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Enschede, The Netherlands, February, 2012

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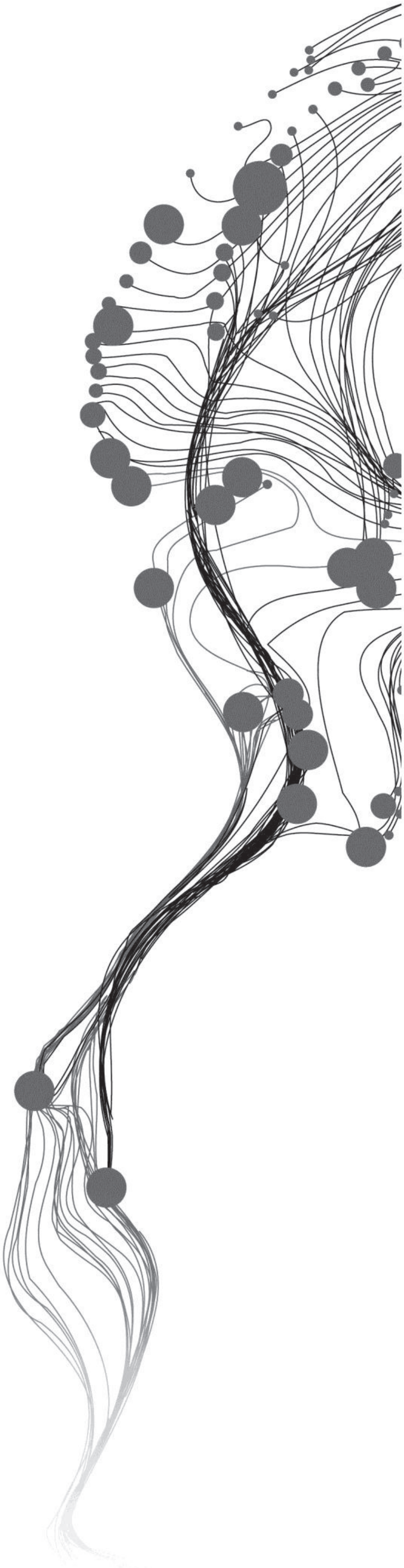

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Thesis submitted to the Faculty of Geo-Information Science and Earth Observation of the University of Twente in partial fulfilment of the requirements for the degree of Master of Science in Geo-information Science and Earth Observation.
Specialization: Natural Resource Management

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ABSTRACT

Traditional methods of counting wildlife (e.g., ground or aerial survey) not only disturb the animals but also can be exceedingly time consuming, labour intensive and costly. In contrast, high resolution satellite images, which have the advantage of covering large areas, short cycling time, silence, and demanding less manpower, offer an alternative method to support animal surveys in the in open savannahs. However, the question about whether current high resolution satellite images are capable of capturing medium to large-sized herd animals such as wildebeest, zebra and buffalo still remain unknown. The present study was conducted in an attempt to map and estimate the population sizes of wildlife from the high resolution GeoEye-1 satellite images in the Masai Mara National Reserve. Two different image classification approaches, i.e. pixel-based approach and object-based approach have been selected to evaluate the capacity of GeoEye-1 imagery to detect animals. Besides, we analysed the factors affecting the performance of the two approaches and compared the performance of pixel-based and object-based approaches in the areas with different animal distribution. We successfully accomplished the objective of mapping wildlife in open savannahs. Specifically, we managed to detect the presence of wildlife in the pilot study area and give an estimation of the population size. Both image classification approaches produced satisfactory results in automated recognition of animals in the pilot study area. The producer's accuracy ranged from 84.2% to 88.2% and the user's accuracy ranged from 85.0% to 92.5% by using pixel-based and object-based approaches respectively. Statistical analysis indicates that the density of animals did not affect the accuracy of both pixel-based and object-based approach, and there is no significant difference between the performance of pixel-based and object-based approaches in user's accuracy and population estimation. However, the pixel-based approach was proved having better producer's accuracy than object-based. We conclude that high resolution GeoEye-1 satellite imagery is suitable for mapping medium to large-sized wildlife as well as population estimation in open savannahs, but not ready for counting absolute number of animals. In addition to the conclusion, we also make recommendations regarding the application fields of the pixel-based and object-based approaches for mapping wildlife in open savannahs applied in this study.

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1. INTRODUCTION

1.1. Background

Biodiversity, including wildlife is decreasing at alarming rates all around the planet. According to a recent survey conducted by the International Union for the Conservation of Nature (IUCN), globally nearly a fourth of all mammals species are extinct or threatened (Vié, Hilton-Taylor, & Stuart, 2009). For example, nearly 70% of the wildlife has been lost from 1976 to 1996 in the Mara part of the Serengeti-Mara ecosystem (Njuguna, Wilson, & Lamprey, 2003). Monitoring of wildlife distribution and population dynamics is therefore essential for biodiversity conservation. In fact, wildlife managers, conservationists, and policy-makers all are interested in indicators which incorporate the information about population status and trend of multiple species (Mawdsley & O'Malley, 2009). For most managers, estimates of population totals are viewed as the most important information obtained from wildlife surveys (Khaemba & Stein, 2002).

Generally, accurate estimates of wildlife populations are important for the following reasons. First, the richness of wildlife is an important indicator for accessing the performance of biodiversity conservation (O'Brien, 2010; Vierikko et al., 2010). Second, wildlife tourism contributes a great portion of the national income of many countries, especially in Africa. For example, mainly based on the abundance of wildlife, tourism in Tanzania constitutes 7.5% of country's GDP, 25% total export earnings, and second leading foreign exchange earner (Wade, Mwasaga, & Eagles, 2001). Third, sustainable management of wildlife resources in regional development also requires a good understanding of population dynamics of the species (Federico & Canziani, 2005).

Traditional methods used for counting wildlife like ground or aircraft survey have many problems (Fleming & Tracey, 2008). First of all, it is exceedingly time consuming, labour-intensive and costly. Moreover, sometimes the counting teams in field survey could experience challenges (Figure 2). The most recent population census for Mara ecosystem of eastern Africa is of the Mara count 2002, which involved 22 vehicle counting teams, 3 aircraft counting teams, 20 organisations and 84 individuals (Njuguna, et al., 2003). Figure 1 (Reid, 2003) show some details of the Mara count 2002. Though some of current census methods can guarantee relatively high accuracy, however, for wildlife biologists, balancing the need for accurate estimates of wildlife populations with survey costs is still going to be a great challenge (Noyes, Johnson, Riggs, Schlegel, & Coggins, 2000). Second, the results of traditional surveying method are not very reliable due to the bias and large standard error of the survey result (Quang & Lanctot, 1991; Samuel, Steinhorst, Garton, & Unsworth, 1992). Therefore, the existing methods are badly needed to be improved.

Contrary to traditional way of animal surveying, the use of satellite imagery to count animals has three main advantages. First of all, satellites have wider covering area than traditional ground or aero survey, which makes it possible to finish animal survey in a short time using satellite imagery. Second, most animals are sensitive to disturbance by human beings (Edwards & Abivardi, 1998; Taylor & Knight, 2003) and also to low-flying airplanes because of the noise of the engine. This leads to another great advantage of using satellite imagery—silence. The survey can be done without disturbing animals and therefore the result potentially can be more accurate than with methods which disturb the animals. Third, using remotely sensed imagery is less manpower demanding than using traditional way (Laliberte & Ripple, 2003). All these points mentioned above make using satellite imagery can be an alternative method to support the animal survey in the large, open, and remote areas.

Though there are many advantages in using satellite imagery to conduct animal survey, we do, however, have to be able to realize automated recognition of animals on the high resolution satellite imagery. This is a key issue for counting animals. Given that few studies have been made to identify animal objects in natural areas using high resolution satellite imagery, in addition to the research has been done about counting or recognizing animals, it may be wise for us to also refer to some relevant studies in other areas.

Counting teams briefing the members on tasks

Counting teams ready to start

Counting teams working

Field survey challenges

Figure 1 Counting teams in the Mara count 2002 (Reid, 2003)

1.2. Feasibility of this study

Pixel-based classification methods using spectral reflectance to identify interest objects are being widely applied in the field of remote sensing. Now, with the development of remote sensing technologies, more and more studies were made with high resolution imagery. For example, GeoEye-1 high resolution satellite imagery was used to assess canopy mortality (Dennison, Brunelle, & Carter, 2010). The average canopy diameter of the trees in the study was 2.4 m, which is similar to the body length of large mammals on the open savannahs. Since large mammals and trees are similar in size, and they have distinct spectral signature, the animals could potentially be identified using pixel-based approach.

Object-based classification and feature extraction from high resolution satellite images is an active research topic in the field of photogrammetry, and it has been applied primarily in urban areas for classification and extraction of urban objects (Kong, Xu, & Wu, 2006), such as roads, buildings, and even vehicles (Jin & Davis, 2007). Instead of pixel-based classification directly classifying each pixel on the image, object-based classification classifies the objects which stand for homogenous areas on the image (Liu & Xia, 2010). Both of spectral and spatial information would be considered in the object-based classification. Besides, expert knowledge can be integrated into the object-based approach as rule set. In fact, the characteristic of object-based classification that considering relationship between pixels in addition to pixels themselves stimulates the way of human eye identifying objects (Hudak & Wessman, 1998), which would be very helpful for recognizing objects in a complex background. Since large mammals have comparable size with vehicles, the object-based approach could potentially be applied as an alternative approach in this study.

In past few years, many algorithms were developed for automated counting animals (Bajzak & Piatt, 1990; Cunningham, Anderson, & Anthony, 1996). However, most of them used aerial photograph or high resolution remotely sensed thermal data (Gilmer, Brass, Strong, & Card, 1988; Wyatt, Trivedi, & Anderson, 1980) instead of satellite imagery, perhaps due to the limitation in spatial and spectral resolution of satellite imagery. The only one attempt on counting animals using high resolution satellite imagery was made by Laliberte & Ripple (2003). It is concluded that animals could be counted in the area containing the cattle and not including trees or shrubs from the IKONOS satellite image, and a panchromatic QuickBird satellite imagery with a 0.61 m resolution would be capable of counting animals under the same condition.

Now, with the new generation of high resolution satellite imagery, like QuickBird, IKONOS, and Geoeye-1, it is becoming possible to apply these methods to automated recognition of wildlife using satellite imagery. Taking Geoeye-1 satellite imagery for example, it has a 0.41m panchromatic (resampled to 0.5m resolution when it is sold to commercial customers) and 1.65m multispectral resolution, which potentially could be enough for recognizing the animals. Based on what we have discussed above, we propose to use two different image classification approaches, i.e. pixel-based and object-based, to realize automated recognition of animals.

1.3. Challenges of confounding factors

Laliberte & Ripple (2003) concluded that the cattle could be counted from the IKONOS satellite image in the area not containing trees or shrubs. However, in this study, the landscapes in this study area are much more complicated than that previous study, including trees, grassland, shrubs, water bodies, bare soil and sand. Some of them can be easily confused with animals in geometric features, i.e. size and shape. Figure 2 demonstrates the difference of landscapes between that pervious study conducted by Laliberte & Ripple in 2003 and this study on the satellite imagery. Table 1 lists the body sizes of dominant species on the open savannahs in Africa (Macdonald, 2001; Nowak, 1999; "San Diego Zoo's Animals Bytes: Zebra," 2012). From the table we could possibly foresee that small shrubs and little ponds might be confused with animals by geometric features in spatial.

Table 1 List of body sizes of dominant species on open savannahs in East Africa

Body size	African elephant	African buffalo	Wildebeest	Zebra
Head-body length (m)	5.4 - 7.5	2.1-3.4	1.5-2.4	2.2-2.5
Shoulder height (m)	2.7-3.3	1.0-1.7	1.1-1.2	1.3-1.5

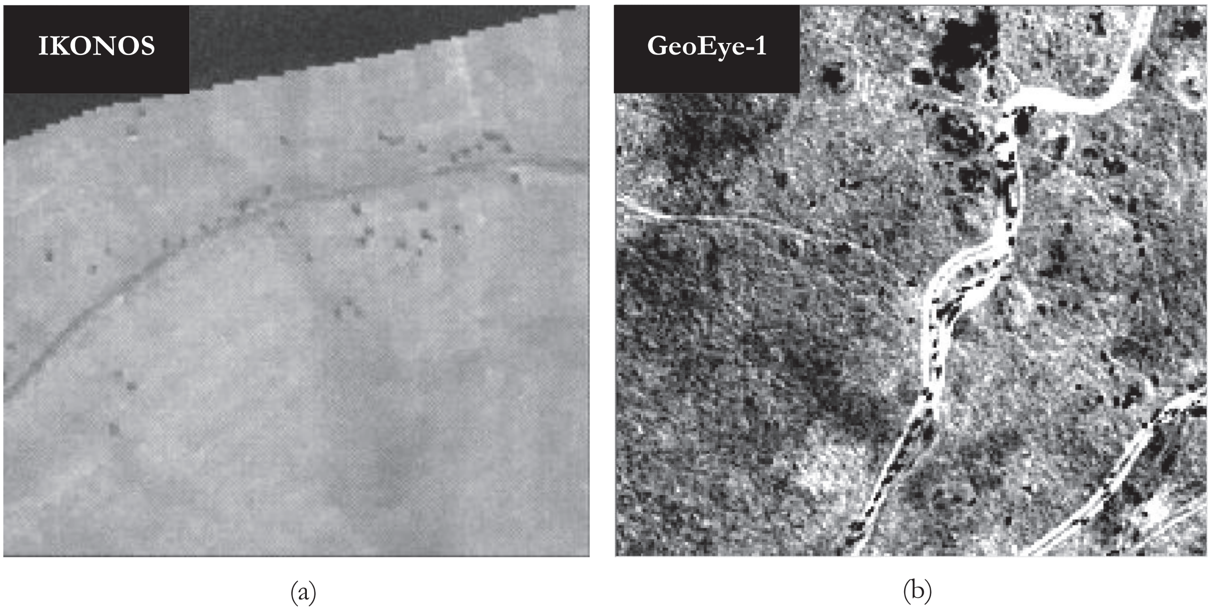


Figure 2 (a) Panchromatic IKONOS satellite image at 1m resolution showing the cattle(Laliberte & Ripple, 2003) and (b) Panchromatic GeoEye-1 satellite image at 0.5m resolution showing the wildebeest

As a result of the much more detailed texture information when using the high resolution GeoEye-1 satellite imagery, the shadow of trees or shrubs contributes to image complexity (Figure 4). Since animals seen on the image in this study area are large ungulates such as African buffalo and wildebeest, which are taller than 1m, shadow also becomes part of the animals' appearance on the images. Figure 3 shows the shadow of trees and figure 4 shows the shadow of zebra and wildebeest. Therefore there might be overlap between animals and shadow in the feature space, namely poor spectral separability between these two classes. Besides, due to the limitation of the resolution, the edge of animals can be easily mixed up with the background on the images such as grassland or bare soil and this may make bare soil another confounding factor. Given the challenges of spatial and spectral confounding factors, it would be wise for us take a method in which both of spectral and spatial analysis would be applied to recognize the animals.

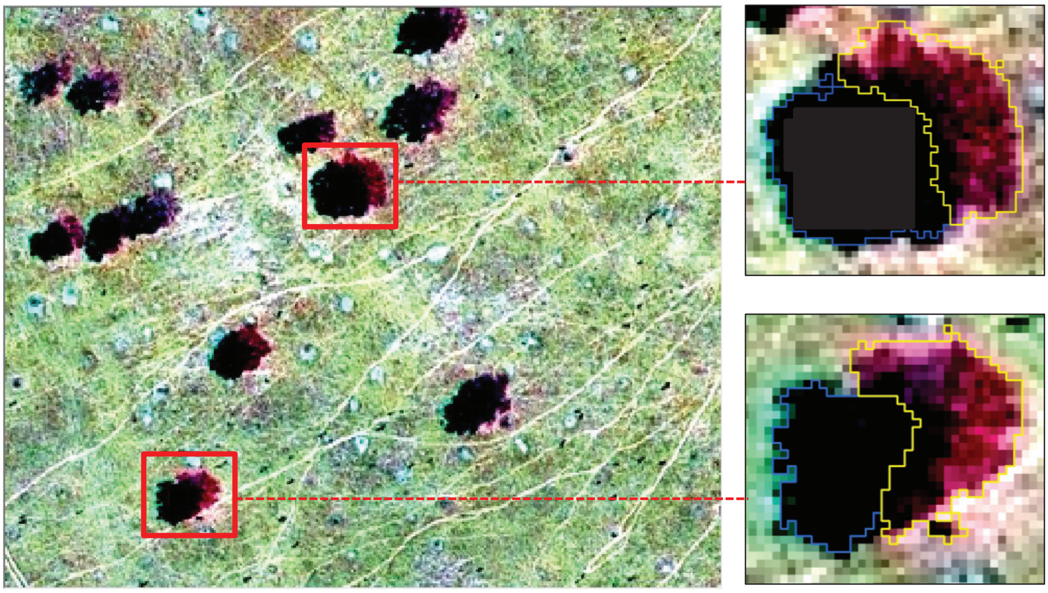


Figure 3 Shadow of the trees (false colour image)

Figure 4 Shadow of a herd of zebra and wildebeest, photographed by Robert B. Haas

Considering the body sizes of large mammals listed in Table 1, one single zebra or wildebeest would be represented by in the pan chromatic band as an image object of 3 to 4 pixels length, and 1 to 2 pixels wide, while buffalo and elephants would be represented by even larger image objects. Given its resolution, the GeoEye-1 imagery should thus offer possibility to extract the geometric features for the large ungulates.

From what have been discussed above, it seems feasible to develop an approach using high resolution satellite imagery (GeoEye-1) to accomplish mapping wildlife in open savannahs and thereby to be able to assess the capabilities of high resolution GeoEye-1 satellite imagery for doing this task. The study area would be the large, open and remote regions, such as the open savannahs in the east Arica. If this approach can be developed and prove that GeoEye-1 satellite imagery have the capabilities for mapping wildlife, the approach proposed in the thesis would be a very useful supplement and an alternative to the future animal population censuses.

1.4. Problem statement

The purpose of this study is to assess the capabilities of high resolution GeoEye-1 satellite imagery for mapping wildlife in open savannahs. To achieve this purpose, we have to be able to recognize the animals on the high resolution GeoEye-1 satellite imagery, which depends on whether high resolution GeoEye-1 satellite imagery having enough spatial and spectral resolution. Therefore, the biggest research problem lies in whether the high resolution GeoEye-1 satellite imagery having the resolution fine enough for recognition of animals.

1.5. Research objective

The general research objective of this study is to assess the capability of high resolution GeoEye-1 satellite imagery for mapping wildlife in open savannahs. To achieve this main objective, the following specific objectives need to be addressed.

- Develop new image processing methods in order to detect the presence of animals on the imagery in all kinds of form, i.e. individuals, migrating herds, clustered herds

- Develop new image processing methods in order to recognize the individual animals and estimate the population size of the animals;

- Assess the accuracy of the pixel-based and object-based approaches and compare their capabilities for mapping wildlife.

1.6. Research questions

- How to differentiate the animals from the surroundings on the satellite imagery?

- How to determine an individual of animal on the satellite imagery?

- How to assess the accuracy of the different methods mentioned above and compare their capabilities for mapping wildlife?

1.7. Research hypothesis

The spatial and spectral information from pan-sharpened high resolution GeoEye-1 satellite maps wildlife at an acceptable accuracy of overall mapping accuracy >70% (in open savannahs) by applying different image classification approaches with expert knowledge.

