

## Research Article

### Scale Transformation of Forest Vegetation Coverage Based on Landsat TM and SPOT 5 Remote Sense Images Data

<sup>1,2</sup>Li Hongzhi, <sup>1</sup>Zhang Xiaoli, <sup>1</sup>Wang Shuhan, <sup>3</sup>Dong Sujing and <sup>1</sup>Li Liangcai

<sup>1</sup>Key Laboratory for Silviculture and Conservation of Ministry of Education, Beijing Forestry University, Beijing 100083, P.R. China

<sup>2</sup>Zhangjiakou Saibei Tree Farm, Zhangjiakou 075000, P.R. China

<sup>3</sup>Zhangjiakou Seed and Seedling Management Station, Zhangjiakou 075000, P.R. China

**Abstract:** Landsat TM and SPOT 5 data are the most popular remote sense data in forest resource monitoring, though, both have advantages and disadvantages. Landsat TM images contain large scale, but with low accuracy; while high resolution Spot 5 images have high accuracy and small scale. We could combine the merits of accuracy and scale by scaling method in the study of forest vegetation cover. Hence, we use Landsat TM and SPOT 5 data to monitor the vegetation cover of three forest types (coniferous forest, broad-leaved forest mixed coniferous and broad-leaved forest) locating around Miyun reservoir in Miyun County in Beijing. These two different resolution images were scaled up by using mathematical statistics and modified the vegetation cover extracted from Landsat TM image by using scale conversion model. Upon testing, SPOT 5 images were used to resolve elements of Landsat TM images. We obtain statistic model from statistic results and information extracted from Landsat TM image. Statistic model may efficiently improve the accuracy of vegetation cover in Landsat TM image. In conclusion, basing on SPOT 5 and Landsat TM data, the scale conversion model has better performance. Combining element resolution and statistic model, we could apply high spatial resolution image to improve information accuracy of low spatial resolution image.

**Keywords:** Element resolution, landsat TM, NDVI, scale conversion model, SPOT 5, vegetation cover

## INTRODUCTION

With the development of earth observation techniques, scale transformation has been a hot research area for years (Meng and Wang, 2005; Peng *et al.*, 2004; Buhe *et al.*, 2004; Li *et al.*, 2004; Liang *et al.*, 2009; Fang *et al.*, 1998). As the largest terrestrial ecosystem, forest represents the hierarchy organization with multi-scale. Multi-Scale is the essential feature in forestry Remote Sensing (RS) data as well. Forestry RS data are multi-resolution from meters to kilometers, which could represent forest vegetation from multispatial and temporal scale. Different scale forestry RS data contains forestry resource detail in different levels. MODIS data are applied widely in larger scale monitoring. Landsat TM and SPOT 5 are more popular in mesoscale and small scale, respectively. Extracting specific information from RS data at different scales is the major application in forestry monitoring.

Since forest vegetation RS information is multi spatial resolution, it should ensure effective spatial scale to describe forestry vegetation by using RS data (Liu and Fan, 2004). Meso-resolution RS data can show

the macro-feature of the surface. However, high-resolution data could show the surface information in detail. Without enough macro-feature, high resolution is barely satisfactory in parameters inversion (Zhong and Zhang, 2008). Therefore, more attentions have been paid on how to combine different spatial resolution RS data (Yang *et al.*, 2006). Since late 1970s, scale transformation has been given to solve the problems discussed above. Using scale transformation technique, researchers aimed to gain high-resolution information on large spatial scales. Qi *et al.* (2000) extracted bush and grass vegetation coverage of Santiago River basin from aerial photo, Landsat TM image and SPOT image respectively. Li *et al.* (2003) estimated the vegetation coverage of Chinese North typical prairie by using community plots data, digital camera data, ETM+ and NOAA images data. ETM+ data were applicable to improve the accuracy of forestry information extracted from NOV (Li *et al.*, 2003). Mayaux and Lambin (1995) used four spatial indexes to correct relationship between Landsat TM and AVHRR data He applied two-step conversion methodsto achieve scaling transformation of vegetation. Kevin *et al.* (2005)

**Corresponding Author:** Zhang Xiaoli, Key Laboratory for Silviculture and Conservation of Ministry of Education, Beijing Forestry University, Beijing 100083, P.R. China

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compared NDVI differences in NOAA and MODIS and the relation models for farmlands, pastures, evergreen broad-leaf forests, shrub and cities. Zhong and Zhang (2008) applied NDVI pixel decomposition method to transferred scale on LAI inverted from Landsat TM/ETM+. Zhang *et al.* (2009) used NDVI from NOAA and MODIS data to establish the precision verification. Li and Pan (2010) used MODIS and CBERS image data to calculate coefficient between farmlands and correct interpretation area of MODIS images. As a method of information aggregation, upper spatial scale relates the process of transformation from small spatial scale information to large spatial scales. Because the aim of upper scale transformation in RS is to ensure the land surface information from coarse space resolution RS data is equal to that from high space resolution RS data (Jin, 2004; Zeng, 2011). The optimal upper scale transformation method should keep internal information in the high-resolution data after

converting information from high-resolution RS image onto low-resolution RS images.

