SPECTRA OF MIXED PIXELS: DO THEY REPRESENT THE ACTUAL LAND COVER ON THE GROUND? - A CASE STUDY FOR A WET SAVANNA ECOSYSTEM IN UGANDA

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ABSTRACT:

Due to increased availability and affordable cost of TM7 data, one envisages its widespread use for land cover mapping in many developing countries. There is need to establish not only the potential but also the limitations of TM data for land cover mapping in some natural ecosystems of the tropics. Uganda is a tropical country with well-distributed rainfall and its landscapes are characterised by luxuriant vegetation, remaining healthy throughout the year. Wet savanna ecosystems, common in Uganda, are characterised by wood-grass mixtures of variable wood density. Mixed pixels characteristic of TM data are believed to effect land cover mapping in wet savanna ecosystems. Given the high expenses required to generate land cover maps from airborne data, TM and SPOT data are preferred for land cover mapping in the country, irrespective of the nature of the landscapes. For example, a number of vegetation mapping exercises have been completed for two savanna national parks using TM and SPOT data. What is not yet understood, by the wider conservation community in Uganda, is whether TM or SPOT data is suitable for land cover mapping of wet savanna ecosystems, despite its availability and affordability. In this study, high-resolution digital airborne data was used as a validation tool to investigate the effect of mixed pixel spectra on land cover mapping in a wet savanna ecosystem. Results indicate that mixed pixels adversely affect land cover mapping in savanna compared to homogeneous landscapes.

1. INTRODUCTION

1.1 Overview

Digital spectral analysis of multispectral imagery data for land cover mapping has fundamental limitations due to spectral overlap. According to Price (1994), spectral overlap is a fundamental problem of healthy leaves of different vegetation categories. Yet, identification of different vegetation categories depends, mostly, on the mass of leaves exposed to incoming solar radiation for an optical imaging sensor like Landsat TM. In Uganda, unlike in temperate areas, wood vegetation categories remain green throughout the year and hence their identification from images based on seasonal leaf shading is limited. Mapping of grassland communities is not straight forward either. This is because mature grass left undisturbed is characterised by dry or near to dry leaves.

Secondly, big patches of grass are seasonally burnt in both protected and non-protected areas. Fire is a common management tool used by both managers of protected areas and pastoralists. Burning results in different stages of grass growth. The net effect is varied spectral responses for a given grassland community for an image snapshot. Identification of grassland communities in a wet savanna ecosystem is, therefore, an additional challenge to spectral image analysis.

The third challenge of spectral analysis for land cover mapping in a wet savanna ecosystem is spectra of mixed pixels. *Do spectral values of mixtures of wood and grass represent the actual variation found on the ground?*

1.2 Aims

The overall aim is to find out whether spectra derived from pixels representing wood-grass vegetation mixtures represent identifiable land cover classes or not.

This paper is organised as follows: A review of related work is presented in the next subsection. This is followed by a discussion of the methods and materials used (Section 2). In Section 3, results are presented and then discussed in Section 4. Finally, conclusions and recommendations are presented in Section 5.

1.3 Literature Review

The development of high-resolution air- and space-borne imaging sensors might be regarded as a response to provide digital multispectral data for precision mapping of both natural and man-made surface features. While high-resolution (4m) IKONOS multi-spectral data is now available even for areas such as East African, Landsat ETM+ data are widely used in the region because of its availability and affordability. For example, according to USGS and Clean Lakes (2000), IKONOS data cost \$29 per km2 of terrain. This is in contrast to only \$0.02 per km2 as the cost of Landsat ETM+ data. The big price differentials between high- and medium-resolution imagery data means that

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pragmatic decisions taken in commissioning vegetation mapping in most countries are most likely to be based on economic considerations, especially if small-scale mapping is envisaged.

In this regard, development of hybrid image classification algorithms, referred to as soft classifiers, may be regarded as a positive effort to overcome the limitations imposed by mixed pixels and hence allowing cost-effective technique for land cover mapping in heterogeneous ecosystems. Soft image classification algorithms, widely encountered in remote sensing literature, include various types of sub-pixel mixture modelling and fuzzy classification techniques. However, as pointed out by Foschi and Smith (1997), sub-pixel mixture modelling appears suitable for identifying few land cover components (such as soil from vegetation) from an image scene. Indeed, a number of authors such as Huguenin et al. (1997), Sohn and McCoy (1997) and Warner and Shank (1997) have used soft classifiers to identify and map few land cover components (called end members) from low/coarse resolution data.

