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Functional Traits of Plant Communities and Their Effect on Land Surface Temperature (LST) in Arid Ecosystems of Kerman Province

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Abstract

The ability of plant communities in natural ecosystems to modify temperature has become increasingly important due to the profound impacts of global climate change, particularly in arid regions. However, previous studies have provided limited information on the long-term temperature feedback of these plant communities and the biotic drivers behind these changes. This study aimed to determine the functional traits and types of plant communities as biotic drivers of land surface temperature (LST) at the plant community scale, with a focus on identifying co-functioning communities in the Sirjan region of Kerman Province. To achieve this, we utilized the MODIS-LST 8-day composite product at the plant community scale and measured functional traits of dominant species through field operations. The results revealed that leaf dry matter content (LDMC), maximum height (MH), and leaf width (LW) traits significantly reduce LST. Additionally, cluster analysis indicated that the plant communities in the study area can be classified into five functional groups, which fall into two co-function categories. The S-strategized co-function (e.g., 26 communities), characterized by high LDMC values and a combination of abrupt and trend feedback in LST, was found to be more effective than the R-strategized co-function (e.g., 13 communities), which exhibited only trend feedback. Therefore, it can be argued that extreme temperatures, as a global concern, can be mitigated through careful selection of vegetation based on functional traits and strategies. This approach, particularly through rangeland improvement practices using species such as *Astragalus spachianus*, *Cornulaca monacantha*, and *Launaea acanthodes*, could play a significant role in addressing this challenge.

Keywords: Co-function, Drylands, Desert rangelands.

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Introduction

Shaped as thermal energy, surface temperature is one of the most important climatic elements resulting from the sun's radiant energy (Akbari et al., 2001; Friedl, 2002; Jin & Dickinson, 2010). Plants, as crucial components of ecosystems, absorb solar energy and utilize it for photosynthesis, playing a pivotal role in energy exchange and moderating thermal islands (Lin et al., 2010). Functional plant traits, particularly leaf traits, significantly influence land surface temperature (LST) through eco-physiological processes such as photosynthesis, respiration, and transpiration (Shi et al., 2020; Wu et al., 2023).

Given the distinct functions of dominant species, plant communities in each region fulfill unique ecosystem roles by altering the microclimate (D'Odorico et al., 2010) and impacting their environment. Changes in plant communities, driven by shifts in dominant species, affect canopy cover, leaf area, surface albedo, surface aerodynamic properties, root depth, and soil water balance (Asner & Heidebrecht, 2005; Beltran-Przekurat et al., 2008). These changes, in turn, influence long-wave radiation, surface temperature, and microclimate (Dugas et al., 1995).

Functional traits thus provide mechanistic links between organisms and their environment and have been widely used as predictors in ecological studies (Lavorel and Garnier, 2002; Hanisch et al., 2020). Specifically, the functional traits of plant species offer promising avenues for understanding how dominant species (i.e., plant communities) influence temperature as a service delivery in natural ecosystems. Similarly, ecosystem processes are partly determined by the trait values of the most abundant species (Díaz & Cabido, 2001; Lavorel & Garnier, 2002; Cadotte et al., 2011).

Functional trait-based ecology has traditionally relied on community-aggregated properties, with a focus on dominant species (Grime & Society, 1998; Garnier et al., 2004; Gaüzère et al., 2023), as they represent the dominant ecological roles within an ecosystem (Denelle et al., 2019). Furthermore, plant functional types, as defined by Grime’s Competition-Stress Tolerant-Ruderal (CSR) strategies, have repeatedly evolved in response to combinations of stress and disturbance (Goud et al., 2023). In this framework: The C-strategy is characterized by large leaf area (LA) and intermediate values of leaf dry matter content (LDMC) and specific leaf area (SLA). The S-strategy is associated with small LA and SLA but large LDMC. The R-strategy features small LA and LDMC but large SLA.

The application of Grime’s CSR strategies at the community level has been shown to effectively predict a community’s responses to stress and disturbance in several case studies (e.g., Bricca et al., 2021; Guerra et al., 2021; Li & Shipley, 2017; Zanzottera et al., 2020; Mastrogianni et al., 2023). Thus, Grime’s CSR strategies can serve as a valuable tool for differentiating co-functioning communities.

Classifying plant functional groups simplifies the study of complex ecosystems and enhances our understanding of the strategies employed by plant communities to regulate their environments (Lello & Hussell, 2008; Wu et al., 2023). We hypothesize that different plant functional groups employ distinct adaptation strategies to alter land surface temperature (LST).

LST has been widely used as a proxy for temperatures beneath plant canopies (Barbeta et al., 2023). Factors influencing satellite-derived LST can generally be categorized into topographic and surface biophysical parameters (Minder et al., 2010; Peng et al., 2018; Chang et al., 2017). Since the boundaries of plant communities in natural ecosystems are shaped by environmental factors such as topography (e.g., Niu et al., 2019; Zheng et al., 2022), soil type and landforms (e.g., El-Keblawy et al., 2015; Azizi et al., 2021), and climatic conditions (e.g., McNichol, 2023), this research assumes that each plant community represents a homogeneous area with respect to the environmental factors influencing LST.

To date, research on the biotic determinants of surface temperature has primarily focused on different plant functional types (Gerken et al., 2019; Teuling et al., 2010). However, evidence suggests that land surface temperature (LST) can vary significantly among different types of plant communities (Wang et al., 2019).

Research on the determinant roles of functional traits has increasingly attracted the attention of ecologists in recent years (e.g., Zanzottera et al., 2020; Heim et al., 2022; Lundgren et al., 2024; Islam et al., 2024). However, measuring these traits requires extensive field operations, is costly and time-consuming, and often relies on specialized laboratory equipment (Bernhardt- Römermann et al., 2008; Kumar et al., 2023).

Examining the relationship between these functional traits and satellite-derived indicators offers the possibility of conducting long-term ecological studies of these traits. This approach represents a promising step toward a deeper understanding of the role of long-term functional traits in plant communities, particularly their ecosystem services such as temperature regulation. Such insights can be applied to management practices, biological planning, and ecosystem-based landscaping. The importance of this approach is further emphasized in regions with limited meteorological stations for temperature measurement.

Previous studies have identified land surface temperature (LST) as a key indicator of biophysical changes in ecosystems (Deng & Wu, 2013; Xiao et al., 2007; Zhang et al., 2009). However, a limitation of using LST data from the Moderate-Resolution Imaging Spectroradiometer (MODIS) is that measuring changes between two single points in time may lack ecological relevance (McVicar & Jupp, 1998). On the other hand, a significant advantage of LST data is its ability to reveal spatial-scale feedback, particularly at the level of plant communities (Li et al., 2018; Muro et al., 2018). Despite its coarse resolution, MODIS LST products are ideal for time series analysis, providing daily LST data on a global scale since 2000 (Neteler, 2010).

While previous studies have investigated spatial changes in LST across different land uses using methods such as the Morgan cluster analysis (e.g., Wang et al., 2019; Zheng et al., 2014), long-term assessments of LST variations remain understudied. Given that prior research (e.g., Zhou et al., 2011; Guo et al., 2015; Wang et al., 2019; Myint et al., 2015; Sahani, 2021) has reported strong LST autocorrelation and significant correlations between LST clusters and various land cover types, annual and long-term changes in LST can serve as a valuable tool for assessing the functions and feedback of plant communities in natural ecosystems.

Since each plant community (as a homogeneous unit) plays a unique role in processes such as carbon uptake, radiative energy exchange, and soil moisture regulation—all of which influence surface temperature—this study hypothesizes that it is feasible to assess and group plant communities based on their long-term temperature feedback (using LST as the primary criterion). Such feedback can be applied to manage land surface temperature changes at both local and regional scales.

Cluster analysis, a multivariate statistical method widely used in sociological and plant studies (Goncharenko & Yatsenko, 2020), was employed to group and separate co-functioning plant communities based on thermal feedback derived from year-to-year and plant community matrices. For example, Pesaresi et al. (2020) used cluster analysis of NDVI time series from satellite imagery to differentiate plant communities with varying species structures.

