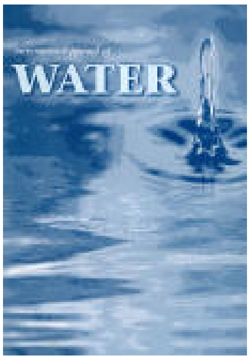

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Monitoring drought condition through detecting the vegetation condition index at Barry City in Wales, UK using temporal Landsat imageries

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Monitoring drought condition through detecting the vegetation condition index at Barry City in Wales, UK using temporal Landsat imageries

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Abstract: Drought impacts economy, ecology, society, and agriculture. Depending on investigating the normalised difference vegetation index (NDVI), the vegetation condition index (VCI) is used to monitor drought due to its dependability and efficiency in studying climatic and environmental events. Dryness in Barry, Wales, UK and its impacts on vegetation are monitored using remote sensing and geographic information systems. Aerial time series data of Landsat images for 1974, 1984, 1994, 2004, 2014, and 2023 from the multispectral scanner (MSS), thematic mapper (TM), enhanced thematic mapper plus (ETM+), and operational land imager (OLI) are inspected. VCI-based drought was greatest in 1994, weaker in 1974, and expected in 2023. According to VCI, average precipitation lowered drought intensity in 1984, 2004, and 2014. 1994 lost the most vegetation comparing to 1974, 1984, 2004, 2014, and 2023. These results show how the VCI helps identify drought patterns and how ecological variables interact with drought.

Keywords: drought detection; VCI; vegetation condition index; NDVI; normalised difference vegetation index; GIS; geographical information systems; Landsat time series remote sensing; Barry City; UK.

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1 Introduction

Water resources are suffering from excessive demand for daily human needs, and this increase in demand coincides with the significant increase in rates of global warming, which has had a negative impact on the generation of drought on the entire planet. If the drought problem that the world is suffering from recently is not put under the microscope by specialists with the aim of solving it, it will worsen and result in a global food shortage, and this in turn will affect the economic budgets of many countries in the world (Riebsame et al., 2019; Xu et al., 2021). The study conducted by Lesk et al. (2016) indicates that the problem of drought led to a decline and decrease in global agricultural production between 1964 and 2007 by more than 10%. Another study conducted by FAO (2018) also indicates an increase in the total costs of all natural resources resulting from environmental and climate disasters by more than 30% as a result of the drought phenomenon to which large areas of agricultural land were exposed to for the period between the years 2005 and 2015 on the surface of the Earth. This poses a serious threat to human efforts to preserve the global production of agricultural crops around the world.

Rainfall, which declines for long periods of time as a result of extreme climate changes and global warming, is considered the most common factor in the deterioration of the agricultural sector and the generation of drought phenomena. Despite the efficient monitoring of climatic factors, the process of predicting rainfall by humans remains somewhat ambiguous (Lawal et al., 2021). The phenomenon of drought that affects the world economically and agriculturally differs from natural disasters that occur on Earth for the following reasons:

1. The difficulty of determining the beginning and end of drought;
2. The effects resulting from drought accumulate and become more severe and can continue for years after the environmental event occurs;
3. The geographical areas that suffer from the problem of drought are wide and sometimes unclear because drought appears over them over time compared to the areas that can be identified resulting from natural disasters.

As a consequence of this, it is not a straightforward comparison to compare the intricate nature of studying the effects of drought with the complexity of responding with emergency measures to other natural catastrophes. Consequently, it is of the utmost importance that research concentrates on identifying, preventing, regulating, and controlling the risks that are linked with the situation, taking into consideration the particular characteristics of the region and the industries that are most at risk. Additionally, the development of ways to address these risks is crucial (Van Quang et al., 2021). Research conducted by Zhang and Jia (2013) indicates that drought is the natural disaster that causes the greatest financial loss to ecosystems, agricultural systems, and municipal water delivery systems. As a direct consequence of this, a great deal of technology has been developed to monitor droughts. According to Ji and Peters's (2003) research, drought indexes are simplified assessments of drought severity that incorporate massive amounts of data on water availability and demand. In order to perform this function, a number of different drought indices were established. A good many of these indicators, which may include things like average temperatures and levels of precipitation, are derived from data that is gathered by weather stations. Standardised precipitation index (SPI) was developed by McKee et al. (1993). In 1965, the scientist

Palmer invented the Moisture Anomaly Index (Z-index) and the Palmer drought severity index (PDSI) with the intention of exploring the phenomena of water retreating from the soil and the creation of drought. Both of these indices were designed with the goal of determining the severity of drought. Indicators like these are differentiated by their capacity to identify regions that are vulnerable to drought when such regions are located in close proximity to one another. As for the weather stations, unfortunately, they fail to give a comprehensive definition of the drought situation and drought area, as well as monitoring area for regions located far away from the weather monitoring stations. On the other hand, for regions with relatively the least number of weather stations or a large difference in regional geography and climate, such stations cannot be applied (Zhang and Jia, 2013).