In our study we use forestry land data (including coniferous forest, broad-leaved forest and mixed coniferous and broad-leaved forest) from Landsat TM and Spot 5 image in Miyun reservoir in Beijing. Statistical method was utilized for Landsat TM and Spot 5 imagery to transfer scale. Landsat TM images pixels were decomposed by SPOT 5 data. Based on the correlation of NDVI of two images, spatial linear scaling model was established between two images to obtain the scale expansion from SPOT 5 to Landsat TM images. Our aim goes to extract coverage information in different forest vegetation types from Landsat TM images.

**Research area:** MiYun county (116°39'33"~117°30'25"E, 40°13'7"~40°47'57"N) is in northeast of Beijing, locating in the Yanshan Mountains and transition zone of the North China plain and Inner

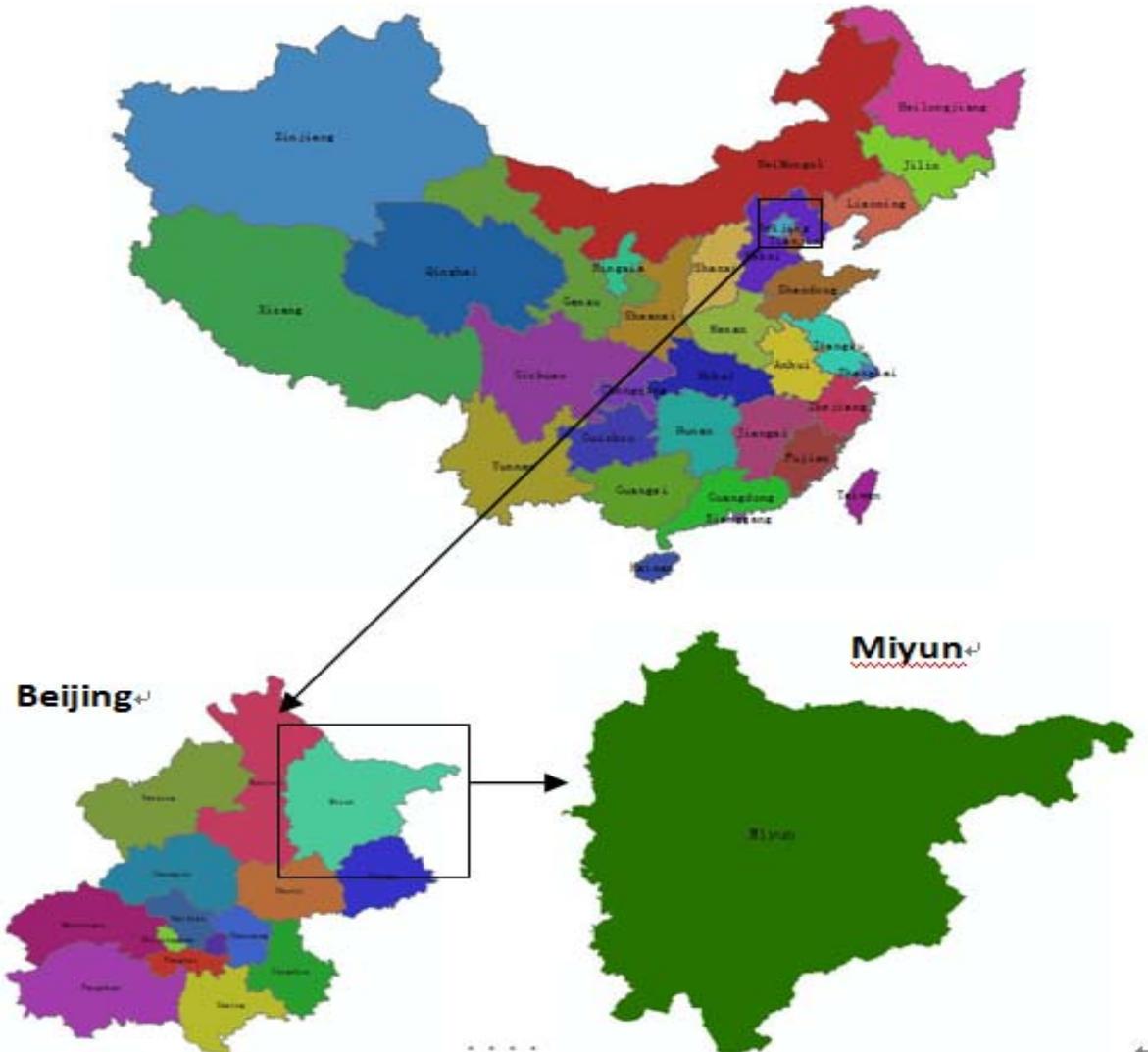


Fig. 1: Location of study area

Mongolia plateau. Elevation is from 45 to 100 m. It is temperate continental monsoon with semi-humid and semi-arid climate. Average annual precipitation is 660 mm and the average annual evaporation is 1783.2 mm. The average annual temperature is 10.9°C and annual sunshine time is 2802~2842 h. Frost-free period is from 183 to 186 days and stable ground freezing depth is from 40 to 70 cm. 93% county land was covered by brown soil. For soil nutrients, N and P are deficient, but K is surplus. Miyun Reservoir with rich water resources, which is the largest reservoir in North China, located in the county center. Miyun County has some mixed coniferous and broad-leaved forest types in different succession process. Natural secondary forest is mainly distributed in low position with less anthropogenic activities. The major tree species are aspen (*Populus davidiana*), Mongolian oak (*Quercus mongolica*) and linden (*Tilia tuan*). Artificial forest mainly include Chinese pine (*Pinus tabulaeformis*), orientalarborvitae (*Platycladus orientalis*), black locust (*Robinia pseudoacacia*), North China larch (*Larix principis-rupprechtii*) and chestnut (*Castanea mollissima*) etc., (Fig. 1).

