Chin. Geogra. Sci. 2011 21(3) 304–311
doi: 10.1007/s11769-011-0471-3
www.springerlink.com/content/1002-0063

Extracting Vegetation Phenology Metrics in Changbai Mountains Using an Improved Logistic Model

LI Ming, WU Zhengfang, QIN Lijie, MENG Xiangjun
(*School of Urban and Environmental Sciences, Northeast Normal University, Changchun 130024, China*)

Abstract: Remotely sensing images are now available for monitoring vegetation dynamics over large areas. In this paper, an improved logistic model that combines double logistic model and global function was developed. Using this model with SPOT/NDVI data, three key vegetation phenology metrics, the start of growing season (SOS), the end of growing season (EOS) and the length of growing season (LOS), were extracted and mapped in the Changbai Mountains, and the relationship between the key phenology metrics and elevation were established. Results show that average SOS of forest, cropland and grassland in the Changbai Mountains are on the 119th, 145th, and 133rd day of year, respectively. The EOS of forest and grassland are similar, with the average on the 280th and 278th, respectively. In comparison, average EOS of the cropland is relatively earlier. The LOS of forest is mainly from the 160th to 180th, that of the grassland extends from the 140th to the 160th, and that of cropland stretches from the 110th to the 130th. As the latitude increases for the same land cover in the study area, the SOS significantly delays and the EOS becomes earlier. The SOS delays approximately three days as the elevation increases 100 m in the areas with elevation higher than 900 m above sea level (a. s. l.). The EOS is slightly earlier as the elevation increases especially in the areas with elevation below 1200 m a. s. l. The LOS shortens approximately four days as the elevation increases 100 m in the areas with elevation higher than 900 m a. s. l. The relationships between vegetation phenology metrics and elevation may be greatly influenced by the land covers. Validation by comparing with the field data and previous research results indicates that the improved logistic model is reliable and effective for extracting vegetation phenology metrics.

Keywords: logistic model; SPOT/NDVI; phenology metrics; Changbai Mountains

Citation: Li Ming, Wu Zhengfang, Qin Lijie, Meng Xiangjun, 2011. Extracting vegetation phenology metrics in Changbai Mountains using an improved logistic model. *Chinese Geographical Science*, 21(3): 304–311. doi: 10.1007/s11769-011-0471-3

1 Introduction

Phenology is the study of the recurring vegetation cycles and their connection to the surrounding environmental factors such as climate, hydrology and soil (Wan and Liu, 1987). In recent years, remote sensing satellite data have been used at the regional and global geographic scales for assessing the inter-annual variation of vegetation phenology. In particular, the time series of Normalized Difference Vegetation Index (NDVI) has been commonly used for monitoring vegetation phenology. NDVI can accurately reflect vegetation greenness, seasonal and annual variations of vegetation photosynthesis intensity and intensive metabolism for phenological studies of large area (Wu *et al.*, 2008). Remote sensing phenologies hold valuable information for describing the coupling of climate and vegetation. Accurate assessments of phenology from satellites will be an important step in understanding climatic influences on phenological variability at large scales (Fisher and Mustard, 2007).

Recently, an increasing number of methods based on satellite data have been used to obtain vegetation phenology metrics. These methods are mainly classified into four categories: threshold (Suzuki *et al.*, 2003; Delbart *et al.*, 2005; Piao *et al.*, 2006; Karlsen *et al.*,

---

Received date: 2010-06-16; accepted date: 2010-10-27
Foundation item: Under the auspices of Major State Basic Research Development Program of China (No. 2009CB426305), Cultivation Foundation of Science and Technology Innovation Platform of Northeast Normal University (No. 106111065202)
Corresponding author: WU Zhengfang. E-mail: wuzf@nenu.edu.cn

2007), derivative (Moulin *et al*., 1997; Zhang *et al*., 2003; Baltzer *et al*., 2007), smooth function (Moody and Johnson, 2001; Archibald and Scholes, 2007; Hermance, 2007) and model fitting (Fisher *et al*., 2006; Fisher and Mustard, 2007). In general, the threshold method is easy to calculate with high efficiency, but the threshold is determined by researchers, which often reduces the assessment precision. To some extent, the derivative method is still limited to empirical threshold. The smooth function method can reduce the NDVI noise further, but sometimes it can not determine the start of growing season (SOS) and the end of growing season (EOS) immediately. The model fitting method has generality with no requirements for setting the threshold or empirical restrictive conditions when dealing with image pixel by pixel. However, the real curve of NDVI time-series is not regularly perfect, and fitting precision will directly influence the acquisition of vegetation phenology metrics.

