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Evaluation of the Wetland Mapping Methods using Landsat ETM+ and SRTM Data

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Abstract

Overarching goal of this paper was to evaluate automated and semi-automated methods of mapping wetlands using Landsat ETM+ and SRTM data.

Automated methods consisted of: (a) slope derived from SRTM, (b) Tasseled cap Wetness Index (TCWI), (c) Normalized Difference Water Index (NDWI), (d) multi-band vegetation indices (MBVIs), (e) two band vegetation indices (TBVIs), (f) normalized difference vegetation index (NDVI), and (g) data fusion involving ETM+ and SRTM and then classifying the same. The best of these indices or methods provide an accuracy of less than 30 percent with high errors of omissions and\or commissions.

Semi-automated methods consisted of 3 key techniques: (a) image enhancements to highlight wetlands, (b) image display to discern precise boundaries of wetlands, and (b) digitizing directly off screen to separate wetlands from their neighboring landscape. The most useful displays of ETM+ image enhancements (e.g., ratios) and band combinations, displayed as false color composite (FCCs) of RGBs were: (a) NIR/SWIR2, NIR/red, NIR/green; (b) NIR, Red, SWIR1; and (c) red, green, blue. The near-infrared (NIR) is centered at 0.825 μm and the short-wave infrared bands 1 and 2 (SWIR1 and SWIR2) are centered at 1.650 μm and 2.22 μm. The SRTM slope threshold of less than 1 percent was also very useful in delineating higher-order floodplain wetland boundaries.

The wetlands were delineated with an accuracy of 86.4 percent using the semi-automated methods. The total wetland area in the Limpopo river basin was 12.5 percent of the total basin area of 41.5 million hectares. The overall accuracy of the 4 aggregated wetland classes in the basin was 82 percent with reasonable errors of omissions (20 percent) and low errors of commissions (12 percent).

Keywords: wetlands, remote sensing, mapping, delineation, automated methods, semi-automated methods, Limpopo river basin.

Introduction

Wetlands are ecosystems of very high interest for agricultural development as well as for environmental conservation. The ability of wetlands to act as sponge that can hold water for a longer period of time as compared to the surrounding areas and their higher soil fertility have made wetlands attractive for agricultural development. With ballooning population and increasing

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pressure on arable lands, sustainability of many wetland ecosystems around the world is becoming problematic. Wetlands are also performing many functions that are beneficial to the environment and humans and if used unwisely these benefits will be destroyed. Hence, the importance of characterizing and mapping wetlands in order to identify and implement proper management planning at national, regional, and local levels is beginning to be well appreciated (Earth Satellite Corporation, 2002, Thenkabail *et al*., 2000b, Thenkabail and Nolte, 2000; Thenkabail and Nolte, 1996, 1995).

The wetland surveys of the world have been mostly localized surveys (EarthSat, 2002; Stefano and Pierre, 2004; Charles, 2000; Patrick *et al*., 2003; Drew, 1999). However, over the past decade several studies (Janel *et al.* 1997; Thenkabail and Nolte, 2000, Thenkabail *et al*., 2000b, Stefano and Pierre, 2004; Charles and Hara, 2000; Patrick *et al*., 2003; Drew, 1999) have identified the potential of satellite remote sensing data and techniques for mapping different types of wetlands at different spatial scales covering larger areas (e.g., river basins, Nations). The Earth Satellite Corporation together with Isciences LLP (2002) examined the utility of Remote Sensing imagery for wetland classification and delineation. The important lesson they learnt through this investigation was the potential use of imagery in conjunction with GIS datasets to investigate the interconnectivity of wetland sites within a larger geographic region. Hence they concluded that these types of analyses at larger spatial scales would greatly enhance capabilities to assess and understand these vulnerable ecosystems as a whole instead of as an isolated entity.

Almost all wetland inventories and mapping, at present, limit themselves to large flood plains, swamps, and water bodies with or without irrigated areas (USACE, 1987). However, a large proportion of the wetlands are inlands, along the stream network and\or occurring as isolated patches. Most of the inland valleys that remain wet during most parts of the year, give rise to many localized wetland ecosystems that are named as dambos (also called as inland valleys, fadamas, mbugas, and vleis). They usually occur along the lower-order streams and are too small to appear on most maps. However, these inland valleys constitute about 9-18 percent of the African landscape (Thenkabail and Nolte, 2000, 1995) and constitute very important ecosystems of interest to both conservationists and agricultural developmentalists. Perennial or seasonal water bodies with smaller land extents and many other small to medium scale localized wetlands have also to be studied and included in the wetland statistics within the basin. For example, the FAO statistics shows that there may be 40,000-60,000 hectares of swamps and floodplains in the Limpopo river basin in Southern Africa but ignores almost all of the inland wetlands.

The remote sensing approach is the only way for consistent mapping of overwhelming proportion, if not all of the wetlands of the World. This will need development of methods and datasets for rapid delineation of wetlands, to map their spatial distribution, and to identify their specific characteristics such as biophysical, ecological, hydrological, and socio-economic values. The US Army Corps of Engineers (USACE) Wetlands Delineation Manual (1987) also supports such delineation without field visit: “in a routine wetland determination when the quantity and quality of information obtained are sufficient for wetland determination onsite inspections of the study area may not be necessary”. However, at larger spatial scales, applicability of remote sensing techniques could vary significantly at different localized areas due to the higher degree of variability in the spectral signatures of the associated ground features. The complexities in these ecosystems in terms of their vegetation, soil and hydrological features themselves impose many limitations for identifying, mapping and characterization of wetland ecosystems. Thereby, the need to investigate methods that can consistently map wetlands over large areas becomes important.

Given the above background, this study investigates globally applicable methodologies for delineating, classifying, and characterizing the wetlands over larger areas. The Landsat Geocover for nominal year 2000 and the SRTM data, which are well processed, available free, and have global coverage, were selected so the methods developed at one location can be applied elsewhere. Emphasis will be to delineate and classify small (e.g., dambos or inland valleys) as well as large wetlands including human-made wetlands such as irrigated areas and artificial tanks. The methodology development was conducted in a large river basin (Limpopo in Southern Africa) with considerable variability and complexity; so that the methods are robust enough to be applied elsewhere in the World. This research was conducted within the scope of the Global Wetland Inventory and Mapping (GWIM) project using remote sensing and secondary data initiated by The International Water Management Institute (IWMI). The overarching goal of the GWIM is to map, characterize, and classify the wetlands of the world at various scales or pixel resolutions through a wide range of partnerships including the Ramsar Convention.

Methods

Study area

The Limpopo River basin straddles four countries: Botswana, Zimbabwe, South Africa and Mozambique (Figure 1). The total basin area is 42.5 million hectares, of which nearly 50 percent is in South Africa (Table 1). Limpopo is large basin (41.5 million hectares). The wetlands in the basin are hardly utilized for agriculture and the diversity of basin from the dry lands of upper catchments to floodplains in Mozambique where the river drains to the Indian Ocean is ideal to develop methodology. Also, in Africa, unlike Asia, most of the wetlands are still un-utilized for agriculture. A large proportion of these areas are known to possess rich soils and sufficient soil moisture to grow at least one crop, with a possibility of second dry season crop. Wetlands in the Limpopo River Basin are predominantly dambos (seasonally or permanently saturated areas, also referred to as pans) and riverine wetlands.

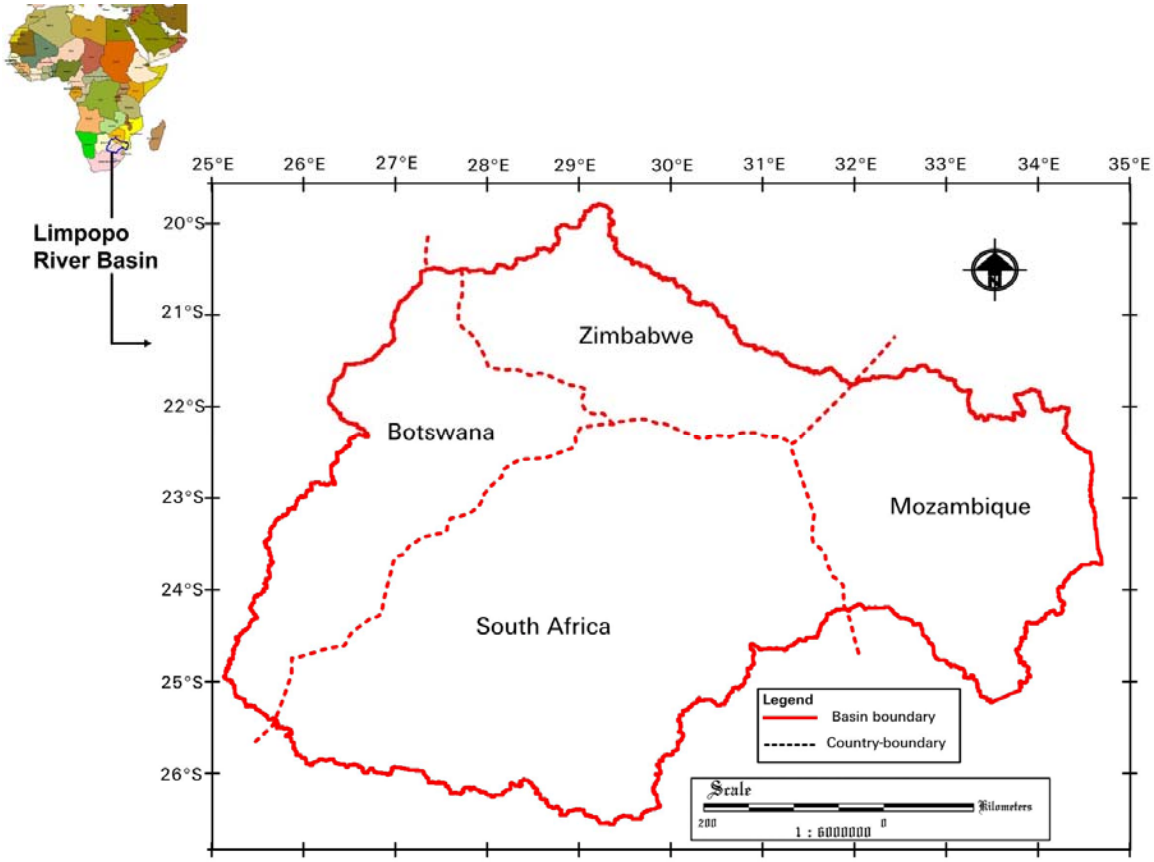


Figure 1. **Location of the study area**.

Table 1. **Distribution of land extents amongst the four countries within the Limpopo River Basin**.

Country	Basin area within the country (million ha)	Area within each country as a percentage of total basin area (%)
Botswana	8.0	19.3
Mozambique	8.8	21.1
South Africa	18.6	44.8
Zimbabwe	6.1	14.8
Total	41.5	100

According to the Koppen classification (Koppen, 1918 cited in FAO, 2005) the basin is predominantly semi-arid, dry, and hot with an average rainfall of less than 400mm. Yet, the area where the river drains to Indian Ocean in Mozambique is a large flood plain with great potential for agriculture. The basin generally experiences short rainfall seasons with 95 percent occurring between October and April. The South African Highlands part of the basin is temperate while the Mozambique coastal plain is mainly warm and humid. Population density in the basin is around 25-50 people per km^2, which although not high compared to other river basins of the World, is still one of the most populated basins in Africa (FAO, 2005). In general the basin has a high level of water deficiency. A short and intense rainy season, with highly unreliable rainfall leads to frequent droughts. Crop production is not secure. The overwhelming proportion of the basin area is arid or semi-desert with significant flood plains in Mozambique that has rich agricultural potential, seasonal wetlands, and highlands. The wetlands in the basin have become more attractive units for their rich soils and year around soil moisture, which is favorable for cropping even during dry season and drought years. Therefore, the wetlands and their important features could be more prone to disappear unless they are not managed in a sustainable manner.

