OPTIMAL RESOLUTION FOR LARGE-SCALE VEGETATION MAPPING USING AIR-BORNE MULTISPECTRAL DATA

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ABSTRACT:

There is an increasing interest in the use of high-resolution multispectral data (acquired by small format digital air-borne imaging sensors) for large-scale vegetation mapping. Recent studies have focused on the potential of air-borne multispectral data as a means of identifying plant communities. This study is concerned with establishing a formal relationship between spatial resolution and large-scale vegetation mapping. The study was necessitated by the fact that economic considerations take precedence over technical recommendations when selecting imagery data for large-scale vegetation mapping in Uganda. The question is whether there is any scientific justification in acquiring sub-meter imagery data for large-scale mapping of 'low-value' natural resources such as vegetation. Rigorous assessment of both thematic and geometric integrity of vegetation patches mapped from digital air-borne imagery data shows that a formal relationship between large-scale vegetation mapping and high-resolution imagery data can be established. The findings show that there is no scientific justification to acquire sub-meter imagery data for large-scale vegetation mapping. It is concluded that digital air-borne data acquired at spatial resolutions greater than sub-meter is optimal for cost-effective large-scale vegetation mapping.

1. INTRODUCTION

1.1 Overview

Between 1998 and 1999, high-resolution *digital air-borne data* (DABD) were acquired for 12 "hotspot" conservation sites in Uganda by a number of organisations including Uganda Wildlife Authority-GTZ, Uganda National Wetland Programme-IUCN and the UNDP-GEF East Africa Cross-Boarder Biodiversity Project. With the exception of one site (Nakivubo Swamp in Kampala District) none of the DABD have been analysed.

There are two compelling reasons why this study is crucial. First, there has not been any aerial photographic survey by the Ugandan state (except for urban areas) since 1955. This situation has resulted in selective aerial surveys for a number of protected areas in the country. It is also observed that all the selective aerial surveys in Uganda have been paid by donor money through short-term conservation projects. Through selective aerial surveys, thousands of conventional black/white photographs were acquired for more than 20 protected rain forests in Uganda in 1989 - 1990. After more than 12 years, vegetation maps have been generated for only 4 out of the 20 rain forests.

Digital aerial surveys commissioned by a number of organisations in 1998-1999 in the country were a reflection of the belief that automated vegetation mapping would be more cost-effective than using conventional manual techniques. However, the advantages of using computers for processing and analysing DABD were outweighed by more image frames (per unit terrain) acquired by digital compared to conventional photographic systems. In short, there is a bottleneck in processing DABD because of the large number of image frames per unit terrain area. This is exemplified by more than 240 image frames (0.5m resolution) acquired for a terrain as small as 10km x 10km for Nabugabo Ramsar site in 1998. The image frames (equivalent to 9Gb of data after importing into MicroImages TNTmips) posed considerable strain on financial, computing and human resources required for generating a large-scale vegetation map (1:10,000) for the area. In the end, no vegetation map was generated, anyway.

Nonetheless, high-resolution imagery data, whether captured by aerial digital photographic systems or space-borne sensors, have a potential for large-scale vegetation mapping in countries like Uganda. However, it is also true that there is general lack of scientific information regarding *optimal spatial resolutions* needed for large-scale vegetation mapping of different landscapes. More often than not decisions regarding resolutions for vegetation mapping are economic-driven. Therefore the huge financial, computing, time and human resources required to generate spatial information from DABD acquired at sub-meter resolutions cannot be underestimated, especially for organisations running on small budgets. What needs to be established is a *formal relationship* between high-resolution imagery data and desired large-scale maps. If a formal relationship between spatial resolution and large-scale vegetation mapping is established, it may indicate that sub-meter images are not needed, after all. This should then be reflected in substantial reductions in financial resources needed to acquire, process, and analyse DABD.

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1.2 Aims

The aim of this investigation was to establish whether *sub-meter resolution* data is largely 'noise', *even* for large-scale vegetation mapping. In the next subsection, related work done elsewhere is reviewed. The methods and materials used are discussed in Section 2. This is followed by a presentation and discussion of preliminary** results in Sections 3 and 4. Finally, preliminary conclusions and recommendations are presented in Section 5.

