Identifying Alpine Wetlands in the Damqu River Basin in the Source Area of the Yangtze River Using Object-based Classification Method

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Abstract: Alpine wetlands are very sensitive to global change, have great impacts on the hydrological condition of rivers, and are closely related to peoples’ living in lower reaches. It is essential to monitor alpine wetland changes to appropriately manage and protect wetland resources; however, it is quite difficult to accurately extract such information from remote sensing images due to spectral confusion and arduous field verification. In this study, we identified different wetland types in the Damqu River Basin located in the Yangze River source region from Landsat remote sensing data using the object-based method. In order to ensure the interpretation accuracy of wetland, a digital elevation model (DEM) and its derived data (slope, aspect), Normalized Difference Vegetation Index (NDVI), Normalized Difference Water Index (NDWI), and Kauth—Thomas transformation were considered as the components of the spectral characteristics of wetland types. The spectral characteristics, texture features and spatial structure characteristics of each wetland type were comprehensively analyzed based on the success of image segmentation. The extraction rules for each wetland type were established by determining the thresholds of the spatial, texture and spectral attributes of typical parameter layers according to their histogram statistics. The classification accuracy was assessed using error matrixes and field survey verification data. According to the accuracy assessment, the total accuracy of image classification was 89%.

Keywords: alpine wetland; remote sensing; object-based classification; Damqu River Basin

1 Introduction

Wetlands are not only valuable as wildlife habitat, floodwater management and water quality improvement, but also in having esthetic and educational benefits to humans. Increased awareness about the functions and benefits of wetlands has pushed them to the forefront of conservation science (Hoffstetter 1983; McCormick 1978), resulting in expanded efforts to inventory wetland ecosystems. Remote sensing is ideal for monitoring wetlands because it is cost and time efficient, and non-invasive (Jensen 2000). Further, analysis of remotely sensed data is an efficient technique to map wetlands across broad geographic areas.

Visual interpretation and manual delineation of remotely sensed imagery are common methods in wetland mapping (Andresen et al. 2002). Manual delineation allows for the delineation of accurate boundaries around objects and the production of visually appealing maps. While effective for some, visual interpretation can be too expensive and time consuming to achieve detailed classification results since these manual methods are not automated, and maps by different interpreters or at different time periods can produce variable results that are not comparable across space or time (Blaschke and Hay 2001).

Automated (computer-assisted) image analysis...
approaches are becoming more common for wetland mapping, including those that involve pixel-based and object-based methods. Automated pixel-based classifiers, like supervised and unsupervised classification and decision tree classification, have been gaining in popularity over the past decade due to the computational power that has made them more operational (Ramsey and Laine 1997; Everitt et al. 1999; Lunetta and Balogh 1999; Everitt et al. 2004), their objectivity, reduced user input (Thomson et al. 1998) and lowered demand for knowledge of ground information. While pixel-based classification methods essentially cluster these pixels into “objects,” they are usually non-hierarchical and single-valued. Especially for wetland mapping with specific difficulties like the severe spectral confusion of different objects, the pixel-based method usually produces “speckled” or “salt and pepper” results (Yu et al. 2006; Guo et al. 2007) that lower mapping precision.

Compared with the traditional pixel-oriented supervised classification method, the object-based classification method can delineate patches into homogeneous areas that are both accurate and visually desirable using methods that are objective, automated and repeatable (Blaschke and Hay 2001; Schiewe et al. 2001). Shape and context are taken into account as well as color and spectral quality of the patch (Schiewe et al. 2001), which can effectively minimize “speckled” or “salt and pepper” results and improve classification accuracy. Soft classifications, or fuzzy modeling based on user knowledge can be integrated into the analyses. In this way, an object is assigned to multiple classes at varying degrees of membership. Moreover, the object-based classification method has the potential to model landscapes in a multi-scale manner because a single image represents a variety of scales and levels of abstraction (Hay et al. 2003). The object-based classification method follows ecological phenomena more closely than traditional pixel-based methods (Blaschke and Strobl 2001) that analyze each pixel independently without taking into account spatial concepts like neighborhood, proximity and homogeneity (Burnett and Blaschke 2003).

