

Article

Spatiotemporal Variation and Drivers of Vegetation Phenology Along an Urban–Rural Gradient in Rapidly Urbanizing Beijing, China

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Highlights

What are the main findings?

- Beijing experienced an overall extension of the vegetation growing season from 2005 to 2024, mainly driven by significant SOS advancement and, to a lesser extent, EOS delay.
- Urban areas showed earlier SOS, later EOS, and longer LOS, whereas SOS advancement, EOS delay, and LOS extension were more pronounced in suburban and rural areas.

What are the implications of the main findings?

- The contrast between multi-year phenological patterns and long-term trends highlights the need to distinguish where the growing season is already longer from where phenological changes are occurring more rapidly.
- The declining contribution of nighttime lights from urban to rural areas suggests a transition from stronger urbanization-related influences to stronger climatic controls along the urban–rural gradient.

Abstract

Urbanization alters the local growth environment of vegetation, including local thermal regimes, moisture availability, and human activity intensity. Yet, the gradient-dependent changes in vegetation phenology and the factors responsible for these changes are still not fully clarified. Taking Beijing as the study area, this study used MOD13Q1 EVI records from 2005 to 2024 to reconstruct annual vegetation trajectories with Savitzky–Golay filtering. The start of the growing season (SOS) and the end of the growing season (EOS) were then identified based on a dynamic threshold criterion, and the length of the growing season (LOS) was derived from the interval between the two phenological dates. Urban–rural gradients were constructed by integrating Global Urban Boundary (GUB) and digital elevation model (DEM) data. Theil–Sen slope estimation and the Mann–Kendall test were then applied to analyze trends in vegetation phenology, while partial correlation analysis and the XGBoost-SHAP method were used to identify the relative effects of climatic and urbanization-related factors. The results showed that (1) vegetation phenology in Beijing varied markedly across space. Mountainous areas in the northwest and south-

Academic Editors: Xuecao Li and Ruyin Cao

Received: 2 June 2026

Revised: 29 June 2026

Accepted: 6 July 2026

Published: 9 July 2026

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west had a later SOS, earlier EOS, and shorter LOS, whereas the central plain and south-eastern regions were characterized by an earlier SOS, later EOS, and longer LOS; (2) from 2005 to 2024, the SOS advanced significantly by -0.65 days/year, EOS showed a weaker delay of 0.46 days/year, and LOS increased significantly by 0.90 days/year, indicating an overall extension of the vegetation growing season over the past two decades. (3) Urban areas had an earlier SOS, later EOS, and longer LOS, but the trends of SOS advancement, EOS delay, and LOS extension were more pronounced in suburban and rural areas; and (4) the SOS was mainly influenced by the combined effects of nighttime lights and heat-related factors, whereas the EOS was primarily affected by temperature and nighttime lights. Along the urban–rural gradient, the importance of nighttime lights gradually decreased from urban areas to suburban and rural areas, while the role of climatic factors became relatively stronger. These findings reveal the gradient differentiation of vegetation phenological status, temporal trends, and associated drivers in Beijing under rapid urbanization, and provide useful information for urban vegetation management and ecological planning.

Keywords: vegetation phenology; start of the growing season; end of the growing season; length of the growing season; urban–rural gradient; XGBoost-SHAP; Beijing

1. Introduction

Vegetation phenology is an important indicator of seasonal vegetation growth processes and their responses to environmental change [1]. The start of the growing season (SOS), the end of the growing season (EOS), and the length of the growing season (LOS) not only characterize the intra-annual rhythm of vegetation growth activity [2], but are also closely associated with the terrestrial ecosystem carbon cycle, land–atmosphere energy exchange, and ecosystem services [3]. Vegetation phenology responds sensitively to changes in environmental conditions, including temperature, precipitation, and radiation [4], and its spatiotemporal dynamics provide an important perspective for assessing regional ecosystem responses [5]. Compared with traditional ground-based observations, satellite observations enable repeated phenological monitoring over large areas and extended time periods by providing consistent vegetation index records, thereby supporting vegetation phenology analysis at urban and regional scales [6].

Rapid urban expansion has reshaped land cover composition, local thermal conditions, and human activity intensity in cities, making vegetation phenology responsive to both climatic variation and urban development [7,8]. Increases in impervious surface coverage, enhanced urban heat storage, and altered local hydrothermal environments can shift spring green-up to earlier dates and postpone autumn senescence, resulting in changes in the SOS, EOS, and LOS [9,10]. However, the effects of urbanization on vegetation phenology are not spatially uniform [11]. Because urban cores, suburban areas, and rural areas differ continuously in built environment intensity, human activity, and natural background conditions, vegetation phenology often exhibits complex spatial differentiation along urban–rural gradients [12,13]. Therefore, analyzing vegetation phenological changes only at the regional-mean scale may fail to reveal the spatial heterogeneity of growing-season changes under urbanization.

Previous studies have investigated the effects of urbanization on vegetation phenology at different scales and have generally shown that urban vegetation tends to exhibit earlier SOS, later EOSs, and longer LOSs than vegetation in surrounding rural areas [14,15]. Urban–rural comparisons [16], single-city case studies [17], urban–rural transects [18], LCZ-based or multi-zone classification schemes [12,19], and dynamic urban–rural

gradient approaches [20] have greatly advanced our understanding of how vegetation phenology varies with urbanization intensity. However, these studies also suggest that phenological responses to urbanization can vary considerably among cities and across space because of differences in topography, land cover composition, climatic background, urban development history, and vegetation management [21–23]. Therefore, broad-scale conclusions based on multiple cities still need to be complemented by detailed investigations in rapidly urbanizing megacities with complex natural and built-environment conditions. Moreover, previous studies have often examined how phenological conditions averaged over multiple years differ along urban–rural gradients [24], or quantified long-term temporal changes in urban vegetation phenology under urbanization [25]. However, whether phenological status and temporal trends show consistent differentiation along the same urban–rural gradient remains insufficiently examined. This distinction is important because recent evidence suggests that spatial urban–rural differences and long-term phenological changes may not follow the same patterns [26], meaning that areas with an earlier SOS, later EOS, or longer LOS are not necessarily the areas where phenological changes are occurring most rapidly. In addition, urban vegetation phenology is jointly influenced by multiple climatic and urbanization-related factors, including thermal conditions, precipitation, radiation, land cover structure, human activity intensity, and regional climatic background [7,27]. These influences may differ between spring green-up and autumn senescence and may involve nonlinear responses and interactions among variables [26,28]. Consequently, integrating linear statistical analysis with interpretable nonlinear modeling in a continuous urban–rural gradient framework can provide complementary insights into how climatic conditions and urbanization-related factors influence vegetation phenology across space.

Beijing is a typical rapidly urbanizing megacity in China [29], characterized by a complex built environment, evident urban–rural transitional features, and pronounced geographical heterogeneity [30], making it a representative region for investigating vegetation phenological changes under urbanization. Accordingly, this study uses Beijing as the study area and uses MODIS EVI time-series data from 2005 to 2024 to extract the SOS, EOS, and LOS. By integrating urban–rural gradient zoning, trend analysis, partial correlation analysis, and the XGBoost-SHAP method, this study systematically analyzes the spatiotemporal patterns, urban–rural gradient differences, and drivers of vegetation phenology in Beijing. Specifically, this study aims to: (1) characterize the spatial patterns and long-term trends of vegetation phenology in Beijing from 2005 to 2024; (2) compare the consistency and divergence between phenological status and temporal trends along the urban–rural gradient; and (3) identify the stage-specific and gradient-dependent differences in the dominant drivers of the SOS and EOS. Through these analyses, this study aims to deepen the understanding of vegetation phenological responses in rapidly urbanizing regions and provide a reference for urban vegetation management and growing-season monitoring.

2. Materials and Methods

2.1. Study Area

Beijing is situated at the northern margin of the North China Plain and extends approximately from 115.7°E to 117.4°E and from 39.4°N to 41.6°N (Figure 1). It lies near Bohai Bay to the southeast, borders Tianjin Municipality to the east, and is surrounded by Hebei Province on the other sides. Topographically, Beijing shows a clear transition from mountainous terrain in the west, north, and northeast to broad plains in the southeast. This topographic transition from mountains to plains leads to pronounced spatial differences in thermal, moisture, and vegetation distribution, providing a suitable natural set-

ting for vegetation phenology research. The regional climate is dominated by warm-temperate monsoon conditions, with moisture conditions ranging from semi-humid to semi-arid and clear seasonal variation in vegetation growth. As a typical rapidly urbanizing megacity in China, Beijing has experienced substantial urban expansion and has developed a complex built environment, with a relatively clear spatial gradient from the urban core to suburban and rural areas. The coexistence of pronounced geographical heterogeneity and intense human activities makes Beijing suitable for investigating the spatiotemporal dynamics and associated drivers of vegetation phenology under urbanization.

