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Article

Estimation of Forest Stand Parameters Using SPOT-5 Satellite Images and Topographic Information

Shiqin Xie[1,†,*], Wei Wang[2,†,*] , and Qian liu[2], Jinghui Meng[3], Tianzhong Zhao[1],Guosheng Huang[2]

[1] Institute of Information, Beijing Forestry University, Beijing 100083, China; E-Mails: shiqinxie@126.com(S.X.); tianzhongzhao@126.com(T.Z.)

[2] Survey & Planning Institute of State Forestry Administration, Beijing 100714, China; E-Mails: didiwangwei1981@163.com(W.W.);liuqian2@yahoo.com(Q.L.);guosheng.huang@263.net (G.H.)

[3] Key Laboratory for Silviculture and Conservation of Ministry of Education, Beijing Forestry University, Beijing 100083, China; E-Mail: Jmeng@bjfu.edu.cn

[*] Author to whom correspondence should be addressed; E-Mail: shiqinxie@126.com (S.X.); didiwangwei1981@163.com(W.W.);Tel.:+86-010-6233-8133(S.X.);Tel.:+86-010-6288-9094(W.W.)

[†] These authors contributed equally to this work.

Abstract: In recent years, remote sensing technology has been widely used to predict forest stand parameters. In order to compare the effects of different features of remote sensing images and topographic information on the prediction of forest stand parameters, multivariate stepwise regression analysis method was used to build estimation models for important forest stand parameters by using textural and spectral features as well as topographic information of SPOT-5 satellite images in northeastern Heilongjiang Province in China as independent variables. The study results show that the optimal window to predict forest stand parameters using textural features of SPOT-5 satellite image is 9×9; the ability of textural features was better than that of spectral features in terms of predicting forest stand parameters; with the inclusion of topographic information, the accuracy of prediction of all models was improved, of which elevation has the most significant effect. The highest accuracy was achieved when predicting the stand volume (SV) (R^2_{adj}=0.820), followed by basal area (BA) (R^2_{adj} =0.778), accuracy of both above models exceeded 75%. The results show that models combined use of textural, spectral features and topographic information of SPOT-5 images have a good application prospect in predicting forest stand parameters.

Keywords: forest stand parameters; SPOT-5 satellite image; textural and spectral features; topographic information; estimation model

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1. Introduction

Forests are the largest terrestrial ecosystems and carbon pool, providing us with ecological services and play a significant role in bringing us with economic benefits[1]. However, in recent years, with the rapid population growth and economic development, global forests are facing a series of threats, including sharp reduction in forest area, degradation in ecological functions and loss of biodiversity[2,3]. Forest resource survey and monitoring are significantly important to study and combat climate change, environmental damage and ecological degradation.

The forest resources monitoring in China has been developing towards large-area, large-scale and short intervals. The traditional approaches to forest resources monitoring are mostly based on time-consuming and laborious field measurements, which are not conducive to large-area or large-

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scale data acquisition, and cannot meet forestry production and ecological construction needs of the time[4,5]. With the advantages of that information can be collected quicker over larger geographical areas at relatively lower costs , remote sensing technology has been widely used in the extraction of forest composition and structural parameters, providing a strong technical support for forest resources monitoring[6-8].

In recent years, using the strong correlation between remote sensing images and forest stand attributes to estimate forest stand parameters has become a hot research area, and most studies have achieved satisfied results[7-9]. At present, these studies mainly focus on using RS image texture and texture derived index[10], spectral features and spectral derivative index[11,12] to estimate tree height[13], basal area[14], stand volume[15], biomass[7] and other forest stand parameters. However, due to wavy terrain, canopy shadows, heterogeneity of forest stand structure and other issues, the quantitative analysis of remote sensing images is heavily affected. To solely rely on remote sensing image to establish estimation models of forest stand parameters has its constrains on accuracy and applicability, etc., which limits the application of the model in large-area and large-scale forest resource monitoring[16]. Related study shows that topographic information is very important for estimating forest stand parameters by using remote sensing images. For instance, Wang et al.[17] estimated the forest stand volume by combining spectral features of ZiYuan 3(ZY-3) image with topographic information, and achieved favorable results; Hilbert and Schmullius[18] found that slope has significant effect on the estimation of tree height by using Pol-InSAR data. However, the influence of topographic factors on the model needs further study when using different remote sensing image features and topographic information to estimate different forest parameters.

