

DEVELOPMENT OF A NEW BUILT-UP INDEX FOR DELINEATING BUILT-UP LAND FEATURE IN SATELLITE IMAGERY: STUDY AREA BLANTYRE

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ABSTRACT

Impervious surface area (ISA) is a key factor for monitoring urban environment and land development. Automatic mapping of impervious surfaces has attracted growing attention in recent years. Spectral built-up indices are considered promising to map ISA distribution due to their easy, parameter-free implementations. This study explores the potentials of impervious surface area extraction for mapping urban expansion from Landsat imagery using a study area of Blantyre city, Malawi. A new built-up index is proposed in this study. To evaluate its effectiveness, the results from this index was compared to the results from ISEI, NDBI, NBI and UI using the Landsat 8 OIL images of 2016 and 2020. Accuracy assessment was calculated on each and every index by using confusion matrix, and from the results, the overall accuracy for the new index in 2016 image was found to be 89% and from 2020 images is 80.45% and the overall kappa coefficient is 75.49% for the 2016 image and 60.6% for the 2020 image. The indices were also applied on Gaborone and Dodoma cities in Botswana and Tanzania in order to ensure the effectiveness of proposed index. And in additional to these, the area covered by the built-up on RGB image of Blantyre city and from the proposed index results of Blantyre were calculated in hectares and the results were closely related. Although the proposed index shows some good performance on Dodoma and Gaborone cities but the results from our study area are more superior than the results from these cities. Therefore, the proposed method is superior index based on ISA mapping in relatively compared with the other indices. However, to ensure its superiority the index must be tested in other areas other than Gaborone and Dodoma, and on other images captured by other sensors for instance worldview, sentinel-2 etc.

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ACRONYMS/ABBREVIATIONS

USGS	United States Geological Survey
SSA	Sub-Saharan Africa
KML	Keyhole Markup Language
ISA	Impervious Surface Areas
DOSI	Dark Object Subtraction
TOA	Top of the Atmosphere
ERDAS	Earth Resource Data Analysis System
MODIS	Moderate Resolution Imaging Spectroradiometer
ISEI	Impervious Surface Extraction Index
NDBI	Normalized Difference Built-up Index
NBI	New Built-up Index
UI	Urban Index

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CHAPTER 1: INTRODUCTION

1.1. Background

Urbanization shown a rapid growth in past few decades, affecting many dimensional of today's world (Bramhe et al., 2018). It is important to have the accurate information about the extent and nature of built-up land cover in order to support the sustainable growth of rural and urban areas. Identification of urban expansion, understanding the urban dynamics along with the associated consequences became an important as well as interesting research domain according to (Karathanassi et al., 2000). However, accurate mapping of urban area is a critical task and problem became more challenging in developing countries of the Sub-Saharan Africa Malawi inclusive due to lack of resources and infrastructure. Remote sensing technology provides feasible and cost effective way to monitor land covered by built-up structures (Pesaresi et al., 2011). Extraction of built-up areas is a challenging task due to the similarity of spectral properties of classes such as sand and built-up area. Initially studies on classifying rural/urban areas using structural information was done by a number of researches (Peng Gong & Howarth, 1990). Advanced image processing transforms raw satellite data into useful maps by multiple stage of processing according to well-defined algorithms. Using satellite images, changes in built up region and its impact on the socio-economic and environmental conditions of any geographic area can be monitored with relative ease.

Over the years, in the field of remote sensing researchers have developed many spectral indices for different domains and applications (Dolean et al., 2020). For example, related to vegetation, indices such as the normalized difference vegetation index (NDVI) and enhanced vegetation index (EVI) have been developed in order to detect vegetation greenness and to rapidly map the distribution of vegetation or a variety of land surface conditions. Water bodies have been extracted by using the normalized difference water index (NDWI) and the modified NDWI (MNDWI). Bare land has been highlighted using the normalized difference bare land index (NBLI) or the normalized difference bareness index (NDBaI). As well notable advantage of NDVI is that it helps to differentiate vegetation from other types of land cover and determine its overall state. Not only this

but it also allows to define and visualize vegetated areas on the map as well as detect abnormal changes in the growth process (Derakhshan et al., 2020). In general, the significance of the indices in remote sensing is that they are easy and fast in mapping of the features on the surface. As in vegetation mapping, in the built-up mapping the spectral indices help in fast mapping of the built-up areas for very large territories where the built surfaces are very fragmented and are characterized by a great diversity in terms of construction types of which in comparison with classification it is difficult and time consuming to choose samples for supervised classification, hence much of researches nowadays they are opting use of spectral indices.

In previous studies (Uduporuwa, 2011) and (Nordhag, 2012) mapping built-up areas usually coarse- resolution satellite imagery such as Moderate resolution imagery spectral (MODIS) and defense meteorological program / operational line scan system (DMSP/OLS), medium resolution satellite imagery such as Landsat and sentinel-2 and high resolution satellite imagery such as Quick Bird and Worldview have been used. However, due to the high cost of highest resolution data much of studies in Africa utilizes Landsat imagery which is found almost for free and has the potential to provide a historical record for mapping built-up areas, as Landsat has been acquiring images since the early 1980s. As mentioned earlier Landsat imagery has been used frequently to extract built-up areas in urban studies (Derakhshan et al., 2020). One of notable advantage of Landsat is that it covers large area, at least suitable spatial resolution of 30meters, it provide historical observation and its ability to provide free access data therefore, it has proven that it is in useful for mapping built-up areas (Weng, 2012). Some researchers are utilizing some current sensors in their studies of urban expansion like sentinel-2 as in the case of (N. Y. D. Twumasi et al., 2020).

1.1.1. Urbanization in Sub-Saharan Africa

Urbanization is transforming the world. According to the 2014 drivers of migration and urbanization in Africa reported by the United National, more than half of the global population lives in urban areas. This figure is projected to increase to 75% by 2050, at a growing rate of 65 million urban dwellers annually. Sub-Saharan Africa (SSA) is often regarded as the world's faster urbanization region. Urban centers play a critical role in

fighting poverty and sustaining economic growth and are often considered the future prosperity in the developing countries according to (Saghir & Santoro, 2018). Reviewing sub-Saharan documents it has shown that sub-Saharan Africa urban population growth constitutes the highest growth rates in the world according to (White et al., 2012). While other regions have dropped below 2% annual urban population growth, it is predicated that Sub-Saharan Africa will maintain a 3% growth until year 2030 (Nordhag, 2012). However, putting this in number, Africa's urban population is expected to increase by almost 450 million people between year 2000 and 2030 (UNFPA, 2007). This is interesting since sub-Saharan Africa is often considered to be the least urbanized region in the world (White et al., 2012).

In an article called urbanization in Developing countries (Ravallion, 2002), Vernon Henderson compared factors that differ between the urbanization processes of today's less developed countries in Sub-Saharan and that of more developed countries. According to (Henderson, 2002), he firstly states that in general, the more developed countries had a much time urbanizing than what the less developed countries now have. Secondly, the urbanization process of the more developed countries was stretched over a very long time period, which allowed these countries to simultaneously develop necessary institutions and market instruments. On this Henderson means that since less developed countries are urbanizing very rapidly in comparison, they do not have time to develop and/or adjust to the institutions and instruments needed ensure decent living standards. This brings us into comparing urbanization in Sub-Saharan Africa and rest of the world's developed countries as firstly developed countries urbanization was stretched out process, whereas less developed countries in Sub-Sahara urbanize rapidly. Less developed countries in Sub-Sahara have a high population increase while developed countries decreased its population size through migration during its industrialization era. And finally developed countries was well off economically compared to the rest of the world contrary to less developed countries in Sub-Sahara.

1.1.2. Urbanization in Malawi

Malawi is among the world's least developed and one of the most densely populated countries in Africa. Like other developing countries in Sub-Saharan Africa, Malawi has experiencing progressive urban growth since it attained its independence on 6th July 1964. According to National Statistical Office, (2019), urban population increased 2-fold from 1,095,419 in 1998 to 2-fold 115,867 in 2018 in its four main cities of Lilongwe, Blantyre, Mzuzu and Zomba where by over 70% lives in informal settlements. The urban population as a percentage of the national population was 16 percent in 2018 and it is projected to rise to 30 percent by 2030 and 50 percent by 2050.

Despite that several studies have been done on urban changes in Malawi, comprehensive studies on urban change in Malawi's cities remain scarce as such the understanding of urbanization is primarily based on population figures only like in 2019, 17.17% of Malawi total population lived in urban areas and cities (World Bank, 2016). Most of countries in Sub-Saharan Africa are most vulnerable region to climate change Malawi inclusive. It is also characterized with high rate of poverty in most of urban and most of countries in this region rely heavily on agriculture as with the case of Malawi.

