

Article

How Spatial Resolution Affects Forest Phenology and Tree-Species Classification Based on Satellite and Up-Scaled Time-Series Images

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Abstract: The distribution of forest tree species provides crucial data for regional forest management and ecological research. Although medium-high spatial resolution remote sensing images are widely used for dynamic monitoring of forest vegetation phenology and species identification, the use of multiresolution images for similar applications remains highly uncertain. Moreover, it is necessary to explore to what extent spectral variation is responsible for the discrepancies in the estimation of forest phenology and classification of various tree species when using up-scaled images. To clarify this situation, we studied the forest area in Harqin Banner in northeast China by using year-round multiple-resolution time-series images (at four spatial resolutions: 4, 10, 16, and 30 m) and eight phenological metrics of four deciduous forest tree species in 2018, to explore potential impacts of relevant results caused by various resolutions. We also investigated the effect of using up-scaled time-series images by comparing the corresponding results that use pixel-aggregation algorithms with the four spatial resolutions. The results indicate that both phenology and classification accuracy of the dominant forest tree species are markedly affected by the spatial resolution of time-series remote sensing data ($p < 0.05$): the spring phenology of four deciduous forest tree species first rises and then falls as the image resolution varies from 4 to 30 m; similarly, the accuracy of tree species classification increases as the image resolution varies from 4 to 10 m, and then decreases as the image resolution gradually falls to 30 m ($p < 0.05$). Therefore, there remains a profound discrepancy between the results obtained by up-scaled and actual remote sensing data at the given spatial resolutions ($p < 0.05$). The results also suggest that combining phenological metrics and time-series NDVI data can be applied to identify the regional dominant tree species across different spatial resolutions, which would help advance the use of multiscale time-series satellite data for forest resource management.

Keywords: time series; trees species identification; phenological metrics; scale effect; up-scaling



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1. Introduction

Accurate spatial distribution information of forest tree species is a precondition for almost all questions dealing with regional forest ecology and is quite important for understanding the land-surface phenology (LSP) processes and the refinement of ecological and atmospheric models [1–3]. In addition, accurate mapping of the dominant tree species is critical for forest-environment monitoring, forest management, and associated decision-making and planning [4,5]. In recent years, remote sensing images with medium to high spatial resolution (≤ 30 m) have been widely used to map and classify dominant tree species

in the different regional forest ecosystems, because the viewing field of the image is close to the size of tree species and of tree stands [6–9]. However, given the limitations to a few bands with wide central bandwidths, it remains challenging to map forests finely and accurately by solving the common problem of foreign bodies with spectra similar to that of tree species with multispectral images of differing resolution [10–13].

With today's continuous improvement in multispectral satellite revisit cycles, temporal characteristics have proven to have high application value for forest classification [14,15]. The time-series normalized differential vegetation index (NDVI) was generally considered to be applicable for identifying vegetation and extracting phenological information [16–18], which plays a key role in classifying the dominant tree species and overcoming the problem of foreign bodies with similar spectra [19,20]. Given this advantage, some studies have confirmed the use of time-series NDVI data and phenological characters would raise the mapping accuracy of forest types in both urban areas [13,21] and rural areas [18,22–24].

MODIS and NOAA satellites can provide images with very short revisit intervals (less than 2 days). Therefore, most previous researches have discussed the results of forest composition mapping and dynamic detection based on time-series NDVI data from a regional to global scale [5,25]. However, the spatial resolution of traditional time-series images such as NOAA AVHRR [26], SPOT Vegetation [27], and MODIS imagery data [28] generally range from hectometers to kilometers, resulting in poor spectral purity and limited identification of broad forest types (such as coniferous or broad-leaved forests). Hence, medium-to-low resolution remote sensing images were considered to be applicable to classify general forest-cover types [29,30] in which finer tree species composition information is not involved [9,31]. As a rule, medium-high resolution satellite images can be used to produce more accurate results of forest species composition by providing detailed spectral features of the canopy of dominant tree species [32,33].

An increasing number of medium- and high-resolution Earth-observation satellites have now entered use in recent years (e.g., Sentinel-2, SPOT-6 and -7, Gaofen-1 and -2, etc.). Some multitemporal medium-high-resolution NDVI images have proven to be applicable to classify the dominant tree species in forests [11,34–36], but less attention has been focused on spatial mapping [37]. In addition to the time-series spectral dynamics, plant phenology should be equally considered for tree species mapping [38–41]. Therefore, it is essential to use multiscale time-series data to explore the effect of image resolution and phenology information on the accuracy of forest tree species classification. The study of vegetation-phenology dynamics by remote sensing mainly involves extracting the corresponding key time nodes and characteristic values by analyzing the significant variations in vegetation index time series data, which are commonly called LSP metrics [11,17,42,43]. LSP metrics are important status parameters for land-vegetation ecosystems, especially at the start of spring (SOS) [44], also called the start of the growing season [45] or the green-up date [46]. These parameters are the most commonly extracted because of their importance in determining the growing season, and they are also powerful indicators of an ecosystem's response to climate change [44].

To date, LSP metrics have been used to identify different vegetation species. For example, Liu et al. (2018) used the combination of fused 30 m time-series NDVI data and phenological metrics to map rice paddies, and they found that using both of the selected NDVI and phenological features could allow the highest accuracy in extracting rice paddy areas [47]. Another recent study suggested that phenological metrics can help improve the accuracy of remote-sensing recognition of different forest stands [17]. In addition, Schwieder et al. (2018) demonstrated that adding phenological information from multitemporal imagery improves the estimation of aboveground biomass through modified discrimination of vegetation types [48]. However, few studies involving the mapping and phenology of forest tree species have integrated different spatial observation scales with multiscale satellite images, which is necessary to compensate for the lack of research on higher-resolution time-series data.

The mapping results of forest types or tree species through remote sensing would be influenced by the spatial resolution of remote sensing data obviously [6,7,49,50]. In addition, most previous studies have focused on single time-phase imagery, which led to no results available on temporal data [51]. In fact, both species classification and phenological metrics are affected by the spatial resolution of remote sensing data. For example, Zhang et al. (2017) explored how spatial resolution affects the start of vegetation season (SOS) by comparing observations obtained from images with 30 m and 500 m spatial resolution, and found the difference of SOS at the high and low resolution was larger in heterogeneous regions [52]. Tian et al. (2020) investigated how spatial resolution affects the difference in spring phenology of rural-urban vegetation as detected by resampling the satellite data from 30 m to 8 km spatial resolution. They found that coarser images overestimate the urbanization effects and that the SOS obtained by coarser time-series NDVI data would be earlier than that of the actual result [53]. It should be noted that the multiresolution imagery data used in the above researches consists of resampled multispectral images by using up-scaled algorithms (e.g., Nearest Neighbor (NN) and pixel aggregation (PA)), which generate a set of lower spatial resolution images using the high-resolution image through pixel resampling. However, the imaging mechanism of these up-scaled images differs from that of satellite imagery data obviously, which may lead to some uncertainty in the final results of relevant studies [51,54,55]. In consequence, it could be assumed that the phenological monitoring results obtained by up-scaled time-series NDVI data may differ from that detected from time-series satellite imagery, which accounts for the necessity to re-evaluate the results associated with time-series resampled images [53].