1.3 Literature Review

The increasing availability of digital air-borne imaging systems has generated a high interest for large-scale vegetation mapping in many countries. For example, high-resolution imagery data acquired by CASI have been used by von Hansen and Sties (2000) for large-scale (<1:25,000) vegetation mapping of plant communities in a wetland ecosystem in Germany. Kurnatowska (1998), too, used high-resolution imagery data to delineate plant communities in mountainous areas of Poland.

However, none of the above authors mentions image 'noise' as a hindrance for large-scale vegetation mapping using DABD. On the other hand, Quackenbush's *et al*. (2000) recognised image 'noise' associated with high-resolution imagery data as a hindrance to vegetation mapping, even though 'noise' is mentioned only in the context of how it affected overall classification accuracy of vegetation information derived from DABD for a forest ecosystem in New York State, USA.

The concept of *optimal spatial resolution* for generating large-scale vegetation information is relatively recent, like aerial digital photographic system technology itself. What are common, in remote sensing literature, are advances in sensor and image processing technologies designed to overcome limitations imposed by mixed pixels or generating high-resolution imagery data. Hence, most studies (see for example, Müller and Segl (1999)) conducted to assess the effects of varying spatial resolutions on image information content are initiated for imaging sensor development. Such studies use *simulated* rather than *actual* data when developing imaging sensors. It is therefore crucial that scientific facts on image 'noise' should be provided to conservation organisations trying to *substitute* unaffordable conventional with *cheap* digital aerial photography.

However, the concept of optimal image resolution for *desired information* has been studied by Atkinson and Curran (1997). Atkinson and Curran's (1997) study, though designed for biomass mapping, provided a useful concept and terminologies adapted in this. This is because the two authors recognised the need for a formal relationship between image pixel size and a *measure of information content* for biomass mapping. The major difference between this study, and Atkinson and Curran's is that vegetation information content is *discrete* while biomass is *continuous*. The authors recognise that current scientific trends cited in GIS and remote sensing literature recommends that vegetation information be treated using *fuzzy set logic*. However, as pointed out by Zhang and Kirby (1997), high-resolution photographic data can still be used for visual delineation of land cover categories without the need for fuzzy set logic. The authors of this paper are of the view that *per-pixel* image classification for vegetation mapping from DABD is possible. For that matter, maps analysed to establish a formal relationship between spatial resolution of DABD and vegetation information (in this study) were produced using per-pixel image classification techniques.

To establish a formal relationship, it was necessary to identify *measurable characteristics* of vegetation information content that might change with decreasing spatial resolutions of DABD. Two measurable vegetation characteristics normally assessed are *shape* and *attributes* of individual patches. Both shape (of boundaries) and attributes (thematic contents) form one *entity* referred to as a *geographic meaning.* An *entity* is a terminology widely used in the field of computer database management systems, and Oxborrow (1989) defines it as something which exists in the real world and posses characteristics of interest to man. On the other hand, Nyerges (1991) points out that a geographic meaning is composed of thematic and geometric properties. It was, therefore, essential to measure how the two characteristics of vegetation entities (shape and attributes) change as resolutions of DABD decreased from sub-meter to smaller resolutions. The trends observed, it was assumed, would provide evidence to allow the authors either accept or reject the following hypothesis:

Digital air-borne data acquired at sub-meter spatial resolution are not significantly 'noisy' for large-scale vegetation mapping.

As it is conventionally done, cartographic scales have to be taken into consideration when generating geographic data. A cartographic scale of 1:10,000 (minimum mapping unit of $100m^2$) was used. A minimum object size of $100m^2$ would still allow identification and mapping of most individual large trees and small patches of other land cover types characteristic of semi-natural and natural Ugandan ecosystems. The next section describes the techniques developed to test the hypothesis.

2. METHODS

2.1 Selection of Study Sites

Two test sites, selected from Nabugabo Ramsar, were characterized by patches of rain forests, shrubs, tall/short grass and papyrus. The third test site, (Nakivubo Swamp) was characterized by papyrus, *Phragmites sp.*, *Echnocloa sp*, *Miscanthus sp*., and to a large extent, yam plantations.