1.2. Problem statement

Studying of urban spatial expansion is vital important for both urban and regional development planning and always needs accurate and up-to-date data on built-up areas such as size, shape (geometry), pattern, spatial context, growth trend and development directions (Dolean et al., 2020). Therefore, mapping urban land in a timely and accurate manner is essential for quality spatial planning and rational territorial management. The urbanization in the small growing cities in the world's countries is steadily increasing sub-Saharan countries inclusive Malawi. This is very serious issues because problems like poverty, lack of decent house etc. arises dues to urbanization. In order to monitor urban growth most of researches are proposing or developing indices to study and monitor the urban expansion for examples NDBI, NBI. However, indices are not available for Sub-Saharan with Malawi inclusive. A study by Twumasi et al developed an extract impervious surface areas index at Wa District city in Ghana. Some of existing indices have been tested at well-known commercial city Blantyre Malawi using Landsat 8 images. The results were

not all that promising to be used in the Malawian setting, hence a need to create a new index that can help in addressing the problem arises due to urbanization and that might help in monitoring the trend of urban areas at small growing city of Blantyre in Malawi.

1.3. Main objective

The main objective of this study is to assess the urbanization trends of small cities in the southern sub-Saharan Africa through creation of a suitable build up index.

1.3.1. Specific objectives

1. Creating a built-up index suitable for small growing cities in tropics sub-Saharan Africa
2. Determining the applicability of existing built-up index in sub-Saharan Africa

1.4. Research questions

i. What is the most suitable extraction impervious surface area index for sub-Saharan terrains?
ii. What applicability does exist built-up indices have in Malawi?
iii. How accurately can Landsat images can be used in extracting impervious surfaces area (ISA) in a sub-Saharan topography or terrain?

1.5. Significance of the study

According to (World Bank, 2016) report urbanization is defined as the transition from a mainly rural to urban society that follows and supports process of concentrating population and economic activities in urban settlements. Blantyre city well known as commercial city, the notable characteristics of urbanization and modernization is, its increase in the impermeable surfaces such as concrete, roads, buildings, asphalts, walkaways, sideways as they also called as impervious surfaces. In order to understand the urbanization in the Blantyre city a good impervious surface extraction index required for urban mapping and monitoring. However, with this understanding the significance of this study aims at identifying the built-up index that can accurately highlight the impervious surface areas in the Blantyre city regarding on its environment using the images from satellite.

CHAPTER 2: LITERITURE REVIEW

2.1. Introduction

Different indices have been developed for built-up area extraction using satellite imagery (GAUTAM et al., 2017). The basics of the development of these indices is the spectral behaviour of the built-up land and various features associated with the wavelength of the electromagnetic spectrum in terms of absorption or reflectance (Bhatti & Tripathi, 2014). Different bands of the satellite image represent the different wavelengths of the electromagnetic spectrum. Accordingly, these indices have been developed with a special combination of image bands (Weng, 2012). However, this chapter offers an overview of the literature on the existing developed impervious surface extraction indices and their applicability from different researches. It will examine the literature on the importance existing built-up indices for the urban monitoring.

2.2. Reviewing existing indices

In literature, some of indices that has been proposed by different authors, (Kawamura et al., 2013) proposed the UI for mapping built-up areas. The UI was calculated by using the bands 7 and 4 from Landsat Thematic Mapper ™ imagery and it was tested at Christchurch in New Zealand. (Kawamura et al., 2013) proposed the UI (Urban index) by considering the spectral difference of land covers in near infrared (NIR) and SWIR2 (the 2nd SWIR band) of Landsat imagery. UI is preferred over other urban indices such as NDBI or EBBI since the distinction between urban/built-up areas versus bare land is better represented from the difference between SWIR2 and NIR, than SWIR1 and NIR. From the binary images of UI all the positive values represent built-up areas. However, one of limitation of UI is that it is not ideal because it is difficult to separate the urban from the soil due to high reflectance in the same short wavelength for both soil and urban. Another author (Zha et al., 2003) developed the NDBI for automatic mapping of built up areas and one area that was selected to test the performance of the NDBI is in NOP located in northern Beijing according to (He et al., 2010). The method takes advantage of the unique spectral responses of built-up areas and other land covers. The built-up areas are effectively mapped through the arithmetic manipulation of recorded NDVI and NDBI images derived from

Landsat Thematic Mapper ™ imagery. However, (Zha et al., 2003) recorded that derived NDBI and NDVI images to create binary images under the assumptions that positive of NDBI should indicate built-up areas and positive value of NDVI should indicate vegetation. As discussed by (Zha et al., 2003) with this process, the approach is unable to separate urban areas from barren and bare land. They suggested that the approach should be tested in other geographic areas just because of the actual complicated spectral response patterns of vegetation. (As-syakur et al., 2012) proposed the Enhanced built-up and bareness index (EBBI) for mapping built up and bare land in urban areas. The index was tested at Denpasar in Indonesia (Search, 1996). The index applied wavelength of 0.83μm, 1.65μm and 11.45μm (NIR, SWIR and TIR respectively) to Landsat ETM+ images. These wavelengths were selected based on the contrast reflection range and absorption in built-up and bare land areas. According to (Herold et al., 2003) the reflectance value of built-up areas are higher due to the longer sensor wavelengths. The NIR wavelength, which corresponds to band 4 Landsat ETM+ and band 5 in SWIR is associated with a high contrast area. In additional, in band 4 and band 5 there is an inverse reflectance ration with respect to detecting built-up or bare land areas compared to vegetation. Vegetation has a high reflectance in band 4 but the reflectance of built-up or bare land in band 4 is low. In contrast, also band 5, there is high reflectance when detecting built-up areas compared with vegetated areas. The TIR is capable in distinguishing high and low levels of albedo in built-up objects. According to (Weng, 2012) the utilization of TIR channels is very effective for mapping built-up areas based on a low albedo, which eliminate the effects of shadows and water while high albedo demonstrates built-up and bare land areas clearly. The binary images ranges of 0.10 to 0.35 represent the built-up area where by less than this represents non-urban areas and greater than this range represent bare land. However, the limitation of EBBI is its high heterogeneous terrains which is problem in subdividing urban areas. Secondary EBBI is limited in distinguishing between homogeneous bare land and heterogeneous bare land mixed in urban areas with high temperature. (J. Chen et al., 2010) proposed new –built-up index incorporating the red band in addition MIR and NIR bands to differentiate between barren land, urban areas and other land use types. According to him this method has been successfully applied to extract the residential areas in Changzhou

city, Jiangsu province of China as a representative of plain areas by manipulating the spectral bands of TM imagery in 2007. NBAI was proposed by (Waqar et al., 2012) for mapping of built-up area and bare soil covers using Landsat TM images. The index extracted built-up areas through BRBA using the ratio of bands 3 and 5 of Landsat TM images. Another index BUI was developed by (Kaimaris & Patias, 2016) by combination of the bands 3, 5 and 7 of Landsat Enhanced Thematic Mapper plus (ETM_+) images.

In Africa mainly Ghana a semi-arid region (Y. A. W. D. Twumasi, n.d.) proposed Impervious Surface Extraction Index (ISEI). The index was developed in order to evaluate the impact of decentralization policy on the urbanization dynamic of Wa District by using Landsat and sentinel images. ISEI utilized blue band, NIR, SWIR1 and SWIR2 of Landsat 8 OLI. The principle behind the ISEI index is that in dry environment of the semi-arid terrain of a developing country Ghana, features that qualify as impervious surface like buildings, roads etc. SWIR reflects highly man-made features and absorb water or moisture whereas NIR is noted for reflecting vegetation. Suppressing the property of NIR tends to highlight more man-made features and from the equation, soil is separated from vegetation between wavelengths 1.55μm and 2.10μm thus the open land and bare soil show slightly behind the impervious surfaces that are most. Values of binary images ranges from 0 to 1 whereby the open bare land show as off white while the impervious areas show as white. However, the results of the index proposed by (Y. A. W. D. Twumasi, n.d.) Showed some good results at Wa District such that the index can be used to develop images that can serve as a reference for other classification techniques to check their accuracy.

The reviewed literatures on spatial indices leads us to conclude that these indices have not entirely successfully addressed the confusion between impervious surface and bare soil in different geographical locations hence this study focuses on identifying appropriate remotely sensed index for small growing city like Blantyre in sub-Saharan regions derived from Landsat 8 data.

CHAPTER 3: METHODOLOGY

3.1. Study Area

The study area of this research is Blantyre city. Blantyre is the largest commercial and industrial capital of Malawi, is in the shire highlands and geographical Centre of the southern region of the country Malawi and it lies 35^0 east of Greenwich Meridian and 15^042^l south of Equator. It is a transport communications mode with road, rail and air links to all part of the country and neighboring countries of Mozambique, Zimbabwe and Tanzania. It covers an area of $228km^2$. The city is classified as a National Urban Centre within the designed six hierarchical levels systems of urban centers of the country and is the regional administrative headquarters of the southern region.

