A HIERARCHICAL MULTISCALE OBJECTED-ORIENTED CLASSIFICATION METHOD FOR GF-2 WALNUT FOREST EXTRACTION

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ABSTRACT: Walnut forest is one of the most important economic forest in south area of Shannxi Province. It is a combination of ecological forestry and people's livelihood forestry. The remote sensing monitoring of walnut forest(WF) acreage is very important for the develop of forestry industry. However, walnut trees' spectral is very similar with other green vegetation, and their canopy is very similar with apple trees. WF in the study area is block distribution not connected distribution, which resulted in less pure walnut forest pixels in Landsat like image. In order to get a high accuracy classification map for WF, high resolution remote sensing image(HRRSI) is priority. But complexity objects and large data volume become another problem in HRRSI, so the extraction of WF is a relatively difficult job.
In this paper, a GF-2 HRRSI was used in this work, which cover the south part of Linwei District. The contribution of this work is that a hierarchical multiscale objected-oriented decision tree classification scheme was proposed for GF-2 WF classification. Firstly, fractal net evolution approach-FNEA in eCognition was used for GF-2 multiscale segmentation, and four scale different objects were produced; secondly, rule based decision tree was applied for coarse level classification, for example, water body, green vegetation, rural area, road, and bare soil; lastly, green vegetation was fine classification by CART classifier. WF is one of the fine classification class type. The overall classification accuracy is 87.98%, and the WF omission error is 11.32%. The method adapted different decision tree model for different classification level, it got high accuracy result effectively. It is expected that other type economic forest mapping may also use this method.

1. INTRODUCTION

With the expansion of rural market economy, walnut has become an advantageous characteristic industry to promote local development and help farmers become rich with its high economic benefit, good ecological benefit and potential nutrition value. In order to optimize the regional layout of walnut planting, strengthen the scientific cultivation of walnut forest and promote the structural development of walnut industry, it is necessary to obtain the planting distribution and area of walnut forest accurately and quickly. Remote Sensing Technology has become a necessary means to solve this problem because of its "wide-area and real-time" characteristics.
A diversity of economic forest classification methods by remote sensing have been proposed in the past years, which can be divided into the pixel-based classification method and the object-oriented classification method(Zhang et al., 2010).The pixel-based classification method mainly

classifies images by judging the distance between each pixel and the corresponding class statistics, which is mostly applicable to low-resolution images, such as MODIS(Chen et al., 2014). Despite the pixel - based classification method has a strong theoretical system and is widely used, this kind of method is limited because it only relies on spectral information to extract vegetation, which will lead to "same object different spectrum, foreign body in the same spectrum" and seriously reduce the classification accuracy(Su et al., 2007). High-resolution images have attracted extensive attention by providing all kinds of efficient object characteristics such as texture, shape, and spectral information(Jin et al., 2017 , Niu et al., 2016). The object-oriented classification method based on the object can integrate the spatial structure, texture information, semantic context and other features in the high-resolution image to build a powerful classification rule, so as to obtain higher cash crop extraction accuracy(Duro et al., 2012 , Li and Shao, 2014 , Li and Cao, 2018).

At present, the commonly used object-based classification methods include K-nearest neighbor (KNN) classification, support vector machine (SVM) classification , decision tree classification etc. Its core principle is to automatically conclude and summarize the rules from the known instances of the data itself, and to establish a prediction model that matches the unknown instances. KNN is suitable for nonlinear classification, and there is no assumption on the data, with high accuracy, but its disadvantage is that it requires a large amount of computation in calculating distance, which requires high memory, and the classification effect is poor when samples are unbalanced. SVM is often used to solve high-dimensional problems, and have strong generalization ability. However, when there are many observed samples, SVM has low operational efficiency. Decision tree is a supervised learning classification method, which is simple in calculation and flexible in structure, and it can make feasible and effective interpretation for a large amount of data in a relatively short time .Therefore, considering the large amount of data and various object features in the actual classification of HRRSI, it is important to find a classification method that can clearly distinguish similar objects and give consideration to the efficiency of computer operation .This paper proposes a multiscale object - oriented classification method.