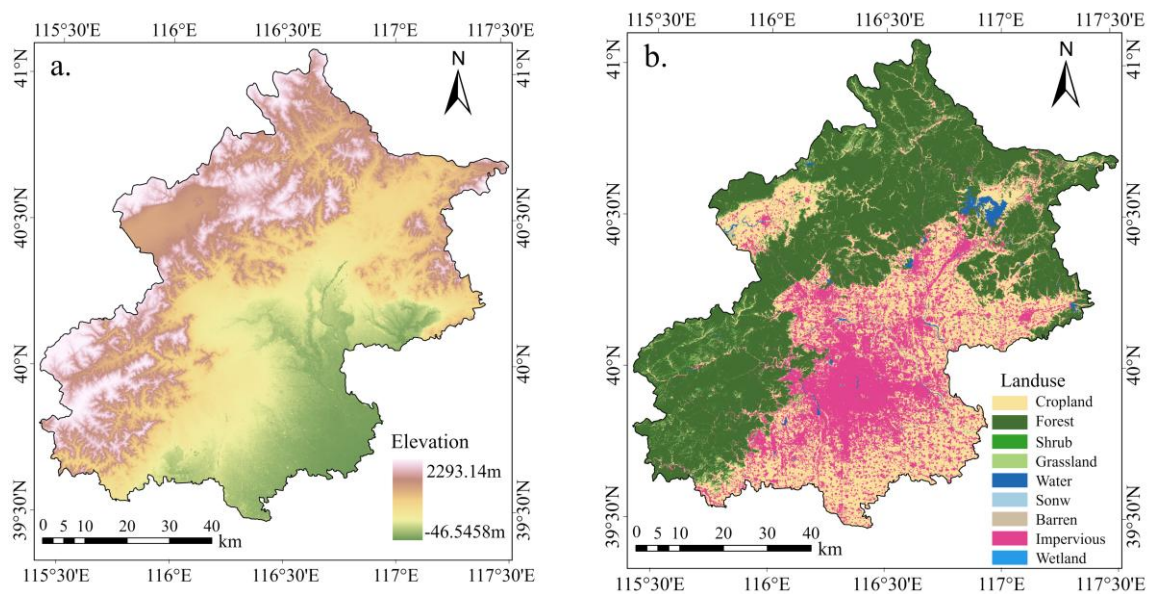


Figure 1. Geographic and land cover setting of the study area. (a) Elevation distribution in Beijing; (b) land cover types within the study area.

2.2. Data Sources

The datasets used in this study included vegetation indices, land cover data, urban boundary data, topographic data, and climatic and urbanization-related data. These datasets were used to support vegetation phenology extraction, urban–rural gradient construction, and driver analysis.

Vegetation phenology was derived from the MODIS/Terra Vegetation Indices product MOD13Q1 Version 6.1, which provides 16-day composite Normalized Difference Vegetation Index (NDVI) and Enhanced Vegetation Index (EVI) data at a spatial resolution of 250 m [31]. In this study, EVI time-series data from 2005 to 2024 were used to extract the SOS, EOS, and LOS in Beijing.

The annual China Land Cover Dataset (CLCD) was used for land cover filtering. CLCD is an annual land cover product for China with a spatial resolution of 30 m and was developed based on long-term Landsat time-series imagery [32]. The construction of the urban–rural gradient was based on the Global Urban Boundary (GUB) dataset. GUB is a global urban boundary dataset derived from the 30 m Global Artificial Impervious Area (GAIA) data and provides urban boundaries for several representative years, including 1990, 1995, 2000, 2005, 2010, 2015, and 2018 [33]. In this study, the 2015 GUB-derived built-up boundary of Beijing was used as the reference boundary for constructing the urban–rural gradient. The Copernicus DEM GLO-30 dataset was further used to impose topographic constraints. This dataset is a global digital elevation model with a spatial resolution of 30 m and was generated from TanDEM-X data [34].

The driving factor data included temperature, precipitation, solar radiation, land surface temperature, and nighttime lights. Monthly temperature and precipitation were

taken from the 1 km gridded datasets for China provided by the National Tibetan Plateau Scientific Data Center. These datasets were produced using the Delta spatial downscaling method by combining CRU global climate data with WorldClim high-resolution climate data, and were used to describe regional hydrothermal climatic conditions [35]. Solar radiation data were obtained from the downward shortwave radiation flux product of the China Meteorological Forcing Dataset (CMFD) v2.0 and were used to characterize radiation conditions during vegetation growth [36,37]. Land surface temperature was derived from the MODIS/Terra MOD11A2 Version 6.1 product, which provides 8-day observations at a spatial resolution of 1 km and was used to characterize the regional surface thermal environment [38]. Nighttime lights were represented by the 500 m “NPP-VIIRS-like” nighttime light dataset from the National Earth System Science Data Center. This dataset integrates DMSP-OLS and NPP-VIIRS nighttime light observations through cross-sensor calibration, ensuring temporal consistency for long-term analysis [39].

2.3. Methods

2.3.1. Vegetation Phenology Extraction

Vegetation phenology metrics in Beijing from 2005 to 2024 were extracted from the MOD13Q1 EVI time series. Before phenology extraction, water bodies and cropland pixels were excluded using the CLCD land cover data to reduce the influence of non-target land cover types and agricultural management activities [40]. The remaining vegetation pixels were used for EVI time-series reconstruction and phenological parameter extraction.

For each pixel, the annual EVI sequence was arranged chronologically and smoothed using the Savitzky–Golay (S-G) filter to reduce noise while preserving the seasonal trajectory of vegetation growth [41]. Based on the smoothed EVI curve, a dynamic threshold method [42] was applied to identify the start of the growing season (SOS) and the end of the growing season (EOS). The relative amplitude ratio at each time step was calculated as follows:

$$EVI_{ratio} = \frac{EVI_t - EVI_{min}}{EVI_{max} - EVI_{min}} \quad (1)$$

where EVI_{ratio} is the relative amplitude ratio at time step t , EVI_t is the EVI value at time step t , and EVI_{max} and EVI_{min} are the maximum and minimum values of the reconstructed annual EVI curve for the corresponding pixel, respectively.

Following previous phenological studies and considering the vegetation conditions in Beijing, 20% of the annual seasonal amplitude was used as the threshold for phenological transition detection [40,42]. SOS was defined as the date during the spring green-up phase when the smoothed EVI curve first reached this threshold, whereas EOS was defined as the date during the autumn senescence phase when the curve decreased to the same threshold. The length of the growing season (LOS) was then calculated as the difference between the EOS and SOS.

2.3.2. Urban–Rural Gradient Classification

Urban–rural gradient zones were constructed based on the 2015 GUB-derived built-up boundary of Beijing to characterize the spatial transition of urbanization intensity from the built-up area to the surrounding regions. The 2015 boundary was selected because it is located near the middle of the 2005–2024 study period and can provide a representative spatial reference for the relatively mature built-up extent of Beijing during the study period. Areas within this boundary were defined as the urban zone, and outward buffer rings of 0–1, 1–2, 2–5, 5–10, 10–15, 15–20, and 20–25 km were generated to represent the continuous urban–rural gradient [43]. It should be noted that this gradient classification was used as a static spatial framework rather than an annually updated dynamic urban

boundary. This gradient classification was used as a static spatial framework rather than an annually updated dynamic urban boundary, allowing phenological status and long-term trends from 2005 to 2024 to be compared within consistent spatial units.

The buffer distances in this study therefore refer to the distance from the main Beijing urban core rather than the distance from every built-up patch within or around the study area. Smaller built-up patches within Beijing and neighboring urban areas outside Beijing were not used as additional buffer origins. As a result, some pixels in the outer buffer zones may still be close to other local built-up areas. This issue is further acknowledged in the limitations section. Nevertheless, this design was adopted because the purpose of the gradient analysis was to examine the core–periphery phenological differences associated with the main urbanized area of Beijing.

For comparative analysis, the continuous gradient zones were further grouped into three categories: the area within the built-up boundary was defined as the urban zone, the area within the 0–20 km buffers was defined as the suburban zone, and the 20–25 km buffer area was used as the rural reference zone [44] (Figure 2). The continuous buffer rings were used to examine detailed phenological variations along the urban–rural transition, whereas the three-zone classification was used to compare phenological characteristics, temporal trends, and driving factors across different urbanization intensities.

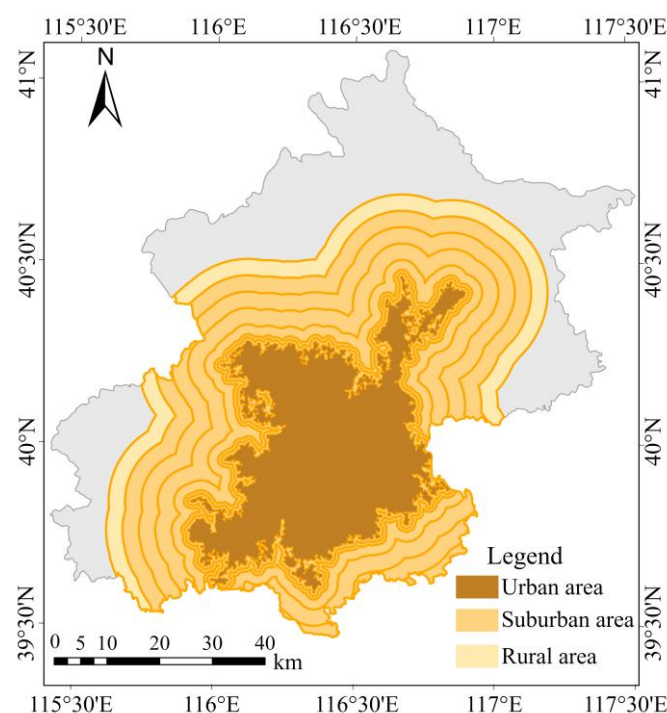


Figure 2. Urban–rural gradient classification in Beijing based on the GUB-derived built-up boundary. Outward buffer rings of 0–1, 1–2, 2–5, 5–10, 10–15, 15–20, and 20–25 km were generated, with the built-up area defined as urban, the 0–20 km buffer as suburban, and the 20–25 km buffer as rural.

Because Beijing has pronounced topographic heterogeneity, especially between mountainous areas and plains, a topographic constraint was applied to reduce the confounding effect of elevation in urban–rural gradient analysis. Specifically, the elevation range of the urban zone was used as a reference, and pixels with elevations more than 50 m higher than the maximum elevation of the urban zone were excluded from the gradient analysis [43,45]. The final urban–rural gradient classification served as the spatial basis for subsequent phenological comparisons and driver analysis.