Land surface temperature (LST) is recognized as a suitable index for evaluating the functions of plant communities (Barbeta et al., 2023). The ability of plant communities in natural ecosystems to modify temperature has gained increased importance due to the profound impacts of global climate change, particularly in arid regions such as the Sirjan area of Kerman Province. However, limited information is available from previous studies regarding the long-term temperature feedback of plant communities in natural ecosystems and the biotic drivers behind these changes.

Therefore, this study aimed to:

1. Identify functional trait-based biotic drivers of LST at the plant community scale.
2. Separate functional groups and analyze their change patterns over a 20-year period (2000 to 2019).
3. Explore the functional strategies of co-functioning plant communities.

Materials and Methods

Study area

The study area is part of the central plateau basin of Iran, located between 55°10' to 56°28' E longitude and 28°40' to 29°59' N latitude (Fig. 1). Covering an area of 7,921 km², the region is predominantly characterized by shrubs and bushy trees. The annual average precipitation is 113.5 mm in the plains and 198.3 mm in the mountainous areas. Elevation ranges from 1,650 to 3,813 meters above sea level.

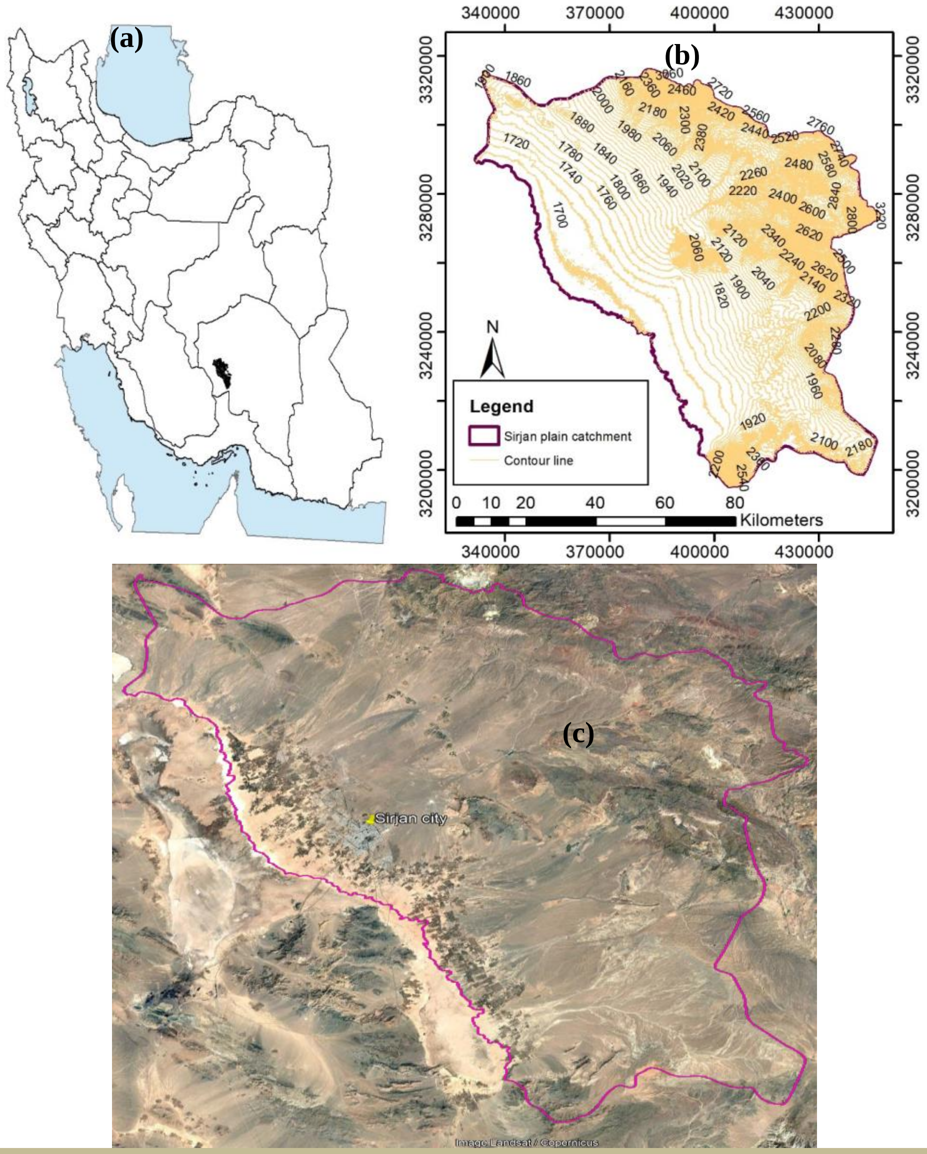


Figure (1): Study area: (a) Location map in Iran, (b) Boundary of catchment area along with its elevation characteristics, and (c) Satellite imagery.

Research Methodology

Data Collection

The MODIS-LST 8-day composite product (available at https://ladsweb.modaps.eosdis.nasa.gov/search/) was obtained from MOD11A2.V006 via NASA’s Earth Observing System for the month of June from 2000 to 2019. Although satellite data undergo geometric and radiometric corrections at various levels, some primary errors may persist, or new errors may arise during the correction process. Therefore, it is essential to review the images before conducting any analyses. Using ENVI 4.5 software, no radiometric errors (e.g., striped disruptions or repeated pixels) were observed in the provided images.

Field Sampling and Measurement

Based on the land use map provided by the Research Institute of Forests and Rangelands of Iran (Engineering Advisory Company of Resources Development and Improvement, 2012), the natural ecosystems of the Sirjan Plain watershed were examined to identify vegetation communities (i.e., homogeneous units for this study) and their functions through field operations conducted in spring (mid-June 2019). Table 1, along with Figure 2, presents the 39 plant communities identified in the study area, along with the vegetative and life forms of their dominant species.

Table (1): Introducing the studied plant communities with an ordinal classification of vegetative form and Raunkiaer life form for dominant species

	VF*			RLF*		
Plant communities	The first dominant species	The second dominant species	The third dominant species	The first dominant species	The second dominant species	The third dominant species
Alhagi camelorum	7			2		
Artemisia aucheri-Astragalus arbusculinus	5	8		2	2	
Artemisia aucheri	5			2		
Artemisia aucheri-Astragalus parrowianus	5	7		2	2	
Artemisia aucheri-Astragalus parrowianus-Ferula oopoda	5	7	7	2	2	3
Artemisia aucheri-Daphne stapfii	5	8		2	2	
Artemisia sieberi	7			2		
Artemisia sieberi- Amygdalus lycioides- Ebenus stellata	7	8	8	2	2	2
Artemisia sieberi- Astragalus arbusculinus	7	8		2	2	
Artemisia sieberi- Zygophyllum eurypterum	7	8		2	2	
Artemisia sieberi-Astragalus parrowianus	7	7		2	2	
Artemisia sieberi-Cousinia stocksii	7	8		2	2	
Artemisia sieberi-Ephedra strobilacea	7	8		2	2	
Artemisia sieberi-Seidlitzia rosmarinus	7	7		2	2	
Artemisia sieberi-Zygophyllum eurypterum-Stipa barbata	7	8	6	2	2	3
Artemisia sieberi-Zygophyllum atriploides	7	8		2	2	
Artemisia sieberi-Ephedra pachyclada	7	8		2	2	
Artemisia sieberi-Hertia intermedia	7	8		2	2	
Artemisia santolina-Ephedra intermedia	7	8		2	2	

Plant communities	VF*			RLF*		
	The first dominant species	The second dominant species	The third dominant species	The first dominant species	The second dominant species	The third dominant species
Artemisia spp.-Hertia intermedia	7	8		2	2	
Asrtagalus arbusculinus-Convolvulus acanthocladus	8	8		2	2	
Astragalus spachianus	7			2		
Astragalus parrowianus-Convolvulus acanthocladus	5	8		2	2	
Convolvulus acanthocladus-Ajuaga chamaecistus	8	5		2	2	
Cornulaca monacantha-Launaea acanthodes	7	7		2	3	
Cornulaca monacantha-Launaea procumbens	7	7		2	3	
Cornulaca monacantha-Salsola orientalis	7	7		2	2	
Dendrostellera lessertii-Noaea mucronata	1	7		3	3	
Dendrostellera lessertii-Noaea minuta	1	7		3	3	
Ephedra intermedia-Cousinia multiloba	8	7		2	2	
Ephedra intermedia-Noaea mucronata	8	7		2	2	
Halocnemum strobilaceum-Seidlitzia rosmarinus	8	7		2	2	
Haloxylon ammodendron	9			1		
Salsola arbusculiformis-Zygophyllum eurypterum	8	8		2	2	
Seidlitzia rosmarinus-Artemisia sieberi	7	7		2	2	
Seidlitzia rosmarinus-Salsola tomentosa	7	7		2	2	
Seidlitzia rosmarinus-Salsola dendroides	7	8		2	2	
Zygophyllum eurypterum-Artemisia sieberi- Astragalus parrowianus	8	7	5	2	2	2
Zygophyllum eurypterum-Artemisia sieberi	8	7		2	2	