Although many model fitting methods, such as Fourier analysis (Wagenseil and Samimi, 2006), logistic model (Zhang *et al*., 2004), can be used to generate smooth time-series from noisy satellite data, these methods may fail when the time profile is more ambiguous. For example, these methods can not describe well the time-profile of coniferous forest and broad-leaved forest simultaneously. This study aims to develop an improved logistic model that combines the merits of double logistic model and global function to increase the flexibility and complexity for fitting time-series curve of NDVI. Based on improved logistic model with the SPOT-VEGETATON (VGT) NDVI data, the key phenology metrics in the Changbai Mountains are extracted and mapped. With this information, the variations of each phenology metric with elevation change are analyzed, which are significantly meaningful in the aspects of ecological security for the Changbai Mountains.

2 Study Area and Data

2.1 Study area

Study area includes Zhangguangcai Mountain, Hada Mountain, Weihu Mountain, Longgang Mountain, Qianshan Mountains, Laoye Mountain and main range of the Changbai Mountains (Fig. 1). The area belongs to the temperate continental monsoon climate that features long and cold winter and short and cool summer. Mean annual temperature is 5.8℃, with mean temperature of –14.2℃ in January and of 22.5℃ in July, and the mean anunal precipitation is 726.9 mm. The elevation of the Changbai Mountains ranges from 500 m to 1000 m above sea level (a. s. l.). The main land cover types are forest, cropland and grassland; the zonal soil is dark brown forest soil. The southern areas (Qianshan Mountains) belong to the warm temperate zone where deciduous broad-leaved forest is dominant. The middle and northern areas fall into the middle temperate zone. These areas are predominated by typical temperate mixed forest, which includes typical needle-leaved forest species, such as *Pinus koraiensis*, *Abies holophylla*, *Picea koraiensis*, and the predominant broad-leaved forest species are mainly *Betula platyphylla*, *Quercus*

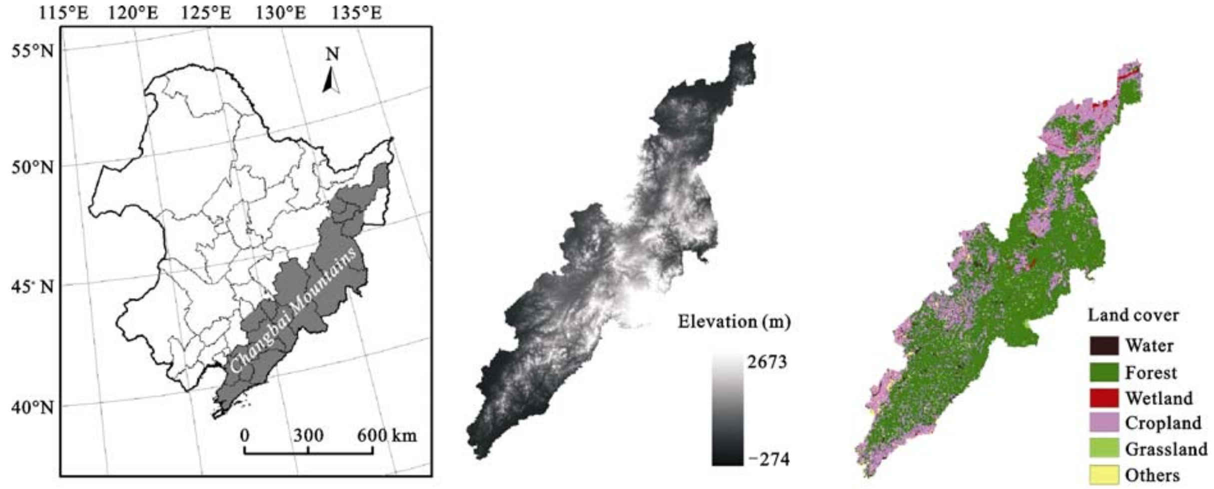


Fig. 1 Location of Changbai Mountains in northeastern China and maps of elevation and land cover

mongolica, *Acer mono*, *Populus davidiana*, *Fraxinus mandshurica*, *Tilia mandshurica* and *Tilia amurensis*.