2.3.3. Trend Analysis

Long-term trends in vegetation phenology from 2005 to 2024 were analyzed at the pixel level for SOS, EOS, and LOS. The Theil–Sen estimator was used to quantify the magnitude and direction of the trend because of its robustness to outliers in long-term remote sensing time series [46]. The trend slope was calculated as follows:

$$\beta = \text{Median} \left(\frac{x_j - x_i}{j - i} \right), \quad 1 \leq i < j \leq n \quad (2)$$

where β is the Theil–Sen trend slope, x_i and x_j are the phenological parameter values in years i and j , respectively, and n is the length of the time series. For SOS and EOS, a negative slope indicates an advancing phenological date, whereas a positive slope indicates a delayed phenological date. For LOS, a negative slope indicates a shortening of the growing season, whereas a positive slope indicates an extension.

The Mann–Kendall test was used to assess the statistical significance of the estimated trends [47]. In this study, $p < 0.05$ was used as the significance threshold, corresponding to $|Z| > 1.96$ under the standard normal approximation. By combining the sign of the Theil–Sen slope with the significance result of the Mann–Kendall test, phenological trends were classified into different categories [48,49]. For SOS and EOS, trends were classified into five categories: significant advancement, non-significant advancement, stable, non-significant delay, and significant delay. For LOS, trends were classified as significant shortening, non-significant shortening, stable, non-significant extension, and significant extension.

2.3.4. Partial Correlation Analysis

Partial correlation analysis was applied to examine the linear relationship between vegetation phenology and each driving factor after accounting for the effects of the remaining variables [50]. In this study, SOS and EOS were selected as response variables, while temperature, precipitation, solar radiation, LST, and NTL were used as explanatory variables.

To compare the differences in phenology–driver relationships under different urbanization backgrounds, partial correlation analysis was conducted at the whole-region scale and within the urban, suburban, and rural zones. The significance threshold was set at $p < 0.05$. After controlling for the remaining variables, the partial correlation coefficient is calculated as follows:

$$\rho_{ij \cdot Z} = - \frac{\Omega_{ij}}{\sqrt{\Omega_{ii} \Omega_{jj}}} \quad (3)$$

where $\rho_{ij \cdot Z}$ denotes the partial correlation coefficient between variables i and j after controlling for the remaining variables Z ; Ω is the inverse of the correlation matrix; and Ω_{ij} , Ω_{ii} , and Ω_{jj} are the corresponding elements of the inverse correlation matrix.

For SOS and EOS, a positive partial correlation coefficient indicates that an increase in the corresponding factor is associated with a delayed phenological date, whereas a negative coefficient indicates an association with an advanced phenological date. A larger absolute value indicates a stronger independent linear relationship.

2.3.5. XGBoost-SHAP Analysis

To capture nonlinear associations between vegetation phenology and its driving factors, XGBoost regression models were combined with SHAP interpretation [51]. Separate models were developed for SOS and EOS. The analysis was performed at the whole-region scale and separately within the urban, suburban, and rural zones to compare the relative importance of driving factors under different urbanization backgrounds.

For each response variable and analysis scale, the samples were randomly divided into training, validation, and testing sets at an approximate ratio of 7:1:2. The training set was used to fit the XGBoost regression model, the validation set was used to monitor model performance during training, and the testing set was used for final model evaluation. Model performance was evaluated using the coefficient of determination (R^2) and root mean square error (RMSE).

SHAP was used to interpret the trained XGBoost models by quantifying the contribution of each variable to model predictions [52]. The SHAP additive explanation can be expressed as:

$$\hat{y}_i = \phi_0 + \sum_{k=1}^M \phi_{ik} \quad (4)$$

where $\hat{y}_i$ is the predicted value for sample i , ϕ_0 is the baseline model output, M is the number of input variables, and ϕ_{ik} represents the contribution of the k -th driving factor to the prediction of sample i .

The mean absolute SHAP value was used to measure the relative importance of each driving factor. A larger mean absolute SHAP value indicates a greater contribution to model prediction. SHAP-based variable importance and bee swarm plots were used to compare the magnitude, direction, and gradient-dependent differences in driving-factor contributions. It should be noted that XGBoost-SHAP reveals statistical associations and relative explanatory contributions, but does not directly demonstrate strict causal relationships [53].

3. Results

3.1. Spatial and Temporal Patterns of Vegetation Phenology

3.1.1. Spatial Patterns of SOS, EOS, and LOS

The multi-year median vegetation phenology during 2005–2024 showed pronounced spatial heterogeneity across Beijing. SOS was generally later in the northwestern and southwestern mountainous areas, but earlier in the central plain and southeastern regions (Figure 3a), indicating that spring green-up in mountainous areas lagged behind that in the plains. The longitudinal profile showed a pattern of higher values on both sides and lower values in the central area, while the latitudinal profile indicated that SOS was generally slightly later in the north than in the south.

EOS displayed an approximately opposite spatial pattern to SOS. A later EOS was concentrated in the central and southern plain areas, whereas an earlier EOS occurred more frequently in the northern and northwestern mountainous regions (Figure 3b). The longitudinal profile showed a clear high-value zone in the central area, suggesting later autumn senescence in this region. The latitudinal profile showed a gradual decrease from south to north, indicating that EOS was generally later in the southern part of Beijing than in the northern part.

The LOS pattern was shaped by the joint timing of spring green-up and autumn senescence. Longer growing seasons were mainly observed in the central and southeastern regions, where SOS occurred earlier and EOS occurred later (Figure 3c). In contrast, a shorter LOS was concentrated in the mountainous northwest and southwest, where a delayed SOS and earlier EOS shortened the growing season. The longitudinal profile showed that LOS generally increased from the western mountainous areas to the central plain, with smaller variations toward the east. The latitudinal profile indicated that LOS was slightly longer in the south than in the north. These results reveal a distinct mountain–plain differentiation pattern: mountainous areas were characterized by a later SOS, earlier

EOS, and shorter LOS, whereas central and southeastern plain areas showed an earlier SOS, later EOS, and longer LOS.

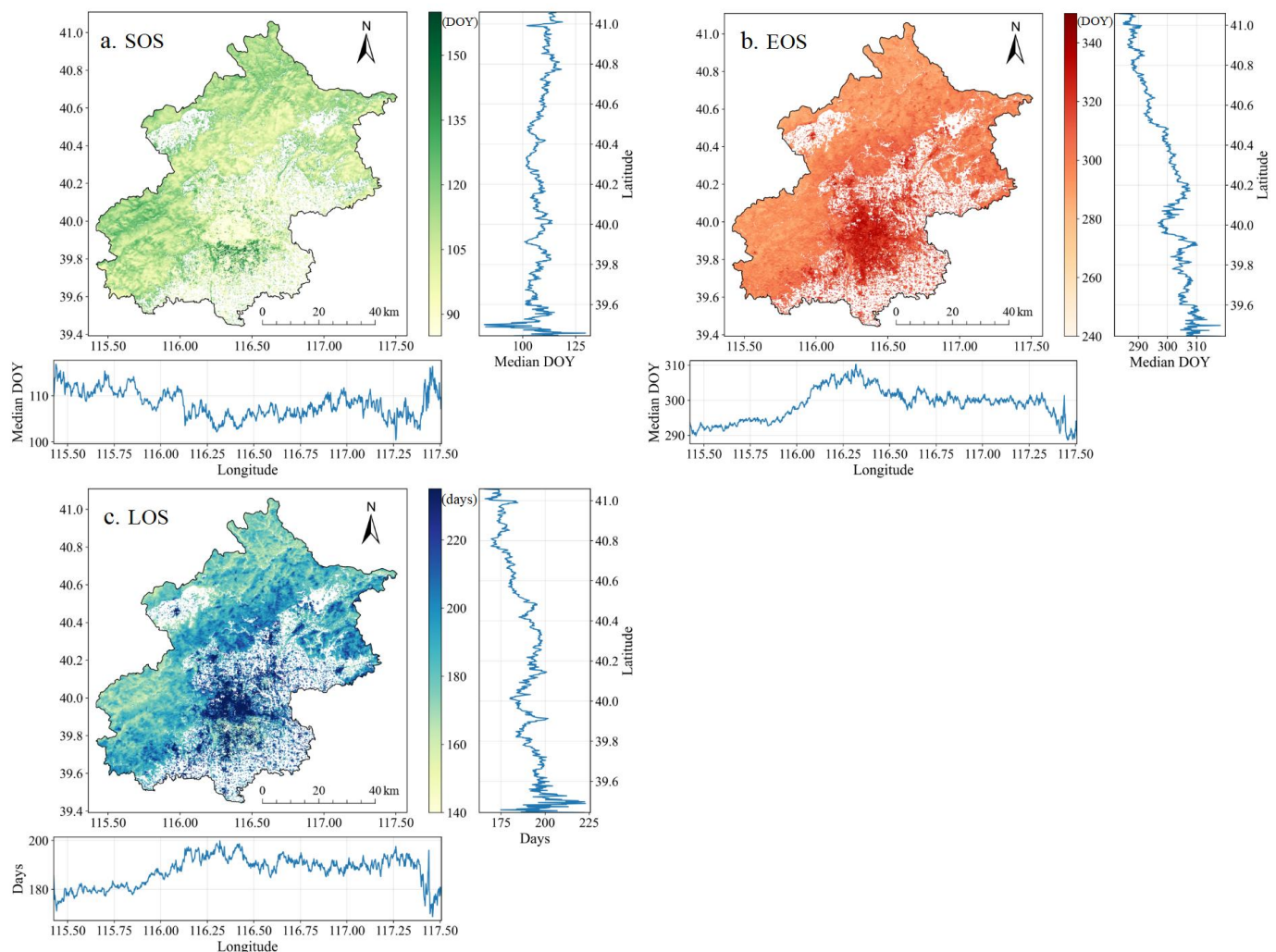


Figure 3. Spatial distributions and longitudinal/latitudinal profiles of multi-year median vegetation phenology in Beijing from 2005 to 2024: (a) SOS, (b) EOS, and (c) LOS. SOS and EOS are expressed as day of year (DOY), whereas LOS is expressed in days. White areas indicate excluded or invalid pixels.