2. MATERIALS AND METHODS

2.1 Study area and Datasets

The research area is located in the south of the Weinan Linwei District in Shaanxi province, namely Qiaonan town and Yangguo Town. The southern part of the study area is the Qinling mountains, and the northern part is the gentle slope tableland, which is a typical mountain town. Because of the rich forestry resources here, the main economic forest is mainly planted walnut, so we choose here as the research area, as shown at Figure 1.

We use the GF-2 as the basic image to extraction the walnut forest(WF). After a series of remote sensing data preprocessing, such as radiometric calibration, atmospheric correction, image registration and fusion, the spatial resolution was improved from 4m to 1m. More details are shown in the following Table1. Another essential data is ASTER data, a digital elevation model with a spatial resolution of 30m, which is mainly used for image geometric correction and orthometric correction, and also participates in the construction of topographical classification features.

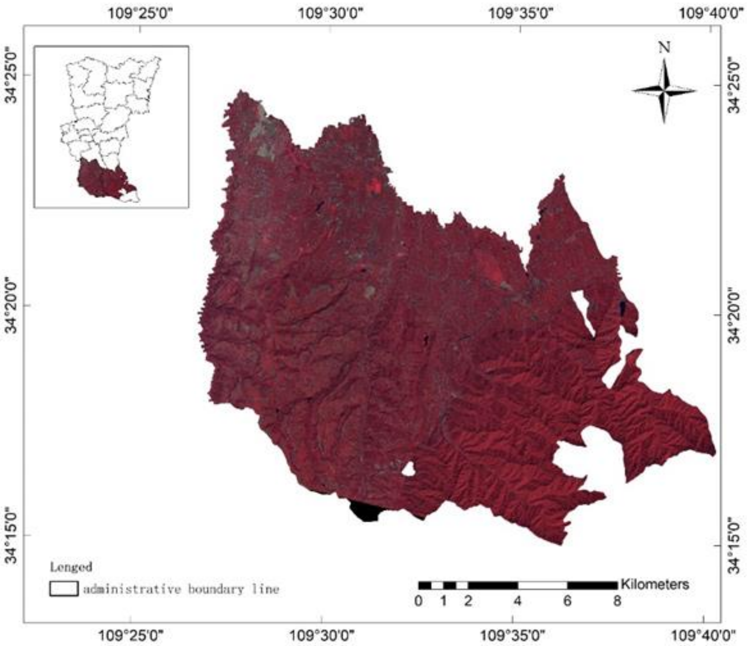


Figure 1 The GF-2 image of Qiaonan town and Yangguo town

Table 1 The parameter table of GF-2

Launch time：	September 2, 2016	Regression cycle:	69 days
Orbital altitude:	631km	Orbit type:	solar synchronous orbit
Local time:	10:30AM	Orbit inclination:	97.9080 °
Spectral range	Red:0.45~0.52um		
	Green:0.52~0.59um		
	Blue:0.63~0.69um		
	Nir:0.77~0.89um		

2.2 Methods

The workflow consisted of the essential steps presented in Figure 2:(1)pre-classification preparation;(2)multiscale segmentation;(3)feature selection; (4) construct classification rules on large scale and medium scale;(5) build CART decision tree on small scale;(6) accuracy assessment and, (7)walnut Forest mapping.

2.2.1 Pre-classification preparation: The pre-classification preparation mainly includes two parts: classification system and interpretation signs. Good classification system can effectively improve the classification quality of images. Considering the topographic features of the study area and the seasonal characteristics of GF-2 data, and referring to the current land use status classification standard (GBT 21010-2007) and land cover classification system, we divided the study area into six categories. In combination with the vegetation cover of the study area and the relevant data of the local forestry department, the six categories were further subdivided, as shown at Table 2. Clear interpretation markers are helpful to better understand the distribution of features in the study area. Reasonable interpretation markers are constructed through field investigation and sampling in the study area, the specific information is shown in Table 3.

