Indices Extraction from Multitemporal Remote Sensing Data for Mapping Urban Built-Up

A. K. Hayati¹, Y. F. Hestrio¹, N. Cendiana¹, and K. Kustiyö¹

¹Remote Sensing Technology and Data Center, National Institute of Aeronautics and Space of Indonesia, Jakarta, Indonesia

Email: anis.kamilah@lapan.go.id

Abstract. Remote sensing data analysis in the cloudy area is still a challenging process. Fortunately, remote sensing technology is fast growing. As a result, multitemporal data could be used to overcome the problem of the cloudy area. Using multitemporal data is a common approach to address the cloud problem. However, most methods only use two data, one as the main data and the other as complementary of the cloudy area. In this paper, a method to harness multitemporal remote sensing data for automatically extracting some indices is proposed. In this method, the process of extracting the indices is done without having to mask the cloud. Those indices could be further used for many applications such as the classification of urban built-up. Landsat-8 data that is acquired during 2019 are stacked, therefore each pixel at the same position creates a list. From each list, indices are extracted. In this study, NDVI, NDBI, and NDWI are used to mapping built-up areas. Furthermore, extracted indices are divided into four categories by their value (maximum, quantile 75, median, and mean). Those indices are then combined into a simple formula to mapping built-up to see which produces better accuracy. The Pleiades as high-resolution remote sensing data is used to assist supervised classification for assessment. In this study, the combination of mean NDBI, maximum NDVI, and mean NDWI result highest Kappa coefficient of 0.771.

Keywords: multitemporal, remote sensing, indices, mapping built-up

1. Introduction

The existence of clouds is still a challenge for remote sensing visual image data processing. Fortunately, multitemporal data could be harnessed to address the problem. When there is no single-date cloud-free data, multitemporal data is commonly used for land cover classification.

Many land cover classification research has been done by using multitemporal data. Most research use one main data and one or more data to complement the area covered by the cloud. Basnet and Vodacek [1] creates a cloud-free composite from one main scene and four to six additional scenes. [2] choose some clear data to be composed based on the best available pixel. While Zhu and Woodcock [3] create cloud-free mosaic data from all available data.

In addition to optical data, SAR data could also be utilized to complement the cloudy area. Lopes et al. [4] using Sentinel-1 data to supplement Sentinel-2 data in cloud persistent area. While [5] adding SRTM DEM in addition to Sentinel-1 data to complete cloudy area in Landsat-8.
Most of the methods that use multitemporal data are assisted, especially for choosing the main data due to its cloud cover. Moreover, creating cloud-free composite are time consuming. In this paper, a method to automatically extract indices from multitemporal data is proposed. By using this method, all available data could be included. There is no need to select the data based on its cloud cover since indices will be extracted from all of the data and chosen statistically to minimize cloud disruption. Therefore, this method should be suitable for a continuous automated process without having to be assisted.

The extracted indices then could be processed further into classification. As a case study, in this paper, the indices are processed to mapping built-up. The indices that are used in this study are normalized difference built-up index (NDBI) [6], normalized difference vegetation index (NDVI) [7], and normalized difference water index (NDWI) [8].

Some methodologies have been proposed for mapping built-up. Zha et al. [6] first developed NDBI and mapping built-up by subtracting NDVI with NDBI. Faridatul and Wu [9] propose modified normalized difference bare-land index (MNDBI) to address the problem of separating bare land from impervious.

The formula used in this paper is a simple modification from the method proposed by [6]. NDWI is added to cope with the pixels of the water body. This method is chosen since it is simple and has also been verified by Karanam and Neela [10] with an accuracy of 93.9%. In addition, this study is not focused on proposing new formula. Instead, this study focused on how to harness multitemporal data to be implemented on any formula.

Furthermore, indices are extracted based on their value statistically. This paper limits the experiment of the indices value into four categories. Those categories are maximum, quantile 0.75, median, and mean. The combination of those values is then applied to the formula to see which result is better. The Pleiades as high-resolution data is utilized to assist manual digitation in the study area. Then the confusion matrices are calculated to produce the Kappa coefficient. From this study, the combination of median NDBI, maximum NDVI, and mean NDWI result in the best Kappa coefficient, which is 0.808.