2.2 Data

The SPOT-VGT NDVI data (from http://free.vgt.vito.be/) used in this study are 10-day-composite data (S10, days 1–10, 11–20, and 21 to the end of a month) with 1 km spatial resolution in plate-carree geographic projection over the period of May 21, 1998 to May 11, 2009 (396 VGT-S10 images). In order to research vegetation phenology during the full growing seasons, the phenology metrics of vegetation between 1999 and 2008 are extracted in the Changbai Mountains.

The land cover data (China WESTDC Land Cover Products 1.0) are based on the land cover data of China in 2000 with 1 km spatial resolution. The data are provided by the Environmental and Ecological Science Data Center for West China (from http://westdc.westgis.ac.cn). The DEM data, Shuttle Radar Topography Mission (SRTM) with 90 m spatial resolution, are obtained from http://srtm.csi.cgiar.org.

2.3 Data pre-processing

Before the phenological retrieval algorithms are performed, all data are projected into Albers Conical Equal Area projection. The DEM data is resampled to 1 km to match with the SPOT-VGT NDVI data. Although Maximum Value Compositing (MVC) algorithm can suppress cloud contamination on the SPOT-VGT NDVI data, there still exists some residual noise for the variability of sensor viewing angle, solar altitude, aerosols and water vapor. Therefore, reducing impacts of spurious values of the NDVI data is necessary. If the values are classified as outlier in the time series that are substantially different from both the left- and right-hand neighbors and from the median in a window, they are removed (Jonsson and Eklundh, 2002). Subsequently, the time-series of SPOT-VGT NDVI are fitted by using the improved logistic model.

3 Method

3.1 Improved logistic model construction

Field measurements have shown that logistic model is effective for depicting vegetation growth curves as a function of time (Ratkowsky, 1983). A general logistic model is given by Equation (1):

$$y(t) = \frac{1}{1 + \exp\left(\frac{x_1 - t}{x_2}\right)} \tag{1}$$

where $y(t)$ is the NDVI at time t; x_1 and x_2 are the factors that control the phase shift and slope of the logistic curve, respectively.

A logistic curve approximates a cumulative distribution function, such that it represents the accumulative sum of a probability density and the first derivative of $y(t)$ is nearly Gaussian. Suppose that the probability of day of year emergence for a single leaf is normally distributed, and the total amount of green cover through time is an accumulation, following a curve similar to that of logistic growth. Over a dense canopy against a non-vegetated background, the area of green leaf cover can be theoretically expected to start at 0 (no leaf cover), and increase to 1 (complete leaf cover) as an accumulation function. However, the difference between deciduous canopies (which reach nearly full leaf canopy) and coniferous species (which maintain chlorophyll in the winter) is a scaling function that controls the average minimum and maximum greenness (Fisher *et al*., 2006). When modeling all kinds of vegetation simultaneously, amplitude parameter (c_2) and minimum parameter (c_1) are used. Leaf abscission can be modeled using a negative logistic curve. The double logistic model used for modeling vegetation phenology is as follows (Fisher and Mustard, 2007):

$$y(t) = c_1 + c_2 \times \left(\frac{1}{1 + \exp\left(\frac{x_1 - t}{x_2}\right)} - \frac{1}{1 + \exp\left(\frac{x_3 - t}{x_4}\right)} \right) \tag{2}$$

where $y(t)$ is the fitted NDVI at time t; c_1 and c_2 determine background greenness value and amplitude, respectively. The nonlinear parameters control the shape of function $y(t)$; x_1 determines the position of the left inflection point and x_2 gives the rate of change. Similarly, x_3 determines the position of the right inflection point and x_4 gives the rate of change at this point. The linear parameters c_1 and c_2, as well as nonlinear parameters x_1, x_2, x_3 and x_4, are obtained by minimizing the merit function:

$$\chi^2 = \sum_{n_1}^{n_2} (y_i' - y_i)^2 \quad i \in [n_1, n_2] \tag{3}$$

where y_i' and y_i are the fitted NDVI and actual NDVI at time i, respectively.