It has varied topography ranging from an elevation of about 780 to 1,612 meters above sea level. There are three types of topographic features which have major implications for the development of the city: the hills, plateau and ridge and the natural drainage system.

The most conspicuous and dominant physical features are the numerous hills found in all parts of the city. The main hills are the headwaters of several rivers and streams that originate and radiate from the city, forming a natural drainage system with nine distinct catchment areas; Likhubula, Lunzu, Mombezi and Khombi, which drain the northern part of the city and Mudi, Chisombezi, Limbe, Luchenza and Mwampanzi draining the middle and southern parts. However, because of the hilly topography, these drainage channels are narrow and have steeps sides and gradient.

3.1.1. Climate and weather of the Blantyre city

The climate in Blantyre is mild and generally warm and temperate. The average temperature in Blantyre is 20.6^0c or 69.1^0F. About 1199mm or 47.2 inch of precipitation falls annually.

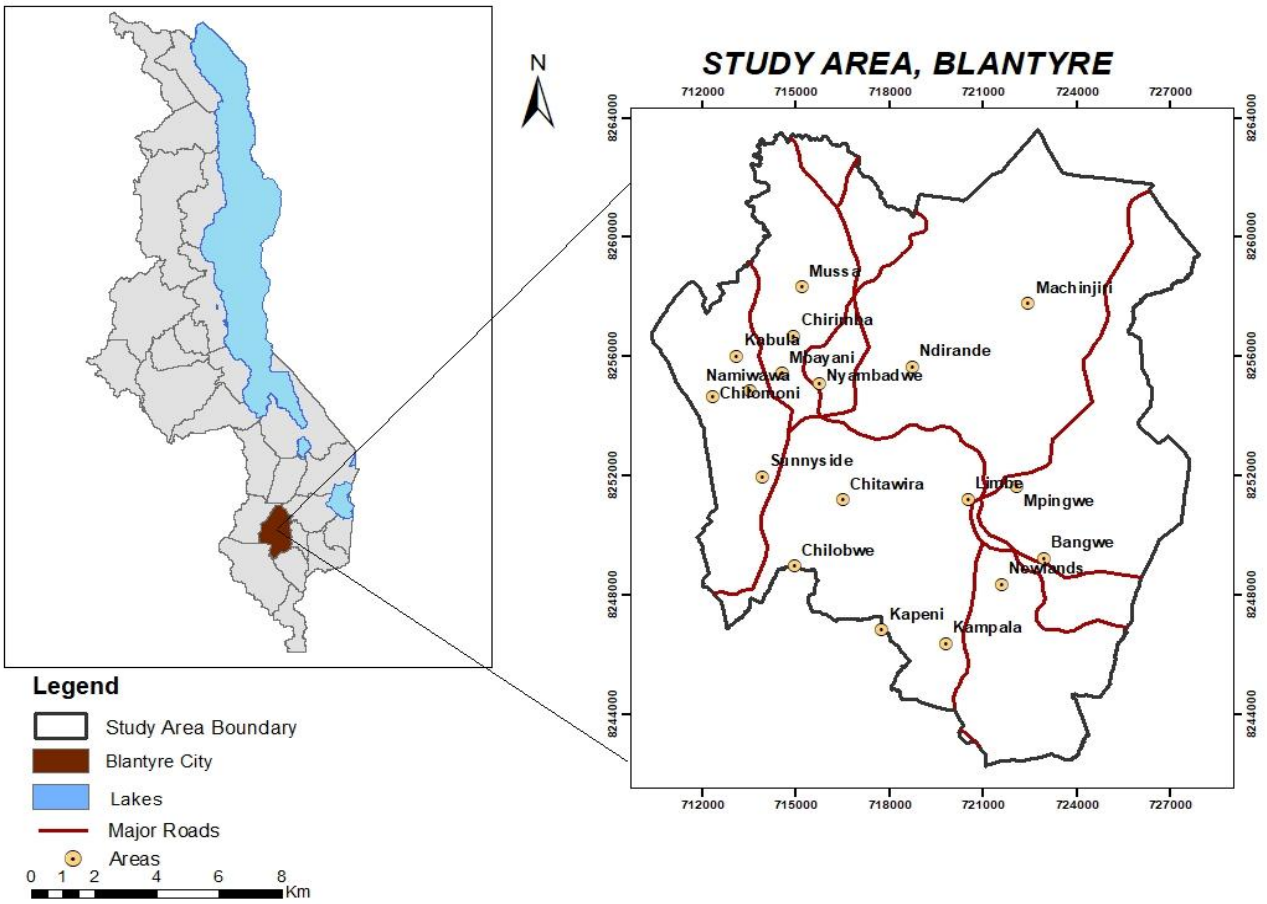


Figure 1: Map of Blantyre city

3.2. Datasets

This study used Landsat 8; Operational Land Imager (Landsat OLI) for 2016 and 2020 multispectral images, all downloaded from the United States Geological Survey (USGS) website (http://earthexplorer.usgs.gov) to map the impervious surface in Blantyre city Malawi. The essential of the multispectral imagery is through its important of different bands in visually distinguish features of interest. For example, Infrared (IR) is commonly used in detecting and extracting vegetation whilst red band is useful for discriminating bare soil. False-colour imagery is good for detecting pervious/impervious features. Blue is useful for discriminating urban features.

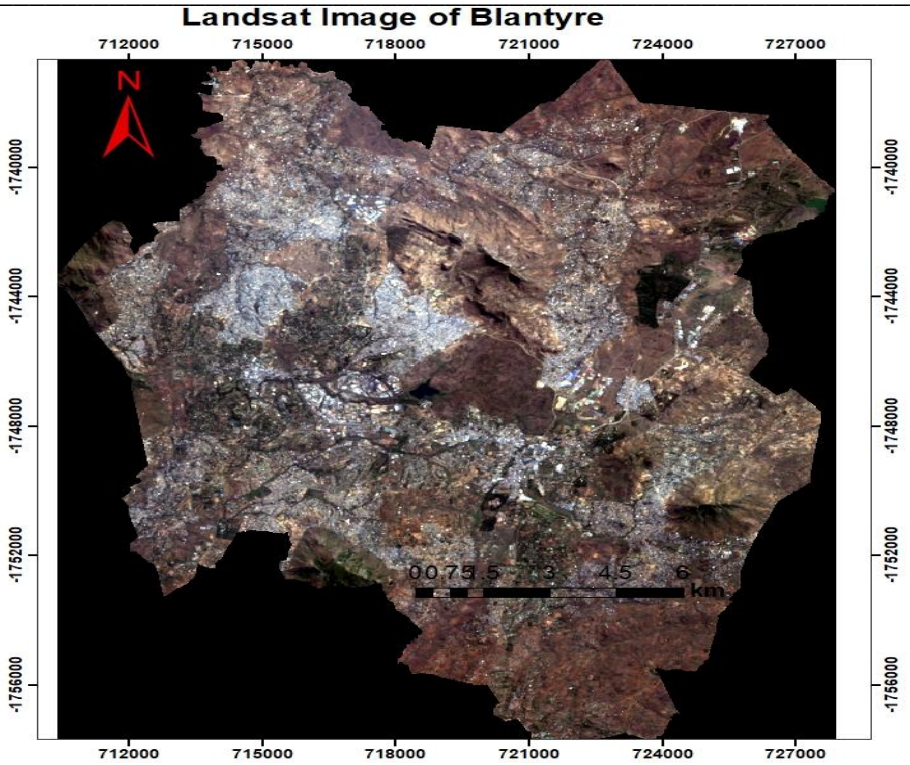


Figure 2: RGB image of Landsat 8 showing a boundary of Blantyre

Table 1: Information of the Landsat 8 Bands used

Band Number	Micrometers range (μm)	Resolution in meters	Image size
2 (Blue)	(0.45-0.51)	30	170 x 183
3 (Green)	(0.53-0.59)	30	170 x 183
4 (Red)	(0.64-0.67)	30	170 x 183
5 (NIR)	(0.85-0.88)	30	170 x 183
6 (SWIR 1)	(1.57-1.65)	30	170 x 183
7 (SWIR 2	(2.11-2.29)	30	170 x 183

Apart from the bands chosen to be used in this study, Landsat 8 OLI has got other bands like band 1, 8, 9, 10 and 11. Band 1 senses deeper blues and violets. This band is hard to

collect from space because it's scattered easily by tiny bits of dust and water in the air molecules themselves. This part of spectrum is hard to collect enough sensitivity to be useful. It's also called the coastal/aerosol band, after its two main uses; imaging shallow water and tracking fine particles like dust and smoke. Its output looks a lot like Band 2 (normal blue), but if contrasting them and highlight areas with more deep blue, difference is seen. Band 8 is the panchromatic or just pan band. It works just like black and white film, instead of collecting visible colors separately, it combines them into one channel because this sensor can see more light at once, and it's the sharpest of all the bands with a resolution of 15 meters. Band 9 covers a very thin slice of wavelengths only 1370 ± 10 nanometers. Few space-based instruments collect this part of the spectrum because the atmosphere absorbs almost all of it hence it just for clouds. Band 10 and 11 are in the thermal infrared (TR). They see heat instead of measuring the temperature of the air, like weather stations do, they report on the ground itself which is often much hotter.

