RESEARCH PAPER

URBAN BIOPHYSICAL QUALITY MODELLING BASED ON REMOTE SENSING DATA IN SEMARANG, INDONESIA

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ABSTRACT. Cities are centres of economic growth with fascinating dynamics, including persistent urbanisation that encroaches adjacent arable lands to build urban physical features and sustain services offered by urban ecosystems. Even though industrial revolution, economic dynamics, and environmental changes affect spatial feasibility for housing, complex urban growth is always followed by the development of environmentally friendly cities. However, with such quality having multiple facets, it is necessary to assess and map liveable areas from a more comprehensive and objective perspective. This study aimed to assess, map and identify the biophysical quality of an urban environment using a straightforward technique that allows rapid assessment for early detection of changes in the quality. It proposed a multi-index approach termed the urban biophysical environmental quality (UBEQ) based on spectral characteristic of remote sensing data for residential areas calculated using various data derived from remote sensing. Statistical analyses were performed to test data reliability and normality. Further, many indices were analysed, then employed as indicators in UBEQ modelling and tested with sensitivity and factor analysis to obtain the best remote sensing index in the study area. Based on PCA Results, it was found that the built-up land index and vegetation index mainly contributed to the UBEQ index. The generated model had 86.5% accuracy. Also, the study area, Semarang City, had varying UBEQ index values, from high to low levels.

KEYWORDS: remote sensing index, urban biophysical environmental quality, principal component analysis

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INTRODUCTION

Urbanisation affects population growth, causes functional shifts in land use and urban climate change and degrades water and air quality (Yuan & Bauer 2007). Within the context of rapid global urbanisation, participatory urban spatial planning plays an essential role in preventing uncontrolled city expansion, dealing with segregation and reducing carbon emission in cities (Psaltoglou & Calle 2018). Sustainable Development Goal (SDG) No. 11.1 states that in 2030, regional governments will guarantee access to housing and basic services that are decent, secure, and affordable for all society members, thus improving the condition of slums. Goal No. 11.7 also mentions that by 2030 regional governments must have provided universal access to green, public open spaces that are safe, inclusive, and easily accessible. To support such planning, it is imperative that actual steps to create a sustainable green environment be taken according to the ecological resilience of an urban biophysical environment to climate change (SDG 13). SDG 13 document deals with increased resilience, adaptive capacity and risks arising as an effect of climate change and disasters in all countries, as well as education improvement, awareness enhancement, human resource capacity, and the role of institutions in the mitigation, adaptation, impact reduction and early warning of climate change.

A large share of urban lives is exposed to conditions that harm human health and well-being and threaten natural resources. With the complex interrelation between urban physical environments, social components, and economic demands, it can be said that most environmental issues like pollution do not originate in urban physical characteristics but rather the behaviour and way of life of the residents that sometimes exacerbate the situation (Li et al. 2016). The liveability of an urban environment depends on three main factors: biophysical features (i.e., built-up land, vegetated areas and water bodies), climate and air quality (Xiao et al. 2018). Therefore, the development of sustainable and liveable cities needs to be supported by effective and efficient planning that also takes into account urban biophysical conditions and ecological resilience (Rezvani et al. 2013). Some examples include building settlements outside hazard-prone areas (e.g., riverbanks), enforcing spatial planning laws and ensuring that new planning simulates mobility and optimises urban structural design so that it does not merely lead to the increasing number of vehicles but also provides new solutions for effective transport (Mao et al. 2014).

Understanding and exploring ecosystems and standards of living (liveability) in various land uses in a city will provide insight into urban planning, governance and management (Fu, Yu, & Zhang 2019). A city is an economic-spatial system that requires biophysical and social approaches in its management. Examples include temperature to characterize urban redevelopment (Pan et al. 2019) and relative humidity generated by fire emissions to model urban air quality (Cuchiara et al. 2017). Some more complex approaches commonly used for spatial ecological analysis in cities are temperature-carbon storage relationship, urban green space calculation and planning and computation of thermal comfort in cities. However, simple urban biophysical factors with remote sensing-derived data have not been widely used for liveability measurement. Therefore, this research proposes the mapping of urban comfort using a simple biophysical approach. Comfort (liveability) is very carefully considered when discussing urban environments, but in general there is no universally acknowledged definition of the parameter because it can be measured from various points of view; the same case applies to quality of life, welfare or development stability. Comfort is also part of urban biophysical environmental quality, which is a function of built-up land and urban vegetation (Hidayati et al. 2019).

Urban Biophysical Environmental Quality (UBEQ) is a term used in scientific studies to assess the quality of the biophysical environment in urban spaces, assuming that a high-quality biophysical environment is a precondition for liveable areas. A biophysical environment comprises biotic components (vegetation) and abiotic components (e.g., built-up land and water) (Hidayati et al. 2019b; Stossel et al. 2017), which in the context of UBEQ shape a city's ecological resistance and sustainable development. UBEQ modelling is a simplified version of the quality of housing environments that determines whether or not and to what extent a residential area provides decent lives for its inhabitants. Urban Environment Quality attempts to address current challenges in urban environmental quality assessment: complicated modelling (Liang & Weng 2011). There is a vast possibility of how many, and which research variables and data can be included to accurately model UBEQ. Multitemporal and multiscale data from many sources can help determine relevant variables and optimise the number of variables used in modelling. The evolution of biophysical parameters starts with Forster (1983), who considered residence quality as an approach to assessing residential biophysical quality. Further development in 1990–2000 defined biophysical quality as a result of surface temperature, building density and socio-economic parameters, namely income per capita and educational attainment (Charreire et al. 2012; Weber et al. 2014). A decade later Deng & Wu (2012) introduced Biophysical Composition Index (BCI) and compared it with several remote sensing indices (NDVI, NDISI, and MNDWI) using Landsat ETM+, IKONOS and MODIS image data. Results prove that BCI can effectively assess impervious surfaces and bare soils. State of the art in biophysical quality assessment techniques is the extraction of vegetation data from high-spatial-resolution images by Aditya et al. (2021) to determine urban greenness.

