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Monitoring of Biodiversity in the Erbil Governorate -Iraq Using Remote Sensing Data

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Abstract

Ensuring the health and diversity of ecosystems has always been a challenge for conservationists. It takes years of direct work in the field for ecologists to gather sufficient data to reliably portray the conditions of an ecosystem. In many instances, their work produces an invaluable picture of the conditions as they are and, more importantly, the conditions that are changing over time. Yet, traditional methods of monitoring biodiversity simply cannot keep up with the demands of today's conservation imperative. They are labor-intensive, fail to produce timely results, and are in large part inaccessible to those who might use the information they produce. In much the same way, the potential of remote sensing to meet those demands remains largely untapped. This study utilizes remote sensing data to monitor biodiversity changes in the Erbil Governorate, Iraq, focusing on the Enhanced Vegetation Index (EVI), Standardized Precipitation Index (SPI), and Net Primary Productivity (NPP) as proxies for biodiversity change. To do this, it combines data from MODIS and Sentinel-2 satellites with meteorological information to evaluate the spatial and temporal changes in vegetation that occurred during the recent recorded drought. The most dramatic improvement observed in the three key variables was with the EVI, which increased almost straight up from below EVI value of 2 in 2017 to almost 3 in 2020, as seen in the plot above, with the EVI gradient increasing around 2019.

In 2017, the median NPP values hovered approximately around 0.15 kgC/m²; however, they had clearly risen to nearly 0.25 kgC/m² by 2020. What's more, this research demonstrated a strong positive correlation between the EVI, derived from Sentinel-2 data, and NPP computed from MODIS. The correlation coefficients for these areas ranged from 0.68 to 0.74.

These results reaffirm the potent capabilities of satellite remote sensing for studying ecosystem dynamics and offer an unprecedented glimpse into the sophisticated ecological interplay of this understudied area. Biologists don't even fully understand the basic organ-level functions of this system, so knowing how a system as complex as this one work and understanding its dynamics are crucial for effective conservation and management of its constituent ecosystems.

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1. Introduction

It is critically important to monitor biodiversity in order to understand and preserve the health of ecosystems. Biodiversity encompasses the variety of life forms in different habitats, including plants, animals, fungi, and microorganisms, that contribute to the stability and resilience of ecosystems (Maclaurin & Sterelny, 2008; Rawat & Agarwal, 2015). A diverse ecosystem is much better situated to withstand environmental stress, recover from disturbances, and maintain ecological processes and services vital for human well-being, such as providing clean air and water, fertile soils, and pollinating crops (Sharma & Birman, 2024). It should be noted that "species diversity" is not the same as "wild relatives of crops in in situ conservation." The latter is only part of the answer for maintaining the genetic diversity that confers resilience on communities and for ensuring that ecosystems function in a sustainable manner (Salgotra et al., 2023).

In the last several years, remote sensing has emerged as a powerful tool and data source for biodiversity monitoring (Kuenzer et al., 2014; Vihervaara et al., 2017; Wang & Gamon, 2019). This technology provides a comprehensive approach to assessing various biodiversity aspects, including species richness, vegetation structure, and evenness, offering valuable insights into the status and trends of ecosystems (Nagendra et al., 2013).. They also describe how some of the significant applications of these tools can provide insight into the ecological conditions of particular areas, which is vital if one considers the value of remote sensing across vast swaths of the Earth's surface (Turner et al., 2003). For example, One major application of these high-tech tools—particularly satellite imagery—in biodiversity conservation is the assessment of Net Primary Productivity (NPP).

Assessing the net primary productivity of diverse ecosystems critically depends on remote sensing (Kooistra et al., 2008; Lei et al., 2020; Taelman, Schaubroeck, De Meester, Boone, & Dewulf, 2016). To the casual observer, the amount of carbon taken up by plants in a given area during photosynthesis and the total amount of carbon released during respiration can be defined as NPP (Roxburgh et al., 2005).

The NPP metric shows how an area's vegetation is growing and thriving, which often correlates closely with what one might consider ecological "health." The prime factor that leads to high net primary productivity basically amounts to an abundance of the right nutrients. Environmental change, such as a warming climate, could cause nutrient dynamics and the natural nutrient supply to ecosystems to shift. That's what we think is happening. So using NPP as a measure, we can kind of see those changes in evergreen needle leaf forest ecosystems more nearly in two dimensions – horizontally, as a kind of stress signal to ecosystem "health," and vertically, as a sign that the amount of carbon being sequestered by those kinds of trees may be decreasing in some places.

A few widely accessible Net Primary Productivity (NPP) products are fundamental to ecological and biodiversity research, deriving from a variety of methods and data sources. The Moderate Resolution Imaging Spectroradiometer (MODIS) on NASA's Terra and Aqua satellites is a prominent NPP data source. It estimates global NPP at 1 km resolution, updates every 8 days, and covers the Earth's land surface. This level of detail allows us to track not only "where" but also "when" vegetation productivity has changed. Another notable model is the CASA (Carnegie- Ames Stanford Approach). Like MODIS, CASA also uses satellite data, but it instead emphasizes the climatic role in controlling NPP (Huete et al., 2002). A third model, VPM (Vegetation Photosynthesis Model) (Hickler et al., 2004), also uses satellite data, but estimates and NPP using a different approach (Yu, Wu, & Guo, 2013). Assessing the NPP over the long term and its bias through the GIMMS (Global Inventory Modelling and Mapping Studies) or VPM (Vegetation Photosynthesis Model) approaches can also give us a better understanding of both the stability and reliability of the NPP product.

Combining spectral indices with NPP products can give us a much clearer picture of how vegetation is faring in a particular ecosystem. This is essential knowledge for any efficient management of the wildlife that calls that ecosystem home. Because satellite imagery is becoming cheaper and more accessible, spectral indices like EVI may take an even more prominent role in the future of biodiversity monitoring. Spectral indices are derived from digital numbers (DNs). The DN is the first step in the conversion of solar radiation reflected from an object into useful information about the object. Dense vegetation pushes traditional spectral indices, such as NDVI, to their limits. They work well, but only up to a point—most of them saturate when used in high biomass areas (Erica et al., 2016). The Enhanced Vegetation Index does not have that problem. From what we can tell, the EVI offers much more accurate monitoring of vegetation dynamics and "subtle" changes in biomass.

On the other hand, climatic indexes such as the Standardized Precipitation Index (SPI) measure precipitation shortfalls and excesses over several timeframes, helping to determine drought conditions and their effects on ecosystems. Apart from drought assessment, the SPI shows the precipitation temporal variability—its distribution over time. This is very important since it can show how the availability of water in the soils and the plant growth observed in the EVI can be positively or negatively affected by the precipitation pattern. Thus, the SPI is very complementary to the EVI since it shows the effect of climatic variables (precipitation in this case) on the vegetation dynamics and the state of the ecosystems overall.

