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Assessing Vegetation Response to Hydroclimatic Variability in Semi-Arid Regions: NDVI–LST–GWL Interactions

Yarı Kurak Bölgelerde Hidroklimatik Değişkenliğe Karşı Bitki Örtüsünün Tepkisini Değerlendirme: NDVI–LST–GWL Etkileşimleri

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Assessing Vegetation Response to Hydroclimatic Variability in Semi-Arid Regions: NDVI–LST–GWL Interactions

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Abstract

This study examined the relationships between NDVI, EVI, NDWI, land surface temperature (LST), and groundwater level (GWL) from 2001 to 2024. NDVI anomalies showed an overall increase, with more pronounced positive deviations after 2015. A strong correlation was found between NDVI and EVI (r=0.84), and a strong negative correlation between NDWI and LST (r=-0.90). The NDVI–GWL relationship was weak (r=0.22; anomalies r=0.16). Linear and multiple regression analyses had low explanatory power (max R^2=0.049; multiple regression 6.9%). Stationarity tests showed that NDVI anomalies were persistent, while LST and GWL anomalies were stationary. Granger causality tests indicated no predictive relationship between NDVI and GWL. As a result, vegetation dynamics were mainly influenced by seasonal climate cycles, with groundwater playing a small but consistent role. The weak linear correlations highlight the need to integrate rainfall, soil moisture, and land-use change using nonlinear and lagged modeling approaches.

Keywords: *NDVI, EVI, NDWI, LST, Groundwater Level, Quality of life, Anomaly Detection, Time Series Analysis, Granger Causality*

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Öz

Bu çalışmada, 2001–2024 döneminde NDVI, EVI, NDWI, yüzey sıcaklığı (LST) ve yeraltı suyu seviyesi (GWL) arasındaki ilişkiler incelenmiştir. NDVI anomalileri artış göstermiş, özellikle 2015 sonrası daha belirgin pozitif sapmalar görülmüştür. NDVI–EVI arasında güçlü (r=0.84), NDWI–LST arasında ise güçlü negatif korelasyon (r=-0.90) bulunmuştur. NDVI–GWL ilişkisi zayıf kalmış (r=0.22, anomalilerde r=0.16). Doğrusal ve çoklu regresyon analizleri düşük açıklayıcılık göstermiş (R^2 max=0.049; çoklu regresyon %6.9). Durağanlık testinde NDVI anomalileri kalıcı, LST ve GWL ise durağan bulunmuştur. Granger testi NDVI–GWL arasında öngörücü ilişki göstermemiştir. Sonuçta bitki örtüsü dinamiklerinin esas olarak mevsimsel iklim döngülerinden etkilendiği, yeraltı suyunun küçük ama tutarlı katkı sunduğu, doğrusal korelasyonların sınırlı kaldığı ve yağış, toprak nemi, arazi kullanımı gibi faktörlerin doğrusal olmayan modellerle dahil edilmesi gerektiği ortaya konulmuştur.

Anahtar Kelimeler: *NDVI, EVI, NDWI, LST, Yeraltı Su Seviyesi, Yaşam Kalitesi, Anomali Tespiti, Zaman Serisi Analizi, Granger Nedensellik*

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1. INTRODUCTION

Rising temperatures and extreme weather events, parallel to global climate change, are significantly increasing the risk and impacts of drought worldwide. Drought is an environmental risk that threatens both natural ecosystems and human settlements, developing slowly but producing widespread consequences, and is one of the most destructive outcomes of climate change [1]. Especially in semi-arid regions with high concentrations of water-dependent socio-ecological systems, drought not only reduces agricultural productivity but also causes severe deterioration in urban quality of life [2-4]. In this context, water stress, changes in vegetation health, surface temperatures, and groundwater reserves directly impact multidimensional urban quality of life indicators, including ecological balance, public health, economic sustainability, and environmental justice [5, 6].

Urban quality of life (UQoL) is a multidimensional concept that refers to a comprehensive assessment of the physical, environmental, economic, social, and psychological conditions in which individuals live [7]. In this context, sub-indicators such as air quality, access to green spaces, thermal comfort, water security, ecosystem integrity, and environmental justice are among the fundamental components of environmental quality of life [8, 9]. However, drought has direct or indirect effects on all these indicators. Drought-related environmental variables such as depletion of water resources, reduction in vegetation cover, and increase in surface temperatures negatively affect individuals' perception of livable cities and their level of environmental satisfaction [10].

Besides water availability, the green space quantity, and climatic comfort are considered the cornerstones of sustainable and livable cities [11]. Healthy vegetation and sufficient green space not only improve air quality but also reduce the urban heat island effect, thereby increasing thermal comfort and supporting climatic balance [12]. Indeed, urban green spaces offer multifaceted ecological benefits to the urban environment by reducing the effects of heat waves, absorbing rainwater to reduce flood risk, and sequestering carbon dioxide to balance greenhouse gas emissions. These benefits not only enhance the quality of the physical environment but also positively impact individuals' life satisfaction through social interaction, recreation, and aesthetic experiences [13]. Therefore, understanding the effects of environmental threats such as drought on urban quality of life is a fundamental requirement for urban planning and sustainable adaptation strategies [10]. Phenomena such as water scarcity, declining green spaces, and rising surface temperatures can threaten living comfort and public health in cities, and monitoring these effects with scientific and measurable indicators will guide decision-makers.

In monitoring such environmental impacts, remote sensing (RS) and geographic information systems (GIS)-based spatial analysis tools offer significant advantages. Remote sensing-based indicators such as the Normalised Difference Vegetation Index (NDVI), Normalised Difference Water Index (NDWI), Land Surface Temperature (LST), and Enhanced Vegetation Index (EVI) enable the monitoring of environmental components such as vegetation health, surface moisture conditions, thermal stress, and ecosystem functions with high spatial and temporal resolution [14-16]. The evaluation of these indicators in conjunction with groundwater level data not only contributes to understanding the dynamics of the hydrological cycle but also to the development of long-term environmental sustainability and urban resilience strategies [17-19]. The integration of RS and GIS-based multiple environmental indicators enables accurate monitoring of environmental changes and provides a scientific foundation for sustainability-based planning processes.