VF* =Vegetative Form (1= Short collar: leaves <0.5 m long that are concentrated close to the soil surface, 2= Long neck: large leaves (petioles) with a length of >0.5 m that emerge from the soil surface, but do not form tussocks, 3=Semi-collar: leaves with a distinct surface that are arranged both near the soil surface and in the upper parts of the plant, 4= Upright leafy: The plant is upright with the leaves concentrated in the middle or top of the plant, 5= Cushen like species, 6= Grass and Grass- like species, 7=Short bushes: woody plants up to 0.8 meters in height, 8= Shrubs: woody plants taller than 0.8 meters with a canopy relatively close to the soil surface on one or more relatively short trunks, 9= Trees: woody plants with the main crown located at the height of a specific trunk, and 10= Leafless trees or shrubs: with green, non-fleshy, succulent stems as the main structure of photosynthesis.
RLF*= Raunkiaer Life Form (1= Phanerophyte, 2= Chaemophyte, 3= Hemicryptophyte, 4=Geophyte, and 5=Therophyte

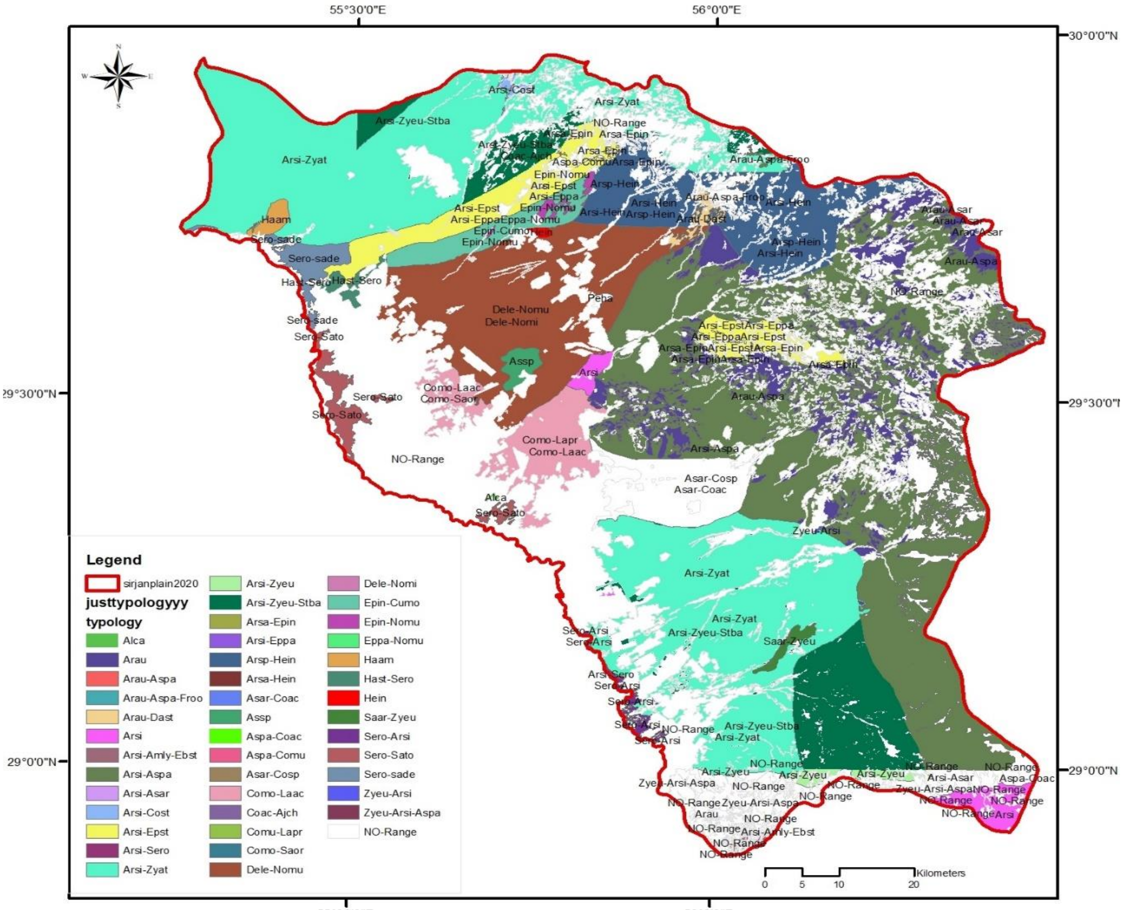


Figure (2): Plant communities map in the studied area

After identifying the plant communities and their dominant species during field operations, the dominant species of all communities were assessed based on plant traits (Garnier et al., 2004; Lavorel et al., 2021). Standardized protocols for sampling and processing plant functional traits were followed (Pérez-Harguindeguy et al., 2013). In total, eight plant traits and three plant functional types (i.e., CSR strategies) were evaluated in this research. The plant traits measured included: Leaf dry matter content (LDMC), Specific leaf area (SLA), Leaf area (LA), Leaf dry weight (LDW, in mg), Maximum height (MH), Leaf length (LL), Leaf width (LW), Leaf length-to-width ratio (LL/LW),

Before measurements began, ordinal data for vegetative form (VF) and Raunkiaer life form (RLF) were recorded for the dominant species. Maximum plant height was measured as the vertical distance from the base of the plant to the tallest leaf. Leaf traits were assessed using three to five healthy adult leaves from each plant position (upper, middle, and lower). Leaf length (LL) and leaf width (LW) were measured using a digital Vernier caliper. For leaf area (LA) measurement, a 1 cm scale was marked on the lower right corner of a sheet of paper. Ten to twenty leaves were placed flat on the paper and photographed with a camera positioned parallel to the paper. The images, showing the one-sided area of the leaves, were processed using Photoshop software to calculate LA.

The clipped leaves were refrigerated in moist paper towels for 24 hours to rehydrate, then blotted dry and weighed to determine leaf fresh weight (Chen et al., 2023). After drying in an oven at 60°C for 72 hours, the leaves were weighed again to determine leaf dry weight. Specific leaf area (SLA) was calculated as the ratio of leaf area to leaf dry weight, leaf dry weight (LDW) was recorded as the dry weight of the leaf, and leaf dry matter content (LDMC) was calculated as the ratio of leaf dry weight to leaf fresh weight.

Additionally, Grime’s CSR (Competition-Stress Tolerant-Ruderal) functional types (Grime, 1977) were evaluated in this study. Initially, the CSR framework was conceptual rather than empirically trait-based. However, Pierce et al. (2016) demonstrated that CSR strategies could be predicted using plant traits. Therefore, quantitative values of C (Competition), S (Stress Tolerance), and R (Ruderal) were calculated for comparison using a series of globally calibrated equations developed by Pierce et al. (2017). These equations form the basis of the globally calibrated CSR ordination tool, *StrateFy*, which focuses on traits such as leaf area (LA), specific leaf area (SLA), and leaf dry matter content (LDMC). To apply this tool, the mean trait values for each dominant species within the plant communities were calculated and entered into the *StrateFy* spreadsheet. The CSR values for each community were then determined using a weighted mean based on the relative canopy cover of the dominant species.

Data Analysis

To conduct factor analysis for functional traits, the Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy was evaluated using the SPSS software. The KMO estimate indicates the proportion of variance in different functional traits explained by underlying components (Kaiser, 1958). The overall significance of the correlation matrix was tested using Bartlett’s test of sphericity for the functional traits. Since the KMO measure of sampling adequacy exceeded 0.5, the data were deemed suitable for factor analysis.

