African Journal of Environmental Science and Technology Vol. 4(10), pp. 709-717, October 2010
Available online at http://www.academicjournals.org/AJEST
DOI: 10.5897/AJEST10.151
ISSN 1991-637X ©2010 Academic Journals

Full Length Research Paper

An improved technique for the prediction of optimal image resolution(s) for large-scale mapping of savannah ecosystems

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Accepted 4 October, 2010

Past studies to predict optimal image resolution required for generating spatial information for savannah ecosystems have yielded different outcomes, hence providing a knowledge gap that was investigated in the present study. The postulation, for the present study, was that by graphically solving two simultaneous equations of values of image noise index (INI) and degradation level Index (LDI), a robust technique for predicting optimal image resolution for the mapping of savannah ecosystems was developed. The technique involved simulating 0.5 m imagery to different spatial resolutions for two savannah test sites in Masaka district, Southern Uganda. By plotting INI and LDI values against the simulated image resolutions, it enabled the authors to objectively predict that image resolution at 2.25 and 2.5 m were optimal for generating spatial information for savannah ecosystems represented by the two test sites. The new technique will enable vegetation ecologists to objectively determine optimal resolution(s) prior to the choice of imagery, offered by different high-resolution air- and space-borne sensors, for generating spatial information for savannah ecosystems. Future research should focus on using the new technique to determine what ranges of image resolutions are optimal for generating spatial information of different savannah ecosystems in different countries.

Key words: Optimal resolution, savannah ecosystems, image noise index, land cover index, level of degradation index.

INTRODUCTION

For vegetation ecologists, there is uncertainty regarding which one of the several high-resolution multi-spectral data (such as GeoEye 1.65 m, QuickBird 2.44 m, IKONOS 4 m, ALOS 10 m) should be used for generating spatial information for savannah ecosystems in a country like Uganda. This uncertainty arises due to the trade-off needed for accuracy vis-à-vis unit cost of generating spatial information per unit area. Image resolution, also known as spatial image resolution, is the level of cartographic detail of an image (Wilkie and Finn, 1996) and is measured in terms of pixel size. The present study is premised on the fact that there have been few and un-validated empirical studies on how to determine the optimal resolution of imagery required for automated generation of accurate and cost-effective spatial information for savannah landscapes.

Few of the past studies that investigated the optimal resolution for generating spatial information for savannah ecosystems yielded different outcomes. For example, Mugisha and Huising (2002) report that a resolution range of 1.5 – 2.5 m is optimal for large-scale automated mapping of Uganda's savannahs. On the other hand, Menges et al. (2001) reported that the optimal image resolution for mapping savannah vegetation in Northern Australia ranges from 5 to 27 m. The two studies, by Mugisha and Huising (2002) and Menges et al. (2001), yielded different optimal resolutions of imagery required for mapping savannahs. The difference, in optimal resolutions for imagery for mapping savannahs, could be an indication that these ecosystems are probably different in Uganda and Australia. The difference could

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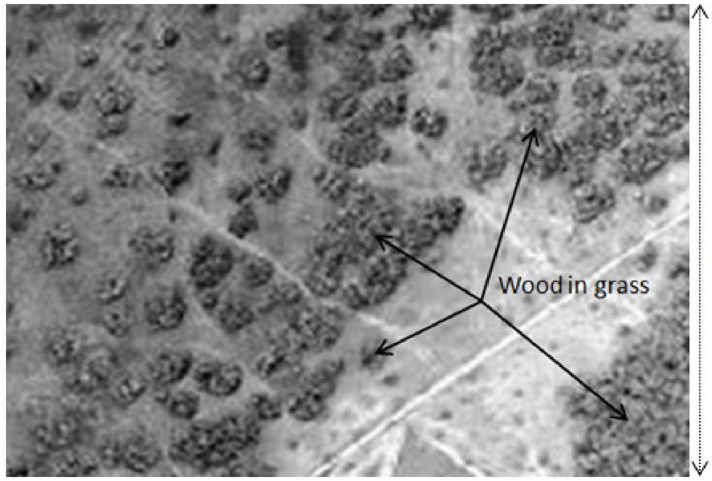

Figure 1. Part of a savannah showing a fragmented ecosystem.

also be attributed to the differences in the techniques used by the authors. The premise that savannah ecosystems, in Uganda and northern Australia, are different might be plausible because the major constituents of the ecosystems are grass/wood mixtures of different sizes and densities that vary across space and time. However, the scope of the present study is premised on the fact that past techniques used for the determination of the optimal resolution(s) for automated mapping of savannah ecosystems were not robust enough.

