CHAPTER THREE
METHODS AND MATERIALS

3.1 INTRODUCTION

Sustainable use of Uganda's savannas is currently constrained by lack of accurate land cover and vegetation maps. As explained in the previous chapter, there is need to improve the accuracy of land cover maps produced for Uganda's savannas. However, it is crucial that the level of accuracy of existing land cover maps is first established (baseline) before embarking on the establishment of the optimal image resolution required for improving the accuracy of land cover maps for Uganda’s savannas. Besides optimal resolution, the improvement of land cover maps generated for Uganda’s savannas can be achieved through the incorporation of wood density as additional knowledge during image classification. The investigations were carried out in 4 test sites depicted in Figure 3.1.

3.2 DESCRIPTION OF THE STUDY SITES

The three types of investigations (i.e. the assessment of the accuracy of existing land cover maps, the evaluation of the quality of imagery and the assessment of wood density as additional knowledge for improving the accuracy of land cover maps for savannas) were carried out in 4 test sites of Uganda: Arua, Nebbi, Murchison Falls National Park (MFNP) and Nabugabo (Figure 3.1). The test sites studied represented, though not exclusively, Ugandans savannas. The selection of each test site was, besides the existence of savannas, based on the availability of IKONOS imagery and to some extent on their ecological and economic importance. For example, MFNP and Nabugabo are important biodiversity conservation areas while Arua and Nebbi are important flue-cured commercial tobacco producing areas in Uganda. Savanna vegetation is important for both biodiversity conservation and as a source of biomass energy for curing tobacco leaves. With about 7% of the total area of the test site covered with savanna vegetation, Arua has the least coverage for savanna vegetation. The rest of the test sites were covered by at least 50% savanna vegetation.
Figure 3.1. Location of each test site.
3.3 APPROACH TO STUDY

The materials and methods that cut across the three study objectives (general cases) on one hand and materials and methods specific to each specific objective on the other are presented in two separate sections. Based on this approach, general equipment, software, image processing and ground truthing are explained in Section 3.3.1 while materials and methods pertaining to each of the three specific objectives are explained in Section 3.3.2.

3.3.1 General methods and materials

3.3.1.1 Materials and equipment

The materials and equipment used in pursuit of the three study objectives (Section 1.4) during the present study included Landsat TM, IKONOS and Kodak imagery. Equipment used included Kodak Multispectral Aerial Photographic System (DCS560); 4-seater winged aircraft; Global Position System receivers; and a personal computer. While the potential of satellite imagery was the focus of the present study, airborne imagery, acquired by a Kodak Camera (DCS560) were used to simulate satellite imagery to different spatial image resolutions as will be explained in section 3.3.2.2.

In addition, professional image processing software (TNTmips, 7.0), GIS software (ArcView, version 3.2) and FAO's Land Cover Classification Legend for Uganda (Appendix A3.1) were available for use for the present study.

3.3.1.2 General methods

The details of the imagery (Landsat TM, IKONOS and Kodak) used in the present study are discussed in detail under each section specific for each objective (Sections 3.3.3). However, the imagery used in the present study was first processed to render it acquire map-like properties, especially their geometry. Most processing techniques modify digital numbers (DNs) of an image according to specific algorithmic rules (Sonka, et al., 1993).
The image processing performed on imagery used during the present study included georeferencing, geometric rectification, resampling, mosaicking and principal component analysis. How each image processing was carried out and why is explained in the next subsections.

3.3.1.2.1 Image processing

(a) Image georeferencing

Georeferencing is the process of bringing remotely sensed imagery, and other data formats, into alignment with a known co-ordinate system (Microlimages, 1998). Conventionally, sensors acquire imagery without real world coordinates and hence need to be georeferenced. As an image processing technique, georeferencing involves identifying points on an image followed by locating their real world co-ordinates (control points) using a Global Positioning System (GPS) or from an existing map. Good sources of control points for georeferencing include road junctions and sharp bends of linear features such as roads and rivers (features that are easily identified and also relatively stable over long periods of time). The accuracy of the georeferencing procedure is influenced by a number of factors including presence/absence of accurate control points and pixel size of the image being georeferenced.

Georeferencing of the imagery used in the present study (Landsat TM, IKONOS and Kodak) was carried out using Microlimages TNTmips software. The georeferencing procedure, in TNTmips, is largely automated. It involves identifying common points (also referred to as ground control points) that are visible both on the image being georeferenced and existing digital maps or image maps. Good sources of ground control points, according to Labovitz and Marvin (1986), include topographic features such as sharp junctions of roads and rivers, and sharp boundaries of geographical entities. Figure 3.2 illustrates a ground control point (indicated by a red +) that was used as a source of coordinates (x, y, z) from Landsat TM image map and transferred to the same point on IKONOS imagery during a georeferencing session. The green 'cross-hair' depicts a potential point that could be added as another control point while
the value 2172 represents the z-coordinate (altitude, in feet). The procedure of selecting control points (x,y,z coordinates) from reference vector maps (or image maps) was repeated and care was taken to ensure well-distributed control points per image scene. The Universal Transverse Mercator (UTM) system was used for the georeferencing/rectification processes given the fact that Ugandan base maps are also based on the UTM co-ordinate system. The georeferenced imagery (Landsat TM, IKONOS and Kodak) were then used in the next image processing technique, image rectification.

![Cross-hair (potential recipient control point)](image1)
![Cross-hair (potential source of control point)](image2)

Figure 3.2 Procedure of adding control points (x-,y- and z coordinates) during an image georeferencing session using TNTmips.

(b) Image rectification

Image rectification (or geometric correction), is the removal of geometric distortions from a raw image. When using automated image-processing techniques, geometric correction is preceded by georeferencing (Section 3.3.2.1). Raw imagery contains internal geometric distortions that arise (for airborne imagery) as a result of tilt of the aircraft during aerial survey, lens distortions, variations in sensor altitude and terrain relief. For space sensors placed hundreds of kilometres above the Earth's surface, variation in sensor altitude may be insignificant (except for very hilly and mountainous areas) but the Earth's curvature is a source of image distortions (Mather,
1987). For this reason, remotely sensed data need rectification to correct for these geometric distortions. Rectification allows the transformation of raw distorted imagery to an image output with map-like characteristics. Ground control points (x, y and z coordinates) are needed during the image transformation process.

The geometric transformation was carried out using an algorithm (in TNTmips) called Piece-wise Affine. Piece-wise Affine is based on the principle of triangulation to transform a georeferenced image to a rectified one. Piece-wise affine was used during the present study because it is considered by many researchers (for example, Ji and Jensen, 2000) to be robust. The accuracy levels of each rectified image were quantitatively determined by the image processing software used (TNTmips). A sample of the software-generated root mean square (RMS) for one of the test sites is shown in Appendix A3.2. Through visual inspections, it was also ensured that correct geometric accuracy, i.e. the same geographic features represented on IKONOS and Landsat TM are correctly aligned (Figure 3.3).

Figure 3.3 Qualitative assessment carried out by superimposing IKONOS on Landsat TM ensured that positional errors were kept at minimum.
The importance of image rectification is to minimise geometric (positional errors) to ensure that subsequent analyses carried using maps (such as cross-tabulation) produce meaningful results. Rectification is an automated image processing technique that is accomplished (when using TNTmips) during image resampling.

(c) Image resampling

The resampling process is a mathematical computation to transform the geometric characteristics of an image (such as changing the image pixel size or rotating an image through a specified angle) (Mather, 1987). The mathematical computations are based on three common resampling algorithms: (a) nearest neighbour, (b) bilinear interpolation, and (c) cubic convolution. The output pixel may be the same, larger or smaller than the input pixel. If the output pixel is larger than the input pixel, it has to ‘overlap’ (replace) several input pixels. In this case, the output pixel must be calculated (interpolated) from some combination of the surrounding input pixels. The outputs of image resampling, among other applications, are widely used to simulate various properties of imagery in absence of actual scenarios. For example, in the preset study, image resampling was used to simulate imagery acquired at 0.5 m to larger pixel sizes in order to study the relationship between image spatial resolution and the geometric/spectral accuracies of land cover maps derived for a typical savanna ecosystem in Uganda (Section 3.3.3.2).

In the nearest neighbour resampling technique, each output pixel brightness value is the unmodified brightness value from the closest input pixel (Microimages Inc., 1998) (Figure 3.3). Preservation of the original brightness pixel values is an advantage if the resampled image is needed for further quantitative analysis (Mather, 1987). On the negative side, nearest neighbour resampling causes edges of boundaries of features to be offset by distances up to half the input pixel size. If the image is resampled to a different pixel size, a blocky appearance may result from the duplication (smaller output cell size) or dropping (larger cell size) of input pixel brightness values.
In the Bilinear interpretation, an output pixel brightness value is the weighted average of the four closest input pixel values (Figure 3.3), with weighting factors determined by the linear distance between output and input pixels. This technique produces a smoother appearance than the nearest neighbour, but it can reduce the contrast and sharpness of feature boundaries. Bilinear resampling technique works best when resampling to a smaller output image pixel size (Mather, 1987; MicroImages Inc., 1998).

Input pixels used by each resampling method:

1) Nearest neighbour \(= 1\)
2) Bilinear interpolation \(= 1 + 2 + 3 + 4\)
3) Cubic Convolution \(= 1 + 2 + 3 + 4 + 5 + 6 + \ldots + 16\)

Figure 3.3 Input pixels for the commonest resampling algorithms
[Source: generated from Landsat TM data using TNTmips based on Mather’s (1987) concept of image resampling]

Lastly, the cubic convolution technique calculates an output pixel brightness value from a 4 x 4 block of surrounding input pixels (Figure 3.3). The output brightness pixel value is a distance-weighted average, but the weight values vary as a non-linear function of distance. This method produces sharper and less blurry images than
bilinear interpolation and is the preferred method (Section 3.3.5) when resampling to a larger output pixel size (Mather, 1987; MicrolImages Inc., 1998).

Two of the three sampling techniques were used during the present study. As already mentioned in Section 3.3.2.2, image rectification is carried out as part of the image resampling technique. Given the advantage of the nearest neighbour resampling technique, i.e. that each output pixel brightness value is the unmodified brightness value from the closest input pixel, this technique was used during the rectification process of Landsat TM and IKONOS imagery. During the rectification, the pixel size of each of the two types of imagery (Landsat TM and IKONOS) was kept constant and hence avoiding duplication and dropping (Section 3.3.2.2) hence implying good quality data for classification/interpretation. However, given the advantages of cubic convolution resampling technique when resampling to a bigger pixel size, the technique was used for simulating Kodak data to different pixel sizes (Section 3.3.5).

(d) Image mosaicking

The mosaic process, using a given image processing system, allows the merging of individual image scenes into a single image file to cover a larger terrain (Mather, 1987). To prevent gaps in the mosaicked imagery, a sensor captures adjacent images with an overlap region. If the images are georeferenced/rectified, they are automatically placed in the required positions and then mosaicked. If some or all of the images are not georeferenced, a manual positioning technique (also known as bundle adjustment) is used to place tie points within the overlapping part of the images (MicrolImages, Inc., 1998). A bundle adjustment algorithm then computes a least-squares best fit for all tie points in order to produce an image mosaic. Image mosaicking was used to patch together small image frames (acquired by Kodak DCS560) as will be explained in Section 3.3.3.2.

(e) Principal components analysis

Principal components analysis (PCA) is a means of transforming a set of multiple data (multispectral in nature) to produce a reduced number of uncorrelated output rasters
(MicroImages, Inc., 1998). According to Mather (1987), data acquired in adjacent regions of the electromagnetic spectrum are correlated. It is also known that the presence of correlation among different imagery acquired in the separate parts of the electromagnetic spectrum signifies information redundancy (repetition of similar information). According to Wilkie and Finn (1996), PCA compresses the information of multispectral image into only 1 - 3 components (bands). For example, the PCA reduces more than 95% of all the useful information contained in a scene of Landsat TM data (7 bands) into 3 components (bands). Both Mather (1987) and Wilkie and Finn (1996) point out that PCA enhances the interpretability of multispectral remotely sensed data in addition to reducing the number of image bands required for a variety of applications. The principal component analysis was used to reduce Landsat TM imagery and the resultant first component used to establish the relationship between wood density and spectra of the imagery (Section 3.3.3.3).

3.3.1.2.2 Ground-truthing

As a remote sensing technique, ground truthing refers to surface or near surface observations aimed at gathering reference information that describes actual geographical features (Wilkie and Finn, 1996; Huang and Dewitt, 2000). The overall aim of ground truthing is to aid in the calibration and classification of imagery by relating actual geographical features with different spectra of an image (Geneletti and Gorte, 2003). Therefore, in order to carry out image analysis described in Sections 3.3.3 - 3.3.5, it was necessary to establish the relationship between the spectral characteristics of imagery used during the present study (IKONOS, Kodak and Landsat TM) and the actual ground geographical features for each test site. Ground truthing was carried out by locating/identifying sample land cover categories on the ground with the help of global Positioning System (GPS) receiver. Appendix B3.1 shows the distribution of fieldwork observations, obtained using a GPS, for each of the four test sites. Appendix A3.3 shows ground photographs depicting sample land cover types observed at some of the locations shown on images presented in Appendix B.3.1. The information obtained during ground truthing was used, inter-alia, to generate:
a) reference information, from IKONOS imagery, for the assessment of the accuracy of existing land cover maps produced for Uganda's savannas (Section 3.3.3.1);
b) land cover maps, from Kodak imagery, used to evaluate the optimal resolution of imagery required for mapping Uganda's savannas (Section 3.3.3.2); and
c) land cover maps, from Landsat TM imagery, used to assess the potential of wood density as a criterion to map land cover classes characteristic of Uganda's savannas when using Landsat TM imagery (Section 3.3.3.3).

3.3.2 Objective-specific materials and techniques

The general methods described in the previous section are all standard and routine in the preparation of image data required for mapping any landscape. In this section, specific techniques used to achieve the aims of each of the three objectives outlined in Section 1.4 are described. The objective-specific techniques used were several. A region-based map error assessment approach, considered to be robust, was used to assess the accuracy of existing land cover maps produced for Uganda's savannas from low/coarse resolution imagery. The determination of optimal resolution for mapping Uganda's savannas was carried out by simulating 0.5 m imagery to decreasing image resolutions and then assessing the impact on the characteristics of desired information at each image resolution. Whether Landsat TM imagery offers a potential to map Uganda's savannas using wood density was investigated by determining actual wood density and correlating the wood density with Landsat TM data spectral. The details of the materials and techniques to achieve the aims of the thesis objectives are described below.
3.3.2.1 Assessing the accuracy of existing land cover maps produced for Ugandan's savannas

(a) Materials

(i) Primary data used

IKONOS data (imagery) was used as a source of reference information for assessing the accuracy of 3-4 types of land cover maps for each of the four test sites. IKONOS imaging sensor is a commercial satellite sensor orbiting the Earth at an altitude of 497 km. It is owned and managed by Space Imaging Incorporated (USA) and was designed to provide 1 m panchromatic and 4 m multi-spectral spatial resolution data (Karpouzli and Malthus, 2002) (Table 3.1). The current operational IKONOS Satellite was launched in October 1999 and its imagery is primarily aimed at detailed map production (Donoghue, 2000; Read et al., 2003). The fact that IKONOS data allows detailed mapping was a justification for using it as a source of reference information in the assessment of the accuracy of the low/coarse resolution-derived land cover maps.

