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The Impacts of Landscape Patterns on the Accuracy of Remotely Sensed Data Classification

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Abstract. The accuracy of the Land Use/Land Cover (LULC) data derived from remote sensing images is critical for many applications. Classification error is caused by the interaction of numerous factors, including landscape characteristics, sensor resolution, spectral overlap, preprocessing algorithms, and classification procedures[1,2]. The purpose of this paper is to analyze the impacts of landscape characteristics on classification accuracy and to analyze the distribution of errors from a landscape pattern perspective. Logistic regression was employed to assess the impact of landscape characteristics on classification accuracy. Two landscape variables, patch size and heterogeneity, were calculated at the pixel's level and sub-pixel's level respectively and their effects were evaluated. The results indicate that classification accuracy increases as land cover patch size increases and as heterogeneity decreases. The effect of patch size is more important than heterogeneity and the impact of variables calculated at sub-pixel level is more important than pixel level.

Keywords: classification, accuracy, landscape, logistic

1. Introduction

Remote sensing images have been widely used in LULC mapping. The accuracy of the LULC map derived from remote sensing data is critical for many applications. Classification error is caused by the interaction of numerous factors, including landscape characteristics, sensor resolution, spectral overlap, preprocessing algorithms, and classification procedures [1,2]. However, how could we know the distribution and extent of classification errors in land cover data sets? A number of researchers have addressed themselves to this problem and some of them have tried to solve this problem from a landscape perspective. Their study results indicate that there are relationships between land cover classification accuracy and landscape patterns, such as patch size and heterogeneity of land covers [2-6].

The purpose of this paper is to identify the impacts of landscape characteristics on classification accuracy and to analyze the distribution of errors from a landscape pattern perspective at the sub-pixel level and pixel level. We try to extend other researchers [2,3,6] work by including sub-pixel level landscape variables as potential explanatory variables of pixel classification accuracy, and to explore the deeply reason for classification error distribution.

2. Data and Methodology

2.1. Data and Research Region

In this study, two sets of land cover products were used to conduct our analysis. The PFT (Plant Function Types) version MODIS (Moderate Resolution Imaging Spectroradiometer) land cover product (MOD12Q1) of Shandong province, China, was used to calculate classification accuracy and pixel level landscape variables. A high resolution land cover map of the same region derived from Beijing-1 small satellite (a

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multi-spectral sensor with a spatial resolution of 32 meters) imagery by manually interpreting was used as reference data for accuracy assessment, and was used to calculate the sub-pixel level landscape indices as well. The common area of these two sets of land cover data covers most area of 14 counties including Taian, Yanzhou, Sishui and Feicheng, Shandong Province in eastern China, with total area about 15300 km^2.

2.2. Methodology

2.2.1 Accuracy assessment

Accuracy assessment of MOD12 data was conducted in the research region, using reference land cover data obtained by interpretation of Beijing-1 satellite images. The purpose of this paper is to compare the explanatory ability of landscape variables at different scales. Therefore, to simplify the problem, regional differences were considered by dividing the whole research region into sub-regions instead of incorporating a regional variable. Five sub-regions were cut out from the whole research region. For each sub-region, Beijing-1 land cover map, originally in vector format, was converted to raster dataset firstly. Then, the MOD12 land cover map was resampled to Beijing-1's pixel size and the two land cover/use products were overlaid in order to make direct spatial comparisons at Beijing-1's level[7]. A statistical analysis was carried out to calculate the sub-pixel components of MOD12 pixels. The majority rule was used to assign a reference land cover class to a MOD12 pixel, that is, for a MOD12 pixel, the land cover class with relative largest area in its corresponding Beijing-1 pixels, was assigned as its reference class. If the reference class matched the class of MOD12, the pixel was assigned correctly classified. Based on above statistics, each MOD12 pixel was assigned a binary value representing whether it was correctly classified (coded as 1) or not (coded as 0).

2.2.2 Explanatory variables

Five explanatory variables were used in this study, including patch size, heterogeneity and a variable representing whether the pixel is a mixed pixel. Patch size and heterogeneity were calculated at both pixel level (MOD12 scale) and sub-pixel level (Beijing-1 scale).

For the pixel level, land cover heterogeneity was defined as the number of land cover classes occurring in a three-by-three pixel window centered on each MOD12 pixel [2]. This variable indicates whether the central pixel is located on a patch edge. A heterogeneity value of 1 indicates that the central MOD12 pixel is located within a homogeneous three-by-three block of pixels. Patch size was defined as the number of contiguous pixels of the same land cover class within the patch which the MOD12 pixel was located. The eight adjacency rule was used for counting contiguous pixel.