In this paper, it is argued that presence of TM mixed pixels hampers land cover identification and mapping in wet savanna ecosystems beyond the remedy of soft classification techniques. This proposition is based on the observation that inconsistent classification errors are obtained for different land cover classes identified from TM data during mapping exercises in different ecosystems of Uganda. For example, using TM data, Fuller et al. (1998) successfully produced a land cover map (overall classification accuracy of 86%) using a Maximum Likelihood Classification technique for Sango Bay area in Uganda. In contrast, using TM data and similar classification techniques, an overall classification accuracy of less than 30% of a land cover map was generated for Murchison falls National Park (Uganda Wildlife Authority-GTZ, 1997). The major difference between Sango Bay and Murchison Falls National Park is that the former is characterised by homogeneous land cover types (rain forests, shrubs, papyrus, tall wetland grass, short grass) while the latter is characterised by wood-grass mixtures of different wood densities.

The phenomenon of mixed pixels is not new and has been studied by many scientists, especially in relation to the development of soft classification algorithms (see for example, Zhang and Kirby (1997) and Warner and Shank (1997)). According to Warner and Shank (1997), mixed pixels are formed when instantaneous field-of-view (IFOV) of an imaging sensor falls on an area that is characterized by more than one spectra. It is often stated that spectra of mixed pixels are formed by 'automatic aggregation' of sub-pixel sized terrain features by an imaging sensor. Warner and Shank (1997) further observed that mixed pixels formed from forest-urban interface had similar spectra as short grassland. While misclassifications between vegetation and urban surfaces might be remedied by the use of soft classifiers, retrieving Termilia sp. from Albizia from wood-grass mixture of different wood densities is deemed unpractical, if one assumes that Price's (1994) observations are true. Yet, more than 50% of total landscape in a wet savanna ecosystem may be covered by wood-grass mixtures of different densities that need identification and mapping from satellite imagery data at scales of 1:50,000 - 1:150,000.

Figure 1 depicts part of a terrain of Murchison Falls national Park (MFNP) that is typical of a wet savanna ecosystem. River Nile is shown in the middle of the photograph. Figure 2 is an illustration of how TM mixed pixels may be formed in a wet savanna ecosystem: the data on the left is a high-resolution (0.5m) airborne image resampled to a spatial resolution of 2.0m. On the right, is the same portion of the terrain as scanned by TM sensor and co-registered to the same map projection as for the airborne image.
Two shrub patches of different sizes are clearly discernable on the digital airborne data. The boundaries of the two shrub patches were delineated to yield a vector file (broken lines) before being overlaid on TM data. The larger shrub patch is somehow visible on TM data, but the smaller shrub patch is not. When TM data is used for land cover mapping, we have to assume that sub-pixel objects (such as trees/shrubs) are 'automatically aggregated' in the surrounding background land cover pixels. Is this assumption true in landscapes (such as wet savanna ecosystem) with small tree/shrub patches but of a significant density as shown in Figure 3? It is in light of this that the following hypothesis was formulated for this study:

Spectra of mixed pixels do not represent wood-grass mixtures of variable wood densities in a wet savanna ecosystem.

2. METHODS

2.1 Selection of Study Sites

Several sites were selected to test the above hypothesis. The test sites were selected from both heterogeneous (representing wet savanna ecosystems) and homogeneous landscapes. Test sites selected from the latter were regarded as controls. A number of analyses were carried out to generate information needed to test the hypothesis:

1) Visual delineation of land cover patches from airborne data. This was carried out for one test site selected in MFNP (wet savanna ecosystem);
2) Spectral segmentation of TM data for the same test site in step (1) above;
3) Determination of wood densities of results derived in steps (1) and (2) above;
4) Determination of relationship between TM-derived land cover categories and wood density; and
5) Estimation of spectral brightness values of both mixed and 'none' mixed pixels.

2.2 Data Used

TM data used for this study was acquired in 1995 i.e. two years before the commencement of this research. High-resolution data (used to validate the outcomes from analysis of TM data) was acquired by a Kodak Aerial Digital Photographic System (model DCS560) in 1998-1999. The data used were acquired in three channels i.e. near infrared (700-900), red (680-700) and green (500-680). For further details regarding the operational principles and data characteristics acquired by Kodak DCS560, the reader is referred Koh et al. (1996).

Digital airborne data (DABD) were used to generate spatial information, which was in turn was used for *validation* of TM data segmentation results. Researchers such as Klöditz *et al.* (1998) have use of high-resolution data as a practical tool to validate results obtained from coarse resolution data.