This research uses remote sensing data with various spatial resolutions (level of mapping scale/detail) and spectral resolutions (the ability to distinguish spectral characteristics of remotely sensed data) in addition to primary spatial data collected through field surveys. Remote sensing is selected because this technology can distinctively provide global coverage data both in pure and mixed pixel relevant to geo-information technology, such as GIS, spatial analysis and dynamic modelling. Further, a combination of remote sensing and GIS data is thereby used extensively for monitoring, synthesising and urban environment modelling that involve internal complexities. Many urban features can be extracted from remote sensing imagery (Silva & Mendes 2012), e.g., built-up land, vegetation and temperature. The data extraction usually involves two main methods, namely digital classification and spectral transformation (index). Based on spectral reflection alone, the red, near-infrared and mid-infrared image bands provide varying spectral responses and can show spectral differences in built-up land (Zha et al. 2003), meaning that remote sensing technology captures the unique appearance and distribution patterns of buildings, vegetation, water and bare land in urban spaces (Xu et al. 2000). The response spectra of developed urban areas increase significantly in near- and mid-infrared bands.

Overall, the city's liveability is indicated by the urban environmental quality that factors in both physical and biophysical factors. The mapping of urban environmental quality uses socio-economic approaches and involves very complex parameters, but this paper attempts to produce the same map using two main parameters, namely vegetation and built-up land, and spatial data derived from remote sensing imagery. Also, it cannot be denied that cities are constantly developing and changing. Therefore, remote sensing products that offer spatial and temporal records are used to help urban communities and decision-makers maintain or improve the liveability of their cities in the future. This approach is beneficial for developing countries like Indonesia, whose big cities are overpopulated and need decent residential spaces. Currently, Semarang is one of the big cities that has problems regarding land availability (Muladica, Murtini & Suprapti 2018). Urban development causes limited land availability. Mijen Semarang area which is in peri urban area also experiences high land conversion. Therefore, it is necessary to analyse the environment quality in Semarang along with the high land conversion. The aims of the research were (1) to select UBEQ parameters based on the spectral characteristics of remote sensing-derived data and spatial data and (2) to analyse the spatial distribution of UBEQ in the Semarang urban areas. This information is expected to provide a straightforward approach for land-use mapping, planning and monitoring in urban areas.

MATERIALS AND METHODS

This study used medium-resolution Landsat 8 OLI images recorded on 13 September 2019, path 120, row 65. To achieve the first goal, it performed various data extractions, i.e., image transformation index: building index, vegetation index, water index, land surface temperature index, and impervious surface index (Table 1). Also, to select the appropriate index, it performed factor analysis on Normalized Difference Built-up Index (NDBI), Normalized Difference Vegetation Index (NDVI), and Soil Adjusted Vegetation Index (SAVI.The transformation index formulas used are presented in detail in Table 1.

Table 1. Formulas of the image transformation indices analysed in the study

Index	Formulas	Sources
NDBI	$\frac{SWIR1 - NIR}{SWIR1 + NIR}$	Zha et al., (2003)
NDVI	$NDVI = \frac{NIR - RED}{NIR + RED}$	Guo et al., (2015)
SAVI	$SAVI = (1+L)\frac{NIR - RED}{NIR + RED + L}; L = 0,5$	Huete (1988)

Landsat 8 image processing involved radiometric and geometric corrections to ensure the quality of the images. In the radiometric correction, pixel values were converted to spectral radiance values, with corrections to the reflectance values made using the formula developed by Chander et al. (2009). Processing of the indices used the normalized difference index formulation.

The research location was the City of Semarang (the Province of Jawa Tengah, Indonesia), which is bordered by the Demak Regency, Semarang Regency, Kendal Regency, and the Java Sea. It has varying topography from lowland to hilly areas. To the south, there is Mount Ungaran, which affects urban environmental quality and vegetation distribution in the city. The research location is shown in Fig. 1.

Selection of the Research Variables

This research stage consisted of four steps: detection of outliers, data normality, sensitivity analysis and factor analysis. The research variables comprised various built-up land and vegetation indices. The best index was chosen to create a composite UBEQ index of urban biophysical environmental quality represented by NDBI, NDVI, and SAVI (Hidayati 2019). Outliers were detected as data that were outside the normalized index range, namely -1 to 1. If an error was found in the image correction process or in the normalized index, the correction process was repeated, starting with radiometric image correction. The next step was to test the data normality using two variables: vegetation and built-up. If one variable fulfils the normality assumption, then all variables are also considered as satisfying data normality. Furthermore, the test between the variables used to determine the perfect relationship between them does not require the two variables to have the same value; to a certain degree values are always accompanied by changes in the value of other variables (Morisson 2012). Statistically, factor analysis was used to complete the index selection, wherein the index was determined whether or not it would be used by considering the return value of Bartlett's test of sphericity or the measure of sampling adequacy (MSA). Analysis of the feasibility of the variables was conducted in stages by performing the sensitivity analysis on the variables one by one to obtain the optimal statistical value. Here, optimal means the correlation value is close to 0, Kaiser-Meyer-Olkin (KMO) and Bartlett's test return values are above 0.5 and an MSA value is > 0.5.

