

Article

Vegetation Dynamics and Driving Mechanisms Considering Time-Lag and Accumulation Effects: A Case Study of Hubao–Egyu Urban Agglomeration

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Abstract: The Hubao–Egyu Urban Agglomeration (HBEY) was a crucial ecological barrier in northern China. To accurately assess the impact of climate change on vegetation growth, it is essential to consider the effects of time lag and accumulation. In this study, we used a newly proposed kernel Normalized Difference Vegetation Index (kNDVI) as the metric for vegetation condition, and employed partial correlation analysis to ascertain the lag and accumulation period of vegetation response to climate by considering different scenarios (No/Lag/Acc/LagAcc) and various combinations. Moreover, we further modified the traditional residual analysis model. The results are as follows: (1) From 2000 to 2022, the HBEY experienced extensive and persistent greening, with a kNDVI slope of 0.0163/decade. Precipitation was identified as the dominant climatic factor influencing vegetation dynamics. (2) In HBEY, the lag effect of temperature was most distinct, particularly affecting the vegetation in cropland and grassland. The accumulation effect of precipitation was pronounced in grassland. (3) Incorporating lag and accumulation effects into models increases the explanatory power of climate impacts on vegetation dynamics by 6.95% compared to traditional residual models. Our findings hold essential implications for regional ecological regulation and climate change response research.

Keywords: kNDVI; lag and accumulation effects; modified residual analysis; partial correlation analysis; Hubao–Egyu Urban Agglomeration



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1. Introduction

Vegetation, a significant element of terrestrial ecosystems, not only provides food and habitat for numerous species through its regulation of material cycles and energy exchanges but also plays an indispensable role in stabilizing climate by sequestering atmospheric carbon dioxide through photosynthesis [1]. However, in recent years, vegetation ecosystems have faced unprecedented challenges due to intensified pressures [2,3]. Global warming and frequent extreme weather events directly impact the growth cycles and rhythm of vegetation [4]. Since entering the “Anthropocene”, the impact of human activities on some regional ecosystems has surpassed that of climate change [5]. Particularly, land-use changes are continually encroaching on vegetation habitats, with this effect still accelerating [6]. Under the combined influence of these factors, the issues are becoming increasingly prominent, posing severe threats to human survival and development [7]. The Hubao–Egyu Urban Agglomeration sits at the junction of the Ordos Plateau and the Loess Plateau, making its vegetation dynamics highly sensitive to climate change. Furthermore, this region has undergone rapid urbanization with frequent land use changes, and it serves as a crucial site

for national ecological projects [8]. This makes it an ideal case for examining the human effects on vegetation.

The Normalized Difference Vegetation Index (NDVI) was extensively used for large-scale research due to its excellent performance, long time series, and easy accessibility [9]. However, Huete et al. [10] noted that the NDVI exhibited non-linearities and saturation effects, which could limit its monitoring capabilities in high vegetation coverage areas. Ryu et al. [1] found that NDVI and other Vegetation Indices (VIs) did not reflect photosynthesis itself but only indicate the presence of leaves, introducing some uncertainty in assessing vegetation physiological conditions. Based on these findings, Camps-Valls et al. [11] applied the kernel method to NDVI, creating a more stable and complex phenology-adaptable vegetation index—kNDVI—which had shown excellent performance across various climate zones and latitude zones [12]. The kNDVI has demonstrated superior performance in ecological assessments, including more accurate estimation of vegetation traits, as well as enhanced crop monitoring and forecasting capabilities [13–16]. Wang et al. has employed kNDVI as an evaluation metric for assessing the dynamics and resilience of vegetation in the Loess Plateau [17]. Additionally, its application in monitoring the arid region's ecological changes indicated that kNDVI is instrumental in understanding the climate's effects on vegetation [18,19].

Vegetation change is a complex and prolonged process. The continuous updates of remote sensing data and the extension of meteorological monitoring data have made vegetation–climate response mechanisms a hot topic in ecological remote sensing [20]. To quantitatively analyze these driving mechanisms, researchers often use correlation analysis methods such as Pearson and Spearman methods to quantify the relationships between NDVI and drivers [21]. To further eliminate the mutual influences of meteorological factors, partial correlation coefficients can be calculated [22]. Additionally, a linear regression model [23], geodetector [24], and structural equation model [25] also reveal the pathways and intensities of the effects on vegetation. Currently, the impacts of climate warming, drought, and the fertilization effect of carbon dioxide are constantly being confirmed [26]. Furthermore, studies indicated that plants in the high latitudes and high-altitude mountain areas are more significantly affected by global warming [27]. A study by Nemani et al. [28] on the driving mechanisms in global arid and semi-arid areas indicates that temperature, Vapor Pressure Deficit (VPD), solar radiation, and precipitation all have varying impacts on vegetation growth. Zhang et al. [29] found that potential evapotranspiration (PET) plays a pivotal role in shaping the carbon sequestration capacity of grassland ecosystems in arid regions. It is noteworthy that these studies all indicate that water supply is the primary limiter for vegetation growth in arid areas, especially in grassland ecosystems.

With further research, studies indicated that the response of vegetation to climate change has a certain temporal effect which included a lag and accumulation effect [30]. Due to the lag in vegetation's response to climate change, previous climate conditions may have a more powerful impact, known as the lag effect [31]. Similarly, the accumulation effect refers to the substantial impact of prolonged and continuous climatic factors on current vegetation [32]. Researchers often quantify the influence of climatic factors on vegetation in different temporal scenarios using correlation or the coefficient of determination from multiple linear regression models [33,34]. Zhao et al. [35] studied the vegetation–climate response of the Loess Plateau, showing that there is a one-month lag between NDVI and precipitation, but no lag effect with temperature. Zhang et al. [36] found that extreme precipitation has a significant impact on at least 98.5% of the Qilian Mountains, with two months' lag. In addition, some researchers have found the existence of an accumulative effect [37]. Wu et al. [31] believe that incorporating the temporal effect can better predict the real vegetation response and reduce uncertainty. Under rapidly changing climate conditions, the temporal effect is a key factor to be considered. However, the impacts of lag and accumulation effects have always been discussed separately, and the bidirectional coupling of the two has had paid less attention paid to it. At the same time, many researchers have tried to separate human activities from climate change and to judge the respective

contributions of vegetation dynamics. At present, researchers mostly use residual analysis to isolate the effects of climatic change on vegetation [38]. However, the attribution usually only considers the climate variables of the corresponding period, and it is unable to deal with the effects of lag and accumulative effects on the model.