Table 3.1 Spectral and spatial characteristics of IKONOS data (Source: NPA, 2002)

<table>
<thead>
<tr>
<th>Spectral band</th>
<th>Spectral range (μm)</th>
<th>Spatial resolution (m)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Panchromatic</td>
<td>0.45 – 0.9</td>
<td>1.0</td>
</tr>
<tr>
<td>Band 1 (blue)</td>
<td>0.45 – 0.53</td>
<td>4.0</td>
</tr>
<tr>
<td>Band 2 (green)</td>
<td>0.52 – 0.61</td>
<td>4.0</td>
</tr>
<tr>
<td>Band 3 (red)</td>
<td>0.64 – 0.72</td>
<td>4.0</td>
</tr>
<tr>
<td>Band 4 (near infrared)</td>
<td>0.77 – 0.88</td>
<td>4.0</td>
</tr>
</tbody>
</table>

(ii) Secondary data

The details of the existing land cover maps whose accuracy was assessed are presented in Table 3.2 and Appendices B2.4 and B3.8.
Table 3.2 Existing land cover maps from which land cover maps for savannas were extracted

<table>
<thead>
<tr>
<th>Type of land cover data set</th>
<th>Author/publication date</th>
<th>Image type and resolution</th>
<th>Production method</th>
<th>Test site covered</th>
</tr>
</thead>
<tbody>
<tr>
<td>1) Africa Global Land Cover</td>
<td>Mayaux et al. (2000)</td>
<td>SPOT 4 (500 m)</td>
<td>Automated</td>
<td>Arua, Nebbi, MFNP and Nabugabo</td>
</tr>
<tr>
<td>4) Murchison Falls National Park (MFNP) vegetation</td>
<td>Jäckal et al. (1997)</td>
<td>TM (30 m)</td>
<td>Automated</td>
<td>MFNP</td>
</tr>
</tbody>
</table>

A number of analytical techniques were used to assess the accuracy of the four land cover maps (covering the entire country) shown in Table 3.2 for each of the test site: Arua, Nebbi, MFNP and Nabugabo test sites. The techniques used to assess the accuracy of existing land cover maps involved the preparation of existing land cover maps to conform to the same coordinate and classification systems; generation of reference information from IKONOS imagery; and cross-tabulation of reference information with the existing land cover maps in order to determine their accuracies. The details of each technique are presented in the following subsection.

(b) Techniques

(i) Preparation of existing land cover maps

The accuracy of each of the four land cover maps shown in Table 3.2 was determined by a spatial comparison between reference information (derived from IKONOS imagery) and each map whose accuracy was assessed. Before spatial comparison (GIS overlaying) of any two maps can be carried out, the input maps had to be transformed to the same coordinate system and map legend. For this reason, the Universal Transverse Mercator (UTM) coordinate system (and other projection parameters for zone 36 such as datum and ellipsoid) was applied to each of the four land maps shown in Table 3.2. The procedure of transforming a map from one coordinate system to
another is an automated technique provided for in most commercial GIS software. In the present study, the transformation of Africover and Africa Global Land Cover 2000 from Latitude/Longitude or decimal degrees to UTM coordinate system was carried out using TNTmips software. Other appropriate project parameters in addition to coordinate system in meters, for East Africa (hence for Uganda) selected for the transformation were the datum (Arc 1960) and the Ellipsoid (Clarke 1880).

Lastly, the mapping units of each of the four land cover maps (Table 3.2) were translated to the same land cover classification legend. This procedure was necessary because the NBS and MFNP land cover maps were produced using different map legends from those of the Africover and the Africa Global Land Cover 2000 land cover maps. The former maps were produced by their authors using in-house created legends; while the latter maps were produced using a Land Cover Classification System (LCCS) developed by FAO (2000). For this reason, the NBS and MFNP land cover maps were also translated to the same legend (using LCCS) as the Africover and Africa Global Land Cover 2000. This translation of the legends was done manually i.e. by the reclassification of each map unit (of NBS and MFNP land cover maps) to corresponding classes provided by the FAO's LCCS. Bringing all the four land cover maps (depicted in Table 3.2) to the same legend was necessary because it can only be practical to compare the labels of any two maps (existing land cover and reference maps in the present study) if their legends and coordinate systems, are the same (Anderson et al., 1976).

(ii) Generation of reference information from IKONOS data

The next step, in the assessment of the accuracy of the existing land cover data maps, was the generation of reference information. Reference information refers, according to Foody (2002), to ground or near ground information used to determine the accuracy of a map, qualitatively or quantitatively. There were two potential techniques available for the generation of reference information. The first and most frequently used technique is recommended by Nusser and Klass (2002). This technique (of generating
reference information) is based on selecting reference information at a given point \((x,y)\) coordinates) as illustrated in Figure 3.4.

![Figure 3.4 Sample points (+) that represent location for gathering reference information for the assessment of map accuracies](image)

The second technique of generating reference information, rarely used by image analysts, involves gathering reference information within a region (polygon). Such polygons (yellow lines) are depicted in Figure 3.4. The polygon-based (or region-based) approach is recommended by Klöditz et al. (1998) and Marceau, Hay (1999) and Lidov et al. (1999) if high-resolution imagery is readily available. Marceau and Hay (1999) argue that the use of the polygon-based approach to assess land cover map accuracy has had limited success because of the high expenses involved in acquiring high-resolution imagery. Polygon-based techniques, as a method of assessing the accuracy of land cover maps, are considered rigorous because of the fact that land cover map units are not independent of their geometrical properties (shape and location of boundaries). It is against this background that the present study selected the polygon-based (region-based) rather than point-based technique to generate reference information for the assessment of the accuracy of existing land cover maps for each of the four test sites. Other researchers have used a polygon-based technique, for the assessment of map accuracies. For example, Domenikiotis et al. (2002) used the method to find the agreement between burnt vegetation (of forest cover) derived from
NOAA/AVHRR and Landsat TM data and the author observes that a polygon-based map accuracy assessment technique is more robust than point-based technique.

Proponents of point-based reference information, such as Nusser and Klass (2002), argue that the technique minimises propagation of errors. However, Foody (2002) and Powell et al. (2004) also argue that reference information, whether point-based or region-based, often contains some errors. However such errors have to be minimised. In the present study, errors associated with reference information were minimised by defining land cover classes on the basis of vegetation structure rather than plant species. Spatial information generated from high-resolution imagery, on the basis of vegetation structure rather than species composition, is considered to be less error-prone (Kent and Coke, 1992). The definition of reference information based on vegetation structure also conformed to the legends of land cover maps whose accuracies were assessed. The information obtained during the ground truthing exercise (Section 3.3.2) (Appendix B3.1) provided the basis for the definition of the mapping units (land cover categories) for the reference maps derived from IKONOS imagery. To ensure that reference information was comparable with existing land cover maps whose accuracy were assessed [Section 3.3.3.1(ii)], the FAO's LCCS was used for the definition of land cover categories derived from IKONOS imagery. A total of 18 land cover categories were identified for the four test sites during the ground-truthing phase (Table 3.3).

For each test site, a combination of unsupervised and visual image classification techniques (Section 2.4.2) was used to derive a reference map (information) from IKONOS images. ISODATA (unsupervised image classification) technique was used to segment IKONOS imagery, for each test site, into a predetermined number of land cover spectral classes. The resultant spectral map was in turn visually classified into a land cover map of each test site. A visual aid used during image interpretation/classification is shown in Appendix A3.4. This approach, i.e. a combination of automated and visual image classification, was adopted because of a major limitation of automated classification techniques (whether unsupervised or supervised): for any automated image classification technique, the output only
represents closed canopy land cover categories which means that wood/grass mixtures of different densities cannot be mapped. However, by segmenting IKONOS imagery into several spectral classes, then using visual image classification on the resultant spectral map, it was possible to map wood/grass of different densities into different land cover categories to represent the desired reference information.

Table 3.3 Land cover categories (based on the FAO Land Cover Classification System) established during the ground-truthing phase of the present study.

<table>
<thead>
<tr>
<th>FAO LCCS Code</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. 2WC7</td>
<td>Closed woody cover with sparse trees</td>
</tr>
<tr>
<td>2. 2WP26</td>
<td>Broad leaved deciduous open with grass layer</td>
</tr>
<tr>
<td>3. TBR247PL</td>
<td>Closed Eucalyptus plantation</td>
</tr>
<tr>
<td>4. 4SCJFF7</td>
<td>Closed shrubs on permanent wet areas</td>
</tr>
<tr>
<td>5. Tea</td>
<td>Tea plantation</td>
</tr>
<tr>
<td>6. 2SCJ7</td>
<td>Closed shrub cover with sparse trees</td>
</tr>
<tr>
<td>7. 2GTCM-B</td>
<td>Palm grass savanna</td>
</tr>
<tr>
<td>8. 2SOJ67</td>
<td>Closed shrubs with grass and sparse trees</td>
</tr>
<tr>
<td>9. 2SVJ/2GC</td>
<td>Very open shrubs and sparse trees with closed grassland</td>
</tr>
<tr>
<td>10. 2GC78</td>
<td>Closed grassland with sparse trees</td>
</tr>
<tr>
<td>11. 4HCJF8</td>
<td>Closed herbaceous with sparse shrubs on wet areas</td>
</tr>
<tr>
<td>12. 4SPJF6</td>
<td>Closed herbaceous on seasonally wet areas</td>
</tr>
<tr>
<td>13. 8S</td>
<td>Closed papyrus/phragmites</td>
</tr>
<tr>
<td>14. 7S</td>
<td>Closed forbs</td>
</tr>
<tr>
<td>15. 6S</td>
<td>Short grass/bare ground</td>
</tr>
<tr>
<td>16. SR47</td>
<td>Subsistence farming</td>
</tr>
<tr>
<td>17. SR47/2SCJ7</td>
<td>Subsistence farming with closed shrub and sparse trees</td>
</tr>
<tr>
<td>18. 8WP</td>
<td>Water</td>
</tr>
</tbody>
</table>

Key to Table 3.6: Closed = greater than 65%; open = 65 - 15%; very open = 40 - (20 - 15%); sparse = 15 - 5% trees [Source: FAO LCCS 2000]

The initial classification of IKONOS imagery through the use of ISODATA classification technique resulted into one spectral map, for each test site, in a raster format. The spectral map was then converted into a vector map of which a sample is depicted in Figure 3.5. For each vector map, all polygons smaller than 1,600 m² were
automatically removed using a relevant ‘Vector Filter’ function provided in TNTmips mapping software. A minimum mapping unit of 1,600 m² (0.16 ha) was used because it is recommended by some researchers (Townshend, 1981) that at least four contiguous pixels of an image should be the smallest mapping unit of land cover maps derived from remotely sensed data. In the present study, the most detailed land cover map whose accuracy was assessed was produced from SPOT XS (20 m) and the four contiguous pixels of SPOT XS is equivalent to 1,600 m². Figure 3.5(a) shows spectral map (after conversion to a vector format) derived from IKONOS imagery using ISODAT (image classification) technique. On the other hand, Figure 3.5(b) shows the same map after visual interpretation and classification. A combination of automated and visual image classification techniques (based on screen-digitising) enabled the author to identify and map land cover categories constituted of wood/grass mixtures of different densities, hence maximising the practical advantages of both visual and automated image classification (Section 2.4.2).

(iii) Assessing accuracy of existing land cover maps through cross-tabulation

The reference maps generated from IKONOS data, for each test site, was cross-tabulated with each existing land cover map for each test site [Section 3.3.3.1(i)]. Cross-tabulation is a standard GIS technique that tabulates areal extents within zones of any two maps that are spatially overlaid. The values in the resulting table identify the area of each zone in map 1 encompassed within each zone in map 2. In the present study, cross-tabulation was used to summarize the area of each land cover type (whose accuracy was being assessed) for each mapping unit derived from IKONOS data (reference map). Table 3.4 is a sample of the outcome of cross-tabulating MFNP-Africover map (rows) with the reference map (columns) derived from IKONOS data. Each cross-tabulated output table, for each test site, was exported to Microsoft Excel and transformed into a standard error classification matrix (Wilkie and Finn, 1996; Short, 1998). The findings of the above investigation, i.e. assessing accuracy of existing land cover maps for each test site, are presented in the next chapter. The next section explains the techniques used to evaluate the optimal resolution for mapping Uganda’s savannas.
3.3.2 Determination of optimal resolution for mapping Uganda’s savannas

(a) Data used

A Kodak Digital Colour System Camera (model DCS560) was used to acquire the imagery used to assess the optimal image resolution for mapping Uganda’s savannas.
The Kodak infrared colour camera was mounted on a hired 4-seater aircraft. The Kodak camera is equipped with an electronic charged couple device (CCD) as its sensor. Each pixel on the CCD is coated with a filter to produce a Bayer Colour Filter array that has twice the number of red (r) pixels as infrared (ir) or green (g) (Dean et al., 2000). The matrix in Table 3.5 shows a hypothetical CCD arrangement of the filter array. The CCD captures a single composite image frame per scene and the constituent image bands were obtained by separating the composite image frame using a commercial graphic software (Paint Shop Pro).

According to Koh et al. (1996), the operational principle of the Kodak DCS560 is the same as that of a colour infrared (CIR) film. Radiation is recorded in three electromagnetic bands: green (0.5 - 0.68 μm), red (0.68 - 0.7 μm) and photo infrared radiation (0.7 - 0.9 μm). The image swath of Kodak DCS560, using a wide-angle lens, may range from 1.5 km - 2.0 km at an altitude of about 2,000 m - 2,500 m above sea level (Koh et al. 1996). The Kodak imagery used during the present investigation was acquired at an average resolution of 0.5 m. Each image frame on, on average, measured 1.5 km by 1.0 km. The digital aerial surveys were conducted by GeoTechnologies based at Bath Spa University (England) in September 1998.

Table 3.5 Arrangement of pixels on the CCD of the DCS560 Kodak camera: ir = infrared, g = green and r = red pixel [Adapted from Dean et al., 2000].

<table>
<thead>
<tr>
<th>Row number</th>
<th>0</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>n</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
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<td>ir</td>
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<td>1</td>
</tr>
<tr>
<td>1</td>
<td>g</td>
<td>r</td>
<td>g</td>
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<td>2</td>
<td>r</td>
<td>ir</td>
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<td>ir</td>
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<td>2</td>
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<tr>
<td>3</td>
<td>g</td>
<td>r</td>
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<td>r</td>
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<tr>
<td>4</td>
<td>r</td>
<td>ir</td>
<td>r</td>
<td>ir</td>
<td>r</td>
<td>ir</td>
<td>3</td>
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<tr>
<td>5</td>
<td>g</td>
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<td>n</td>
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<td>n</td>
</tr>
</tbody>
</table>

The Kodak images were used to evaluate the optimal spatial resolution suitable for mapping Uganda's savannas as described in the next section.
(b) Techniques used

In chapter 2 (Section 2.4.1.2), it was stated that spatial image resolution of imagery directly affects land cover map accuracies. It is this relationship between land cover map accuracy and spatial resolution that make the latter a robust technique for evaluating the optimal resolution of imagery required for mapping Uganda’s savannas. A number of existing techniques were adopted, and new ones developed, to determine the effect of image pixel size (spatial image resolution) and the accuracy of land cover maps produced for savanna landscapes. The existing techniques adopted include overall classification accuracy (measured in terms of percent correct or Kappa values) and the level of terrain noise. New techniques developed during the present study included land cover index, average patch size (of land cover features), file size of each image mosaic and areal extent of each land cover category mapped from Kodak images of different pixel sizes (spatial resolution). The details of the technique used to evaluate the optimal image resolution, using Kodak imagery, for mapping Uganda’s savannas are described in the following subsections.

(i) Preparation of Kodak imagery

Adjacent image scenes, acquired by the Kodak camera, for two test sites in the Nabugabo area, were selected from the same flight line and mosaicked as explained in Section 3.3.2.1(d). The selection of adjacent image frames in the same flight line was intended to use images taken under similar atmospheric conditions at the time of the aerial surveys. Each image mosaic was georeferenced and rectified as described in Sections 3.3.2.1(a) and (b). The image mosaic for site 1 covered a ground area of 172 ha while the image mosaic for site 2 covered a ground area of 296 ha. The two image mosaics are shown in Appendix B3.2.

