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Evaluation the Soil-Adjusted Vegetation Indices SAVI and MSAVI for Bristol City, United Kingdom Using Landsat 8-OLI Through Geospatial Technology

Hayder H. Kareem[1*], Muammar H. Attaee[2], Zainab Ali Omran[3]

[1] Structures and Water Resources Engineering Department, Faculty of Engineering, University of Kufa, Al-Najaf, Iraq

[2] Department of Civil Engineering, College of Engineering, University of Misan, Misan, Amarah 62001, Iraq

[3] Department of Civil Engineering, Faculty of Engineering, University of Babylon, Babil, Iraq

* Corresponding author's e-mail: hayderh.alshaibani@uokufa.edu.iq

ABSTRACT

Soil moisture is highly variable in space and time; moreover, it has nonlinear effects on a wide variety of environmental systems. Understanding the multiple hydrological processes, developing more accurate models of those processes, and applying those models to conservation planning all benefit greatly from a better characterization of temporal and geographic variability in soil moisture. Vegetation indices (VIs) are used to assess vegetative coverings objectively and subjectively through spectral observations. The spectral responses of vegetated areas are influenced by many factors, including vegetation and soil brightness, environmental influences, soil color, and moisture. This research looked into the soil adjusted indices SAVI and MSAVI for the city of Bristol in the United Kingdom and assessed them. The Landsat 8 OLI of the research area was downloaded, whereas Bands 4 and 5 were processed in a geographic information system (GIS) to provide SAVI and MSAVI. The obtained values for the SAVI index are between -0.557 and 0.425, and the obtained values for the MSAVI index are between -1.183 and 0.441. The MSAVI is able to extract a thicker layer of vegetation than the SAVI. Similarly, MSAVI has revealed more non-vegetated locations compared to those extracted by SAVI. Since the MSAVI index provides reliable signals of land cover, it should be used in research applications. Technically, the work presented the GIS functionality of a raster calculator for processing Landsat 8 OLI data, and regionally, it added to the studies of Bristol City.

Keywords: soil adjusted evaluation, SAVI, MSAVI, Landsat 8 OLI, GIS, Bristol City, United Kingdom.

INTRODUCTION

The evaluation of the density of vegetation cover, crop discrimination, forestry, and crop prediction are just some of the many areas where vegetation indices can be employed. Research fields in environmental science that use land surface temperature (LST) extensively include climate modeling, human-environment interactions, and global environmental change. Vegetation expansion and glacier formation are both influenced by land surface temperature (LST) (Saber et al., 2020; Bannari et al., 1995). Critical applications that represented by the management of regional resource during flooding or drought, could benefit from watershed-scale knowledge of surface soil moisture. The ability to predict and plan for periods of moisture stress, determine the optimal cropping scheme and density, as well as make educated estimates of crop yields all depend on an understanding of soil moisture. It will also be useful in determining the drought situation in the basin throughout various times of the academic year. Soil moisture estimation is also widely used for the purpose of crop administration and planning.

Vegetation indices (VIs) combine reflectivity at the surface measurements at two or more wavelengths to emphasize a specific characteristic of plants. They are obtained from the reflectance qualities of vegetation. The purpose of each VI is to draw attention to a different quality of the plant life being viewed (Singh et al., 2010; Jassim et al., 2007). There are both external and internal elements that can affect the vegetation indices (Basso, 2004): sensor angularity, sun and angle of view angle, factors such as humidity, temperature, wind speed, leaf transparency, as well as canopy structure. Vegetation indices can be used to evaluate a canopy's quality, foliage, cover, and phenology in addition to activities like evapotranspiration (ET) and primary productivity (Petursdottir et al., 2020; Glene and Huete, 2008). To obtain accurate radiometric assessment of plant life's area, VIs have been employed for the purposes of tracking plant life on Earth. The assessment and monitoring of natural resources relies heavily on the examination of vegetation and the identification of change in the patterns of vegetative regions. The detection and measurement of plant life is a key use case for remote sensing information (Ahmad, 2012).