2. Data and Methods

2.1 Data

Data used in this paper are 16 scenes of Landsat-8 level 1 that were acquired during 2019. Each of the data has a different percentage of cloud cover. Landsat-8 data are used since it has an adequate temporal resolution, where acquisition is done every 14 days. Those data then cropped in the study area to ease the process. Figure 1 Shows cropped data for this study.

The band that is used in this study is according to the needs of the index used. Band 4 and 5 for NDVI, band 5 and band 6 for NDBI, while band 3 and band 5 for NDWI. Other than Landsat-8 data, high-resolution data are used for assessment. For this purpose, Pleiades data acquired in 2019 are utilized to assist supervised classification.

For every band that is used, the 16 data that have been cropped in the study area are then stacked into three dimensions array (Error! Reference source not found.). Thus, the pixel in the same location will create a list according to the acquisition date. From that list, indices are then calculated for every acquisition date which results in a list of indices for a specific pixel location. Equation 1, 2, 3 are the indices that used in this study

\[
\text{NDBI} = (\text{SWIR} - \text{NIR})/(\text{SWIR} + \text{NIR}) \quad (1)
\]

\[
\text{NDVI} = (\text{NIR} - \text{RED})/(\text{NIR} + \text{RED}) \quad (2)
\]

\[
\text{NDWI} = (\text{GREEN} - \text{NIR})/(\text{GREEN} + \text{NIR}) \quad (3)
\]

Four values are then extracted from the list of indices, which are maximum, quantile 0.75, median, and mean. The process is repeated for every pixel location in the study area resulting in four sets of values for every index. For simplification, the set of values for each index will be called accordingly. For example, the set of maximum NDVI will be called maxNDVI for the rest of this paper (Figure 3).
Figure 1. 16 Cropped data in part of Central Java area that is used in this study

2.2 Method
Figure 2. Stacked data, red circles illustrate the pixel in the same location create an array.

![Image of data stacked from maxNDBI to quanNDBI]

![Image of data stacked from maxNDVI to quanNDVI]

![Image of data stacked from maxNDWI to quanNDWI]

Figure 3. NDBI, NDVI, and NDWI image result from each value: Maximum, Mean, Median, and Quantile 0.75

The combinations of those sets of values are then applied to a simple formula to map built-up. In this study, Equation 4 is used to map built up. This formula is based on the methodology proposed by [6] (Equation 5). Four sets of values are combined in Equation 4 produced 64 combination results.

\[
BU = 2NDBI - NDVI - NDWI
\]

\[
BU = NDBI - NDVI
\]

In the method proposed by [6], the indices (NDBI and NDVI) are recoded to create a binary image with zero as a fixed threshold. Since the pixels of the water body has negative values, they are recoded into 0. Thus, what is left are the pixels of built-up and barren when NDBI is subtracted by NDVI.

Since the data used in this study are multitemporal data, a fixed threshold may not suitable for some specific value of the indices. Therefore, in this study, we preserved all indices and add NDWI as complementary to sever water bodies from other land cover types.

After all combinations of the set of values are calculated, K-means clustering is performed to distinguish built-up and non-built-up. K-means clustering is used to avoid fixed thresholds. Therefore, the classification could be done on each combination result accordingly. K-means clustering itself is a popular cluster analysis for unsupervised learning. K-means used in this study is developed in Scikit-learn [11].
For assessment, Pleiades data is used to assist the supervised classification as a reference. Then confusion matrices are calculated between the reference and each combination result. Figure 4 shows the workflow used in this paper.

![Figure 4. Method used in this study](image)

3. Results and Discussion

Visually, each set of values has a different contrast to distinguish the land cover. As seen in Figure 3, the meanNDBI and medNDBI have a better contrast to distinguish built-up from non-built-up than the maxNDBI and quanNDBI. Meanwhile, for NDVI, maxNDVI is visibly best at distinguishing vegetation. In addition, for NDWI, all sets seem to be good for distinguishing water in the sea. However, some traces of cloud appear in maxNDWI and quanNDWI.

