Classification of Wetland from TM imageries based on Decision Tree

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Abstract: - The traditional method of application of remote sensing data for land cover mapping is the use of supervised classification and unsupervised classification. Decision tree, showing great advantages in remote sensing classification, is computationally fast, makes no statistical assumptions, and can handle data that are represented on different measurement scales. Decision tree classification has been successfully applied to many classification problems, but rarely applied to mapping of wetlands. In this study, decision tree was proposed to extract wetland from Landsat 5/Thematic Mapper (TM) imageries in a wide area of Yinchuan plain. Tasseled Cap (TC) transformation was used to identity the different wetland types and normalized difference vegetation index (NDVI) was computed to distinguish paddy wetland and lake wetland. Results from this analysis show that the decision tree has an outstanding performance compared with the supervised classification in maximum likelihood method. The overall accuracy of supervised classification is 64.60%, while that of decision tree classification was 83.80%. Besides, it appears that a decision tree combinations different useful knowledge is an effective and promising classification method.

Key-Words: - Classification methods; Decision tree; Wetland; Tasseled cap transformation; NDVI

1 Introduction

In the current application of remote sensing classification, the mainly classification approach are artificial interpretation and computer automatic interpretation. The advantages of artificial interpretation is utilizing the visual of human and reasoning skills fully. But interpreting artificially performs low efficiency, and the classification precision depends largely on the subjectivity and personal experience of the investigator. In computer automatic interpretation, for most users, traditional classification methods-supervised and unsupervised classification-are the most choices because of their ready availability. However, if any class undefined during the process, supervised classification can not identify it. Besides, spending lots of time and energy to select and evaluate samples is another disadvantage in supervised classification. Although it is not to select and evaluate samples, it can not control the classes and hard to obtain the expected classes in unsupervised classification.

In the recent years, the use of decision tree to classify remotely sensed data has increased. This technique has substantial advantages for remote sensing classification problems because of its flexibility, intuitive simplicity, and computational efficiency. It has been successfully applied to many classification problems.

1.1 Decision tree

A decision tree is a graph or model of decisions and their possible consequences. It is a special form of tree structure. In their simplest form, decision trees successively partition the input training data into more and more homogeneous subsets by producing optimal rules or decision, also called nodes, which maximize the information gained and thus minimize the error rates in the branches of the tree [1] [2]. Each final leaf is then the result of following a set of mutually exclusive decision rules down the tree (Fig. 1). Each node includes the exclusive and exhaustive logical conditions and each condition is like

$$A<T \quad \text{or} \quad A>T$$

for a continuous attribute A, where T is some threshold, or

$$A=V \quad \text{or} \quad A \text{ in } \{V_i\}$$

for a discrete attribute *A*, where *V* is one of its possible values and $\{V_i\}$ is a subset of them. These conditions divide the data into different parts to get one class.

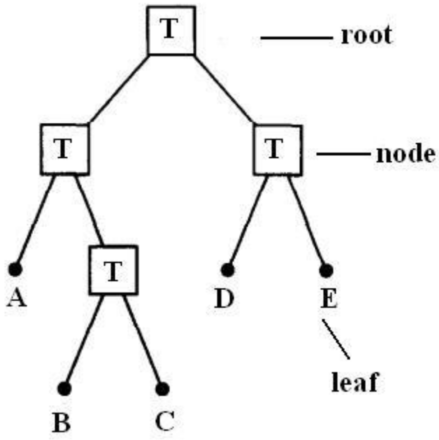

Fig. 1 A decision tree model. Each box is a node at which tests (T) are applied to partition the data into successively groups. The labels (A, B, C, D, E) at each leaf node refer to the class label assigned to each observation.

In order to classify an object, we start at the root of the tree, evaluate the test, and take the branch appropriate to the outcome. The process continues until a leaf is encountered, at which time the object is asserted to belong to the class named by the leaf. If the attributes are appropriate, it is always possible to construct a decision tree which could correctly classifies each object in the training data set. The decision tree must capture some meaningful relationship between a class and its values of the attributes.

Decision tree can be divided into three types: (1) univariate decision tree, (2) multivariate decision tree, and (3) hybrid decision tree [3].