Appropriate and effective monitoring of drought-prone regions requires resort to the most recent technological innovations that are developed to keep pace with the environmental and climate sciences. Satellite pictures are utilised as the most important technology, as they provide a wide range of geographical, weather, environmental, sub-surface information. The inputs from the weather stations about the climatic parameters are, in fact, observed with a high extent of spatial and temporal variations and are the major factors for prediction of future events (Sandeep, et al., 2021). Remote sensing technology is widely used for assessing environmental and climate changes, and it has been an important and effective means. Remote sensing technology systematically collects and provides data and information, which can be used for a more systematic and all-round monitoring of the earth's surface, such as drought and other environmental changes. It has proved its effectiveness as a tool of monitoring drought in those areas which lack weather stations in the ground (Rhee et al., 2010; Wu et al., 2013). Remote sensing provides more accurate information to researchers by analysing some climate variables, such as soil moisture and vegetation cover. The method can measure some indexes, and obtain the severity, duration, and global impact of drought by some indicators (Kogan, 1995; Kuri et al., 2014; Shen et al., 2014). The vegetation condition index (VCI) is a simple indicator of damage which derived from the normalised difference vegetation index (NDVI) (Kogan, 1995). The calculation process is easy and clear and has been introduced by Quiring and Papakryiakou (2003). The Vegetation Condition Index identified as one of drought indices. The VCI has been made specific to the detection and monitoring of that drought. The VCI is by and large considered the best or the better targets of drought. The detection of a drought, indicate the level of ground vegetation coverage and reflect the spatial distribution are all accomplished with a high level of accuracy with the Vegetation Condition Index. Additionally, changes in NDVI can reflect areas more accurately than various ground-based climate observation stations. VCI derived from the NDVI index provides digital information that can be used to monitor drought conditions in different parts of the world. For example, remote sensing of short-term vegetation indices can provide nearly real-time indicators of the impacts of seasonal drought on agriculture for the main crop-growing seasons in South America, Africa, Asia, North America, and Europe (Kogan, 1997). The VCI obtained from the Kazakhstan area (Gitelson et al., 1998) enables us to judge the influence of climate conditions on vegetation conditions. This includes the comparison of such considerations when using vegetation area, biomass, and surface reflection from field measurement station data. The relationship shows that the green biomass is closely related to environmental conditions. The change of environmental conditions will lead to changes in vegetation. According to the relationship between environmental conditions and green biomass, the change rules of vegetation under environmental conditions can be analysed and reflected, and that this quantitative relationship has been widely used in the field of vegetation for many years (Kogan, 1995; Wang et al., 2010; Wu et al., 2013; Yoshida et al., 2015; Wang et al., 2016; Han et al., 2021). The environmental plant indicators can capture and evaluate plant water stress, thereby providing information on the plant's state and the extent of drought in the local area. There are numerous studies that have looked into different plant indicators to study the state of plants. These investigations have utilised remote sensing of different time series patterns and different sensors to describe the state of the region. In Shen et al. (2019) terms, the drought is among the most affecting natural disasters for millions of people globally, and particularly so for the agricultural sector, as an uncertain and unpredictable climatic phenomenon with unknown future conditions.

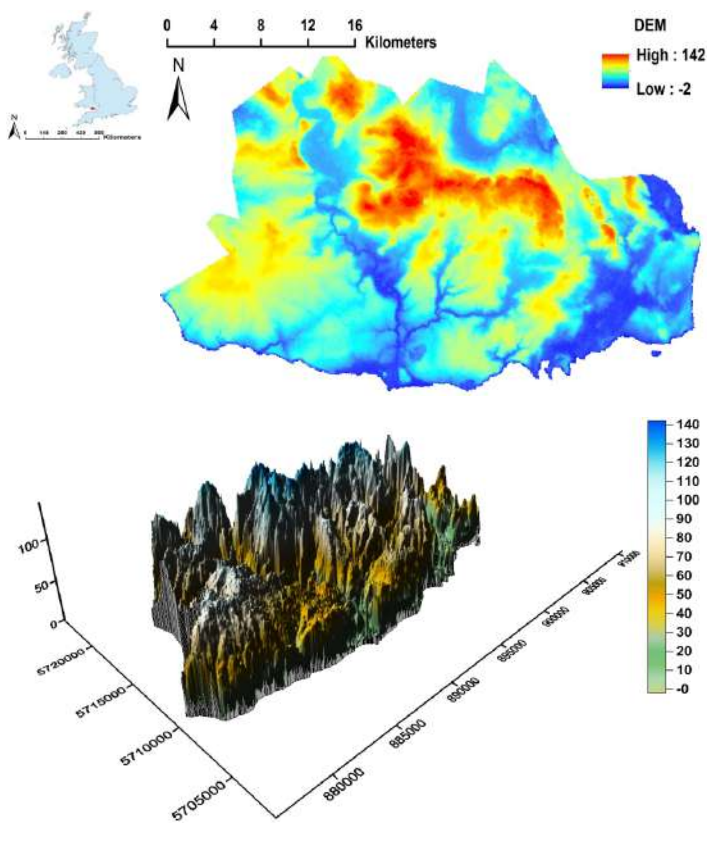
The purpose of this research is to identify, investigate, and describe agricultural drought in Barry City, Wales, UK, and its surrounding planning macroregions through the application of a rigorous approach of analysis to the aerial time series data of Landsat images downloaded from the multispectral scanner (MSS), Thematic Mapper (TM), enhanced thematic mapper plus (ETM+), and operational land imager (OLI). The VCI is a technique that will be used to achieve this goal. Its primary purpose is to reduce the impact of geographically distinct differences in vegetation areas and physiographical settings. Our goal is to undertake an in-depth study of the spatiotemporal distribution of VCI, classifying it into a variety of categories in order to evaluate the incidence of drought at different points in time for the years 1974, 1984, 1994, 2004, 2014, and 2023.

2 Study area

Barry, Wales is located roughly 14 km south-southwest of Cardiff on the northern coast of the Bristol Channel in the Vale of Glamorgan. It's developed into a bustling beach destination with lots to do, from relaxing on one of its many beaches to visiting the recently revitalised Barry Island Pleasure Park. Barry, a little community, has joined forces with Cadoxton, Barry Island, and now Sully, all larger villages. Barry Docks, built in the 1880s, sparked the city's explosive expansion that would see it become the world's largest coal port by 1913. Barry has a marine climate, so expect chilly summers, mild winters, and frequent strong winds, just like the rest of the British Isles. There is more sunshine there than in other parts of Wales because of its southern and coastal location. About 5 km west of Barry's downtown, at Cardiff Airport in Rhoose, is the closest official weather observation station (The History of Barry, 2023) for the area. The geologic time scale in this region spans from the Mississippian (lower Carboniferous) limestone to the Lower Lias of the Mesozoic. Despite the dearth of minerals, certain stretches of coast are rich in fossils (Morgan, 1960).

