

Article

Evaluating the Time-Lag and Cumulative Effects of Climatic Factors on Vegetation Dynamics of Different Land-Use Types in the Circum-Tarim Basin

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Abstract

Monitoring vegetation dynamics in drylands and disentangling their driving mechanisms are essential for deciphering vegetation–climate feedbacks and supporting targeted ecological restoration. Taking the Circum-Tarim Basin as the study region, this study adopted the modified soil-adjusted vegetation index (*MSAVI*) as a vegetation proxy and integrated multiple statistical approaches to quantify spatiotemporal vegetation variations across four land-use types from 2000 to 2021. The relative importance of time-lag and cumulative climatic effects on vegetation growth were evaluated for specific land-use types. The main results show that: (1) Widespread vegetation greening occurred across the study area, and croplands dominated this positive trend. (2) Vegetation generally exhibited more immediate responses to climate change in cropland and woodland, whereas grassland and unused land showed more heterogeneous, lagged responses. (3) Despite the inherently low absolute R^2 values typical of hyper-arid pixel-scale modeling, climate models incorporating cumulative and lagged effects showed substantial relative improvements in explanatory power (ΔR^2) compared to contemporaneous models, particularly in cropland and woodland. These improvements were consistently retained under out-of-sample validation (positive $\Delta CV-R^2$). These findings highlight the importance of considering land-use-specific lagged and cumulative climate effects when assessing dryland vegetation–climate interactions, which provides useful implications for ecological restoration and climate adaptation in arid basins.

Keywords: modified soil-adjusted vegetation index; vegetation greening; climatic forcing; land-cover heterogeneity; drylands



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1. Introduction

Vegetation activity is a key indicator of regional environmental changes, highly sensitive to both climatic and anthropogenic impacts [1–3]. Vegetation changes in turn can generate profound climatic and environmental feedbacks through affecting energy–water exchanges and carbon sequestration [2,4,5]. Vegetation cover can also serve as an effective barrier to prevent soil from being eroded by wind and water [6,7]. Accordingly, monitoring vegetation changes and disentangling its driving forces lay a theoretical foundation for understanding vegetation–climate interaction mechanisms, and provide actionable guidance for combating land degradation and mitigating climate-induced hazards.

A range of vegetation indices have been applied to quantify vegetation dynamics and their responses to climate change, such as the normalized difference vegetation index (NDVI), the leaf area index (LAI), the *MSAVI*, the fractional vegetation cover (FVC), net primary productivity (NPP), and the enhanced vegetation index (EVI). However, the vegetation–climate relationship is inherently complex, leading to great uncertainties in evaluating climatic impacts on vegetation growth. Such inconsistencies result from differences in selected vegetation indices [8,9], influencing factors [3,10], and analytical methods [11,12]. This complexity is further compounded by time-lag and cumulative effects in vegetation–climate responses.

It is widely documented that vegetation dynamics integrate antecedent moisture and thermal conditions across sub-seasonal to multi-month timescales, and accounting for these temporal effects would substantially improve the explanatory power of climatic predictors [13–16]. Importantly, these lagged and cumulative responses are highly context-dependent, varying with hydroclimatic conditions [17,18], meteorological factors [19,20], vegetation types [16,21] and vegetation growth phase [15,22]. Furthermore, substantial discrepancies exist among studies that only accounted for time-lag effects versus those integrating both time-lag and cumulative effects. For instance, some research have detected negligible time-lag signals to temperature at mid-to-high latitudes [16], whereas other studies identified no time-lag effect and up to a one-month cumulative effect at the same regions [15]. Likewise, a consistent one-month lag to precipitation across arid and semiarid regions has been reported [16], while alternative research found that lag duration varied considerably across these regions (from immediate to two-month delays), and that cumulative effects (often exceeding one month) constituted the dominant temporal response mode [15]. However, the 3-month time window adopted in previous studies was relatively short [15,22], which may fail to adequately capture the longer-term delayed vegetation responses documented in other studies [23–25]. Moreover, NDVI is often employed for vegetation monitoring, yet it is vulnerable to soil-background noise over sparsely vegetated arid lands [26,27].

Herein, this study adopted the *MSAVI* as an indicator to characterize the spatiotemporal characteristics of vegetation changes and their responses to climate change for the Circum-Tarim Basin in southern Xinjiang. As China's largest endorheic basin and a globally representative hyper-arid ecotone, this region serves as an ideal testbed for elucidating dryland vegetation dynamics under climatic stress, which may provide broader implications for advancing understanding of global dryland ecosystem sensitivity and climate adaptation. However, previous studies within this region have focused predominantly on time-lag effects, and overlooked the cumulative effects [20,28,29]. More importantly, differences in water availability and anthropogenic regulation among land-use types may lead to distinct response patterns to climate change. For example, more strongly managed types may exhibit weaker dependence on climatic conditions compared to less-managed ecosystems. To address this knowledge gap, the present study aims to: (1) characterize the vegetation dynamics of different land-use types; (2) identify the predominant temporal response patterns of vegetation to precipitation and temperature; and (3) evaluate the role of time-lag and cumulative effects in explaining vegetation variability across different land-use types.

2. Materials and Methods

2.1. The Study Area

The Circum-Tarim Basin, with a total area of $3.29 \times 10^5 \text{ km}^2$ ($35^\circ 59' 24'' \sim 42^\circ 01' 34'' \text{ N}$, $74^\circ 18' 53'' \sim 91^\circ 24' 15'' \text{ E}$), is located in the southern half of the Xinjiang Uygur Autonomous Region (Figure 1). It is characterized by the temperate continental dry climate, with a mean

annual temperature of 17.4 °C and mean annual precipitation (evaporation) of 74.9 mm (1837.3 mm) during the period 2000–2021. The fragile ecosystem makes this region highly vulnerable and prone to desertification. As the primary population center and a major hub for industrial and agricultural development in southern Xinjiang, the Circum-Tarim Basin has experienced intensive anthropogenic interventions that profoundly influence regional vegetation dynamics [30,31].