Combining the Research Variables

Principal component analysis (PCA) is a transformation that identifies an equation that is the optimum linear combination of several input bands that can calculate the image variance value (Campbell & Wynne 2011; Danoedoro 2012). It is basically a rotation technique applied to a multiband coordinate system resulting in a new image with fewer bands. PCA can reduce the dimensionality of data; thus, it is often seen as a very efficient data compression technique (Danoedoro 2012). Its role in this study was to combine the research variables derived from remote sensing data with different spatial and temporal

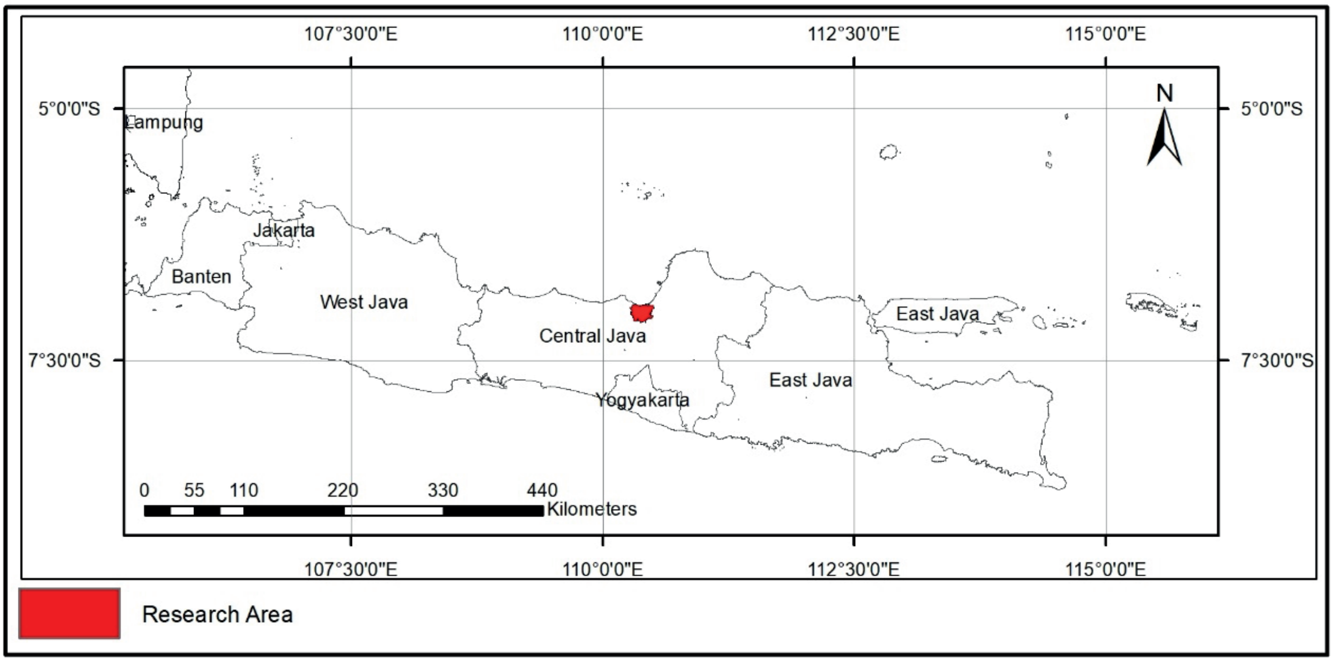

Fig. 1. The location of the research area on Java Island, Indonesia

resolutions. Therefore, because the variables are on different scales, PCA was performed based on a correlation matrix to obtain the desired standard value.

RESULTS

Selected Research Variables

Vegetation data were extracted from the Landsat imagery using several normalized index values. One of these is NDVI (infrared and red bands), which was found to be in the range of -0.185 to 0.752. Soil reflection has a positive correlation with wavelengths; in other words, the greater the wavelength, the higher the electromagnetic energy reflected by the soil, especially at wavelengths between 0.4 µm and 1.0 µm. For example, the normalization used in NDVI is the spectral response between the near-infrared and red band reflections. However, a very typical spectral response such as NDVI is not in the range of soil reflections because soils have widely diverse and complex physical and chemical properties. Therefore, in this study the combination used is adjusted to the spectral reflectance of the soil sample. Soil indexing is directly related to the complexity of soil properties and the spectrum used. Here, indexing aims to calculate the ratio of differences in the indices that had been selected effectively based on the reflection curve used in order to avoid spectral variability in different geographic studies. SAVI was used to observe vegetation reflections by involving near-infrared (NIR) with red reflections. SAVI is an algorithm developed from NDVI that suppresses the influence of soil background on canopy brightness. It uses vegetation isoline equations (vegetation with the same density and different soil backgrounds) derived from canopy reflectance approximation with a first-order photon interaction model between the canopy and the soil layer. The spectral reduction of the red mixture, the darker ground area, causes a significant increase in NDVI values.

The index developed from the unique spectral response of built-up land had higher reflections at SWIR than at NIR wavelengths. Several image transformations were used for the transformation of urban built-up land indices, such as NDBI (Normalized Difference Built-up Index), EBBI (Enhanced Built-up and Bare Land Index), UI (Urban Index) and NDBaI (Normalized Different Built-up and Bare Land Index) (Hidayati 2019). These indices are intended to ascertain which is the most suitable for detecting built-up area because each has its own advantages and disadvantages. The statistical correlations between NDBI and the two vegetation indices (NDVI and SAVI) are presented in Table 2. In general, NDVI is the standard method used to measure and distinguish healthy vegetation and is expressed in the range of -1 to 1. Utilisation of other indices such as infrared/red will produce a simple ratio whose values are always positive, and it gives the possibility that there are also certain unlimited mathematical values. Apart from NDVI, SAVI is also used in the research to produce different variables from NDVI.