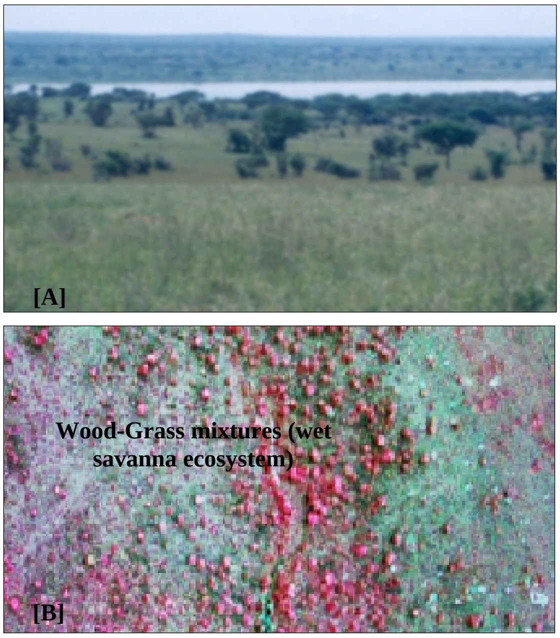

Figure 1. Typical appearance of a wet savanna landscape: [A] in MFNP; [B] shows individual trees on DABD (MFNP)

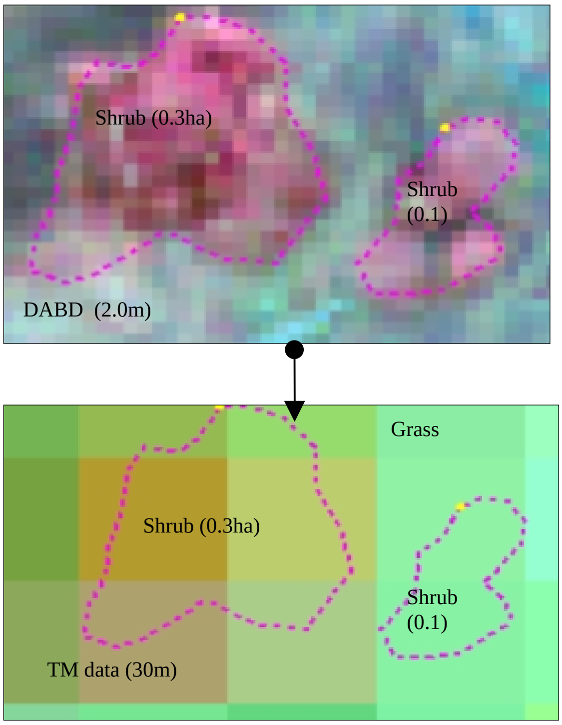

Figure 2. Spectral appearance (colour) of two different shrub sizes growing in grassland

2.3 Image Classification

2.3.1 Delineation of land cover from airborne data: Using standard visual classification techniques, five major land cover categories were delineated from DABD for a test site selected from a wet savanna ecosystem. The five land cover categories were defined in the field prior to DABD interpretation and boundary delineation. A wood density classification system employed during vegetation mapping of MFNP (Uganda Wildlife Authority-GTZ, 1997) was used in the estimation of field wood density. Table 1 shows a description of the five land cover categories delineated from DABD.

2.3.2 TM data Classification: A Maximum Likelihood Classifier was used to segment TM data into similar land cover categories generated from DABD as explained in (a) above. To take care of different spectra of the same land cover category, it was necessary to define sub spectral classes for each land cover category. Spectral classes belonging to the same land cover were merged together after image classification. The expectations of this investigation were that land cover classes 101, 203 and would be identified and mapped in the usual way, with misclassifications explained in terms of normal spectral overlap. However, for the hypothesis to be declared true, land cover categories 201 and 202 (characterised by significant mixed pixels) would have to be identified and mapped from both digital airborne and TM data.

Major land cover	**Wood density (%)** [Based on subjective estimation]	**Spectral code**	**Spectral subdivisions**
1. Very dense woodland	> 65	101	101- to 101-2
2. Tall grass with some wood cover	5 – 35	201	201-1 to 201-6
3. Tall grass with significant wood cover	35 - 65	202	202-1 to 202-6
4. Tall grass with insignificant wood cover	< 5	203	203-1 to 203-7
5. Short grass with insignificant wood cover	< 5	301	301 & 301-2

Table 1. Major land cover categories and their spectral subdivisions

2.3.3 Determination of Wood Density: Individual trees/shrubs or small clumps of the two are not discernable on TM data due to the limited spatial resolution. In order to investigate whether spectra of mixed pixels are of any value or not, for land cover mapping, actual wood density information was needed. Wood density was quantitatively determined from wood cover information derived from DABD. This was achieved as follows: in ArcView, polygons were created for each patch of woody vegetation, and stored as a shape file. Subsequently, a 1 ha grid was created and overlaid on the woody vegetation shape file, giving information on percentage of woody and grass patches in each grid. Lastly, more than 150 of 1 ha (i.e. grid cells) were selected using a stratified random sampling technique. That is, 1 ha sample plots were selected for each of the land cover classes identified in Table 1.