1.8. Thesis outline

This thesis consists of five chapters: introduction, materials and methods, result, discussion, conclusion and recommendation. Chapter I introduces the background, practical significance and feasibility for this study. Research objective, research questions and hypothesis are also presented in this chapter. Chapter II presents the study area and materials, and then illustrates the methods for recognizing animals on the high resolution GeoEye-1 satellite imagery step by step. Chapter III explains the results by validating and analysing the results produced, including accuracy assessment, spatial analysis and statistical analysis. In addition, the performances of two different methods are compared and evaluated. Chapter IV discusses the advantages and limitation of the new approach for mapping wildlife, characteristics of the methods, and the future perspective. Chapter V gives a conclusion about the capacities of high resolution GeoEye-1 satellite imagery for mapping wildlife in open savannahs, and provides some recommendations for relevant studies in future.

Figure 5 demonstrates the overall framework for evaluating the capabilities of the high resolution GeoEye-1 satellite imagery for mapping wildlife in open savannahs. Generally it can be divided into three steps. Step 1 basically is the preparation for automated recognition of animals. Specifically it justifies the rule for recognizing animals and then prepares the data needed for next step. Step 2 is mainly focusing on how to recognize animals automatically. In this step two different methods are applied to recognize animals. In the final step, we will conduct accuracy assessment of the new approach being applied and analyse the refined result to give a conclusion about the capabilities of the high resolution GeoEye-1 satellite imagery for mapping wildlife in open savannahs.

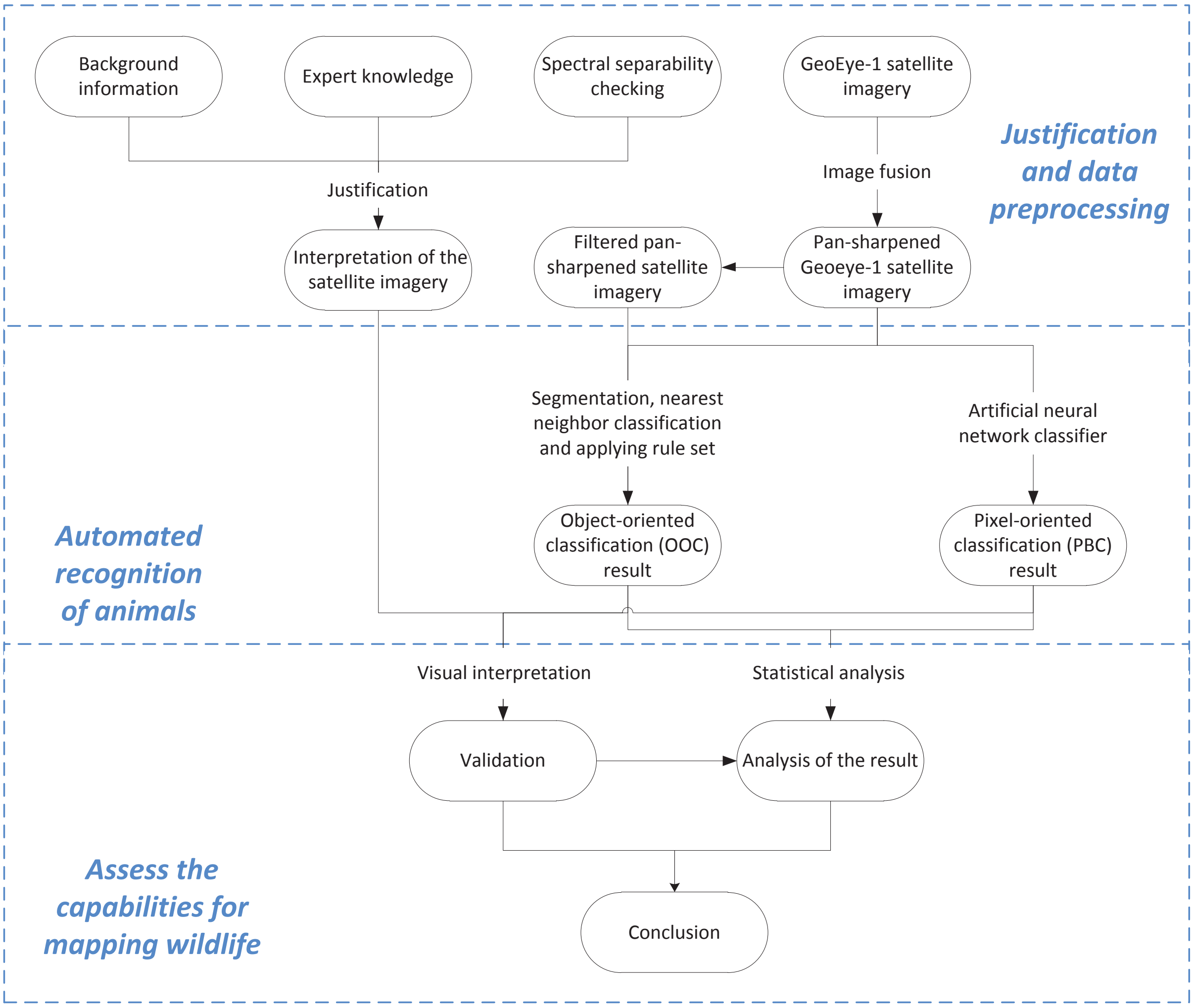


Figure 5 The overall framework of using high resolution satellite imagery for mapping wildlife in open savannahs

2. MATERIALS AND METHODS

2.1. Study area

The study area is located in north-western part of Masai Mara National Reserve, a game reserve in south-western Kenya (Onchwati, Sommerville, & Brockway, 2010).

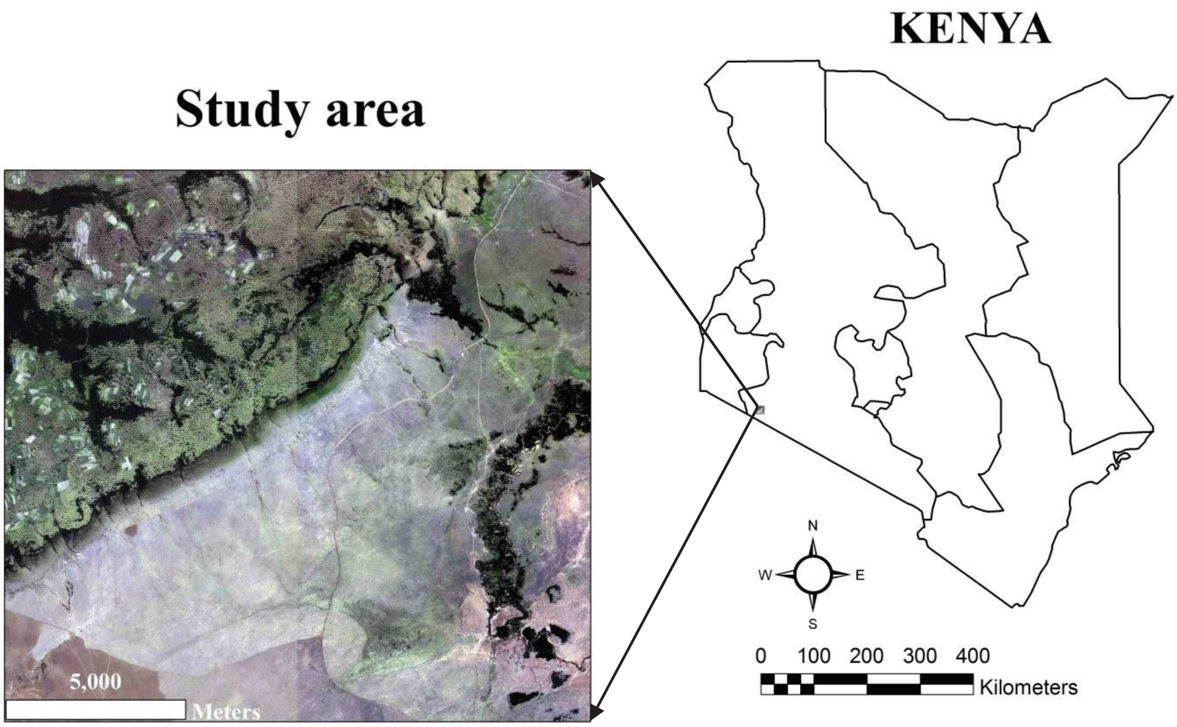


Figure 6 Location of the study area on the GeoEye-1 satellite imagery

2.2. Satellite imagery

Two sets of GeoEye-1 images are available, each including a panchromatic band with 0.5m resolution and 4 multispectral bands with 2m resolution. The multispectral bands include: blue, green, red, and near infrared (NIR). At the time of its launch, GeoEye-1 was the world's highest resolution commercial earth-imaging satellite. These two GeoEye-1 images were captured in August 2008, each of them covering an area of 129.53 km2. Most part in the images locates in the Masai Mara National Reserve.

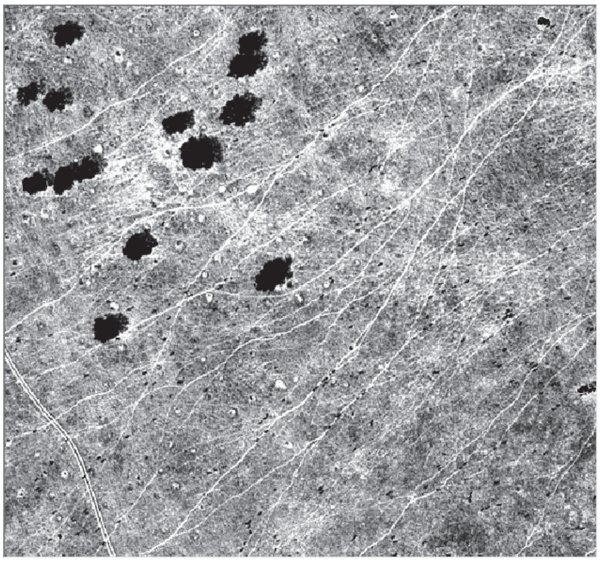
2.3. Image pre-processing

2.3.1. Image fusion

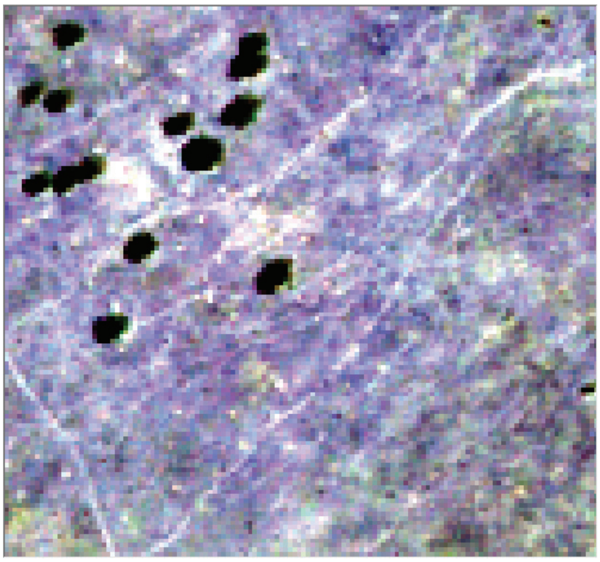
For this study, the 2m resolution of the multispectral images is not fine enough to identify the large mammals on the image. Image sharpening is therefore required. The existing image sharpening techniques being widely used such as intensity-hue-saturation (IHS) transform, wavelet transform and principal components analysis (PCA) methods can generally meet the requirement of processing low or medium resolution satellite imagery. However, they are not suitable for high resolution images (Hu & Zhang, 2010). Specifically, these techniques still produce spatially enhanced pan-sharpened images but usually at the expense undermining spectral fidelity (Ehlers, 2008).

According to previous studies comparing fusion algorithms for sharpening high resolution commercial satellite images, Ehlers was found having better performance than common fusion algorithms like PCA or HIS in improving spatial resolution details and avoiding color distortion (Sascha Klonus & Ehlers, 2007; Nikolakopoulos, Vaiopoulos, & Tsombos, 2010). The Ehlers fusion algorithm is based on the IHS transform accompanied with a Fourier domain filtering (S. Klonus & Ehlers, 2009). However, in this study, we found that the Ehlers fusion algorithm is not suitable for sharpening GeoEye-1 high resolution images, at least not suitable for the images of the study area in this study. Specifically, we found the spatial fidelity was serious undermined in the pan-sharpened image by using Ehlers fusion algorithm. Besides, we also found the problem of color distortion. Figure 7 demonstrates the original panchromatic GeoEye-1 satellite imagery at 0.5m resolution, multispectral Geoeye-1 satellite imagery at 2m resolution, and the pan-sharpened images produced by Ehlers fusion and Gram-Schmidt at 0.5m resolution with cubic convolution resampling techniques.

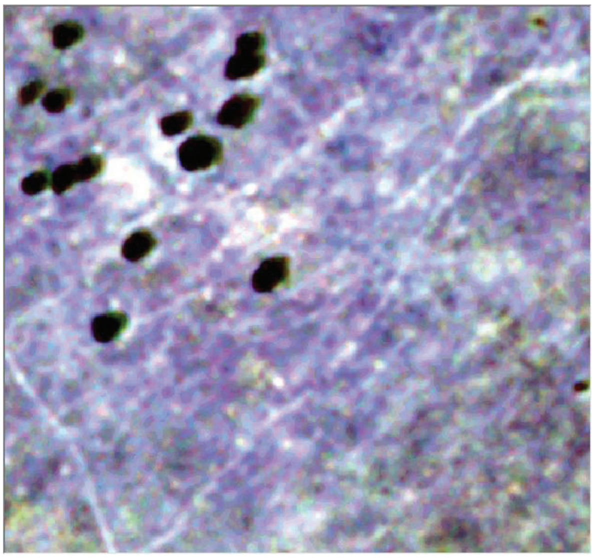
We compared the results produced by several popular fusion techniques (HIS, PCA, wavelet transform and Gram-Schmidt spectral sharpening). By visual inspection, we found that the pan-sharpened images produced by Gram-Schmidt spectral sharpening and wavelet transform were found having more detailed texture and less spectral distortion than other pan-sharpened images produced by other sharpening techniques. As for the resampling techniques, bilinear interpolation and cubic convolution generally are supposed to have better performance than nearest neighbor, which is often believed having some impact on the precision of the pan-sharpened image (Q. X. Zhou, Jing, & Jiang, 2003). In the end, Gram-Schmidt spectral sharpening with cubic sampling method was chosen for the method of image fusion in this study.



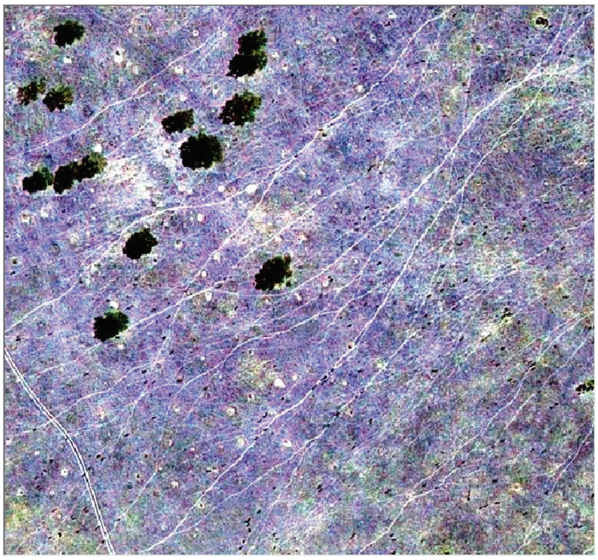
(a) Panchromatic GeoEye-1 satellite imagery at 0.5m resolution, large dark objects represent shadows cast by trees, small black objects are animals



(b) Multispectral GeoEye-1 satellite imagery at 2 m resolution, in which trees remain visible, but animal objects are not



(c) Pan-sharpened image by using Ehlers fusion at 0.5 m resolution



(d) Pan-sharpened image by using Gram-Schmidt spectral sharpening at 0.5 m resolution

Figure 7 Original and pan-sharpened images produced by different fusion techniques

2.3.2. Image enhancement

In this step, we will filer the images. Image filtering is an image enhancement technique which is generally believed to be a useful tool for improving the visual interpretability of an image by increasing distinction between different features or removing noise, etc. (Fevralev et al., 2010) and has been applied on a variety of data sets such as SAR, aerial and satellite imagery (Fatemi, Mirhassani, & Yousefi, 2009; Ponomarenko, Lukin, Zelensky, Egiazarian, & Astola, 2005; Xiao & Cai, 2011). However, it does not apply to this study for the reason that it would greatly distort the spectral information for pixels showing animals on the image.

In general, image filtering uses a convolution kernel, for example, one 3*3 low pass convolution kernel, to change the pixel values on the image to fulfill the image enhancement. In this study, an individual animal takes approximately 4 to 8 pixels on the image on average. Therefore the pixels showing the animals on the image would be seriously affected. Via trying different filters, we found that there was no commonly used filter (low pass, high pass, edge detection and sharpening) which could improve visual interpretability for recognizing animals.

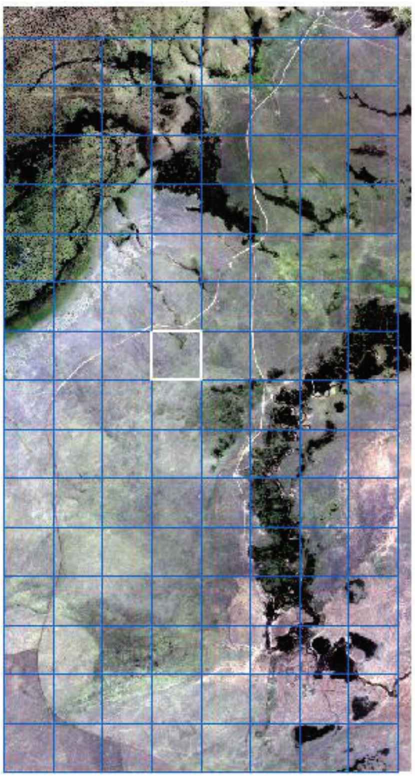
By applying the filters which smooth the image such like 3*3 Low Pass convolution kernel, it would blur the edge of animals on the image and made it harder to recognize animals; for the filters used for sharpening image and enhancing contrast between classes, they did improve the interpretability for recognizing animals, but some confounding factors such as soil surface or shrubs were confused with animals in appearance. Perhaps it is because the average size of our study objects is too small compared to the objects commonly processed, such as buildings, vehicles, etc. and any changes in pixel values can lead to serious distortion in spectral reflectance and texture information. Nonetheless, image filtering, for example, a low pass filter with a 3*3 kernel, is still helpful for classifying objects using object-based approach on landscape level, such like shrubs (Laliberte et al., 2004). Therefore, we applied a 3*3 Low Pass convolution kernel on smoothing the image to facilitate the process of classifying confounding factors including trees, shrubs and water bodies.

