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Population mapping in Kudus Regency using spectral built-up index with Google Earth Engine

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ABSTRACT

Population data plays a pivotal role in environmental management and regional development. However, a significant challenge in Indonesia lies in the reliance on administrative boundaries for population data, hindering integration with physical environmental boundaries like watersheds or ecoregions. This article endeavors to map grid-based population distribution in the Kudus Regency. Data sources encompass Landsat 8 satellite imagery, SRTM DEM, land cover maps (shp), and census population data. The research methodology involves creating a settlement map via machine learning on Google Earth Engine, followed by the development of built-up land index transformations (NDBI, VrNIR-BI, VgNIR-BI) and subsequent linear regression analysis. Findings reveal that the grid-based population map derived from VrNIR-BI demonstrates superior accuracy compared to other indices. Errors in population mapping primarily stem from the amalgamation of dry agricultural land and non- settlement built-up land within the index. Addressing this challenge entails employing a built-up land index capable of effectively discerning built-up areas from open land while accurately delineating urban and rural regions.

Keywords: *Mapping population, Gridded population data, Built-up index, Landsat 8, Google Earth Engine*

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1. INTRODUCTION

Demographic data provides information about the population in an area. Population data is very useful in environmental management, political decision-making, spatial planning, and observational health studies (Fecht et al., 2020; Moos et al., 2021; Rakuasa & Lasaiba, 2024). To simplify the interpretation process, population data is also highly effective when presented in the form of a population map (Ischak, 1993). In general, population information from census data is presented in a choropleth map with administrative borders, which does not accurately reflect the actual distribution. Furthermore, census data are difficult to integrate with other spatial data sets and are less representative for multitemporal studies, considering that administrative boundaries can change over time (Wang et al., 2018; Zhuang et al., 2021).

To overcome the limitations of census data, grid-based population data need to be produced (Leyk et al., 2019; Zhuang et al., 2021; Zulkarnain et al., 2019). Providing grid-based population data at an appropriate resolution is important, especially for vulnerability assessment, disaster risk, and spatial planning (Aubrecht et al., 2013; Kienberger, 2012). Grid-based population data also functions to assess the carrying capacity of the environment related to needs (Kementrian Lingkungan Hidup dan Kehutanan, 2019). Additionally, grid-based population data is easier to fractionate, enabling us to determine the population of a watershed or ecoregion.

Grid-based population mapping can be carried out using several approaches. One approach that is quite familiar is dasymetric mapping, which allocates the population to a variable. These variables can include land (Khomarudin et al., 2010; Yulianto et al., 2014), building volume (Kaimaris & Patias, 2016; Wu & Lung, 2012), Night-Time Light (Hall et al., 2019; Ma, 2018), and mobile phone data (Peng et al., 2020).

Indonesia is one of the countries with the highest population density in the world. The need for grid-based population data is crucial for development, but it cannot be denied that Indonesia, being a developing country, faces a lack of supporting data as mentioned previously. Population mapping using spectral values may also be done using an impervious surface density mapping approach (Romdhoni, 2020; Zulkarnain et al., 2019). Impervious surface mapping can use the built-up land index, while building density can be used as an indication of population (Fariz & Faniza, 2023; Nuissl & Siedentop, 2021; Wolff et al., 2018). This approach has been implemented by Li and Lu (2016) using medium-resolution satellites. The advantage of medium-resolution satellite imagery, such as Landsat, is that it can be obtained free of charge, making it suitable for use at district and city scales. Therefore, we tried to map the population using various built-up land index transformations from Landsat 8 satellite imagery. The mapped location is Kudus Regency, the most populous district in Central Java Province, with a population density of 1997.38 per km² (Statistics Agency of Kudus Regency, 2021). The challenge of the study location is the composition of the settlement, which consists of both urban and rural areas.

2. METHODS

The research location is Kudus Regency, one of the regencies in Central Java, located between four regencies: to the north, it borders Jepara Regency and Pati Regency; to the east, it borders Pati Regency; to the south, it borders Grobogan Regency and Pati Regency; and to the west, it borders Demak Regency and Jepara Regency. According to Statistics Agency of Kudus Regency (2021), Kudus Regency is administratively divided into 9 sub-districts and 123 villages.