There have been several studies published on object-based techniques for mapping wetlands (Bock 2003; Dorren et al. 2003). However, these studies mainly focused on coast zones or low altitude areas. Studies on alpine wetland, especially on source regions of great rivers are scarce. Alpine wetlands are very sensitive to global change and in river source regions have great impacts on the hydrological condition of rivers. These systems are closely related to the standard of living of local peoples inhabiting lower reaches. Wetland monitoring is crucial to understand the status, safety condition and protection of wetlands in such areas. However, wetland maps with high resolution and related wetland databases are lacking, restricting the management and protection of wetland resources. Fieldwork in high altitude areas is also tough due to a harsh climate and poor infrastructure.

We identified different wetland types in the Damqu River Basin located in the Yangze River source region from Landsat remote sensing data using the object-based method. Interpretation results with high precision will provide important reference to the restoration of wetland ecosystems, regulation and utility of wetland resources, and scientific basis for wetland monitoring in such regions.

2 Study area
The Damqu River is the south source of the Yangtze River in China. It is 331 km long with a total basin area of 1.67×10⁴ km², (92.14°E – 94.62°E and 32.40°N – 33.96°N) (Fig. 1). It is the highest wetland distribution area in the world with an average altitude of 4700 m. The Damqu
River Basin is located in the hinterland of the Tibetan Plateau with the Tanggula Moutain to the south, the watershed with the Lantsang River to the east and north, and the watershed with the Biqu River to the west. The large area of inter-mount basin is distributed among the mountains and watersheds with gentle topography, poor drainage and tundra below, which prevent the pervasion of snow and rain, and contribute to the formation of widespread alpine wetlands. The climate characteristics of this area include low temperatures, abundant sunlight, strong solar radiation, distinct wet and dry seasons, and contemporaneous rain and heat. Alpine wetlands, meadows, grasslands and sparse vegetation are the main ecosystems. The species composition of alpine wetland is simple and mainly composed of hygrophyte or perennial herbaceous plants. Dominant species are Kobresia tibetca, K. humilis, Carex moorcroftii, C. atrofuscua and K. pygmaeae, and the companion species Astragalus confertus, Sausurea japonica, Potentilla saundersiana, P. fruticosa and Leontopodium namum. Bog soil is widely distributed in the Damqu River Basin, and occupies the whole inter-mount basin.

3 Data and methods

3.1 Data

3.1.1 Remote sensing data

Two scenes of Landsat TM images were used in this study: Path137/Row37, August 2, 2007 and Path136/Row37, July 26, 2007, applied by the Global Land Cover Facility (GLCF) and the US Geological Survey (USGS).

Digital Elevation Models (DEMs) outline local depressions and potential hydrological patterns across the landscape, as elevation and topographical data can assist image-based wetlands mapping. The latest ASTER Global Digital Elevation Model (ASTER GDEM) with a spatial resolution of 30m is used in this study. The slope and aspect data were derived from DEM.

3.1.2 Field survey data

The wetland types, position and vegetation data in the Damqu River Basin were collected during three sessions of field survey carried out in September 2008, September 2009 and August 2010. The GPS waypoints and track, investigation of vegetation sampling, soil wetness measurements, and sampling of typical plants were done during field surveys. One hundred and four plant quadrat surveys, 98 soil samples and 2500 photos were taken. The field survey route is shown in Fig.1. The alpine wetland is mainly distributed in the upper reaches of the Damqu River, and less in middle and lower reaches where there are few people and no accessible roads. Therefore, the field surveys were carried out to focus on the upper reaches of the river, which is the middle and eastern part of the basin.

3.1.3 Auxiliary data

The auxiliary data includes the topographic map (1 : 100 000; 1967), vegetation map of China (1 : 1 000 000; 2004), land use map of Qinghai Province, China (1 : 1 000 000; 1989), Chinese wetland database (1 : 1 000 000; 2000), etc.

