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Detection and attribution of long-term and fine-scale changes in spring phenology over urban areas: A case study in New York State

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ABSTRACT

Spring phenology plays an essential role in climate change, terrestrial ecosystem, and public health. Field-based monitoring and understanding of changes in spring phenology for long periods and in large regions are challenging due to the limited in-site observations. Space-based remotely sensed observations offer great potentials for monitoring decadal spring phenology changes from regional to global scales. However, the coarse-scale remotely sensed observations are insufficient to capture fine-scale spring phenology dynamics, especially in urban areas, and this makes it challenging for understanding the combined effects of climate change and urbanization on spring phenology. We derived the start of phenology season (SOS) in New York State using 30 m Landsat observations from 1990 to 2015 to understand the impact of the environment and urbanization on SOS. The results show that SOS for different years reveals heterogeneous spatial distribution. Most regions of New York State have been experiencing significant spring phenology changes in form of earlier onset of vegetation greening, ranging from 0.2 to 0.6 day/year during 1990 to 2015, and this trend varies slightly with latitudes and urbanization levels. Further, spatial correlation analysis shows that the increase in temperature and urbanization could both promote the advancement of SOS. However, the effect of urbanization (partial correlation coefficient (R) ranges from −0.289 to −0.542) on SOS is greater than the effect of temperature (R ranges from 0.006 to −0.192). The study generates a high spatio-temporal resolution spring phenology dataset for ecological, environmental and public health studies, especially in urban areas, and reveals the importance of better accounting for the urbanization effects when quantifying the SOS dynamics in phenology models.

1. Introduction

Spring phenology, the timing of vegetation growth stages of budding, leafing and flowering, can affect many terrestrial ecosystem processes such as surface energy balance (Ryu et al., 2008), evapotranspiration (Duchemin et al., 2006) and photosynthesis (Wong et al., 2019). The spring phenology is also affected by anthropogenic activities e.g., urbanization (Edwards and Richardson, 2004). Previous studies have reported that the changes in environmental conditions (e.g., light intensity, solar radiation, temperature, precipitation) affect spring phenology dynamics at regional and even global scales (Flynn and Wolkovich, 2018; Denéchère et al., 2021). Detection and attribution of fine-scale spring phenology and its dynamics are essential for ecosystem studies and public health advisories (Sapkota et al., 2020).

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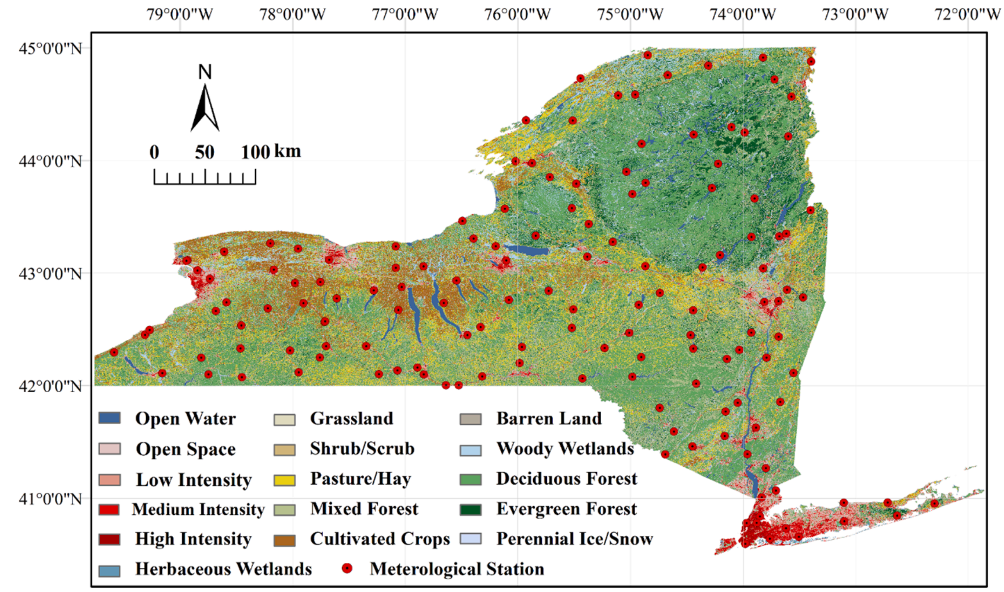

Fig. 1. The spatial distribution of land cover types and meteorological stations in New York State (NYS), US.

The process-based models can predict spring phenology and dynamics by simulating the vegetation growth mechanisms under different climate conditions. However, such process-based models are highly dependent on meteorological observations over the study sites and are limited for understanding and quantifying large-scale spring phenology changes (Lang et al., 2019; Chmielewski et al., 2011). Spring phenology information derived from satellite-based remote sensing has shown great potential as a proxy for ground-based and near-surface observations in the past few decades. These data have been widely used for monitoring the long-term phenological transition dates/stages, such as the start of phenology season (SOS) and end of phenology season (EOS). Although coarse spatial-resolution observations with frequent revisits can be extensively used for phenology mapping over large areas, the spatial resolution of these observations ranges from 250 m to ~ 10 km, limiting their ability to identify the spatial heterogeneity, especially in urban areas. Moreover, accurately monitoring spring phenology dynamics over urban areas is of vital importance due to: 1) rapid urbanization and its influence on spring phenology in the embedded and surrounding ecosystem; 2) impacts of climate and other environmental conditions on spring phenology over urban ecosystems; and 3) the consequence of these changes on human health (e.g., respiratory diseases and allergies). Therefore, it is becoming important to observe, understand and model the changes in spring phenology at fine resolution (e.g., 10–30 m) over urban areas. Among them, Landsat observations are promising to provide the opportunities to address these challenges due to the advantages of fine spatial resolution and long temporal span (Zipper et al., 2016; Li et al., 2017a).

The attribution of changes in spring phenology in response to different influencing factors is complicated. For example, the increase of temperature in the Northern Hemisphere is related to the advancement of spring phenology, and a 1 °C increase of temperature may contribute to the advancement of the flowering stage by 2 to 10 days (Bock et al., 2014; Menzel et al., 2006). The changes in temperature and precipitation also contribute to the end of the spring phenology season (Denéchère et al., 2021; Jin et al., 2019). Moreover, it has been reported that urbanization can contribute to changes in terrestrial ecosystems due to the urban heat islands (UHI) effects (Zhang et al., 2012). The response of spring phenology dynamics to the changes in environmental conditions, urbanization, other biotic and abiotic factors and their complex interactions remain an active area of research.

