International Journal of Environmental Sciences
ISSN: 2229-7359
Vol. 11 No. 24s, 2025
https://www.theaspd.com/ijes.php

Web Mapping Monitoring the Health of Trees and Urban Green Spaces in Baghdad

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Abstract
Thriving urban forests are a testament to the vitality of metropolitan landscapes, whose role in purifying air, mitigating heat islands, and enhancing aesthetic appeal is unparalleled. web-based mapping applications have emerged as a promising solution, leveraging Geographic Information System (GIS) technology to integrate spatial data on tree locations with comprehensive information on species, age, and condition. This is particularly crucial in the case of Baghdad, the capital of Iraq, which has grappled with challenges such as rapid urbanization, war, and environmental degradation, all of which have exacerbated the plight of its arboreal assets. By harnessing the capabilities of web mapping applications, stakeholders in Baghdad can proactively monitor and manage the health of their urban trees and green spaces, enabling timely intervention to address issues like disease, pest infestations, and insufficient maintenance. This research endeavors to explore the application of web mapping technology in this context, examining existing platforms, assessing their efficacy, and proposing enhancements to improve their functionality and usability. The findings of this study will contribute to the development of more efficient and sustainable strategies for preserving the vitality of Baghdad's urban forests, ultimately enhancing the quality of life for its residents.
Keywords: *Web map application (WMA), Google Earth Engine, urban forests Baghdad ,Mapping*

1. INTRODUCTION

Urbanization is not only a side effect of the economic growth of a country, but it is an integral part of the modern world. The Characteristic Public Urban Green Space for Enhancing Community Social Sustainability in Baghdad[1]. The ratio of Greenspace to one citizen represents in Iraq the fact about Lack of Greenspace and open space reserve in the Baghdad. To improve the social and environmental health, small parks and low-cost green areas are playing essential roles. The lack of pocket parks, shortage in green spaces and interaction outdoors, make many challenges for people and the environment, on the other hand, the previous green areas are suffering from lack of health in green area and trees' inactivity[2].
As in many countries, monitoring urban spatial growth and trees and urban green areas using remotely sensed data has been a well-recognized technique. One of the methods to this aim is using LIDAR point clouds, where the [3] presents an automated method for extracting woodland areas in urban settings. The study highlights the importance of LiDAR data for automating tree height determination, species identification, and stand frequency estimation in forestry applications.
Remote sensing is being utilized more and more to track environmental factors, especially in regions impacted by ecological changes. the application of remote sensing is important for various reasons such as its accessibility and data integration. It enables the observation of difficult-to-access locations without the need for extensive fieldwork and information can be combined with other data sources (such as climate data) to offer a holistic perspective on ecosystem health[4].
Now, satellite imageries are captured frequently; hence, the same location can be observed for changes in land use over time. Furthermore, the digital format of satellite imagery can be directly studied using innumerable image processing programs. In rural and remote areas, the land use and cover remain constant over longer periods, revealing an equilibrium between various human activities, agricultural activities, and climate. However, in an urbanizing area, including trees and urban green areas, land use and cover undergo drastic changes over a longer period due to population and economic growth. The importance of green spaces has been increasing over time due to their impact on the human environment. According to a recent NASA study, the vegetation concentration around the Earth has increased by 5% as of 2023[5] .
By combining optical data with radar data it can become clear that how land cover mapping accuracy improves. In [6] the performance of Support Vector Machine (SVM) and Random Forest (RF) machine

learning algorithms compares within the Google Earth Engine system for detecting and differentiating forest cover by using Landsat-8 and Sentinel-2 images with radar data from Sentinel-1.

Last three years is considered as golden time for using drones in monitoring. Nowadays, UAVs are the number one choice for data acquisition[7]. the UAVs' high accuracy and its low cost make it popular for users. Moreover, the option which provide no pre proceeding level for collected data facilitate its utilization[8].

Many studies in the monitoring and managing green spaces and urban trees have been carried out in recent decades. The study represents the connection between rainfall patterns and vegetation changes throughout Rwanda, utilizing sophisticated geospatial analysis methods[9]. the study investigates how variations in precipitation affect vegetation health and density in Rwanda, a country characterized by diverse ecosystems, including rainforests and savannas.

In [10] the health impacts of urban trees is examined and its role as a green infrastructure that provides various environmental, economic, social, and health benefits in cities is highlighted. Moreover, the study analyzes their effects on human health. Some othe papers try to understand the specific benefits of tree planting using the information like ocation, density, and extent. In [11], it becomes obviuos that although localized tree planting may not substantially reduce urban greenhouse gas emissions on its own, it provides valuable advantages for climate resilience, thermal comfort, and biodiversity within specific areas. Another study focused on the quality of green spaces, linking well-maintained urban trees to better health outcomes for residents.

There are methods aim to enhance the accuracy and efficiency of urban tree inventories, which are crucial for urban planning and environmental management. [12]presents a novel approach for identifying individual street trees using airborne Light Detection and Ranging (LiDAR) data. İt shows that the different data comes from different platform of remote sensing can be use in detection of green space, single data and urban or rural green land covers.

Regarding [13], different types of environments, vegetation, and the size and connectivity of green spaces have been linked to physical and mental health outcomes, with variations noted by age and gender. Health benefits were more consistently observed in populations with a greater tree canopy, while grassland did not show similar effects.

Due to the increasing dynamism and evolution of different aspects of information technology, satellite imaging, and GIS tools and analysts[14] investigated using UAV (drone) technology for monitoring urban green spaces in Guangzhou. Their study illustrated that UAVs could provide high-resolution imagery and accurate vegetation assessments, revealing that green space quality had deteriorated due to pollution and invasive species proliferation. Lastly, Alhassan in [15] focused on the role of GIS in urban forestry management in Accra.

They utilized remote sensing data to map and analyze urban tree canopy cover, concluding that strategic tree planting initiatives could enhance urban green spaces by 20% over the next decade, thus improving air quality and community well-being. [16] designed, developed, and implemented a Web GIS-based platform to monitor and identify diseases transmitted by insects (such as malaria). Their goal was to find the relationship between climatic factors (temperature, humidity, and precipitation) to identify the breeding places of these vectors. Their platform used machine learning models to estimate the above causal relationship and was developed in a user-friendly way for concerned citizens and policymakers.

In a review study, [17] explored the role of Web GIS systems as part of geoinformatics technologies in future infrastructure development and planning. Their study sought to answer these questions: How does Web GIS help infrastructure management? Can Web GIS be implemented for free? Is it flexible and user-friendly?

One of the solutions for capturing high-cost data and monitoring the object on the earth is using remote sensing technology. The google earth engine is one of the most common tools for this aim. It can do its task very well in the case of monitoring the environmental and assessment the hazard[18].