Definition of wetlands

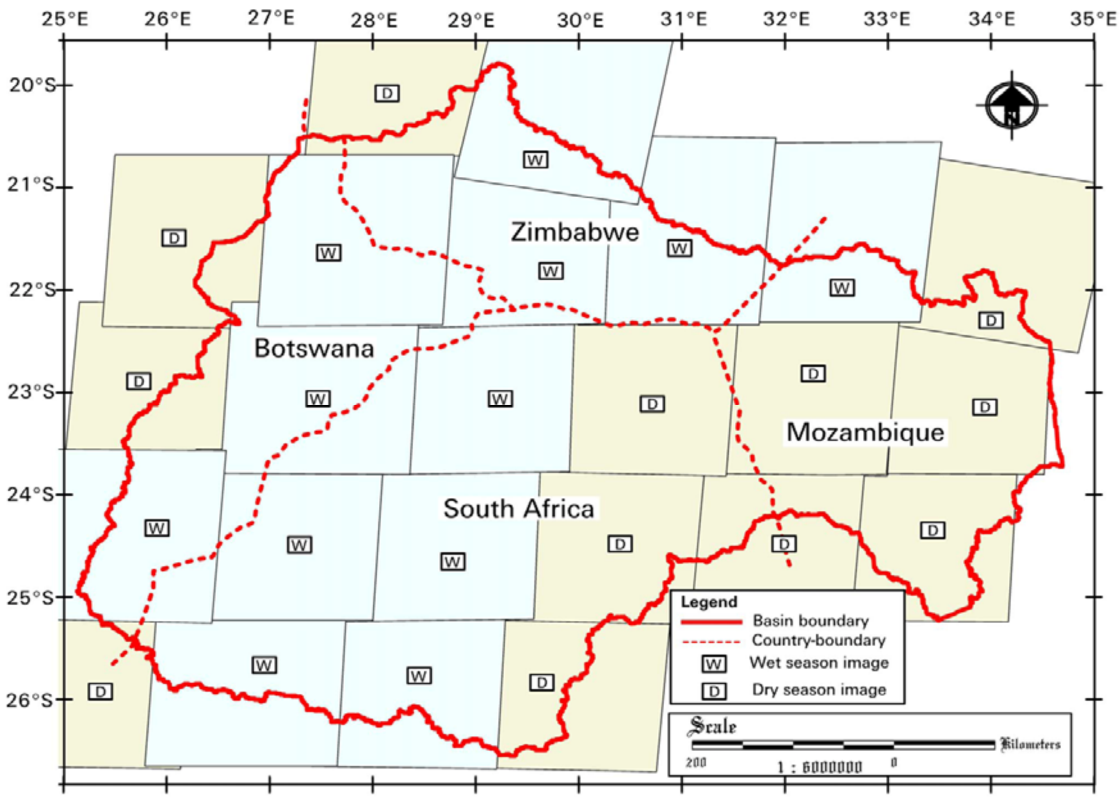
The definition of wetlands is the key for proper mapping and inventory of wetlands. In our definition, we have included both the natural and man-made (e.g., irrigated areas, reservoirs) wetlands for delineation and mapping. According to the Ramsar Convention on Wetlands, "wetlands are areas of marsh, fen, peatland or water, whether natural or artificial, permanent or temporary, with water that is static or flowing, fresh, brackish or salt, including areas of marine water the depth of which at low tide does not exceed six meters." Further it explains that the " wetlands may incorporate riparian and coastal zones adjacent to the wetlands, and islands or bodies of marine water deeper than six meters at low tide lying within the wetlands". In the US Army Corps of Engineers Wetlands Delineation Manual (USACE, 1987) wetlands are defined as: "Those areas that are inundated or saturated by surface or ground water at a frequency and duration sufficient to support, and that under normal circumstances do support, a prevalence of vegetation typically adapted for life in saturated soil conditions. Wetlands generally include swamps, marshes, bogs, and similar areas." In our mapping effort both the above definitions from these two sources were taken into consideration.

Data

Landsat ETM+ 30 m and the Shuttle Radar Topographic Mission (SRTM) 90 m were the primary data sources used in this study. Both have global coverage, available free, well calibrated and processed, and available from reliable sources. Methodologies developed using such data sources can be applied anywhere in the world. A brief description of the datasets used in the study is given below and are streamlined in standard formats as in IWMI's data storehouse pathway (http://www,iwmidsp.org):

Satellite sensor data

A total of 24 tiles (Figure 2) of orthorectified Landsat ETM+ images for the nominal year 2000 were downloaded from the Earth Science Data Interface (ESDI) at the Global Land Cover Facility (http://glcfapp.umiacs.umd.edu) of the University of Maryland. The images were from either dry or wet season; which were mosaicked separately and analyzed.



Source: Global land Cover Facility, University of Maryland

Figure 2. **Landsat ETM+ images used in the study** - Distribution of wet season and dry season Landsat ETM+ images.

SRTM Data

The Space Shuttle Radar Topography Mission (SRTM) data of the world at 90 meter horizontal resolution is gap filled and made available through the Consortium for Spatial Information (CSI) web portal (http://srtm.csi.cgiar.org/).

Secondary data

Monthly mean rainfall data for the period from 1961 to 2000 were obtained from Dr. Tim Mitchell of the Climate Research Unit of the University of East Anglia, UK. Elevation, slope, drainage network, and catchment boundaries were derived using SRTM DEM 90 m dataset available for free download from the data archive of the United States Geological Survey (USGS). Topographic map sheets of 1:25000, 1:100000 and 1:50000 were used where available.

Ground-truth (GT) data

Ground-truth data on spatial location, land cover, agricultural land use, soil moisture status, hydro-geomorphic, and topographic characteristics were collected from selected sample sites during the period from 28 June – 20 July 2005. A total of 220 Points (Figure 3) were collected. Stratified random sampling design was adopted for the selection of sample sites. Stratification was based on the accessibility of the sites from road-network. Structured field survey forms were used in data recording. Spatial locations were obtained from GPS readings. Ground cover percentages for each sample site were estimated using four random samples of 30 m × 30 m size. Data on agricultural land use, soil moisture status and hydro-geomorphic characteristics were recorded based on visual observations.

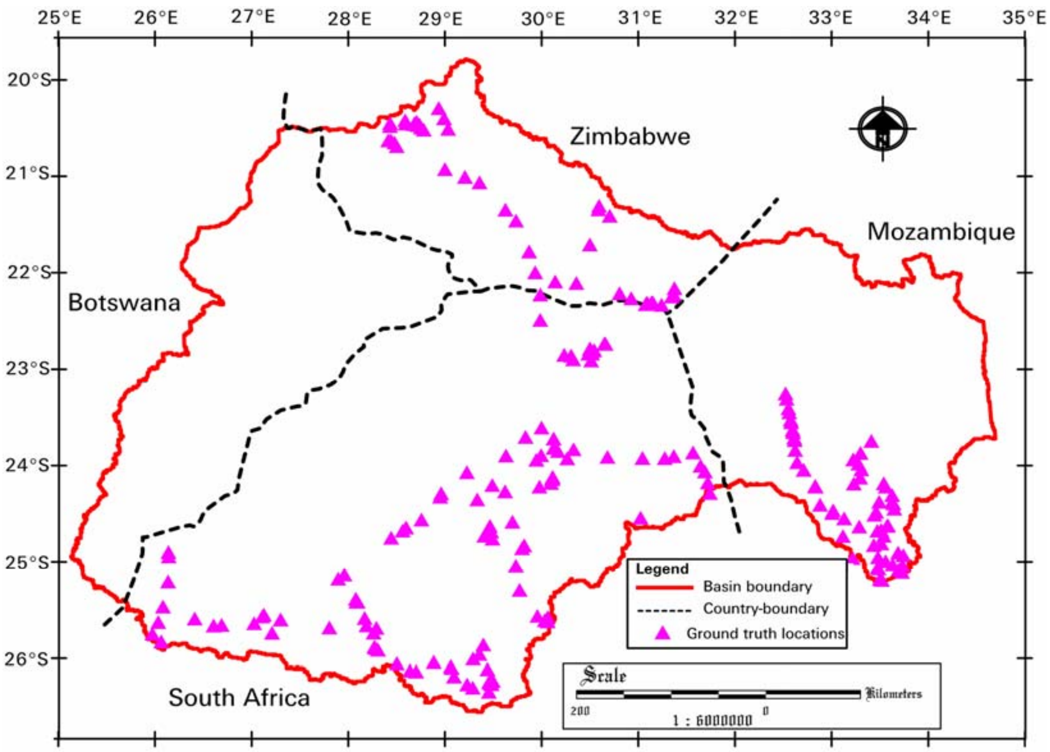


Figure 3. **Spatial distribution of Ground-truth data points in the study area**

Delineation of wetlands

Automated and semi-automated approaches investigated for delineating the wetlands are shown in Figure 4. Data processing, extraction of information and analyses were performed using ERDAS (Earth Resources Digital Analysis System) Imagine (Version 9.0), Earth Resource Mapping software (ERMapper version 7.0), ArcGIS 9.0, and Arc View (version 3.2) software packages.

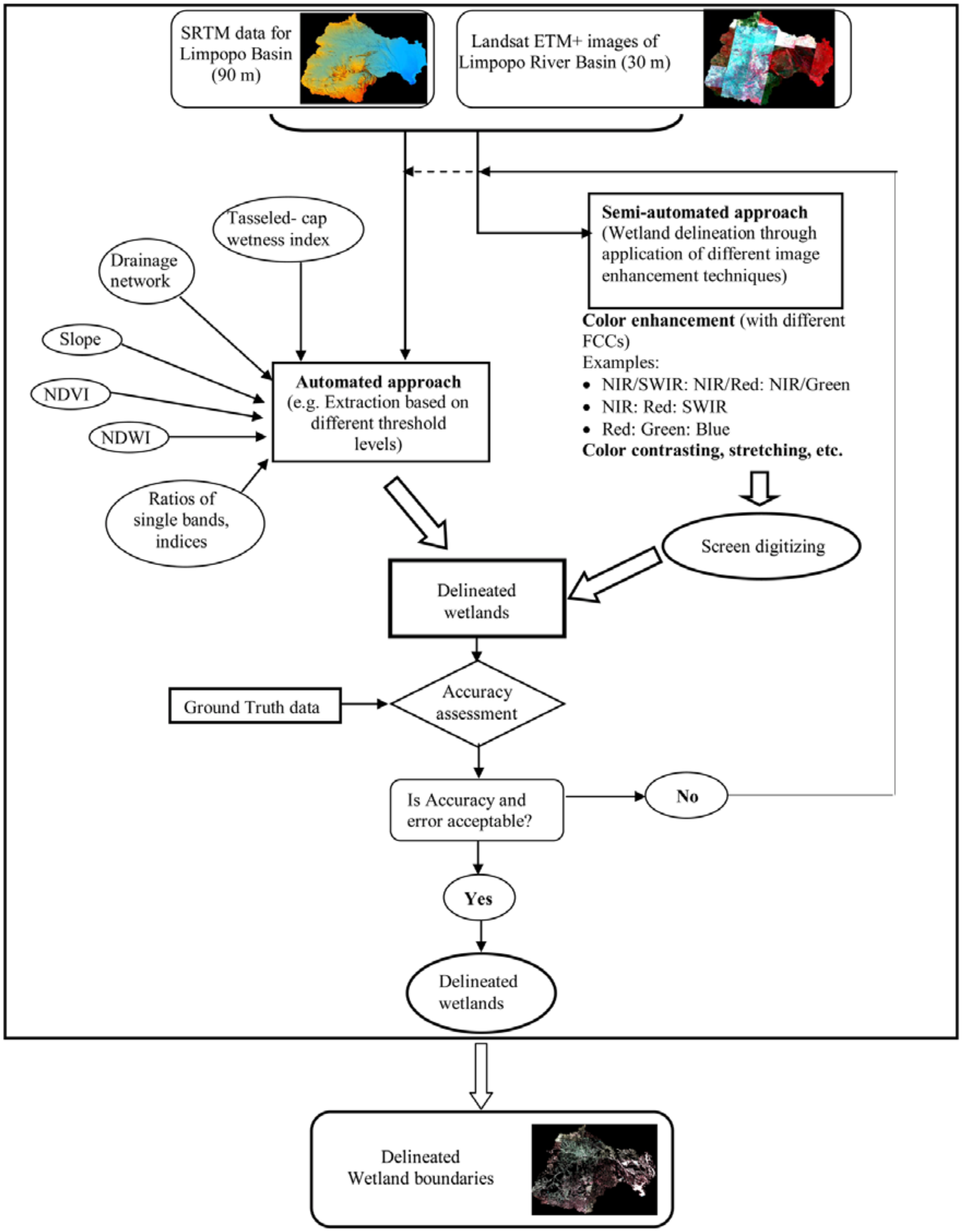


Figure 4. **Illustration of automated and semi-automated methods for wetland delineation**.

