp. 61–72, 2004.

[45] Z. L. Li and F. Becker, “Feasibility of land surface temperature and emissivity determination from AVHRR data,” *Remote Sens. Environ.*, vol. 43, no. 1, pp. 67–85, 1993, doi: 10.1016/0034-4257(93)90065-6.

[46] R. G. Congalton, “A review of assessing the accuracy of classifications of remotely sensed data,” *Remote Sens. Environ.*, vol. 37, no. 1, pp. 35–46, 1991, doi: 10.1016/0034-4257(91)90048-B.