The increasing use of Google Earth Engine (GEE) for earth observation studies, highlighting its ability to process large amounts of data with relative ease. GEE is particularly valuable for assessing natural disasters such as droughts, earthquakes, floods, fires, and landslides. Its ability to process vast amounts of satellite imagery allows for rapid evaluation of affected areas, facilitating timely responses and recovery efforts. The platform enables the creation of high-precision global maps that provide insights into land use and cover, various vegetation indices, and critical geophysical and climatic data[19]. Some studies like [18], combines

multi-satellite information and citizen science data to monitor lake and river ice by using Google Earth Engine (GEE) resources analyse and visualize of ice conditions.
monitoring dynamic urban green spaces (UGSs) in cities worldwide is one of the latest technology using whole around the world. An automated workflow was developed in [20], utilizing Otsu's algorithm, a Random Forest (RF) classifier, and the migrating training samples method within the Google Earth Engine (GEE) platform to generate current UGS maps.
So far, no valid study has used the integrated capabilities of Sentinel 2 and Web GIS images to monitor the health status of urban green spaces. This research focuses on monitoring the health of trees and urban green spaces in Baghdad through the utilization of web mapping applications. The monitoring and management of the health of trees and urban green spaces in Baghdad is a crucial task for ensuring their long-term sustainability and maximizing their benefits. However, the lack of comprehensive and efficient tools for this purpose has been a challenge. Research Objectives in this study are firstly, to evaluate the effectiveness of web mapping applications, specifically Esri and Google Earth Engine, in monitoring the health of trees and urban green spaces in Baghdad. Then, assess the usability and functionality of these platforms for managing urban green spaces and preserving the health of trees in Baghdad. Finally, proposing recommendations for improving the integration and functionality of web mapping applications in the context of urban green space management in Baghdad.
The integration of Esri and Google Earth Engine web mapping applications will significantly improve the monitoring and management of trees and urban green spaces in Baghdad. Moreover, the use of GIS-based indices, such as NDVI, EVI, VCI, and VHI, will provide valuable insights into the health and changes in urban green spaces in Baghdad. The adoption of web mapping applications will enhance the decision-making process and the implementation of proactive measures for the long-term sustainability of Baghdad's trees and green spaces.

2. METHOD

The present study tries to monitor the health of urban green spaces in Baghdad City. The flowchart (Figure 1) shows that the methodology is structured around two primary approaches that leverage advanced remote sensing techniques and data integration to analyze vegetation health. The first approach is Google Earth Engine (GEE) Implementation which gets the location of the study area and the data and calculates several key vegetation indices by using Python scripts. Moreover, the visualization and reporting are done by using Cascading Style Sheets[1]The second approach, which uses Esri Web App Builder, integrates the data and designs a customized map. The same indices are calculated in this approach, too, and a temporal analysis is conducted. Finally, through the combination of Google Earth Engine and Esri Web App Builder, this research achieves a comprehensive methodology for monitoring urban vegetation health.

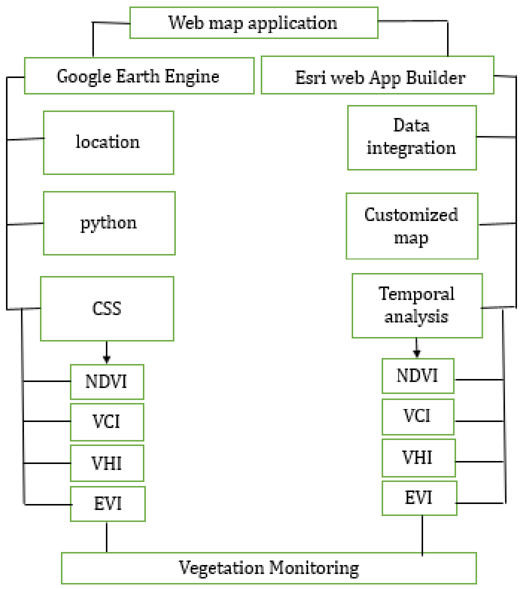

Figure 1. Research Flowchart

[1] CSS

The dual approach not only enhances the accuracy of vegetation indices but also provides a flexible and interactive platform for ongoing monitoring and assessment. This methodology ensures that we can effectively track changes in urban green spaces in Baghdad, thereby contributing to informed decision-making regarding urban planning and environmental management.

2.1. Case study

The case study is the city of Baghdad (figure 2). Baghdad is the capital of Iraq and of Baghdad Governorate, which it is also coterminous with. With a municipal population estimated at 7,000,000, it is the largest city in Iraq and the second-largest city in the Arab World (after Cairo). The city is located on a vast alluvial plain, 112 feet (34 meters) above sea level).

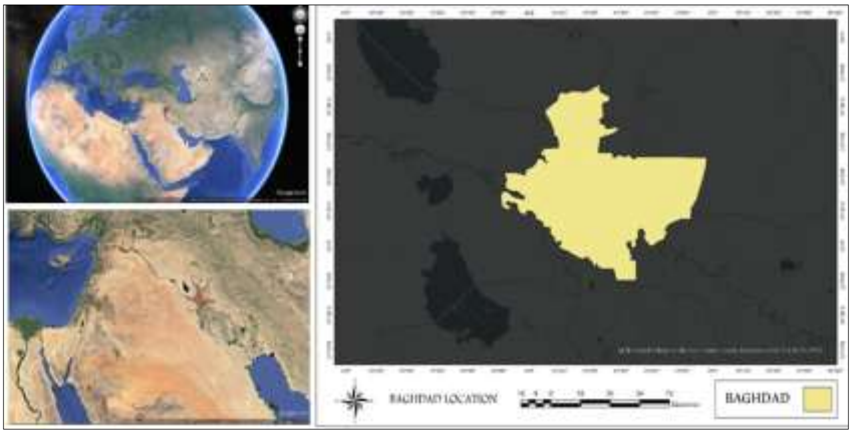

Figure 2. Maps of Study Area- Baghdad city in Iraq

The Tigris splits Baghdad in half, with the Eastern part called Risafa and the Western half known as Karkh. The land on which the city is built is almost entirely flat and low-lying, being of alluvial origin due to the periodic large floods that have occurred on the river. The completion of a dam on the Tigris at Samarra to the north, in 1956, stopped flooding[21]. Baghdad has a hot arid climate. Annual rainfall, almost entirely confined to the period from November to March, averages around 5.5 inches (140 mm) but has been as high as 23 inches (575 mm) and as low as less than one inch (23 mm). On January 11, 2008, light snow fell across Baghdad for the first time in memory. The land area of the city was 5169 square kilometers.

Although large area of main streets in Iraq turns into green space, the small shrub which are planted for this amin are not effective enough. Moreover, the green space along the river or local streets of Iraq has decreased in recent year. It can question the mental and physical health of society[22].

2.2. Data

The study area is defined based on the urban green spaces in Baghdad. A geographic boundary was established to focus the analysis on areas with significant tree cover and vegetation. Relevant satellite imagery and environmental data were collected from GEE. This included time-series data from various sources, such as Landsat and Sentinel-2, which provide valuable information about vegetation cover over the years. This information is generated for a period of 10 years, spanning from 2013 to 2023.

The web map application treats the layers of green spaces and their descriptive characteristics as separate entities, allowing users to view the corresponding characteristics by interacting with the platform. Users can input location and time intervals to obtain information about the health status of selected green spaces. The system provides descriptive information about Baghdad's green spaces, and users can view characteristics by selecting specific locations and timeframes in the Baghdad metropolitan area. It also generates layers and graphs of vegetation indicators and images.

2.3 Methods

Monitoring the health of trees and urban green spaces in Baghdad using GIS and remote sensing methodologies involves several steps. Firstly, remote sensing data is acquired from sources like satellite imagery, aerial photographs, or base maps, covering the study area and the desired time period. The next step is selecting the study area and then vegetation index calculation, which involves selecting appropriate spectral bands and using specific formulas to calculate indexes.

The analysis in the present study helps identify trends, seasonal variations, and changes in vegetation health over time.

2.3.1 Google Earth Engine [2] Implementation

The first approach utilizes the Google Earth Engine, a powerful open-source platform designed for geospatial analysis. This platform allows for the processing and analysis of large datasets, making it ideal for monitoring vegetation health[23].