In terms of the sub-pixel scale, the heterogeneity value of a MOD12 pixel was calculated as follows: search all the corresponding Beijing-1 land cover pixels in a three-by-three MOD12 pixel window centered on the sample MOD12 pixel, then count the number of its components, i.e. number of land cover classes occurring at the sub-pixel scale. Another variable, mixing index, was calculated in a slightly different way. This variable, which representing whether a MOD12 pixel is a pure one, was calculated by counting the number of the MOD12 pixel's subcomponents. It is a little more complex to calculate the last variable, patch size at sub-pixel scale. For a MOD12 pixel, the dominant land cover class in its sub-pixel level was found out based on a statistical analysis firstly. Then, for this dominant class, perhaps there are more than one sub-pixel patches in the area of the sample MOD12 pixel (see the central pixel in figure 1), and the largest patch was selected. Next, within a five-by-five MOD12 pixel window, the area of the largest patch of the dominant class in the center pixel was counted, and this area is the sub-pixel level patch size value. As the case shown in figure 1, the dominant class of the central MOD12 pixel is class A, and the area covered by patch A-3(the section in the central pixel) is the largest one of the three class A patches in the center pixel. Patch A-3's area in the five-by-five window is the sub-pixel level patch size value we expected of the center pixel.

Some researchers have found that a transformation to a logarithmic scale would improve the linearity of the logistic regression models [2,3,6]. Based on a preliminary analysis of this data, we transformed patch size at both pixel and sub-pixel's level to a logarithmic (base e) scale.

Then, for each MOD12 pixel, values of the five variables were worked out. Some sample pixels were selected randomly from each of the five sub-regions, in order to prepare for a further statistic analysis.

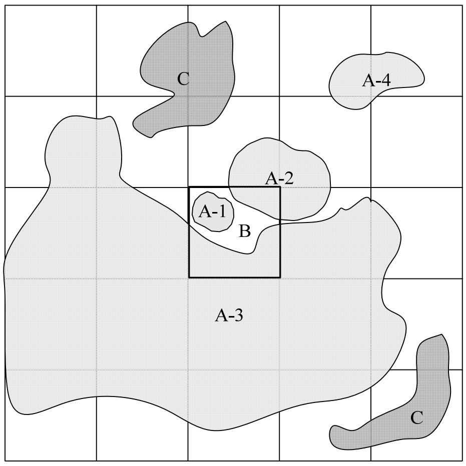

Figure 1. An example of sub-pixel level patch size.

2.2.3. Logistic Regression

Logistic regression analysis models the relationship between a binary response variable and one or more explanatory variables [8]. The logistic regression model is:

$$Ln\left(\frac{p(i)}{1-p(i)}\right)=\beta_0+\beta_1X_1+\beta_2X_2+\cdots+\beta_nX_n \tag{1}$$

where X_1 through X_n are the explanatory variables, β_1 through β_n are the parameters, and $p(i)$ is the probability of correct classification of pixel i.

Formula (1) can be expressed as follows:

$$p(i) \ = \frac{\exp(\beta_0+\beta_1X_1+\beta_2X_2+\cdots+\beta_nX_n)}{1+\exp(\beta_0+\beta_1X_1+\beta_2X_2+\cdots+\beta_nX_n)} \tag{2}$$

Using this model, the distribution of correct classification can be analyzed as a function of the landscape variables introduced above.

Table 1. Description of models

Model Number	Model	Variables	Region
A	β_0	Interception	
B1	$\beta_0+\beta_1X_1$	Interception, Patch size—pixel level	
B2	$\beta_0+\beta_2X_2$	Interception, Heterogeneity—pixel level	
B3	$\beta_0+\beta_3X_3$	Interception, Patch size—sub-pixel level	
B4	$\beta_0+\beta_4X_4$	Interception, Heterogeneity—sub-pixel level	
B5	$\beta_0+\beta_5X_5$	Interception, Mixing index	
C1	$\beta_0+\beta_1X_1+\beta_3X_3$	Interception, Patch size—pixel level Patch size—sub-pixel level	1,4
C2	$\beta_0++\beta_2X_2+\beta_4X_4$	Interception, Heterogeneity—pixel level Heterogeneity—sub-pixel level	
D1	$\beta_0+\beta_1X_1+\beta_3X_3+\beta_4X_4+\beta_5X_5$	Interception, Patch size—pixel level Patch size—sub-pixel level Heterogeneity—sub-pixel level Mixing index	2
D2	$\beta_0+\beta_2X_2+\beta_3X_3$	Interception, Heterogeneity—pixel level Patch size—sub-pixel level	3
D3	$\beta_0+\beta_2X_2+\beta_3X_3+\beta_4X_4$	Interception, Heterogeneity—pixel level Patch size—sub-pixel level Heterogeneity—sub-pixel level	5

In order to investigate these variables' ability of explaining classification correctness, for each of the five regions, a set of models including different variables were built (table 1).Model Chi-square, Akaike Information Criterion (AIC), Wald (used to test the statistical significance of each coefficient β in the model), coefficients *β, and* Odds Ratio (OR) were used to evaluate models and the effects of explanatory variables. Differences in the −2 log likelihood (−2LL) values for the models was used to test the effect of incorporating additional variables. This difference follows a chi-square distribution with degrees of freedom equal to the difference in the number of explanatory variables [8].The forward stepwise method was used to select an optimum model for each region.