This study aims to examine the temporal relationships between vegetation dynamics indicated by NDVI, EVI, and NDWI and essential hydroclimatic variables such as land surface temperature (LST_C) and groundwater level (GWL) over a 24-year period (2001–2024) in the Afşin region of Türkiye. Although numerous research reports could be found in literature regarding assessing vegetation response to hydroclimatic variability in various regions, our study reveals a novel approach due to its integrated application of long-term remote sensing datasets, anomaly-based vegetation evaluation, and causal inference methodologies (Granger causality) to differentiate between surface-driven and subsurface-driven influences on vegetation health.

However, the study provides a comprehensive and data-intensive analysis of how vegetation responds to climatic and hydrological fluctuations, in contrast to previous studies that typically investigate these variables in isolation or over shorter timeframes. The results are especially significant for semi-arid areas where water availability and vegetation productivity are closely linked, necessitating that sustainable land and water management practices be guided by solid, evidence-based understanding of vegetation-climate-groundwater interactions.

2. MATERIAL and METHOD

2.1 Study Area

The study was conducted in the Afşin district of Kahramanmaraş Province, located in southeastern Türkiye (Latitude: 38.218° N, Longitude: 36.851° E). The region lies within a high-elevation basin influenced by a continental semi-arid climate, characterized by cold, snowy winters and hot, dry summers. Annual precipitation averages between 400-500 mm, with marked seasonal and interannual variability. Afşin is primarily agricultural, dependent on both surface and groundwater resources, and has experienced increasing hydroclimatic stress in recent decades due to rising temperatures, declining water tables, and recurring vegetation degradation. These characteristics make it a suitable case for assessing vegetation–climate water interactions using integrated environmental indicators.

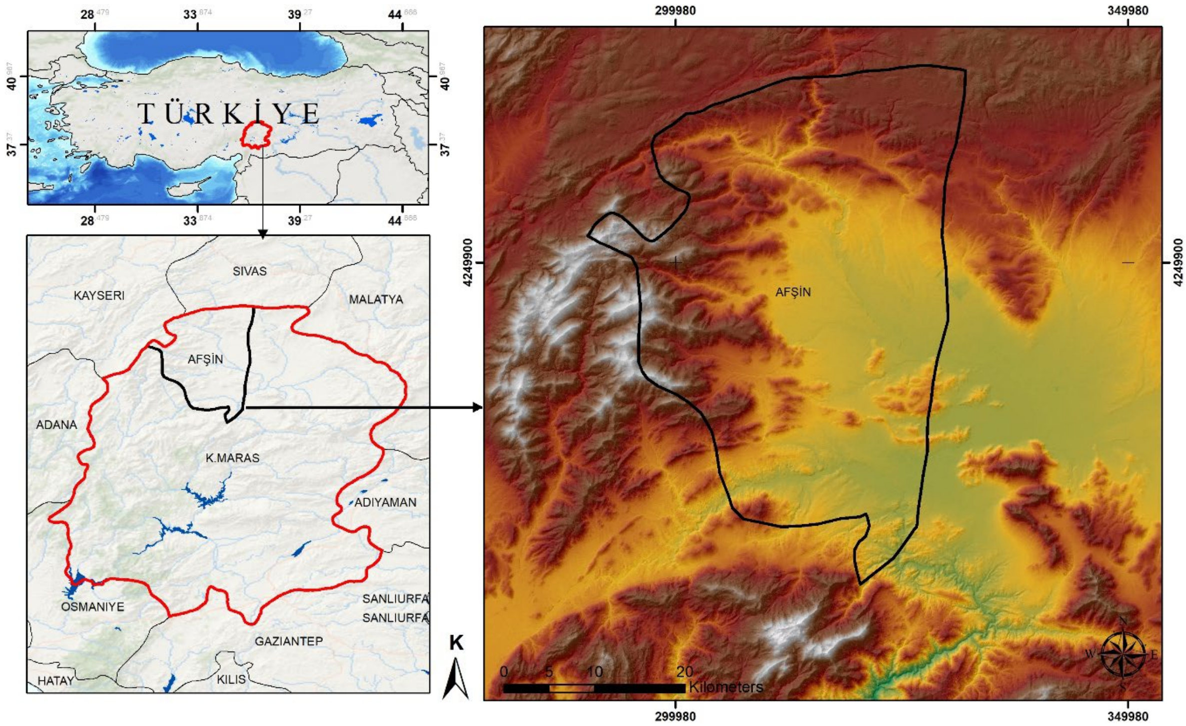


Figure 1. Location of Afşin district in Türkiye, its position within the province, and topographic features

2.2 Data Description and Sources

The analysis employed monthly time series data from January 2001 to December 2024, encompassing 288 monthly observations (Table 1). Two primary data sources were used as below:

2.2.1. Groundwater Level (GWL) Data

GWL data was provide from General Directorate of State Hydraulic Works (DSİ). The observation sites were chosen to reflect the hydrogeological conditions in the study area. Measurements are in meters (m), and negative values indicate that the water level is lower than the reference elevation. The dataset was prepared as monthly mean values, and its temporal coverage matched that of the remote sensing data.

2.2.2. Remote Sensing Data

Data on vegetation, water index, and land surface temperature were collected using the Google Earth Engine (GEE) cloud platform and two standard products from the Moderate Resolution Imaging Spectroradiometer (MODIS) sensor.

(a) MOD13Q1: Vegetation Indices (Terra MODIS) has spatial resolution of 250 meters and temporal resolution of sixteen days.