In this study, we combined textural and spectral features of SPOT-5 remote sensing images with topographic information of the study area (such as elevation, slope, slope aspect, slope position, etc.) to estimate forest stand parameters, including the number of trees (NT), basal area (BA), tree canopy cover (TCC) and stand volume (SV). Three models were established to predict forest stand parameters, including model only using textural features, model using both textural and spectral features and model combined using textural, spectral features and topographic information. The optimal forest stand parameter prediction model was selected. In the end, the selected prediction model is used to produce forest stand parameters thematic maps of the study area.

2. Materials and Methods

2.1. Study area

The study area is located in the northeastern part of Heilongjiang Province, China, mainly covering Hegang City of Heilongjiang Province and some surrounding counties (Figure 1). The study area is situated in the transitional zone of the Xiaoxinganling to the Sanjiang Plain, covering a total area of 14,784 km^2, which has a temperate continental monsoon climate. The annual average temperature is 2.8℃ and the average precipitation is about 640 mm. The elevation is between 52-1,022m, decreasing from the northwest with low-mountain and hilly areas, to the southeast which is predominately plains. Hegang City is rich in forest resources, with forest area of 851,000ha, forest stand volume of 56,100,000 m^3, forest coverage rate of 58%. Forest type and composition is diverse, with rich tree species, including red pine, white pine, water willow, amurcork-tree, birch, oak and so on.

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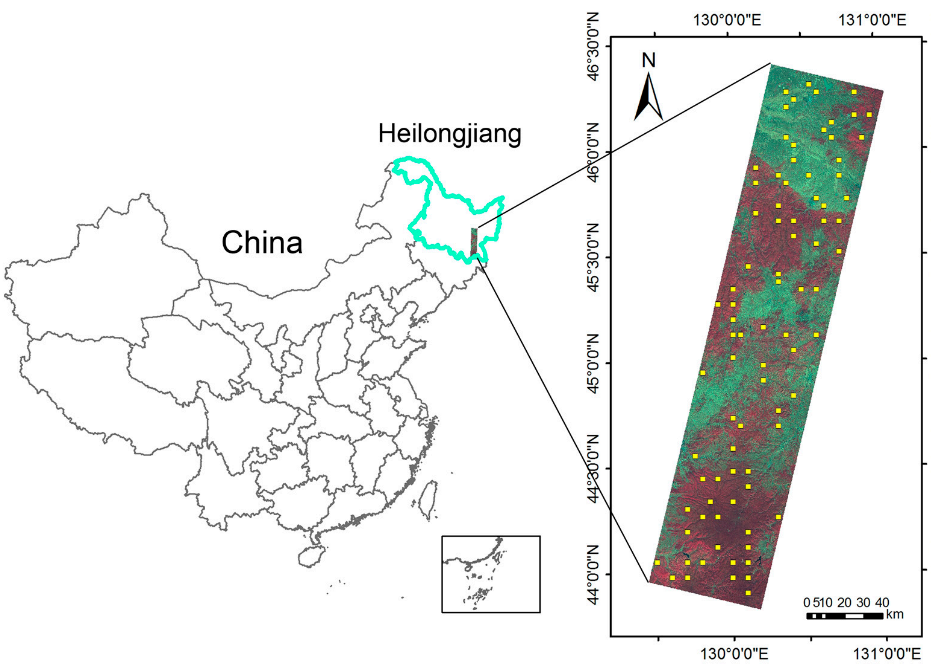

Figure 1. Overview and zoomed map of the study area. The zoomed maps consist of four SPOT-5 image footprints with sample plots.