This study focuses on the Hubao–Egyu Urban Agglomeration, a typical ecologically fragile area, which experiences large human activity impacts. The kNDVI is employed as a monitoring indicator for vegetation dynamics. The study is structured around three clear objectives: (1) Characterize Vegetation Cover: delineate the distribution patterns and change characteristics of vegetation cover in the study area using trend analysis in the Google Earth Engine; (2) Understand kNDVI Responses: we seek to explore how kNDVI responds to climatic factors by establishing four temporal effects—no temporal effect (No), lag effect (Lag), accumulation effect (Acc), and bidirectional coupling of lag and accumulation (LagAcc). This analysis evaluates the explanatory power of climate change on vegetation dynamics under various scenarios; (3) Refine Model Uncertainties: We seek to refine the uncertainties of the residual model by incorporating temporal effects. This enhancement will allow us to better quantify the impacts of human activity (HA) and climate change (CC) on vegetation dynamics, thereby providing a more robust foundation for our research approach. The findings are crucial for understanding the mechanisms of regional vegetation behavior and maintaining ecosystem balance.

2. Materials and Methods

2.1. Study Area

The Hubao–Egyu Urban Agglomeration (HBEY), situated in Northwest China, comprises the cities of Hohhot, Baotou, Ordos, and Yulin, encompassing 175,000 km². The respective cities contribute 9.8%, 15.9%, 49.7%, and 24.6% to this total (Figure 1). Characterized by an average elevation of around 1300 m, the terrain predominantly slopes towards the southeast. The region experiences an arid to semi-arid climate, leading to uneven precipitation and a relative scarcity of water resources, which contribute to a sensitive and fragile ecological environment [39]. The heart of the region is the expansive Ordos Plateau, with its northwestern frontier abutting the Kubuqi Desert, China's seventh-largest desert, often referred to as "China's last ecological barrier". This area is subject to intense wind erosion, posing significant challenges to regional ecological conservation [40]. Mu Us Sandy Land has evolved into a "desert oasis" following more than half a century of ecological rehabilitation efforts [41]. In recent years, leveraging its abundant coal resources, the urban agglomeration has undergone rapid economic development. However, this growth has brought with it substantial ecological and environmental pressures, now recognized as a critical strategic challenge for the area.

2.2. Datasets

We used multiple datasets, including kNDVI, the China land cover dataset (CLCD), DEM, meteorological, and administrative division data (Table S1), all of which were converted to the same projection coordinates by ArcGIS 10.8.

2.2.1. kNDVI

kNDVI is a state-of-the-art index produced by nonlinear processing of NDVI using the kernel method. Specifically, we defined NDVI in Hilbert space using a Radial Basis Function (RBF) reproducing kernel, which generated the kernel NDVI. The NDVIs were sourced from the MOD13Q1, with 16 days and 250 m resolution from 2000 to 2022 (accessed on 13 January 2024). Due to its high resolution and lower error incidence, it is widely used in mid- to high-latitude areas [42]. To ensure the reliability and mitigate the effects of clouds, aerosols, and solar zenith angles, we used a maximum value composite method to preprocess the raw data and generate a monthly NDVI dataset. Furthermore, we used Savitzky–Golay filter to smooth the data, effectively reducing noise [43]. The kNDVI have

the ability to adapt effectively to areas with either sparse or dense vegetation coverage, and have exhibited robust performance in other applications [44].

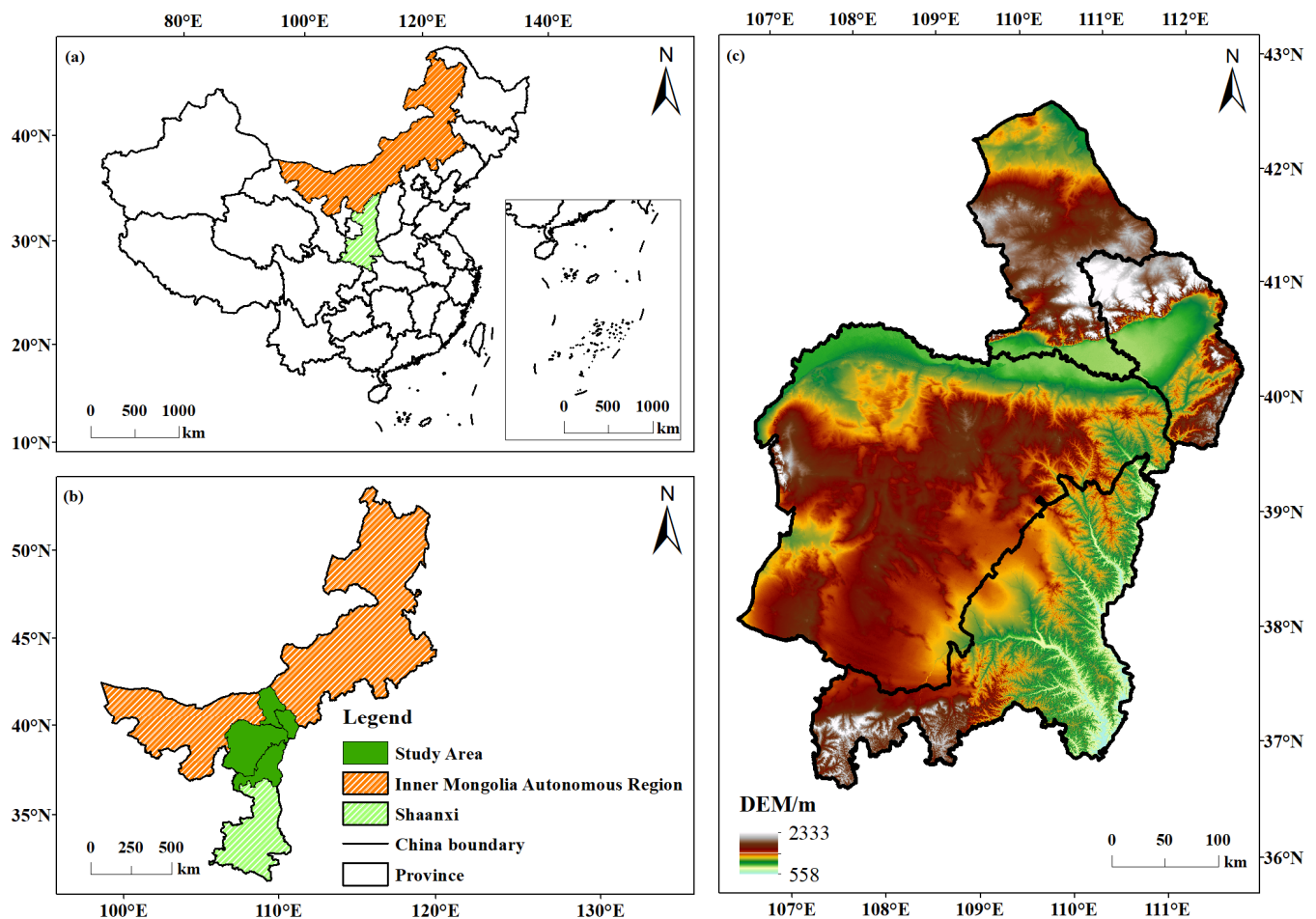


Figure 1. Hubao–Egyu Urban Agglomeration ((a), Location; (b), Administration division; (c), Elevation).