Automated methods used for wetland delineation

In this section, the results of automated wetland delineation via generation of drainage network from SRTM data are discussed. This is followed by the evaluation of wetland delineation using the thresholds of SRTM derived slopes. Finally, the strengths and limitations of the Landsat ETM+ derives indices (Table 2) in automated wetland delineation are investigated.

Table 2. **Indices and their thresholds for automated wetland delineation (only the selected best indices and their thresholds used to delineate wetlands).**

Index or parameter	Definition	Range -1.0 to 1.0 dimensionless or 0 to 100 %	Threshold values that best delineated wetlands
a. Slope derived from SRTM DEM	Percentage slope derived using spatial analyst tools available in Arc GIS	0 to 100	<0.5 %
b. Normalized Difference Vegetation Index (NDVI) (Rouse *et al*., 1974)	$NDVI = \frac{\rho_4 - \rho_3}{\rho_4 + \rho_3}$ ρ_3 and ρ_4 are the reflectance values derived from the bands 3 (Red) and 4 (NIR) of Landsat ETM+ data respectively.	-1.0 to +1.0	-0.25 to 0.10
c. Tasseled-cap Wetness Index (TWI) (Crist and Cicone, 1984)	TWI = ([B**1**] * 0.1509 + [**B2**] * 0.1973 + [**B3**] * 0.3279 + [**B4**] * 0.3406 + [**B5**] * -0.7112 + [**B7**] * -0.4572) B1 to B7 are the DN values of the respective bands of Landsat ETM+ data. This index represents the overall degree of wetness over the area as reflected by image data.	0 to 100	0 to 30
d. Normalized Difference Water Index (NDWI) (McFeeters, 1996)	$NDWI = \frac{\rho_2 - \rho_4}{\rho_2 + \rho_4}$ ρ_2 and ρ_5 are the reflectance values derived from the bands 2 (Green) and 4 (NIR) of Landsat ETM+ data respectively.	-1.0 to+ 1.0	-0.15 to 0
e. Mid Infrared Ratio (MIR) (Coppin and Bauer, 1994)	$MIR = \frac{Band4}{Band5}$ Band 4 and 5 are NIR and Mid Infra-red bands of Landsat ETM+ data respectively.	0 to 4	>0.25
f. Ratio Vegetation Index (RVI) (Tucker, 1979)	$RVI = \frac{Band4}{Band3}$ Band 4 and 3 are NIR and Red bands of Landsat ETM + data respectively	0 to 6	<0.6
g. Green Ratio (GR) (Lo, 1986)	$GR = \frac{Band4}{Band2}$ Band 4 and 2 are NIR and Green bands of Landsat ETM+ data respectively.	0 to 4	0.5 to 0.8

h. Ratio of indices (this study)	RoI = B4/B7 * B4/B3 * B4/B2	0 - 240	12.5 - 20
i. Reflectance of SWIR 1 band (this study)	Band 5 where, Band 5 is the Shortwave Infra-red band 1 of Landsat ETM+ data.	0 to 47	<1

A. Drainage derived from SRTM data

Wetlands are mainly along the lower elevations in the landscape, along the flow paths or drainage systems. These are areas of inland valley bottoms and flood plains. Therefore the delineation of stream lines could be used as a better indication for mapping inland wetlands that are associated with the valley bottoms and the hydromorphic valley fringes. Drainage network was delineated using spatial analyst tools in ArcGIS software which is available for hydrological analyses. This involved a step-by-step procedure in which flow direction, flow accumulation, and stream network are derived in respective order. The DEM was first corrected by filling up the sinks using the tool 'fill' in ArcGIS This ensures that water will flow over the DEM without any stagnation. The 'Flow Direction' and 'Flow Accumulation' tools were used in respective order and these two layers were then used to generate the stream network. While generating the stream network different threshold levels were applied to get a satisfactory level of accuracy of stream network delineation. Threshold is the minimum number of pixels that is considered to constitute a drainage link. The best threshold levels were selected through visual interpretations made on the derived stream network overlays on Landsat and SRTM DEM data. This process is automated and rapidly delineates the drainage networks.

B. Slope derived from SRTM data (see table 2)

Slope determines the relative topographic position of the landscape at every point in space; thus determining uplands from lowlands. Theoretically, slope is a better indicator of topographic position than elevation. This is because, the same elevation can be present in two different locations while one can be uplands and another is lowland. In contrast, slope is always determined relative to the elevation of the surrounding pixels. As a result, lowland pixels get separated from upland pixels.

C. Indices derived from Landsat ETM+ data (see table 2)

The threshold values recommended in Table 2 for different indices were based on "trial and error" experimentation conducted using these indices and varying their thresholds to determine maximum seperability of the wetlands from other land units. Thereby, the best threshold values for delineating wetlands appear for different indices and reflectance or radiance band values (Table 2) of Landsat ETM+ data. There were numerous other indices and bands that were used to separate wetlands, but only the best are presented in Table 2 and discussed.

Semi-automated methods for delineating wetlands

Semi-automated methods have the following distinct steps:

A. Image enhancement techniques to highlight the wetlands from the neighboring landscape (see Figures 5a, 5b, 5c, and Table 2).

B. Image display techniques involving the use of various false color composites (FCCs) of Landsat ETM+ data (see Figures 5a and 5b).

C. Onscreen digitization to delineate wetlands (Figures 5a, 5b and 5c) from non-wetlands. Screen digitization was done on the colour enhanced and "zoomed in" images. For the lowland areas of the basin (where the Limpopo river drains to the sea) where the visual interpretation of Landsat ETM + data with the application of above techniques was problematic, wetland areas were delineated using SRTM derived elevation thresholds. Wetlands within this lower flood plain area of the basin were characterized by the elevated ground water tables due to their location at a lower elevation much closer to the coast line.

Following image enhancement techniques provided best distinguishable features that facilitated accurate delineation of wetland boundaries when "zoomed in" and viewed onscreen;

(a) FCC of Landsat ETM+ band ratios - NIR/SWIR2: NIR/red: NIR/green (Figures 5a, 5b);

(b) FCC of NIR: Red: SWIR1; and

(c) True Colour Composite (TCC) of Red: Green: Blue.

Where, band 1 = blue, band 2 = green, band 3 = red, band 4 = NIR, band 5 = SWIR1, and band 7 = SWIR2.

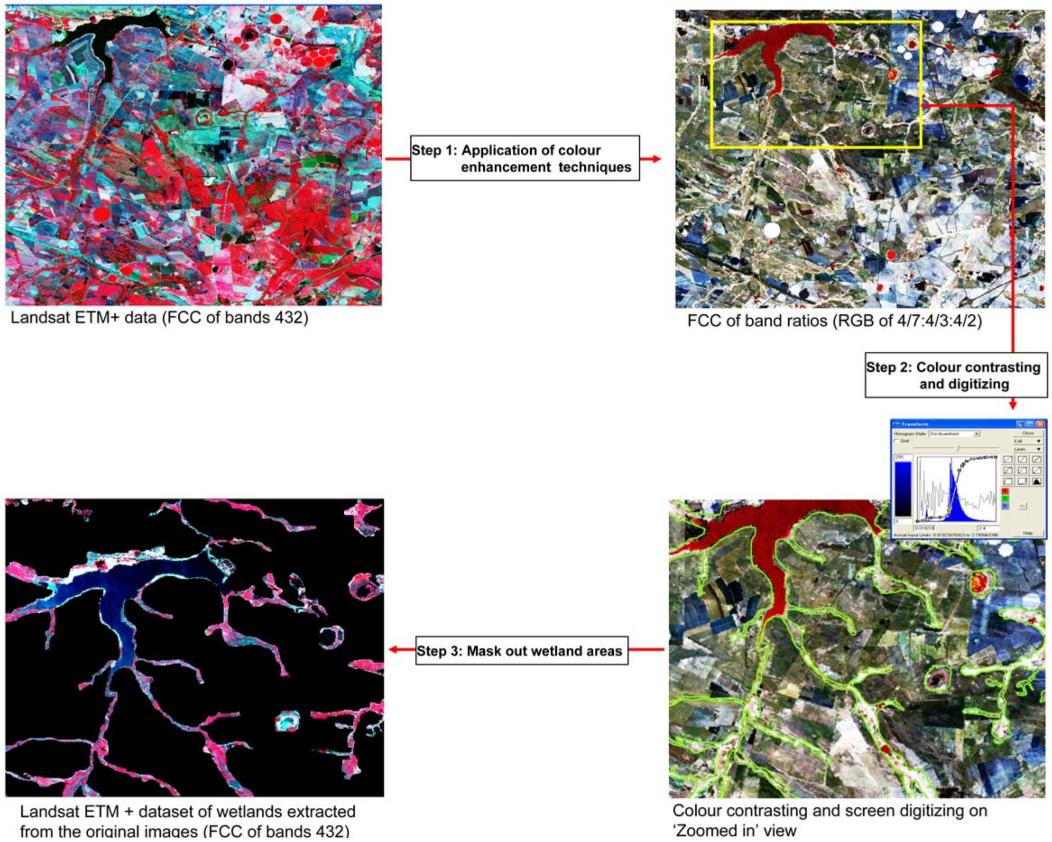


Figure 5a

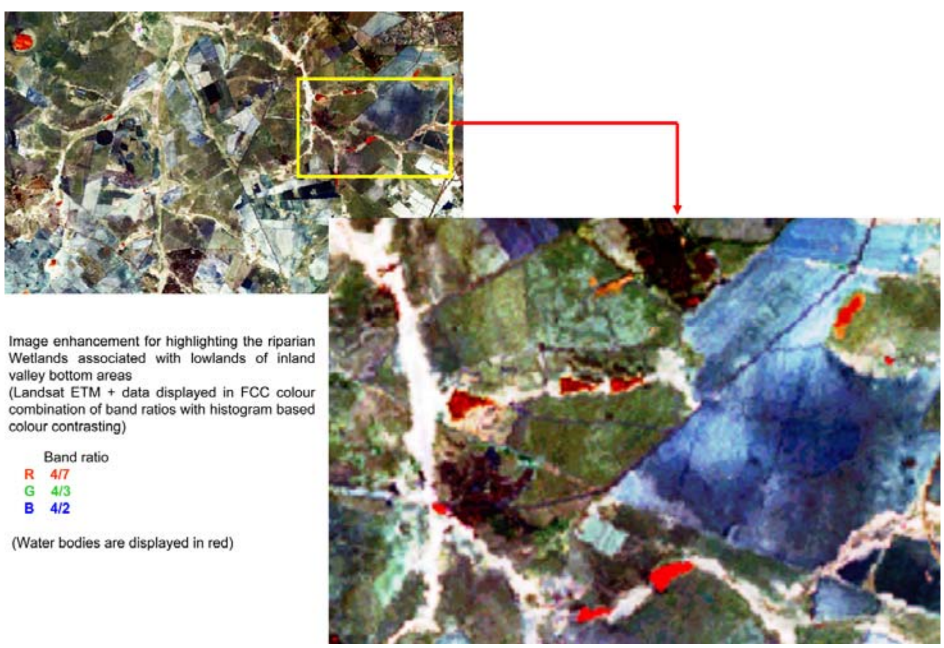


Figure 5b

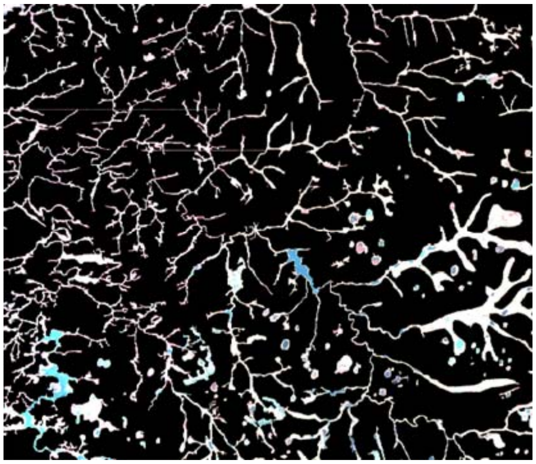


Figure 5c

Figure 5. **Delineation of wetlands through semi-automated process**. Wetlands are highlighted using image enhancement and display techniques (e.g., Figure 5a, 5b) and delineated (e.g., Figure 5c) through online digitizing process.