It's important to explore and monitor biodiversity in an area that's so heterogeneous and variable in climate; monitoring the impacts of environmental change is essential to understanding the effects on ecosystem health. Therefore, main objective of this study is to use remote sensing data to look at biodiversity changes in the governorate of Erbil, Iraq. The study attempts to assess how NPP, EVI, and SPI vary over time and space in the Erbil Governorate, to look at their interrelationships, and to try to discern what they might be telling us about climatic variability and its impacts on biodiversity in this region. The work pulls together a disparate set of data and assays ways in which the variables can inform conservation strategies and development policy in this part of Iraq.

2.Methods

2.1Study Area

The study site is located in the northern Kurdistan region of Iraq; the Erbil Governorate shares borders with Turkey and Iran (see Figure 1). It sits at an elevation of about 411–426 meters (about 1,397 feet) above sea level. Spanning an area of 164,840 square kilometers, The Erbil region has a semi-arid continental climate with an average temperature that ranges from more than 48°C in the summer to well below 0°C in the winter in some part of the governorate (Hussein, Kovács, Tobak, Abdullah et al., 2018; Alee et la., 2023). The precipitation primarily occurs in the spring and winter seasons, and the amounts increase substantially as the altitude and the topography of the area change; the heavy snowfall in the higher altitudes during winter is famous. Pouring rains are also guaranteed, especially in the spring.

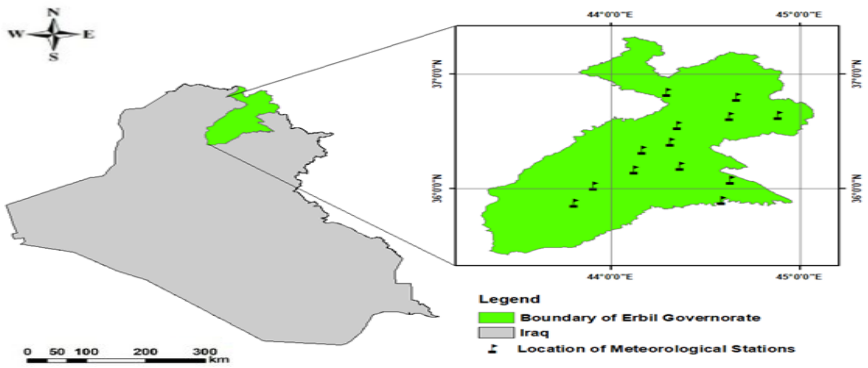

Figure 1. The location of Erbil Governorate and the distribution of selected meteorological stations.

2.2 Data

A set of remote sensing and ancillary data was utilized to achieve the study's objective, as shown in Figure 2.

2.2.1 Calculating Standardized Precipitation Index

The standardized precipitation Index (SPI), is a widely used metric that quantifies how much precipitation falls over a specific region and determines the time period. It was first introduced in 1993 by Klaus P. Szalai and his colleagues. These scientists were motivated by the need to combine and compare many thousands of daily, monthly, and yearly precipitation gauges across the globe. They used a sophisticated statistical approach based on the first 50 years of the last 150 years of the Gaussian-normal daily climate model (Zhang et al., 2000). This pioneering work and the SPI have since been widely accepted and applied by the World Meteorological Organization and by many national meteorological and hydrological services. In general, the computation of the Standardized Precipitation Index (SPI) requires that basin-selected precipitation data from a station or area within the basin be available. For a complete explanation and description of the stepwise methods used to calculate SPI basin data, see Wu et al. (2009). The objective of this study is to utilize SPI data along with a spectral vegetation index calculated from remotely sensed data to monitor the effects of climate variability and change on biodiversity in the study area by means of Net Primary Productivity (NPP) data. To that end, in this study, we have calculated the SPI-12 for our three chosen meteorological stations. The SPI-12 represents the rainfall data for the last 12 months (or 1 year), which coincides with the annual mean Enhanced Vegetation Index (EVI) from our study area derived from remote sensing data.

After the SPI-12 was computed for each of the meteorological stations, we used the inverse distance weighting (IDW) method to interpolate the data. IDW was chosen because it is a simple and efficient geostatistical method that assumes closer points have more influence on the estimated values, which suited our goal of creating a straightforward map showing spatial variability. Unlike Kriging, which requires a more complex variogram model and is computationally intensive, IDW provided a fast and adequate interpolation for our study area, especially given the limited station data and the absence of strong spatial autocorrelation in our dataset.

2.2.2 Remote sensing data

In order to achieve the objectives of this study, two groups of remotely sensed data and products were utilized. For the annual monitoring of the cover of vegetation, including the types of agriculture, grassland, shrubland, and forest, a spectral vegetation index called the Enhanced Vegetation Index (EVI) was computed using Sentinel-2 data. The Google Earth Engine (GEE) platform was used to compute the per-pixel median for the annual EVI values. The EVI is preferable to the often-used Normalized Difference Vegetation Index (NDVI) for this type of monitoring because it reduces the atmospheric and canopy background noise that can confound this type of data. The following equation was utilized to calculate the EVI index:

$$EVI = 2.5 * (NIR - RED) / ((NIR + 6*RED - 7.5*BLUE) + 1 \quad \textbf{(Eq.6)}$$

Where NIR, RED and BLUE are the spectral bands in the region of Near Infrared, Red and BLUE region respectively.

To keep track of and evaluate developments in biomass as a stand-in for changes in biodiversity, we obtained the annual Net Primary Productivity (NPP) product. This uses data from MODIS (Moderate Resolution Imaging Spectroradiometer) to measure the amount of carbon captured by plants (indicating their growth and health). The NPP product is generated from satellite data of daily vegetation observations and computations using several "environmental" factors known to affect plant growth (such as light, temperature, and moisture) to estimate net carbon fixation. Information from MODIS has a spatial resolution of 500 meters, allowing fairly detailed and comprehensive global coverage. The annual data we downloaded extended from 2017 to 2020. The EVI data has a spatial resolution of 30 meters. So, to bring it into alignment with the spatial resolution of the calculated NPP data (500 meters), we used the nearest neighbor method to resample the EVI data to 500 meters.

2.3 Statistical analysis

This research employed a number of statistical analyses (see Figure 2). We began by looking at the interrelationships among the SPI, EVI, and NPP. To do this, we calculated a correlation coefficient matrix. Analyzing this matrix revealed quite a bit about the associations among these three key variables. Our second analytical step was to generate annual percentage change data for the NPP. We used the following equation to do this:

NPP percentage change= [(NPPy – NPPr) / NPPr]×100 …………………… **(Eq.7)**

where NPPr is the NPP for the reference year (2017 in this case), and NPPy is the NPP for a given year (e.g., 2018, 2019, 2020).

The last step consisted of using a geographically weighted regression (GWR) approach to estimate NPP using both EVI and SPI data. This was done to shed light on the interplay between the remote sensing-based index (EVI), the meteorological-based index (SPI), and the NPP field data in the study area, as a proxy for changes and variations in biodiversity.