The term savannah is of West Indies origin and refers to landscapes with a type of vegetation dominated by grasses with varying wood densities across space (Groombridge and Jenkins, 2002), hence making the ecosystems fragmented as illustrated in Figure 1. Savannahs owe their origin and maintenance to adverse soil and climatic conditions, competition between grass and woody vegetation, fire, and anthropogenic factors (Cloudsley-Thompson, 1979; Mahesh et al., 2004). The economic importance of savannahs, in terms of pastoralism and biodiversity conservation, is enormous and thus cost-effective and accurate spatial information is required for the management of these ecosystems. Yet, experience shows that spatial information generated from SPOT (20 m) and Landsat TM (30 m) imagery for Uganda's savannah is very inaccurate (Mugisha, 2007). This observation is supported by Seyler et al. (2002) who point out that attempts to map land cover classes from imagery like Landsat TM for fragmented tropical regions have had limited success despite an advancement in the use of improved statistical image classification procedures. For savannahs, the varying canopy size and density of woody vegetation makes these ecosystems fragmented, hence requiring high-resolution imagery to accurately map the vegetation there in. However, the question that has not yet been answered, by previous studies, is what minimum parameters need to be combined to objectively predict optimal image resolution for mapping vegetation categories of grass/wood mixtures of different densities within savannah ecosystems.

The concept of optimal image resolution is based on the premise that unnecessarily high-resolution imagery is not only costly to acquire, process, and analyse, it also has no added informational value for mapping pre-determined set of geographic features (Townshend, 1981). On the other hand, low/coarse imagery, whose pixel size is far less than the size of the smallest map-able features, often yields spatial information whose geometric and class accuracies are unacceptably low (Foody, 2002; Seyler et al., 2002; Moody and Woodcock, 1995). The subject of optimal image resolution is very relevant to mapping and has been studied in many different disciplines ranging from soil/geomorphology (Holden, 2001), agriculture (Coulter et al., 2000), biomass (Atkinson and Curran, 1997) to land cover surveys (Harvey and Hill, 2001). Yet, despite their economic and conservational importance, there has been little interest to develop a robust technique for an objective determination of the optimal image resolution required for mapping savannah ecosystems.

Most techniques, including those employed by Mugisha and Huising (2002) and Menges et al. (2001), for the determination of optimal image resolutions are based on a measure of image spectral variance with changing image resolution (Bedward et al., 1992). However, other techniques (for example employed by Turner et al., 2002; Iron et al., 1985) are based on the image classification errors with varying image resolution when determining the optimal resolutions for mapping different landscapes. In our study, we took the view that a measure of internal spectral variance or image classification errors, with changing image resolution, alone has fundamental weaknesses when used for determining the optimal image resolution for mapping a given landscape. Internal

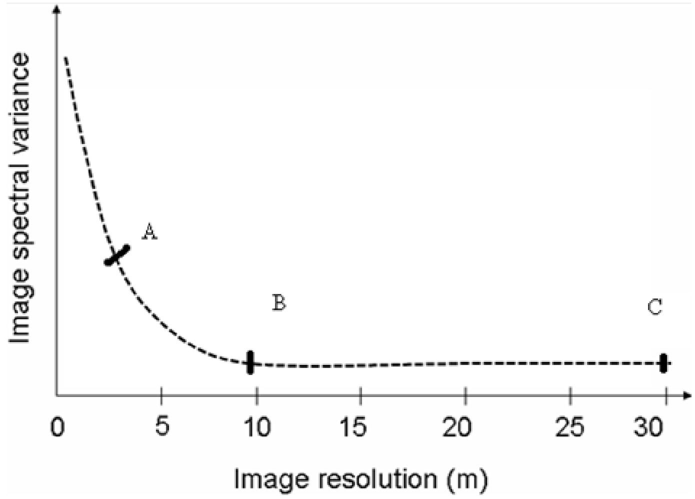

Figure 2. Ageneralised variation of image spectral variance with image resolution.

image spectral variance, an indicator of image 'noise' for a given landscape, is inversely proportional to image resolution as hypothetically shown in Figure 2. Menges et al. (2001) used the variation of internal spectral variance of high resolution video-captured imagery to predict that the optimal image resolution, for generating spatial information for savannahs in Northern Australia as 15 – 27 m. Based on Figure 2, there is probable lack of objectivity in deciding whether the optimal resolution is reached when the internal image spectral variance starts levelling off significantly (point A), levels of (point B) or across the whole spatial resolution range when the internal spectral variance has levelled off that is between points B and C.

Another weakness of internal image spectral variance and classification error-based techniques is that the geometric integrity (in terms of size/shape) of image objects is assumed to remain unaffected when a landscape is scanned by digital imaging sensors of different resolutions that is between points B and C in Figure 2. In other words, it is assumed that the size/shape of the numerous grass/wood mixtures, typical of savannah landscapes, do not influence their spectral characteristics for a given image. Yet, it is reasonable that the geometric integrity of image objects continues to be degraded with decreasing image resolution, that is between points B and C in Figure 2, hence affecting the spectral and geometric accuracies of spatial information generated from imagery with increasing pixels sizes. On the other hand, the use of high-resolution imagery, whose spectral variance is very high such as before point A in Figure 2, increases the cost of mapping without necessarily improving the accuracy of resultant vegetation maps. Consequently, the knowledge gap addressed in this paper is how to objectively predict an optimal image resolution that preserves both the spectral and geometric integrity of geographic phenomena of savannah ecosystems. Therefore, the purpose of the study was to identify relevant parameters whose sensitivity with changes in image resolution improve the prediction of optimal resolution(s) for generating spatial information for fragmented savannah ecosystems.