Accuracy of wetland delineation

Wetlands were first delineated using the methods described in this paper prior to the field visit. Hence, the accuracy of wetland classifications was based on an independent ground-truth data set (see section 3.3.3). The ground-truth mission was conducted after delineating the wetlands using automated (section 3.4.1) and semi-automated (section 3.4.2) methods. Therefore, the GT dataset formed an ideal dataset for determining the accuracies of wetland mapping. Selection of wetland ground-truth points was based on the information provided by local wetland experts who had an independent view on different wetland types and knowledge on their spatial occurrence over the region.

Percentage accuracy of mapping wetlands was determined by overlaying a total number of 220 wetland points (Figure 3) which were identified during the ground truth on the delineated wetland map.

Wetland Classification

Delineated wetlands (Figure 5) were classified separately taking the wet and dry season images (Figure 2). The image data was first normalized by converting to reflectance (see Thenkabail *et al.* 2002, 2004a, 2004b) using an inbuilt model in ERDAS Imagine. A hierarchical class grouping was adopted to label and identify the classes (Thenkabail et al., 2006, 2005). To classify wetland classes, unsupervised ISOCLASS clustering algorithm in ERDAS Imagine was used, separately on wet and dry season images. The classification was initiated with a maximum number of 50 classes separately for both sets of images.

Class identification and labeling

Following the classification, class statistics were viewed and used in class identification and labeling process which involved following steps (also see Figure 6).

A. Bispectral plots:

Unsupervised class means for Landsat ETM+ band 4 (near-infrared) versus band 3 (red) were plotted to obtain the bi-spectral plots (see Figure 7a through 7c). This provides one of the key steps in class identification process.

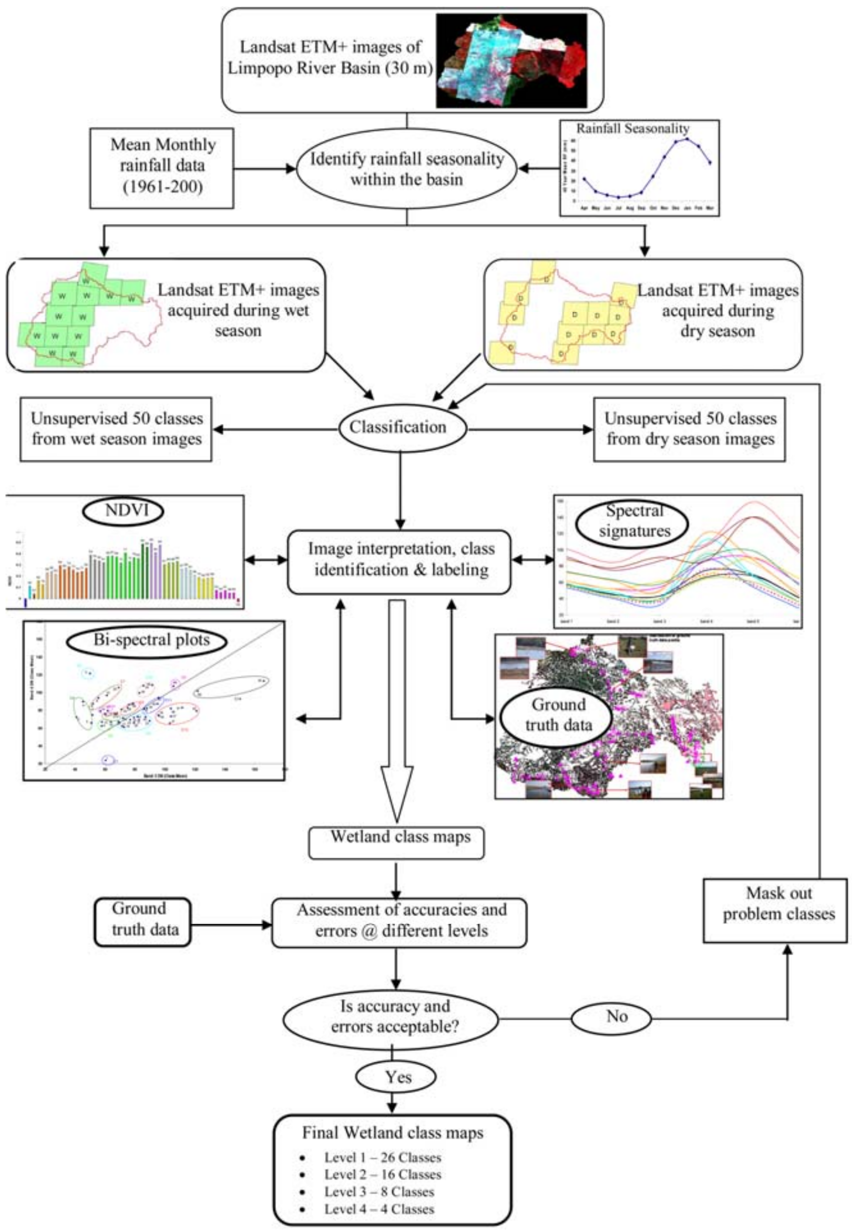


Figure 6. **Wetland classification and class identification process**. Illustration of methods for wetland class identification and labeling.

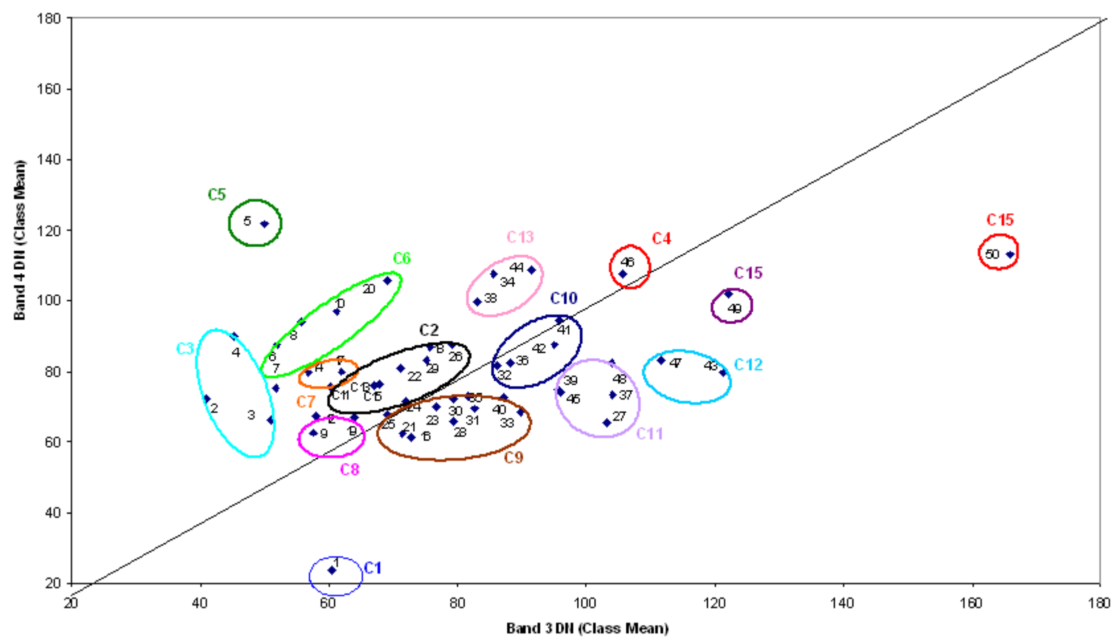


Figure 7a (cont.)

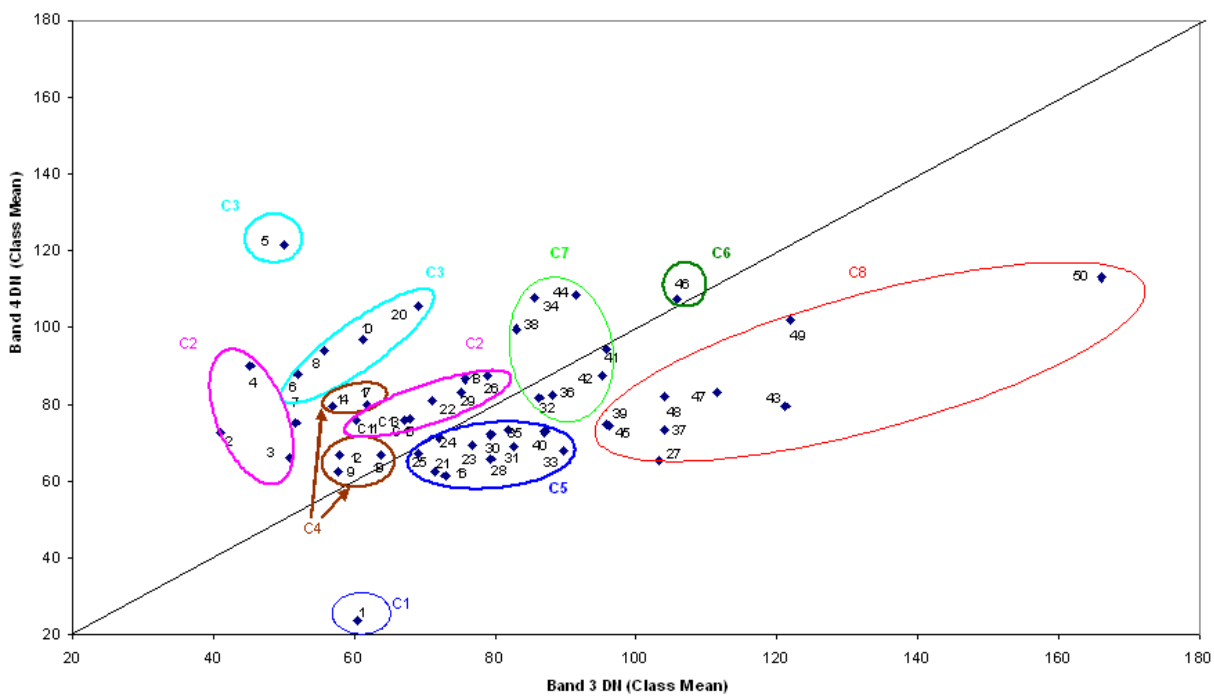


Figure 7b (cont.)