To fill these gaps in understanding of spring phenology, this study aims to identify the SOS dynamics from long-term (i.e., multi-decades) Landsat data and further investigate the effects of different influencing factors on SOS dynamics. Specifically, we 1) derived annual SOS from Landsat observations for New York State that comprises of several dominant land cover types from 1990 to 2015; 2) investigated the influence of environmental conditions, urbanization, and latitude on SOS for different land cover types; 3) characterized the contribution of different factors to SOS.

2. Study area and data preprocessing

2.1. Study area

The New York State (NYS), located in the northeastern climate zone of the United States, was selected for this study. The main reasons for choosing this area are: 1) it covers diverse land cover types (Fig. 1), including representative urban built-up areas, forest, grassland, and croplands; 2) it has a large latitude span that includes various topographic terrains and temperature variations, which helps for studying the effects of the environment, urbanization and their interactions on spring phenology dynamics during the last several decades. There are 16 different land surface types in the study area, and four land cover types are dominant, i.e., Open Space, Deciduous, Evergreen, and Mixed Forest. What's more, there is an extensive network of 168 weather stations that provide high-quality measurements of environmental factors (Fig. 1).

2.2. Data collection and preprocessing

Landsat surface reflectance (L1T-level) datasets were used to derive spring phenology maps for the study area. The remotely sensed observations obtained by different Landsat sensors/satellites include: Landsat-5 TM (Thematic Mapper); Landsat-7 ETM+ (Enhanced Thematic Mapper Plus); and Landsat-8 OLI (Operational Land Imager). The surface reflectance observations were pre-processed using radiation and atmospheric correction methods developed by Masek et al. (2006). The entire dataset was then used to develop a composite time series of the enhanced vegetation index (EVI). Due to the sensor difference on Landsat-8 (OLI), Landsat-7 (ETM +) and Landsat-5 (TM), a linear regression model was used to cross-calibrate the derived EVIs. Clouds and shadows were removed using the Fmask algorithm (Zhu and Woodcock, 2012) before compositing the EVI time series.

The in-situ meteorological observations such as temperature and

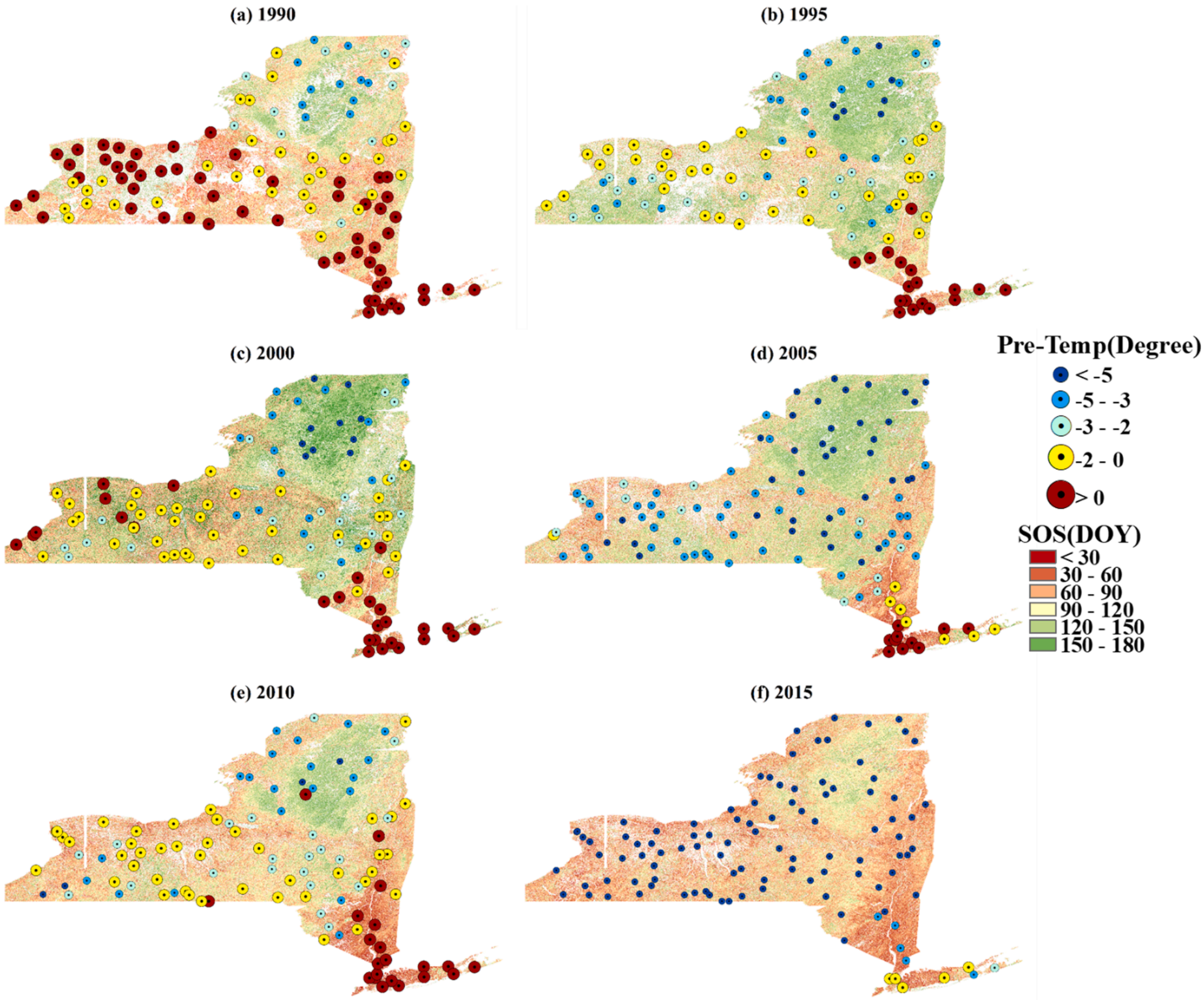

Fig. 2. The spatial distribution of SOS derived from Landsat EVI data over the entire New York State from 1990 to 2015.

precipitation were obtained from the Global Historical Climatology Network through https://www.ncdc.noaa.gov. Specifically, we used the daily maximum and minimum temperature observations collected by the 168 meteorological stations in New York State from 1990 to 2015. The daily mean temperature was calculated as the mean value of the maximum and minimum temperature. Considering that SOS for most urbanized areas in New York State has been earlier than day-of-year 100 since 1990, the pre-season temperature (Pre-Temp) was calculated as the average daily mean temperature from January to March, and used in the correlation analysis. Similarly, the pre-season precipitation (Pre-Prcp) was calculated as the cumulative daily precipitation from January to March and used in the subsequent analysis. The land cover information with 30 m spatial resolution for years 2001, 2006, 2011 and 2016 were obtained from the National Land Cover Database (NLCD) developed by the U.S. Geological Survey. The urban areas were extracted from the NLCD using impervious surface areas (ISA) map, including open space and other urban development areas (i.e., low, middle and high intensity). We used the proportions of urban areas within the 10 km buffer zone surrounding each station to represent the extent and urbanization level.