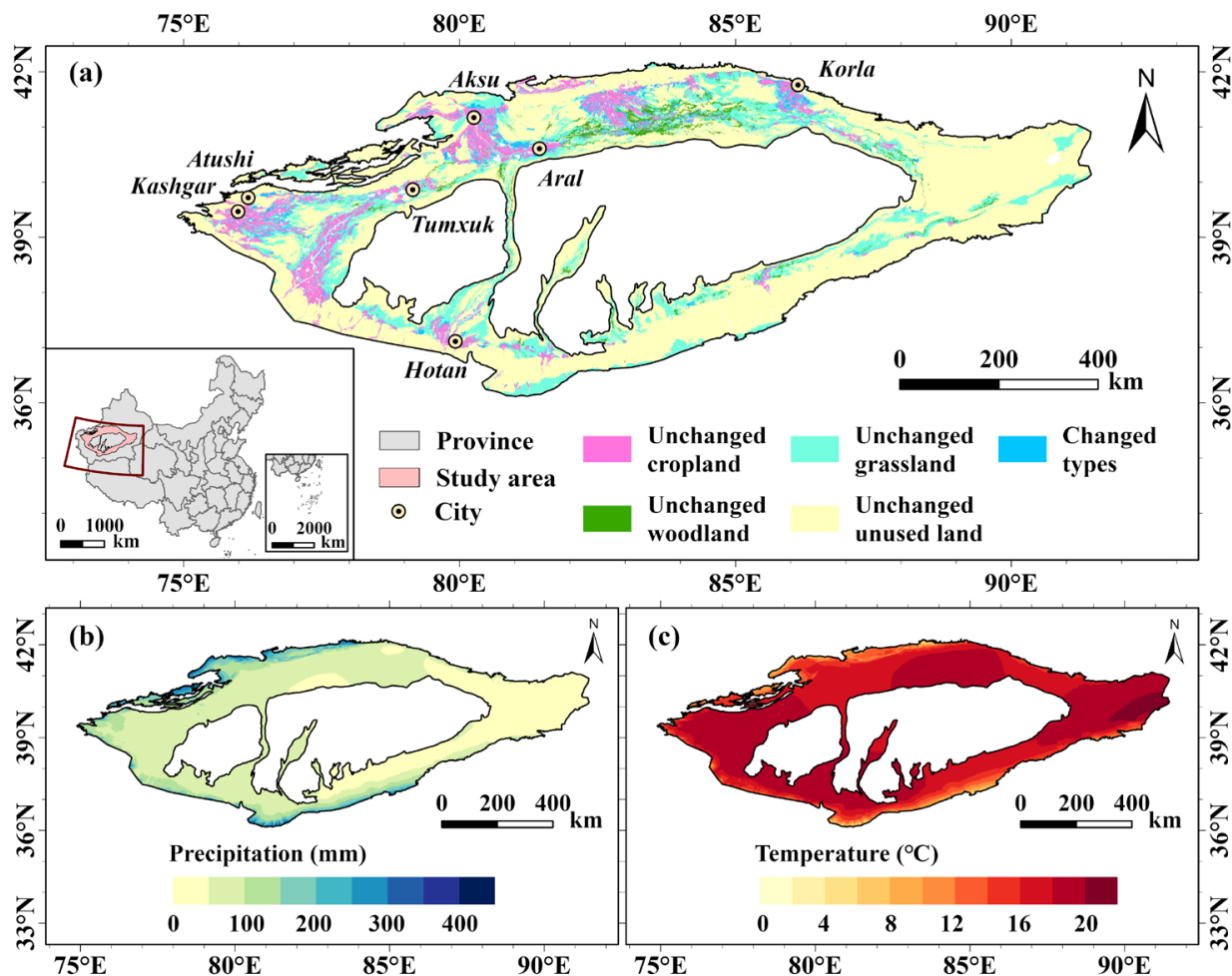


Figure 1. Land-use changes (a) and climatic characteristics (b,c) of the Circum-Tarim Basin during 2000–2021.

2.2. Datasets

2.2.1. MSAVI Data

The MSAVI was adopted due to its advantages in minimizing the effect of soil background and the fact that its self-adjusting soil factor requires no region-specific calibration, ensuring consistency across the heterogeneous surfaces [27,32]. Moreover, the MSAVI series exhibit higher sensitivity to sparse vegetation, indicating a less noisy vegetation signal for trend and lag analyses than NDVI in arid regions [26,27]. The MSAVI data were computed from the Moderate Resolution Imaging Spectroradiometer (MODIS) Apparent Reflectance Daily L2G Product (MOD09GA, Collection 6.1), using the Google Earth Engine cloud-based platform. The formula was as shown in Equation 1. Based on the state_1 km band, the daily reflectance data (500 m) were firstly pre-processed to remove clouds, shadows and water bodies. Snow- and aerosol-contaminated observations were additionally excluded according to the corresponding quality flags. The remaining valid observations were used to calculate monthly MSAVI values using the maximum value composite (MVC)

method; only observations that passed the quality-control criteria within each month were considered. When no valid observation was available for a given pixel in a month, that monthly value was retained as missing rather than being artificially filled. It is noted that only the valid observations that passed quality control in that month were included in the maximum value composite. Finally, monthly *MSAVI* images were resampled from the native Sinusoidal projection to 1 km resolution using bilinear interpolation to match climatic data. The monthly *MSAVI* series during the growing season (April–October) over 2000–2021 were subsequently computed.

$$MSAVI = \frac{2 \times (NIR + 1) - \sqrt{(2 \times NIR + 1)^2 - 8 \times (NIR - Red)}}{2} \quad (1)$$

where *NIR* denotes the reflectance value at the *Near-Infrared* band, and *Red* denotes the value at the *Red* band.

2.2.2. Climatic Data

The climatic data were derived from the monthly gridded dataset provided by the Resource and Environmental Science Data Platform of the Chinese Academy of Sciences (<https://www.resdc.cn>, accessed on 2 April 2026). This dataset was generated from daily meteorological observations of more than 2400 stations, and was spatially interpolated to the 1 km grid scale by using the thin plate smoothing spline algorithm. Two climatic variables (precipitation and temperature) for the growing season over 2000–2021 were adopted for subsequent analysis.

2.2.3. Land-Use Data

The land-use data were extracted from the China Multi-period Land Use Dataset, which was published by the Resource and Environmental Science Data Platform of the Chinese Academy of Sciences (<https://www.resdc.cn>, accessed on 2 April 2026). This dataset was produced from visual interpretation of Landsat satellite imagery over multiple periods since the late 1970s, in which land-use types were divided into six primary categories and twenty-three sub-categories. The dataset exhibits high classification accuracy, with $\geq 95\%$ for croplands and residential areas, $\geq 90\%$ for grasslands, woodlands, and water bodies, and $\geq 85\%$ for unused land [33]. This work only focused on four primary types, including cropland, woodland, grassland and unused land. Based on land-use data for five periods (2000, 2005, 2010, 2015, 2020), the areas of these four types that remained unchanged were extracted for subsequent analysis, which comprised 8.68%, 3.08%, 18.42% and 64.05% of the total area, respectively.