A one-hectare sample plot was used for two reasons: first, it is widely used for vegetation mapping in savanna ecosystems of East Africa (Pratt and Gwynne, 1977). Secondly, a one-hectare sample plot allows most small patches of vegetation patches to be identified from TM data. Wood density, *Wd*, of each sample plot (grid cell) was calculated as follows:

$$Wd\ (\%) = area\ of\ wood\ cover\ (m)/10{,}000 \times 100 \qquad (1)$$

The resultant wood-density-map was classified into 20 equal (5% each) interval classes. A classification system with a narrow and equal interval was considered more appropriate for generating wood density information needed for further analysis.

Secondly, wood density information was generated for each land cover class obtained from DABD. The same procedure as described above was used. The only difference was that the basis of calculating wood was based on all polygons belonging to the same land cover category.

2.4 Data Analysis

In order to establish whether there is any significant correlation between wood density and two wood-grass mixtures (201 and 202) derived from TM data, it was necessary to carry out a spatial cross-tabulation. Spatial cross-tabulation was carried out in ArcView GIS and outputs were further analysed in Microsoft Excel.

Secondly, two *land cover indices* were determined for spatial information derived from both TM and airborne data. The indices were required to spatially validate whether land cover classes 201 and 202 are mapped as unique classes, or as homogeneous classes belonging either wood or grass. To allow spatial comparison of indices derived from TM and DABD, two minimum mapping units (MMU) i.e. $900m^2$ and $3600m^2$ were used as a basis of calculating the indices. The indices were determined using a technique developed by the authors to determine the spatial resolution at which geometric properties of vegetation patches obtained from sub-metre resolution data significantly deviate from actual patches with decreasing image resolution (Mugisha and Huising, 2002). Two land cover indices, *Spatial Land Cover Index* and *Land Cover Patchiness Index*, were determined as follows:

2.4.1 Spatial Land Cover Index: Spatial Land Cover Index (SLCI) was determined as a measure of how accurate it is to identify and map wood-grass mixtures (represented by classes 201 & 202) in a wet savanna ecosystem. SLCI was measured as a ratio of two different areas (CA:RA) derived from airborne and TM data. CA refers to 'corresponding area' obtained by overlaying TM and DABD derived wood/grass patches, while RA refers to 'reference area' obtained for wood/grass derived from DABD at a spatial resolution of 2.0m. Area of only two land cover classes (wood and grass) was used in order to avoid spectral overlap associated with wood-wood and grass-grass.

To obtain an accurate and reliable SLCI, both TM and airborne data were carefully registered to a common map projection (UTM). *Piecewise Affine Model* recommended by Ji and Jensen (2000) for rectification of digital airborne data was used. It was assumed that any errors associated with the image rectification process were the same for all the test sites and hence affected the results in a similar manner. Based on other studies (Mason et al., 1997), it has been possible to attain a high level of planimetric accuracies after rectification of digital airborne data. Calculation of SLCI was achieved using the following equation:

$$SLCI(\%) = CA/RA \times 100 \quad (2)$$

The calculated SLCI may be equated to conventional overall classification accuracies of both wood and grass patches. However, the three geometric properties (attributes, size and shape) of land cover patches were taken into consideration during the calculation of SLCI. As pointed out by Zhu (1997), this is a better technique for establishing overall classification accuracies than conventional methods, which concentrate on sample reference thematic data only.

In addition to SLCI calculated as discussed above, Aspatial Land Cover Indices (ALCI) were calculated. However, instead of using 'corresponding area' (see equation 2), *TM-A* and *DABD-A* were used. TM-A and DABD-A refers to area of wood or grass derived from TM and DABD information respectively. The following equations were used for the calculation of ALCI:

$$ALCI(\%) = TM\text{-}A/RA \times 100 \quad (3)$$

$$ALCI(\%) = DABD\text{-}A/RA \times 100 \quad (4)$$

2.4.2 Land Cover Patchiness Index: Land Cover Patchiness Index, LCPI, in this paper refers to the ratio of the sum of wood/grass patches to the sum of reference patches. LCPI were determined using the following equations:

$$LCPI(\%) = TM\text{-}P/RP \times 100 \quad (5)$$

$$LCPI(\%) = DABD\text{-}P/RP \times 100 \quad (6)$$

Where:
TM-P denotes the sum of wood or grass patches (polygons) derived from TM data;
DABD-P denotes the sum of wood or grass patches (polygons) derived from DABD; and
RP denotes the sum of wood or grass patches (polygons) derived from reference data.

2.5 Determination of Spectral Characteristics of Mixed and Unmixed Pixels

Lastly, mean spectral brightness values of sample mixed pixels and pixels representing homogeneous land cover categories were determined for a TM image of Nabugabo Ramsar site. Spectra of mixed pixels determined would have been formed from shrubs of different sizes growing in grassland. This was achieved as follows: A "seed" mixed pixel was selected using the 'Feature Mapping Operations' of MicroImages TNTmips. The selected 'seed' mixed pixel was used in an 'exact decision' rule to as a statistical basis of identifying other mixed pixels of the same brightness value.