- NDVI: Normalized Difference Vegetation Index (provided directly by the product)
- EVI: Enhanced Vegetation Index (provided directly by the product)
- NDWI: Normalized Difference Water Index, calculated from the reflectances of Near-Infrared (NIR, Band 2) and Shortwave Infrared (SWIR, Band 6). NDWI was calculated by adding NIR and subtracting SWIR as follows [20, 21]:

$$NDWI = \frac{NIR-SWIR}{NIR+SWIR} \tag{1}$$

(b) MOD11A2 Land Surface Temperature (Terra MODIS) has a spatial resolution of 1 km and temporal resolution of eight days.

The MODIS data was spatially clipped to the study area. The time series of each product was resampled using monthly averages to ensure that all remote sensing data matched the temporal resolution and coverage of the GWL series.

Table 1. Data and data sources used in the study

Variable	Description	Unit	Source
NDVI	Normalized Difference Vegetation Index	Unitless	MODIS MOD13A2
EVI	Enhanced Vegetation Index	Unitless	MODIS MOD13A2
NDWI	Normalized Difference Water Index	Unitless	MODIS MOD09A1
LST	Land Surface Temperature (°C)	°C	MODIS MOD11A2
GWL	Groundwater Level	m	General Directorate Water Works (DSİ)

2.3 Data preprocessing

2.3.1. Missing Data Management

Missing observations in the dataset were addressed in three stages. Missing values were filled with forward-backward linear interpolation. If it is possible, LST Fusion Method was used for missing values in LST_C were filled with a weighted average of ERA5_LST (weight 0.6), Landsat_LST (weight 0.8), and Sentinel_LST (weight 0.8). To reduce noise, the NDVI and LST_C series were smoothed with a 9-window Savitzky-Golay filter of polynomial order 2. The window length was automatically adjusted to an odd number based on the available data length.

2.3.2. Anomaly Calculation

To eliminate seasonality, a monthly climatology was calculated for each variable. The anomaly value was defined as:

$$\text{Anomaly} = X_{i,j} - \overline{X}_j \tag{2}$$

where $X_{i,j}$ is the value of a given variable in year while $\overline{X_j}$ is the long-term climatological monthly mean over 2001–2024. This procedure was performed separately for NDVI, EVI, NDWI, LST_C, and GWL to detect stress and variability beyond normal seasonal ranges.

2.4 Statistical Analysis

2.4.1. Stationarity Tests

Stationarity is important in time series analysis. As a result, the anomaly series underwent both the Augmented Dickey-Fuller (ADF) and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) tests [22, 23].
When p is smaller than 0.05 in ADF it is accepted as series is stationary. Similarly, series is stationary for KPSS test when p is bigger than 0.05 ($p>0.05$)

2.4.2. Granger Causality Analysis

The potential lagged effects of groundwater level (GWL) on NDVI were investigated using the Granger causality test [24]. A bivariate system (NDVI_anom and GWL_anom) was created. The optimal lag order between 1 and 12 was determined using the Akaike Information Criterion (AIC) as the primary criterion, with the Bayesian Information Criterion (BIC) serving as a backup. Moreover, ssr_ftest p-values were computed for all lags up to the chosen maximum.

2.3.3. Multi-Linear Regression

The dependent variable was NDVI anomalies, while the predictors were LST_C and GWL anomalies.
Multicollinearity was assessed via Variance Inflation Factor (VIF). If VIF was greater than 10, the predictors were subjected to principal component analysis (PCA). All regressions were estimated using covariance matrices that were both heteroskedasticity and autocorrelation consistent (HAC, Newey-West).

2.4.4 Correlation Analysis

Pearson correlation was used to assess linear relationships and Spearman rank correlation was used to evaluate monotonic relationships. Both methods were used for raw and anomaly series.

3. RESULTS and DISCUSSIONS

3.1 Descriptive statistics

Table 2 shows the descriptive statistics for the five important environmental variables from 2001 to 2024. Moderate vegetation cover with little variability is indicated by the NDVI (mean=0.22, SD=0.12, min=-0.04, max=0.63) and EVI (mean=0.13, SD=0.08, min=-0.03, max=0.43). With slightly heavier tails (kurtosis=0.75, 1.27) and positive skewness (0.93 and 1.12), both indicate that most values tend to cluster toward the lower range with sporadic high outliers. DWI (mean=-0.21, SD=0.13, min=-0.48, max=0.02) exhibits predominantly low or negative water index values, near symmetrical (skewness=0.01), and a flat distribution (kurtosis=-1.25), indicating a scarcity of extreme wet or dry anomalies beyond the prevailing dryness. LST_C (mean=25.59 °C, SD=15.23, min=-6.53 °C, max=49.01 °C) exhibits a broad thermal range, characterized by a slight left skew (–0.24) and a flat-tailed distribution (kurtosis=-1.05), signifying the presence of both cooler and extremely warm surfaces, with a predominance of warmer conditions. The GWL (mean=-11.32 m, SD=1.23, min=-15.15 m, max=-8.95 m) remains consistently below ground level, exhibiting symmetry (skewness=0.10) and a flat-tailed distribution (kurtosis=-0.64), indicative of stable groundwater conditions throughout the dataset. Descriptive metrics reveal consistent yet positively skewed vegetation indices, consistently low NDWI, significant variability in LST_C, and stable GWL levels.

Table 2. Descriptive statistics of variables

Variable	Minimum	Maximum	Mean	Standard deviation (SD)	Skewness	Kurtosis
NDVI	-0.04	0.63	0.22	0.12	0.93	0.75
EVI	-0.03	0.43	0.13	0.08	1.12	1.27
NDWI	-0.48	0.02	-0.21	0.13	0.01	-1.25
LST_C	-6.53	49.01	25.59	15.23	-0.24	-1.05
GWL	-15.15	-8.95	-11.32	1.23	0.10	-0.64

The boxplots of the raw dataset reveal that NDVI and EVI are centered around positive medians, with NDVI marginally higher, suggesting moderate vegetation cover (Fig. 2). Both indices possess relatively narrow interquartile ranges yet display numerous upper outliers, indicating sporadic peaks in greenness. NDWI values predominantly exhibit negativity with a narrow range, indicating generally low surface water content, while also presenting outliers in both directions. LST_C exhibits an extensive range, spanning from approximately 0 °C to exceeding 40 °C, indicative of significant seasonal variation. GWL values are consistently negative, as anticipated for subterranean measurements, exhibiting a narrow range with a few deeper outliers. The raw dataset encompasses the complete range and seasonal fluctuations of each parameter, while the anomaly dataset delineates short-term deviations, diminishing the central tendency and emphasizing episodic extremes.