2.3. Methods

2.3.1. Mann–Kendall Trend Test and Theil–Sen Median Estimator

The Mann–Kendall trend test (henceforth the MK test) and the Theil–Sen median estimator (henceforth the TS method) were jointly applied to characterize the interannual variations in vegetation. The MK test was used to detect a monotonic trend and its significance, while the TS method was employed to estimate the magnitude of the observed trend [34,35]. The significance of the trend was determined at least at the 95% confidence level (i.e., $p < 0.05$), corresponding to an absolute standardized MK test statistic $|Z|$ greater than 1.96. All statistical analyses were conducted by using MATLAB software (MathWorks Inc., version R2022a). Accordingly, the *MSAVI* change trend was further categorized into five levels (Table 1), following the classification of previous research [36,37]. It is noted that a threshold of $\pm 0.0005 \text{ yr}^{-1}$ for Sen's slope was applied in this study, as this value

approximated both the median slope across the study area (0.00053 yr^{-1}) and the median value of regional significant pixels (0.00058 yr^{-1}).

Table 1. Criteria for determining the *MSAVI* change trend.

MK Z Value	TS Slope	<i>MSAVI</i> Trend
$Z \geq 1.96$	$\text{Slope} \geq 0.0005$	Significant improvement
$-1.96 < Z < 1.96$	$\text{Slope} \geq 0.0005$	Insignificant improvement
—	$-0.0005 \leq \text{Slope} < 0.0005$	Basically stable
$-1.96 < Z < 1.96$	$\text{Slope} \leq -0.0005$	Insignificant degradation
$Z \leq -1.96$	$\text{Slope} \leq -0.0005$	Significant degradation

2.3.2. Identification of Lagged and Cumulative Effects

A linear regression was conducted for each climatic factor to explore the time-lag and cumulative effects on vegetation, following the method of previous research [15,16]. As previous studies suggested that the temporal effect was generally within 0 to 6 months [23–25], the maximum temporal effect window was set to 6 months in this study, longer than the 3 months adopted previously [15]. The regression models for temperature and precipitation are formulated as follows:

$$MSAVI_t = c_1 \times \sum_{i=0}^n TEM_{t-m-i} + c_2 \quad (2)$$

$$MSAVI_t = c_3 \times \sum_{i=0}^n PRE_{t-m-i} + c_4 \quad (3)$$

where c_1 to c_4 denote regression coefficients; $MSAVI_t$ represents a monthly value for the growing season from April to October during 2000–2021. The response time step is set at a monthly scale over a 22-year study period. m and n refer to the lag period and the number of preceding accumulation months, respectively, both ranging from 0 to 6 months. The actual accumulation duration was therefore defined as $n + 1$ months, including the current month and the preceding n months. For example, $n = 0$ corresponds to a 1-month window (current month), and $n = 6$ corresponds to a 7-month window ($t - 6$ to t). When both lag and accumulation effects were considered, the parameters were constrained such that $m + n \leq 6$, thereby ensuring that the resulting temporal window did not extend beyond the predefined 7-month period. For instance, $m = 2$ and $n = 2$ correspond to a 3-month window ($t - 4$ to $t - 2$). For each pixel, the best scheme was identified based on the combination of the best-fit time-lag parameter (m) and preceding accumulation parameter (n) for both precipitation and temperature. It is noted that accumulation periods were reported using the actual total duration ($n + 1$ months) rather than the parameter value n throughout the manuscript. To ensure statistical reliability, only statistically significant results ($p < 0.05$) were retained.

For each climatic variable (precipitation and temperature), 28 candidate lag–accumulation windows were generated by varying lag duration and accumulation-window length within a predefined parameter range of 0–6 months (Table S1). Combined lag and accumulation parameters were constrained to exclude cross-year windows. Before model fitting, the *MSAVI*, precipitation, and temperature time-series were first deseasonalized by subtracting month-specific means (creating month-specific anomalies) and were then linearly detrended to remove long-term trends. The ordinary coefficient of determination (R^2) was first computed for all 28 candidate windows to perform preliminary screening. The highest-ranked candidate windows were further assessed via leave-one-year-out cross-validation (LOYO-CV). Under this framework, each year was sequentially withheld as the test dataset, while the remaining years were solely used for model calibration. Cross-validated R^2 was derived from predictions for the withheld year, and the candidate window yielding

the maximum LOYO-CV R^2 was selected as the optimal temporal response structure for the corresponding climate variable. This workflow was implemented independently for precipitation and temperature at every pixel. To assess the adequacy of the anomaly-based preprocessing and rule out seasonal confounding, we performed monthly residual diagnostics based on the best-fitting univariate models. For each calendar month (April–October), we extracted the model residuals for every valid pixel. We then calculated the Ljung–Box test p -values and the Durbin–Watson (DW) statistic.

2.3.3. Combined Effects of Temperature and Precipitation on Vegetation Dynamics

A multiple linear regression model was established to quantify the climatic contributions to vegetation changes. All processes were carried out using MATLAB software (MathWorks Inc., version R2022a). The general regression model is presented as follows:

$$MSAVI_{\text{base}} = c_1 + a_1 \times PRE_{\text{base}} + b_1 \times TEM_{\text{base}} + \varepsilon_1 \quad (4)$$

$$MSAVI_{\text{lag}} = c_2 + a_2 \times PRE_{\text{lag}} + b_2 \times TEM_{\text{lag}} + \varepsilon_2 \quad (5)$$

$$MSAVI_{\text{acc}} = c_3 + a_3 \times PRE_{\text{acc}} + b_3 \times TEM_{\text{acc}} + \varepsilon_3 \quad (6)$$

$$MSAVI_{\text{both}} = c_4 + a_4 \times PRE_{\text{both}} + b_4 \times TEM_{\text{both}} + \varepsilon_4 \quad (7)$$

where $c_1 \sim c_4$ is the intercept, $\varepsilon_1 \sim \varepsilon_4$ is the error term, and $a_1 \sim a_4$ and $b_1 \sim b_4$ are regression coefficients. The climatic time series are adjusted corresponding to the optimal lagged and cumulative months identified in Section 2.3.2. Accordingly, four categories were defined: contemporaneous effect (all $m = 0$ and $n = 0$), pure lagged effect (any $m > 0$ while all $n = 0$), pure cumulative effect (all $m = 0$ while any $n \geq 1$), or coupled lag–accumulation effects (both m and n exhibit non-zero values). The time-lag effect refers to vegetation responses driven solely by the climatic conditions of one preceding month, independent of multi-month climatic integration. The cumulative effect denotes vegetation responses to aggregated climatic signals over successive antecedent months, with no explicit time-lag offset. The coupled lag–accumulation effect integrates the above two mechanisms: vegetation responds to climate variables that are first shifted by a specific time-lag offset and subsequently aggregated across a consecutive accumulation window.