A univariate decision tree (UDT) is a type of decision tree in which the decision boundaries at each node of the tree are defined by a single feature of the input data [3]. The data is split into two or more subsets based on a condition of a single feature of the input data at each internal node in a UDT. In this hierarchical structure, a UDT classification proceeds partitioning the input data by recursively until a leaf node is reached, and the class value associated with the leaf is then assigned to the observation. The characteristics of the decision boundaries in a UDT are estimated empirically from the training data. In the case of continuous data, a test of the form $x_i>c$ is performed at each internal node of the UDT, where x_i is a measurement in the feature space and c is a threshold estimated from the distribution the x_i. The value of c maximizes the dissimilarity or minimises the similarity of the descendant nodes, using one feature at a time.

Multivariate decision tree (MDT) is similar to UDT, but the splitting test at each node may be on the basis of more than one feature of the input data. The set of allowable splits may consist of linear combinations of features. And the linear discriminant functions are estimated at each interior node of a MDT, with the coefficients for the linear discriminant function at each interior node being estimated from the training data. MDT is often more compact and can also be more accurate than UDT [4]. The greater complexity of MDT relative to UDT algorithms introduces a number of factors that affect their performance. Firstly, any different algorithms can be used to estimate the splitting rule at internal nodes, and the relative performance of these algorithms can differ depending on the nature of the data and the complexity of the classification problem. Secondly, as the split at each internal node based on one or more features, so several different algorithms may be used to perform feature selection at each node within a MDT [5]. These algorithms choose the features to include in each test based on the data observed at a particular node, rather than selecting a uniform set of features on which tests for the entire tree are based.

A hybrid decision tree (HDT) is a decision tree where different classification algorithms may be used in different sub-trees of a larger tree. A system named the model class selection system (MCS) is used to build HDT. MCS can combine as many as three commonly used classification algorithms in a recursive tree-structured hybrid classifier. The candidate algorithms are decision tree, linear discriminant functions, and k nearest-neighbor classifiers. MCS employs a hill-climbing search guided by a set of heuristic rules to estimate a HDT by using a set of training data [6]. As part of this implementation, MCS applies a heuristic pruning procedure based on the same procedure used for UDTs and MDTs to ensure that the resulting classifier does not overfit the training data at the expense of generalization.

Decision trees have several advantages. They easily accommodate data from all measurement scales (i.e., nominal, ordinal, interval, and ratio scales) and make no distributional assumptions [7]. Besides, decision trees typically outperform other classifications in terms of classification accuracies [8].

Decision trees are sometimes more interpretable than other classifiers such as neural networks and support vector machines because they combine simple questions about the data in an understandable way. Decision trees naturally support classification problems with more than two classes and can be modified to handle regression problems. Finally, once constructed, they classify new class quickly.

Mahesh Pal and Paul M. Mather demonstrated the advantages of the decision tree for land cover classification in comparison with other classifiers, like the maximum likelihood method and artificial neural networks [3]. Thoreau Rory Tooke and Nicholas C. Copps used decision tree to extract urban vegetation characteristics, including species and condition [9]. Eric C. Brown de Colstoun and Michael H. Story had examined the feasibility of using a decision tree to instrument to map 11 land cover types [10]. Decision tree classification has been successfully applied to many classification problems, but rarely applied to mapping of wetlands.

1.2 Importance of wetland

Wetland are described both as “the kidneys of the landscape”, because of the functions they perform in the hydrological and chemical cycles, and as “biological supermarkets” because of the extensive food webs and rich biodiversity they support. Wetland systems directly support millions of people and provide goods and services to the world outside the wetland [11].

Wetlands are dynamic systems, continually undergoing natural change due to subsidence, drought, sea-level rise, or infilling with sediment or organic material. In recent years, direct and indirect human activity has considerably altered the rate of change of wetlands. Great changes have taken place in the area of wetlands.

In recent years, the dynamic changes of wetlands monitoring based on GIS (Geographic Information System) and remote sensing technology are deeper. Scholars are focusing on the high-resolution and high-precision remote sensing image. It has become an important issue to obtain high quality wetland classification map.

Considering these situations, it is meaningful to analyze wetland using a decision tree, which is a new technique for wetland extracting. The objective of this study is to develop a decision tree to extract wetland from TM imagery in Yinchuan plain. We extracted NDVI from TM imagery, had TC transformation with TM imagery, and produced the spectral characteristic curve of typical classes. Then, a decision tree which is used to distinguish the different type of wetlands was built. From the TM imagery in Yinchuan plain, we gained three types of wetlands: river wetland, lake wetland and paddy wetland. To assess whether the decision tree perform well for wetlands extracting, we evaluated the accuracy of results. Compared with supervised classifications, decision tree appeared an outstanding performance.