2.2. Data source

2.2.1. Remote sensing data

The remote sensing data used in this study are SPOT-5 images of panchromatic image at a resolution of 2.5m and multi-spectral images at a resolution of 10m. The multi-spectral image consists of near infrared (0.78-0.89um), red (0.61-0.68um), green (0.50-0.59um) and shortwave infrared (1.58-1.75um) band. In this study, a total of 4 scenes of SPOT-5 images are used covering Hegang City. All images were taken on 21 September 2006. The pre-process of SPOT-5 images mainly includes: firstly, convert the image DN value to the surface true reflectivity value by using radiometric calibration and FLAASH atmospheric correction ,and then orthorectification of images based on the 1: 10000 topographic map of study area combining with DEM data (source: Academy of Forest Inventory and Planning, State Forestry Administration), to ensure the pixel positioning errors of four images are limited to the sub-pixel level after orthographic correction.

2.2.2. Sample plots field data in the study area

The sample plots field data of Heilongjiang Province during the eighth national forest resource inventory in 2005 was used in this study. Each plot was systematically sampled with fixed size of 0.067 ha, distributed in a 4 × 6 km grid. In total, 60 sample plots within the study area were used for model estimation, of which 45 sample plots were employed in model construction and the remaining 15 sample plots were used for accuracy evaluation. In this study, the forest stand parameters of each

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sample plot were calculated by using forest resource inventory data, including number of trees (NT), basal area (BA), tree canopy cover (TCC) and stand volume (SV). The above four traditional forest stand parameters selected in this study reflect the basic information of forest structure and can provide the theoretical basis for forest management decision-making.

2.3. Extraction of imagery features and topographic information

2.3.1.Textural features of images

As important features of remote sensing images, textural features reveal the structural arrangement of surfaces and their relationship with the surrounding environment, which are helpful to improve the accuracy of image interpretation and feature extraction[19,20]. Some studies show that favorable experimental results have obtained by using textural features of panchromatic images in forest composition and structural analysis[21-23]. In this study, the widely used GLCM method (Gray level co-occurrence matrix) was used to extract the eight most commonly used textural features of SPOT-5 panchromatic image[24], as shown in Table 2, the eight features are Mean, Variance, Homogeneity, Contrast, Dissimilarity, Entropy, Second Moment and Correlation. Textural features were extracted from six different size of window namely, 3 × 3, 5 × 5, 7 × 7, 9 × 9, 11 × 11 and 13 × 13, respectively. The effects of different window sizes on the estimation of forest stand parameters were analyzed.

2.3.2. Spectral features of images

The vegetation index extracted from the remote sensing image by using spectral information can better reflect the vegetation type, growth and spatial distribution of green plants, and is widely used in the estimation of forest structure parameters[25]. Based on previous studies, the spectral band value and the multi-band combination value were extracted for the estimation of the forest stand parameters in this study: 1) The spectral band values are specified as B1, B2, B3 and B4, for near infrared (NIR), red (RED), green (GREEN) and shortwave infrared (SWIR) band respectively; 2) The combination values of different spectral bands refer to normalized difference vegetation Index (NDVI)[26], simple ratio vegetation index (SR)[27], red/green ratio index (GR)[28], green/red ratio index (VI)[29], soil adjusted vegetation index (SAVI)[30], Global Environmental Monitoring Index (GEMI)[31], calculated as Table 1.

Table 1. descriptions and formulas of spectral factors of images

Factors	Description	Formula
NDVI	Sensitive to green vegetation, can be used for detection of vegetation growth status, vegetation coverage and elimination of partial radiation errors.	NDVI=(NIR-RED)/(NIR+RED)
SR	Very sensitive to vegetation coverage, can be used for detection of plant biomass.	SR=NIR/RED
GR	Can estimate growing process of vegetation canopy, can be used for plant growth cycle research and crop yield estimation.	GR=NIR/GREEN
VI	Reflect spectral information of vegetation and soil, can be used for identification and growth prediction of crops.	VI=GREEN/RED