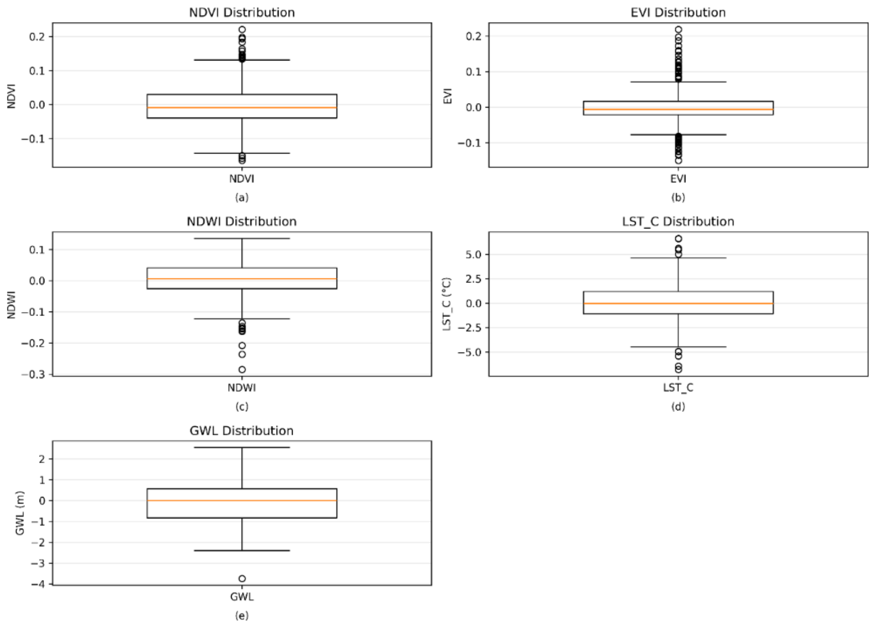


Figure 2. Distribution of variables based on raw data (Boxplot analysis)

Figure 3 demonstrates seasonal fluctuations in NDVI, EVI, NDWI, and LST_C, characterized by recurring annual maxima and minima. NDVI and EVI elevate during greener seasons and decline during arid periods, whereas NDWI predominantly remains negative, indicating consistently low surface water content. LST_C exhibits significant seasonal temperature fluctuations, ranging from approximately 0 °C during the cooler months to exceeding 40 °C in the warmer months. For GWL, the raw values are perpetually negative as they denote depths beneath the ground surface. The series exhibits multi-year variations instead of seasonal patterns, characterized by intervals of reduced groundwater levels (fewer negative values for 2010–2015) succeeded by increased depths (more negative values, for post-2016), signifying long-term alterations in groundwater level.