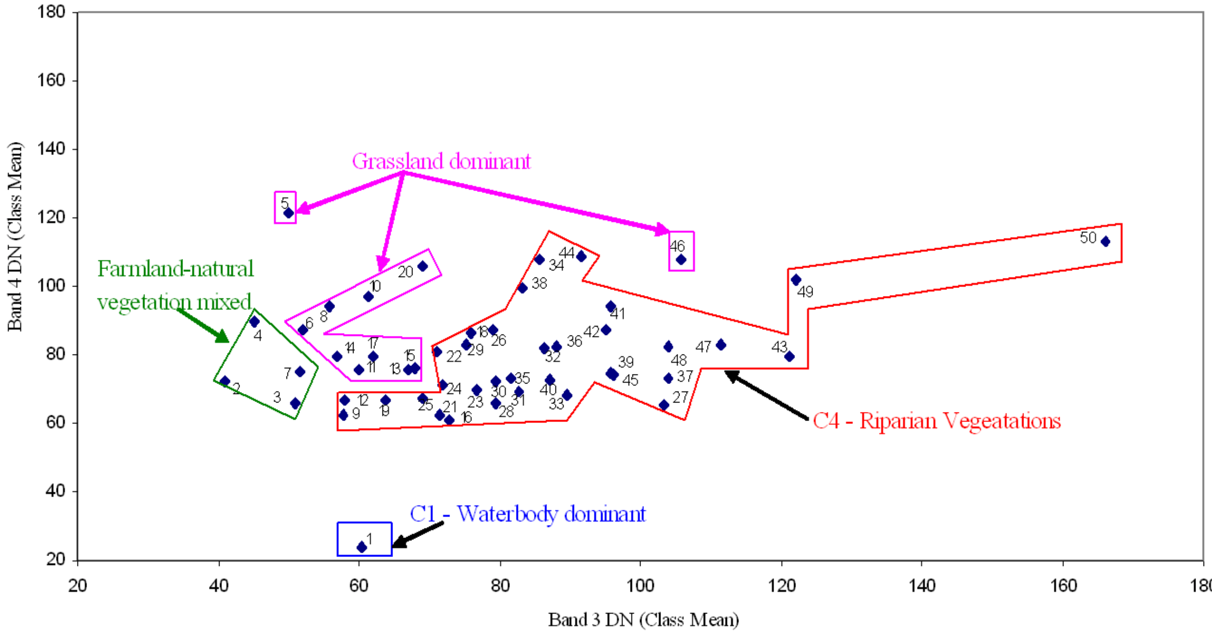


Figure 7c (cont.)

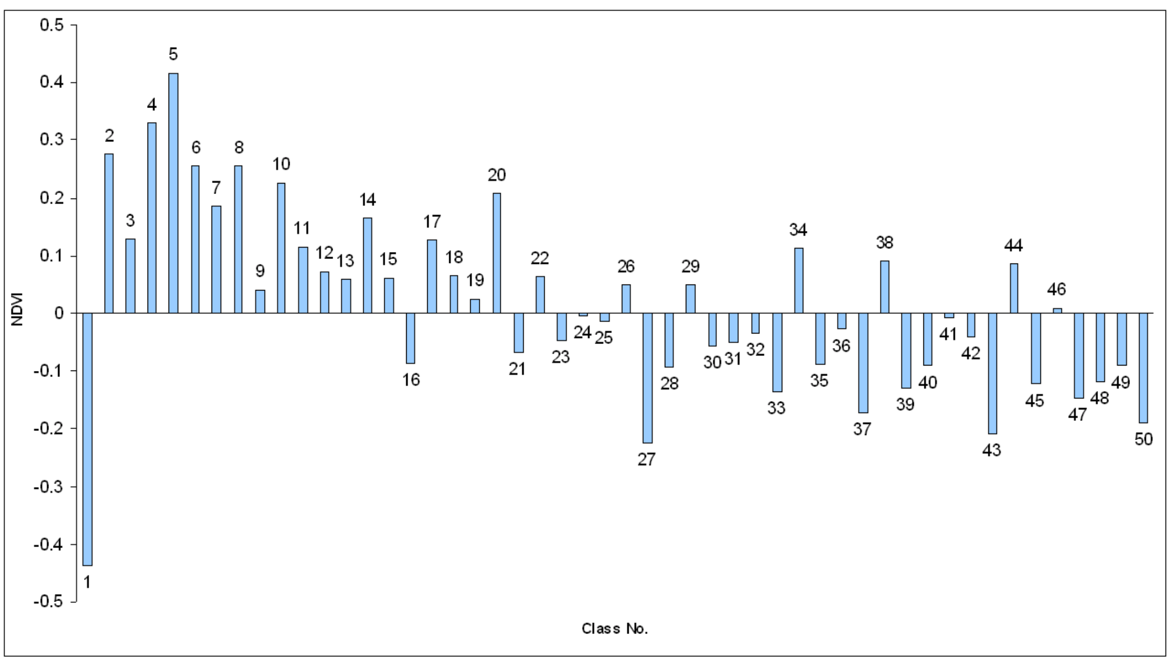


Figure 7d.

Figure 7. **Hierarchical classes at different levels reduced from initial 50 classes.** Bi-spectral plots show hierarchical classification and labeling process at 3 different levels: for 15 classes (Figure 7a), 8 classes (Figure 7b), 4 classes (Figure 7c) and NDVI of 50 classes (Figure 7d).

B. Ground truth data

The quantitative and qualitative observations that were made during ground-truth including the extensive series of geographically precise digital photos were used in class identification and labeling process.

C. Normalized Difference Vegetation Index (NDVI)

The NDVI values of the unsupervised classes were plotted (see Figure 7d) to assist in class identification process. Wetlands with barren lands and\or with sparse vegetation have lower NDVI as a result of soil moisture that is relatively higher than the surrounding uplands. When wetlands have natural vegetation or crops the NDVI will vary depending on vegetation density and vigor. The NDVI values were used in conjunction with ground-truth data to assist in interpretation.

D. Hydro-geomorphic and topographic features

The valley bottoms along the lowlands (e.g, inland valleys) are easily tracked on high resolution satellite imagery from their neighboring uplands. Data from topographic maps (especially from 1:50,000 or better) were used where available.

E. Contextual and textural characteristics

False color composites (FCCs) were used to identify distinct features on the imagery that helped distinguish lowlands from uplands. These differences were mainly resulted from the differences in vegetation type and conditions as well as the moisture differences between the uplands and lowlands.

F. Hierarchical classification scheme

Based on the above information (point A to E), stepwise aggregation of identified classes were illustrated in Figure 7a through Figure 7d for the wet season images. The most disaggregated classes are shown in Figure 7a and most aggregated classes in Figure 7c. Similar approach was used to determine the classes in dry season images. Wetland class names were refined with the equivalent Ramsar Classification names where appropriate.

Accuracy assessment of the wetland classes

The ground sample points (Figure 3) were overlaid on each of the land use\land cover (LULC) maps to determine the classification accuracies and errors of each class. Correspondence between classified and ground verified cover types was determined using a confusion matrix approach in Arcview. The levels of accuracies and errors at different classification levels were estimated and compared amongst different hierarchical classification levels.

Following equations were used to derive percentage accuracies, errors of omissions, and errors of commissions:

Equation 8

$$\text{Overall accuracy (\%)} = \frac{\text{Total no. of GT points of class 'X' that falling on class 'X'}}{\text{Total no. of GT points of class X}} * 100 \quad \text{Equation 8}$$

$$\text{Error of omission (\%)} = \frac{\text{Total no. of GT points of class 'X' not falling on class 'X'}}{\text{Total no. of GT points of class X}} * 100 \quad \text{Equation 9}$$

$$\text{Error of commission (\%)} = \frac{\text{Total no. of GT points of other classes falling on class 'X'}}{\text{Total no. of GT points of class X}} * 100 \quad \text{Equation 10}$$

Results and Discussion

Accurate delineation of the wetland boundaries is the major challenge in wetland mapping. The results of the automated (see section 3.4.1) and semi-automated (see section 3.4.2) methods are presented and discussed.

Automated approach for delineating wetland boundaries: SRTM derived drainage network

The SRTM derived stream density (S_d) and stream frequency (S_f) were compared with the S_d and S_f values derived from Landsat ETM+ data (see Table 3). The optimal S_d and S_f values derived from SRTM data were higher by about 200 to 400 percent when compared with the same values derived from Landsat ETM+ (Table 3). The number of streams generated by SRTM data depends on the level of threshold value used in the algorithm for deriving the stream network from SRTM data. However, there are significant limitations of SRTM derived S_d and S_f. They are (see Figure 8); (a) spurious / non existing streams; (b) absence of stream width; (c) spatial dislocation of the stream network; and (d) non-smooth or pixilated boundary of the stream.

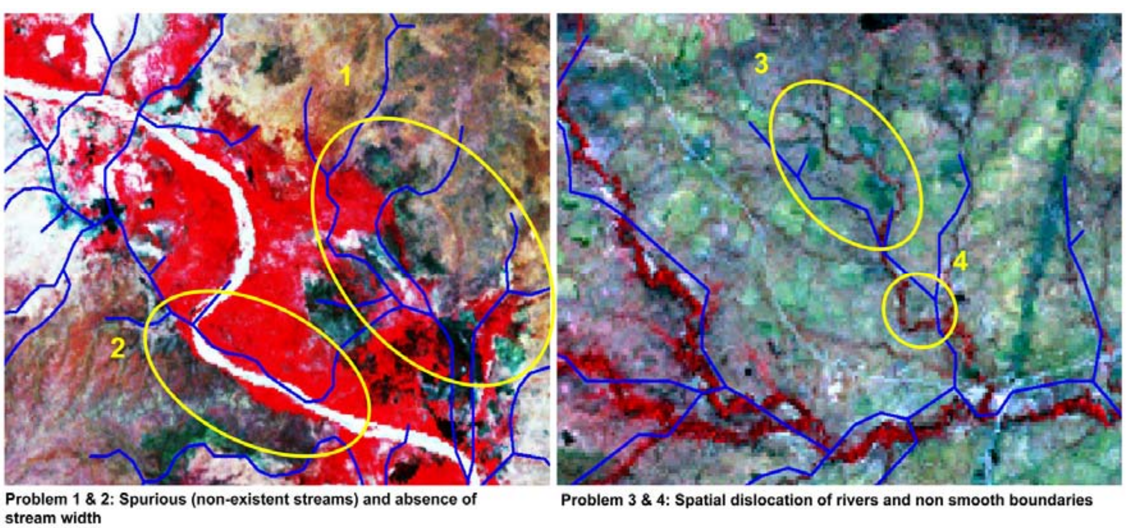


Figure 8. **Problems associated with wetland delineation by automated approach using SRTM data**. The SRTM derived wetlands have the illustrated limitations: (1) spurious streams, (2) absence of stream width, (3) dislocation of streams from their actual location, and (4) non-smooth boundaries.

Table 3. **Wetland drainage systems mapped using SRTM vs. Landsat ETM+.** Stream density (S_d) and stream frequency (S_f) as derived from two different methods: (a) SRTM drainage (b) Landsat ETM + data.

