Urban and Regional Planning Review 2 (1 & 2) 2010

Remote Sensing for Wetland Resource Delineation and Assessment: A Perspective on Basic Techniques and Readily Available Imageries

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Abstract
Increased awareness of the functions and values of wetlands to the ecosystem and human habitats has spawned increased efforts to delineate and conserve them. With repetitive and large geographic coverage, satellite remote sensing has augmented traditional methods as tools for timely and cost effective delineation and monitoring of wetlands. Thus, it is appropriate for developing countries with usually limited funds and scanty information on wetlands. This paper reviewed literature on wetland delineation and mapping with remote sensing. Basic techniques and readily available imageries applicable in a developing country like Nigeria were identified. Types of wetlands studied, imageries and classification techniques employed, change detection, classification accuracy and relevant ancillary data were all reviewed. Permanently flooded large wetlands or intermittently exposed open water ponds larger than pixel size are the easiest to detect with imageries. Landsat imageries are the most widely used and most readily available online with bands 3, 4, 5 as the best combination for wetland detection. Unsupervised classification is the most commonly used wetland classification technique while supervised classification is the next commonly used. Ancillary data and ground truth enhance wetland delineation. Accuracy assessment is desirable. Although no standard procedure exists, producer's and user's accuracies along with Kappa index are acceptable measures. High resolution satellite imagery like Ikonos and Quickbird can presently serve for ground-truthing and accuracy assessment

Introduction

Wetlands are valuable for a variety of functions, goods and services to both the human habitat and the ecosystem. They are valued for their contribution to ecological balance and biodiversity, ability to store and distribute flood waters, protect shorelines, improve water quality and recharge groundwater aquifers, provide fish and wildlife habitats in addition to providing aesthetic and educational benefits to mankind (Kindscher *et al.* 1998; USEPA 2009). Increased awareness of these functions and values has led to increased efforts to inventory and conserve these valuable resources especially against threats posed by anthropogenic factors such as indiscriminate reclamation, sand filling and urban development. Wetlands in the landscape are areas where water covers the soil or is present either at or near the surface of the soil all year or varying periods of the year. These areas support the prevalence of plants (hydrophytes) which are typically adapted to life in saturated (hydric) soil conditions. Two recognized categories of wetlands are coastal or tidal wetlands and inland or non-tidal wetlands (USEPA 2009).

To conserve existing wetlands, it is necessary to inventory and map their location and characteristics. Traditional methods of inventory and delineating wetlands involve field survey with manual classification, including sketching polygons on printed aerial photos, delineating with Global Positioning Systems (GPS) and other field labour intensive techniques. These methods are time consuming and sometimes are impossible to conduct in some wetland and riparian systems because of inaccessibility and complexity (Neale *et al.* 2007).

Aerial photographs and later colour infrared (CIR) aerial photographs became the preferred tool for inventory and mapping of wetlands faster and at less cost. Over large geographical areas and for a developing country like ours, aerial photographic coverage and mapping can be expensive.

Satellite remote sensing, because of repetitive coverage, has become the newest tool for inventory, mapping and assessing wetlands over large geographical areas at less cost and time. Especially, it has become appropriate for inventorying and monitoring wetlands in developing countries where usually funds are limited and scanty information is available on wetland areas and their losses over time (Ozesmi and Bauer 2002). Almost every type of wetland has been studied with satellite imagery. But very few of these studies have been reported recently in a developing country like Nigeria.

The purpose of this paper is a review of literature on wetland delineation and mapping with remote sensing with a view to identifying readily available imageries as well as basic techniques applicable to a developing country like Nigeria. The review is organized in the following ways. Types of wetlands studied with remote sensing are identified. Then, imageries and satellite systems used in wetland delineation and classification are discussed while advantages and limitations of satellite imagery were subsequently listed. Applicable classification techniques along with change detection in wetlands are discussed. Classification accuracy assessments as well as relevant ancillary data are also highlighted.