NDVI was selected as the most suitable index, or in this case variable, for assessing UBEQ in that the results of the NDVI radiometric correction were high, unlike SAVI. Some vegetation indices incorporate certain numbers that are determined using reflectance data, e.g., spectral bands used in SAVI and NDVI. The vegetation index was adjusted to soil reflection in the SAVI calculation by adding a constant 0.5 and a multiplying factor 1.5 to the formula used. It is assumed that the red and near-infrared spectral reflections are on a scale of 0–1. The spatial distributions of NDVI and NDBI are shown in Fig. 2 and Fig. 3, respectively.

Table 2. Formulas of the image transformation indices analysed in the study

Correlations				
		NDVI	NDBI	SAVI
NDVI	Pearson Correlation	1	0.091**	1.000**
	Sig. (2-tailed)		0.000	0.000
	Sum of Squares and Cross-products	78138.792	1989.265	115401.660
	Covariance	0.087	0.002	0.129
	N	893514	893514	893514
NDBI	Pearson Correlation	0.091**	1	0.088**
	Sig. (2-tailed)	0.000		0.000
	Sum of Squares and Cross-products	1989.265	6091.454	2836.282
	Covariance	0.002	0.007	0.003
	N	893514	893514	893514
SAVI	Pearson Correlation	1.000**	0.088**	1
	Sig. (2-tailed)	0.000	0.000	
	Sum of Squares and Cross-products	115401.660	2836.282	170438.064
	Covariance	0.129	0.003	0.191
	N	893514	893514	893514
** Correlation is significant at 0.01 (2-tailed)				

Sensitivity Analysis and Factor Analysis Results

The factor analyses of three variables, namely NDBI, NDVI and SAVI, were based on KMO, Bartlett's test, and MSA values. The KMO and Bartlett's test return values were 0.500 for NDBI and NDVI (a significance value of 0.000<0.005), meaning that the combination of the three variables is suited for factor analysis (Table 3). As seen in the MSA calculation results in Table 3, one of the factors must be reduced to get an MSA value 0.5, which would indicate that the variable is predictable and further factor analysis can be performed. Because SAVI and NDVI both represent vegetation characteristics, one of which was reduced. Hidayati (2019) has also tested several variables for UBEQ modelling and found that the KMO and Bartlett's test results of the NDBI, NDVI and SAVI were 0.343, meaning that the three indices are statistically not accepted for further modelling.

The factor analysis and sensitivity analysis results showed that the MSA of NDBI and NDVI (0.500).). This indicates NDVI as the most representative vegetation index. After the SAVI was omitted, the MSA of NDBI and NDVI was 0.500 (Table 4). The return value of the KMO and Bartlett's tests for NDBI and NDVI was 0.500 (Table 5). Therefore, NDBI and NDVI can be used for liveable index analysis. The assumption used for the factor analysis was the determinant of the correlation matrix test, which shows that the variables were interrelated. KMO is an index comparing the distance between the partial correlation coefficients and the variable pairs of low values and the number of correlation coefficients.

The combination of NDVI and NDBI indicates that the built-up land has a negative value (-), while the vegetation has a positive value (+) (Table 6). This proves that vegetation and built-up land directly affect UBEQ, although with different effects. NDBI is associated with discomfort: a higher building density results in more uncomfortable living and lower UBEQ (less liveable city). Similarly, when combined with NDVI to create a composite index, NDBI contributes to inconvenience and is inversely proportional to NDVI: the more extensive the built-up land in urban areas, the narrower the vegetated land.

Principal component analysis was used to identify uncorrelated components and to provide wide variance to the original indicator. Based on PCA analysis, eigen values greater than 1 are retained and used in modelling, while eigen values less than 1 are excluded from the model. An eigen value shows the contribution of the factor to the variance of all original variables. In order to obtain optimal PCA results, the varimax method was used to rotate several components to make them consistent. The factors formed were in accordance with the existing theory: UBEQ modelling requires the simplest variables, namely built-up and vegetated land. The more extensive the built-up land, the fewer the vegetated area. Thus, component 1 is termed

Table 3. Formulas of the image transformation indices analysed in the study

Anti-image Matrices				
		NDVI	NDBI	SAVI
Anti-image Covariance	NDVI	1.108E-5	-0.002	-1.108E-5
	NDBI	-0.002	0.521	0.002
	SAVI	-1.108E-5	0.002	1.108E-5
Anti-image Correlation	NDVI	0.406[a]	-0.689	-1.000
	NDBI	-0.689	0.017[a]	0.689
	SAVI	-1.000	0.689	0.406[a]
a. Measures of Sampling Adequacy (MSA)				

Table 4. MSA analysis results of NDBI and NDVI

Anti-image Matrices			
		NDVI	NDBI
Anti-image Covariance	NDVI	0.992	-0.090
	NDBI	-0.090	0.992
Anti-image Correlation	NDVI	0.500[a]	-0.091
	NDBI	-0.091	0.500[a]
a. Measures of Sampling Adequacy (MSA)			

Table 5. KMO and Bartlett's test return values of NDBI and NDVI

KMO and Bartlett's Test		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy		0.500
Bartlett's Test of Sphericity	Approx. Chi-Square	7459.495
	Df	1
	Sig.	0.000

Table 6. Component Matrix result

Component Matrix[a]	
	Component
	1
NDVI	0.739
NDBI	-0.739
Extraction Method: Principal Component Analysis	
a. 1 components extracted	

Table 7. Total variance explained for the principal component analysis of NDVI and NDBI as the Urban Biophysical Environmental Quality (UBEQ) variables

Total Variance Explained						
Component	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	1.091	54.559	54.559	1.091	54.559	54.559
2	0.909	45.441	100.000			
Extraction Method: Principal Component Analysis						

'the impact of land-use change'; the higher the component's score, the worse the biophysical environmental conditions (UBEQ).

