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Land use classification in Zambia using Quickbird and Landsat imagery

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Abstract. *High resolution satellite imagery can provide significant new tools and information to support natural resource management. Although the increased resolution also introduces challenges in typical classification, the fine resolution data itself reveals features that are desirable. The possibility of visual interpretation of these new data makes some types of classification simpler.*

Quickbird imagery over eastern Zambia (0.6m pan, 2.4m multispectral) and Landsat7 ETM+ from the same period were used together to derive land cover layers for the study region. Various classification approaches including different band combinations, alternatives for defining training fields, and different classification methods were compared in terms of classification accuracy. The error matrix and Kappa statistic for the approaches were calculated and accuracy of the classified images evaluated with 255 randomly sampled reference data points. Using a combination of principal components and a vegetation index resulted in better classification accuracy than did a typical false color infrared band combination. Different approaches in defining training fields and different classification algorithms did not result in significant differences in classification accuracy.

Keywords. land use classification, remote sensing, Quickbird, Landsat, band combinations, false color, principal components, vegetation index, training fields, error

Introduction

While remotely sensed data are widely used, it is still not easy to define land use for areas where qualified reference data are not available. Ground truth data are crucial for classifying the data to informational classes and for assessing classification accuracy. Remotely sensed data of very high resolution can potentially provide a convenient source of high quality information and serve as "ground truth" for land use classification. In this study, one Quickbird scene (DigitalGlobe, Inc.) was used in selecting training data for the classification process and in generating reference data.

There are various ways to group image pixels into information classes, and different band combinations and classification algorithms can yield different results. In addition, the selection of training data can have a great influence on the classification result. For supervised classification, in particular, the training areas used have been found to be even more important than the choice of classification algorithm in determining classification accuracies of agricultural areas in the central United States (Scholz et al., 1979; Hixson et al., 1980; Campbell, 2002). Although a strategy for selecting training fields will depend on the objectives of the classification and on the landscape characteristics of the study area, there are common criteria that can be followed (Jensen, 2005).

In classification using multispectral imagery, the spectral characteristics of each pixel as three or more image layers represents the landscape. There are many band combinations used in remote sensing, and a "false color infrared" is very commonly used. The band combination or selection of layers should be selected in consideration of informational classes of interest, characteristics of the landscape of the study area, and spectral resolutions of an object image. Usually the bands are selected among the original spectral bands of an object image considering the characteristics and information content of each spectral band. However we may miss some features that cannot be characterized by the raw bands on the image. For instance, "false color infrared" is limited in its ability to detect soil and vegetation moisture because the band combination does not have a mid-infrared band that is sensitive to moisture variation. So when there is little ground-truth information defining the landscape, there is added benefit in using enhanced layers that integrate spectral information from multiple spectral bands for classifying the image.

The objective of this study was to assess the benefit of different approaches for using high-resolution imagery (represented by Quickbird imagery with 0.6m panchromatic and 2.4m multispectral data) to classify lower resolution imagery (Landsat7 ETM+ at 30m resolution). The classification approaches were compared in terms of classification accuracy and included different band combinations, different training fields, and different classification methods.

Study Area and Data

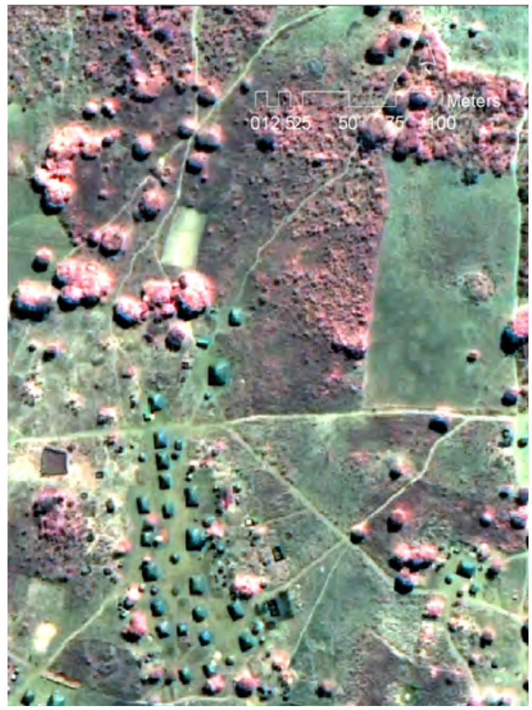
Magodi in Eastern Zambia

The study area, Magodi, is located in the Lundazi district in the Eastern Province of Zambia, and is a part of the upland plateau region of the Luangwa River basin. Land use mainly consists of crop fields, forest (Miombo and Mopane), and wetland (Dambo). Some mixed forests cover areas where the forest and wetland interface, and village areas are sparsely scattered. Crop fields are encroaching into forest lands as fertility declines and old fields are abandoned. (Figure 1a).