3.3. Research design

The proposed method for extraction of built-up areas using Landsat 8 OLI imagery comprised six major steps; Data archive from United State Geological Survey (USGS), preprocessing and examination of the satellite data, running the four already existing indices, development of the built-up area extraction method for Blantyre and run on the 2016 and 2020 images and also applying it on some selected cities of Gaborone and Dodoma and finally accuracy assessment.

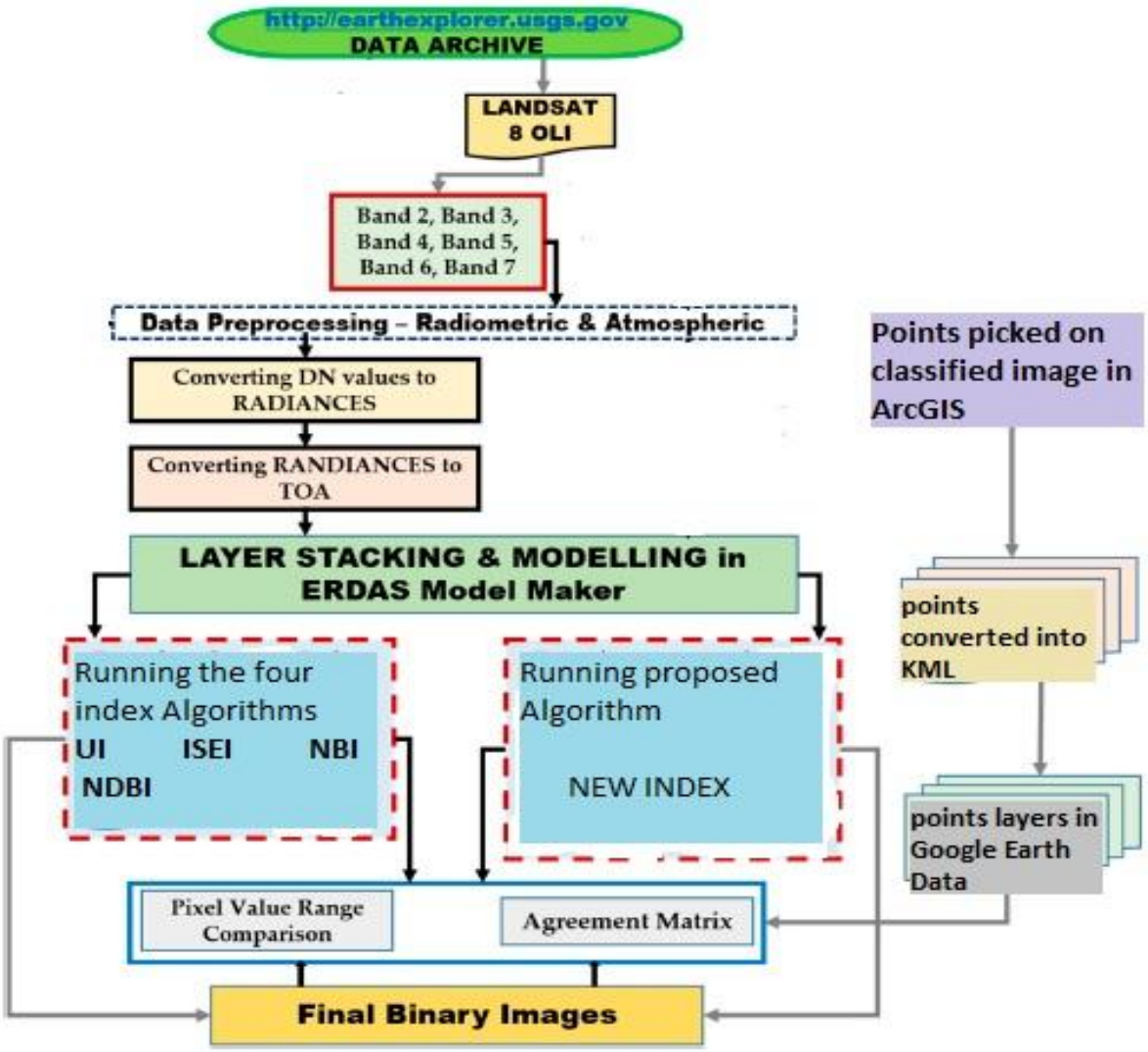


Figure 3: Methodology workflow and process

3.4. Preprocessing of Landsat 8 imagery

All the images used in this study have been atmospherically and radiometrically corrected. Atmospheric correction has been done using "Dark Object Subtraction (DOSI) model-based atmospheric correction algorithm (Mustak, 2013) and the radiometric calibration has been done using the conversion to TOA reflectance algorithm through which digital number (DNs-radiance) values have been converted in the "top of the atmosphere reflectance". These pre-processing methods are considered by many scientists being the most efficient and recommended for urban studies (Gao et al., 2012).

Given a remote sensing optical dataset, the first step is to convert the captured radiance, the raw digital number to the "top of atmosphere values". This step is necessary because it removes the cosine effect of different solar zenith angles due to the time difference between data acquisition, it compensates for different values of the atmospheric solar irradiance arising from spectral band differences and corrects for the variation in the Earth-sun distance between different data acquisition dates. Due to the fact that images are level 1 data products, geometrically corrections have been already made by the image provider (The United States Geological Survey, European Space Agency- USGS). The ERDAS image 15 software environment were used in this preprocessing of the images. Final preprocessing single band images were stacked to obtain a final prepared data consisting of the required number of bands which is band 2 up to band 7. In converting the DN values to TOA equations 1 and 2 below applied. Equation 1 below illustrate the conversion of DN values to radiance and equation 2 illustrate the conversion of radiance to top of atmosphere reflectance for Landsat 8 OLI.

$$P\lambda = M_P \times Qcal + A_P \qquad 1$$

Were

$\boldsymbol{\rho\lambda'}$ = TOA planetary reflectance, without correction for solar angle. Note that $\rho\lambda'$ does not contain a correction for the sun angle.

$\boldsymbol{M\rho}$ = Band-specific multiplicative rescaling factor from the metadata (REFLECTANCE_MULT_BAND_ x, where x is the band number)

$\boldsymbol{A\rho}$ = Band-specific additive rescaling factor from the metadata (REFLECTANCE_ADD_BAND_x, where x is the band number)

$\boldsymbol{Qcal}$ = Quantized and calibrated standard product pixel values (DN)

$$\boldsymbol{\rho\lambda} = \left(\frac{\rho\lambda}{\mathbf{COS}\theta SZ}\right) = \left(\frac{\rho\lambda}{\mathbf{COS}\theta SE}\right) \qquad 2$$

Were

ρλ = TOA planetary reflectance.

ϑSE = Local sun elevation angle. The scene center sun elevation angle in degrees is provided in the metadata (SUN_ELEVATION).

ϑSZ = Local solar zenith angle; $\vartheta SZ = 90° - \vartheta SE$

The results are binary image of each band. These were then stacked together to obtain the full composite image for 2016 and 2020 image. These became the input data for the index algorithm.

3.4.1. Application of the already built-up area extraction indices

After the data under go through preprocessing stage, some four already existing built-up indices were calculated to each of the images in the ERDAS imagine 2015 software through the model maker. NDBI, UI, ISEI and NBI have been developed by different researches and the performance of these indices were tested in different areas rather than in the sub-Saharan African countries (Saghir & Santoro, 2018). These indices were calculated using the formulas below;

Normalized difference built-up index proposed by (Zha et al., 2003)

$$\text{NDBI} = \frac{(\text{SWIR}-\text{NIR})}{(\text{SWIR}+\text{NIR})}$$

Urban index proposed by (Kawamura et al., 2013)

$$\text{UI} = \left(\left[\frac{SWIR1-NIR}{\text{SWIR1}+\text{NIR}}\right] + 1\right) \times 100$$

Impervious Surface Extraction index proposed by (Y. A. W. D. Twumasi, n.d.)

$$ISEI = \frac{Bblue}{\frac{Bnir}{Bswir1} + \frac{Bnir}{Bswir2}}$$

New built-up index proposed by (J. Chen et al., 2010)

$$NBI = \frac{Bred + Bswir1}{Bnir}$$

The results from the both indices are binary images (black and white) with the following ranges; NDBI ranges from -0.49 to 0.46, ISEI ranges from 0 – 0.25, NBI ranges from 0 – 2.75 and UI ranges from 0 – 18.79.