The data used is population data for 2016, sourced from Statistics Agency of Kudus Regency (2021). We also use spatial data, including Landsat 8 satellite imagery recorded in 2016, DEM SRTM (Shuttle Radar Topography Mission), WorldView-2 satellite imagery acquired in 2016, and land cover maps of Kudus Regency (shp). Landsat 8 USGS Surface Reflectance Tier 1 and DEM SRTM satellite images were obtained via the Google Earth Engine (GEE) platform; additionally, the image analysis process also uses this platform.

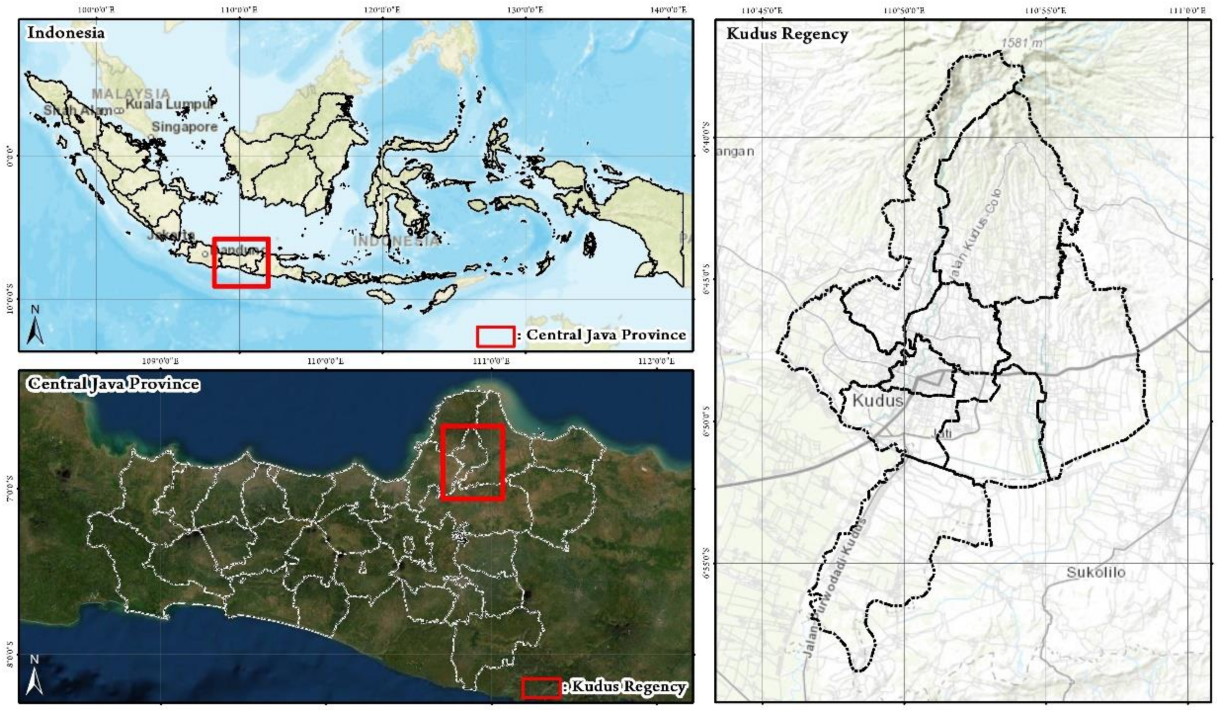

Figure 1. Research location

As previously explained, population mapping in this research uses the built-up land index. The hypothesis is that the higher the built-up land index value, the greater the population density. High-density built-up land has a greater population density than less-dense built-up land, let alone natural areas (Zhuang et al., 2021). The stages of data processing and analysis are as follows:

2.1. Identify settlement areas

Identification of settlement areas in this research uses remote sensing analysis in the form of multispectral classification. The input bands from Landsat 8 used for the classification process include bands 1, 2, 3, 4, 5, 6, 7, and elevation. Bands 1 to 7 are used because their combination yields the highest accuracy compared to using all bands (excluding panchromatic and cirrus) in Landsat 8 imagery (Fariz & Nurhidayati, 2020; Yu et al., 2019). The elevation obtained from the SRTM DEM is useful for improving the accuracy of land cover mapping results, especially in hilly areas (Wagle et al., 2020).

Classified land cover classes are divided into impervious surfaces and non-impervious surfaces (vegetation and water bodies). Seventy-five training samples were used per class. After collecting the training samples, the classifier was determined using machine learning. Random Forest, which is suitable for areas with complex land use classes such as the research area, was employed (Amalia et al., 2024; Oliphant et al., 2019).