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SAVI	Can explain the change of optical characteristics and adjust the sensitivity of vegetation index to soil background.	SAVI=(NIR-RED)/(NIR+RED+L)
GEMI	Can eliminate bad atmospheric disturbance, keep concerned vegetation cover information.	GEMI=[η(1-0.25η)-(RED-0.125)]/(1-RED), η=[2((NIR)^2-(RED)^2)+1.5NIR+0.5RED]/(NIR+RED+0.5)

2.3.3. Topographic information

In this study, the topographic information such as elevation, slope, slope aspect and slope position of sample plots was extracted based on the digital elevation model (DEM) of the study area (data source: Academy of Forest Inventory and Planning, State Forestry Administration) .

2.4. Model establishment and verification

Studies show some disadvantages of general multiple linear regression method lead the poor model stability[32,33]. Those disadvantages include multicollinearity occurs among the independent variables, and the change of samples easily leads to the deviation of estimation result from the measured value. Multivariate stepwise regression analysis can be used to solve above problems to a certain extent and is widely used in the inversion experiment of forest stand parameter model[34,35]. In this study, multivariate stepwise regression analysis was used to build regression model by using textural, spectral features and topographic information extracted from SPOT-5 images as independent variables, and forest stand parameters (number of trees (NT), basal area (BA), tree canopy cover (TCC), stand volume (SV)) as the dependent variables; results of three forest stand parameters prediction models were compared which are respectively based on textural features, based on both textural and spectral features, combined use of textural and spectral features and topographic information. To avoid multicollinearity in independent variables, tolerance and variance inflation factor (VIF) were used as the criteria for model screening, of which the tolerance should be greater than 0.1 and VIF should be less than 10[36]. R^2_{adj} and root mean square error (RMSE) were used to evaluate the models. In addition, the model was verified by sample plots of estimated value and the actual value. Two statistics including R^2 and RMSE were used for verification.

3. Results

3.1. Regression model using textural features

We firstly used the multivariate stepwise regression analysis method to establish the prediction model, using textural features extracted from six windows. Change of R^2_{adj} (Figure. 2) using textural features extracted from different windows shows a parabolic trend along with growth size of the window, and most models' R^2_{adj} reached to the maximum in the 9 × 9 window. Therefore, the textural feature based on 9 × 9 window was selected for model prediction test. In addition, prediction results of forest stand parameters model by using textural features extracted from 9× 9 window show that the textural features of SPOT-5 images are highly correlated with the forest stand parameters, and the maximum predicted R^2_{adj} is in basal area (BA) model (R^2_{adj} = 0.449), followed by the stand volume (SV) model (R^2_{adj} = 0.423). Those two models contain same textural variables, namely Mean and Correlation.

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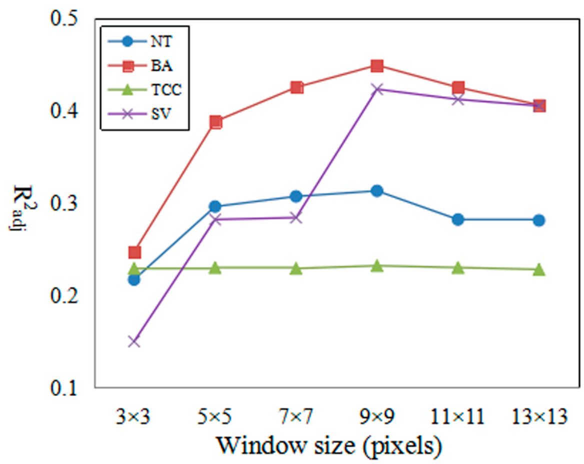

Figure 2. R^2_{adj} of forest stand parameters models based on textural feature, as a function of window size

Table 2. Regression model predicting forest stand parameters using textural features based on 9 × 9 window

Forest stand parameters	Prediction model	R^2_{adj}	RMSE	p
Number of trees (NT)	NT=2456.552-1014.120*Entropy	0.313	474.315	0.001
Basal area (BA) (m^2/ha)	BA=27.156+0.616*Correlation-4.095*Mean	0.449	5.954	0.000
Tree canopy cover (TCC)	TCC=82.799-61.342*Contrast	0.232	13.221	0.001
Stand volume (SV) (m^3/ha)	SV=232.215-37.448*Mean+3.366*Correlation	0.423	43.765	0.000