2 Methods

The general objectives of this study are (1) to present the basic properties of decision tree, (2) to build a decision tree model to classify wetland, (3) to compare the accuracy of decision tree with that of supervised classification in maximum likelihood algorithm, and (4) to assess its utility for the purpose of wetland mapping from remotely sensing data.

2.1 Study area

Fig. 2 Location of Yinchuan plain within the state of China.

Yinchuan plain, the southwest of Hetao Plain, known as Ningxia plain and Xitao plain, locates at the centre of Ningxia Hui Autonomous Region in China (Fig. 2). To the north it faced Shizui Shan, just south Loess Plateau, the east border is Ordos Plateau, the west Helan Shan. Yinchuan plain covers an area of about 7,793 km^2, roughly between latitudes 37°14′N and 39°23′N and longitudes between 105°43′E and 106°51′E. Approximately 280 km long from south to north and 10~50 km from east to west. The elevation in the study area ranges from approximately 1000 to 1200 m. Because of its climate and the diversity of the natural environment, there are many typical wetland landscape and abundant wetland tourism resources in Yinchuan plain. Wetlands in Yinchuan plain mainly belonged to the river wetland and lake wetland two categories. Wetland vegetation and water birds are variety and distribute widely. In recent years, with the investment of State Forestry Administration, four provincial natural reserves (Qingtongxia reservoir wetland, salt lake wetland, Xiji lake wetland and Ningxia ShaHu wetland) have been successfully built.

2.2 Data acquisition and processing

Two Landsat 5/TM images were acquired from Geographical Science and Natural Resources Research, Chinese Academy of Sciences on September 12, 1999. The images had a spatial resolution of 28.5 m with 7 spectral bands (TABLE 1). And the scenes covered Path/Row 129/033 and Path/Row 129/034 and were delivered registered to a Universal Transverse Mercator (UTM) projection using a World Geodetic System 1984, Zone 48.

Table 1 Landsat 5 TM Band Descriptions

Band	Wavelength (µm)	Spectral Region
1	0.45 - 0.52	Visible Blue
2	0.52 - 0.60	Visible Green
3	0.63 - 0.69	Visible Red
4	0.76 - 0.90	Reflective Infrared
5	1.55 - 1.75	Mid-Infrared
6	10.40 - 12.50	Thermal Infrared
7	2.08 - 2.35	Mid-Infrared

Topographic maps (Scale: 1:100000) published in 1979, provided by the National Geomatics Center of China, was used to extract the vector data of study area boundary.

With the vector data of contour and elevation points which were acquired by vectorizing from topographic map, a Digital Elevation Model (DEM) was produced to calculate slope of Yinchuan plain. The area, where slope degree less than 5°, were defined as plain. Then the range of Yinchuan plain was extracted by vector layer. The two scenes were mosaiced together to provide complete coverage of the study area. After referencing the slop map of Yinchuan plain and the studies by researchers in local in Ningxia, a subset of these scenes covering the study area were extracted for classification.

2.3 Supervised classification

Following the Ramsar Convention and the fact of study area and observing the characteristic of feature displayed directly in imagery, such as shape, size, hue, shade and texture, we divided wetlands in study area into wetland and non-wetland two category. Wetland consisted of three types: river wetland, lake wetland and paddy wetland. The rest of land cover were set as non-wetland.

Before developing a decision tree, we did the traditional supervised classification first. Although it was anticipated the supervised classification using a maximum likelihood classifier may not produce the highest classification accuracy, it was supplied in the experiment to establish a decision tree. We also could compare the accuracy with the results of decision tree classification.

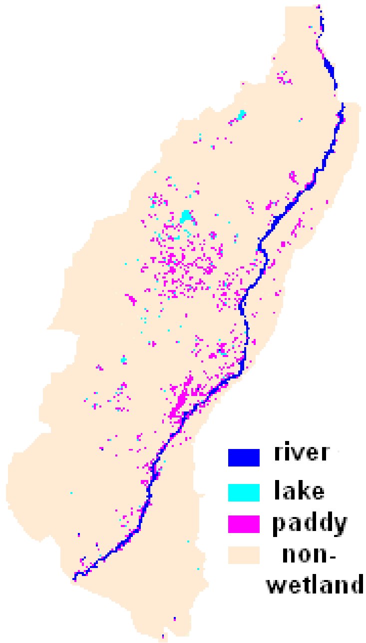

Fig. 3 The result of wetland classification using supervised classification.

