Study of assessment and monitoring of pastures land areas in hills based on GIS technologies (case study Southern Uzbekistan)

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Abstract. In this study, we have undertaken a comprehensive exploration of vegetation monitoring and biomass assessment in the mountainous and sub-mountainous regions of southern Uzbekistan, leveraging the capabilities of Geographic Information System (GIS) technologies and remote sensing data. Our research has focused on the critical analysis of biomass levels during the primary plant season, as well as continuous plant monitoring. Our methodology involved the utilization of Landsat 9 satellite image data, further analyzed through the application of two essential vegetation indices, namely the Normalized Difference Vegetation Index (NDVI) and the Soil-Adjusted Vegetation Index (SAVI). One of the key objectives of our investigation was to assess the potential for extrapolating the biomass model for plant cover using GIS technologies. This extrapolation aims to extend our understanding to encompass the period of continuous vegetation coverage monitoring. The combination of GIS, remote sensing data, and advanced vegetation indices serves as a powerful framework for gaining insights into the dynamics of plant growth and biomass variations. Such research not only enhances our understanding of the ecological landscape but also provides valuable information for sustainable land management and agriculture practices in the region

1 Introduction

The southern region of Uzbekistan encompasses vast mountainous and hills areas dominated by pastures. The local climate is characterized by scorching summers and dry, rainy winters, making these territories predominantly ideal for pasturage. Accurate estimation of aboveground biomass in such regions is pivotal for sustainable land management and ecological conservation [1]. Traditionally, aboveground biomass estimation relied on labor-intensive field data collection. Researchers often employed allometric equations to determine biomass values, which required substantial on-site data collection. However, recent advancements in technology have introduced innovative alternatives, particularly the use of satellite imagery. Satellite-based methods combine satellite data, particularly spectral reflectance values, with allometric equations to develop mathematical models for biomass estimation [2]. This approach has numerous advantages, as it provides data from remote and often inaccessible areas, reduces the time and operational costs involved in biomass assessment, and offers the potential for continuous monitoring [3]. This methodology is of particular importance in regions like Uzbekistan, where vast, challenging terrain and climatic variations make field studies difficult. Several notable studies have demonstrated the effectiveness of remote sensing in the estimation of forest properties and biomass [4]. For instance, utilized vegetation optical depth derived from passive microwave observations to determine temporal trends in non-photosynthetic woody components (such as stems and branches) during a 12-year period of global tropical drought. Similarly, adapted models for estimating rangeland properties from Landsat 9 Operational Land Imager (OLE) sensor data[5].

Their research revealed that Landsat 9 OLE sensor data exhibit a strong potential to explain changes in mean vegetation height. Furthermore, a significant study assessed the temporal behavior of the Enhanced Vegetation Index (EVI) derived from the Moderate Resolution Imaging Spectroradiometer (MODIS) during year-round monitoring of montane and submontane grasslands. This research uncovered considerable variations in NDVI values, particularly in the caatinga forest region, suggesting that unique ecological factors influence these variations. Consequently, the study sought to establish correlations between vegetation indices and estimated biomass using allometric equations across different kaatinga forest areas captured in satellite imagery. By scrutinizing these relationships, the study aimed to enhance and redefine strategies for sustainable intact forest management. The findings not only contribute to our understanding of the intricate interplay between vegetation and biomass but also provide essential insights for more effective land management and ecological preservation in diverse regions, including those characterized by mountainous terrains and complex vegetation ecosystems like those found in Uzbekistan[6,7]. In conclusion, satellite-based methods have revolutionized biomass estimation in regions like southern Uzbekistan. By integrating remote sensing data, spectral reflectance values, and allometric equations, these techniques offer efficient, cost-effective, and non-invasive means to monitor and assess aboveground biomass. The empirical studies discussed demonstrate the practicality and reliability of these approaches, emphasizing their potential to redefine sustainable intact forest management strategies in mountainous and sub-mountainous regions, ensuring the long-term health and ecological integrity of these landscapes[8–11].