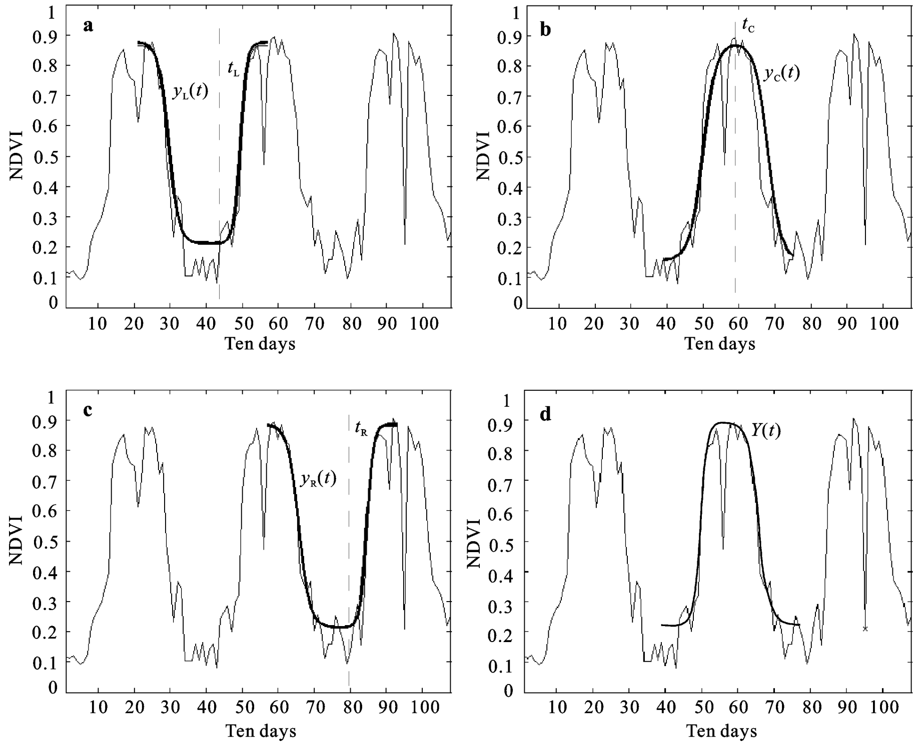
The double logistic model can describe sensor data very well in broad intervals around the maxima and the minima, but the fits are not as good at the limbs. Firstly, the double logistic function is used to model the left minimum $y_L(t)$ (Fig. 2a), the central maximum $y_C(t)$ (Fig. 2b) and the right minimum $y_R(t)$ of time-series separately (Fig. 2c). Then, the global function $Y(t)$ (Jonsson and Eklundh, 2002) is applied to connecting all the sub-intervals to complete the fittings for the full interval [t_L, t_R] (Fig. 2d), which could increase flexibility and complexity of double logistic model for fitting the time-series curve. Shown as Equation (4), the model combining double logistic model and global function is just the improved logistic model used in this paper.

$$Y(t)=\begin{cases}\alpha(t)y_L(t)+[1-\alpha(t)]y_C(t), & t_L<t<t_C\\ \beta(t)y_C(t)+[1-\beta(t)]y_R(t), & t_C<t<t_R\end{cases} \quad (4)$$

where $\alpha(t)$ and $\beta(t)$ are standard distance factors (0 to 1) that t gets to the central maxima and the right minima, respectively.

3.2 Phenology metrics extraction

In the present study, the date of leaf onset is defined as the date on which the logistic curve reaches its half-maximum value (White *et al.*, 1997). The half-maximum on the decreasing slope is the leaf offset. The date of half-maximum greenness has several unique properties that make it suitable for tracking the changes of vegetation phenology with time. The half-maximum is the steepest point on the logistic curve; meanwhile, the peak of the first derivative is similar to the Gaussian probability density function. The date that the half-maximum appears can be regarded as the date when most leaves are likely to emerge. This point is temporally stable when the absolute values of asymptotes fluctuate between 0 and ∞, even the date of onset or offset of vegetations with different maximum canopy closures or little amount of conifer cover (or high minimum greenness) can still be compared. Moreover, half-maximum points are constrained by the entire shape of phenology curve, and the variability or noise in the extreme portion of the curve minimally impacts the date of onset or offset (Fisher *et al.*, 2006).



$y_L(t)$, $y_C(t)$ and $y_R(t)$ are left minimum, central maximum, and right minimum of NDVI time-series, respectively; t_L, t_C and t_R represent the time when corresponding fitting curves reach left minimum, central maximum and right minimum, respectively

Fig. 2 Fitted NDVI curves by improved logistic model

In this paper, the whole processes are performed by using the software of Matlab and ArcMap 9.2. The images are processed pixel by pixel, and 396 values of each pixel are treated as the original data for fitting. The parameters of improved logistic model are dynamic, changing with the pixel number, which can avoid the simulation error for adopting the same parameters.