2.2.2. Meteorological Data

Temperature (T), precipitation (P), and potential evapotranspiration (PET) data were sourced from the National Tibetan Plateau Data Center (TPDC, accessed on 27 January 2024), encompassing monthly records from 2000 to 2022 [45]. The potential evapotranspiration of this product was calculated using the Hargreaves formula based on monthly average, minimum, and maximum temperature data. This product has been extensively validated by various studies, and its credibility has been confirmed for assessing climate change impacts across different regions in China [46,47].

2.2.3. LULC Data

The land use data were sourced from the 30 m resolution annual China Land Cover Dataset (CLCD, accessed on 27 January 2024) [48]. The dataset includes nine land use types. In the Hubao–Egyu region, eight categories are presented. Given the negligible pixel number of Shrub and Wetland categories, these were overlooked, to streamline the data interpretation.

2.3. Methods

Our research methodology is illustrated in Figure 2. Specifically, we first constructed a dataset of kNDVI and driving factors on the GEE [49]. We then analyzed the trend and significance of kNDVI using Theil–Sen analysis and Mann–Kendall test. Next, we calculate the second-order partial correlation coefficients between kNDVI and climatic factors under

different temporal scenarios to determine the lag and accumulation periods. Finally, we refine the traditional residual model by considering the temporal effects, and analyze the contributions under various temporal scenarios.

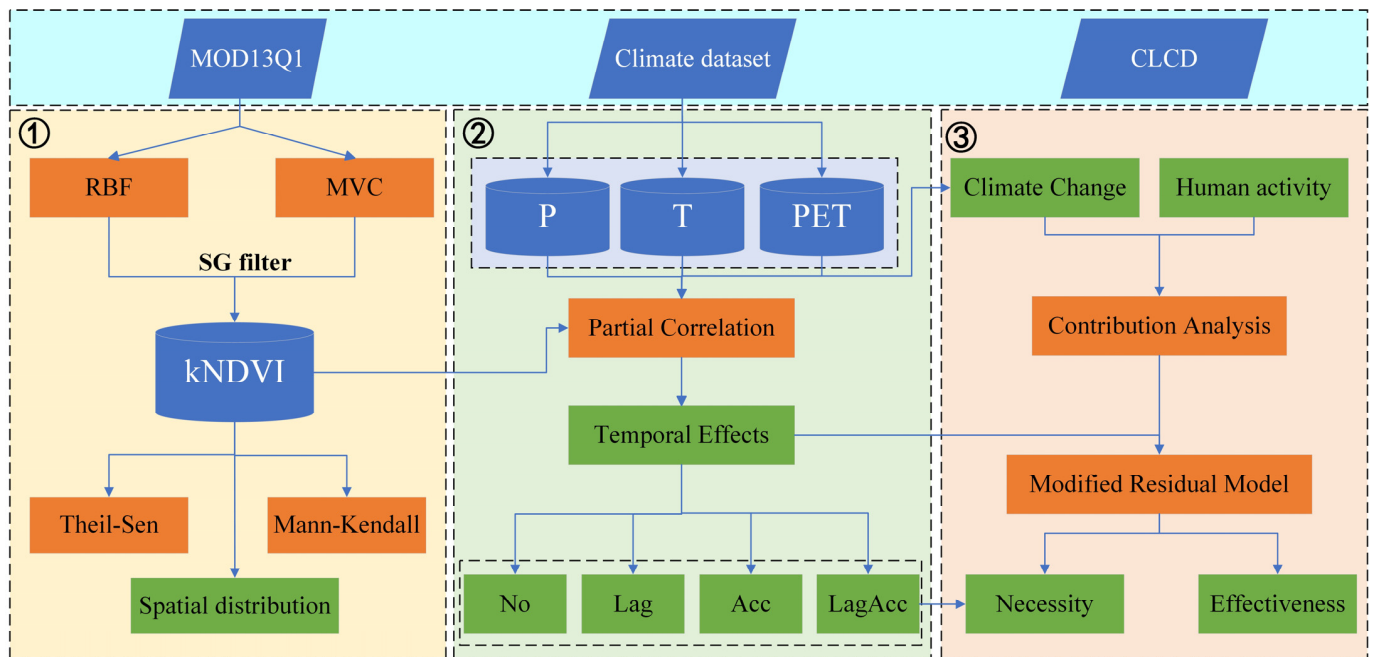


Figure 2. Flow chart for the data analysis.

2.3.1. Theil–Sen Trend and Mann–Kendall Test

This study used the Theil–Sen trend analysis and the Mann–Kendall test to analyze the change characteristics of kNDVI at the pixel level. The Theil–Sen trend was used to calculate the trends of the kNDVI [50]. The Mann–Kendall test can detect abrupt changes while assessing the significance of trends and does not require data to adhere to a specific distribution, such as the normal distribution [51]. This test utilized the statistic Z to assess the significance [52]. It is frequently used in conjunction with the Theil–Sen trend as a basis for analyzing long-term series trends (Table S2).

2.3.2. Evaluating Time-Lag and Accumulation Effects

This study incorporated T, P, and PET as drivers to quantify their effects on kNDVI. We used partial correlation analysis to accurately assess the impact of each variable on kNDVI while eliminating interference from others [53]. Additionally, it was used to evaluate the influence of time-lag and accumulation effects. Based on this, our study calculated the second-order partial correlation coefficients between kNDVI and meteorological factors under different temporal effects. We then compared a total of ten sets of partial correlation coefficients to identify the combination with the strongest correlation, which represents the lag-accumulation period (Figure 3).

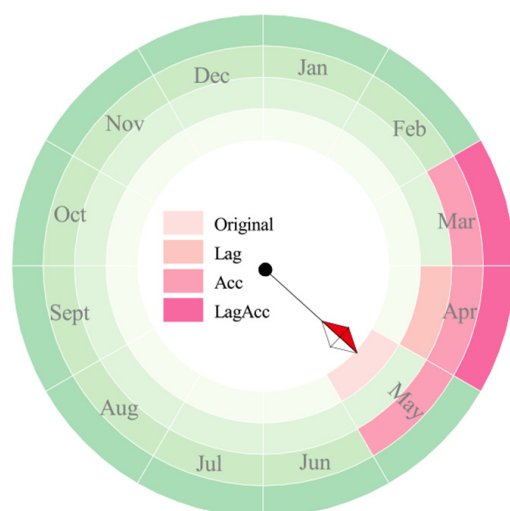


Figure 3. Temporal effects of vegetation response to climate factors. Taking kNDVI in May as an example (pointer), the loop from inside to outside represents (i) no time effect (Lag0 and Acc0), with kNDVI and climate factors in May; (ii) lag effect (Lag1 and Acc0), with kNDVI in May and climate factors with a lag of one month (i.e., April); (iii) accumulation effect (Lag0 and Acc2), with kNDVI in May and climatic factors accumulated for two months (i.e., March + April + May); (iv) bidirectional coupling effect (Lag1 and Acc2), with kNDVI in May is correlated with climatic factors with a lag of one month and an accumulation of two months (i.e., March + April).