3.1.2. Interannual Variations in Vegetation Phenology from 2005 to 2024

Between 2005 and 2024, vegetation phenology in Beijing fluctuated from year to year, but the overall pattern pointed to an earlier SOS, later EOS, and increased LOS. The multi-year median SOS moved toward earlier dates during 2005–2024, with a fitted slope of -0.65 days/year (Figure 4a), with a linear slope of -0.65 days/year. This trend was statistically significant at the 0.05 level ($p = 0.003$), indicating a significant advancement of spring vegetation green-up in Beijing.

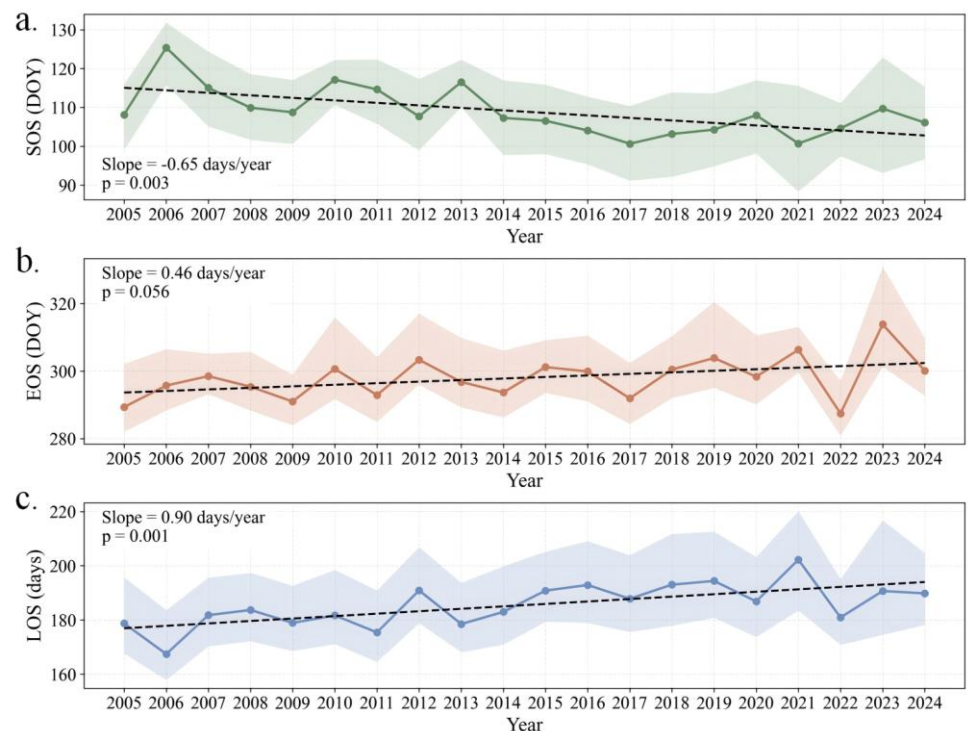


Figure 4. Interannual variations and linear trends of vegetation phenology in Beijing from 2005 to 2024: (a) SOS, (b) EOS, and (c) LOS. Points represent annual median values across valid vegetation pixels, shaded areas indicate the interquartile range across valid vegetation pixels, and dashed lines indicate fitted linear trends. SOS and EOS are expressed as DOY, whereas LOS is expressed in days.

Compared with SOS, the long-term trend of EOS was weaker. The multi-year median EOS showed a slight increasing trend (Figure 4b), with a linear slope of 0.46 days/year. However, this trend did not reach the 0.05 significance level ($p = 0.056$), indicating that autumn phenology tended to be delayed but with relatively large interannual variability.

Under the combined influence of SOS advancement and EOS delay, LOS showed a significantly increasing trend (Figure 4c). The linear slope of LOS was 0.90 days/year, and the trend was highly significant ($p = 0.001$). Therefore, the growing season in Beijing was significantly extended over the past two decades, mainly because of the advancement of spring phenology and, to a lesser extent, the delay of autumn phenology.

3.1.3. Spatial Trends and Significance of Vegetation Phenology

Pixel-level trend analysis revealed widespread phenological changes across Beijing, although the significance and spatial distribution of these changes differed among SOS, EOS, and LOS. For SOS, advancement was the dominant trend. Non-significant and significant advancement accounted for 63.3% and 25.8% of the study area, respectively, together representing 89.1% of the total area (Figure 5a). Spatially, areas with significant SOS advancement were mainly concentrated in western, northern, and northeastern Beijing, with some parts of the southwest also showing clear advancement. Non-significant advancement was widely distributed across most of the study area (Figure 6a). In contrast, areas with SOS delay accounted for a relatively small proportion, with non-significant and significant delay accounting for only 10.7% and 0.3%, respectively, mainly scattered in the central-southern and local plain areas.

EOS showed an overall trend opposite to that of SOS, with delay being the dominant pattern. Non-significant and significant EOS delays accounted for 67.2% and 8.5% of the study area, respectively, together reaching 75.7% (Figure 5b). A significant EOS delay was mainly observed in northeastern Beijing, the eastern margin, southwestern areas, and

parts of the western region, while areas with an EOS advancement accounted for a smaller proportion and were mainly scattered in the central, southern, and local plain areas (Figure 6b).

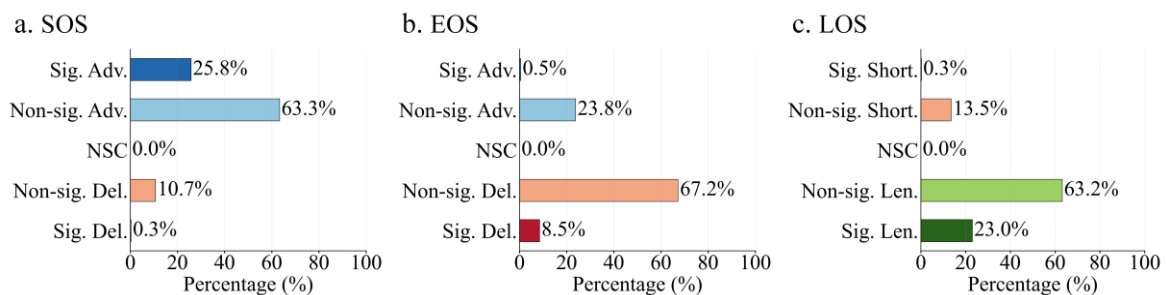


Figure 5. Area proportions of different trend significance classes for (a) SOS, (b) EOS, and (c) LOS in Beijing from 2005 to 2024. Sig. indicates significant trends at $p < 0.05$, Non-sig. indicates non-significant trends, Adv. indicates advancement, Del. indicates delay, Short. indicates shortening, Len. indicates lengthening, and NSC indicates no significant change.

LOS showed a widespread extension pattern. Non-significant and significant LOS extensions accounted for 63.2% and 23.0% of the study area, respectively, totaling 86.2% (Figure 5c), indicating that most areas of Beijing experienced an increase in growing-season length. A significant LOS extension was mainly concentrated in the western, southwestern, and parts of the northern regions. In contrast, areas with LOS shortening accounted for a small proportion, with non-significant and significant shortening accounting for 13.5% and 0.3%, respectively, and were mostly scattered (Figure 6c). These results indicate that SOS advancement and LOS extension were more spatially extensive and statistically significant than EOS delay, suggesting that spring phenology made the larger contribution to growing-season extension.

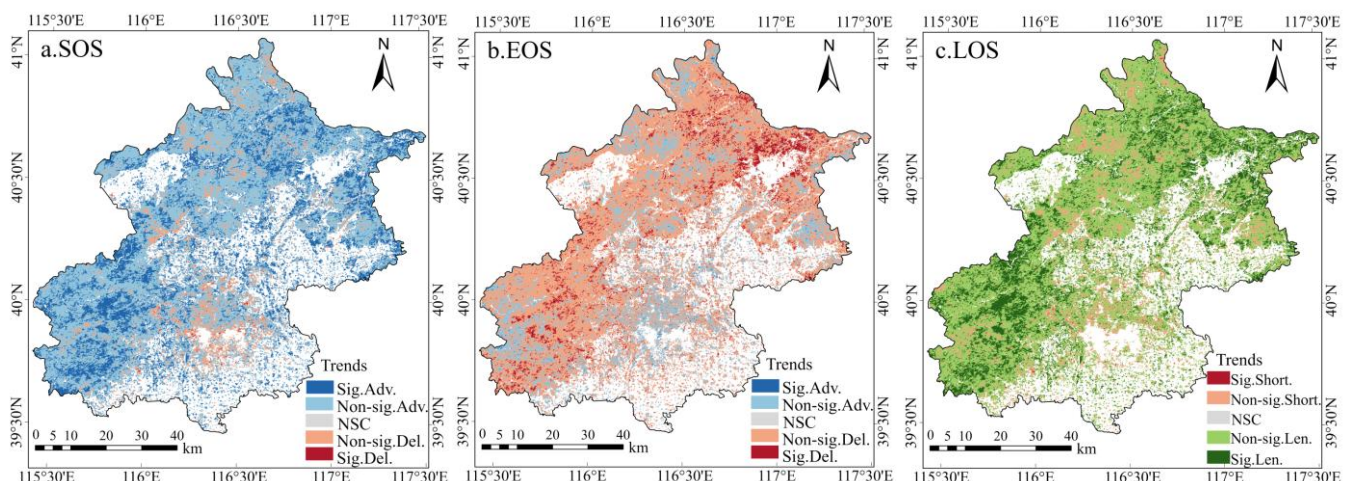


Figure 6. Spatial distribution of trend significance classes for vegetation phenology in Beijing from 2005 to 2024: (a) SOS, (b) EOS, and (c) LOS.