Raster masks were created from the selected mixed pixels belonging to one group. Each mask was used to extract pixels from the first image *component* generated from TM data (bands 1,2,3,4,5 & 7) using Principal Component Analysis. A mean spectral brightness value was determined from mixed pixels of the same category. This procedure was repeated for pixels representing homogenous land cover classes.

3. RESULTS

Figure 4 depicts the distribution of wood density classes for each of the land cover classes. The graph is characterised by three peaks centred at wood density classes 5-10, 20-25 and 45-50%. A second feature of the graph is that the five land cover categories are associated with a wide wood density range. For short grass, the wood density range does not go beyond 25%. Tall grass is associated with wood density ranging from 0 - 60%, while dense/very dense wood occurs over the entire range of wood density, 0 - 100%. From the results presented in Figure

4, there is no evidence to suggest that wood density is a useful criterion for spectral image segmentation.

Table 2 shows summary statistics of the five land cover categories derived from airborne and TM data. The results in Table 2 wood densities determined using three techniques: a) field estimates, b) visual interpretation of DABD, and c) 1 ha samples. The results shows that about 44% of the total cover patches (in the test site) are wood-grass mixtures represented by classes 201 and 202. The rest of the land cover categories (101, 203 and 301) can be described as homogeneous. Secondly, the average wood densities (determined from DABD) have some similarities with wood density classes associated with the three peaks shown in Figure 4. There is a good match between peak wood densities at 7.5% and 47.5%. This is not surprising given the fact that the three peaks represent wood density classes at which homogeneous land cover classes (101, 203 & 301) are identified and mapped. In addition, the wood density depicted by the shorter peak (20-25%) seems to combine wood density classes of land cover categories represented by 201 and 202.

In summary, the results presented show that there is a tendency for all the five land cover classes to be identified under three broad spectral groups represented by a) 'stressed', b) grass, and c) dense wood vegetation categories. However, this explanation does not account for wood-grass mixtures associated with 201 and 202 land cover classes. To which land cover category were the mixed pixels land cover class 201 and 202 allocated? There are two possible scenarios: First, 201 could have been 'automatically aggregated' with tall grassland (203) and likewise 202 could have been aggregated with very dense woodland (101). Secondly, depending on the spectra of other land cover categories (such as papyrus, *Vossia sp*. and to some extent some acacia woodlands), there is a possibility that spectra of 201 and 202 can be classified as any of the listed land cover classes. This would result in *'geometric absence'* of 201 and 202 as actual land cover classes.

If 'geometric absence' is defined in terms of attributes and boundaries of land cover patches, then the next set of results provides some evidence to explain the fate of mixed pixels after a statistical image classification. Tables 4 and 5 show Spatial Land Cover Indices (SLCI) and Aspatial Land Cover Indices (ALCI) calculated for grass and wood for control and test sites. While overall SLCI of mapped wood and grass is over 70% in control sites, the value is only 47.7% for test sites. In addition, ALCI are more predictable in control rather than in test sites.

Land Cover Patchiness Indices (LCPI) shown in Tables 6 and 7 are an indication that a high ALCI may be associated with 'geometrically absent' land cover patches. Why should LCPI derived from TM be higher than those derived from DABD? If we assume that wood/grass patches derived from TM and airborne data occupy the similar terrain positions as depicted in Figure 5, an explanation of 'geometric absence' of wood and grass patches from TM data is possible. Figure 6 illustrates that wood-grass mixtures formed from shrubs and short grass are misclassified as tall wetland grass. Also, note that spectra of mixed pixels (insignificant in number though) formed on both high-resolution airborne and TM data are misclassified as tall wetland grass.