METHODS

Overview

Images used were acquired, for two tests sites in Southern Uganda, at a resolution of about 0.5 m by a multispectral Kodak Camera System (DCS560) mounted on a small winged aircraft. The 0.5 m imagery was simulated to 14 different resolutions to give a total of 15 images (including the reference imagery that is 0.5 m) for each test site. The variation of three parameters (image classification errors, image noise, and degradational level) was determined for each of the 15 images for each test site. The image classification errors were measured as 'Kappa' values (Lu and Weng, 2007) for each of the land cover maps derived from the 15 images for each test site. The other two measured values (image noise and degradational level) were transformed into two indices namely Image noise index (INI) and degradation level index (DLI) and the outcomes used in to solve, graphically, two simultaneous equations in order to predict the optimal image resolution for generating spatial information for savannah ecosystems represented by the two test sites..

Image preparation and analysis

The DCS560 Kodak Camera System captures small frames of multi-spectral composite image per scene. For the present study, each composite image frame was separated into constituent spectral bands that is green (0.5 – 0.68 µm), red (0.68 - 0.7 µm) and photo infrared (0.7 – 0.9 µm) before any image processing was carried out. For each test site, two adjacent image frames were geo-referenced, rectified and mosaicked using TNTmips Version 6.8 image processing software. The rectified image mosaics, after trimming the unwanted edges and masking out non-savannah landscapes, covered a ground area of 172 and 296 ha for test site 1 and 2, respectively.

The pixel size of each image mosaic (0.5 m) was increased to bigger pixel sizes using TNTmips' Automatic Resampling Procedure. The process of increasing an image to bigger pixel sizes simulates imagery to the desired spatial resolution. Image simulation process, from existing data, was cheaper and more practical than acquiring actual data for an investigation carried out in the present study. In the past, other researchers (for example, Ringrose et al., 2003; Lass et al., 2000; Iron et al., 1985) have also used simulated images for a variety of analyses. The simulation of different image resolutions, by increasing an image's pixel size, was each time carried out from each of the original image mosaics (0.5 m resolution) using 'cubic convolution' resampling procedure. Resampling imagery using cubic convolution was used because it is recommended by Müller and Segl (1999) for studies where the preservation of image object shapes is the goal. In short, the simulation of the resolution of each image mosaic involved a systematic change of pixel size from 0.5 to 1.0, 1.5, 2.0, 2.5, 3.0, 3.5, 4.0, 4.5 and 5.0 m.

The authors assumed, based on a preliminary study by Mugisha and Huising (2002), that an optimal resolution of imagery for Uganda's savannahs would be between 1.5 to 5 m and hence the nature of image simulation carried out. However, in case the authors' assumption was wrong, the 0.5 m imagery was also simulated to 10 m resolution that is 0.5 to 6.0, 7.0, 8.0, 9.0 and 10.0 m for each test site. The simulation of images beyond a spatial resolution of 10 m was deemed unnecessary since the geometric integrity of the smallest geographic phenomena (individual trees and small clumps of small of shrubs) are not preserved by sensors like ASTER, SPOT XS and Landsat TM. In any case, the findings of this study are intended to help vegetation ecologists to decide whether to purchase multi-spectral imagery acquired by GeoEye-2 (1.65 m), QuickBird (2.44 m), IKONO (4 m) or SPOT (10 m) when generating categorical information, using automated image analysis, when mapping savannah ecosystems.

Each of the 15 images was classified into 5 and 4 homogeneous land cover categories for test site 1 and 2, respectively using a non-supervised classifier. For test site 1, the homogeneous land cover categories were short grass, tall grass, closed canopy woodland, herbaceous wetland and burnt grass/shadows. For test site 2, the homogeneous land cover categories were short grass, tall grass, closed canopy woodland, and burnt grass/shadows. After classification, each of the 15 land cover maps, for each test site, was used to determine the variation of 'Kappa' values, INI and DLI for each of the land cover maps derived from the 15 images for each test site.

Determination of classification errors with changing image resolution

Existing knowledge shows that image classification error is a function, among others, of image resolution (Townsend, 1981; Iron et al., 1985) and hence the use of this parameter in the present study. The image classification error was determined for each of the 15 land cover maps (for each test site) using pixel-based reference information. The pixel-based reference information was collected during a ground-truthing exercise with the help of hand-held global position system (GPS). Only homogeneous parts of the land cover map, for each test site, were included in the pixel-based reference information as recommended by Lewis (1998).

The level of image classification error, for each of the 15 land cover maps, was determined by comparing reference information and the land cover map whose accuracy was being determined for each test site. The process of comparing two co-registered maps, on a pixel-by-pixel basis, to generate a classification error matrix for all the land cover classes is recommended by Nusser and Klass (2002). Using a land cover map whose accuracy was required and the ground-truthed reference map, an error classification matrix was automatically generated by TNTmips Image Processing Software. The overall classification error (OCE) was determined by subtracting 'Kappa' value from 100% (that is 100 – 'Kappa' value) for each land cover map and for each of the two test sites. A plot of OCE against each of the 15 image resolutions enabled the authors to construe if image classification errors are sensitive predictors of optimal image resolutions for savannah ecosystems.