2.4. Pilot study area selection

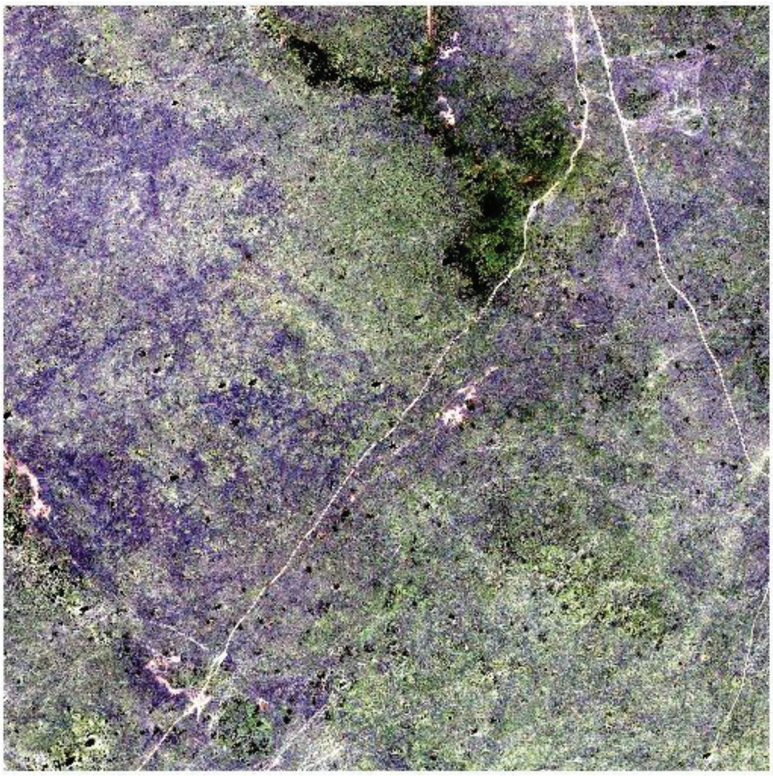
The size of each sharpened multispectral image is nearly 4 GB. Processing such mass data is exceedingly time consuming and a desktop is incapable of undertaking this task unless supercomputers. Therefore, it is necessary for us to conduct a pilot study by selecting representative regions in our study area. The total area each image covering is 8304m by 15598m. Each image was divided into 144 grids and the size of each grid is 1000m by 1000m. We have two images so technically we should select samples from the 288 grids from these two images. However, nearly half of the first image is outside of the Masai Mara National Reserve, so we only consider the 144 grids in the second image. There are grids which only partly inside the image, and therefore grids on the boundary will not be considered in the study. In the end, we selected 2 representative regions for conducting the pilot study from these 120 grids in total (Figure 8). These two regions of the pilot study area are named as Pilot_No.1 and Pilot_No.2 respectively. For the selection criteria, we considered factors including the location of samples, characteristics and complexity of landscapes, density and distribution patterns of animals, etc. Table 2 lists the specific characteristics for each pilot study area selected.

Table 2 Characteristics of Pilot_No.1 and Pilot_No.2

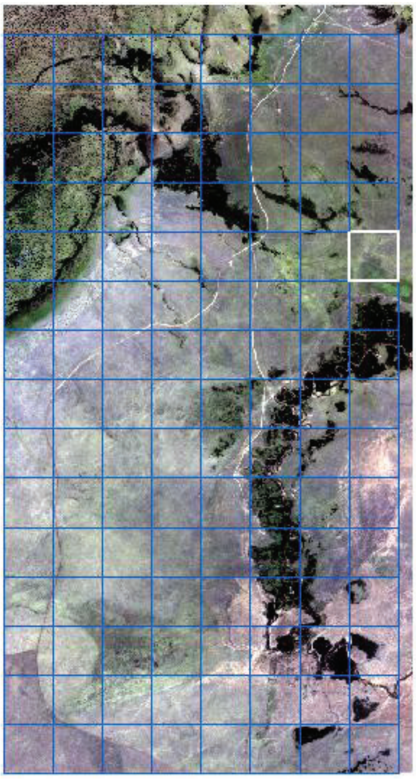
Characteristics	Pilot_No.1	Pilot_No.2
Landscapes	Complex landscapes including forest with shadow, shrubs, grassland, bare soil, sand, and water bodies	Relatively simple landscapes compared with Pilot_No.1, basically high vegetation area (forest, grassland and shrubs mixed together)
Distribution of animals	Large herd of animals (hundreds of animals) clustering around forest	Small amount herd of animals (around 30 to 100) moving along the road



Location of Pilot_No.1 on the image



The first region in pilot study area, Pilot_No.1



Location of Pilot_No.2 on the image

The second region in pilot study area, Pilot_No.2

Figure 8 Pilot study area

2.5. Visual interpretation

We perform visual interpretation to manually differentiate the animals from the surrounding landscapes and determine the features of individual animals, which is not only the foundation for developing new image processing methods in order to detect the presence of animals and recognize the individual animals, but also the reference for conducting validation of the classification results.

There are two important facts about the study area we should be aware of. First of all, the study area locates in the Masai Mara National Reserve, which is famous for its abundance of all kinds of wildlife including large ungulate on the open savannahs (Caro, 2003) and it is part of the Serengeti-Mara ecosystem. Figure 9 shows a snapshot of one group of different kinds of large ungulates on the open savannahs. The Serengeti-Mara ecosystem is a vast area of rangelands, ranging from Tanzania to Kenya across the border in East Africa (Serneels & Lambin, 2001). Second, there is the great migration of 1.3 million wildebeest and 0.6 million zebra (*Equus burchelli*) and gazelle (*Gazella thomsoni*) (Thirgood et al., 2004) in each year occurring in the Serengeti-Mara ecosystem. The great migration of wildebeest from Serengeti to the Masai Mara National Reserve occurs during August to November each year (Musiega, Kazadi, & Fukuyama, 2006). The images of the study area are captured in August, 2008, when the wildebeest started the great migration from Serengeti to Masai Mara.

Therefore, based on these two reasons, we are confident that the study area filled with large migratory ungulates, such as wildebeest and zebra. Accordingly, there should be lots of large ungulates on the satellite images of our study area. Figure 10 shows the great annual migration of wildebeest from Serengeti to Masai Mara.

Figure 9 A snapshot of large ungulates on the open savannahs ("Elephant, wildebeest and zebra," 2012)

Figure 10 The great annual migration of wildebeest form Serengeti to Masai Mara, photographed by Felix Borner

2.5.1. Spectral separability

Although we have various reasons based on the knowledge we have for visual interpretation, however, we cannot rule out the possibility that some confounding landscapes would be confused with animals in spatial. Under this circumstance, spectral reflectance becomes an important source for determining the characteristics of the animals from confounding factors. Therefore, using spectral reflectance to differentiate animals from the confounding factors in spatial would be a reliable method for this study.

To check the spectral separability of the large mammals, the maximum Jeffries-Matusita (JM) distance was calculated. The Jeffries-Matusita (JM) distance between two classes indicates whether they are separable in multidimensional feature space. Specially, JM distance is asymptotic to the value 2 ranging from 0 to 2 and the spectral separability increases along with the value; a value of 2 indicates that two classes are completely separable by spectral reflectance (Richards, 1993). ENVI was selected as the platform for spectral separability checking. In preparation for this task, all kinds of landscapes including shadow and animals were selected for regions of interest in ENVI to check the spectral separability via computing the JM distance. Then we exported the regions of interest to n-D visualizer to visualize the distribution of these regions of interest in feature space. In this case, we found false color image could properly demonstrate the difference between animals and the surrounding landscapes in feature space. Therefore, we selected band 4, 3, 2, i.e. NIR, red and green as the three dimensions of the feature space.

By general standard, a JM distance between two classes larger than 1.9 indicates good separability (Thomas et al., 2003). From the list of JM distance between animals and the landscapes including shadow (Table 3), we can see that animals have good separability with other landscapes and poor separability with shadow. The overlap in spectral reflectance between animals and the shadow confirms our conjecture in the section of analyzing the confounding factors, and the reason leads to the poor spectral separability has been discussed. Figure 11 and Figure 12 reflect the result of spectral separability by the distribution of animals and the surrounding landscapes in the feature space (axes 4, 3, 2 representing the band 4, 3, 2, i.e. NIR, red and green).

In spite there is overlap of spectral reflectance between animals and shadow, we still can get rid of shadow by contextual analysis of the image. Specifically, we try to identify the shadow by its relationship with trees or shrubs in spatial (we will further explain this process in the next sections).

Table 3 JM distance between animals and the surrounding landscapes including shadow in Pilot_No.1

	Trees	**Grassland**	**Bare soil**	**Water bodies**	**Sand**	**Shadow**
JM distance	1.95	1.95	1.92	1.98	1.97	1.33

Table 4 JM distance between animals and the surrounding landscapes in Pilot_No.2

	Trees	**Shrubs**	**Bare soil**	**Water bodies**	**Sand**
JM distance	1.99	1.93	1.91	1.99	1.99

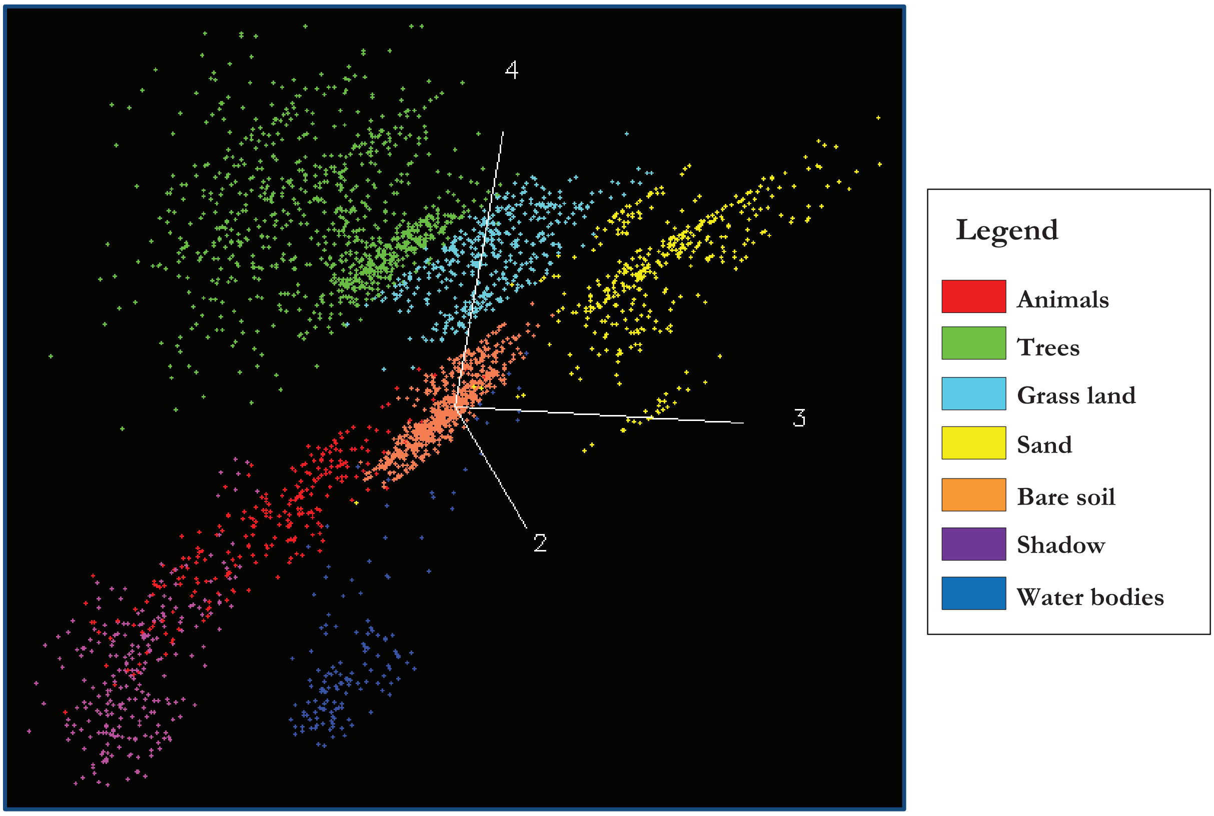


Figure 11 Distribution of animals and surrounding landscapes in the feature space, Pilot_No.1

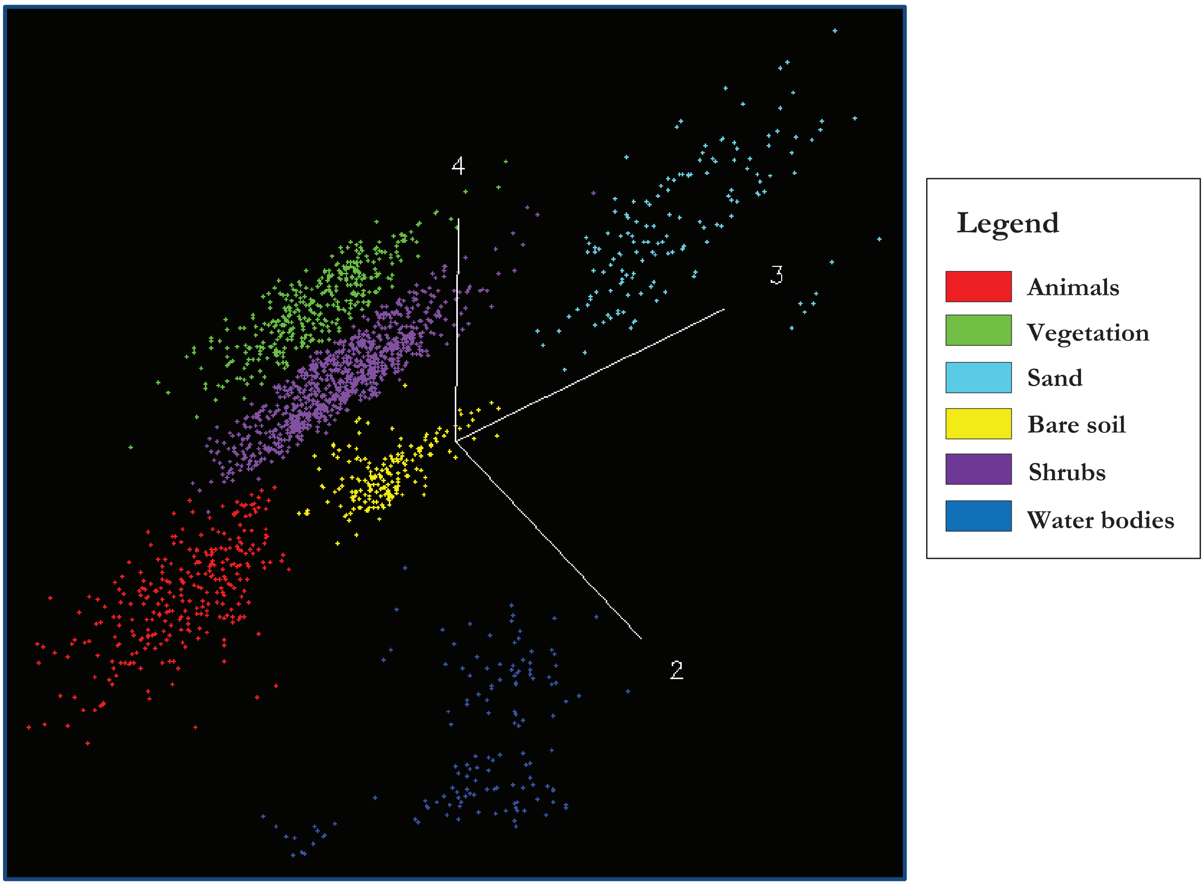
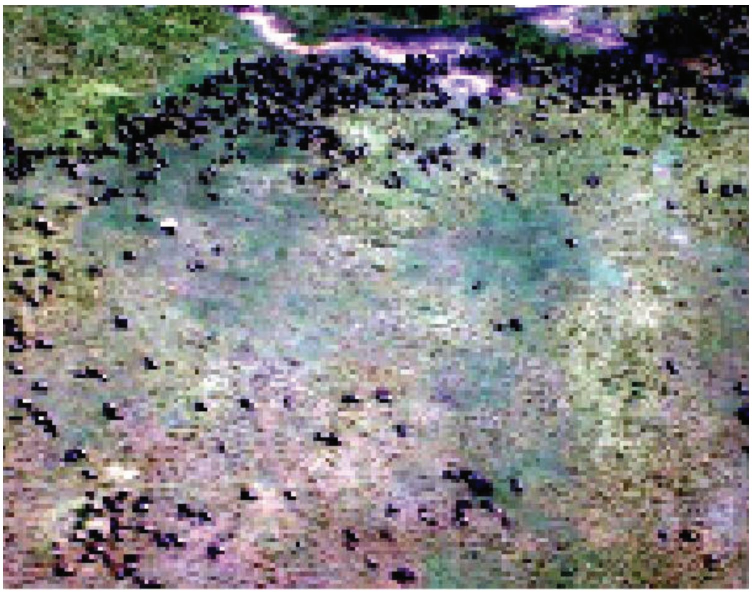


Figure 12 Distribution of animals and surrounding landscapes in the feature space, Pilot_No.2

2.5.2. Expert knowledge

Expert knowledge plays an important role in recognition of animals in this study. First of all, by comparing the body sizes of animals (Table.1) with the spatial resolution of the panchromatic or pan-sharpened image, we can have a general idea that the number of pixels a large mammal would take on the satellite imagery. Second, we resampled the aerial photograph above the study area to the resolution similar to panchromatic satellite imagery. We carefully observed the geometric features of the animals on the resampled aerial photo (Figure 13). By this means, we had the idea about what geometric features the animals would have on the panchromatic or pan-sharpened satellite imagery. Figure 13 shows the aerial photo filling with wildebeest, provided by International Livestock Research Institute (ILRI), and the resampled image. Third, the dominant large ungulates on the open savannahs are living in herds. For example, the herd sizes of wildebeest can be ranging from thirty to more than one thousand (Joseph, 2006 ; Khaemba & Stein, 2002; Rija & Hassan, 2011; Unwin, 2003); therefore the animals would have certain spatial distribution patterns such as clustering pattern or moving pattern in general. We can rule out other landscape attributes might be confused with animals in geometric features by setting the standards about the distribution patterns of the animals.

Original aerial photograph after image enhancement



Resampled aerial image at 1/4 resolution of the original aerial photograph

Figure 13 Wildebeest on original aerial photograph and resampled aerial photograph

2.5.3. Visual interpretation method

Most of the animals on the imagery appear individually; however, some of them gather together forming a cluster or moving one after another forming a line feature. Clustered animals can only be recognized as a group of animals instead of individuals. For these objects, we may refer to the method of counting the number of bacteria. Specifically, we estimate number of animals it represents by the average size of the animals in this area (Grivet, Morrier, Souchier, & Barsotti, 1999). Then we compare the number with the number of objects, i.e. polygons in the vector layer. Therefore, in this case, we assess the accuracy by the estimated number of correct objects of animals being recognized.

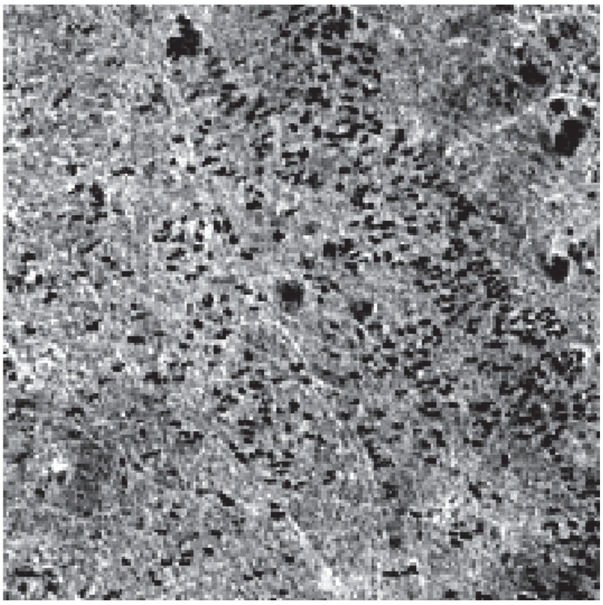
The validation is conducted based on the result of visual interpretation, which can be subjective. In order to reduce subjectivity, we validate the results eventually according to the opinions from multiple visual interpreters. Specifically, we have five visual interpreters who have different academic backgrounds and knowledge on the study area. Table 5 illustrates the status of the five interpreters. Finally we took the average accuracy of different validation results from the multiple interpreters.