3.4.1.1. Advantages and disadvantages of already existing indices

Some of advantages and disadvantages associated with these existing indices are; NBI helps in distinguishing residential areas and bare areas although the universality of this proposed method required to be tested further in other geographic areas as spectral response of the various land covers may vary spatially. Normalized difference built-up index (NDBI) estimate urban built up area although is unable to distinguish properly between urban and bare land areas. ISEI is very simple to compute and easy to implement with a high accuracy results however it requires more testing particularly in more complex heterogeneous landscape to help differentiating more land cover classes. And UI is not ideal because it is difficult to separate the urban from the soil due to high reflectance in the same short wavelength for both soil and urban.

However, the results from indices shows that none of these indices performed well in delineating impervious surface area for a small growing city of Blantyre, therefore the methodology proceeded into next step of development of the new index (which is the whole purpose of this study) for the small growing city of Sub-Saharan African countries like Blantyre Malawi.

3.5. General knowledge on the creation of indices

Since the development of NDVI, various other indices have been developed in order to extract land cover from remotely sense data. The concept for developing such indices is to identify the weakest and strongest reflectance band from multi-spectral data. Then, based on the identified weakest and strongest bands, indices are formed respectively to enhance a particular land cover class. The output of these indices, efficiently especially if a suitable threshold is used.

3.5.1. New built-up extraction index for the growing city of Blantyre

The concept of developing new built-up index for this study is based on understanding that the urban area is a complex ecosystem composed of four main heterogeneous components; impervious surface material, green vegetation, exposed soil or bare soil and water body. Therefore, this index applies some part of wavelengths of Landsat 8 images to highlight the impervious surface areas. The index is formulated as;

$$\text{New Built-up index} = \frac{\text{Bred} + \text{Bblue}}{\text{SWIR} + \text{NIR}}$$

SWIR reflect highly man-made features and absorb water or moisture whereas NIR is noted for reflecting vegetation. The reflection of the man- made features are very weak in the red, blue band is associated with atmospheric scattering therefore, suppressing the properties of red and blue band tends to highlight more man- made features in the Blantyre city, Malawi. After the formulation of this new index, it was applied in all Landsat images of Blantyre city including on Gaborone city in Botswana and Dodoma in Tanzania, and from the results of binary images, open bare land shows as off white while the impervious areas show as white. Lastly the results from this index were compared to the results of the four existing indices. However, this new index performs well compared with the other indices.

3.6. Accuracy assessment

The performance of the proposed new built-up index for the Blantyre city and other four already existing indices were tested through accuracy assessment. The advantages of accuracy assessment are that it helps in assessing how well the classification worked. It also measures the degree of agreement between a correctly assumed standard and a classified image of unknown quality. It estimates how accurate the land cover data are in terms of thematic categories to determine whether the derived maps meet the requirements of the intended application. Mostly important is the validating of the categorized results or the algorithms. In this study the accuracy assessment was done using the Google earth pro. Using this approach requires a very good source of reference data. The platform gives geometrically- corrected high resolution image. Google Earth allows the user to obtain around the same time of the acquisition date of the Landsat images for collecting ground truth to serve as validation data. It is also providing historical records feature model location for five key classes (i.e., vegetation, open bare land, roads, buildings and water) because it allows users to go back in time to give a real time validation date and comparison can be made alongside. In this study the process of accuracy assessment begins by creating a point shapefile in the ArcGIS where by 102 points from the classified output of each index as impervious surface and pervious surface was taken. 75 points were representing impervious surface and 27 points were representing non-impervious areas were taken from each output image and in the attribute table the user and producer fields were created. The shapefile was then converted into KML as reference point in order to compare the user and producer. From each KML files after opening in the Google earth, the year was set basing on year the images were acquired of which in this study it is 2016 and 2020 for Blantyre and 2020 for Gaborone and Dodoma cities. However, through this method, the overall accuracy was calculated by the ratio between all correct predictions and the total number of the validation samples for all the output images. The kappa coefficient which is a measure of how the classification results compare to values assigned by chance, was also determined from the confusion matrix. The overall accuracy, kappa coefficient, user and producer accuracy were calculated using the formulas below

$$\text{Overall accuracy} = \frac{\text{Total number of correctly classified pixel (Diagonal)}}{\text{Total number of reference pixel}}$$

$$\text{Kappa coefficient} = \frac{(\text{Ts} \times \text{Tcs}) - \mathcal{E}(Column\ total \times Row\ Total)}{Ts^2 - \mathcal{E}\ (Column\ total\ \times\ Row\ total)}$$

$$\text{User accuracy} = \frac{Number\ of\ correctly\ classified\ pixel\ in\ each\ category}{Total\ number\ of\ classified\ pixel\ in\ that\ \ category}$$

$$\text{Producer accuracy} = \frac{Number\ of\ correctly\ classified\ pixel\ in\ each\ category}{Total\ number\ of\ reference\ pixel\ in\ that\ category}$$

CHAPTER 4: RESULTS

4.1. Results of the Binary image from each index

The results of the index algorithms are presented in this section in a binary form of black and black. The contrast between white and black represents the goal and background features respectively. However, the grey representation, which shows the degree of features that are seen as context and vice versa, is often the source of error. The greater the visual contract, the better the outcome or output of the index used. It's worth noting that the white areas are supposed to be impervious (built-up areas). The results of the index algorithms are shown in the figures below with the impervious surface areas as bright white and the pervious surface areas as dark. Other features that may have identical spectral characteristics to the impervious surface areas, such as bright and exposed rocks or bare soil, are depicted in grey colour. Generally, images were captured by sensors in the dry season in order to avoid clouds. Nothing was done for the small presence of clouds, however the proposed index distinguished itself well from the other indices as shown in the figures.



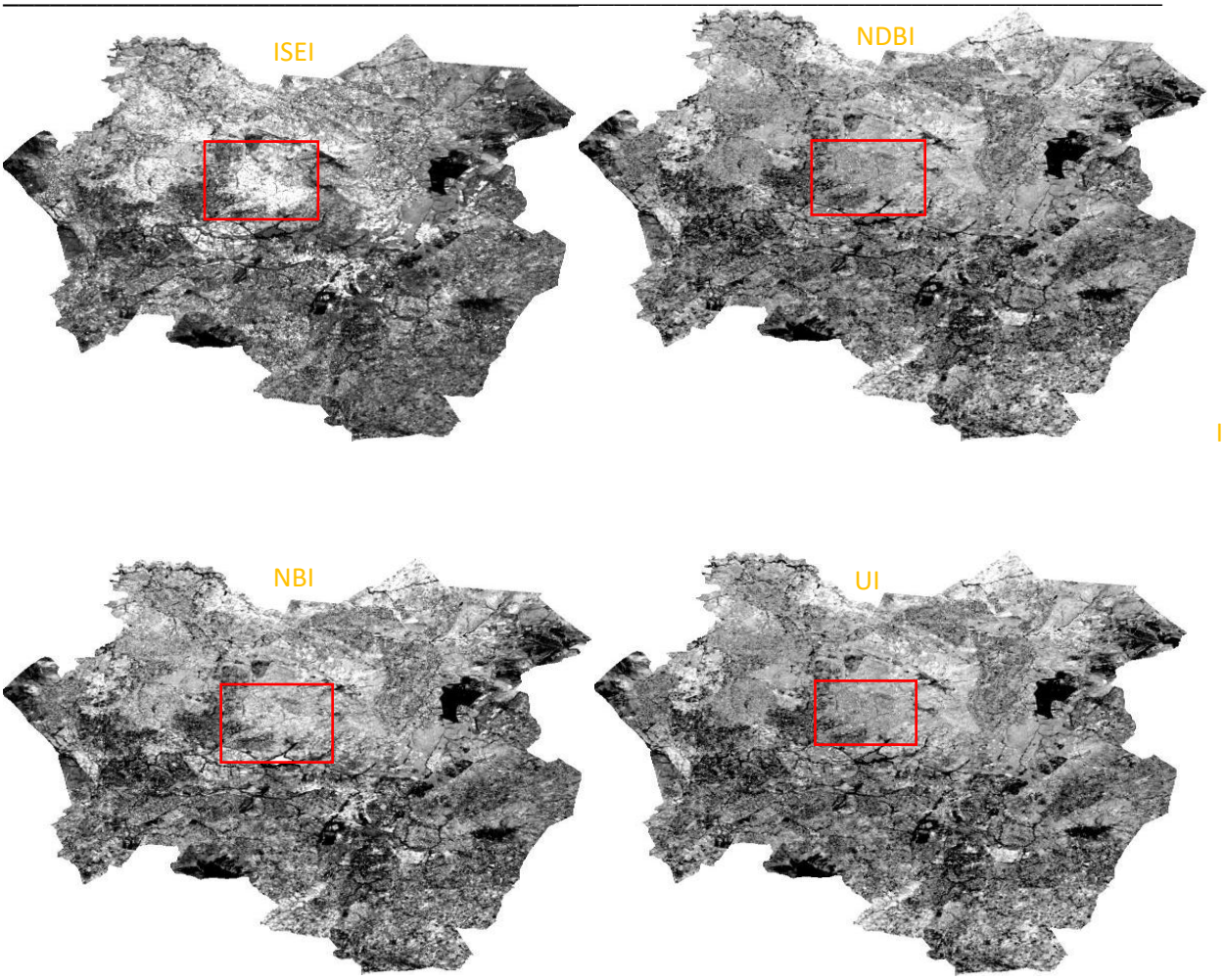


Figure 4: Index results of algorithms applied on 2016 Landsat image on a small growing city Blantyre.