3.2 Methods

3.2.1 Wetland classification

Based on the wetland classification system used home and abroad (Scott and Jones 1995; Pressey and Adam 1995; Niu et al. 2009; Zhang et al. 2010), the remote sensing based alpine wetland classification system was constructed after consulting the characteristics of alpine wetland in the Damqu River Basin. We divided wetlands according to the hydrological situation into three first class types: riverine, lacustrine and palustrine. As for the second class classification, we subdivided the river wetland according to river morphology into river and flooded wetland; subdivided lake wetland according to the area dimensions and origin into lake, lacustrine pond, and glacial lake; subdivided the marsh wetland according to the soil moisture and vegetation community into Carex - Kobresia swamp, Kobresia swampy meadow, and K. pygmaeae wet meadow.

3.2.2 Pre-process of remote sensing data

Control points chosen from the topographic map were taken to achieve geometrical correction using the quadratic polynomial fitting method. Pixel re-sampling was processed using the nearest neighbor method. Errors of the revised image were less than one pixel, according to the RMSE (Tucker et al. 2004). Mosaic and subset of images were processed to fit the range of the Damqu River Basin.

3.2.3 Key parameters for interpretation

The Normalized Difference Water Index (NDWI) is widely used to identify water body and humidity condition. We used the NDWI to distinguish water wetlands (riverine and lacustrine) and palustrine following McFeeters (1996):

$$\text{NDWI} = (\text{Green} - \text{NIR}) / (\text{Green} + \text{NIR})$$

The Normalized Difference Snow/Ice Index (NDSII) was used to derive glacial lakes. Some glacial lakes that were frozen could not be indentified well by the NDWI. Snow and ice have very high reflectance values in visible spectral bands (TM2 [0.52–0.60 μm], TM3 [0.63–0.69 μm], TM4 [0.76–0.90 μm]), but very low reflectance in shortwave infrared bands (TM5 [1.55–1.75 μm]) (Racoviteanu et al. 2008b). The NDSII formula (Nie et al. 2010) used was as follows:

$$\text{NDSII} = (\text{Red} - \text{SWIR}) / (\text{Red} + \text{SWIR})$$

The Normalized Difference Vegetation Index (NDVI) is widely used to indentify vegetation types. The NDVI value increases as the vegetation coverage grows. We used
the NDVI to distinguish three marsh wetlands along with the Kauth-Thomas transformation, which can identify different soil moisture conditions.

Kauth-Thomas transformation (K-T) transformation (Kauth and Thomas, 1976) is commonly used for image transformation and enhancement. The K-T transformation not only provides a mechanism to reduce data volume with minimal information loss, but its spectral features are also directly related to the important physical parameters of the land surface (Crist and Cicone, 1984; Jin and Sader, 2005). In this study, the K-T transformations of the six non-thermal ETM bands were performed to produce six multi-spectral features. We were primarily interested in the wetness feature, because it is associated strongly with observed differences in soil moisture and is the most important index for wetland classification. The wetness feature made a great contribution to the boundary identification of each wetland type, especially for palustrine.

3.2.4 Object-based classification

After the pre-processing of images and the calculation of key parameters, we combined all the bands of TM images, DEMs, NDSII, NDWI, NDVI, and wetness feature as one dataset, which was used to identify each wetland type through object-based classification. The process of wetlands extraction was run on the ENVI ZOOM platform provided by ITT Visual Information Solutions. The main steps included: segmenting images, merging segments, computing attributes (spatial attributes, spectral attributes, texture attributes, etc.), refining segments (setting thresholds), and exporting outputs (Nie et al. 2010). The main workflow is described in Fig.2.

Segmenting images is a key step as it partitions an image into segments with similar pixel values using an edge-based segmentation algorithm. There are two parts to the segmenting process: segmenting images and merging segments, both with the scale extent of 0%~100%, but with different meaning. During the segmenting images process, the differences between segmented objects increase with increase in scale index, which leads to more patch numbers and higher patch density. The merging segments step is to reprocess the segmented image from the previously segmented images to find the relative consistency between objects to generate an object-based image for interpretation. Oppositely to the segmenting process, the larger the scale index, the lower the consistency of objects, which leads to a decrease in patch number and patch density. The scale index of segmenting and merging should be carefully determined to guarantee the correct extraction of the object boundaries (Zhang et al. 2010).