The result of the GWR is a pixel-wise R-squared map of the NPP outcome, which previous studies provisionally interpret as the local explanatory power of EVI and SPI in the regression model that estimated NPP.

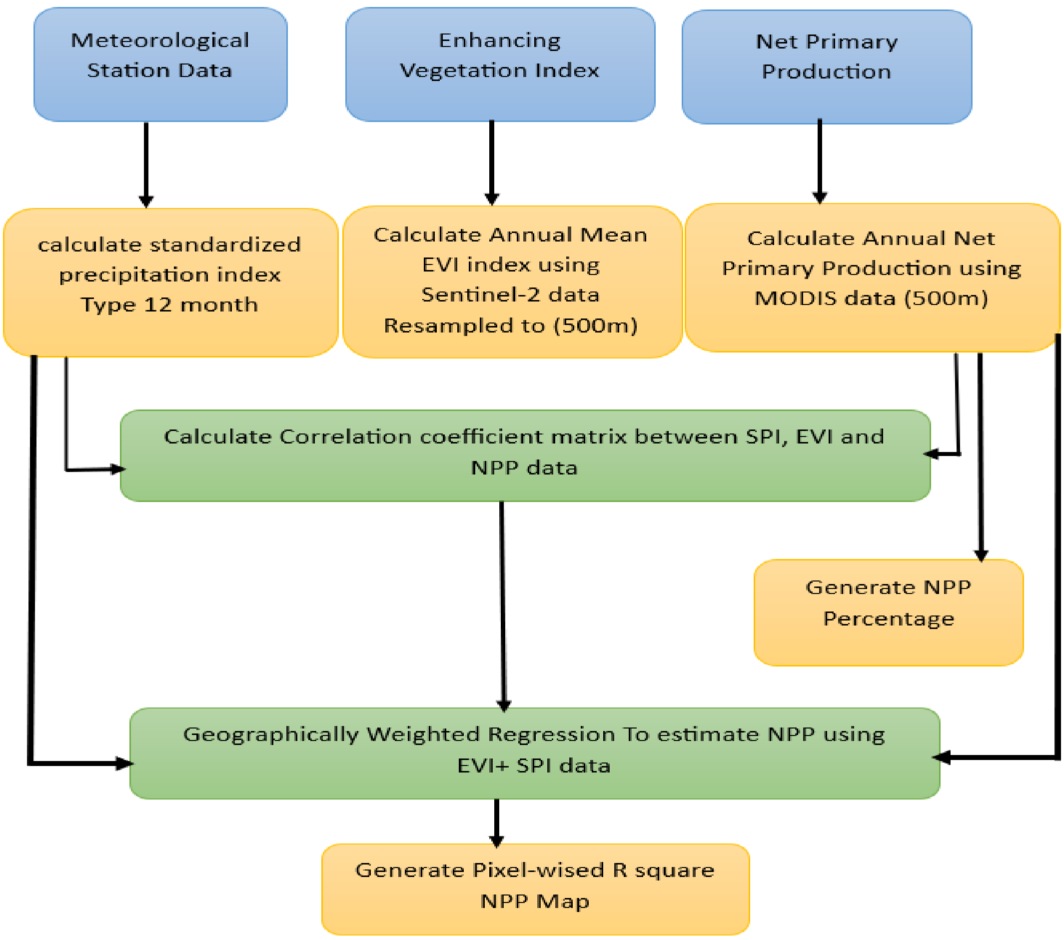

Figure 2. General workflow of methodology and utilized data in this study.

3.Results

3.1Temporal Trends in EVI, NPP, and SPI-12 Across the Study Area

The box plot technique was used to present the annual temporal changes of derived NPP data, as well as EVI data 2017 to 2020. The EVI data trends from this four-year period are shown in Figure 3a. In 2017, the median value of EVI was consistently low (i.e., below 2), but in 2018, it increased slightly. Although the EVI remained relatively low during both years, there were consistent periods in 2017 and 2018 where these low values persisted over several months. From 2019 to 2020, the EVI rose considerably! By 2020, the appearance of EVI was pretty wild — several months with high values that looked like grass- and/or herbaceous-dominated conditions, and then a few months with really low values indicating essentially bare ground and/or dark conditions.

Net Primary Productivity (NPP) in kilograms of carbon per square meter was shown across the same four consecutive years in the second part of Figure 3. In 2017, the NPP median was around 0.15 kgC/m², with the interquartile range extending from just above 0.1 kgC/m² to nearly 0.2 kgC/m². In 2018, it increased to just under 0.25 kgC/m², with the IQR that year extending from approximately 0.15 to almost 0.35 kgC/m². In 2019, it decreased to just above 0.25 kgC/m². That year's IQR was from nearly 0.15 kgC/m² to just below 0.30 kgC/m². Finally, NPP increased again in 2020, with the median near 0.25 kgC/m². The range that year extended from nearly 0.20 kgC/m² to a bit over 0.30 kgC/m². The amounts in the NPP, especially the medians, likely relate to the amounts shown in the NPP for the ecosystem and the expressed variation in carbon sequestration.

Moreover, figure 3c illustrates how the Standardized Precipitation Index (SPI-12) has changed over the four successive years taken into consideration for this investigation. There seems to be an overall upward trend in the spread (IQR) and in the median values of this particular index. The most pronounced change came about in 2020, where you can see both the central tendency and the spread take off from 2019's values and head upward.