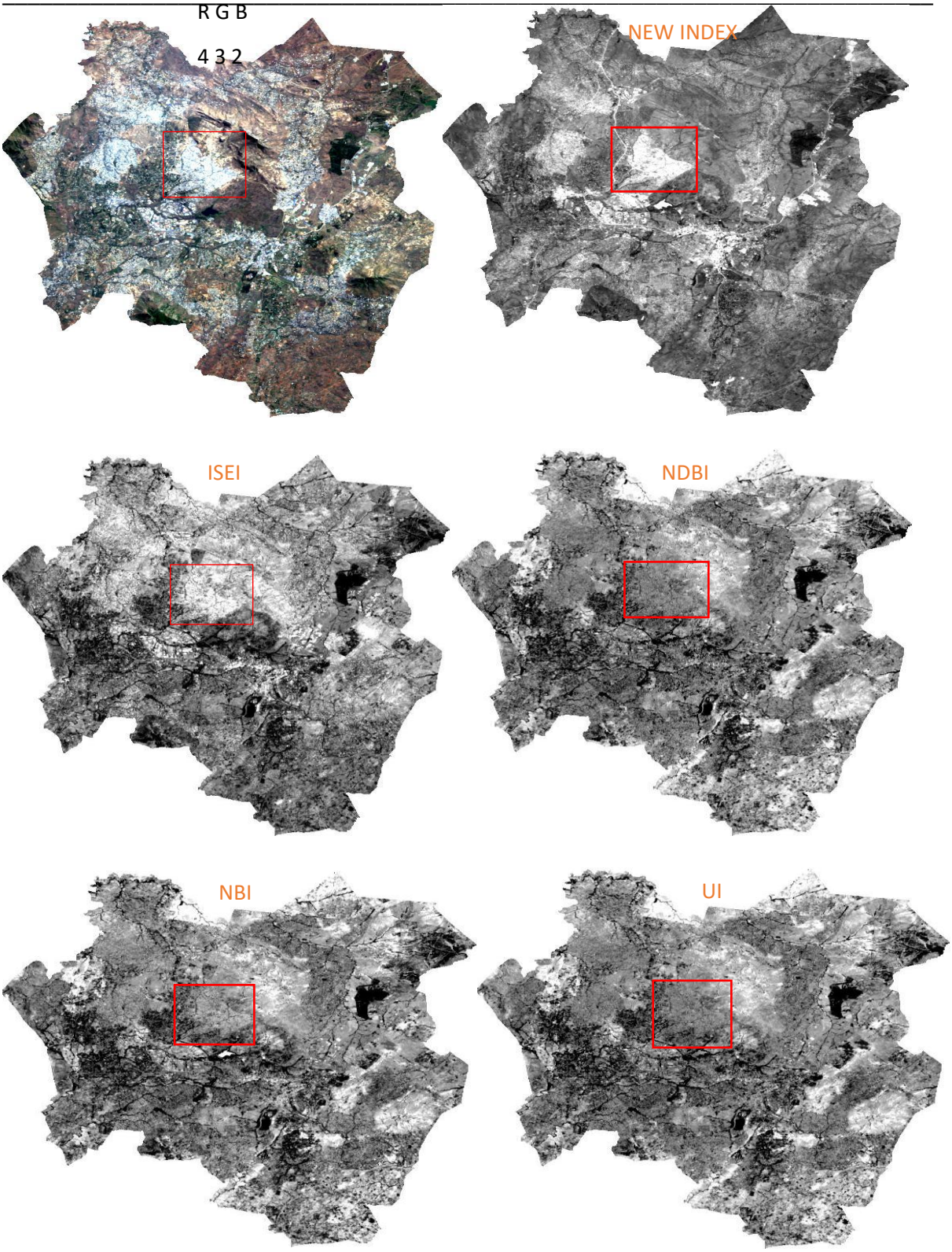


Figure 5: index results of algorithms applied on 2020 Landsat image of a small growing city Blantyre.

Generally, highways in the urban areas and built-up or paved areas appear as brighter tone while forest, water body and croplands appear darker. Indices mostly enhance these spectral properties, where the index that does, the enhancement better is said to have performed better. However, from the visual observation new proposed index is showing a good performance compared to other indices.

Results of binary images from Dodoma and Gaborone cities

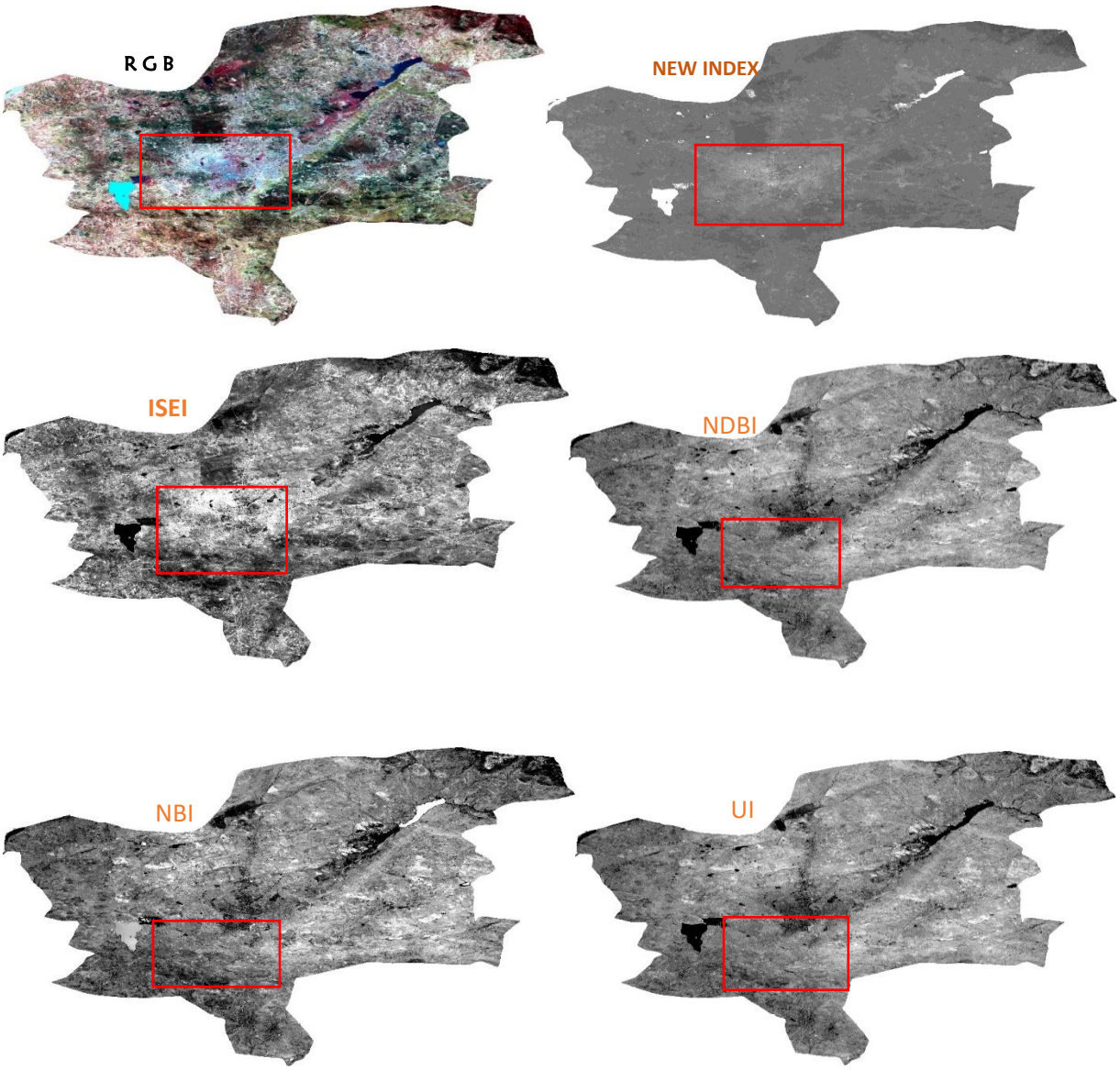


Figure 6: index results of algorithms applied on 2020 Landsat image of Dodoma, Tanzania

