Mapping Rural Savanna Woodlands in Malawi: a Comparison of Maximum Likelihood and Fuzzy Classifiers.

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***Abstract*— Changes in land cover system represent a key variable in managing and understanding the environment, as well as driving many environmental assessment mechanisms such as hydrological models for large river basins water budgeting. Remote sensing can provide information on the spatial pattern of land cover features, but analysis and classification of such imagery primarily suffers from the problem of class mixing within pixels. To reflect the actual land cover conditions rigorously and well defined, statistical algorithms have to 'bridge the gap' between legend requirements and the input satellite imagery. While studies have been done using Maximum Likelihood and Fuzzy classifiers in forestry, urban planning and savannah woodlands, appropriate methods to map land cover distributions in savanna woodlands associated with rural settlements are yet scarce. The distribution of savanna woodlands, rural residential areas (especially grass-thatched housing) and cultivated/grazing areas within the Shire River catchment in Malawi, represent classes which have similar spectral signatures (especially during the dry season). They occur in similar environments and are often in adjacent or mixed stands. Two classification methods i.e. purely using a Maximum Likelihood Classification and when improving this classification using a contextual Fuzzy Convolution filter were assessed to map land cover dynamics of the Shire River catchment using Landsat 7 ETM+. With respect to classification methodologies and the ability to correctly identify land cover features, accuracies (before and after applying the filter) were compared and tested for the catchment's hydrological modelling. Spatial characteristics of the catchment, digital elevation data, precipitation and the Landsat mapped land cover data were derived and exported into a Geographic Information Systems (GIS) to provide thematic data layers from which to delineate hydrologic response units (HRU). Eight detailed land cover classes were mapped for the Shire River catchment. The hierarchical legend structure determined by the Food and Agriculture Organization (FAO) Land Cover Classification System (LCCS) was used to label land cover variables. The purely Maximum Likelihood statistical classifier accurately mapped individual classes in more detail which could not be discriminated using Fuzzy Convolution filter. The spatial scale for land cover parameterization can play a significant role in how specific land surface hydrological processes are simulated.**

Keywords: land cover, classifiers, Landsat, catchment, Malawi

I. INTRODUCTION

The Shire River system forms the most important water resource for Malawi. Hydro-electric power plants of about 200 MW generation output, based on a firm flow of 170 $m^3 s^{-1}$, have been developed on this river, providing 98% of electricity current provision needs in Malawi [1]. An estimated 20-25 $m^3 s^{-1}$ of water is abstracted for irrigation and Blantyre City abstracts 1 $m^3 s^{-1}$ of the water supply for both domestic and industrial use. The Shire River has also led to the development of the fisheries industry, water-transport and tourism. This translates into increased demands for water by different groups, with different needs and values. When water supply is limited in quantity or quality, or distributed unevenly, it can be both a source of cooperation and contestation within its different users [2, 3].

Over the last three decades, the Shire River catchment has undergone considerable changes in its structure and composition of land cover [4]. Causes include vegetation clearing for farming, building of houses and charcoal production. Consequently, processes of land hydrology, such as run-off, infiltration, evapotranspiration and interception have been modified.

Land cover mapping and classification for the Shire River catchment were carried out previously, based on spectral homogeneous clusters [5]. However, appropriate mapping procedures were not applied and this project did not produce satisfactory results applicable, for example, in hydrological modelling. Any further modelling of hydrological impacts of changes in land cover would thus require a revision of these earlier classification attempts. Therefore, it was imperative to accurately map land cover classes and changes in the Shire River catchment to provide input data needed.

Various ecological regions present major classification challenges because of diversity within and between the landscapes [6]. Many geographical applications describe the spatial extent of natural geographic objects by well-defined regions that have a sharp boundary [7]. Conventional image classification algorithms, such as Maximum Likelihood classification, assume that the study area is composed of such unique, internally homogeneous classes [8]. However, such an assumption of determinate and crisp objects is inadequate for mapping the spatial phenomena of savanna woodlands. Most landscape types within these savannas have gradual boundaries, such as transitions from water body to forested wetland to upland forest [9]. Typically, such characteristics of vegetated areas are distributed gradually and continuously rather than abruptly. Savanna woodlands comprise mainly shrubs with a cover of between 5 and 40 percent. Where savannas are disappearing, landscapes are dominated by medium to tall grasslands with forest relics and isolated stands of shrub-lands. In close association with the savanna woodlands, includes village settlements (both clustered and scattered) with grass thatched roofing, mud walls and occasionally iron sheet roofing. The ambiguity of natural land cover composition in the transitional zones leads to uncertainty and thus to classification errors (Fig. 1). In such circumstances, different classification algorithms may produce different results, even where the same training sets are used [10]. Specifically, classification of mixed pixels can present difficulties as it is not sensible to assign a mixed pixel to one or other single class.