Determination of image noise with changing spatial resolution

Each of the 30 land cover maps (for the two rest sites) was converted from raster to a vector data format in order to enable the targeted geographic phenomena (e.g. individual trees, clumps of bushlands and grasslands of different sizes) to be treated as individual mapping units (polygons). The total number of the individual geographic phenomenon (that is polygons) of short grass, tall grass, dense wood, herbaceous wetland, and burnt grass/shadows was counted for each of the 15 land cover maps for each test site. The use of polygons, as an indicator for image noise, was based on the premise that a land cover map, generated using automated image classification techniques, has both unwanted polygons (terrain noise such as openings in tree canopies) and wanted polygons representing real geographic features. The unwanted polygons were deemed geometrically unwanted (intra image noise) but numerically far greater than the polygons that represent actual geographic phenomena (individual trees, clumps of bushlands and grassland) of different sizes. Hence the removal of the polygons representing image noise, through increasing an image pixel size, should not in a significant manner affect the geometric integrity of geographic features composed of individual trees, clumps of bushlands and grassland. However, beyond a certain pixel size, degradation of the geometric integrity of geographic features sets in hence making the image unsuitable for automated mapping of individual trees, clumps of bushlands and grassland. It is postulated that the land cover polygons would decrease in a predictable manner to enable the investigators obtain approximately the same curve, for each test site, shown in Figure 2. The recorded number of land cover polygons, for each test site, was transformed into an image noise index (INI) using the following expression:

$$INI = (P_s/P_{0.5})100$$

where $P_{0.5}$ represents the number of land cover polygons recorded for spatial information derived from Kodak imagery at a spatial resolution of 0.5 m (reference data) for each of the two test sites; P_s represents the number of land cover polygons recorded for spatial information derived from Kodak imagery whose spatial resolution was simulated from 0.5 m for each of the two test sites.

Determination of geometric integrity of image objects at varying spatial resolutions

A third index, the land cover index (LCI), was determined through a raster GIS overlay process between each of the reference maps (derived from 0.5 m) and all other land cover maps generated from imagery whose image resolutions were simulated. The LCI was developed during the present investigation as a robust technique for tracking any spatial changes in shape/size (or geometric integrity) of image objects whose spatial resolutions were simulated. By selecting all pixels belonging to a particular land cover type from reference information (0.5 m) "and" pixels of the same land cover type generated from an image whose resolution would have been simulated, it was possible to track any changes in shape/size of image objects with changing image resolution. The

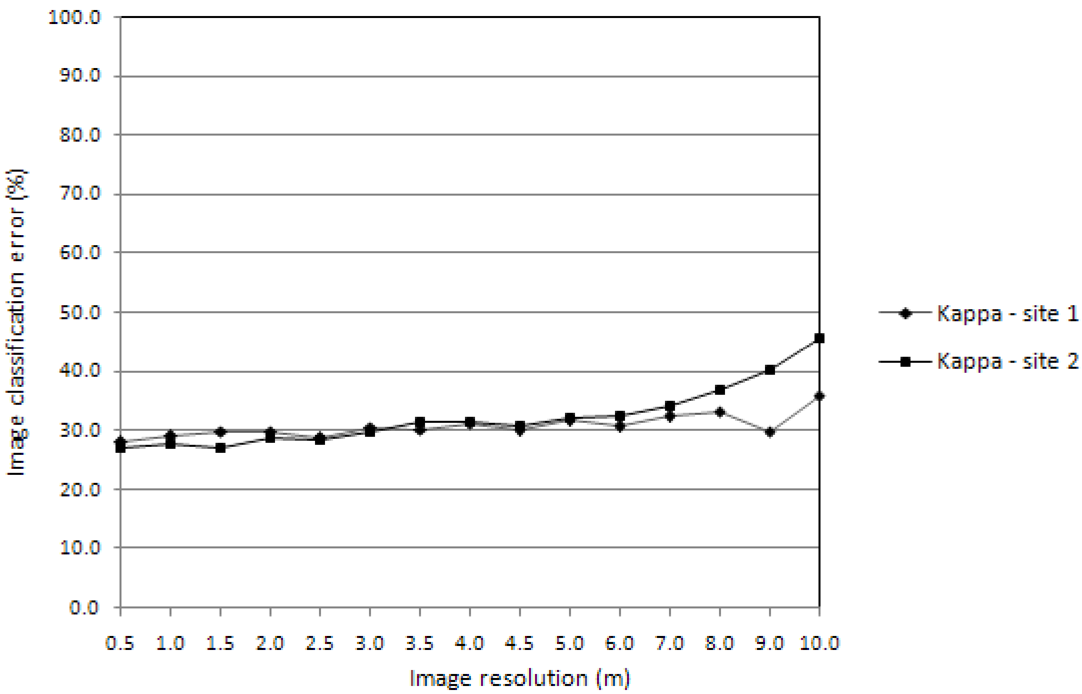

Figure 3. Plot of image classification errors (100-Kappa) against image resolution.

output pixels were transformed into area coverage (in hectares) and summed up for each test site. Area was used as a surrogate for shape/size of image objects as recommended by Comber et al. (2003). The area, for each land cover category, was transformed into LCI using the following expression:

$LCI = (A_s/A_{0.5})100$

where: $A_{0.5}$ represents the total area of land cover recorded for spatial information derived from Kodak imagery at a spatial resolution of 0.5 m (reference data) for each of the two test sites; A_s represents the total area of land cover recorded for spatial information derived from Kodak imagery whose spatial resolution was simulated from 0.5 m for each of the two test sites.

