Spatial-Temporal Uncertainty in Lake Extent Trends

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Abstract
Mapping and monitoring the extent of geographical features on the surface of the Earth includes 023l;-handling of their inherent uncertainty. The uncertainty may originate from the feature’s definition (vagueness), the type of boundary (crisp or fuzzy), the accuracy with which it can be detected (scale of observation) and the moment of observation. In environmental studies for trend characterization such as change of size of forests as a result of deforestation or climate change, or the shrinking and expansion of a lake due to increasing water extraction for irrigation and sedimentation, respectively, it is important to include the spatial distribution of uncertainty regarding the mapped feature for each date. If both spatial and temporal uncertainties are known, a more reliable assessment of the trend can be made. In some selected previous studies in the Nile Basin it was evident that wetlands and lakes are major hydrological controlling features to be safeguarded and monitored. In these studies, however, the uncertainties of wetland/lakes data were not quantified. In this paper, we present an approach to include uncertainty of the mapped feature into multi-temporal analysis using remote sensing technology. We explain the method by using a case study on the spatial extent of Lake Naivasha in Kenya. We used object-oriented image analysis to estimate the spatial extent of the lake at a given date.
We started by grouping pixels (homogeneous regions) belonging to the lake based on criteria such as scale parameters and weighted image layers using the multiresolution segmentation algorithm. Using the resulting image object attributes such as individual band contribution per image object, we generated NDVI map that showed the spatial distribution of uncertainty in lake extent. Areas with deep and shallow water were identified based on the magnitude of NDVI values. We further used NDV indices to establish the membership function that was used to assign class labels to all image objects belonging to class ‘water’. In addition to the class labeling, we determined degree to which the image object belonged to class ‘water’ as a means of quantifying uncertainty due to poor definition, limitation of pixel in location (mixed pixels), and seasonal variations in water level.
We finally analysed trends in lake extent while considering uncertainty due to observations. A combination of spatial statistical tools and probabilistic procedures was used to analyze trend in lake extent while quantifying uncertainty due to seasonal variations in the lake environment. The results show that Lake Naivasha experienced a decrease in size regardless of unpredictable seasonalities caused by shift rainfall patterns, water currents, and evaporation rate and wind direction as observed by ASTER and ETM+ sensor.

Key words: Lake Extent, GIS tools, Membership function, multiresolution image segmentation, object-oriented image analysis, remote sensing technology.

1. INTRODUCTION

Sustainable use of available natural or artificial resources in a country is an important aspect towards restoring these resources. However, the sustainability of the resources requires detailed geo-information for proper planning and management. For centuries, ground surveys and aerial photographs have been used to collect detailed geo-information to characterise selected resources. Nevertheless, these methods are time- consuming and expensive since they require some investment and resources. In addition, these traditional survey methods are limited both in space and time thus limiting the monitoring activities. In space, the methods are limited by inaccessibility of some areas which results into improper sampling strategy when taking measurements while in time domain they are constrained by lack of enough capital (mostly less developed countries) to collect data that can be used to analyse trend of changing of resources of interest. Despite the limitations in these methods of surveying, they are considered crucial in providing geo-information that supports local resource management.

It is worth noting that in some selected previous studies in the Nile Basin it was evident that wetlands and lakes are major hydrological controlling features to be safeguarded and monitored (Ndomba et al., 2010). In these studies, however, the uncertainties of wetland/lakes data were not quantified (Ndomba, 2010; Ndomba et al., 2010).

For the past few decades, earth observation (EO) technologies provide synoptic data at low or no cost, at refined spatial, spectral and temporal scales (Bijker, 2009). This advance in surveying technology has greatly mitigated constraints that hinder the performance of traditional surveys in a number of ways: provision of synoptic data at a point in time and over time regardless of intervisibility and accessibility, use of various visual characteristics of geographic objects such as colour, texture, shape and contextual information. Thus, this technology has been widely used in landcover/use inventorying, assessing and managing at national, regional and global levels. However, the problem is how to extract meaningful information from these increasingly expanding mixed archives of remotely sensed data while quantifying inherent uncertainty in geographic phenomena. In addition to this problem, some of geographic phenomena require large number of observations for their detection due to the high speed of change in space and time which again limits the use of single sensor/platform combination observations. This again may require combining different sensor/platforms as a means of increasing the number of required observations necessary for change detection.

Increasing availability of remotely sensed data at low or no cost, at finer spatial, spectral and temporal resolutions has greatly raised many questions about applications of these data such as monitoring forest fires (Umamaheshwaran et al., 2007), flooding lakes (Stein,2008) and dynamics in coastal landscape units (Tao et al., 2009). However, many environmental processes occur at high speeds which again require an increased number of observations so as to track temporal patterns within geographic phenomena. In this context we may think of combining different measurements from different sources in the same time span. This will reduce uncertainty when modelling geographic phenomena of interest over time.

In this study we estimated the lake extent as observed from two sensors, that is, ASTER and ETM+ sensor, the change in lake extent and its uncertainty from multiple sensors. The approach is to start from the definition of lake extent to identify what causes uncertainty in lake extent. Based on the lake definition as a large inland waterbody occupying a basin with no continuity to the sea or ocean (O'Sullivan and Reynolds , 2004), it is evident that the spatial extent of the lake is defined by the boundary points at which water interacts with land. Therefore, the lake extent is determined by the presence of water at the boundary of the lake. In most cases the lake boundary points are uncertain due to various environmental factors such as wind and water currents causing horizontal in- and outflow of water and other factors such as climate change or human influence. Therefore, what is observed at one time cannot be observed at another time thus causing uncertainty in identifying these points.