2.2 Data Used

High-resolution data used during this study was acquired by an Aerial Digital Photographic System (model DCS560) developed by Eastman Kodak Company. GeoTechnologies, a company owned by Bath Spa University College, England, was hired to conduct digital aerial surveys for the study sites in 1998 (Nabugabo Ramsar Site) and 1999 (Nakivubo Swamp). The sensor mounted in DCS560 is an electronic Charged Couple Device (CCD) with a 9 чm square picture cell arranged in a 2034 x 3060 array, producing approximately 3.1 million pixels in the multispectral mode (Koh *et al.*, 1996). The DCS560 captures a composite image frame per scene. Each pixel on the CCD is coated with a filter to produce a *Bayer colour filter* array that has twice the number of red pixels as infrared/green or blue (Dean *et al*., 2000). The matrix in Table 1 shows part of a hypothetical part of the CCD showing the arrangement of the filter array. This study is not in position to comment on the technical implications of such a technique of data acquired by DCS560 on vegetation identification. However, Dean *et al*.

** study still in progress.

(2000) point out that such a technique reduces the overall spatial resolution of Near Infrared and Green channels.

	0	1	2	3	4	5	.
0	r	ir	r	ir	r	ir	
1	g	r	g	r	g	r	
2	r	ir	r	ir	r	ir	
3	g	r	g	r	g	r	
4	r	ir	r	ir	r	ir	
5	g	r	g	r	g	r	
.							

Table 1. Arrangement of color filters on sensor elements of the DCS560 CCD *(adapted from Dean et al. (2000))*

On the other hand, R. Birnie (personal communication, 2002) is of the view that each image covers a slightly different area, a situation that is likely to increase 'noise' effect. Birnie's observation may be of concern especially if vegetation entities are very small. However, for even small clumps of trees and shrubs, 'noise' emanating from the technical operation of Kodak DCS560 may be insignificant.

The operational principle of DCS560 is the same as a normal color infrared (CIR) film. Radiation is recorded in three channels: photo infrared radiation (700-900nm), red (680-700nm) and green (500-680nm). Blue (400-500nm) is filtered out.

Prior to importing the data into TNTmips (MicroImages Inc.), each image frame was separated into its constituent bands (photo infrared, red and green). The size of each image frame was 36Mb after importing into TNTmips, giving more than 360Mb of data for the 10 image frames used during this study.

2.3 Image Processing and Classification

DABD of each site was processed/classified using standard techniques. Prior to image classification, individual image frames for each study site were georeferenced, rectified and mosaicked together. *Piecewise Affine* transformation model was used to rectify each image frame. While planimetric accuracies of the rectified DABD images were not determined quantitatively, visual comparison with existing vector linear features overlaid on rectified image frames showed a good match. This was an indication that DABD can be accurately rectified to generate information for further integration in a GIS environment as pointed out by (Mason *et al.*, 1997). In their study (Mason *et al.*, 1997), the two authors found out that rectified DABD yielded acceptable errors of ±0.2m and ±0.6m in the horizontal and vertical directions respectively (Mason *et al.*, 1997).

Each image mosaic was *resampled* using an interval of 0.5m, hence generating the following data sets: 0.5m, 1.0m, 1.5m, 2.0m,…,4.5m, and 5.0m for two sites selected from Nabugabo Ramsar site; and 2.0m, 2.5m, 3.0m,…,4.5m and 5.0m for Nakivubo Swamp. Best results were generated when resampling was carried out using *Cubic Convolution* technique.

Ground truthing was conducted to define vegetation categories and select training data prior to image classification. *Random stratified* sampling technique was used as a basis of collecting field data. This was achieved by stratifying vegetation categories into broad classes (forests, shrubs, papyrus and grass) before randomly describing and selecting training sites. Complete random sampling was not possible for any randomly selected vegetation strata due to limited accessibility of some areas. A GIS database was generated from the field-collected data for each site. The database was used for carrying out a supervised image classification of all the DABD sets obtained by resampling each image mosaic. The generated vegetation information was used as a basis for determining the *integrity* and *patchiness levels* of vegetation patches of each test site, as described in the following subsections.

2.4 Data Analysis

Vegetation entity characteristics (shape and attributes) were assessed not by direct measurement but by assessing two vegetation indices: *Vegetation Patch Integrity* (VPI) and *Vegetation Patchiness Level* (VPL). Patchiness, in this paper, refers to the sum of area derived from all polygons (patches) of a given vegetation category for each test site. *Area* was used as a surrogate for assessing not only vegetation entity attributes but also shape of boundaries. On the other hand, the number of vegetation patches (VPL) was used as a measure of terrain complexity (both image 'noise' and actual vegetation entities) for each map. The next two subsections describe how both VPI and VPL were measured for each of the 27 maps.