3.2. Regression model using both textural and spectral features

As for models predicting forest stand variables using both textural and spectral features, the results (Table 3) show that the spectral feature of SPOT-5 images were highly correlated with the forest stand variables. After introducing the spectral features, accuracy of most prediction models was improved except the number of trees. The R^2_{adj} of model predicting basal area was the greatest (R^2_{adj} = 0.732), followed by models to predicting stand volume (SV) and tree canopy cover (TCC). Among all the spectral variables introduced, NDVI was involved in most models, including basal area and stand volume prediction models.

Table 3. Regression model predicting forest stand parameters using both textural and spectral features

Forest stand parameters	Prediction model	R^2_{adj}	RMSE	p
Number of trees (NT)	NT=2456.552-1014.120*Entropy	0.313	474.315	0.001
Basal area (BA) (m^2/ha)	BA=7.095+39.785*NDVI+0.420*Correlation-17.139*Contrast	0.732	4.153	0.000
Tree canopy cover (TCC)	TCC=197.744-47.769*Contrast-50.358*MSI-58.266*VI	0.443	11.258	0.001

Stand volume (SV) (m^3/ha)	SV=94.048+229.861*NDVI+3.068*Correlation-18.983*Mean	0.658	33.694	0.000

3.3. Regression model using textural, spectral and topographic information

The results of model predicting forest stand variables using textural, spectral features and topographic information are shown in Table 4. From Table 2 to 4, it can be concluded that all significance P values of models using above three methods are less than 0.001. Compared with model using textural feature and model using both textural and spectral features, the model predicting forest stand parameters using combined textural, spectral features and topographic information was significantly improved in terms of goodness of fit, in which the stand volume (SV) model showed the greatest R^2_{adj}, followed by basal area (BA) and tree canopy cover (TCC) model. The R^2_{adj} of stand volume (SV) model increased from 0.658 to 0.82, the correlation between the topographic factors (elevation and slope aspect) and stand volume was relatively good, the goodness of fit was significantly improved (R^2_{adj} = 0.820, RMSE = 24.457m^3/ha). The R^2_{adj} of basal area (BA) model increased from 0.732 to 0.778, of which the prediction accuracy was only behind the SV model. Among all introduced topographic variables, the elevation was most involved in the model, including predicting the following three forest stand parameters, number of trees (NT), tree canopy cover (TCC) and stand volume (SV).

Table 4. Regression model predicting the forest stand parameters using textural, spectral features and topographic information

Forest stand parameters	Prediction model	R^2_{adj}	RMSE	p
Number of trees (NT)	NT=2566.169-910.848*Entropy-1.733*elevation+22.888*slope	0.448	425.213	0.001
Basal area (BA) (m^2/ha)	BA=10.741+40.972*NDVI+0.424*Correlation-19.572*Contrast-0.717* slope aspect	0.778	5.954	0.000
Tree canopy cover (TCC)	TCC=287.069--28.677*Contrast-63.903*MSI-91.877*VI-0.040*elevation-6.843*Mean	0.522	10.434	0.000
Stand volume (SV) (m^3/ha)	SV=169.030+206.397*NDVI+0.231*elevation-63.522*Entropy-6.108* slope aspect - 13.376*Mean	0.820	24.457	0.000

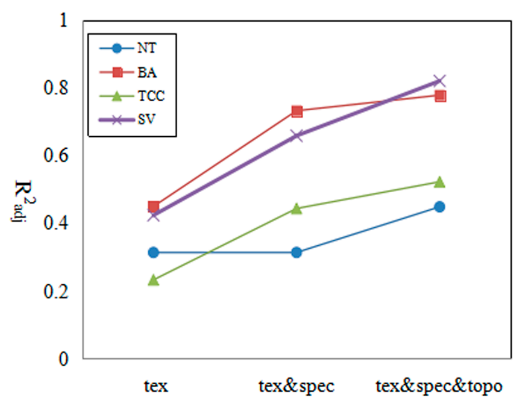

Figure 3. R^2_{adj} of forest stand parameters models based on textural, spectral features and topographic information combination (textural features, textural&spectral features, textural&spectral features& topographic information)