Google Earth Engine provides access to a wide range of satellite imagery, including high-resolution imagery from sources like Landsat and Sentinel. These images can be used to monitor vegetation dynamics, identify changes in green space coverage, and assess the health of trees in the urban environment. Google Earth Engine offers a comprehensive set of image-processing functions and algorithms that can be applied to satellite imagery. These functions allow for the extraction of relevant information, such as vegetation indices, which provide insights into the health and vigor of vegetation.

It is obvious that the google earth has both free and payment version. The free version has limitation in the case of storage and programming so it is not suitable for big data processing. The sophisticated or complex programming or analysis are not available in google earth engine free version. Additionally there are some algorithms that are nontransparent, so make it a weak tool for many professional projects.

2.3.1.1 calculation of times series indices

Remote sensing technology can provide the vegetation indices (VIs) which are very simple and effective for monitoring and analysis the landcovers. Theses indices are used to evaluate the patterns, covers and growth of vegetations. Different platforms of remote sensing technology provide vegetation indices with different accuracy. The mentioned indices expressed by mathematical definitions[24].

Using Python scripts, several key vegetation indices are calculated to assess the health of urban greenery. By utilizing web mapping applications such as the Esri platform and Google Earth Engine, four vegetation monitoring indicators such as VCI, VHI, EVI, and NDVI are developed.

- Normalized Difference Vegetation Index[3]: This index measures the difference between near-infrared[4] and red-light reflectance, providing insight into vegetation health[25]. By simplifying the complex definition of plants and vegetations properties, NDVI is popular nowadays. this index is very useful to passement the vegetations health, status and patterns[26].

This index is calculated based on equation (1) :

$$\text{NDVI} = \frac{(\text{NIR} - \text{Red}-\text{light})}{(\text{NIR} + \text{Red}-\text{light})} \quad (1)$$

- Enhanced Vegetation Index[5] : This index offers improved sensitivity in high biomass regions and is less affected by atmospheric conditions[27]. These enhancements allow for index calculation as a ratio between the R and NIR values while reducing the background noise, atmospheric noise, and saturation in most cases. This index is calculated based on equation (2), NIR, Red, and Blue are atmospherically-corrected and partially atmosphere-corrected (Rayleigh and ozone absorption) reflectance. L is the canopy background adjustment that addresses non-linear, differential NIR, and red radiant transfer through a canopy, and C1, and C2 are the coefficients of the aerosol resistance term, which uses the blue band to correct for aerosol influences in the red band. G is a gain factor.

$$\text{EVI} = \frac{\text{G}*((\text{NIR} - \text{Red\_light})}{(\text{NIR}+\text{C1}*\text{Red\_light}-\text{C2}*\text{Blue} + \text{L})} \quad (2)$$

- Vegetation Condition Index [6]: This index helps assess the current state of vegetation by comparing the current NDVI value to the historical range[28]. This index is calculated based on equation (3)

$$\text{VCI} = \frac{100 * (\text{NDVI} - \text{NDVI min})}{(\text{NDVI max} - \text{NDVI min})} \quad (3)$$

- Vegetation Health Index[7]: This index combines VCI and temperature data to evaluate overall vegetation health[29]. VHI is a proxy characterizing vegetation health or a combined estimation of moisture and thermal conditions. it is calculated based on equation (4), where a is a coefficient determining the contribution of the two indices.

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[2] GEE
[3] NDVI
[4] NIR
[5] EVI
[6] VCI
[7] VHI

$$VHI=a*VCI + (1- a) *TCI \qquad (4)$$

These indicators were generated for a period of 10 years, spanning from 2013 to 2023.

2.3.1.2 Temporal Analysis, Visualization and Reporting

The analysis covered a period from 2013 to 2023. This temporal framework allowed users to observe trends and changes in vegetation health over the decade, thereby providing a comprehensive view of how urban green spaces have evolved[30, 31]. Visualization Cascading Style Sheets are utilized for the design and formatting of the output maps and reports generated from the analysis. The final output included visual representations of the calculated indices, which facilitated an intuitive understanding of the vegetation health status across the study area.

2.3.2 Esri Web App Builder[8] Implementation

The second approach involved the use of the Esri Web App Builder, which enabled a customized web mapping application created for data integration and visualization[32]. With Esri Web Map, users can design customized maps tailored to their specific monitoring needs. They can choose from a wide range of base maps, overlay multiple layers, and apply symbology to represent different variables related to tree health, such as species diversity, vegetation indices, and land cover types.

The custom datasets are integrated into the Esri platform, ensuring that the data used for analysis is comprehensive and relevant. This step is crucial for producing accurate indicators and insights regarding vegetation health[33]. Esri Web App Builder allowed for the development of a user-friendly interface tailored to specific needs[34]. The arrangement of map elements to enhance user interaction and Custom styling options to ensure that the maps were visually appealing and aligned with research goals.

Similar to the GEE approach, a temporal analysis is conducted from 2013 to 2023. This involved tracking changes in the vegetation indices (NDVI, EVI, VCI, VHI) over time.

By implementing both the Google Earth Engine and the Esri Web App Builder, a robust monitoring system that automatically retrieves data from GEE is established. This integration allows for real-time monitoring and support for the analyses conducted in the WAB, reinforcing the reliability of findings.

Through the combination of Google Earth Engine and Esri Web App Builder, this research achieves a comprehensive methodology for monitoring urban vegetation health. The dual approach not only enhances the accuracy of vegetation indices but also provides a flexible and interactive platform for ongoing monitoring and assessment. This methodology ensures that we can effectively track changes in urban green spaces in Baghdad, thereby contributing to informed decision-making regarding urban planning and environmental management.

3. RESULTS

In this study, by utilizing web mapping four vegetation monitoring indicators are explored. A classification process is conducted to extract different vegetation classes based on the chosen dates. Subsequently, the values specifically for the relevant categories after classification are extracted. To facilitate comparison and analysis of the vegetation monitoring results, the Attribute Table, which contains the analysis values, is converted into an Excel sheet.

The analysis of the VCI and EVI results for monitoring vegetation cover in Baghdad using web mapping applications such as Esri and Google Earth Engine is investigated. The analysis reveals the vegetation health and condition in Baghdad over the studied period. The distribution of different vegetation conditions, such as extreme drought, severe drought, wet, and extreme wet, provides valuable information about the environmental stressors and their impact on the vegetation cover. This information can indicate areas of concern, such as drought-prone regions or areas with potential waterlogging issues. Understanding the spatial distribution and changes in vegetation density can aid in assessing the potential impacts on these ecosystem services and inform conservation and management strategies. In conclusion, the analysis of VCI and EVI values for monitoring vegetation cover in Baghdad using web mapping applications provides an understanding of the vegetation conditions and density over the years. On the other hand, the analysis of the NDVI and VHI data provides valuable insights into the vegetation dynamics and drought conditions in Baghdad over the studied period.

[8] WAB

International Journal of Environmental Sciences
ISSN: 2229-7359
Vol. 11 No. 24s, 2025
https://www.theaspd.com/ijes.php

3.1 Vegetation Condition Index Analysis

The Vegetation Condition Index is a measure of vegetation health and is calculated based on satellite data. The VCI values for the years 2013 to 2023 are represented in (figure 3). In (figure 4) the mentioned results are presented in the chart by considering the time series and (figure 5) shows the visual format of outputs.