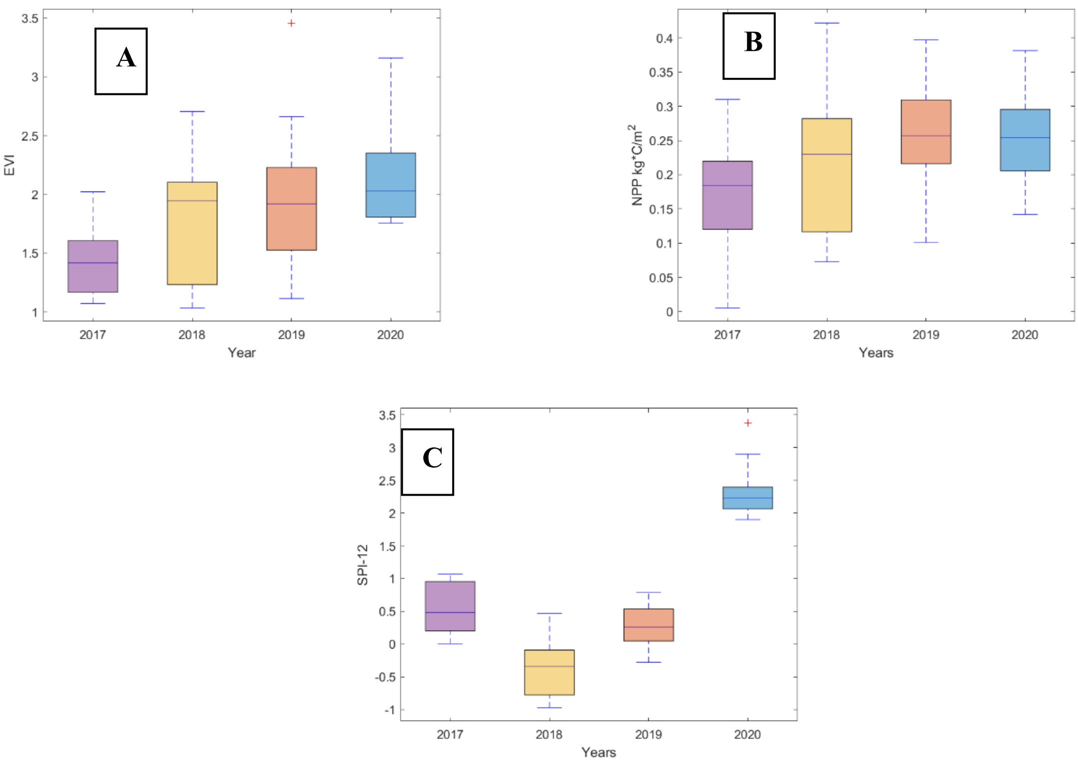

Figure 3. Annual temporal changes of calculated; A- EVI, B- NPP, and C- SPI

3.2. Temporal Analysis of Net Primary Productivity (NPP) Percentage Change Maps

The maps in Figure (4) that illustrate the Net Primary Productivity (NPP) changes from 2017 to the present day indicate the biggest changes over the previous five years... In 2018, compared to the baseline year of 2017, the areas in red spotlight steep NPP declines (≤-50%); the yellow-shaded areas show mostly stable NPP, while the green-shaded sectors show significant increases (≥ +50%): For 2019, the same color-coding scheme was used to highlight in red those areas that have experienced the most significant NPP declines. One change in NPP in yellow for 2019. The areas in green highlight some significant (+50%) increases in 2019.

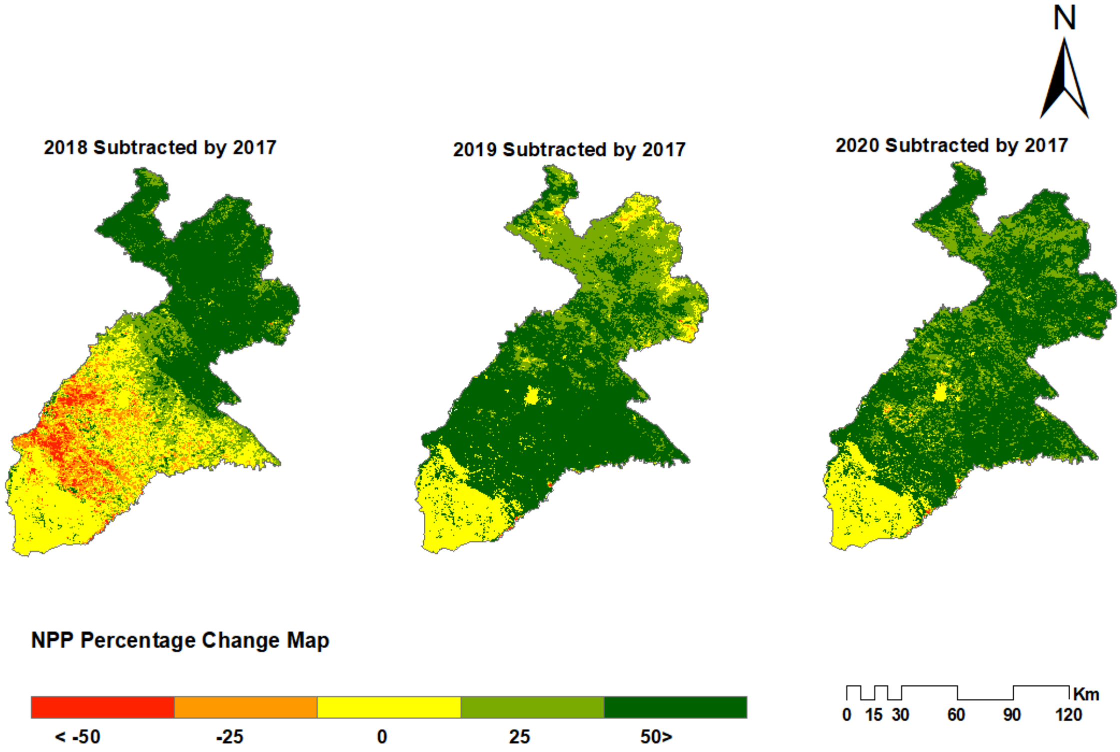

Figure 4. Map of NPP percentage change from 2017 to 2020.

3.3. Spatial and Temporal Analysis of SPI and EVI Maps:

To characterize meteorological drought over different timescales, Figure (5a) displays the Standardized Precipitation Index (SPI) maps over a 12-month period... In 2017, the northern part of the region exhibited high SPI values (depicted in blue), while the southern areas predominantly showed low values (in red). However, 2018 saw an overall decrease in SPI values, indicating drier conditions. By 2019, there was a recovery, with increased positive SPI values across most of the region, although some southern areas remained persistently dry. In an unspecified subsequent year, extremely high SPI values suggested a substantial increase in precipitation compared to previous years. These trends provide valuable insights into evolving climatic conditions and regional variability, impacting ecosystems, agriculture, and water resources.

Furthermore, Figure (5 b) illustrates EVI maps revealing intriguing patterns in vegetation dynamics over the observed years from 2017 to 2020. In 2017, the EVI values were generally lower across most of the region, especially in the peripheral areas, indicating sparse vegetation cover, while the central regions displayed moderate values, suggesting initial signs of vegetation health. In 2018, there was a noticeable improvement in EVI values, particularly in the central region, indicating an increase in vegetation density or recovery, although the peripheral areas continued to exhibit lower values, implying less vegetation or urbanization effects. By 2019, the central region showed further increases in EVI, reflecting significant improvement in vegetation health, but the peripheral areas still maintained lower values, consistent with previous years in terms of limited vegetative cover. In 2020, the upward trend of EVI values in the central region continued, with even higher values indicating stable and healthy vegetation, while the peripheral areas remained unchanged with low EVI, reinforcing the contrast between the densely vegetated core and the sparse periphery

On the other hand, Figure (5 c) presents the Net Primary Productivity (NPP) maps for the same region over the years 2017 to 2020, providing complementary insights when compared with the EVI maps in Figure (5 b). In 2017, both the NPP and EVI values were generally lower, especially in the southern and peripheral areas, indicating lower vegetation productivity and density. This trend aligns with the sparse vegetation indicated by lower EVI values during the same year. As we move to 2018, there is a clear increase in NPP, particularly in the northern and central regions, which corresponds to the improvement in EVI values for the same areas, suggesting both denser and more productive vegetation. In 2019, the central region continues to show high NPP values, reinforcing the vegetation health observed in the EVI map. This positive trend in vegetation productivity is consistent with the upward trend in EVI, signaling recovery and stability in vegetative cover. By 2020, NPP values remain elevated in the central areas but decrease slightly in peripheral regions, where EVI values also remain lower. This suggests that while the core of the region continues to maintain strong vegetative growth and density, as indicated by both NPP and EVI, the peripheral areas still face challenges in vegetation recovery, likely due to urbanization or other environmental stresses...