A rotated Principal Component Analysis (PCA) procedure was then applied to the functional traits of each plant community to identify the principal components accounting for the most significant variance. A variable loading matrix with Varimax rotation (Stone et al., 2022) was used to explore variables in the principal components, with a loading value threshold of ≥ 0.5.

To evaluate the suitability of MODIS satellite-based LST at the plant community scale, a preliminary validation assessment was conducted. This involved measuring under-canopy land surface temperature near the main stem of different life forms (RLF) in the study area. The results showed an acceptable correlation ($R = 0.93$, $N = 31$, $P < 0.01$) between the satellite-derived LST and ground measurements.

To identify the determinant traits of LST as drivers, a Multivariate Linear Regression (MLR) model was applied using a stepwise procedure in the SPSS software. Collinearity among predictors was assessed using the variance inflation factor ($VIF < 10$) to avoid multicollinearity issues (Gonzalez & Noble, 2014; Cho & Lee, 2018; Mohamadi and Bagheri, 2022). The significance of the regression equation was determined using the F-test, and the coefficient of determination (R^2) was used to evaluate model performance based on the following equation:

$$R^2 = \frac{\left[\sum_{i=1}^{n}(Q_{est,i} - \overline{Q}_{est,i})(Q_{obs,i} - \overline{Q}_{obs,i})\right]^2}{\sum_{i=1}^{n}(Q_{est,i} - \overline{Q}_{est,i})^2 \sum_{i=1}^{n}(Q_{obs,i} - \overline{Q}_{obs,i})^2} \quad (1)$$

Where $Q_{est,i}$ is the estimated value, $Q_{obs,i}$ is the observed value, and $\overline{Q}$ is the mean.

Since multiple linear regression (MLR) models are designed to analyze linear relationships between dependent and independent variables, and independent variables are excluded from the model if they do not improve its accuracy in the stepwise procedure, non-linear relationships are not accounted for in MLR models. However, a significant advantage of MLR models in environmental sciences is their ability to concurrently consider multiple independent variables to identify influential factors under natural ecosystem conditions, as demonstrated in this study.

All land surface temperature (LST) data were constrained by the plant community layer using the ArcGIS 10.4.1 software to extract zonal statistics for each community. Two indicators—Spatial Coefficient of Variance (SCV) and Temporal Coefficient of Variance (TCV)—were used to investigate changes in spatiotemporal dimensions for each plant community, based on the following formula:

$cv = \left(\frac{st}{m}\right) * 100$ (2)

In which *st* is the standard deviation and *m* is the mean of data.

As a multivariate statistical method, cluster analysis was applied to identify co-functioning groups based on thermal feedback from plant communities. To achieve this, a matrix was created to represent land surface temperature (LST) changes in plant communities over the years 2000 to 2019. Hierarchical Cluster Analysis (HCA), a widely used multivariate statistical method (Brown et al., 2013), was then performed using SPSS software. The analysis employed an agglomeration schedule, the between-groups linkage method, and the squared Euclidean distance procedure to distinguish co-functioning communities.

Additionally, this study utilized functional groups derived from cluster analysis to examine potential differences in their CSR strategies using One-Way ANOVA. Where ANOVA results were statistically significant, the means of the subgroups were compared using Duncan's multi-domain procedure.

Finally, a representative community from each identified cluster was selected for trend and abrupt change analysis using the Sequential Mann-Kendall (SMK) method (Sneyers, 1990). The SMK method involves a progressive analysis of the Mann-Kendall test applied to time series data (*xi*) to detect event or change points in long-term time series. In this procedure, the sequential values include *u(t)* and *u'(t)*, where *u(t)* represents the z-values calculated from the first to the last data point. The following steps are applied sequentially:

The magnitudes of the annual mean time series *xj* (where *j = 1, ..., n*) are compared with *xk* (where *k = 1, ..., j-1*). At each comparison, the number of cases where *xj >xk* is counted and denoted as *nj*

The t-test is then calculated as below formula:

$t = \sum_{i-1}^{n} n_i$ (3)

The mean and variance of the test statistic include:

$E(t) = \frac{n(n-1}{4}$ (4)

$Var(t) = \frac{n(n-1)(2n+5)}{72}$ (5)

The sequential values of the statistic u(t) are then indicated as

$U(t) = \frac{t-E(t)}{\sqrt{Var(t)}}$ (6)

Similarly, the values of u'(t) are calculated backward, beginning from the end of the series. In plotted u(t) and u'(t) curves, if the intersection of u(ti) and u'(ti) happens beyond ±1.96 (95% confidence level) of the standardized statistic, a dimensional change (i.e., trend) at that point in the time series can be interpreted. However, if the intersection of curves occurs inside ±1.96, a sharp change (i.e., abrupt change) at that point is found.

Results

Functional Traits in Plant Communities

The first set of analyses examined variations in functional traits at the plant community scale. Table 2 presents the summary statistics for the studied functional traits. The data in Table 2 indicate that the leaf area (LA) trait exhibited the most variation, ranging between 6.9 and 1697.4, while the leaf length-to-width ratio (LL/LW) trait showed the least variation. To further distinguish the role of each dominant plant species within the plant communities, additional analysis was conducted, as illustrated in Figure 3. A key observation from this figure is that the differences between the first, second, and third species become significant and specialized for all traits within each plant community.

To identify the most influential traits, a PCA-rotated analysis was performed. The results of this analysis are presented in Table 3. The bottom row of the table shows the proportion of variance explained by each component. A closer examination reveals that the first component, represented by LA and LW, explains the largest proportion of trait variation, with a justification coefficient of 40%. This is followed by the second component, represented by LDMC, SLA, LWD, and MH, which has a justification coefficient of 25.4%.

Table (2): Statistical characteristics for the studied functional traits

Traits	Mean	Standard error	Minimum	Maximum	Range
LDMC (%)	34.0750	.78130	24.00	44.00	20.00
SLA (mm2/mg)	20.3000	.70271	11.40	29.40	18.00
LA (mm2)	62.4050	21.93	6.90	1697.40	1690.50
LDW (mg)	26.7775	.62103	19.50	41.00	21.50
MH (cm)	68.3775	5.39671	30.00	198.00	168.00
LL (mm)	35.8925	23.88136	4.00	967.00	963.00
LW (mm)	26.9713	21.04318	.80	847.50	846.70
LL/LW	2.2941	.14939	1.10	5.30	4.20

Figure (3): The role of dominant species (e.g., FDS: First Dominant Species, SDS: Second Dominant Species, and TSS: Third Dominant Species) for functional traits including LDMC (A), SLA (B), LA(C), MH (D), LL (E), LL (F), LW (G), and LDW(H)

Table (3): The loads obtained for each trait in the components using principal component analysis rotated by the Varimax procedure