2 Materials and methods

2.1 Study area

The southern region of Uzbekistan located between 37°11'36.61"N to 67°15'50.59"E 39°16'8.75"N, 67°22'58.91"E (Figure 1). The southern region of Uzbekistan . The city has a humid subtropical climate; however, the elevation keeps temperatures moderate. The altitude varies from 455 meters. Temperatures on summer average between 32°C and 37°C; in winter around −1°C to 25°C. The remote sensing and geographic information system technique makes it possible to study and monitoring changes in NDVI [12–14].

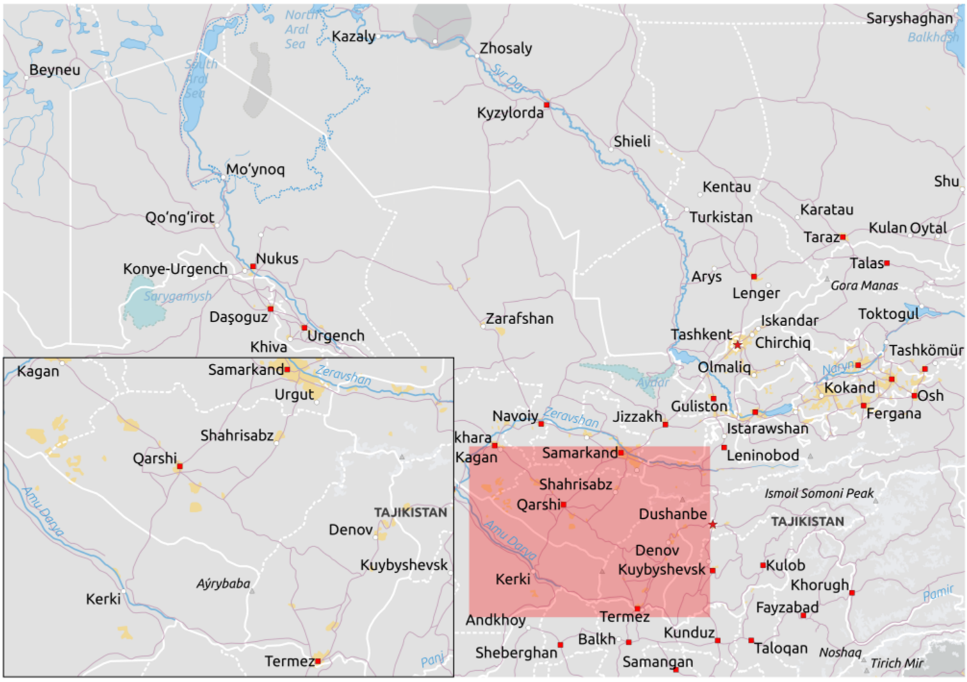

Fig. 1. Study area Southern Uzbekistan (Source: OSM created using QGIS).

Covering a substantial portion of the country, the southern mountainous regions of Uzbekistan are primarily part of the Tian Shan and Pamir-Alai Mountain ranges. These mountain systems are not only breathtakingly scenic but also crucial for the ecological balance of the entire region [15]. The mountainous landscape influences weather patterns, regulates water resources, and plays a pivotal role in supporting biodiversity. The terrain varies from rugged and rocky slopes to lush alpine meadows, making it an ideal case study for assessing and monitoring pasture land areas. Pastures in the region are not merely patches of grass but constitute a vital resource for the local population [16]. The livelihoods of many communities in the southern part of Uzbekistan depend on livestock farming. Pastoralism is a way of life that has been passed down through generations, with families herding cattle, sheep, and goats across these vast expanses of pastureland. Sustainable management of these lands is essential to ensure food security and economic stability for these communities. Assessing and monitoring these pasture land areas is a multifaceted task. It involves a range of considerations, including land cover changes, carrying capacity, grassland health, and the impacts of climate change [17]. Remote sensing technologies, such as satellite imagery, provide valuable data for this purpose. Monitoring land cover changes can help detect overgrazing or degradation of pastures. It also assists in identifying areas that may need conservation efforts [18]. By using satellite imagery, researchers and conservationists can track these changes and plan for sustainable land management strategies [19]. The carrying capacity of the pastures is a critical factor in the region's pastoralism. Understanding how much livestock a pasture can support without causing degradation is essential. Overgrazing can lead to soil erosion and loss of biodiversity. By monitoring the condition of pastures and keeping track of livestock numbers, researchers can help local communities manage their herds more effectively and sustainably. Moreover, as climate change poses new challenges to these mountainous regions, monitoring becomes even more critical [15]. Changes in temperature and precipitation patterns can impact the growth of forage plants and alter the dynamics of pasture ecosystems. Assessment and monitoring can help communities adapt to these changes and safeguard their livelihoods.