(ii) Simulation of Kodak imagery to different image pixel size

The resolution of each Kodak image mosaic (0.5 m) was decreased through a systematic degradation to bigger pixel sizes using TNTmips’ Automatic Resampling procedure [3.3.3.1(c)]. This process of degrading an image to bigger pixel sizes was
aimed at simulating imagery acquired at 0.5 m to actual data that would have been acquired at the specified pixel sizes (spatial resolutions). The simulation of image resolution through degrading high-resolution data has been used, and also recommended by van der Meer et al. (1999), Iron et al. (1985), Ringrose et al. (2003) and Sá et al. (2003). Medical imaging experts, too, such as Baveye et al. (1998) have simulated high- to low-resolution imagery in order to assess the effect of decreasing image resolution on the economy of storing digital radiotherapy data while at the same time preserving its quality.

The degradation of an image through resampling is a two-step process involving filtering out the unwanted pixels and changing the remaining pixels to a larger pixel size (Müller and Segl, 1999). The simulation of image resolutions, through increasing an image's pixel size, was each time carried out from the original image mosaic (0.5 m resolution) and using the cubic convolution resampling algorithm in order to minimise any negative effects that are associated with this type of resampling process [Section 3.3.2.1(c)] (Müller and Segl, 1999). The technique of simulating image resolution, through increasing the pixel size, is based on the assumption that the simulation does not significantly alter the geometric and spectral properties of an image. This assumption, to a large extent, is correct as illustrated in Figure 3.6 where a simulated Kodak image (from 0.5 m to 4.0 m) preserves the vegetation structure (a mixture of grass and trees) to a level comparable to the data acquired by IKONOS sensor (4 m resolution) for the same terrain.

![Figure 3.6 Part of the Nabugabo test site: simulated (Kodak) and actual (IKONOS) data maintain the spectral and geometric integrity of geographic features.](image-url)
During the simulation, the resolution of each image mosaic, for each site, was systematically changed from 0.5 m to 1.0 m, 1.5 m, 2.0 m, 2.5 m, 3.0 m, 3.5 m, 4.0 m, 4.5 m and 5.0 m; and then 0.5 m to 6.0 m, 7.0 m, 8.0 m, 9.0 m and 10.0 m. A resampling interval of 0.5 m was used because it had been used and recommended by researchers such as Lamb et al. (1999) and Lass et al. (2000). However, degrading each image mosaic beyond 5.0 m, at an interval of 1.0 m, was deemed practical in order to reduce the number of imagery simulated to different resolutions. Image simulation did not go beyond 10.0 m because it was deemed that a pixel size bigger than 100 m² might be too coarse to allow the identification of targeted individual savanna trees. Samples of simulated images are depicted in Appendix B3.3.

(iii) Classification of Kodak image mosaics

The determination of the optimal resolution of imagery required for mapping Uganda’s savannas was assumed to make sense if the investigation is based on measuring how the information desired changed with varying spatial resolution. This concept has been proposed by Atkinson and Curran (1997) who point out that a measure of information content is a prerequisite in studies designed to determine the optimal resolution of images for a given application. In this investigation, a measure of information content was given by the level at which the spectral and geometrical integrity of geographical entities, derived from imagery of different pixel size, were preserved. Features representing dense wood, tall grass, short grass and herbaceous vegetation were extracted from each image mosaic and for all simulated images (using ISODATA image classification technique). Burnt vegetation/shadow was included as an extra spectral class. Only homogeneous land classes were defined for this investigation, avoiding classes defined based on vegetation density. This approach (mapping only homogeneous entities) was adopted for practical reasons to conform when using standard automated classification techniques in a way recommended by Lewis (1998). In any case, this is in agreement with the overall aim of this investigation i.e. of determining the optimal resolution that preserves the integrity of geographical entities within Uganda’s savannas.
(iv) Determination of optimal resolution for mapping Uganda’s savannas

The reasons for using two types of techniques, i.e. both existing (overall classification accuracy, level of terrain noise) and new techniques developed during the present study (land cover index, average patch size, file size, areal extent) in the determination of optimal image resolution for mapping Uganda’s savannas was to select the most robust out of the several techniques listed. While terrain noise (a measure of ‘homogeneity’) is recommended by Bedward et al. (1992) and Marceau et al. (1994) when determining optimal spatial resolution for mapping a given landscape, terrain noise alone appears not to precisely define optimal spatial resolution for determining the required optimal resolution. This is because the “measure of homogeneity technique” is based on the concept that decreasing the resolution of imagery until internal spectral variance/terrain noise is at its minimum gives a measure of optimal image resolution for mapping a given landscape. For example, research conducted by Menges et al. (2001) based on measuring the ‘homogeneity’ of 0.15 m imagery shows that the optimal resolution of imagery for mapping savanna vegetation communities in Northern Australia ranged from 15 – 27 m (Figure 3.7).

![Figure 3.7 A plot of image spectral variance against decreasing image resolution as a technique for determining optimal resolution for mapping Northern Australian savannas [Source: Menges et al., 2001].](image-url)
Due to the above limitations of the current techniques to allow the definition of a narrow range when determining an optimal resolution for mapping landscapes such as savannas, a triangulation of old (notably image noise or homogeneity) and new techniques was used to define a precise but narrow range of the optimal resolution for mapping Uganda’s savannas. Some of these new techniques involved various types of indices – the land cover and the average patch size indices. The indices were based on the premise that both shape and size determine the geometric integrity of geographic features and hence should be incorporated with terrain noise (triangulation of techniques) when determining optimal image resolution for mapping Uganda’s savannas. Each technique used to contribute to the evaluation of optimal spatial resolution for mapping Uganda’s savannas is described, in detail, below.

**Optimal resolution as indicated by classification accuracy**

It was postulated, in the present study, that trends in the overall classification accuracy (OCA) measured as percent correct and Kappa value are a function of image pixel size (spatial resolution). By decreasing the image resolution progressively (increasing pixel size), one assumes deterioration in the accuracy of land cover maps (due to the deterioration of the geometric properties of geographic features) and hence low OCA values for a given terrain. The OCA was determined for each of the 30 land cover maps using reference information. The reference information, point-based, was produced from the parts of the image representing known homogeneous land cover categories (Figure 3.8). The location of reference information (in the form of circular polygons superimposed on each image mosaic) is shown in Appendix B3.4. The white polygons in Figure 3.8 did not constitute land cover heterogeneity but was part of terrain noise characteristic of homogeneous geographical features.
The OCAs (in terms of percent correct pixels and Kappa values) were determined using TNTmips. TNTmips automatically generates an error classification matrix based on two inputs: a land cover map (whose accuracy is required) and a reference map. Both the land cover and the reference maps had to be in a raster format since the generation of a classification error matrix is possible by a process of comparing two maps on a pixel by pixel basis (Nusser and Klass, 2002). Because of this, the circular polygons (samples representing reference map) were converted into a raster map using the same resolution of the land cover map whose accuracy was to be assessed. The OCA (in terms of percent correct pixels and Kappa values) of each of the 30 land cover maps, generated as described in 3.3.3.2(iii), was determined automatically by TNTmips and recorded. The recorded percent correct pixels and Kappa values was then plotted against varying simulated image resolutions.

**Optimal resolution as indicated by the level of terrain noise**

As already pointed out, image homogeneity or image spectral variance is a standard parameter used for the determination of optimal image resolution. The minimum spectral variance is ideally a measure of unwanted intra-terrain noise. There are many approaches used to measure terrain noise. Since an object-oriented mapping model was employed in the present study, the level of terrain noise was determined by
quantifying the number of land cover polygons generated for each image mosaic (at different spatial resolutions). The assumption made is that a decrease in image resolution should result in dramatic decrease in terrain noise but the desired shape and size of actual geographical entities (such as individual trees) geometry should be preserved as image resolution decreases (increasing image pixel size) till the optimal spatial resolution. However, any further reduction of terrain noise will have a degrading effect on the shape and size of individual geographic features and hence is undesirable. This principle is illustrated in Figure 3.10.

The level of unwanted intra-terrain noise (associated with very high resolution imagery) was determined using a standard GIS procedure of querying a vector database. Each of the 30 land cover maps [derived from the simulated images as explained in Section 3.3.3.2(i)-(ii)] was converted from a raster to a vector data format. Using ESRI’s ArcView GIS software, all polygons belonging to each of the five (test site 1) or four (test site 2) land cover maps were selected using a query. The summary statistics of the selected polygons, using a query, were displayed as shown in Figure 3.11.

![Figure 3.10](image)  
Figure 3.10 A vector map (a subset of test site 1) superimposed on an image (0.5 m) showing intra-terrain noise within woodland and grassland land covers.
From Figure 3.11, 'count' represented the total number of polygons for each land cover type. The number of polygons, representing both terrain noise and actual land cover polygons, were recorded and plotted against the resolution of imagery.

[Image of ArcView GIS queries]

Figure 3.11 A sample of how terrain noise (and other parameters) were obtained from a vector land cover map (derived from Kodak data of one of the test sites) using ArcView GIS queries.

Optimal resolution as indicated by the land cover index

The Land Cover Index is a technique developed during the present study. The technique is based on the premise that changing the resolution of an image leads to changes in the geographical patterns of reality (Marceau and Hay, 1999). However, as noted in the previous sub section, the removal of intra-terrain noise (through decreasing image resolution) should not lead into any significant changes in the geometric properties of geographical entities – hence the level of land cover map accuracies. On the other hand, a continued decrease of image resolution, beyond a certain threshold, should lead to degradation of geographical entities, either geometrically or spectrally. The threshold, lowest point of each curve in Figure 2.13 (Chapter Two), may be regarded as the optimal resolution for a given landscape, such as savannas. It is the degradation of geographical entities, in terms of geometric
properties, that forms the theoretical basis of the land cover index as a robust indicator of optimal image resolution for mapping savanna ecosystems.

The land cover index was determined through a raster GIS overlay procedure (multiplication) between the reference map (derived from 0.5 m) and all other land cover maps generated from imagery whose resolution was simulated from 0.5 m to 10.0 m. ArcView GIS Queries (using the operator “AND”) were used to select all those pixels that belonged to a particular land cover class from the reference map “AND” the same land cover class derived from an image whose resolution would have been simulated. The outcome of this map multiplication was all those regions (represented by pixels) whose sizes and shapes (integrity) fitted both the reference map and individual maps derived from the simulated imagery. The pixels, for each land cover type, were used to quantify how area varied with decreasing image resolution. In this case, area was used as a surrogate for both size and shape.

Figure 3.12 illustrates the logic of using the Land Cover Index approach: the land cover maps in Figure 3.12 are part of the test site maps derived from Kodak data of different resolutions. The yellow and orange colours represent short and tall grassland respectively, while the magenta colour represents herbaceous wetland vegetation. Based on Figure 3.12, the magenta land cover patches can be regarded as terrain noise and so are some of the small short/tall grassland patches.

![Figure 3.12](image)

Figure 3.12 Part of a land cover map derived for one of the test sites. The geometric integrity of the land cover patch in the circle changes with decreasing image resolution.

As already noted, the land cover index approach is based on the premise that intra-terrain noise can be eliminated whilst at the same time preserving the integrity (in
terms of geometric and spectral properties) of the desired geographical entities. For example, not all the terrain noise (magenta coloured pixels in Figure 3.12) has been removed at 1.0 m resolution but the integrity of the geographical entities is, to a large extent, preserved. At 5.0 m, all the terrain noise (magenta coloured pixels in Figure 3.12) has been removed but the integrity (in terms of size and shape) of the geographical entities has been significantly degraded. Hence, by comparing reference information (derived from 0.5 m imagery) with all maps derived from imagery whose resolution was simulated, it was possible to determine the overall integrity (Land Cover Index) of the spatial information generated from imagery simulated from 0.5 m to larger pixel sizes (different resolutions).

Optimal resolution as indicated by the average land cover patch size

The potential usefulness of the average patch size was also based on the premise that the size of a polygon is a function of its shape (Comber et al., 2003). Shapes (hence sizes) of different geographical entities change with decreasing image resolution and hence the average patch size of geographical entities, in a given map, should be a function of image resolution. Like for the land cover index determined as explained above, the change in the patch size of a land cover polygon (depicted within the circle) is insignificant between 0.5 m and 1.0 m but the change is significant between 0.5 m and 5.0 m (Figure 3.12). Therefore, measuring the average size of polygons (for each land cover category) was used as a surrogate indicator of the integrity of geographical entities with decreasing resolution of imagery from 0.5 m to 10.0 m. The average patch size was determined using ArcView Query by selecting all polygons belonging to the same land cover category (for each of the 30 land cover maps) and then recording the average polygon size from the statistical data displayed above.

Optimal resolution as indicated by the other parameters

In addition to the overall classification accuracy, the level of terrain noise, the land cover index and the average patch size, two additional parameters were determined. These were the file size of each image mosaic and areal extent of each land cover category for each of the 30 land cover maps derived from reference and simulated
images. The file size, for each simulated data, was determined using TNTmips. On the other hand, areal extent of each land cover category was determined from the statistics displayed when polygons belonging to a particular land cover class were selected by an ArcView Query (Figure 3.11).

Data analysis

The parameters derived from the 30 land cover maps (from 2 reference and 28 simulated images) for the two test sites in the Nabugabo study area are quantitative in nature. The data for each of the parameters (e.g. classification accuracy, terrain noise, land cover index and patch size) were entered into Microsoft Excel before analysis. Analysis of the data was carried out with the aim of determining relevant trends and statistical measures (ratios and Chi Square Tests) for the parameters measured. For every parameter value measured (except the overall classification accuracies and Kappa coefficients), its ratio to the value obtained from land cover information generated from 0.5 m Kodak imagery was determined. The ratio was determined using the following formula:

\[ \frac{V_i}{V_{0.5}} \]

where:

1) \( V_{0.5} \) represents value parameter measured from land cover information derived from reference Kodak data at a resolution of 0.5 m
2) \( V_i \) represents value parameter measured from land cover information derived from simulated Kodak data at a resolution ranging from 1.0 m, 1.5 m, 2.0 m, 2.5 m to 10.0 m

The trends in the ratios were determined by drawing appropriate graphs between the variables measured (on y-axis) and the square of image resolution (on x-axis). The Chi Square Test values for overall classification accuracies and areal extents of individual land cover types (with decreasing image resolution) were determined at 14 degrees of freedom (15 observations - 1) and significance level of 0.05 for each test site. The findings of this specific investigation are presented in the next chapter.

3.3.2.3 Wood density: potential for a framework for mapping Uganda’s savannas

There were two aspects of the above investigation: the possibility that there is a correlation between spectra of Landsat TM imagery and wood/grass mixtures of the
same different densities; and whether wood density can be harnessed during classification of Landsat TM imagery in order to improve the accuracy of land cover maps produced for Uganda’s savannas. Both Landsat TM imagery and panchromatic aerial photographs were used to generate the required results in order to establish whether wood/grass mixtures of different densities are characterised by unique spectra and whether such spectra have a potential to be harnessed for image classification when producing land cover maps for Uganda’s savannas.

To relate wood density to spectra of Landsat TM in a quantitative manner, land cover classes were defined based on wood density (derived from IKONOS imagery) and the resultant training set used to classify a Landsat TM image for the same terrain. On the other hand, to relate wood density to the spectra of Landsat TM in qualitative manner, mapping units (polygons) derived from high-resolution imagery were compared, visually, with spectra of Landsat TM for the same terrain. The triangulation of the two techniques, i.e. quantitative and qualitative image analysis allowed the author to show that Landsat TM has a potential to be used in the identification and mapping of wood/grass mixtures of different densities, provided that wood density classes are practically (rather than subjectively) determined for mapping. The details of the data and techniques employed for the investigation are described below.