Table 5 Status of the five interpreters

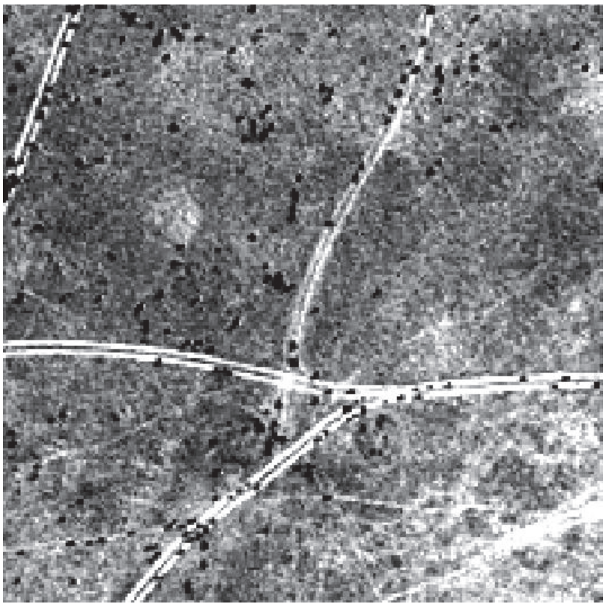
Interpreter	Status
No.1	Academic faculty member who has background knowledge of this area
No.2	Researcher of this study
No.3	Student not involved in other activities related to this study
No.4	Researcher of another study sharing the same study area
No.5	Student comes from Kenya who have been in the Masai Mara National Reserve

According to the primary results for the estimation of population sizes by estimating the density of animals based on visual interpretation, the total number for the pilot study area is greater than 10000. Apparently it is not practical for us to count all of the animals being recognized. Therefore, we selected two representative areas (100m*100m) from Pilot_No.1 and Pilot_No.2 for validation. We named these two validation areas VA1 and VA2.

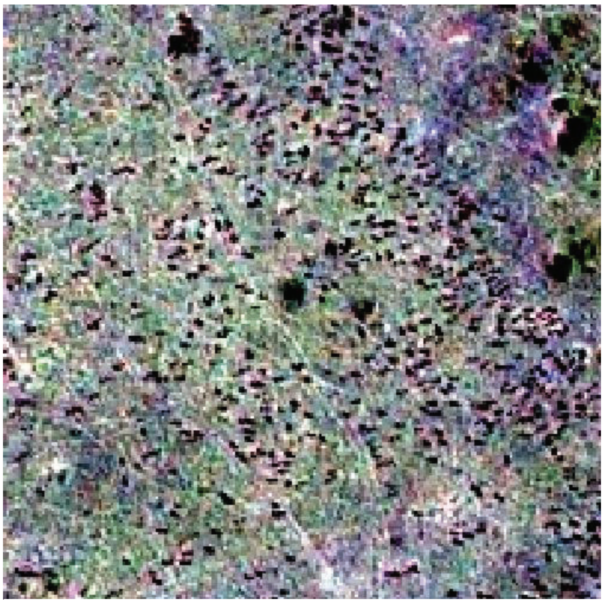
These two regions are representative of the landscapes, animal density and distribution patterns for Pilot_No.1 and Pilot_No.2. Specifically, we conduct the validation of the classification result of pixel-based approach and object-based approach based on the visual interpretation of the panchromatic and pan-sharpened images on the two validation areas mentioned above (Figure 14). From the panchromatic and pan-sharpened images we can clearly see that VA1 has a relatively complex surrounding landscapes and large amount of animals in migration while VA2 has relatively simple surrounding landscapes (high vegetation area) and small herd of animals in migration.



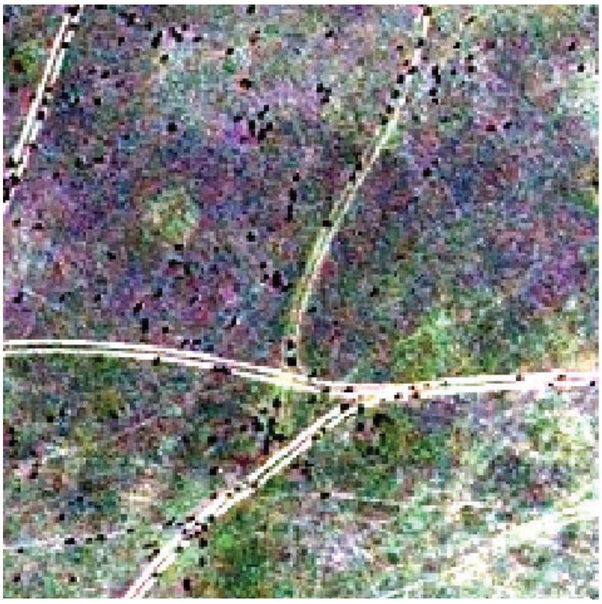
(a) Panchromatic image of VA1, the validation area in Pilot_No.1



(b) Panchromatic image of VA2, the validation area in Pilot_No.2



(c) Pan-sharpened image of VA1, the validation area in Pilot_No.1



(d) Pan-sharpened image of VA2, the validation area in Pilot_No.2

Figure 14 Two validation areas selected from the pilot study area

2.6. Pixel-based approach

Traditional pixel-based classification method is applied in this study since it has been widely used in remote sensing applications and it is proved to be a robust classification approach which can ensure relatively high accuracy. In this study, we used an artificial neural network (ANN) classifier for pixel-based classification. The biggest difference between ANN and other traditional classification methods lies in that ANN classifier is a non-parametric and non-linear approach which has a strong adaptability to handle complex nonlinear relationships (Bao & Ren, 2011).

Specifically, traditional parametric approaches such as support vector machine (SVM) and maximum likelihood classification are based on statistical information regarding statistical distribution and inferences of the data, so its success depends on correspondence of data with the statistical distribution inferred; on the contrary, ANN classifier is non-parametric and based on human learning and processing mechanism (Toshniwal, 2005). Figure 13 illustrates the learning process of a three layer ANN classifier and each node acts as a simplified biological neuron. Therefore the success of the ANN classifier more relies on the learning process instead of the data set. In previous study of image processing applying ANN filter, it is proved to be capable of processing complicated images, and has better performance than conventional image filters (Wit & Busscher, 1998).

Given the complexity of the landscapes on the images and a variety of the appearance of animals such as individual animals, clustered animals, and moving animals, ANN would be a suitable choice for processing these high resolution satellite images in this study. We chose ENVI as the platform for this pixel-based classification. After conducting classification by ANN classifier, we conducted spatial analysis using expert knowledge in ArcMap. Specifically, the expert knowledge refers to the knowledge in three aspects: the geometric features of animals and the relationship of the features on the image, for example, shadow always appearing with the trees on the image. Therefore, the pixel-based approach applied in this study is a hybrid of pixel-based classification and spatial analysis based contextual contents. Figure 14 shows the framework of it.

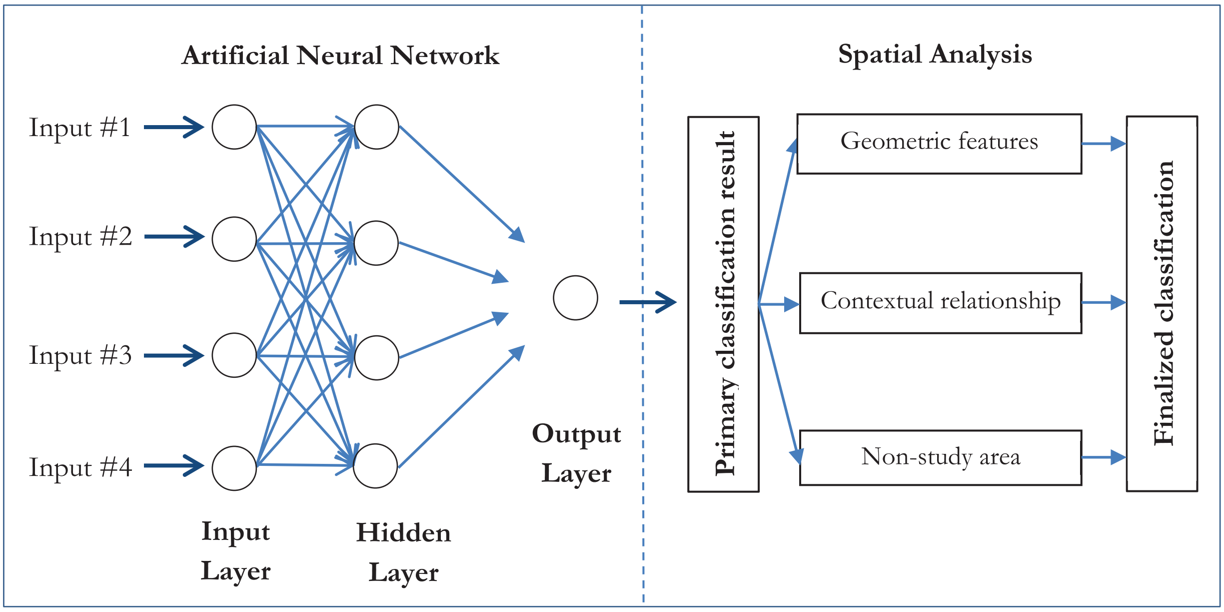


Figure 15 The framework of pixel-based approach

2.6.1. Training sets selection

As mentioned above, ANN is a non-parametric approach which directly depends on the learning process based on the input layers. Therefore, training sets selection is as vital for this machine learning method. We have to ensure that all the input training sets are separable by spectral reflectance. In previous work of checking spectral separability between animals and landscapes, we can see that animals and 6 kinds of landscapes are separable by spectral reflectance. Therefore, we selected regions of interest based on the 6 basic landscapes which could be separated from animals in feature space (trees, shrubs, grass land, bare soil, sand, and water bodies).

Specially, we compared the classification results produced with different number of regions of interest ranging from 6 to 9 (some classes of landscapes may be merged or be subdivided) and we found the optimization number of regions of interest for classification, i.e. the regions of interest which could produce most satisfactory result. Besides, we also modified the training sets according the distribution of regions of interest in the feature space, namely getting rid of those outliners for each class in the training sets. After comparing different classification results produced with different regions of interest, we finalized the number of regions of interest for each pilot study area: 7 regions of interest for Pilot_No.1 and 6 regions of interest for Pilot_No.2 (in Pilot_No.2 grassland and forest are not very separable by spectral reflectance and therefore both of them are categorized as 'vegetation' in regions of interest). Table 6 shows the specific regions of interest selected in Pilot_No.1 and Pilot_No.2.

Table 6 Regions of interest selected in Pilot_No.1 and Pilot_No.2

Pilot study area	Regions of interest selected for classification
Pilot_No.1	animals, bare soil, forest, grassland, sand, shrubs, water bodies
Pilot_No.2	animals, vegetation, water bodies, bare soil, sand

Given that ANN is based on the spectral reflectance of each pixel on the image and as discussed above the pixels on the edge of animals easily mixed with the spectral reflectance of the background such as grassland or soil surface, thereby we only selected the central part of the animals as training sets to avoid spectral overlap between classes.

2.6.2. Optimizing learning process

After selecting the training sets, the next step is to optimize the training process. Specifically, we optimize the learning process in two aspects. One aspect is modifying the input layers, i.e. the training sets and the proportion of each class in the regions of interest. In addition to the external factors out of the ANN classifier such as data set and training sets selection, it is important for us to properly optimize settings for the internal parameters, including the number of hidden layers, type of activation function (logistic or hyperbolic), training rate, training momentum, training threshold contribution, and number of training iterations. Among them, number of hidden layers, activation function, and training rate are proved to have significant effect on the classification accuracy (L. B. Zhou & Yang, 2011).

In this study, we conducted a trail-and-error process to optimize the internal parameters which have substantial impact on the classification result, i.e. number of hidden layers, type of activation function, and training rate. Specifically, we tried different values for each parameter while we kept other parameters constant values. We found that the optimal settings for these parameters are: one hidden layer, logistic activation function, a training rate ranging from 0.01 to 0.05, and training momentum of 0.8. After the training sets and internal parameters being finalized, we conducted the pixel-based classification and exported classification results.

2.6.3. Exporting classification results

After the classification result in ENVI being finalized, we exported the results to the platform i.e. ArcMap, for analysis and validation. The classified results are raster layers, which are inconvenient for spatial analysis. Therefore, it is needed to be converted to vector layers. Specifically, we imported the classified images in ArcMap and converted the raster layers of classified result to shpfiles and then extracted the polygons of animals by attribute to conduct the spatial analysis in the next step.

2.6.4. Refine classification results

So far the pixel-based approach only considered the spectral reflectance of the pixels on the images; as we discussed above the spatial information also plays an important role in the framework of recognizing animals. We certainly are aware of the possibility that some animals in the pixel-based classification result might be misclassified. Instead of animals, they are confounding factors which may have overlap with animals in feature space, e.g. the shadow of trees or shrubs. We were aware of the mixture of animals with shadow already when we were selecting the training sets. Specifically, we chose ArcMap as the platform for the refinement of the pixel-based classification result and we also analyzed the attributes of the features exported.

For the shadow in the vegetated areas, we came up with two solutions. One is to set the threshold of the upper limit of the area of individual animals according to the average body sizes. In this case we cannot refer to the actual body size of animals because when we were selecting the training sets we only selected the central part of the animals. Instead, we should refer to the average body size of the animals in the pixel-based classification result. The other solution is to detect the shadow by its relationship with trees or shrubs in spatial since shadow always is accompanied with trees or shrubs. By these means, we managed to get rid of most shadow in the pixel-based classification result. For the other confounding factors misclassified as animals, we use the layer of 'Non-study area' which contains the landscapes of trees, shrubs and water bodies to eliminate the unwanted result.

2.7. Object-based approach

High spatial resolution increases internal variability of the image and may lead to the 'salt-and-pepper' effect (Pu, Landry, & Yu, 2011). In this study, considering there is no remarkable difference between the average body sizes (body length ranging from 1.5m to 2.5m) of dominant migratory large ungulates (wildebeest, zebra, and gazelle) and resolution of the satellite images (0.5m), this 'salt-and-pepper' effect inevitably would decrease the classification accuracy of pixel-based classification approach. Moreover, such a small pixel size with only four spectral bands may lead to great variation of spectral reflectance within the same class (Laliberte, et al., 2004). According to the studies of land cover classification, object-based classification generally would have better performance than traditional pixel-based classification methods in reduction of the speckle noise, overall accuracy in land cover classification (Huang & Ni, 2008; Ma, Zhang, Yang, & Xu, 2009; Qi, Yeh, Li, & Lin, 2010) and reducing spectral overlap between classes (Nichol & Wong, 2008). Therefore, we used object-based approach for recognizing the animals in addition to pixel-based approach in this study. It fits the requirement of classifying high resolution satellite imagery for its advantages over traditional pixel-based approaches.

Specifically, we integrated the expert knowledge into the object-based approach as rule set. We conducted the object-based classification with two steps. The first step is to refine study area and the second step is automated recognition of animals. Specially, the second step includes two sections: nearest neighborhood classification and classification by the rule set based on expert knowledge. Figure 15 shows the framework of the object-based approach.

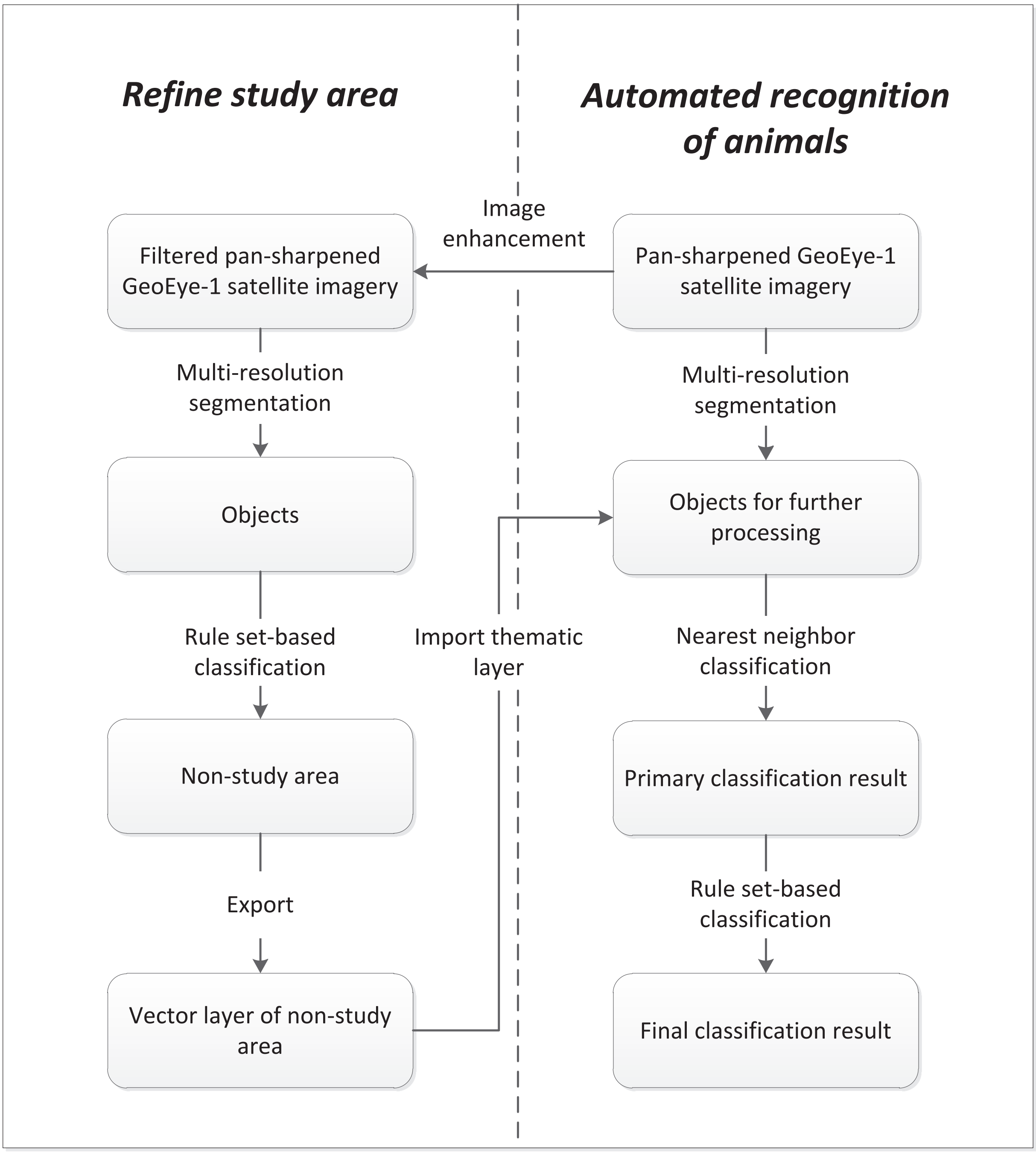


Figure 16 The framework of object-based approach

There are several choices of platforms for the object-based approach, such as SPRING, ENVI EX (formerly integrated in ENVI Zoom), Erdas Objective and eCognition. Among them eCognition and ENVI EX are most commonly used, and they have the same framework of object-based classification. In this study we used eCognition as the platform for this object-based approach.