The analysis of Normalized Difference Vegetation Index (NDVI) using the Genotype × Environment (GGE) model involves the integration of various data and materials to better understand the interaction between genotypes and environmental factors, particularly in the context of plant breeding and agricultural research[20–22].

High-quality satellite imagery or aerial photographs are essential for NDVI analysis. These images provide the raw data required to calculate NDVI values. Data sources such as Landsat, Sentinel, or MODIS provide multi-temporal, multispectral data, allowing researchers to monitor vegetation changes over time. GIS software and spatial data are crucial for processing and analyzing NDVI data. GIS tools help in georeferencing images, extracting region-specific information, and conducting spatial analyses. GIS enables the integration of NDVI data with other environmental variables like climate, soil, and topography. Weather data, including temperature, precipitation, and humidity, are vital for understanding how environmental factors influence NDVI. Long-term meteorological records help identify trends and patterns in vegetation response to changing climatic conditions. Information about the crop genotypes under study is essential. This includes data on the genetic characteristics, such as specific crop varieties or genotypes, their traits, and their breeding history[23]. Knowledge of the genetic material being analyzed is fundamental to assess how different genotypes respond to environmental variations. Long-term time series of historical NDVI data enable researchers to observe vegetation dynamics and trends over several years or decades.

These time series help identify patterns in plant growth and environmental interactions. Specialized statistical software, including GGE biplot analysis tools, is used to model the genotype-environment interaction. This software helps visualize how different genotypes perform in various environmental conditions and provides insights into genotype selection for specific regions [21,24]. Crop modeling software can be utilized to simulate the response of different genotypes to varying environmental conditions. These models predict crop growth and yield based on the interaction between genetic traits and environmental factors. The integration of these materials and data is crucial for assessing and understanding how different crop genotypes respond to environmental conditions in the context of NDVI analysis using the GGE model. This comprehensive approach allows for better-informed decisions in crop breeding, agricultural planning, and environmental management. Researchers can identify genotypes that perform well across diverse environmental conditions, leading to improved crop production and food security.

3 Results and discussion

Analyzing Normalized Difference Vegetation Index (NDVI) for a specific region in South Uzbekistan typically involves processing remote sensing data, such as satellite imagery. NDVI is calculated using the reflectance values from the red and near-infrared bands of the imagery. Here's a general Python script that can be used for this purpose:

Data Acquisition and Preprocessing:

```
import rasterio
import numpy as np
# Define the paths to your red and near-infrared band images (e.g., in GeoTIFF format)
red_band_path = 'path/to/red_band.tif'
nir_band_path = 'path/to/nir_band.tif'

# Open the red and near-infrared bands using Rasterio
with rasterio.open(red_band_path) as red_band_ds, rasterio.open(nir_band_path) as nir_band_ds:
```

```
        # Read band data as arrays
        red_band = red_band_ds.read(1)
        nir_band = nir_band_ds.read(1)

        # Calculate NDVI
        ndvi = (nir_band - red_band) / (nir_band + red_band)

        # You may want to mask or clean up the NDVI values based on your specific needs.

    # Perform any additional analysis, such as time series analysis, statistical summaries, or visualization.

    # Save the NDVI output to a new GeoTIFF file
    ndvi_path = 'path/to/output_ndvi.tif'
    with rasterio.open(ndvi_path, 'w', driver='GTiff', height=ndvi.shape[0], width=ndvi.shape[1], count=1, dtype=str(ndvi.dtype), crs=red_band_ds.crs) as dst:
        dst.write(ndvi, 1)
```