2.4.1 Measurement of Vegetation Patch Integrity

To estimate VPI, it was necessary to assess the two characteristics that characterise a vegetation patch as geographic entity. These characteristics, as explained earlier, are boundary properties and attributes of vegetation patches. Conventional classification accuracies are determined to assess attributes of mapped geographic entities. This is achieved by comparing sample reference data with mapped terrain features. A single statistical parameter such as *overall classification accura*cy (OCA) or *Kappa value* is then derived as a measure of the accuracy level of the produced map (Lo and Watson, 1998).

However, measuring overall classification accuracies using conventional techniques falls short of deriving VPI required for this study. This is because conventional techniques only focus on one aspect of geographic entities i.e. attributes. The second component of a geographic entity (shape characteristics of boundaries) is not assessed. To assess VPI, both thematic and shape characteristics were measured. However, mathematical description of shape of natural phenomena is not an easy exercise. While there are relevant algorithms designed to characterise geometric properties of terrain object entities in standard Vector GIS software, none of them was used. This is because, as pointed out by MicroImages Inc. (1998), shape is a difficult property to measure or define precisely and interpretation of outputs derived from overlays performed in Vector-based GIS is not easy. There is a way out though: use of *area*, not only as a practical technique of comparing shapes of vegetation patches (derived from images of different resolutions) in a raster format, but also as a rigorous measure of classification accuracies. Area is thought to be a good indicator of size. For example, Monmonier (1991) found out that polygon boundaries can be suitably generalized for presentation at different scales if the algorithm focuses on their internal areas, rather than on the network of boundaries. The limitation though is that objects of different shapes may have the same area. A technique, described later, was developed to this limitation of using area (size) of different vegetation patches as a measure of vegetation patch integrity.

The above argument does not mean that shape indices cannot be derived from vector boundaries: they can and have been used in other studies. For example, Comber *et al*. (2001) used an index derived from shape (ratio of *perimeter* to *square root of area*) to test the *propensity of land cover to change* in semi-natural ecosystems of Scotland. Two relevant Vector GIS algorithms are also being used to validate the results of obtained in this study. The two algorithms, provided in TNTmips, are '*Complexity and Integrity of Polygon Boundary Shape*' and '*Polygon Proportions*'. The first algorithm is a coefficient between *x*- and *y*-coordinates and the second is derived by determining the *elongation* of a polygon by dividing *Short Axis* with *Long Axis.* However, the two algorithms are being used with only sample polygons to validate the technique developed for this study.

Therefore, in this study, VPI derived from area of patches belonging to the same vegetation category for each site. This approach was deemed practical because sub-meter spatial resolution of DABD (0.5m) used in this study is so fine that it actually represents well actual vegetation boundaries. The key question is: *at what DABD spatial resolution does area obtained from resampled sub-meter data significantly deviate from actual vegetation boundaries?*

As stated earlier, while area is a surrogate for entity size, it cannot represent the various vegetation entity shapes that have equal area. To overcome this limitation, it was necessary to determine the *ratio* of area (derived from different maps produced from DABD resampled at different resolutions) to *reference* area (derived from nonresampled DABD). The calculated ratio, is what gives vegetation patch integrity, VPI, used to test the working hypothesis. This approach was deemed robust enough to yield accurate VPI values whilst at the same time allowing simple raster overlays to be used during data analysis.

VPI was determined as follows: (a) two binary maps (representing each vegetation category derived from nonresampled and resampled DABD) were overlaid together in ArcView GIS. Area of the resultant map was determined from the total number of pixels. The area determined in (a) is referred to as V*ariable Area*, VA. (b) Reference area (referred to as *Constant Area*, CA) of each vegetation category was derived from DABD at a resolution of 0.5m (2.0m for test site 3). VPI was calculated as a ratio between the two areas using the following formula:

$$VPI(\%) = VA/CA \times 100 \quad (1)$$

Different VPIs were calculated for each defined vegetation category (not each patch) and for all the spatial information derived from the 27 DABD images. Note that for the reference data, VPI was 100%.