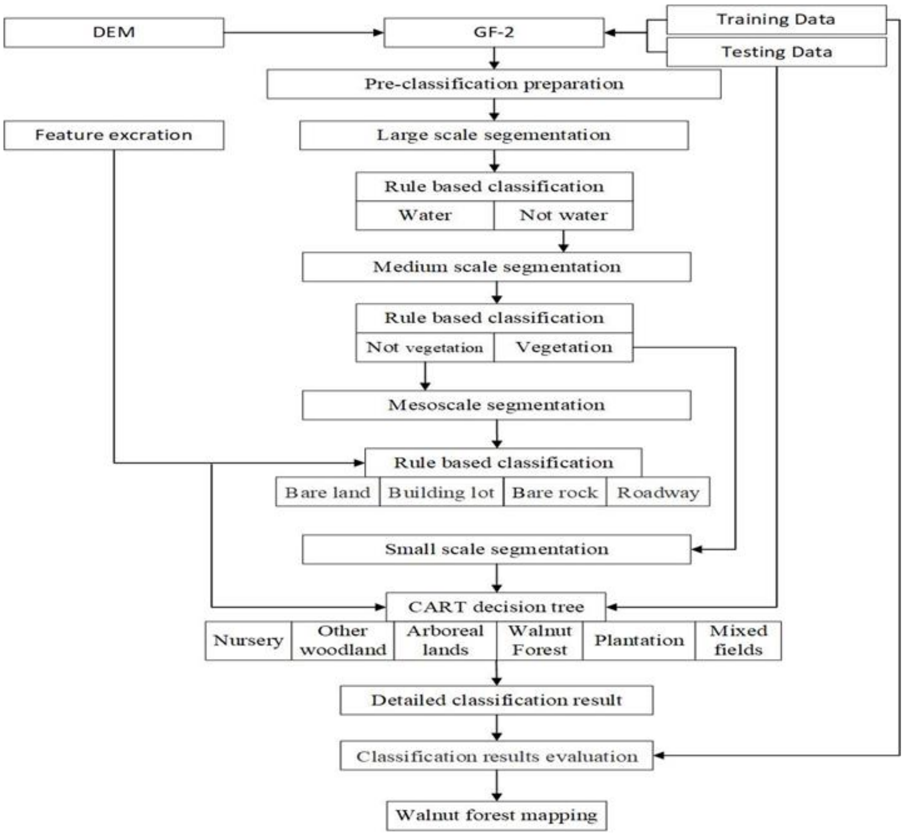


Figure 2 Object-oritend workflow of WF extraction using a hierarchical multiscale segmentation

Table 2 Object oriented classification system

Classification System	Level 1	Level 2
Vegetation	Plantation	-
	Forest	Nursery, Arboreal lands, Mixed fields of shrubs and grasses, Other woodland
	Garden plot	Walnut forest
Not vegetation	Water	-
	The surface of the artificial	Building lot, Road
	Others	Bare land, Bare rock

2.2.2 Multiscale segmentation: Due to the different scales of all kinds of features in high-resolution images, the segmentation scale conforming to the boundary of features should be selected to complete image segmentation when adopting object-oriented classification of features. Multiscale segmentation greatly solved this problem. The core of multi-scale segmentation is fractal net evolution approach (FNEA). This algorithm is a heuristic optimization process, starting from a single pixel, merging the pixels with greater homogeneity, and repeating this process until it reaches the threshold of homogeneity, thus forming the image object with the greatest internal homogeneity. Multi-scale segmentation parameters include: segmentation scale, band weight, spectral factor and shape factor. This paper we use eCognition to conduct multi-scale image segmentation experiments, and then determines the optimal segmentation parameters by comparing and validating the results of multiple segmentation. Detailed parameter settings are shown in Table 4.