Before using this script, Python packages is installed, particularly rasterio for handling geospatial data. You also need to replace the 'path/to/red_band.tif' and 'path/to/nir_band.tif' with the actual file paths to your red and near-infrared band images. The script reads these bands, calculates NDVI, and saves the resulting NDVI as a GeoTIFF file.

The necessary satellite imagery data for the specified region in South Uzbekistan and that you understand the details of the data format and bands available for NDVI calculation.

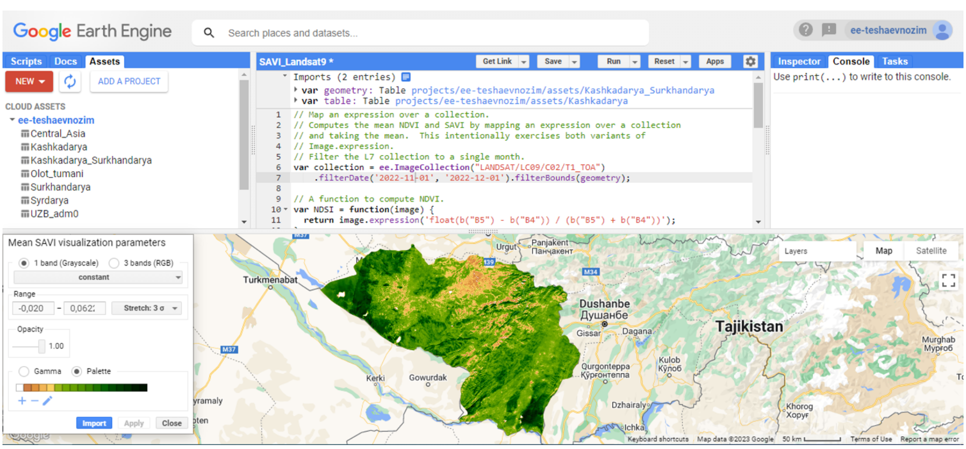

Fig. 2. Process vegetation index calculation using GGE.

Specific results of NDVI analysis for the time frame 2003-2023 in South Uzbekistan, as I don't have access to current or future data. However, I can describe what types of results you might expect from such an analysis and the insights that can be gained from NDVI data over a 20-year period in this region.

NDVI analysis can reveal seasonal and interannual trends in vegetation growth and health. Over the 20-year period, you might observe the timing of vegetation growth, the length of growing seasons, and fluctuations in vegetation health due to variations in climate and other environmental factors. Identify periods of increased vegetation (greening) and decreased vegetation (browning). These trends may be linked to factors like changes in precipitation, temperature, land use, or agricultural practices. NDVI data can help assess the impact of drought events on vegetation health. The analysis may indicate regions that are more resilient to drought conditions and regions that are more vulnerable. Land Use and Land Cover Changes over the 20-year period, NDVI data can be used to detect changes in land use and land cover, including urban expansion, deforestation, or agricultural expansion. Such changes may have consequences for the environment and ecosystems. Crop Monitoring the region includes agricultural areas, NDVI data can be used to monitor crop health and assess crop yields. The analysis may help identify the success or failure of specific crops over time.