3.2. Vegetation Phenology Along the Urban–Rural Gradient

3.2.1. Interannual Variations in Vegetation Phenology Along the Urban–Rural Gradient

Vegetation phenology in Beijing showed clear interannual fluctuations along the urban–rural gradient, but the degree of gradient differentiation differed among SOS, EOS, and LOS. In the continuous buffer zones, SOS was generally earlier in the urban core and tended to become later with increasing distance from the built-up area boundary (Figure

7a). Compared with SOS, EOS generally occurred later in the inner gradient zones and became earlier toward the outer gradient zones (Figure 7b), indicating that autumn senescence was delayed in areas with stronger urbanization influence. Correspondingly, LOS was longest in the urban core and shortened outward along the gradient (Figure 7c). Although different gradient zones showed similar interannual fluctuations, the relative ranking of phenological parameters among gradient zones remained generally stable during the study period.

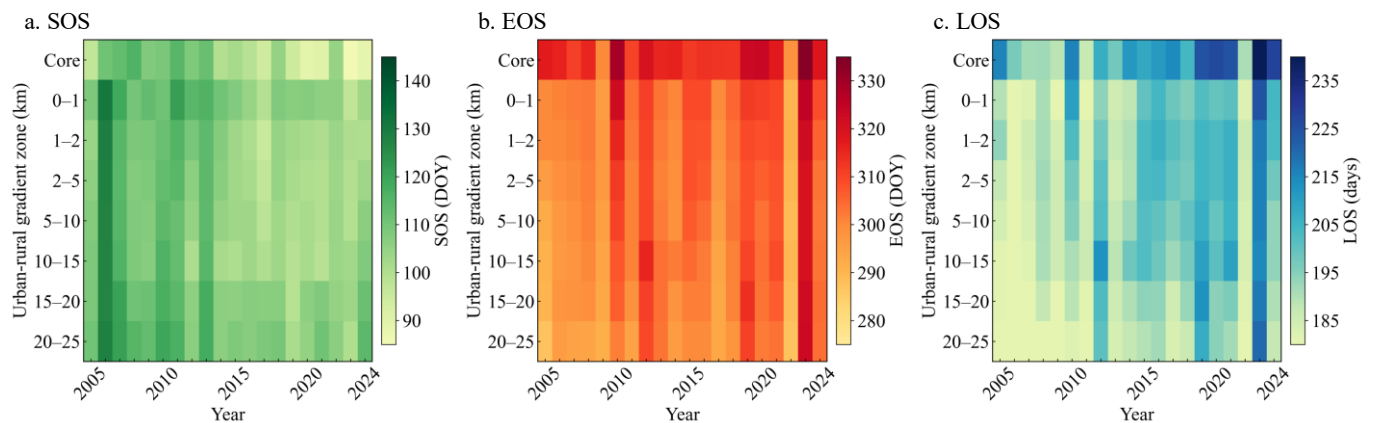


Figure 7. Interannual variations in vegetation phenology along the continuous urban–rural gradient from 2005 to 2024: (a) SOS, (b) EOS, and (c) LOS. SOS and EOS are expressed as DOY, whereas LOS is expressed in days.

The interannual curves for the urban, suburban, and rural zones further summarize these gradient differences. SOS was earliest in urban areas, followed by suburban and rural areas, indicating that vegetation in urban areas entered the growing season earlier than that in surrounding areas (Figure 8a), while EOS showed the opposite stratification pattern, with the latest EOS in urban areas, intermediate values in suburban areas, and the earliest EOS in rural areas (Figure 8b). As a result of the combined effects of SOS and EOS, LOS was longest in urban areas, followed by suburban areas, and shortest in rural areas (Figure 8c). Nevertheless, the stratification of SOS was less stable than that of EOS and LOS, with several years showing overlap or reversal among the three zones. In contrast, EOS and LOS maintained a clearer urban–suburban–rural hierarchy during most years.

Overall, the continuous gradient analysis captured the gradual transition of phenological metrics with distance from the built-up boundary, while the three-zone comparison confirmed the general pattern of earlier spring green-up, delayed autumn senescence, and longer growing seasons in urban areas relative to rural areas.

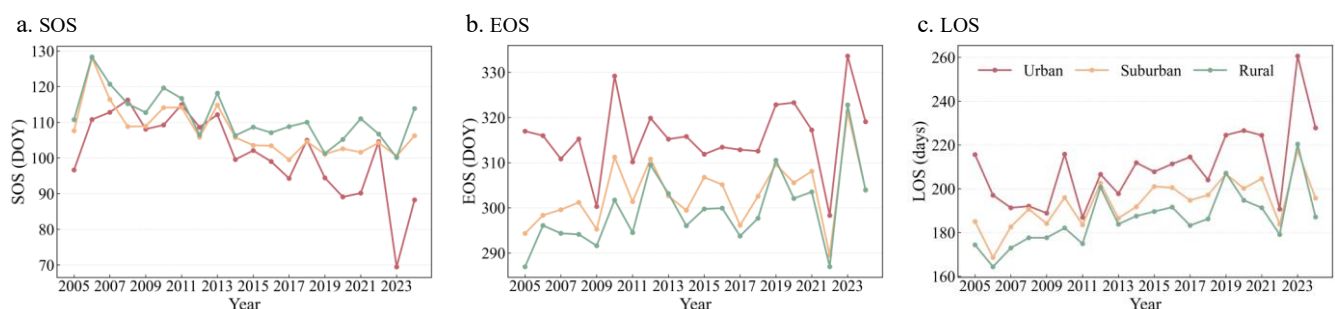


Figure 8. Interannual variations in vegetation phenology in urban, suburban, and rural zones: (a) SOS, (b) EOS, and (c) LOS. Points represent annual median values within each zone.

3.2.2. Trend Characteristics Along the Urban–Rural Gradient

The composition of phenological trend types differed among the urban, suburban, and rural zones. For SOS, advancing trends dominated all three zones, but their proportion increased from urban to suburban and rural areas. SOS advancement accounted for approximately three-quarters of the urban area and nearly 90% of both suburban and rural areas; the proportion of significant advancement also increased slightly toward the peripheral zones (Figure 9a).

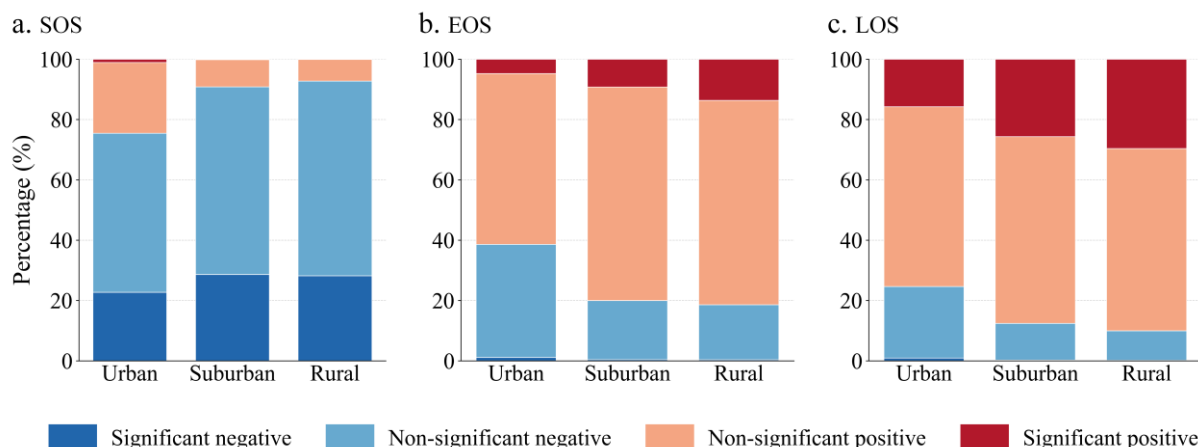


Figure 9. Percentage composition of phenological trend types along the urban–rural gradient. The stacked bars show the proportions of different trend categories for (a) SOS, (b) EOS, and (c) LOS in urban, suburban, and rural zones.

EOS delay showed a similar outward-increasing pattern. Delayed EOS trends accounted for a higher proportion in suburban and rural areas, reaching approximately 80%, whereas the urban zone showed a relatively lower proportion of EOS delay (Figure 9b). LOS extension also increased from the urban zone to the suburban and rural zones. It covered approximately three-quarters of the urban area, increased further in suburban areas, and occurred in almost all rural areas; the proportion of significant LOS extension also increased continuously outward (Figure 9c).

These results indicate a contrast between the multi-year phenological patterns and long-term phenological trends along the urban–rural gradient. Urban areas showed an earlier SOS, later EOS, and longer LOS in the multi-year median patterns, whereas SOS advancement, EOS delay, and LOS extension were more extensive in suburban and rural areas during 2005–2024.