2.3.3. Modified Residual Model

We propose a modified model that allows for the examination of the impacts of climate change and human activity on vegetation under varying temporal effects. To verify the performance of our modified residual model, we conducted a systematic assessment using three key performance metrics: R^2 , Root Mean Square Error (RMSE), and Mean Absolute Error (MAE) [54]. R^2 represents the proportion of the dependent variable that is accounted for by the model, RMSE gives an estimate of the error magnitude, and MAE offers an average of the absolute errors. To further evaluate the impacts of CC and HA on vegetation, we delineate interaction scenarios and calculate contribution rates under four temporal effects according to the rules specified in Table S3 [55].

3. Results

3.1. Spatiotemporal Variations of Vegetation Dynamic

The kNDVI in HBEY was lower in the west and higher in the east. High coverage was primarily found in the eastern part of Yulin and the northern part of Hohhot, aligning with the geomorphological distribution of the western highland barren areas and the eastern hilly grassland regions of the study area (Supplementary Figure S1). HBEY's average kNDVI ranged between 0.030 and 0.072, with the minimum and maximum values occurring in 2001 and 2018, respectively. Typically, the values clustered near the lower quartile, suggesting that the vegetation coverage consistently remained at a relatively low level (Supplementary Figure S2). Throughout the study period, kNDVI exhibited an upward trend (slope = 0.0163/decades, $p < 0.005$, $R^2 = 0.85$), with minor interannual fluctuations. It is worth mentioning that after 2011, fluctuations in kNDVI noticeably increased, and the improvement trend slowed, signaling a need for enhanced continuous monitoring of the restoration areas to consolidate ecological recovery gains.

The vegetation dynamic in HBEY was illustrated in Figure 4. The results indicate that 70.96% of the area exhibited significant change, of which nearly all (99.49%) were positive, demonstrating overall greening. It revealed distinct differences in trend across the cities, with the order of improvement areas (SLI and SII) in descending order as follows: Yulin (97.44%) > Ordos (83.63%) > HBEY (78.87%) > Hohhot (71.80%) > Baotou (39.31%).

Yulin showed an extremely high proportion of significant improvements (95.76%), with almost no degradation. The Mu Us Sandy Land has also continued greening over the past two decades, reflecting the substantial efforts in ecological protection in this area. Baotou and Hohhot had relatively high proportions of stable areas (59.12% and 26.73%), with scattered regions of degradation sporadically in the central, northern, and southern fringes. Although these proportions are small, they still warrant attention. Furthermore, there were areas where kNDVI showed a declining trend (Slope < 0), although only 10.24%, often concentrated in urban centers, along the Yellow River, and in some heavy industrial areas. This indicates that excessive land development and urban expansion are still significant constraints on vegetation growth.

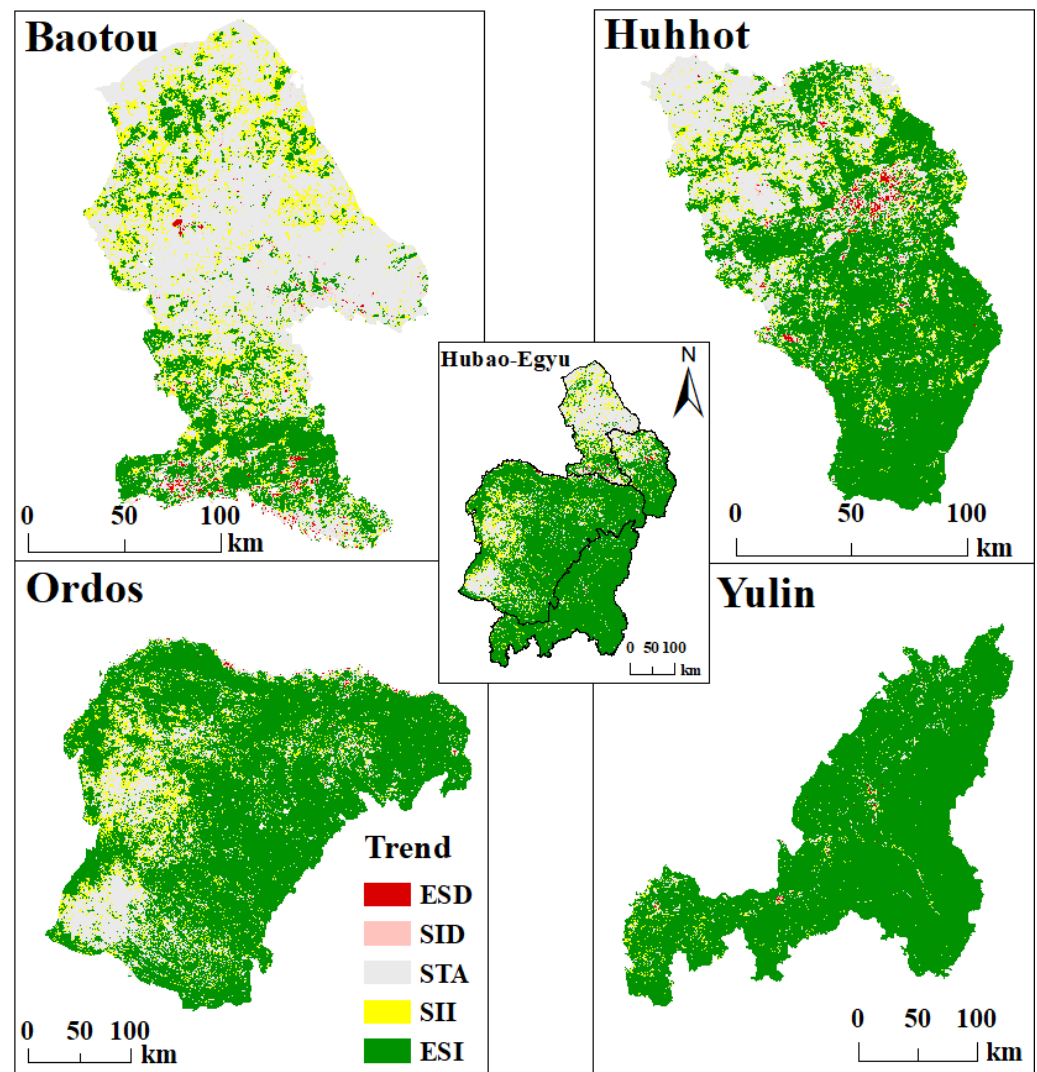


Figure 4. Trends in each region of kNDVI from 2000 to 2022. Full meaning of the abbreviation in Legend: ESD: Extremely Significant Degradation; SID: Significant Degradation; STA: Stable; SII: Significant Improvement; ESI: Extremely Significant Improvement.

3.2. Time-Lag and Accumulation Effects of Climate Factors on kNDVI

The results indicated that kNDVI was generally positively correlated with temperature, precipitation, and PET across the study area (Figure 5a–c). Notably, the partial correlation coefficient with precipitation was obviously higher than with the other factors, suggesting that precipitation was the dominant climatic driver of kNDVI changes in HBEY. Specifically, the central and eastern parts of HBEY showed strong positive correlations with precipitation, indicating a substantial influence of water availability on vegetation growth.