#### DATA AND PREPROCESSING

**RS data:** SPOT 5 image RS data on June 5<sup>th</sup> 2004 and Landsat TM images on October 4<sup>th</sup> 2010 were downloaded from International Science Data Services Platform. The study mainly applied red and infrared band of SPOT 5 with 10 m resolution and Landsat TM with 30 m resolution. Atmospheric correction and geometric precision correction was made before data analysis.

**Atmospheric corrections:** The ENVI FLAASH was applicable to SPOT 5 and Landsat TM images for atmospheric correction:

- Using header information of image itself, DN value of pixels was transformed into radiation.
- FLAASH atmospheric correction was finished by imputing the sensor type, date and imaging time, solar azimuth, solar elevation and latitude and longitude information in the header file. The spectral curve after and before FLAASH is showed in Fig. 2 and 3, respectively.

**Geometric corrections:** Using orthorectified SPOT 5 multispectral images as a reference image, the Landsat TM and SPOT 5 image matched and the registration error controlled within 0.5 pixels.

**NDVI calculated from two images:** NDVI was calculated by using Eq. (1):

$$NDVI = (NIR - R) / (NIR + R) \quad (1)$$

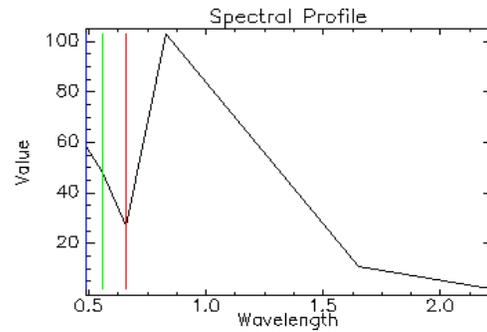


Fig. 2: Spectral curve of landsat TM image FLAASH atmospheric correction before

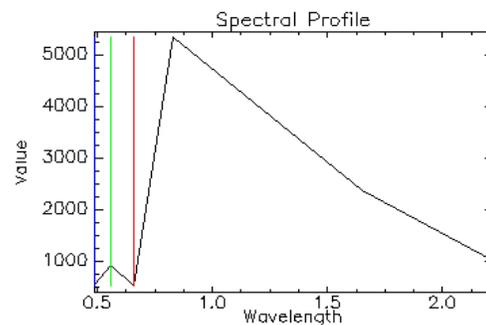


Fig. 3: Spectral curve of landsat TM image FLAASH atmospheric correction after

**Forest resource inventory vector:** Vector projection which created from Miyun county of Beijing Forest Resource Inventory Data (namely, the second type data) was changed to be compatible with the RS data. The coniferous forest, broad-leaved forest, mixed coniferous and broad-leaved forest-vegetation was used to obtain vegetation vector boundary map. Landsat TM and SPOT NDVI images were cut NDVI image maps by using vegetation vector boundary map.