A marine climate, also referred to as an oceanic climate, is the moderate climate typically found along the western coastlines in the higher mid-latitudes of continents. It has a narrow yearly temperature range and few temperature extremes because to its generally cold summers and pleasant winters (for its latitude). Both hemispheres feature oceanic climates, with the majority found between 45 and 63 degrees north and south. They can be seen in abundance in the far northwest of Europe, the far northwest of US, and New Zealand. Subtropical highland climates, and in particular cold subtropical highland climates, are another climate categorisation sometimes combined alongside oceanic climates. These weather patterns predominate in the tropical and subtropical mountain ranges that are affected by monsoons. Subpolar oceanic climates and colder climate types can be found in close proximity to polar or tundra regions. Cloudy conditions, regular precipitation, low-hanging clouds, and the regular passage of weather fronts and storms are typical of oceanic climates. Infrequent daytime heating and the collision of warm and cool air masses mean that thunderstorms are uncommon in these latitudes. Thunderstorms are less common in the temperate lowlands because these air masses rarely interact; however, in the subtropical highlands, where they are impacted by the monsoon, they can be more prevalent. While snowfall does occur occasionally, rain is the more common kind of precipitation throughout the year in most oceanic climatic zones. Because of the extreme cold, snowfall is more regular and heavy in subpolar oceanic regions. Oceanic climates, in general, are characterised by mild temperatures and infrequent temperature extremes. In contrast to continental climates, which have a coldest month with a mean temperature below 0°C or –3°C, these climates have a mean temperature above 0°C or at least above –3°C. The hottest month in an oceanic environment has an average temperature of about 22 degrees Celsius (UK environment Averages, 2023) and is therefore warm but not oppressively so. Figure 1 provides a visual representation of the study area's placement within UK, accompanied by the Digital Elevation Model (DEM) and a three-dimensional illustration displaying the natural terrain elevation.

Figure 1 The DEM with a 3D sketches of Barry City, UK (see online version for colours)



3 Methodology

A drought is a prolonged and sustained period of insufficient precipitation that causes water scarcity and has negative consequences for ecosystems, agricultural production, and human settlements. Droughts are widely acknowledged as major environmental stresses with varying degrees of intensity, duration, and geographic extent. The VCI is a statistic derived from remote sensing that is used to evaluate the health and vitality of plant cover of all types, including crops and wild vegetation. The reflections produced into the atmosphere from various activities can quantify the geographical properties and features of the Earth's surface, including industrial, human, and agricultural processes. In this context, 'plant health' means the ability to measure it using the VCI. The data used to compile this index came from a variety of remote sensing platforms that satellites have collected. The effect of rainfall on vegetation can be numerically represented by the VCI, even in a relative sense. This quantifies the health of the vegetation and makes it easy to track how the vegetation is growing and determine how much stress humans might be putting on it, so its growth can be monitored, as can the effects potential stresses are having on it. The VCI can be used to assess the potential impact of drought on the vegetation. If the underground aquifers are overdrawn, the plants will have to work harder to get water. If they cannot get enough, they will not be able to grow, and then either die, or fall prey to other maladies. The VCI and NDVI indices suggest that plants may be under stress in this scenario. Before the drought causes irreparable harm to the plants, these can be utilised to track its impacts (Gaznayee et al., 2021). According to Wenzhe et al. (2016), the VCI might be utilised to determine dry skin as well as tension in plants prior to it triggers wilting or injury to the plants. Beyond, the VCI may assist farmers, land supervisors together with ecologists find the threat together with at some point devise or perform methods to minimise dry spell's results. We can make use of the VCI index to anticipate exactly how dry spells would certainly influence plant outcome, which is among its primary usages. The VCI is a crucial device that can conserve lives in times of dry spell. Decreased worths for the VCI show much less water readily available for plant advancement plus survival (Adriano et al., 2023).

VCI estimation entails carrying out a variety of formulas, however, an extensively made use of method is to contrast present plants problems about a standard or lasting mean. According to Kogan in 1995, the formula for VCI is:

$$VCI = \left[\frac{NDVI - NDVI_{\min}}{NDVI_{\max} - NDVI_{\min}} \right] \times 100 \qquad (1)$$

VCI values around 100 suggest the presence of very bright and thriving vegetation, displaying a natural state so near to the ideal one. VCI values below 100 indicate suboptimal circumstances, potentially suggesting stress or a decline in plant health. When the VCI value falls below 0, the amount of stress rises.

One of the most important and fundamental indicators in the field of environmental research and remote sensing is the NDVI. It opens the door to studying the amount, health, and existence of plant cover in different verdant settings. Agricultural, forestry, land use planning, and climate change studies are just a few of the numerous geological and geographical scientific applications of the NDVI. This is because it is really good at tracking changes in vegetation and determining how healthy it is. The NDVI metric is based on satellite imagery that was taken in the visible and near-infrared (NIR) regions of the Earth's electromagnetic spectrum. The NDVI may be calculated using red and near infrared (NIR) data from several subsurface images; its values range from –1 to 1. Vegetation is strong and growing when the NDVI is close to 1, which means there is adequate water for the plants to get water without stress. As a result, the red light reflections would be very weak and there would be a touch of chlorophyll reflections with a large proportion. Typically, NDVI of urban areas, bodies of water and small water bodies is near zero, that is, these areas are free from vegetation. If most of the TSS in still water emulates red and near-infrared light, then the NDVI may indeed be less than zero. The amount of the two bands being absorbed by water throughout a higher range, and all water absorbing the two bands, because of a too high reflection. In return, this would provide a very high NDVI. The same magnitude of red and near-infrared light (Liu et al., 2018).

The NDVI emphasises on environmental protection, as it defines the most concise formulas of ecosystem changes and biodiversity over time. In fact, NDVI is sensitive to the soil moisture changes, which is an excellent indicator for monitoring the extension of deserts, dry zones, and other arid regions. As is well-known, deserts and dry areas have low NDVI values. Therefore, when using the NDVI for investigation, it is also possible to monitor and analyse the drought status of the plants and ecosystems. Thanks to remote sensing technology, data from space satellites can be obtained accurately. In this method, we take advantage of the changes of spectral reflections under different wavelengths to scan a larger area on the surface of the Earth. NDVI readings are necessary for supervising the climatic and environmental changes over the world. Recently, governments and international organisations have been giving much attention to the data obtained from satellites. It helps in controlling specific and preemptive weather, ecosystem, and geographic variations. As it is declared by Gaznayee et al. (2019), there is a potential to prevent bad things from happening. It goes without saying that different remote sensors show different characteristics, depending on the satellite and the required precision level. However, one of the things to be measured is the NDVI. It always turns out to be crucial for the attention of scientists, politicians, and land managers to the world's ecosystems. Being an essential tool, NDVI helps to make the right decisions about the use of water resources and the environment, no matter whether long-term or short-term decisions are needed. According to Rouse et al. (1974), the following is the formula for NDVI:

$$NDVI = \frac{NIR - RED}{NIR + RED} \tag{2}$$

These specific years have been selected based on historical information available about the area under study. It has been anticipated that rapid developments in fields like agricultural practices and significant shifts in climate patterns had ecological consequences that influenced the breakdown of rainfall into its constituent elements. Since the climatic effects of these major changes were not clearly discernible in terms of their impact on land and watersheds before 1974, we considered this year as our starting point or baseline. Subsequent 10-year intervals were chosen to better capture the extent to which alterations in the agriculture land cover within the study area had occurred due to both natural and human activities. It's worth noting that changes in vegetation cover often evolve slowly, even in the face of prompt actions. The characteristics of the Landsat images used in our analysis can be found in Table 1. Our selection of the optimal data collection times took into account factors such as image quality, scene availability and coverage (Path/row), and cloud cover (less than 1%). Consequently, we opted for images from years marking the transition between wet and dry seasons to best represent the vegetation maturity of the plant life under study.