2.4.2 Measurement of Vegetation Patchiness Level

Vegetation Patchiness Level ratio, VPL*(%)* was determined from *Variable Patchiness, VP,* and C*onstant Patchiness, CP*. Patchiness was derived from the total number of polygons of each vegetation category for each site. Unlike VPI, VPL was determined as an nonspatial value, i.e. VP was not obtained through an overlap process. VPL was determined using the following formula:

$$VPL\ (\%) = VP/CP \times 100 \quad (2)$$

2.4.3 Other Variables Measured

Three other variables were determined for the 27 maps. First, conventional overall classification accuracy was determined for each vegetation category. Data collected during fieldwork was used to determine conventional overall classification accuracies for each map and test site. Each map was smoothed using a 3x3 followed by 5x5 filter before determining overall classification accuracies. Secondly, time (minutes) required to complete a supervised image classification was recorded for each image data set. Third, file size (in megabytes) of each of the 27 image mosaics was determined.

3. RESULTS

Results presented in this paper are still preliminary. Only overall VPI and VPL for each test site are presented. VPI and VPL of individual vegetation categories are still being validated.

Table 2 shows a summary of the different vegetation categories (and other land cover types) defined for each of the three test sites. In all, eight land cover categories were identified and mapped in the three test sites.

Land cover	**Area per land cover category (ha)**		
	Site 1 (0.5m)	*Site 2 (0.5m)*	*Site 3 (2.0m)*
Yam plantations	-		87.2
Papyrus	-	16.8	257.3
Tall grass (Miscanthus)	120.1	211.2	28.8
Short grass/bare soil	40.2	11.4	52.6
Wood/forest	71.4	26.8	-
Bananas	-		68.1
Eucalyptus	-		7.5
Water	44.8		6.8
Total	276.5	266.2	508.3

Table 2. Total area for each vegetation (cover) category mapped from DABD

Figure 1 shows the *overall Vegetation Patch Integrity (VPI)* and *Vegetation Patchiness Level (VPL)* plotted against square of spatial resolution of DABD for each test site. A small variation in VPI is observed between image resolutions 1.5 – 4.0m. On the other hand, there is a moderate VPI decline (not more than 20%) between reference data (0.5m) and spatial resolution of 1.5m. On the other hand, VPL, while showing a similar trend as VPI, exhibits a larger (on average about 70%) between image resolutions 0.5m – 1.5m. Beyond 1.5m, VPL (like VPI) shows a small but stead decline for each test site.

The results also show that while the general trends in VPI and VPL are similar for all the three test sites, each site has its unique line curves. This is a reflection of some differences in heterogeneity of vegetation entities found in the three test sites. For example, test site 2 is characterized by two major homogeneous vegetation categories (big forest and tall grass patches). Test site 1 is characterized by smaller patches of shrubs and short grass/bare soil, in addition to big forest and tall grass patches. Lastly, test site 3 is characterized by big patches

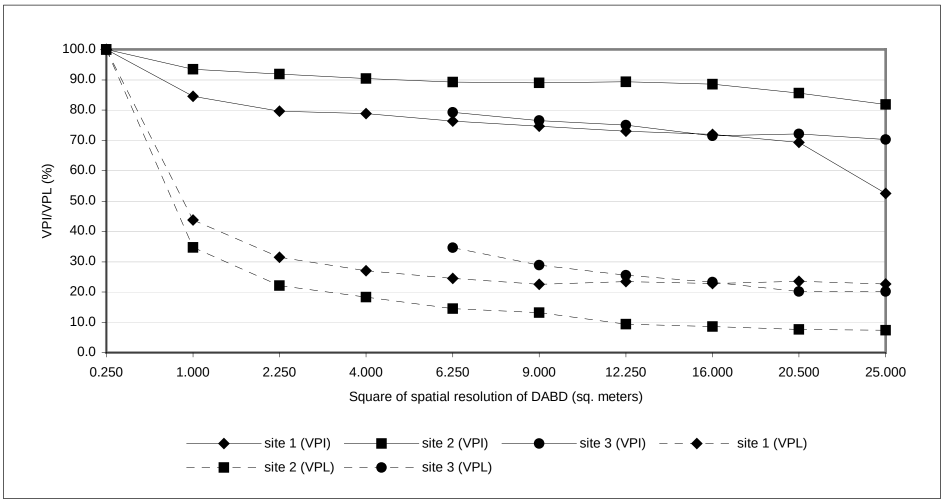

Figure 1. VPI (solid lines) and VPL (broken lines) for the three test sites

of papyrus and tall grass, but with numerous patches of yam and bare soil gardens (at the time of acquiring DABD).