Finally, the LCI was transformed into the level of degradation index (LDI) for each of the 15 land cover maps for each test site. LDI, for each land cover map, was determined by subtracting the value of LCI from 100 (that is LDI = 100% – LCI).

Data analysis

Given the nature of the research problem, it was important that the variation of each of three parameters (OCE, INI and LDI) with changing image resolution be determined. Since all the three parameters were converted into values using the same scale (that is 0 to 100%), it was possible to plot the derived values against image resolution on the same graph. The following indices were plotted against image resolution (image pixel size in m):

1. Image noise index (INI) showing the relationship between image noise with changing image resolution;
2. Level of degradation index (LDI) showing the relationship between image object shapes/sizes with changing spatial resolution, and
3. Image classification errors expressed as a percentage.

FINDINGS

Overview

By combining two conventional parameters (image noise and level of classification errors) with a new parameter (LDI), an objective and robust technique for the determination of optimal image resolution, for generating spatial information for savannah grass/wood mixtures of different densities was developed. Using the improved technique, it we estimated that an image resolution range of 2.25 and 2.5 m was optimal for automated image analysis for the savannah ecosystems represented by test sites 1 and 2, respectively.

Variation of image classification errors with image resolution

Image classification errors remained relatively stable at about 30% over 11 image resolutions ranging from 0.5 to 6.0 m (Figure 3). The stability of image classification errors between image resolutions 0.5 to 6.0 m can be interpreted to imply that the spatial information content, in spectral terms, is the same over the defined range of image resolutions. However, from Figure 3, there is a moderate but noticeable increase in image classification errors to about 37 and 43% for test sites 1 and 2, respectively between image resolutions 6 – 10 m. In spectral terms, it can be concluded that an image resolution of 0.5 m results into the same level of image

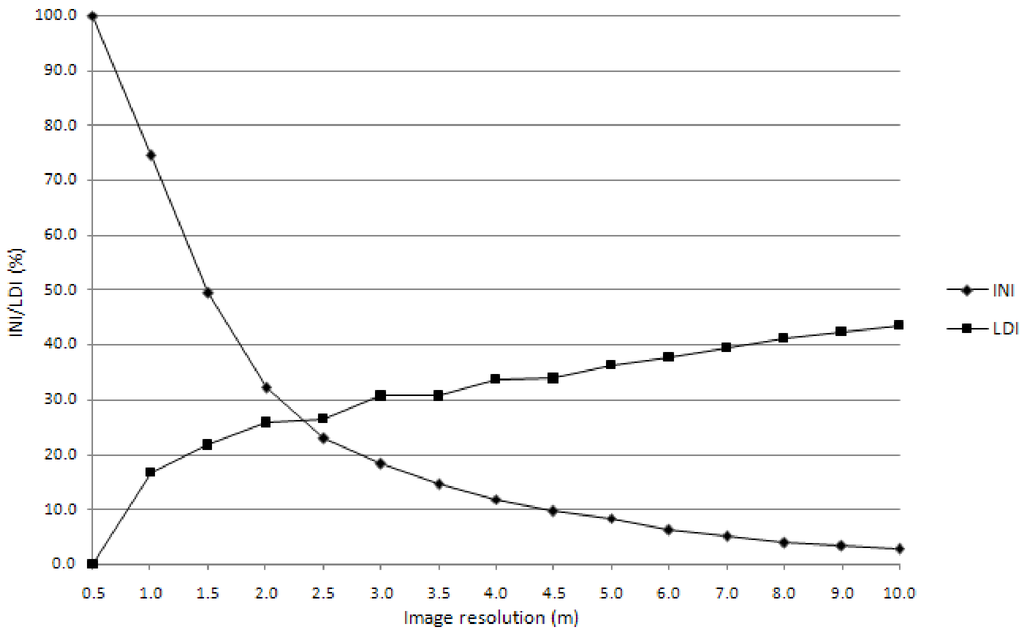

Figure 4a. Plot of LDI against resolutions for test site 1.

classification accuracy as an image resolution of 6 m. Hence, the optimal image resolution for generating spatial information for savannah ecosystems, represented by the two test sites, would be about 6 m based on image classification accuracy curves. However, we also note that image classification errors are not very sensitive to changing image resolution.

Variation of INI with image resolution

There was an approximate and expected negative inverse relationship between image noise index (INI) with decreasing image resolution for each of the two test sites (Figures 4a and b).

The two exponential equations that describe the relationship between INI (y-axis) and image resolution (x-axis) was $y = (115.34)^{-0.288x}$ and $y = (124.69)^{-0.271x}$ for test site 1 and 2, respectively. Fore reference data (image resolution at 0.5 m), the INI is at its maximum of 100% for each land cover map (Figures 4a and b). From Figure 4, it is also observed that between 0.5 and 2.5 m there was a significant reduction in terrain noise by a factor of about 77 and 70% for test sites 1 and 2, respectively.