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3.4. Model accuracy verification

In this paper, we obtained the optimal estimation model by comparing R^2_{adj} of all prediction models shown in Figure 3, which was, model predicting forest stand parameter by combined use of textural and spectral features and topographic information, and its accuracy was verified. Figure 4 shows plots of estimated values and actual values generated from 15 testing samples. The study results show that plots R^2 between estimated value and actual value of the optimal model was close to 1, and the constructed model to predict forest stand parameters was better for prediction of the actual values. The RMSE estimated by model predicting stand volume (SV) reached the greatest to 13.65m^3/ha, and the RMSE of model predicting Tree canopy cover (TCC) was the lowest to 0.05.

According to the results of the optimal estimation model (combined use of textural and spectral features as well as topographic information), the R^2_{adj} of models predicting stand volume (SV) and basal area (BA) both were greater than 0.75, and the prediction effect was ideal. In this study, maps of the stand volume and basal area for a county in the study area were generated based on optimal estimation model, shown as Figure 5.

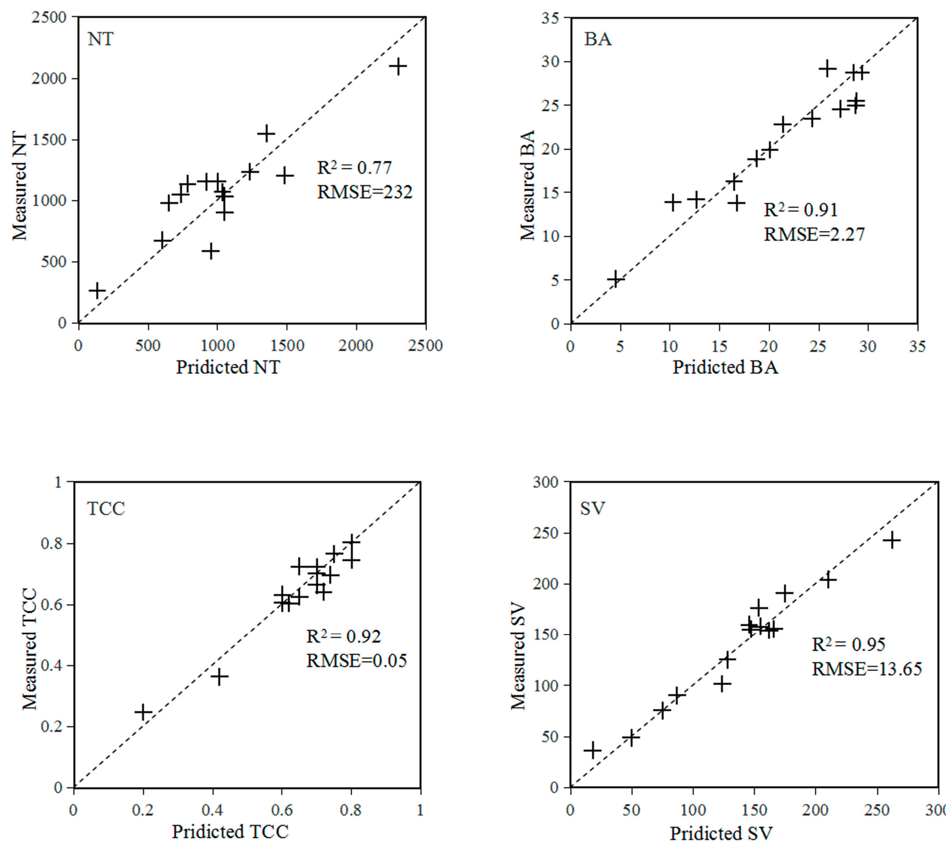

Figure 4. Field-measured forest stand parameters and satellite-derived forest stand parameters (number of trees (NT), basal area (BA), tree canopy cover (TCC), stand volume (SV))