3.3. Drivers of SOS and EOS

Before interpreting the driver analysis results, multicollinearity among the explanatory variables was first examined using the variance inflation factor (VIF). All VIF values were below 5 at both the whole-region and zonal scales, indicating that severe multicollinearity was not present among the explanatory variables. In addition, the predictive performance of the XGBoost models was evaluated before interpreting the SHAP results. Across the whole-region and zonal analyses, the models showed acceptable predictive performance, with test R^2 values ranging from 0.597 to 0.789 and RMSE values ranging from 5.25 to 13.39 days. These results indicate that the explanatory variables and model performance provided a reasonable basis for subsequent partial correlation and SHAP-based interpretation.

3.3.1. Drivers of SOS and EOS at the Whole-Region Scale

At the whole-region scale, SOS and EOS showed different associations with climatic and urbanization-related factors. The partial correlation results showed that SOS was negatively correlated with NTL, temperature, and LST after controlling for the other variables, with NTL having the largest absolute partial correlation coefficient (Figure 10a). This indicates that stronger urbanization-related signals and warmer thermal conditions were associated with earlier spring green-up. In contrast, precipitation and solar radiation showed weak positive correlations with SOS, indicating slight associations with delayed SOS. For EOS, the partial correlation pattern differed from that of SOS. Temperature showed the strongest positive correlation with EOS, followed by NTL (Figure 10b). Precipitation and solar radiation were also positively correlated with EOS, whereas LST showed a weak negative correlation. These results indicate that autumn phenology was more closely associated with temperature and urbanization-related signals, while the relationship between LST and EOS differed from that of temperature.

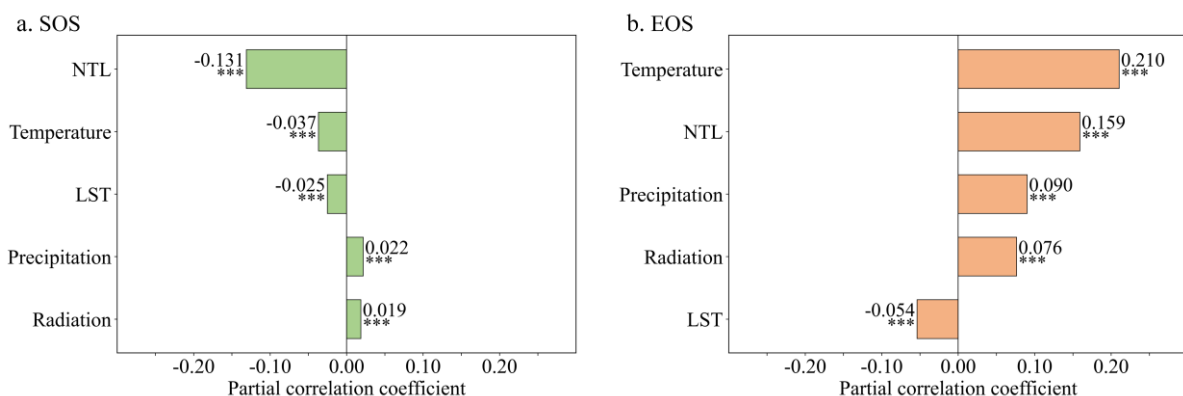


Figure 10. Partial correlations between phenological metrics and driving factors at the whole-region scale: (a) SOS and (b) EOS. Asterisks indicate significance levels: *** $p < 0.001$.

Based on the trained XGBoost models, SHAP analysis further identified the nonlinear contributions of the driving factors. For SOS, the mean absolute SHAP values ranked as NTL, radiation, LST, temperature, and precipitation (Figure 11a). NTL had the highest contribution, and the SHAP bee swarm plot showed that high NTL values were mainly associated with negative SHAP values, indicating an advancing effect on SOS (Figure 12a). Radiation and LST also contributed substantially to SOS variation. For EOS, the mean absolute SHAP values ranked as NTL, temperature, precipitation, LST, and radiation (Figure 11b). The bee swarm plot showed that high NTL and high temperature values were mainly associated with positive SHAP values, indicating their contributions to delayed EOS (Figure 12b). Precipitation also showed a moderate contribution, whereas radiation had the lowest relative importance.

The partial correlation and XGBoost-SHAP results consistently indicate different driver patterns between spring green-up and autumn senescence. SOS was mainly associated with NTL and heat-related factors, whereas EOS was primarily associated with NTL and temperature.

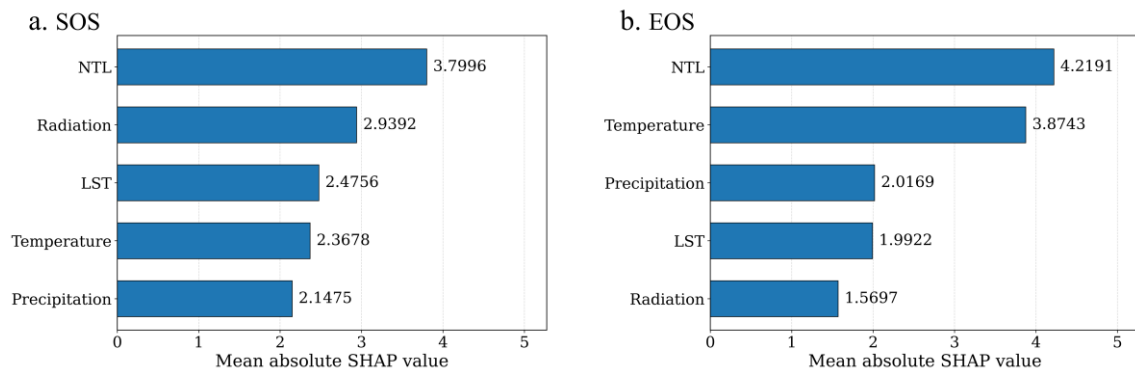


Figure 11. Mean absolute SHAP values of driving factors for (a) SOS and (b) EOS at the whole-region scale.

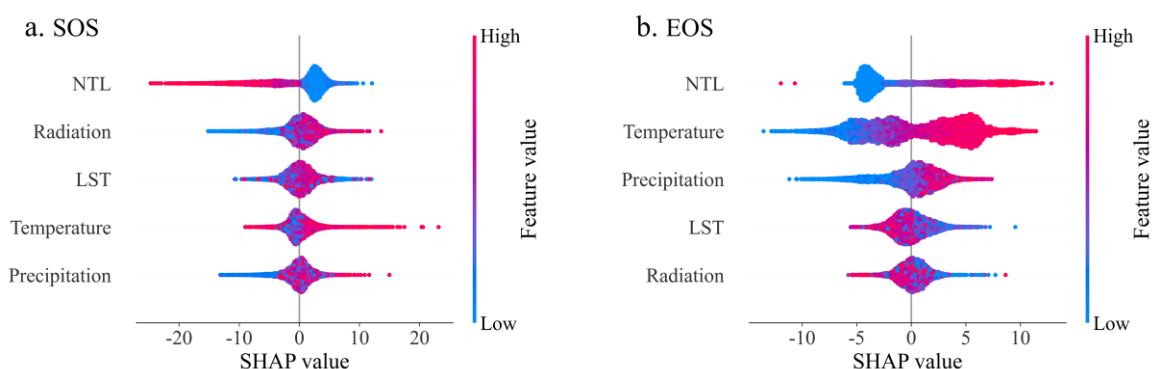


Figure 12. SHAP bee swarm plots showing the effects of driving factors on model outputs for (a) SOS and (b) EOS at the whole-region scale. Red and blue points indicate high and low feature values, respectively.

3.3.2. Driver Differences Along the Urban–Rural Gradient

The relationships between vegetation phenology and driving factors varied clearly among the urban, suburban, and rural zones, indicating gradient-dependent differences in the factors associated with SOS and EOS. For SOS, the partial correlation results showed that NTL had the strongest negative association in urban areas, followed by temperature (Figure 13a). Precipitation and solar radiation showed positive but relatively small partial correlations with SOS in urban areas. In suburban areas, temperature and NTL showed relatively strong negative associations, while in rural areas, temperature and precipitation were more closely associated with SOS advancement. The XGBoost-SHAP results showed that NTL had the highest contribution to SOS in urban areas, followed by LST. In contrast, solar radiation became the most important factor in suburban and rural areas, followed by LST, while the contribution of NTL decreased sharply from the urban zone to the suburban and rural zones (Figure 13b).

For EOS, the partial correlation results showed a different gradient pattern (Figure 14a). In urban areas, NTL had the highest positive correlation with EOS, followed by temperature. In suburban and rural areas, temperature became the strongest positive factor, with partial correlation coefficients of 0.28 and 0.25, respectively. By contrast, the positive correlations of NTL decreased to 0.10 and 0.11 in suburban and rural areas. LST showed negative correlations with EOS in all three zones. The XGBoost-SHAP results also showed gradient-dependent differences in EOS drivers. Precipitation and NTL were relatively important in urban areas; temperature became the most important factor in suburban areas, followed by LST. In rural areas, precipitation and temperature were the two leading factors (Figure 14b).