In supervised classification, we did the classification as following steps:

(1) Define training data. It is important that these classes should be a homogenous sample of the respective class. Each training class will be defined a Region of Interest (ROI) of the specified colour.

(2) Evaluate the training data. When the training data were selected, it must be evaluated to make

sure the image is high divisible. It should be adjusted if the training data is not satisfactory.

(3) Select the decision rule. There are many different rules which can be applied in a supervised classification. In this study, we selected the maximum likelihood algorithm as the decision rule.

(4) Run the classification.

The result of wetland classification using supervised classification method in maximum likelihood algorithm was shown in Fig. 3.

2.4 Decision tree building and wetlands mapping

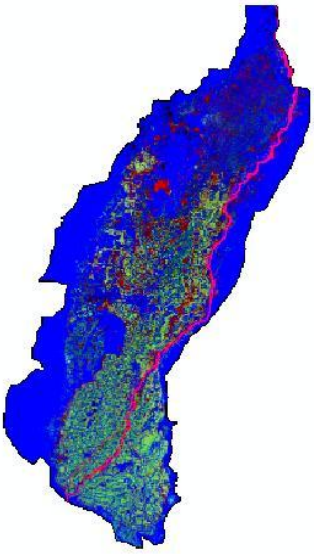

Fig. 4 The first three channels of TC transformation.

The TC transformation had been used for classification to acquire more knowledge about wetness (Fig. 4). The tasseled cap transformation was presented in 1976 by R.J. Kauth and G.S. Thomas. This transform not only provides a mechanism for reducing data volume with minimal information loss but its spectral features can also be directly associated with the wetlands classification. The first three features usually account for the most variation in an image [12] [13] [14]. These first three features have been labelled brightness, greenness and wetness, respectively. The third feature, wetness, has been shown to be sensitive to soil and plant moisture and vegetation structure [15] [16]. This correlation improves the separation of river and lake wetlands from vegetation and other wetland types.

Fig. 5 The result map of NDVI

NDVI was computed from the TM image using two bands of light, red and near-infrared. Vegetation index is often regarded as an effective method to enhance the difference among spectral features and suppress topographic (Fig. 5). NDVI was expected to be helpful to improve wetland classification accuracy.

In our analysis, we selected pixels which were the typical classes of wetland in the image after TC transformation and NDVI image, computed the mean digital number of each pixels (Table 2.). Then we drew the spectral signature curve of typical features with the mean digital number. Because the last two feature of TC transformation has little information, we didn't add them in the signature curve (Fig. 6).

Table 2 The mean digital number (DN) of each wetland type on each channel of TC transformation image and NDVI image.

	river	lake	paddy filed
feature 1	205.687	115.043	170.487
feature 2	0	0	0
feature 3	97.978	46.44	21.6
feature 4	15.333	43.833	34.569
feature 5	0	0.003	0.005
feature 6	0	0	0
NDVI	-0.124	-0.392	-0.055

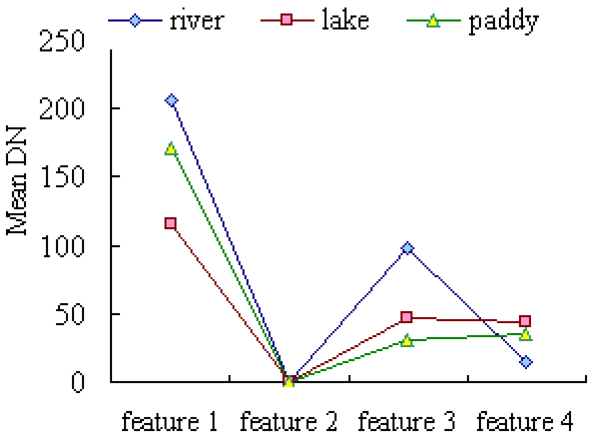

Fig. 6 The spectral signature curve of typical features on TC transformation image.

From the mean digital number of each wetland type on TC transformation image, NDVI image and the spectral signature of typical features, we could realise that: ① the first feature of TC transformation had the most information; ② the value of each wetland type on the second feature of TC transformation image was zero; ③ river had a significant higher value in feature 3 than lake and paddy field; ④ the mean value of river, lake and paddy field on NDVI image all were less than zero, and lake wetland was lowest, second is river wetland, and paddy wetland was last.

After understanding the remote sensing data more deeply, we explored a decision tree as following several steps: (1) select the best split (variable and its threshold) at the root node of the tree through the examination of each variable, (2) create two child nodes, (3) determine the child node into which each catchments goes, and (4) repeat recursively the process [17].