On the other hand, Figure 2 shows variation of overall classification accuracies (OCA) plotted against square of spatial resolution of DABD. There is a steady, though small, increase in OCAs with decreasing spatial resolution. This is expected, since decreasing spatial resolution tends to reduce image 'noise'. As shown by three logarithmic line curves derived from the plotted data, there is a moderate increase in OCA of each test site. The mean square error value for each logarithmic line curve is also shown. There is a false impression of a slight but continuous increase in OCAs between reference data and resampled images.

The results depicted in Figure 3 show that change in image file size (solid lines) and time required to complete a supervised classification (broken lines) show a similar trend of sharp decline between 0.5m to 1.5m as observed for VPL. Between image resolutions 0.5m and 1.5m, image file falls by an average of 90%, reflecting a reduction in file size from 36Mb to 3.6Mb per image frame. Given that vegetation patch integrity (VPI) declines by a factor of only 15%, it is fair to conclude the sharp fall in VPL and image size with decreasing spatial resolution of DABD is largely due to the removal of image 'noise', but not actual vegetation entities.

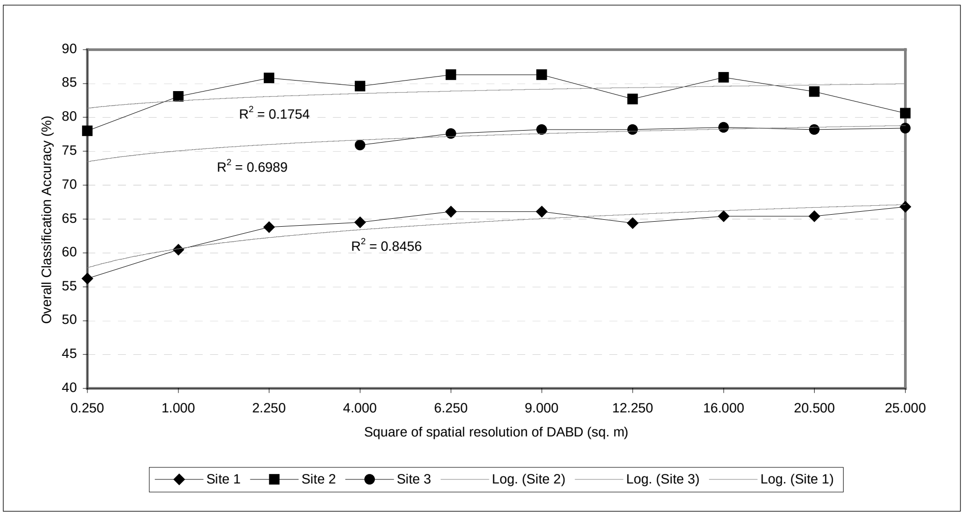

Figure 2. Overall classification accuracies determined by conventional techniques

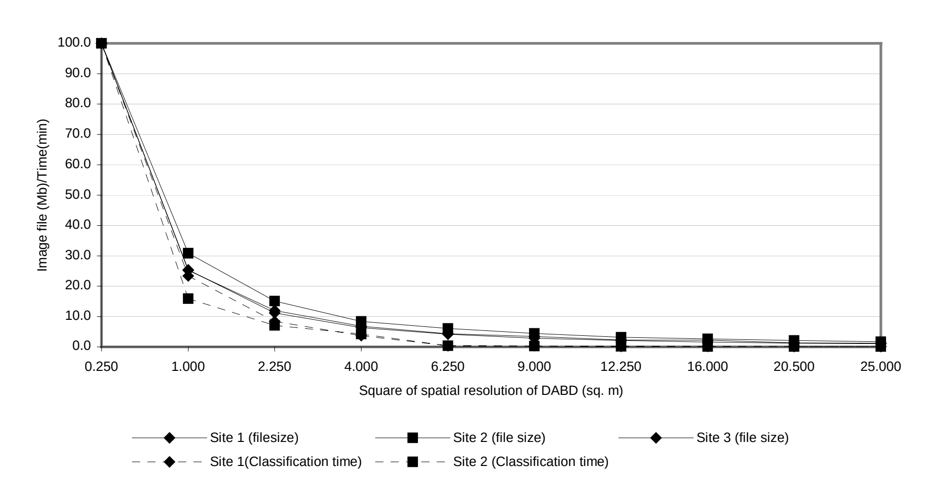

Figure 3. DABD image file size/time (ratios between reference data and decreasing spatial resolution)

