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USE OF REMOTE SENSING TO INVENTORY MOUNTAIN PEATLANDS IN LESOTHO.

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SUMMARY

Remote sensing is the only practical means of conducting a detailed inventory of wetlands in remote mountainous regions. In this paper we assess two different approaches for using remote sensing data to inventory wetlands in the Lesotho Maloti Mountains. An inventory was conducted in 2004 using SPOT5 imagery with the wetlands delineated optically by an operator. To assess the accuracy of that inventory we selected a first-order watershed forming the headwaters of the Motete River, and delineated the wetland areas using classification software on high resolution IKONOS 2006 imagery. Those determinations using SPOT imagery were compared to those identified from IKONOS imagery and known ground points to assess the accuracy of the wetland boundary. The manual delineation of wetlands resulted in an overestimate of the area, primarily due to difficulties accurately tracing intricate boundaries as compared to the high resolution digital assessment.

KEY WORDS: mountain peatlands, remote sensing, wetland inventory, Lesotho.

INTRODUCTION

Peatlands are generally associated with boreal or tropical regions. However, peatlands may also exist in mountainous terrain, providing ecologically and sociologically important services. Besides the merits on the ecological system such as carbon storage, flood mitigation, and habitat provision for plants and wildlife, the peatlands in Lesotho are an indispensable natural resource for local and national economy. Wetland inventory is a prerequisite for evaluating wetland functions and values, and in planning management priorities (Taylor et al., 1995). Maloti Drankensberg Transforntier Project (MDPT) conducted an inventory of wetlands in the Lesotho highlands using SPOT5 imagery. The study used conventional, on-screen, manual, photo-interpretation methods (Maloti Drankensberg Transfrontier Proeject, 2007). The accuracy of that inventory was not assessed with a comprehensive field validation. This study is a comparison of the manual photo-interpretation method and an automatic image process called object-oriented segmentation and classification for wetland delineation. The object-oriented segmentation and classification was applied to an IKNOS satellite image of a representative area in the Maloti mountains that contain the high elevation wetlands. The accuracy of the two approached was evaluated by ground information from field survey.

MATERIAL AND METHODS

Study Area

Lesotho is located in southern Africa and the entire country is completely enclosed by the Republic of South Africa. The wetlands typically occur in the Maloti Mountains, which are an incised basaltic plateau that has been eroded over the millennia giving rise to steep, narrow valleys that drain into streams. Wetlands are a common feature in the high elevation (> 2,500 m a.s.l.) first-order watersheds.

We analyzed the Khalong-la-Lithunya catchment which contains the first order watersheds that form the headwaters of the Motete River. This catchment was chosen as a representative of the high elevation wetlands that have been degraded. The catchment is located in the Butha-Buthe District (28.88 S, 28.78 E) bordering Mokhotlong District. The catchment comprises approximately 36 km^2 with elevation ranging from 3,100 to 3,200 m a.s.l.

Data

The Wetland Inventory of the Lesotho Highlands or Maloti Mountains was conducted by the MDPT in 2005 (Maloti Drankensberg Transfrontier Proeject, 2007). The inventory was built based on the true color 2.5 m resolution SPOT5 images, acquired in 2004 and projected in UTM Zone 35 S, datum WGS84. The conventional on-screen manual photo-interpretation was adopted for wetlands delineation. The on-screen identification of vegetation and/or wet area boundaries was carried out at a 1:10,000 screen resolution. The wetlands were identified in the same projection as the SPOT5 image.

IKONOS images covering the study area were taken on November 14, 2006, and provided the basis for assessing an automatic process of wetland delineation. IKONOS satellite multispectral images include 4 bands (i.e. Blue band (0.45-0.52μm), Green band (0.52-0.60μm), Red band (0.63-0.69μm), and Near Infrared band (0.76-0.90 μm) with 4 m spatial resolution.

Analyses

Image Pre-processing

The IKONOS image was rectified using image to image registration. The reference image is an aerial photo of the study area with 0.5 m spatial resolution acquired by Land Resources International (Pty) Ltd between October 06, 2009 and November 29, 2009 under cloudless conditions. It was ortho-rectified by GPS/Inertial Measurement Units with a maximum spatial error of 10 m. The registration was performed in the geometric model of IKONOS in ERDAS which incorporates information of the Rational Polynomial Camera (RPC) supplied with IKNOS images and a 30 m Digital Elevation Model (DEM). Eleven Ground Control Points (GCPs) were collected and a RMSE (Root Mean Square Error) of $\pm$0.25 pixel ($\pm$ 0.96 m) was achieved. After registration, clouds covering about 11% of the study area were removed from the image before further analyses.