Landsat ETM and Quickbird

For this study we used archived Landsat ETM+ from 8 May 2002 and a Quickbird image acquired on 23 July 2002. The acquisition dates are close in time, and images are assumed to represent the same land cover. Resolution of six Landsat bands (1 - 5 and 7) is 30m. The Quickbird image has a panchromatic resolution of 0.6m and four multispectral bands at 2.4m resolution. The high resolution makes it possible to easily identify individual field boundaries, tree crowns, narrow roads, and roofs of houses (Figure 1.b), so it can be used as a reference for ground truth data in classifying the Landsat image. The study area used for the analysis is the extent of the Quickbird image which is approximately 11x12km.

a. Encroaching of crop fields on forest



b. Small features on the Quickbird image

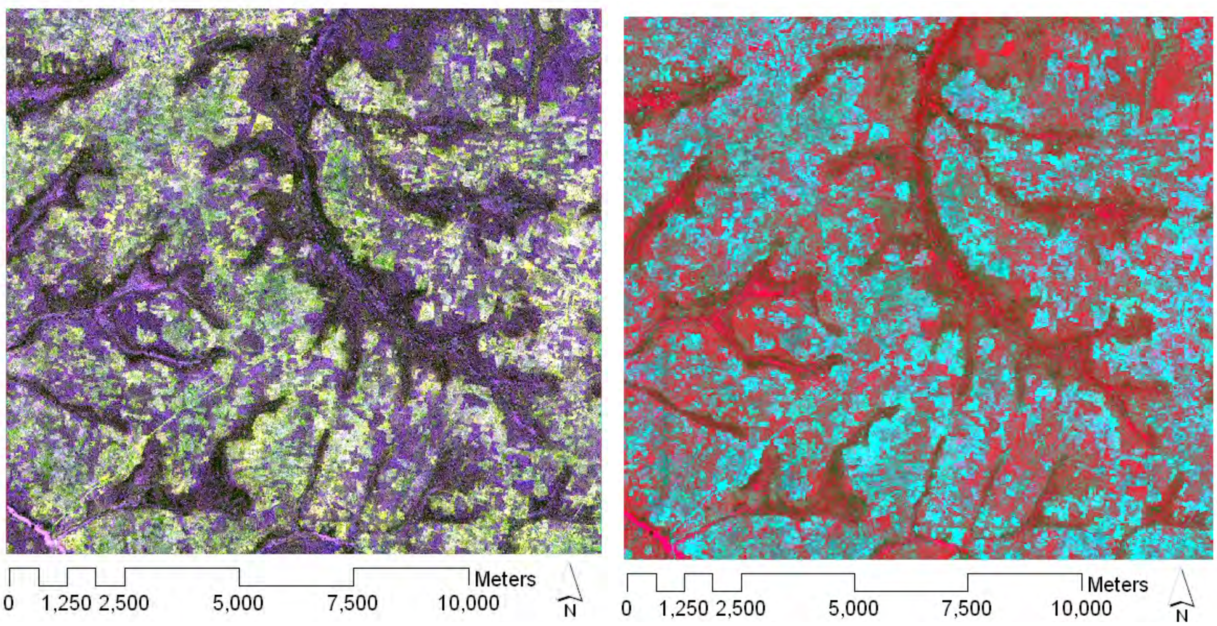
Figure 1. Landscape detail on the Quickbird image

Methods

Band combination

Many band combinations, which have three different spectral or informational layers, can be used in classifying images. Because features that are detected by the band combinations can be different, informational classes of interest and landscape of a study area should be considered in selecting a band combination for an effective classification. For example, a combination of bands 4 (NIR), 3(Red), and 2 (Green) of Landsat is well known as “false color infrared” and generally used for vegetation and crop analysis. Also, because band 5 of Landsat is sensitive to moisture variation in vegetation and soils, a combination of bands 4 (NIR), 5 (MIR), 3 (Red) is good for the analysis of soil moisture and vegetation conditions.