Predictive performance across the four scenarios was assessed using the identical LOYO-CV framework, in which each year was sequentially withheld as an independent test dataset and the remaining years were used for model calibration. The resultant LOYO-CV R^2 values were compared among scenarios to examine whether the inclusion of lagged and/or cumulative climate information improved out-of-sample explanatory power. In parallel, changes in ordinary R^2 relative to the contemporaneous baseline were used to quantify the corresponding changes in in-sample variance explained. Moreover, year-block permutation tests were additionally implemented for the best-performing single-factor models and the coupled lag–accumulation scenario. For each permutation iteration, complete annual time blocks were randomly shuffled while retaining intra-annual temporal structures. Empirical p -values were computed as the fraction of permuted test statistics that equaled or exceeded the observed statistic. Pixel-wise empirical p -values were then separately adjusted for precipitation and temperature via the Benjamini–Hochberg false-discovery-rate (BH-FDR) correction procedure.

Accordingly, the primary comparison of the relative contributions of lagged and cumulative effects was based on their changes in variance explained (ΔR^2), while $\Delta CV\text{-}R^2$ was used as a complementary measure to determine whether the observed improvements in explanatory performance were supported by out-of-sample prediction. The analysis therefore did not seek to maximize the absolute goodness of fit of an individual model, but

rather to compare the relative explanatory and predictive improvements associated with different temporal response scenarios.

3. Results

3.1. Interannual Trends of MSAVI

As shown in Figure 2 and Table S1, three statistical MSAVI values (mean, 90th percentile, and 10th percentile) exhibited similar interannual trends, with a general upward trend from 2000 to 2021 in the Circum-Tarim Basin. The regional mean MSAVI increased at a rate of 0.0014 yr^{-1} , while the 90th percentile value showed a markedly higher growth rate of 0.0054 yr^{-1} . With respect to different types, the MSAVI value of cropland was the highest, followed by the woodland, whereas the values of grassland and unused land were relatively low (Figure S1). The increasing rate of the mean MSAVI value in cropland was also the highest (0.0040 yr^{-1}), which was at least twice that of other land-use types. In contrast to three other types, the rising rate of the 10th percentile value in cropland was the highest, twice that of the 90th percentile value. It suggests that vegetation greening was notable in cropland, especially in areas that were previously poorly cultivated (Table S2).

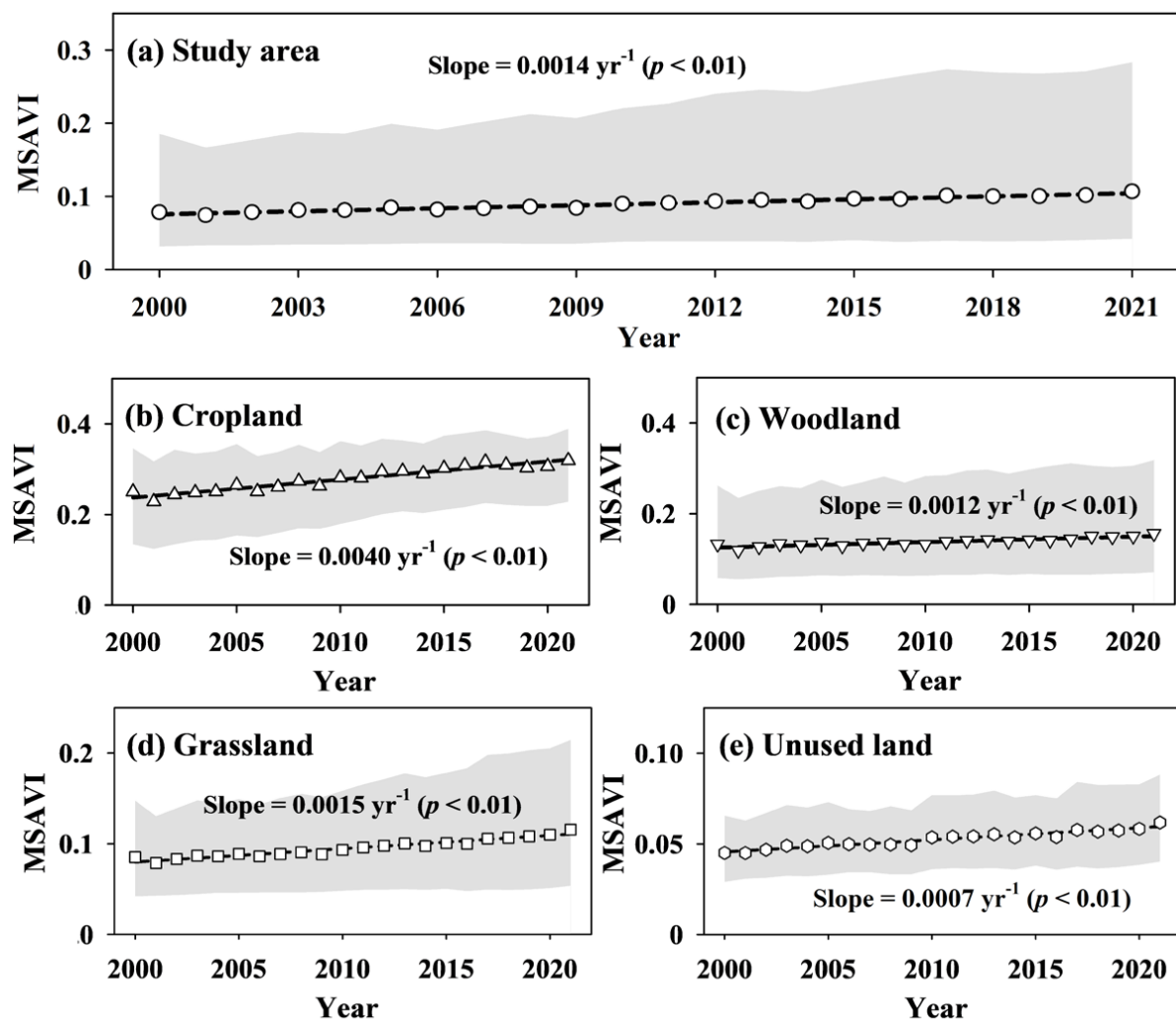


Figure 2. Theil–Sen’s Slope and the significance of the identified Mann–Kendall trend for the MSAVI trends in the Circum-Tarim Basin during the growing season from 2000 to 2021. The gray-shaded area in each subplot indicates the interval between the 10th and 90th percentiles of MSAVI values.

3.2. Spatial Trend Patterns of MSAVI

As illustrated in Figure 3, approximately 52.96% of the total area witnessed a vegetation greening trend, which was mainly distributed in the interior and fringe of oases wherein the northern, western and southern parts. In comparison, vegetation condition in about 44.88% of the total area basically remained stable, which primarily occurred in the unused land distributed in the eastern part. The areal percentage of the region with a vegetation browning trend was less than 3%. From the perspective of land-use types, vegetation greening in cropland was the most significant, with 91.41% exhibiting improvement and less than 5% experiencing degradation. As for woodland and grassland, both nearly 60% of the area revealed vegetation greenness, while those with a browning trend accounted for 13.31% and 4.30%, respectively. Moreover, vegetation greening in unused land was also considerable, covering 42.55% of the area.