Table 3 Interpretation signs

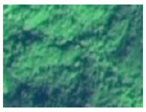
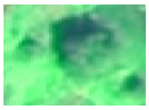
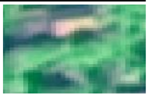
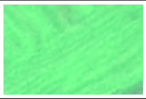
Number	Category	Characteristic	Lengend
1	Water	The color is black or dark blue, mainly for artificial reservoirs or lakes	
2	Building lot	The color are white, black, gray, blue, red, etc, and the shapes are clustered and regular.	
3	Bare land	The color is light brown or brown, irregular shape.	
4	Road	The main road is dark blue or black and has a long and narrow appearance	
5	Walnut forest	The color is green, and texture has obvious rules.	
6	Arboreal lands	The color is dark green and the texture is large and dense.	
7	Mixed fields of shrubs and grasses	The color is bright green and the vegetation coverage is smooth and sparse.	
8	Other woodland	The color is dark green, distributed around building sites, often used for greening purposes	
9	Plantation	The color is green, the shape is regular rectangle, the surface is smooth.	
10	Nursery	The color is bright green, the shape is regular, and the distribution is usually large and clustered	
11	Bare rock	The color is grayish black, located in the Qinling Mountain area, flake distribution	

Table 4 Segmentation parameter table

Layer	Scale	Shape parameter	Color	Compactness	Smoothness	Object
Layer 1	140	0.1	0.9	0.5	0.5	Water, Not water
Layer 2	120	0.2	0.8	0.5	0.5	Vegetation, Not Vegetation
Layer 3	100	0.5	0.5	0.3	0.7	Roadway, Building lot, Bare land, Bare rock
Layer 4	60	0.4	0.6	0.7	0.3	Nursery, Plantation, Arboreal lands, Mixed fields of shrubs and grasses, Other woodland, Walnut forest

2.2.3 Feature selection : As the main basis of information extraction and classification, the feature attributes of segmented objects reflect the related information of actual features. Currently, commonly used object feature attributes consist of these following parts:1) Spectral features are used to describe the spectral information of image targets, which is related to the gray value, including mean value, brightness, standard deviation, ratio,etc.2) Texture features are used to describe the spatial relationship between adjacent pixel gray levels, including: mean, standard deviation, homogeneity, variance, etc.(Hong and Yang, 2011).3) Geometry is used to describe the shape features of objects, including: length, width, area, length/width, boundary index,etc.4) Spectral index is used to emphasize and describe the attributes of fixed target objects, including NDVI, NDWI, G/B,etc.5) Auxiliary features are used to add features to an object and are usually selected according to the characteristics of the classified object. For example, DEM and slope and other auxiliary feature data are often added when classifying mountain areas.

2.2.4 Rule based classification: According to the characteristics of the feature, the suitable feature is selected on the large scale and medium scale , and the rule classification of the feature is realized by means of artificially defined rules with reference to the feature attribute and threshold value, as shown in Table 5.

Table 5 Classification rules of different features of large scale layer and mesoscale layer

Layer	Category	Classification rule
Level 1	Water	NDVI>0.14, Mean nir<160
	Not water	not water
Level 2		with Existence of super objects “Not water”
	Vegetation	not “Not Vegetation”
	Not Vegetation	NDVI<0.06
Level 3		with Existence of super objects “Not Vegetation”
	Building lot	Mean dem≤903.203， NDVI>-0.0329,Length\Width≤5.981， Standard deviation b≤22.987， Compactness≤5.994
	Roadway	Mean dem≤903.203， NDVI>-0.0329,length\Width>5.981
	Bare land	Mean dem≤902.03,NDVI≤-0.0329， Standard deviation g≤56.171， Length\Width≤4.86， Mean g\Brightness≤1.024,Border index>1.272
	Bare rock	Mean dem>1009.885

2.2.5 CART decision tree classification: CART decision tree includes two parts: the generation of decision tree and the pruning of decision tree. The CART decision tree is generated mainly through the input of training data set. Starting from the root node, the feature with the minimum Gini index and its corresponding segmentation point are selected as the optimal feature and segmentation point. According to the optimal feature and the optimal segmentation point, two child nodes are generated from the existing node recursively to each node and then the above operation is repeated.