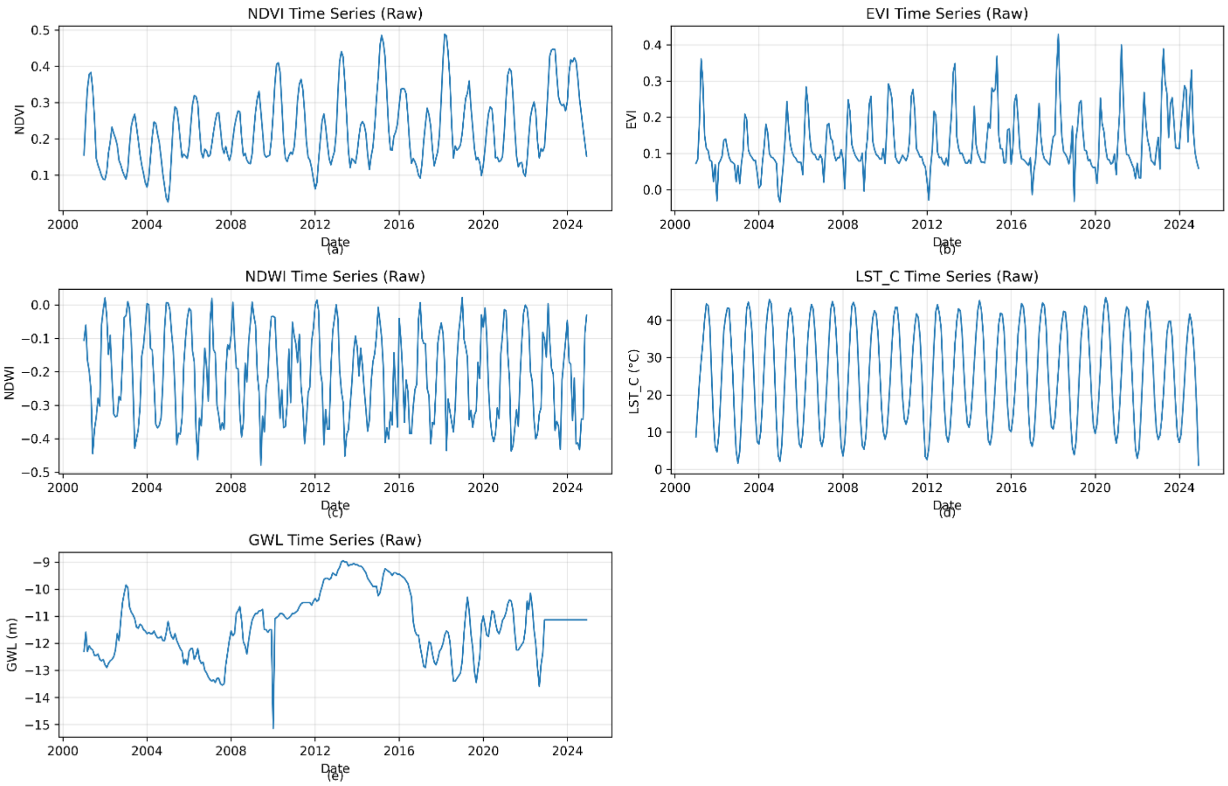


Figure 3. Temporal dynamics of hydro-vegetation variables based on raw data

Figure 4 highlights deviations from long-term averages. NDVI and EVI anomalies indicate years of exceptionally elevated vegetation productivity, especially following 2016. NDWI anomalies indicate periods of relative moisture or aridity, exhibiting significant declines during drought conditions. LST_C anomalies indicate atypically warm or cool intervals, whereas GWL anomalies demonstrate prolonged increases and decreases in groundwater, signifying fluctuations in recharge and extraction over time. The raw series delineates the fundamental seasonal and depth patterns, whereas anomalies identify climatic and hydrological deviations from the norm during the period of 2001 to 2024.

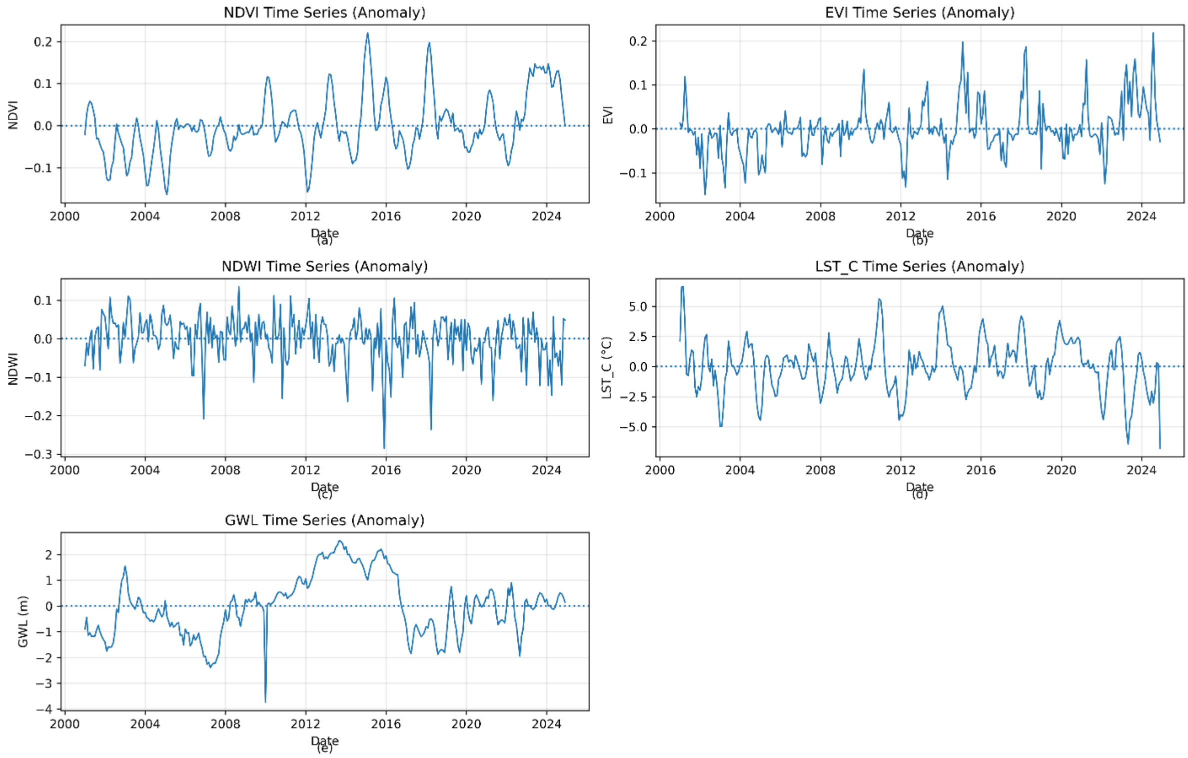
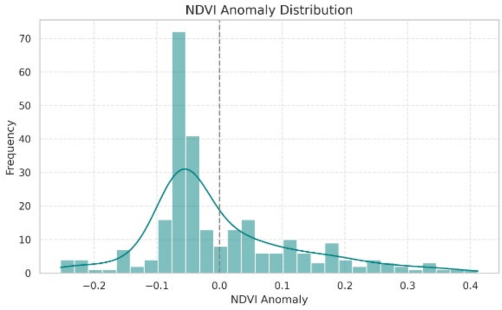


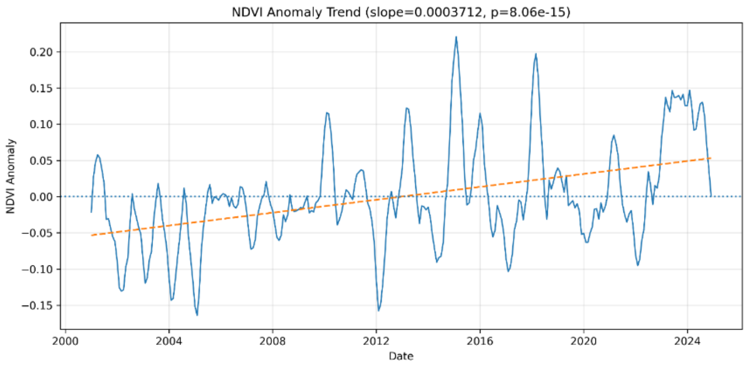
Figure 4. Temporal dynamics of hydro-vegetation variables based on anomaly data

Figure 5 shows where and how the NDVI anomalies changed over time during the study period (2001–2024). This shows how vegetation stress and greening changed over time in the Afşin region. Figure 5(a) shows how the frequencies of NDVI anomalies are spread out. The histogram was slightly skewed to the right, and most of the observations are grouped around negative values (centered around -0.1). This means that below-average vegetation greenness was more common over time. The fitted kernel density curve shows a one-mode distribution with a long positive tail, which shows times when plants are stronger but not very often. The long-term NDVI climatological mean is shown by the vertical dashed line at zero anomaly. This helps to separate dry or stressful conditions from greener-than-average conditions.