Sub catchment	Area (km^2)	Stream density (S_d) (km/km^2)		Stream Frequency (S_f) ($\#/km^2$)	
		SRTM	Landsat ETM+	SRTM	Landsat ETM+
1	1450	0.7	0.4	0.3	0.1
2	3400	0.8	0.2	0.3	0.03
3	1100	0.7	0.4	0.3	0.1
4	1900	0.7	0.4	0.3	0.1
Average		0.7	0.3	0.3	0.1

Automated approach for delineating wetland boundaries: Thresholds of SRTM slopes and Landsat ETM+ Indices

Different threshold levels of: (a) SRTM derived slopes, and (b) Landsat ETM+ derived indices (Table 4) were investigated for automated and rapid delineation of wetlands. Many of the automated approaches (Table 4) were useful in delineating open water bodies of large surface areas, flood plains, and associated wetlands. None of the methods were, however, effective in delineating the wetlands of smaller widths, especially the riverine wetlands associated with the lower order streams in upper reaches of the basin. They also failed in delineating many of the localized wetland areas of smaller sizes and the wetlands of seasonal occurrence. As a result, the wetlands delineated by automated approaches showed very low accuracies and\or very high errors (see Table 4). Indeed, when the accuracies are increased the errors of omissions or commissions shoot up to unacceptable levels. For example, the tassel cap wetness index (TCWI) with value range of $-40 \leq a < 0$ provides, seemingly, moderate accuracy of 57 percent. However, the error of commission of 343 percent clearly implies that large areas that are not wetlands also get added in as wetlands. In the past studies TCWI is being extensively used for mapping wetlands (McFeeters, 1996; Li et al, 1998). It is related to soil features, including moisture status (Jensen et al, 1995). This is mainly because of the sensitivity of the longer infrared channels to soil (Karnieli, 2000). Spectral data coming from the near infrared (band 4), mid infrared (bands 5 and 7), red (band 3) and green (band 2) region of the spectrum were used in the present study in many of the indices. Madra (2005) shown that the spectral data coming from red and near-infrared region of the spectrum clearly distinguishes the wetlands from non wetlands within the lower part of Limpopo basin within Gaza province of Mozambique. NDVI is a good measure of the health and vigor of the vegetation cover and therefore been used widely in wetland related studies (Li et al, 1998; Hogg et al, 2006). Numerous studies have shown strong correlations between NDVI and plant primary productivity, biomass, leaf area index (Tucker et al, 1986; Running et al, 1994; Justice et al., 1985). Therefore, it could be used mainly to capture the differences among different types of wetland vegetations and also for distinguishing the wetland boundaries from the surroundings. However, in the present study, the best of these indices provided only an accuracy of less than 30 percent with high levels of errors of omissions and commissions. The major limitation observed with almost all the different threshold levels of each index was the greater levels of commission error. For example the distribution of wetlands within lower Limpopo flood plain in Gaza province of Mozambique as delineated by Madra (2005) using scaled NDVI threshold value of less than 98 (NDVI= 0.23) showed greater similarity to the distribution of wetlands that were delineated in the present study using semi-automated approaches. However, in our attempts to delineated wetlands using similar threshold values of NDVI (<-0.25) mapped only 3% of the wetlands within the basin. Findings of the same study by Madra (2005) showed that different methods applied for wetland delineation using medium resolution satellite images resulted greater differences in spatial and area coverage of delineated wetlands. They also showed that larger wetlands could be identified in all methods but were not useful for wetlands of smaller widths. The best possible results reported in the present study are given in Table 4. This clearly implies the inappropriateness of the automated approaches for delineating wetlands at larger spatial scales. A primary cause for this is because when wetlands have vegetation canopies or agriculture, they can look similar to uplands with similar vegetation or agricultural crop cover. Even when, the lowland vegetation is characteristically different from uplands, the difference in spectral reflectivity may not be consistently significant over space.

Table 4. **Accuracies and errors of automated methods for wetland delineation**.

	Data used	Threshold value	Accuracy of wetland delineation (%)	Errors of omission (%)	Errors of commission (%)
a.	Slope derived from SRTM	a ≤ 0	1	99	3
		0 ≤ a < 0.5	29	71	160
		0.5 ≤ a < 1	31	69	206
		1 ≤ a < 2	20	80	165
		2 ≤ a < 20	18	82	160
		a ≥ 20	1	99	8
b.	Normalized Difference Vegetation Index (NDVI)	a ≤ (-0.25)	3	97	1
		(-0.25) ≤ a < 0	14	86	19
		0≤ a < 0.1	29	71	496
		0.1 ≤ a < 0.2	12	88	73
		0.2 ≤ a < 0.4	34	66	142
		0.4 ≤ a < 0.6	9	92	27
c.	Tasseled-cap Wetness Index (TCWI)	a ≤ (-40)	26	74	322
		(-40) ≤ a < 0	57	43	343
		0 ≤ a < 10	11	89	29
		10 ≤ a < 30	6	94	7
		a ≥ 30	1	99	0
d.	Normalized Difference Water Index (NDWI)	a < (-0.30)	17	83	239
		(-0.30)≤ a <(-0.25)	22	78	202
		(-0.25)≤ a <(-0.20)	24	76	142

		(-0.20) ≤ a <(-0.15)	18	82	71
		(-0.15) ≤ a < 0	14	86	42
		a ≥ 0	5	95	5
e.	Ratio 4/7	0.3) ≤ a < 0.5	1	99	5.7
		0.5) ≤ a < 1.25	42	58	425
		1.25) ≤ a < 1.75	22	78	144
		1.75) ≤ a < 2.5	24	76	90
		a ≥ 2.5	12	88	36
f.	Ratio 4/3	0 ≤ a < 0.6	3	97	5
		0.6 ≤ a < 0.8	8	92	76
		0.8 ≤ a < 0.95	12	88	121
		0.95 ≤ a < 1.0	4	96	41
		1 ≤ a < 1.5	33	67	291
		1.5 ≤ a < 2.25	40	60	188
g	Ratio 4/2	0 ≤ a < 0.5	2	98	1
		0.5 ≤ a < 0.8	3	97	10
		0.8 ≤ a < 1.0	12	88	112
		1.0 ≤ a < 1.25	22	78	220
		1.25 ≤ a < 1.30	5	95	35
		1.30 ≤ a < 1.6	24	76	175
		1.6 ≤ a < 1.8	15	85	81
		1.8 ≤ a < 2.5	17	83	64
		a ≥2.5	1	99	2
h	Ratio 4/7 * 4/3*4/2	0 ≤ a < 0.3	2	98	11
		0.3 ≤ a < 1.0	21	79	216
		1.0 ≤ a < 1.5	12	88	114
		1.5 ≤ a < 2.5	13	87	111
		2.5 a 5.0	19	81	127
		5.0 ≤ a < 7.5	13	87	54
		7.5 ≤ a < 10	7	93	27
		10 ≤ a < 12.5	4	96	15
		12.5 ≤ a < 20	5	95	17
		a ≥ 20	2	98	8
i	Reflectance of SWIR-1 band	a < 1	1	99	0
		1 ≤ a ≤ 4	1	99	2
		4 < a ≤ 5	1	99	4
		5 < a ≤ 7	3	97	18
		7 < a ≤ 10	12	88	71
		10 < a ≤ 15	35	65	331

15 < a ≤ 20	33	67	346
20 < a ≤ 25	14	86	119
25 < a ≤ 30	2	98	17
30 < a ≤ 40	0	100	1
40 < a ≤ 47	0	100	0

A limitation for application of the automated technique was the single date imagery used in this study. However, this could not be avoided since the main goal of the study was to develop methods for a consistent global wetland mapping making use of freely available high resolution satellite imagery, and secondary data. The use of multi-date high resolution (30 m or better) imagery at global level is not feasible given the resource requirements to handle very large volumes of data. In an earlier study, Thenkabail *et al.* (1996; 1999) showed that the use of single date dry season images provided very good seperability between the uplands and the lowlands. This is because, during dry season, lowlands have significantly: (a) higher moisture, and (b) greener vegetation when compared with dry uplands. Acquisition of global mosaic of high resolution imagery only for the dry season alone is a complex proposition. However, a large proportion of images available in the data archive of the University of Marylands' Global Land Cover Facility (http://glcf.umiacs.umd.edu/data/) are from dry season. Madra (2005) showed that the spectral data coming from red and near-infrared region of the spectrum clearly distinguishes the wetlands from non wetlands within the lower part of Limpopo basin in the Gaza province of Mozambique. The NDVI has also been widely used in wetland related studies (Li et al, 1998; Hogg et al, 2006). Numerous studies have shown strong correlations between NDVI and plant primary productivity, biomass, leaf area index (Tucker *et al*, 1986; Running *et al*, 1994; Justice *et al.*, 1985). Therefore, it could be used mainly to capture the differences among different types of wetland vegetations and also for distinguishing the wetland boundaries from the surroundings. The TCWI has also been extensively used in wetland related studies (McFeeters, 1996; Li *et al*, 1998). It is related to soil features, including moisture status (Jensen *et al*, 1995). All of these earlier studies in which the similar approaches have been used for delineation and mapping wetlands have been carried out at much lower spatial scale while our attempts were to map the wetlands at much larger spatial scale. However, The huge difference that exist across the basin in terms of the climate, soil, and many other geo-morphological features have made its wetlands to differ widely across different regions over the basin; making the application of automated approaches that use particular indices and threshold untenable. Even though the above limitations are associated with the automated approaches for wetland delineation the main advantage of them is the reduction in time and human interference. Hence, it is still worth while to explore the possibilities of using them at various spatial scales.

Semi-automated approach for delineating wetlands: image enhancement, display, and digitizing

Various enhancement models were tested to determine the best technique for obtaining a better contrast among wetland versus non-wetland land cover types across different regions over the basin. The most useful displays of ETM+ image enhancements (e.g., ratios) and band combinations that highlighted the wetlands from non-wetlands, when displayed as RGB (red, green, blue) false color composite (FCC) combinations were:

- ETM+4/ETM+7, ETM+4/ETM+3, ETM+4/ETM+2 (or simply: 4/7,4/3,4/2);
- ETM+4, ETM+3, ETM+5; and
- ETM+4, ETM+5, ETM+2.

A typical RGB FCC display for highlighting wetlands from non-wetlands is illustrated in Figure 5a and 5b. The wetland boundaries were digitized directly off screen using these enhancements and displays. The 4/7, 4/3, 4/2 (NIR/SWIR2, NIR/red, NIR/green) combination captured most of the wetlands, but when the above technique failed to distinguish wetlands from other land cover classes, other combinations were scanned to digitize any missing wetlands. Every other possibility such as the SRTM slope threshold is used to add wetlands that were missing from combinations displayed above. The same band combinations were also remarkable for delineating both fresh water and salt water pans that were concentrated mostly in upper reaches of Olifants sub basin that occurs within South African part of the basin. Harvey *et al.* (2001) have followed similar approaches for delineation and mapping of wetlands within Northern territory of Australia. They have shown that the use of contextual and textural characteristics as seen on Landsat and SPOT images as desirable to map vegetation communities in wetland environments, especially for those with highly heterogeneous structural composition where similar vegetation communities occur in different forms and densities.

The stream density (S_d) and stream frequency (S_f), the two indicators of wetlands, delineated by semi-automated methods using Landsat ETM+ data are compared with the S_d and S_f obtained from the topographic maps (Table 5; Figure 9) . The results showed that when compared with 1:250,000 topographic maps the S_d and S_f values were comparable (Table 5; Figure 9). For example, the S_f from 1:250,000 topographic maps was 0.58 (numbers per square kilometers) when it is compared with an S_f value of 0.62 from Landsat ETM+ . The S_d from Landsat ETM+ (0.42 kilometers\square kilometers) was significantly higher than the S_d from 1:250,000. However, the S_d and S_f obtained using 1:50,000 topographic maps were 100 to 300 percent higher than the Landsat ETM+ derived S_d and S_f. The results imply that the performance of ETM+ data in delineating wetlands using semi-automated methods was similar to that of 1:250,000 topographic maps but misses a large number of wetlands when compared to 1:50,000 topographic maps. There are 2 important advantages in the Landsat ETM+ derived wetlands when compared with topographic map derived wetlands; (a) areas of wetlands: presence of stream width helps derive areas of wetlands; and (b) Land use\ land cover (LULC) characterization of wetlands: availability of data in multiple bands will help derive land use\ land cover (LULC) characteristics of the wetlands.

Table 5. **Performances of Landsat ETM+ in comparison with topographic maps in delineating wetlands.** Stream density (km\km^2) and stream frequency (# /km^2) delineated using semi-automated techniques on Landsat ETM+ and topographic maps.