(a) Materials

Landsat TM imagery

The Landsat TM and ETM+ imagery, used for this specific investigation in the Nabugabo test site, were acquired in 1990 and 2000, respectively. Data acquired by Landsat TM/ETM+ sensors are useful in mapping vegetation types, plant vigour, plant and soil moisture, clouds, and the identification of hydrothermal alteration in certain rock types (Sabins, 1987; Wilkie and Finn, 1996; Vogelmann et al., 2001) (Table 3.6). Six of the bands of Landsat TM/ETM+ (excluding band 6) have a spatial resolution of 30 m and were ideal for mapping vegetation types, plant vigour, and plant/soil moisture. It is in light of these desirable characteristics and the fact that Landsat TM is readily and cost-effectively available to developing poor countries that this
investigation decided to establish the potential of Landsat TM/ETM* as a source of accurate land cover maps for Uganda's savannas.

Table 3.6 Spectral characteristics of Landsat TM

<table>
<thead>
<tr>
<th>Band (channel)</th>
<th>Spectral range (μm)</th>
<th>Spectral response</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 (Blue)</td>
<td>0.45 to 0.52</td>
<td>Provides increased penetration of water bodies and absorbs blue chlorophyll from healthy green vegetation.</td>
</tr>
<tr>
<td>2 (Green)</td>
<td>0.52 to 0.60</td>
<td>Corresponds to the green reflectance of healthy vegetation.</td>
</tr>
<tr>
<td>3 (Red)</td>
<td>0.63 to 0.69</td>
<td>Chlorophyll absorption band of healthy green vegetation. Represents one of the most important bands for vegetation discrimination.</td>
</tr>
<tr>
<td>4 (Reflective-infrared)</td>
<td>0.76 to 0.90</td>
<td>Responsive to the amount of vegetation biomass present in a scene; emphasizes soil-crop and land-water contrasts.</td>
</tr>
<tr>
<td>5 (Mid-infrared)</td>
<td>1.55 to 1.75</td>
<td>Sensitive to the turgidity or amount of water in plants. Useful for plant vigour investigations.</td>
</tr>
<tr>
<td>6 (Mid-infrared)</td>
<td>2.08 to 2.35</td>
<td>Discrimination of rock formations.</td>
</tr>
<tr>
<td>7 (Thermal infrared)</td>
<td>10.4 to 12.5</td>
<td>Band that measures the amount of infrared radiant flux emitted from surfaces. It is useful for locating geothermal activity; vegetation classification; vegetation stress analysis; and soil moisture studies.</td>
</tr>
</tbody>
</table>

[Source: Wilkie and Finn, 1996]

Traditionally, if financial resources are not limited, panchromatic aerial photographs are used to map land cover classes (for savannas landscapes) at detailed cartographic scales. It is for this reason that panchromatic aerial photographs (acquired in 1990; scale of 1:30,000) were used as a source of detailed reference information to establish to what extent Landsat TM can allow, in a qualitative manner, the identification and mapping of grass/mixtures of different densities in Uganda. The techniques used to achieve the objectives of the two aspects of this particular investigation are now described.

(b) Techniques

(i) Quantitative correlation of wood density and the spectra of Landsat TM
A technique to determine how the spectra of Landsat TM varied with changing wood density (for Uganda's savannas) was developed and used during the present study. The
technique involved determining wood density, quantitatively, within 475 square
sample plots. Each sample plot measured 1 ha (100 m x 100 m). Sample plots were
selected based on the differences in their wood density as visually shown on IKONOS
imagery for the Nabugabo test site (Appendix B3.5). A sample plot of 1 ha was used
for two reasons. First, conventionally, a plot of 1 ha is recommended when estimating
ground vegetation density in savanna landscapes of East Africa (Pratt and Gwynne,
1977). Second, a plot size of 1 ha was used because other researchers, such as Murtha
et al. (1997) and Anderson et al. (1976) consider it to be the absolute minimum size of
a mapping unit (cartographic scale of 1:100,000) when using Landsat TM imagery.
Since the resultant wood density, per plot, was used as a training site for Landsat TM
imagery of the same terrain, it was practical to use a plot size of 1 ha. The procedure
used to determine correlation between quantitative wood density and spectra of
Landsat TM is summarised in the following steps:

Step 1:

Using MicroImages' TNTmips, a vector polygon grid (each grid measuring 100 m x
100 m) was automatically created basing on the geographic coverage of the Nabugabo
IKONOS image scene. The vector polygon grid was then superimposed on the
IKONOS imagery before sample plots, each 1 ha, were systematically selected to
reflect plots with different wood densities. Since the IKONOS imagery represented a
landscape characterised by other land cover classes (in addition to wood/grass
mixtures of different densities), such non-savanna land cover categories were also
sampled. Each sample plot was identified using a code representing the actual land
cover as visually determined through image interpretation/classification (Figure 3.13).
In all, 475 sample plots (polygons) were selected. The resultant labelled sample plots
were isolated and saved as a separate file and used as will be described in Step 3
below.

Step 2:

Using an unsupervised image classification technique (ISODATA) of MicroImages'
TNTmips, the IKONOS imagery (on which basis the sample plots were selected) was
classified into only two vegetated land cover classes: wood and non-wood (Appendix B3.6). The resultant raster map was converted into a vector data format, then exported to ESRI's ArcView GIS shape file, and used as described in Step 3 below.

Figure 3.13 Part of the Nabugabo site showing one-hectare plots (within which wood density was determined) superimposed on IKONOS data.

Step 3:

Using the ArcView GIS, the 475-polygon map (created as described in Step 1) was used as a mask to extract all polygons (representing wood or grass) from the wood/grass land cover created as described in Step 2 above (Appendix B3.6). Figure 3.14 shows some of the extracted polygons (both wood and non-wood) within a single sample plot (1 ha).
Step 4:

The extent of wood cover (m²) was calculated by summing up the area of individual wood cover polygons within each sample polygon plot (Figure 3.14). Wood density per ha, WD, was calculated as follows:

\[
WD \% = \frac{\text{Area of wood cover (m}^2\text{)/10,000}}{\text{X 100}} \quad \text{[since 10,000 m}^2\text{ = 1 ha]}
\]

The above procedure was repeated for all the 475 sample plots. The resultant wood density map was reclassified into 5% interval classes and the results added into the relevant field (column) of the attribute table of the polygon map created in Step 1. In other studies, large wood density ranges bigger than 5% (for example, Menges et al., 2001) have been used but a narrow wood density classification system was considered to be flexible in the present study. Other parameters determined for each plot (Figure 3.14) included average wood patch size and the number of woody patches. The resultant polygon map, showing land cover types representing both wood/grass mixtures of different densities and other homogeneous land cover classes (such as herbaceous wetlands, grassland, dense woodland) was finally used as described in Step 5 below.

Step 5:

The aim of the technique described in steps 1-4 was to find out to what extent Landsat TM spectra (associated with mixed pixels formed from the wood/grass mixtures of
different densities) might be correlated wood/grass mixtures of wood densities characteristic of Uganda’s savannas. The procedure used to find out the correlation between wood densities and spectra of Landsat TM was as follows: using the 475 polygon map as training sites (refer to the land cover types in Table 4.3 of Chapter Four), a Maximum Likelihood Classifier was used to classify the first 3 principal components (Section 3.3.2.1) of Landsat TM data acquired 1990 and 2000. The Landsat TM imagery (both 1990 and 2000) was classified into 26 spectral classes, of which 20 classes belonged to wood/grass mixtures of different densities and 6 represented closed canopy classes. A decision to use the first principal components, rather than individual image bands, is that the former are a representation of the latter but fewer in number (Section 3.3.2.1) and hence, interpretation of statistical parameters was practical. The approach, using principal components, is also recommended by Menges et al. (2001). The spectral means, for each resultant land cover class, were correlated with different wood density classes through the use of classification dendrograms.

(ii) **Qualitative correlation of wood density and the spectra of Landsat TM**

The basis of this aspect of the current investigation hinges on the premise that Landsat TM data have sufficient spectral information to allow the identification and mapping of land cover classes based on wood/grass mixtures of different densities provided an appropriate mapping framework is used. It is against this background that a mapping framework to harness wood density during image interpretation/classification was developed and evaluated as follows: based on information collected during ground-truthing (Section 3.3.2.2), major land cover categories of Nabugabo test site were visually mapped using scanned panchromatic aerial photographs. Because high-resolution aerial photographs and visual image classification techniques were used to generate the land cover map, it was possible to map (in addition to homogeneous land cover classes) land cover classes defined on the basis of wood/grass mixtures of different densities. The generated land cover map was then used to establish to what extent a similar land cover map could be generated, using the proposed mapping
framework, for the same terrain but using Landsat TM data. The 2 sets of Landsat TM data used for this exercise was acquired both in 1990 and 2000.

The proposed framework is based on the recommendations made by Skelsy (1997), Wright et al. (1997), and Geneletti and Gorte (2003) that a baseline for accurate land cover mapping should, as a matter of principle, be established from high resolution imagery and any subsequent land cover mapping should use the baseline and low/coarse resolution imagery as inputs for future land cover maps. It is on the basis of this recommendation that a baseline land cover map for the Nabugabo test site was derived from aerial photographs acquired in 1990 (Appendix B3.7). The baseline land cover map was obtained through a process of visual interpretation/classification described in Section 2.4.2.1 Prior to the extraction of the baseline land cover map from the aerial photographs, they were georeferenced and rectified as described in Section 3.3.2.1. The generated baseline land cover map formed the basis of evaluating the potential of the proposed mapping framework for the identification and mapping of Uganda’s savanna land cover types using Landsat TM imagery. The evaluation of the proposed mapping framework proceeded as follows: the baseline land cover map (derived from high-resolution aerial photographs) was overlaid on a false colour Landsat TM image composite (Figure 3.15) as required during visual image interpretation/classification (Fuller et al., 1998; Dymond et al., 2002). In addition, a scoring scheme was devised to assess the potential of geographic features (mapped from aerial photographs) to be mapped but using Landsat TM imagery. The following scoring scheme was employed during the evaluation phase:

a) if there were no ambiguity in making a decision about the identity of any geographical entity (baseline polygon), a score of 1 was given;
b) if any of the components that make up a geographical entity (boundaries or class type) could not be detected with clarity, a score of 2 was given, and;
c) if it were impossible to make a decision about the identity of a geographical entity, a score of 3 was given.
Figure 3.15 Part of geographic entity boundaries (yellow lines) derived from panchromatic aerial photographs and superimposed on TM image composite during evaluation of the proposed mapping framework.

Overall, Landsat TM imagery was assessed to establish whether 219 closed woody, 158 wood/grass mixtures of different densities, 100 closed grass, 106 cultivated and 10 water polygons could be effectively mapped using the steps outlined in (a) – (c) above.

The findings of the investigations described in Section 3.3.3.1 – 3.3.3.3 are presented in the next chapter.
CHAPTER FOUR
RESULTS

4.1 OVERVIEW

The findings of the present study are now presented. The presentation of the findings is organized on the basis of the three objectives of the present study. To be presented first (Section 4.2) are the results specific to objective 1. The overall aim of objective 1 was to assess the accuracy of existing land cover maps, of savannas landscapes, whose origin is from low/coarse resolution imagery. Reference maps, generated from IKONOS imagery, are presented as part of the findings of objective 1. The second set of the results, presented in Section 4.3, relate to the specific objective number 2 i.e. the evaluation of the optimal spatial image resolution for mapping land cover classes characteristic of Uganda’s savannas. This chapter is wrapped up by a presentation of the results, in Section 4.4, pertaining to the third objective of the present study i.e. an assessment of the potential of using wood density as a key component of a framework to improve the accuracy of land cover maps produced from Landsat TM imagery for Uganda’s savannas.

4.2 UGANDA’S SAVANNAS: ACCURACY OF EXISTING LAND COVER MAPS

4.2.1 Reference land cover map for each test site

As explained in Section 3.3.3.1(ii), a polygon-based (region-based) assessment of the accuracy of the existing land cover maps, for each test site, was possible because of detailed reference information (maps) generated from high-resolution IKONOS imagery. The summary and details of the characteristics of the reference information, for each test site, are shown in Table 4.1 and Appendix B4.1, respectively. It is observed, based on Table 4.1, that MFNP is dominated by savanna landscapes (94% if cloud/shadow cover is excluded from the calculation). Savanna dominance is also significant (75%) for Nebbi test site. On the other hand, savannas account for about 47% and 6% for the Nabugabo and Arua test sites, respectively. In case of the Arua test site, the dominating land cover type (87%) was subsistence farming.
Table 4.1 Details of reference information generated for each of the 4 test sites

<table>
<thead>
<tr>
<th>Land cover code</th>
<th>Land cover description</th>
<th>Land cover areal extent (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>MFNP</td>
</tr>
<tr>
<td>1. 2WC7</td>
<td>Closed woody cover with sparse trees</td>
<td>7.5</td>
</tr>
<tr>
<td>2. 2WP26</td>
<td>Broad leaved deciduous open with grass layer</td>
<td>2.8</td>
</tr>
<tr>
<td>3. TBR247PL</td>
<td>Closed Eucalyptus plantation</td>
<td>0.02</td>
</tr>
<tr>
<td>4. 4SCJFF7</td>
<td>Closed shrubs on permanent wet areas</td>
<td>12.7</td>
</tr>
<tr>
<td>5. Tea</td>
<td>Tea plantation</td>
<td></td>
</tr>
<tr>
<td>6. 2SCJ7</td>
<td>Closed shrub cover with sparse trees</td>
<td>2.2</td>
</tr>
<tr>
<td>7. 2GTCM-B</td>
<td>Palm grass savanna</td>
<td>4.2</td>
</tr>
<tr>
<td>8. 2SOJ67</td>
<td>Closed shrubs with grass and sparse trees</td>
<td>12.6</td>
</tr>
<tr>
<td>9. 2SVJ2GC</td>
<td>Very open shrubs and sparse trees with closed grassland</td>
<td>12.5</td>
</tr>
<tr>
<td>10. 2GC78</td>
<td>Closed grassland with sparse trees</td>
<td>17.6</td>
</tr>
<tr>
<td>11. 4HCJF8</td>
<td>Closed herbaceous vegetation with sparse shrubs on wet areas</td>
<td>6.5</td>
</tr>
<tr>
<td>12. 4SPF6</td>
<td>Closed herbaceous vegetation on seasonally wet areas</td>
<td>0.9</td>
</tr>
<tr>
<td>13. 8S</td>
<td>Closed papyrus/phragmites</td>
<td>0.05</td>
</tr>
<tr>
<td>14. 7S</td>
<td>Closed forbs</td>
<td>1.5</td>
</tr>
<tr>
<td>15. 6S</td>
<td>Short grass/bare ground</td>
<td>2.0</td>
</tr>
<tr>
<td>16. SR47</td>
<td>Subsistence farming</td>
<td>0.15</td>
</tr>
<tr>
<td>17. SR47/2SCJ7</td>
<td>Subsistence farming with closed shrub and sparse trees</td>
<td>3.7</td>
</tr>
<tr>
<td>18. 8WP</td>
<td>Water</td>
<td>4.1</td>
</tr>
<tr>
<td>19. CS</td>
<td>Cloud/shadow</td>
<td>26.5</td>
</tr>
</tbody>
</table>

**Total area (ha)**

<table>
<thead>
<tr>
<th>MFNP</th>
<th>Nebbi</th>
<th>Nabugabo</th>
<th>Arua</th>
</tr>
</thead>
<tbody>
<tr>
<td>100.0</td>
<td>100.0</td>
<td>100.0</td>
<td>100.0</td>
</tr>
</tbody>
</table>

4.2.2 Accuracy of existing land cover maps

The details of the findings regarding the level of accuracy of existing land cover maps, for each test site, are shown in Appendix A4.1. The results shown in Appendix A4.1 were obtained through a cross-tabulation analysis (Section 3.3.3.1(b)(iii)). In Appendix A4.1, x signifies 0 ha of a land cover class mapped from low/coarse resolution imagery, even though the land cover class exists on the ground (its existence on the ground is confirmed by the reference information). The results presented in Appendix A4.1 were further summarised and presented in Figure 4.1. Green colour code represents high accuracy (equal or greater than 75%); orange colour represents some reasonable accuracy (50 – 74%); and red represents low accuracy (0 - 49%).
Figure 4.11. Level of the accuracy of the existing land cover maps for the 4 test sites. The percentage, in brackets, represents the areal extent of each land cover category mapped from a given imagery for each test site.
The following presentation of the key findings, for each test site, is based on the summary results shown in Figure 4.1 and Appendix A4.1.