In this study, we systematically evaluate how temporal images with a medium-high spatial resolution (4, 10, 16, and 30 m) affect the accuracy of forest tree species mapping and the variability of spring phenological information. The multiscale time-series satellite remote sensing data were obtained from Gaofen-2 (4 m), Sentinel-2 (10 m), Gaofen-1 (16 m), and Landsat-8 (30 m), respectively, acquired over seasonal deciduous forests in 2018 from a state forest farm region in Harqin Banner, China. In addition, we evaluate the performances obtained by using up-scaled time-series images of different spatial resolutions. Eight phenological metrics are extracted to classify forest tree species based on the random forest (RF) algorithm combined with time-series NDVI data. Accordingly, we tried to find out (1) what is the regular pattern for monitoring spring phenology within the medium-high remote sensing spatial resolution range; (2) which scales of time-series images most effectively reflect spectral differences in each forest tree species and the relationship between these phenological metrics and tree species classification; and (3) whether the spatial patterns in up-scaled images are competitive to map the distribution of forest tree species from multiscale satellite datasets. Answers to these points should improve the credibility of using time-series remote sensing images to monitor and map forest tree species for use in forest resource management or regional eco-climate models.

2. Materials and Methods

2.1. Study Area

The study area is in northeast China near the city of Chifeng and has a size of approximately 55,100 ha of which over 45,500 ha are forested landscape. An overview of the area is given in Figure 1. The study area belongs to the border area of the Greater Hinggan Mountains and Yanshan Mountains within a range of 878 to 1890 m, and the climate here is temperate monsoon. The dominant tree species occurring in the local forest are deciduous forest dominated by *Quercus mongolica* (Qm), *Populus davidiana* (Pd), *Betula platyphylla* (Bp), and *Larix gmelinii* (Lg), accounting for about 84% of the total forest area in 2018; there is also an evergreen forest, which is dominated by *Pinus tabulaeformis* (Pt). The five dominant tree species mentioned above account for over 95% of the total forest area in 2018 [19].

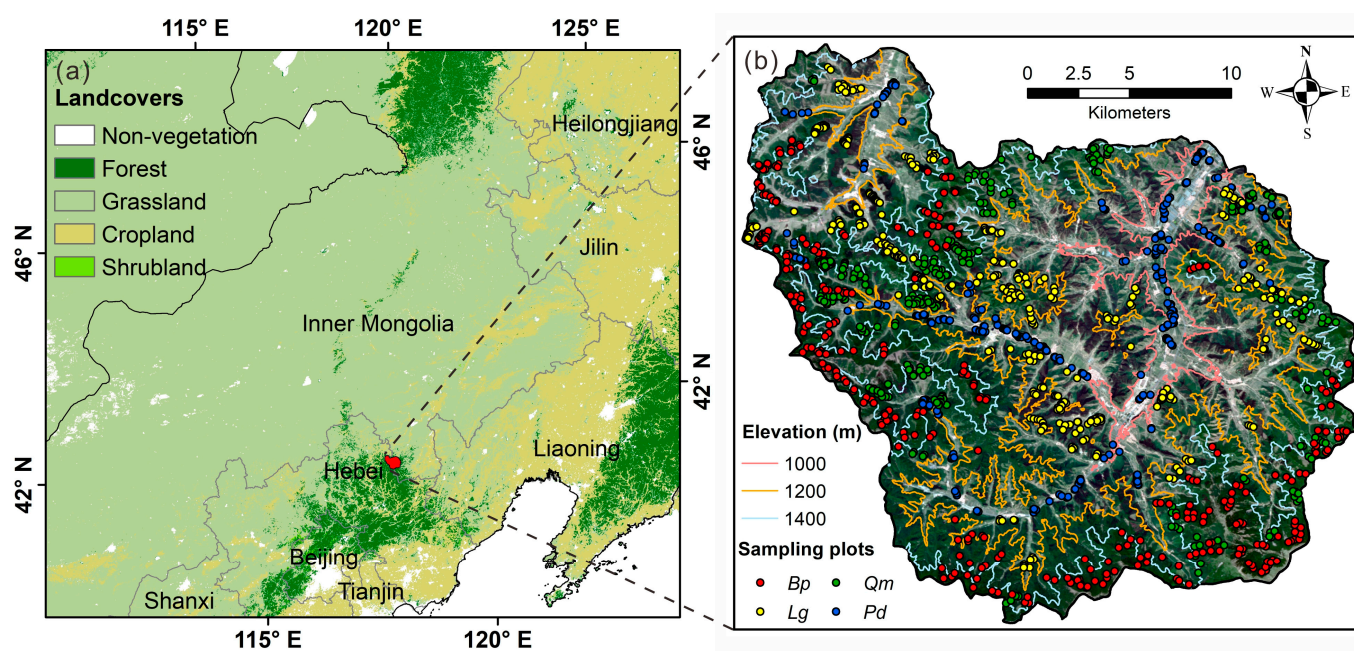


Figure 1. The study area located in northeast China with major vegetation cover types in the background (a), and sampling plots of the four deciduous tree species, including *Betula platyphylla* (Bp; $n = 330$), *Larix gmelinii* (Lg; $n = 330$), *Quercus mongolica* (Qm; $n = 331$), and *Populus davidiana* (Pd; $n = 329$), overlaid on a Landsat-8 imagery (21 June 2018) in the background (b).

2.2. Methods

The methodological workflow is illustrated by the flowchart presented in Figure 2. The research process includes four main steps. First, the collection and preprocessing of both remote sensing data and ground observation data were completed. Next, we calculated forest phenological metrics based on multiscale time-series data and analyzed the scale effect of spring phenology. Then, forest tree-species mapping was performed using satellites and up-scaled time-series NDVI data and phenological metrics with different spatial resolutions. Finally, comparisons of multiple considerations on the accuracy of forest mapping were conducted to illustrate how spatial resolution affects tree-species classification.

2.2.1. Data Resources and Preprocessing

We selected four sets of multiresolution remote sensing images acquired once per month to make a series of spatial scale images respectively (Table A1 in Appendix A) and acquired with cloudiness less than 15%. The main parameters of the images used in this study can be seen in Table 1. This study used a total of 48 satellite remote sensing images covering the entire study area; there were 46 of them acquired in 2018 while the other two with poor imaging quality were replaced by the data of the same period in 2017, which was proven to be feasible [19]. All Sentinel-2 images were obtained from the European Space Agency (ESA; <https://scihub.copernicus.eu>; accessed on 18 December 2019); Landsat-8 images were obtained from the United States Geological Survey (USGS; <http://glovis.usgs.gov>; accessed on 15 January 2020); Gaofen-1 and Gaofen-2 images were obtained from the China Center for Resources Satellite Data and Application (CCRSDA; <http://www.cresda.com/CN>; accessed on 12 September 2020).