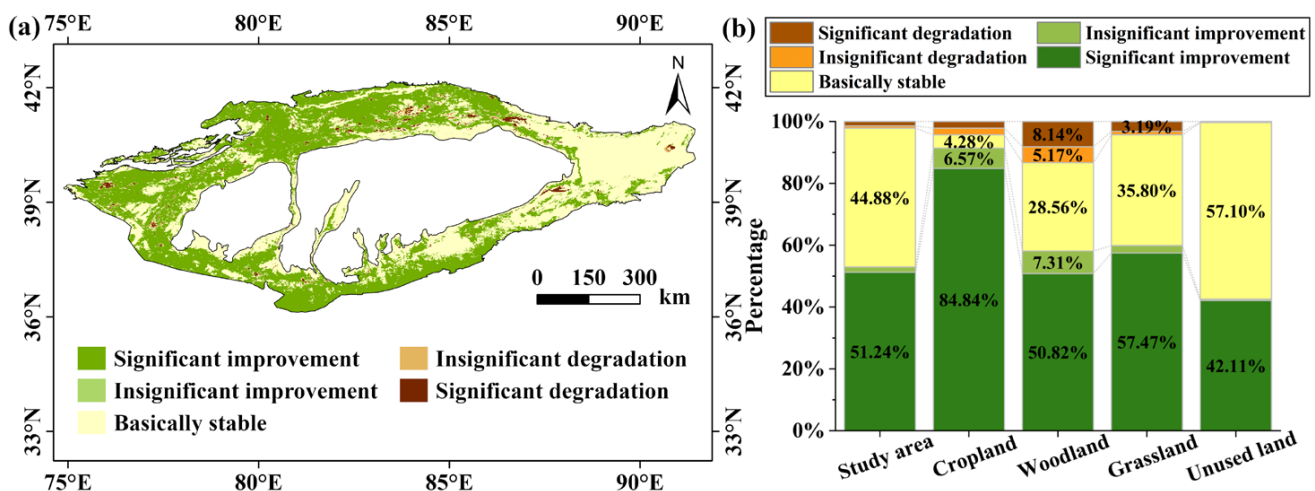


Figure 3. Change trends of the mean MSAVI value during the growing season from 2000 to 2021. (a) Spatial pattern of change trends, and (b) statistical results of change trend types for different land-use types. The bar without numeric annotation indicates the percentage is less than 3%.

3.3. Temporal Response Patterns to Climatic Factors

Vegetation in the Circum-Tarim Basin exhibited distinct lag–accumulation response patterns to precipitation (Figure 4) and temperature (Figure S2). As shown in Figure 4, cropland exhibited the strongest clustering of optimal response windows, characterized by a dominant peak at zero lag and a 2-month accumulation period (accounting for 35.0% of pixels). Likewise, woodland showed mainly contemporaneous and short-term responses, albeit with more dispersed optimal response windows. By contrast, grassland and unused land displayed a substantially more heterogeneous distribution, shifting towards longer accumulation periods and pronounced lagged responses. Specifically, 9.7% of pixels for unused land exhibited a 6-month accumulation period with a 1-month lag. Compared with precipitation, temperature responses generally exhibited a more heterogeneous distribution of optimal lag–accumulation windows across land-use types, particularly for grassland and unused land (Figure S2). Cropland and woodland were characterized mainly by contemporaneous or short-term responses, with the highest proportions occurring at zero lag and accumulation periods of 1–2 months. In contrast, grassland and unused land exhibited a more dispersed response structure, with both contemporaneous and delayed temperature effects represented. Overall, the results indicate that vegetation responses to precipitation and temperature were relatively more immediate in cropland and woodland, and more temporally heterogeneous and delayed in grassland and unused land.