3. Methods

3.1. Mapping spring phenology dynamics from satellite observations

The long-term averaged SOS was first obtained for each pixel (about 30 m by 30 m area on Earth surface) using the double logistic model shown in Eq (1) in the Google Earth Engine (GEE) platform (Gorelick et al., 2017; Li et al., 2017b).

$$EVI(t) = EVI_{\min} + (EVI_{\max} - EVI_{\min})\left(\frac{1}{1+e^{-m_1(t-n_1)}} - \frac{1}{1+e^{-m_2(t-n_2)}}\right) \quad (1)$$

where $_t$ is the time in the day of year (DOY),m_1, m_2, n_1, n_2 are the pair-based fitted parameters. $EVI_{\min}$ and $EVI_{\max}$ indicate the minimum and maximum EVI for the observation year, respectively. We only included the pixels with good fitting performance of coefficient of determination (R^2) over 0.8, and p-value less than 0.05, to reduce the effects of the fitting error. Then SOS is identified as the date when the first derivation of EVI reaches the maximum during the green-up phases.

We captured the annual spring phenology information by determining the gap in observations for each year relative to the long-term averaged value (Li et al., 2019b). Specifically, we determined the difference of phenological transition dates when EVI reaches the same magnitude as its long-term averaged value for each year. During this step, a noise removal approach was implemented to ensure high-quality annual observations to detect better and quantify their interannual variability. Thus, over past decades, the annual dynamics of spring phenology can be calculated from 30 m Landsat observations. In addition, this method has been proved to have a good performance when compared to in-situ phenology observations (e.g., PhenoCam (Figure S1), Harford forest), other satellite phenology products (e.g., MCD12Q2) and the transition dates of tree pollen (Li et al., 2017a,

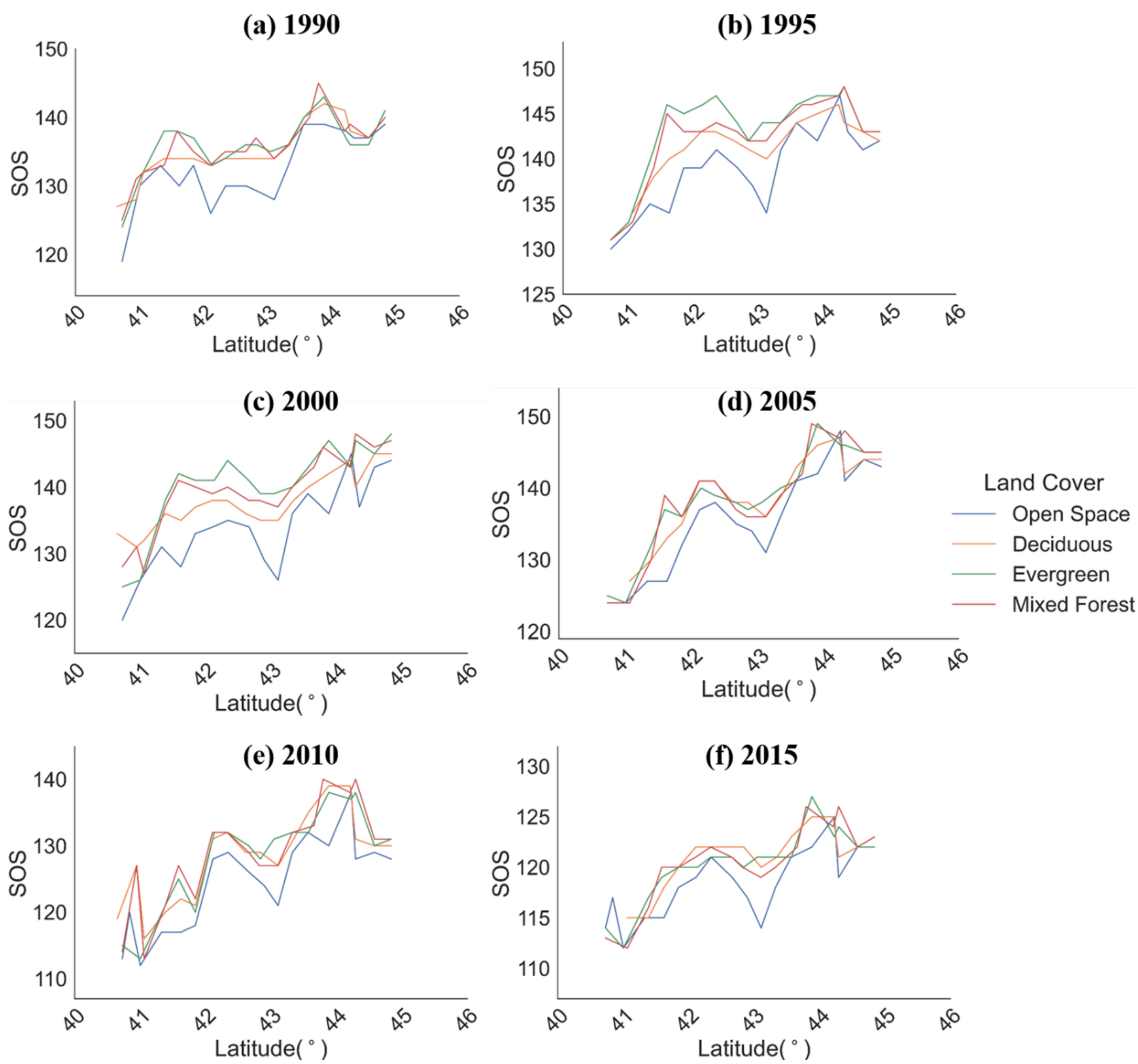

Fig. 3. The variation of SOS across latitudes and different land cover types for different years.

2019b; Li et al., 2022).