VCI 2013

Vegetation Classes	Count	Percentage
Extreme Drought	642933	9.3
Severe Drought	505258	7.3
No Drought	947878	13.7
Wet	998100	14.5
Extreme Wet	3805620	55.2

VCI 2014

Vegetation Classes	Count	Percentage
Extreme Drought	645293	9.3
Severe Drought	501319	7.2
No Drought	987244	14.3
Wet	1177866	17.1
Extreme Wet	3588067	52.1

VCI 2015

Vegetation Classes	Count	Percentage
Extreme Drought	1945778	28
Severe Drought	942304	13.8
No Drought	1240576	18
Wet	913283	13.2
Extreme Wet	1857848	27

VCI 2016

Vegetation Classes	Count	Percentage
Extreme Drought	457626	6.6
Severe Drought	394431	5.7
No Drought	845743	12.3
Wet	1051244	15.2
Extreme Wet	4150745	60.2

VCI 2017

Vegetation Classes	Count	Percentage
Extreme Drought	1956294	28.5
Severe Drought	816590	11.8
No Drought	1100824	15.9
Wet	959773	13.9
Extreme Wet	2066308	29.9

VCI 2018

Vegetation Classes	Count	Percentage
Extreme Drought	346038	5
Severe Drought	471369	6.8
No Drought	1101928	16
Wet	1253475	18.2
Extreme Wet	3726979	54

VCI 2019

Vegetation Classes	Count	Percentage
Extreme Drought	299008	3.3
Severe Drought	281143	4.8
No Drought	625071	9.6
Wet	847907	12.3
Extreme Wet	4846660	70

VCI 2020

Vegetation Classes	Count	Percentage
Extreme Drought	919833	13.3
Severe Drought	703851	10.2
No Drought	1020997	14.8
Wet	1000003	14.4
Extreme Wet	3255105	47.3

VCI 2021

Vegetation Classes	Count	Percentage
Extreme Drought	775917	11.2
Severe Drought	757805	11
No Drought	1158302	16.8
Wet	1111962	16.1
Extreme Wet	3095803	44.9

VCI 2022

Vegetation Classes	Count	Percentage
Extreme Drought	3389442	49.1
Severe Drought	699286	10.1
No Drought	893373	12.9
Wet	735133	10.6
Extreme Wet	1182555	17.3

VCI 2023

Vegetation Classes	Count	Percentage
Extreme Drought	704919	10.2
Severe Drought	438448	6.3
No Drought	925023	13.4
Wet	1065393	15.4
Extreme Wet	3766006	54.7

Figure 3 VCI Results and Statics

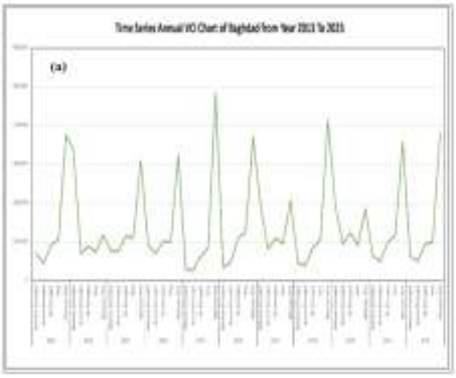

Figure 4. Showing VCI Time Series

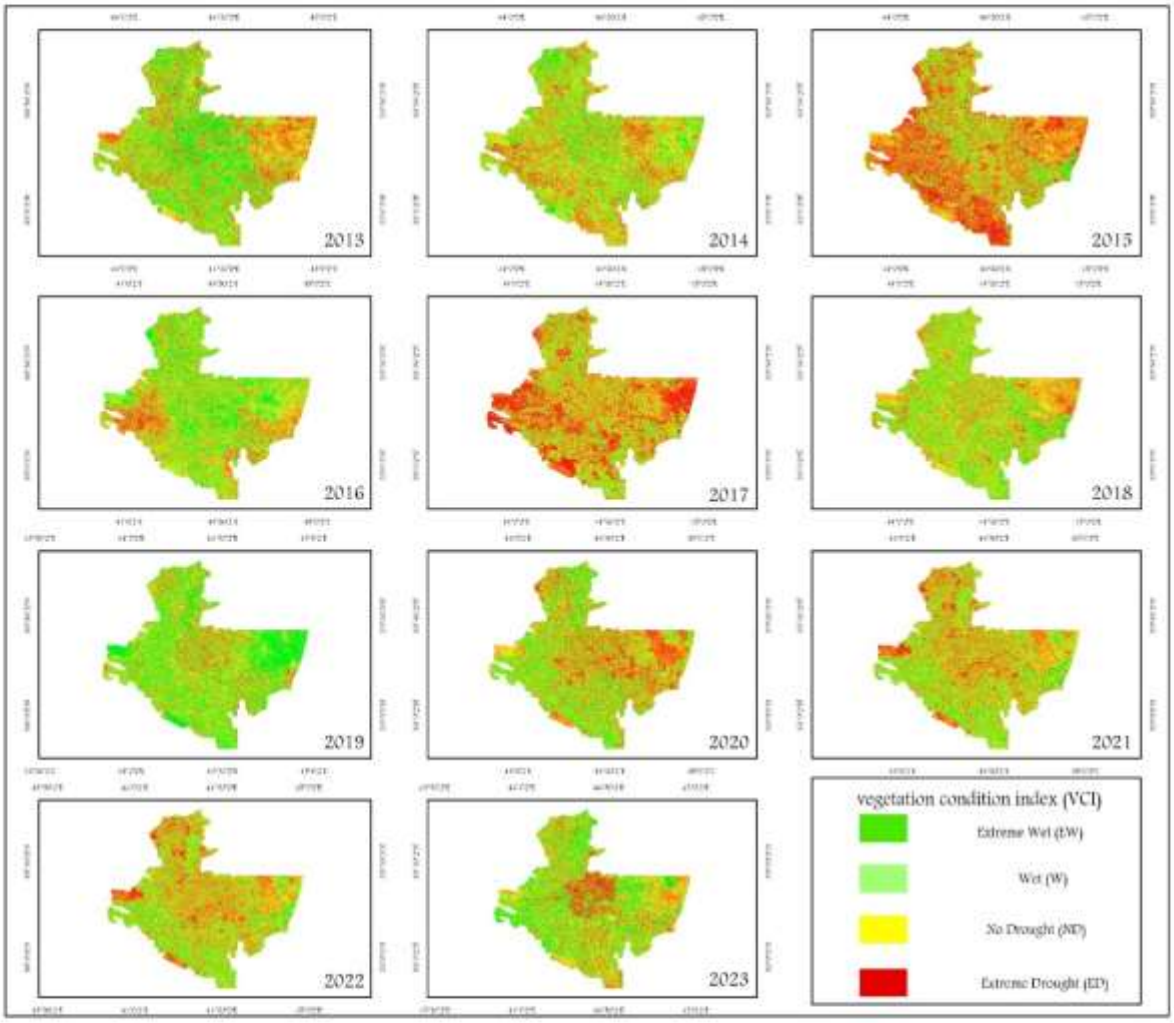

Figure 5- Showing VCI outputs

The percentage of extreme drought conditions varied between 4.3% (2019) and 55.2% (2018). The highest count of extreme drought occurred in 2018, with 3,805,620 instances, while the lowest count was in 2019, with 299,008 instances (figure 3). The percentage of severe drought conditions ranged from 6.4% (2023) to 17.1% (2022). The highest count of severe drought occurred in 2022, with 3,389,442 instances, while the lowest count was in 2023, with 438,448 instances. The percentage of no drought conditions ranged from 9.1% (2019) to 18.0% (2015). The highest count of no drought occurred in 2015, with 1,240,576 instances, while the lowest count was in 2018, with 625,071 instances. The percentage of wet conditions ranged from 10.7% (2022) to 17.1% (2021). The highest count of wet conditions occurred in 2021, with 1,111,962 instances, while the lowest count was in 2022, with 735,133 instances. The

International Journal of Environmental Sciences
ISSN: 2229-7359
Vol. 11 No. 24s, 2025
https://www.theaspd.com/ijes.php

percentage of extreme wet conditions ranged from 29.9% (2017) to 70.2% (2019). The highest count of extreme wet occurred in 2019, with 4,846,660 instances, while the lowest count was in 2017, with 2,066,308 instances. This analysis shows the distribution of vegetation conditions over the years, highlighting the occurrence of extreme drought, severe drought, no drought, wet, and extreme wet conditions.