Vegetation index values can change in appearance when exposed to red and near-infrared light reflection in places with low vegetative cover (i.e., 40%) and exposed soil surface. This is especially difficult when comparing soils of varying brightness levels, as different types of soil may reflect varying quantities of red and near infrared light. To account for the impact of soil brightness when plant cover is sparse, the Soil-Adjusted Vegetation Index (SAVI) was developed as a variant of the Normalized Difference Vegetation Index (NDVI). Structure-wise, the SAVI is quite similar to the NDVI; however, a "soil brightness correction factor," has been included. The Modified Soil-Adjusted Vegetation Index (MSAVI) is a soil-vegetation component developed to compensate for the shortcomings of NDVI in highly exposed soil locations. The issue with the first iteration of the SAVI was that it necessitated trial-and-error determination of the soil-brightness correction factor (L) in respect to the amount of vegetation in the area under study. As a result, most people used the safest default L value of 0.5, and despite the fact that the primary function of SAVI is to inform of the amount of vegetation there, the circular logic problem of first needing to know how much vegetation persists. MSAVI was created by Qi et al. (1994) to make determining a soil brightness compensation factor easier and more accurate.

SAVI (Haifa et al., 2018; Huete, 1988) and MSAVI (Qi et al., 1994) are more cost-effective dynamic indices than NDVI (Polina, 2020; Rouse et al., 1974), which has a different value depending on brightness. This is why a comparison of SAVI and MSAVI is necessary to determine whether one is more precise than the other (Singh et al., 2010).

Collecting ground-level data for forest resource management using approaches like field samples can be time-consuming and costly. Size, accessibility, and the ability to take measurements repeatedly throughout time (regular time-series datasets) also cause difficulties. However, ground truth data acquired by means such as geographic information systems (GIS) is essential for a proper understanding and analysis of remote data collecting methods like satellite images, aerial photography, and others. Consistent monitoring of land cover changes over vast geographical areas can be difficult and expensive without the help of satellite remote sensing (SRM) (Shimabukuro et al., 2014). Land managers rely heavily on satellite imagery for detecting and monitoring deforested regions, since it can be used to create regular time-series information at varying spatial resolutions. In addition to detecting changes in land cover, Lunetta et al., (2002) and Chiteculo et al., (2019) assigned that these data sets can be utilized to accurately estimate structural (e.g., height, stem capacity, and chest-height diameter) and textural metrics (Abdollahnejad et al., 2017; Stibig et al., 2014; Ozdemir and Karnieli, 2011; St-Onge et al., 2008; Kayitakire et al., 2006). Satellite pictures can be used to extrapolate volume from field measurements, or to estimate the size of different land cover groups (Abdollahnejad et al., 2018).

Specifically, the primary objective of this paper was to make full use of the data included in very high-resolution (VHR) satellite images, whereas its novel contribution resides in its combination of GIS and remote sensing. This will allow researchers to compare the estimates of SAVI and MSAVI using multi-spectral VHR and cheap satellite pictures for Bristol City in the United Kingdom and choose the more reliable one for independent study in the future.

STUDY AREA

Bristol, often known as the City of Bristol, is a major city in southwestern England. It is widely considered to be one of the most attractive and culturally significant places in the United Kingdom today. Nearly 40 square miles in size, the city is one of the largest in the entire southwestern United Kingdom. Famous for its museums, parks, gardens, bars, stunning architecture, and cutting-edge sports and amusement facilities, it attracts a large number of visitors every year. Bristol is located in the huge delta of the river Severn and is roughly 100 miles south of Birmingham, 25 miles due east of Cardiff, and 120 miles due west of London. The city of Bristol is located in England. With 463,400 residents, it easily surpasses all other cities in the southwest of England. Bristol and its surrounding area are home to ninth most Britons. The metro region is home to 670,000 people, making it the 11th most populous in the UK (The population of Bristol, 2023).

Some ancient artifacts suggest that the area around modern Bristol has been inhabited since prehistoric times, but Bristol's historical significance lies in its role as a departure point for numerous overseas expeditions and exploitative missions, focus on the numerous Middle Ages European expeditions to the recently discovered North American continent. Bristol used to be one of the country's major cities in the late Middle Ages, when it had a thriving economy and a high standard of living. Bristol is a popular tourist spot nowadays due to its many well-known sites, such as the Brandon Hill park, Cabot Tower, Wills Memorial Building, and the ancient Clifton Suspension Bridge. Like Liverpool and London, Bristol is often cited as one of the United Kingdom's most important cultural hubs (Taylor, 1872).