#### RESEARCH METHODOLOGY

**Vegetation coverage:** Vegetation coverage is the proportion of vegetation vertical projection area to the surface area. It is a very important parameter of land surface vegetation and an indicator of ecosystem change (Zhang *et al.*, 2003). Vegetation coverage could gain from RS by empirical models, regression models, vegetation index and sub-pixel decomposition (Zhang *et al.*, 2003; Xing *et al.*, 2009; Ma *et al.*, 2007). Empirical models normally establish the model between vegetation index and field data and then extend to a large area to calculate vegetation coverage (Duncan *et al.*, 1993; Yang, 2000). Regression model method, which is widely used in recent studies, could combine bands of RS data with the vegetation coverage to establish empirical model. However, empirical model can get higher accuracy for specific vegetation (Xing

Table 1: NDVI value from the data obtained with two different sensors over the three vegetation coverage types

Vegetation types	Remote sensing image	NDVI threshold range
Coniferous forest	Landsat TM	0.006979-0.893507
	SPOT5	0.001559-0.855638
Broad leaved forest	Landsat TM	0.005404-0.945074
	SPOT5	0.010868-0.874007
Mixed coniferous and broad-leaved forest	Landsat TM	0.001067-0.945074
	SPOT5	0.002857-0.865356

et al., 2009). Vegetation index method is based on the analysis of vegetation spectral information to select vegetation index, which has better relationships with vegetation coverage. By establishing conversion relationship with vegetation coverage, the vegetation coverage was calculated (Yang et al., 2006; Larsson, 1993; Purevdor et al., 1998). Sub-pixel decomposition method is utilized to RS images with mixed pixels. According to the distribution of vegetation in different sup-pixel, the sub-pixel is divided into sub pixel and mixed sub-pixel, then subdividing the mixed sub-pixel and finally establishing different vegetation cover models (Gutman and Ignalov, 1998). NDVI, which is most widely used as a vegetation index, contain visible and near infrared bands. Vegetation index method is more common than a regression model; it can be extended to wider areas to generalize vegetation coverage models.

Based on the difference of spatial resolution of two kinds of Landsat TM and SPOT 5 RS data, we utilize vegetation index model to calculate vegetation coverage. Each pixel can be decomposed into pure vegetation and pure soil spectral information (such as NDVI, the value is  $N_{NDVI}$ ). According to the linear combination rule of the two pure components by area weighted Eq. (2), vegetation percentage of vegetation coverage could be defined as the area percentage of pure vegetation in the study area Eq. (3) (Ma et al., 2012; Guan and Liu, 2007; Zhang, 1996):

$$N_{NDVI} = N_{NDVIsoil} * (1 - f_{veg}) + N_{NDVIveg} * f_{veg} \quad (2)$$

$$f_{veg} = (N_{NDVI} - N_{NDVIsoil}) / (N_{NDVIveg} - N_{NDVIsoil}) \quad (3)$$

$f_{veg}$  is vegetation coverage;  $N_{NDVI}$ ,  $N_{NDVIsoil}$  and  $N_{NDVIveg}$  represent the NDVI value of any pixels, pure soil pixels and pure vegetation pixels, respectively. In the actual application,  $N_{NDVIsoil}$  is the minimum of NDVI and  $N_{NDVIveg}$  is the maximum of NDVI.

In our study, coniferous forest, broad-leaved forest, mixed coniferous and broad-leaved forest was chosen. Vegetation types were extracted from two RS images NDVI after preprocessing basing on Eq. (1). We estimated NDVI threshold value for different vegetation types from two RS data (Table 1) and then put the maximum NDVI into  $N_{NDVIveg}$  and put the minimum of NDVI into  $N_{NDVIsoil}$  in the Eq. (2). Finally, the vegetation coverage was based on two RS data.

**Landsat TM correction method to extract vegetation coverage:** Different heights of satellites and sensors could result in the distinctive accuracy of vegetation coverage from RS data with different resolution. High resolution images get higher accuracy of vegetation coverage (Niu et al., 2005). Because one pixel from high resolution RS data represent small area, the NDVI threshold value extracted from pixels is close to pixels with full coverage of one vegetation type. Therefore, putting the threshold value into the Eq. (3) to obtain the vegetation coverage is more feasible. In the process of amending vegetation coverage extracted from Landsat TM images, mathematical statistics scaling transformation method were used and the relationship between vegetation coverage and NDVI in SPOT 5 and Landsat IM images should be considered. After modifying Landsat TM images by using the statistical model, extraction accuracy of vegetation coverage can be improved. Random sampling method was followed in the two RS images of vegetation types. The specific method is as follows:

- Seventy two samples with size of 30\*30 m to one pixel were used each vegetation types in Landsat TM and nine pixels in SPOT 5 image.
- NDVI value is estimated for each sample (Landsat TM, one pixel; SPOT 5, average value of nine pixels).
- NDVI data were transformed into the vegetation coverage. Linear relationship could be set up from scatter plot. Selecting two-thirds of the samples to establish a linear regression model and the left one-third sample data were to test the accuracy of the linear model.