Conversely, kNDVI exhibited a relatively weak correlation with temperature overall, with a noticeable negative correlation particularly concentrated in the northern Baotou and the western Ordos Plateau. In these areas, a negative correlation between kNDVI and PET was also observed. Additionally, we examined the vegetation response under nine different temporal effect scenarios (Supplementary Figures S3–S5). When incorporating the temporal effect, the correlation coefficients of kNDVI and climate factors changed to different degrees. Specifically, the correlation changes between PET and kNDVI were minimal, whereas the correlation with precipitation showed a marked decrease, and the correlation with temperature exhibited an increase. We also found that when the lag and accumulation time were sufficiently extended, the correlation may reverse, often occurring in areas with weak initial correlations. For example, in the southeastern region of the study area, what was initially a positive correlation between precipitation and kNDVI shifted to a negative correlation in scenarios with extended lags. Similarly, in eastern Yulin, an initially negative correlation with temperature transitioned to a positive correlation when the accumulation period was prolonged.

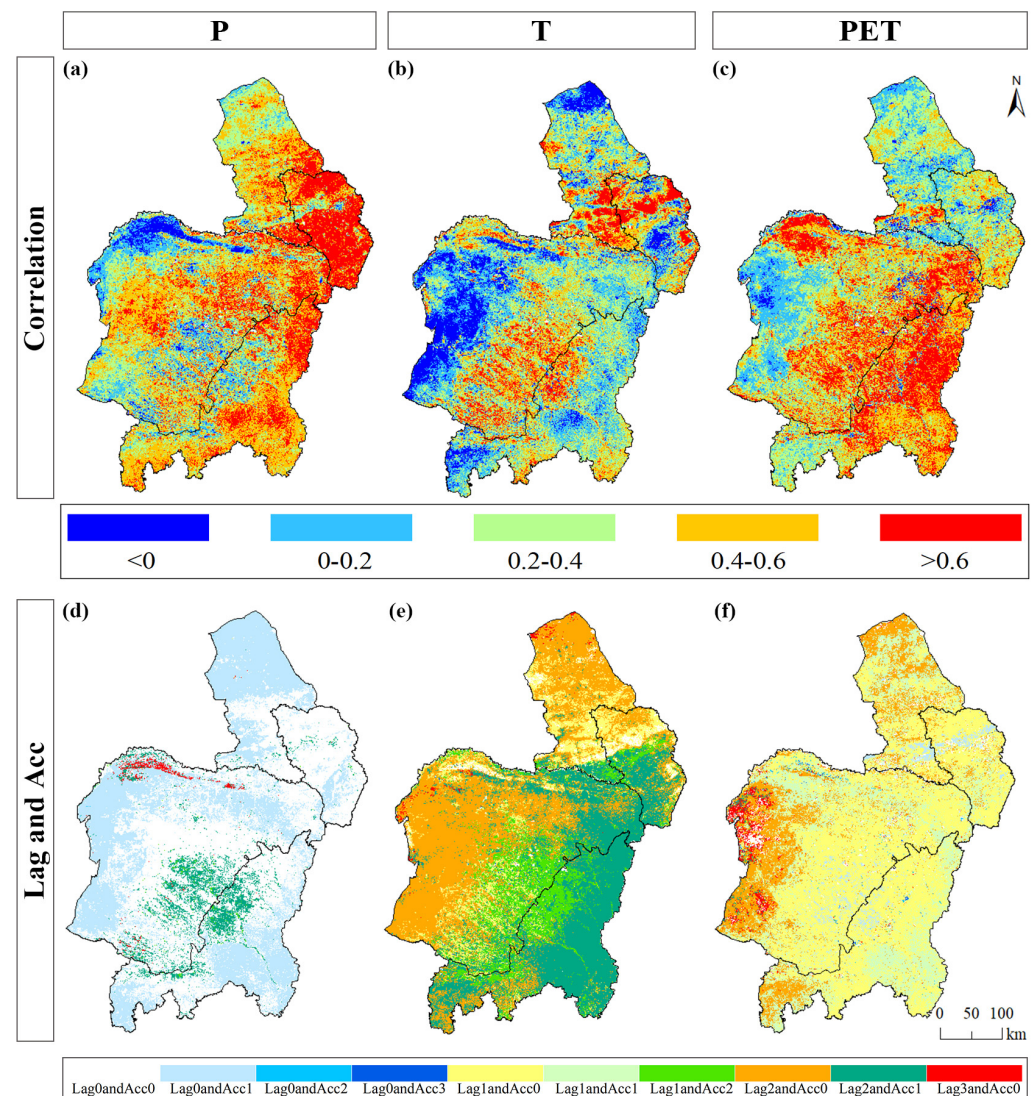


Figure 5. Partial correlation and the lag and accumulation period of vegetation kNDVI with precipitation (a,d), temperature (b,e), and potential evapotranspiration (c,f) in the Hubao–Egyu Urban Agglomeration. Here, Lag *i* and Acc *j* means *i* months lag and *j* months accumulation.

The strength and direction of the climatic factors driving vegetation change—including both direct and lag/accumulation effects—vary greatly across regions. Generally, the lag effects of temperature and PET were more pronounced, while the accumulation effects of precipitation were stronger. Specifically, for lag and accumulation effects, temperature, PET, and precipitation exhibited lag periods of 1.708 ± 0.98 , 1.16 ± 0.79 , and 0.155 ± 0.33 months, and accumulation periods of 0.565 ± 0.63 , 0.282 ± 0.31 , and 0.462 ± 0.42 months, respectively. According to Figure 5d–f, the temporal effects of temperature on kNDVI were predominantly characterized by the scenario of Lag2 and Acc0 (41.13%), Lag2 and Acc1 (30.64%), Lag1 and Acc0 (13.2%), and Lag1 and Acc2 (12.54%). The response of vegetation to temperature was primarily dominated by the lag effects and the bidirectional coupling effect (LagAcc), accounting for 54.79% and 43.33% (Supplementary Table S4), respectively. The bidirectional coupling effects mainly affected the eastern part, while the lag effects were dominant across most of the Ordos Plateau and Baotou. Among the different land use types (Supplementary Figure S6b), almost none show accumulation effects solely. Nearly half of the forest areas exhibited no temporal effects. Cropland exhibited the most pronounced LagAcc effects, at 70.65%.

In terms of precipitation and PET, the predominant temporal effects were: Lag0 and Acc0 (53.55%), Lag0 and Acc1 (38.85%), and Lag2 and Acc1 (6.53%) for precipitation, and Lag1 and Acc0 (49.76%), Lag1 and Acc1 (23.7%), and Lag2 and Acc0 (18.03%) for PET. In terms of precipitation, no temporal effect (53.55%) and acc effect (38.87%) had the greatest impact, predominantly affecting the central and peripheral areas. From Supplementary Figure S6, the vast majority of forest vegetation showed no temporal response to precipitation (88.03%), while grasslands exhibited a relatively pronounced accumulation effect (42.89%). Conversely, for PET, the lag effect (69.65%) and LagAcc effect (24.15%) were the dominant temporal effects. The accumulation effect of forest was particularly prominent (46.14%), while cropland and grassland showed the most pronounced lag effects (Supplementary Figure S6 and Supplementary Table S5). This phenomenon highlights the complex interactions and adaptive mechanisms between vegetation and different climatic factors, underscoring adaptability as a key to vegetation survival in varied climatic environments.