As seen in Fig. 5(b), NDVI anomaly trend plot indicates a statistically significant upward trend from 2000 to 2025 (slope=0.0003712, $p \approx 8.06\times10^{-15}$). This signifies a progressive rise in vegetation greenness anomalies over time, indicating that recent years exhibit above-average vegetation productivity relative to the long-term mean. The escalation becomes more evident post-2015, with numerous significant positive anomalies reaching their zenith in the late 2010s and early 2020s, indicating potential enhancements in vegetation health or productivity influenced by climatic or land management variables. These subplots show how the health of plants deviates from long-term norms. They show both how often abnormal conditions happen and how they change over time, which is important for figuring out how resilient plants are to hydroclimatic stress.



(a)



(b)

Figure 5. Spatiotemporal patterns of NDVI anomaly distribution and trends

3.2 Regression results

Figure 6 shows the outcomes of simple linear regression analyses that looked at how hydrometeorological and vegetation indices are related. The linear regression analyses for both raw and anomaly datasets reveal predominantly weak correlations among NDWI, LST_C, GWL, and NDVI. In the raw data, NDWI exhibits negligible correlation with GWL (R^2=0.001), whereas LST_C demonstrates a modest positive association with NDVI (R^2=0.034). GWL exhibits the most robust correlation among the raw relationships (R^2=0.049), indicating that shallower groundwater levels are weakly correlated with increased vegetation greenness (Fig. 6).

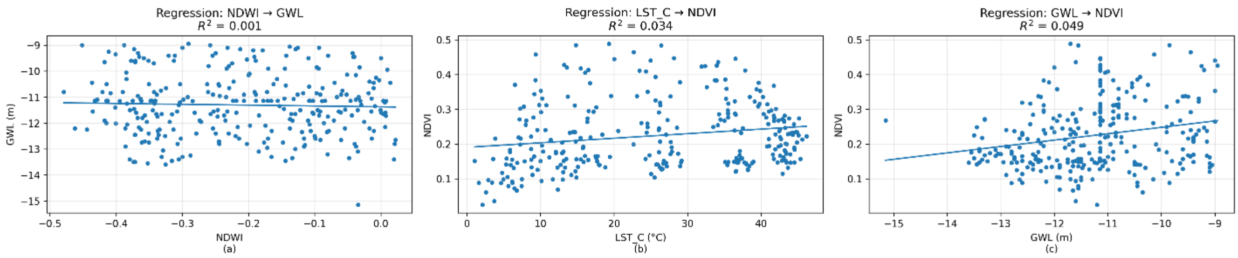


Figure 6. Results of linear regression between key variables based on raw data

In the anomaly data, associations remain tenuous. NDWI exhibits a marginally elevated yet still negligible correlation with GWL (R^2=0.013) and a negative slope, suggesting that wetter anomalies may be linked to shallower groundwater levels. LST_C anomalies exhibit negligible correlation with NDVI anomalies (R^2=0.002), while GWL anomalies demonstrate a modest positive association with NDVI anomalies (R^2=0.024), indicating that short-term increases in groundwater may marginally improve vegetation productivity (Fig. 7). The persistently low R^2 values indicate that these variables, when evaluated linearly, account for minimal variation among one another, suggesting that the interactions between vegetation, water, and temperature are likely influenced by more intricate, nonlinear, or external factors.

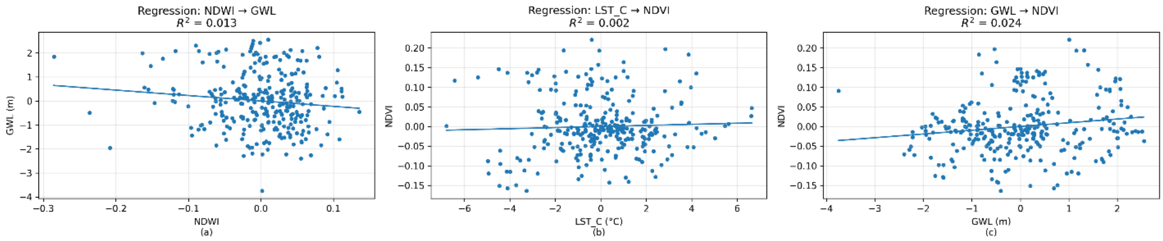


Figure 7. Results of linear regression between key variables based on anomaly data

The linear regression findings indicate predominantly weak correlations among the variables (Table 3). The raw dataset reveals a negligible negative correlation between NDWI and GWL (slope=-0.32, R^2=0.0013, p =0.5353), signifying minimal explanatory capacity. LST_C exhibits a slight positive correlation with NDVI (slope ≈ 0.00, R^2=0.0335, p=0.0018), whereas GWL demonstrates the most substantial raw correlation with NDVI (slope=0.02, R^2=0.0492, p=0.0001), indicating that shallower groundwater levels are weakly associated with increased vegetation greenness. The anomaly dataset reveals a marginally stronger yet still weak negative correlation between NDWI and GWL (slope=-2.26, R^2=0.0132, p=0.0513). LST_C anomalies exhibit negligible correlation with NDVI anomalies (R^2=0.0017, p=0.4828), while GWL anomalies demonstrate a modest positive correlation with NDVI anomalies (slop= 0.01, R^2=0.0244, p=0.0080).

Stationarity testing reveals that LST_C anomalies are stationary according to the ADF test (p = 0.00354) and the KPSS test (p=0.1). GWL anomalies are stationary according to both tests (ADF p=0.0184; KPSS p=0.0791). NDVI anomalies are non-stationary according to the KPSS test (p=0.01), although they approach the ADF significance threshold (p=0.0922), suggesting a residual trend or persistence.