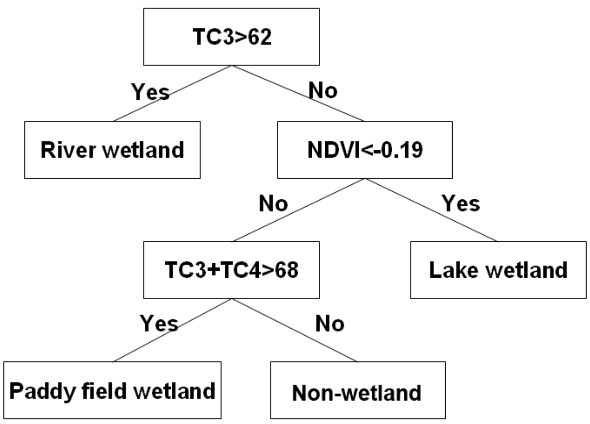

Fig. 7 Decision tree model of 1999 TM image. TC3 and TC4 represent the third and fourth features.

In our analysis, we sampled the training data form the TC image and NDVI image. Observing the training data, we found that the digital number of pixels which expected to be river wetland classes were more than 62. This would help us to distinguish river wetland from others wetland easily. Repeated contrast the digital number of lake wetland and paddy wetland, we detected that the lake wetland could be derived by different NDVI. Further, because paddy wetland was richer in water than non-wetland, it made paddy wetland be extracted possible. According to these steps, a decision tree was built (Fig. 7).

Each wetland type was extracted from TM imagery step by step (Fig. 8). The area of river wetland is relative rich compared with lake and paddy field wetland, occupying approximately 110 km^2. The area of paddy wetland and lake wetland is 105.028798 km^2 and 38.075843 km^2 (Table 3).

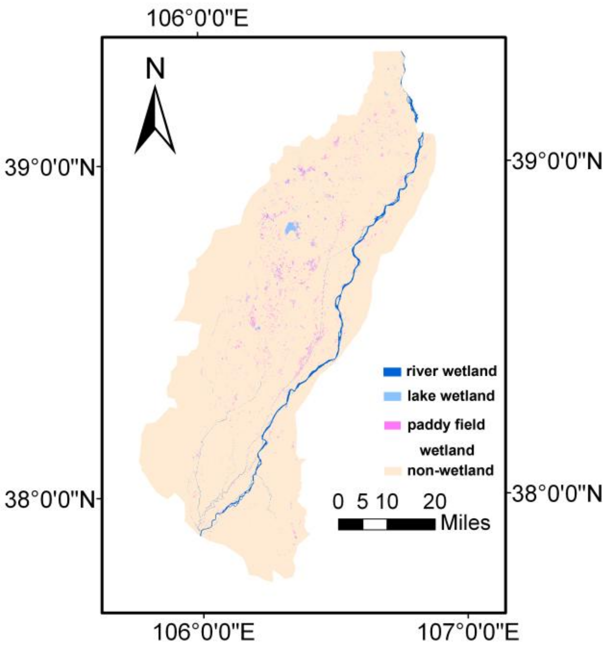

Fig. 8 The wetland classification map using decision tree.

Table 3. The area of each wetland class.

classes	pixels	Area (km^2)
River wetland	135496	110.056626
Lake wetland	46877	38.075843
Paddy wetland	129306	105.028798

2.5 Accuracy assessment

Accuracy assessment was considered to be an essential component of the investigation to quantify whether one classification method was superior over the others. Therefore, accuracy assessment was used to prove whether the decision tree built in this study was appropriate and superior over maximum likelihood method.

The overall percentage correct and Kappa coefficient was computed for error matrix. The user's and producer's accuracies were calculated for each four types. Story and Congalton describe the user's accuracy as the number of correctly classified samples of category X divided by the total samples classified to category X (row total), whereas the producer's accuracy is the number of correctly classified samples of category X divided by the total number of reference samples of category X (column total) [18]. User's accuracy is a measure of commission error and producer's accuracy corresponds to the omission error.

Stratified random sample plots were proportionally allocated to the four land cover types. Selected 1000 random sample plots in total in each type. The supervised classification in maximum likelihood algorithm was selected to determine how well an automated classification method would perform in identification of wetland.