Types of Wetlands Studied With Satellite Imageries

Regardless of classification, almost all types of wetlands have been studied with remote sensing. In these studies, multi-temporal imageries often aided classification of wetlands as well as their separation from other landcover classes. Included in the types of wetlands studied with remote sensing are marshes, swamps, lagoons, coastal tidal marshes, mangroves and other coastal wetlands, bogs and fens, inland freshwater marshes, forested wetlands or swamps, open water areas, wet meadows and submerged aquatic vegetation. Some parts of the world covered by these studies include Harike wetland, Punjab (India), Sango Bay, Lake Victoria (Uganda), Florida everglades, Prairie Pothole region of US and Canada, mangrove and other coastal wetlands of West Bengal (India) and Forested wetlands of Brazilian Amazon (Ozesmi and Bauer 2002). Some more recent studies to identify or monitor wetlands and their changes, involve the assessment of the extent and changes in the mangrove ecosystem of Niger Delta (James *et al.* 2007); the detection of change in the lower Ogun River flood Plain (Odunuga and Oyebande 2007); monitoring of land degradation along Ondo Coastal Zone of Nigeria (Abbas 2008); the monitoring of wetlands in the semi-arid west, USA (Neale *et al.* 2007); the mapping of Canada's wetland with optical, radar and DEM data (Li and Chen 2005); and the inventory, monitoring of temporary and permanent wetlands of Western Cape, South Africa (De Roeck *et al.* 2008).

Satellite Systems and Imageries Used For Wetland Delineation and Classification

Earlier traditional methods of demarcating wetlands were time consuming, labour intensive, involved manual classification. They were however supplanted by the use of aerial photographs, color IR, spectral field radiometry and airborne multispectral vidiography or video remote sensing (Neale *et al.* 2007).

Landsat Imageries

With the launch of Landsat 1, 2, 3 many studies used the Landsat MSS data, with its 80m spatial resolution for the discrimination of large vegetated wetlands. Since then, Ozesmi and Bauer (2002) opined that Landsat MSS, Landsat TM, SPOT, AVHRR – NOAA (Advanced Very High Resolution Radiometer), Indian Remote Sensing (IRS - 1B LISS II) Linear Image Scanning Sensor were all satellite remote sensing systems whose imageries have been used to study wetlands. All are optical sensors as they detect and record imageries in the optical portion of the spectrum. For instance, IRS-1B LISS II imagery was used to identify wetland meadows in Wyoming, USA (Kindscher *et al.* 1998).

Improved spectral, radiometric, temporal and spatial resolution of Landsat TM over MSS made it more useful for delineating wetlands and other landcover types. Hence, many studies employed it (Lunetta & Balogh, 1999; Helmschrot *et al.* 2000; James *et al.* 2007; De Roeck *et al.* 2008 and Islam *et al.* 2008). Through these studies, Ozesmi and Bauer (2002) concluded that the most important Landsat TM band for wetland identification is Band 5 due to its ability to discriminate vegetation and soil moisture levels. Further, they noted that Landseat TM and hence ETM+ bands 3, 4, and 5 are usually the BEST combination of bands for wetland detection. This is because vegetation absorbs much of the incident blue, green and red radiation for photosynthesis. As such, vegetated areas appear dark in TM band 1 (blue), band 2 (green) and band 3 (red) images. Conversely, the same vegetation reflects about half of the incident near IR radiation hence it appears bright in band 4 (near IR) image (Jensen 2007). Also, band 4 shows a strong contrast between land and water bodies. Bands 5 and 7, both mid IR provide more detail on wetlands due to their sensitivity to soil and plant moisture conditions. Landsat TM and ETM^{+} are accessible online at http://edc.usgs.gov/products/ satellite/tm. html and http:// landsat7.usgs.gov/ respectively or at http:// glovis.usgs.gov/.

Landsat 7 ETM^{+} has identical characteristics with Landsat TM which it succeeded. It maintains bands 1 to 5 and 7 with a 30m x 30m spatial resolution as the predecessor but with band 6, thermal IR of improved 60m x 60m spatial resolution and a 15m x 15m panchromatic band -0.52μm – 0.9μm (Jensen 2007).

Spot Imageries

Multispectral images from earlier SPOT satellites systems with 20 x 20m spatial resolution and a panchromatic band of 10 x 10m have been used to study wetlands but not necessarily for their identification (Ozesmi and Bauer 2002).

This may be due to the narrow spectral bands and lower spectral resolution of SPOTS 1 – 3 when compared to that of Landsat TM. SPOT 4 HRV offered panchromatic band in both 10 and 20m resolution and an additional shortwave IR (SWIR) at 20m x 20m spatial resolution. However, SPOT 5 HRVIR (High Resolution Visible and IR) sensors offer improved multispectral spatial resolution of 10m x 10m with the same spectral resolution and an improved panchromatic band (0.48 – 0.71μm) of 2.5m x 2.5m spatial resolution at nadir. All these enhanced the use of SPOT imagery in wetland resource inventory and assessment.