Table 1 Downloaded Landsat of Barry City

Satellite	*Year*	*Sensor*	*Wavelength of used bands* (nm)	*Spatial resolution* (m)	*Cloud cover*
Landsat-3	1974	MSS	B5 = 0.60–0.70	30	0%
			B6 = 0.7–0.8		
Landsat-5	1984	TM	B3= 0.63–0.69	30	0%
	1994		B4 = 0.76–0.90		
	2004				
Landsat-7	2014	ETM+	B4 = 0.63–0.69	30	0%
			B5 = 0.77–0.90		
Landsat-8	2023	OLI	B4 = 0.64–0.67	30	0%
			B5 = 0.85–0.88		

The U.S. Drought Monitor (USDM) detects regions experiencing drought conditions and categorises them based on their severity. The USDM distinguishes between short-term and long-term drought. Short-term drought can affect agriculture and grasslands and can undergo rapid changes in its classification. In contrast, long-term drought has more profound effects on hydrology and ecology and can endure even when there are brief periods of increased precipitation. The map skeleton of drought employs a scale consisting of four drought categories, ranging from “Moderate Drought”, which represents the mildest form, to “Exceptional Drought”, signifying the most severe. Additionally, it draws attention to regions without drought and designates abnormally dry areas, potentially transitioning into or rebounding from drought. Table 2 demonstrates the drought skeleton considered by the U.S. Drought Monitor (USDM) (2023) and Kogan (1990).

Table 2 VCI drought classification

Drought category	*VCI* (%)
Normal or wet conditions	≥50
Abnormally dry	41–50
Moderate drought	31–40
Severe drought	21–30
Extreme drought	11–20
Exceptional drought	0–10

4 Landsat imageries temporal processing

Time-series data stands as the benchmark for examining shifts in the environment. Looking forward, the focus of future advancements will increasingly centre on the analysis of vast datasets through remote sensing systems. The approach of time-aware mapping surpasses conventional categorisation techniques in terms of effectiveness. The utilisation of imagery captured across multiple seasons has proven to enhance the accuracy of biomass assessments conducted in aquatic environments. Similarly, the application of multi-temporal data to estimate successional processes has yielded positive results. Studies and research that aim to monitor time series through the use of sensor maps preferably use spectral products obtained from a single sensor because their data show greater spatial and temporal consistency and are clearer compared to those images obtained from multiple sensor sources. The Landsat images resulting from satellite sensors are characterised by their exceptionally high spatial resolution, as has been observed by many scientists, in addition to the huge and comprehensive data repository they contain for extended and long periods of time (Tariq et al., 2021). Despite the above, remote sensing products for time series produced by satellite images need to intensify the accuracy of their data due to data gaps that affect their quality, as a pixel classification approach was used to monitor the frequencies of the image data reflected to the satellites by an effective and efficient way especially for time series image products. A comprehensive sequence of Landsat images can be used by collecting image products for a specific period of time and fitting them together at a single pixel scale to obtain accurate outputs (Somasundaram et al., 2020).

Satellite images with clear, uninterrupted time series are distinguished by their ability and efficiency to produce accurate integrated images of the changing characteristics of agricultural land use for any location and across multiple time periods. Recently, the ‘frequency per pixel’ approach has been relied upon as a way to determine large changes occurring on the Earth’s surface. This method has proven to be particularly effective when the sensed data is not stored in limited cloud-based systems. The hydrodynamic complexity that characterises most areas of the Earth’s surface due to fluctuating weather conditions requires that additional importance be given to pixel size and accuracy in order to obtain reliable temporal analyses, as determining the pixel frequency requires an extensive study of all theoretical and practical aspects to reach accurate determinations. The current study added another source about calculating pixel frequency by studying and classifying annual events and analysing them with the aim of observing their relationship to the drought phenomenon. Climate changes, which have become more complex and whose future events are not difficult to predict, greatly affect the ecosystem, and thus this effect extends to the surface vegetation, as plant ecosystems are linked to changes in the atmosphere, which makes them sensitive and greatly affected by climate changes that are witnessing complex and incomprehensible developments. Time series maps have become necessary, as they can be used to observe the seasonal effects that have occurred or are likely to occur in the future on land cover, especially for small plant areas.

The time series of surface reflectance data from Landsat 3-8 images of the city of Barry in UK will be under study in the current research with the aim of deriving maps of the previous and current VCI, which will provide a future vision of vegetation cover and thus develop solutions to potentially dangerous areas that may occur in the future. The study will also provide the relationship between extreme climate and vegetation cover by presenting an integrated set of satellite images and the data on climate changes they carry and how they affect vegetation cover. Time series data of Landsat were collected extending from 1974 to 2023 every 10 years. In order to prepare the photos for analysis, we utilise a procedure that effectively removes any disruptions caused by traffic and cloud interference by focusing on certain image bands. The bands mentioned include Landsat-3 MSS bands 'B5' and 'B6', Landsat-5 TM bands 'B3' and 'B4', Landsat-7 ETM + and Landsat-8 OLI bands 'B4' and 'B5'. These bands are specifically calibrated to capture wavelengths in the red and near-infrared range. The bands play a crucial part in the extraction process of vegetation cover as they serve as the basis for selecting sample sites. In order to create a spectral profile that accurately represents typical ground features in Barry City and assesses the quality of sample point selection, we employ the geographical information systems (GIS) to apply equation (2) to investigate the NDVI. This index calculates the average reflectance of diverse ground features within specified sample areas for each Landsat series.