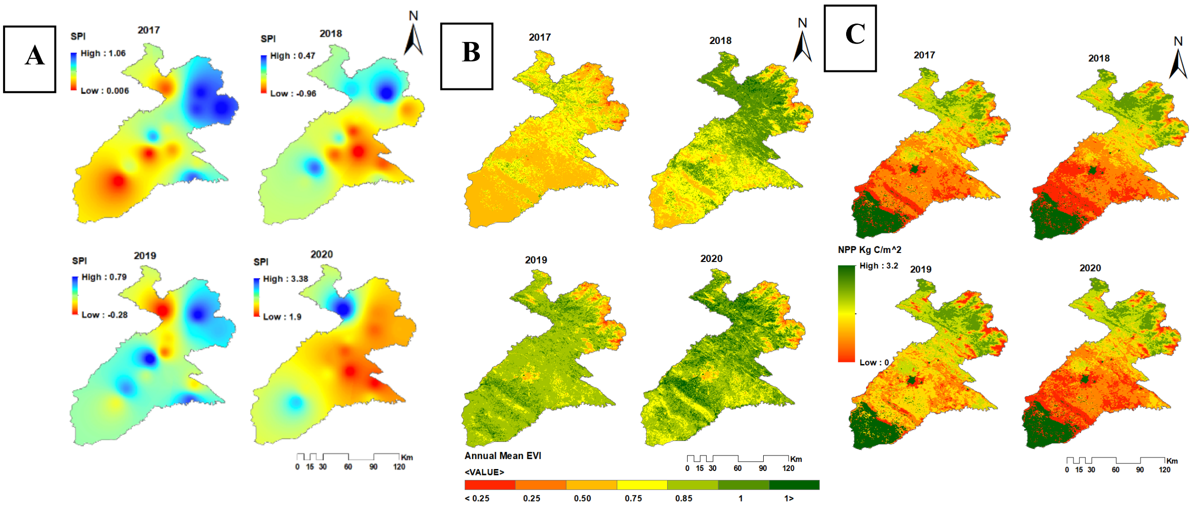

Figure 5. Spatial and temporal variation of calculated. A- SPI, B- EVI, and C- NPP data

3.4. Analysis of EVI, SPI and NPP Correlations over Different Years

A correlation matrix representing the relationships between the several entities EVI, SPI, and NPP is shown in Figure 6... The variables in this correlation matrix can be found on both the horizontal and vertical axes. The nature of the relationship between pairs of variables is represented in the cells. Each cell contains a correlation coefficient (a number between -1 and 1) that denotes the strength and direction of the association. A correlation coefficient of 1 indicates a perfect positive correlation, and a coefficient of -1 indicates a perfect negative correlation. A correlation coefficient of 0 indicates no apparent relationship.

In 2017, the Standardized Precipitation Index (SPI) exhibited a solid positive relationship with the Net Primary Productivity (NPP) and Enhanced Vegetation Index (EVI). The NPP makes a relatively direct estimate of plant growth and photosynthetic processes, while the EVI is a satellite-based measure of vegetation cover. SPI's combination of direct and indirect relationships with plant productivity and vegetation growth makes it a potentially strong correlation for understanding the relationship between precipitation and these two plant-related variables.

While the 2017 SPI exhibited solid relationships with both NPP and EVI, the 2020 EVI demonstrated a weak inverse relationship with the 2017 SPI.

Moreover, between 2018 and 2019, we see a much stronger correlation (0.7477) between EVI values in two consecutive years than we do the correlation between EVI and NDVI. This means that if a particular pixel has a high EVI value in 2018, there is a very good chance that the same pixel will have a similarly high EVI value in 2019.

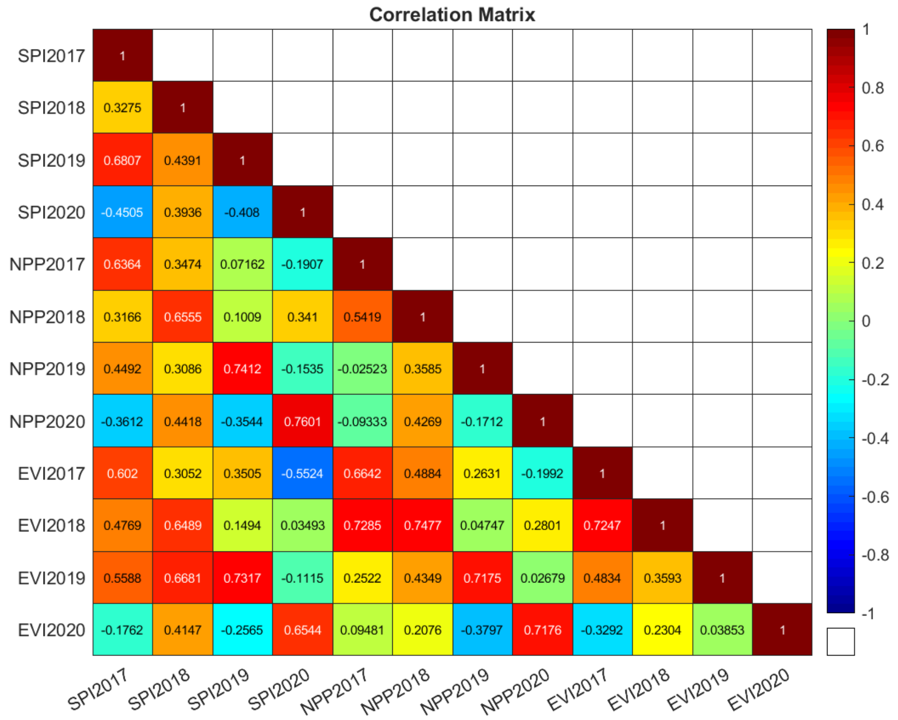

Figure 6. Correlation matrix between EVI, SPI, and NPP data from 2017 to 2020

3.5. Geospatial Analysis of SPI, EVI, and NPP Relationships Using GWR

To investigate how well the EVI and SPI can work together to estimate NPP, we employed the Geographically Weighted Regression (GWR) model. Figure 7 displays the pixel-wise R-squared values derived from the GWR. In our study, we interpreted higher R-squared (R2) values as indicating a stronger relationship between EVI, SPI, and NPP, and used the GWR results to illustrate this relationship geographically. We also noted that the pixels with the lowest relationships were clustered at the top of the image, which is a.k.a. the map at the top of the study area.