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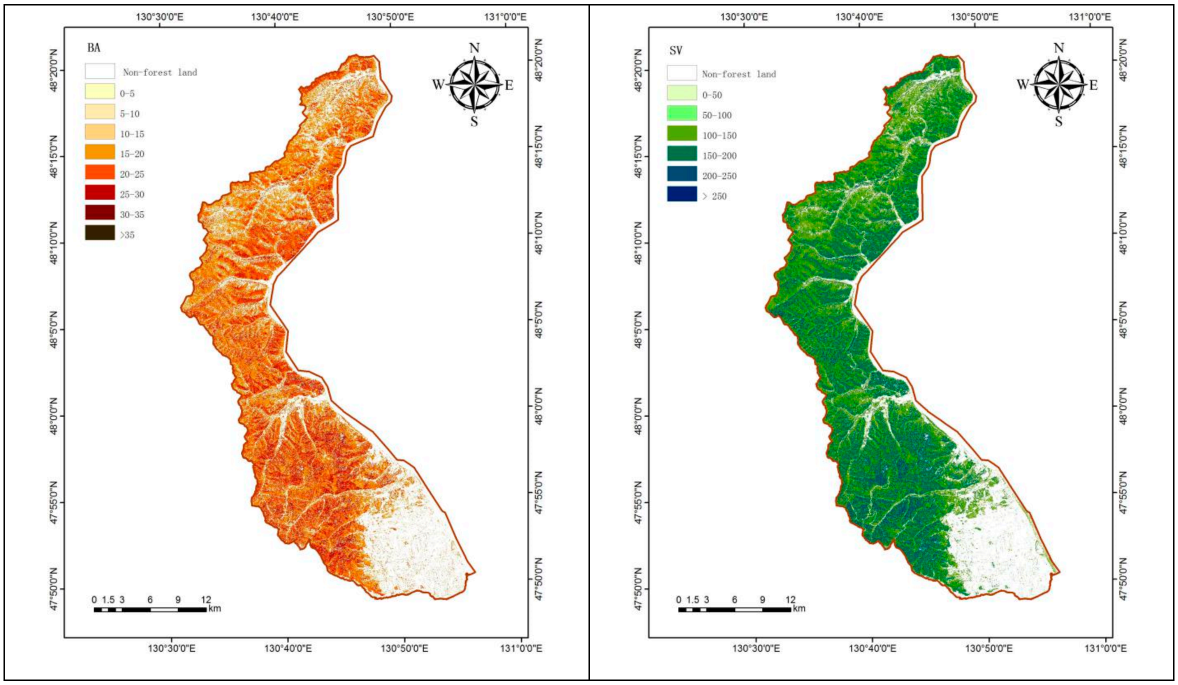

Figure 5. Thematic map of basal area (BA) and stand volume (SV) of a county in Heilongjiang province

4. Discussion

Results predicting forest stand parameters by using textural features of different image windows show that, the ability of textural feature of remote sensing image to estimate the forest stand parameters increased first and then decreased with the growth of window size, showing a slight parabolic trend. Similar to the results of this study, Liu et al.[37] using textural features of different windows of ALOS images to estimate stand volume also found the same trend. In addition, the textural features of SPOT-5 image show the maximum value of R^2_{adj} in the 9 × 9 window, indicating that the 9 × 9 window is the ideal window for using textural features extracted from SPOT-5 image to predict forest stand parameters, which is consistent with study results by Castillo-santiago et al.[38] . However, the optimal window size to predict forest stand parameters by using textural feature of remote sensing image may vary due to different data sources, and it needs to be further studied.