Figures 2–7 depict the results of the NDVI resulted from the analysis for Landsat's imageries bands for the years 1974, 1984, 1994, 2004, 2014, and 2023. These images illustrate the similarity between the reflection spectra of ground features in the study area and those of typical ground objects, confirming the accuracy of our sample site selection process.

Figure 2 NDVI of Barry City in Wales, UK for 1974 (see online version for colours)

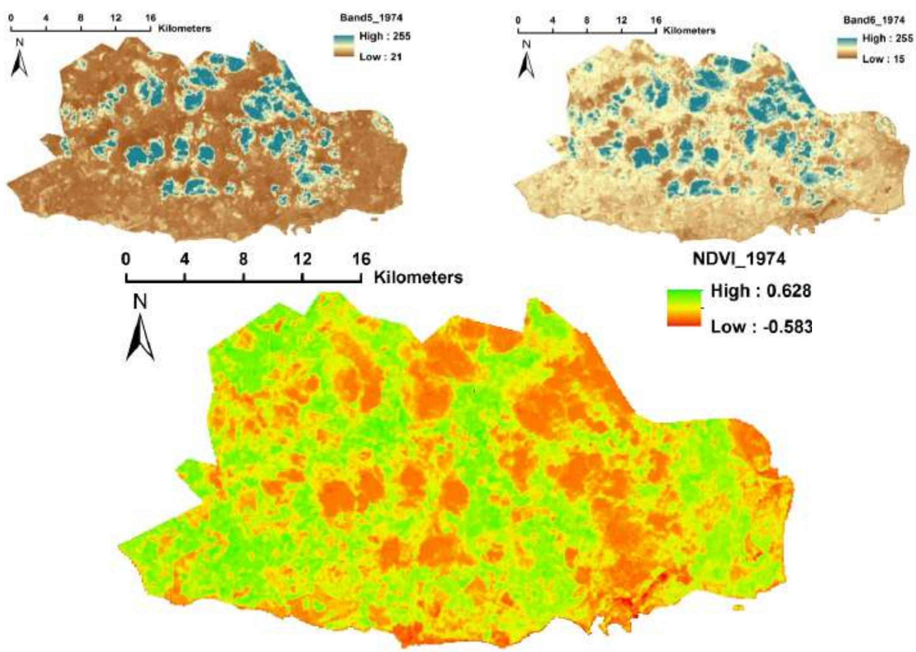


Figure 3 NDVI of Barry City in Wales, UK for 1984 (see online version for colours)

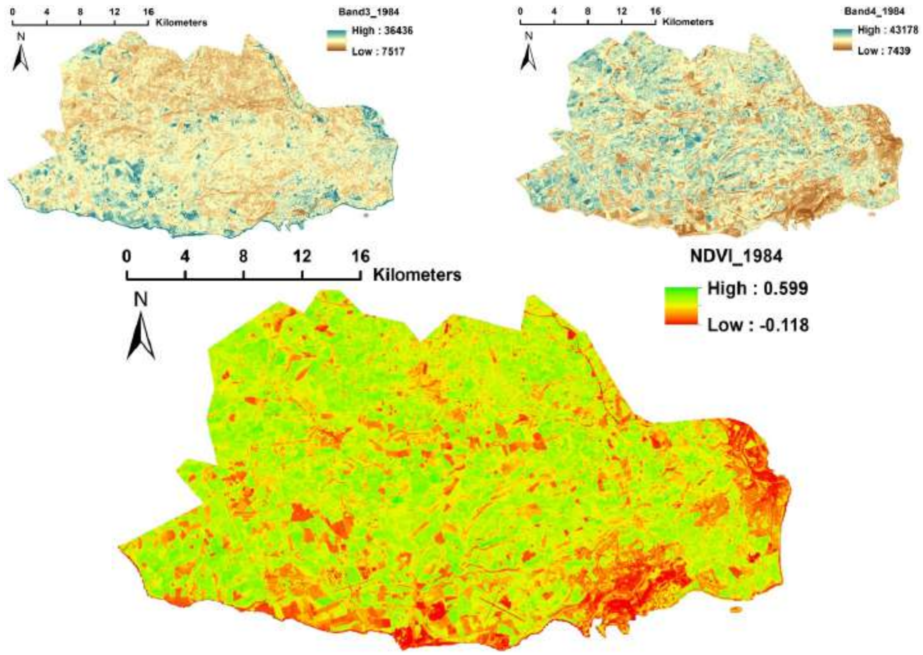


Figure 4 NDVI of Barry City in Wales, UK for 1994 (see online version for colours)

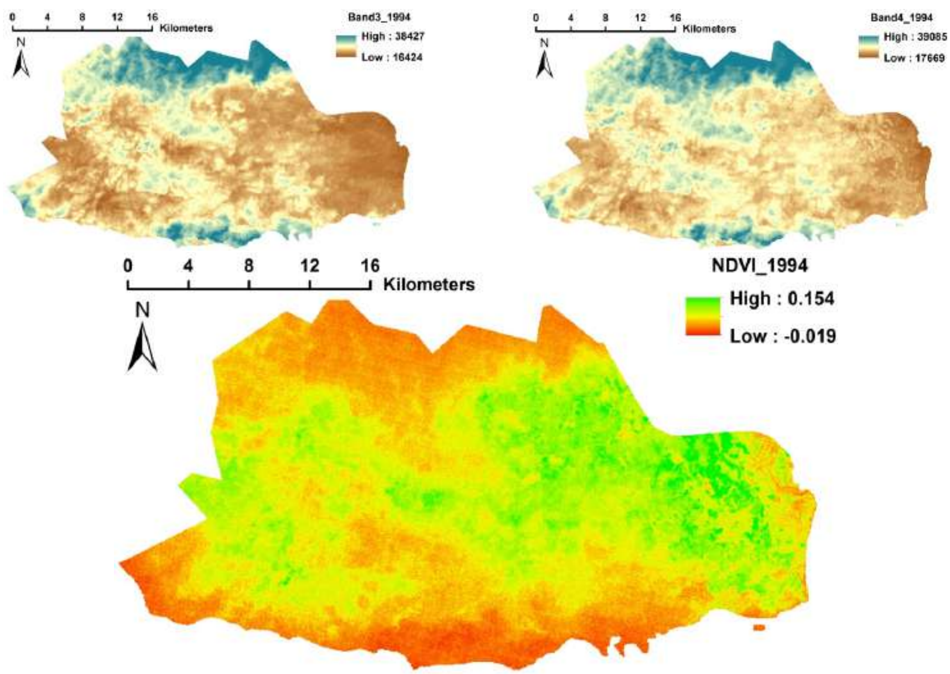


Figure 5 NDVI of Barry City in Wales, UK for 2004 (see online version for colours)