The results highlight the spatial variability in the associations among EVI, NPP, and SPI. The associations were strongest in the north and centre of the study area and weakest in the south. The image does not allow one to draw any definitive conclusions about the reason for that, but one possible explanation is that the southern part of the study area may be in a quasi-arid state for much of the year.

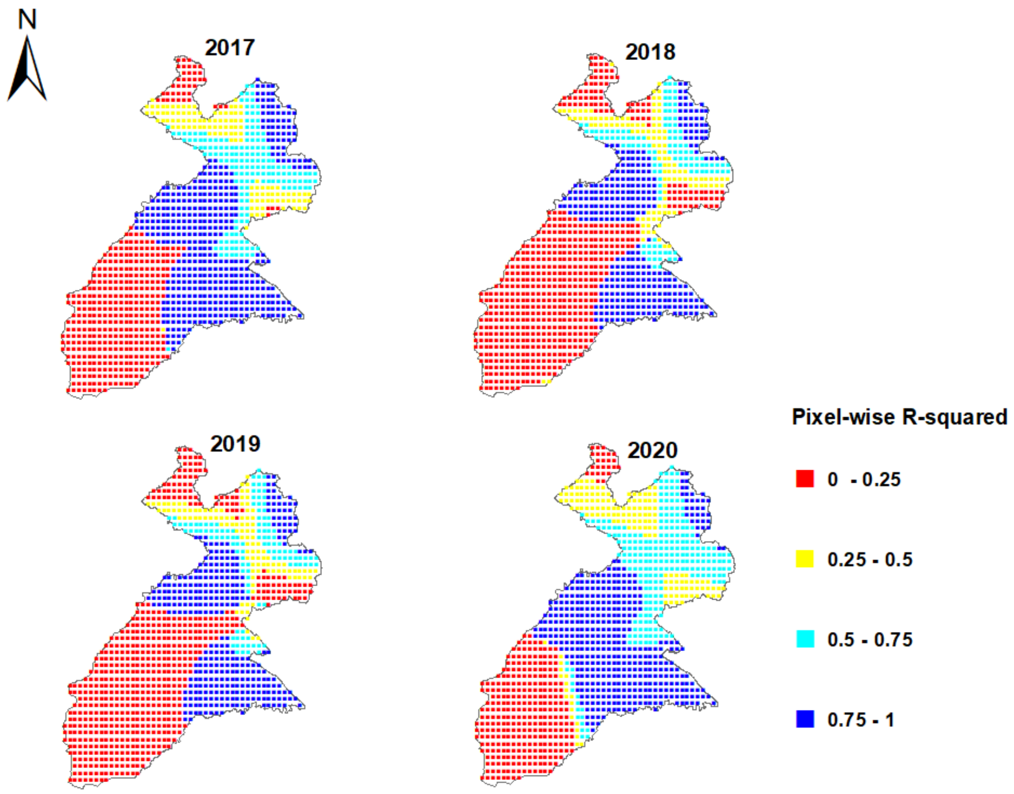

Figure 7. Pixel-wise R-squared map for estimated NPP using a geographical weighted regression approach with EVI and SPI data during the periods between 2017 to 2020.

4. Discussion and Conclusions

The temporal shifts in biodiversity in the Erbil Governorate have never been scientifically examined. In other words, investigating changes in biodiversity over time is a difficult and resource-intensive endeavor. This study is the first of its kind to look at this issue and to employ a relatively novel and user-friendly tool for examining changes in biodiversity in Erbil Governorate. The study utilized Net Primary Productivity (NPP), which can be computed using remote sensing data, as a stand-in for estimating shifts in biodiversity. In addition, the study further examined (using regression analyses) relationships between NPP and two other remote sensing index estimation tools (Enhanced Vegetation Index [EVI] and Standardized Precipitation Index) that also stand in for changes in biodiversity and associated environmental conditions.

Figure 4, the NPP percentage change map, details the change in the northern part of the study area, which has shown a steady and persistent increase in net primary productivity, while the southern portion appears quite different. The southern area has experienced the most pronounced decline in NPP (Gaznayee et al., 2021). This is likely due to the fact that the southern part of the Erbil Governorate (Razvanchy & Fayyadh, 2022) is primarily agricultural. Agricultural areas are more strongly affected by the quantity and timing of precipitation, as well as by other seasonal changes. Grazing and crop production also can impact local biodiversity in ways that are net negative for primary productivity—reducing it. In comparison, the northern region, which is mostly mountainous and heavily forested, is seeing a steady uptick in biodiversity. Our findings bear this out. As seen in Figure 5, the apparent distribution of the northern part's vegetation cover—represented here as EVI—when compared to the cover in the southern part, indicates that the northern part far outpaces the southern part in not only vegetation cover but also in the amount of precipitation received (compared using SPI). Specifically, the northern part is not just wetter; it's also much greener than the southern part (Al-Hedny, Muhaimeed, & Iraq, 2020; Daham et al., 2018).

It is important to note that, the results revealed a strong positive relationship exists between the calculated spectral index EVI and the NPP product from the MODIS satellite. The correlation ranges from 0.68 to 0.76. This association is essential for the work described in this paper, which aims to use spectral indices and NPP data to monitor changes in biodiversity. Since EVI and NPP can be tracked using satellite remote sensing, they provide very powerful indices for assessing what is happening to the changes and dynamics of biodiversity across a large swath of land over time species (Elmqvist et al., 2012). Data from satellites allow for the consistent and repeatable measurement of important ecological indicators over vast stretches of land and extended periods of time. The power of satellite-based measurements lies in their ability to cover large swaths of not just terrain but also vegetation, making them a kind of "vegetation autopsy" (Cohen et al., 2016). Vegetation indices like EVI and NPP can pinpoint places where stress or even degradation is occurring. They can also highlight places where those indicators are not performing as expected, which might seem like "false vegetation fidelity" (Cohen et al., 2016). Understanding the causes and the consequences for biodiversity associated with these trends is vitally important if we are to make informed decisions about conservation priorities and ensure that both ecosystems and the diverse array of species that inhabit them remain healthy over both the short and long terms (Zeng et al., 2022).

In a similar vein, when the Geographically Weighted Regression (GWR) method is used to analyze the data, it highlights the EVI and SPI indices' real potential for estimating NPP. The images display the GWR model's R-squared values at a fine spatial resolution. In essence, the higher values indicate a stronger relationship between the indices and the NPP at certain locations. The northern and central parts of the study area have R-squared values much higher (0.5 to 0.7) than the southern section. Not only is this result interesting, but it is also suggestive of a strong wet-to

dry gradient. It seems to indicate a much stronger correlation in the wetter northern and central parts of the study area.