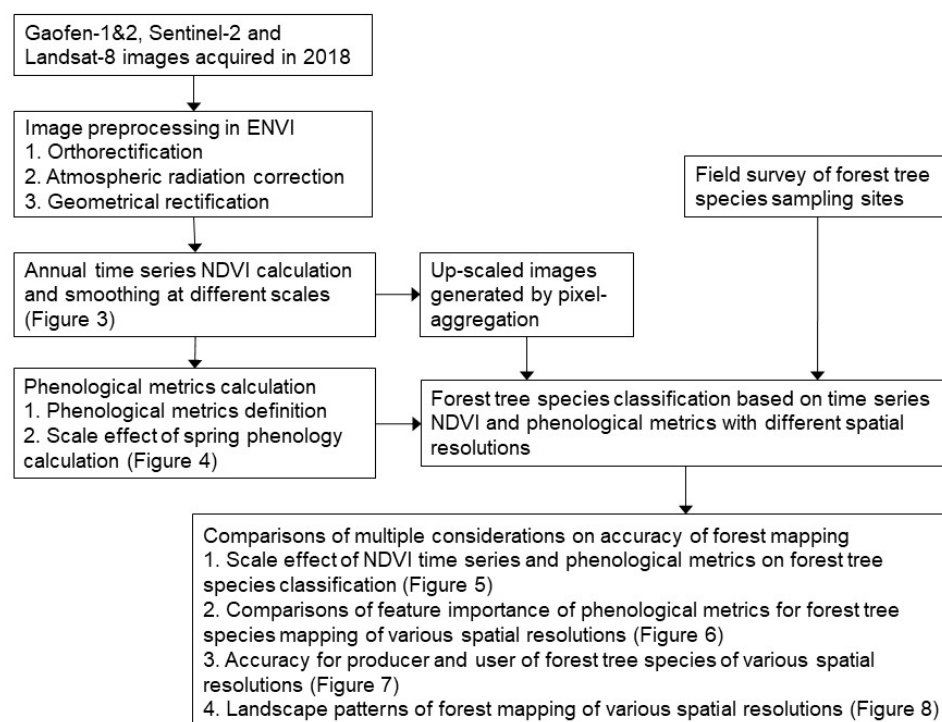


Figure 2. The methodological framework developed in this study.

Table 1. The main parameters of satellite images used in this study.

Satellite Sensor	Revisit Interval (day)	Spatial Resolution (m)	Swath Width (km)	Radiometric Resolution (bit)	Blue (μm)	Green (μm)	Red (μm)	Near-Infrared (μm)
Gaofen-2 PMS	4	4	45	10	0.45–0.52	0.52–0.59	0.63–0.69	0.77–0.89
Sentinel-2 MSI	5	10	290	12	0.46–0.52	0.54–0.58	0.65–0.68	0.79–0.90
Gaofen-1 WFV	4	16	800	10	0.45–0.52	0.52–0.59	0.63–0.69	0.77–0.89
Landsat-8 OLI	16	30	185	12	0.45–0.52	0.53–0.60	0.63–0.68	0.85–0.89

Before analysis, the four sets of time-series datasets with different spatial resolutions were carefully harmonized. A Savitzky–Golay (SG) algorithm served for polynomial filtering of the time-series NDVI data because it better maintains the temporal vegetation dynamics and minimizes atmospheric effects [56,57]. This also implied a smoothing and filtering of the four time-series could remove undesired artifacts due to poor atmospheric conditions and undetected clouds [58]. The four sets of multiscale time-series data pre-processing by using a series of related models and algorithms in ENVI (Environment for Visualizing Images; version 5.3) and IDL (Interactive Data Language; version 8.5) software platform (Research Systems Inc., Boulder, CO, USA). The orthorectification, atmospheric radiation correction, and geometrical rectification were carried out in sequence to preprocess all images used in this study, to transform the digital value into the actual surface spectral reflectance at different image resolutions (Figure 2). The radiometric correction methods include the incident causational matrix (ICAM), and pseudo-invariant feature (PIF) models [59], and the corresponding parameters of radiation correction of different satellite remote sensing data were obtained from their official websites, that is CCRSDA, ESA, and USGS, respectively. In addition, the geometric root means squared error (RMSE) of all images was controlled within 0.5 pixels.

The PA algorithm was selected for up-scaled images (Figure 2). PA assigns different weights to each pixel based on mapping distance which is integrated at the ENVI software, and it is widely used in researches of multiscale remote sensing [46,53]. One related study suggests that PA better maintains pixel values than do other up-scaled algorithms (e.g., nearest neighbor, bilinear, and cubic convolution) [51]. The NDVI data then were calculated

as Equation (1). To ensure that different time series can be compared to each other, the up-scaled datasets were smoothed in the same way as the satellite data. To better analyze the timing of (phenological) events, the (smoothed) monthly NDVI series were saved as 30 daily values on the 15th of each month were assigned as DOY (day of the year; Julian date) for the compositing period of the month.

$$NDVI = \frac{\rho_{NIR} - \rho_{red}}{\rho_{NIR} + \rho_{red}} \quad (1)$$

where ρ_{NIR} and ρ_{red} are the surface reflectance of near-infrared (NIR) and red bands.

2.2.2. Collection of Forest Inventory Data

The field surveys in the study area were undertaken in July 2018 and May 2019. A total of 1320 sample plots (30 m × 30 m) were selected randomly. Approximately 330 sample sites for each deciduous dominant tree species (Table A2 in Appendix A) are shown in Figure 1 (more than 85% of the tree population is single species). Then, 70% of these data were randomly set as training samples and the rest as verification samples. Therefore, the spectral reflectance of different dominant tree species was extracted from the center of each stand plaque at each sample point in the imagery to guarantee the spectral purity of the different image pixels.

2.2.3. Calculation of Forest Phenological Metrics

From the time series NDVI images with different spatial resolutions for related functions in TIMESAT [60], eight typical phenological metrics were obtained: the start of growth season (SOS), end of growth season (EOS), length of growth season (LOS), peaking time of growth season (POS), length of the peak-time (LOP), middle of SOS (SOS_m), middle of EOS (EOS_m), and amplitude (AMP). All the mentioned phenology-related metrics are noted as the Julian date. Here, both the SOS and EOS were calculated from the fitting function when the trees grow to a certain fixed time phase, e.g., the time position ranges from the position where 10–30% of the left (right) minimum of the NDVI value and the maximum NDVI value [61,62], which was indicated as a suitable time point. Nevertheless, the threshold of the determined phenological time points ranged around 20% according to the geographical locations and tree species selected [19,63,64]. The LOS is further calculated as the difference between the EOS and SOS, the POS is identified as the date when the trees grew to the maximum NDVI value at the fitted temporal dynamic curve, then the LOP is the length between 80% of the left and right maximum NDVI of the temporal dynamic curve. The amplitude (AMP) presents the maximum ranges of the tree photosynthetic dynamics across the whole growing season, and SOS_m and EOS_m stand for the average days of the growing season when the trees grow above their 80% level on the right and left side of the peaking time. A more detailed description of the calculated metrics can be found in Schwieder et al. (2018) [48] and Lebrini et al. (2019) [65].