Considering that the classification results are only in the form of impervious surface classes, the clip or erase process is then carried out. The erase process aims to obtain information on actual settlement areas because the data used, namely Landsat 8 satellite imagery, cannot accurately distinguish between settlement areas, industrial areas, service economic areas, and so on. The erase process is carried out by intersecting the classification results with the delineation results of non-settlement built land. This delineation was obtained from the land use map of Kudus Regency from 2010, which was then updated with WorldView-2 satellite imagery in 2016.

2.2. Built-up Land Index

Built-up land indices generally utilize the near-infrared (NIR), shortwave infrared (SWIR), and far infrared (SWIR 2) bands. One frequently used built-up land index is NDBI (Zha et al., 2003). Although NDBI is a generic built-up land index, it performs well in mapping impervious surfaces because it uses a combination of bands with high reflectance on built-up land and bare soil objects (As-syakur et al., 2012). There are also impervious surface indices that use visible bands, such as VgNIR-BI, which uses the green channel, and VrNIR-BI, which uses the red channel (Estoque & Murayama, 2015). Despite involving visible bands, VgNIR-BI and VrNIR-BI, in fact, perform better in mapping impervious surfaces (Estoque & Murayama, 2015; Setiyono et al., 2017). Therefore, the indices we use include NDBI, VgNIR-BI, and VrNIR-BI with the following formula:

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

$$VrNIR - BI = (Red - NIR) / (Red + NIR) \quad (2)$$

$$VgNIR - BI = (Green - NIR) / (Green + NIR) \quad (3)$$

2.3. Making Population Maps and Accuracy Assessment

The spectral value of the built-up land index does not directly represent the population. Therefore, statistical analysis in the form of linear regression was carried out. This analysis aims to determine the degree of influence between variable Y, the population, and variable X, the built-up land index value. Since the population data from BPS Kabupaten Kudus / Kudus Regency (2021) is per village administration, the population used as the Y variable is the average number of residents per village in one pixel. The average population value per village in one pixel is obtained by dividing the number of residents per village by the number of settlement pixels in that village. The pixel size of the settlement is 30x30 meters, matching the pixel size of the Landsat 8 satellite image.

The results of linear regression provide not only equations for building population maps but also correlation and regression values. The correlation value (R) indicates the degree of relationship between variables, while the regression coefficient or coefficient of determination (R^2) indicates the degree of influence between variables. The closer the value of R or R^2 is to 1, the stronger the relationship and influence between variables X and Y.

Subsequently, the accuracy of the population mapping results from the built-up land index was tested by comparing the average population value per sub-district in the mapping results with data from (Statistics Agency of Kudus Regency, 2017). The method used was the PDE (Population Distribution Error) calculation (Khomarudin et al., 2010).

$$PDE\ (\%) = \frac{|Pij - PijRQ|}{PijRQ}\ x\ 100\% \quad (4)$$

3. RESULTS AND DISCUSSION

3.1. Results of settlement mapping and Built-up Land Index

Multispectral classification is used to separating between settlement and non-settlement objects in Kudus Regency. In addition to separate settlement and non-settlement objects, this process can also determine the settlement area, which can be quantified by the number of classified pixels (Figure 2).