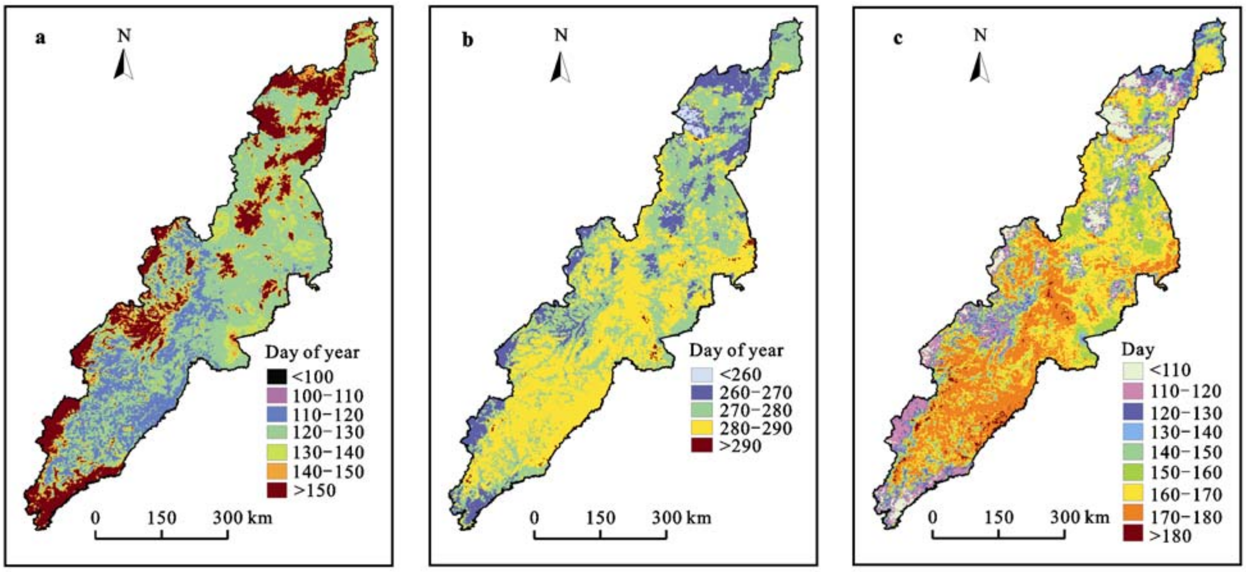
4 Results

4.1 Spatial patterns of average phenophases

Using the improved logistic model, the SOS, EOS and LOS of different land covers from 1999 to 2008 in the Changbai Mountains are extracted and the corresponding spatial patterns are obtained pixel by pixel (Fig. 3).

As shown in Fig. 3a, the average SOS of forest in the Changbai Mountains commences on the 110th to 130th day of year, which is consistent with the period of leaf unfolding for forest in late April and early May. That of grassland and cropland start relatively later; the SOS of grassland occurs mainly on the 130th to the 140th day while that of cropland occurs on the 140th to the 150th day. Figure 3b shows that the EOS ceases on the 260th to the 290th day in the Changbai Mountains, especially from 275th to 285th day, which correspond to the period of forest defoliation and grass wilting in fall. The EOS of cropland is relatively earlier, from the 260th to the 275th day. As shown in Fig. 3c, the LOS of forest stretches mainly from 160th to the 180th day, and that of grassland is from the 140th to the 160th day. The LOS of cropland is the shortest, extending from the 110th to the 130th day.

To compare the differences of phenology metrics in different latitudes, the study area is divided equally into three parts along the latitude. The average phenological dates of vegetations are listed in Table 1. From the south to the north in the Changbai Mountains, the latitude increases gradually, and the SOS delays and EOS brings



a. SOS, start of growing season; b. EOS, end of growing season; c. LOS, length of growing season

Fig. 3 Spatial patterns of vegetation phenology metrics in Changbai Mountains

Table 1 Average SOS and EOS of vegetation (day of year)

Vegetation	SOS				EOS			
	North	Middle	South	Whole	North	Middle	South	Whole
Forest	122	119	116	119	277	280	282	280
Cropland	150	142	142	145	269	274	277	273
Grassland	136	133	130	133	275	279	280	278

Note: SOS is the start of growing season; EOS is the end of growing season forward. These results conform to the Hopkin's Law, that is, SOS commences later while EOS ceases earlier at higher latitudes.