## ESTABLISHMENT AND VALIDATION OF THE MODEL

**Establish the statistical model:** Using SPOT 5 images to decompose Landsat TM image, each vegetation cover types correspond to one pixel from decomposition. A linear regression model was developed by vegetation coverage extracted from Landsat TM and SPOT 5 images. Determination coefficients are given in Fig. 4 to 6.

Figure 4 to 6 shows the vegetation converges extracted from Landsat TM have linear correlation with SPOT 5. Coniferous forests fitting equation

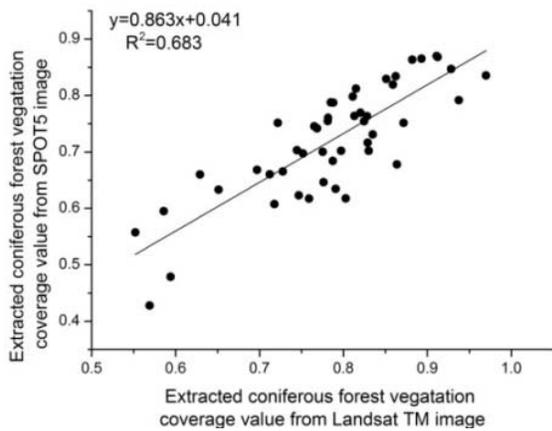


Fig. 4: Statistic fit model of coniferous forest vegetation fractional coverage

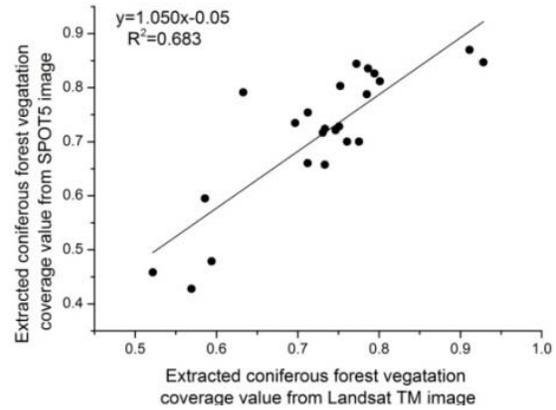


Fig. 7: Test model of coniferous forest vegetation coverage

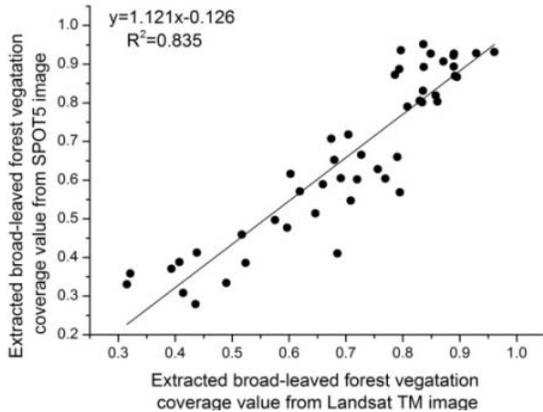


Fig. 5: Statistic fit model of broad-leaved forest vegetation fractional coverage

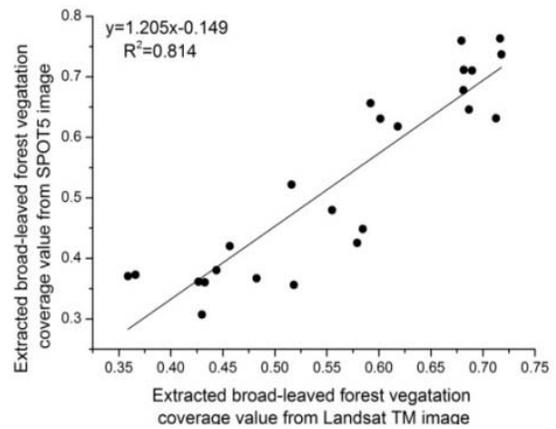


Fig. 8: Test model of broad-leaved forest vegetation coverage

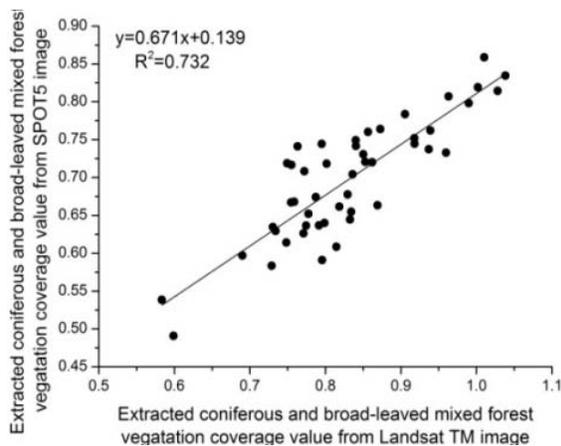


Fig. 6: Statistic fit model of mixed coniferous and broad-leaved forest vegetation fractional coverage