Depending on the history of formation of the lakes which determines the geology of the lake boundary, some of the areas fringing lakes turn into bogs, marshes and swamps related growth of vegetation. With time these areas no longer appear as part of lake, as vegetation become dominant and changes their characteristics. Since 1971 some of these areas have been recognised as wetlands of international importance by the international treaty for wise use of wetlands of international importance (RAMSAR) (Matthews, 1993). These areas change with time particularly during rainy season when they are submerged. Thus, when observed at that time, they can be classified as part of lake therefore complicating the definition of the lake extent.

It is possible to argue that lake extent is larger in the rainy season than in the dry season. This is obvious since during rainy season fringing shoreline vegetation is submerged although it will depend on the type of vegetation and amount of rainfall. In contrast, the size of the lake will be small during dry season as water retreats towards the centre of the lake. Therefore, seasonality in mapping and monitoring of these important landscape features is of great importance for identifying underlying trend over time.

Remote sensing technology has been a major source of geo-information for many applications. The full usage of information contained in remotely sensed data requires appropriate tools that handle spatial relationships of patterns discernable on an image. However, many applications rely on classification algorithms that were developed in the 1970's where a single pixel is class labelled in a multi-dimensional feature space (Blaschke et al., 2000). These algorithms were developed based on signal processing concepts which cannot model the complex nature of real world objects. The development trend in classification algorithms shows that soft classifiers are developed to account for uncertainty inherent in remotely sensed data by incorporating fuzzy logic concepts (Bezdek et al., 1984; Wang, 1990) developed in 1980's (Zadeh, 1999). Despite this development real world objects relations are not modeled as these algorithms apply on pixel basis.

Recently, data mining methods for extracting meaningful information from large sets of observations with emphasis on uncertain objects are proposed (Stein, 2008; Bijker, 2009). However, as a rule of thumb, proper selection of classification algorithm depends on understanding of the process to be modeled (Stein, 2008). The knowledge about the phenomena to be modeled and monitored will lead to proper selection of a suitable dataset for that application as each dataset is collected for a particular application and has its own inherent uncertainty. In this study remotely sensed data from two sensors were used to analyze trend in lake extent between 1999 and 2009. The datasets were selected on the basis of their similar characteristics.

In remote sensing, at a single point in time of observation, uncertainty depends on spatial resolution, spectral resolution and the definition of the geographic phenomenon under study (Fisher, 1999; Stein, 2008; Stein et al., 2009). Looking at the spatial resolution, the pixel itself contains uncertainty in location. The same object can appear different in size and shape, in consecutive images, if the pixels of both images are not recorded over the same areas of the Earth's surface. This problem has been addressed as a Modifiable Area Unit Problem (MAUP) by Openshaw (1984). In addition, the digital number recorded in a pixel contains uncertainty originating from ambiguity due to point spread function (PSF) of a sensor (Fisher, 1997) and from distortions between object and the sensor or between source of illumination, object and sensor (Bijker, 2009; Stein et al., 2009). However, there is also uncertainty in the geographic phenomenon to be modelled. Because of spatial resolution problem, objects may have crisp boundaries in reality but in images they are represented as vague objects and vice versa; this depends on the relative position of the object with respect to the sensor. Furthermore, there exists uncertainty due to sampling scheme when classifying images, since the grouping of pixels belonging to the same object involves subjective decision due to lack of spatial support to describe real world objects.

Since large sets of images are analysed together in image mining studies, uncertainty may arise from co-registration of the images, from uncontrollable differences in atmospheric parameters and illumination and from the temporal resolution of the observations, compared to the speed of the process (Bijker, 2009). Thus, conceptual understanding of different types and possible sources of uncertainty in image mining methods enables proper selection of remotely sensed data and classification algorithms incorporating models of uncertainty.

2. MATERIALS AND METHODS

2.1. Description of the Study Area

Lake Naivasha in Kenya has been used in this study (Figure 1). The lake is located at approximately $00^0$45'00''S, $36^0$21'00'' E. It is situated in the West of Naivasha town in Kakuru district within Rift Valley Province. It is a shallow (mean depth of 6 m, endorheic, freshwater lake in warm and semi-arid conditions in the eastern Rift Valley of Kenya, lying within an enclosed basin at an altitude of 1886 m above mean sea level with surface area fluctuating between 100 and 150 km^2. It is world famous for its high biodiversity, especially for birds (more than 350 bird species). In the year 1995, Lake Naivasha was declared as Ramsar site (Wetland of International Importance) because of its diverse acquatic and terrestrial ecosystems. The climate of this wetland area is hot and dry with a high potential evaporation exceeding the rainfall by around three times (Harper, 1990). The area receives rainfall between April to June and October to December. The rest of the year is dry season. The lake system has fringing swamps dominated by papyrus and submerged vegetation and an attendant riverine floodplain with a delta into the lake. These swamps vary in size especially during the rainy season resulting into uncertainty in lake/water boundary definition. However, there are acquatic plants (water hyacinth) that live and reproduce freely on the surface of fresh water or can be anchored in mud. There are also other submerged vegetation species. The presence of these types of vegetation makes the delineation of water/land boundary difficult especially when they are submerged due to water level rise. Figure 1 shows the location of Lake Naivasha, the study area in this research, and its corresponding images from

ETM+ and ASTER sensors. The lake boundary is fringed by vegetation shown in red. In the north, there are two rivers, namely Malewa and Gilgil which discharge water to the lake. These two major rivers play a great role in balancing the lake water level. However, the two rivers form a delta which influences growth of various vegetation species that may impact the spatial extent of the lake with time.