The major findings underscore the critical role that the SPI and EVI play in monitoring changes in vegetation. They function as a sort of advance alert system to pick up on changes in what some scientists regard as the most vital land-based ecosystems: forests and grasslands and other kinds of vegetation.

5.References

-Abdullah, H., Omar, D. k., Polat, N., Bilgili, A. V., & Sharef, S. H. (2020). A comparison between day and night land surface temperatures using acquired satellite thermal infrared data in a winter wheat field. *Remote Sensing Applications: Society and Environment, 19*, 100368. doi:https://doi.org/10.1016/j.rsase.2020.100368

-Al-Hedny, S. M., Muhaimeed, A. S. J. E. R. S., & Iraq, G. i. (2020). Drought monitoring for Northern Part of Iraq using temporal NDVI and rainfall indices. 301-331.

-Daham, A., Han, D., Rico-Ramirez, M., & Marsh, A. J. E. e. s. (2018). Analysis of NVDI variability in response to precipitation and air temperature in different regions of Iraq, using MODIS vegetation indices. *77*, 1-24.

-Elmqvist, T., Maltby, E., Barker, T., Mortimer, M., Perrings, C., Aronson, J., . . . Norberg, J. (2012). Biodiversity, ecosystems and ecosystem services. In *The Economics of Ecosystems and Biodiversity: Ecological and economic foundations* (pp. 41-111): Routledge.

-Gaznayee, H. A. A., Al-Quraishi, A. M. F., & Al-Sulttani, A. H. A. J. I. J. o. S. (2021). Drought spatiotemporal characteristics based on a vegetation condition index in Erbil, Kurdistan Region, Iraq. 4545-4556.

-Hickler, T., Smith, B., Sykes, M. T., Davis, M. B., Sugita, S., & Walker, K. J. E. (2004). Using a generalized vegetation model to simulate vegetation dynamics in northeastern USA. *85*(2), 519-530.

-Huete, A., Didan, K., Miura, T., Rodriguez, E. P., Gao, X., & Ferreira, L. G. J. R. s. o. e. (2002). Overview of the radiometric and biophysical performance of the MODIS vegetation indices. *83*(1-2), 195-213.

-Hussein, S. O., Kovács, F., Tobak, Z., Abdullah, H. J. J. A. G. D. L., & series, E. (2018). Spatial distribution of vegetation cover in Erbil city districts using high-resolution Pléiades satellite image. *12*(1), 10-22.

-Kooistra, L., Wamelink, W., Schaepman-Strub, G., Schaepman, M., van Dobben, H., Aduaka, U., & Batelaan, O. J. R. S. o. E. (2008). Assessing and predicting biodiversity in a floodplain ecosystem: Assimilation of net primary production derived from imaging spectrometer data into a dynamic vegetation model. *112*(5), 2118-2130.

-Kuenzer, C., Ottinger, M., Wegmann, M., Guo, H., Wang, C., Zhang, J., . . . Wikelski, M. J. I. J. o. R. S. (2014). Earth observation satellite sensors for biodiversity monitoring: potentials and bottlenecks. *35*(18), 6599-6647.

-Lei, T., Feng, J., Lv, J., Wang, J., Song, H., Song, W., & Gao, X. J. J. o. e. m. (2020). Net Primary Productivity Loss under different drought levels in different grassland ecosystems. *274*, 111144.

-Maclaurin, J., & Sterelny, K. (2008). *What is biodiversity?* : University of Chicago Press.

-Mustafa Alee, M., Danandeh Mehr, A., Akdegirmen, O., & Nourani, V. J. S. (2023). Drought assessment across erbil using satellite products. *15*(8), 6687.

-Nagendra, H., Lucas, R., Honrado, J. P., Jongman, R. H., Tarantino, C., Adamo, M., & Mairota, P. J. E. I. (2013). Remote sensing for conservation monitoring: Assessing protected areas, habitat extent, habitat condition, species diversity, and threats. *33*, 45-59.

-Rawat, U., & Agarwal, N. K. J. E. C. J. (2015). Biodiversity: Concept, threats and conservation. *16*(3), 19-28.

-Razvanchy, H. A., & Fayyadh, M. A. J. B. J. o. A. S. (2022). GIS and AHP Based Techniques for Agricultural Land Suitability Assessment in Erbil Province, Kurdistan region, Iraq. *35*(1), 140-157.

-Roxburgh, S., Berry, S. L., Buckley, T., Barnes, B., & Roderick, M. J. F. E. (2005). What is NPP? Inconsistent accounting of respiratory fluxes in the definition of net primary production. *19*(3), 378-382.

-Sharma, I., & Birman, S. (2024). Biodiversity Loss, Ecosystem Services, and Their Role in Promoting Sustainable Health. In *The Climate-Health-Sustainability Nexus: Understanding the Interconnected Impact on Populations and the Environment* (pp. 163-188): Springer.

-Taelman, S. E., Schaubroeck, T., De Meester, S., Boone, L., & Dewulf, J. J. S. o. t. T. E. (2016). Accounting for land use in life cycle assessment: the value of NPP as a proxy indicator to assess land use impacts on ecosystems. *550*, 143-156.

-Terwayet Bayouli, O., Zhang, W., & Terwayet Bayouli, H. J. A. J. o. G. (2023). Assessment of drought characteristics and its impacts on net primary productivity (NPP) in southeastern Tunisia. *16*(1), 26.

-Turner, W., Spector, S., Gardiner, N., Fladeland, M., Sterling, E., Steininger, M. J. T. i. e., & evolution. (2003). Remote sensing for biodiversity science and conservation. *18*(6), 306-314.

-Vihervaara, P., Auvinen, A.-P., Mononen, L., Törmä, M., Ahlroth, P., Anttila, S., . . . Conservation. (2017). How essential biodiversity variables and remote sensing can help national biodiversity monitoring. *10*, 43-59.

-Wang, R., & Gamon, J. A. J. R. S. o. E. (2019). Remote sensing of terrestrial plant biodiversity. *231*, 111218.

-Yu, X., Wu, Z., & Guo, X. (2013). *Investigating the potential of GIMMS and MODIS NDVI data sets for estimating gross primary productivity in Harvard Forest.* Paper presented at the MultiTemp 2013: 7th International Workshop on the Analysis of Multi-temporal Remote Sensing Images.

-Zeng, X., Hu, Z., Chen, A., Yuan, W., Hou, G., Han, D., . . . Luo, D. J. G. C. B. (2022). The global decline in the sensitivity of vegetation productivity to precipitation from 2001 to 2018. *28*(22), 6823-6833.

-Zhang, C. I., Lee, J. B., Kim, S., & Oh, J.-H. J. P. i. O. (2000). Climatic regime shifts and their impacts on marine ecosystem and fisheries resources in Korean waters. *47*(2-4), 171-190.