We determined the segmenting and merging index based on multiple tests following the principle that the wetland patches with an area larger than $3 \times 3$ pixels could be identified correctly. The object-based image was generated with a segmenting scale index of 30% and merging scale index of 70%.

Another key step is to build optimal rule-based classification for each wetland type based on the expert knowledge, and samples analysis to determine the appropriate indicators and their reasonable thresholds to classify the objects. The spectral attributes (including maximum, minimum, mean and standard deviation), spatial attributes (including area, perimeter, compact, elongation, etc.), and the texture attributes (including range, mean, variance and entropy) of each dataset layer are computed during the segmenting process. Based on the computed results and the histogram statistics, the thresholds of each attribute of each dataset layer was determined. The extraction rules of each wetland type could then be established by integrating all thresholds.

We used the NDWI to extract water bodies including rivers and lakes. Lakes with an area less than 1 km$^2$ were classified as lacustrine ponds. Glacial lakes were extracted according to the DEM and NDSII. We also used the spectral difference between glacial lakes and glaciers in Band3 to distinguish them. The river exemplifies a long and narrow shape, which is significantly different from other objects and could be identified using the elongation index combined with the DEM. Flooded wetland have lower vegetation coverage than palustrine, and higher soil moisture than non-wetland. Therefore, we used the NDVI and wetness index to distinguish flooded wetland from palustrine and non-wetland. The three palustrine types Carex - Kobresia swamp, Kobresia swampy meadow, and
K. pygmaea wet meadow differ in vegetation coverage and soil moisture. The Carex-Kobresia swamp community is mainly composed of C. moorcroftii, C. atrofusca, K. tibetca, and K. humilis with coverage of more than 90% and an average height of 12cm. It distributes in the intermount basin with superior water collecting ability. The Kobresia swampy meadow community is dominated by K. tibetca and K. humilis with coverage of 50%–70%. It distributes in the open valley and slope base where the soil moisture is comparatively lower than that of Carex-Kobresia swamp.

K. pygmaea wet meadow is a non-swampy meadow, where K. pygmaea is the constructive species of the community. Although the coverage of K. pygmaea wet meadow is high (>90%), the average height is only 4cm, which makes the NDVI value lower than other palustrine types. The soil moisture of K. pygmaea wet meadow is higher than that of a forb meadow or alpine grassland, but lower than that of a Kobresia swampy meadow. Extraction rules of each wetland type are shown in Table 1.

### Table 1 Extraction rules of each wetland type.

<table>
<thead>
<tr>
<th>Classes</th>
<th>Reference Points</th>
<th>Classified Points</th>
<th>Correct Number</th>
<th>Producer Accuracy</th>
<th>User Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>River</td>
<td>49</td>
<td>49</td>
<td>49</td>
<td>100.00</td>
<td>100.00</td>
</tr>
<tr>
<td>Flooded wetland</td>
<td>60</td>
<td>59</td>
<td>54</td>
<td>90.00</td>
<td>91.53</td>
</tr>
<tr>
<td>Lake</td>
<td>45</td>
<td>45</td>
<td>45</td>
<td>100.00</td>
<td>100.00</td>
</tr>
<tr>
<td>Lacustrine pond</td>
<td>40</td>
<td>44</td>
<td>36</td>
<td>90.00</td>
<td>81.82</td>
</tr>
<tr>
<td>Glacial lake</td>
<td>12</td>
<td>12</td>
<td>12</td>
<td>100.00</td>
<td>100.00</td>
</tr>
<tr>
<td>Carex - Kobresia swamp</td>
<td>104</td>
<td>100</td>
<td>94</td>
<td>90.38</td>
<td>94.00</td>
</tr>
<tr>
<td>Kobresia swampy meadow</td>
<td>98</td>
<td>107</td>
<td>80</td>
<td>81.63</td>
<td>74.77</td>
</tr>
<tr>
<td>K. pygmaea wet meadow</td>
<td>92</td>
<td>84</td>
<td>75</td>
<td>81.52</td>
<td>89.29</td>
</tr>
<tr>
<td>Total</td>
<td>500</td>
<td>500</td>
<td>445</td>
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### Table 2 Accuracy assessment of wetland interpretation.