Compared to Landsat TM, a SPOT imagery (except SPOT 5 vegetation) covers a relatively smaller area of 60km x 60km or $3600km^2$ to Landsat's 170km x 185km or $31,450km^2$. Thus, about 9 (8.74) images are required to cover a single Landsat TM scene (Jensen 2007). This may be a limitation in regional studies but is of advantage in sub-regional and urban studies.

Radar Imagery

Some of the available satellite radar imagery include the European Space Agency (ESA) ERS – 1, 2, ESA – Envisat ASAR, JERS – 1 (Japan), RADARSAT (Canada) and Shuttle SIR – C/X – SAR of USA (Jensen 2007; Ozesmi and Bauer 2002).

The combination of satellite radar imagery with optical data was envisaged to hold more promise for improved delineation of wetlands. This was because radar has dual advantage of ability to collect data any time of day and under almost any weather conditions including frequent cloud cover. Also radar backscatter allows inundation to be clearly mapped where standing water is present under vegetation than optical sensors. Indeed radar imagery is useful in distinguishing flooded and non-flooded areas even under forests, between forest and marsh vegetation and for the discrimination of mangrove wetlands.

In conjunction with optical imagery, radar has been used to detect and monitor wetlands. But as noted in their study, De Roeck *et al.* (2008), the number of small wetlands (smaller than 1.5ha) detected was lower for ENVISAT –ASAR imagery than for optical imagery. This was possibly attributed to the degradation of spatial information arising from extensive pre-processing required to use radar imagery. According to Jensen (2007), most existing satellite radar, ENVISAT-ASAR, RADARSAT 1, JERS -1, ERS 1, 2 with their relatively coarse spatial resolutions may be of value for obtaining only general Level I land use and land cover information. To extract Level II and III landuse and landcover information, he concluded, optical remote sensor data is superior.

Advantages and Limitations of Satellite Imagery in Wetland Delineation and Monitoring

Advantages

For inventorying and monitoring wetlands, satellite remote sensing and imageries have many advantages. Among these are:

- Ability to cover large areas; arguably the only practical way for mapping and monitoring wetlands in a timely manner over a large area (Neale *et al.* 2007; Li and Chen 2005).

- Repeat coverage enabling large wetlands to be monitored seasonally, yearly over time for changes.
- Less time consuming and less costly in mapping land cover classifications
- Provides information on contextual landuses and their changes over time
- Due to the distinctive spectral characteristics of open water, it is sufficient for reliable detection of open water wetlands (De Roeck *et al.* 2008).
- Being in digital format, satellite data are readily easy to integrate into GIS.
- Can be particularly appropriate for wetland inventory/monitoring in developing countries such as ours where funds are limited and little information is available on wetland areas, their losses or changes over time as well as surrounding land uses (Ozesmi and Bauer 2002).

Limitations

When compared to aerial photography and high resolution imagery, limitations include:

- With a spatial resolution of generally 20 – 30m. for most readily available imagery such as Landsat, it is difficult to identify small or long narrow wetlands smaller than the pixel size of 0.09ha, that is wetlands of ≤0.04 – 0.081ha (De Roeck *et al.* 2008; Ozesmi and Bauer 2002).
- Difficult to separate different wetland types from each other or separate wetlands from uplands forests and agricultural crops or distinguish fine ecological divisions between certain wetland and riparian class because of similarities or overlap in their spectral signatures (Neal *et al.* 2007; Ozesmi and Bauer 2002). Fig. 1 Example of Spectral signatures.
- The pixel resolution of most low spatial resolution satellite imagery is coarser than the fine scale variability present in wetlands (Neale *et al.* 2007).