2.7.1. Image segmentation

Segmentation is one of the most important aspects for object-based approach, since the rest work directly relies on the result of segmentation. There are several parameters for image segmentation as the following: segmentation approach, segmentation scale, image layer weights, composition of homogeneity criterion (weight for shape/color and weight for compactness/smoothness). For the segmentation approach, we selected multi-resolution segmentation, which means it is possible to generate image objects at different resolution. Given the remarkable difference between the size of animals and the surrounding landscapes, multi-resolution segmentation is suitable for segmenting images to generate the objects of individuals of animals. For segmenting parameters, segmentation scales are proved to have a full impact on the segmentation accuracy and overall effect of classification (Liu & Xia, 2010). Accordingly for the first step of segmentation, segmentation parameters optimization was conducted. Given that pixel value varies with the pixels inside an individual animal, therefore a segmentation scale which can ensure each individual animal can be segmented as one integrated object would be a proper setting for our study. The body length for the dominant migratory species i.e. wildebeest is around 1.5-2.5m and most of individual animals are found having 4-12 pixels on the image. Accordingly we tested different segmentation scales from 4 to 12, and the segmentation with a segmentation scale of 8 could meet our requirement for image segmentation. For other segmentation parameters, we determine these parameters by referring to relevant studies and visual inspection of the segmentation results as well. Table 7 and Table 8 show the setting for the segmentation parameters.

Table 7 Settings of segmentation parameters for refining the study area

Segmentation parameters	Pilot_No.1	Pilot_No.2
Segmentation approach	Multi-resolution segmentation	Multi-resolution segmentation
Segmentation scale	20	20
Image layer weights	1,1,1,1	1,1,1,1
Shape/color	0.1/0.9	0.1/0.9
compactness/smoothness	0.5/0.5	0.5/0.5

Table 8 Settings of segmentation parameters for automated recognition of animals

Segmentation parameters	Pilot_No.1	Pilot_No.2
Segmentation approach	Multi-resolution segmentation	Multi-resolution segmentation
Segmentation scale	8	8
Image layer weights	1,1,1,1	1,1,1,1
Shape/color	0.1/0.9	0.1/0.9
compactness/smoothness	0.5/0.5	0.5/0.5

2.7.2. Refine study area

This part aims at providing a simplified background of the study area, namely, getting rid of the confounding factors on the imagery, including trees, shrubs, and water bodies, which may cause interference to the recognition of individual animals or herds of animals. However, we noticed that sometimes animals could be part of the confounding factors like vegetation. Therefore we have to strike a balance between getting rid of the confounding factors and do not misclassify animals as part of the confounding factors at the same time. Accordingly, we adjusted the threshold for each parameter in developing the rule set for each pilot study area. In this step, we applied the smoothened images from the previous section of 'image enhancement'. This case includes three steps in general: image segmentation, optimize parameters in the rule set, rule-based classification.

For the first step, as listed above (table 5), segmentation scale parameters optimization was conducted and a segmentation scale of 20 was found to be suitable for classifying vegetated areas and water bodies. According to general approaches for identifying vegetated areas and water bodies, we mainly used rule set with customized features as the following: Normalized Difference Vegetation Index (NDVI), brightness, area, and Ratio Blue (RB). Among them, NDVI and RB were used for identifying vegetation such as trees and shrubs and water bodies respectively. However, due to the detailed texture information on the high resolution satellite imagery, shadow also takes a great proportion in the vegetation areas. Therefore we applied brightness to identify shadow of trees or shrubs. Finally, given that animals might be misclassified as confounding factors, we also set the rule that only the objects larger than certain area would be considered as confounding factors. Specially, we have to define the rule set according to the situation of each pilot study area, to eliminate confounding factors as much as possible and prevent animals being misclassified at the same time. Of course it is almost impossible for us to eliminate the confounding factors without misclassifying any animals. Therefore, we have to strike a balance between eliminating confounding factors and misclassifying animals. Table 9 demonstrates the specific rule set defined in light of specific situation for each region in the pilot study area.

Table 9 Rule set of object-based classification on Pilot_No.1 and Pilot_No.2

	Pilot_No.1	**Pilot_No.2**
Trees or shrubs	NDVI >= 0.6	NDVI >= 0.65, then Area >= 800 for the objects merged
Shadow	Brightness <= 330 and Existence of tree (0) = 1	N/A
Water bodies	Ratio Blue >= 0.18	Ratio Blue >= 0.185 and Area >= 12

2.7.3. Nearest neighbor classification

Nearest neighbor classifier classifies different classes by the distribution of pixels in feature space and the cluster of pixels close to each other is considered to be as a class. It is also one of nonparametric methods and it has the advantage of handling multimode classes and not requiring the training set fitting in the Gaussian distribution for the remotely sensed date set (Jia & Richards, 2004). Given the complexity of the images in this study, it is an appropriate approach for this study. Here we used the nearest neighbor classifier integrated in eCognition. Specially, we selected the samples considering the background of landscapes, individual difference between animals, and distribution patterns of animals as groups. After selecting training samples, we also applied optimized feature space i.e. best separation distance and dimension for classification. Table 10 shows the optimized feature space for nearest neighbor classification in eCognition. The nearest neighbor classifier in eCognition uses fuzzy classification, and therefore each of the classes in the final result of object-based approach has a probability for assigning the class it has been classified.

Table 10 Optimized feature space for nearest neighbor classification

Feature space	**Pilot_No.1**	**Pilot_No.2**
Best separation distance	3.061	1.048
Dimension	4	4

2.7.4. Rule set of expert knowledge

We develop rule set based on expert knowledge and finalized by visual interpretation in two aspects: geometric features and relationship features. By trying different parameters to develop the rule set, among geometric features, area, length/width and roundness are found to be useful indicators for differentiating animals from other confounding factors. For relationship features, the existence of a herd larger than certain size is an effective indicator for determining if it fits in the distribution pattern for an animal in herd. Specifically, Table 11 shows the description of the features in the rule set.

Table 11 Description of the rule set

Features	Expert knowledge	Image interpretation
Size	Average body size for dominant migratory ungulate	Average body size of the animals randomly selected
Roundness	An individual of animal on the image is close to a point feature, which indicates a small roundness	Average roundness of the animals randomly selected
Length/width	Animals in migration close to line features, not fitting the standard for object size but having a relatively high value for length/width	Minimum length/width of the animals in migration randomly selected
Existence of a herd	Dominant migratory animals live in herds ranging from 30 to more than 1000 animals	Minimum number existence of animals within certain distance

2.7.5. Export classification results

After the project in eCognition being finalized, we exported the results to the platform for analysis and validation in ArcMap. Specifically, we exported the class of 'animals' with the features used in the rule set. Table 12 lists all of them. The exported results are shpfiles which can be viewed and analyzed in ArcMap.

Table 12 Features exported with the object-based classification result of animals

Features exported	Description
Spectral reflectance	Values of layer 1,2,3,4 (blue, green, red and NIR) of the objects
Geometric features	Area, length/width, roundness
Relationship feature	Existence of a herd
Fuzzy classification	Possibility of an object classified as some class

2.8. Accuracy assessment

Kappa indices of agreement have been widely used in the area of remote sensing and it has been a routine for assessing the classification result of remote sensing images (Congalton, 1991; Congalton & Green, 1999). However, one of the most important assumptions of applying Kappa indices of agreement is randomness, specifically, random distribution of the quality and random spatial distribution of all the categories, and therefore Kappa indices of agreement are not suitable for the situations that do not fulfill the assumption of randomness discussed above (Pontius & Millones, 2011).

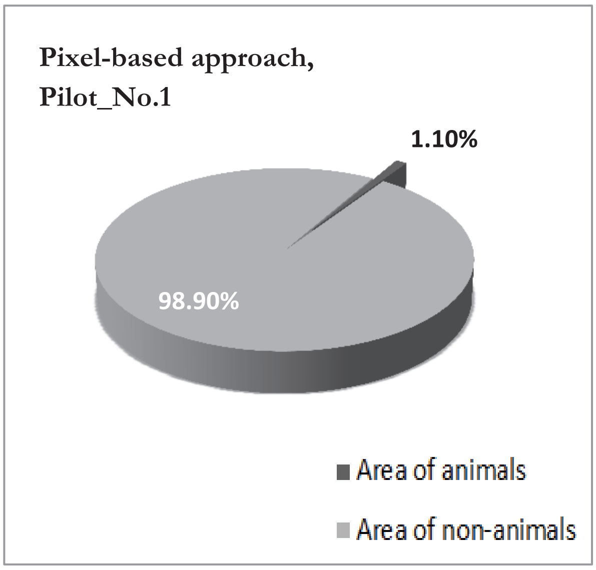
This study is exact one of the cases in which Kappa indices of agreement are not suitable the accuracy assessment. First of all, the area of all the objects in the category of animals only takes a tiny proportion in the pilot study area, namely Pilot_No.1 and Pilot_No.2. As we can clearly see from Figure 17, there is a great disproportion between the category of animals and the category of non-animals. Specific numbers are listed in Table 13 and Table 14. This means that there would be a great disproportion between the 'true negative' field (the number of non-animals correctly classified) and other fields in the error matrix (Table 15) for accracy assessmet. Second, neither of animals in the reuslt of visual interpretation nor in the reuslt of automated recognition are randomly distributed in spatial. We will conduct spatial statistical analysis to conclude the spatial distribution patterns of animals in the pilot study area in next section to justify this hypothesis.

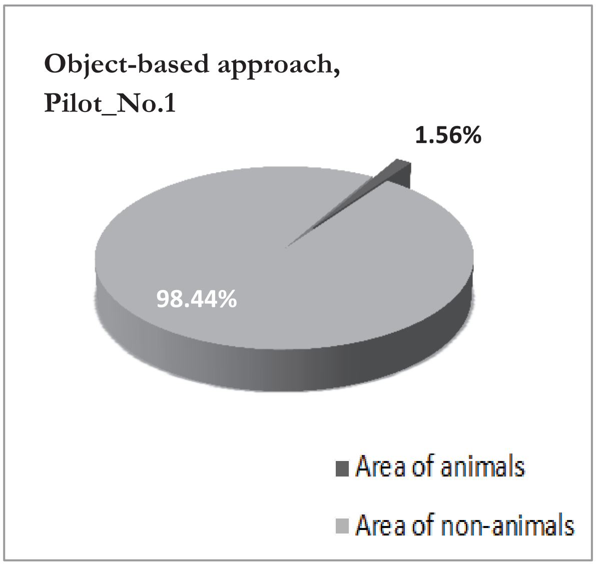
Table 13 Area of animals and area of non-animals in the classification results, Pilot_No.1

Method	Area of animals (m^2)	Area of non-animals (m^2)
Pixel-based approach	11004.50	988995.50
Object-based approach	15575.75	984424.25

Table 14 Area of animals and area of non-animals in the classification results, Pilot_No.2

Method	Area of animals (m^2)	Area of non-animals (m^2)
Pixel-based approach	1761.00	988995.50
Object-based approach	998239.00	996352.25





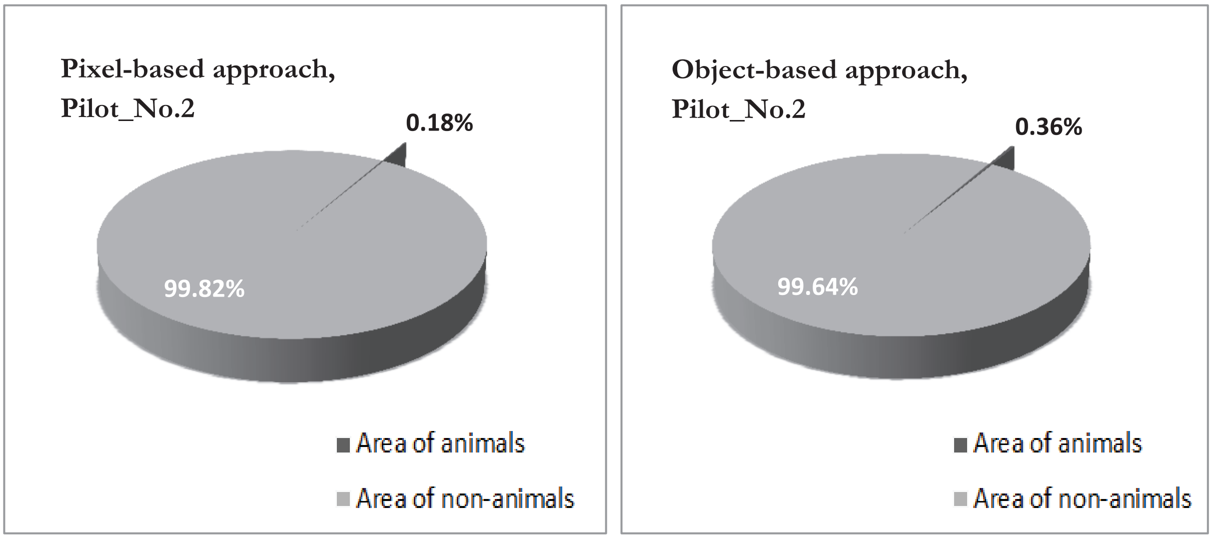


Figure 17 Proportion of the area of animals and the area of non-animals in Pilot_No.1 and Pilot_No.2

Table 15 Error matrix

		Classified result	
		YES	**NO**
Reference	**YES**	True positive	False negative
	NO	False positive	**True negative**

True Positive (TP): all the animals on ground correctly classified
False positive (FP): the objects of non-animals misclassified as animals
False negative (FN): the animals on ground not recognized
True negative (TN): the objects of non-animals on ground are correctly classified

As we discussed above, there is a disproportion between the sum of FN+TN and the sum of TP+FP; moreover, considering a relatively satisfactory user's accuracy, there is a disproportion between TN and the sum of the rest three fields.

The overall accuracy is computed by dividing the sum of all the fields on the diagonal (TP+TN) by the sum of all fields in the error matrix. To properly evaluate the performance of each approach, we need to correct that disproportion between TN and other fields. One solution for that is weighing, i.e. using weighted fields to derive the overall accuracy; however, that would diminish the precision of evaluating the performance of each approach since it is difficult and subjective to decide the weight for each field.

Therefore, to precisely evaluate the overall performance of each approach, we decide to avoid the disproportion by using the reference data only contains the animals on the imagery (true positive). Consequently, since there is only true positive in the reference data, therefore there are three fields in the error matrix, namely true positive, false negative and false positive and true negative in the error matrix is non-applicable. Although by that means overall accuracy would be non-applicable in this study, however, we can precisely evaluate the performance of each approach by assessing the capabilities in two aspects:

one is the capability of correctly recognizing the animals on the imagery, i.e. the capability in reducing omission error; the other one is the capability of avoid misclassifying non-animals as animals, i.e. the capability of reducing commission error.

Based on the discussion mentioned above, we assess the accuracy using producer's accuracy and user's accuracy to evaluate the performance of each approach in the two aspects mentioned above. Producer's accuracy refers to the probability of a pixel in the reference data being correctly classified, which can be used for measuring omission error; on the other hand, user's accuracy means the probability of a pixel being correctly classified in the category classified, i.e. the probability that it actually representing ground truth (Congalton, 1991; Story & Congalton, 1986).

Besides, the great disproportion between the area of animals and non-animals means a disproportion between these two categories in pixel number to the same extent. Therefore, we will use the number of objects correctly classified or misclassified as the unit to assess the accuracy of classification result instead of the number of pixels. In this case, the producer set is all the animals recognized by some interpreter and the user set is the animals in the classification results of pixel-based approach and object-based approach.

3. RESULTS

3.1. Visual interpretation

Table 16 shows the results of interpretation made by different interpreters and descriptive statistics about the different results.

Table 16 Results and descriptive statistics of visual interpretation

Interpreter	Pilot_No.1	Pilot_No.2
No.1	517	152
No.2	508	147
No.3	538	147
No.4	515	134
No.5	495	139
Mean	515	144
Standard deviation	16	7
Coefficient of Variation	3.04%	5.00%

3.2. Classification of pixel-based approach

3.2.1. Mapping wildlife in the study area

The main objective of this study is to evaluate the capabilities of using high resolution GeoEye-1 satellite imagery for mapping wildlife in open savannahs. Therefore, mapping wildlife in the study area is a necessity. According to the results of the pixel-based approach, we managed to produce two maps of the detected wildlife in the pilot study area, namely Pilot_No.1 and Pilot_No.2 (Figure 18 and Figure 19).

To emphasize the presence of animals, we do not use the vector layer of all objects (polygons) from the classification result. Instead, we converted the extracted features to points, which are the centroids of the features. Therefore the detected wildlife on the map is presented by point features. Consequently the area of detected wildlife does not represent actual area of ground truth.

In addition to the two maps of detected wildlife in the pilot study area, we also provide two snapshots of the pixel-based approach classification results in the validation areas (Figure 20 and Figure 21).