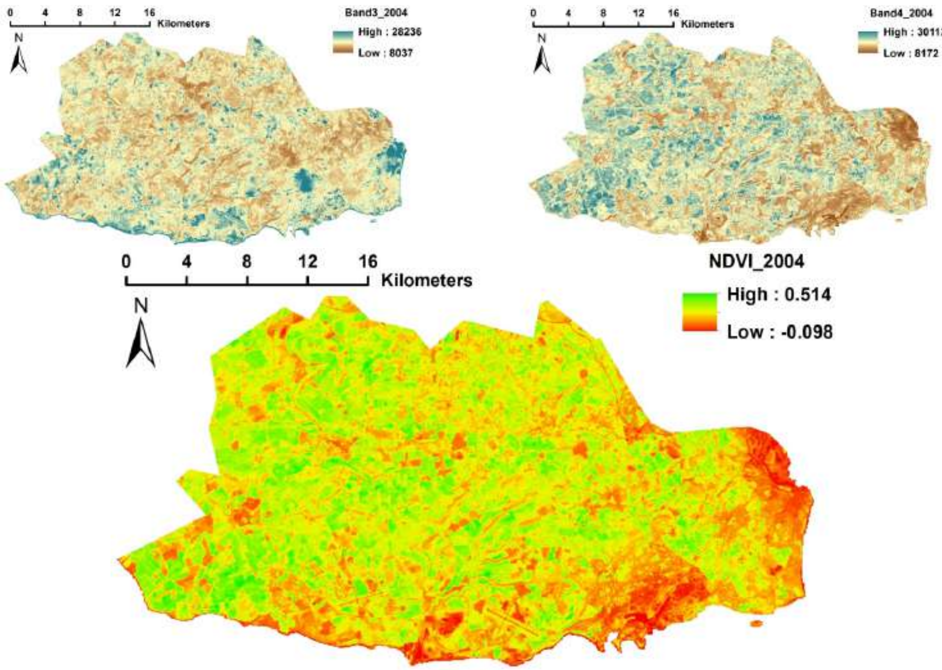


Figure 6 NDVI of Barry City in Wales, UK for 2014 (see online version for colours)

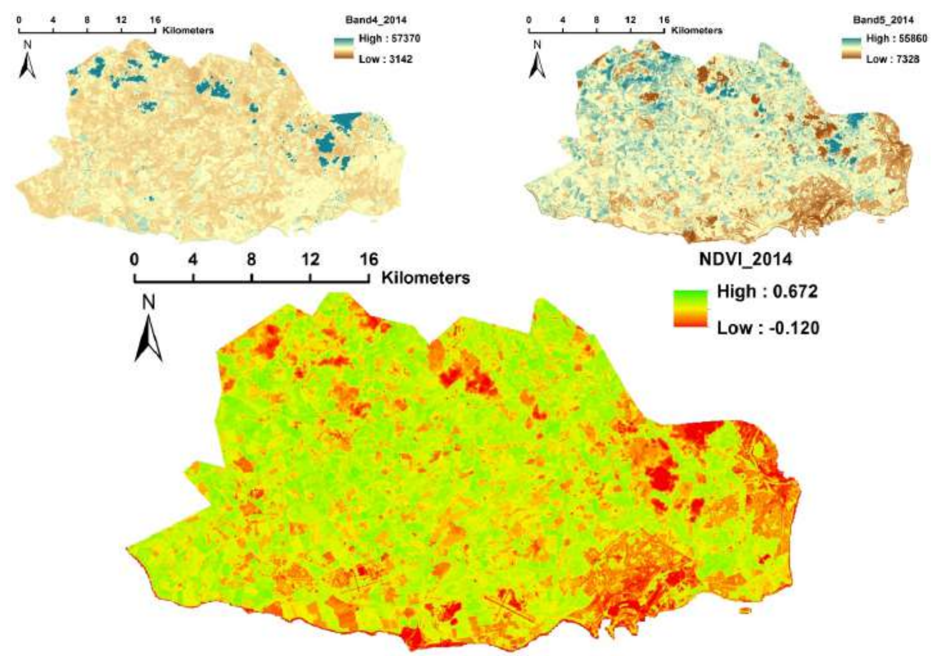
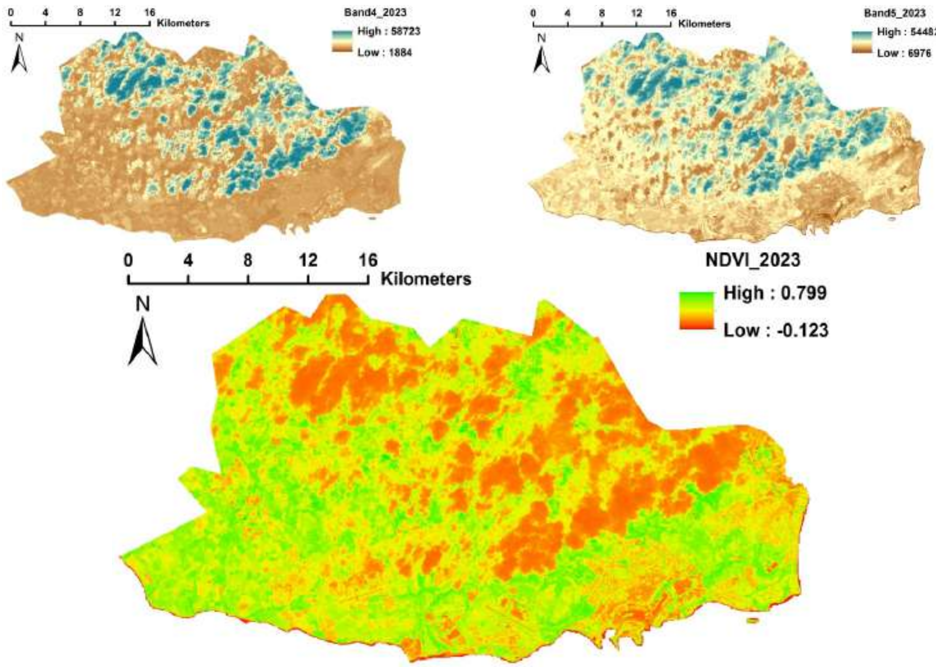