2.2.4. Classification and Accuracy Assessment

Supervised classifiers are believed to be more clearly preferable while the prior knowledge for ground objects is enough [66]. In this study, we used the Random Forest (RF) classifier to identify deciduous tree species, and set its *ntree* to 500 and the *mtry* to the square root of the number of input features, as suggested [67–69]. RF is derived from statistical learning theory to process high-dimension datasets and reduce the overfitting issues [69–71], which was considered to be one of the most robust classifiers compared with other algorithms, such as maximum likelihood (ML), linear discriminant analysis (LDA), support vector machine (SVM), and decision tree classifiers (DTC) [72–74]. Therefore, it integrates hundreds of decision-making trees and encapsulates an important ranking predictor (the mean decreases of accuracy; MDA), which was designed to be used to evaluate the importance of variables in the accuracy efficiently [75]. Then, we extracted the forest boundary and used winter images to separate the dominant evergreen forest landscape.

Based on this, we focused on the remote-sensing classification results for the four deciduous forest tree species: *Betula platyphylla* (Bp), *Populus davidiana* (Pd), *Quercus mongolica* (Qm), and *Larix gmelinii* (Lg) based on time-series NDVI data and the combination of NDVI and phenological metrics.

In addition, we calculate the overall accuracy (OA), kappa, and the accuracies of producer and user to examine and compare each result from different image datasets by constructing corresponding error matrices [76]. By randomly selecting training samples and validation samples, each set of classification results was cross-validated 10 times and averaged. The one-way analysis of variance (ANOVA) was used to decide significant differences in the classification results among the different spatial resolutions and methods. This was followed by multiple comparisons using the least-significant difference (LSD) to identify where the differences lay ($p < 0.05$).

3. Results

3.1. Multiscale Sequence NDVI Curve of Different Deciduous Forest Stands

The annual NDVI curves of the four deciduous forest species with spatial resolution range from 4 to 30 m show obvious unimodal characteristics, with clear forest stand growth stage characteristics (Figure 3). However, the mean NDVI values of four dominant deciduous tree species in the study area were significantly different, in especial, the spectral reflectance captured in 4 m high-resolution images is significantly less than that in lower-spatial-resolution images ($p < 0.05$). In addition, the NDVI curves of different dominant tree species differ, where the NDVI curve of Qm is higher than that of the other deciduous tree species, and that of Pd is the lowest.

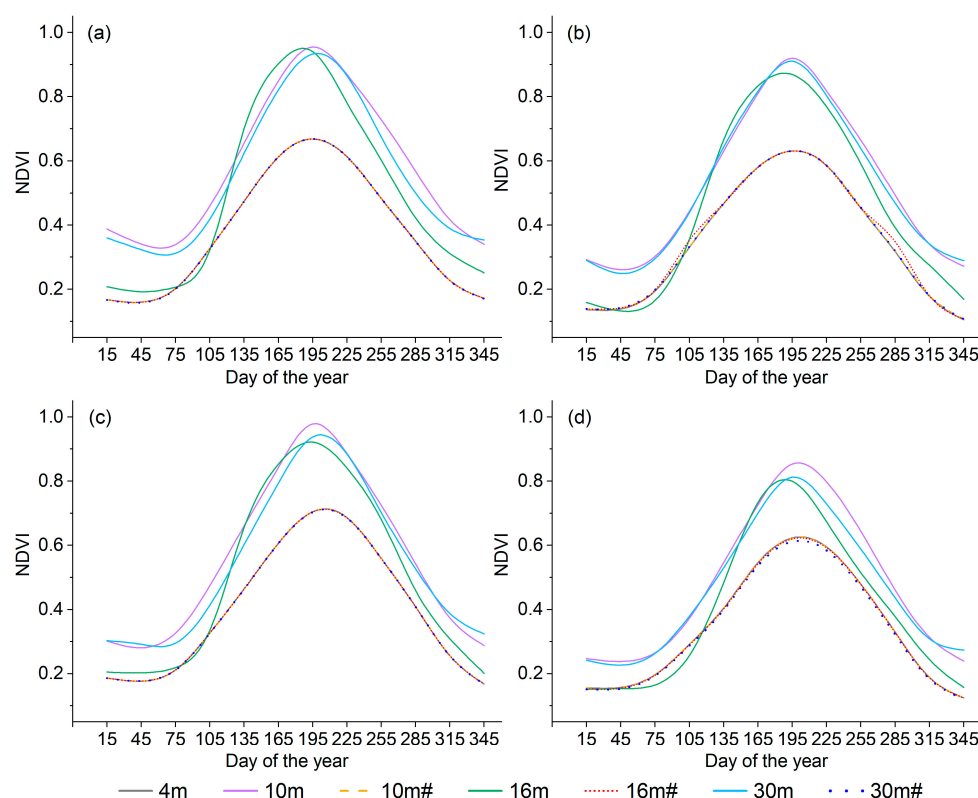


Figure 3. Time-series image training NDVI curves for different deciduous tree species of (a) *Betula platyphylla*, (b) *Larix gmelinii*, (c) *Quercus mongolica*, (d) *Populus davidiana*. The symbol # refers to the up-scaled images, the same below.

In terms of the up-scaled NDVI curves, there are no significant changes in almost all NDVI data observed ($p > 0.05$), which is significantly below the NDVI value from

multiscale satellite images at each given spatial resolution ($p < 0.05$), meaning the up-scaled NDVI curves were underestimated compared to that obtained from actual satellite data at the same resolution.

3.2. Multiscale SOS Results by Satellite Images

The SOS results of multiscale images of different dominant tree species differ significantly ($p < 0.05$; Figure 4). For different tree species, the mean SOS for Lg (109–121) is the earliest, Bp (117–129) is relatively later than all species (including four deciduous tree species; 116–128), and Pd (118–134) is slightly earlier than Qm (122–132), showing the phenological difference among the four deciduous tree species in this study region. For different spatial resolutions, almost all dominant deciduous tree species reveal a significant difference in the mean SOS based on native multiscale images at the same spatial resolution from 4 to 30 m ($p < 0.05$). Overall, the mean SOS increases from 4 to 16 m and then decreases slightly to 30 m ($p < 0.05$). Similarly, the SOS results of all species first increase and reach a peak at 16 m resolution and then begin to decrease as the resolution comes to 30 m ($p < 0.05$), where the mean SOS delay time ranges from 8.02 to 11.95 days.