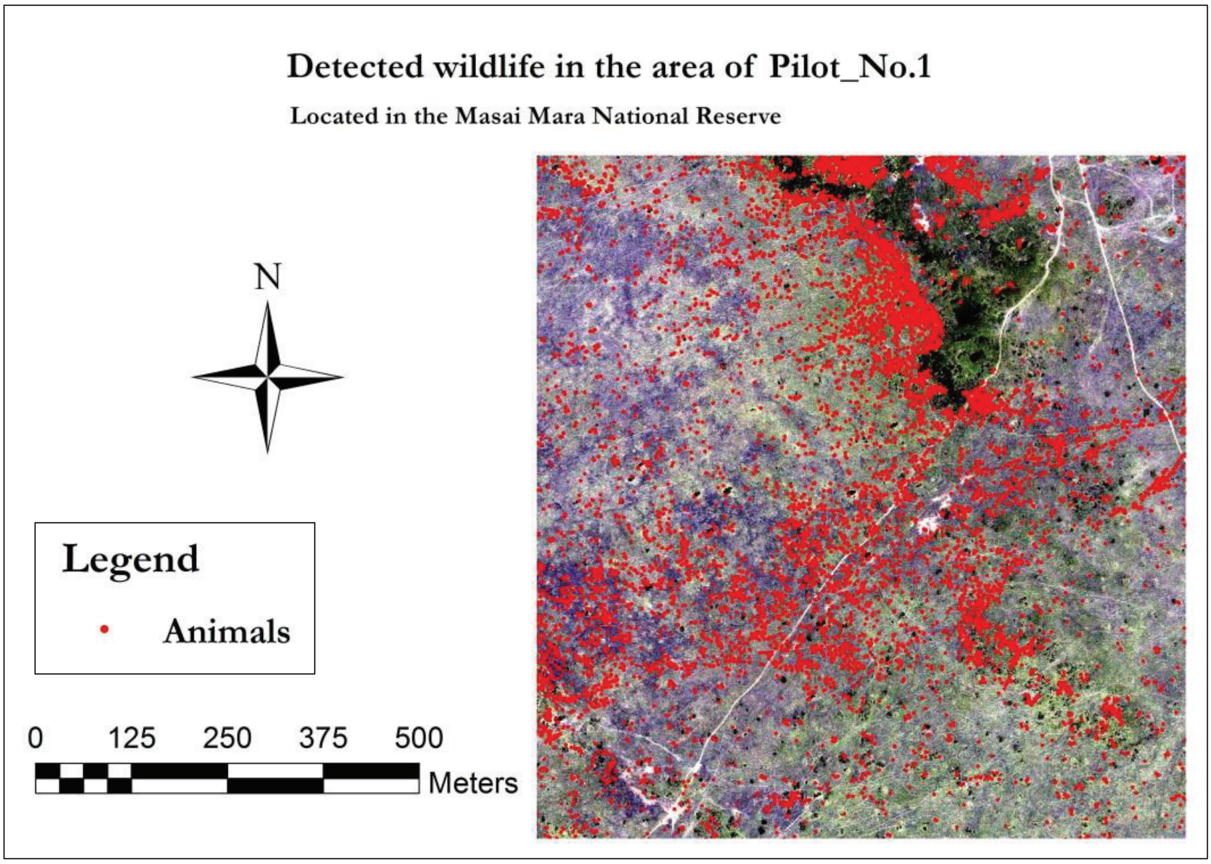


Figure 18 Detected wildlife in the area of Pilot_No.1 by pixel-based approach

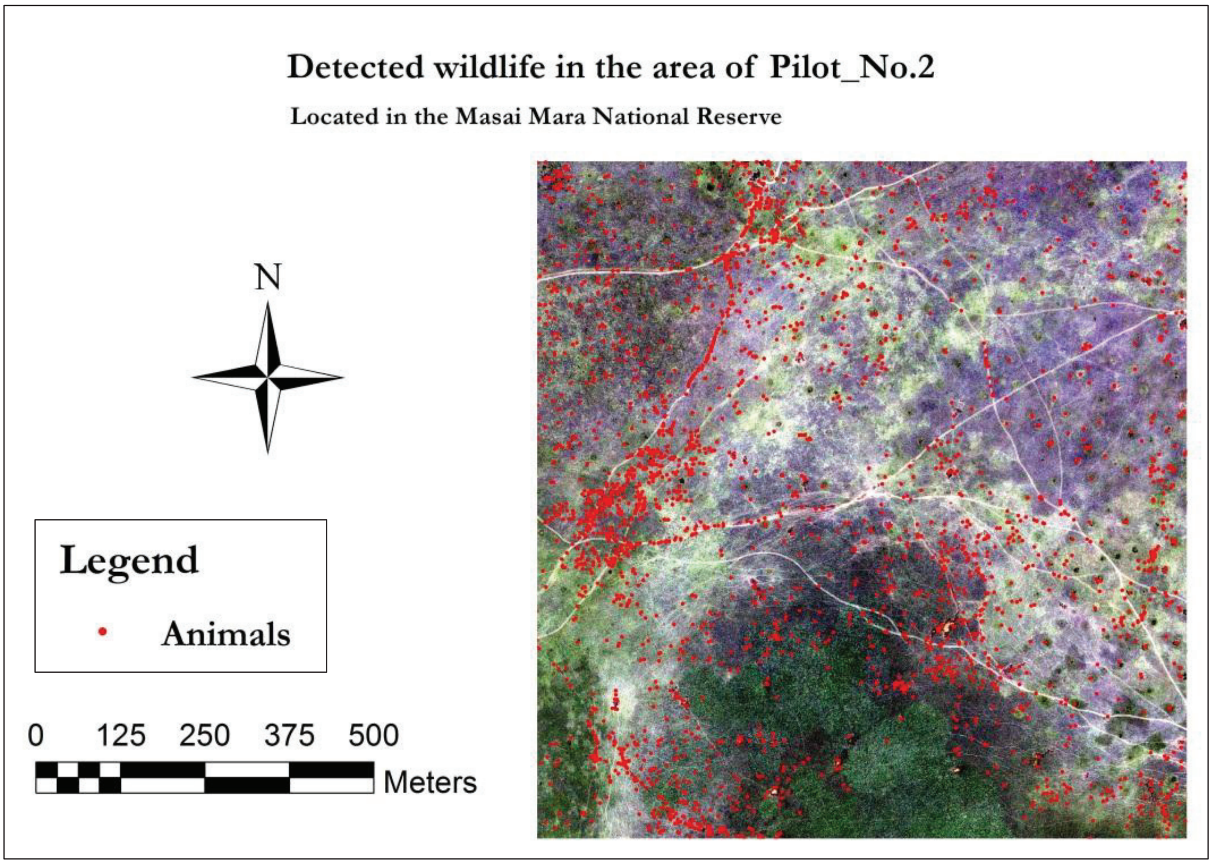


Figure 19 Detected wildlife in the area of Pilot_No.2 by pixel-based approach

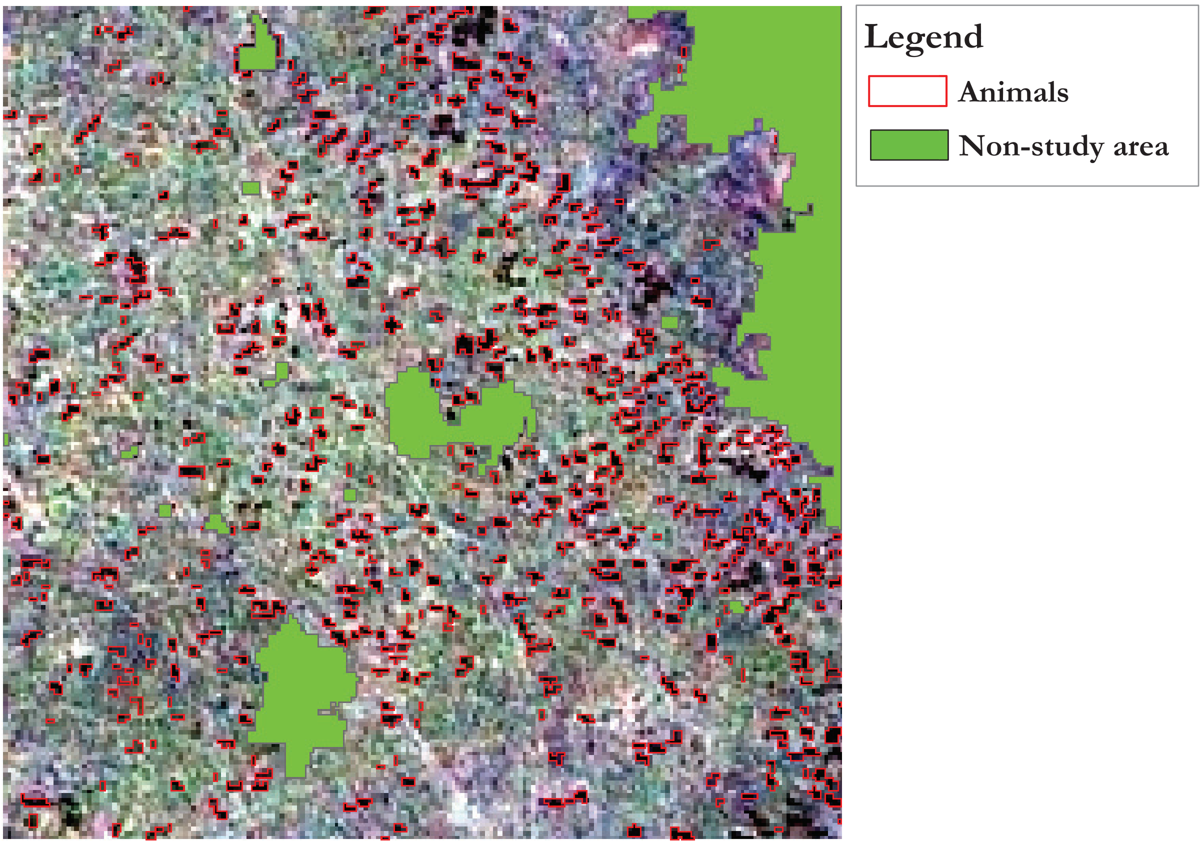


Figure 20 Detected animals by using pixel-based approach in the validation area of Pilot_No.1

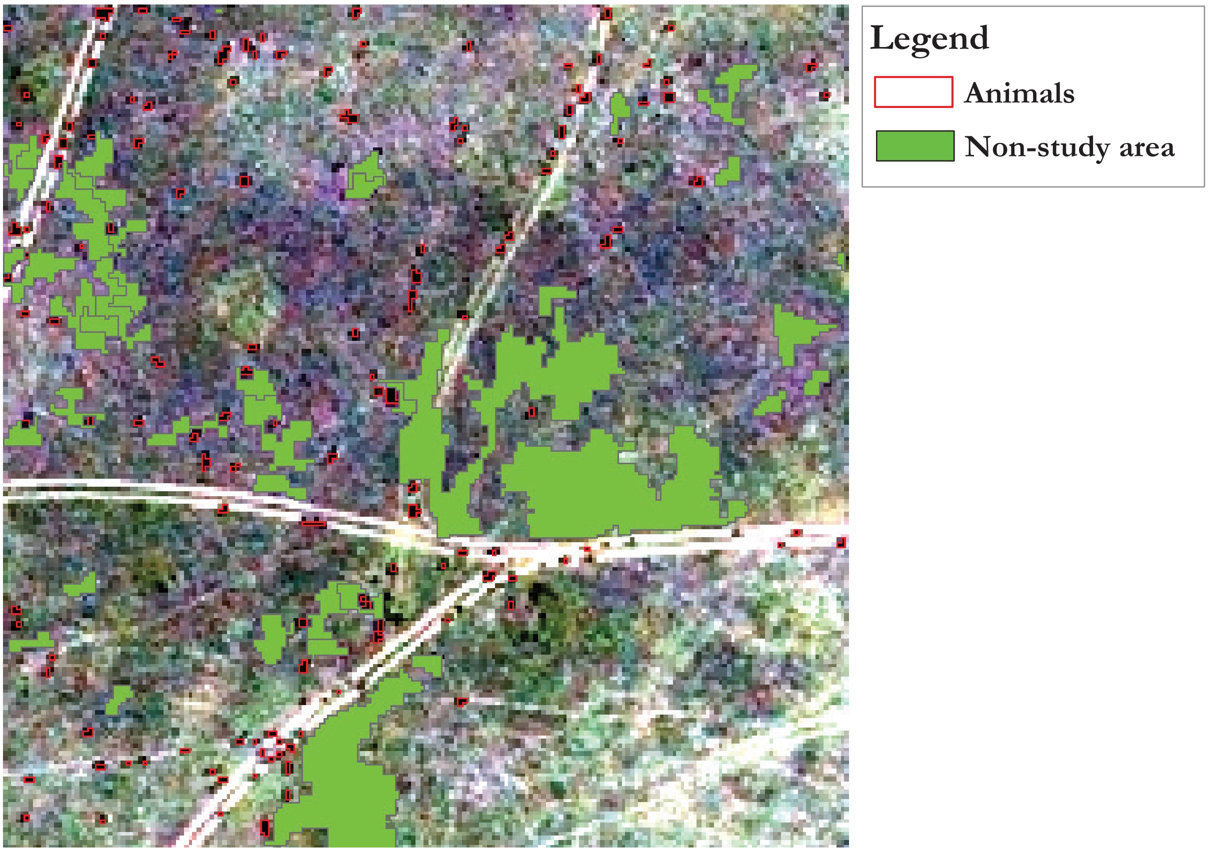


Figure 21 Detected animals by using pixel-based approach in the validation area of Pilot_No.2

3.2.2. Accuracy assessment

Based on the results by multiple interpreters, we assessed the accuracy of the pixel-based approach. Table 17 and Table 18 summary the accuracy reports of each validation area.

Table 17 Accuracy report of pixel-based approach in Pilot_No.1

Interpreter	Reference totals	Classified totals	Number correct	Omission error	Commission error	Producer's accuracy	User's accuracy
No.1	517		463	10.4%	12.6%	89.6%	87.4%
No.2	508		445	12.4%	16.0%	87.6%	84.0%
No.3	538	530	460	14.5%	13.2%	85.5%	86.8%
No.4	515		447	13.2%	15.7%	86.8%	84.3%
No.5	495		437	11.7%	17.5%	88.3%	82.5%
Average	**515**	**530**	**450**	**12.5%**	**15.0%**	**87.5%**	**85.0%**

Table 18 Accuracy report of pixel-based approach in Pilot_No.2

Interpreter	Reference totals	Classified totals	Number correct	Omission error	Commission error	Producer's accuracy	User's accuracy
No.1	152		134	11.8%	5.63%	88.2%	94.4%
No.2	147		132	10.2%	7.04%	89.8%	93.0%
No.3	147	142	135	8.16%	4.93%	91.8%	95.1%
No.4	134		115	14.2%	19.0%	85.8%	81.0%
No.5	139		119	14.4%	16.2%	85.6%	83.8%
Average	**144**	**142**	**127**	**11.8%**	**10.6%**	**88.2%**	**89.4%**

3.2.3. Factors affecting the accuracy

We are aware that there are some factors may have positive or negative effect on the final accuracy. Therefore, it is necessary for us to study the factors which potentially may have effect on the accuracy and to reveal whether these factors would lead to significant difference on accuracy. After refining the study area, Pilot_No.1 and Pilot_No.2 have similar background for image classification. Therefore, among all the factors, the density of animals is the most notable difference between Pilot_No.1 and Pilot_No.2 and our primary concern among all the factors.

We conduct statistical analysis to test the significance of the effect of density of animal distribution on the accuracy of pixel-based approach. Considering the different samples of accuracies on Pilot_No.1 and Pilot_No.2 are independent with each other, conducting a two sample t-test to compare two sample means would be suitable for this study. Before conducting the t-test on the two sample means, we test the normality of the two samples and the result indicates they follow a normal distribution. Table 19 shows the samples of accuracies for t-test.

Table 19 Samples of producer's accuracies of pixel-based approach

No. of samples	Pilot_No.1	Pilot_No.2
No.1	89.6%	88.2%
No.2	87.6%	89.8%
No.3	85.5%	91.8%
No.4	86.8%	85.8%
No.5	88.3%	85.6%

Table 20 Samples of user's accuracies of pixel-based approach

No. of samples	Pilot_No.1	Pilot_No.2
No.1	87.4%	94.4%
No.2	84.0%	93.0%
No.3	86.8%	95.1%
No.4	84.3%	81.0%
No.5	82.5%	83.8%

Before conducting the t-test, we test the equality of variances to decide conducting a two sample t-test with equal variances or unequal variances. Table 21 shows the result of the test for equality of variances.

Table 21 Test for equality of variances for the samples of accuracies of pixel-based approach

	Levene's Test for Equality of Variances	
	F	**Sig.**
Producer's accuracies	1.76	0.221
User's accuracies	20.07	0.002

From the test for equality of variances, we can see that there is no significant difference between the variances of the samples of producer's accuracy, and there is significant difference between the variances of the samples of user's accuracy. Therefore we conducted a two sample t-test with equal variances at a significance level of 0.05 for the samples of producer's accuracy and a two sample t-test with unequal variances at a significance level of 0.05 for the samples of user's accuracy. Table 22 shows result of t-test.

Table 22 t-test of the samples of accuracies of pixel-based approach

	Producer's accuracies	User's accuracies
df (degree of freedom)	8	5
t Stat	-0.51	-1.45
P(T<=t) two-tail	0.624	0.206
t Critical two-tail	2.31	2.57

The result of t-test indicates that there is no significant difference between the means of the both producer's and user's accuracies of pixel-based approach on Pilot_No.1 and Pilot_No.2.

3.2.4. Estimation of the population size

One of the most important potential applications of using high resolution satellite imagery for mapping wildlife is being a supplement and alternative for wildlife population estimation. Therefore, a preliminary attempt to estimate population size of wildlife was made in this study. Here we have two situations: the individual of the animals can be identified and it cannot be identified. For the first case, we can estimate the population size by counting the number of the individuals. For the second case, we count the individuals sticking together as one object of animals. Although this kind of situation is rare in the sample images, there definitely would be an underestimation of the population size to some degree for this reason. The number of animals recognized by pixel-based approach in the pilot study area is: 9539 in Pilot_No.1 and 2872 in Pilot_No.2. According to the results of pixel-based approach, we give an estimation of the population size by omission error and commission error since the overall accuracy is non-applicable in this study.

To estimate the population size, we need to determine the upper limit of confidence interval for the means of omission error and commission error of the pixel-based approach. Before analyzing the confidence interval, we tested the normality of the samples of omission error and commission error and the result indicates that they follow the normal distribution. Table 19 and Table 20 list the upper limit of the confidence interval of the omission and commission error at a 95% confidence level respectively.

Table 23 Upper limit of the means of omission and commission errors of pixel-based approach on Pilot_No.1

	Omission error	**Commission error**
Average	12.5%	15.0%
Standard deviation	0.0153	0.0205
df	4	4
t critical	2.78	2.78
Upper limit of confidence interval (95%)	14.6%	17.9%

Table 24 Upper limit of the means of omission and commission errors of pixel-based approach on Pilot_No.2

	Omission error	**Commission error**
Average	11.8%	10.6%
Standard deviation	0.0265	0.0655
df	4	4
t critical	2.78	2.78
Upper limit of confidence interval (95%)	15.4%	19.7%

We determine the lower limit of the estimation of the population by the commission error and determine the upper limit by the omission error. Table 21 shows the estimation of the population size using pixel-based approach in the pilot study area.

- Lower limit of population =classified number * (1- upper limit of commission error)
- Upper limit of population =classified number * (1+upper limit of omission error)

Table 25 Population size estimation by using pixel-based approach

	Pilot_No.1	Pilot_No.2
Number classified	9539	2872
Upper limit of commission error	17.9%	19.7%
Lower limit of population	7834	2308
Upper limit of omission error	14.6%	15.4%
Upper limit of population	10929	3315
Confidence interval of population size (95%)	7834~10929	2308~3315

Based the discussion above, we give the estimation of the population size as: 10142~14244 (12193±2051) in the pilot study area. Since the upper limit of the errors are derived from the confidence interval of the error (95%). This estimation is the range of the population size in each region of the pilot study area at a 95% confidence level.

3.2.5. Spatial statistics

In addition to the estimation of the population size, we also conduct a spatial statistics about on the spatial distribution patterns of the animals being recognized. Generally there are three spatial distribution patterns: clustered, random and dispersed. Figure 22 shows a comparison between a snapshot of animals in Pilot_No.1 and three types of spatial distribution pattern. Specifically, we analyzed the spatial distribution patterns of the detected animals by using average nearest neighbor distance ArcMap. Table 26 summarizes the result of spatial statistics. Generally, an expected mean distance larger than observed mean of average nearest neighbor distance indicates clustering of the objects being analyzed (Dodds, Garman, & Ross, 2006). From the result of z-test, we can see that there is a probability less than 1% that the clustered patterns of the results could be the result of random chance. Therefore, the distribution pattern of the animals in the pilot study area is clustered according to the result by pixel-based approach with a significance level of 0.01.

Table 26 Spatial statistics of the result by pixel-based approach

	Pilot_No.1	Pilot_No.2
Observed Mean Distance (m)	3.7	5.2
Expected Mean Distance (m)	5.1	9.3
z-score	-51.49	-45.62
Critical value (z-score)	<-2.58 or >2.58 with a significance level (p-value) of 0.01	
p-value	0.00	0.00

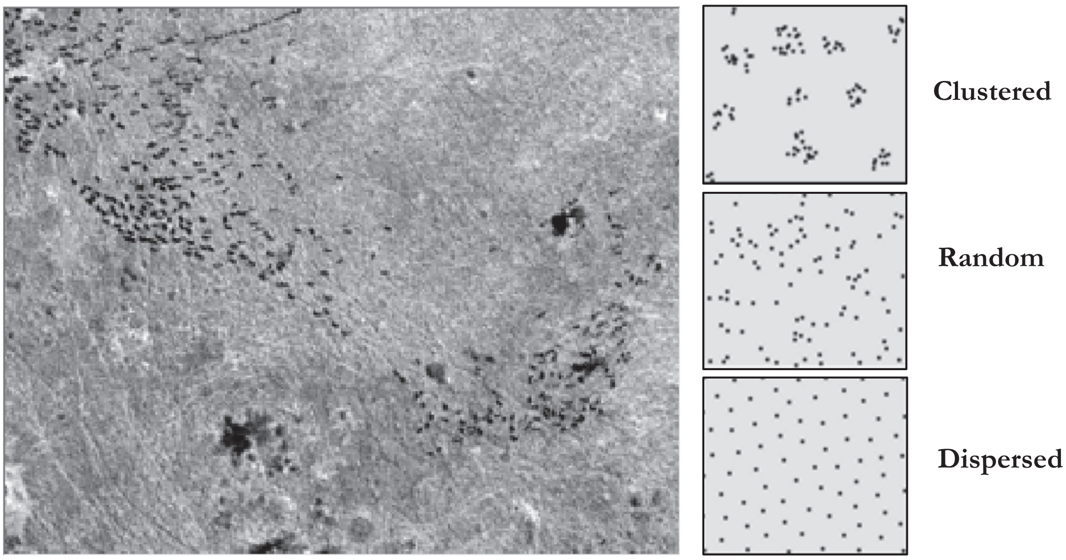


Figure 22 Comparison between a snapshot of animals in Pilot_No.1 and three spatial distribution patterns

3.3. Classification of object-based approach

3.3.1. Mapping wildlife in the study area

According to the results of the object-based approach, we managed to produce two maps of the detected wildlife in the pilot study area, namely Pilot_No.1 and Pilot_No.2 (Figure 23 and Figure 24). In addition to the two maps of detected wildlife in the pilot study area, we also provide two snapshots of the object-based approach classification results in the validation areas (Figure 25 and Figure 26).