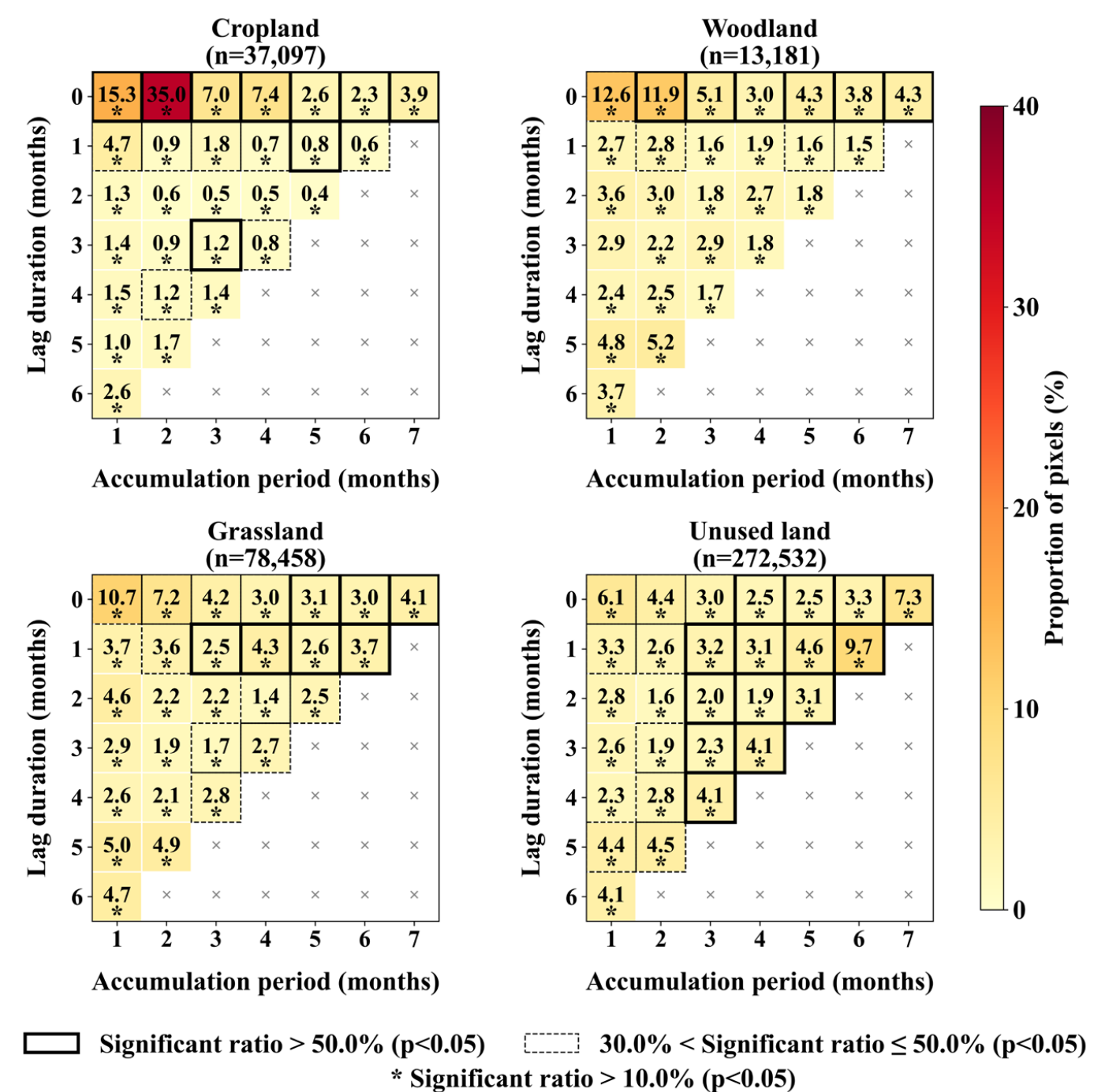


Figure 4. Temporal response patterns of vegetation to precipitation in the Circum-Tarim Basin, shown as the areal percentage distribution of optimal lag–accumulation windows across four land-use types. The numbers in each cell represent the proportion of pixels (%) corresponding to the specific lag–accumulation window. Solid and dashed boxes indicate cells where the proportion of statistically significant pixels exceeds 50% and 30%–50%, respectively. The star symbol denotes that the cell contains statistically significant pixels exceeding 10% (statistically significant at FDR-corrected $p < 0.05$).

These spatial patterns were strongly corroborated by the statistical results of the cross-validated model (Table S3). Generally, the proportion of significant pixels (FDR-corrected $p < 0.05$) was notably higher for precipitation (ranging from 34.5% to 61.5%) than for temperature (ranging from 15.0% to 24.1%), implying the dominant role of water availability. Consistently, the median CV- R^2 for precipitation models outperformed those

for temperature, which were generally negative, indicating that temperature alone provides limited out-of-sample predictability in this hyper-arid region.

Monthly residual diagnostics for the best-fitting univariate models revealed that the vast majority of pixels (>77.7%, up to 88.8%) showed non-significant Ljung–Box p -values (>0.05), with median Durbin–Watson statistics consistently ranging between 1.65 and 1.75 (Table S4). These findings indicate that residual autocorrelation is weak, confirming that the observed relationships are driven by interannual anomalies rather than shared seasonal cycles.

3.4. Variance Explanation Changes Induced by Temporal Effects

As illustrated in Figure 5a, the contemporaneous model generally yielded relatively low R^2 values across the study area (predominantly below 0.10), suggesting that in-season hydrothermal conditions alone provided limited explanatory capacity for vegetation variability. Incorporating time-lag effects resulted only a marginal improvement, with the R^2 values remaining predominantly below 0.2 and displaying a scattered pattern of slightly elevated values (Figure 5b). By contrast, the pure cumulative model exhibited a more pronounced improvement in explanatory power, although the enhanced values (0.4–0.8) were primarily concentrated in localized patches along the southern and northern margins, as well as the western parts of the basin (Figure 5c). The coupled model further amplified this pattern, exhibiting a slightly broader spatial extent and increased magnitude in these marginal regions compared to the cumulative model (Figure 5d), highlighting the complementary role of lag and accumulation effects in this hyper-arid region.

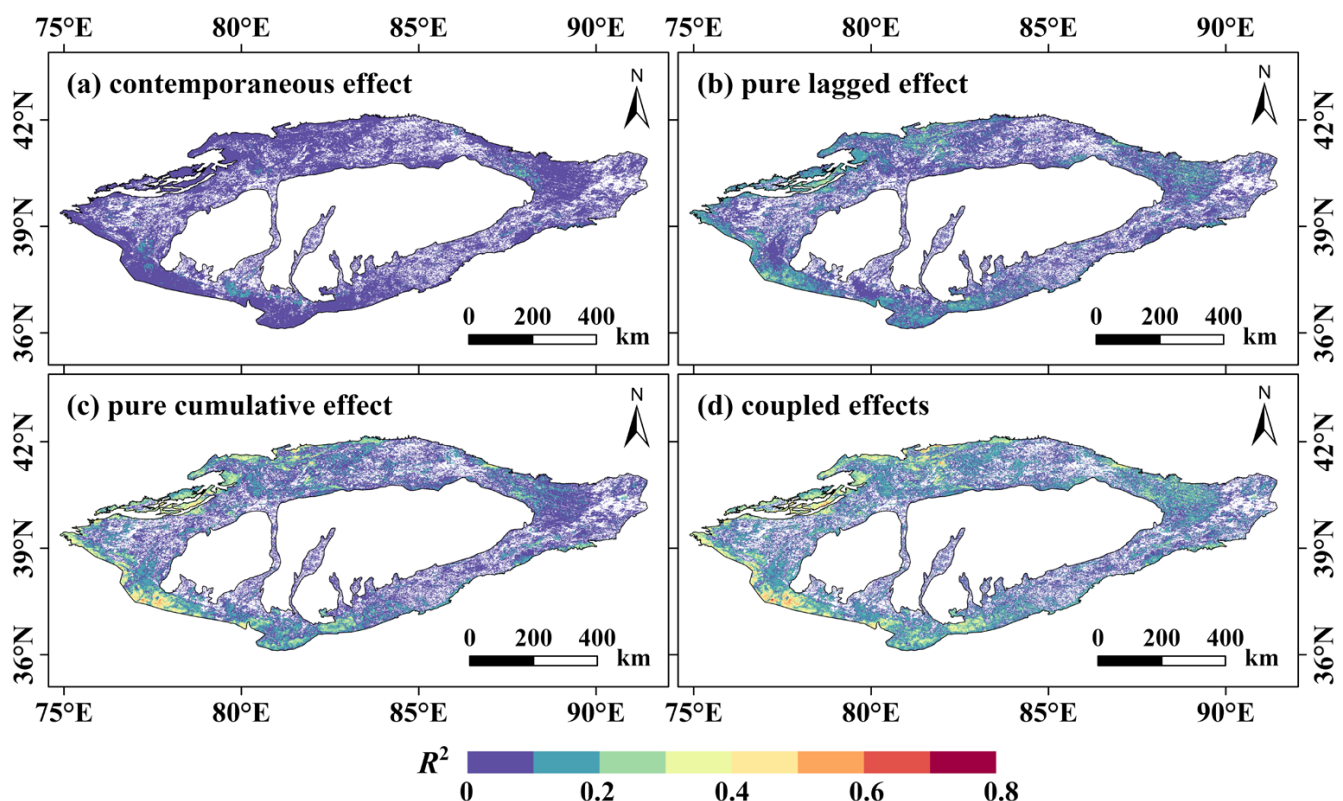


Figure 5. Spatial patterns of R^2 for the (a) contemporaneous, (b) pure lagged, (c) pure cumulative, and (d) coupled effects of precipitation and temperature on growing-season MSAVI across the Circum-Tarim Basin during 2000–2021 (statistically significant at $p < 0.05$).