4.2.2.1 Arua test site

The Arua test site is an intensively cultivated landscape interspersed with savanna vegetation accounting for about 6%. The accuracy of savanna land cover categories was found to be extremely low (ranging from 0 – 10%) for maps derived from SPOT XS and Landsat TM imagery. On the other hand, as shown in Figure 4.1 and Appendix 4.1(a), small-scale farmed land cover category was identified and mapped with a high degree of accuracy using SPOT XS (94%) and TM imagery (96%).

The accuracy of the land cover map derived from SPOT 4 Vegetation imagery (500 m), for the Arua test site, is 0%. The small-scale farmed ecosystem (accounting for 88% of the total area of the Arua test site and mapped correctly to the tune of 94-96% from SPOT XS and TM imagery, respectively) is wrongly mapped as deciduous woodland from SPOT 4 Vegetation imagery. The rest of the Arua test site about 10%) is identified and mapped as a mosaic of forest/crop/cropland, a category that does not exist in the reference map.

The overall classification accuracy of the existing maps for the Arua site is high for SPOT XS (83%) and Landsat TM (84%) but is extremely low for SPOT 4 land cover map (about 8%).

4.2.2.2 Nabugabo test site

Overall, the accuracy of existing land cover data maps for the Nabugabo test site was found to be very low, ranging from about 42% (Landsat TM) to 45% (SPOT XS) and 50% (SPOT 4 Vegetation) (Figure 4.1 and Table 4.2). The land cover categories characteristic of savanna landscapes (labelled as 2WC7, 2SCJ7, 2GC78 in Table 4.1) account for about 33% of the total area of the Nabugabo test site. Closed woody cover (savanna) with sparse trees derived from SPOT XS agrees well with reference information at 83.4% but not with the land cover data sets derived from Landsat TM and SPOT 4 data. The accuracy of the rest of the land cover categories (closed
Eucalyptus and tea plantations, closed shrub cover with sparse trees, closed forbs and short grass/bare ground) is low, ranging from 0% to about 38%.

Interestingly, for this test site, water was correctly identified on all the three land cover data maps derived from SPOT XS, ETM and SPOT 4 data at 96.4%, 92.9% and 74.3%, respectively (From Figure 4.1). However, the percentage of water pixels mapped correctly reduces with reducing image resolution, probably due to the presence of mixed pixels. Small-scale farmed areas are also mapped with a high accuracy at 84.1%, 74.7% and 96.2% for maps derived from SPOT XS, Landsat TM and SPOT 4 Vegetation data, respectively.

4.2.2.3 Nebbi test site

The Nebbi site is dominated by savanna and to some extent small-scale farmed ecosystems. Again, Figure 4.1 summarises the degree of accuracy of the existing land cover maps for the Nebbi test site. For the SPOT XS derived land cover map, small-scale farmed landscape (accounting for 26% of the total area) shows an accuracy of about 56%. Closed wood cover that accounts for 30% of the Nebbi test site has an accuracy of only about 2% for the SPOT XS-derived land cover map and closed grassland with sparse trees has an accuracy of 12%. Closed shrub cover with sparse trees and closed shrubs on permanent wet areas are non-existent on the land cover map derived from SPOT XS implying that their accuracy, when compared with reference information, is 0%.

For land cover types derived from Landsat TM, the accuracy of small-scale farmed land stands at about 29%, while the accuracy of the rest of the land cover classes is 0%.

It is worth noting that there is no resemblance (0% accuracy) at all between land cover maps derived from SPOT 4 imagery and reference information for the Nebbi test site.
4.2.2.4 Murchison Falls National Park

Based on the findings presented in Table 4.1 and Figure 4.1, homogeneous land cover types such as water bodies are accurately identified and mapped for the MFNP test site using SPOT XS (1990), TM (2002), SPOT 4 (2000) and Landsat TM (1997). For example, closed grassland (land cover category 2GC78) is mapped with a high accuracy of 93% from SPOT XS data. Closed shrubland (2SCJ7) is also mapped with high accuracy of 96% from SPOT XS data. However, these homogeneous vegetated land cover classes (closed grassland and closed bushland) are poorly identified and mapped from the rest Landsat TM and SPOT Vegetation 4 imagery.

The agreement between heterogeneous land cover classes (derived from SPOT XS, TM and SPOT 4 images) and reference information is, however, low as depicted by the orange to red colour codes of Figure 4.1. Indeed, the accuracy of all the heterogeneous land cover categories (i.e. closed woody cover with sparse trees, broad-leaved deciduous open wood with a grass layer, closed herbaceous with sparse trees on wet areas, palm grass savanna and papyrus/phragmites) is 0% for all the existing land cover data sets whose accuracy was assessed. The overall accuracy of the existing land cover maps stands at about 29% for SPOT XS, about 25% for 1997 TM, 11% for 2002 TM, and 0.09% for 2000 SPOT 4.

Table 4.2 is a summary of the overall classification accuracies for each existing land cover map and for each test site.

<table>
<thead>
<tr>
<th>Source of land cover map</th>
<th>Overall map accuracy (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Arua</td>
</tr>
<tr>
<td>IKONOS (2002) - reference information (assumed to be 100% accurate)</td>
<td>100</td>
</tr>
<tr>
<td>SPOT XS (1996) - existing land cover map</td>
<td>83</td>
</tr>
<tr>
<td>Landsat TM (1997) - existing land cover map</td>
<td>-</td>
</tr>
<tr>
<td>Landsat TM (2002) - existing land cover map</td>
<td>84</td>
</tr>
<tr>
<td>SPOT Vegetation (2000) - existing land cover map</td>
<td>8</td>
</tr>
</tbody>
</table>

100
It is observed, based on Figure 4.1 and Table 4.2, that the lower the resolution of imagery and the more the savanna landscape dominates, for each test site, the lower the overall classification accuracies of the existing land cover maps are.

4.3 OPTIMAL RESOLUTION FOR UGANDA’S SAVANNAS

As observed in the previous section, the accuracy of land cover maps generated from low/coarse imagery for Uganda’s savannas is very low. This is because, it is speculated in the present study, of the insufficient cartographic details offered by low/coarse resolution imagery for mapping Uganda’s savannas. The optimal image resolution, for mapping Uganda’s savannas, was determined as 3.5±1 m. Appendices A4.2 and A4.3 provide a summary of the measured values for each of the parameters used in the determination of optimal resolution for mapping Uganda’s savannas. A summary of the finding regarding the optimal resolution of imagery required for mapping Uganda’s savannas are now presented.

4.3.1 Variation of the classification errors with decreasing image resolution

The variation of the overall map classification accuracy with varying image pixel size (spatial resolution) is a conventional technique for determining optimal spatial image resolution for mapping vegetated landscapes (Figure 2.5). In the present study, the variation of the overall classification accuracy (OCA) with decreasing image resolution is shown in Figure 4.2. The curves shown in Figure 4.2 indicate that the OCA values follow the same general trends, i.e. a slight and gradual decrease in the OCA values measured when the image pixel size was increased from 0.5 m to 8.0 m. The OCA values were subjected to a Chi Square Test and it was revealed that the observed OCA values (measured along the 0.5 m to 10.0 m image resolution gradient) are not significantly different from each other. At 14 degrees of freedom and significance level of 0.05, the Chi Square Test values are 1.5 (test site 1) and 0.4 (test site 2). This confirms that the postulation made is true i.e. the observed OCA and values are not significantly different. The postulation would have been rejected if the Chi Square Test value for each test site were greater than the critical probability value of 23.68 at a significance level of 0.05 (Ebdon, 1985). It was therefore concluded that
the OCA trend shows that the simulated imagery represents the same information (represented by simulated image spectral classes) for the defined land cover classes.

![Graph showing variation of overall classification accuracy (OCA) and Kappa (%) with decreasing image resolution.](image)

**Figure 4.2 Variation of overall classification accuracy (%) and Kappa (%) with decreasing image resolution.**

From Figure 4.2, the *Kappa* curves follow the same general trends as the OCA curves. Using the *Chi Square* Test, the *Kappa* value is 5.6 (test site 1) and 1.9 (test site 2) at 14 degrees of freedom and at a significance level of 0.05. Again, the postulation that the *Kappa* values, for each test site, are not statistically different was accepted; hence the simulated imagery represents the same information for the defined land cover categories.

### 4.3.2 Variation of the Land Cover Index with decreasing image resolution

The variation of the Land Cover Index (LCI) with decreasing image resolution is depicted in Figure 4.3 and Appendix A4.4. The LCI values, determined as explained in Section 3.3.4.4, are characterised by a negative gradient approximating a linear trend.
The general linear equation relating LCI (y-axis) to image resolution (x-axis) is $y = mx + c$. For test site 1, $y = 90.154 - 2.8156x$; and for test site 2, $y = 90.874 - 3.5019x$. As explained in Section 3.3.4.4, the LCI was developed to be a robust technique for the assessment of map accuracy. This is because it quantifies classification errors in terms of both the classification categories and geometric integrity of image objects (geographic features). Hence, assuming that a decrease in the image resolutions (simulated from 0.5 m imagery) preserves both the classification categories and geometric integrity of the geographical entities for each site, the curves depicted in Figure 4.3 would have been parallel to the x-axis, or the variations of LCI with decreasing image resolution would have been insignificant as was the case for OCA, Kappa and area (Sections 4.3.1 – 4.3.2). However, Figure 4.3 shows that the LCI values, for each test site, decreases gradually but significantly with increasing image pixel size. For example, between image resolutions 0.5 m and 10.0 m (or 0.25 – 100 m²), the LCI values decreased by a factor of 43% (test site 1) and 51% (test site 2). The interpretation of LCI values is straightforward: at an image resolution of 0.5 m, the classification accuracy of test site 1 is 100% while it is 57% at an image resolution...
of 10.0 m. Similarly, at an image resolution of 0.5 m, the classification accuracy of test site 2 is 100% while it is 49% at an image resolution of 10.0 m. The results depicted in Figure 4.3 is characterised by a general linear trend (line) with a negative gradient implying that the LC1 values are more sensitive to changing image resolutions than OCA or Kappa.

4.3.3 Variation of areal extent with decreasing image resolution

The trends in the areal extent of different land cover categories, with decreasing image resolution, were also assessed using a Chi Square Test (Table 4.3). The interpretation of the Chi Square values (Table 4.3) is that the differences between the areal extents (of each land cover category derived from simulated imagery) at 14 degrees of freedom and at a significance level of 0.05 are insignificant and attributed to random errors. The suggestion that the areal extents (of land cover categories derived from decreasing image resolution) are not statistically different has to be accepted because the Chi Square Test values are less than the critical probability value of 23.68 at a significance level of 0.05.

<table>
<thead>
<tr>
<th>Table 4.3 Determined Chi Square Test probabilities for each land cover category with changing image resolution</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Test site 1</strong></td>
</tr>
<tr>
<td>Land cover</td>
</tr>
<tr>
<td>----------------</td>
</tr>
<tr>
<td>Short grass</td>
</tr>
<tr>
<td>Tall grass</td>
</tr>
<tr>
<td>Dense wood</td>
</tr>
<tr>
<td>Burnt grass/shadow</td>
</tr>
<tr>
<td>Wetland Herbaceous</td>
</tr>
</tbody>
</table>

Figure 4.4 depicts the trend in the variation of the ratio of the areal extent \( (V/V_{0.5}) \) with decreasing spatial image resolution. In a perfect situation, i.e. assuming that a decrease in image resolution does not have any impact on the areal extents of individual geographical entities, the ratio would be 1.
Figure 4.4 Variation of areal extent ($V/V_{oa}$) with decreasing image resolution. Note that the y-axis begins at 96 and 97% for test sites 1 and 2, respectively.
However, the variation observed oscillates between -3.2% and +4.7% for test site 1; and -3.0% and +1.4% for site 2 (Figure 4.4). As already noted from the Chi Square Test values calculated for areal extents, the oscillations are insignificant for both test sites. Based on the three parameters, i.e. OCA, Kappa and ratio of areal extents, the results show that an image acquired at 0.5 m through to 10.0 m yields statistically the same spatial information. This is contrary to the findings presented in Section 4.3.2 and those presented in the next sub sections.

4.3.4 Variation of terrain noise with decreasing image resolution

There is a predictable variation in terrain noise with changing image resolution (Figure 4.5 and Appendix A4.5). The general exponential equations that describe the relationship between terrain noise (y-axis) and image resolution (x-axis) are $y = (115.34)^{-0.288x}$ (test site 1) and $y = (124.69)^{-0.271x}$ (test site 2). Between 0.5 m and 2.5 m, there was a reduction in terrain noise by a factor of about 77% (test site 1) and 70% (test site 2). On the other hand, terrain noise reduced by a factor of about 97% (test site 1) and 96% (test site 2) between 0.5 m and 10.0 m. The significant decline of terrain noise with decreasing image resolution happened even though OCA, Kappa, and areal extents remained statistically the same as already explained in Sections 4.3.1 and 4.3.3. It is also true that terrain noise is even more sensitive to varying image resolutions (of a given landscape) than LCI.

4.3.5 Variation of image file size with decreasing image resolution

The variation of image file size with decreasing image resolution is also sensitive (Figure 4.6) like terrain noise. There is a significant reduction in image file size of up to 94.0% and 95% between 0.5 m to 2.5 m for test sites 1 and 2, respectively. Between 0.5 m and 10.0 m, the reduction in image file size was 99.0% and 98.4% for test sites 1 and 2, respectively.
Figure 4.5 Overall variation of terrain noise (measured in terms of polygons for each land cover category) with decreasing image resolution for each site.

Figure 4.6 Variation of image file size (for each test site) with decreasing image resolution.
The general exponential equations that describe the relationship between image file size (y-axis) and image resolution (x-axis) are \( y = (38.1)^{-0.294x} \) (test site 1) and \( y = (31.7)^{-0.2492x} \) (test site 2). The size of the image file starts levelling off at an image resolution of 2 m (4 m²). Like the case of terrain noise, image file size is very sensitive to image resolution because the two are inversely related i.e. the high the resolution (hence high terrain noise) the bigger the image file size.

4.3.6 **Variation of image file size with decreasing image resolution**

The average land cover patch size (or patch size), for each test site, increases with decreasing image resolution (Figure 4.7 and Appendix A4.6). The general exponential equations that describe the overall ratio of the average patch size with decreasing image resolution are \( y = (0.86)^{-0.2954x} \) (test site 1) and \( y = (0.86)^{-0.2834x} \) (test site 2). The trend depicted in Figure 4.7 is, for practical purposes, a mirror of Figures 4.5 and 4.6.