3.2 Enhanced Vegetation Index Analysis

The Enhanced Vegetation Index is another index used to assess vegetation density and health. The Enhanced Vegetation Index values for the years 2013 to 2023 are represented in (figure 6). In (figure 7) these results are presented in the chart by considering the time series and (figure 8) shows the visual format of outputs.

EVI 2013

Vegetation Classes	Count	Percentage
No Vegetation (ND)	2051815	29.7
Slightly Density (SD)	2286922	33.1
Moderately Density (MD)	1810408	26.2
Highly Density	750644	10.9

EVI 2014

Vegetation Classes	Count	Percentage
No Vegetation (ND)	1896268	27.5
Slightly Density (SD)	2386877	34.6
Moderately Density (MD)	1905441	27.6
Highly Density	711203	10.3

EVI 2015

Vegetation Classes	Count	Percentage
No Vegetation (ND)	2042414	29.6
Slightly Density (SD)	2455707	35.6
Moderately Density (MD)	1729798	25.1
Highly Density	671870	9.7

EVI 2016

Vegetation Classes	Count	Percentage
No Vegetation (ND)	1492576	21.6
Slightly Density (SD)	2561876	37.1
Moderately Density (MD)	2116899	30.7
Highly Density	728438	10.6

EVI 2017

Vegetation Classes	Count	Percentage
No Vegetation (ND)	2630081	38.1
Slightly Density (SD)	2128418	30.8
Moderately Density (MD)	1484168	21.5
Highly Density	657122	9.5

EVI 2018

Vegetation Classes	Count	Percentage
No Vegetation (ND)	2318470	33.6
Slightly Density (SD)	2291077	33.2
Moderately Density (MD)	1649703	23.9
Highly Density	640539	9.3

EVI 2019

Vegetation Classes	Count	Percentage
No Vegetation (ND)	1881195	27.3
Slightly Density (SD)	2600678	37.7
Moderately Density (MD)	1674164	24.3
Highly Density	743752	10.8

EVI 2020

Vegetation Classes	Count	Percentage
No Vegetation (ND)	162695	2.4
Slightly Density (SD)	3122390	45.3
Moderately Density (MD)	2481057	36.0
Highly Density	1133647	16.4

EVI 2021

Vegetation Classes	Count	Percentage
No Vegetation (ND)	2517933	36.5
Slightly Density (SD)	2193700	31.8
Moderately Density (MD)	1573538	22.8
Highly Density	614618	8.9

EVI 2022

Vegetation Classes	Count	Percentage
No Vegetation (ND)	2929835	42.5
Slightly Density (SD)	1959092	28.4
Moderately Density (MD)	1428807	20.7
Highly Density	582055	8.4

EVI 2023

Vegetation Classes	Count	Percentage
No Vegetation (ND)	2160762	31.3
Slightly Density (SD)	2435035	35.3
Moderately Density (MD)	1661840	24.1
Highly Density	642152	9.3