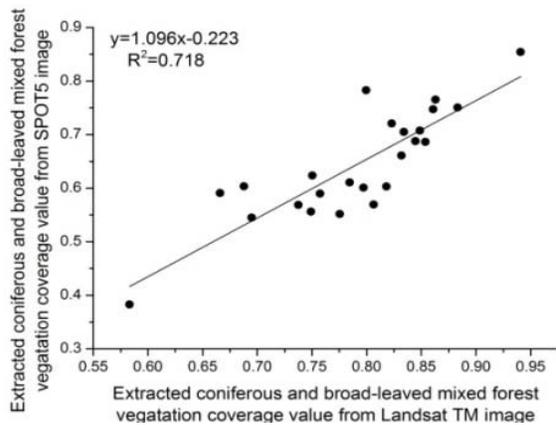


Fig. 9: Test model of mixed coniferous and broad-leaved forest vegetation coverage

$y = 0.863x + 0.041$ , coefficient of determination was  $R^2 = 0.683$ ; broad-leaved forest fitting equation  $y = 1.121x - 0.126$ , coefficient of determination was  $R^2 = 0.835$ ; coniferous and broad-leaved mixed forest

fitting equation  $y = 0.671x + 0.139$ , coefficient of determination was  $R^2 = 0.732$ . It is suggested that vegetation coverage from Landsat TM images can be scaled up by SPOT 5 images.

**Model validation:** To verify the reliability and stability of the fitted model, one third of the sample data was

selected. Comparison and discussion on the relationship between the predicted value and the actual value are necessary.

Figure 7 to 9 show that vegetation coverage extracted from Landsat TM correlated well with that extracted from SPOT 5 images, where coniferous forest fitting equation for  $y = 1.05x - 0.05$ , the coefficient of determination  $R^2 = 0.683$ ; broad-leaved forest fitting equation  $y = 1.205x - 0.149$ , coefficient of determination was  $R^2 = 0.814$ ; Mixed coniferous and broad-leaved forest fitting equation  $y = 1.096x - 0.223$ , coefficient of determination was  $R^2 = 0.718$ .

**Statistical models of vegetation coverage:** According to the principle of the pixel decomposition, vegetation coverage which derived from Landsat TM NDVI Eq. (3) is an independent variable. Each vegetation type was imported into its statistical model (Fig. 4 to 6) to get TM vegetation coverage. Thus, the application of Landsat TM to Eq. (3) could rule out. According to the statistical model, the relationship between the NDVI of Landsat TM and vegetation coverage of SPOT5 was established (Table 2). As a result, revised vegetation coverage is the dependent variable  $y$  and NDVI is independent variable  $x$ .

### RESULTS AND ASSESSMENT

According to vegetation coverage of three forest types, the converge degree is classified isometrically into ten classes, (10, 20, 30, 40, 50, 60, 70, 80, 90 and

100%, which are corresponding to 1, 2, 3, 4, 5, 6, 7, 8, 9 and 10 level, respectively). Figure 10a is the vegetation coverage degree of SPOT 5, Fig. 10b is vegetation coverage degree map of Landsat TM before revising. Figure 10c is vegetation coverage degree map of Landsat TM after amending. Figure 10a, b to 13a, b show the strong consistency between vegetation coverage of SPOT 5 images and Landsat TM. Part C in Fig. 10 to 13 is the revision of the figure a has scale transition from a high-resolution of SPOT 5 to medium-resolution of Landsat TM. Considering the determination coefficient of linear model and the classification map, the vegetation coverage grade of three forest types in SPOT 5 and Landsat TM are consistent with the order of determination coefficient (coniferous forest (0.683) < coniferous and broad-leaved mixed forest (0.732) < broad-leaved forest (0.835), Which indicate our scaling model is feasible.

### DISCUSSION AND CONCLUSION

Figure 4 to 6 showed that all slope of linear relationship is not 1, it means the scale extension from 10 m resolution of SPOT 5 NDVI to 30 m resolution of Landsat TM NDVI is not the same. However, the relationship of vegetation coverage in Landsat TM and in the SPOT image is very close. In our study, SPOT 5 images are applied for pixel decomposition, then sample mean from SPOT 5 and corresponding sample from Landsat TM were chosen to establish model. This method could effectively improve the accuracy of forest

Table 2: Statistic models of three vegetation types

Vegetation types	Statistical model/NDVI as the independent variable
Coniferous forest	$y = 1.0477NDVI - 0.0321$
Broad-leaved forest	$y = 1.1938NDVI - 0.1325$
Coniferous and broad-leaved mixed forest	$y = 0.7108NDVI + 0.1389$