Under the dual-factor framework, the coupled lag–accumulation model consistently yielded the highest in-sample explanatory power across all land-use types and showed the

largest increments in ΔR^2 relative to the contemporaneous baseline (median value: cropland 0.061; woodland 0.058; grassland 0.062; unused land 0.076), indicating that the combination of lag and accumulation mechanisms was most effective in capturing vegetation growth variability. Under out-of-sample validation, the coupled model also exhibited the highest predictive performance, with consistently positive $\Delta CV-R^2$ gains. Although both the pure lagged and pure cumulative models improved performance compared to the baseline, they were consistently inferior to the coupled model (Table S5).

4. Discussion

4.1. Spatiotemporal Patterns of Vegetation Dynamics

Over the past 22 years, an overall greening trend was observed in the Circum-Tarim Basin during the growing season (Figures 2 and 3). This trend aligns well with variations in the FVC in this region [38], and is broadly consistent with the widespread greening phenomenon on regional, national and global scales [2,39,40]. The trend analysis results further reveal that vegetation greening in cropland was the most pronounced (Figure 3). This finding suggests that cropland was a major contributor to vegetation greening, which coincides with previous studies [41,42]. By contrast, portions of woodland exhibited notable degradation, which was probably attributable to wood aging, pest and disease infestations, and improper management measures [43]. Generally, from a global perspective, this greening trend mirrors the widespread vegetation greenness observed in other dryland regions (e.g., Central Asia), where anthropogenic activities (e.g., agricultural reclamation and ecological restoration projects) have played a progressively more important role in shaping land surface dynamics [2].

4.2. Land-Use-Dependent Temporal Response Modes of Vegetation to Climate

Overall, cropland and woodland generally showed relatively short accumulation windows (1–2 months), suggesting that vegetation responses in these land-use types were associated primarily with climatic conditions over the recent preceding months (Figures 4 and S2). These identified response patterns across different land-use types were broadly consistent with the land-use-specific differences shown in NDVI–temperature/precipitation correlations across China [44], Central Asia [45] and those results at the global scale [15]. In cropland, this pattern may partly reflect the buffering effects of irrigation and agricultural water management, which can reduce the dependence of vegetation growth on longer antecedent precipitation conditions. Similarly, the relatively short response windows in woodland may be related to the availability of shallow groundwater and/or managed ecological water inputs in riparian areas [46–48].

In contrast, grassland and unused land exhibited more heterogeneous temporal response patterns, including relatively longer lagged and accumulation windows. These patterns may reflect the stronger dependence of natural and sparsely vegetated ecosystems on antecedent water availability and soil–groundwater processes. In the hyper-arid Circum-Tarim Basin, precipitation and temperature signals may influence vegetation through delayed hydrological processes, such as soil-water storage, groundwater recharge, snowmelt or glacier-melt contributions to runoff, and subsequent redistribution of water through river–groundwater systems [49,50]. However, these mechanisms were not directly tested in the present study and therefore should be regarded as plausible explanations rather than demonstrated causal pathways.

Collectively, these divergent patterns suggest that vegetation growth in this region does not respond instantaneously to single climatic events; instead, it requires a prolonged seasonal window of moisture and thermal accumulation to trigger detectable greenness,

with this dependency becoming particularly critical in areas lacking artificial irrigation and deep groundwater access.

4.3. Enhancement of Climate Explanatory Power by Temporal Effects

The contemporaneous hydrothermal conditions were insufficient to adequately capture vegetation variability (Figures 5 and 6), which is in accordance with the low variance explained for FVC in this region [38]. Incorporating lagged and cumulative climate information generally improved model performance, with cumulative effects providing a slightly greater improvement than lagged effects alone and the coupled lag–accumulation framework achieving the strongest overall performance. This pattern suggests that vegetation growth in this hyper-arid region depends not only on current climatic conditions but also on climatic information accumulated over preceding months. This finding is broadly consistent with previous studies showing that incorporating antecedent climatic information can improve vegetation–climate relationships in dryland ecosystems [15,16,51,52].