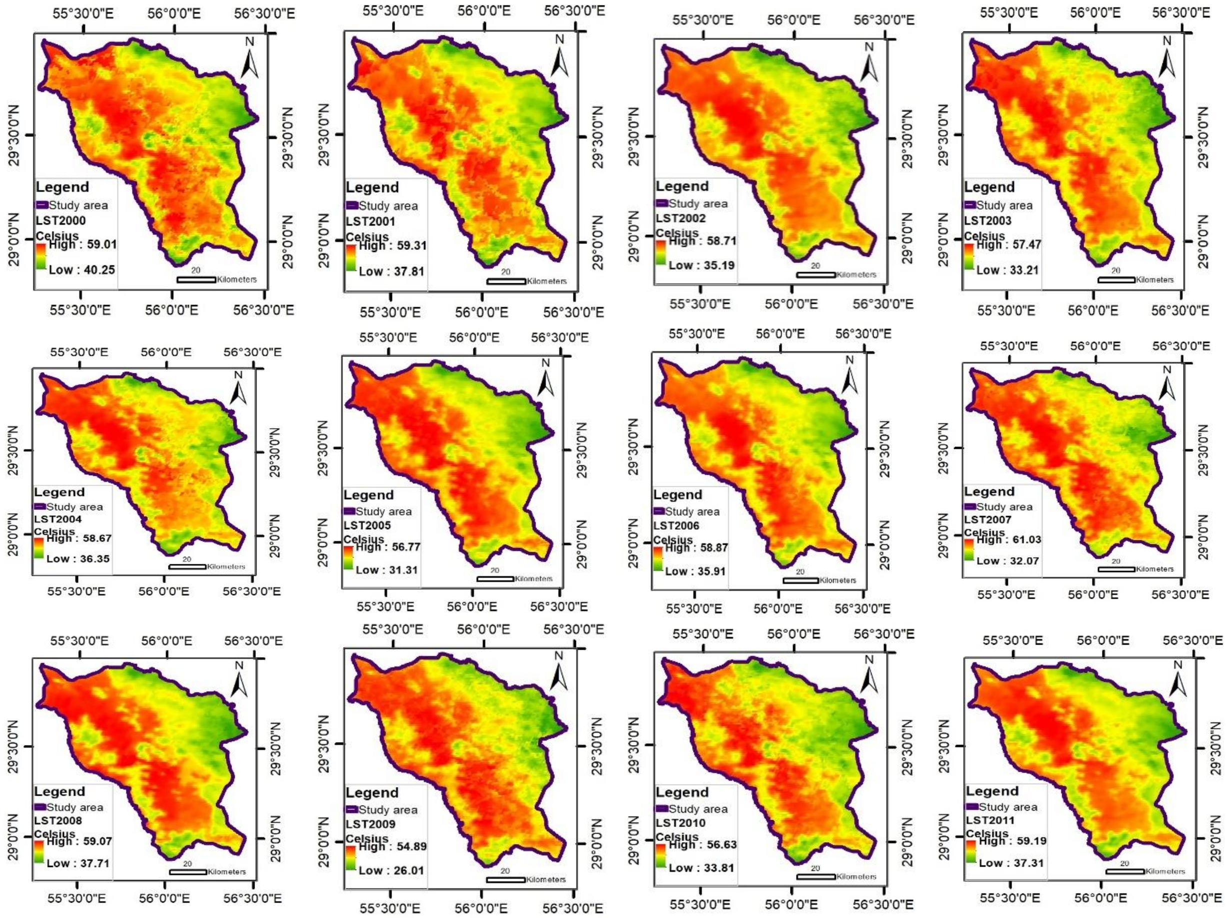
Traits**	Component Rotated[1*]	
	1	2
LDMC	.140	**-.818**
SLA	.107	**.823**
LA	**.991**	-.021
LDW	.394	**.575**
MH	.045	**.667**
LL	.491	-.022
LW	**.991**	-.019
LL/LW	-.289	-.119
Variance explained by each component	40	25.4

[1]: Rotation Method: Varimax with Kaiser Normalization

**: KMO and Bartlett's value>0.7 (p>0.01)

Tempro-Spatial Characteristics of LST

Figure 4 illustrates the results of land surface temperature (LST) analysis across plant communities in the Sirjan watershed over a 20-year study period (2000 to 2019), presented in chronological order. As shown in Figure 4, LST values are lower around the borders of the study area, particularly in the eastern and northeastern regions, where high altitudes and mountain plant communities dominate. In these areas, LST ranged from 26.01°C in 2009 to 40.25°C in 2000. In contrast, LST values are consistently higher across almost all years in the plain areas along the northwest-southeast axis in the central part of the study area, where desert plant communities are prevalent. In these regions, LST ranged from 54.89°C in 2009 to 61.03°C in 2007.



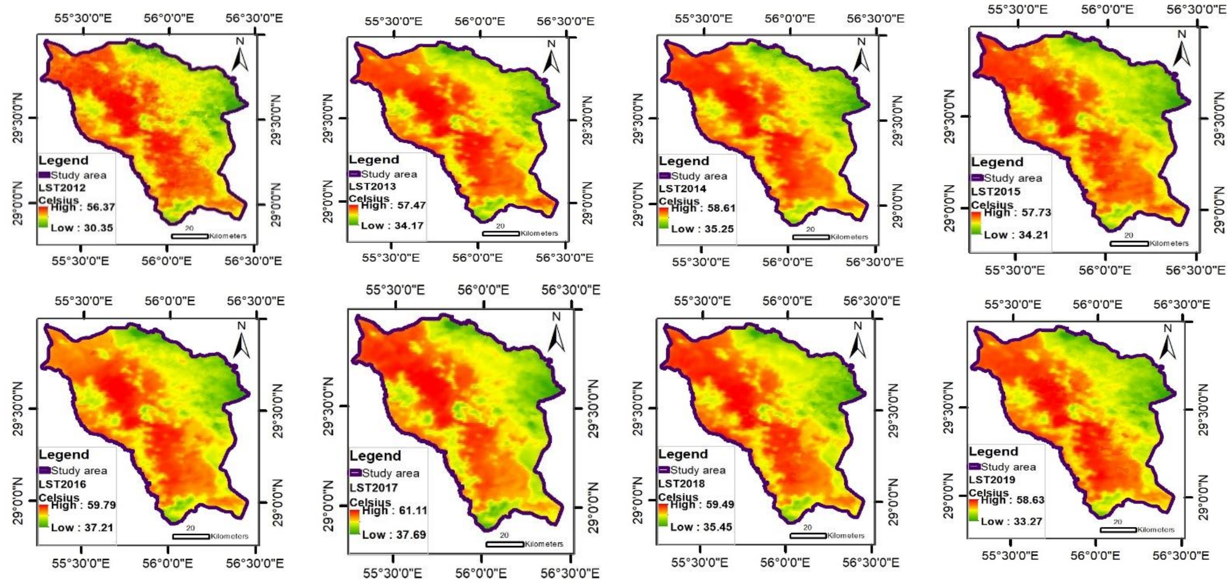


Figure (4): The LST maps of studied area from 2000 to 2019

Table 4 presents the results of the assessment of annual land surface temperature (LST) spatial variation across different plant communities in the region. According to Table 4, the *Artemisia aucheri-Astragalus parrowianus* plant community exhibited the most spatial changes, ranging from 6% in 2000 to 10.5% in 2009. In contrast, the *Astragalus spachianus* community experienced the least spatial changes, ranging from 0.2% in 2008 to 2.6% in 2001.

Table (4): SCV (%) of plant communities for each year.

Year	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
Alca	0.1	0.9	0.6	1.5	1.0	0.1	0.4	1.5	0.6	3.8	2.1	0.4	0.7	0.9	0.3	1.3	0.7	0.5	1.0	0.7
Arau-Asar	0.6	1.4	1.1	2.0	1.5	0.3	0.9	2.0	1.1	4.3	2.6	0.9	1.2	1.4	0.8	1.8	1.2	1.0	1.5	1.2
Arau	4.9	5.2	4.5	3.6	3.2	4.2	3.7	4.2	3.1	5.0	4.3	3.6	3.7	3.3	3.2	3.7	3.9	3.9	3.3	4.1
Arau-Aspa	6.0	7.0	7.8	8.8	7.3	9.1	7.4	9.6	7.8	10.5	7.7	7.5	8.4	7.8	8.8	8.5	7.9	7.3	7.8	9.0
Arau-Aspa-Froo	1.5	1.9	1.2	1.8	1.1	1.0	1.4	2.2	1.5	2.4	2.0	1.3	2.0	1.1	2.2	1.5	1.3	1.5	1.3	1.1
Arau-Dast	1.7	2.2	2.3	1.1	1.1	2.2	2.0	1.9	1.7	2.6	3.5	1.6	1.8	1.5	2.1	1.6	2.0	1.5	1.5	2.3
Arsi	3.9	5.4	5.9	5.2	5.5	6.4	5.5	8.8	6.2	5.2	5.7	5.5	5.7	4.7	5.7	6.2	5.3	6.1	5.1	5.7
Arsi-Amly-Ebst	0.9	1.2	2.0	0.7	0.4	0.1	1.1	1.3	1.0	2.2	1.0	1.5	0.2	1.5	0.8	2.5	3.0	2.6	2.9	2.5
Arsi-Asar	1.8	2.1	1.4	2.3	2.0	1.4	1.3	2.8	1.5	1.5	1.5	0.9	1.0	1.4	1.5	2.8	1.1	1.0	1.1	1.7
Arsi-Zyeu	4.6	5.2	5.0	5.6	5.1	5.5	5.4	5.6	5.5	6.0	5.3	5.2	5.5	5.1	5.5	5.8	5.0	5.5	5.0	5.1
Arsi-Aspa	4.3	5.0	5.5	5.7	4.5	6.3	5.3	6.5	5.2	9.2	5.2	5.1	6.4	5.5	5.8	6.2	5.3	5.0	5.5	6.5
Arsi-Cost	1.5	2.8	1.4	0.9	2.4	1.0	1.1	2.1	0.9	1.4	2.3	1.1	0.7	1.0	1.3	1.4	1.1	0.8	0.7	0.9
Arsi-Epst	4.4	5.3	7.4	7.5	6.9	8.5	6.3	9.0	6.9	8.6	6.7	7.0	7.1	6.8	8.1	8.1	6.6	7.0	7.5	8.6
Arsi-Sero	0.9	1.3	0.4	1.3	0.5	0.2	0.6	0.2	0.6	1.4	0.6	0.4	1.1	0.3	0.3	0.5	0.2	0.8	0.2	0.5
Arsi-Zyeu-Stba	4.6	5.2	5.6	5.9	5.8	6.7	6.0	6.7	6.0	6.9	6.1	5.6	6.0	5.8	6.1	5.9	5.8	5.7	5.6	6.8
Arsi-Zyat	5.6	7.3	7.8	8.1	8.0	9.0	7.6	8.2	7.7	9.0	8.4	7.5	8.2	7.7	8.4	8.8	7.2	7.9	8.0	9.0
Arsi-Eppa	2.4	3.4	4.8	5.5	5.1	6.1	4.4	6.1	4.6	5.1	4.8	4.9	5.2	5.0	4.9	5.5	4.0	5.0	5.5	5.6
Arsi-Hein	2.6	3.4	3.7	3.7	3.2	4.1	3.2	3.8	3.8	6.3	3.3	3.8	4.4	3.8	4.4	3.7	4.2	3.8	3.6	3.9