The image noise reduced by a factor of only about 10% for both test sites when the image resolution was decreased from 2.5 to 5.0 m. Furthermore, the image noise reduced by a factor of only about 6% for both test sites when the image resolution was decreased from 5.0 to 10.0 m. It is difficult to use the two INI curves to predict an optimal image resolution for each of the two test sites because the two curves do not level of within the range of image resolutions considered that is 0.5 – 10.0 m.

Variation of geometric integrity of object shapes/sizes with decreasing image resolution

Fore reference data (at 0.5 m), the level of degradation index (LDI) with respect to the size/shape of geographic phenomena is 0% as shown in Figures 4a and b. However, from Figures 4a and b, it is observed that the LDI increases in a predictable manner between image pixel sizes 0.5 - 10 m. Indeed, the LDI increased by a factor of 43 and 51% for test site 1 and 2, respectively between image pixel sizes 0.5 – 10.0 m. From Figure 4, it is observed that INI and LDI are sensitive parameters, in a predictable manner, with changing image resolution. It is for this reason that we suggest that the optimal image resolution, for mapping savannah ecosystems represented by the two test sites, can be objectively defined at a point where INI and LDI curves intersect in Figures 4a and b. For the two test sites, the optimal image resolution is given as 2.25 m (test site 1) and 2.5 m (test site 2).

DISCUSSION

The continuous degradation of the geometric integrity of object shapes/sizes with decreasing image resolution is an indication that the geometric integrity of savannah features (within and at the boundaries) gets compromised with increasing image resolution as indicated in Figures 4a and b. In Figure 5, it is observed that some level of degradation of the geographic features (associated with the removal of object intra-noise at pixel size 2 m) could be acceptable since it does not significantly compromise

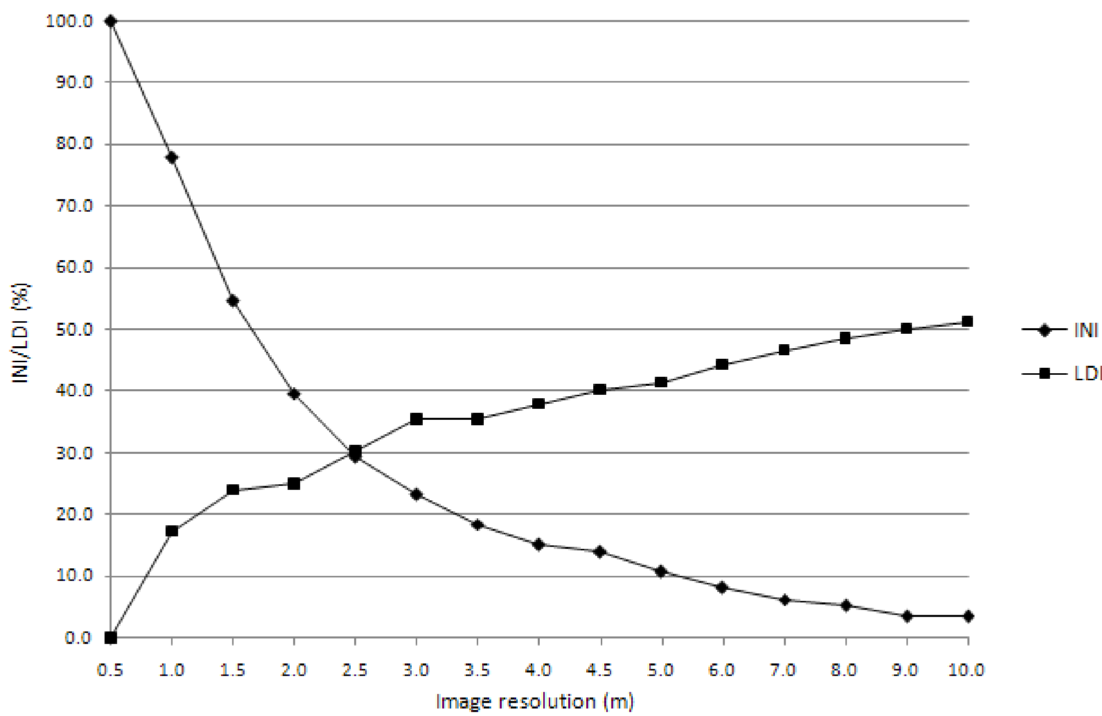

Figure 4b. Plot of INI and LDI against image resolutions for test site 2.