Figure 6 EVI Results and Statics

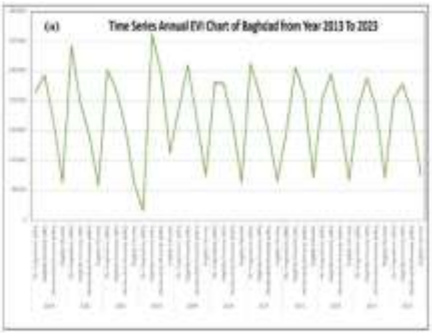

Figure 7- Showing EVI Time Series

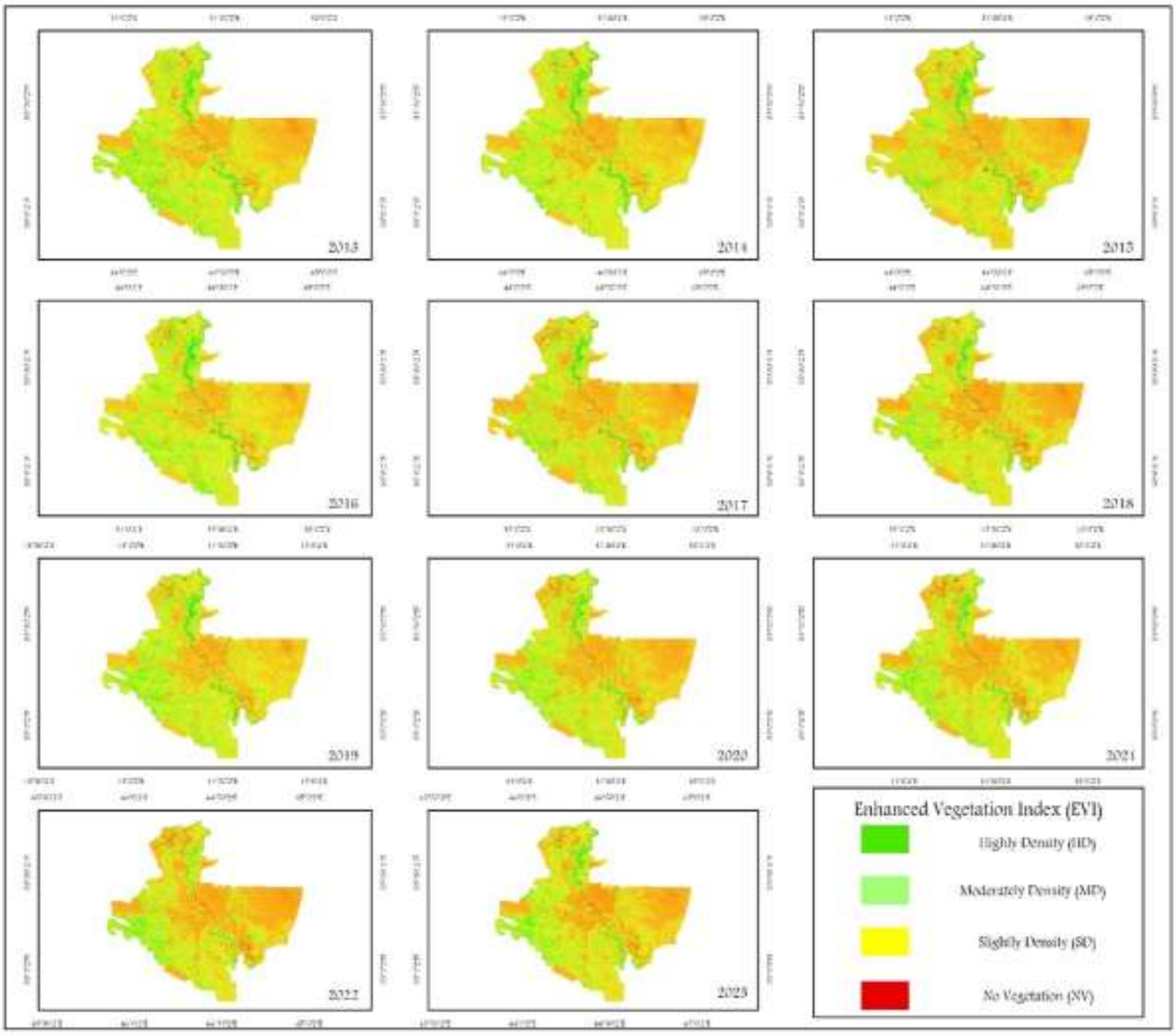

Figure 8- Showing EVI outputs

According to the above figures, the percentage of areas with no vegetation (NV) ranged from 21.6% (2016) to 42.5% (2022). The highest count of no vegetation occurred in 2022, with 2,929,835 instances, while the lowest count was in 2016, with 1,492,576 instances. Slightly Density (SD) shows the percentage of areas with slightly dense vegetation ranged from 20.7% (2022) to 37.7% (2019). The highest count of slightly dense vegetation occurred in 2019, with 2,600,678 instances, while the lowest count was in 2022, with 582,055 instances. Moderately Density (MD): The percentage of areas with moderately dense vegetation ranged from 20.7% (2016) to 36.0% (2020). The highest count of moderately dense vegetation occurred in 2020, with 2,481,057 instances, while the lowest count was in 2016, with 1,484,168 instances. Highly Density: The percentage of areas with highly dense vegetation ranged from 8.4% (2022) to 10.9% (2013). The highest count of highly dense vegetation occurred in 2013, with 750,644 instances, while the lowest count was in 2022, with 582,055 instances.

3.3 Normalized Difference Vegetation Index Analysis

Another index that is used to quantify vegetation greenness and is useful in understanding vegetation density and assessing changes in plant health, is the Normalized Difference Vegetation Index. These index values for the years 2013 to 2023 are represented in (figure 9). The (figure 10) shows the visual format of NDVI outputs.

NDVI 2013

Vegetation Classes	Count	Percentage
No Vegetation (ND)	70862	1.0
Slightly Density (SD)	2692529	39.0
Moderately Density (MD)	2747910	39.8
Highly Density	1388488	20.1

NDVI 2014

Vegetation Classes	Count	Percentage
No Vegetation (ND)	74468	1.1
Slightly Density (SD)	2790326	40.4
Moderately Density (MD)	2917345	42.3
Highly Density	1117650	16.2

NDVI 2015

Vegetation Classes	Count	Percentage
No Vegetation (ND)	66986	1.0
Slightly Density (SD)	3569319	51.7
Moderately Density (MD)	2335679	33.9
Highly Density	927805	13.4

NDVI 2016

Vegetation Classes	Count	Percentage
No Vegetation (ND)	93284	1.4
Slightly Density (SD)	2705536	39.2
Moderately Density (MD)	2937770	42.6
Highly Density	1163199	16.9

NDVI 2017

Vegetation Classes	Count	Percentage
No Vegetation (ND)	99283	1.4
Slightly Density (SD)	3398857	49.3
Moderately Density (MD)	2353821	34.1
Highly Density	1047828	15.2

NDVI 2018

Vegetation Classes	Count	Percentage
No Vegetation (ND)	90276	1.3
Slightly Density (SD)	2864170	41.5
Moderately Density (MD)	2779827	40.3
Highly Density	1165516	16.9

NDVI 2019

Vegetation Classes	Count	Percentage
No Vegetation (ND)	103911	1.5
Slightly Density (SD)	2701035	39.1
Moderately Density (MD)	2843523	41.2
Highly Density	1251320	18.1

NDVI 2020

Vegetation Classes	Count	Percentage
No Vegetation (ND)	117789	1.7
Slightly Density (SD)	2968967	43.0
Moderately Density (MD)	2526470	36.6
Highly Density	1286563	18.6

NDVI 2021

Vegetation Classes	Count	Percentage
No Vegetation (ND)	128024	1.9
Slightly Density (SD)	2915565	42.3
Moderately Density (MD)	2668011	38.7
Highly Density	1188189	17.2

NDVI 2022

Vegetation Classes	Count	Percentage
No Vegetation (ND)	127695	1.9
Slightly Density (SD)	3244712	47.0
Moderately Density (MD)	2437871	35.3
Highly Density	1089511	15.8

NDVI 2023

Vegetation Classes	Count	Percentage
No Vegetation (ND)	79895	1.2
Slightly Density (SD)	2710168	39.3
Moderately Density (MD)	2938921	42.6
Highly Density	1170805	17.0

Figure 9 NDVI Results and Statics

International Journal of Environmental Sciences
ISSN: 2229-7359
Vol. 11 No. 24s, 2025
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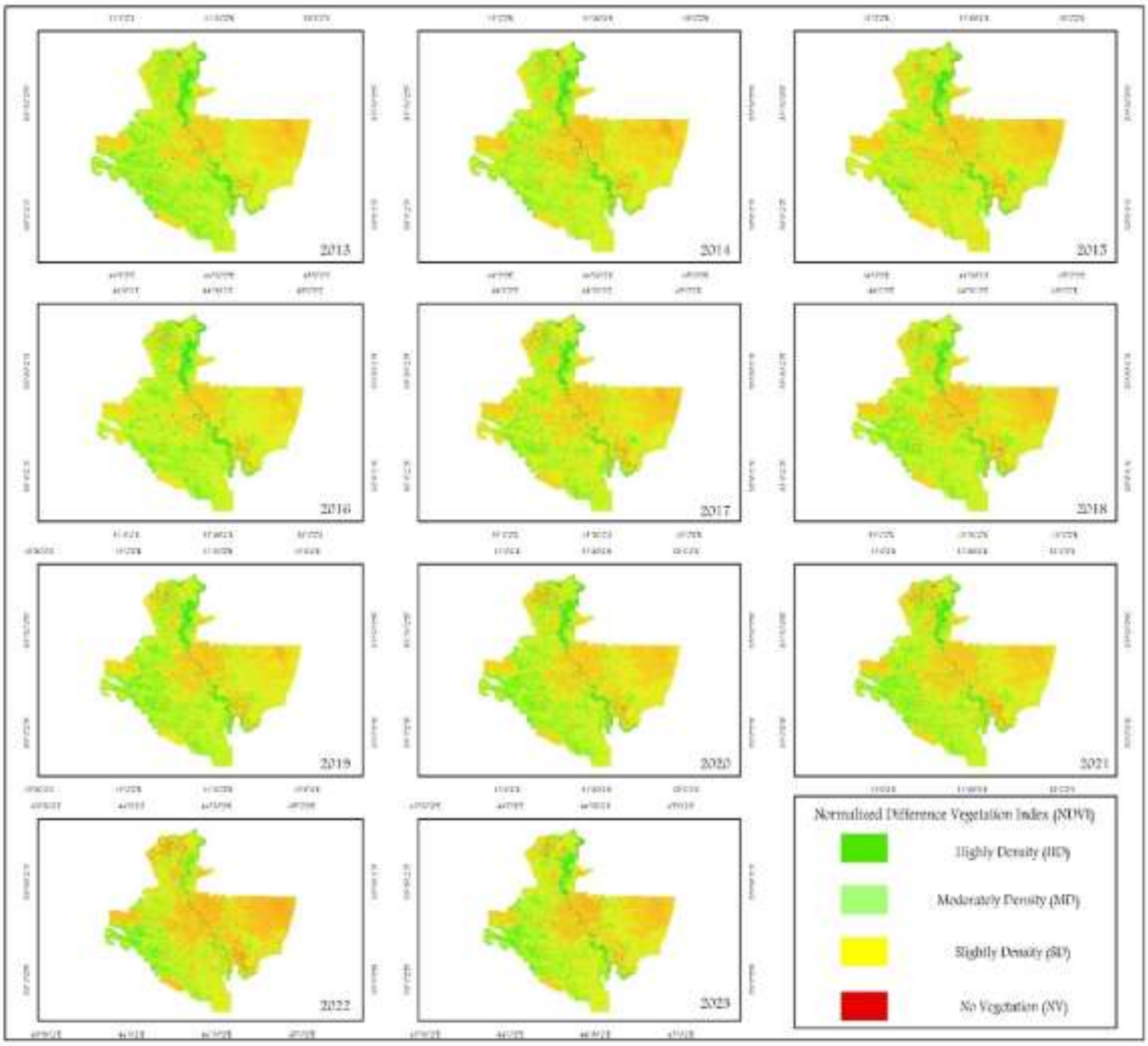