3.2. Statistical analysis

To match the site observation, we derived SOS for every pixel from Landsat and then calculated the mean SOS values among the pixels with the same vegetation type corresponding to the buffer area (10 km) of a single weather station. The effects of different buffer areas on our analysis (i.e., 5 km, 10 km and 15 km) were also investigated.

For the temporal statistical analysis, we first summarized the SOS dynamics of each station by calculating the yearly SOS tendency in pixels without land cover changes, ranging from 1990 to 2015. We used a linear regression model with the yearly SOS as the dependent variable and year as an independent variable to detect the long-term trend. Then, we used the Pearson correlation analysis to analyze the correlation of SOS dynamics and temperature or urbanization changes of each station. Only when p-value less than 0.05, the results after these analysis are deemed as significant.

For the spatial correlation analysis, we first used the partial correlation analysis (PCA) to analyze the relationship between SOS and environment and urbanization factors. Given that the spring phenology is related to many factors such as temperature, precipitation, urbanization, and latitude, it is necessary to eliminate the intervention of other influencing factors when studying the relationship between spring phenology and a specific factor. PCA can be used for this purpose, and we studied the effects of three factors on SOS. Three-factor PCA can be formulated as:

$$r_{12(3)} = \frac{r_{12} - r_{12}r_{23}}{\sqrt{1 - r_{13}^2}\sqrt{1 - r_{23}^2}} \tag{2}$$

where r_{12} represents the correlation coefficient (R) between factors 1 and 2 when factor 3 is not considered, while r_{13} and r_{23} denote the R-value of factors 1 and 3, and that of factors 2 and 3, respectively.

Then, we further utilized a regression model to investigate how much temperature and urbanization can affect the spatial variability of SOS, and whether latitude can affect the SOS changes over the study area. In the study, temperature, urbanization and latitude were chosen as the factors due to their large contributions on spring phenology dynamics in the regression model:

$$Y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_n x_n \tag{3}$$

where Y represents the value of SOS, x_1 to x_n represent environment and urbanization factors, β_0 to β_n are the fitting coefficients, and $_n$is the number of factors involved in the study. To quantify the model

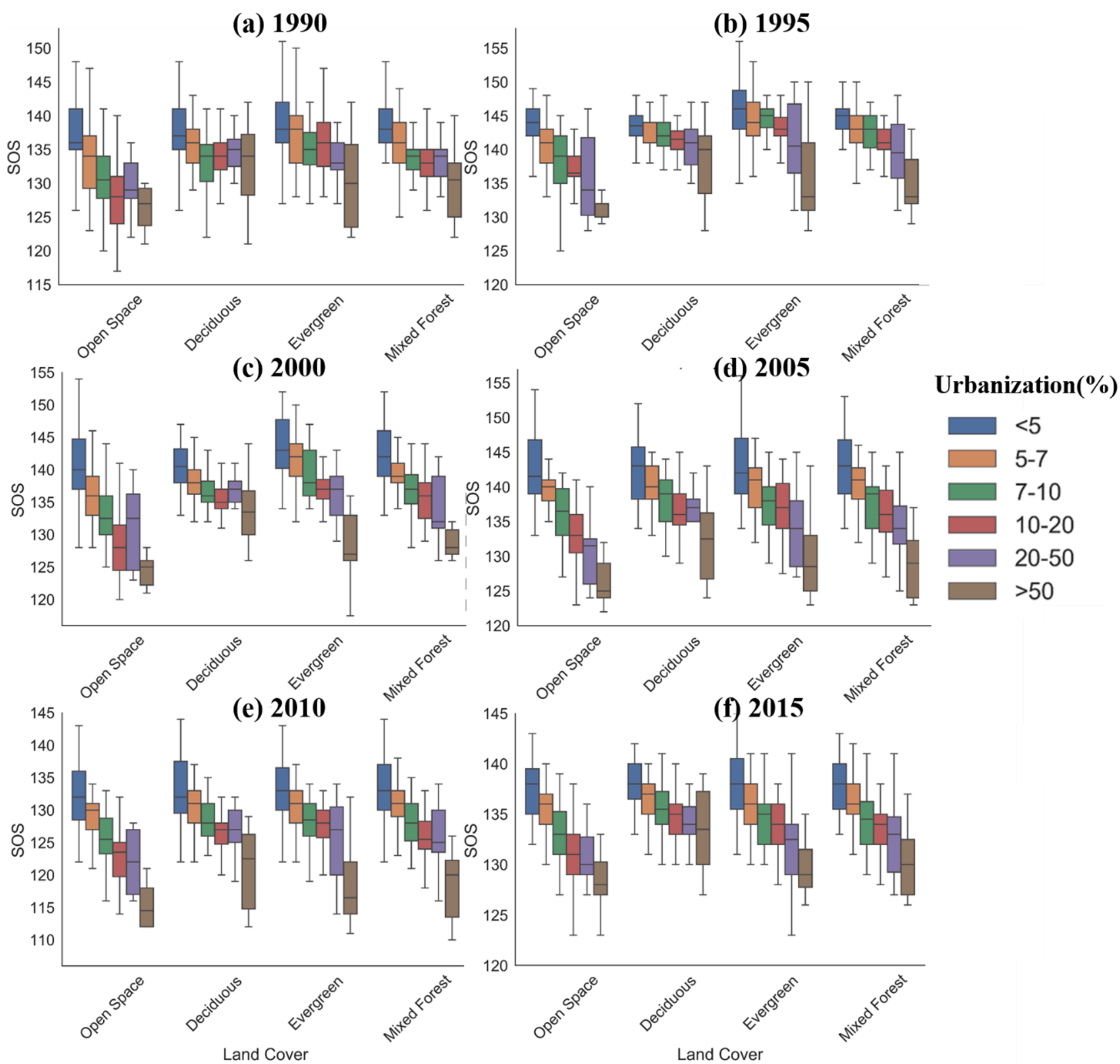

Fig. 4. The relationship between SOS and urbanization with different land cover types for different years.

performance, we used R, the absolute mean error (MAE), root-mean-square error (RMSE), the spectral angle mapper (SAM), and the relative dimensionless global error in synthesis (ERGAS) in the analysis.

4. Results

4.1. Spatial distribution of SOS

The pixel-level SOS was acquired using the two-step Landsat phenology model for New York State from 1990 to 2015 (Fig. 2). The SOS for different years shows the heterogeneous spatial distribution. Generally, the areas with advanced SOS increased significantly from the boundaries and the central strip region to the entire New York State. In urban built-up and densely populated areas (i.e., Manhattan in New York City), the SOS was significantly earlier than other land cover types. In addition, overall Southern regions have earlier SOS than northern regions.