The PCA results of NDVI and NDBI showed that PC1 had a variance value of 54.55%, which means that PC1 constitutes 54.55% of information of the UBEQ index (Table 7). This figure serves as a coefficient in UBEQ index calculation. Meanwhile, PC2 explains 45.45% of UBEQ. The coefficients of PC 1 and PC2 are the values used for UBEQ modelling that describe the spatial distribution of the biophysical environments. The formed factors correspond to the theory that UBEQ modelling needs the simplest variables, namely built-up land and vegetated land—and an increase in built-up land almost means a decrease in vegetation. Based on the communalities, the two variables have a negative correlation value for NDBI (-0.739), which is a reflection of urban built-up land (i.e., asphalt, concrete and paved roads), and has a positive correlation value for NDVI (0.739), which closely represents vegetation characteristics. This urban environment quality component decreases by growing the urban built-up land and impervious area and reducing urban vegetation and green areas. The results of the rotation matrix also illustrate that built-up land and vegetation are components of liveability, which are expressed by component 1: built-up land with a negative value and vegetation with a positive value.

In this research, the index representing built-up land was primarily observed because this object is typical of urban areas. Based on the designed UBEQ model, NDBI tended to have negative effects, making it a degrading factor in UBEQ. In the UBEQ model, the variant value of NDBI and NDVI was multiplied by the result of PCA derived from NDBI and NDVI, NDBI multiplied by -1 and NDVI multiplied by 1. The statistical analysis and factor analysis results showed that the combination of NDBI and NDVI could be a simple parameter in measuring UBEQ.

DISCUSSION

A settlement can be defined as an area with a certain scope dominated by a residential environment and equipped with infrastructure, environmental facilities and a workplace that provides limited services and opportunities. An environment consists of many elements, both in natural and built-up areas. It also comprises physical parameters and social, economic and political forces that control human life and eventually form a separate settlement pattern. In urban residential areas, the symbiosis between physical and social factors is highly visible and intercorrelated. Every day human activities are greatly influenced by and depend on the physical conditions of the area. The liveability concept, which in this case is actualised as urban biophysical environmental quality (UBEQ), refers to people's perception of their residence. Basically, it is determined by three issues, namely water, soil and air. Urban biophysical data were extracted by making use of remote sensing data from Landsat 8 OLI imagery. The variable sensitivity analysis was conducted if the statistical analysis results showed that the variable observed did not fulfil the requirements. Factor analysis combined various research parameters and was intended to ensure that each variable on each parameter did not experience information redundancy both spatially and spectrally.

Spatial Pattern of Liveability in the City of Semarang

Semarang is one of the big cities in Indonesia with rapid urban development that directly impacts changes in built-up land and vegetation in urban areas. The image transformation index NDBI was in the range of -0.82 (lowest) to 0.69 (highest). In this case, negative NDBI indicates non-built-up land, while positive NDBI means built-up land. Most of the built-up land is located at the city centre and close to the sea, for example, the northern part of Semarang. In this part of the city, the level or flat topography attracts the development of offices, settlements, trade and services. Urban development in the north is different from that in the south. The built-up land distribution in the south depends on transportation networks and industrial areas; therefore, more trade and industrial areas are developing in the southern city. Other urban activities in this area are scattered around the Simpang Lima Semarang, the trade