<table>
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<tr>
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According to the test, the overall classification accuracy of the wetland interpretation was 89.00%. The interpretation accuracies of most wetland types are above 90%, some of which such as that of rivers, lakes, and glacial lakes, reach 100%. The water wetlands were better interpreted than palustrine. The interpretation accuracy of Carex-Kobresia swamp is larger than that of the other two palustrine types. Most confusion exists between the Kobresia swampy meadow and K. pygmaea wet meadow. The typical examples of wetland extent derived by object-based classification method are shown in Fig.3.

### 4 Conclusions and Discussion

Wetland ecosystems occupy a wide variety of habitats and display an equally expansive range of vegetation and hydrology. Using the object-based classification method, the wetland was extracted in objects instead of pixels, which effectively eliminates any “speckled” or “salt and pepper” results. The spectral characteristics of remote sensing images, vegetation coverage, topographic feature of wetland distribution and soil moisture condition were analyzed integrally by using related parameters such as NDVI, DEMs, and K-T transformation. According to...
multiple experiment trials, 30% and 70% were found to be the most optimal scale index for the segmenting and merging process. We used a rule-based classification pattern to extract each wetland type based on the computed results and histogram statistics of the spectral attributes, spatial attributes, and texture attributes of each dataset layer. We determined the thresholds of the spatial, texture, and spectral attributes of typical parameter layers that helped distinguish one wetland type from the others and established the extraction rules for each wetland type. According to the precision test, water wetlands are better interpreted than palustrine. The overall classification accuracy of the wetland interpretation was 89%.

Remotely sensed data can be used to identify spectrally and ecologically distinct wetland meadow communities. Because vegetation composition and structure govern the spectral reflectance of meadows, spectral response characteristics can be linked to distinct plant species assemblages to identify different palustrine types. However, only communities that have significantly different environmental needs from other palustrine types can be interpreted correctly. Communities with similar soil moisture, vegetation coverage, or environmental interests were not interpreted precisely and visual interpretation is needed to correct these confusions.

Soil moisture and vegetation coverage can effectively reflect the basic environmental requirements of wetland communities, thus the NDVI and wetness layer obtained through K-T transformation are key parameters in identifying different wetland communities. DEM data can assist image-based wetland mapping by outlining local depressions and potential hydrological patterns across the landscape. Field surveys are also extremely important not only for collecting verification data, but for understanding the natural environment of regional wetlands. The thresholds of the NDVI, wetness and DEM values should be determined based on spectral and texture features of images. Understanding the environmental requirements of each wetland community can only be accomplished by sufficient field survey work and plant quadrat surveys, sample collection and soil moisture measurement.

Acknowledgement
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References


## 面向对象的长江源区当曲流域高寒湿地信息提取

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**摘要:** 长江南源当曲流域是长江高寒沼泽湿地的集中分布地区之一，是青藏高原腹地重要的水源涵养地。对该地区湿地资源及分布的准确把握直接关系到当地牧民的生产生活及下游地区的经济社会发展。由于湿地光谱特征复杂，易于其他地类混淆，传统的遥感信息提取方法很难保证湿地信息提取的精度。本文运用面向对象的图像信息自动分类方法，对当曲流域的湿地信息进行提取。在对各类型湿地的光谱特征、纹理特征及空间特征进行分析的基础上，充分结合DEM及其衍生数据（坡度、坡向）、归一化植被指数（NDVI）、归一化水体指数（NDWI）及缨帽变换（Kauth–Thomas transformation）得到的湿度图层等参数，设置各参数阈值，建立各湿地类型的信息提取知识规则，并结合野外实地调查对信息提取精度进行验证。经检验，湿地信息提取的总体精度达到89.00%。

**关键词:** 高寒湿地; 遥感; 面向对象图像分类; 当曲流域