The Mendip Hills to the south and the Cotswolds to the north form a limestone belt around Bristol. Bristol's distinctive mountainous environment is the result of the rivers Frome and Avon cutting through the limestone to the underlying clay. From Bath's eastern flood plains and places that were once marshes before the city was built up comes the Avon. The Avon Gorge, located to the west, was carved out of the limestone bedrock by glacial meltwater following the last ice age (Hawkins, 1973).

The oceanic climate is far more temperate than that of mainland Britain. Bristol, in southern England, has a yearly mean temperature of around 10.5 °C (50.9°F), making it one of the hottest cities in the UK. With an annual average of 1,541–1,885 hours of sunshine, it is among the sunniest places on Earth. The Mendip Hills offer some protection, although the city is still vulnerable to the Bristol Channel and the Severn Estuary. Average annual precipitation is in the 600–900 mm (24–35 in) range north of the Avon and in the 900–1,200 mm (35–47 in) range south of the river. The wettest months are fall and winter; however, precipitation is rather consistent throughout the year. Although Bristol has year-round temperatures above freezing because to the impact of the Atlantic Ocean, frosts are common in winter and snow does occasionally fall between early November and late April. The weather in spring is unpredictable, whereas summers are hot and dry with sporadic bouts of rain and cloud cover (National Meteorological Library and Archive Fact sheet 7 — Climate of South West England, Climate, 2023).

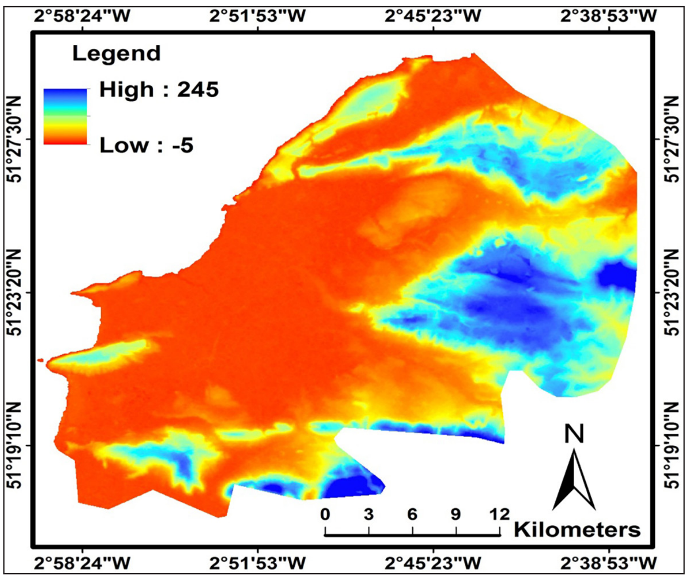

Figure 1. Downloaded digital elevation model of Bristol City

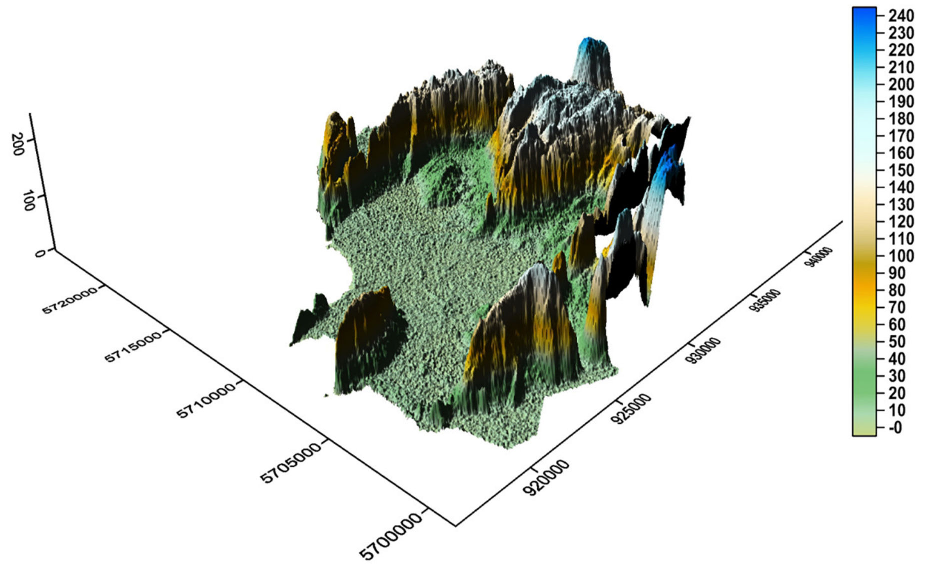

Figure 2. 3-Dimensional view of land surface elevations of Bristol City

Figures 1 and 2 show the downloaded Digital Elevation Model (DEM) of Bristol City and its 3-Dimensional view of the land surface with ground elevation levels, respectively.

