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REMOTE SENSING EVALUATION OF CLIMATIC FACTORS INFLUENCING AGRICULTURAL CROP GROWTH IN THE BUKHARA REGION

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Abstract: This research examines how key climatic variables influence cotton crop development through remote sensing data analysis. The study, conducted in the Bukhara region, explores the relationships between vegetation indices (NDVI, EVI, MNDWI, SAVI) and climatic parameters such as land surface temperature, air temperature, precipitation, solar radiation, and reference evapotranspiration (ET_0). Pearson correlation analysis revealed that crop growth had significant negative correlations with air temperature and evapotranspiration, whereas precipitation and solar radiation were positively correlated with vegetation indices. The findings demonstrate the potential of combining remote sensing and climatic data for effective crop monitoring and yield prediction in arid regions.

Keywords: remote sensing, vegetation indices, cotton, climatic factors, NDVI, ET_0, Bukhara region, correlation analysis.

Introduction

Agricultural productivity is highly influenced by climatic variability, particularly in arid and semi-arid regions where heat stress and limited water availability are major factors affecting crop growth [1–5]. Understanding the interaction between vegetation dynamics and climatic conditions is essential for sustainable agriculture and reliable yield forecasting [4]. The advancement of remote sensing technologies has enabled efficient monitoring of vegetation status, evaluation of surface parameters, and assessment of climate-induced impacts on crops across different spatial and temporal scales [5–7, 10].

Vegetation indices such as the Normalized Difference Vegetation Index (NDVI), Enhanced Vegetation Index (EVI), Modified Normalized Difference Water Index (MNDWI), and Soil Adjusted Vegetation Index (SAVI) are commonly used to describe vegetation vigor, canopy structure, and soil moisture conditions [10–13]. When analyzed alongside climatic variables including air and land surface temperatures, precipitation, solar radiation, and reference evapotranspiration (ET_0), these indices provide an integrated understanding of the environmental factors influencing crop development [1, 6–9].

The Bukhara region of Uzbekistan represents a typical arid zone where agricultural productivity is tightly linked to climatic constraints. Extreme summer temperatures, scarce rainfall, and intense evapotranspiration pose significant challenges for crop growth and water management. Therefore, evaluating the correlation between vegetation indices and climatic variables in this region offers valuable insights into crop–climate interactions and identifies the most critical factors influencing crop performance.

This study employs Pearson correlation analysis to quantify the relationships between vegetation indices and climatic parameters using remote sensing and meteorological datasets. The results

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enhance the understanding of climate–vegetation interactions in arid agricultural systems and highlight the importance of remote sensing for sustainable crop monitoring and management.

Materials and Methods

Study Area

The study was conducted in the Bukhara region of Uzbekistan, which is characterized by an arid climate with hot summers and limited precipitation. Agriculture in this region is highly dependent on irrigation, making the evaluation of climatic drivers critical for sustainable crop production, especially for cotton.

Data Sources

Remote sensing data were obtained from the Sentinel-2 MSI (MultiSpectral Instrument) satellite, which provides high-resolution multispectral imagery with a spatial resolution of 10–20 m and a revisit time of 5 days. Climatic variables, including land surface temperature (LST), air temperature at 2 m height, precipitation, solar radiation, and reference evapotranspiration (ET0), were acquired from MODIS Terra/Aqua, ERA5 satellites.

Vegetation indices were calculated from Sentinel-2 spectral bands, specifically the red (B4: 665 nm), near-infrared (B8: 842 nm), and shortwave infrared (B11: 1610 nm; B12: 2190 nm) bands. The following indices were derived:

Normalized Difference Vegetation Index (NDVI):

NDVI = (NIR-Red)/(NIR+Red)

Enhanced Vegetation Index (EVI):

EVI = G*((NIR-Red)/(NIR+C1*Red-C2*Blue+L))

where G=2.5, C1=6, C2=7.5, and L=1

Soil Adjusted Vegetation Index (SAVI):

SAVI = (NIR-Red) *(1+L)/ (NIR+Red+L)

where L=0.5L = 0.5L=0.5 is the soil brightness correction factor.

Modified Normalized Difference Water Index (MNDWI):

MNDWI = (Green-SWIR)/(Green+SWIR)

where the green band is B3 (560 nm) and SWIR is B11 or B12.