According to the results predicting forest stand parameters by using textural and spectral features and combined use of textural and spectral features and topographic information (Table 3 ~ 4), textural features of SPOT-5 image were involved in all prediction models, but spectral features of SPOT-5 image were only involved in predicting basal area, tree canopy cover and stand volume and stand volume, indicating that the ability of textural features of SPOT-5 image is stronger than spectral features in terms of predicting forest stand parameters. Similar to the results of this study, Eckert[1] found that the correlation between the textural features of the worldview-2 image and the biomass and carbon content is higher than that of the spectral features, and with inclusion of textural features, the accuracy predicting biomass and carbon content using spectral characteristics can be improved. Levesque and King[39], and Kayitakire et al.[40] used textural features to study the tree health and age, respectively, and the results show that the information achieved after introducing the textural features is more accurate than the approach simply uses spectral features. Compared with previous studies, the reason might be: the influence of canopy shadow, the heterogeneity of the vegetation site structure and the saturation of the spectral data, which will reduce accuracy of model predicting forest stand parameters by using spectral features, while the textural features of remote sensing image enlarges the spatial information recognition based on the brightness of the original image, which is more helpful for prediction model[41,42].

When textural and spectral features were used in prediction model, the inclusion of topographic information will greatly improve the prediction accuracy. Same as the textural features of remote sensing image, the topographic information was involved in all optimal models predicting forest stand parameters, indicating that the topographic information has a positive effect on the prediction of number of trees, basal area, tree canopy cover and stand volume. Similar results were reported by Kimes et al.[43]. They found that the introduction of topographic information is also effective in estimating the age of forests using remote sensing images. In addition, among all the factors involved in estimation of forest stand parameters, the elevation had the greatest influence on estimation of forest stand parameters, and it was involved in predicting three models, which indicated that elevation contains abundant forest structure information, and has significant impact in predicting forest stand variables. The reason might be: the forest structure is complex in the study area, and the elevation is between 52-1022m. The wavy terrain causes significant difference between adjacent pixels in terms of solar radiation, atmospheric scattering in the sky and significant difference in cross radiation between adjacent terrain, resulting in phenomena of "same object with different spectra" and "different objects with same spectra", which might affect the accuracy to extract image information[44,45]. Therefore, accuracy of model predicting forest stand parameters using textural and spectral features of SPOT-5 remote sensing image was not great, while the accuracy was improved after inclusion of topographic information.

5. Conclusions

In this paper, we studied the potential of textural, spectral features of SPOT-5 remote sensing images and topographic information to estimate the number of trees, basal area, tree canopy cover and stand volume, and the following conclusions can be drew:

1)The optimal window using textural features of SPOT-5 images to predict forest stand parameters is 9 × 9, and the R^2_{adj} showed a weak parabolic trend with growth of window size.

2)Models using both textural and spectral features of SPOT-5 images could accurately predict the forest stand parameters, of which prediction accuracy of basal area (R^2_{adj} = 0.732) and stand volume (R^2_{adj} = 0.658) was relatively good. In addition, ability of textural features of SPOT-5 images was better than that of spectral features in terms of predicting forest stand parameters.

3) Models combined use of textural and spectral features as well as topographic information is the optimal model to predict forest stand parameters, which the accuracy was higher than the model only using textural and spectral features. The introduction of topographic information has a positive effect on all models, and the elevation has the greatest impact on estimation model for forest stand parameters.

4)Among all optimal estimation models for forest stand parameters in this study, the accuracy of predicting stand volume (SV) (R^2_{adj}=0.820, RMSE=24.457m^3/ha) was the highest, followed by basal area (BA) (R^2_{adj} = 0.778, RMSE=5.954m^2/ha), both exceeded 75%. The R^2_{adj} of prediction models for number of trees (NT) and tree canopy cover (TCC) was close to or greater than 0.50, and the prediction results were reliable.

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Author Contributions: All authors have made significant contributions to the manuscript. Shiqin Xie and Wei Wang conceived, designed and performed the experiments; Wei Wang processed the remote sensing data and derived the remote sensing parameters responding to the field plots. Shiqin Xie analyzed the data and results; Shiqin Xie and Wei Wang are the main authors who developed and revised the manuscript. All authors contributed with ideas, writing, and discussions.

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