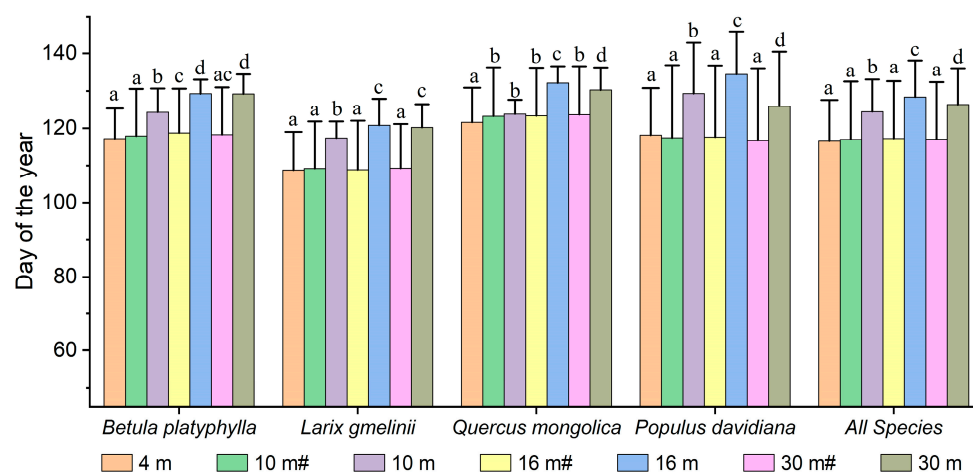


Figure 4. SOS of different forest species at multiscale time-series NDVI data. The letters' differences denote for a given image resolution significant differences ($p < 0.05$).

However, the SOS results for each tree species at different up-scaled spatial resolutions are similar relatively, and an analysis of variance demonstrates that no significant difference appears between image resolutions from 4 to 30 m ($p > 0.05$), whereas the SOS results differ markedly from that of native multiscale satellite data at each same given resolution ($p < 0.05$). Therefore, for SOS results of different dominant tree species across different resolution images, the standard deviation incurred in up-scaled images is generally several times greater than that of native satellite images with the same resolution, ranging from 1.33 to 3.39 ($p < 0.05$).

3.3. Multiscale Classification by Satellite Images and Up-Scaled Images

There were significant differences among the OA values of the dominant forest species at different spatial resolutions ($p < 0.05$; Figure 5a), while the Kappa values show consistent results ($p < 0.05$; Figure 5b). For multiscale satellite time-series NDVI images, the mean OA (Kappa) first increases while image resolution goes from 4 to 10 m ($p < 0.05$) at the highest accuracy of 83.63% (0.7825), and then decreases to the minimum accuracy of 78.60% (0.7154) at 30 m resolution ($p < 0.05$). The classification accuracies of forest tree species are closely related to the image resolutions, and an analysis of variance reveals significant differences between classification accuracies based on time-series satellite data of differing resolution ($p < 0.05$). Combining phenological metrics and time-series NDVI data can improve the mapping of the regional dominant tree species at each given resolution ($p < 0.05$; Figure 5).

When the contrast is integrated with time-series NDVI and LSP metrics, the best overall accuracy (Kappa) of forested landscape identification with 10 m resolution increases to 86.05% (0.8147; $p < 0.05$).

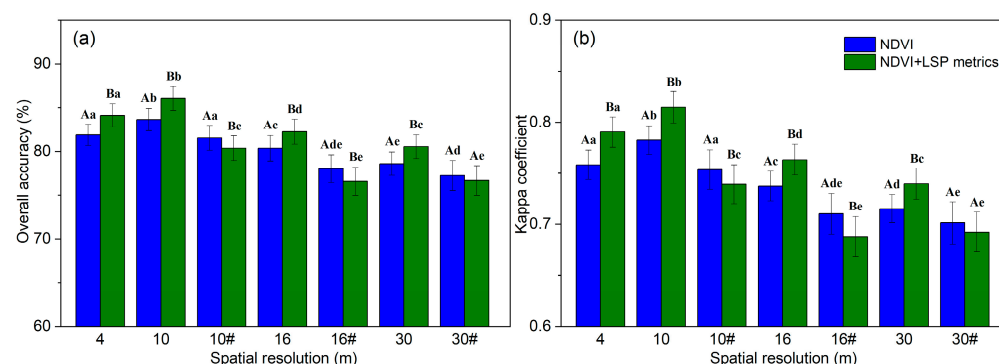


Figure 5. The OA (a) and kappa (b) of classification results of deciduous species at different image resolutions. The uppercase letters differences above the error bar refer to a significant difference between the two-given datasets, while lowercase letters differences denote for a given image resolution significant differences ($p < 0.05$).

However, for up-scaled time-series images, the classification accuracy of the dominant tree species decreases from 81.88% (0.7583) to 77.23% (0.7014) with the spatial resolution ranging from 4 to 30 m# ($p < 0.05$). Therefore, there is no significant difference appears between the classification accuracies of dominant tree species of up-scaled time-series data at the resolution of 16 and 30 m ($p > 0.05$). Finally, combining phenological metrics and time-series NDVI data does not increase the recognition accuracy but leads to the decline from 10 to 30 m# resolution, which differs obviously from the results of native multiscale satellite data at each same given resolution ($p < 0.05$).

3.4. Contributions of Different LSP Metrics to Multiscale Tree Species Classification

The feature importance for identifying forest tree species using the eight LSP metrics of four image resolutions are different (Figure 6). Before analysis, each final feature importance for variables was averaged after ten cross-verifications. The results show that the LSP metrics are valuable for differentiating among forest tree species in the study region ($p < 0.05$). The various LSP metrics produce different positive effects on the classification of dominant tree species, although the magnitude of the influence varies ($p < 0.05$; Figure 6). When considering the four different spatial resolutions, the importance of each LSP metric turns out to be inhomogeneous (Figure 6). The phenological information such as SOS_m , EOS, and POS are more important at higher image resolution, whereas only the LOS achieves the highest importance at lower spatial resolution. In addition, AMP and SOS show roughly the same degree of importance at different resolutions.

Testing the cumulative importance of each LSP metric for individual spatial resolutions reveals the importance of each variable from medium to high resolutions (Figure 6). At first, the LSP metrics in AMP, SOS_m , and SOS are by far the three most important features ($p < 0.05$), showing the middle and early growth period account for the most important contribution in tree-species phenological observations. They are followed by LOP and LOS, which control the length of the growth period and the peak period. Subsequently, the remaining EOS_m and EOS metrics represent the period of declining growth which has less importance. Finally, POS is the least important metric which indicates the peak time, and the differences of POS among the different dominant tree species are small.