Climatic Variables

Land Surface Temperature (LST) was retrieved from thermal remote sensing products. Air Temperature (2 m), precipitation, and solar radiation were obtained from the ERA5 reanalysis dataset. Reference evapotranspiration (ET0) was calculated using the FAO Penman–Monteith equation:

$$ET_0 = \frac{0.408\Delta\left(R_n - G\right) + \frac{900}{T-273} u_2 (e_s - e_a)}{\Delta + \gamma(1 + 0.43 u_2)}$$

ET0 - Evapotranspiratsiya ko'rsatkichi (mm/s), Rn-tashqi radiatsiya (MJ/m²), G- Tuproqdan chiqadigan energiya (MJ/m²), T - Havoning harorati (°C), u2 - Shamol tezligi (m/s), es - Havodagi to'yingan bug' gazining bosimi (kPa), ea - avodagi bug' gazining bosimi (kPa), Δ - Havodagi to'yingan bug' gazining bosimining haroratga bog'liq o'zgarishi (kPa/°C), γ - Psixrometrik doimiy (kPa/°C).

Statistical Analysis

Pearson correlation analysis was used to evaluate the relationships between vegetation indices and climatic factors. The Pearson correlation coefficient (rrr) was calculated as:

$$r = \frac{\sum (x_i - \bar{x})(y_i - \bar{y})}{\sum (x_i - \bar{x})^2 (y_i - \bar{y})^2}$$

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where xi and yi represent paired values of vegetation indices and climatic variables, and x¯, y¯ are their respective means. The correlation coefficient ranges from –1 (strong negative correlation) to +1 (strong positive correlation). Correlation matrices were generated to visualize the strength and direction of associations. This approach allowed for the identification of the most influential climatic drivers affecting crop development in the Bukhara region.

Results

The correlation analysis revealed distinct relationships between vegetation indices and climatic variables in the Bukhara region (Figure 1). The results demonstrated that vegetation indices were strongly associated with each other, while their correlations with climatic parameters varied in magnitude and direction.