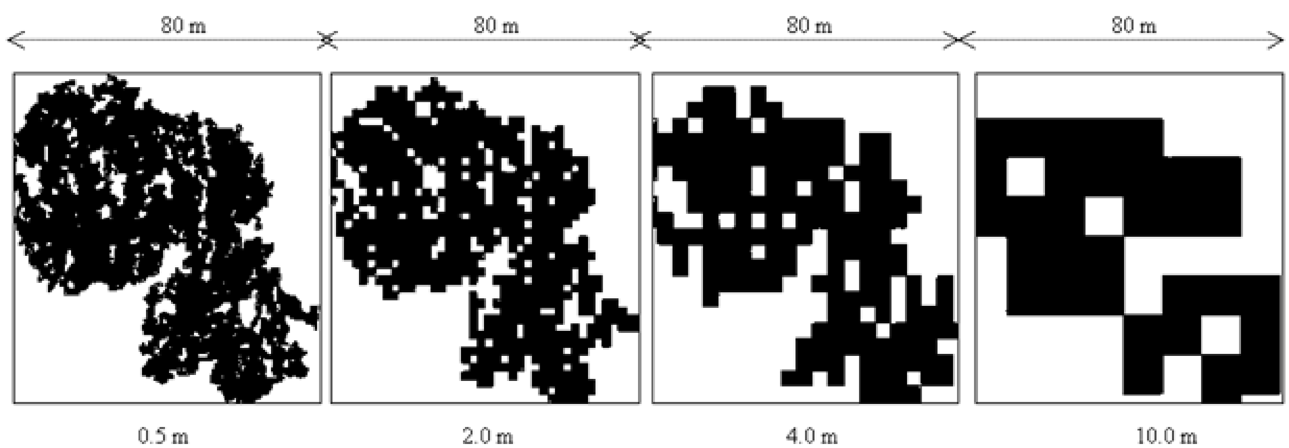

Figure 5. Visual changes in the geometric intergrity of a savannah shrub (dark pixels) with increasing pixel size.

the geometric integrity of the target vegetation objects. However, the removal of object inter-noise (associated with the removal of object inter-noise at pixel 4 and 10 m) significantly degrades the integrity of target objects and may not be acceptable.

Due to this observation, large pixel sizes of imagery do not represent the actual geometric shapes of target objects of savannah vegetation. It is also true that with very large image pixel sizes; most of the small savannah geographic features (like small clumps of wood) that define these ecosystems disappear completely as illustrated in Figure 6. From Figure 6, the relatively large clumps of wood that do not disappear on large image pixel sizes yield mixed spectra (mixed pixels) that do not represent woody or grass vegetation, hence resulting into image misclassifications that lower the accuracy of spatial information generated from Landsat TM for savannah ecosystems (Mugisha, 2007). Since the size/shape of the smallest savannah features may vary from savannah type/phase to another, it can be postulated that there could be different optimal image resolutions for these ecosystems.

By combining INI and LDI, the optimal image resolution for the automated generation of spatial information for

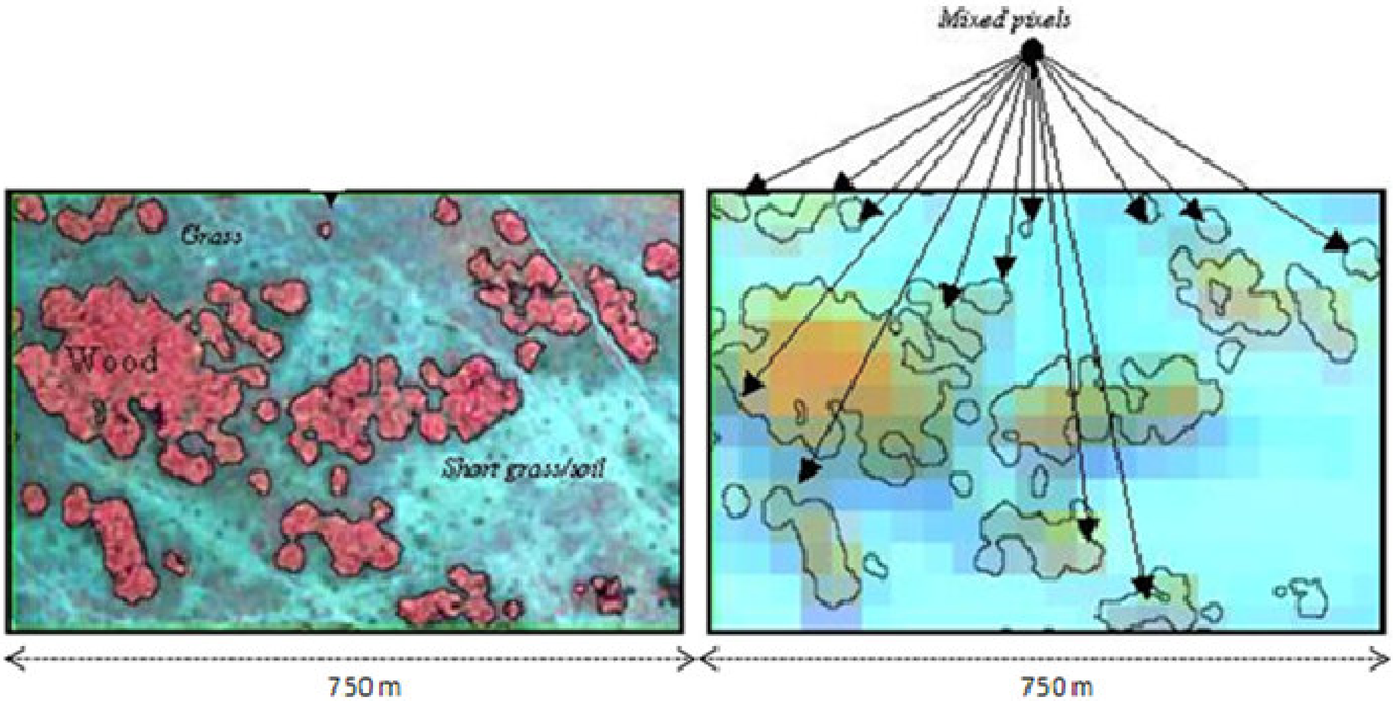

Figure 6. The spectra of high-resolution imagery (0.5 m) represent shapes/sizes of small wood features (shades of red) characteristic of savannah ecosystems but low resolution imagery (30 m) does not.