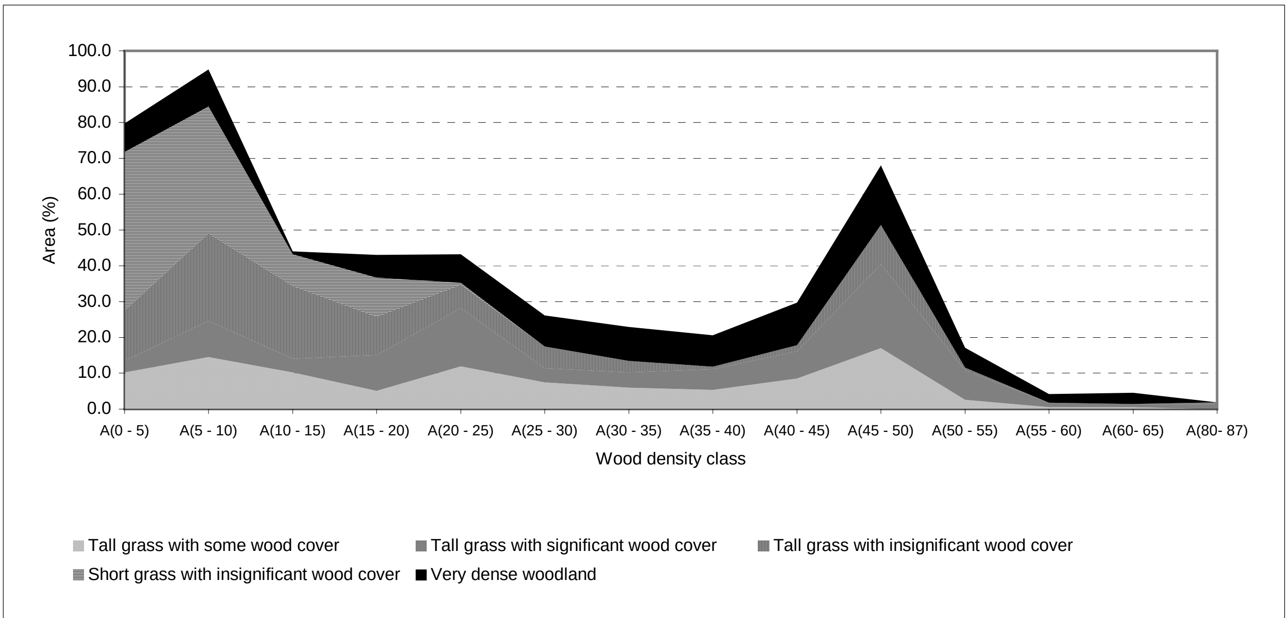

Figure 4. Distribution of wood density for the five land cover classes

Results in Figure 6 show that very small wood patches in a background of short grassland result in spectra of mixed pixels showing a small deviation from spectral characteristics of short grassland. However, as the size of wood patches increases, the spectra of mixed pixels start resembling spectral characteristics of other homogeneous land cover categories as depicted in Figure 6. This observation explains the 'geometric absence' of both wood and short grass patches at particular locations for SLCI calculated from TM data. In a homogeneous landscape, such misclassifications would be limited to boundaries between grass and wood covers and hence do not adversely affect SPLI as is the case for control sites. However, in heterogeneous landscapes (such as wet savanna ecosystems), the effect of mixed pixels on overall accuracy of TM-derived spatial information cannot be underestimated.

Vegetation type		**Average wood density (%)**		**% Cover**
	Field estimates	*DABD visually produced map*	*TM (Peak s)*	
Very dense woodland	>65	47.9	47.5	6.7
Dense woodland	35 - 65	24.9	22.5	18.9
Wooded grassland	5 - 35	19.5	-	25.4
Tall grass (insignificant trees/shrubs)	< 5	7.4	7.5	28.4
Short grass (insignificant trees/shrubs)	< 5	7.4	7.5	20.6

Table 2. Comparison of wood density determined using three different techniques

Land cover	**Reference Data**	**DABD-ALCI (%)**		**TM-ALCI (%)**		**SLCI (%)**
	$4m^2$	*$900m^2$*	*$3600m^2$*	*$900m^2$*	*$3600m^2$*	
Herbaceous (mainly grass)	**100**	98.9	98.1	98.3	92.4	**71.7**
Wood	**100**	94.7	90.5	108.2	94.4	**76.8**
Total area	**100**	98.1	96.5	100.3	92.8	**72.8**

Table 3. Calculated SLCI and ALCI for control sites

Land cover	**Reference Data**	**DABD-ALCI (%)**		**TM-ALCI (%)**		**SLCI (%)**
	$4m^2$	*$900m^2$*	*$3600m^2$*	*$900m^2$*	*$3600m^2$*	
Herbaceous (mainly grass)	**100**	94.9	87.2	116.2	96.1	**55.5**
Wood	**100**	92.2	85.6	63.9	41.5	**29.1**
Total area	**100**	94.1	86.7	100.7	79.9	**47.7**

Table 4. Calculated SLCI and ALCI of test sites

Land cover	**Reference Data**	**DABD-LCPI (%)**		**TM-LCPI (%)**	
	$4m^2$	*$900m^2$*	*$3600m^2$*	*$900m^2$*	*$3600m^2$*
Herbaceous (mainly grass)	**100**	15.8	4.9	63.4	13.1
Wood	**100**	12.3	4.0	53.4	7.0
Total patchiness	**100**	14.7	4.6	60.2	11.1

Table 5. LCPI calculated for control sites

Land cover	**Reference Data**	**DABD-LCPI (%)**		**TM-LCPI (%)**	
	$4m^2$	*$900m^2$*	*$3600m^2$*	*$900m^2$*	*$3600m^2$*
Herbaceous (mainly grass)	**100**	9.8	5.6	31.5	15.7
Wood	**100**	9.6	3.6	33.5	10.4
Total patchiness	**100**	9.7	4.6	32.5	13.1

Table 6. LCPI calculated for test sites

4. DISCUSSION

Conventionally, vegetation mapping involves identification of homogeneous units based on three major criteria: plant *life forms*, *cover* and *taxonomical class* (Di Gregorio and Jansen, 2000). However, spectral overlap makes it difficult to identify and map all plant communities in many healthy ecosystems. This study has shown that presence of substantial mixed pixels is an additional limitation of using TM data for land cover mapping in wet savanna ecosystems.