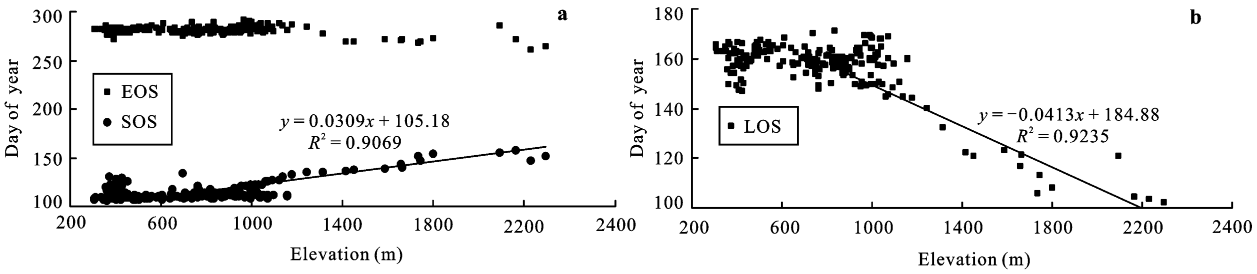
4.2 Relationships between phenology metrics and elevation

For researching the vertical distribution characteristics of vegetation phenology, the main range of the Changbai Mountains is taken as an example due to its significant differences in elevation. A vertical belt is selected along the same latitude, from which phenology metrics and the corresponding elevation of each pixel are extracted to analyze the relationship between them.

The SOS changes not significantly in the areas with elevation below 900 m a. s. l., where the majority of the vegetation are mixed forest (Fig. 4a). A linear fitting is performed between the SOS and elevation above 900 m a. s. l. The result is as follows: $y = 0.0309x + 105.18$ ($R^2 = 0.9069$). That is to say, the SOS delays approximately three days as the elevation increases 100 m in the areas with elevation above 900 m a. s. l. The EOS ceases slightly earlier as elevation increases, especially in the areas with elevation below 1200 m a. s. l. The fitting equation between the LOS and elevation is $y = -0.0413x + 184.88$ ($R^2 = 0.9235$) (Fig. 4b), which indicates that the LOS shortens obviously as elevation increases.

4.3 Validation

Validation is the key issue in the phenology studies based on the remote sensing data over large areas (Schwartz and Reed, 1999). In this study, fitted phenological data using the improved logistic model are compared with the ground phenological data provided by Chinese Yearbook of Animal and Plant Phenological Observation (Institute of Geography, Chinese Academy of Sciences, 1988) and Tonghua Meteorological Bureau of Jilin Province and Benxi Meteorological Bureau of Liaoning Province, and research results from the paper published (Table 2). The results show that the fitted phenological data in this paper are similar to the ground data and other's research results in general. Taking the average of phenology data of different vegetations in each station, the differences of both the SOS and EOS are less than 9 days, and LOS differs by around 10 days.



a. SOS, start of growing season; b. EOS, end of growing season; c. LOS, length of growing season

Fig. 4 Variations of key phenology metrics with elevation increase in same latitude

Table 2 Validation of fitted phenological data using improved logistic model (day of year)

Station/area	Latitude (°N)	Longitude (°E)	Vegetation	Year	Ground/other's phenological data			Fitted phenological data		
					SOS	EOS	LOS (day)	SOS	EOS	LOS (day)
Dunhua**	43.37	128.2	*Populus ussuriensis*	1988	132	260	128	129	267	138
			Betula platyphylla		131	263	132			
Tonghua***	41.68	125.9	*Populus canadensis*	2006	115	269	154	114	279	165
			Salix matsudana		118	278	160			
Benxi***	41.31	123.78	*Populus canadensis*	1980–1998	118	271	153	117	285	168
			Prunus armeniaca		123	281	158			
Changbai Mountains*			Forest	2003	110–120	280–290	170–190	110–130	280–290	160–180

Notes: ***: data from meteorological bureaus; **: data from Chinese Yearbook of Animal and Plant Phenological Observation; *: data from Yu and Zhuang (2006); Fitted phenological data are the average values of the pixels corresponding to three stations and average values for the Changbai Mountains from 1999 to 2008

According to Yu and Zhuang (2006), the leaves of forest begin to unfold between the 110th and the 120th day and defoliate between the 280th and 290th day, and the LOS of forest extends from the 170th to the 190th day in the Changbai Mountains, all of which are generally consistent with the results fitted in this study. Validation illuminate that the extracted phonology metrics in the Changbai Mountains are reliable, and also confirm the precision of improved logistic model in identifying vegetation phenophases.