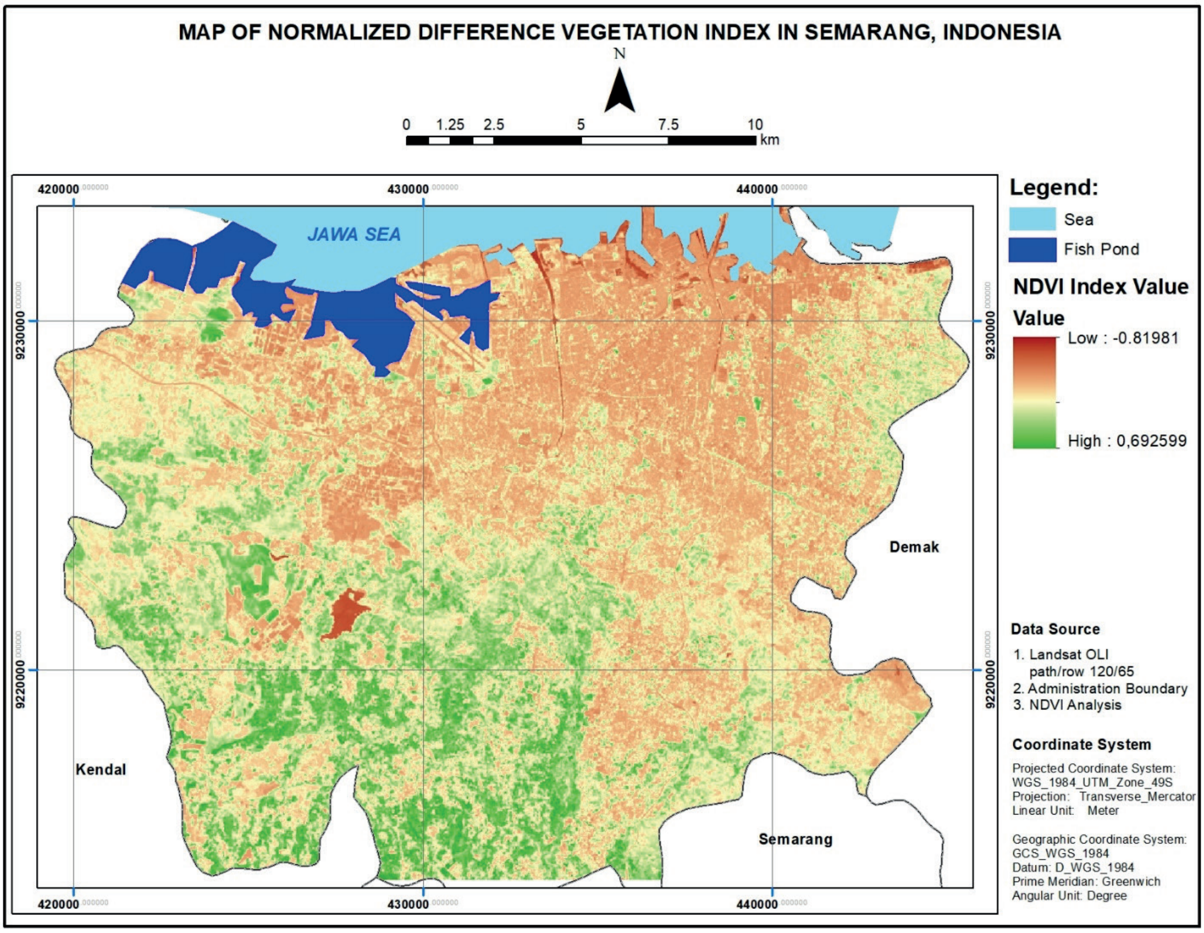

Fig. 2. Spatial distribution map of NDVI in Semarang, Indonesia

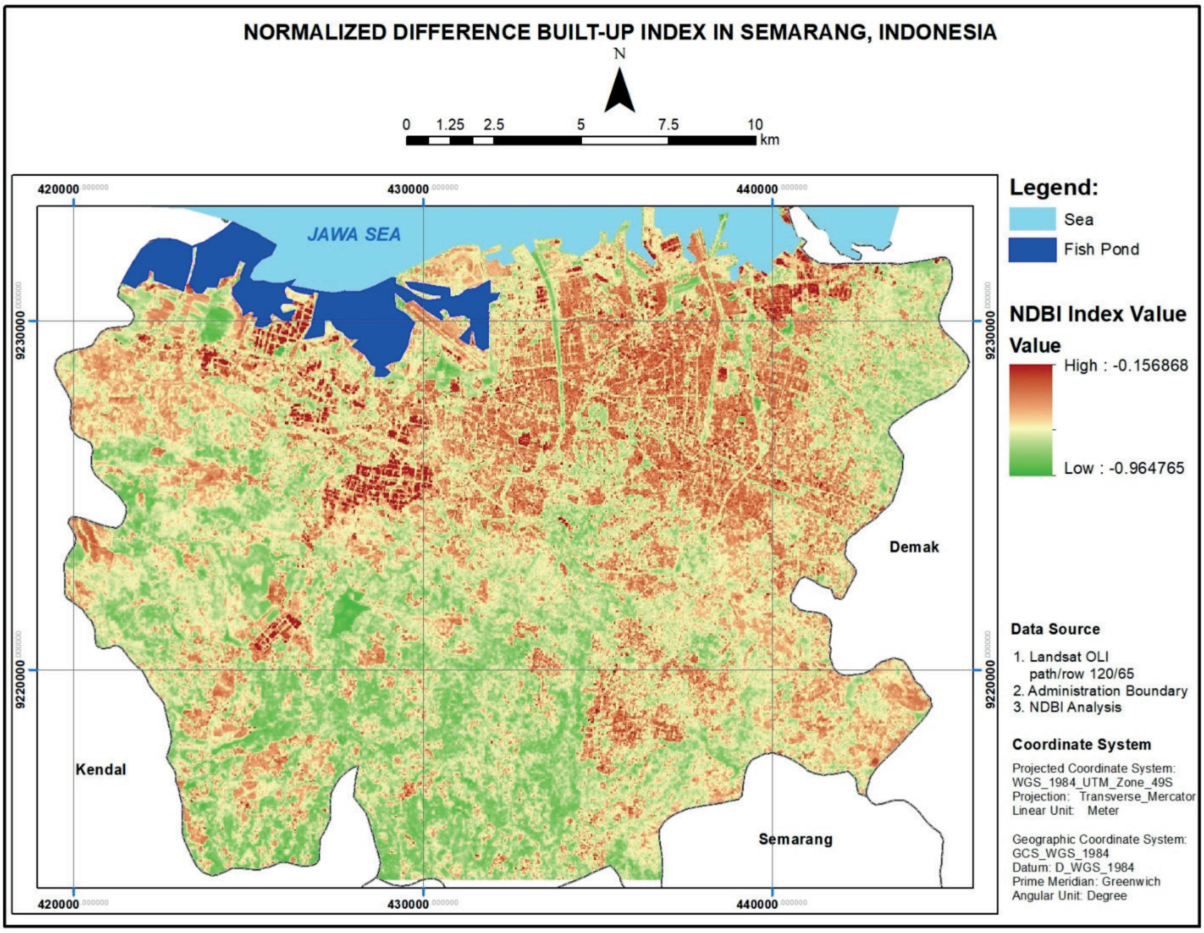

Fig. 3. Spatial distribution map of NDBI in Semarang, Indonesia

and business area along Jalan Pemuda and Jalan Gadjah Mada and the Johar trade and market. The development of the road network in Semarang, especially the ring road network at the city centre, strongly influences the existence of built-up land (Fig. 4). The liveable city modelling for Semarang illustrates that some areas with extensive built-up land inevitably create poor living conditions because of various other physical aspects. In Fig. 3, it is shown that the areas with pooriving conditions are located in Kelurahan in East Semarang, including Tambakrejo Village on the city's outskirts. Some of the residents in these areas are economically disadvantaged (Gultom & Sunarti 2017) and live in normally uninhabitable regions. These conditions result from economic and social limitations of the community and issues in spatial management so that comprehensive cooperation between the community and local officials is needed to overcome the problem. The local government in the PLPBK and NUSP-2 (Neighbourhood Upgrading and Shelter Project-2) programs has planned and arranged the distribution of the settlements in the Tambakrejo Sub-district to provide more liveable space for the residents.

Residential areas with low living conditions are situated around industrial locations. High building density and low indices in this location are influenced by the development of built-up land and urban industries. In general, people have two principles in their lives: residing in a liveable place and fulfilling daily needs. The settlements on the coast of Genuk Sub-district have become very developed after industries sprung up in the area and started to pull a large influx of workers from Genuk (i.e., Muktiharjo Lor, Genuksari and Gebangsari Villages) to