There is a distinct delayed trend of SOS with the increase of latitude for different years (Fig. 3). For instance, the SOS of four dominant land cover types with relatively high proportions of vegetation became later from the south to the north for the entire New York State. SOS showed an advancing trend in the last decades of study as urbanization increased (Fig. 4). SOS in areas with urbanization higher than 50% was significantly earlier than SOS in other areas. Among different land cover types, SOS of Open Space had the largest increase with urbanization, while Deciduous areas had the smallest increase.

4.2. Temporal dynamics of SOS

Most regions of New York State have been experiencing significant spring phenology changes resulting in the earlier onset of vegetation greening, ranging from 0.2 to 0.6 day/year from 1990 to 2015. The advance of SOS is 10-days or longer in New York City in 2015, compared to 1990 (Fig. 2). The SOS tendency among the four dominant land cover types showed small differences. In general, areas with delayed SOS only accounted for 9.03% of Open Space, 3.01% of Deciduous, 2.41% of

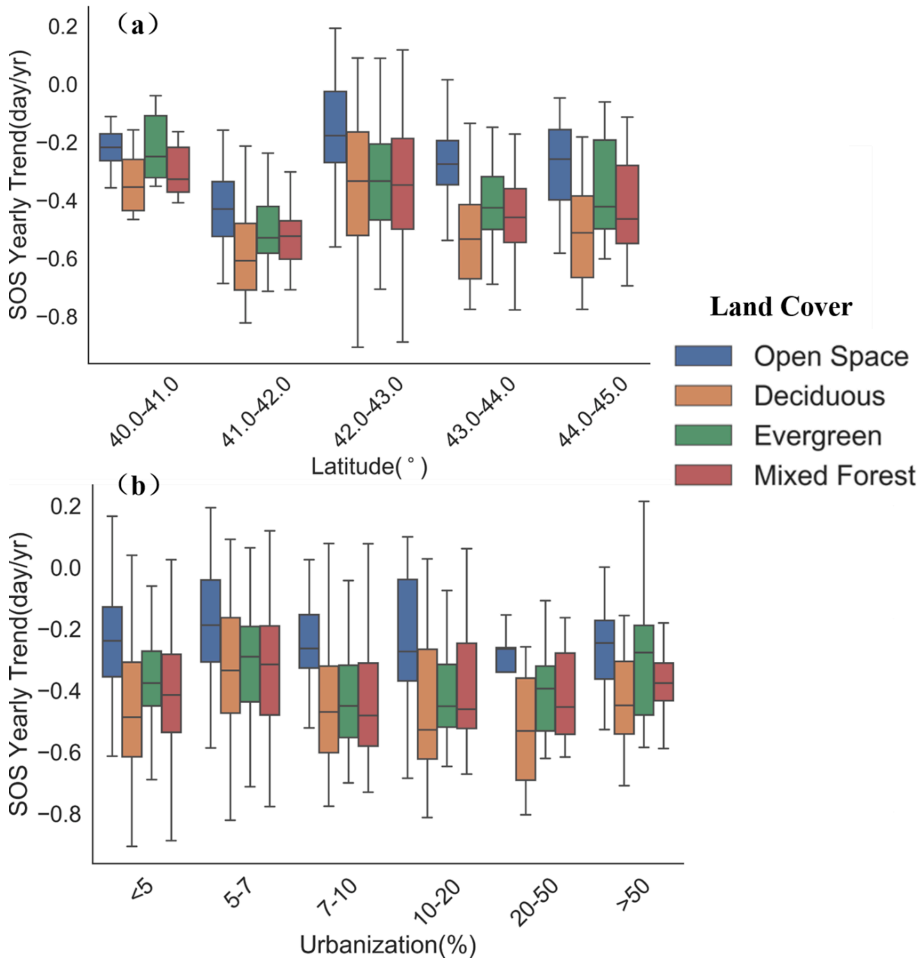

Fig. 5. The long-term trend of SOS from 1990 to 2015 for different land cover types with different (a) latitude and (b) urbanization. The unit 'day/yr' in the y-axis represents days per year.

Evergreen, and 2.40% of Mixed Forest, suggesting that SOS in most areas advanced during the last few decades of this study period. In Open Space, SOS advanced in 44.57% areas from 0.2 to 0.4 day/year (p-value less than 0.05). For other land cover types, SOS advanced varying from 0.4 to 0.6 day/year, occupied 40.36% of Evergreen, 39.76% of Mixed Forest and 33.37% of Deciduous areas, separately. The SOS tendency had no obvious relationship with the changes of latitude or urbanization from 1990 to 2015 (Fig. 5). For most sites, SOS was negatively correlated with both temperature and urbanization (Figures S2-S3).

4.3. Spatial correlation between different influencing factors and SOS

As one of the critical factors affecting spring phenology, temperature showed a significant negative correlation with SOS with R values varied from −0.60 for Deciduous to −0.69 for Mixed Forest (Fig. 6 and Table S1). The relationship between temperature and SOS can also be affected by the urbanization and latitude. SOS occurred earlier in low latitude areas with higher urbanization. On the contrary, SOS in areas with lower urbanization and higher latitudes was generally delayed compared to other areas. Compared to the effect of temperature on SOS, precipitation contributed little to SOS, with the R values of −0.19 for Open Space and −0.27 for Deciduous (Fig. 7). Considering the small effect of precipitation, it was omitted from the subsequent analysis.

The partial correlation between SOS and temperature was low (Table 1) when excluding the effects of urbanization and latitude, varying from −0.19 for Open Space to −0.11 for Mixed Forest. The temperature and SOS had a very low correlation in Evergreen. Urbanization had the strongest negative correlation with SOS, ranging from −0.29 in Deciduous to −0.54 in Evergreen. The change in latitude had a positive partial correlation with SOS, which varied from 0.30 in Evergreen to 0.20 in Open Space. Generally, the main factors affecting SOS in Evergreen were urbanization and latitude, while in Open Space, the influence of temperature and latitude was smaller than urbanization. By further analyzing the partial correlation among temperature, urbanization, and latitude, we found the influence of urbanization and latitude on temperature to be significant and there were small differences among these four land cover types. Although the relationship between temperature and urbanization was strong in PCA (Figure S4 and Table 1), we found only some of these changes can be explained by urbanization. The internal characteristics of non-temperature changes caused by urbanization were essential to promote spring phenology dynamics. Generally, we found the effect of urbanization on SOS to be greater than the effect of temperature.