Arsa-Epin	2.3	3.9	3.8	3.1	2.8	3.1	2.7	1.9	3.3	4.5	4.8	3.3	3.7	3.1	3.9	3.3	4.1	2.8	2.6	4.1
Arsp-Hein	2.8	3.1	2.9	4.1	3.3	3.9	3.3	3.1	3.5	6.0	3.5	3.3	3.7	3.2	4.1	3.4	3.8	3.5	3.3	3.4
Asar-Coac	3.2	3.5	3.1	3.8	3.5	3.6	3.3	4.4	3.7	4.0	4.3	3.4	3.5	3.2	3.6	3.7	3.5	3.7	3.4	4.1
Assp	1.1	2.6	0.4	0.6	0.3	0.8	0.3	0.6	0.2	1.0	1.3	0.6	0.5	0.4	0.4	0.4	0.6	0.5	0.4	0.5
Aspa-Coac	1.5	1.9	1.5	2.8	2.8	3.5	1.7	1.8	3.2	2.5	1.8	1.7	2.4	2.0	1.1	2.8	1.1	1.8	1.1	1.7
Coac-Ajch	3.6	2.6	5.1	4.7	4.8	6.7	5.1	6.2	4.4	5.3	3.1	4.7	4.2	4.6	4.7	3.9	4.9	5.2	4.5	5.2
Como-Laac	3.9	4.9	4.4	5.0	4.7	4.6	5.0	5.3	4.9	5.9	4.9	5.0	5.1	4.7	5.0	5.1	4.9	5.1	4.6	5.5
Como-Lapr	4.1	2.8	2.8	3.3	4.4	3.5	4.0	4.1	2.7	5.5	2.3	3.2	3.0	3.0	3.4	4.1	3.8	4.1	2.3	3.3
Como-Saor	2.1	3.2	2.6	2.0	3.1	3.6	2.8	2.1	2.1	4.5	2.7	2.1	1.9	2.1	1.6	1.4	1.4	1.0	1.5	1.1
Dele-Nomu	3.1	3.9	4.0	4.9	4.2	4.8	4.7	6.3	4.1	5.1	4.5	4.4	4.6	4.3	4.6	4.9	4.6	4.2	4.4	5.3
Dele-Nomi	2.3	2.7	2.8	3.8	3.9	3.9	4.1	4.7	3.7	4.7	5.1	3.5	4.9	3.5	3.9	3.9	3.8	3.5	4.1	4.3
Epin-Cumo	2.6	2.6	3.0	3.9	4.0	4.3	3.1	4.5	3.4	3.9	3.8	3.5	4.3	3.2	3.5	4.1	2.8	3.5	3.7	3.9
Epin-Nomu	2.1	2.8	4.8	5.1	3.1	5.0	4.5	4.7	3.9	4.4	3.0	4.1	4.3	4.4	4.5	4.1	4.3	3.6	3.5	5.9
Hast-Sero	0.7	1.4	1.3	1.6	1.7	1.9	1.6	1.4	2.1	2.1	1.8	1.9	2.5	1.6	1.9	1.4	1.2	1.8	1.4	1.3
Haam	1.6	0.6	1.0	1.4	0.6	1.0	0.8	0.6	0.2	1.0	0.8	1.2	0.9	1.0	0.8	0.6	0.8	1.4	0.7	1.2
Saar-Zyeu	1.1	0.8	0.6	0.7	0.7	1.3	1.1	0.9	0.5	1.9	1.2	0.6	1.0	0.6	0.6	1.0	0.7	0.7	0.5	0.7
Sero-Arsi	0.9	1.0	2.8	0.9	1.0	1.0	1.4	1.5	2.2	1.3	1.3	0.9	1.6	1.4	1.7	1.2	1.1	1.0	0.9	0.9
Sero-Sato	2.2	2.9	1.7	2.5	2.4	2.4	2.6	2.9	2.9	2.7	2.7	2.4	2.4	2.9	2.3	2.6	2.5	1.9	2.5	3.0
Sero-sade	2.2	2.3	2.9	2.5	2.8	1.9	2.5	2.5	2.1	3.9	2.5	3.6	2.8	3.4	2.8	1.8	2.2	2.9	2.7	3.2
Zyeu-Arsi-Aspa	4.7	6.0	5.5	5.5	5.5	5.4	5.6	6.2	5.5	6.5	6.2	5.3	6.0	5.4	5.6	5.7	6.0	5.7	4.9	5.9
Zyeu-Arsi	0.7	2.0	1.5	1.5	1.5	1.4	1.6	2.2	1.5	2.5	2.2	1.3	2.0	1.4	1.6	1.7	2.0	1.7	0.9	1.9

As shown in Figure 5, the assessment of land surface temperature (LST) across plant communities revealed significant spatial variations in LST over time. Specifically, the *Artemisia aucheri-Astragalus arbusculinus* community exhibited the highest coefficient of variation (CV) at 5.64, while the *Cornulaca monacantha-Launaea acanthodes* community showed the lowest CV at 2.73 over the 20-year period.