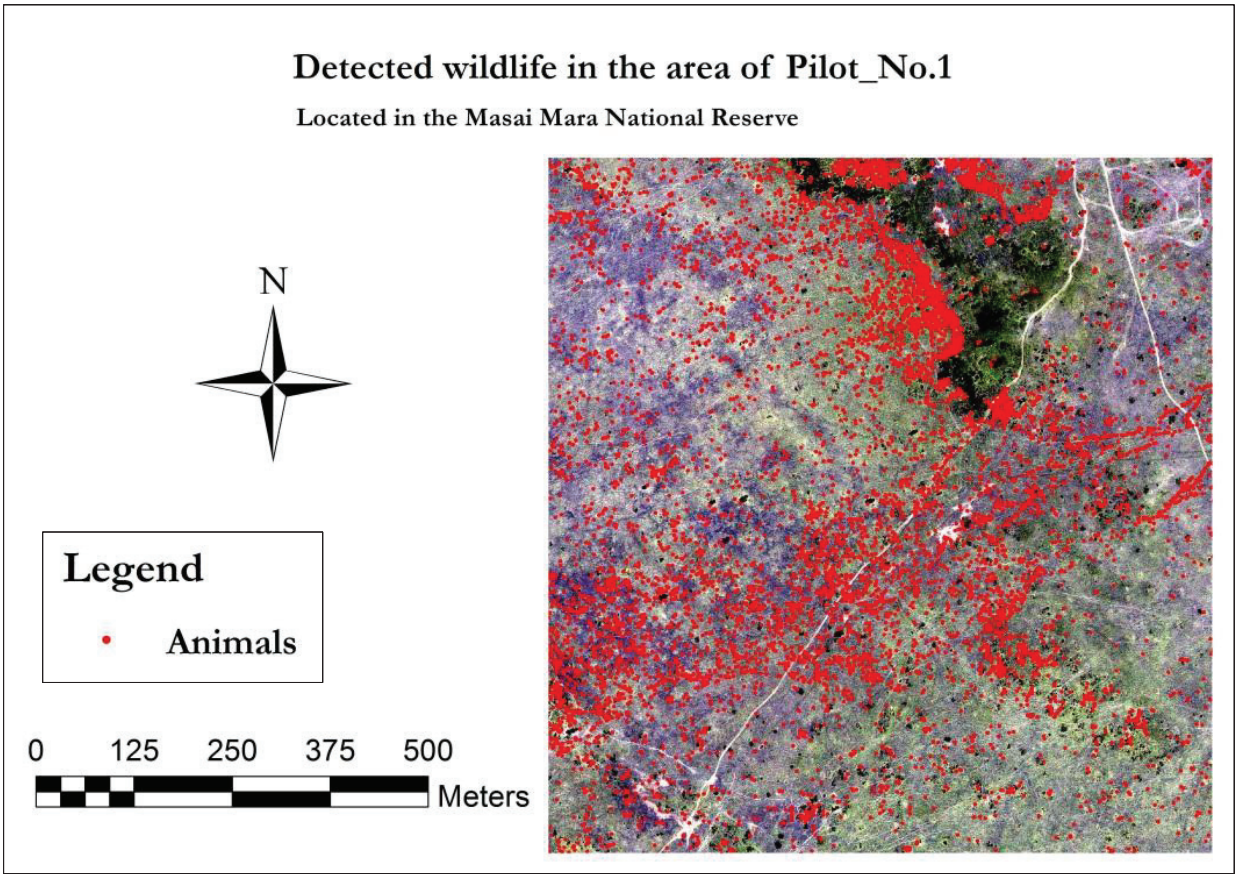


Figure 23 Detected wildlife in the area of Pilot_No.1 by object-based approach

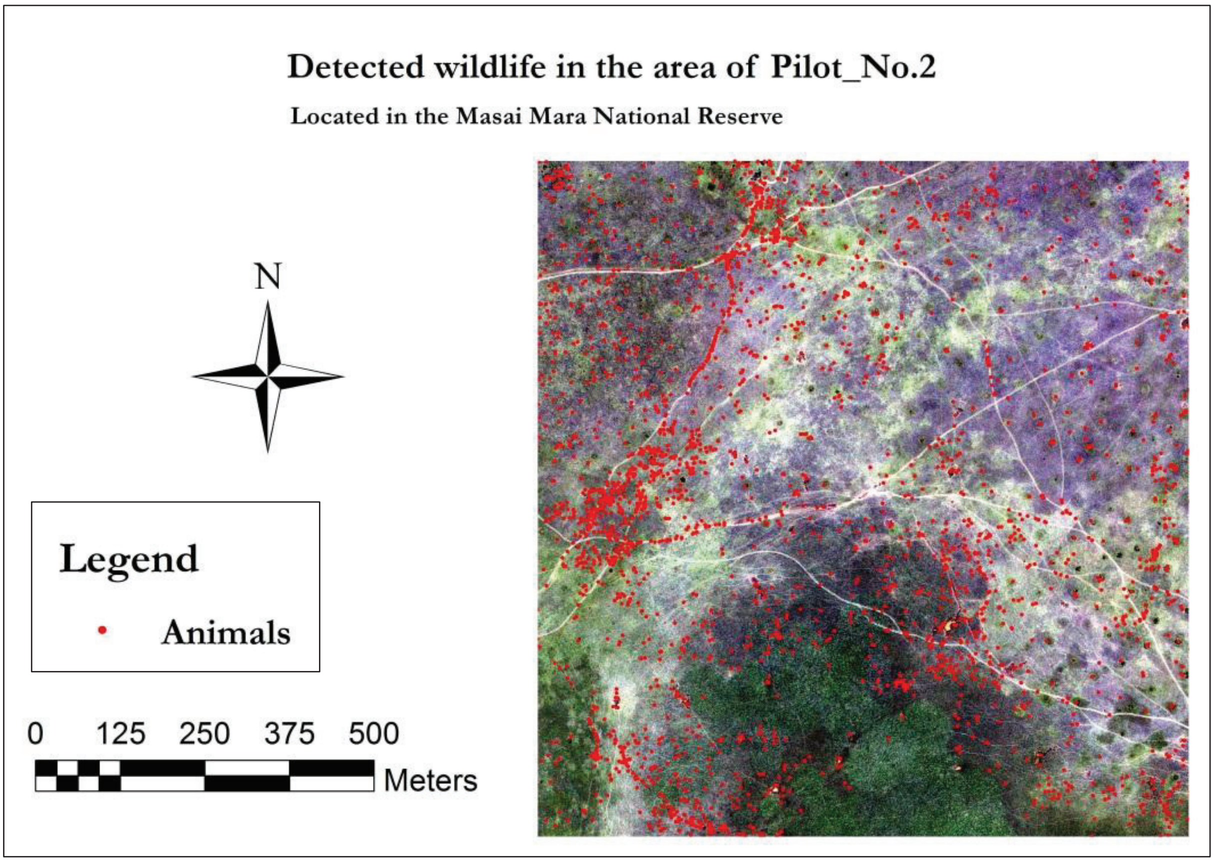


Figure 24 Detected wildlife in the area of Pilot_No.2 by object-based approach

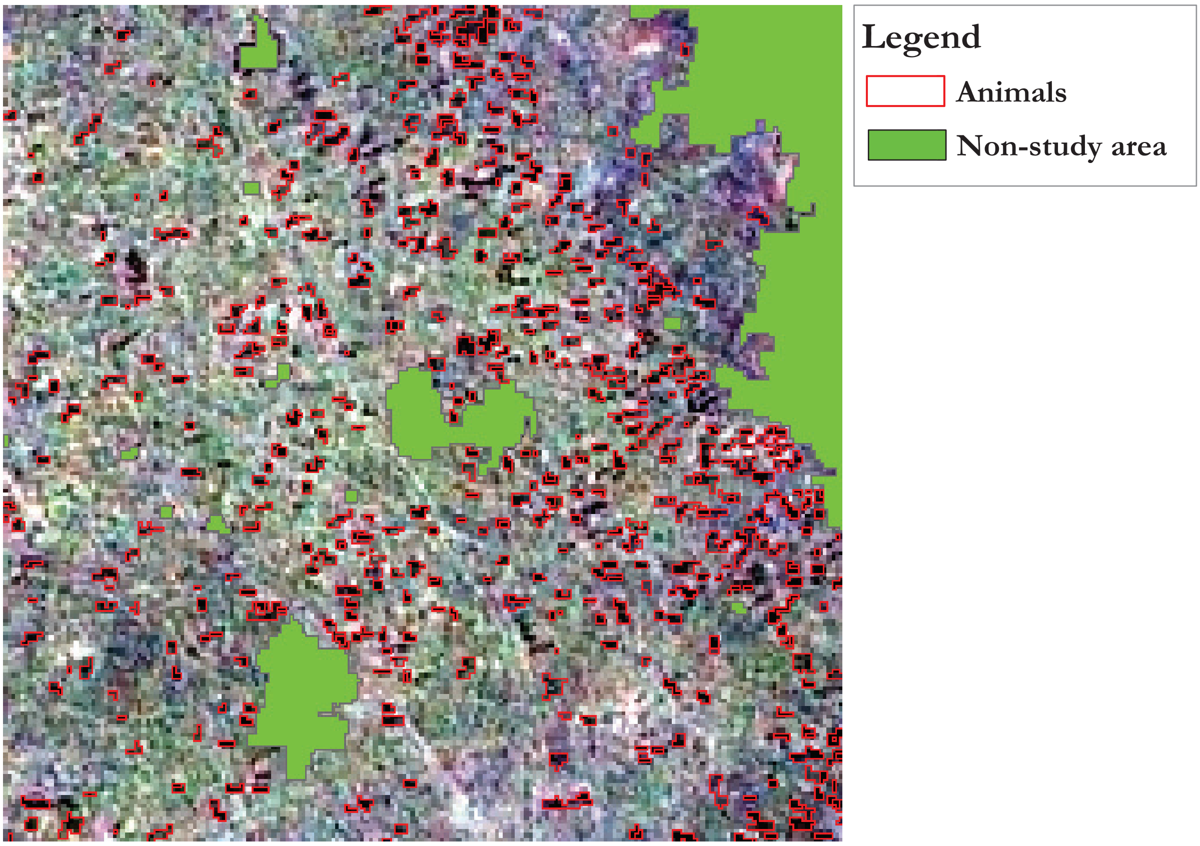


Figure 25 Detected animals by using object-based approach in the validation area of Pilot_No.1

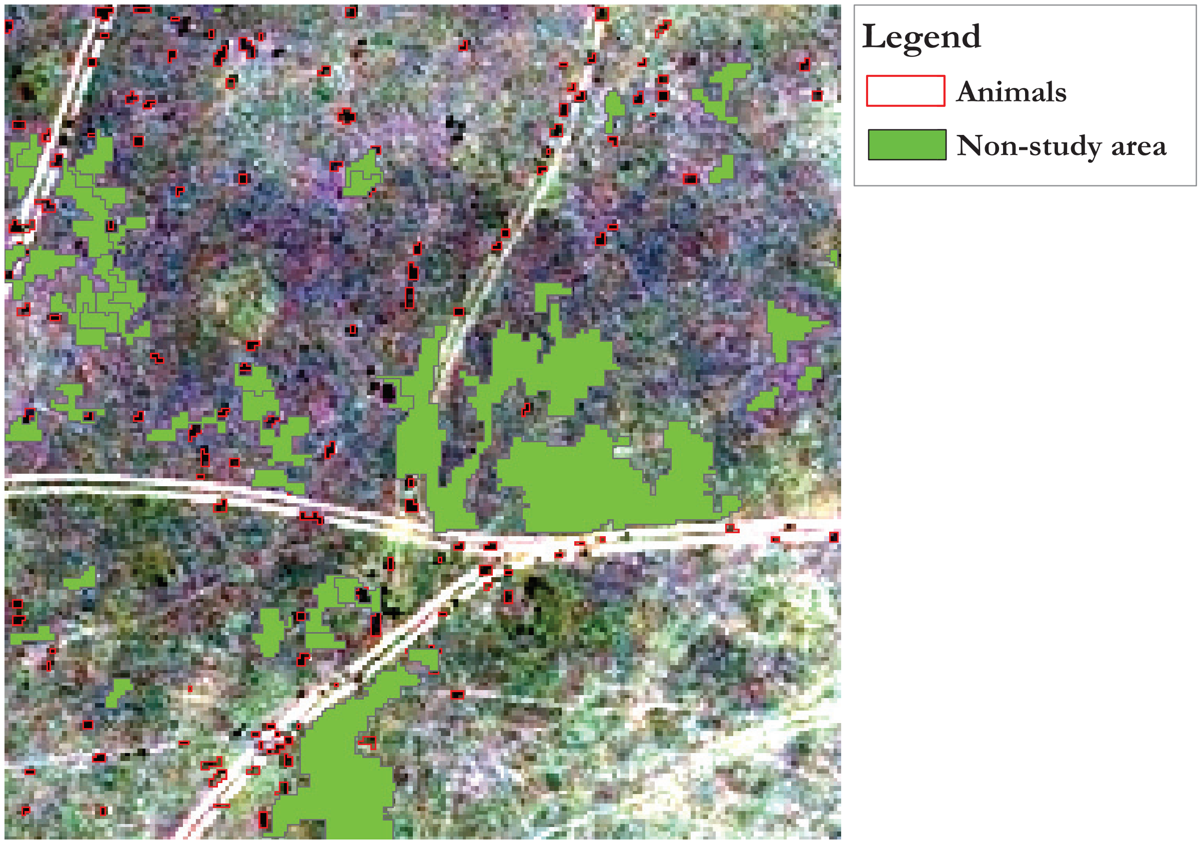


Figure 26 Detected animals by using object-based approach in the validation area of Pilot_No.2

3.3.2. Accuracy assessment

Based on the results by multiple interpreters, we assessed the accuracy of the object-based approach. Table 27 and Table 28 summary the accuracy reports on each validation area.

Table 27 Accuracy report of object-based approach in Pilot_No.1

Interpreter	Reference totals	Classified totals	Number correct	Omission error	Commission error	Producer's accuracy	User's accuracy
No.1	517		447	13.5%	13.5%	86.5%	86.5%
No.2	508		465	8.46%	10.1%	91.5%	89.9%
No.3	538	517	452	16.0%	12.6%	84.0%	87.4%
No.4	515		450	12.6%	13.0%	87.4%	87.0%
No.5	495		426	13.9%	17.6%	86.1%	82.4%
Average	**515**	**517**	**448**	**12.9%**	**13.3%**	**87.1%**	**86.7%**

Table 28 Accuracy report of object-based approach in Pilot_No.2

Interpreter	Reference totals	Classified totals	Number correct	Omission error	Commission error	Producer's accuracy	User's accuracy
No.1	152		129	15.1%	1.53%	84.9%	98.5%
No.2	147		126	14.3%	3.82%	85.7%	96.2%
No.3	147	131	125	15.0%	4.58%	85.0%	95.4%
No.4	134		112	16.4%	14.5%	83.6%	85.5%
No.5	139		114	18.0%	13.0%	82.0%	87.0%
Average	**144**	**131**	**121**	**15.8%**	**7.48%**	**84.2%**	**92.5%**

3.3.3. Factors affecting the accuracy

We conduct independent two-sample t-test to test the significance of the effect of density of animal distribution on the accuracy of pixel-based approach. Table 29 and 30 summarize the samples of accuracies of object-based approach.

Table 29 Samples of producer's accuracies of object-based approach

No. of samples	Pilot_No.1	Pilot_No.2
No.1	86.5%	84.9%
No.2	91.5%	85.7%
No.3	84.0%	85.0%
No.4	87.4%	83.6%
No.5	86.1%	82.0%

Table 30 Samples of user's accuracies of object-based approach

No. of samples	Pilot_No.1	Pilot_No.2
No.1	86.5%	98.5%
No.2	89.9%	96.2%
No.3	87.4%	95.4%
No.4	87.0%	85.5%
No.5	82.4%	87.0%

Before conducting the t-test on the two sample means, we test the normality of the two samples and the result indicates they follow a normal distribution. Besides, we also test equality of variances to decide conducting a two sample t-test with equal variances or unequal variances. Table 31 shows the result of the test for equality of variances.

Table 31 Test for equality of variances for the samples of accuracies of object-based approach

	Levene's Test for Equality of Variances	
	F	**Sig.**
Producer's accuracies	0.742	0.414
User's accuracies	8.24	0.021

From the test for equality of variances, we can see that there is no significant difference between the variances of the samples of producer's accuracy, and there is significant difference between the variances of the samples of user's accuracy. Therefore we conducted a two sample t-test with equal variances at a significance level of 0.05 for the samples of producer's accuracy and a two sample t-test with unequal variances at a significance level of 0.05 for the samples of user's accuracy. Table 32 shows result of t-test.

Table 32 t-test of the samples of accuracies of object-based approach

	Producer's accuracies	User's accuracies
df (degree of freedom)	8	6
t Stat	2.03	-2.03
P(T<=t) two-tail	0.077	0.088
t Critical two-tail	2.31	2.45

The result of t-test indicates that there is no significant difference between the means of the both producer's and user's accuracies of object-based approach on Pilot_No.1 and Pilot_No.2.

3.3.4. Estimation of the population size

The number of animals recognized by object-based approach in the pilot study area is: 10162 in Pilot_No.1 and 2598 in Pilot_No.2.

Similar with the estimation for population size by pixel-based approach, before we can apply the method for estimating the population size, we should determine the confidence interval for the means of omission error and commission error. Before analyzing the confidence interval, we test the normality of the samples of omission error and commission error and the result indicates that they follow the normal distribution. Table 33 and Table 34 list the upper limit of the confidence interval of the omission and commission error at a 95% confidence level respectively.

Table 33 Upper limit of the means of omission and commission errors of object-based approach on Pilot_No.1

	Omission error	Commission error
Average	12.9%	13.4%
Standard deviation	0.0277	0.0273
df	4	4
t critical	2.78	2.78
Upper limit of confidence interval (95%)	16.8%	17.1%

Table 34 Upper limit of the means of omission and commission errors of object-based approach on Pilot_No.2

	Omission error	**Commission error**
Average	15.8%	7.48%
Standard deviation	0.0147	0.0585
df	4	4
t critical	2.78	2.78
Upper limit of confidence interval (95%)	17.8%	15.6%

We determine the lower limit of the estimation of the population by the commission error and determine the upper limit by the omission error. Table 35 shows the estimation of the population size using object-based approach in the pilot study area.