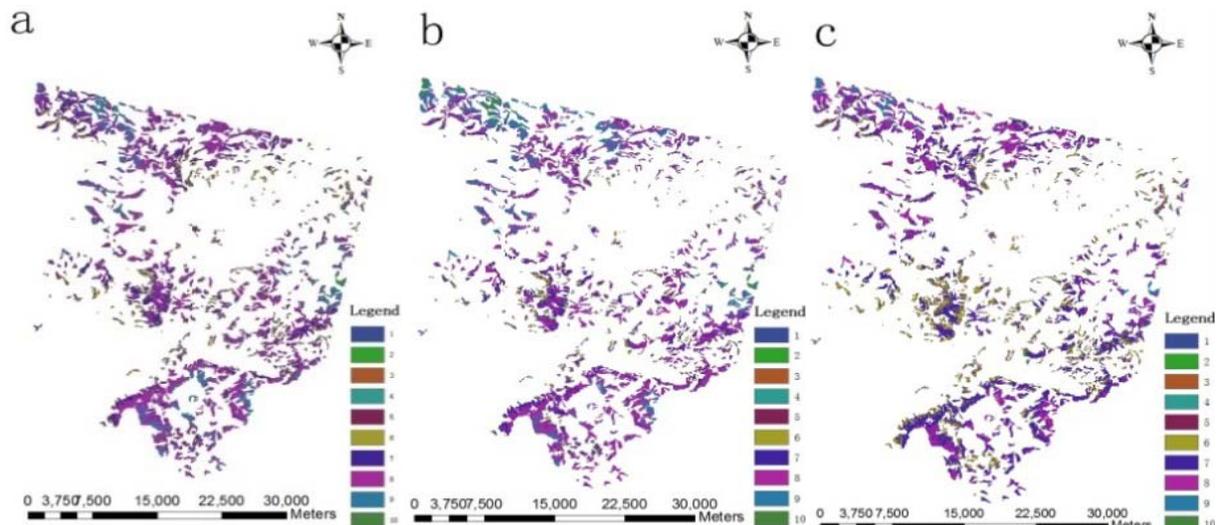


Fig. 10: Coniferous forest vegetation coverage

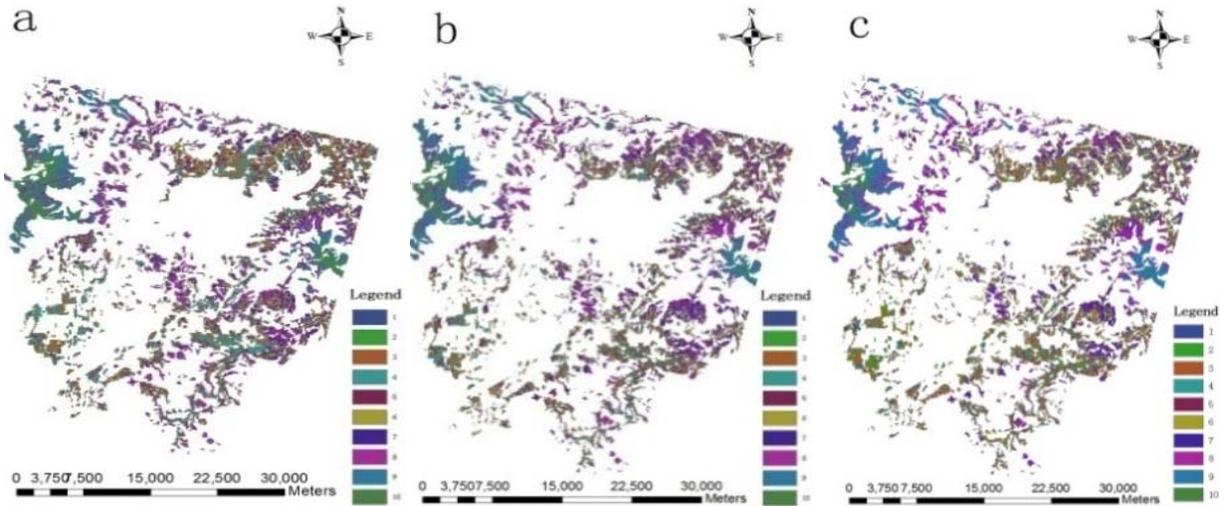


Fig. 11: Broad-leaved forest vegetation coverage

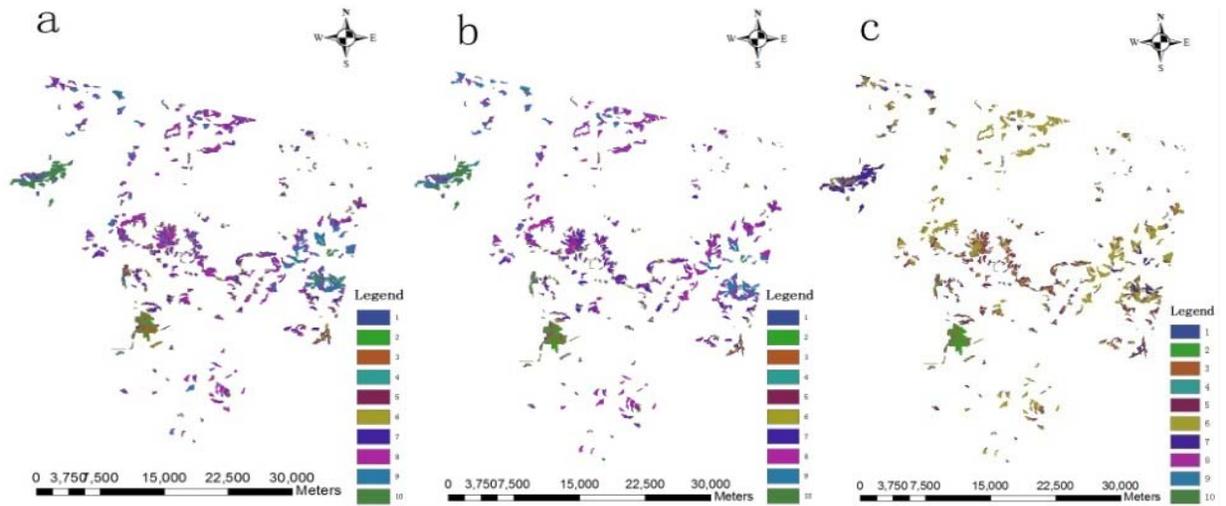


Fig. 12: Coniferous and broad-leaved mixed forest vegetation coverage

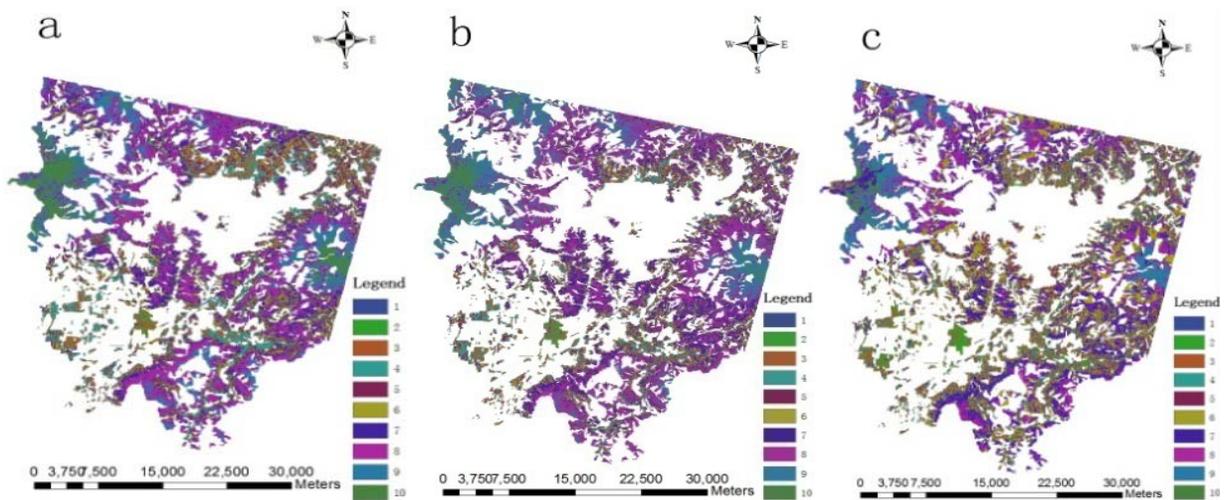


Fig. 13: Three types of vegetation coverage

vegetation coverage monitoring based on Landsat TM images. In other side, if there are no proper high-resolution RS images, Landsat TM images could be used by applying our method to estimate vegetation coverage more accurately on a large spatial scale.

There is the inaccuracy existing in vegetation coverage model, more work has to do to reduce the inaccuracy coming from inter-sensor RS data, surface heterogeneity, a geometric precision correction, changes in surface feature of different periods, atmospheric factors. In addition, the predict value will come closer to the actual value, if field survey is conducted to gain NDVI<sub>soil</sub> and NDVI<sub>veg</sub>.

#### ACKNOWLEDGMENT

This research was supported by Beijing City Department of education of forest cultivation and protection of building the Province Ministry Key Laboratory Project (2009GJSYS02); Ministry of education supported by the specialized research fund for the doctoral program of Higher Education (20100014110002) to Zhang Xiaoli. I am grateful for the help of Yang Junlong, Wang Shuhan in the revising, polish, translation and other aspects.

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