5 Discussion

Compared with the dynamic threshold method or the piecewise logistic model which could only extract vegetation phenophases for one year used by Yu and Zhuang (2006) and Gong and Chen (2009), the improved logistic model used in this study can extract vegetation phenophases for several years simultaneously, moreover, the influence from boundary effects of time-series curve can be avoided. With this feature, the data obtained are more flexible and complicated for fitting curves. However, it also has a limitation, when the curves of NDVI time-series are fitted, six parameters must be estimated, but it remains unclear how the parameter estimation is influenced by temporal resolution of data.

Fitting both sides of the curve using symmetric ratios is improper because the SOS and EOS are different biophysical processes. Therefore, future studies on the vegetation phenology metrics in the Changbai Mountains should determine the thresholds of SOS and EOS separately. The onset date of greenness in the spring and the offset date in the fall are strongly influenced by climatic conditions (Zhang *et al.*, 2004). The interrelationship between vegetation phenology and climate factors, such as temperature, precipitation and solar radiation, is another topic for the future research.

A variety of field programs for monitoring phenology have been performed. However, data provided by these field programs are typically species-specific and generally for local spot, which are incompatible with the remote sensing observations for coarse resolution and multiple species. The spatial resolution of the NDVI data used in this paper are 1 km, and each pixel reflects the integrated conditions and phenological behavior of diverse species, so it is difficult to make the comparisons with the field observations accurately. Although errors are inevitable, comparisons with field data are frequently-used and relatively reliable way for precision validation of research results based on remote sensing data.

6 Conclusion

In this paper, an improved logistic model based on remote sensing data has been developed. This model is used to extract phenology metrics of vegetation during the growing season between 1999 and 2008 in the Changbai Mountains. The model treats each pixel individually without setting absolute thresholds or empirical constants, in which way, the model can characterize the physical meaning of different pixels more accurately. Validations through comparing with the field data and previous research results demonstrate that the improved logistic model used in this paper is appropriate for the study of vegetation phenology in the Changbai Mountains.

The average SOS, EOS and LOS of vegetation in the Changbai Mountains show obvious spatial patterns that depends mainly on the land cover types. The average SOS for different land cover types is as follows: forest (119th day), grassland (133rd day) and cropland (148th day). In contrast, the average EOS exhibits the opposite trend: cropland (273rd day), grassland (278th day) and forest (280th day). Therefore, the average LOS of the forest, grassland and cropland are 161, 145 and 125 days, respectively. Moreover, the SOS delays and the EOS brings forward as the latitude increases for the same land cover type. In the areas with elevation below 900 m a. s. l., the SOS, EOS and LOS slightly change as the elevation increases, while the strong relationships between SOS, LOS and elevation can be observed in the areas with the elevation above 900 m a. s. l., where the vegetation types change quickly.

References

Archibald S, Scholes R J, 2007. Leaf green-up in a semi-arid African savanna-separating tree and grass responses to environmental cues. *Journal of Vegetation Science*, 18(4): 583–594. doi: 10.1111/j.1654-1103.2007.tb02572.x

Baltzer H, Gerard F, George C *et al.*, 2007. Coupling of vegetation growing season anomalies and fire activity with hemispheric and regional-scale climate patterns in Central and East

Siberia. *Journal of Climate*, 20(15): 3713–3729. doi: 10.1175/JCLI4226

Delbart N, Kergoat L, Le T T *et al*., 2005. Determination of phenological dates in boreal regions using normalized difference water index. *Remote Sensing of Environment*, 97(1): 26–38. doi: 10.1016/j.rse.2005.03.011

Fisher J I, Mustard J F, 2007. Cross-scalar satellite phenology from ground, Landsat, and MODIS data. *Remote Sensing of Environment*, 109(3): 261–273. doi: 10.1016/j.rse.2007.01.004