Secondly, absence of large-scale vegetation maps coupled with little differentiation in different landform types of most wet savanna ecosystems means that contextual correction techniques described by Groom *et al.* (1996) might not be a useful technique to improve accuracies of spatial information derived from TM data for a wet savanna ecosystem.

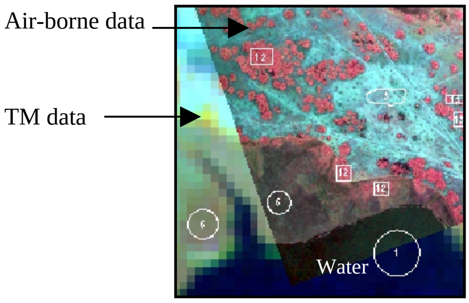

Figure 5. Image rectification was considered accurate enough to allow overlay of spatial information derived from both airborne and TM data in the determination of 'corresponding area'

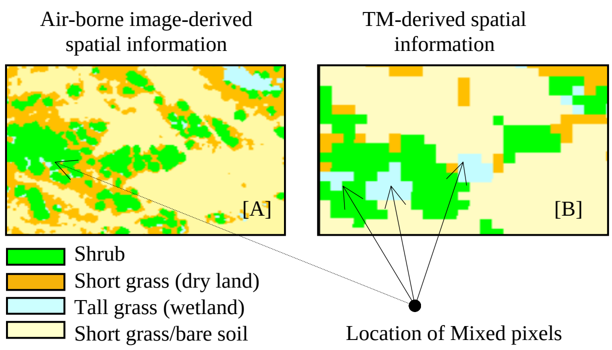

Figure 6. Illustration of 'geometric absence' of wood-grass mixtures and homogeneous wood or grass at locations occupied by mixed pixels

Land cover	*Shrub size ($<450m^2$)*	*Shrub size ($450m^2$ - $900m^2$)*	*Shrub size ($900m^2$ - $3600m^2$)*	*Shrub size ($3600m^2$ – $25,000m^2$)*
Shrub-bare/short grass	149.33	147.78	136.37	131.64
Shrub-medium dry tall grass	135.03	135.23	135.75	129.29

Table 7(a). Mean of brightness values of mixed pixels determined for different sizes of shrubs growing in two types of grasslands (Nabugabo Ramsar site)

Shrubs (very dense)	112.22
forest (fully stocked)	109.04
Forest (degraded)	106.36
Tall grass (mature) in wetlands	129.28
Tall grass (healthy and not mature) in wetlands	98.37
Tall grass	132.97
Bare/short grass	149.31

Table 7(b). Brightness mean values of pixels of various homogenous cover types (Nabugabo Ramsar site).

Other remote-sensing scientists are increasingly raising the concern that mixed pixels hamper land cover mapping for heterogeneous surfaces. For example, Paul Houser in 2001 writing in a News Letter (Biospheric Aspects of the Hydrological Cycle-Global Energy and Water cycle Experiment), asks a similar question: "*Is a land surface scheme which includes sub-grid surface heterogeneity really representing the same kind of varied surface that is viewed by the satellite?*" While the concerns of Houser were raised in the context of coarse resolution satellite data used for global monitoring of land surface variables (vegetation indices, soil moisture and temperature), this study has shown that mixed pixels associated with TM data impose severe limitations for land cover mapping in a wet savanna ecosystem.

5. CONCLUSIONS

Based on the findings of this study, it is concluded that wood-grass mixtures are not represented by spectra of mixed pixels as unique land cover classes. The hypothesis is thus accepted. Secondly, neither do the spectra of mixed pixels formed from wood-grass mixtures represent homogeneous wood or grass patches from which they were derived. Therefore, in wet savanna ecosystem where patches of wood-grass mixtures are of significant density, mixed pixels hamper land cover mapping.