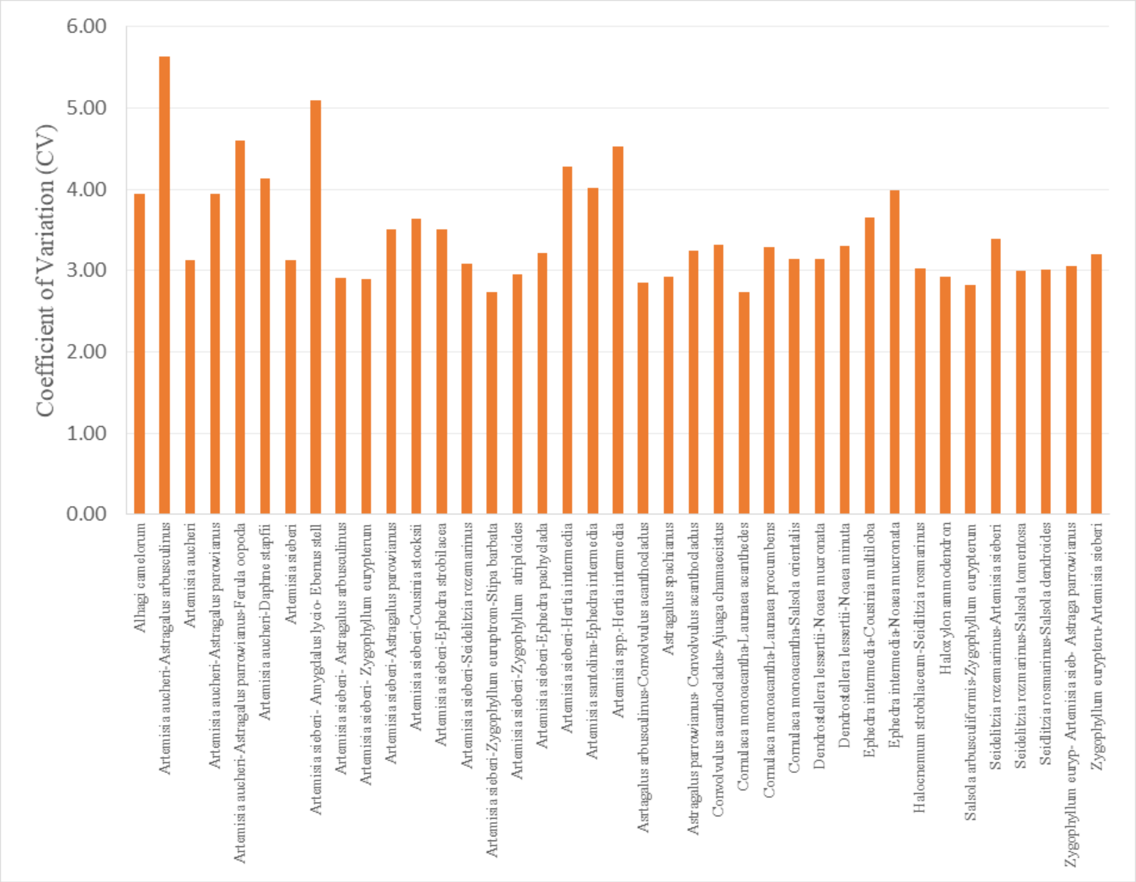


Figure (5): TCV (%) of plant communities during 20 years (from 2000 to 2019)

Relation Between Plant Communities' Functional Traits and The LST

The results of the stepwise multivariate regression model revealed that functional traits—including leaf dry matter content (LDMC), specific leaf area (SLA), leaf area (LA), leaf width-to-length ratio (LWD), maximum height (MH), leaf width (LW), and leaf length-to-width ratio (LL/LW)—influenced the dependent variable, land surface temperature (LST), derived from satellite imagery. The best-fitted regression model achieved a determination coefficient of 59% (Table 5).

As shown in Table 5, LST decreases with increasing values of LDMC, MH, and LW traits. This suggests that taller plant communities are more effective at moderating temperature. Additionally, plant communities with higher dry matter content in their leaf cells are better equipped to reduce LST under ecosystem conditions. In other words, plant communities adapted to the stressful conditions of arid lands have specialized their leaf traits to moderate temperature.

It is important to note that grazing in natural ecosystems significantly influences the traits of plant communities. Therefore, the validity of the resulting model is contingent on the assumption that there are no substantial changes in grazing intensity within the study area.

Table (5): Multi-variate Linear Regression (MLR) model for exploring determinants of LST in ecosystem conditions using a stepwise regression model

Model number	Dependent variables	Regression model[1*]	R^2	test of ANOVA regression	Sig
1	LST (Celsius)	$Y= -0.145\ X_1 + 0.172\ X2 + 0.094\ X3 + 0.569\ X4 - 0.008\ X5 - 0.197\ X6 + 0.738\ X7 + 35.173$	0.59	5.34	0.000**

[1*] -Independent variables of functional traits included in the model are X_1: LDMC (%), X_2: SLA (mm^2/mg), X_3: LA (mm^2), X_4: LDW (mg), X5: MH (cm), X6: LW (mm), and X7=LL/LW.

Determining Functional Plant Community Groups through Temperature Feedback

Figure 6 presents the results of the cluster analysis conducted on different plant communities. According to these results, the plant communities in the region (comprising 41 communities) were divided into five homogeneous clusters based on their land surface temperature (LST) modification function, at an 80% similarity level. To assess the extent of LST changes within these clusters (as temperature feedback), each group was analyzed using the Sequential Mann-Kendall test.

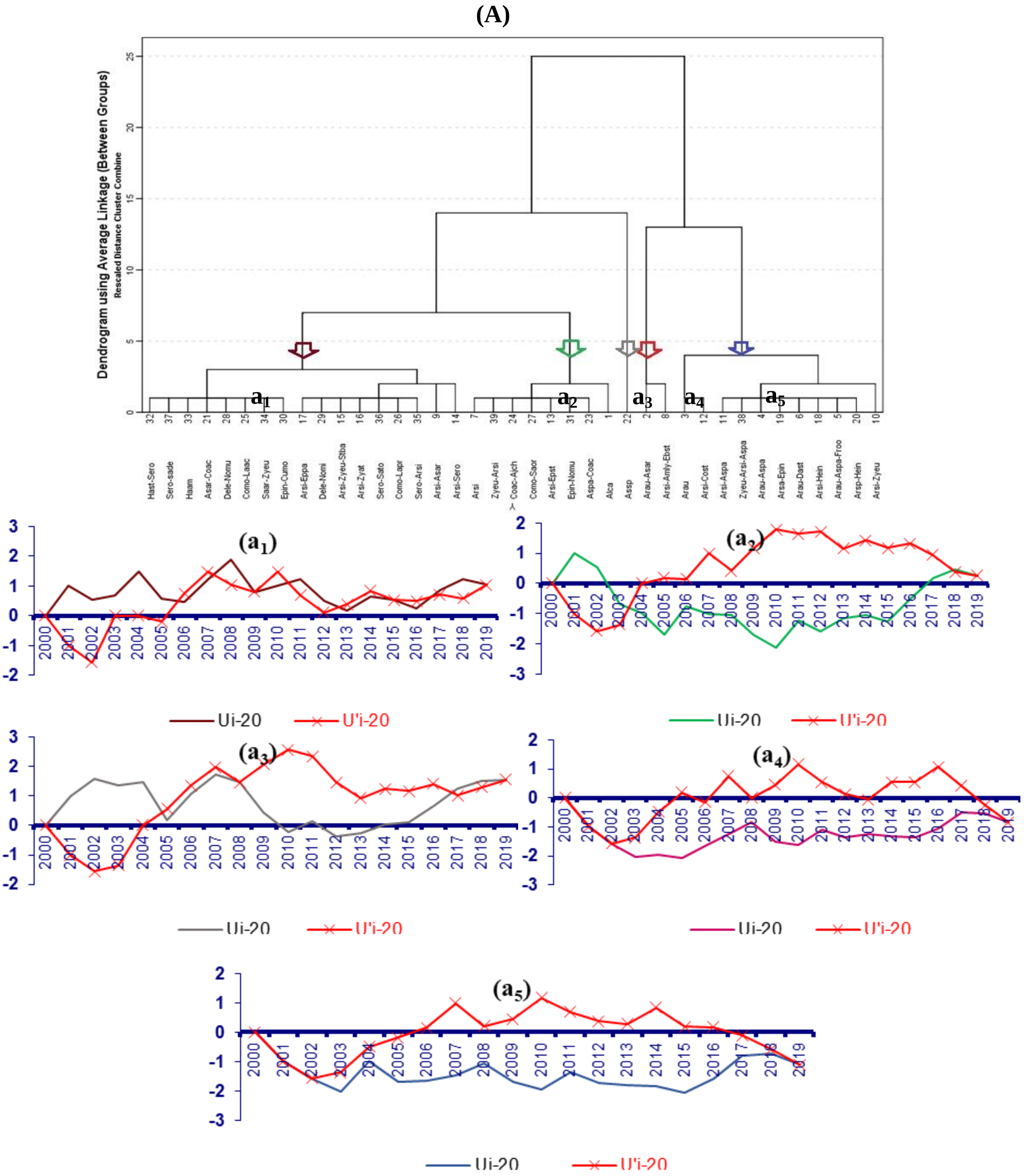


Figure (6): Cluster analysis of plant communities

CSR strategies of groups in cluster analysis

The variance analysis of CSR strategies was conducted for the plant community groups identified through cluster analysis, using a one-way ANOVA test. As shown in Table 6, while the C strategy did not show significant differences, the S and R strategies exhibited significant variations (p-value < 0.05) among the groups separated by cluster analysis. To further analyze these differences, a mean comparison test was performed using Duncan's method.