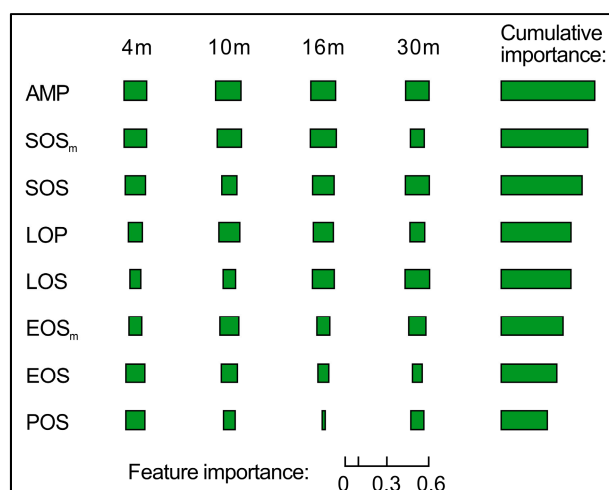


Figure 6. Feature importance for the forest tree species identification using the eight LSP metrics across different image resolutions. Cumulative bars on the side illustrate the sum of the importance for each phenological metric.

3.5. Comparisons of Accuracy for Producer and User of Dominant Tree Species

In native satellite images, the PA of Bp, Lg, Qm, Pd, and the UA of Bp, Lg, Qm show a downward trend on the whole with the decrease in spatial resolution goes from 4 to 30 m; except for the UA of Pd which increases at first and then decreases (Figure 7). None of the dominant classes of tree species have both a low UA and PA. The confusion matrix shows that many Bp, Lg, and Qm are misclassified into Pd in different spatial resolutions, which also leads to an over-mapping for Pd, so the UA of Pd is less than the PA from 4 to 30 m resolution, especially at 4 m. For the mapping results of forest tree species landscape (Figure 8), the comparison shows that the worst classification result occurs in imagery with 30 m resolution, where a portion of Qm and Lg is misclassified as Pd. In addition, some Lg are misclassified as Qm at 16 m resolution and the overall forest mapping at 10 m resolution is better than at 4 m resolution, which is mainly due to the higher mapping accuracy of Qm and Bp.

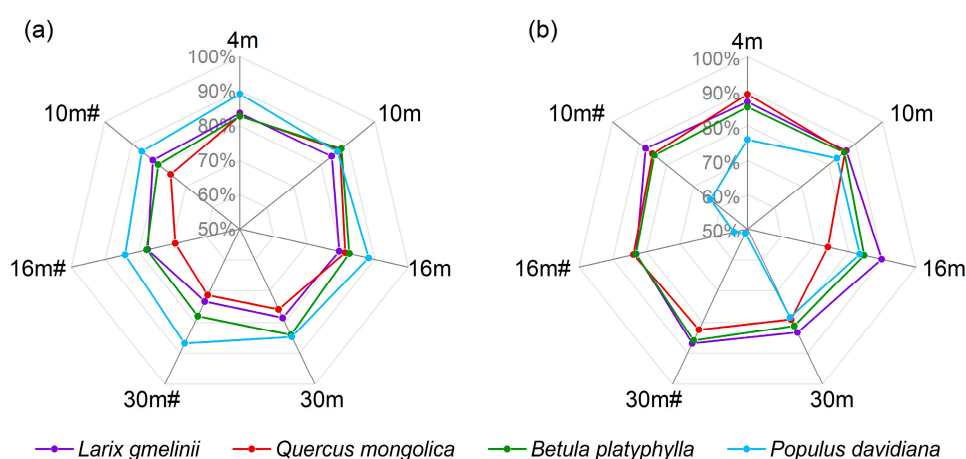


Figure 7. Comparison of accuracy for the producer (a) and user (b) of four deciduous species combining LSP metrics and NDVI from multiscale time-series images.

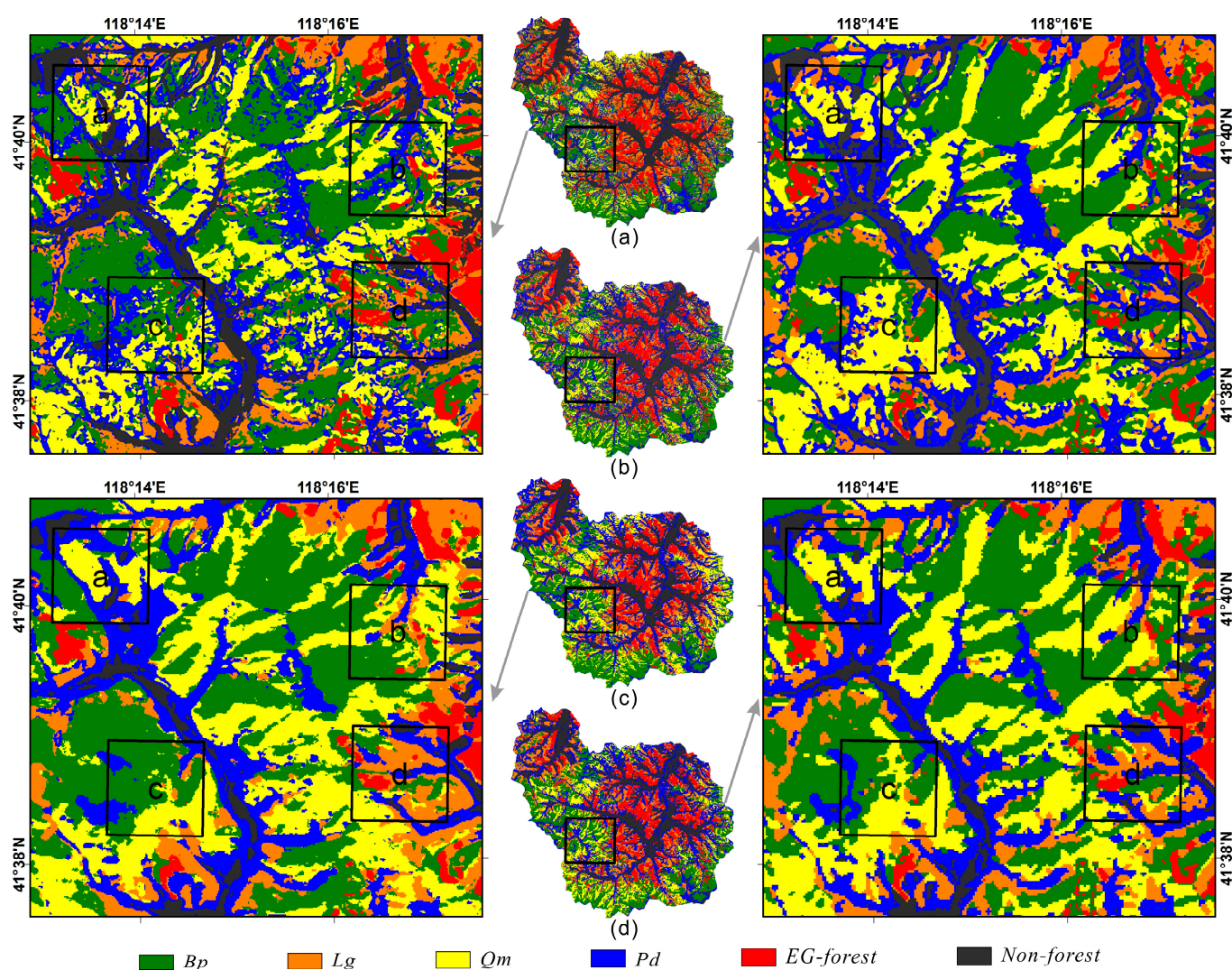


Figure 8. The distributions of forest tree species landscape in the study region based on the combination of time-series NDVI and LSP metrics in different resolutions, including (a) 4 m, (b) 10 m, (c) 16 m, and (d) 30 m. EG-forest means evergreen forest.