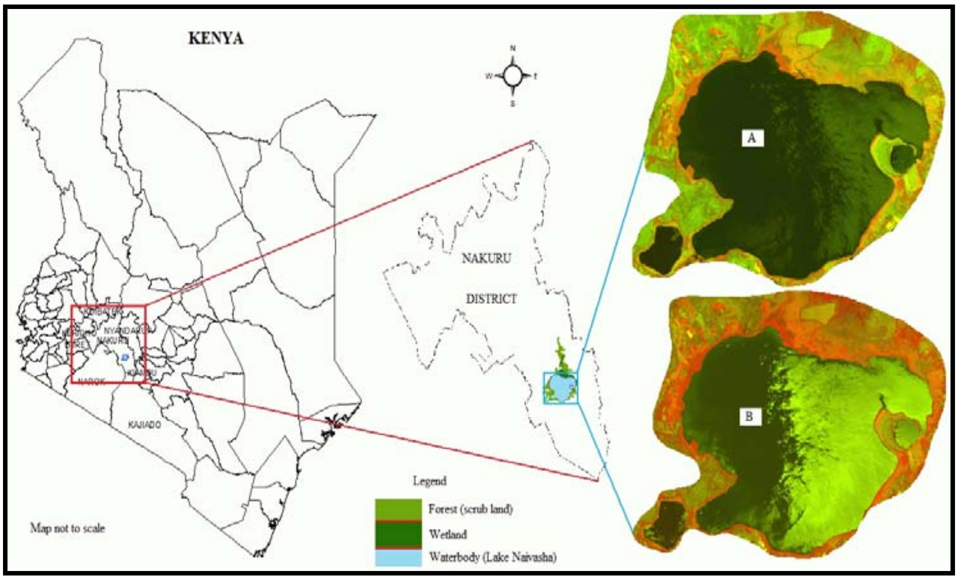

Figure 1: Location of study area and corresponding Landsat7 ETM+ (A) and Terra ASTER (B) images acquired on the same date 15th October 2002

2.2. Study Area Selection Criteria

In this study, time series images from two sensors ASTER and ETM+ were used. The selection was based on free availability of these images and prior knowledge of the study area via literature. In addition, these sensors are on-board satellites in the same orbit. The study area is within equatorial zone, where cloud cover is a big problem for remote sensing. Selected images in this application were cloud free at the area of interest as indicated on Figure 1.

2.3. Satellite Image Geometric Correction

Landsat ETM+ images were downloaded from the United States Geological Survey (USGS) archive in GeoTIFF format whereby each band was stored independently while ASTER images were provided in colour composite. The first step was to combine ETM+ image bands to generate colour composite images which enabled the co-registration process. The images were geometrically corrected with respect to mapping system within the study area. In this procedure two topographic map sheets no. 133/4(Longonot) and 133/2(Naivasha) both at scale 1:50,000 were used. First order polynomial transformation was adopted and applied. A total number of four GCP’s were selected for geometric registration of a single image in UTM projection with Clarke 1880 (Modified) Spheroid, Arc 1960 datum and zone 37 S. An automatic procedure was developed within ERDAS Imagine software and used to geometrically correct all satellite images using selected GCP’s. The over all root mean square error of the georeferencing process was ±0.016 m.

2.4. Object-Oriented Image Analysis and Classification

2.4.1. Multiresolution image segmentation

Multiresolution segmentation is a bottom-up merging algorithm. It begins by considering a single pixel as a separate object and subsequently merging adjacent objects that fulfill user defined criterion. The merging decision is based on local homogeneity criterion that describes the similarity between adjacent image objects. Adjacent image objects having smallest increase in the defined criterion are merged. Nevertheless, this process stops when the smallest increase of homogeneity exceeds the defined scale parameter. A 'trial and error' approach was adopted while observing the resulting image objects and associating them to the reality in the study area. The great emphasis was on the boundary of the lake which depends on the fringing shoreline dominated by deep-rooted, submerged and freely floating vegetation (water hyacinth).

An application of different scale parameters (levels) and colour/shape combinations results into a hierarchical network of image objects (Figure 2 & Table 1)

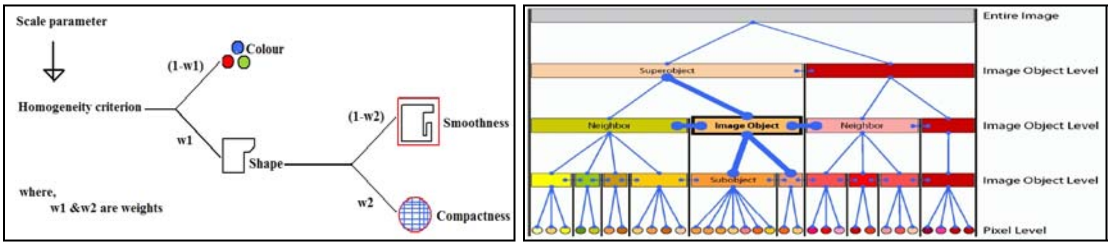

Figure 2: Composition of homogeneity criterion and hierarchical image objects (Definiens Imaging).