For a given sample set D, Ck is the sample subset belonging to the K class in D, and K is the number of classes. The Gini index is defined as:

$$Gini(D) = 1 - \sum_{K=1}^{K} \left(\frac{C_k}{D}\right)^2 \quad (1)$$

The pruning of CART decision tree mainly consists of two parts: First, pruning is carried out from the low end of the decision tree T_0 generated by the algorithm until the root node of T_0 forms a sub-tree sequence [T_0, T_1..., T_n]. The second is to test the subtree sequence on the independent validation data set through cross-validation, and finally get the optimal decision tree T_0. It can optimize the model and predict the unknown data accurately. In this paper, representative features are selected to complete the detailed classification of features on a small scale by constructing CART decision tree, and the details are shown in Figure 3.

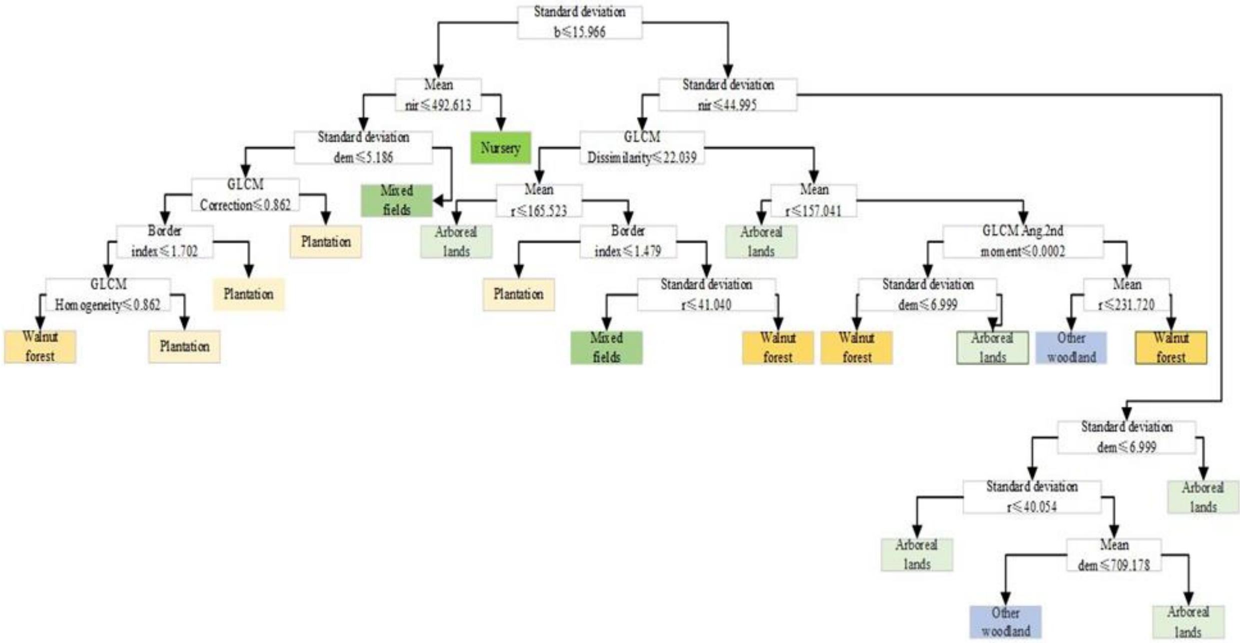


Figure 3 The classification rule of CART decision tree

2.2.6 Accuracy assessment: Before classification, representative training sample points should be selected, and all kinds of sample points should be evenly distributed in the study area. After classification, 201 polygon ROIs, a total of 200977 pixels, were uniformly selected from GF-2 data by referring to Google Earth images as test samples. The degree of separation between ROI is good, and there are obvious distinctions between categories. The detailed number of each sample is shown in Table 6.