Table 7 presents the results of the mean comparison test using Duncan's multi-domain method. It reveals a significant decrease in the S value when transitioning from one main group (cluster a1a2a3, which includes sub-clusters a1, a2, and a3) to another main group (cluster a4a5, which includes sub-clusters a4 and a5). Conversely, a notable increase in the R value was observed during this transition.

Additionally, a meaningful decrease in the S value was found when comparing subgroup a1 to subgroups a2 and a3, highlighting the unique behavior of the a1 subgroup in applying the S strategy.

Table (6): Investigation of CSR strategy differences among co-function communities using One-Way ANOVA test

Variation sources		Df	Mean Square	F	Sig.
C strategy (%)	Between groups	4	0.069	0.658	0.625^{ns}
	Within groups	35	0105		
	Total	39			
S strategy (%)	Between groups	1	404.9	2.850	0.038^{*}
	Within groups	33	142		
	Total	34			
R strategy (%)	Between groups	1	427.1	2.555	0.048*
	Within groups	33	160.2		
	Total	34			

*, ** =Significant at 5%, 1%, respectively and ^{ns}=Nonsignificant

Table (7): Compare mean test by Duncan's method for CSR strategies of plant communities' groups in cluster analysis

Cluster-based subgroups	N	C strategy	R strategy	S strategy
a1	17	27.51a±0.00	49.17 b±3.6	23.30a±3.6
a2	8	26.11a±0.10	58.8 b±4.6	15.06b±3.7
a3	2	25.50 a±0.00	58.63b±0.00	13.85b±0.0
a4	2	28.51a±0.01	70.65a±0.92	1.83c±0.92
a5	11	26.69a±0.18	62.12a±2.6	7.68c±2.26

Discussion

This research aimed to assess the importance of biotic drivers (i.e., functional traits) in moderating land surface temperature (LST) at the plant community scale. The study identified traits such as leaf dry matter content (LDMC), specific leaf area (SLA), leaf area (LA), leaf width-to-length ratio (LWD), maximum height (MH), leaf width (LW), and leaf length-to-width ratio (LL/LW) as key influencers, with a combined justification coefficient of 59%.

Plant communities with higher values of LDMC, MH, and LW were found to effectively reduce LST. Specifically, taller plant communities (higher MH) can moderate LST by providing greater shading on the land surface, thereby cooling the ecosystem (Moles et al., 2009; Pérez-Harguindeguy et al., 2013; Dendoncker et al., 2023). These findings highlight the critical role of functional traits in regulating microclimatic conditions and emphasize the potential of plant communities with specific trait combinations to mitigate temperature extremes in arid and semi-arid environments.

Furthermore, dominant species in plant communities with higher values of leaf dry matter content (LDMC) can effectively moderate temperature due to their specialization in maximizing dry material in their leaves, which aids adaptation to the harsh conditions of drylands (Van der Merwe et al., 2021). High LDMC values are indicative of species' tolerance to abiotic stress and are associated with resource conservation and defense mechanisms (Onoda et al., 2011; Pérez-Harguindeguy et al., 2013). Since these plant communities typically have leaves with longer lifespans (Rippy et al., 2021; Goud et al., 2023), this finding is particularly useful for ecosystem-based landscaping and planning in arid regions.

In contrast, plant communities with high specific leaf area (SLA) and leaf area (LA) are more efficient at acquiring resources from the environment. These traits are typically associated with lower abiotic stress and represent a more resource-acquisitive strategy (Poorter et al., 2009; Wright et al., 2004; Chen et al., 2023). However, decision-makers should exercise caution when applying these communities in arid ecosystems for two key reasons: (1) their lack of specialization in resource use under arid conditions, and (2) their limited efficiency in reducing land surface temperature (LST).

According to the assessment of spatial changes in land surface temperature (LST) across different plant communities in the region, the *Artemisia aucheri-Astragalus parrowianus* community exhibited the highest spatial changes, while the *Astragalus spachianus* community experienced the lowest changes from 2000 to 2019. Since a high coefficient of spatial changes indicates heterogeneity within plant communities, the *Artemisia aucheri-Astragalus parrowianus* and *Astragalus spachianus* communities can be classified as heterogeneous and homogeneous, respectively.

On the other hand, high spatial heterogeneity in plant communities is generally considered a negative indicator for creating greenery. Therefore, it is recommended to investigate the reasons behind the high heterogeneity observed in the *Artemisia aucheri-Astragalus parrowianus* community. Additionally, developing a coefficient for assessing plant community heterogeneity could be a valuable research direction stemming from this study.

Given that changes in the cover percentage and composition of accompanying plants in the *Artemisia aucheri-Astragalus parrowianus* community are influenced by the allelochemicals of the dominant *Artemisia* species (Shirmardi et al., 2013; Arjmand et al., 2014; Gholami et al., 2015), it is recommended that future studies consider the role of allelopathy as an important eco-physiological factor in creating spatial heterogeneity. This could be achieved through field studies and ground observations of vegetation.

On the other hand, the results of the assessment of long-term temporal changes in land surface temperature (LST) across different plant communities revealed clear differences in LST trends over time. Specifically, the *Artemisia aucheri-Astragalus arbusculinus* community exhibited the highest coefficient of variation (CV) at 5.64, while the *Cornulaca monacantha-Launaea acanthodes* community showed the lowest CV at 2.73 over the 20-year period.

By demonstrating a meaningful relationship between the functional traits of plant communities and land surface temperature (LST) using a multiple linear regression (MLR) model, these findings provide further support for the hypothesis that additional, unmeasured traits could be considered to enhance this relationship.

The results of multivariate cluster analysis of different plant communities revealed that the study area’s plant communities can be distinguished and separated into five functional groups/clusters based on their spatial and temporal modification of land surface temperature (LST), at an 80% similarity level. Assessments of LST changes within these clusters, conducted using the graphical Mann-Kendall test, showed that each cluster followed a unique and specific pattern.

This approach aligns with the findings of Moreira et al. (2019), who used cluster analysis of enhanced vegetation index (EVI) seasonal changes to group ten types of grassland plants based on phenological similarity. Their study classified the plant types into four homogeneous groups, which is consistent with the high efficiency of cluster analysis in grouping plant communities observed in the current study.

Given the high similarity of LST changes within each cluster of plant communities examined in this study, it is possible to replace plant communities with different ecological needs at the cluster scale (at an 80% similarity level) to modify temperature. This can be achieved through vegetation development, creating green spaces, and improving rangelands.

Based on the integration of cluster analysis findings and the functional strategies of plant communities, the five functional sub-groups/clusters identified in this research were categorized into two co-function groups using S and R functional strategies. Plant communities with the S strategy (e.g., 26 communities), which are capable of creating a combination of abrupt and trend changes in land surface temperature (LST), were found to be more effective than those with the R strategy (e.g., 13 communities), which only produced directional (trend) changes in LST.

Therefore, the S-strategized co-function, characterized by a high value of the leaf dry matter content (LDMC) trait, is recommended for biological programs and ecosystem-based landscaping initiatives.

Conclusion

This study was designed to identify functional groups within plant communities and analyze their spatial and temporal changes in relation to land surface temperature (LST). The results support the idea that functional groups of plant communities can be substituted for one another (with an accuracy of 80%) by decision-makers and executive officials, based on their goals, available resources, and limitations, while aligning with the ecological needs of species within the desired functional group. This approach can enhance greenness and improve rangelands, serving as an effective tool for combating global warming.

The findings suggest that species such as *Astragalus spachianus*, *Cornulaca monacantha*, and *Launaea acanthodes* are suitable for rangeland improvement practices aimed at addressing this challenge. In particular, focusing on S-strategized co-functionality—characterized by stress-tolerant traits—is more appropriate for moderating temperatures in arid lands with severe ecological resource limitations. This is evidenced by the fact that all dominant species in the study belonged to the a1, a2, and a3 subgroups in the cluster analysis.

The findings highlight the critical role of functional traits in dominant species for reducing LST, which is a key factor controlling ecohydrological processes such as evapotranspiration and photosynthesis. Additionally, these traits contribute to enhancing ecosystem services, including recreation, in dryland environments. Therefore, it can be argued that extreme temperatures, as a significant environmental challenge, can be mitigated through biological practices that focus on functional traits and strategies.

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