Data used	Stream frequency (# /km^2)	Stream density (km\km^2)	Area of wetlands (km^2)
Landsat ETM+	0.58	0.42	71.1
Topographic maps of 1:250,000 scale	0.62	0.31	Not possible
Topographic maps of 1:50,000 scale	1.03	1.2	Not possible

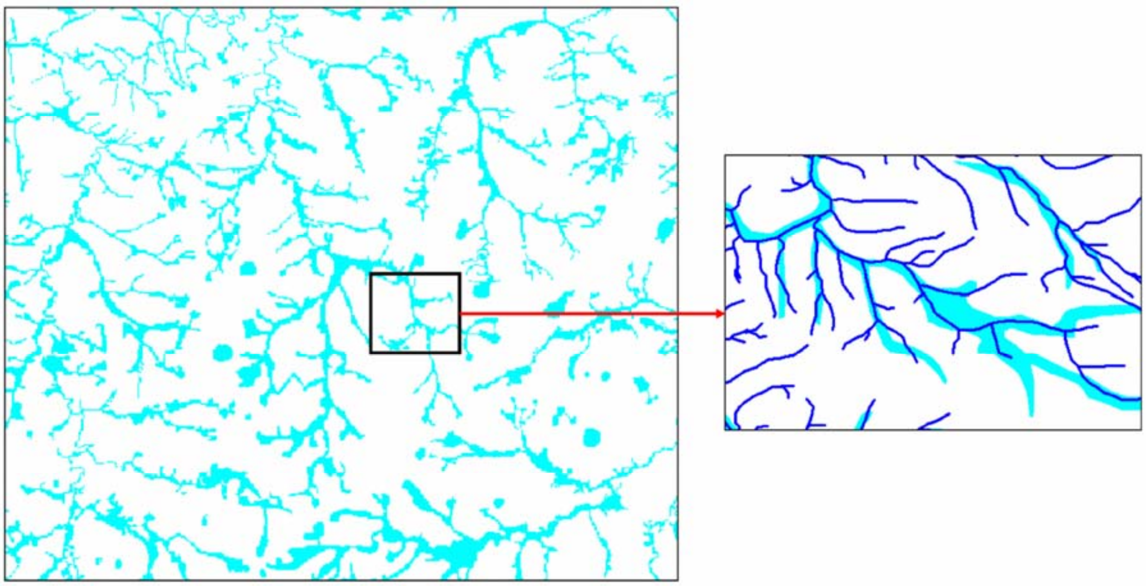


Figure 9. **Comparison of wetlands delineated using Landsat ETM+ vs. topographic map.** Illustration of the wetlands delineated using 1:50,000 topographic map overlaid on wetlands delineated using Landsat ETM+ through semi-automated process.

Wetland distribution and areas of the Limpopo River basin

The spatial distribution of the wetland areas are shown in Figure 10. The total area of wetlands delineated within the basin was 5.2 million hectares (Mha) which accounts for 12.5 percent of the total basin area of 41.5 million hectares. In contrast, the World Resources Institute (2004) reported Limpopo wetland areas to be only 3 percent. This is because the WRI study only accounts for large flood plains as wetlands. This is often the problem with most wetland mapping and inventory studies. Indeed, the overwhelming proportion of the wetlands are along the lower order streams (see Figures 10) that are only visible from high or very high resolution imagery. The wetlands boundaries mapped in this study is comprehensive that includes the following categories: (a) seasonal and perennial, (b) large flood plains, (c) small inland valleys along the lower order streams, (d) pans or natural depressions, and (e) human made irrigation systems.

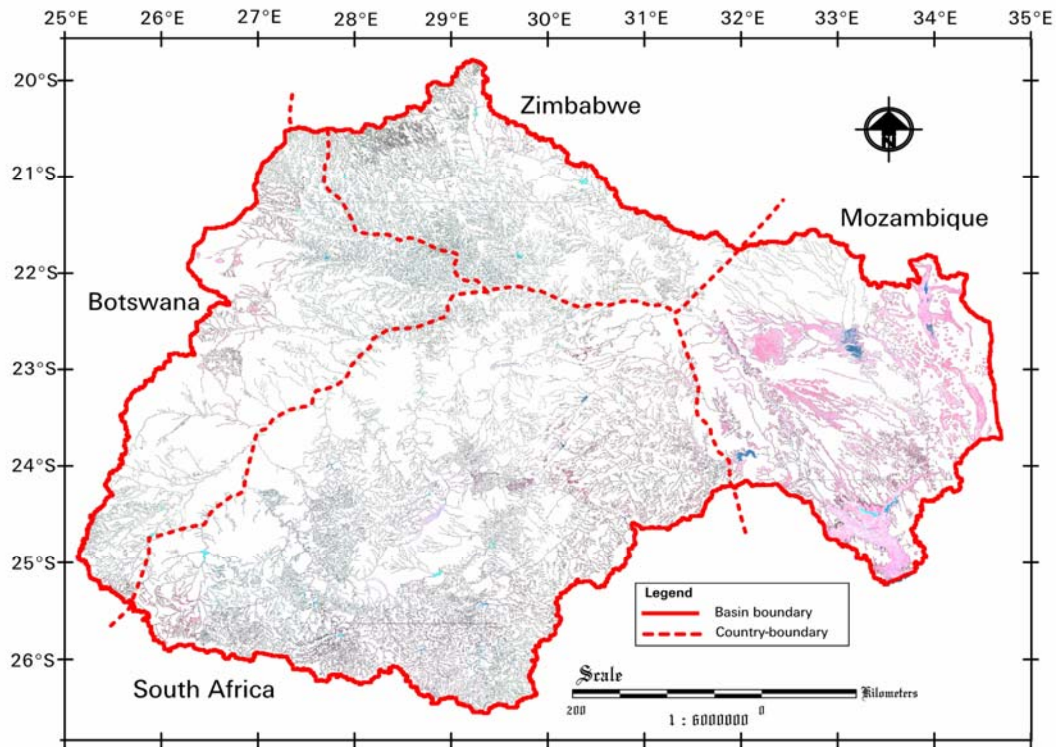


Figure 10. **Wetlands of the Limpopo river basins.** The wetlands of the Limpopo river basin delineated using the semi-automated approach described in this paper. Of the 41.5 Mha basin area 12.5 % (5.2 Mha) was wetland area.

Distribution of wetlands among the four countries varied significantly (Table 6) with: (A) low percentages for Zimbabwe (3.8 percent of the total basin area within the Country) and Botswana (4.2 percent)- both of which are upstreams of the basin; (B) Moderate percentages for South Africa (8.9 percent) which has most of the middle reaches of the basin; and (C) High percentage for Mozambique (24.7 percent) which is in the lower reaches of the basin.

Table 6**. Distribution of wetland land extents among four countries within the Limpopo River basin.**

Country	Basin Area within the country (Mha)	Area of wetlands (Mha)	Wetland area as a % of total basin area within each country (percent)
Botswana	8.0	0.8	4.2
Mozambique	8.8	2.1	24.7
South Africa	18.6	1.7	8.9
Zimbabwe	6.1	0.6	3.8
Total	41.5	5.2	12.5

The lower Limpopo flood plain is characterized almost entirely by flat terrain where most of the areas measuring 100m below mean sea level (INGC *et al.*, 2003). These topographic features as well as the hydrological conditions have made the soils to hold much moisture throughout the year. There are numerous wetlands which are inundated during rainy seasons. The net basin wetland areas are 12.5 percent. In an earlier study for West Africa, Thenkabail *et al.* (2000b, 1996, 1995) showed the wetland areas varied between 9 to 18 percent.

Accuracy of wetland delineation

The accuracy of wetland delineation with the use of above semi-automated approaches was assessed based on ground truth data. The overall level of accuracy reported for wetland delineation was 86.4 percent; with an additional 7.7 percent of ground truth points falling within 1 pixel (30 m) of wetland area (Table 7). In automated and other methods of wetland delineation, Sader *et al.* (1995) have shown that the spectral overlap between wetland and upland cover types is a problem frequently identified in the application of remote sensing techniques to wetland environments. The use of spectral enhancement techniques as well as with the use of human interpretations during the process of screen digitizing, the problem of spectral overlap among wetland and non-wetland cover types was minimized to a great extent. Hence a high level of accuracy could be achieved for wetland delineation even for such large river basin.

Table 7. **Accuracy of wetland delineation using semi-automated methods**.

	Accuracy[1] (%)
Completely within digitized boundaries	86.4
Just outside (within 30 m) the digitized boundaries	7.7
completely outside the digitized boundaries	5.9
Total	100

[1]Percent of wetland ground-truth points falling on delineated wetlands

Classes of wetlands and their spatial distribution

The delineated wetland dataset was classified using unsupervised ISOCLASS classification algorithm and classes were identified and labeled as illustrated in Figure 6 and Figure 7a through 9d. Hierarchical classification system was adopted and classes at 4 different aggregation levels (24, 15, 8, and 4 classes) were identified (Table 8) and illustrated (e.g., Figure 11 for class 8 and Figure 12 for class 4). The majority of the wetlands within the basin are covered by the natural vegetations (see Figures 11 and 12 and Table 8). The highest percentage was reported for the grassland dominant wetlands which accounted for 33.8 percent of the total wetland area within the basin followed by the riparian natural vegetations dominant wetlands (35.9 percent) and natural vegetation-farmland mixed land cover dominant wetlands (25.3 percent). It is obvious that overwhelming proportion of the wetlands remain unexploited for agriculture. As observed during the ground truth mission, these wetlands have very high potential for agricultural expansion given the richness of soils and moisture availability. Nearly 5 percent of the total wetland area within the basin reported to be the water body dominant wetlands. This category however, includes most of the inland water bodies that include inland lakes, ponds, reservoirs, perennial streams, fresh water and salt water pans, other perennial water bodies, marshy lands, and peat lands.

Table 8. **Classes of wetlands based on hierarchical classification system**. The land use\land cover (LULC) characteristics of the Limpopo wetlands reported at 4 levels of aggregation.

Level 1: 24 Classes			**Level II**: 15 Classes			**Level III**: 8 Classes			**Level IV**: 4 Classes		
Class #	Class Name	Land extent (km^2)	Class #	Class Name	Land extent (km^2)	Class #	Class Name	Land extent (km^2)	Class #	Class Name	Land extent (km^2)
1	wetlands, waterbodies dominant	1699	1	Wetlands, water bodies dominant	2618	1	Wetlands, water bodies dominant	2618	1	Wetlands, water bodies dominant	2618
2	Wetlands, Riparian zone -water (shallow) significant-mixed with grass & shrubs	919									
3	Wetlands, grasslands in moist flood plains covered with vigorous garss mixed with water bodies	4789	2	Wetlands, seasonally flooded grass lands/ grass dominant vegetation cover in riparian zone	9170	2	Wetlands, grasslands dominant	10211	2	Wetlands, grass dominant	16472
4	Wetlands,grass dominant riparian natural vegetation-water-significant	4381									
5	Wetlands, grasslands in moist flood plain covered with vigorous garss	520	3	Wetlands,grasslands - moist/wet low lands - Vigorous grass cover	520						
6	Wetlands, riparian natural vegetation -grass dominant very low NDVI	522	4	Wetlands, grasslands covered with less vigorous grass -low NDVI	522						
7	Wetlands, grass lands dominant - short grass, less vigorous and disturbed natural vegetations in riparian zone	797	8	Wetlands, Riparian vegetation (Grass dominant, less vigorous & dry) with some farming	3318	7	Wetlands, grass dominant natural vegetations	6261			
14	Wetlands, grasslands-riparian natural vegetations-farmlands mixed	2521									
17	Wetlands, riparian natural vegetation-grass-shrub dominant, V. high NDVI	382	11	Wetlands, riparian natural vegetation-grass-shrub dominant,	382						