METHODOLOGY

Satellites provided the opportunity to monitor land cover and predict accurate and real information about land use and land cover and the changes taking place therein. It also predicts the quality of vegetation cover with higher and faster accuracy than ground measurements and field visits, which contributes to early detection of environmental hazards in the study area, especially since vegetation is a strong indicator of environmental degradation and desertification. Remote sensing devices have been used to monitor the change in the natural and agricultural vegetation cover, integration with geographic information systems, analysis of changes in vegetation cover in the study area using vegetation indicators in the year 2023 and monitoring the problems that vegetation suffers from. These solutions can stop the rapid deterioration of the region, filling the gap in data and presenting the results to decision-makers to contribute to the development and management of regions, especially the issue of the vegetation cover in Bristol City which has become clear from the decline in areas, soil degradation, decline in crop productivity, as well as change in crop type size and intensity, which leads to desertification (Bhambure et al., 2018).

The long-term viability of plant wealth, the evaluation and interpretation of the current state of the vegetation cover, and the identification of changes that occur within it have all been supported by remote sensing applications for natural resource management. Extracting the vegetation cover, identifying changes with mathematical equations, employing spectral vegetation indicators, deriving values, and representing them via maps that show the spatial distribution of changes and their size were all done with the help of the descriptive analytical method, which was then used to analyze the data. Satellite visuals of the Landsat 8 were used from the US Geological Survey website (http://earthexplorer.usgs.gov/) with a resolution of 30 m. The process of correcting the coordinates of the satellite visuals was carried out by determining the astronomical coordinates and checking them through the topographic map to ensure that they are free from the influence of the atmospheric conditions, then cutting the study area based on the distribution of soil units.

NDVI products developed from empirical data have been demonstrated to be unreliable due to their sensitivity to changes in soil color, soil moisture, and saturation effects caused by dense plant cover. Huete (1988) considered the difference of the red and near-infrared extinction to create a vegetation index that might be used to enhance NDVI which is the Soil-Adjusted Vegetation Index (SAVI). Soil brightness affects from red and near-infrared (NIR) spectral vegetation indices are reduced using this index, which is a transformation approach. The formula of the SAVI is as follows (Mehdi, 2021):

$$SAVI = \frac{Band5 - Band4}{Band5 - Band4 + L} \cdot 1.5 \quad (1)$$

where: L is a background correction value for canopies. Minimizing soil brightness differences was found to be achieved by setting L to 0.5 in reflectance space. The vegetation index differences caused by soil were found to be drastically reduced when the change was implemented.

In contrast to conventional vegetation indices, MSAVI is useful during the germination of seeds and the development of leaves. When there is a lot of empty space in the field, MSAVI can be utilized on Crop Monitoring to keep an eye on seedlings. Uneven growth, cold stress, heat stress, unexpected precipitation, elevation differences, and other environmental factors are just some of the many threats to seed development. Uneven seed development can be spotted using remote sensing using MSAVI. It can be compared to meteorological data on the graph, which shows how extreme weather affects crop yields. If the farmer has this information when the plant is still young, he or she can make changes to the way the land is managed and increase crop yields. When other indices fail to offer reliable data because of insufficient plant cover or chlorophyll, MSAVI is meant to fill in the gap. The following equation is used to represent MSAVI (Mehdi, 2021):

$$MSAVI = \frac{2 \cdot Band5 + 1 - \sqrt{(2 \cdot Band5 + 1)^2 - 8 \cdot (Band5 - Band4)}}{2} \quad (2)$$

Landsat 8 OLI image processing

Agricultural research, land categorization and uses, geological research, water resources research, meteorological research, and other types of research all benefit from the study of remote sensing science. The first of seven Landsat satellites was launched by the US Geological Survey in 1972. It was employed to track Earth and environmental changes before further satellites in the series, including Landsat 8, were launched. There are three different kinds of sensors on board these satellites: (1) Instruments Return-Beam Vidicon (RBV) (2) Multispectral Scanners (MSS) and (3) Thematic Mapper (TM) (Lillesand and Kiefer, 1994). The original Landsat satellites carried two distinct types of sensors: a three-band Return-Beam Vidicon (RBV) video device and a four-band spectral wavelength Multispectral Scanning (MSS) device. The data recorded by the TM sensor system, which provides the most information about the area to be studied, stands out due to its multiple channels and wide spectral dimensions (the wavelengths on which data is captured). This is because this data can distinguish between the components of different soil surfaces.