The quantitative assessment also proves that each of the combined results from equation 1 also has a different ability to distinguish built-up from non-built-up. Table 1 shows the assessment from all combination results. The highest Kappa coefficient of 0.771 was reached by the combination of meanNDBI, maxNDVI, and meanNDWI.

Table 2 shows the average of Kappa coefficient that produce by each set of value. Following the visual assessment, meanNDBI and medNDBI produce better Kappa coefficient than the combination that uses maxNDBI and quanNDBI. Furthermore, the result from the combination that includes maxNDVI is far better than the other set of values.

Generally, false positive and false negative happens due to the pixel resolution of Landsat-8. Higher resolution will result better for built-up mapping especially in this study area, where most built-up are small clusters of a housing area. In addition, most omission and commission errors happen at the edge of the identified area. Furthermore, commission error in this case study also happens because bare land such as coast and uncultivated agricultural land are identified as built-up as shown in Figure 5. In addition, human error in performing supervised classification should also take into account.
Table 1. Assessment from each value combination. TN: True Negative; FP: False Positive; FN: False Negative; TP: True Positive.

| NDBI | NDVI | TN | FP | FN | TP | Kappa |
|------|------|----|----|----|----|-------|
| max  | max  | 74284 | 11487 | 3712 | 15493 | 0.581 |
| max  | mean | 74652 | 11119 | 3534 | 15671 | 0.595 |
| max  | med  | 75390 | 10381 | 3176 | 16029 | 0.623 |
| max  | quan | 73782 | 11989 | 3085 | 16120 | 0.593 |
| max  | mean | 58684 | 27087 | 4438 | 14767 | 0.511 |
| max  | mean | 64993 | 20778 | 6225 | 12980 | 0.335 |
| max  | mean | 67346 | 18425 | 5379 | 13826 | 0.400 |
| max  | mean | 65673 | 20098 | 5266 | 13939 | 0.378 |
| max  | med  | 55889 | 29882 | 4942 | 14263 | 0.262 |
| max  | med  | 53049 | 32722 | 4865 | 14340 | 0.234 |
| max  | med  | 64171 | 21600 | 6051 | 13154 | 0.330 |
| max  | med  | 62648 | 23123 | 5968 | 13237 | 0.312 |
| max  | quan | 59672 | 26099 | 4393 | 14812 | 0.325 |
| max  | quan | 58426 | 27345 | 4385 | 14820 | 0.309 |
| max  | quan | 64427 | 21344 | 4587 | 14618 | 0.383 |
| max  | quan | 60082 | 25689 | 4058 | 15147 | 0.340 |
| max  | mean | 78629 | 7142 | 2714 | 16491 | 0.712 |
| mean | mean | 81349 | 4422 | 2973 | 16232 | 0.771 |
| mean | mean | 80028 | 5743 | 2385 | 16820 | 0.757 |
| mean | mean | 79137 | 6634 | 2445 | 16760 | 0.733 |
| mean | mean | 73581 | 12190 | 3484 | 15721 | 0.575 |
| mean | mean | 76463 | 9308 | 4342 | 15773 | 0.637 |
| mean | mean | 79315 | 6456 | 4351 | 15754 | 0.702 |
| mean | mean | 77103 | 8668 | 3452 | 15753 | 0.651 |
| mean | mean | 70795 | 14976 | 4245 | 14960 | 0.497 |
| mean | mean | 71078 | 14693 | 3866 | 15339 | 0.515 |
| mean | mean | 75489 | 10282 | 3522 | 15683 | 0.613 |
| mean | mean | 71573 | 14198 | 3602 | 15603 | 0.533 |
| mean | mean | 67501 | 18270 | 2961 | 16244 | 0.483 |
| mean | mean | 73326 | 12387 | 3690 | 15515 | 0.564 |
| mean | mean | 76506 | 9265 | 3552 | 15653 | 0.634 |
| mean | quan | 73322 | 12449 | 3551 | 15654 | 0.568 |