For the regression-based analysis, the fitted coefficients for different factors in Eq. (3) are presented in Fig. 8 and Table S2. The statistical R values varied from 0.66 in areas covered by Deciduous to 0.78 in Mixed Forest. The MAE was 2.95 days in Open Space, 2.44 days in Deciduous, 2.43 days in Evergreen, and 2.57 days in Mixed Forest. Overall, the scattered points in Fig. 8 were distributed around the 1:1 line. For the areas where SOS was larger than 135, the RMSE between the simulated and referenced values was small, with 2.96 days in Open Space, 2.81 days in Deciduous, 3.28 days in Evergreen, and 3.07 days in Mixed Forest. These demonstrate that temperature, urbanization, and latitude can well account for the spatial variations of SOS. For every 1 °C increase

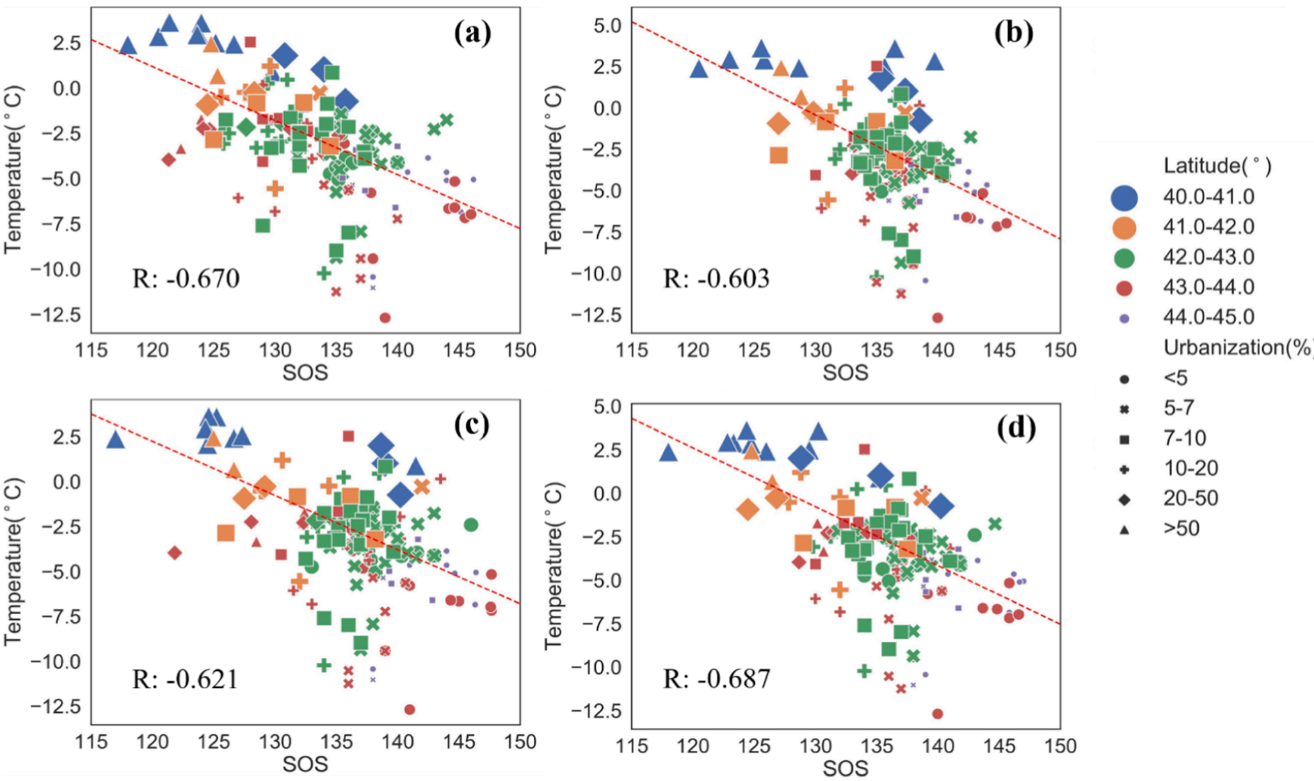

Fig. 6. The spatial correlation between SOS and temperature for (a) Open Space, (b) Deciduous, (c) Evergreen, and (d) Mixed Forest. The 26-year average SOS and temperature from 1990 to 2015 for each station were used.

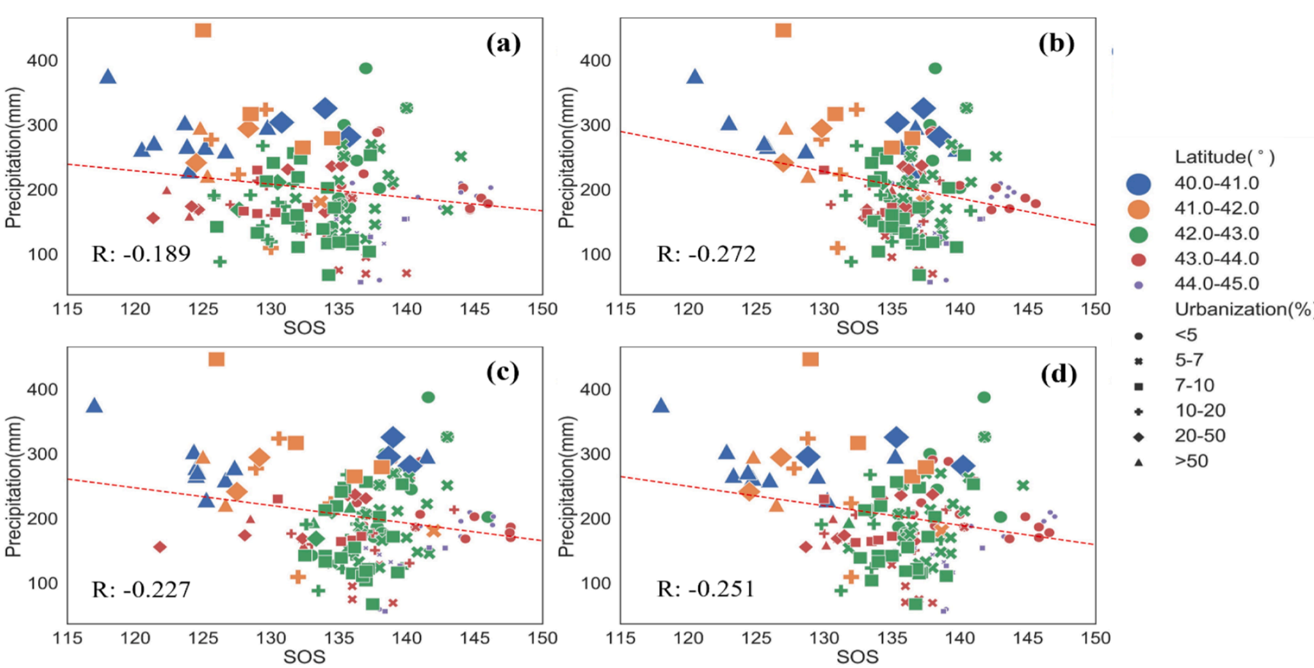

Fig. 7. The spatial correlation between SOS and precipitation for different land cover types: (a) Open Space, (b) Deciduous, (c) Evergreen, and (d) Mixed Forest. The 26-year average SOS and precipitation from 1990 to 2015 for each station were used.