live close to their workplaces. The rapid industrial growth, especially coupled with industrial clusters in Terboyo Wetan and Trimulyo, has resulted in greater land development. The growth of built-up land, e.g., boarding houses and rented houses, and the narrowing of urban green space means Genuk has a low index. The settlement development has an enormous impact on UBEQ. Urbanisation and commuting routes sometimes make unfavourable contributions to certain areas. The UBEQ model shown in Fig. 4 also illustrates that Genuk has a low index because it has many industrial buildings, non-residential built-up land, irregular settlements and only a few vegetated areas. An index value below -2 means that the location has a very low UBEQ index. Secondary data also show high PM10 as a consequence of motorised vehicles in the study area.

In addition, the north coast of Semarang has also grown into a centre for trade and services, industry and transportation. The coastal area developed into densely populated settlements, as opposed to a coastal management zone. In a low-lying land like the coast, the residents are at risk of coastal floods – a precondition for a low UBEQ index. The UBEQ index developed from biophysical components (i.e., built-up land and vegetation) has relatively good results.

Other densely populated areas with high NDBI are Ngaliyan and Babankerep Sub-districts. Ngaliyan and Tugu Sub-districts are priorities for the development of industrial and housing areas in the city development zone II. Therefore, the combination of population density and limited green open space yielded a low UBEQ index. Some areas are also priorities for settlement or housing development, which are scattered in Ngaliyan, Tambak Aji, Bringin, Gondoriyo, Podorejo and Tugurejo Villages. Regarding some sub-disricts with a fairly good urban quality index, namely Tembalang, Mranggen and Pedurungan, the Tembalang area has been developed as an education zone,