- Lower limit of population =classified number * (1- upper limit of commission error)
- Upper limit of population =classified number * (1+upper limit of omission error)

Table 35 Population size estimation by using object-based approach

	Pilot_No.1	**Pilot_No.2**
Number classified	10162	2598
Upper limit of commission error	17.1%	15.6%
Lower limit of population	8420	2193
Upper limit of omission error	16.8%	17.8%
Upper limit of population	11864	3060
Confidence interval of population size (95%)	8420~11864	2193~3060

Based the discussion above, we give the estimation of the population size as: 10613~14924 (12769±2156) in the pilot study area. Since the upper limit of the errors are derived from the confidence interval of the error (95%). This estimation is the range of the population size in each region of the pilot study area at a 95% confidence level.

3.3.5. Spatial statistics

Here we used the same method to check the spatial distribution patterns of the animals detected by object-based approach, i.e. analyzing the spatial distribution patterns of the animals using average nearest neighbor distance in ArcMap. Figure 27 show a comparison between a snapshot of animals in Pilot_No.2 and three types of spatial distribution pattern. From the spatial statistics (Table 36), we can see an expected mean distance larger than observed mean of average nearest neighbor distance and there is a probability less than 1% that the clustered patterns of the results could be the result of random chance. Therefore, the distribution pattern of the animals in the pilot study area is clustered according to the result by object-based approach with a significance level of 0.01.

Table 36 Spatial statistics of the result by object-based approach

	Pilot_No.1	Pilot_No.2
Observed Mean Distance (m)	3.6	7.2
Expected Mean Distance (m)	5.0	9.8
z-score	-52.99	-25.99
Critical value (z-score)	<-2.58 or >2.58 with a significance level (p-value) of 0.01	
p-value	0.00	0.00

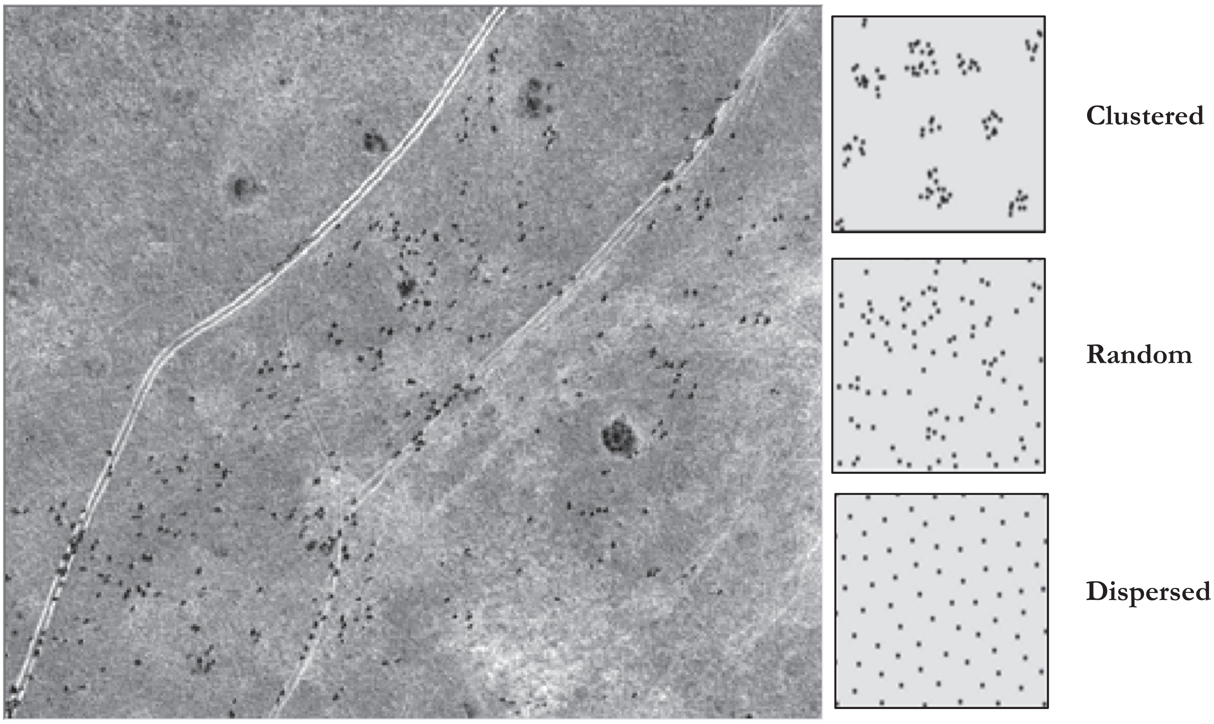


Figure 27 Comparison between a snapshot of animals in Pilot_No.2 and three spatial distribution patterns

3.4. Comparison between the results of pixel-based approach and object-baed approach

We conduct statistical analysis to test whether there is significant difference between the accuracy producer's accuracy and user's accuracy of pixel-based and object-based approaches. The normality for the accuracy of pixel-based and object-based approach in Pilot_No.1 and Pilot_No.2 has been tested, and the result proves that all samples of accuracies follow a normal distribution.

Since previous independent two-sample t-test indicates that the there is no significant difference of the accuracy of these two approaches on Pilot_No.1 and Pilot_No.2, therefore, for the following statistical analysis, we categorize the samples of accuracies in the pilot study area into two groups: producer's accuracy and user's accuracy without specifying which region in the pilot study area.

3.4.1. Producer's accuracies

We conducted an independent two-sample t-test for means at a significance level of 0.05 to check the significance of the difference between the producer's accuracies of pixel-based approach and object-based approach. Table 37 summarizes the producer's accuracies from different interpretation results by the multiple interpreters, which will be used for the dependent two-sample t-test. Table 38 shows the result of the test for equality of variances. Table 39 shows the result of the independent two-sample t-test.

Table 37 Summary of the producer's accuracies of pixel-based and object-based approaches

	Group1: Pixel-based approach	Group2: Object-based approach
Pilot_No.1	89.6%	86.5%
	87.6%	91.5%
	85.5%	84.0%
	86.8%	87.4%
	88.3%	86.1%
Pilot_No.2	88.2%	84.9%
	89.8%	85.7%
	91.8%	85.0%
	85.8%	83.6%
	85.6%	82.0%

Table 38 Test for equality of variances for the producer's accuracies of pixel-based and object-based approaches

	Levene's Test for Equality of Variances	
	F	Sig.
Equal variances assumed	0.040	0.844

Table 39 t-test of producer's accuracies of pixel-based and object-based approaches

	df	t Stat	P(T<=t) two-tail	t Critical two-tail
Value	18	2.13	0.047	2.10

The result of the independent two-sample t-test indicates that there is a significant difference between the means of the accuracies of pixel-based approach and object-based approach. The positive t-value on the right side indicates that pixel-based approach having higher producer's accuracy than object-based approach.

3.4.2. User's accuracies

We conducted the independent two-sample t-test at a significance level of 0.05 to check the significance of the difference in user's accuracies between pixel-based approach and object-based approach. Table 40 summarizes the user's accuracies from different interpretation results by the multiple interpreters. Table 41 shows the result of the test for equality of variances. Table 42 shows the result of the independent two-sample t-test.

Table 40 Summary of the user's accuracies of pixel-based and object-based approaches

	Group1: Pixel-based approach	Group2: Object-based approach
Pilot_No.1	87.4%	86.5%
	84.0%	89.9%
	86.8%	87.4%
	84.3%	87.0%
	82.5%	82.4%
Pilot_No.2	94.4%	98.5%
	93.0%	96.2%
	95.1%	95.4%
	81.0%	85.5%
	83.8%	87.0%

Table 41 Test for equality of variances for the user's accuracies of pixel-based and object-based approaches

	Levene's Test for Equality of Variances	
	F	Sig.
Equal variances assumed	0.016	0.902

Table 42 t-test of user's accuracies of pixel-based and object-based approaches

	df	t Stat	P(T<=t) two-tail	t Critical two-tail
Value	18	-1.02	0.322	2.10

The result of the independent two-sample t-test indicates that there is no significant difference between the means of the user's accuracies between pixel-based approach and object-based approach.

3.4.3. Population estimation

So far we have compared the results of pixel-based and object-based approaches in producer's and user's accuracy. Since one of the most important potential uses of using high resolution satellite imagery for mapping wildlife is being a supplement and alternative for wildlife population estimation. Therefore, it is necessary to test the significance of the difference between these two approaches in wildlife population estimation of the pilot study area.

First of all, we conduct the normality test of the upper limits and lower limits of the confidence interval for each methods and it proves that they follow the normal distribution. Then we test the equality of the variances. Since these two samples have equal variances, therefore we conduct an independent two-sample t-test for the means with equal variances of these two groups. Table 45 summarizes the result of t-test for means.

Table 43 Population estimation results by pixel-based and object-based approaches

	Pixel-based approach	Object-based approach
Lower limit of Pilot_No.1	7834	8420
Upper limit of Pilot_No.1	10929	11864
Lower limit of Pilot_No.2	2308	2193
Upper limit of Pilot_No.2	3315	3060

Table 44 Test for equality of variances of population estimation results by pixel-based and object-based approaches

	Levene's Test for Equality of Variances	
	F	**Sig.**
Equal variances assumed	0.231	0.648

Table 45 t-test of population estimation results by pixel-based and object-based approaches

	df	t Stat	P(T<=t) two-tail	t Critical two-tail
Value	6	-0.095	0.928	2.45

From the result of independent two-sample t-test we can see there is no significant difference between the population estimation results by pixel-based and object-based approaches.

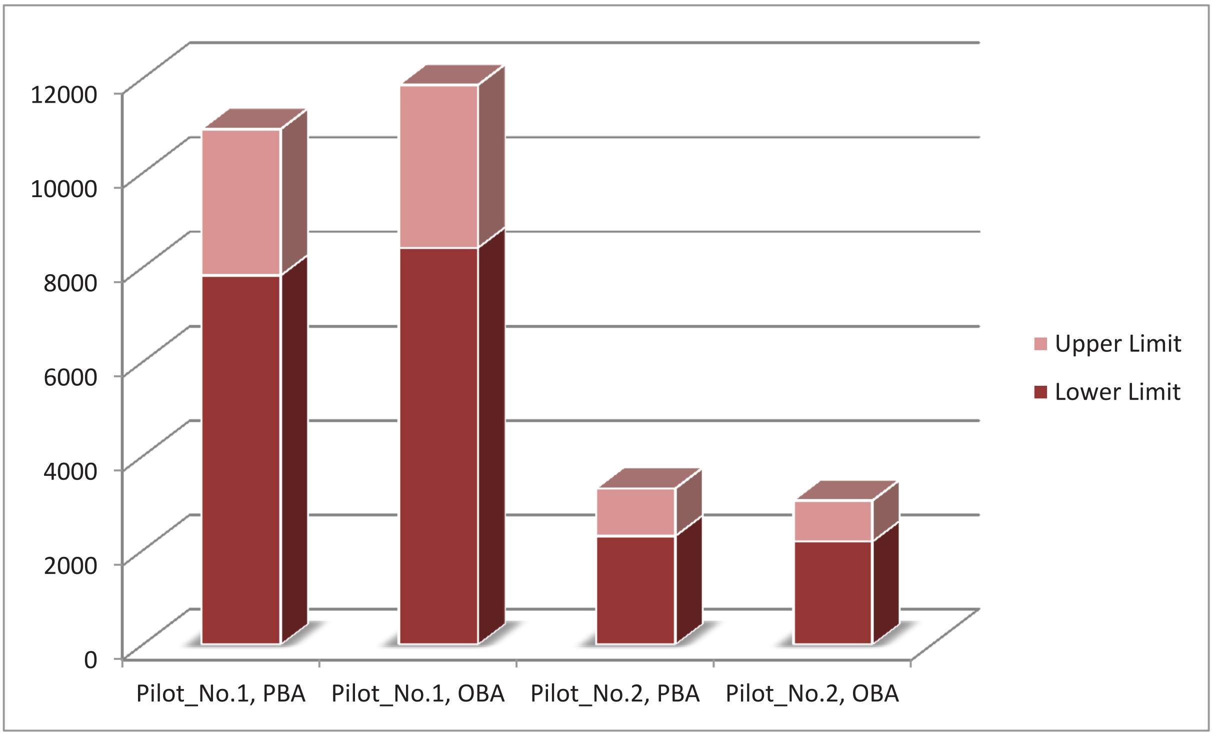


Figure 28 Population estimation results by pixel-based approach (PBA) and object-based approach (OBA)

4. DISCUSSION

4.1. Accuracy

From the accuracy assessment of the pixel-based and object-based approaches, we can see that both of them have produced results with satisfactory accuracy, which proves that both of these two approaches are suitable for mapping wildlife in open savannahs. By conducting statistical analysis of the accuracies, we find that the pixel-based approach has better performance in producer's accuracy than object-based approach, which is beyond our expectation.

Here we summarized several reasons for that. First of all, ANN classifier did prove to be capable of handling images with complicated background. Second, the spatial analysis played an important role in refining the primary classification result produced by ANN classifier. Especially the 'non-study area' layer, it eliminated most of the unwanted pixels misclassified as animals due to the confounding factors in the primary pixel-based classification result. Therefore, for processing high resolution satellite imagery, how to deal with the complicated background or image noises is still an important issue. This study shows that incorporating pixel-based classification based on the spectral reflectance with spatial analysis on the context would be a practical solution. On the other hand, object-based approach being used in this study resulted in similar accuracy with pixel-based approach. Moreover, the layer produced by refining the study area contributed a lot in eliminating the noise of primary pixel-based classification result, which is important for improving the accuracy of finalized pixel-based classification result.

4.2. Stability of performance

From the results we can see that the statistical analysis result proves that there is no significant difference between the performance of both pixel-based and object-based approaches in areas with high density of animals (hundreds of animals) and areas with relatively low density of animals (ranging from 30 to 100). This demonstrates that both of these two approaches have stable performance in areas with different density of animals, which expends the application area of applying these two approaches in recognizing animals in open savannahs.

4.3. Population estimation

This study has made an attempt to estimate population size of wildlife in the study area and we successfully gave population estimation by using pixel-based and object-based approaches. By conducting t-test to compare the difference between the population estimation results by pixel-based and object-based approaches we find that there is no significant difference. This indicates that both of these approaches are suitable for population estimation in the study area.

4.4. Spatial distribution patterns

For our case, according to the expert knowledge, wildlife on the open savannahs lives in herds rather than living alone in East Africa. Therefore it should follow a highly clustered pattern. Consequently, we conducted spatial statistics to check whether the classification result follows the distribution pattern in ground truth. The result indicates that both of the classification results by pixel-based and object-based approaches have a clustered pattern in spatial distribution, which accords with our assumption of the spatial distribution pattern of animals in visual interpretation.

4.5. Advantages of high resolution satellite imagery for mapping wildlife

There are significant advantages for using very high resolution satellite imagery for mapping wildlife in open savannahs. Specially, it has practical significance for biodiversity study and wildlife conservation. Comparing to traditional way of wildlife survey, using the new approach in this study for mapping wildlife is less time consuming, less manpower demanding and a more economical solution. Besides, it could be conducted without disturbing animals, which is very helpful for the protection of the natural reserves. All the advantages make it possible for this new approach to become a supplement and an alternative to the future animal population censuses.

4.6. Limitations of high resolution satellite imagery for mapping wildlife

There are lots of limitations for putting the new approach into practice. First of all, due to the limitation of resolution, currently we can only recognize animals without distinguishing species and for the animals gathering together we cannot specify the individuals. This would have an impact on the accuracy of population estimation for the animals, although this kind of cases only takes very small proportion of all the animals. Second, the limitation of resolution of the satellite imagery makes the result of visual interpretation would be less reliable compared with traditional aerial photograph. Third, the study area is limited to in open savannahs; thereby we cannot recognize the animals under cover of trees or shrubs, etc. Besides, due to the limited number of bands, for the pixels on the edge of animals, there might be spectral overlap between the animals and the confounding factors.

5. CONCLUSIONS AND RECOMMENDATIONS

5.1. Conclusions

This study evaluates the capability of high resolution GeoEye-1 satellite imagery for mapping medium to large-sized wildlife in the study area located in the Masai Mara National Reserve by using two different image classification approaches: pixel-based approach and object-based approach. This is the very first attempt for mapping wildlife on the open savannahs in East Africa with relatively complex surrounding landscapes. The producer's accuracy ranged from 84.2% to 88.2% and the user's accuracy ranged from 85.0% to 92.5% by using pixel-based approach and object-based approach respectively. Efforts on three aspects have been made corresponding to the research objectives: a) detecting the presence of animals on the imagery; b) recognizing individual animals and estimating the population size of animals; c) assess the accuracy produced by pixel-based approach and object-based approach and compare their capabilities for mapping wildlife. The specific conclusions are drawn from this study and they are summarized as follows:

- The fact that we successfully accomplished mapping wildlife with satisfactory accuracy and estimating the population size in the pilot study area shows that it is suitable for using high resolution GeoEye-1 satellite imagery for mapping medium to large-sized wildlife as well as population estimation in open savannahs.

- We managed to detect animals on the satellite imagery. However, we cannot ensure that all objects of animals being recognized are individuals of animals. There are clustering animals which cannot be separated individually. This leads to the uncertainty on population estimation to some degree. Therefore we conclude that it is not ready for using high resolution GeoEye-1 satellite imagery to count absolute number of animals.

- Statistical analysis indicates that both of pixel-based and object-based approaches having a stable performance in both of the area with large herd of animals and the area with small herd of animals, and there is no significant difference between the performance of pixel-based and object-based approaches in user's accuracy and population estimation. However, the pixel-based approach was proved having better producer's accuracy than object-based.

Based on the points discussed above, we may safely reach the conclusion that high resolution GeoEye-1 satellite imagery is suitable for mapping medium to large-sized wildlife as well as population estimation in open savannahs, but not ready for counting absolute number of animals.

5.2. Recommendations

We have concluded that it is suitable for mapping wildlife in open savannahs using high resolution GeoEye-1 satellite imagery. Specially, the two different image classification approaches for mapping wildlife applied in this study would be highly suitable for detecting the presence of wildlife instead of absolute number counting. Therefore, this new approach can be applied on the areas of wildlife conservation on large scale, especially for monitoring wildlife in the study regarding the great migration of the migratory ungulates. It is also highly suitable for the study about the relationship between wildlife and the habitats on landscape level, such as forest, shrubs, and water bodies.

There is constant improvement of spatial resolution with a new generation of high resolution satellite imagery, for example, GeoEye-2, scheduled to launch in 2013, will have a spatial resolution of 0.25m ("GeoEye Begins Phased Procurement of GeoEye-2 | GPS World," 2011). This could possibly enhance the potential to distinguish between species. It might also allow distinguishing clusters of animals which show up as one dot instead of multiple dots into separate entities. Agglutination of nearby image objects into one object tends to bias population estimates downwards. The higher spatial resolution might also offer possibility to reduce such bias in population size estimates. With more available bands of a new generation of high resolution satellite imagery, there would be less spectral overlap between the animals and the confounding factors, and hence the final accuracy might be further improved. Moreover, with enough spatial and spectral resolution, it is becoming possible for us to identify animals and specify the species at the same time by its unique geometric features in spatial and spectral signature (Rodriguez-Fernandez et al., 2011).

To sum up, we have confidence in the prospect of the approach that applies very high resolution satellite imagery for mapping wildlife in open savannahs, and with the development of very high resolution satellite imagery, this approach could potentially be an alternative for traditional surveying methods currently being used.

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