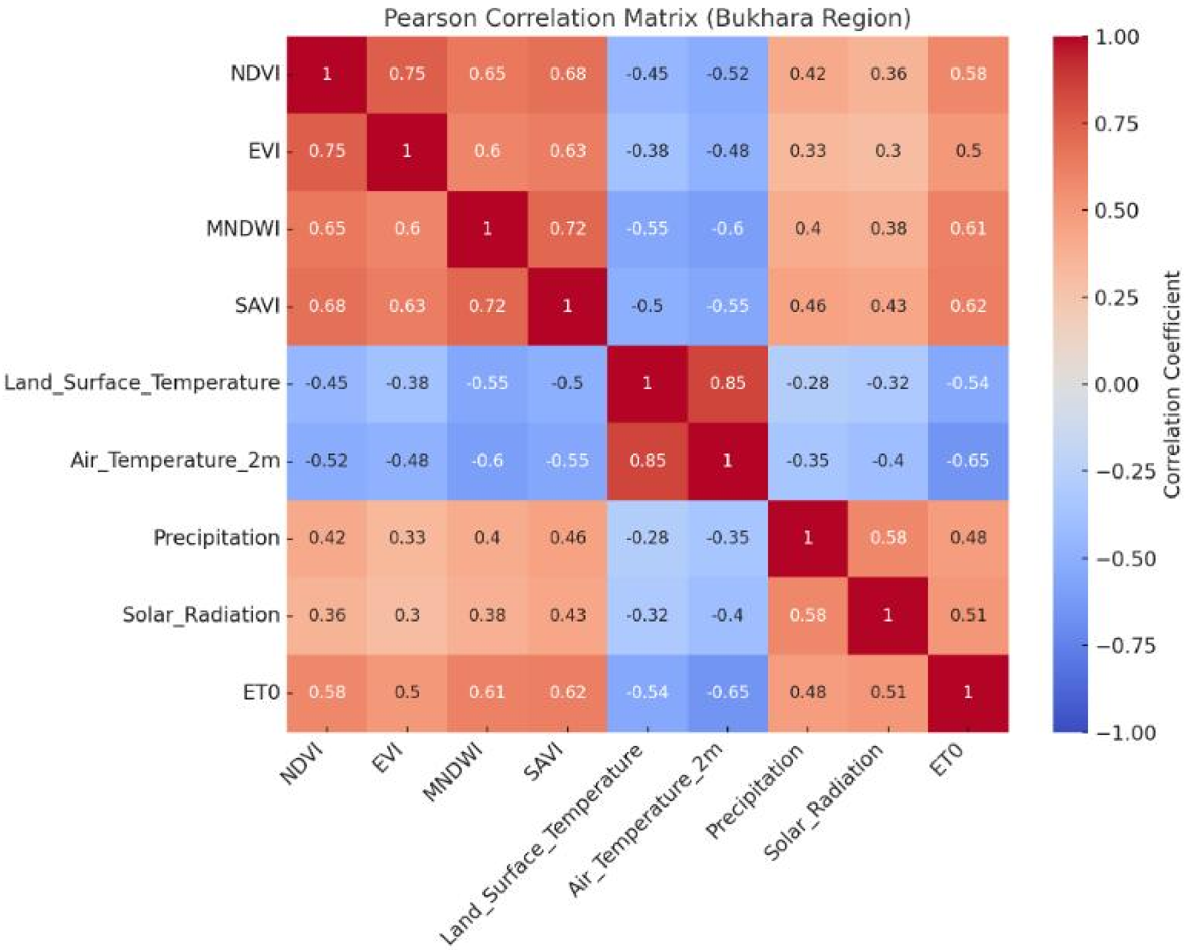

Figure 1. Pearson correlation matrix between vegetation indices (NDVI, EVI, SAVI, MNDWI) and climatic variables (air temperature, land surface temperature, precipitation, solar radiation, and ET0) in the Bukhara region. Positive correlations are indicated by warmer colors, while negative correlations are shown by cooler tones. The figure highlights the negative impact of temperature on vegetation growth and the positive role of precipitation and solar radiation.

Vegetation Indices Correlations: NDVI, EVI, SAVI, and MNDWI showed high positive correlations among themselves (NDVI–EVI: r = 0.75; NDVI–SAVI: r = 0.68; SAVI–MNDWI: r = 0.72), indicating consistency in detecting crop vigor and canopy dynamics. These indices reflect similar vegetation conditions, although MNDWI also accounts for surface moisture effects.

Temperature Effects: A strong negative correlation was observed between vegetation indices and both land surface temperature (LST) and air temperature at 2 m. For instance, NDVI was negatively correlated with air temperature (r = –0.52) and LST (r = –0.45). The highest negative correlation was between MNDWI and air temperature (r = –0.60), suggesting that higher thermal stress reduces vegetation activity and surface water availability.

Moisture and Radiation Effects: Positive correlations were found between vegetation indices and precipitation (NDVI–precipitation: r = 0.42; SAVI–precipitation: r = 0.46) as well as solar radiation (NDVI–solar radiation: r = 0.36; SAVI–solar radiation: r = 0.43). These results indicate that crop growth is favored under adequate rainfall and solar energy supply, both of which contribute to photosynthetic activity and vegetation greenness.

Evapotranspiration (ET0): Reference evapotranspiration (ET0) exhibited positive correlations with vegetation indices (NDVI–ET0: r = 0.58; SAVI–ET0: r = 0.62; MNDWI–ET0: r = 0.61). This suggests that periods of active crop growth are associated with higher evapotranspiration demand, reflecting increased vegetation water use. However, excessive ET0 values combined with high air temperature may also indicate water stress conditions in the absence of sufficient irrigation.

Overall, the results emphasize that crop development in the Bukhara region is highly sensitive to climatic variability. Temperature extremes exert a negative influence on vegetation dynamics, while precipitation and solar radiation contribute positively to crop performance. The correlation with ET0 highlights the dual role of evapotranspiration as both a driver of plant productivity and a potential stress factor under water-limited conditions.

Conclusions

This study demonstrated the usefulness of remote sensing techniques in assessing the influence of climatic drivers on agricultural crop development in the Bukhara region of Uzbekistan. By integrating Sentinel-2 vegetation indices (NDVI, EVI, SAVI, MNDWI) with climatic variables (air temperature, land surface temperature, precipitation, solar radiation, and ET0), Pearson correlation analysis revealed several important findings.

First, vegetation indices were highly correlated with each other, confirming their reliability in capturing crop canopy dynamics under arid conditions. Second, strong negative correlations between vegetation indices and temperature variables highlight the detrimental impact of heat stress on vegetation activity. In contrast, positive correlations with precipitation and solar radiation emphasize their beneficial role in supporting crop growth. Finally, the significant associations between vegetation indices and ET0 underline the importance of water demand as both a productivity indicator and a potential stress factor when irrigation is insufficient.

Overall, the findings indicate that crop development in arid regions such as Bukhara is highly sensitive to climatic variability. The integration of remote sensing data with climatic parameters provides a valuable framework for monitoring crop performance, forecasting yield, and developing sustainable agricultural management strategies. Future work should focus on expanding the temporal scale of analysis, incorporating additional biophysical variables, and validating remote sensing–based results with in-situ field observations.

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