Figure 7 NDVI of Barry City in Wales, UK for 2023 (see online version for colours)

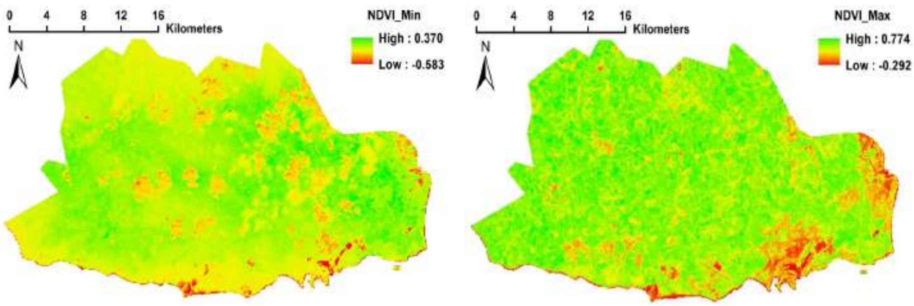


5 Results and analysis

Additional analysis of the retrieved NDVI values from 1974 to 2023 is required to acquire the desired results from the vegetation analysis in order to determine the drought situation for the area under study. In this evaluation, we take an average, mean of the minimum and maximum NDVI values of these NDVIs of the period 1974–2023. The mean minimum and maximum NDVI are critical remote sensing and environmental monitoring metrics used to assess the health and vitality of vegetation within a given area.

One of the most important benefits of NDVI usage is to know the “minimum, maximum and average” NDVI Values in any case of vegetation cover estimation for any area or time of the year, because this value expresses the nature of the vegetation cover and the magnitude of its fluctuation as a result of surrounding environmental and climate changes, knowing that the vegetation of any area under stress is inclined to shrink and disappear. We can utilise the NDVI metric in small and limited vegetated areas, and the outcome of this metric has a value and reliability especially as areas of risk decline in vegetation, as suggested by the average of the minimum and maximum NDVI values as the basic model of the field survey of the farmer of his farm to predict and stipulate the lowest values of vegetation integrity and drought pollution. The NDVI can be a standard measure to manage the agricultural sector with the ultimate goal of achieving full agricultural development, by the right and ideal distribution of the plant's resource. It helps in the correct management and guidance of applying the most ideal technique for success in execution of the agriculture. It is possible, using NDVI values, to monitor the environment, investigating those locations exposed to drought and those regions most robustly and tenaciously resisting the environmental; places from which agricultural exploitation is possible and, furthermore, placing those areas categorised as resistant against drought in a relatively stable environmental context. Thus, NDVI values, at a minimum and maximum, can also be seen as a useful for assessing vegetation cover and its ability to exist in the face of critical, extreme and complicated environmental and climatic conditions and land regions can be categorised into a topographical regime in terms of NDVI. This classification can be used by land managers, environmental scientists, and researchers in providing a comprehensive vision of terrestrial vegetation, its complexities, and the challenges it is likely to face. Figure 8 displays the average minimum and maximum NDVI values for the Landsat image time series for the period 1974–2023. These values were derived through the application of remote sensing technology and in conjunction with GIS software.

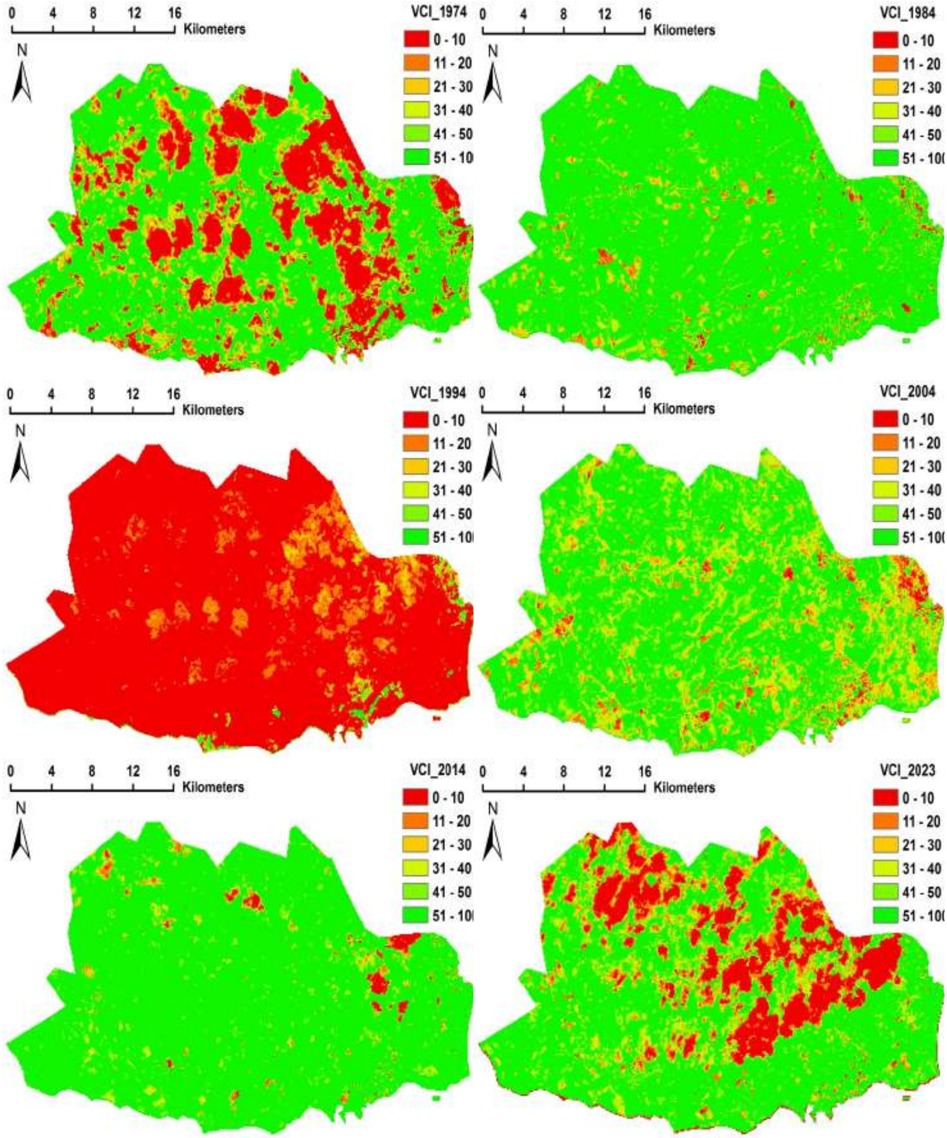
Figure 8 The average minimum and maximum NDVI values for the period 1974–2023 (see online version for colours)