After the aerial satellite image has been downloaded, it will be categorized and analyzed so that digital data can be studied showing the many sorts of features based on the characteristics of their spectrum reflections and emissions. As the spectrum pattern influences the classification of each pixel, multispectral data is employed in the classification process, and this method is regarded as one of the most effective ways to transform visual data into knowledge. The goal of the classification is to create a classification map that organizes all visible cells into groups based on homogeneity and symmetry, allowing for the identification of the features and land cover represented by those groups. This enables to determine how crucial classification is when making land cover maps. The success of the classification procedure used to analyze the downloaded image of the research region is a major factor in the reliability of the resulting maps (Manar, 2008).

This research will show how to use meteorology to estimate SAVI and MSAVI, which are crucial indicators. The GIS will process the aerial image (Landsat 8) of the study area (Bristol City, UK) to extract SAVI and MSAVI. The Landsat 8 consists of eleven spectral bands and was passed from NASA to the United States Geological Survey. The Operational Land Imager (OLI) and the Thermal Infrared Sensor (TIRS) are both linear array systems aboard this satellite. The spectral bands in the Enhanced Thematic Mapper Plus (+ETM) sensor are similar to the spectral bands in the OLI, with the addition of two new spectral bands: Band 1 (the blue), which is optimized for water resources and coastal areas and tracking fine particles like dust and smoke; and Band 9, which represents the new infrared range and is optimized for detecting the areas of cirrus clouds (thin, high) through which clouds, water, as well as snow can be identified and mapped (Azadeh et al., 2019).

Bands 4 (Red wavelength) and 5 (Near Infrared wavelength) of the downloaded Landsat 8