Table 1: Segmentation parameters used

Scale parameter	Colour	Shape	
		Compactness	Smoothness
30	0.7	0.2	0.8
60	0.7	0.2	0.8
90	0.7	0.2	0.8
120	0.7	0.2	0.8
150	0.7	0.2	0.8
15	0.7	0.2	0.8
30	0.7	0.2	0.8
45	0.7	0.2	0.8
60	0.7	0.2	0.8
75	0.7	0.2	0.8
90	0.7	0.2	0.8

A combination of the above segmentation criteria results into a number of image objects that are topologically linked. Based on spectral variations within an image, each image object has a number of attributes such as individual band contribution (band ratio), size (spatial extent) related to a number of pixels, etc. Using the topological relationship and spatial attributes of each image object at different scale level, it is possible to access the spatial context of the respective image object and assign class label with minimal uncertainty. It should be noted that each level of segmentation results into a different number of image objects. The decision on meaningful image objects depends on the problem being addressed. Therefore, a trial and error approach in this case is required together with prior knowledge of the phenomena being studied.

2.5. Fuzzy Rule-Based Image Objects Classification

We considered image object features to develop rules used to discriminate image objects that represent lake extent. In this case we considered the green contribution in each image object, the normalized difference vegetation index (NDVI) and the topological relationship using spatial analyst tools available in Definiens software such as 'relative area to' and 'relative border to'.

2.5.1. Individual layer contribution in each image object

The individual layer contribution to an image object of interest is determined as the ratio of mean intensity of that layer and total brightness of that image object. However, this operation is applicable to multi-spectral data which is believed to contain useful geo-information. The parameter is mathematically determined as,

$$LC = \frac{\bar{C}_k(v)}{\bar{C}(\mathrm{v})} \qquad (1)$$

Where; LC: individual layer contribution, $\bar{C}_k(v)$: mean intensity of layer k of an image object v, $\bar{C}(v)$: Brightness of image object v

From equation 1 above, it is clearly seen that individual layer contribution to any meaningful image object will take any value between [0, 1]. It will be zero if and only if there was no reflectance in that band during data

2.5.2. Normalized difference vegetation index (NDVI)

The following are assumptions we made in this study:

- Water tends to have a low reflectance across all optical bands in the spectrum unless there are suspended sediments near its surface and/or has shallow depth.
- Regardless of the impurities in water and shallow depth, water has very low reflectance in the near infrared band of the spectrum
- Water will always have NDVI values in range of -1 and 0 based on mathematical formula (equation 2). However, this will depend on water constituents.

Based on the above assumptions and literature on Lake Naivasha, the near infrared band, green band and NDVI were considered to be of great importance in providing spectral information of the lake extent. Therefore, we determined the NDVI for all image objects using the following mathematical function:

$$NDVI_v = \frac{\left[\bar{C}_{NIR}(v) - \bar{C}_{\mathrm{Re}d}(v)\right]}{\left[\bar{C}_{NIR}(v) + \bar{C}_{\mathrm{Re}d}(v)\right]} \qquad (2)$$

Where:

$\bar{C}_{NIR}(v)$: Mean intensity value for NIR layer in object v, $\bar{C}_{\mathrm{Re}d}(v)$: Mean intensity value for red layer in object v

$$NDVI_v = \begin{cases} 0 & for \quad \bar{C}_{NIR}(v) = \bar{C}_{\mathrm{Re}d}(v) \\ 1 & for \quad \bar{C}_{\mathrm{Re}d}(v) = 0 \\ between \quad [0,1] & for \quad \bar{C}_{NIR}(v) > \bar{C}_{\mathrm{Re}d}(v) \\ -1 & for \quad \bar{C}_{NIR}(v) = 0 \\ between \quad [-1,0] & for \quad \bar{C}_{\mathrm{Re}d}(v) > \bar{C}_{NIR}(v) \end{cases}$$

2.5.3. Relative border to a defined class

To identify all image objects that share common boundary with water class, we used the attribute "Relative border to" in Definiens software. It refers to the length of the shared border of neighbouring image objects. This attribute describes the ratio of the shared border length of an image object with a neighbouring image object assigned to a defined class to the total border length. If the relative border of an image object to other image objects of a certain class is 1, the image object is totally within/ embedded in these image objects. If the relative border is 0.5 then the image object is surrounded by half of its border. Further attributes such as NDVI values and green layer ratio for the case of shallow water bodies.

$$RBW = \frac{\sum_{u \in N_v(d,m)} b(v,u)}{b_v} \qquad (3)$$

Where; RBW: relative border to class water, $b(v,u)$: Topological relation border length, $N_v(d,m)$: Neighbours of an image object v in class m at a distance d and b_v : Image object border length.

2.5.4. Relative area of a defined class

Using this attribute we identified all image objects adjacent to water and vegetation class. The prior knowledge of the lake extent under study was very important in using this attribute in identifying image objects that have similar properties with water class. The value of this attribute is determined as area covered by image objects assigned to a defined class in a certain perimeter (in pixels) around the image object concerned divided by the total area of image objects inside this perimeter (Definiens Imaging).Mathematically it is determined as follows,

$$RAWV = \frac{\sum_{u \in N_v(d,m)} \# P_u}{\sum_{u \in N_v(d)} \# P_u} \qquad (4)$$

Where; *RAWV*: relative area to class water and vegetation; $N_v(d)$: Neighbours to an image object v at distance d, $\# P_u$: Total number of pixels contained in P_u .