3. Results and Discussion

Statistics from single variable models (model B1-model B5) for each region are shown in table 2. All the models' Chi-squares are statistically significant at the 0.05 level, indicating that all the explanatory variables show linear relationships with the log odds of a correct classification. Wald statistics were calculated for the variables in the models to determine whether a variable should be included in the model. The asymptotic distribution of the Wald statistic is chi-square. It is shown in table 2 that all Wald statistics are significant at the 0.05 level, that is, all variables have effects on classification accuracy and should be included in the models.

Table 2. Statistics of logistic regression models

Region	Model Number	AIC	*β*	OR	Classification Table Overall Percentage	Wald	
						Wald	p
1	B1	385.852	0.535	1.707	91.8	12.830	.000
	B2	389.729	-1.294	0.274	91.2	12.865	.000
	B3	99.027	4.570	96.508	98.4	73.587	.000
	B4	369.474	-0.776	0.460	91.5	32.207	.000
	B5	337.828	-1.997	0.136	90.9	49.668	.000
2	B1	758.007	0.475	1.609	62.6	9.206	.002
	B2	775.698	-0.481	0.618	60.5	4.292	.038
	B3	721.884	1.180	3.254	66.4	41.184	.000
	B4	643.113	-1.102	0.332	72.4	105.585	.000
	B5	775.312	-0.277	0.031	59.6	4.671	.031
3	B1	179.650	0.733	2.081	96.9	14.816	.000
	B2	175.982	-1.951	0.142	96.8	25.564	.000
	B3	16.721	11.983	160013.7	99.7	15.73	.000
	B4	191.366	-0.845	0.429	96.6	5.705	.017
	B5	175.327	-2.446	0.087	96.6	13.414	.000
4	B1	551.939	0.286	1.331	56.7	3.875	.049
	B2	552.248	-0.660	0.517	57.5	4.135	.042
	B3	436.663	2.392	10.935	73.6	64.114	.000
	B4	550.304	-0.268	0.765	52.7	6.070	.014
	B5	542.627	-0.634	0.531	56.0	13.220	.000
5	B1	607.741	0.202	1.224	57.9	6.089	.014
	B2	570.648	-1.186	0.306	65.8	34.131	.000
	B3	563.570	1.243	3.468	64. 4	36.928	.000
	B4	588.954	-0.443	0.642	64. 2	23.976	.000
	B5	609.420	-0.338	0.713	55.4	4.844	.028

It can be seen from table 2(model B1 and model B3) that, for all the five regions, patch size has positive coefficient estimates and odd ratio greater than one at both pixel and sub-pixel level. This indicates that classification correctness increases as patch size increase, that is, if a pixel located in a large land cover patch, the probability of this pixel been correctly classified will be high. Conversely, heterogeneity has negative slope estimates and odds ratios less than 1 at both pixel and sub-pixel level, indicating that when a pixel located on the boundaries of land cover patches, its probability been correctly classified will be low. This means classification correctness will increase when land cover heterogeneity decreases. For each region, the parameter estimate of mixing index is a negative value, which shows a decreasing trend in accuracy as mixing index increases. This is consistent with the conventional notion that mixed pixel is one of the most important factors that caused the classification errors [9].

AIC value was used to compare the effects of these single variable models, and the lower the value, the better the model. It can be seen from the AIC statistics listed in table 2 that patch size at sub-pixel level shows a best performance among all of the five variables (has the lowest AIC value), with an exception of region 2(has a lowest AIC value for sub-pixel level heterogeneity).

At pixel and sub-pixel scale, we compared the performance of patch size and heterogeneity base on the AIC statistic and overall percentage of correct classification in classification table (see table 2). At sub-pixel level, patch size has a stronger effect than heterogeneity in four of the five regions (comparison of model B3 vs. B4). However, from the comparison of model B1 versus B2, it can be seen that at the pixel level, this advantage shows only in three of the five regions according to AIC value. Therefore, generally speaking, patch size provides a better model than heterogeneity does at both sub-pixel and pixel level.

The main purpose of this study is to analyze whether landscape characters have effects on classification accuracy and to compare pixel scale variable's effects with sub-pixel scale variable's effects on classification correctness. Therefore, the following comparisons were conducted.