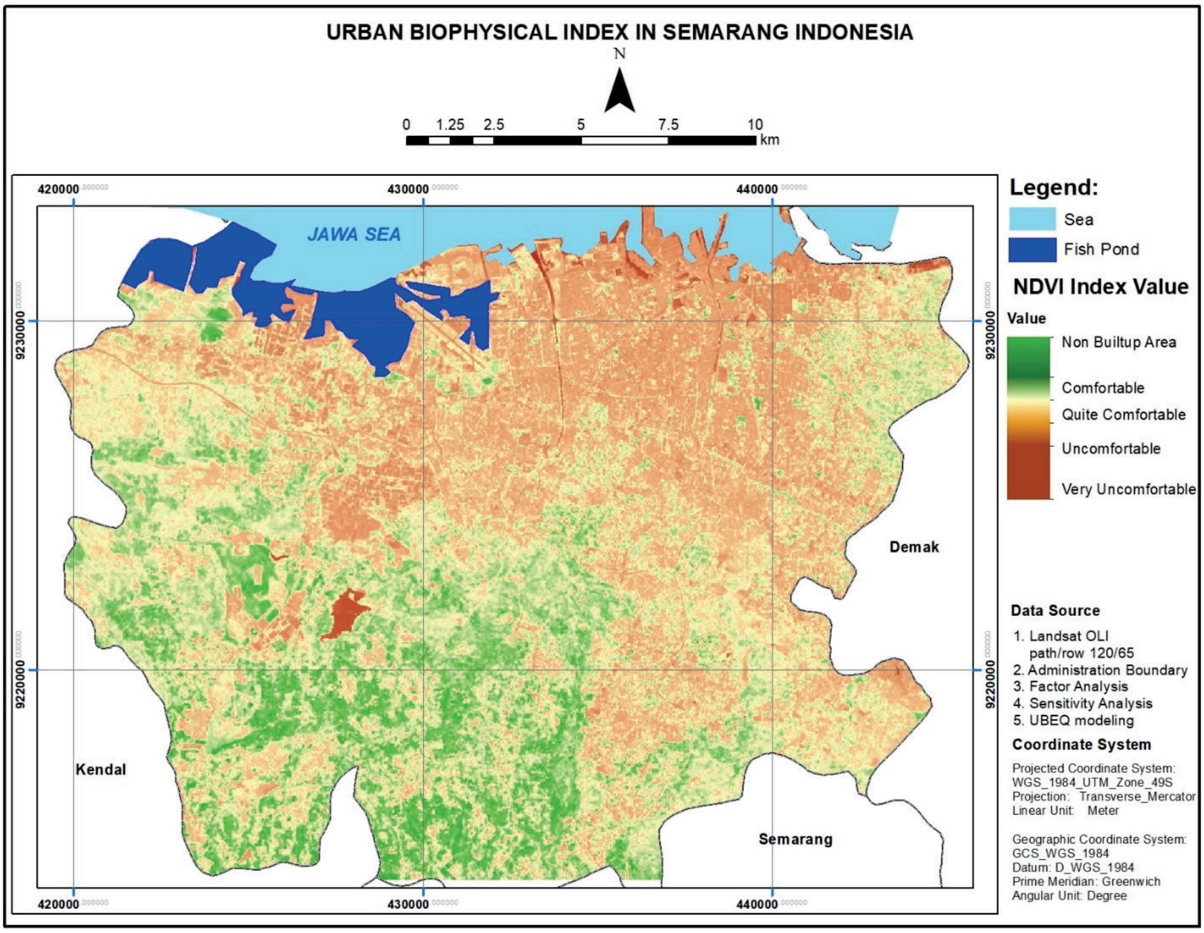

Fig. 4. Spatial distribution map of NDBI in Semarang, Indonesia

because the locations are very comfortable. However, changes in residential areas also often occur because many students come to stay in the area throughout their studies. An example includes the urban area near Diponegoro University that has a moderate built-up land index and an acceptable vegetation index.

Residential areas with a high UBEQ index are located in Gunungpati and Mijen Sub-districts. The results of the remote sensing image analysis illustrate that the area continues to have high vegetation covers. The UBEQ values were 0–2, indicating a comfortable area for living. Haidir & Rudiarto (2019) stated that Gunungpati Sub-district still has 13,727,048 m2 of land potentials for development into settlements. This implies that Gunungpati is still very comfortable for living because it still has a large green open space and adequate vegetated lands; high vegetation density is associated with very good air quality. Gunungpati had three development areas: an urban development area including Gunungpati, Plalangan, and Sekaran Villages, rural development areas and conservation development areas. Protected areas in Gunungpati are also maintained, such as river borders, spring borders, degraded land and disaster-prone areas. Therefore, the balance of the ecosystem in this area is highly maintained for high UBEQ at Semarang.

Unlike the case of Mijen Sub-district in Semarang City – which also has a high UBEQ index, this Mijen suburban area is growing quite rapidly. This area is part of the development of the BSB Satellite City (Bukit Semarang Baru), with the concept of integrated urban development with an environmental perspective (Adiana & Pigawati 2015). The area also has an elite zone equipped with housing support facilities, such as offices and industrial, educational, and service areas. The behaviour of people who live in certain locations strongly determines the conditions of the environment in which they live. The relationship between an environment and its residents is reciprocal and influential (Soemarwoto 1983).

The UBEQ model constructed with biophysical parameters shows that the factors of each parameter are constant. The research variables, i.e., NDBI, NDVI and SAVI, contributed to the first factor with different roles. NDBI always gives the opposite direction to NDVI and SAVI. The formed factors correspond to the theory that says simple UBEQ index modelling is influenced by two factors: built-up land and vegetation. The more extensive the built-up land, the narrower the vegetated areas. Based on the communalities, these three variables (NDBI, NDVI and SAVI) have a negative correlation value for NDBI (-0.739), which is a reflection of urban built-up land, asphalt, concrete and paved roads, and has a positive correlation value for NDVI and SAVI (0.739), which closely represent vegetation characteristics. This component increases by expanding the level of urban built-up, impermeable land, reducing urban vegetation and green areas. The vegetation index is the second variable that must be used in UBEQ modelling. Based on the component matrix, NDVI always contributes to NDBI. Therefore, the NDBI and NDVI indices are the most basic UBEQ indicators that both can be used in the simplest UBEQ modelling.

CONCLUSIONS

The mapping of liveable areas at Semarang City involves two indices. The index selected as the representative of medium-resolution built-up land is NDBI (using SWIR and NIR wavelengths). NDBI is the most suitable index to identify built-up land and assess the UBEQ or liveability at the research location based on the transformation index. The accuracy test shows 86.57%. In addition to the built-up land index, the UBEQ modelling uses two vegetation land indices: NDVI and SAVI, with 87.65 and 85% accuracies, respectively. Also, based on the factor analysis and sensitivity analysis results, it can be concluded that the combination of these three indices (NDVI, SAVI and NDBI) can represent urban biophysical parameters. Increasing the number of indices used to examine UBEQ does not necessarily produce better results. Redundancy of information on the spectral channel gives suboptimal results. In simple terms, the vegetation and built-up land indices can be used for UBEQ research, assuming that the urban areas consisted mostly of vegetation and built-up land. This simple method of mapping is highly applicable for medium-scale UBEQ mapping based on remote sensing imagery as long as the SWIR, NIR and visible wavelengths are used. The liveability aspect highlighted in this research is the urban biophysical environmental quality (UBEQ) instead of socio-economic factors like environmental preservation and exploitation patterns or perceptions about garbage disposal. The UBEQ modelling operates on the concepts that (1) high vegetation density decreases temperatures and increases humidity and (2) high building density induces urban heat island as a result of expanding impervious surfaces.

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