However, for up-scaled images, both PA and UA values of different deciduous species change only slightly when the spatial resolution goes down (Figure 7). The UA of Bp, Lg, and Qm and the PA of Pd change slightly from 4 to 30 m# resolution. At the same time, the UA of Bp, Lg, and Qm are significantly higher than their PA, except for Pd, implying over-mapping occurred. On the contrary, the forest tree species with high UA but low PA refer to under-mapping [77]. In this study, low PA of Bp, Lg, and Qm show that large areas of Bp, Lg, and Qm are not properly classified into their respective class, and their PA decrease as the image resolution goes down (Figure 7). In general, PA and UA of the most tree species for up-scaled data are often diminished and more unstable than that for real satellite data, furthermore, almost all tree species reaching their maximum value at the image resolution of 4 m.

4. Discussion

Spatial resolution significantly affects the identification of forest species and mapping based on single-date images [7,12,50,78]. Some studies have indicated that the NDVI temporal variation of stand canopy shows the detailed dynamics of timeline-based spectra of different forest types [14,15]. However, less attention has focused on the spatial scale of the uncertainty in the results. The present study confirms that the overall accuracy gradually extends from 78.59% to 83.63%, while the kappa synchronously increases from

0.7154 to 0.7825, which indicates that the classification accuracy of the dominant tree species is strongly linked to the spatial resolution of the time-series satellite data ($p < 0.05$). In this study, for a spatial resolution of 4 and 10 m, the classification accuracy is high ($>81.88\%$), where the forest landscape identification is apparent, and each dominant species are classified correctly ($p < 0.05$). Overall, the time-series images with higher resolution (4–10 m) providing higher and more stable OA and kappa perform better in identifying the regional forest tree species than those with lower resolution (16–30 m). However, it does not mean that images with finer resolution can always provide more accurate results because it also depends on the selected feature datasets and classification methods.

The mean NDVI values of 4 m images are less than that of 10 m ($p < 0.05$; Figure 3), which we attribute to the NDVI being prematurely saturated at the higher resolution because a higher resolution correlates with less energy incident on the sensor, which decreases the spectral resolution [51,79]. Hence, the annual peak NDVI is mostly below 0.7 for the various dominant deciduous species at 4 m resolution, which is significantly less than the NDVI at the resolution of 10, 16, and 30 m, respectively ($p < 0.05$; Figure 3). Furthermore, the result is also assisted by the narrower near-infrared band and higher radiation resolution of Sentinel-2 image (12 bit, whereas 10 bit of the Gaofen-2 image), which could provide a better capability of vegetation information monitoring. It actually may overcome the negative effects of its coarser resolution to some extent. In addition, the multiscale annual mean NDVI of the sample data for different forest land remains essentially stable for up-scaled data (Figure 3). The spectral information in up-scaled images has a strong dependence on the input high-resolution images, which leads to discrepancies in comparison to actual imaging results at the given spatial resolution (Figure 3). As the image resolution decreases, the spectral information related to the forest tree species was smoothed which would increase omission and commission errors [80]. These results imply that the resampled time-series data have different spectral reflectance in comparison to native images acquired at the same resolution evidently ($p < 0.05$), which reduces the susceptibility to spatial resolution and barely represents the satellite image features of the same scale due to the spectral distortion [51]. Therefore, the classification results of tree species based on up-scaled images differ from those of native images for a given resolution ($p < 0.05$), indicating that native satellite data cannot be accurately replaced by up-scaled images.

Satellite remote sensing imagery is widely applied to monitor forest phenology on global and regional scales [42–44]. Plant phenology provides valuable information for classifying vegetation types [43], and some studies use spectral and phenological parameters to map crops [52,65,81]. However, research on mapping forest tree species has not considered the phenological metrics with images at a medium-high spatial resolution, which might introduce uncertainties in identifying and mapping different tree species [19]. Our classification results combined with NDVI and LSP metrics increases the OA (Kappa) by 2.24% (0.0322), 2.42% (0.0322), 1.89% (0.0258), and 1.94% (0.0243) at 4, 10, 16, and 30 m, respectively. For the 10 m time-series data, all deciduous tree species are correctly classified into their respective categories (Figure 8), and their UA and PA can reach more than 83.12%. These results show that using spatial resolution NDVI data combined with temporal phenological characteristics improves the accuracy of the results at each scale from 4 to 30 m ($p < 0.05$), which indicates that combining the spectral curve and the LSP metrics is a good way to identify and monitor the main forest ecosystem and may improve the precision of spatial mapping in temperate regions from medium to high spatial resolution.

Although differences appear in the phenological metrics at different resolutions, to some extent they have positive effects on the classification of forest tree species in this study region (Figure 6). The three highest phenological variables are AMP, SOS_m , and SOS, based on the contribution of different phenological metrics and the classification of tree species. This indicates that the growth stage from germination to maximum growth and the amplitude of the growth spectrum contribute the most to the identification of the tree species. In addition, after combining the phenology metrics, the accuracy of the

classification results based on the up-scaled data decreases by different degrees compared with the previous results (Figure 5). This is mainly contributed to the decrease in effective spectral information after the smoothing of up-scaled NDVI data and the increase in invalid band information, which would increase feature redundancy, leading to the further degradation of classification results [51,82].