![Figure 4.7 Overall variation of the overall ratio of average patch size of all land cover categories with decreasing image resolution.](image-url)
4.3.7 Predicted optimal image resolution for mapping Uganda's savannas

From the preceding subsections (4.3.1 – 4.3.6), it has been established that a number of parameters (OCA, Kappa, LCI, area of mapped polygons, terrain noise, patch size) show different sensitivities with decreasing image resolution acquired for Uganda's savannas. For example, the OCA, Kappa and area of mapped features are insensitive to changing image resolutions (0.5 – 10.0 m). It was also noted that the LCI values are sensitive to decreasing image resolution. On the other hand, the level of terrain noise, image file size and average patch size values are very sensitive to decreasing image resolution. Since the file size values also are indicators of the level of terrain noise, it was decided to triangulate from terrain noise and average patch size in order to derive the optimal image resolution for mapping Uganda's savannas. The outcome is depicted in Figure 4.8 and Appendix A4.7.

Based on the level of terrain noise and average patch size of savanna geographic features, it can be stated that the optimal resolution of imagery needed for mapping Uganda's savannas is about 3.5±0.5 m (or 3.0 – 4.0 m). This range of image resolution range does not only do away with bulk of the image terrain noise, it also preserves at least 60% of the integrity of smallest geographical entities characteristic of savanna ecosystems. It has to be stated, therefore, that imagery acquired by Quick Bird (0.6 – 2.5 m), IKONOS data (1.0 m) and SPOT (2.5 m) are largely noise and yet expensive for mapping Uganda's savannas. However, IKONOS (4.0 m) appears to be within the optimal range (3.0 – 4.0 m) for mapping Uganda's savannas and is relatively affordable (USD 18/km² of terrain) compared to Quick Bird (0.6 – 2.5 m), IKONOS data (1.0 m) and SPOT (2.5 m) whose costs are greater than USD 30/km² of terrain.
4.4 THE POTENTIAL OF WOOD DENSITY AND LANDSAT TM IMAGERY FOR MAPPING UGANDA'S SAVANNAS

The findings presented in Sections 4.2 and 4.3 suggest that existing land cover maps, derived from low/coarse resolution imagery, for Uganda's savannas, have a low/extremely low accuracy. To improve the accuracy of land cover maps for Uganda's savanna landscapes, future-mapping projects should consider using an optimal image resolution (3 - 4 m) established in the previous section (Figure 4.8). However, whereas the use of optimal resolution (3 - 4 m) should significantly improve the accuracy of land cover maps produced for Uganda's savannas, it is important to note such imagery is at least 900 times more expensive (USD 18/km²) than Landsat TM (USD 0.02/km²). There is therefore, a need to explore other alternatives to improving the accuracy of land cover maps, derived from low-resolution imagery especially Landsat TM, in case there are insufficient funds to acquire optimal imagery in a poor country like Uganda. It is for this reason that the utilisation of wood density was
suggested as practical way of improving the accuracy of land cover maps for Uganda’s savannas. The findings presented below show that if an appropriate mapping framework is used, the relationship between the spectra of Landsat TM imagery and mixtures of wood/grass of different densities is, to a large extent, sufficient enough to allow the improvement of the accuracy of land cover maps derived for Uganda’s savannas.

4.4.1 Correlation between wood density and the spectra of Landsat TM

The results of the assessment of whether wood/grass mixtures of different densities can be identified and mapped from readily available and low cost Landsat TM imagery are presented in Table 4.4. Twenty (20) spectral classes were composed of wood/grass mixtures of different densities and six (6) of the spectral land cover classes identified were homogeneous (e.g. water, soil i.e. 0% wood density). The results shown in Table 4.4 further show that 366 out of the 475 (77%) one-hectare sample plots can be described as savannas (wood density in grass varying from 0 – 100%) and account for 66% of the total areas sampled. These results further show that, for the study Nabugabo study area, savannas are more than three times (366:109) more fragmented than homogeneous land cover types.

A plot of the land cover spectral means, for TM imagery acquired in 2000 and 1990, against wood density is shown in Figures 4.9. The spectral means generally decrease with increasing wood density. There are both similarities and differences between the results depicted in Figures 4.9. For example, there is a general linear trend (Figure 4.9) showing that increased wood density leads to a decrease in TM spectral reflectances. A linear relationship between the spectra of Landsat TM imagery and wood density of different classes should be a predictor of different land cover classes typical of Uganda’s savannas. Any differences between the graphs of Figure 4.9 can be attributed to the different atmospheric and terrain conditions that existed at the time of acquiring the imagery in 1990 and 2000 for the same land cover categories.
Table 4.4 Variation of wood density within 1 ha sample plots in Nabugabo study area

<table>
<thead>
<tr>
<th>Wood density for different land cover class</th>
<th>Average wood density ((%))</th>
<th>Number of plots</th>
<th>Areal extent of wood cover (m(^2))</th>
</tr>
</thead>
<tbody>
<tr>
<td>0 – 5</td>
<td>2.36</td>
<td>19</td>
<td>4479</td>
</tr>
<tr>
<td>5 – 10</td>
<td>8.11</td>
<td>18</td>
<td>14592</td>
</tr>
<tr>
<td>10 – 15</td>
<td>12.22</td>
<td>18</td>
<td>22000</td>
</tr>
<tr>
<td>15 – 20</td>
<td>17.6</td>
<td>17</td>
<td>29920</td>
</tr>
<tr>
<td>20 – 25</td>
<td>22.74</td>
<td>21</td>
<td>47760</td>
</tr>
<tr>
<td>25 – 30</td>
<td>27.75</td>
<td>15</td>
<td>41632</td>
</tr>
<tr>
<td>30 – 35</td>
<td>32.36</td>
<td>19</td>
<td>61490</td>
</tr>
<tr>
<td>35 – 40</td>
<td>37.18</td>
<td>16</td>
<td>59488</td>
</tr>
<tr>
<td>40 – 45</td>
<td>42.2</td>
<td>22</td>
<td>92848</td>
</tr>
<tr>
<td>45 – 50</td>
<td>48.2</td>
<td>9</td>
<td>43376</td>
</tr>
<tr>
<td>50 – 55</td>
<td>52.08</td>
<td>14</td>
<td>72911</td>
</tr>
<tr>
<td>55 – 60</td>
<td>57.27</td>
<td>12</td>
<td>68720</td>
</tr>
<tr>
<td>60 – 65</td>
<td>63.1</td>
<td>11</td>
<td>69408</td>
</tr>
<tr>
<td>65 – 70</td>
<td>66.84</td>
<td>7</td>
<td>46768</td>
</tr>
<tr>
<td>70 – 75</td>
<td>72.03</td>
<td>6</td>
<td>43216</td>
</tr>
<tr>
<td>75 – 80</td>
<td>77.6</td>
<td>9</td>
<td>69840</td>
</tr>
<tr>
<td>80 – 85</td>
<td>83.36</td>
<td>6</td>
<td>50016</td>
</tr>
<tr>
<td>85 – 90</td>
<td>87.35</td>
<td>18</td>
<td>157232</td>
</tr>
<tr>
<td>90 – 95</td>
<td>92.26</td>
<td>14</td>
<td>129164</td>
</tr>
<tr>
<td>95 – 100</td>
<td>97.85</td>
<td>15</td>
<td>146768</td>
</tr>
<tr>
<td>Short grass</td>
<td>0</td>
<td>51</td>
<td>510000</td>
</tr>
<tr>
<td>Tall grass</td>
<td>0</td>
<td>29</td>
<td>290000</td>
</tr>
<tr>
<td><strong>Subtotal (for savanna classes)</strong></td>
<td><strong>366</strong></td>
<td></td>
<td><strong>2,071,628</strong></td>
</tr>
<tr>
<td>Herbaceous wetland</td>
<td>0</td>
<td>56</td>
<td>560000</td>
</tr>
<tr>
<td>Tea</td>
<td>0</td>
<td>5</td>
<td>500000</td>
</tr>
<tr>
<td>Water</td>
<td>0</td>
<td>10</td>
<td>100000</td>
</tr>
<tr>
<td>Papyrus</td>
<td>0</td>
<td>38</td>
<td>380000</td>
</tr>
<tr>
<td><strong>Subtotal (for non-savanna homogenous classes)</strong></td>
<td><strong>109</strong></td>
<td></td>
<td><strong>1,090,000</strong></td>
</tr>
<tr>
<td><strong>Grand total</strong></td>
<td><strong>475</strong></td>
<td></td>
<td><strong>3,161,628</strong></td>
</tr>
</tbody>
</table>
It is on the basis of the spectral means that any image classification system (such as TNTmips) segments an image (such as Landsat TM) into real land cover. The correlation between the various wood density classes and actual TM land cover classes, for the Nabugabo study area, is presented in form of classification dendrograms in Figure 4.10(a)-(b). For each classification dendrogram, class pairs that join together near the left edge of the diagram are closely related in their spectral properties and the degree of relatedness decreases if the joining is further to the right (MicroImages Inc., 1998). For example, based on Figure 4.10(a), wood/grass mixtures of wood densities 0 – 5% and 5 – 10% were the most similar, having the lowest separability. It is also observed from Figure 4.10(a) that wood/grass mixture of wood density class 10 – 15% is spectrally similar to 0 – 5% and 5 – 10% than any other spectral class and hence the three classes are joined together to the left than to another class.
Figure 4.10 Spectral classes, representing potential land cover categories, derived from the 2000 (a) and 1990 (b) Landsat TM imagery.

Overall, a close examination of the dendrograms shown in Figure 4.10(a)-(b) shows that there is a systematic grouping of land cover spectral classes based on realistic wood/grass mixtures of different densities and other homogeneous actual land cover categories. The dendrograms (Figure 4.10) also give an indication of the spectral
overlaps between different land cover categories, for example between papyrus and wood/grass mixtures of different densities.

An interesting observation, from Figures 4.10(a)-(b), is that the wood/grass mixtures of wood density classes can be grouped further to the right to form broad land cover categories such as $0 - 15\%$, $20 - 30\%$, $30 - 50\%$, $50 - 80\%$ and $80 - 100\%$ [Figure 4.10(a)] or $0 - 15\%$, $20 - 30\%$, $35 - 55\%$, $55 - 80\%$ and $85 - 100\%$ [Figure 4.10(b)]. Another observation is that potential spectral overlap is implied by the dendrograms depicted in Figure 4.10 by joining their spectral classes to the extreme left. In light of this observation, tall grassland and wood/grass mixtures of wood density classes $20 - 30\%$ [Figure 4.10(a)] are likely to be misclassified. The same explanation of spectra overlap is indicated [Figure 4.10(a)] between managed tea plantation and wood/grass mixture of density $65 - 70\%$. Also, in spectral terms, papyrus resembles wood/grass mixtures in a wood density class ranging from $30 - 75\%$. On the other hand, herbaceous wetland, short grassland and water are spectrally distinct from the rest of the land cover in that order.

In summary, there is a strong tendency of some wood/grass mixtures of different density classes to be grouped together based on distinct spectra of Landsat TM imagery for the savanna landscape of the Nabugabo study area. This is a strong indication, among very rare investigations, that the spectra of mixed pixels (due to presence of wood/grass of different densities) are correlated to differences in wood density classes. However, currently, there is no appropriate image classification framework that can apply wood density to improve the accuracy of land cover maps using Landsat TM imagery for Uganda's savannas. The results presented in the next subsection, however, was an attempt, by the present study, to assess the potential of wood density for an image classification framework required to logically and reasonably identify and map land cover classes to a level of accuracy that has not been so far achieved for Uganda's savannas using Landsat TM data.
4.4.2 A framework to map/monitor Uganda’s savannas from Landsat TM data

The findings presented in previous subsection reveal that there may be sufficient correlation between some specific wood density classes and the spectra of Landsat TM imagery to allow delineation of wood/grass mixtures of different densities. However, an appropriate image classification framework is not available to harness the relationship between wood density and its spectra because conventional automated image classification techniques act in a ‘global’ manner and assume the target land cover classes to be closed canopy in nature and big enough to be identified and mapped as individual features given the resolution of imagery used. An appropriate image classification technique is required because the spectra of key wood/grass mixtures of different densities (that can be identified and mapped as individual features) are more likely to be similar to other closed-canopy land cover classes. The present study focussed on how wood density can be incorporated into existing image classification techniques in order to improve the accuracy of land cover maps derived from the most available and cost-effective imagery (Landsat TM) for Uganda’s savannas. The results of the investigation, presented in the next subsection, indicate that it is possible, to some extent, to incorporate wood density classes during visual image classification (of Landsat TM imagery) to identify land cover maps characteristic of savanna landscapes of Uganda.

The mapping framework evaluated, as described in Section 3.3.5.3 generated results that are presented in Tables 4.5 – 4.7 and Appendix 4.5. As pointed out in Section 3.3.5.3, the evaluated framework is based on the SYMOLAC principles (Sections 2.4.2.2) that hinges on the notion that image interpretation/classification techniques should be able to adopt logical reasoning based on both quantitative and qualitative data. Table 4.5 shows how practical it is to map closed canopy woodland patches of different sizes (characteristic of Uganda’s savannas) from Landsat TM data.
Table 4.5 Ability to distinguish between typical woody land cover categories from the surrounding land cover types when using TM data and a reference vector map derived from high-resolution aerial photographs/IKONOS imagery.

<table>
<thead>
<tr>
<th>Cover</th>
<th>Area (ha)</th>
<th>Average patch size (ha)</th>
<th>Ability to detect boundaries/class label</th>
<th>No. of patches</th>
<th>Correctly-identified patches (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Multi-layered canopy forest (101)</td>
<td>3177.0</td>
<td>127.2</td>
<td>1</td>
<td>25</td>
<td>95.3</td>
</tr>
<tr>
<td>Multi-layered canopy forest (101)</td>
<td>156.7</td>
<td>52.2</td>
<td>2</td>
<td>3</td>
<td>4.7</td>
</tr>
<tr>
<td>Multi-layered canopy forest (101)</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td><strong>3333.7</strong></td>
<td><strong>-</strong></td>
<td><strong>-</strong></td>
<td><strong>28</strong></td>
<td><strong>100.0</strong></td>
</tr>
<tr>
<td>Single canopy forest (102)</td>
<td>1193.0</td>
<td>20.9</td>
<td>1</td>
<td>57</td>
<td>77.0</td>
</tr>
<tr>
<td>Single canopy forest (102)</td>
<td>53.0</td>
<td>3.3</td>
<td>2</td>
<td>16</td>
<td>21.6</td>
</tr>
<tr>
<td>Single canopy forest (102)</td>
<td>2.5</td>
<td>2.5</td>
<td>3</td>
<td>1</td>
<td>1.4</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td><strong>1248.5</strong></td>
<td><strong>-</strong></td>
<td><strong>-</strong></td>
<td><strong>74</strong></td>
<td><strong>100.0</strong></td>
</tr>
<tr>
<td>Dense wood/shrub (204)</td>
<td>1077.3</td>
<td>11.3</td>
<td>1</td>
<td>65</td>
<td>71.5</td>
</tr>
<tr>
<td>Dense wood/shrub (204)</td>
<td>415.6</td>
<td>20.8</td>
<td>2</td>
<td>20</td>
<td>27.5</td>
</tr>
<tr>
<td>Dense wood/shrub (204)</td>
<td>14.5</td>
<td>7.2</td>
<td>3</td>
<td>2</td>
<td>1.0</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td><strong>1597.4</strong></td>
<td><strong>-</strong></td>
<td><strong>-</strong></td>
<td><strong>117</strong></td>
<td><strong>100.0</strong></td>
</tr>
<tr>
<td>Eucalyptus woodlots (501)</td>
<td>87.3</td>
<td>2.7</td>
<td>1</td>
<td>32</td>
<td>27.4</td>
</tr>
<tr>
<td>Eucalyptus woodlots (501)</td>
<td>196.7</td>
<td>8.6</td>
<td>2</td>
<td>23</td>
<td>61.7</td>
</tr>
<tr>
<td>Eucalyptus woodlots (501)</td>
<td>34.7</td>
<td>2.3</td>
<td>3</td>
<td>15</td>
<td>10.9</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td><strong>318.7</strong></td>
<td><strong>-</strong></td>
<td><strong>-</strong></td>
<td><strong>70</strong></td>
<td><strong>100.0</strong></td>
</tr>
<tr>
<td>Tea (402)</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Tea (402)</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Tea (402)</td>
<td>73.4</td>
<td>73.4</td>
<td>3</td>
<td>1</td>
<td>100.0</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td><strong>73.4</strong></td>
<td><strong>-</strong></td>
<td><strong>-</strong></td>
<td><strong>1</strong></td>
<td><strong>100.0</strong></td>
</tr>
</tbody>
</table>

Key to column "ability to detect boundaries/class label".