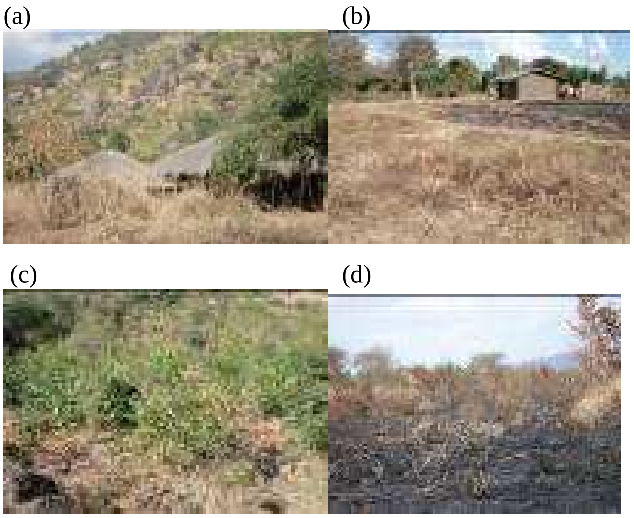

Figure 1. Examples of land cover in Malawi: (a, b) rural village settlements, showing similarity of spectral properties of dwellings and grassland; (c) savanna woodlands (d) recently burnt savanna

A number of approaches have been developed and tested for solving pixel unmixing to reduce classification errors. For example, Zhang [11], applied fuzzy approaches and statistical classification to ecological habitats using field data from mixed-species forest stands. Their study showed the ability of fuzzy classifiers to improve classification accuracy, and flexibility in classifying ecological habitats that have a mixture of over-story and under-story species.

Fuzzy classification attempts to handle the mixed-pixel problem by employing the fuzzy set concept, in which a pixel may have membership in more than one category [7, 12]. This approach is similar to application of Maximum Likelihood classification, the difference being that fuzzy mean vectors and covariance matrices are developed from statistically weighted training data [13]. As such, both the spatial continuity and the fuzziness of spatial data can be involved in the classification process. When two or more classes occupy a single pixel the mixed pixel would be appropriate in conceiving the different landscapes as a set of fuzzy classes. Therefore, algorithms to provide an improved spatial representation of mixed pixels for deriving land cover data are imperative to increase classification accuracy.

While studies have been done using Maximum Likelihood and Fuzzy classifiers in forestry, urban planning and savanna woodlands [9, 11], appropriate methods to map land cover distribution in savanna woodlands associated with rural settlements are yet to be examined. The purposes of this paper are: (i) to identify non-linear land cover classes incorporating rural settlement areas; and (ii) to classify and map land cover within the Shire River catchment of Malawi. Two classification methods were utilized: pure Maximum Likelihood Classification, and contextual Fuzzy Convolution filters. Accuracies were compared, using field data collected as part of this project.

II. Methodology

A. Data

A Landsat 7 Enhanced Thematic Mapper Plus (ETM+) image, level 1G, p167 r72 imaged on 26th July, 2002, was obtained from Global Land Cover Network, FAO/Africover project[1]. Supplementary digital data sets were obtained from the Department of Surveys in Malawi to complement the satellite data. From these, a number of digital GIS layers were created including: towns, road networks, administrative borders, soil types and hydrography (river flow networks). Slope, aspect and altitude were delineated from digital elevation data downloaded from Consultative Group International Agricultural Research (CGIAR).[11]

1) *Image pre-processing*

Land cover mapping and subsequent quantitative change detection requires geometric registration between TM and ETM scenes, and radiometric rectification to adjust for differences in atmospheric conditions, viewing geometry and sensor noise and response [7, 12]. The Landsat image had been geometrically corrected by the Global Land Cover Facility (GLCF). The image was registered to the Malawi UTM Zone36/Arc1950 Datum projection system to match with *in situ* vector data [5]. The image was further pre-processed by converting the digital numbers (DN) to radiance units, and then reflectances (ρ) were calculated for each band as described in Vermote [14].Conversion to reflectance was aimed to minimize variation due to varying solar zenith angles and incident solar radiation.

B. *Methodology*

1) *Maximum Likelihood Classification.*

Pixel based classification was undertaken using the Maximum Likelihood algorithm [7, 12]. This involved the selection of training areas representative of the eight land cover classes. A number of training areas were selected to represent each class. The signature (or spectral mean) of the training area

[1]Acknowledgements to Mr David Stevens, UNOOSA; and US Geological Survey for image.

[11]CGIAR Digital Elevation Model data. http://srtm.csi.cgiar.org/ (accessed 14/08/06).