For this study area, there is limited information about vegetation and soils, so it is not certain which band combination is the most appropriate for the classification. Thus, the “false color infrared” which is the most conventional band composite (Figure 2.a) and a combination of two principal components (PCs) and a vegetation index (VI) layer (Figure 2.b) were used in classifying the image. The first and second principal components have 99% of the spectral variance of the original Landsat image, and a VI was added to the combination in order to take into account the distribution of vegetation.



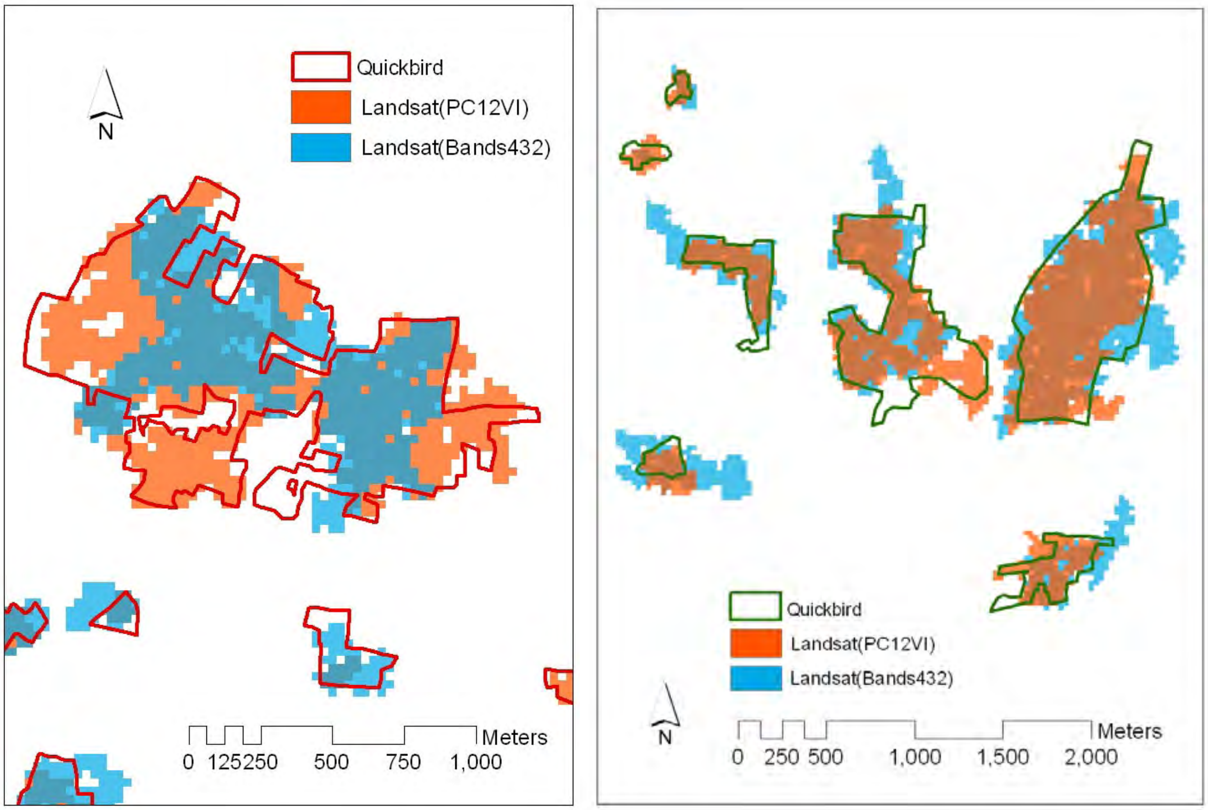
a. PCs and VI combination

b. False color infrared

Figure 2. Band combinations of Landsat ETM+

Training fields selection

Training data can be created from reference images under the assumption that the reference and object images were taken on the same date, or at least that there is a direct correspondence between the land cover represented in the two images. When defining training fields on the reference image, one approach is to use an automated “region growing” tool that expands an area to include pixels within a specified threshold or spectral Euclidean distance. But the created training data on the object image sometimes do not agree with training data made on the reference image because of different acquisition dates, characteristics of sensors, and errors caused by processing, atmospheric effects, etc (Figure 3). Although a manual designation of training fields on the reference image can potentially cause bimodal distributions of spectral histograms of each training field, it is usually handy to make them on the reference image manually because of its possibility of better interpretation. So, two approaches, the training field selection on the object (Landsat) and the reference (Quickbird) images were tried in the classification of the object images.



a. Training data for crop field

b. Training data for forests

Figure 3. Training fields created from object and reference images

Classification Method