1 = no ambiguity to detect both boundary/class attribute of a land cover patch;
2 = some ambiguity to detect either boundary or class attribute part of a land cover patch; and
3 = impossible to make class and boundary distinctions of a land cover patch from its surroundings.

Closed canopy woody vegetation (both natural and planted) accounts for 14% of the 477 km² of the Nabugabo study area. The closed natural (classes 101 and 102) and dense (class 204) woody patches are detected with an accuracy score of 1, yielding an overall accuracy ranging from 70 - 95% (Table 4.5). On the contrary, planted woody land cover categories (Eucalyptus and tea) could not easily be differentiated from their natural wood cover counterparts, an observation attributed to spectral overlap. It was particularly difficult to differentiate between Eucalyptus patches if they were adjacent to closed single canopy forest (class 102) and some patches of dense shrubs (class
In the case of tea, its spectral properties appeared to resemble wooded grassland (class 203), a result that was also observed on the classification dendrograms presented in Figure 4.10. Based on Table 4.5, the confidence of distinguishing *Eucalyptus* from other closed wood cover categories, due to spectral overlap, is less than 30%. There was zero confidence in the identification and mapping of the only tea plantation in the Nabugabo study area again due to spectral overlap. For all the woodland patches (Table 4.4), the confidence to accurately map each patch decreased with decreasing patch size.

Table 4.6 shows the ability to make distinctions between grassland, forbs, and wood/grass mixtures of different densities using the proposed mapping framework, again using TM data. Closed grasslands, wood/grass mixtures of different densities and forbs were widespread, occupying approximately 40% of the Nabugabo study area. The results show that the ability to detect, accurately, closed-canopy grassland is high, ranging from about 84 - 98%. However, forbs (which are broad-leaved herbaceous plant communities) are confused with small patches of woody cover. On the other hand, the ability to detect land cover categories characterised by wood/grass mixtures of different densities (classes 202 and 203) is low. For the wood/grass mixture land cover labelled 202, 57% of the polygons were correctly identified. However, it was only possible to identify and map 29.5% of the wood/grass class labelled 203. In many cases, 202 and 203 were spectrally similar to crop-fields (class 401).

Lastly, while there was no difficulty in detecting the water body, accounting for 10% of the Nabugabo study area (Table 4.7), there were significant limitations to the detection of crop-fields (Table 4.8). The spectral signatures of crop-fields, occupying about 36% of the Nabugabo study area, are grossly confused with spectral signatures of wood/grass mixtures of different densities, an observation also made for some of the results presented in Section 4.2.2.
Table 4.6 Ability to distinguish between typical grass and wood/grass mixtures categories from the surrounding land cover when using TM data and a reference vector map derived from high-resolution aerial photographs/IKONOS imagery.

<table>
<thead>
<tr>
<th>Cover</th>
<th>Area (ha)</th>
<th>Average patch size (ha)</th>
<th>Ability to detect boundaries/class label</th>
<th>No. patches</th>
<th>Correctly-identified patches (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Short grass (205)</td>
<td>916.5</td>
<td>36.7</td>
<td>1</td>
<td>25</td>
<td>97.8</td>
</tr>
<tr>
<td>Short grass (205)</td>
<td>206.6</td>
<td>3.4</td>
<td>2</td>
<td>6</td>
<td>2.2</td>
</tr>
<tr>
<td>Short grass (205)</td>
<td></td>
<td>-</td>
<td>3</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Total</td>
<td>937.1</td>
<td></td>
<td>31</td>
<td>100.0</td>
<td></td>
</tr>
<tr>
<td>Medium-tall grass (201)</td>
<td>3303.0</td>
<td>122.3</td>
<td>1</td>
<td>27</td>
<td>84.1</td>
</tr>
<tr>
<td>Medium-tall grass (201)</td>
<td>624.0</td>
<td>44.6</td>
<td>2</td>
<td>14</td>
<td>15.9</td>
</tr>
<tr>
<td>Medium-tall grass (201)</td>
<td></td>
<td>-</td>
<td>3</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Total</td>
<td>3927.0</td>
<td></td>
<td>28</td>
<td>100.0</td>
<td></td>
</tr>
<tr>
<td>Dense forbs (206)</td>
<td>35.6</td>
<td>17.8</td>
<td>1</td>
<td>2</td>
<td>54.4</td>
</tr>
<tr>
<td>Dense forbs (206)</td>
<td>22.9</td>
<td>7.6</td>
<td>2</td>
<td>3</td>
<td>35.0</td>
</tr>
<tr>
<td>Dense forbs (206)</td>
<td>6.9</td>
<td>6.9</td>
<td>3</td>
<td>1</td>
<td>10.6</td>
</tr>
<tr>
<td>Total</td>
<td>65.4</td>
<td></td>
<td>6</td>
<td>100.0</td>
<td></td>
</tr>
<tr>
<td>Wetland tall grass/papyrus (301/302)</td>
<td>858.3</td>
<td>296.0</td>
<td>1</td>
<td>29</td>
<td>90.3</td>
</tr>
<tr>
<td>Wetland tall grass/papyrus (301/302)</td>
<td>841.5</td>
<td>168.3</td>
<td>2</td>
<td>5</td>
<td>8.9</td>
</tr>
<tr>
<td>Wetland tall grass/papyrus (301/302)</td>
<td>76.1</td>
<td>76.1</td>
<td>3</td>
<td>1</td>
<td>0.8</td>
</tr>
<tr>
<td>Total</td>
<td>9500.7</td>
<td></td>
<td>35</td>
<td>100.0</td>
<td></td>
</tr>
<tr>
<td>Medium-tall grass with significant wood (202)</td>
<td>1976.2</td>
<td>98.2</td>
<td>1</td>
<td>44</td>
<td>57.2</td>
</tr>
<tr>
<td>Medium-tall grass with significant wood (202)</td>
<td>1460</td>
<td>85.9</td>
<td>2</td>
<td>34</td>
<td>42.3</td>
</tr>
<tr>
<td>Medium-tall grass with significant wood (202)</td>
<td>19.0</td>
<td>9.5</td>
<td>3</td>
<td>2</td>
<td>0.5</td>
</tr>
<tr>
<td>Total</td>
<td>3455.2</td>
<td></td>
<td>80</td>
<td>100.0</td>
<td></td>
</tr>
<tr>
<td>Wooded grassland (203)</td>
<td>387.4</td>
<td>29.8</td>
<td>1</td>
<td>13</td>
<td>29.5</td>
</tr>
<tr>
<td>Wooded grassland (203)</td>
<td>871.3</td>
<td>43.6</td>
<td>2</td>
<td>20</td>
<td>66.4</td>
</tr>
<tr>
<td>Wooded grassland (203)</td>
<td>54.2</td>
<td>13.5</td>
<td>3</td>
<td>4</td>
<td>41.1</td>
</tr>
<tr>
<td>Total</td>
<td>1312.9</td>
<td></td>
<td>37</td>
<td>100.0</td>
<td></td>
</tr>
</tbody>
</table>

Key to column "ability to detect boundaries/class labels":
1 = no ambiguity to detect both boundary/class attribute of a land cover patch;
2 = some ambiguity to detect either boundary or class attribute part of a land cover patch, and
3 = impossible to make class and boundary distinctions of a land cover patch from its surroundings.
Table 4.7 Ability to distinguish between water from the surrounding land cover types when using TM data and a reference vector map derived from high-resolution aerial photographs/IKONOS imagery.

<table>
<thead>
<tr>
<th>Cover</th>
<th>Area (ha)</th>
<th>Average patch size (ha)</th>
<th>Ability to detect boundaries/class label</th>
<th>No. patches</th>
<th>Correctly-identified patches (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Water (601)</td>
<td>4941.7</td>
<td>494.7</td>
<td>1</td>
<td>10</td>
<td>100.0</td>
</tr>
<tr>
<td>Total</td>
<td>4941.7</td>
<td></td>
<td></td>
<td>10</td>
<td>100.0</td>
</tr>
</tbody>
</table>

Table 4.8 Ability to distinguish cultivated patches from the surrounding land cover types when using TM data and a reference vector map derived from high-resolution aerial photographs/IKONOS imagery.

<table>
<thead>
<tr>
<th>Cover</th>
<th>Area (ha)</th>
<th>Average patch size (ha)</th>
<th>Ability to detect boundaries/class label</th>
<th>No. patches</th>
<th>Correctly-identified patches (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mixed crops (401)</td>
<td>9832.1</td>
<td>702.3</td>
<td>1</td>
<td>14</td>
<td>57.5</td>
</tr>
<tr>
<td>Mixed crops (401)</td>
<td>7183.9</td>
<td>1026.3</td>
<td>2</td>
<td>7</td>
<td>42.0</td>
</tr>
<tr>
<td>Mixed crops (401)</td>
<td>88.7</td>
<td>222.2</td>
<td>3</td>
<td>4</td>
<td>0.5</td>
</tr>
<tr>
<td>Total</td>
<td>17104.7</td>
<td></td>
<td></td>
<td>35</td>
<td>100.0</td>
</tr>
</tbody>
</table>

Key to the column ‘visual ability to detect boundaries/class labels’ of Tables 7.4 and 7.5:

1 = no ambiguity to detect both boundary/class attribute of a land cover patch;
2 = some ambiguity to detect either boundary or class attribute part of a land cover patch; and
3 = impossible to make class and boundary distinctions of a land cover patch from its surroundings.

The results of evaluation of the proposed mapping framework presented in Tables 4.5–4.8 revealed that it has a potential to allow automated generation of accurate land cover maps for Uganda’s savannas. Basing on visual image (Landsat TM data) interpretation, the practicability to detect typical land cover patches of different types was found to be higher for closed-canopy than for mixtures of vegetation across the landscape. The size of a land cover patch, and the nature of surrounding/adjacent land cover, was also found to influence the accuracy a given patch identified using the proposed framework. The low levels of accuracy attained using visual interpretation of Landsat TM image for the identification of wood/grass mixtures of different densities compared with the classification dendrograms (Figure 4.10) was attributed to the limitations of the human eye that cannot distinguish between more than 16 different spectral classes for a given colour image (Section 2.2.4.2). Improvements in the performance of the proposed mapping framework will necessitate automation of an image classification algorithm.
CHAPTER FIVE
DISCUSSION

The findings presented in Section 4.2 will enable the reader reflect on a number of aspects regarding practical remote sensing techniques for ensuring the accuracy of land cover maps produced from low/coarse resolution imagery for Uganda’s savannas. In particular, the present study emphasised a robust technique (region-based) for assessing the accuracy of land cover maps generated from low/coarse resolution imagery for Uganda’s savannas. The conclusion drawn from the assessment of the accuracy of existing land cover maps is that, both low/coarse spatial resolution of imagery and the nature of the Uganda’s savanna contribute to the significant lowering of the accuracy of land cover maps. While there may be different solutions to overcome the limitations of low/coarse resolution imagery when mapping Uganda’s savannas, the use of imagery acquired at an optimal spatial resolution ranging from 3.5 – 4.5 m was demonstrated as one such practical solution to produce more accurate land cover maps than has been the case for Uganda’s savannas. Lastly, the findings of the present study showed that there is potential, to some extent, of improving the accuracy of land cover maps if wood density is an integral part of Landsat TM image classification. In the following sections, the robustness of the techniques used and the relevancy of findings are discussed.

5.1 ACCURACY OF EXISTING LAND COVER MAPS

The finding that existing land cover maps (generated from low/coarse resolution imagery for Uganda’s savannas) are of very low accuracy i.e. less than 50% (except for Arua test site in case of SPOT XS and Landsat TM data) (Table 4.2) is consistent with the experience of many end-users of such maps. Satellite remote sensing, whose imagery was used to generate the land cover maps whose accuracy is shown in Table 4.2, is an extension of the concepts of aerial photography to higher altitudes (Short, 1998). Notwithstanding some advantages of low/coarse resolution satellite remote sensing (such as enabling us to map large geographic areas), the very low accuracy of existing land cover maps obtained for Uganda’s savannas (Table 4.2 and Figure 4.1)
indicates a significant deviation from what is considered the norm. This is because Thunisen et al. (1992) and Anderson et al. (1976) state that the overall classification accuracy, for operational purposes, of any land cover map should not be less than 75%. The fact that existing land cover maps derived from low/coarse resolution imagery were found to be very inaccurate (Table 4.2) can be explained in terms of two aspects: (a) the error assessment technique employed was robust enough to detect the actual accuracy levels of existing maps and (b) the assumptions that underpin mapping land cover/vegetation categories from low/coarse resolution imagery do not hold for fragmented landscapes, Uganda's savannas in this case.

The high levels of errors that characterise land cover maps generated for Uganda's savannas might not have been detected, in the past, by the map producers because of the non-robustness of conventional techniques used to assess image classification accuracies. However, in the present study, a robust image classification error assessment technique (based on both geometric and class attributes of a geographic feature) was employed. The use of a region-based technique for assessing image classification errors is supported by Marceau and Hay (1999) who are of the view that land cover map units (whose accuracy were assessed) are not independent of their two geometrical properties (class labels and location of boundaries). Geometric properties are best represented as polygons (regions) and hence a region-based (reference information) is a robust technique for the assessment of the accuracy of land cover maps, as was used for the four test sites in the present study.

It may be stated that both SPOT (20 m) and Landsat TM (30 m) imagery are optimised for mapping land cover categories of most countries in Europe and North America (Figure 2.5) and other large homogeneous land covers (such as forests and wetlands) of a country like Uganda. However, SPOT (20 m) and Landsat TM (30 m) imagery are not optimised to map Uganda's savannas. Hence the basic assumption of merging/annihilation of geographical entities by imaging sensors (Section 2.4.1.2) is not a universal rule to be applied when identifying and mapping wood/grass mixtures of different densities characteristic (of Uganda's savannas) when using low/coarse resolution imagery and standard image classification techniques. This may explain,
largely, the very low accuracy of savanna land cover categories observed for MFNP, Nebbi and Nabugabo test sites (Table 4.2 and Figure 4.1).

The observation that low/coarse resolution imagery is not optimised for mapping savannas is supported by other studies. For example, Foody (2004) agrees that the spatial patterns (wood/grass mixtures of different densities) evident with one imaging resolution (e.g. IKONOS) may be greatly misrepresented at another resolution (e.g. Landsat TM) (Figure 2.10) leading to erroneous spatial information to be derived for landscapes, example for savannas as shown in (Table 4.1 and Figure 4.1). On their part, Stow and Chen (2002) compared land cover derived from AVHRR imagery acquired at different dates (1990 and 1995) for a rapidly expanding city in USA, and demonstrated that expanded urban areas were mixed with non-urban areas, even when the extent of the expanded urban areas was greater than the resolution of AVHRR (1 km). Stow and Chen's (2002) findings serves as another pointer to the fact that merging/annihilation of geographical entities by imaging sensors on which basis we use low/coarse resolution imagery to map any landscape is not a universal rule and hence, explains the very low land cover accuracies associated with savannas if mapped from low/coarse resolution imagery. Seyler et al. (2002) also warns that attempts to map vegetation classes from low/coarse imagery in tropical regions (where savannas are dominant) have often had limited success despite an advancement in the use of improved statistical image classification procedures. Therefore, this investigation has made a modest contribution in affirming Seyler et al.'s (2002) observation that improved image classification technology alone (devoid of the ecological knowledge such as use of wood density) are not enough to generate accurate land cover maps from low/coarse resolution imagery especially for fragmented landscapes such as Uganda's savannas.