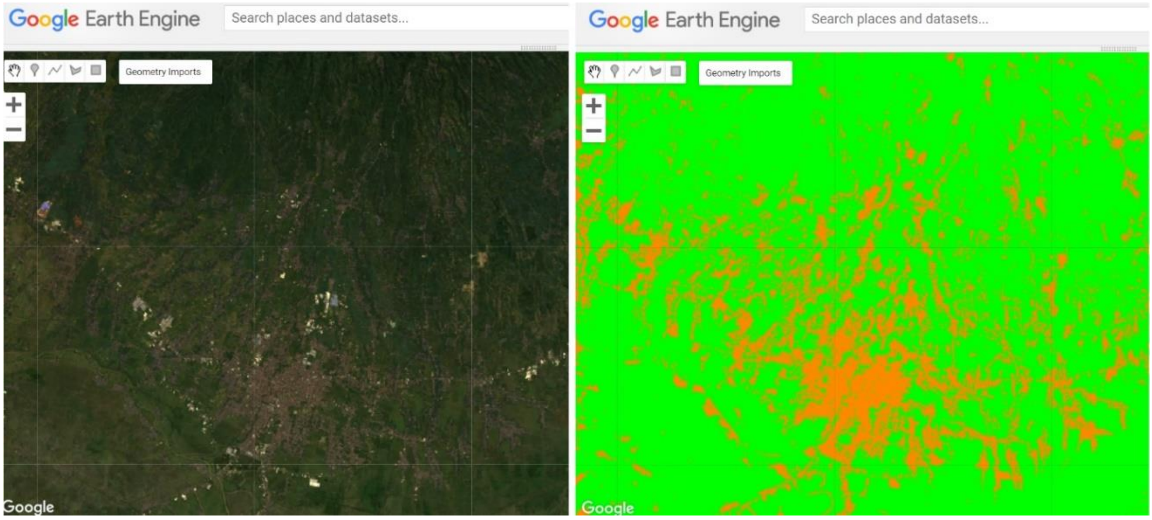

Figure 2. Appearance of settlements as a result of classification using Random Forest machine learning

The classification results using Random Forest machine learning yielded an overall accuracy of 0.88. Subsequently, upon clipping, the results revealed that the total settlement area in Kudus Regency amounted to 8072.83 hectares. Notably, the largest concentration of settlement areas was observed in Jekulo District, spanning 1277.71 hectares. This prominence can be attributed to Jekulo District's status as the largest sub-district in Kudus Regency and its role as a Local Central District (Pusat Kegiatan Lokal), fostering industrial development and settlement services (Kudus Regency Goverment, 2012).

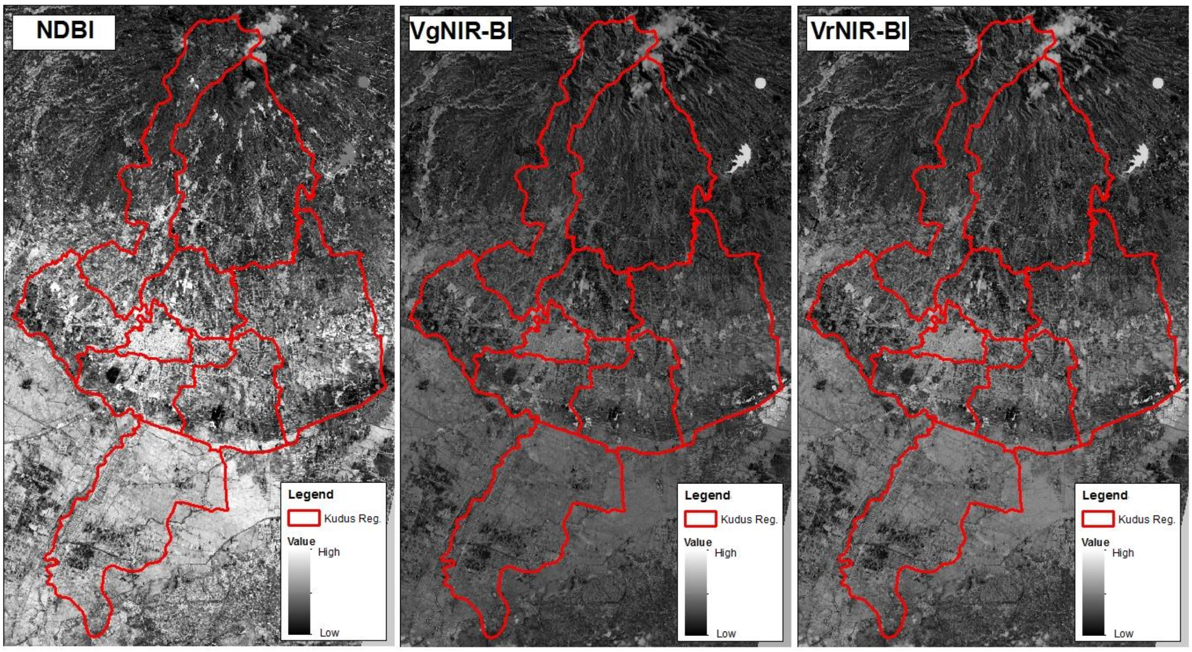

Figure 3 . Appearance of the built-up land index in Kudus Regency and its surroundings

In parallel with the data collection, the results of the built-up land index are presented in greyscale color gradations. It can be observed that brighter shades indicate a higher intensity of built-up land (Figure 3). Visually, all the built-up land indices exhibit a very bright gradation in the central part of Kudus Regency. Moving northwards, the color gradation darkens, suggesting a decrease in the intensity of built-up land and an increase in vegetation cover.