For image objects where the value is 0 implies that the predefined class does not exist whereas 1 implies that objects belong to a predefined class. However, there are image objects where the value is between 0 and 1 exclusively. Due to this uncertainty a combination of other spectral characteristics of the respective image object can be considered.

2.6. Fuzzy Object Classification Process

We first defined two broader classes, that is, ‘water’ and ‘not water’ .A combination of NDVI and green contribution per object, we estimated fuzzy parameters that were subsequently used to classify image objects that constitute the lake extent. Figure 3 shows the developed class hierarchy while figure 4 and 5 show possible image objects constituting the lake extent using green band contribution and NDVI respectively as fuzzy functions.

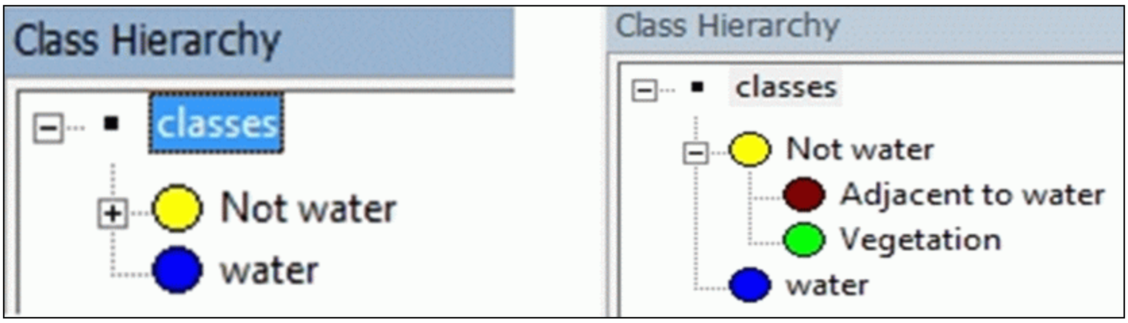

Figure 3: Class hierarchy definition

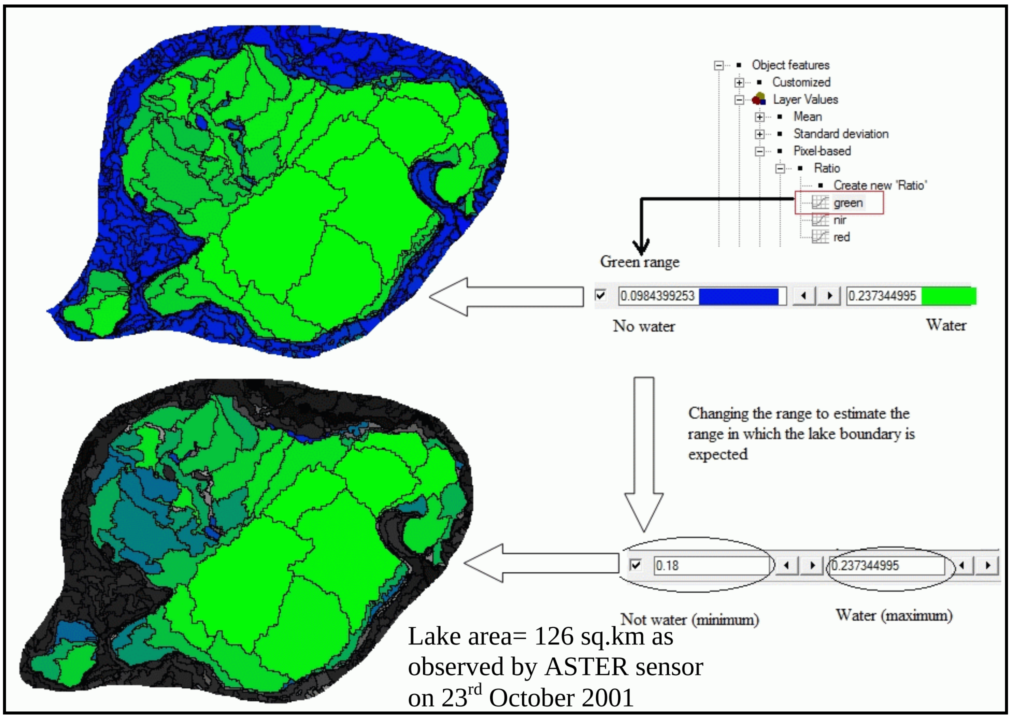

Figure 4: Fuzzy parameter estimation using green band ratio

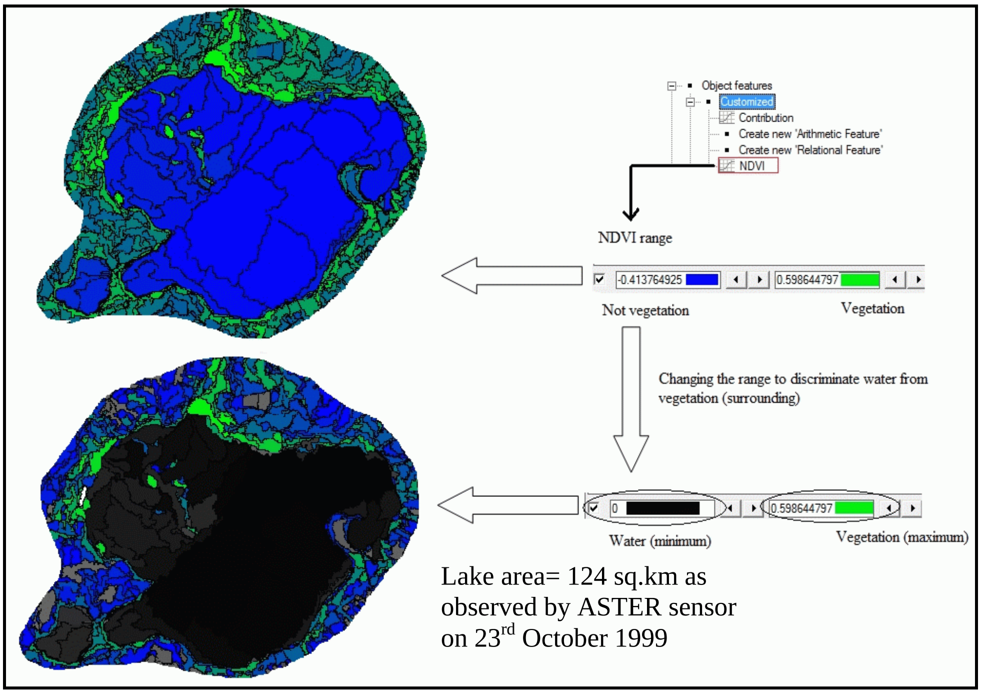

Figure 5: Fuzzy parameter estimation using NDVI

From figures 4 and 5 it is clear that the lake extent definition is parameter dependent. Using the NDVI, the lake extent lies between {0.18 and 0.24} and the lake area is 124 sq.km while the same lake lies between {0 and 0.6} using the green band contribution and the lake area is 126 sq.km. Conditioning the classification algorithm using two constraints in combination on the same image yielded 125 sq.km which is equivalent to taking the average of the values from independent classifications, that is,

$$A_{Lake\ area} = \frac{A_{NDVI[0,0.6]} + A_{GREEN[0.18,0.24]}}{2} \quad\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(5)$$

Therefore, the estimation of the lake extent may require a combination of parameters to minimize uncertainty in class labeling process. Equation 5 will always change depending on the number of parameters used to estimate the spatial extent of the geographical phenomena being studied. The general mathematical formula could be:

$$A_{spatial\ \ extent} = \frac{\sum_{i=0}^{N} A_i}{N} \text{..} (6)$$

$where\ ;\ N = number\ \ of\ \ parameters\ \ used\ \ to\ condition\ \ the\ class\ \ labelling\ \ a\lg orithm$

$A_i = spatial\ \ extent\ \ when\ \ parameter\ \ is\ applied$

It should also be noted that uncertainty in spatial extent of geographical objects has a greater influence on the volume of the same objects. For instance, the water balance establishment could be erroneous unless a greater effort is put on optimizing the surface area estimation. In remote sensing, many environmental researchers are faced with biasedness especially when dealing with vague and fuzzy objects such as lakes, wetlands, river basin, forests, etc. Applying the approach we present in this paper, it is clear that image understanding before classification is an important step. For deep understanding of the image contents it is also better to decompose the entire image into homogeneous regions that correspond to entire or part of real world object.

2.6.1. Parameters used to classify images

Tables 2 and 3 show a set of rules developed and applied to extract lake extent information and quantify its uncertainty from ASTER and ETM+ images respectively.

Table 2: Rule set for classifying ASTER images

Scale	Class name	Condition	Membership range
90	Vegetation	NDVI>0	NDV[0, 0.56]
	Water	NDVI=<0	NDVI[-1, 0]
	Adjacent to water	-	Relative Border to water[0, 1]

Table 3: Rule sets for classifying ETM+ images

Scale	Class name	Condition	Membership range
60	Vegetation	NDV>=0	NDV[0, 0.7]
	Water	NDV<0	Ratio green[0.18, 0.24]
	Adjacent to water	-	Relative Area to water[0, 1]

2.6.2. Accuracy assessment

We assessed the quality of the classification process both qualitatively and quantitatively. Quantitatively we looked at the resulting membership function value for each classified image object. In this case we were able to identify the least and best classified image object as water. The least classified image objects as water appeared at the boundary of the lake while the best classified appeared within the lake as figure 6 shows.