The limitations imposed by mixed pixels cannot be overcome by selecting a suitable mapping scale as recommended in standard mapping manuals and other reference literature. For example, NPA Group (2002) recommends a mapping scale of 1:100,000 and 1;250,000 when using TM and MSS data respectively. A past vegetation-mapping project in MFNP (Uganda Wildlife Authority-GTZ, 1997) using TM data and pre-determined mapping scale of 1:125,000, as mentioned earlier, yielded low overall classification accuracies. It appears that the recommended mapping scales are suitable for identification and mapping of land cover categories in homogeneous rather than heterogeneous ecosystems when using TM data. This study, therefore, recommends use of image data of suitable resolution for land cover mapping in wet savanna ecosystems.

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REFERENCES

Di Gregorio, A. and L. J.M. Jansen, 2000. Land cover classification system (LCCS): Classification concepts and user manual. FAO, Rome, http://www.fao.org/DOCREP/003/X0596E/X0596E00.HTM (accessed 7 March 2002).

Foschi, P.G., Smith D.K., 1997. Detecting Subpixel Woody Vegetation in Digital Imagery Using Two Artificial Intelligence Approaches. *Photogrammetric Engineering & Remote Sensing*, 64(5): 493-500.

Fuller, R.M, Groom, G.B., Mugisha, S., Ipulet, P., Pomeroy, D., Ogutu-Ohwayo, 1998. Integration of Remote Sensing, GIS and Field surveys for biodiversity Assessment: a case study in the tropical forests and wetlands of Sango Bay, Uganda. Biological Conservation, 86(3), 379-391.

Groom, G. B., Fuller, R. M. and Jones, A.R. 1996. Contextual Corrections: Techniques for Improving Land Cover Mapping from Remotely Sensed Images. *International Journal of Remote Sensing,* 17(1), pp. 69-89.

Huguenin, R.L., Karaska, M.A., Van Blaricom, D. and Jensen, J., 1997. Subpixel Classification of Bald Cypress and Tupelo Gum Trees in Thematic Mapper Imagery. *Photogrammetric Engineering & Remote Sensing,* 64(3): 717-725.

Klöditz, C., van Boxtel A., Carfagna E., van Deursen, W., 1998. Estimating the Accuracy of Course Scale Classification Using High Scale Information. *Photogrammetric Engineering & Remote Sensing,* 64(2): 127-133.

Koh, A., Edwards E., Curr, R. and Strawbridge, F., 1996. Techniques in Electronic Imaging for Natural Resource Monitoring. In: Remote Sensing and GIS for Natural Resource Management, C.H. Power, L.J. Rosenberg, I. Downey (Eds.), University of Greenwich, UK, pp. 47-54.

Ji, M. and Jensen, J.R., 2000. Continuous Piecewise Geometric Rectification for Airborne Multi-spectra Scanner Imagery. *Photogrammetric Engineering & Remote Sensing,* 66 (2): 163-171.

Mason, C., Rüther, H. and Smit, J., 1997. Investigation of Kodak DCS460 for small-area mapping. *ISPRS Journal of Photogrammetry & Remote Sensing, 21 (5): 202-214.*

Mugisha, S., Huising, J., 2002. Optimal Resolution for Large-Scale Vegetation Mapping Using Air-Borne Multispectral Data. International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, Vol. XXXIV, Part 6/W6, pp. 155-161.

NPA Group, 2002. Satellite Exploration and Mapping. http://www.npagroup.com/ (accessed 7 March 2002).

Pratt, D.J. and Gwynne, M.D., 1977. Rangeland Management and Ecology in East Africa. Holder and Stoughton, London, 310 p.

Price, J.C., 1994. How unique are spectral signatures? Remote Sens. Environ., 49(3): 181-186.

Sohn, Y. and McCoy, R.M., 1997. Mapping Desert Shrub Rangeland Using Spectral Unmixing and Modeling Spectral Mixtures with TM Data. *Photogrammetric Engineering & Remote Sensing*, 63 (6): 707-716.

Uganda Wildlife Authority-GTZ, 1997. Vegetation mapping of Murchison Falls national park using TM imagery. Technical Report, Uganda Wildlife Authority, Kampala, Uganda.

USGS, Clean Lakes Inc., 2000. Systems for monitoring water hyacinth in the Lake Victoria Basin. Technical report submitted to USAID (see also http://edcsnw3.cr.usgs.gov/ip/lakevictoria.html).

Warner, T.A. and Shank, M., 1997. An evaluation of the potential for fuzzy classification of multispectral data using artificial neural networks. *Photogrammetric Engineering & Remote Sensing*, 63 (11): 1185-1294.

Zhang, J. and Kirby, R., 1997. An evaluation of fuzzy approaches to mapping land cover from aerial photographs. ISPRS Journal of Photogrammetry & Remote Sensing, 52 (5): 193-201.

Zhu, A-X., 1997. Measuring uncertainty in class assignment for natural resource maps under fuzzy logic. Photogrammetric Engineering and Remote Sensing, 63(10): 1195-1202.