3.2. Linear Regression of Population Number with Built-up Land Index

The results of the statistical analysis, conducted in the form of linear regression on the population with respect to the built-up land index, indicate that all the tested indices fall within the moderately correlated category, as their values range from 0.50 to 0.70 (Hinkle et al., 2003). Therefore, it can be concluded that the built-up land indices examined in this study exhibit a reasonably strong relationship with population data.

Among all the tested built-up land indices, the NDBI (Normalized Difference Built-up Index) demonstrates the strongest correlation. The NDBI yields a correlation coefficient (R) of 0.72 and a coefficient of determination (R2) of 0.52. Conversely, the VGNIR-BI (Visible and Near Infrared Built-up Index) exhibits the weakest correlation among the tested index, with a correlation coefficient (R) of 0.49 and a coefficient of determination (R2) of 0.24 (Figure 4)

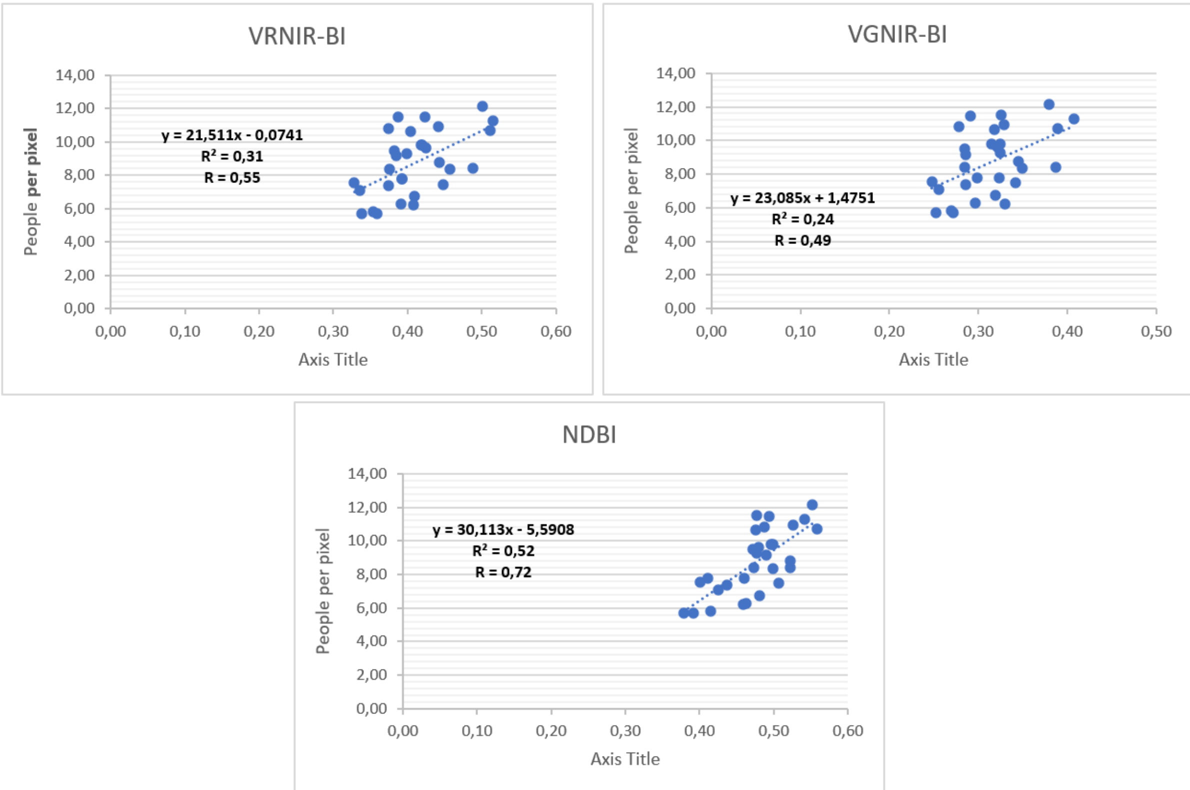

Figure 4. Linear regression scatter diagram between built-up land index and population data

The equation obtained from simple linear regression analysis is used to create a population map. Accuracy test results based on PDE calculations show that the VRNIR-BI built-up land index tends to have the lowest PDE value per sub-district (Table 2).