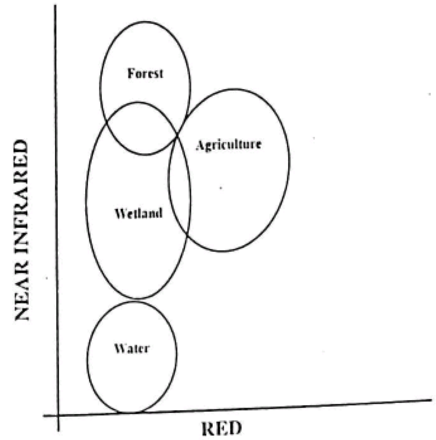

Fig. 1: Example of the variability in spectral signatures of different classes plotted of the red and near infrared bands. Note that water is spectrally distinct but there is an overlap between wetland and agriculture and forest classes. Source: Ozesmi and Bauer (2002).

For these limitations, aerial photography and recently high resolution satellite imagery are generally preferred for detailed mapping of wetlands for small areas particularly if different vegetation types are to be mapped. In mapping small wetlands, some recent studies have attempted to overcome these limitations through the use of airborne multispectral imagery (Neale *et al.* 2007) and Ikonos High–Resolution pan-sharpened multispectral satellite imagery (Fuller *et al.* 2006). In their study in Battle Creek, Michigan, Fuller *et al.* (2006) combined visual interpretation of Ikonos High-Resolution imagery with manual digitization of automated supervised and unsupervised classifications, NWI data and field verification to delineate accurate wetland boundaries in the study area of about 3065ha.

In order to fill the need for detailed mapping and service needs of GIS and cartographic mapping markets, traditionally serviced by aerial photogrammetric industries, the commercial very-high-resolution satellite imageries of spatial resolution 1m x 1m to 4m x 4m came into being over 10 years ago (Jensen 2007). Such imageries as Ikonos offer spatial resolution of 1m x 1m panchromatic and 4m x 4m multispectral bands while Quickbird offers 0.61 x 0.61 pan and 2.44m x 2.44m in the multispectral band. While these offer opportunity for detailed mapping of wetlands and landcover generally, affordability in a developing country like ours is debatable at the moment. Ikonos is accessible at GeoEye, Inc., ww.GeoEye.com while their African product partners are GIS Transport Ltd., www.gistransport.com while Quickbird is accessible at DigitalGlobe, Inc., www.digital-globe.com/about/quickbird.htm. For reconnaissance, Google Earth offers freely high resolution imageries for many important places in the country and world- wide on its website http://earth.google.com/

Classification Techniques Used For Wetland Delineation

Despite previous use of visual interpretation, most recent studies rely mostly on computer or automated classification for wetland identification and delineation because of the reduction in time. Automated classification techniques used include unsupervised, supervised and hybrid classifications.

Unsupervised Classification

Unsupervised classification or 'clustering' is the identification, labeling and grouping together of pixels with similar spectral values into natural clusters or groups (Fuller *et al.* 2005, Ozesmi and Bauer 2002, Campbell 1996). The analyst usually specifies the number of output classes and uses various clustering algorithms to achieve the groupings. This is an interactive process leading to optimal allocation of pixels to categories within the constraints specified by the analyst (Campbell 1996). Such constraints may be convergence value, minimum and maximum number of iterations (James *et al.* 2007). With ancillary information, the analyst then assigns the clusters information class labels.

The most commonly used wetland classification method is unsupervised classification (Ozesmi and Bauer 2002). This is because of its suitability for natural areas which generally have spectral variability and gradual transitions between vegetation types. It allows natural spectral clusters to be defined with high level of objectivity and reliability (James *et al.* 2007). This classification technique is also most successful when a large number of clusters are used or when 'cluster busting' is performed. Cluster busting is the progressive separation of mixed clusters until no further spectral separation is possible.

One of the advantages of unsupervised classification is that the spatial resolution of the image is retained. Another is the elimination of the time consuming training data phase characteristic of supervised classification. The drawback is that clear matches between spectral clusters and informational classes are not always possible (Campbell 1996).

Kindscher *et al.* (1998) used unsupervised classification of IRS – 1B LISS II imagery to identify wetland meadows in Grand Teton National Park, Wyoming, USA. Using ISODATA (Interactive Self-Organizing Data Analysis) clustering algorithm in ERDAS image processing software with the aid of aerial photos and knowledge of the area, 50 initial clusters were combined to create a final map of spectrally distinct six meadow types. Similarly, James *et al.* (2007) used unsupervised classification and ISODATA algorithm (in ERDAS imagine software) to classify spectral classes in Landsat TM and ETM$^+$ imageries in their assessment of the extent of spatial changes in the mangrove ecosystem of Niger Delta. In determining the optimum number of spectral classes for the study, several numbers were tried progressively from 10, 20, 30 and finally to 60 classes in which the mangroves were satisfactorily discriminated from other landcover types. The reliability of the unsupervised classification was verified with accuracy assessment analysis of the derived maps. Overall classification accuracy of pixels ranged from 89% - 95%.