Table 6 Statistics of training samples and test samples

Category	Number of training data(Objects)	Number of testing data(Pixels)
Arboreal lands	1521	89534
Plantation	2618	11036
Walnut forest	2245	19687
Other woodland	384	5092
Mixed fields	1045	6442
Nursery	27	16821
Building lot	2155	13310
Roadway	292	5591
Water	40	19452
Bare rock	139	5687
Bare land	270	9913

Verification of classification accuracy is the best way to evaluate the quality of image classification. In this paper, the method of confounding matrix is used to verify the accuracy of classification results in the study area. The detailed confusion matrix is shown in Table 7.

Table 7 Confusion matrix of classification results

Category	Arboreal lands	Plantation	Other woodland	Nursery	Walnut forest	Mixed fields	Sum	User accuracy
Arboreal lands	86186	0	1263	594	762	283	89434	96.37%
Plantation	170	8028	0	3099	418	573	13551	59.24%
Other woodland	1103	0	3037	275	853	0	5656	53.7%
Nursery	0	968	0	10539	0	394	11901	88.56%
Walnut forest	520	71	0	2314	15933	2	19324	82.45%
Mixed fields	1555	1730	21	0	197	5190	9658	53.72%
Sum	89534	10986	5092	16821	19687	6642	200977	
Producer accuracy	96.26%	73.07%	59.64%	62.65%	80.93%	80.57%		
Total accuracy	87.98%							
Kappa	0.84							

2.2.7 Classification Results Mapping: The classification results of the large scale and medium scale are inherited to the small scale, and finally the mapping of the classification results of the whole research area is completed. The classification result is shown in Figure 4 and the exraction result of walnut forest is shown in Figure 5.