Table 2. Population mapping accuracy test results

District	Population				Difference			PDE		
	BPS (Central Bureau of Statistics	VGNIR-BI	VRNIR-BI	NDBI	VGNIR-BI	VRNIR-BI	NDBI	VGNIR-BI	VRNIR-BI	NDBI
Bae	72627	65357.0	65340.2	64745.3	7270.0	7286.8	7881.7	0.1	0.1	0.1
Dawe	107000	68154.7	68704.4	68699.7	38845.3	38295.6	38300.3	0.4	0.4	0.4
Gebog	103005	81702.8	79794.3	79527.4	21302.2	23210.7	23477.6	0.2	0.2	0.2
Jati	108103	102950.0	105619.0	104455.4	5153.0	2484.0	3647.6	0.0	0.0	0.0
Jekulo	107336	110854.5	109312.0	99017.7	-3518.5	-1976,0	8318.3	0.0	0.0	0.1
Kaliwungu	94616	95993.5	96698.8	102970.5	-1377.5	-2082.8	-8354.5	0.0	0.0	0.1
Kota Kudus	98363	94195.0	100467.6	109148.4	4168.0	-2104.6	-10785.4	0.0	0.0	0.1
Mejobo	75818	69143.2	69993.9	67885.1	6674.8	5824.1	7932.9	0.1	0.1	0.1
Undaan	74631	85247.9	81499.4	73805.0	-10616.9	-6868.4	826.0	0.1	0.1	0.0
Total	841499	773599	777430	770255				0.081	0.076	0.085

Based on the difference with the total population in Kudus Regency, the population map constructed from VrNIR also has the lowest error, namely 0.076% of the total population in Kudus Regency. This shows that in this study, the VrNIR-BI built-up land index is the best built-up land index in mapping population, although in a linear regression assessment the VrNIR built-up land index is not as good as NDBI. The built-up land index generally uses the SWIR-1/SWIR-2 band which is very sensitive in discriminating built-up land, but VrNIR-BI which uses the red and NIR bands is also superior and more accurate than other index in discriminating built-up land (Xi et al., 2019; Zhang et al., 2020).

3.3. Evaluation of Population Mapping Results

Population mapping using the VrNIR-BI (Visible and Near Infrared Built-up Index) built land index reveals a range of pixel values, with the lowest rounded result being 1 and the highest being 21 (see Figure 5). This indicates that within a single pixel measuring 30x30 meters, there can be a maximum of 21 residents. Regions with high pixel values are depicted in red gradations, predominantly observed in parts of Jati District and Kota Kudus District. This observation aligns with the natural distribution of population density, as Jati District is recognized for having the largest population, while Kota Kudus District exhibits the highest population density within Kudus Regency. The utilization of grid-based population data facilitates the analysis of resident numbers within defined physical boundaries, such as watersheds. Figure 5 also includes a population map of the Piji Watershed, revealing an estimated population of approximately 279,334 individuals within this area.