Although many different methods have been devised to implement supervised classification, the maximum likelihood method is still one of the most widely used supervised classification algorithms (Jensen, 2005). Also it is well known that Parallelepiped classification method can produce the most accurate classification because of its conservative decision rule even though it may leave large areas in data space and on the image unassigned to informational classes (Campbell, 2002). Of these two methods, only maximum likelihood and a mixture of Parallelepiped and maximum likelihood methods were applied together in the classification.

Random sample size for validation

There are several sampling methods to collect ground reference data for assessing the accuracy of classification results: random, systematic, stratified random, stratified systematic unaligned, and cluster sampling (Jensen, 2005). In this study, 256 ground truth points were randomly sampled on the reference image without any consideration of informational class distribution to avoid statistical bias. The sample size, 256 was determined based on an equation that Fitzpatrick-Lins (1981) suggested under a setting that 95% two-sided confidence interval and the expected accuracy of 80% at allowable error of 5%. Following Jensen (2005), the calculation for this image is:

$$N = \frac{Z^2(p)(q)}{E^2} = \frac{1.96^2(0.80)(1-0.80)}{0.05^2} \approx 246$$

Ten points were added to the calculated sample size for safety and after assignment, 1 point was discarded because it was outside a valid image space. Thus, the final random sampling size of 255 was used in this study. Locations of the points are shown in Figure 4.

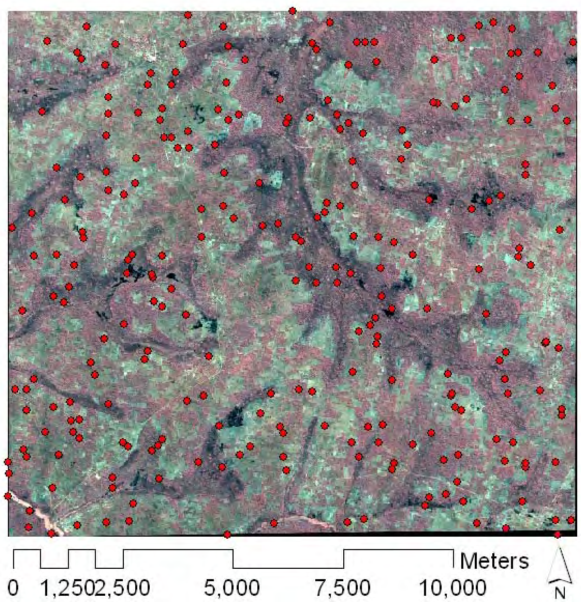


Figure 4. Random sample points

Result and Discussion

Classification results

Eight different classification approaches were implemented, and the results are listed in Table 1 and presented in Figure 5. The methods, a maximum likelihood and a combination of Parallelepiped and maximum likelihood did not produce big differences in the classified areas of the informational classes. But the band combinations and alternatives for defining training fields caused significantly different results in the classifications.