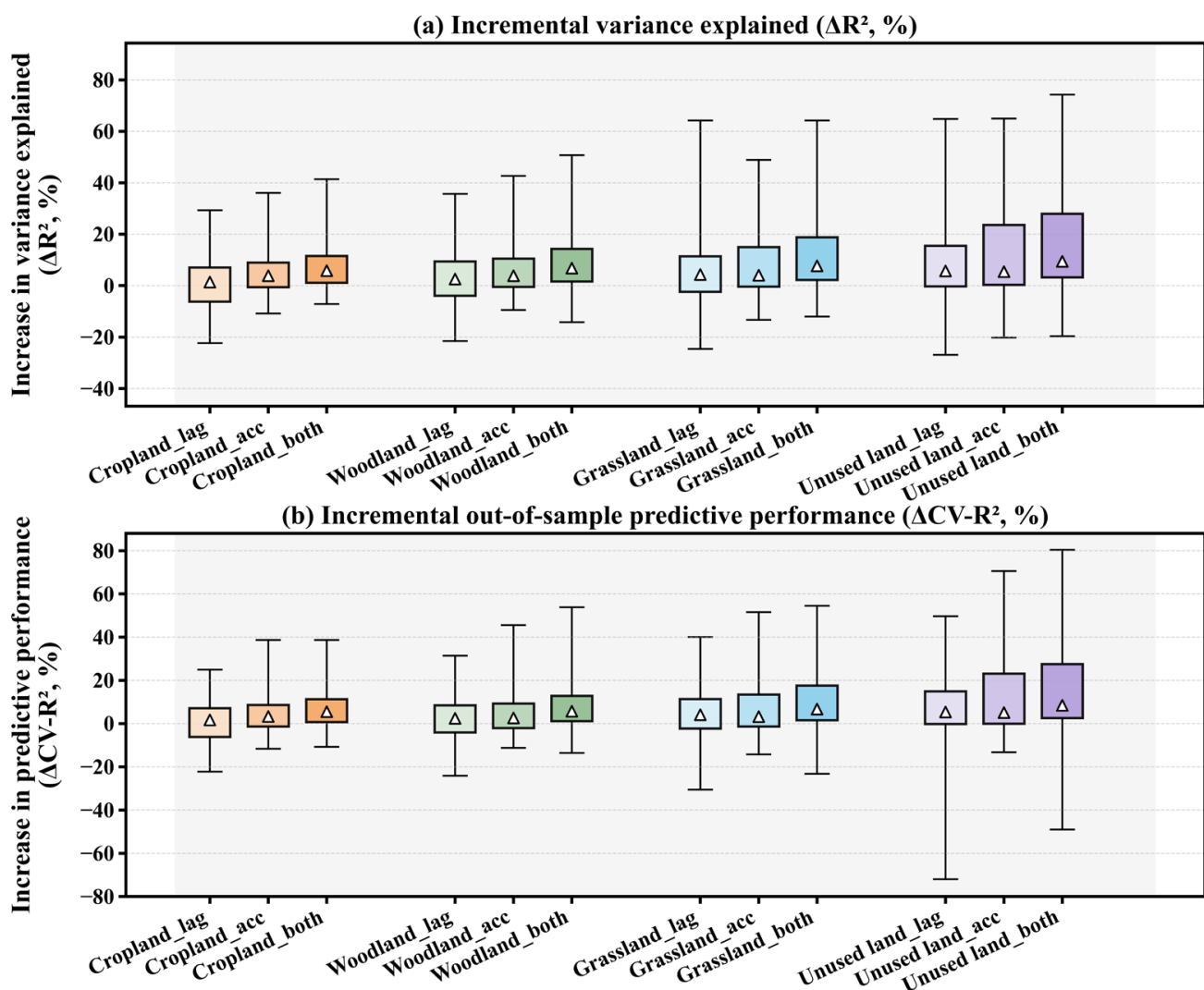


Figure 6. Boxplots of changes in the percentage of variance explained (R^2) and predictive performance ($CV-R^2$) by the contemporaneous (_no), pure lagged (_lag), pure cumulative (_acc), and coupled (_both) models for four land-use types (statistically FDR-significant at $p < 0.05$). The box plot represents the statistical values of R^2 , including the median (triangle), the interval between the 10th and 90th percentiles (box), and the maximum and minimum values (whiskers).

The strength and patterns of the climate–vegetation relationship varied substantially among land-use types, as reflected by the magnitude of ΔR^2 when temporal effects were incorporated (Figure 6 and Table S5). Cropland and woodland showed the largest relative gains, likely due to irrigation conveyance and groundwater/ecological water inputs, which buffer short-term climatic fluctuations and amplify cumulative signals [46,48]. Grassland showed moderate gains, likely reflecting the influence of local hydrological and edaphic conditions, which may have weakened the direct relationship between vegetation dynamics and climatic variability [53]. Unused land exhibited the weakest predictability and most heterogeneous responses; despite positive $\Delta CV-R^2$, the majority of its variance remained unexplained, indicating dominance of non-climatic controls such as soil salinity, topography, and sporadic water redistribution.

Importantly, the observed improvements should not be interpreted simply as evidence that more complex models provide better explanations. The purpose of incorporating temporal effects was to determine whether antecedent climatic information improved the characterization of vegetation variability and whether such improvements were robust to out-of-sample prediction. The consistency between the improvements in explained variance and cross-validated performance supports the interpretation that temporal information provides useful predictive information beyond contemporaneous climatic conditions, rather than merely increasing in-sample model fit.

4.4. Limitations and Perspectives

There are still some uncertainties and limitations remaining in the characterization and attribution of vegetation dynamics in this study. Firstly, the uses of mean values and linear methods may not capture the nonlinear and nonstationary characteristics of vegetation and climate changes well, thereby obscuring the short-term trends [54,55]. Although cross-validation was used to evaluate out-of-sample predictive performance, the available observation period remains relatively limited for assessing long-term changes in climate–vegetation relationships. Second, because the time series were deseasonalized and linearly detrended, the R^2 values represent only the variance explained in the preprocessed anomalies, not the total *MSAVI* variability. Additionally, as the optimal windows were selected using the entire 22-year record rather than within each training fold, absolute $CV-R^2$ may be slightly inflated by mild data leakage. However, as this procedure was applied uniformly across all four models, it does not bias the relative improvements (ΔR^2 and $\Delta \Delta CV-R^2$). Thus, absolute explanatory power should not be interpreted as direct climatic contribution, whereas the relative increments robustly support our conclusions. Finally, the analysis focused primarily on precipitation and temperature and did not incorporate groundwater dynamics, river discharge, soil moisture, snow and glacier meltwater, irrigation intensity, or other anthropogenic water-management variables. As the climatic signals detected by the models may partly covary with human-regulated and subsurface water dynamics, future studies integrating hydrological and land-management observations with nonlinear or time-varying modelling approaches could provide further insight into the mechanisms underlying land-use-specific vegetation responses. Despite these limitations, the combination of temporal-response analysis, cross-validated model evaluation, and statistical significance testing provides a useful framework for comparing climate–vegetation relationships across land-use types. More broadly, the findings highlight that climatic controls on dryland vegetation should be evaluated within their temporal and environmental contexts rather than solely on the basis of contemporaneous climate conditions.

5. Conclusions

Based on multiple statistical methods, this work used the *MSAVI* to characterize the spatiotemporal variations in vegetation among different land-use types and their responses to temperature and precipitation in the Circum-Tarim Basin over the past 22 years. The relative contributions of time-lag and cumulative effects of two climatic factors were further evaluated. The main results are as follows:

Vegetation showed an overall greening tendency across the study area, with croplands exhibiting the most pronounced positive trend. Vegetation responses to precipitation were dominated by medium-term cumulative and long-/medium-term coupled effects, whereas the responses to temperature shifted toward shorter time scales with a higher prevalence of lag-associated modes. Cropland, woodland, and grassland were primarily characterized by the medium-term cumulative effect, while unused land exhibited more complex and spatially heterogeneous patterns.

Incorporating temporal effects substantially enhanced the explanatory power of the climate for vegetation dynamics, especially when cumulative effects were considered. Cropland and woodland showed higher statistically explained variance attributable to the combined climatic factors compared with grassland and unused land, which may reflect the combined effects of climatic variability and human water management activities. These findings demonstrate that overlooking temporal effects, especially cumulative effects, would lead to a substantial underestimation of climatic control over vegetation dynamics, which may provide a more robust basis for projecting dryland vegetation responses under accelerating climate change. Incorporating temporal effects improved the explanatory power of climate–vegetation models, although the magnitude, response patterns and potential mechanisms varied among land-use types. Overall, these findings emphasize the importance of considering both temporal climate memory and land-use-specific environmental conditions when assessing vegetation responses in hyper-arid ecosystems.

Supplementary Materials: The following supporting information can be downloaded at: <https://www.mdpi.com/article/10.3390/land15091599/s1>.

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Data Availability Statement: The original satellite imagery data used in this study are openly available from the NASA's Land Processes Distributed Active Archive Center (LP DAAC), and can be accessed and processed through the Google Earth Engine platform (<https://earthengine.google.com/>). The MATLAB scripts generated during the current study are available from the corresponding author upon reasonable request.

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