				V. high NDVI							
18	Wetlands,riparain natural vegetation -grass dominant-moderate vegetation cover	2561	12	Wetlands,riparain natural vegetation - grass dominant-moderate vegetation cover	2561						
8	Wetlands, grasslands in moist flood plain with significant farming and water bodies	1864	5	Wetlands, Grass lands (moist) farmlands significant (Low vegetation cover)	4381	3	Wetlands - grasslands-Farmlands-Significant	7083	3	Wetlands, farmlands-natural vegetations mixed	9386
9	Wetlands, grasslands in moist flood plains with significant farming	1093									
10	Wetlands, farmlands mixed with grasslands in moist flood plains	1424									
11	Wetlands, Grass lands (moist) farmlands significant (High vegetation cover)	2701	6	Wetlands, Grass lands (moist) farmlands significant (High vegetation cover)	2701						
15	Wetlands, farmlands (less intensive farming), open lands/ fallow farmlands dominant	1605	9	Wetlands, Farmlands significant (fallow/ barren) mixed with short grass -very low vegetation cover	1605	5	Wetlands-natural vegetation farmlands mixed	2303			
16	Wetlands, farmlands (Intensive farming)	698	10	Wetlands, Farmlands significant (High Veg Cover)	698						
12	Wetlands, Riparian vegetation-grass, shrubs & farmlands mixed (high vegetation)	3783	7	Wetlands, Riparian vegetation (grass, shrubs & trees mixed) with some farming	5258	4	Wetlands, Riparian vegetation (grass, shrubs & trees mixed) with some farming	5258	4	Wetlands, riparian natural vegetations	23365
13	Wetlands, Riparian vegetation-less vigorous & sparse -grass & shrubs dominant with some farming	1475									

19	Wetlands, Riparian natural vegetation -sparse vegetation cover	5302	13	Wetlands,riparain zone covered with sparse cover of trees, shrubs and grass-very low vegetation cover	11077	6	Wetlands, riparian zone, sprase veg cover	11077			
20	Wetlands, Riparian natural vegetation -barelands significant	5775									
21	Wetlands, Riparian natural vegetation minimum vegetation cover	1807	14	Wetlands, riparian natural vegetation, open lands dominant	2951	8	Wetlands-riparian zone-minimum vegetation cover	7030			
22	Wetlands, dry streambed; sand beds dominant with few vegetation cover	1144									
23	Wetlands, moist streambed; sand beds/ rocks/ open lands dominant with minimum vegetation cover	2520	15	Wetlands, stream beds, open lands, sand, rocks dominant	4079						
24	Wetlands, dry streambed; sand beds/ rocks/ open lands dominant	1559									
Total Area		51840	Total Area		51840	Total Area		51840	Total Area		51840

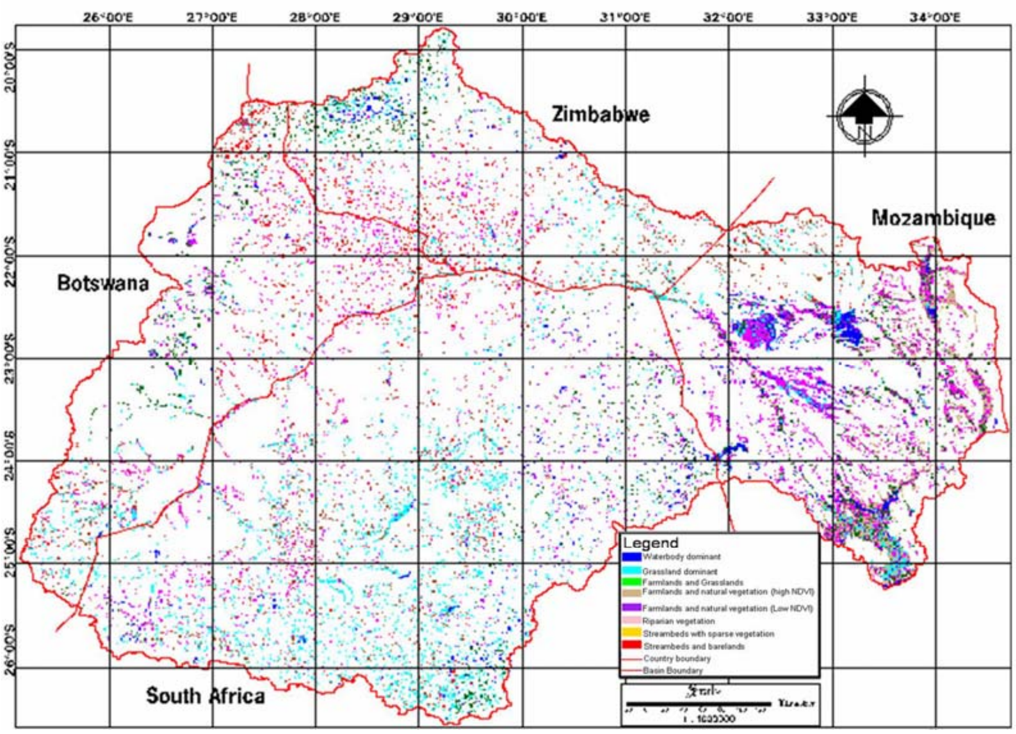


Figure 11. **Dis-aggregated wetland classes of the Limpopo wetlands**. The wetland classes are mapped at different levels. Illustrated here is a 8-class classes.

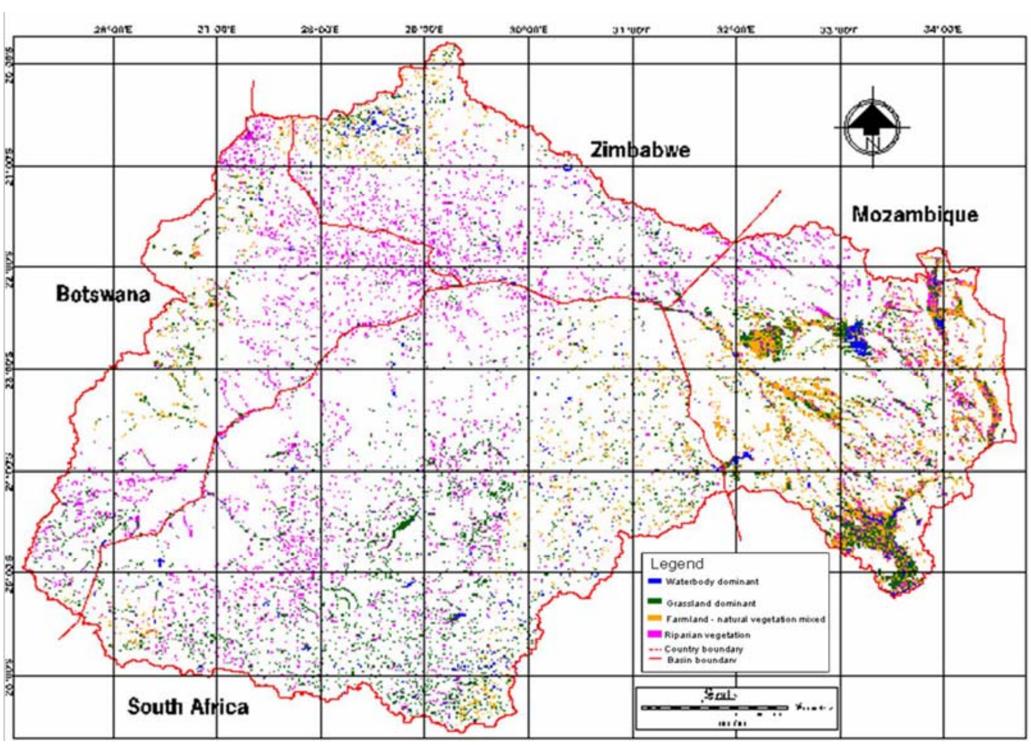


Figure 12. **Aggregated wetland classes of the Limpopo wetlands** – Four (4) aggregated wetland classes.

4.7 Accuracies and errors of Wetland Classification

Accuracy assessment was done based on ground truth points for different levels of wetland class maps. The accuracies and errors for the most aggregated 4 class map are reported in Table 9. The overall accuracy was 82 percent (k_{hat} = 0.80) with errors of omission not exceeding 21 percent and errors of commission not exceeding 13 percent.

Table 9. **Accuracies and errors of wetland classes for** level IV wetland classes.

Land Use/ Land Cover (LULC) category	Percentage of ground-truth observations of four categories classified in to each LULC category				Errors of Commission[2] (%)
	C1	C2	C3	C4	
Water-body dominant (C1)	87.5	2.4	0.0	0.0	1.0
Grassland dominant (C2)	8.3	79.8	13.3	12.7	12.5
Farmland-natural vegetation mixed (C3)	4.2	10.7	80.0	7.0	8.6
Riparian vegetation (C4)	0.0	7.1	6.7	80.3	6.0
Errors of omission[1] (%)	12.5	20.2	20.0	19.7	

Overall mapping accuracy: 82%[3]
Khat = 0.80
[1]Errors of omission is the percentage of ground-truth observations of each LULC category omitted in the respective LULC class of the classified map
[2]Errors of commission is the percentage of ground-truth observations of other LULC categories included in the respective LULC category in the classified map.
[3]Overall mapping accuracy is the total percentage of ground-truth observations accurately mapped in the classified map.

For the 8-class map (results not presented) the overall accuracy was 71 percent with errors of omission not exceeding 21 percent and errors of commission not exceeding 12 percent. The 14 and the 24 class maps have lower accuracies and higher errors. However, most of the classes spectrally mix within classes. For example,, classes 3, 4, and 5 mix amongst themselves. Madra (2005) used similar approach for classification of wetlands within lower Limpopo flood plain within Gaza province of Mozambique and reported an overall accuracy of 75% at more specific level of classification (8 classes). Accuracies can always be raised if the focus of the study is a small area with use of multiple images. But the challenge is to achieve high levels of accuracy over large areas through innovative methods.

5.0 Conclusions

The study investigated the automated and the semi-automated methods and protocols for delineating and mapping wetlands over very large areas using Landsat ETM+ and SRTM data. None of the automated approaches were able to delineate wetlands with reasonable accuracies.

Semi-automated methods provided high levels of accuracies in delineating and classifying wetlands. The semi-automated methods consisted of:

- image enhancements;
- image display techniques; and
- Digitizing of wetland boundaries using various enhancements and displays.

The best results in highlighting wetlands from non-wetlands were obtained when the images were enhanced using ratios and displaying the enhanced images in RGB false color composite (FCC) combinations of:

(a) NIR/SWIR2, NIR/red, NIR/green;

(b) NIR, Red, SWIR1; and

(c) red, green, blue.

Where, Landsat ETM+ band 2 = green; band 3= red; band 4 = NIR, band 5 = SWIR 1, and band 7 = SWIR 2.

In addition, the SRTM slope threshold of < 1 percent was found to be very useful in delineating higher-order (e.g., floodplain) wetland boundaries.

The methods were evaluated in the Limpopo river basin (41.5 million hectares) which is spread across 4 countries in Southern Africa. The automated methods had poor accuracies and high errors of omissions and\or commissions. The semi-automated methods determined the wetland areas of Limpopo to be 12.5 percent of the total basin area and were mapped with an accuracy of 86.4 percent with other 7.7 percent mapped within a pixel of where wetland ought to be. The distribution of wetlands varied widely: low percentages along the upstreams of the basins with 3.8 percent in Zimbabwe and 4.2 percent in Botswana; moderate percentages along the middle of the basin with 8.9 percent in South Africa; and a high percentage in the mouth of the basin where the river drains to the Indian Ocean with 24.7 percent in Mozambique.

Hierarchical classification system was used to classify wetlands into different aggregation level. Good accuracies were obtained for the 4-class and 8-class maps. The dominant classes were: (a) grasslands (33.8 percent), (b) riparian vegetation (35.9 percent), (c) farmlands and natural vegetation mosaic (25.3 percent), and (d) water body and marshland wetlands (5 percent). The overall accuracy of 4-class wetland classification was high (82 percent) with errors of omission less than 20 percent and the errors of commissions less than 12 percent. For 8-classes the accuracy was 71 percent and errors of omission 21 percent and errors of commission 12 percent.

The feasibility for accurately and rapidly delineating the wetland boundaries of large river basins and classifying them, with good accuracies, using Landsat ETM+ data and SRTM data through semi-automated techniques has been demonstrated. The same approach and methods can be used to map wetlands of the entire World using Landsat ETM+ and SRTM data.

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