Table 1. Areas as classified by the eight different approaches (km^2)

Combination	PC1-PC2-VI				Band 4-3-2			
Training fields	Landsat(seeding tool)		Quickbird(manual)		Landsat(seeding tool)		Quickbird(manual)	
Method	Max.	PP-Max.	Max.	PP-Max.	Max.	PP-Max.	Max.	PP-Max.
Crop	52.31	52.97	36.01	37.37	46.57	47.43	41.45	41.80
Forest	54.96	55.14	57.58	58.41	34.70	34.56	37.44	37.44
Mixed	4.31	4.39	7.59	7.60	9.28	9.49	13.53	13.55
Wetland	29.15	29.03	27.44	27.59	48.68	48.56	38.30	38.38
Resident	13.72	12.91	25.41	22.87	14.99	13.98	23.28	22.79
Water	0.77	0.77	1.19	1.38	0.66	0.83	0.88	0.91

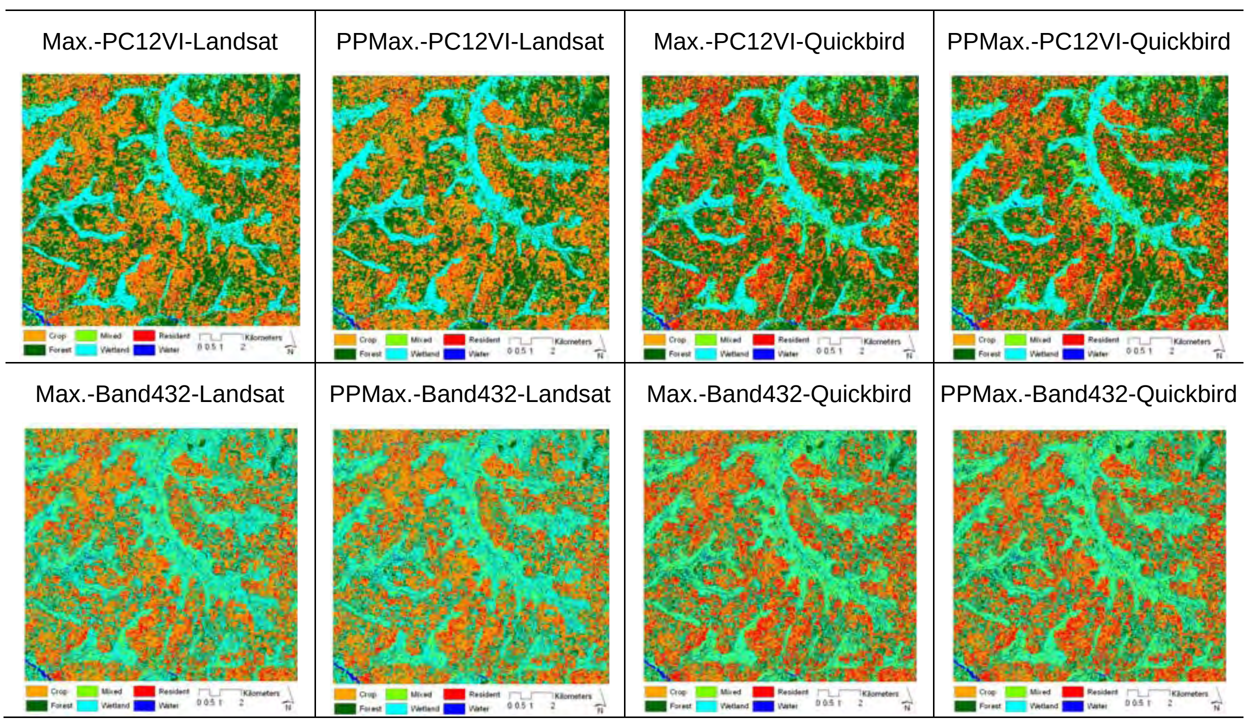


Figure 5. Result images from the eight different classification approaches.

In using the first and second principal components and vegetation index layers generated from the Landsat image, training fields created from the Landsat image with a seeding tool of ERDAS IMAGINE® produced relatively large crop fields and small resident areas, but training fields made on the Quickbird image manually (visually) had the opposite result. Similarly, in using bands 4, 3, and 2, the training fields from the Landsat image resulted in relatively large crop field and wetland areas and small resident area, but training data created from the Quickbird image had the opposite outcome.

The use of the different band combinations produced significant differences in the classification results of area depending on how training fields were defined. The use of the band 4, 3, and 2 of the Landsat image resulted in relatively large wetland and mixed area and small forest areas. At the same time, resident areas were larger than reasonably expected for all methods, but especially for training fields from Quickbird which produced relatively large resident areas.