in the Open Space area, SOS occurred earlier by only 0.03 days. For the urbanization effect, generally, for every 1% increase in urbanization, SOS occurred earlier by at least 0.1 days. Meanwhile, for every 1° increase in latitude, SOS is delayed by at least 1.2 days. However, temperature showed a good relationship with urbanization and latitude. For every 1% increase in urbanization, the temperature increased at least 0.5 °C. Meanwhile, for every 1° increase in latitude, the temperature decreased by more than 12.4 °C.

5. Discussion

The spring phenology (i.e., SOS) derived from Landsat observations

Table 1
The partial correlation analysis of SOS/temperature and different factors influencing different land cover types. The symbol '*' indicates that p-value is less than 0.05 and CI denotes the 95% confidence interval.

Target Variables	Factors	Open Space		Deciduous		Evergreen		Mixed Forest	
		R	CI (95%)	R.	CI (95%)	R.	CI (95%)	R.	CI (95%)
SOS	temperature	−0.192(*)	[-0.34, −0.03]	−0.130(*)	[-0.29, 0.03]	0.006	[-0.16, 0.17]	−0.106	[-0.26, 0.06]
	urbanization	−0.429(*)	[-0.55, −0.29]	−0.289(*)	[-0.43, −0.13]	−0.542(*)	[-0.65, −0.42]	−0.489(*)	[-0.6, −0.35]
	latitude	0.199(*)	[0.04, 0.35]	0.275(*)	[0.12, 0.42]	0.299(*)	[0.14, 0.44]	0.290(*)	[0.13, 0.43]
Temperature	urbanization	0.487(*)	[0.35, 0.6]	0.483(*)	[0.35, 0.6]	0.478(*)	[0.34, 0.59]	0.484(*)	[0.35, 0.6]
	latitude	−0.474(*)	[-0.59, −0.34]	−0.468(*)	[-0.59, −0.33]	−0.466(*)	[-0.58, −0.33]	−0.468(*)	[-0.59, −0.33]

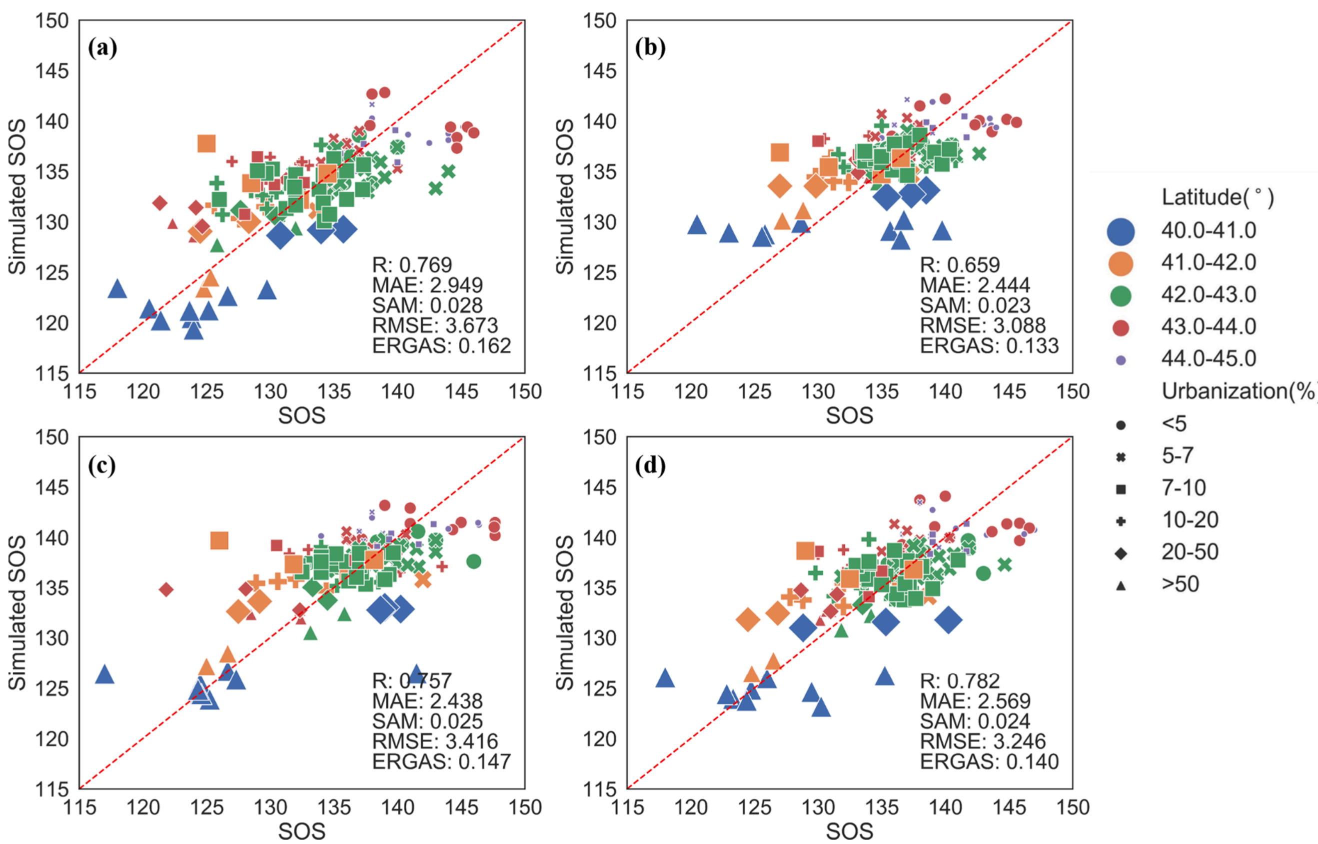

Fig. 8. The relationship between SOS derived from remotely sensed observations and the regression-based model for different land cover types: (a)represent Open Space, (b) Deciduous, (c) Evergreen, and (d) Mixed Forest. The 26-year average SOS and precipitation from 1990 to 2015 for each station were used.