Fisher J I, Mustard J F, Vadeboncoeur M A, 2006. Green leaf phenology at Landsat resolution: Scaling from the field to the satellite. *Remote Sensing of Environment*, 100(2): 265–279. doi: 10.1016/j.rse.2005.10.022

Gong Pan, Chen Zhongxin, 2009. Regional vegetation phenology monitoring based on MODIS. *Chinese Journal of Soil Science*, 40(2): 213–217. (in Chinese)

Hermance J F, 2007. Stabilizing high-order, non-classical harmonic analysis of NDVI data for average annual models by damping model roughness. *International Journal of Remote Sensing*, 28(12): 2801–2819. doi: 10.1080/01431160600967128

Institute of Geography, Chinese Academy of Sciences, 1988. *Chinese Yearbook of Animal and Plant Phenological Observation*. Beijing: Geology Press. (in Chinese)

Jonsson P, Eklundh L, 2002. Seasonality extraction by function fitting to time-series of satellite sensor data. *IEEE Transactions on Geoscience and Remote Sensing*, 40(8): 1824–1832. doi: 10.1109/TGRS.2002.802519

Karlsen S R, Solheim I, Beck P S A *et al*., 2007. Variability of the start of the growing season in Fennoscandia, 1982–2002. *International Journal of Biometeorology*, 51(6): 513–524. doi: 10.1007/s00484-007-0091-x

Moody A, Johnson D M, 2001. Land-surface phenologies from AVHRR using the discrete Fourier transform. *Remote Sensing of Environment*, 75(3): 305–323. doi: 10.1016/S0034-4257(00)00175-9

Moulin S, Kergoat L, Viovy N *et al*., 1997. Global-scale assessment of vegetation phenology using NOAA/AVHRR satellite measurements. *Journal of Climate*, 10(6): 1154–1170. doi: 10.1175/1520-0442(1997)010

Piao S L, Fang J Y, Zhou L M *et al*., 2006. Variations in satellite-derived phenology in China′s temperate vegetation. *Global Change Biology*, 12(4): 672–685. doi: 10.1111/j.1365-2486.2006.01123.x

Ratkowsky D A, 1983. *Nonlinear Regression Modeling—A Unified Practical Approach.* New York: Marcel Dekker Inc., 61–91.

Schwartz M D, Reed B C, 1999. Surface phenology and satellite sensor-derived onset of greenness: An initial comparison. *International Journal of Remote Sensing*, 20(17): 3451–3457. doi: 10.1080/014311699211499

Suzuki R, Nomaki T, Yasunari T, 2003. West-east contrast of phenology and climate in northern Asia revealed using a remotely sensed vegetation index. *International Journal of Biometeorology*, 47(3): 126–138. doi: 10.1007/s00484-003-0164-4

Wagenseil H, Samimi C, 2006. Assessing spatio-temporal variations in plant phenology using Fourier analysis on NDVI time series: Results from a dry savannah environment in Namibia. *International Journal of Remote Sensing*, 27(16): 3455–3471. doi: 10.1080/ 01431160600639743

Wan Minwei, Liu Xiuzhen, 1987. *Methods of Phenological Observation of China*. Beijing: Science Press. (in Chinese)

White M A, Thornton P E, Running S W, 1997. A continental phenology model for monitoring vegetation responses to inter-annual climatic variability. *Global Biogeochemical Cycles*, 11(2): 217–234. doi: 0886-6236/97/97GB-OO330

Wu Yongfeng, Li Maosong, Li Jing, 2008. Research on a detection nethod of Chinese terrestrial vegetation greenness periods based on remote sensing. *Journal of Remote Sensing*, 12(1): 93–103. (in Chinese)

Yu Xinfang, Zhuang Dafang, 2006. Monitoring forest phenophases of Northeast China based on MODIS NDVI data. *Resources Science*, 28(4): 111–117. (in Chinese)

Zhang X Y, Fried M A, Schaaf C B *et al*., 2003. Monitoring vegetation phenology using MODIS. *Remote Sensing of Environment*, 84(3): 471–475. doi: 10.1016/S0034-4257(02)00135-9

Zhang X Y, Friedl M A, Schaaf C B *et al*., 2004. Climate controls on vegetation phenological patterns in northern mid- and high latitudes inferred from MODIS data. *Global Change Biology*, 10(7): 1133–1145. doi: 10.1111/j.1365-2486.2004.00784.x