It is also important to note that the inaccurate land cover maps are unlikely to have been exclusively caused by spectral overlap discussed in Section 2.4.1.1. This is because the accuracy of land cover maps (derived from SPOT XS and Landsat TM data) is very high for Arua test site (dominated by non-savanna landscape) and
medium for Nabugabo test site (dominated equally by both savanna and non-savanna landscapes). Indeed, other studies, in Uganda, have shown that if homogeneous geographical features constitute the landscape mapped, the accuracy of land cover maps derived from Landsat TM imagery is very high (Fuller et al., 1998). On the other hand, the accuracy of land cover maps if derived from Landsat TM imagery for fragmented landscapes (savannas) is very low (Jäckel et al., 1997). Indeed Appendix B5.1 shows that land cover boundaries delineated from low/coarse resolution imagery for Uganda’s savannas are, to a large extent, arbitrary if compared with reference imagery.

The present study has demonstrated that existing land cover maps, derived from low/coarse resolution imagery for Uganda’s savannas, are of very low accuracy (< 50%). The importance of accurate land cover maps cannot be over-emphasised if sustainable use of Uganda’s savannas is to be insured in future. The implication of using land cover maps whose accuracy is very low (Figure 4.1 and Table 4.1) means that there is significant error propagation in the many analyses and models (such as soil erosion and land use change modelling) in which the existing land cover maps are key inputs. Hence, better knowledge about the optimal resolution of imagery for mapping Uganda’s savannas is required.

5.2 OPTIMAL SPATIAL RESOLUTION FOR MAPPING UGANDA’S SAVANNAS

The results presented in Figures 4.8 show that the optimal resolution of imagery needed for mapping Uganda’s savannas falls within a range of 3.5±0.5 m (or 3.0 – 4.0 m). This finding is in sharp contrast with Menges et al. (2001) study that showed that the optimal resolution of imagery required for mapping savanna vegetation communities in Northern Australia ranges from 15 – 27 m. This difference can be explained in two ways. First, the vegetation structure of Australian is different from that of Ugandan savannas and hence requires different optimal resolutions. Such an accountability of the differences in imagery required for mapping Australian and Uganda’s savannas implies that the average tree canopy cover area for Australian
savannas is 15 – 27 m while the average tree canopy cover area for Uganda’s savannas is 3 – 4 m. This is because, in case of Uganda’s savannas, reduction of an image from high to low resolution affects the geometric integrity (average patch size in Figure 4.7) of actual geographical features (such as individual trees) rather than a mere removal of terrain noise. Overall, average patch size values are very sensitive to image resolution and hence, can be used as an indicator of optimal image resolution for mapping Uganda’s savannas.

The second way of explaining why optimal resolution of imagery required for mapping Ugandan and Australian savannas exhibit differences can be attributed to the different techniques Menges et al. (2001) and the present study used. Specifically, the optimal resolution determined for Australian savannas was solely based on image spectral variance (terrain noise) while the optimal image resolution for Uganda’s savannas was determined by combining terrain noise and the average patch size of terrain features (Figure 4.8). The technique used in the present study (by combining two variables) to determine the optimal resolution for mapping Uganda’s savannas was based on Marceau and Hay (1999) premise that the characteristics of land cover map units, of any given terrain, should always be defined in terms of both class labels and shape (represented by size in the present study). It is postulated, in the present study, that conventional techniques used to determine spatial resolution of imagery for mapping given landscapes have not been vigorous. This is because such techniques ignore an important attribute i.e. shape/size of the smallest terrain features of target image objects. Hence, by introducing the average patch size into the equation, besides terrain noise, the present study has improved a technique traditionally used to determine optimal resolution of imagery required to map vegetated landscapes, including savannas. The optimal resolution determined for Uganda’s savannas, 3.5±0.5 m, supports the theoretical arguments illustrated in Figure 2.13 i.e. the point at which both terrain noise and mixed pixels are at their minimum (3.5 m in Figure 4.8) represents, practically, the optimal image resolution for mapping a given landscape.

Based on Figure 4.8, the significant reductions in the level of terrain noise (and image file sizes in Figure 4.6) with decreasing image resolution are desirable if the reduction
is largely attributed to the removal of intra-terrain noise [Figure 5.1(a)]. The overall enlargement of the geographical features [Figures 4.7 and 5.1(b)] with decreasing image resolution, if attributed to the reduction in terrain noise level, is also desirable (Townshend (1981)). What is not desirable is the removal of inter-terrain noise that represents desirable individual trees and other small but homogeneous geographical features (Sonka et al., 1993). The individual trees, small tree clumps (in a background of grassland) and or vice-versa define the vegetation structure of Uganda’s savannas and hence, should be preserved on any imagery before it qualifies to be optimal.

The changes in the Land Cover Index, with decreasing image resolution (Figure 4.3), show that the sizes of geographical features indeed declined by a factor of about 43% (test site 1) and 51% (test site 2) between 0.5 m to 10.0 m. Part of this deterioration can be attributed to the terrain noise removed from each of the simulated imagery. However, as shown in Figures 5.1(a) and 5.1(b), the areal extent attributed to the intra-terrain noise (of land cover derived from imagery of different resolutions) is insignificant compared to the degradation at the boundary of geographical features at lower image resolution.

Figure 5.2 illustrates the importance of removing image noise (terrain noise or spectral variance). While the imagery, for acquired the same terrain, have different spatial resolutions (0.5, 2.5, and 4.0 m), they depict geographical features that are geometrically and spectrally the same, at least to the naked eye. Therefore, to generate accurate and cost-effective land cover maps for Uganda’s savannas, IKONOS (4 m) rather than Quick-Bird (0.61 m) imagery is sufficient. On the other hand, imagery simulated from 0.5 m to 20.0, 30.0 and 500 m (Figure 5.3) appears not to represent the geographical features characteristic of Uganda’s savannas, both geometrically and spectrally. This may explain why land cover maps derived from low/coarse resolution imagery (for Uganda’s savannas) are extremely low as already discussed in Section 4.2 (Figure 4.1 and Table 4.2).
Figure 5.1(a) Variation of intra-terrain noise and integrity of geographic boundaries with decreasing image resolution.

Figure 5.1(b) Variation of integrity of geographic boundaries with decreasing image resolution. Green colour codes depict boundary derived from 0.5 m – 2.0 m and shades of red 2.5 – 10.0 m.

Figure 5.2 Imagery acquired for a savanna ecosystem at 0.5 m spatial resolution but simulated to 2.5 m and 4.0 m represent geographical features that are the geometrically the same.
Another observation emanating from the results presented in Section 4.3 is that overall classification accuracy (OCA or Kappa) and areal extents are not robust techniques for the determination of optimal resolution for mapping Uganda’s savannas. The findings that overall classification accuracy, determined using conventional techniques described in Section 3.3.3.2(b)(iv), are not robust enough for the determination of optimal resolution, is supported by other researchers such as Zhu (1997), Smith et al. (1999) and Friedl et al. (2000). Indeed, Friedl et al. (2000) found out that the error classification matrix, as a technique for assessing classification accuracies of spatial information generated from low-resolution imagery, hence optimal image resolution as exemplified in Figure 2.5, may be associated with a margin error of up to 50%.

5.3 THE POTENTIAL OF LANDSAT TM IMAGERY FOR MAPPING WOOD/GRASS MIXTURES OF DIFFERENT DENSITIES

Based on the results presented in Section 4.4, wood density could have a potential to improve the accuracy of land cover maps generated from Landsat TM for Uganda’s savannas. The use of woody density, as additional knowledge, during land cover mapping is in consonance with Foody’s (2004) observation that the information content is a function of image qualities (Section 2.4.1) and also of terrain characteristics (Section 2.4.3). In the present study, wood density is an important terrain characteristic for mapping Uganda’s savannas. The results presented in Section
4.4.1 indicate that the spectra of Landsat TM data may be correlated with some wood/grass mixtures of different densities. In particular, the results presented in Figure 4.10 and Table 4.5 show that the groupings of TM spectra significantly correlated with wood density are likely to be 0 – 15%; 15 – 30%; 30 – 55%; 55 – 80% and 80 - 100%. The findings of this study are, to some extent, in agreement with those of Zribi et al. (2003) who found that when correlating vegetation density and reflectance values of a low resolution imagery in an arid landscape, appropriate vegetation classes, defined on the basis of vegetation density, were 0 – 10%; 10 – 25%; 25 – 50% and 50 – 100%. In a related study, Menges et al. (2001) noted that the spectra suitable for mapping northern Australian savannas are related to wood density classes 0 – 10%; 10 – 30%; 30 – 50%; 50 – 75% and 75 – 100%. Therefore, the findings of the present study (while unique in their own right for Uganda’s savannas) conform to a general trend that some wood (vegetation) density classes are significantly correlated with spectra of low/coarse resolution imagery.

However, even though this study, and other studies by Menges et al. (2001) and Zribi et al. (2003) show a significant correlation between wood (vegetation) density and the spectra of low resolution imagery, conventionally, it is not recommended to define vegetation density as a criterion during per-pixel image classification (Lewis, 1998). It is, therefore, probable that the spectra of most wood/grass mixtures of different densities are represented by mixed pixels. If a per-pixel image classification system is used, such spectra (of wood/grass mixtures) may be misclassified as something else in an image scene, hence resulting in the inaccurate land cover maps depicted in Table 4.2. This observation is supported by the findings of Warner and Shank (1997) who observed that spectra formed from a mixture of urban and forest cover, using Landsat TM, were misclassified as short grassland when a per-pixel classification technique was used. This fact is illustrated in Figure 5.4 where a small portion of the Nabugabo study site shows the spectra of Landsat TM mixed pixels formed from wood/grass mixtures are misclassified as herbaceous wetland vegetation.

Therefore, for wood density to be of any practical value during automated land cover mapping, a potential mapping framework for harnessing the spectra of Landsat TM
imagery for mapping grass/mixtures of different densities was evaluated and the findings presented in Section 4.4.2. To harness wood density, the recommended classes should be 0 – 15%; 15 – 30%; 30 – 55%; 55 – 80% and 80 - 100% rather than the conventional and subjective wood density classes depicted at the bottom of Table 3.3. The redefinition of appropriate wood density classes has been done in the context of the significant correlation observed between the wood density classes (0 – 15%; 15 – 30%; 30 – 55%; 55 – 80% and 80 - 100%) and the spectra of Landsat TM imagery representing Uganda’s savannas. The approach of redefining wood density classes is also in line with McLver and Friedl (2002) observations that vegetation classification systems should never be designed independent of the remote sensing techniques used for mapping.

Figure 5.4 Spectra of mixed pixels aggravate image misclassifications on Landsat TM [B] but not on high-resolution imagery [A].

The results presented in Tables 4.4 and 4.7 show evidence that a region-based rather than a per-pixel is a practical approach to use wood density as a criterion to map land cover characteristic of wood/grass mixtures of different densities in Uganda’s savannas. A region-based approach to the development of a mapping framework, for Uganda’s savanna, presupposes the existence of boundaries of geographical features (preferably generated from high-resolution imagery) as one of the inputs during the
classification of Landsat TM imagery. This should be a precondition because the boundaries of small but numerous polygons (vector maps) of geographical features cannot be easily recognised from Landsat TM imagery as observed for the results presented in Tables 4.4 – 4.5. The use of existing vector boundaries to improve mapping of land cover has been evaluated in other studies and appears to have great potential (Skelsey, 1997). The use of existing vector maps has also been experimented by other researchers such as Reed et al. (1994), Wright et al. (1997), Shoshany (2000), Smith and Fuller (2001), Aplin and Atkinson (2002), Franklin et al. (2002) and Geneletti and Gorte (2003), an indication that the proposed land cover mapping framework is a concept that is evolving with great potential.

Not only does the proposed mapping framework allow accurate placement of boundaries, it also allows partial or complete changes in the status of an individual geographical feature to be determined, hence making the approach suitable for land cover monitoring, as illustrated in Figure 5.5.

Figure 5.5 A forest cover patch (labelled 102) can be updated to reflect the changes that occurred between 1989 and 2000 using Landsat TM imagery.
CHAPTER SIX

CONCLUSIONS AND RECOMMENDATIONS

6.1 CONCLUSIONS AND RECOMMENDATIONS

Based on the findings and discussion of the present study, a number of conclusions regarding the three specific objectives can be made.

By employing a robust error assessment technique (cross-tabulation of reference information generated from IKONOS imagery with land cover maps derived from low/coarse resolution imagery), the accuracy of existing land cover maps for Uganda’s savannas was found out to be extremely low. Hence, the generally accepted theory that merging/annihilation of small geographical features (numerous trees in grassland or vice versa in case of savanna) allows the mapping of dominant land cover categories from low/coarse resolution imagery is invalid in case of Uganda’s savannas. Therefore, continued use of the existing land cover maps that were produced from low/coarse resolution imagery for Uganda’s savannas means that error propagation is significant in the many applications for which the maps are used.

The conventional techniques (based on either image classification errors or image variance with decreasing image resolution) of determining an optimal spatial resolution of imagery for mapping a given landscape were found to be non-robust during the present study. Instead, terrain noise (representing image variance) combined with the average patch size of image features provided a robust technique for the determination of optimal resolution (3 – 4 m) for mapping Uganda’s savannas. A practical implication of this finding is that there is scientific confidence to use IKONOS (4 m) rather than SPOT 2.5 m for mapping Uganda’s savannas. Imagery acquired at the optimal resolution range of 3 – 4 m is not only cost-effective to use and also ensures the accuracy of land cover maps generated for Uganda’s savannas.

Finally, for purposes of improving the accuracy of land cover maps derived from Landsat TM imagery there is a quantifiable relationship between spectra and
wood/grass mixtures of some density classes (20–30, 30–50%, 50–80%) that can be harnessed for Uganda’s savannas. However, land cover classes, within savannas, characterized by wood density classes of either 0–15% or 80–100% should be regarded as homogeneous in nature just like closed canopy herbaceous wetlands or forests which in turn render themselves to be accurately mapped from low/coarse resolution imagery. However, land cover types characterised by wood density classes 20–30, 30–50% and 50–80% cannot be mapped, practically and accurately, from low/coarse resolution imagery using standard image classification techniques. Wood density will only be harnessed, for land cover mapping, if the proposed mapping framework is operationalised.

6.2 RECOMMENDATIONS

Based on results for objectives 1 it is recommended that great care should be exercised when using existing land cover maps generated from low/coarse resolution imagery for Uganda’s savannas because the maps are inaccurate.

Based on results for objective 2 it is recommended that imagery acquired at an optimal spatial resolution of 3-4 m be used to generate accurate land cover maps for Uganda’s savannas.

Finally, based on results for objective 3 it is recommended,

- that the proposed mapping framework be operationalized;
- a region-based image classification approach be validated for automation by a transdisciplinary research team composed of vegetation ecologists, computer programmers and image analysts;
- wood density be harnessed for improving of land cover maps derived from Landsat TM for Uganda’s savannas;
- further studies be done to determine the best period of the year (season) when to acquire imagery whose spectra is significantly related to wood density.
7.0 REFERENCES