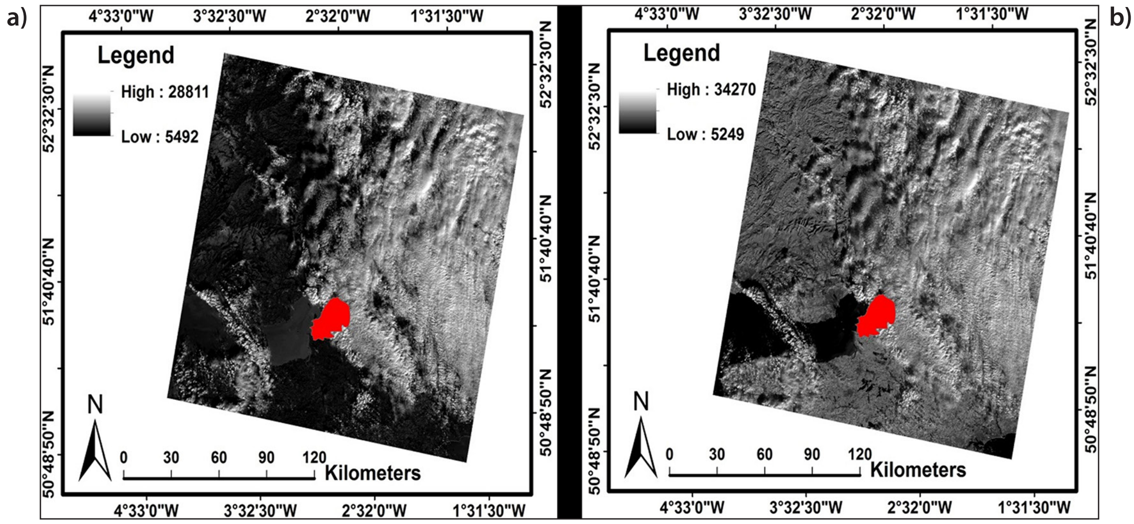

Figure 3. Landsat 8 OLI downloaded: (a) Band 4 and (b) Band 5

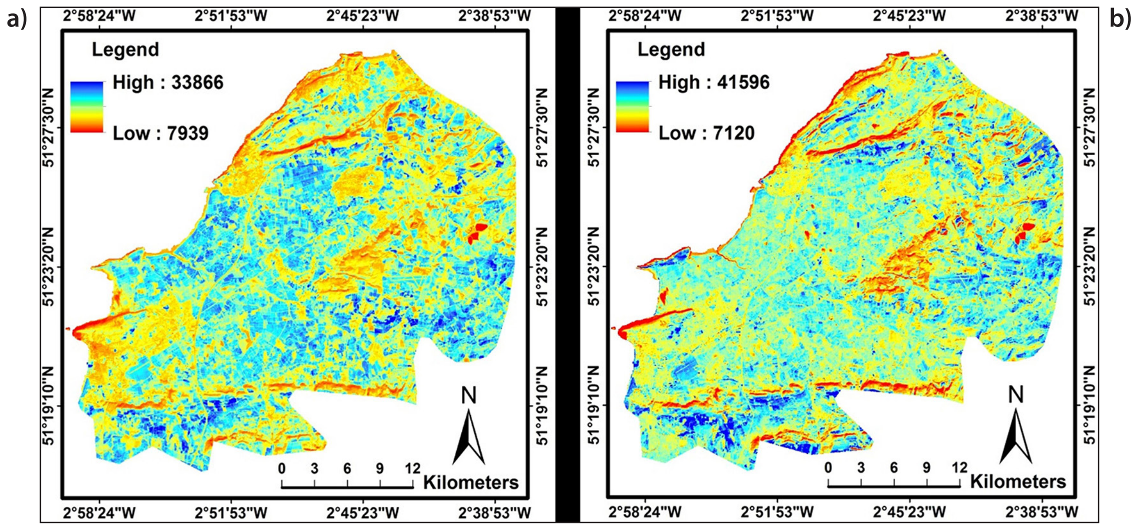

Figure 4. Extracted Landsat 8 OLI of Bristol City: (a) Band 4 and (b) Band 5

images that included the study area illustrated in Figure 3 are needed to extract the study area and then to be ready under consideration to detect the soil adjusted indicators. The capacity in the area covered by this visual leads to many problems, perhaps the most important of which are the reflectivity values, as well as the problems of time and effort required when processing operations, and so the cutting process of the satellite image is performed using the GIS program to obtain the study area only. Figure 4 shows the end outcome of the extracting procedure.

RESULTS ANALYSIS

The proliferation of GIS and other remote sensing techniques in recent years has led to a popularization of satellite image processing applications. The methods used to calculate the VIs and apply them to a wide variety of landscapes have proven immensely useful in studying vegetation and analyzing biophysical aspects in forests and agricultural crop kinds. Selecting combinations of bands displaying reflectance of a surface at many wavelengths is the functional basis underlying the VIs in the Landsat 8 image. A certain characteristic of plants can be highlighted by the use of such a combination or the use of a mathematical formula. The details of each VI vary with the method used to create it and the feature of plant (pigments, water, carbon, chlorophyll, nutrients) that is being highlighted. However, all of the Landsat 8 band combination techniques rely on the reflectance characteristics of plants.

The range of SAVI is between -1 and 1 as the areas have SAVI less than 0.2 means that the vegetation cover is very low or these locations are either water or urban regions. In turn, when the SAVI closes to 0.5, it means the green cover is in the moderate limit. However, regions having SAVI close to 1 can be considered having dense vegetation cover. The MSAVI can be considered better than the SAVI indicator due to the focusing on the lands that having high/dense vegetation. It is range in values as same as SAVI, but those locations located in the minus can be having lesser indications.

Figure 5 a and b displays the SAVI and MSAVI calculation results of Bristol City, which reveal a dataset with values from -0.557 to 0.425 for the SAVI and from -1.183 to 0.441 for MSAVI. The algorithms details explain the disparate range of values: the soil adjustment factor is density-dependent; therefore, higher densities result in higher real values. It can be seen from Figure 5a that SAVI indicates some areas as a vegetated and having values greater than 0.2, while the same areas highlighted as an urban or water region according to the MSAVI index values as seen in Figure 5b. Similarly, those regions highlighted as a less vegetation cover according to SAVI, it has been noticing that those locations may be considered as vegetated lands (Figure 5 a, b). Additionally, it can be noticed that the vegetation lands that covering Bristol City according MSAVI are greater than those areas indicated by SAVI.