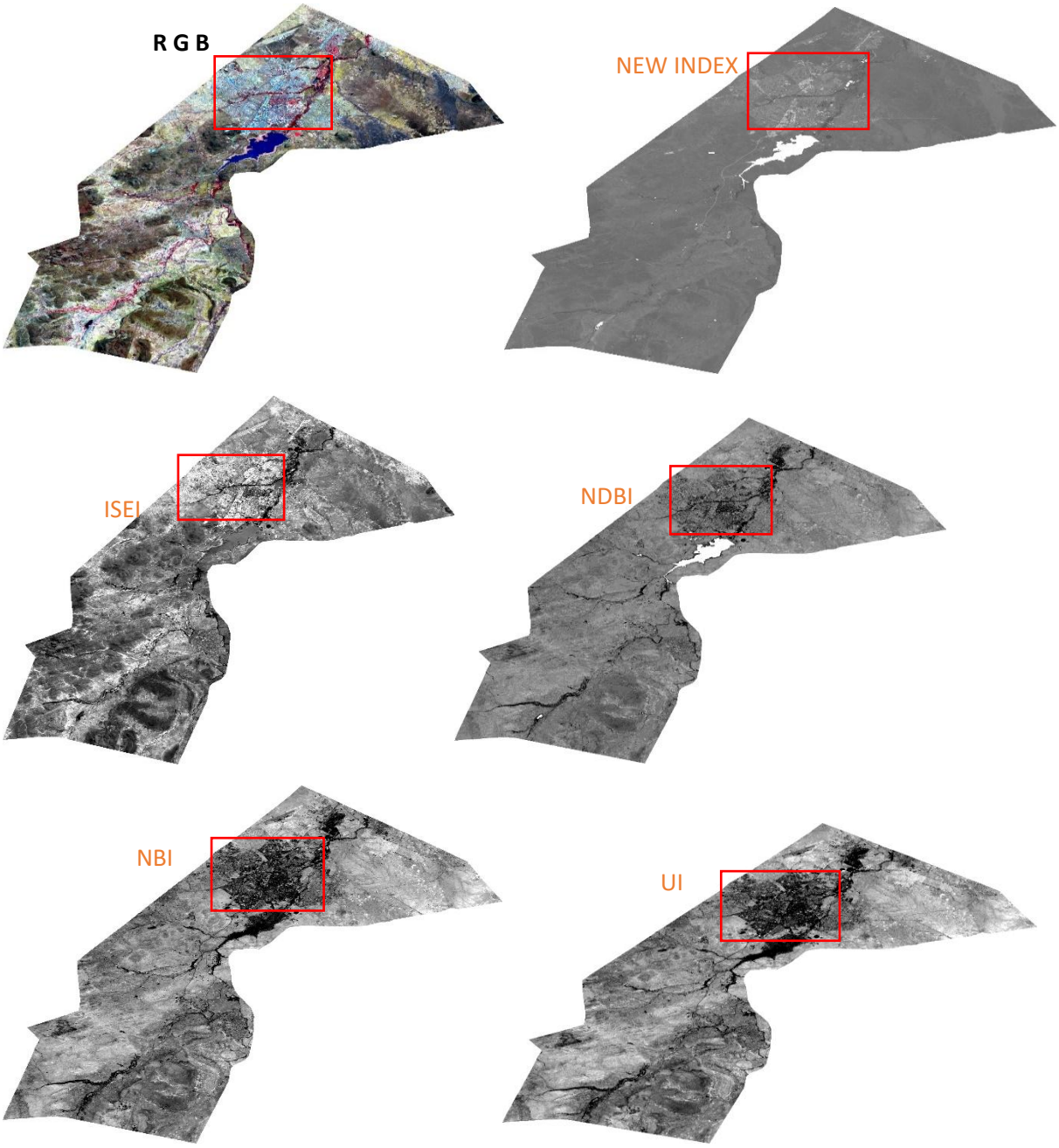


Figure 7: Index results of algorithms applied on 2020 Landsat image on small growing city Gaborone, Botswana

From the RGB images of Dodoma and Gaborone cities, we are noticed that the impervious surface area appears as bright colour, water is appearing as blue and the other pervious

surfaces appears with difference colour. However, we are seen that the impervious surfaces appear as bright colour from the proposed index and ISEI binary images whereas pervious surfaces appear as dark and some areas as grey colour. On NDBI, NBI and UI binary images in both cities' areas qualified as impervious areas appears as dark and of course water appears as white on other indices and as black on other indices.

4.2. Accuracy Assessment of Results

The accuracy assessment of study is made by multiple quantitative methods so that the degree of trust can be clearly determined. This study used the traditional confusion (error) matrix for accuracy assessment with the help of 102 randomly generated validation points, evaluated and codified according for each index based on satellite imagery and high-resolution images from Google earth covering the study area. By this method, the overall accuracy is calculated by the ratio between all correct predictions and the total number of the validation samples. The Kappa coefficient which is a measure of how the classification results compared to values assigned by chance is also determined from the confusion matrix on each index result. Commission and Omission error (%) were also calculated in every index respectively. Commission error is the rate at which site are correctly classified as "reference site" but were erroneously omitted from the correct class in the classified map where by Omission error is the rate at which sites where erroneously omitted from the correct class in the map. User accuracy and producer accuracy were also calculated from each index result.

Table 2: Summary of accuracy assessment and validation based on confusion matrix method.

INDEX FROM EACH IMAGE	OVERALL ACC. (%)	K-COEFF. (%)	PRODUCER ACCURACY (%)		USER ACCURACY (%)		COMMISSION ERROR (%)		OMISSION ERROR (%)	
			IS	N-IS	IS	N-IS	IS	N-IS	IS	N-IS
NI- 2016	89.43	78.49	100	71.05	85.33	100	14.67	0	0	40.74
ISEI-2016	72	35.71	93.62	43.64	58.66	88.88	41.33	11.11	6.38	56.36
NDBI-2016	45	-0.97	74.19	25.35	30.66	66.66	69.33	33.33	29.0	73.24
NBI- 2016	60.94	12.35	81.40	32.20	46.66	70.37	53.33	29.63	18.6	67.80
UI-2016	49.13	-2.38	71.79	25.40	37.33	59.26	62.67	40.74	28.2	74.60
NI -2020	80.45	60.6	98.15	54.17	70.67	96.30	29.33	3.70	1.85	45.83
ISEI-2020	70	18.25	90.63	34.29	58.66	88.88	61.33	11.11	9.38	65.71
NDBI-2020	40	-14.34	60.61	20.20	26.66	51.85	73.33	48.15	39.4	79.71
NBI-2020	56	0.90	74.28	26.87	34.66	66.66	65.33	33.33	25.7	73.13
UI-2020	43	-19.27	60	17.74	32	40.74	68	59.26	40	82.26

NI = New Index, K-coeff. = Kappa Coefficient, Overall, Acc. = Overall Accuracy,

IS = Impervious Surface, N-IS = Non-Impervious Surface

As can be seen in the accuracy assessment and validation based on confusion matrix method, overall accuracy for the new proposed index in 2016 image is 89% and in 2020 image is 80.45%, this is considered a good result, taking into account the heterogeneity of the study area. Comparing the commission and omission error, the already existing indices is showing a high commission and omission error signifying that there are highly areas wrongly extracted as built-up areas, however error in the new proposed index indicate

that the approach were able to extract built-up areas quite well. Nevertheless, its low values of omission and commission error and the high k-coefficient value suggested that the new proposed index was more accurate than the already existing indices.

Table 3: Summary of accuracy assessment and validation based on confusion matrix method for Gaborone and Dodoma cities.

Dodoma, Tanzania						
YEAR	NI	ISEI	NDBI	NBI	UI	INDICATOR
2020	68%	60%	43%	50%	45%	Overall Accuracy
	38.87%	23.3%	-10.34%	11.76%	-2.18%	Kappa Coefficient
Gaborone, Botswana						
2020	65%	70%	40%	53%	42%	Overall Accuracy
	37.16%	27.10%	-9.61%	12.47%	-2.03%	Kappa Coefficient

Visual analysis of the white (ISA) areas and the darker (pervious surface areas) areas, as provided in Section 4.1, reveals that the contrast between the white (ISA) areas and the darker (pervious surface areas) areas. Pervious surfaces are the darker portions, while impervious surfaces respond readily to light and show whitish zones. The maximum and minimum pixel values of the various algorithms are shown in Table 4

Table 4: Pixel value comparison of algorithm results

Blantyre city						
YEAR	NI	ISEI	NDBI	NBI	UI	Range
2016	0.806060	0.476550	0.463597	2.764860	14.360	Maximum
			-0.487244			Minimum
2020	0.632880	0.477718	0.501253	2.551370	15.125	Maximum
			-0.373077			Minimum
Dodoma, Tanzania						
2020	0.534630	0.697940	0.847619	1.337100	18.440	Maximum
			-0.883071			Minimum
Gaborone, Botswana						

2020	0.604621 0	0.670564 0	0.64564 -0.932429	1.4025 0	16.564 0	Maximum Minimum

Range values; UI= -1 to +1, NBI=0 to +1, ISEI = 0 to +1, NDBI =-1 to +1, NI= 0 to +1

As seen in the table, UI generated positive maximum values, all of which were greater than +1, indicating an overestimate. The NBI exhibits the same patterns, but with a maximum value of less than 5. The ISEI, which produced both positive and negative values as maximum and lowest, is the closest well-performing index to the suggested index (NI). The binary picture pixel values will often range from -1 to +1 when using indices in this way. Because the target feature is emphasized, it will usually represent pixels near +1, while the background will be predominantly 0 or less than 0.