3.3. Contributions of Human Activity and Climate Change to Vegetation Dynamics

According to Figure 6, the vegetation changes in HBEY were mainly influenced by both HA and CC (greening: 68.3%, browning: 9.21%). Among these were regions where vegetation browning was primarily distributed in urban built-up areas and along the Yellow River, while the most extensive greening driven by the two is concentrated in the southeastern and northeastern parts of HBEY. Vegetation greening driven by human activity accounts for 17.32%, mainly distributed in the Ordos Plateau and the Kubuqi Desert. In contrast, greening driven by climate change accounts for only 4.15% and is sporadically distributed in the northern and southwestern corners of the study area. Comparatively, human activity exerted a stronger influence on vegetation than climate change. The extensive greening experienced by the urban agglomeration is mainly influenced by both human activity and climate change. As shown in Figure 6, in built-up urban areas (A), the significant traces of urban expansion reveal the direct and drastic impact of HA on vegetation degradation. In the Jizi Bay (B), floodplain sedimentation caused by CC is the main reason for vegetation browning [56]. The case of area (C) further demonstrates this complexity. On the one hand, humans actively improve vegetation by reclaiming barren land ③; on the other hand, climate change affects vegetation through natural processes such as grassland succession ④. In area (D), the joint action of human activity and climate change is fully reflected in sand control, demonstrating their synergistic effects on vegetation improvement [57]. In addition, the vegetation degradation caused by the development of artificial lakes ⑥ and the vegetation improvement brought by industrial park ecological management ⑦ in area (E) coexist, highlighting the duality of human activities and climate change in influencing vegetation. More importantly, our findings also demonstrate that the modified residual model can maintain objectively true results within individual pixels,

indirectly demonstrating the importance of time effects in attributing vegetation changes, and of adaptability as a key to vegetation survival in varied climatic environments.

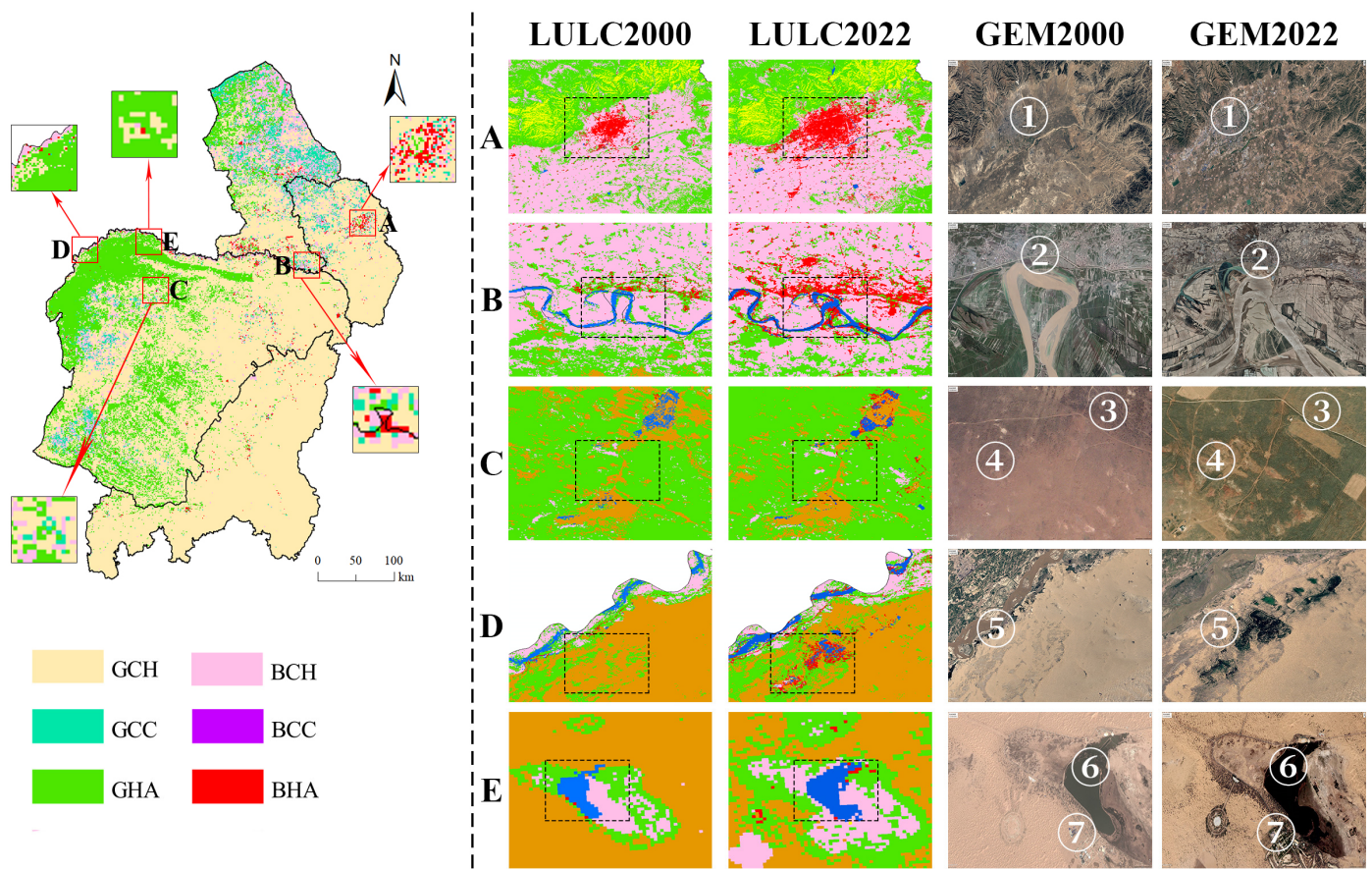


Figure 6. The driving mechanism of CC and HA on vegetation dynamics. The meaning of abbreviations in the legend is shown in Table S3. Columns 1 to 4 in the submap are the land use maps and Google Earth Maps in 2000 and 2022, respectively, which reflect the land use change and real images. The colors of the land use types are consistent with those in Supplementary Figure S7.