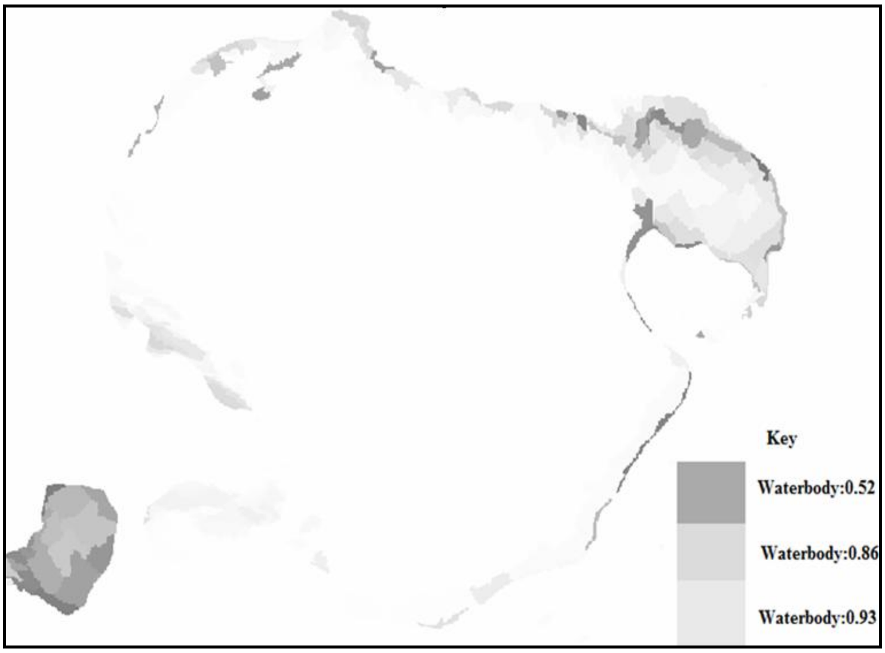

Figure 6: Accuracy assessment of the image objects classified as water

2.7. Determination of Image Objects Constituting Lake Extent

In estimating the spatial extent of the lake at a moment in time we considered seasons of the year as sensors record reflected or emitted electromagnetic energy regardless of spatial distribution of phenomena being studied. Therefore, we exported the classified image objects into ArcGIS 9.3.1 software where the spatial distribution of image objects classified as water could be visualized. In this case we considered the NDVI for each object to obtain image objects representing the lake extent. Figure 7 shows image objects classified as water and image objects constituting the lake extent after applying NDVI<0 condition.

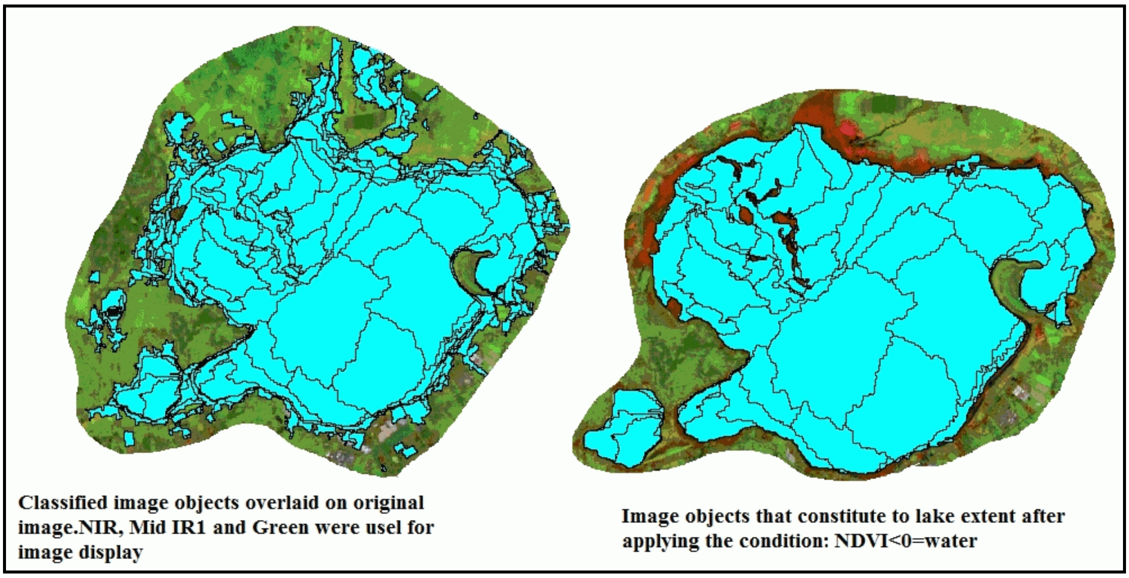

Figure 7: Identification of image objects constituting the lake extent

3. RESULTS, ANALYSIS AND DISCUSSIONS

3.1. Lake Extent and Observation Uncertainty

Table 4: Estimated lake extent and uncertainty from ASTER satellite images

Date	Area (sq.km)	Uncertainty
22nd January 2001	125	0.97
2nd February 2002	123	0.94
17th February 2002	125	0.94
29th June 2002	124	0.92
15th October 2002	124	0.92

Table 5: Estimated lake extent and uncertainty from ETM+ satellite images

Date	Area (sq.km)	Uncertainty
23rd October 1999	127	0.90
27th January 2000	128	0.99
12th February 2000	126	0.92
15th March 2000	126	0.70
22nd August 2000	125	0.85
14th February 2001	123	0.93
25th August 2001	124	0.86
12th October 2001	124	0.95
13th September 2002	122	0.95
15th October 2002	123	0.99
2nd December 2002	123	0.99

Tables 4 and 5 show the estimates surface area of the lake at different dates between 1999 and 2002, as observed by ASTER and ETM+ sensors. In addition the uncertainty in lake extent due to limitation of a pixel in location and fuzziness at the lake boundary has been quantified as indicated in the last column of the two tables. The lake extent changes from time to time, day to day, month to month and year to year. However, the manner in which the lake extent changes depends of the time when one observes and how often he or she looks. Therefore, an extended observation time and time schedule are pre-requisites to trend analysis during change detection.