Wetland Delineation

The wetland delineation was conducted by the object-oriented segmentation and classification method with two steps using the eCognition software (Benz, 2001). It first step creates image objects that are relatively homogenous individual areas in term of shape and spectral, then it classifies the image based on these image objects according to their characteristics.

The multi-resolution segmentation and nearest neighbor algorithm embedded in eCognition were adopted in the segmentation and classification process. It is a bottom-up, region growing technique which recursively merges pixels or existing image objects starting with single pixel objects. The merging process is controlled by the scale parameter, the threshold of the maximum increase of heterogeneity that allows two segments to merge. The heterogeneity is defined on the basis of two complementary criteria: color and shape. The sum of the weights of the two criteria equals one. In turn, the shape criterion is determined by two other criteria, smoothness and compactness, the weights of which also sum up to one. These weights allow for the adaption of the heterogeneity definition in considered applications (Benz et al., 2004). In this study, all four bands (i.e. the red, blue, green, and near infrared bands) were used in the segmentation process. The scale parameter was set to 30. The weights of the spectral and shape were assigned to 0.9 and 0.1 respectively. The weights of compactness and smoothness were assigned equally (0.5 for each of them).

The classification was performed using the nearest neighbor algorithm, a supervised classification method. After the user specifies the training data, the unlabeled objects and labeled objects (i.e. the training data) are mapped in n-dimensional space in which each dimension represents the features of objects that user selects for classification (e.g. the mean brightness value of certain band in the objects, the area of the objects). The algorithm searches away from the object to be classified in all directions in the n-dimensional space until it encounters user specified training objects. It then assigns the object to the class with the majority of objects encounter (Jensen, 2005). The features of the objects for classification were determined by Feature Space Optimization tool in eCognition. The candidate features included: the mean brightness values of four bands in the objects and the pseudo NDVI (Normalized Difference Vegetation Index). NDVI is a widely used index for vegetation detection. The strict definition of NDVI is:

$$NDVI = (\rho_{nir} - \rho_{red})/(\rho_{nir} + \rho_{red})$$

where ρ is the reflectance rate of a band (i.e. near infrared or red band here). In pseudo NDVI, the reflection rate was substituted by the Brightness Value (BV) in the corresponding bands:

$$\text{pseudo } NDVI = (BV_{nir} - BV_{red})/(BV_{nir} + BV_{red})$$

Field Survey

Points for field validation were obtained in November, 2011. Catchments were traversed to allow the demarcation of wetlands (n=61), uplands and inclusions within wetlands (n=37), rock outcrops within wetlands and uplands (n=4), erosion features (n=10), stream channels (n=1) and open pools (n=4). The points were obtained with a Trimble GPS Unit, horizontal accuracy was within 2 m.

Accuracy Assessment

The study area was classified into wetlands and non-wetlands by the manual and automatic approaches. The accuracy was assessed using the ground validation points obtained in the field survey. The performance was evaluated by three measurements of accuracy (Story and Congalton, 1986): user accuracy (i.e. error of commission), producer accuracy (i.e. error of omission), and overall accuracy, and the Kappa coefficient which compares the accuracy of classification to that of a random classification (Congalton et al., 1983).

RESULTS AND DISCUSSION

The object-oriented segmentation and classification method outperformed the manual delineation (Table 1-3). Feature Space Optimization suggested that pseudo NDVI is a key feature to distinguish the wetland and non wetland. The brightness value of the near infrared band is a component in the calculation of pseudo NDVI because foliage reflects a large amount of the near infrared energy. Accordingly, vegetation is typically recognized by area with a high NDVI. The lower accuracy of the manual delineation was partly due to the absence of near infrared band in SPOT 5 imagery.

Table 1 Error matrix of the classification map using the manual approach.

		Reference Data	
		Wetlands	Non wetland
Classification	Wetlands	55	12
	Non wetland	34	22

Table 2 Error matrix of the classification map using the object-oriented image segmentation and classification method.