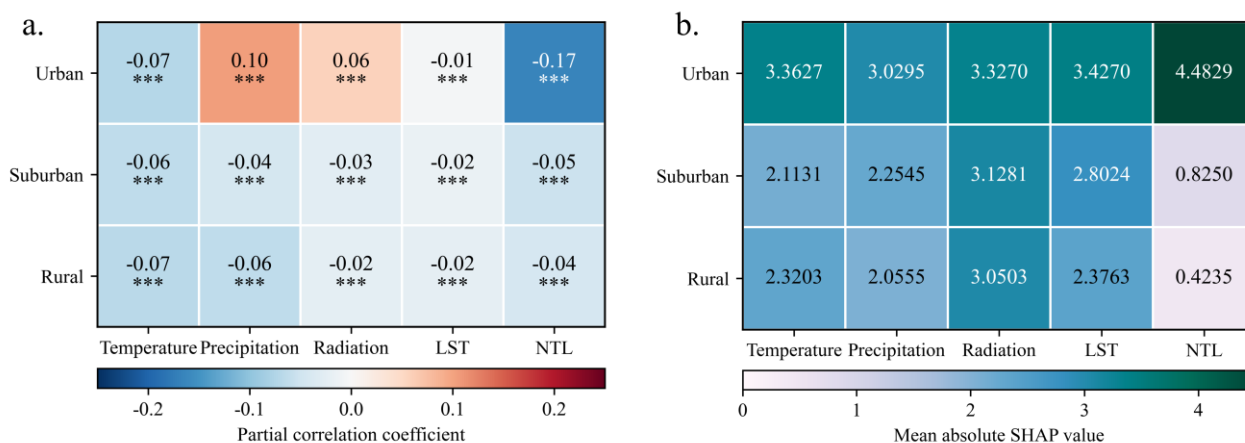


Figure 13. Urban–rural gradient differences in SOS drivers: (a) partial correlation coefficients between SOS and driving factors (Asterisks indicate significance levels: *** $p < 0.001$), and (b) mean absolute SHAP values of driving factors for SOS.

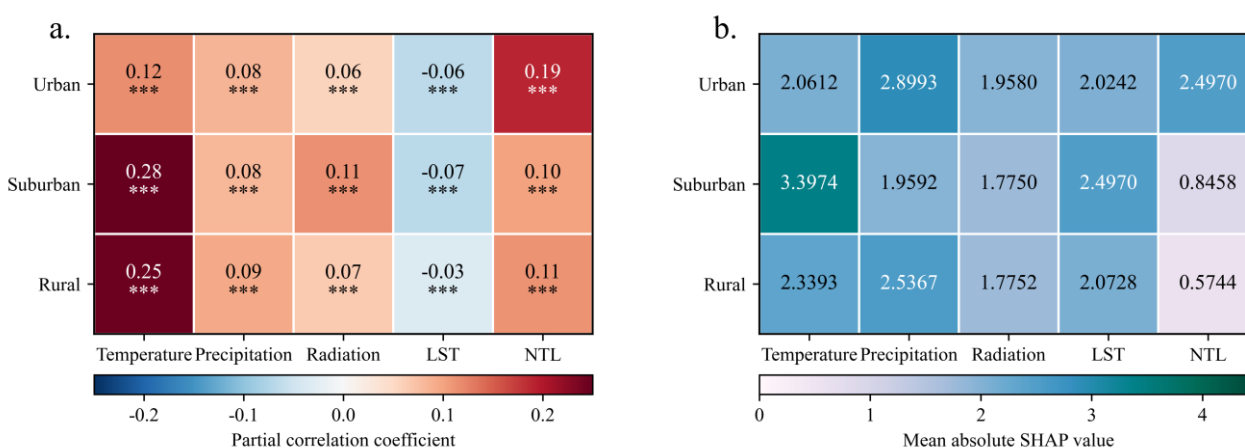


Figure 14. Urban–rural gradient differences in EOS drivers: (a) partial correlation coefficients between EOS and driving factors (Asterisks indicate significance levels: *** $p < 0.001$), and (b) mean absolute SHAP values of driving factors for EOS.

Across both SOS and EOS, the contribution of NTL declined markedly from urban to suburban and rural zones, while climatic and thermal environmental factors became more important. These results indicate a transition from stronger urbanization-related effects in urban areas to stronger climatic controls in peripheral zones.

4. Discussion

4.1. Spatiotemporal Patterns of Vegetation Phenology in Beijing

This study revealed a distinct mountain–plain differentiation pattern in vegetation phenology across Beijing. Mountainous areas in the northwestern, northern, and southwestern parts of the city were characterized by a later SOS, earlier EOS, and shorter LOS, whereas the central and southeastern plain areas generally showed an earlier SOS, later EOS, and longer LOS. This pattern indicates that the spatial variation in growing-season length was jointly shaped by spring green-up and autumn senescence rather than by a single phenological phase. In mountainous areas, higher elevation and slower spring heat accumulation may delay vegetation green-up, while faster cooling in autumn may promote earlier senescence [54,55]. By contrast, the plains generally provide more favorable

thermal conditions, which may advance spring growth and postpone autumn senescence, thereby extending the growing season [56,57].

The interannual results further showed that Beijing experienced a clear extension of the vegetation growing season from 2005 to 2024. This extension was mainly associated with significant SOS advancement, whereas EOS showed only a weaker, marginally significant delaying trend. This asymmetric contribution suggests that spring phenology responded more consistently to changing thermal conditions than autumn phenology [58]. Compared with SOS, EOS is usually affected by a wider range of factors, including temperature, moisture availability, radiation, vegetation physiological status, and local environmental stress [59,60]. These multiple controls may explain the larger interannual variability and weaker statistical significance of EOS delay. Therefore, interpreting growing-season extension only from LOS changes may obscure the different roles of spring and autumn phenological shifts.

The spatial trend analysis also indicated that the directions of phenological change were broadly consistent across Beijing, with dominant SOS advancement, EOS delay, and LOS extension. However, areas with significant trends were spatially uneven, suggesting that vegetation phenology did not respond uniformly across the study area. This spatial heterogeneity may reflect the combined influence of topography, regional climatic background, land cover heterogeneity, and local environmental conditions [61,62]. These findings highlight the need to analyze both regional-scale trends and pixel-level spatial patterns when evaluating vegetation phenological responses [63]. Regional mean values can summarize the overall direction of change, but they may mask local differences in response intensity and significance.

4.2. Effects of the Urban–Rural Gradient on Vegetation Phenology

This study found that vegetation phenology in Beijing exhibited clear stratification along the urban–rural gradient. Urban areas generally showed earlier SOS, later EOS, and longer LOS than suburban and rural areas, while rural areas showed the opposite pattern and suburban areas were mostly intermediate. This pattern suggests that urbanization can affect vegetation phenology by modifying local environmental conditions, including land cover structure, surface heat storage, hydrothermal conditions, and human activity intensity. Areas with stronger urbanization influence may accumulate heat earlier in spring and maintain relatively favorable thermal conditions later in autumn, thereby advancing spring green-up and delaying autumn senescence [62].

This urban–rural phenological stratification is broadly consistent with recent studies conducted in the conterminous United States, northern mid-latitude cities, European capital cities, and pan-European phenological observation networks [7,13,15,64]. These studies have commonly reported that urban vegetation tends to exhibit earlier spring green-up, delayed autumn senescence, and longer growing seasons than surrounding rural vegetation. The consistency between the Beijing results and previous findings suggests that urbanization-related environmental modification can produce similar phenological responses across different urban contexts. However, the pronounced mountain–plain background in Beijing may further modulate these urban–rural differences, leading to spatially heterogeneous phenological patterns.

Beyond this general urban–rural stratification, a key finding of this study is that multi-year phenological characteristics and long-term trend patterns were not fully consistent along the urban–rural gradient. Urban areas generally had earlier spring green-up, later autumn senescence, and a longer growing season, indicating a longer growing season under long-term urbanization. However, SOS advancement, EOS delay, and LOS extension were more extensive and more significant in suburban and rural areas during 2005–2024. This contrast suggests that phenological status and phenological change rates

reflect different aspects of urbanization effects. The urban core had already experienced strong and persistent urbanization influences before and during the study period, including enhanced heat storage, intensified human activity, and modified local hydrothermal conditions. As a result, vegetation phenology in urban areas may have approached a relatively stable state, in which additional environmental changes produce smaller marginal shifts in SOS and EOS. This interpretation is consistent with previous findings that urban warming can advance spring phenology but reduce the sensitivity of phenology to further temperature changes [15]. In contrast, suburban and rural areas are located in the transitional zone between the built-up core and the surrounding natural background. These peripheral areas may be simultaneously affected by regional climate warming and continuing urban expansion [65], and dynamic urban–rural gradient studies have also suggested that phenological responses can differ substantially across urbanization stages. Therefore, the fact that urban areas had the longest growing season but weaker temporal trends does not contradict the urbanization effect; instead, it indicates that long-term accumulated urbanization mainly shaped the current phenological status, whereas recent environmental changes were more strongly expressed in the peripheral zones.

Taken together, these findings demonstrate the value of using a continuous urban–rural gradient rather than a simple urban–rural comparison [19]. Multi-level buffer zones constructed outward from the built-up boundary help capture gradual changes in phenological characteristics with decreasing urbanization intensity and reduce the risk of oversimplifying the urban–rural transition. This gradient-based framework is useful for distinguishing phenological differences among urban, suburban, and rural environments and for linking phenological patterns with different urbanization backgrounds.

4.3. Differences in Driving Factors Across Phenological Stages and Their Spatial Heterogeneity

The driving factor analysis indicated that SOS and EOS were associated with different combinations of climatic and urbanization-related factors. At the whole-region scale, SOS was mainly related to NTL and heat-related factors, whereas EOS was more closely associated with NTL and temperature. This suggests that spring green-up and autumn senescence may be regulated by different environmental and physiological mechanisms. Spring phenology is closely linked to heat accumulation and vegetation growth onset [66], while autumn phenology is often affected by more complex controls, including temperature, moisture conditions, radiation, and vegetation stress [60]. This may explain why EOS showed more variable driver relationships and stronger interannual fluctuations than SOS.