Considering the special significance of phenology in spring [38,44,53], many previous studies were conducted to investigate the effects of forest spring phenology with different resolutions. However, most of them used up-scaled images due to a lack of multiresolution satellite data covering the area with a shorter revisit period [83]. Therefore, we investigate herein how scaling affects spring phenology (SOS) via a comparison between results from low- and high-resolution data. The results show that retrievals of SOS date reflect the difference in spatial scale, resulting in a delay as the resolution worsens. In this study, the SOS results of all species of Landsat-8 data (30 m) are earlier than that of Genfen-1 data (16 m). This result is mainly attributed to the better radiometric precision of Landsat-8 OLI (12 bit, whereas 10 bit of the Genfen-1) and the spectral range refinement of the near-infrared band (Table 1), which improves the overall signal to noise ratio for vegetation monitoring [51] and somewhat avoid overestimation [44] and further reasons need to be verified in follow-up studies. Relative to data with a medium-low resolution that is commonly used to monitor vegetation phenology, medium-high resolution satellites can achieve higher classification accuracy. This is because the observation of deciduous vegetation phenological characteristics is vulnerable to the interference of the evergreen forests or other background factors such as the stand age and topography [84,85]. As a consequence, medium-high resolution satellites can observe more spatial detail information and therefore capture the spectral variation of vegetation in phenology which is not normally detectable in data from sensors with lower spatial resolution.

However, the results show that estimations of spring phenology from up-scaled imagery have little noticeable change, corresponding less to the results derived from multiscale satellite remote sensing data. These findings are consistent with related studies based on up-scaled data. For example, Tian et al. (2021) resampled time-series images with 10 m to a series of lower spatial resolution images from 30 m to 8 km and obtained relatively stable vegetation SOS data in rural areas with a resolution ranging from 10 m to 8 km [53]. Similarly, another study found that the overall SOS averaged from images with a resolution ranging from 1×250 m to 35×250 m is generally similar but with a difference of fewer than five days [44]. Therefore, Zhang et al. (2017) suggested SOS datasets should be calculated from actual time-series images of different spatial scales but not the time-series data up-scaled from finer resolution imagery data using simple resampling methods [52].

In this study, both phenological monitoring and the classification of forest tree species differ significantly when using multiscale satellite images and up-scaled images because of the differences in the imaging mechanism. Related research revealed the difference between the native satellite data and up-scaled data is determined by the mechanism of remote sensing imaging, in which the most up-scaled results are spatial insensitive because of not considering the spatial adjacent information of landscapes [51,86], nor adjusting as the variation of spectral reflection properties at different spatial resolutions [87]. Therefore, the up-scaled images cannot be directly used to replace remote sensing images in time-series monitoring or quantitative analysis. Therefore, methods are gradually being developed to scale-transformation model involving physical mechanism [86–89] and temporal–spatial fusion algorithms [23,53,90], to ensure image features from different spatial resolutions can be integrated into applications.

This study expands on previous work in two important ways: First, we continue to compare tree species classification for multiscale time-series images and explore the applicability of remote sensing images to the study of LSP metrics. Next, we discuss how spatial-scale uncertainty affects phenological observations and the classification of dominant tree species. In addition, we try to construct herein monthly time-series multiscale satellite

images with resolutions ranging from 4 to 30 m. In fact, the monthly time-series data has proven to suffice to describe the one-year spectral curve dynamics of forest tree species when cloud-free imagery is available at specific phenological stages [17,24,70]. However, some studies have shown that more intensive time-series images would be better at capturing fine dynamic differences to separate information on similar forest tree species [19,91]. With recent breakthroughs in multispectral remote-sensing, the temporal-spatial resolution of satellite data is improved obviously. Using imagery from more advanced sensors will enhance the precision of forest phenology monitoring and tree species classification. Therefore, more intensive time-series multiscale images are required to extend the results in this paper.

5. Conclusions

The spatial resolution of satellite remote sensing data has a major impact on forest information extraction and dynamic monitoring, and it is critical to the success of regional dominant tree species mapping. This study develops a process for reconstructing time-series satellite images with medium-high spatial resolution and applies it to monitor forest phenology and map tree species. The study also examines how time-series spectral data responds to the scaling effect obtained from various spatial resolution satellites. Moreover, we discuss how spatial resolution and LSP metrics affect the classification of dominant tree species. The results indicate that remote sensing images with 10 m resolution are more appropriate for the time-series-based forest tree-species classification with superior performance in the study region. In addition, the use of additional LSP metrics further improves the classification results, so they are highly recommended.

Nowadays, though the temporal resolution of remote sensing data is improving, few pieces of research have been designed to investigate how up-scaled time-series images affect forest mapping on landscapes. The present results elaborate the general pattern of time-series remote-sensing tree species identification and spring phenology extraction with medium-high spatial resolution. Therefore, a significant difference was found by contrasting the forest landscape classification results obtained from real multiscale time-series satellite data with that of up-scaled time-series images. This work thus provides a primary understanding of how to use and compare time-series remote sensing images with different spatial resolutions for forest monitoring.

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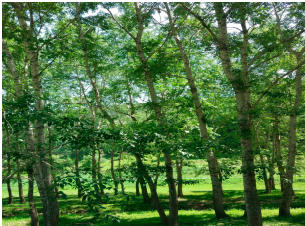
Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

Table A1. The information of satellite images used in this study.

Month	Imaging Date (Gaofen-2)	Imaging Date (Sentinel-2)	Imaging Date (Gaofen-1)	Imaging Date (Landsat-8)
January	20180121	20180120	20180117	20180111
February	20180215	20180214	20180214	20180212
March	20180316	20180311	20180311	20180316
April	20180430	20180415	20180418	20180417
May	20180510	20180515	20180515	20180519
June	20180608	20180614	20180621	20180620
July	20180722	20180729	20180722	20180706
August	20180816	20180823	20180820	20180823
September	20170920	20170922	20180916	20180924
October	20181019	20181017	20181019	20181025
November	20181118	20181121	20181120	20181126
December	20181213	20181216	20181215	20181213

Table A2. Characteristics of the dominant tree species in this study.

Species Name	Picture	Main Characteristics
<i>Larix gmelinii</i> (Lg)		A deciduous tree (30 m), D.B.H. 90 cm or so. The barks are taupe, and the branches consist of obvious long branches and short branches. Light-loving, cold-resistant, drought-resistant. Mainly distributed in Northeast China as well as the mountainous areas from eastern Inner Mongolia to eastern Siberia of Russia.
<i>Populus davidiana</i> (Pd)		A deciduous tree (25 m), D.B.H. 60 cm or so. The barks are gray or gray-green, and the leaves are ovate or nearly round with incised margin. Light-loving, cold-resistant, and soil are adaptable. Mainly distributed in valleys of high mountains in Northeast China, Northwest China, North China and Southwest China.
<i>Betula platyphylla</i> (Bp)		A deciduous tree (27 m), D.B.H. 80 cm or so. The barks are white and smooth or local cracking, and the leaves are ovate with a jagged margin. Light-loving, cold-loving, and soil adaptable. Mainly distributed in Northeast China, North China and the mountainous areas on the outer edge of the Qinghai-Tibet Plateau.
<i>Quercus mongolica</i> (Qm)		A deciduous tree (30 m), D.B.H. 60 cm or so. The barks are dark taupe, the branches are purplish-brown, the leaves are obovate with around margin. Light-loving, soil adaptable. Mainly distributed in Northeast China and part of northern North China.

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