A comparison summary of AIC values from table 2 is shown in table 3. From this comparison table, it can be seen obviously that the impact of sub-pixel scale patch size on accuracy is stronger than that of pixel scale patch size. While for heterogeneity, the variable at sub-pixel level possesses a stronger relationship with classification accuracy than the relationship provided by the variable at pixel level only in three regions.

Table 3. Comparison of models' AIC values

Region	Variables	AIC		
		Pixel scale		Sub-pixel scale
1	Patch size		>	
	Heterogeneity		>	
2	Patch size		>	
	Heterogeneity		>	
3	Patch size		>	
	Heterogeneity		<	
4	Patch size		>	
	Heterogeneity		>	
5	Patch size		>	
	Heterogeneity		<	

The -2LL differences of different models were listed in table 4, which were used to estimate the effect of incorporating an additional variable, then, to evaluate the importance of the explanatory variables. The comparison of model B1-C1 represents the importance of the sub-pixel level patch size relative to the pixel level patch size(see table 4. for other comparisons' meanings). For all regions, the contribution of the sub-pixel level patch size is statistically significant when adjusted for the effect shared by the pixel level patch size. The Chi-square statistic of model B3 versus C1 comparison is significant in four of the five regions, and these Chi-square values are smaller than those of model B1 versus C1 comparisons. This suggests that sub-pixel level patch size may be more important than pixel level patch size. Similarly, from the Chi-square statistic derived from the comparison of model B2 versus C2 and B4 versus C2, it can be concluded that sub-pixel level heterogeneity has a slight stronger explanatory ability than pixel level heterogeneity.

Overall, sub-pixel level landscape variables have stronger relationships with classification accuracy than pixel level variables provided.

The forward stepwise method was used to select an optimum model for each region (table 1). Model C1, model D1-D3 are the most appropriate model selected for the five regions. Sub-pixel level patch size is included in all of the five models (C1, D1-D3), and this perhaps reflects the importance of this variable. Base on the logistic model and the coefficients estimated for landscape variables, a probability of correct classification for each pixel in the research region can be worked out. Figure 2 is the correct classification probability map for region 1.

Table 4. Chi-square values of model comparisons

Model	Region1	Region2	Region3	Region4	Region5	Description
B1-C1	305.88	57.868	164.514	125.446	56.089	the importance of the sub-pixel level patch size relative to the pixel level patch size
B3-C1	19.055	21.745	1.585*	10.17	11.927	the importance of the pixel level patch size relative to the sub-pixel level patch size
B2-C2	31.077	146.498	8.941	6.706	43.141	the importance of the sub-pixel level heterogeneity relative to the pixel level heterogeneity
B4-C2	10.822	13.913	24.325	4.762	61.447	the importance of the pixel level heterogeneity relative to the sub-pixel level heterogeneity

* Not significant at α=0.05 significant level.

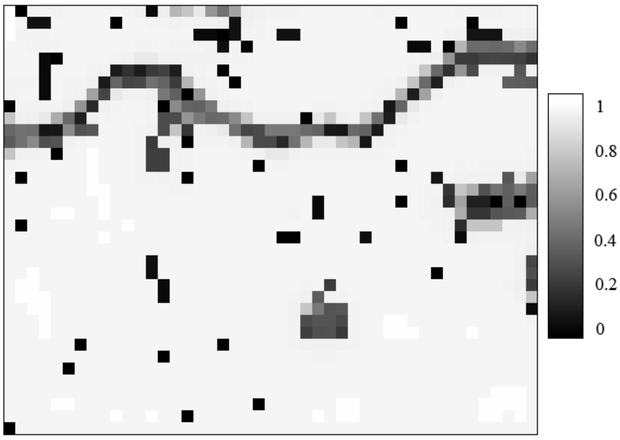

Figure 2. Correct classification probability map for region 1.

4. Conclusions

From the results of above statistical analysis, we found that the accuracy of land cover classification is relative to the spatial distribution feature of the land cover patches. Several particular remarks can be drawn as follows:

- Classification accuracy shows an increasing trend as the land cover patch size (pixel level and sub-pixel level) increases.
- Classification accuracy has a negative correlation with land cover heterogeneity (pixel level and sub-pixel level), that is, there's a relationship in which accuracy decreases as heterogeneity increases.
- It seems that patch size has a stronger relationship with classification correctness than heterogeneity possessed.
- Variables at sub-pixel level show stronger effects on classification accuracy than pixel level variables.

In this study, we try to use the landscape indices to describe the causes and distribution of classification errors. The relationship between classification correctness and landscape variables at different scales will be helpful for improving classification accuracy. Furthermore, logistic regression model perhaps can be used as a new method for providing a probability based accuracy map (see figure 2) for a land cover product.

Future research will focus on how the impacts of landscape indices may vary among land cover types and spatial scales.

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