The multiple regression analysis of NDVI in relation to LST_C and GWL indicates a statistically significant yet weak combined effect (R^2=0.069). LST_C (coefficient=0.001, p=0.005) and GWL (coefficient=0.020, p=0.001) positively influence NDVI, indicating that elevated surface temperatures and reduced groundwater levels collectively promote minor enhancements in vegetation greenness, yet they account for less than 7% of the variation in NDVI. The cumulative evidence indicates that although statistically significant correlations exist among vegetation, temperature, and groundwater, their strength is minimal, and vegetation dynamics are probably more profoundly affected by alternative climatic, hydrological, and land-use variables, potentially via nonlinear interactions.

Table 3. Linear regression and stationarity results for the parameters and multi regression for NDVI relationship between LST and GWL.

Linear regression

mode	x	y	Slope	intercept	r2	p value	Std. error
raw	NDWI	GWL	-0.32	-11.37	0.0013	0.5353	0.52
raw	LST_C	NDVI	0.00	0.19	0.0335	0.0018	0.00
raw	GWL	NDVI	0.02	0.43	0.0492	0.0001	0.00
anom	NDWI	GWL	-2.26	0.00	0.0132	0.0513	1.15
anom	LST_C	NDVI	0.00	0.00	0.0017	0.4828	0.00
anom	GWL	NDVI	0.01	0.00	0.0244	0.0080	0.00

Stationarity results

series	ADF_stat	ADF_p	KPSS_stat	KPSS_p
NDVI_anom	-2.60401	0.092172	0.860471	0.01
LST_C_anom	-3.74362	0.00354	0.103152	0.1
GWL_anom	-3.22905	0.018364	0.395516	0.079088

Multi regression results for NDVI relationship between LST and GWL

Variable	Coefficient	Std. Err	t-value	p-value	r^2
const	0.405	0.067	6.058	0.000	0.069
LST_C	0.001	0.000	2.818	0.005	0.069
GWL	0.020	0.006	3.421	0.001	0.069

The Granger causality analysis between NDVI and GWL reveals no statistically significant relationships at any of the examined lags (1–9), with p-values consistently exceeding the 0.05 threshold (Table 4). The F-statistics are low, signifying the limited predictive capability of GWL for NDVI at any specified lag length. This indicates that, within the examined temporal framework, historical fluctuations in groundwater levels do not yield significant predictive insights for future alterations in vegetation greenness, and vice versa, suggesting that their relationship is either indirect, influenced by external factors, or functions at disparate time scales than those assessed.

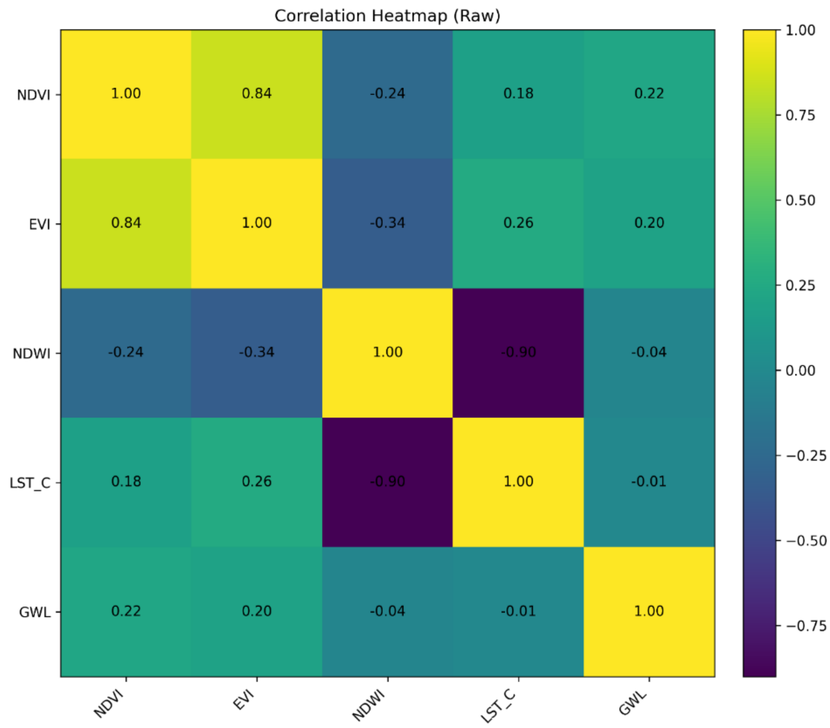
Table 4. Granger results between NDVI and GWL

Lag	F-statistic	p value
1	0.477	0.490
2	1.129	0.325
3	0.608	0.610
4	0.464	0.762
5	0.867	0.504
6	0.807	0.566
7	0.653	0.712
8	0.615	0.765
9	0.86	0.56

3.3 Correlation results

The correlation heatmaps for raw and anomaly datasets exhibit consistent patterns, with significant variations in strength and direction for certain relationships (Fig. 8). In the raw dataset, NDVI and EVI exhibit a strong positive correlation (r=0.84), indicating their common function as vegetation indices. NDWI exhibits a robust negative correlation with LST_C (r=-0.90), signifying that elevated land surface temperatures are generally linked to diminished water content. NDVI and NDWI exhibit a weak negative correlation (r=-0.24), whereas NDVI and LST_C demonstrate a low positive correlation (r=0.18). The correlations between GWL and NDVI (r=0.22) and EVI (r=0.20) are weak yet positive, indicating a marginal relationship between shallower groundwater levels and increased vegetation greenness.