The proposed index was also compared with the RGB images in terms of the area coverage of built-up. This ensure how effective the proposed index is by comparing the area covered by RGB image and also from the results of the proposed image. This has been achieved by doing supervised classification on RGB image and then calculate area in hectares whilst from proposed index results it was reclassified into bult up area and non-bult up areas then followed by area calculation.

Table 5: Built-up coverage comparison between RGB and proposed index in hectares at Blantyre city

	Year	Total amount of built-up (hectares)
RGB	2016	8206
	2020	8924
Proposed Index	2016	8100.18
	2020	9164

From the results, the RGB value of built-up coverage in 2016 image is a bit high with a slight difference from proposed index and in 2020 image the value of proposed index is slightly high compared to RGB value. This might be due to other factors like different pixel similarity. Therefore, the proposed index is superior since it is able to delineate the built-up area with closely related to the amount of the built-up coverage over the Blantyre city.

CHAPTER 5: DISCUSSION

5.1. Established Satellite ISA Extraction indices

Information about spatial distribution is essential for city studies and also helpful to address some environmental problems. Built-up area extraction becomes interesting subject to study (Y. Chen et al., 2018). Previous studies have applied various approaches in built-up area, but limitations still exist an issue which is addressed in this paper. (Zha et al., 2003) conducted a pioneered research related to the built-up extracting using NDBI. NDBI identified built-up areas accurately in cities in humid climate, for instances in Colombo city in Sri Lanka, Montreal in Canada, São José dos Campos city in Brazil, Beijing and Guangzhou city in China (Hidayati et al., 2018), in contrast NDBI has performed poorly for mapping built-up areas in the semi-arid cities of Urumqi and Shihezi in western China and even in some cities in developing countries in Africa Ghana as an example. Zhou et al. also reported a low accuracy (57.4%) of NDBI for Zhengzhou city in China from Landsat 8 OLI data. In line with this research NDBI has also performed poor since it is unable to distinguish between urban and bare land area. With UI it is not ideal because it is difficult to separate the urban from soil due to high reflectance in the same short wavelength for both soil and urban. NBI is strongly affected by drier month images where there is difficulty to differentiate between bare land and urban areas. Impervious surface extraction index was proposed by the (Y. A. W. D. Twumasi, n.d.) in Ghana in studying the effect of decentralization on the expansion of the urban areas, Wa District as study area. The index performed well in the semi-arid region of Ghana compared to other indices. ISEI accuracy varied from 86.62-94.00% while existing indices varied from 73.85-90.00%. However, this is quite different on how this index performed in the Sub-Saharan environment condition at our study area of which the accuracy of ISEI varied from 70-72% from the 2016 and 2020 Landsat 8 OLI images of Blantyre city.

5.2. The proposed New Index for Blantyre city (NI)

Sensors capture the reflected component of the energy from the spectrum of incident energy, depending on the target within the environment and the wavelength. At the level of the satellite sensor, the apparent reflectance, or reflectance at the TOA, gives that portion of the solar energy reflected by the Earth's surface and atmosphere. Conversion to

reflectance allows for image normalization in a range of continuous values between 0 and 1, as well as image comparison. Ratio indices reduce background features while highlighting the targeted feature, with the numerator being the bands responsive to the targeted feature and the denominator being the bands that absorb energy from background features, boosting the qualities even more. In these advantages, the bands chosen for this index were carefully evaluated. The proposed index utilizes the band 2, band 4, NIR and SWIR 1 with the understanding that, the NIR from multispectral sensors reflects vegetation very strongly. This band is kept as denominator in order to suppress the background vegetation. Band 2 (Blue) is associated with distinguishing soil from vegetation and band 4 (Red) is associated with discriminating vegetation slopes. Both Band 2 and band 4 were kept as numerator from equation.

Man-made features can be located, categorized, and classified using data-rich SWIR imaging. They're great for distinguishing between bare soil and telling what's wet and what's dry in a landscape, which is another reason why dry season images were favored. To uncover important information, SWIR bands provide information that is not accessible to the human eye. These wavelengths penetrate smoke and haze, allowing for the most confident decision-making conceivable. With information not available from other bands, the particular attribute allows for high-confidence decision-making. The results reported in Section 4.1 show that a lot of rocks and bare soil are exposed, but the proposed index discrimination is better in that it was able to suppress the background better, highlighting the built-up better than the peripherals, indicating that the peripherals have less imperviousness if any. The proposed index works extremely well on Blantyre city though the index shows trends of good performance from Dodoma and Gaborone cities from table 3 but these are not as extremely good as it is in Blantyre city. These results indicating that the proposed index is extremely good for Blantyre city regarding to its environment.

Some extraction indices, such as NDVI, have a range of 1 to +1, whereas others have a range of 0 to 1. The binary findings' range is always between these values. Minimum range values are used to represent background features in a scene, whereas maximum range values are used to represent targeted features. Table 4 shows the binary outcome of the

extraction indices minimum and maximum values. The proposed index results reveal that background features are suppressed and impervious regions are highlighted more clearly.

5.3. Accuracy performance of the indices

In reference to table 2 and 3, the overall accuracy percentage for each index represent how good it is in highlighting the impervious surface areas. For example, with the overall accuracy of 40%, means that 6 for every 10 impervious pixels are in reality miss-labeled by the algorithm and 4 are correctly labeled as impervious pixels. With 70% means that 3 of every 10 impervious pixel in reality are missed by the algorithm and 7 labeled as impervious pixels, likewise with the overall accuracy of 80% and 90%. From the summary of accuracy assessment and validation based on confusion matrix displayed in table 2. The minimum overall accuracy for comparable four indices is 40% while the maximum is 72%. This is 32% difference and 8.98% less compared to the proposed index (NI). ISEI performed closely better to the proposed index than the other indices. The maximum accuracy achieved for the proposed index (NI) is 89.43% and minimum 80.45%.

Although the proposed index shows some good performance from the table 3, it is not as accurately delineating the impervious surface from Dodoma and Gaborone cities as it is performing on our study area Blantyre. And from the table 5, the results of area covered by built-up from RGB and proposed index shown closely related therefore this is telling us that the proposed index is good for the Blantyre city.

CHAPTER 6: CONCLUSION

In summary, a remote sensing-based indices in urban areas are generally used to distinguish different urban land use features such as built-up, barren land, vegetation and water body. The study reviewed that the Sub-Saharan terrains lacks the most suitable extraction impervious surface area indices, hence the new index has been proposed for the Blantyre city. The proposed method (new built-up index) is highlighting built-up areas based on information from near infrared, shortwave infrared, red band and blue band data. The results obtained by the index were compared with some of commonly used built-up indices like, the ISEI, NDBI, NBI and UI and the good performance in accuracy assessment was found in new index proposed over the four indices in terms of built-up area extraction.

The indices are well known with different applicability they do have on land surface features. Some of applicability of built-up indices revered from this study are; NBI is associated in working out the problem of distinguishing residential areas and bare areas. NBAI techniques was proposed due to the effect of the two most confusing general land covers classes – soil and built-up – to the accuracy of the classified image. The NBAI effectively enlarges the intensity contrast between bare soil and urban surfaces. Normalized difference built-up index (NDBI) estimates urban built-up area. In general, the applicability of the spectral indices is that it helps in fast mapping of the built-up areas for very large territories where the built surfaces are very fragmented and are characterized by a great diversity in terms of construction types. This is heavily applicable to the urban planners and researches.

However, using a free cloud cover and a good spatial resolution images like Landsat can help in accurately extracting impervious surface area for Sub-Saharan topography or terrain just as most of researches have done. This study has also shown the importance of using the Landsat images in studying the urbanization just like the study by Twumasi et.,. In addition to what have been said, the proper pre-processing of the Landsat images is required in order to have accurate and recommendable results. The results from this study could allow urban planner to understand and evaluate urbanization growth of the Blantyre city for sustainable usage of urban land system.

CHAPTER 7: RECOMMENDATION

Although the proposed index has been tested on Dodoma in Tanzania and Gaborone in Botswana, the index is required to be tested in other Sub-Saharan African countries in order to ensure its effectiveness. In additional to this it must be applied on images from other sensor other than Landsat sensor for instance MODIS, sentinel-2 etc., Furthermore, more reference sample points have to be randomly picked during accuracy assessment in order to ensure the efficiency of the index. Finally, the research requires much times for better results.

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