has significant advantages of long-term records and fine (30 m) spatial resolution that becomes a good proxy for detecting changes in SOS at local, regional, and global scales across multiple decades. We found that most areas of New York State have been experiencing advancement of SOS in the past three decades, consistent with the conclusions from previous studies (Pearse et al., 2017; Wolfe et al., 2005). SOS is significantly earlier in areas with a high urbanization level (such as the Manhattan area of New York City) than other areas with lower urbanization levels. Our results demonstrate that the remotely sensed SOS is useful for monitoring large areas where in situ phenology observations are limited. With fine spatial resolution and long period, the Landsat observations show great potential in detecting spring phenology dynamics among land cover types and exploring the influence of biotic and abiotic factors on SOS (Fisher et al., 2006; Melaas et al., 2013).

Since the spring phenology is influenced by environmental conditions and human activities, quantifying the impact of environmental and urbanization factors on spring phenology dynamics (especially in urbanized areas) is important under climate change. Our results illustrate the contributions of different factors to the SOS dynamics for New York State during the past several decades. Temperature is usually considered to have a significant impact on spring phenology dynamics (Bock et al., 2014; Murray et al., 1989). The increase of pre-season temperature can lead to the advancement of spring phenology by as much as 1–2 days (Table S1). However, the effect of urbanization on SOS may be more significant than the effects of temperature (Table 1; Li et al., 2017a; Zhou et al., 2016). This demonstrates the sole effect of temperature cannot represent the total impact of urbanization on spring phenology. Generally, urbanization impacts on phenology and its dynamics not only by temperature, but also from population activities, wind speed, humidity, and rainfall (Pozsgai and Littlewood, 2014; Laube et al., 2014; Suepa et al., 2016), which should be identified as one of the critical factors affecting spring phenology dynamics, especially in rapidly urbanizing areas. Although both the increase in temperature and urbanization can promote the advancement of spring phenology, it is found that the variation of spring phenology may not show a linear relationship with these two factors when considering their combined effects. For example, the experimental results showed that the simultaneous increase of urbanization and temperature did not significantly promote the advance of vegetation phenology SOS and instead, the self-regulating mechanism of vegetation phenology may oppositely prevent the excessive advancement of SOS (Meng et al., 2020). Besides, SOS doesn't appear to be significantly delayed under low temperatures and urbanization (Li et al., 2019a; Qiu et al., 2020). We also examine the influence of precipitation on SOS and find that the accumulated pre-season precipitation has a negative but insignificant effect on the advancement of the spring phenology and its dynamics. Previous studies reported the influence of precipitation on phenology is significantly weaker than temperature and urbanization, and the use of different statistical methods may result in some differences when analyzing its impact on spring phenology dynamics (Bradley et al., 2011; Jin et al., 2019). Latitude can affect the day-length, hence the spring phenology. The increase in latitude often leads to changes in temperature, which in turn affects the SOS. Therefore, latitude is also an essential factor in this study (Guo et al., 2021; Huang et al., 2020). To ensure our unbiased results, we defined urban areas based on three different buffer zones (5, 10, and 15 km). We found the results from the three buffer zones are similar, and they are not biased due to our methodology/approach for selecting urban areas and extent (Tables S3 and S4).

In this study, the remotely sensed spring phenology SOS is used as the reference to suitably analyze the correlation between phenology variability and environmental factors and urbanization under long-term, large-scale regional conditions. However, there are still inherent uncertainties about remotely sensed observations and SOS identification methods compared with the in-situ phenology information that may cause differences in phenology transition dates. To minimize the impact of the uncertainty of remotely sensed observations and models on the analysis results, we only chose Landsat data to avoid differences caused by multi-source data. Meanwhile, we selected one of the most classic remotely sensed phenology extraction models and only used the pixels with high model fitting accuracy.

There are still some limitations in this study. Previous studies have shown that chilling and photoperiod effects on vegetation phenology are complex, and quantifying this relationship using satellite data is challenging (Meng et al., 2020). Future studies are needed to build on our findings and investigate this complex phenomenon. In addition to the influence of the natural environment on the dynamic changes of spring phenology, the role of anthropogenic factors on spring phenology is also important. Since human activities and urban construction mainly occur in urban areas, this study regards urbanization as an anthropogenic factor and investigates the coupling relationship between urbanization and environment change. However, urbanization can also include the comprehensive impacts of natural environments such as urban environment and urban heat island effects. This study doesn't divide the combined factors individually. Topography can also affect the surface reflectance (Hao et al., 2018) and thus the remotely sensed estimation of spring phenology. Considering the influence of these factors warrant further investigation in the future. We selected New York State as a case study, and we plan to examine the efficacy of our method/models for the entire United States or even the globe. Fusing Landsat observation data with other advanced remotely sensed observations such as geostationary satellites that have a high temporal resolution of less than 1 h (Shen et al., 2021), the European Sentinel satellites with a higher spatial resolution (Bolton et al., 2020; Moon et al., 2021) and EPIC-DSCOVR that has global coverage (Weber et al., 2020) will allow improving the spatio-temporal resolution of satellite-based spring phenology for ecological, environmental and human health studies. There still is a scale gap between station-based temperature/precipitation observations and pixel-level SOS. Remotely sensed meteorological products should be included in the future study to decrease the error by spatial scale effects.

6. Conclusions

In this study, we estimated the fine-scale and long-term SOS for the dominant land cover types in New York State based on Landsat observations. Most of the areas in New York State showed an advanced SOS, and SOS varied with changes in urbanization and latitude. We found urbanization had the highest spatial correlation with SOS, followed by latitude and temperature based on the partial correlation analysis. Precipitation has minor effects on SOS. We found the effect of urbanization on SOS to be greater than the effect of temperature. Our result demonstrates the feasibility of spring phenology (i.e., SOS) from remotely sensed observations for large areas and over multiple decades, to advance our understanding of the driving factors contributing to the spring phenology, especially over rapidly urbanizing areas. It also demonstrates the need and importance of the phenology models being able to include the combined effects of abiotic and biotic factors to simulate more realistically the dynamics of spring phenology realistically.

Declaration of Competing Interest

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

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jag.2022.102815.

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