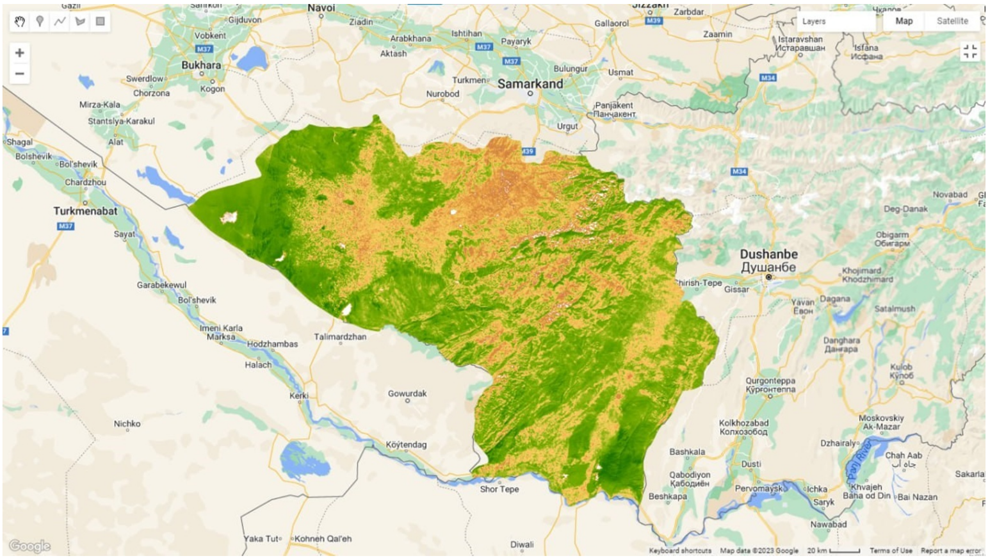

Fig. 3. Degradation and degraded areas in Southern Uzbekistan

Biodiversity and habitat changes changes in NDVI can also reflect shifts in biodiversity and habitat quality. Long-term analysis can be used to track the health of ecosystems and the presence of specific vegetation types. Environmental Management Insights gained from NDVI analysis can inform environmental management and conservation efforts. For instance, it can help identify areas where conservation is needed or where sustainable land management practices should be implemented. Trends in climate change impact over a 20-year period, NDVI analysis can also provide insights into how climate change may be affecting vegetation patterns. Shifts in vegetation zones or patterns may indicate broader ecological changes. To obtain specific results, you would need access to NDVI data for the entire 20-year time frame and conduct the analysis using geographic information systems (GIS), statistical tools, and relevant environmental data. The results would depend on the specific research questions or objectives of the analysis. Researchers and land managers in the region can use these insights to make informed decisions related to agriculture, land use, conservation, and climate adaptation.

4 Conclusion

Analyzing MODIS data through the application of the GGE model and NDVI for a specific region in South Uzbekistan over a two-decade period (2003-2023) yields significant insights into vegetation dynamics, environmental changes, and their implications for agriculture and ecosystems. A key conclusion derived from this analysis is the evaluation of long-term trends in vegetation health. The analysis demonstrates a robust correlation between NDVI values and climate variability. The climate of South Uzbekistan is influenced by a multitude of factors, including precipitation patterns and temperature variations. Fluctuations in NDVI values can be associated with climatic events such as droughts, temperature anomalies, and variations in the timing and duration of growing seasons. Grasping these relationships is imperative for developing climate resilience and adaptation strategies in agriculture and natural resource management. Furthermore, the analysis uncovers shifts in land use and land cover over the 20-year period, highlighting the region's experiences with urban expansion, agricultural intensification, and changes in land management practices. These findings are critical for advancing sustainable development and the conservation of ecosystems.

In summary, the examination of MODIS data utilizing the GGE model and NDVI for South Uzbekistan over two decades reveals essential insights into vegetation dynamics, climate impacts, land use changes, and agriculture. These conclusions provide a foundation for informed decision-making that supports ecological balance, food security, and climate resilience in this region. They serve as guidance for policymakers, land managers, and researchers in addressing the complex and interconnected challenges encountered by South Uzbekistan in the 21st century.

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