Figure 10- Showing NDVI outputs

In terms of the NDVI results, the percentage of the ND class remained relatively stable, ranging from 1.0% in 2014 to 1.9% in 2022 and 2023. This indicates a consistently low presence of vegetation in the region. The SD class shows a moderate to high presence of vegetation, ranging from 35.3% in 2022 to 51.7% in 2015. The MD class exhibits a moderate presence of vegetation, ranging from 33.9% in 2014 to 42.6% in 2015 and 2023. The high-density class indicates a relatively lower presence of dense vegetation, ranging from 13.4% in 2015 to 20.1% in 2013. These variations highlight the changes in vegetation cover in Baghdad over the studied period. On the other hand, the VHI analysis reveals the drought conditions in Baghdad. The Extreme Drought class shows varying percentages, with the highest value of 11.9% in 2017 and the lowest value of 4.2% in 2019. The severe drought class ranges from 5.6% in 2016 to 22.7% in 2015. The moderate drought class ranges from 12.4% in 2016 to 16.7% in 2021. The mid-drought class ranges from 13.9% in 2017 to 16.1% in 2021. Finally, the No Drought class demonstrates the absence of drought conditions, ranging from 29.9% in 2017 to 70.2% in 2019. These percentages illustrate the prevalence of different drought levels in Baghdad over the studied period.

The results of the NDVI analysis shed light on the health and condition of vegetation in Baghdad. The presence of ND and low-density classes may suggest areas with limited or degraded vegetation, potentially indicating environmental stressors such as water scarcity, soil degradation, or pollution. The identification of areas with moderate to high vegetation density can indicate healthier and more robust vegetation cover.

3.4 Vegetation Health Index Analysis

The Vegetation Health Index illustrates the severity of drought based on the vegetation health and the influence of temperature on plant conditions. VHI index values for the years 2013 to 2023 are represented in (figure 11). (figure 10 a and b) shows the VHI Time Series and its outputs spatial maps.

International Journal of Environmental Sciences
ISSN: 2229-7359
Vol. 11 No. 24s, 2025
https://www.theaspd.com/ijes.php

VHI 2013

Vegetation Classes	Count	Percentage
Extreme Drought	642658	9.3
Severe Drought	503983	7.3
Moderate Drought	944588	13.7
Mild Drought	1001826	14.5
No Drought	3804855	55.2

VHI 2014

Vegetation Classes	Count	Percentage
Extreme Drought	645137	9.4
Severe Drought	501168	7.3
Moderate Drought	986945	14.3
Mild Drought	1177558	17.1
No Drought	3587163	52.0

VHI 2015

Vegetation Classes	Count	Percentage
Extreme Drought	382331	5.5
Severe Drought	1563112	22.7
Moderate Drought	942753	13.7
Mild Drought	1527119	22.1
No Drought	2483206	36.0

VHI 2016

Vegetation Classes	Count	Percentage
Extreme Drought	457475	6.6
Severe Drought	385862	5.6
Moderate Drought	854010	12.4
Mild Drought	1017900	14.8
No Drought	4183183	60.6

VHI 2017

Vegetation Classes	Count	Percentage
Extreme Drought	1948046	28.2
Severe Drought	823906	11.9
Moderate Drought	1100483	16.0
Mild Drought	959527	13.9
No Drought	2065688	29.9

VHI 2018

Vegetation Classes	Count	Percentage
Extreme Drought	345962	5.0
Severe Drought	471264	6.8
Moderate Drought	1100045	15.9
Mild Drought	1254806	18.2
No Drought	3726210	54.0

VHI 2019

Vegetation Classes	Count	Percentage
Extreme Drought	293064	4.2
Severe Drought	281523	4.1
Moderate Drought	618251	9.0
Mild Drought	859545	12.5
No Drought	4845247	70.2

VHI 2020

Vegetation Classes	Count	Percentage
Extreme Drought	919684	13.3
Severe Drought	703714	10.2
Moderate Drought	1020813	14.8
Mild Drought	999935	14.5
No Drought	3254344	47.2

VHI 2021

Vegetation Classes	Count	Percentage
Extreme Drought	775695	11.2
Severe Drought	757648	11.0
Moderate Drought	1152581	16.7
Mild Drought	1112006	16.1
No Drought	3100230	44.9

VHI 2022

Vegetation Classes	Count	Percentage
Extreme Drought	3375449	48.9
Severe Drought	706730	10.2
Moderate Drought	885641	12.8
Mild Drought	746721	10.8
No Drought	1181343	17.1

VHI 2023

Vegetation Classes	Count	Percentage
Extreme Drought	704772	10.2
Severe Drought	438353	6.4
Moderate Drought	924804	13.4
Mild Drought	1065107	15.4
No Drought	3764677	54.6

Figure 11 VHI Results and Statics

International Journal of Environmental Sciences
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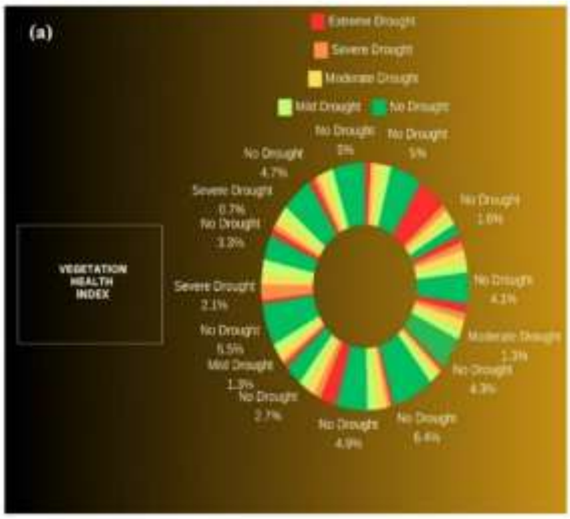