Assessment of the classification accuracy

The study assessed accuracy of the classification results with 255 randomly sampled reference points. The error matrix for each classification (Table 3) was created and then overall accuracy and Kappa coefficient were calculated and evaluated (Table 2).

Table 2. Overall error and Kappa for the classifications

Combination	PC1-PC2-VI				Band 4-3-2			
Training fields	Landsat		Quickbird		Landsat		Quickbird	
Method	Max.	PP-Max.	Max.	PP-Max.	Max.	PP-Max.	Max.	PP-Max.
Overall	72.94	73.73	70.98	71.37	55.69	55.69	53.33	53.73
Kappa	62.40	63.18	60.65	61.10	39.90	39.88	38.53	38.93

As seen in Table 2, it produced relatively high accuracy of the classification that the approaches that employed training field created on the combination of layers, which consist of the first and second principal components and vegetation index of the Landsat image, with seeding tool by the mixture of maximum likelihood and Parallelepiped algorithms. Based on the Kappa values, the approach that uses the principal components and vegetation index layers resulted in moderate agreement between the classified map and the reference points and Kappa values are between 0.40 and 0.80 (Landis and Koch, 1977). But using a combination of band 4, 3, and 2 represented poor agreement and the values are less than 0.40.

In Table 3, it is revealed that the mixed and resident areas are main sources of the classification errors. Because the mixed areas mainly distributed on between the forest and wetland, it may have averaged characteristics of them. Also because a house roof was thatched with straw not artificial materials like concrete and steel and paved roads do not exist in the study area, it is not easy to discriminate resident areas from crop fields. So the accuracy was recalculated without distinguishing crop field with resident areas and the results are presented in Table 4. With disregarding resident areas, the overall accuracy and Kappa values were increased over 10%, and using training fields created manually on the Quickbird showed a little better accuracy than did training fields made on the Landsat.

Table 3. Error matrix for the classifications of the validation data set

Max.-PC12VI-Landsat

Class	Crop	Forest	Mixed	Wetland	Resident	Water	Total
Crop	69	7	1	0	2	0	79
Forest	7	68	4	6	0	0	85
Mixed	0	0	5	0	0	0	5
Wetland	3	8	4	41	0	1	57
Resident	23	3	0	0	2	0	28
Water	0	0	0	0	0	1	1
Total	102	86	14	47	4	2	255
Producer's	67.6	79.1	35.7	87.2	50.0	50.0	
User's	87.3	80.0	100.0	71.9	7.1	100.0	

PPMax.-PC12VI-Landsat

Class	Crop	Forest	Mixed	Wetland	Resident	Water	Total
Crop	72	8	1	0	2	0	83
Forest	7	68	4	6	0	0	85
Mixed	0	0	5	0	0	0	5
Wetland	3	8	4	41	0	1	57
Resident	20	2	0	0	2	1	25
Water	0	0	0	0	0	0	0
Total	102	86	14	47	4	2	255
Producer's	70.6	79.1	35.7	87.2	50.0	50.0	
User's	86.7	80.0	100.0	71.9	8.0	100.0	

Max.-PC12VI-Quickbird

Class	Crop	Forest	Mixed	Wetland	Resident	Water	Total
Crop	61	4	1	1	0	0	67
Forest	7	72	5	5	0	0	89
Mixed	0	0	4	1	0	0	5
Wetland	0	6	4	39	0	1	50
Resident	31	1	0	1	4	0	37
Water	3	3	0	0	0	1	7
Total	102	86	14	47	4	2	255
Producer's	59.8	83.7	28.6	83.0	100.0	50.0	
User's	91.0	80.9	80.0	78.0	10.8	14.3	

PPMax.-PC12VI-Quickbird

Class	Crop	Forest	Mixed	Wetland	Resident	Water	Total
Crop	62	4	1	1	0	0	68
Forest	7	72	5	5	0	0	89
Mixed	0	0	4	1	0	0	5
Wetland	0	6	4	39	0	1	50
Resident	30	1	0	0	4	0	35
Water	3	3	0	1	0	1	8
Total	102	86	14	47	4	2	255
Producer's	60.8	83.7	28.6	83.0	100.0	50.0	
User's	91.2	80.9	80.0	78.0	11.4	12.5	