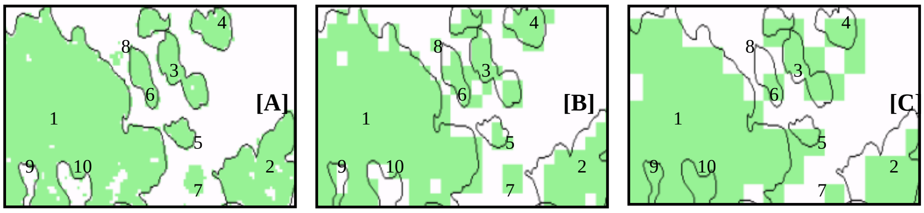

Figure 4. Graphical illustration of how VPI and VPL change with decreasing resolution of DABD

Figure 4 is a graphical illustration of how image 'noise' is removed without adversely affecting vegetation patch integrity. Part [A] of Figure 4 shows 8 clumps of shrubs (solid green colour) and grassland (white background). The dark solid boundaries (overlaid on the three images) depict boundaries generated from DABD at a spatial resolution of 2.5m. There are eight wood patches generated from DABD at a resolution of 0.5m. At this resolution, the geographic integrity of both wood and grass is at its highest quality, meaning that the boundaries of the two terrain features are as near to reality as the scale of mapping could allow.

However, spatial information generated from DABD resampled at 2.5m (dark lines) shows that two small wood patches are excluded in the final map. Part [B] of Figure 4 depicts the quality of the spatial information generated from the same image but resampled at 4.0m. Compared with spatial information at 0.5m and 2.5m, all the wood polygons are still present but several small grass patches have been eliminated. Further more, the geometric boundaries between wood and grass have deteriorated.

Lastly, spatial information generated from DABD resampled at a spatial resolution of 8m shows that another small polygon (8) has disappeared. Further, two small grass polygons (9 & 10) have been aggregated into the largest wood polygon. A further deterioration of boundaries between wood and grass is also observed.

4. DISCUSSION

A sharp fall in VPI and VPL between 0.5m – 1.5m is a reflection of the removal of a few very small vegetation patches and significant image 'noise'. On the other hand, the small decline of VPI and VPL between 1.5m – 4.0m is an indication that most of the very small polygons and much of the image 'noise' associated with sub-meter image resolutions are less significant. From the results presented in Figure 4, it can be concluded that the slight decline of both VPI and VPL is due to continued but moderate deterioration of vegetation boundary characteristics as the spatial resolution decreases beyond 1.5m. This is of practical importance since it implies that cost-effective large-scale vegetation mapping (1:10.000) is possible with image resolutions acquired at a spatial resolution greater than 1.5m.

Secondly, an image frame acquired at a resolution of 1.5m would cover more than 14 km^2 (1.5m x 2034 x 1.5m x 3060/1,000,000). Such image frames can be acquired by a C-172 plane flying at an average altitude of 15,000 feet, according to A. Koh, (personal communication, 1998). In contrast, each image frame used in this study (0.5m) covers only 1.5 km^2 (0.5m x 2034 x 0.5m x 3060/1,000,000). In summary, acquiring DABD at a resolution of 1.5m instead of sub-meter resolution would mean processing and analysing *one* instead of at least *nine* image frames (14/1.5). The resources saved (both financial and time), while not quantified during this study would be immense if image frames are acquired at a resolution of 1.5m.

5. CONCLUSIONS

Based on the preliminary results presented in this paper, the null hypothesis is thus false: *Digital air-borne data acquired at sub-metre spatial resolution are largely 'noise' when used for large-scale vegetation mapping.* Large-scale vegetation mapping (e.g. at 1:10,000) require high-resolution data, but not sub-metre resolutions. Acquiring DABD at a resolution of 1.5m – 2.0m not saves financial resources required to pay for acquisition of DABD but also costs required to store, process and analyse the huge volumes of data.

It is, therefore, recommended that the thousands of image frames acquired for the 12 "hotspot" conservation areas in Uganda be resampled to spatial resolutions between 1.5m - 4.0m before using the data for vegetation mapping.

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