By utilising equation (1) to calculate VCI values spanning from 1974 to 2023 and categorising them according to Table 1, we require the minimum and maximum NDVI values, as deduced, along with the NDVI value for the specific year in question for deriving the VCI value. Consequently, we obtained the VCI results for the city of Barry, as depicted in Figure 9.

The findings that were gathered and displayed in Figure 9 demonstrate that the year 1994 was the most vulnerable to drought according to the VCI index, followed by the years 1974 and 2023. On the other hand, the amount of vegetation cover that was present during the research witnessed a considerable decrease in comparison to past years' results. The severity of the drought was at its worst in 1994, making that year the driest one that was included in the study's context. Nevertheless, during the dry years, conditions of extremely severe drought extended to cover the entirety region under study, with the bulk of the region experiencing drought conditions ranging from moderate to severe. Because of the influence of the climate, the region under investigation exhibited hardly any indicators of the adverse effects of drought in the years 1984, 2004, and 2014. The amount of land damaged by drought was quite small, and the region as a whole presented a beautiful green environment. This is an indication of good humidity levels, which minimised concerns linked to drought. In contrast to the prevalence of high values, the occurrence of VCI values below 10%, which indicate areas afflicted by drought, was essentially nonexistent. This suggests that the studied area was mostly undisturbed by extreme climate changes.

Figure 9 VCI values for Barry City in Wales, UK over the period from 1974 to 2023 (see online version for colours)



The classification of VCI values for drought that can be found in Table 2 enables us to make the following observation: throughout the study years 1974, 1994, and 2023, there was a significant amount of spatial variability in the vegetation cover. This was the case despite the fact that Table 2 contains this information. The region consistently had the least amount of vegetation, and this was most noticeable in 1994 when a severe drought was present. It would appear that there is a strong connection between VCI and precipitation, as there are certain small regions that have not been damaged by the drought because they have received sufficient rainfall. In general, the area under consideration receives a substantial quantity of annual rainfall, which acts as a deterrent against the onset of severe droughts. With the remarkable exception of 1994, it is clear that drought was not a significant problem during the years that were investigated. However, there is one year that stands out as an important exception: 1994. The underlying cause of this might be linked to a lack of water, which could be the consequence of insufficient rainfall or insufficient quantities to fully hydrate agricultural lands, both of which have contributed to an extreme degree of aridity in the region. In recent years and decades, the effects of global warming have been increasingly obvious, leading to climate events that are both unpredictable and frequently catastrophic. It may be difficult to handle some of these events since some of them can make drought conditions worse, while others can lead to unanticipated flooding. When compared to 2014, when drought-affected areas were small, the year 2023 provided conclusive evidence of the influence of global warming due to the fact that the research area suffered a higher degree of drought than in 2014. It is not out of the question that this problem could become much more severe in the future as a result of rising temperatures, in particular in the Middle East, where drought has emerged as one of the most pressing concerns. When evaluating the severity of the drought affecting the research region, the utilisation of drought indices that are based on time series provides a useful framework. When compared to the years 1984, 2004, and 2014, variations in VCI values suggested that the vegetation cover was under minimal stress in 1974 and 2023, while it was substantially stressed in 1994, signifying the emergence of drought conditions due to below-average precipitation. The elements that influence soil moisture and plant growth can be broken down into three categories: atmospheric, topographic, and hydrological. Droughts are caused by a complex interaction between all of these categories.

6 Conclusions

To a greater extent than any other natural hazard, drought limits the availability of field crops and fodder. Vegetation cover is altered as a result of drought because plant moisture is lost. As a result, there are numerous methods available for tracking drought conditions. Large-scale measurements of soil moisture and plant health are now feasible thanks to remote sensing technology. Improved computer capabilities of remote sensing and GIS, along with novel processing and analytic methodologies, have opened up new avenues for drought monitoring. For the purpose of monitoring the spatiotemporal drought and its influence on vegetation in the city of Barry in Wales, UK from 1974–2023, VCI maps are computed using the NDVI. This allows for mitigation efforts and the management of water resources. In order to determine the VCI, we downloaded a series of Landsat images covering the study area from 1974, 1984, 1994, 2004, 2014, and 2023 taken with the MSS, Thematic Mapper (TM), ETM+, and OLI.

This study's findings show that the method used is a practical option for locating, categorising, and mapping out the spatial and temporal distribution of drought events, which in turn facilitates the identification of the most at-risk areas and times of year for drought and the execution of related planning and risk management processes. Drought had a significant influence on Barry City in 1994, with lesser effects in 1974 and 2023. Droughts in 1984, 2004, and 2014 all had rather minor impacts. Consequently, the lack of rain and the high land surface temperature during the crucial plant growth stage are to blame for the droughts. Maps obtained from the DEM were equally useful for analysing the distribution of plant cover in the study region. The VCI and NDVI readings were shown to be significantly correlated due to the low rate of precipitation being closely tied to the decline in crop yield. Therefore, precipitation is the primary contributor in these regions' vegetative stress. Here, the VCI correlated with rain more strongly than latitude did. Over the period of analysis, vegetation cover was revealed to decline. Droughts are a common problem in this region, and the resulting land degradation seems to have a significant impact, especially in 1994 (by a high percentage) and 1974 and 2023 (by a moderate percentage). Some ecological and terrain variables (precipitation and DEM), in particular in 1974, 1994, and 2023, had a stronger statistical relationship with the vegetative cover area. The VCI measured by Landsat had strong relationships with rainfall, latitude, and digital elevation model. One of the most important factors in determining rainfall amounts was altitude, especially in mountainous regions where water is lost due to the sloping terrain. The proposed methodology can be used in other drought-affected locations, not just in Wales or UK.

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