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was then used to determine to which class the pixels were assigned.

2) *Fuzzy Convolution filter Classification*

The fuzzy convolution filter classification process can be split into two steps, classification and filtering. The first step is similar to the Maximum Likelihood method; the second step creates a single classification layer by calculating the total weighted inverse distance of all the classes in a window of pixels and assigning the center pixel the class with the largest total inverse distance summed over the entire set of fuzzy classification layers [13]. The filtering option, based on the distance file, allows for each pixel in the window to be weighted, based on its geometric distance from the center pixel. The neighborhood weighting factor is influenced by the heterogeneity of the pixels. Classes with a very small distance values will remain unchanged while classes with higher distance values may change to a neighboring value if there are sufficient neighboring pixels with class values and small corresponding distance values. A visual inspection of the objects resulting from variations in the weightings was used to determine the overall values for the parameter weighting at each scale level. In this study, neighborhood weighting factors were developed using spectral signatures, shape, location and contextual relationships. The weightings were then used as a basis for the fuzzy classification of the data with the most probable/likely class being assigned to each object.

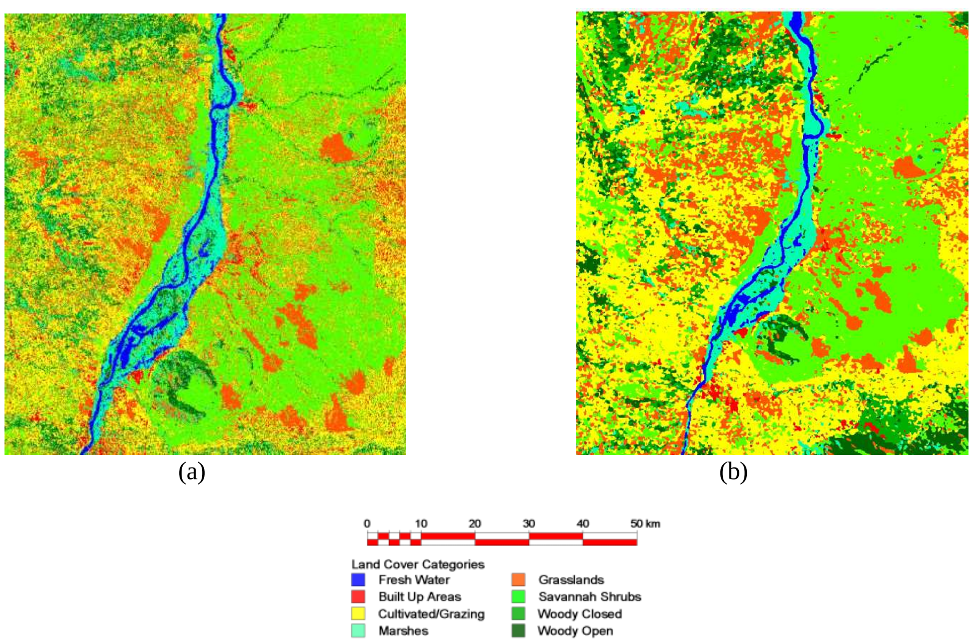
The Food and Agricultural Organization (FAO) legend structure: Land Cover Classification System (LCCS) was used [15]. This legend structure aims to achieve land cover harmonization within Africa and on a global scale through a self-consistent, scalable set of criteria and labels.

C. *Accuracy assessment and field data collectiont*

Accuracy assessments of both classifications were undertaken using producer and user accuracies for each class along with the overall accuracies [16]. The accuracies were evaluated with error matrix using reference ground-truth data along the columns and classified image data along rows. The producer accuracy (the probability for a reference sample to be correctly classified i.e. errors of omission), the user accuracy (the probability that a sample from the classified image actually represents that category on the ground i.e. errors of commission), and the overall classification accuracy (ratio of number of correct classifications to total number of samples) were calculated [16, 17]. The reference data were collected from 83 points within the study area during field work. Choice of sampling areas was biased by proximity to passable roads. These points were geo-referenced by GPS. Notes of vegetation cover and photographs of the sites were collected.

III. RESULTS

A visual comparison of the resultant land cover images shows differences between the classifications (Fig. 1). While both methods produce aggregations of pixels based on land cover classes, the fuzzy convolution filter classification yields multi-pixel features whereas the pixel-based classification contains many small groups of pixels or individual pixels. This produces classes with mixed clusters of pixels as displayed by the heterogenic nature of the image. A complexity of the maximum likelihood classification occurred due to the similarity in reflectance characteristics of savanna shrubs, cultivated/grazing areas and built up areas which resulted in either greater or lesser representation of their spatial extents.