Table 4 provides an evaluation of the final wetland classification produced from supervised classification in maximum likelihood algorithm. The overall accuracy of this classification method is 64.60%. Producer's and user's accuracy for the river wetland is 96.12% and 99.20%, highest than other wetland types. However, the lowest producer's accuracy for non-wetland indicates that there were lots of non-wetland were not identified. And for the paddy wetland, the user's accuracy was very low. It suggests that a number of non-wetland were mistaken as paddy field wetland.

Table 4. Supervised classification error matrix of four classes

	Reference Data					
Classified Data	River	Lake	Paddy field	Non-wetland	total	Users Accuracy
River	248	0	0	2	250	99.20%
Lake	0	159	31	49	239	66.53%
Paddy field	8	8	130	249	395	32.91%
Non-wetland	2	0	5	109	116	93.97%
Column Total	258	167	166	409	1000	
Producers Accuracy	96.12%	95.21%	78.31%	26.65%		
Overall Classification Accuracy = 64.60%						

Table 5. Decision tree classification error matrix of four classes

	Reference Data					
Classified Data	River	Lake	Paddy field	Non-wetland	total	Users Accuracy
River	168	0	0	1	169	99.41%
Lake	4	162	32	9	207	78.26%
Paddy field	6	55	134	15	210	63.81%
Non-wetland	9	12	19	374	414	90.34%
Column Total	187	229	185	399	1000	
Producers Accuracy	89.84%	70.74%	72.43%	93.73%		
Overall Classification Accuracy =83.80%						

Table 6. Conditional Kappa for each category

Class Name	Kappa(Maximum likelihood)	Kappa(Decision tree)
River	0.9892	0.9927
Lake	0.5982	0.7180
Paddy field	0.1956	0.5559
Non- wetland	0.8979	0.8392
Overall Kappa Statistics	0.5476	0.7587

Although the producer's accuracy for river wetland and lake wetland in decision tree was lower than that in supervised classification, the overall classification accuracies of the decision tree was improved to 83.80%(Table5). And river wetland had the producer's and user's accuracies of 89.84% and 99.41%. The producer's accuracy in non-wetland was significantly improved to 93.73% and user's accuracy in paddy wetland was improved over 63%. It is suggested that paddy wetland was distinguished with non-wetland very well.

The variance of the Kappa coefficient was used to perform a significance test on each matrix [19] [20]. The classification derived from the decision tree was of significantly higher accuracy than those from supervised classification (Table 6). Especially in paddy wetland, the Kappa coefficient was improved from 0.1956 to 0.5559. And the overall Kappa statistics in decision tree was higher than that in supervised classification.

3 Discussions

The accuracy results demonstrate successful extraction of wetland using decision tree. Several factors contribute to these results, the most important being that the hierarchical structure of decision tree. Each class could be extracted one by one with this structure from TM imagery. It avoided the influence of linear relation observed between different classes. The second factor is that decision tree could combine the different data. Here, TC transformation image and NDVI were brought into decision tree together. The wetness feature was prominent because of TC transformation. NDVI provided assistance to distinguish lake wetland from paddy wetland and non-wetland.

However, the hierarchical structure brings about another problem. When a rule test in the node of decision tree divides the data into two data sets, the error existing in one data set will be brought to the next level. When we want extract one class from a group data, another class which should be acquired at previous level might presents again. To avoid these mistakes, we should select the variables carefully, decide the rules and conditions in each node prudentially and repeat the experiment to find an optimal threshold to build a decision tree. Another way to resolve this problem is that distinguishing the data from present data set, then going on building the next level tree, merging all the class which belongs to one class at last. This method will be troublesome and time consuming when the decision tree is complicated.

4 Conclusions

This paper is just attempt to explore a decision tree to extract wetland from TM imagery. Highly significant increased in overall accuracies and Kappa coefficient compared with that of supervised classification in maximum likelihood algorithm demonstrate the superiority of decision tree.

The proposed decision tree was successfully applied to the remote sensing data. Different remotely sensed data integrated together to build the decision tree, helped us to classify more exactly. Besides, because of the interpretability of decision tree, we can examine a decision tree and identify the important variables that distinguish wetland classes from one another.

In summary, study presented here demonstrates several important and generally properties of decision tree classification. It is an efficient and robust tool to examine the hierarchical relations among the input data. From this study, it appears that decision tree is a promising approach to pursue in future work, especially for wetland classification. Further study should focus on keeping improving the decision tree performance, evaluating the performance of the proposed model for different structures, different data and high-resolution remote sensing imagery, and building spectrum knowledge bases.

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