-Salgotra, Romesh Kumar, and Bhagirath Singh Chauhan. "Genetic diversity, conservation, and utilization of plant genetic resources." Genes 14.1 (2023): 174.

-Garroutte, Erica L., Andrew J. Hansen, and Rick L. Lawrence. "Using NDVI and EVI to map spatiotemporal variation in the biomass and quality of forage for migratory elk in the Greater Yellowstone Ecosystem." Remote Sensing 8.5 (2016): 404.

چاودێریکردنی فرەچەشنی زیندەگی لە پارێزگای هەولێر -عێراق بە بەکارهێنانی داتاکانی هەستکردن لە دوورەوە

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پوختە
چاودێریکردنی فرەچەشنی زیندەگی زۆر گرنگە بۆ پاراستنی لەباری تەندروستی ئیکۆسیستەم، بەڵام لەگەڵ ئەوەشدا شێوازە تەقلیدییەکان ڕووبەڕووی ئاستەنگ دەبنەوە لەرووی دەستپێگەیشتن و دووریەکانی. لەم توێژینەوەیە داتای هەستکردن لە دوورەوە بەکارهاتووە بۆ چاودێریکردنی گۆڕانکارییەکانی فرەچەشنی زیندەگی لە پارێزگای هەولێر، عێراق، بە بەکارهێنانی پێوەرەکانی ڕووەکی چاککراو (EVI پێوەرە ستانداردەی بارانبارین (SPI)، و بەرهەمهێنانی سەرەتایی تۆڕ (NPP) وەک گۆڕاو بۆ گۆڕانی فرەچەشنی زیندەگی. توێژینەوەکە MODIS، وێنەی Sentinel-2، و داتای کەشناسی تێکەڵ دەکات بۆ هەڵسەنگاندنی گۆڕانکارییە شوێنی و کاتیەکانی NPP، EVI، و SPI. دەرئەنجامە سەرەکییەکان ئاماژەن دەکەن بۆ گۆڕانکاری ساڵانەی بەرچاو لە EVI. بەهای ناوەندی EVI لە ساڵی 2017 لە 2 بەرز بۆتەوە بۆ نزیەی 3 لە ساڵی 2020، ئەمەش ئاماژەیە بۆ بەرزبوونەوەی چڕی ڕووەک و تەندروستی. بە هەمان شێوە، NPP بەرزبوونەوەی بەها ناوەندییەکان لە نزیکەی 0.15 کگم کاربۆن/م2 لە ساڵی 2017 بۆ نزیکەی 0.25 کگم کاربۆن/م2 لە ساڵی 2020 نیشان دا، کە ئەمەش ڕەنگدانەوەی باشتربوونی تواناکانی هەڵمژینی کاربۆنە. ئەم ئاراستانە جەخت لەسەر خۆڕاگری و توانای ناوچەکە دەکەنەوە بۆ گۆڕانی کەشوهەوا، هەروەک لە پەیوەندی نێوان بەهاکانی EVI، NPP و SPIدا دەردەکەوێت. سەرەڕای ئەوەش، توێژینەوەکە پەیوەندییەکی ئەرێنی بەهێزی ئاشکرا کرد کە لە نێوان 0.68 بۆ 0.74 بوو، لە نێوان EVI کە لە داتاکانی Sentinel-2 وەرگیراوە و NPP کە لە مانگی دەستکردی MODIS وەرگیراوە.

ئەم توێژینەوەیە تیشک دەخاتە سەر کاریگەری هەستکردن لە دوورەوە لە دەستنیشان کردنی داینامیکی ئیکۆلۆژی ورد، کە تێڕوانینێکی چارەنووسساز بۆ پاراستنی فرەچەشنی زیندەگی و بەڕێوەبردنی ئیکۆسیستەمی بەردەوام لە پارێزگای هەولێر دابین دەکات

ووشە سەرەکییەکان: چاودێریکردنی فرەچەشنی زیندەگی، هەستکردن لە دوورەوە، Sentinel-2، MODIS ؛ پێوەری ستانداردەی بارانبارین (SPI)؛ بەرهەمهێنانی سەرەتایی تۆڕ (NPP) و پێوەرەی ڕووەکی چاککراو (EVI)

مراقبة التنوع الحيوي في محافظة أربيل – العراق باستخدام بيانات الاستشعار عن بعد

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ملخص
يعد مراقبة التنوع الحيوي أمرا ضروريا للحفاظ على صحة النظام البيئي، إلا أن الأساليب التقليدية تواجه تحديات في إمكانية الوصول و مستوياته. تستخدم هذه الدراسة بيانات الاستشعار عن بعد لـمراقبة التغيرات في التنوع الحيوي في محافظة أربيل، العراق، مع التركيز على مؤشر معزز للغطاء النباتي (EVI)، و مؤشر الموحد للامطار (SPI)، وصافي الإنتاجية الأولية (NPP) كعوامل بديلة لتغير التنوع الحيوي. يدمج البحث صور MODIS وصور Sentinel-2 وبيانات الأرصاد الجوية لتقييم الاختلافات المكانية والزمانية في NPP وEVI وSPI. وتشير النتائج الرئيسية إلى حدوث تغيرات سنوية كبيرة في صحة الغطاء النباتي وإنتاجيته. من عام 2017 إلى عام 2020، ارتفع متوسط قيمة مؤشر EVI من أقل من 2 في عام 2017 إلى ما يقرب من 3 في عام 2020، مما يشير إلى تعزيز كثافة الغطاء النباتي وصحته. وبالمثل، أظهرت NPP تقلبات مع زيادة القيم المتوسطة من حوالي 0.15 كجم كربون/م^2 في

عام 2017 إلى ما يقرب من 0.25 كجم كربون/م² في عام 2020، مما يعكس تحسن قدرات امتصاص الكربون. وتؤكد هذه الاتجاهات قدرة المنطقة على الصمود واستجابتها للتقلبات المناخية، كما يتضح من العلاقة بين قيم مؤشر EVI و NPP و SPI. علاوة على ذلك، كشفت الدراسة عن وجود علاقة إيجابية قوية، تتراوح من 0.68 إلى 0.74، بين مؤشر EVI من بيانات Sentinel-2 وNPP التي تم الحصول عليها من القمر الصناعي MODIS.

تسلط هذه الدراسة الضوء على فعالية الاستشعار عن بعد في التقاط الديناميكيات البيئية التفصيلية، مما يوفر رؤى مهمة للحفاظ على التنوع الحيوي والإدارة المستدامة للنظام البيئي في محافظة أربيل.

الكلمات المفتاحية:مراقبة التنوع الحيوي؛ الاستشعار عن بعد؛ Sentinel-2؛ MODIS ؛ مؤشر الموحد للامطار (SPI)؛ صافي الإنتاجية الأولية (NPP) و مؤشر معزز للغطاء النباتي (EVI)