Under the consideration of four temporal effects—No, Lag, Acc, and LagAcc—the explanatory power of CC on vegetation shows an increasing trend (Figure 7), with values of $40.90\% \pm 21.32\%$, $46.91\% \pm 17.56\%$, $43.03\% \pm 21.03\%$, and $47.85\% \pm 18.58\%$, respectively. It confirmed that considering the lag effect rather than the accumulation effect can more strongly reveal the contribution of climate change. Compared to the No temporal effect, the LagAcc effect shows a relative increase of 6.95% (R^2 increase of 0.08), particularly noticeable within the Ordos Plateau. This finding implied that the contribution of CC is somewhat obscured by temporal effects. By accounting for lag and accumulation effects, we can effectively restore the true contribution of CC and reduce the uncertainty in the climate–vegetation response. Under the LagAcc effect, the regions where climate change dominate were mainly located in the northern part of Baotou, Hohhot City, and the eastern area of Yulin. According to the results presented in Figure 7e,f, human activity consistently plays a dominant role on vegetation dynamics in HBEY. In regions with harsh natural environments, as well as in highly urbanized areas, a significant human contribution is observed. However, it is important to note that these contributions are not always positive, underscoring the need for a thorough understanding of the mechanisms driving the impact of CC and HA on vegetation dynamics. This finding is important for making informed, sustainable decisions within this complex ecosystem.

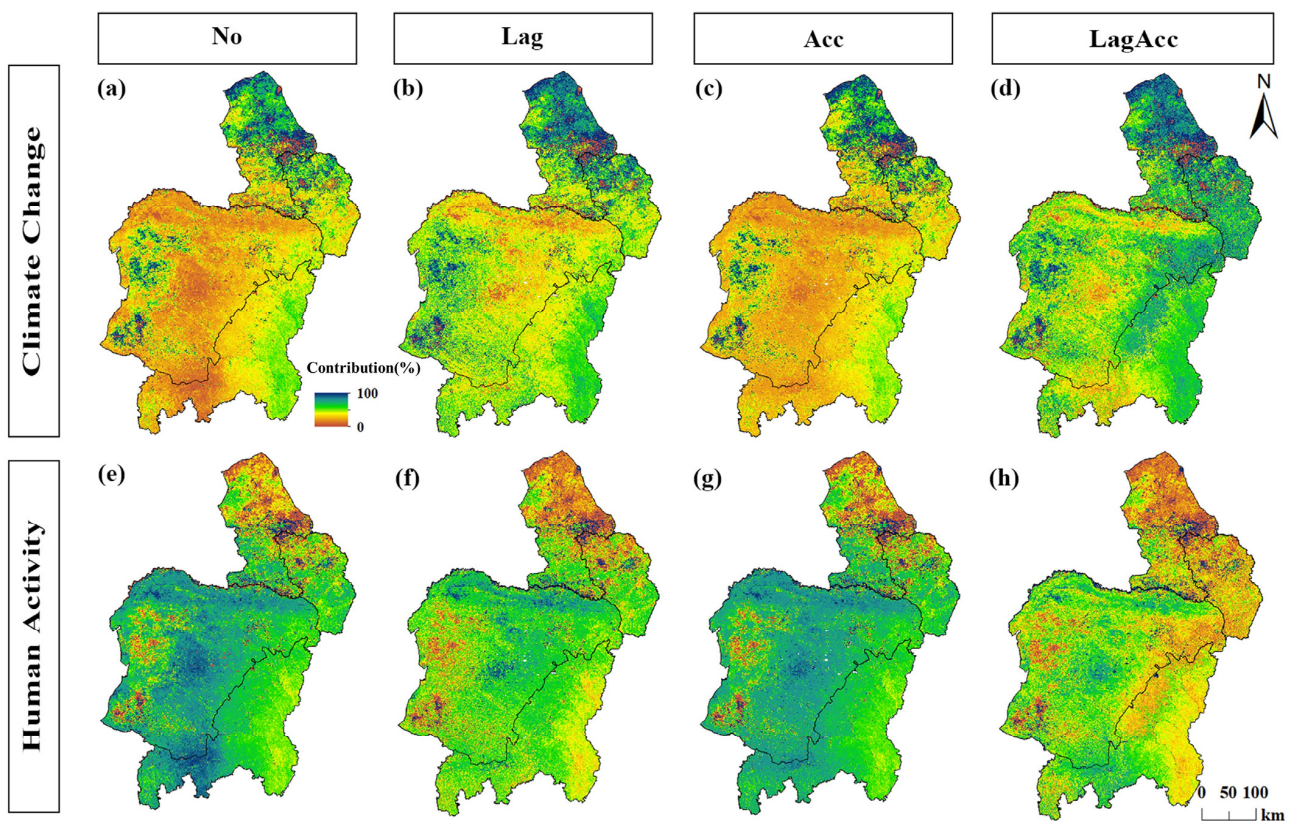


Figure 7. The contribution of CC (a–d) and HA (e–h) to kNDVI in HBEY from 2000 to 2022, based on a modified model. Columns 1 to 4 represent the contribution rate under four scenarios: no temporal effect (No), lag effect (Lag), accumulation effect (Acc) and bidirectional coupling effects (LagAcc).

To further assess our modified model's effectiveness, we calculated its performance metrics (R^2 , MAE, RMSE) using ten-fold cross-validation under four scenarios [30]. The results indicated that incorporating lag and accumulation effects enhanced model performance (Figure 8). Specifically, the introduction of lag effects, by capturing the delayed response of vegetation to climate change, greatly improved the model's explanatory power and predictive accuracy. The inclusion of accumulation effects further refined the model's understanding of vegetation dynamics. Additionally, the model that considered both lag and accumulation effects (LagAcc) excelled across all performance metrics. This suggests that it can most effectively capture the complexity of vegetation dynamics, fully demonstrating the effectiveness of the modified residual model.

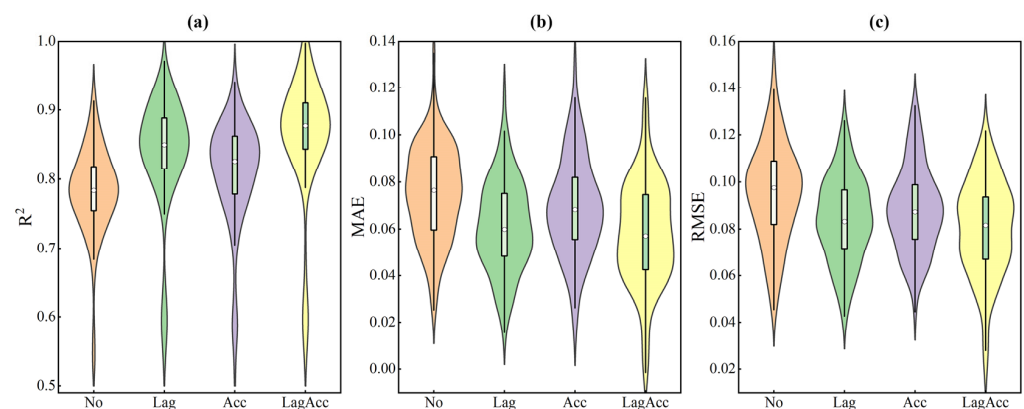


Figure 8. Performance of residual models between kNDVI and climate variables under four scenarios. The diagram depicted the violin diagram of the three evaluation indicators: (a) R^2 , (b) MAE, (c) RMSE.