Therefore, finally, it would like to note that the MSAVI results provide more precise values for evaluating land uses, so they might be used to other places in Iraq or anywhere else in the world. However, the results can be considered close to SAVI that the difference is insignificant.

The indicators used in the current study performed well in terms of classification, change detection technology, and the information provided by Landsat images, leading the authors to conclude that satellite data possesses a special and unusual ability to detect changes in land cover rapidly and accurately.

CONCLUSIONS

This study demonstrated how GIS may be used in environmental observation. In particular, the ability of Landsat 8 OLI to visualize different VIs has been demonstrated. The Soil-Adjusted Vegetation Indices and the Maximum Soil-Adjusted Vegetation Index (MSAVI) were tested by processing a Landsat 8 image of Bristol, UK, which has data to represent a wide range of vegetation conditions. Variations in sensitivity to plant growth circumstances were evaluated throughout the resulting spectral VIs. The provided VIs generally showed a numerical association to the distribution and extent of vegetation. In addition to regional variances in vegetation cover, there are also regional differences in the VIs. The soil indices SAVI and MSAVI were derived from remote sensing data after being processed using a Geographic Information System for cartographic mapping. The moderate vegetation portions in the research area were reflected by the SAVI range of -0.557 to 0.425, whereas significant swaths of the territory are bare of vegetation. The MSAVI values, ranging from -1.183 to 0.441, provided

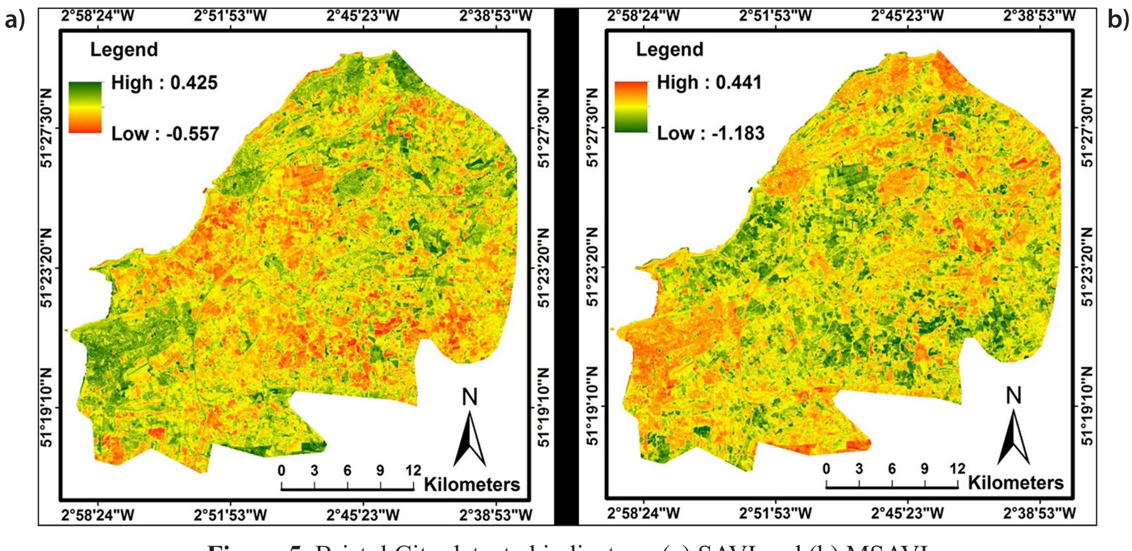

Figure 5. Bristol City detected indicators: (a) SAVI and (b) MSAVI

more precise estimates of vegetation cover than the SAVI values, which reveal that the green regions are smaller. The MSAVI findings suggest that there are more places without vegetation cover compared to those classed as water or snow. Therefore, the MSAVI Index is recommended for use in extracting the Soil-Adjusted Vegetation Cover, as it provides accurate findings. The lack of plant cover in some parts of Bristol City also needs to be considered if plants are to thrive there. For places with extreme weather, like the United Kingdom and particularly Bristol City, various VIs can be a helpful estimator for canopy health mapping and other botanical studies. Thematic mapping of global vegetation is considerably aided by the ability of GIS to interpret cartographic data, providing visual evidence of plant growth and health. The procedure that was shown is applicable to other studies with the same goal of environmental forest monitoring.

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