3.2. Time Series Analysis in Lake Extent

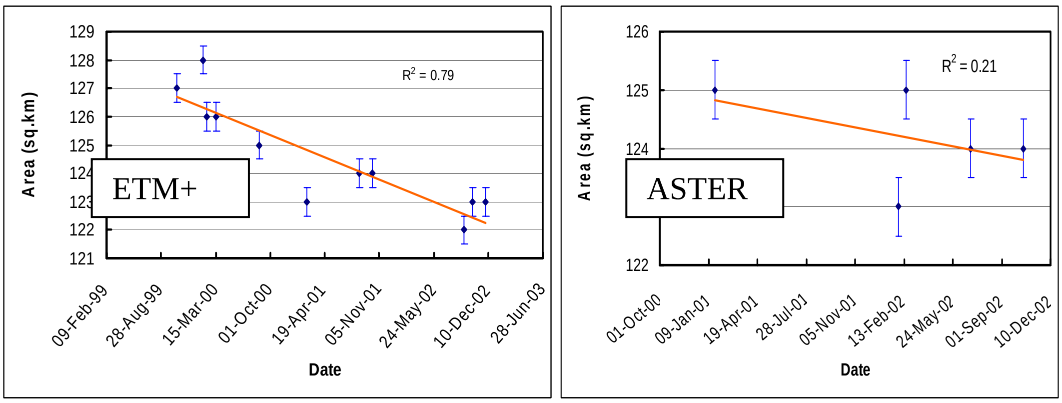

Figure 8: Lake extent trends between 1999 and 2002 for ETM+ and ASTER, respectively.

From figure 8, trend detection depends largely on the number of observations. ASTER observations are more uncertain compared to ETM+ observations due to less number of observations between 1999 and 2002 as indicated by the adjusted R-square.

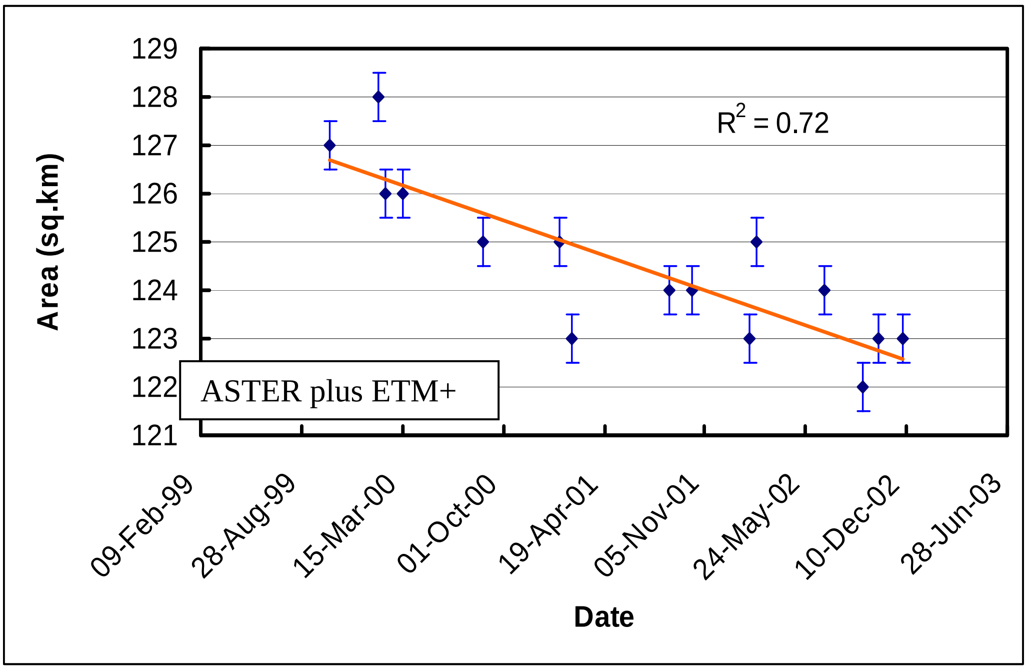

Figure 9: Lake extent trends between 1999 and 2002-Over time for ASTER plus ETM+

Figure 9 shows the trend characteristics after combining observations without considering seasonality. A clear falling trend is identified. The adjusted R-square has changed from 0.79 (ETM+ over time) to 0.72 (ASTER & ETM+ over time). The reason behind this change is that each sensor has its own characteristics (uncertainty both spatial and spectral) and is affected differently by the atmosphere through which electromagnetic energy travels to the sensor from targets on the earth's surface.

4. CONCLUSION AND RECOMMENDATIONS

Increasingly, available mixed archives of remotely sensed data at irregular time interval can be used to study changes taking place within our planet Earth which may be difficult to detect using a single sensor/platform combination. However, full usage of such datasets requires appropriate image mining methods in which uncertainty inherent in each dataset can be explicitly quantified and stated. The uncertainty quantified using by membership functions is very important especially when dealing with large sets satellite images with different temporal scales. For instance, the smaller membership function value will always be discarded when time series studies are conducted. The results of this study indicate that natural and unpredictable seasonal variations within and between years in water level have an impact on the trend in lake extent. In addition, the trend prediction model depends on sensor characteristics, the number of observations required and sampling strategy of datasets. As sensors operate on routinely basis their temporal scale may not coincide with scale of change in geographical phenomena requiring multiple sensors at irregular time interval. In that aspect, a combination of spatial statistical tools and probabilistic procedures are required to handle uncertainty in observations due to pixel limitation in space and poor definition of spatial referenced objects. As a rule of thumb, a clear understanding of scale of occurrence of geographical phenomena will lead to proper selection of spatial datasets and appropriate classification scheme and subsequent modeling and monitoring procedures. The procedures applied in this study can further be adopted in identification, mapping and tracking changes in mapped objects for better decisions.

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