Figure 12 VHI Time Series map,

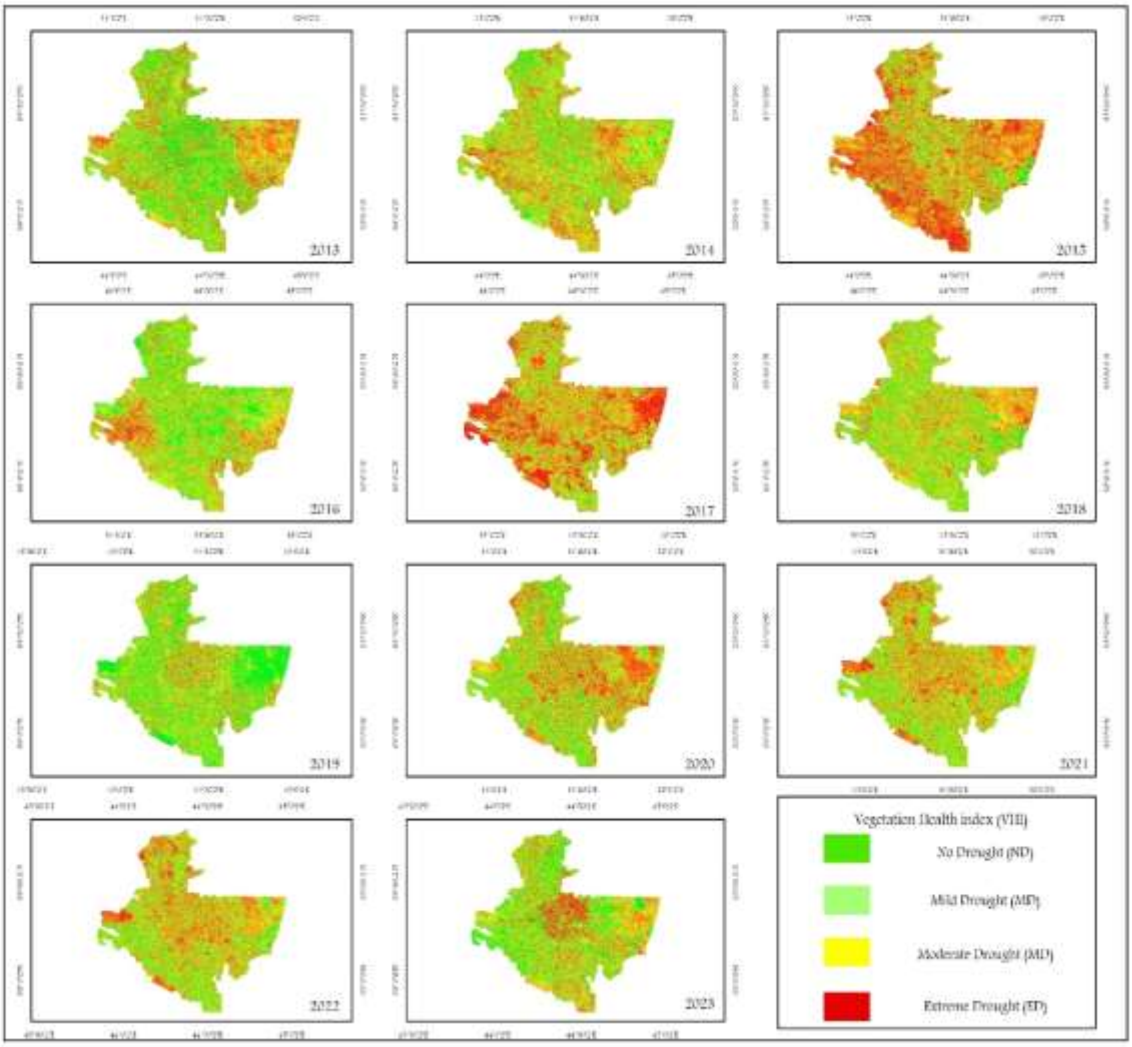

Figure 13- Showing VHI outputs

The investigation Drought Patterns whit using the VHI analysis provides insights into the occurrence and intensity of drought conditions in Baghdad. The percentages of different drought classes indicate the severity and extent of drought events over the studied period. This information is crucial for understanding the vulnerability of vegetation to drought stress and assessing the potential impact on agricultural productivity, water resources, and overall ecosystem resilience.

The findings from the analysis can support informed decision-making and effective management strategies for vegetation and environ-mental conservation in Baghdad. The identification of areas with low vegetation density or severe drought condition ns can guide targeted interventions such as reforestation initiatives, water resource management, or land-use planning to mitigate environmental degradation and enhance vegetation resilience.

4. DISCUSSION

Enhancing the resilience of vegetation cover in the face of extreme drought or wet conditions requires a combination of proactive measures and adaptive strategies. Here are some potential strategies Including Water Management that Implement efficient irrigation techniques, such as drip irrigation or precision irrigation, to optimize water use and minimize losses.

Develop and maintain water storage infrastructure, such as reservoirs or rainwater harvesting systems, to capture and store water during wet periods for use during droughts. Promote water conservation practices, such as mulching, to reduce evaporation and soil moisture loss. Encourage the use of native or drought-tolerant plant species that require less water and are adapted to local climatic conditions. Also Implement soil conservation practices, such as terracing or contour plowing, to pre-vent soil erosion during heavy rainfall and retain moisture during droughts. Use cover crops or green manure to protect the soil, reduce evaporation, and enhance soil fertility.

Practice sustainable land management techniques, such as rotational grazing or agroforestry, to improve soil health and increase water infiltration. Reforestation and Afforestation Undertake reforestation initiatives to restore degraded areas and increase the overall vegetation cover. Plant trees strategically to create windbreaks or shelterbelts that can mitigate the impacts of extreme weather events. Ecosystem-Based Protect and restore natural ecosystems, such as wetlands or riparian zones, which can act as buffers against extreme weather conditions and support biodiversity. Implement ecosystem-based adaptation strategies, such as restoring or creating green infrastructure, to enhance water retention, regulate temperature, and provide habitat for species. They raise awareness among local communities, farmers, and landowners about the importance of vegetation cover for ecosystem services and climate resilience. Provide education and training on sustainable land management practices, water conservation techniques, and climate-smart agriculture.

Foster community engagement and participation in conservation efforts, such as community-based reforestation programs or watershed management initiatives. It's important to note that the specific strategies for enhancing vegetation resilience may vary depending on the local context, including climate, soil conditions, and available resources. Therefore, a comprehensive assessment of the local conditions and consultation with relevant stakeholders is crucial for designing and implementing effective resilience-building measures.

5. CONCLUSION

This research endeavors to explore the application of web mapping technology in the context of monitoring the health of trees and urban green spaces in Baghdad city, examining existing platforms, assessing their efficacy, and proposing enhancements to improve their functionality and usability.

The integration of Esri and Google Earth Engine web mapping applications will significantly improve the monitoring and management of trees and urban green spaces there. The use of GIS-based indices NDVI, EVI, VCI, and VHI, will provide valuable insights into the health and changes in urban green spaces.

To analyze vegetation health, two approaches are employed in this study. The first approach utilizes the Google Earth Engine and the second one involves the use of the Esri Web App Builder. The data included time-series data from Landsat and Sentenal-2 from 2013 to 2023. They were collected from GEE. To provide a comprehensive view of how urban green spaces, the trends and changes were observed in vegetation health over the decade. Python scripts helped to assess the health of urban greenery by calculating four related indexes in both approaches.

The dual approach enhances the accuracy of vegetation indices and provides a flexible and interactive platform for ongoing monitoring and assessment.

In conclusion, fostering community participation in conservation efforts is crucial for achieving sustainable and effective environmental stewardship. By implementing a combination of strategies, including raising awareness, fostering collaboration, providing economic incentives, building capacity, creating opportunities for recreation and education, and recognizing achievements, communities can be encouraged to actively engage in conservation practices. Encouraging communities to participate in conservation efforts requires a combination of education, engagement, and incentives.

Acknowledgment: This work was supported by the Faculty of Planning and Environmental Science, University Tabriz, Tabriz, Iran.

Conflicts of interest: We wish to confirm that there are no known conflicts of interest associated with this publication..

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