In the anomaly dataset, NDVI and EVI exhibit a strong correlation (r=0.82), albeit slightly diminished compared to the raw data. Negative correlations between NDWI and both NDVI (r=-0.35) and EVI (r=-0.42) are more pronounced in anomalies, indicating that short-term increases in vegetation anomalies frequently correspond with diminished water index anomalies. The relationship between NDWI and LST_C diminishes in anomalies (r=-0.26), indicating reduced seasonal predominance in their short-term variations. The correlations between GWL and NDVI (r=0.16) and EVI (r=0.15) are weak, suggesting a negligible short-term relationship between groundwater variations and vegetation alterations. Heatmaps indicate that vegetation indices are closely correlated, NDWI and LST_C exhibit an inverse relationship, and groundwater levels demonstrate only minimal associations with vegetation, particularly regarding short-term anomaly fluctuations.



(a)

(b)

Figure 8. Correlation results among hydro-vegetation variables

The findings reveal distinct seasonal patterns in NDVI, EVI, NDWI, and LST_C, with vegetation indices reaching their highest levels during green seasons, NDWI predominantly remaining negative due to restricted surface water availability, and LST_C exhibiting pronounced annual thermal fluctuations. GWL, conversely, demonstrates multi-year variations instead of seasonal trends, indicative of gradual hydrological recharge and depletion processes affected by rainfall variability, extraction rates, and aquifer properties. Anomaly analysis eliminates seasonal signals, uncovering specific occurrences such as vegetation surges, drought events, temperature extremes, and alterations in groundwater. NDVI anomalies exhibit a statistically significant positive trend ($p<0.001$), with notable increases post-2015, indicating heightened vegetation productivity possibly influenced by favorable climatic conditions, enhanced irrigation practices, land rehabilitation initiatives, or CO_2 fertilization effects.

Correlation patterns reveal robust NDVI-EVI relationships ($r\approx0.82$-0.84) and a significant negative NDWI–LST_C association in raw data ($r=-0.90$), which diminishes in anomalies, suggesting a seasonal temperature–moisture trade-off rather than a consistent causal mechanism. The correlation between groundwater levels (GWL) and vegetation indices is weak in both datasets, likely since vegetation growth is more directly affected by recent precipitation and soil moisture than by deeper groundwater reserves, particularly in regions with restricted rooting depth. Linear regressions indicate minimal explanatory power, with GWL→NDVI exhibiting the most robust raw correlation ($R^2=0.049$) and GWL anomalies →NDVI anomalies at $R^2=0.024$. Multiple regression indicates that LST_C and GWL collectively account for merely 6.9% of the variation in NDVI, despite both predictors being statistically significant. This limited influence may result from the dependence of vegetation greenness on various interacting factors, including precipitation timing, evapotranspiration rates, soil type, and land cover, which were not explicitly incorporated into the models. Stationarity tests reveal that LST_C and GWL anomalies are stationary, while NDVI anomalies exhibit persistence, suggesting long-term ecological or climatic changes.

Granger causality tests indicate no predictive relationship between NDVI and GWL at lags of 1–9 months, suggesting that their association functions over extended time scales or is obscured by other factors. Boxplot distributions elucidate the seasonal variations in raw data and the more constrained, zero-centered distributions in anomalies, occasionally exhibiting extremes associated with droughts, heatwaves, or extraordinary wet seasons. In summary, vegetation dynamics in the study area are primarily governed by seasonal climatic cycles, while groundwater has a minimal yet consistent impact. The ascending NDVI anomaly trend since 2015 may be associated with climate-related factors such as augmented precipitation during essential growing periods, diminished drought intensity, or alterations in temperature patterns, alongside anthropogenic factors including irrigation expansion, reforestation, and sustainable land management practices. Additional research integrating precipitation, evapotranspiration, soil moisture, and land use change data, alongside nonlinear and lagged modeling techniques, may elucidate the causal pathways and more accurately represent the intricacies of vegetation-water-temperature interactions.

This study depends on monthly averaging, gap-filling with interpolation and fixed-parameter Savitzky-Golay filtering, stationarity tests (ADF, KPSS), Granger causality, and multiple regression. However, these approaches have limitations in terms of data quality, sample length, the omission of relevant climatic/hydrological drivers, scale mismatches, and sensitivity to methodological assumptions. Granger analysis identifies statistical associations but does not establish true causality, whereas interpolation and fixed filter parameters can introduce uncertainty into the results. Findings should be interpreted in light of these constraints, and future research should include seasonality adjustment, cointegration testing, additional driver variables, and sensitivity analyses to strengthen the analysis.

4. CONCLUSION

This study offers a thorough evaluation of the interactions between vegetation dynamics and hydroclimatic factors such as vegetation indices (NDVI, EVI), surface water index (NDWI), land surface temperature (LST_C), and groundwater level (GWL) in the Afşin region from 2001 to 2024. The findings indicate pronounced seasonal fluctuations in vegetation, water availability, and temperature, while groundwater level exhibits multi-year rather than seasonal variability. NDVI anomalies demonstrated a notable upward trajectory, particularly post-2015, indicating increased vegetation productivity. Correlation and regression analyses demonstrate that GWL and LST_C have only weak yet consistent effects on vegetation greenness, collectively accounting for less than 7% of the variation in NDVI. Granger causality tests revealed no short-term predictive relationships between NDVI and GWL, indicating that any interaction functions over longer or more intricate time scales. The weak statistical correlations are probably attributable to the impact of various climatic, hydrological, and land use factors not accounted for in basic linear models. The results underscore the necessity of integrating precipitation, soil moisture, and land management data, in conjunction with nonlinear and lagged analyses, to enhance comprehension of vegetation–water–temperature interactions in the area.

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CONFLICT OF INTEREST

The authors declare no competing interests. The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

STATEMENT OF PUBLICATION ETHICS

We confirm that this article is original research and has not been published previously in any journal in any language.

AUTHOR STATEMENT

Esra Bayazıt: Investigation, Analysis, Methodology, Visualization, Writing – original draft.
Veysi Kartal: Investigation, Validation, Methodology, Visualization, Writing – original draft, Methodology, Resources, Writing – original draft, Data curation.

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