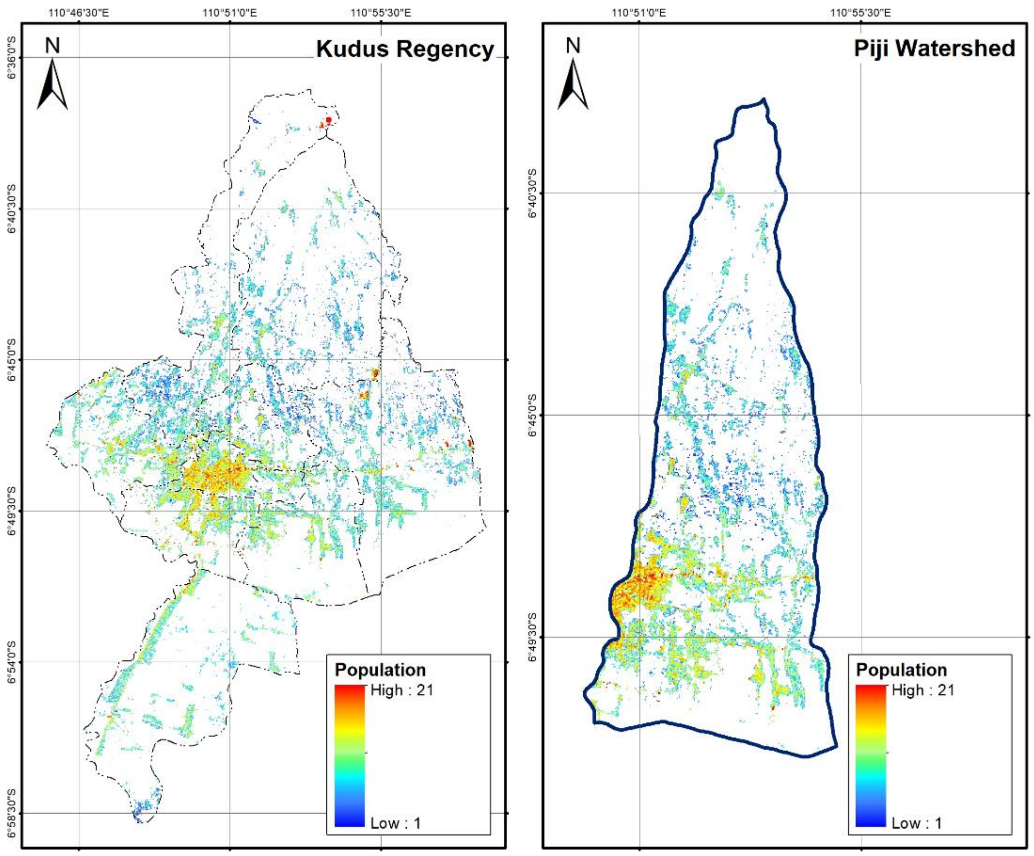

Figure 5. Grid-based population map from the VrNIR-BI built land index

In Table 2, the lowest PDE (Population Distribution Error) value is observed in Dawe District. Topographically, Dawe District is situated on the slopes of Mount Muria, with agricultural land and rural settlements dominating the land cover. Rural settlements have special characteristics, namely being associated with cropland, gardens or forest. This makes it difficult to detect via remote sensing (Figure 6). This inherent complexity renders them challenging to detect via remote sensing techniques (see Figure 6).

Figure 6. Comparison of the appearance of city settlements and village settlements from satellite imagery

According to Xu (2021), rural settlement mapping tends to be less accurate than urban settlement mapping because many settlement objects are mixed pixels with other objects (non-settlement). Apart from the mixing of settlement objects with cropland or gardens, another thing that causes high levels of error in Dawe District is the involvement of bare land and dry agricultural land. In addition, the type of residential houses on the island of Java in general use *genteng* (clay tiles) as roofs so that they have the same spectral response as bare land and dry agricultural land. Dry agricultural land, in particular, may exhibit high values on built-up land indices, leading to misclassification as built-up areas, as demonstrated in research by Sukristiyanti (2007). To mitigate the inclusion of non-built-up land objects, researchers have proposed the use of modified built-up land indices, such as the MNDSI (New Modified Normalized Difference Soil Index) and NRUI (New Ratio Urban Index), as employed by Piyoosh & Ghosh (2018). These indices have been successful in discriminating between built-up land and open land with a confidence level of 95%.

In general, the framework presented in this article is applicable primarily to urban settlements and may not be suitable for areas predominantly comprising rural villages. This research has identified several limitations concerning data availability and the robustness of results. However, it is anticipated that the findings of this study will contribute to advancing grid-based population mapping methodologies in Indonesia. Given the critical importance of accurate population mapping in various aspects of development planning—including social, economic, and political domains—it is imperative to ensure the representativeness and reliability of population data, as the population serves as both the subject and object of development.

4. CONCLUSIONS

The conclusion drawn from this research is that the VrNIR-BI (Visible and Near Infrared Built-up Index) exhibits a correlation coefficient (R) of 0.55 and a coefficient of determination (R2) of 0.31. While these values are not as favorable as those obtained with the NDBI (Normalized Difference Built-up Index), which demonstrates the strongest correlation, the VrNIR-BI proves to be the most effective in population mapping with the lowest Population Distribution Error (PDE). The observed errors in population mapping are attributed to the inclusion of dry agricultural land and non-residential built-up areas within the built-up land index utilized by population map developers. To address this issue, employing a built-up land index capable of distinguishing between built-up areas and open land, while effectively delineating urban and rural regions, is recommended.

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