(a) (b)

Figure 1: Results of: (a) Maximum Likelihood; and (b) Fuzzy Convolution classifications

Class	Maximum Likelihood		Fuzzy Convolution		Ratio of % values for each method
	Area (ha)	*%*	*Area (ha)*	*%*	
Fresh water	37 178	8.1	37 105	8.1	1.00
Built-up areas	14 326	3.1	7 264	1.6	1.94
Cultivated/ grazing	117 071	25.7	147 462	32.3	0.81
Marshes	29 490	6.5	21 106	4.6	1.4
Grasslands	63 664	14.0	54 052	11.8	1.19
Savanna shrubs	112 356	24.6	119 056	26.1	0.94
Woody Open	38 446	8.4	30 418	6.7	1.25
Woody closed	43 967	9.6	40 035	8.8	1.09
Total	456 498	100	456 498	100	

Table 1: Land cover classes and their spatial extents

Based on the difference ratio between Maximum Likelihood and Fuzzy Convolution filter, there is no difference in the spatial extent of fresh water. Fuzzy Convolution appears to classify more details in cultivated (ratio = 0.81) and savanna shrubs area (ratio = 0.94) though the differences are not significant. Significant differences are noted in built-up areas, marshes, grasslands, woody open and woody closed areas in which Maximum Likelihood classifies more details compared to Fuzzy Convolution (Table 1). For example, the built-up area and grassland classes appear noticeably less in the Fuzzy Convolution filter classification.

From the results of the confusion matrices, the overall accuracy of the pixel-based classification was better than for Fuzzy Convolution classification, 87% versus 77% respectively (Table 2). The producer and user accuracies were greater for the majority of the classes in the Maximum Likelihood classification. The land cover classes that were more accurately classified using the pixel-based method were grasslands, woody closed, marshes and savanna shrubs. The classes that had poor accuracy in both classifications were built up areas and cultivated/grazing areas.

This is possibly due to built up areas (especially grass-thatched) and cultivated areas/grazing occurring in similar environments and are often in adjacent or mixed stands. During dry periods when there is little chlorophyll in the vegetation, grazing causes exposure of soil between remaining vegetation resulting into similar spectral values making it difficult to distinguish the two classes.

Class	Maximum Likelihood		Fuzzy Convolution	
	Producers (%)	*Users (%)*	*Producers (%)*	*Users (%)*
Fresh water	100	100	91	100
Built up areas	83	77	42	50
Cultivated /grazing	87	78	78	58
Marshes	77	92	80	83
Grasslands	97	100	77	96
Savanna shrubs	91	91	60	95
Woody open	80	80	95	82
Woody closed	92	96	92	100
	Overall accuracy =87%		Overall accuracy =77%	

Table 2: Error matrices for land cover classes

IV. DISCUSSION

The difference between the two classifications is visually obvious: Maximum Likelihood is fine grained and fuzzy while Fuzzy classifier yields less speckled output pushing pixels into consolidated larger objects. Maximum Likelihood retains fine grained differentiation while Fuzzy emphasizes the macro-structure. Fuzzy classifiers do misclassify pixels, particularly in land covers that are spectrally heterogeneous, such as rural built up areas and savanna shrubs with producers' accuracy of 60%, 42% respectively and cultivated/grazing areas yielded users' accuracy of 58%. While it is evident that pixel-based classification is still quite successful in classifying land cover of a homogenous nature, both classification methods appear to be able to differentiate more accurately the woody open and woody closed classes.

The pixel-based classification method used in this paper provided results with 87% accuracy higher than 77% of the fuzzy convolution filter. This suggests that maximum likelihood analysis has great potential for extracting land cover information from satellite imagery captured in tropical savanna woodlands associated with rural settlements such as Malawi. This will be the case particularly with the increasing application of higher resolution imagery and the greater information content it holds.

V. CONCLUSION

While recent research results claim that the fuzzy convolution filter has greater potential for classifying higher resolution imagery than pixel-based methods [18, 19, 20], this study has revealed that Maximum Likelihood method yields greater accuracy based on confusion matrix evaluation, in a case study mapping rural savanna woodlands. It can further be concluded that the majority of pixels showed real complexity in the landscape rather than noise. Maximum likelihood classifier proved to be useful in discriminating heterogeneous environments, which is well suited for applications such as hydrological modelling. Although Maximum Likelihood classification assumes a Gaussian distribution, this algorithm can be easily implemented to produce land cover maps of higher accuracy in a complex environment from image data of resolution, such as the Landsat ETM images. However, to improve the accuracies of the Fuzzy Convolution classification, contextual information to be applied during neighborhood weighting should be further developed. The use of multi-sensor data and ancillary data, such as derivative data sets and extensive field data could be investigated.

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