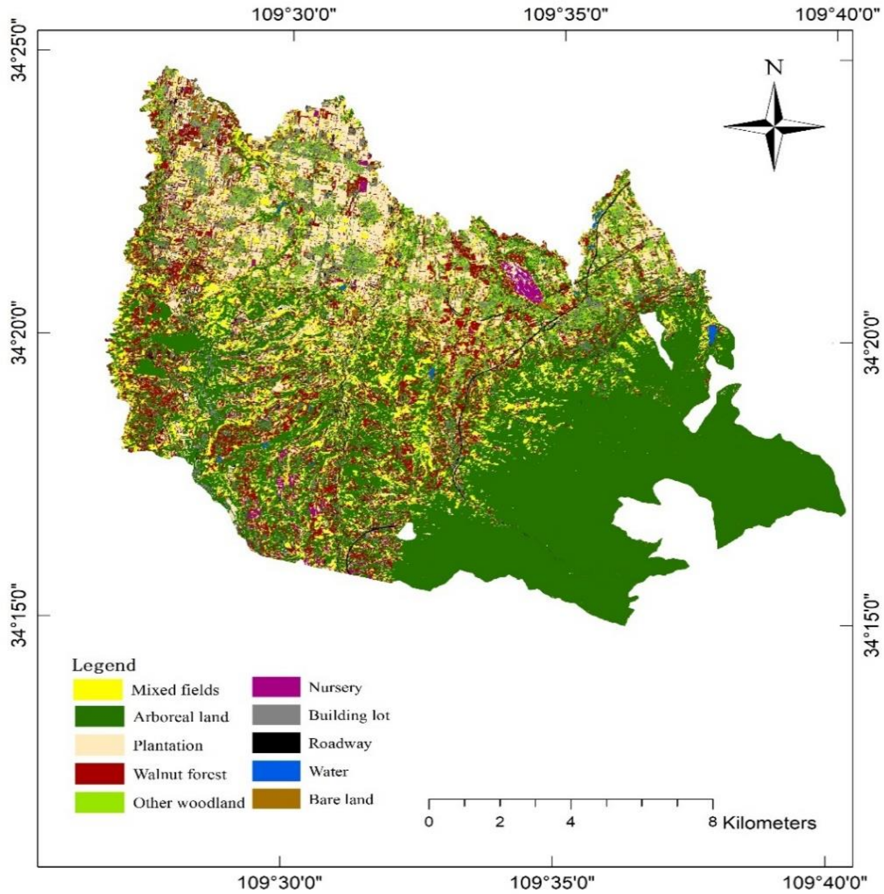


Figure 4 Classification result

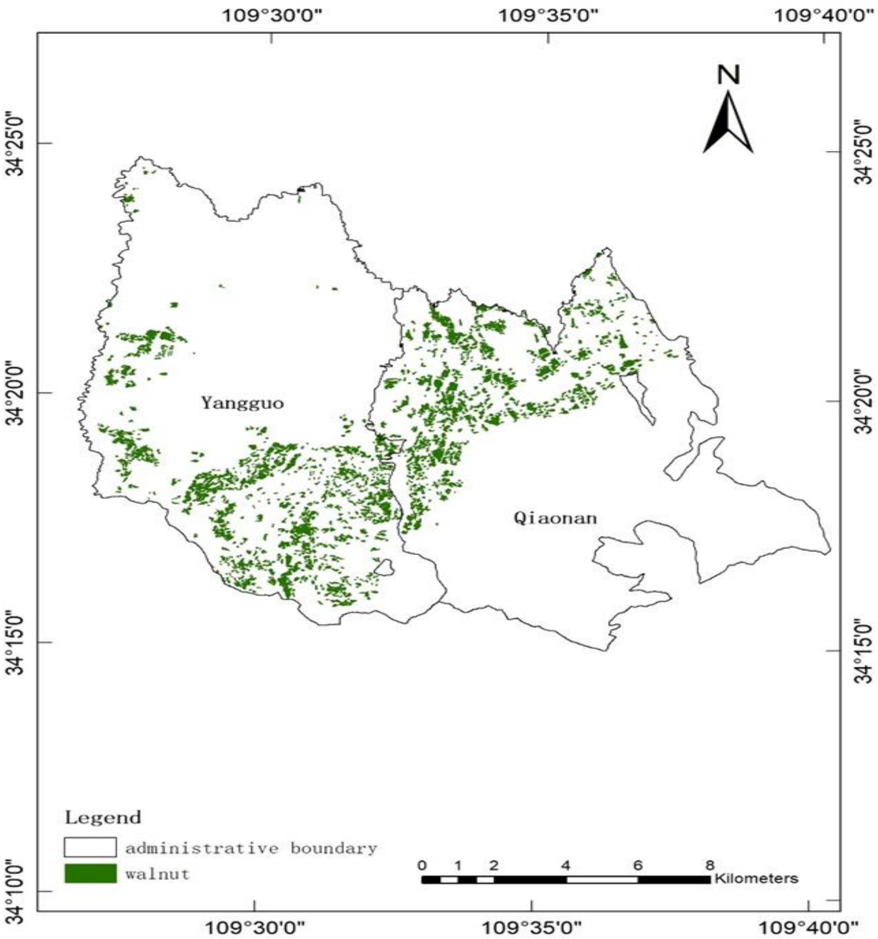


Figure 5 Walnut mapping in Qiaonan and Yangguo town

3.CONCLUSION AND DISCUSSION

In this paper, we propose a hierarchical multiscale object - oriented classification method for walnut forest extraction from high resolution remote sensing images. This method is composed of multiscale segmentation, feature selection and classifier, among which the large scale and mesoscale segmentation objects adopt the rule based classification, while the small scale segmentation objects adopt the CART decision tree classification. The accuracy of classification shows that this method can effectively extract the basic distribution of walnut forest. From the perspective of the whole object-oriented process, this pattern of adopting different classification methods at different scales can effectively improve the classification performance of high-resolution images. On the basis of considering the operating efficiency of computers,we provides a new idea for other economic forest mapping based on high resolution remote sensing image. The shortcoming of this experiment is that only a single classification method is adopted. In the future object-oriented classification research, more classification results which adopt different classifier should be contrasted at different segmentation scales, so as to make the classification method more universal.

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