4. Discussion

4.1. The Temporal Effect Mechanism of Climate Factors on Vegetation

The existence of temporal effects was attributed to the specific rhythm of vegetation growth and development, which requires a certain cycle to occur [31]. When climate changes, vegetation needs time to adapt and exhibit a corresponding response. The adaptive mechanisms of vegetation physiology can also mitigate the impacts of temporary climate changes [58,59]. Wen's research indicated that, on a global scale, the accumulation effects of vegetation and temperature were dominant in low-latitude regions, while in arid and semi-arid areas, the lag effects of precipitation prevail [60]. Our findings showed that the temporal effect of temperature in HBEY is predominantly characterized by lag effects, followed by accumulation effects. This seems contradictory to the conclusion of Wen [60] and Ding [61], who claimed that vegetation response to temperature was mostly accumulative or instantaneous in Central and North Asia. However, it was worth noting that Liu's research suggested that temporal effects vary with different climates and vegetation types. Furthermore, Kong found that in arid regions, grasslands exhibited a more pronounced lag effect to temperature compared to other vegetation types [62]. This is in line with our findings, given that HBEY primarily consists of grassland and cropland, both of which exhibited longer lag periods (Tables S5 and S6). The root system of grassland can store nutrients to regulate growth imbalances caused by temperature fluctuations, which aligns with previous research [63]. Ma [30] found that vegetation in high-altitude areas required a longer time to accumulate heat to support its growth and development in relatively cold environments, which also corroborated the accumulation effects observed on the Ordos Plateau. Additionally, Wan [64] found that in the northern temperate regions, the large seasonal temperature variations lead to stronger resistance of vegetation to temperature fluctuations. Therefore, combined with previous studies, we believe that in temperature-limited areas, such as high-altitude and high-latitude regions, vegetation responses to temperature tends to have relatively longer lag times.

The temporal effect of PET is generally consistent with temperature but relatively weaker in magnitude, which was basically consistent with the studies carried on the arid areas [60]. Zhao's study on the temporal effects of arid grassland vegetation also found similar phenomena [35]. In semi-arid areas, an increase in PET implied more severe soil moisture depletion. Ershadi [65] suggests that higher PET requires vegetation to accumulate more precipitation to maintain the water necessary for photosynthesis. Without additional water supply, this could further exacerbate water stress, requiring time for vegetation to adjust its physiological strategies to cope with the increased challenges [66]. Precipitation's temporal effect on vegetation was primarily characterized by an instantaneous response, followed by accumulation effect. Anderegg [67] found that vegetation in semi-arid region exhibited heightened sensitivity to precipitation changes, coupled with a comparatively weak resilience to water scarcity. From this perspective, measures such as artificial irrigation and improving water availability were effective interventions to influence vegetation growth conditions. Additionally, a previous study by Paudel and Andersen [68] suggested that vegetation does not directly respond to precipitation but rather to actual soil moisture. The soil's memory of water was long-term and accumulative: when rainfall is sufficient, the soil can store excess water to meet the constant growth requirements. Moreover, Braswell [69] and Zhang [70] argued that the process of soil moisture being transferred to the surface also requires time. In comparison, root systems in grasslands can effectively absorb soil moisture, but they also require more accumulated water to bring about significant changes in vegetation [71].

4.2. The Necessity and Effectiveness of the Modified Residual Model

Relying solely on immediate climate data may not fully explain the growth patterns of vegetation in arid areas [61]. However, traditional residual models mainly consider the influence of independent variables within the same period. This approach does not fully capture the lag and accumulation effects of vegetation's response to climate change,

potentially leading to errors in vegetation attribution analysis [31,72,73]. Ding's study indicated that accounting for lag effects increases the explanatory power of residual models by 9% during the growing season [61]. Similarly, Ma [34] discovered that extreme climate factors also exhibited temporal effects, and by establishing linear models between vegetation indices (VIs) and climate variables under different lag and accumulation scenarios, the explanatory power of residual models improved by approximately 8%. However, traditional linear relationships may involve interactions between seasonal variations and climate change, leading to uncertainty [74]. Our proposed model addresses this by using partial correlation analysis to eliminate the interdependence among climate variables, thereby enhancing reliability. The results confirmed that scenarios incorporating both lag and accumulation effects are the most effective, enhancing the explanatory power of climate factors on vegetation dynamics, particularly in barren and grassland areas (Supplementary Table S4). Moreover, Wu [31] found that when considering lag effects, the contribution of climate change to global vegetation dynamics increased from 58% to 64%, and when considering cumulative effects, it increased to 68%. Ma [30] integrated both lag and accumulation effects and discovered that the contribution of temperature and precipitation on vegetation in the Qilian Mountains rose from 35.6% to 54.1%. Those were largely consistent with our findings. Therefore, we claimed that climate variables that consider temporal effects more accurately reflect the actual contribution of climate change, effectively reducing the interference and errors caused by non-climatic factors. This allowed for a more precise isolation of the independent contribution of climate change to vegetation dynamics.

4.3. Uncertainty and Future Outlook

Considering temporal effects, we propose a second-order lag accumulation partial correlation analysis and modify the residual analysis model. It quantifies vegetation response characteristics in four scenarios and ten sets, providing new insights into the interaction among climate, vegetation, and human activity. However, there are limitations. Firstly, the driving factors of vegetation change are complex and difficult to fully enumerate. This study attributes vegetation changes in the HBEY to three influential driving factors in arid to semi-arid regions: temperature, precipitation, and potential evapotranspiration. The effects of solar radiation, CO₂ fertilization, nitrogen deposition, and extreme weather were not considered [75–77]. Moreover, human activities such as ecological engineering and land abandonment, as well as vegetation pests cannot be quantified at the pixel scale [78,79]. Additionally, the driving mechanisms are extremely complex and cannot be fully reflected by simple statistical models. Future research may consider using the SEM model to identify the interaction effects [25]. This could further deepen our understanding of vegetation driving mechanisms.

5. Final Remarks

Our study explored the spatiotemporal dynamics of kNDVI in the Hubao–Egyu Urban Agglomeration from 2000 to 2022, employing second-order partial correlation analysis and a modified residual model to more accurately quantify the contributions of climate change and human activity to vegetation dynamics. Over the study period, notable vegetation increases were observed in HBEY, particularly in Yulin City. Precipitation emerged as the primary climatic factor driving these changes, with early climate impacts proving more significance due to lag effects. Considering temporal effects, the modified residual model restored the contribution of climate change to vegetation dynamics (increasing explanatory power by 6.95%), demonstrating the necessity and effectiveness of modifying temporal effects in residual models. Vegetation dynamics in HBEY are primarily influenced by both human activity and climate change, with human activities playing a dominant role in greening, especially in urban areas. This approach not only offers new insights into the interplay among climate, vegetation, and human activity in arid to semi-arid regions, but also holds profound implications for ecological conservation and resource management in

these areas. Future research will further explore the underlying mechanisms of vegetation dynamics to promote the sustainable development of ecosystems.

Supplementary Materials: The following supporting information can be downloaded at: <https://www.mdpi.com/article/10.3390/land13091337/s1>, Figures S1–S7, Tables S1–S6.

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