Along the urban–rural gradient, the relative importance of driving factors changed substantially. In urban areas, NTL showed relatively high explanatory importance for both SOS and EOS, indicating that urbanization-related conditions were closely associated with vegetation phenology in highly urbanized environments [67]. However, the contribution of NTL declined toward suburban and rural areas, while climatic and thermal environmental factors, such as temperature, precipitation, solar radiation, and LST, became more important. This pattern suggests a transition from stronger urbanization-related influences in urban areas to stronger climatic controls in peripheral zones.

The role of NTL should be interpreted cautiously. In this study, NTL was used primarily as a proxy for urbanization-related conditions [68] rather than as a direct physiological driver of vegetation growth or senescence. Although artificial light at night can affect plant phenology through changes in light exposure and photoperiodic responses [69], satellite-derived NTL also captures multiple urbanization-related signals, including built environment intensity, human activity density, land cover composition, and associated thermal conditions [70,71]. Therefore, the high explanatory importance of NTL in the

XGBoost-SHAP results should be interpreted as evidence of compound urbanization-related effects rather than the isolated effect of nighttime light itself.

In addition, partial correlation analysis and XGBoost-SHAP provided complementary perspectives on phenology–driver relationships. Partial correlation analysis quantified independent linear associations after controlling for other variables, whereas XGBoost-SHAP identified nonlinear contributions and relative variable importance under multi-factor interactions. The consistency between these two approaches strengthens the interpretation of the main driver patterns, while their differences also indicate that vegetation phenology may respond to environmental factors in nonlinear and spatially heterogeneous ways.

4.4. Limitations and Implications

Although this study revealed the spatiotemporal patterns, urban–rural gradient differentiation, and associated factors of vegetation phenology in Beijing, several limitations should be acknowledged. The MODIS EVI data used in this study have a spatial resolution of 250 m, which may lead to mixed-pixel effects in fragmented urban landscapes [72]. Urban vegetation often consists of parks, roadside trees, residential green spaces, and transitional vegetation near mountainous areas, which may be mixed within a single pixel [73]. Therefore, the results are more suitable for interpreting regional-scale and urban–rural gradient patterns than for detecting fine-scale differences among specific urban green-space types.

The selection of explanatory variables also has limitations. In this study, temperature, precipitation, solar radiation, LST, and NTL were selected as the main explanatory variables, and DEM data were used to reduce topographic interference in the urban–rural gradient analysis. Elevation was not included as an independent explanatory variable in the partial correlation and XGBoost-SHAP analyses because the driver analysis focused mainly on climatic and urbanization-related factors that vary across space and time. Moreover, the influence of elevation had already been partly controlled during gradient construction by excluding pixels with elevations substantially higher than the urban reference zone. However, residual topographic effects may still influence vegetation phenology, especially in transitional areas between plains and mountains. Vegetation phenology, especially EOS, can also be affected by other environmental and biological factors, such as soil moisture, vapor pressure deficit, air pollution, irrigation and maintenance intensity, vegetation type, and species composition [74–76]. The absence of these variables may limit the interpretation of fine-scale phenological heterogeneity within urban areas. Moreover, partial correlation analysis and XGBoost-SHAP are statistical interpretation methods. They can identify linear associations, nonlinear contributions, and relative variable importance, but they cannot establish strict causal relationships. Therefore, the interpretation of driving factors in this study should be understood as statistical association and mechanistic inference rather than causal verification.

Another limitation is related to the construction of the urban–rural gradient. In this study, the buffer zones were generated from the largest contiguous built-up patch in the 2015 GUB dataset, which represents the main urban core of Beijing. This design was suitable for examining the core–periphery phenological gradient associated with the main urbanized area of Beijing, but it did not explicitly consider the influence of smaller built-up patches within Beijing or neighboring urban areas outside the study area. Therefore, some pixels classified as being farther from the main urban core may still be close to other local urbanized areas. In addition, the 2015 GUB was used as a static spatial reference. Although this design ensured consistent spatial units for comparing phenological status and temporal trends from 2005 to 2024, it did not explicitly capture the annual expansion of built-up land during the study period. Future studies could use multi-center buffer

zones, the distance to the nearest built-up patch, or annual impervious surface products to better distinguish the phenological responses of newly urbanized areas, secondary urbanized areas, and long-established urban areas.

Despite these methodological constraints, the findings of this study also provide practical implications for urban vegetation planning and climate adaptation. The longer growing season in urban areas suggests that urban vegetation is strongly affected by modified thermal environments and human activity intensity, which may increase seasonal maintenance requirements and exposure to heat-related stress. Therefore, urban afforestation and green-space management should not only focus on increasing vegetation coverage, but also consider phenological responses, species composition, canopy quality, heat tolerance, and seasonal maintenance during an extended growing season. In suburban and rural transition zones, where SOS advancement, EOS delays, and LOS extensions were more pronounced, planning should pay greater attention to rapid environmental changes, ecological connectivity, and the protection of semi-natural vegetation during urban expansion. More broadly, phenology-based monitoring can provide useful information for sustainable urban development, climate-resilient planning, biodiversity conservation, and the maintenance of urban ecosystem services. Properly planned and maintained urban vegetation can also contribute to improved environmental quality, heat mitigation, and human well-being in rapidly urbanizing regions.

Future studies could further integrate higher-resolution remote sensing data, urban green-space classification data, and ground phenological observations to better capture phenological differences among different vegetation and green-space types. Additional environmental and management-related variables should also be considered to improve the interpretation of urban phenological responses. Methodologically, combining gradient analysis with process-based models, field observations, or quasi-experimental approaches may further clarify the coupled effects of urbanization and climate on vegetation phenology. These efforts would support more refined assessments of urban vegetation growing seasons and provide useful information for urban ecological management.

5. Conclusions

Based on MODIS EVI time-series data from 2005 to 2024, this study analyzed the spatiotemporal patterns, urban–rural gradient differentiation and driving factors of vegetation phenology in Beijing. The results showed that vegetation phenology exhibited a clear mountain–plain differentiation pattern. Mountainous areas in northwestern and southwestern Beijing generally had a later SOS, earlier EOS, and shorter LOS, whereas the central and southeastern plains showed an earlier SOS, later EOS, and longer LOS. During the past two decades, Beijing experienced an overall extension of the vegetation growing season, mainly driven by significant SOS advancement and, to a lesser extent, EOS delay.

Along the urban–rural gradient, urban areas showed an earlier SOS, later EOS, and longer LOS, while SOS advancement, EOS delay, and LOS extension were more pronounced in suburban and rural areas. This contrast indicates that multi-year phenological status and long-term phenological trends are not necessarily spatially consistent. In other words, areas with a longer existing growing season are not always the areas undergoing the fastest phenological changes. This distinction provides a useful perspective for understanding vegetation phenology in rapidly urbanizing regions.

The main contribution of this study is twofold. First, by combining a continuous urban–rural gradient with long-term phenological trend analysis, this study distinguishes the spatial pattern of phenological status from the spatial pattern of phenological change. Second, by integrating partial correlation analysis with XGBoost-SHAP interpretation, this study reveals gradient-dependent differences in phenological drivers, especially the

decreasing contribution of NTL from urban to suburban and rural areas and the increasing relative importance of climatic and thermal factors. These findings improve the understanding of how accumulated urbanization effects and recent environmental changes jointly shape vegetation phenology in a rapidly urbanizing megacity.

Author Contributions: Conceptualization, M.Y. and Y.Z.; methodology, M.Y.; software, M.Y.; validation, M.Y. and J.L.; formal analysis, J.L.; investigation, M.Y. and Y.Z.; resources, Y.Z.; data curation, M.Y.; writing—original draft preparation, M.Y.; writing—review and editing, Y.Z., W.L. and J.L.; visualization, M.Y. and W.L.; supervision, J.L.; project administration, J.L.; funding acquisition, J.L. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Data Availability Statement: The datasets analyzed in this study were obtained from publicly available sources, as described in Section 2.2. and the Acknowledgments section. The processed datasets and derived results generated during this study are available from the corresponding author upon reasonable request.

Acknowledgments: We gratefully acknowledge the National Aeronautics and Space Administration (NASA) for providing the MODIS/Terra MOD13Q1 vegetation index product and the MOD11A2 land surface temperature product (<https://search.earthdata.nasa.gov/>) (accessed on 20 October 2025). We also acknowledge the developers of the China Land Cover Dataset (CLCD) (<https://zenodo.org/records/15853565>) (accessed on 20 October 2025), the Global Urban Boundary (GUB) dataset (<http://data.ess.tsinghua.edu.cn>) (accessed on 20 October 2025), and the Copernicus DEM GLO-30 dataset (<https://dataspace.copernicus.eu>) (accessed on 20 October 2025) for providing valuable open-access geospatial data. We are grateful to the National Tibetan Plateau Scientific Data Center for providing the 1 km monthly air temperature and precipitation datasets for China (<https://data.tpdc.ac.cn/zh-hans/data>) (accessed on 20 October 2025), the China Meteorological Forcing Dataset (CMFD) for providing downward shortwave radiation data (<https://data.tpdc.ac.cn/en/data>) (accessed on 20 October 2025), and the National Earth System Science Data Center for providing the “NPP-VIIRS-like” nighttime light dataset (<http://www.geo-data.cn>) (accessed on 20 October 2025).

Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviations

The following abbreviations are used in this manuscript:

SOS	start of the growing season
EOS	end of the growing season
LOS	length of the growing season
DOY	day of year
Sig. Adv.	Significant advancement
Non-sig. Adv.	non-significant advancement
Sig. Del.	significant delay
Non-sig. Del.	non-significant delay
Sig. Short	significant shortening
Non-sig. Short	non-significant shortening
Sig. Len.	significant lengthening
Non-sig. Len.	non-significant lengthening
NSC	no significant change

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