savannah ecosystems, represented by the two test sites, was predicted to be 2.25 – 2.5 m. The developed technique provides an objective way to predict optimal image resolution(s) for automated generation of spatial information for savannahs and probably for other fragmented ecosystems. This is because the technique is based on solving two simultaneous equations, graphically in this study, as shown in Figures 4a and b when determining the optimal image resolution for each test site. On the other hand, the techniques used by Mugisha and Huising (2002) and Menges et al. (2001) determined the optimal image resolution by subjectively locating the lowest point attained by spectral variance with changing image resolution.

The development of a new parameter, that is LDI, to improve how optimal image resolutions are determined was based on Marceau and Hay's (1999) observation that shape/size is a key attribute that should always be incorporated in image analyses like one conducted in the present study. The significant reduction of terrain noise (INI) with decreasing image resolution is desirable if it does not affect the quality of imagery (Townshend, 1981). What is not desirable is the degradation of the woodland patches with respect to shape/size. This is because the shape/sizes of individual trees, small patches of woodland or grassland that define the vegetation structure of savannahs should be preserved for an image resolution to be optimal. However, terrain noise that is represented by canopy openings is not desirable because it increases the costs of acquiring and analysing remotely sensed data.

In conclusion, by combining image noise index (INI) and the level of degradation index (LDI) of geographic phenomena, it was possible to develop a robust technique for the determination of optimal resolution required for generating large-scale spatial information for savannah vegetation types. Subsequently, it was concluded that multi-spectral imagery acquired by QuickBird 2.44 m rather than GeoEye 1.65 m is optimally suited, both in terms of data quality and cost-effectiveness, for generating spatial information for savannah ecosystems represented by each of the two test sites. However, future research should investigate, using the developed technique, to what extent different savannahs (or their evolutionary phases) hypothetically require different optimal image resolutions (Figure 7) for automated generation of detailed spatial information.

Since the scope of the this study was limited to developing a technique for determining optimal resolution of imagery required for automated image analysis, further research may also be required to determine the optimal resolution of imagery when used visually for mapping savannah ecosystems.

ACKNOWLEDGEMENTS

The authors acknowledge GTZ and IUCN for the financial

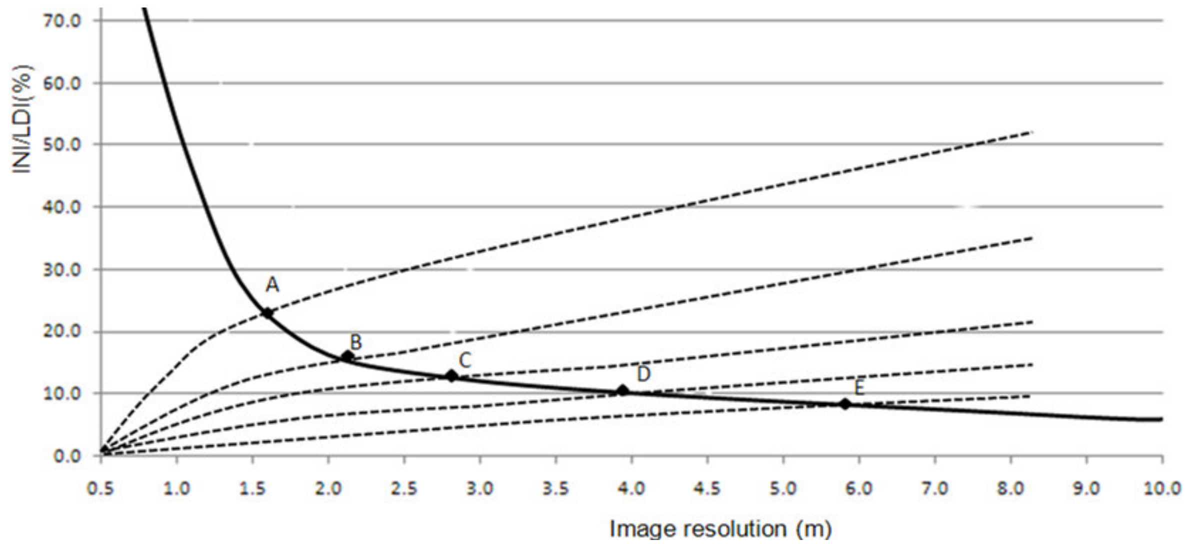

Figure 7. The developed techniques should have the potential to determine to what extent different savannah ecosystems have different optimal resolutions.

support that enabled the authors undertake digital aerial surveys for test sites in Uganda. However, the opinions expressed in this paper are those of the authors but not GTZ and IUCN.

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