		Reference Data	
		Wetlands	Non wetland
Classification	Wetlands	55	12
	Non wetland	34	22

Table 3. The Producer’s, User’s and Overall accuracy, and Kappa Coefficient of the classification using the manual approach (MA) and automated approach (AA).

	Accuracy					Kappa Coefficient
	Producer's		User's		Overall	
	Wetlands	Non Wetlands	Wetlands	Non Wetlands		
MA	62%	65%	83%	39%	63%	0.22
AA	76%	79%	85%	68%	77%	0.58

The manual delineation also had the drawback of simplifying and generalizing the wetland boundaries. The boundaries from inventory covered the non-wetland area. For example, a large gully (8,102 m^2) was included as part of the wetland in the MDTP inventory (Fig. 1). The area of wetlands detected from the image of the study area after the clouds were masked by the automatic approach was 2.4 km^2, while that from wetland inventory was 4.7 km^2. Thus, the manual delineation of wetlands resulted in an overestimate of the area. Moreover, the experience of the photo interpreter greatly affects the representation in the process of building the inventory. In contrast, the automated approach repeatable, transparent, and quantifiable.

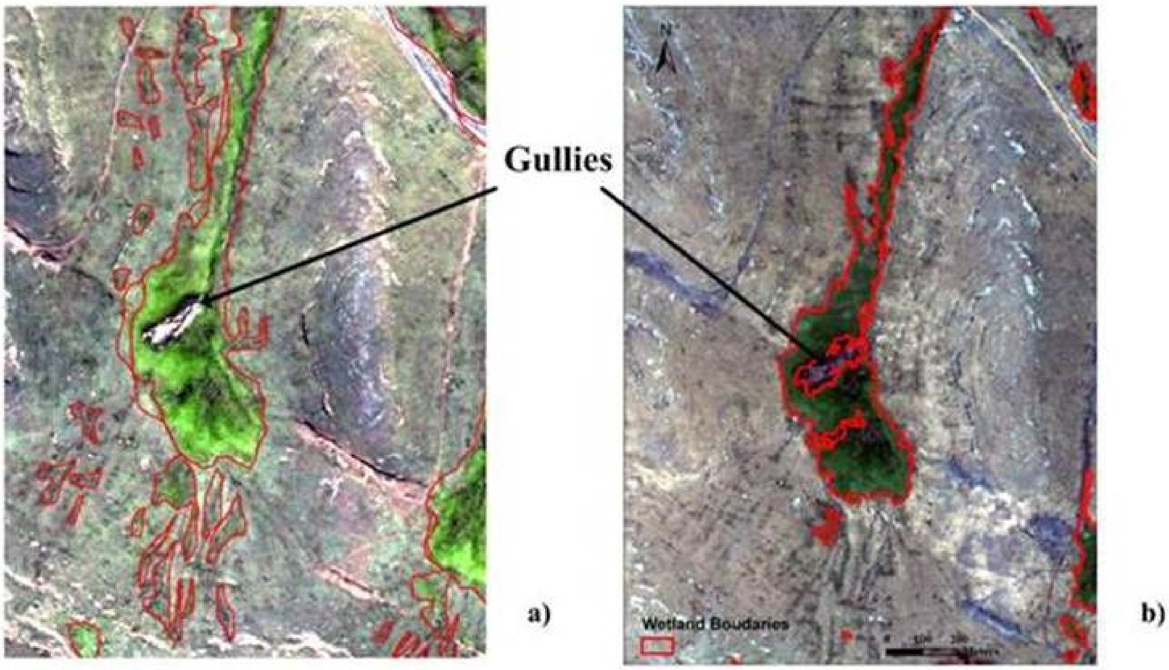

Fig.1 Comparison of wetland boundaries on the same site selected from the Lesotho wetland inventory that was delineated manually on a SPOT5 image (a), with those derived from an IKONOS image using the object-oriented image segmentation and classification method (b).

CONCLUSIONS

Remote sensing is an effective tool to identify wetland areas especially in inaccessible mountainous regions. The object-oriented segmentation and classification for wetland delineation produced a higher accuracy than the manual approach, and provides a more reliable way to inventory the wetlands in mountainous areas. The recent advances in classification software and availability of high-resolution multi-spectral remote sensing data provide the necessary capabilities to inventory wetlands accurately.

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