Max.-Band432-Landsat

Class	Crop	Forest	Mixed	Wetland	Resident	Water	Total
Crop	71	10	1	0	1	1	84
Forest	6	34	3	7	0	0	50
Mixed	0	1	2	9	0	0	12
Wetland	5	40	8	31	0	0	84
Resident	20	1	0	0	3	0	24
Water	0	0	0	0	0	1	1
Total	102	86	14	47	4	2	255
Producer's	69.6	39.5	14.3	66.0	75.0	50.0	
User's	84.5	68.0	16.7	36.9	12.5	100.0	

PPMax.-Band432-Landsat

Class	Crop	Forest	Mixed	Wetland	Resident	Water	Total
Crop	71	10	1	0	1	1	84
Forest	6	34	3	7	0	0	50
Mixed	1	1	2	9	0	0	13
Wetland	5	40	8	31	0	0	84
Resident	19	1	0	0	3	0	23
Water	0	0	0	0	0	1	1
Total	102	86	14	47	4	2	255
Producer's	69.6	39.5	14.3	66.0	75.0	50.0	
User's	84.5	68.0	15.4	36.9	13.9	100.0	

Max.-Band432-Quickbird

Class	Crop	Forest	Mixed	Wetland	Resident	Water	Total
Crop	59	15	2	0	0	0	76
Forest	6	35	0	8	0	0	49
Mixed	1	3	7	10	0	0	21
Wetland	4	31	5	29	0	0	69
Resident	32	2	0	0	4	0	38
Water	0	0	0	0	0	2	2
Total	102	86	14	47	4	2	255
Producer's	57.8	40.7	50.0	61.7	100.0	100.0	
User's	77.6	71.4	33.3	42.0	10.5	100.0	

PPMax.-Band432-Quickbird

Class	Crop	Forest	Mixed	Wetland	Resident	Water	Total
Crop	60	15	2	0	0	0	77
Forest	6	35	0	8	0	0	49
Mixed	1	3	7	10	0	0	21
Wetland	4	31	5	29	0	0	69
Resident	31	2	0	0	4	0	37
Water	0	0	0	0	0	2	2
Total	102	86	14	47	4	2	255
Producer's	58.8	40.7	50.0	61.7	100.0	100.0	
User's	77.9	71.4	33.3	42.0	10.8	100.0	

* Classification algorithm - Layer combination - Image where training fields were created

Table 4. Overall error and Kappa without distinguishing crop field with resident area

Combination	PC1-PC2-VI				Band 4-3-2			
Training fields	Landsat		Quickbird		Landsat		Quickbird	
Method	Max.	PP-Max.	Max.	PP-Max.	Max.	PP-Max.	Max.	PP-Max.
Overall	82.47	82.07	82.87	82.87	63.35	62.95	66.80	65.34
Kappa	73.97	73.32	74.73	74.79	47.49	47.02	52.59	50.40

Conclusion

The most accurate approach for classifying the Landsat image of the study area was a combination that consist of principal components and vegetation index layers in contrast to a 4-3-2 band combination. Directly digitizing training fields from the Quickbird image produced similar accuracy to using training areas based on ‘seeding’ the Landsat image. So it can be handy to compare classification accuracies for the study area from other different band combinations and classification algorithms with the same training fields. The different classification algorithms evaluated, a maximum likelihood and a combination of Parallelepiped and maximum likelihood, did not result in significant differences in classification accuracy for the study region.

Because of the landscape characteristics of the study area, there was greatest difficulty in discriminating between crop field and resident area and between mixed and wetland or forest areas. The distinction between these needs to be reconsidered based on further study of their hydrological function and considering techniques that can be used to separate resident and mixed areas in classification.

The Quickbird high-resolution image, provided useful information in classifying the study area in eastern Zambia. Because for many areas on the earth aerial photographs are not readily available, and ground truth points are difficult to acquire, land use classification of those regions is difficult with high uncertainty. Satellite imagery like Quickbird could provide useful and effective information about the landscape that is otherwise undefined and inaccessible due to cost and time requirements.

Although this study was constrained to the Magodi area covered by the available Quickbird image, further research will focus on classification of regions beyond the current extent using different or mixed types of reference data. Effective and sound approaches for land use classification can help hydrological modeling and support natural resource management in developing countries.

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