| NDBI | NDVI | TN | FP | FN | TP | Kappa |
|------|------|----|----|----|----|-------|
| med  | max  | 80765 | 5006 | 3563 | 15642 | 0.733 |
| med  | mean | 82135 | 3636 | 3772 | 15433 | 0.763 |
| med  | med  | 81202 | 4569 | 3217 | 15988 | 0.759 |
| med  | quan | 79934 | 5837 | 2928 | 16277 | 0.736 |
| med  | mean | 73955 | 11816 | 2863 | 16342 | 0.604 |
| med  | mean | 80519 | 5252 | 4214 | 14991 | 0.705 |
| med  | mean | 80037 | 5734 | 4450 | 14755 | 0.684 |
| med  | med  | 68655 | 17116 | 3433 | 15772 | 0.487 |
| med  | med  | 69308 | 16463 | 3209 | 15996 | 0.506 |
| med  | med  | 73400 | 12371 | 2970 | 16235 | 0.589 |
| med  | quan | 75589 | 10182 | 4228 | 14977 | 0.590 |
| med  | quan | 70202 | 15569 | 3160 | 16045 | 0.523 |
| med  | mean | 72300 | 13471 | 3151 | 16054 | 0.562 |
| med  | quan | 73963 | 11808 | 2859 | 16364 | 0.604 |
| med  | quan | 69212 | 16559 | 2593 | 16612 | 0.524 |
| quan | max  | 75651 | 10120 | 3220 | 15985 | 0.627 |
| quan | mean | 76280 | 9491 | 3051 | 16374 | 0.647 |
| quan | mean | 77261 | 8510 | 2980 | 16225 | 0.671 |
| quan | mean | 74781 | 10990 | 2671 | 16534 | 0.627 |
| quan | mean | 70780 | 14991 | 5110 | 14095 | 0.466 |
| quan | mean | 71171 | 14600 | 5374 | 13831 | 0.464 |
| quan | mean | 72160 | 13611 | 4740 | 14465 | 0.504 |
| quan | mean | 70625 | 15146 | 4610 | 14595 | 0.481 |
| quan | mean | 68589 | 17182 | 5588 | 13617 | 0.412 |
| quan | mean | 68527 | 17244 | 5780 | 13425 | 0.404 |
| quan | mean | 69742 | 16029 | 5018 | 14187 | 0.451 |
| quan | mean | 68772 | 16999 | 5113 | 14092 | 0.432 |
| quan | quan | 69947 | 15824 | 5119 | 14086 | 0.451 |
| quan | quan | 71296 | 14795 | 5254 | 13564 | 0.550 |
| quan | quan | 71316 | 14455 | 4770 | 14435 | 0.488 |
| quan | quan | 69846 | 15925 | 4702 | 14503 | 0.464 |

Table 2. Average of Kappa coefficient for every set of values.

| NDBI | NDVI | NDWI |
|------|------|------|
| max  | 0.394396 | 0.683167 | 0.49981 |
| mean | 0.621598 | 0.527873 | 0.522854 |
| med  | 0.619967 | 0.447876 | 0.57575 |
| quan | 0.502842 | 0.479887 | 0.540389 |

Figure 5. Classification result, white pixels denote identified built-up. (a) Pleiades data. (b) Reference image from supervised classification. (c) Method proposed in this paper, using combination meanNDBI, maxNDVI, and meanNDWI.
4. Conclusion

Built-up identification could be performed using multitemporal data by extracting some indices. Using combinations of some statistical value, NDBI, NDVI, and NDWI could be used for mapping built-up. This study limits the value to maximum, mean, median, and quantile 0.75. The result shows that a combination of mean NDBI, maximum NDVI, and mean NDWI produce a Kappa coefficient of 0.771. It shows the potential of harnessing the method used in this study to perform classification. It is expected that this method will be useful for automatic processing without having any human to assist. However, omission and commission errors are found in this study. Errors found in this study were mainly due to Landsat-8 data pixel resolution. Other errors are caused by miss-detected bare-land and the human factor in performing supervised classification. Nevertheless, more testing needs to be done. Further research should include more areas to see how this method works with different land covers. Other statistical values such as standard deviation and more quantile values should also be considered to be included to see if their combination works better. In addition, more formulas should also be tested to see how multitemporal data works well with any formula used. The percentage of cloud cover in each and overall scene should also be counted to see to what extent this method will works.

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