Supervised Classification

Supervised classification involves the use of training data obtained from training sites to identify areas of pixels with known class type which are used to train the computer algorithm to recognize various classes (Ozesmi and Bauer 2002). Usually the analyst identifies sample training sites for various landcover types in the image as have been marked out from field sampling or transects. Then, the image is classified by how similar the pixels in the image are to the training data from the training sites (Fuller *et al.* 2005).

Maximum likelihood classification is the most commonly used supervised classification technique for mapping wetlands due to its performance (Ozesmi and Bauer 2002; De Roeck *et al.* 2008). However, other methods are minimum distance to means and parallelepiped, also called box decision rule or level slice procedure. In maximum likelihood classification, the means and variances of the training data are used to estimate the probability that a pixel is a member of a class. Then, the pixel is placed in the class with the highest probability.

Neale *et al.* (2007) employed supervised classification to classify airborne multispectral imagery in their mapping of Brigham City, Utah wetland mitigation area of 1514ha achieving a classification accuracy of 92%. Similarly, in their study of ecological characteristics and wetland ecology of temporary and permanent isolated open water wetlands of Western Cape, South Africa, De Roeck *et al.* 2008 used this method to classify Landsat TM and ETM$^+$ imageries of the area for both summer and winter seasons. Three supervised classification techniques were compared, namely, maximum likelihood, minimum distance and Fisher. Overall, maximum likelihood had the highest mean overall accuracy, user's accuracy for wetland detection higher than 0.91. All classifications and accuracy analysis were done in IDRISI Andes and Arc GIS.

The study further compared the result of this classification for an area in the optical imagery with that of ENVISAT-ASAR radar imagery of the same area. Results showed that the smallest detectable wetlands in the Landsat imageries had an area of 0.16ha while those smaller than the spatial resolution of Landsat imagery of 0.081ha were not detected. On Envisat images, wetlands smaller than 1.5ha were even more difficult to discern. Ground survey revealed that at least 88% of wetland in the area especially temporary ones were not detected in the optical image classification due to their small size. More were missed out in the Envisat classification. It concluded that the resolution of both images were insufficient for mapping small and temporary wetlands.

Hybrid Classification

This involves the combination of supervised and unsupervised classification. Combining the strengths of the two, it is not as commonly used as the two separately. One hybrid approach is to perform unsupervised classification or clustering on only a portion of the study area. Then after the clusters are assigned information classes, the statistics from the clustering algorithm is input into maximum likelihood classifier to classify the entire study area (Ozesmi and Bauer 2002).

Fuller *et al.* (2006) is one of the few studies which applied both classifications in delineating wetlands at the 3065ha (7570 acres) Fort Custer Training Center, Battle Creek, Michigan. The study tested whether supervised and unsupervised classifications done separately were adequate to classify wetland features in the relatively small area using Ikonos high - resolution pan-sharpened imagery of cell resolution of 0.77m. A supervised classification with maximum likelihood classification was used with known wetland locations to identify similar wetland features in the Ikonos image. Unsupervised classification with 200 classes and 25 iterations were used to identify wetland features not identified by supervised classification and areas not visually obvious on the imagery or not included in the NWI maps. Image processing was done with ERDAS imagine software while, digitizing and map editing were done with ArcMap.

It was concluded that the two automated classification techniques did not result in accurate wetland boundaries which were hope for. The high resolution Ikonos image seemed not to classify well possibly because the 16 bit image with cell size of 0.77m was too much information to process readily. Thus, the final wetland size and boundaries were manually digitized using visual identification from the imagery, GPS field verification with NWI maps and classification results as locational references. However, recent versions of image processing software such as ENVI 4.6.1 EX with its feature extraction tool holds promise in overcoming this classification handicap.

Change Detection in Wetlands

With availability of repeat coverage of satellite remote sensing such as Landsat TM, ETM+, SPOT and so on, satellite imageries have been used to evaluate changes over time in wetland ecosystems. Important factors in change detection with satellite imageries are to use dates of imageries such that wetlands are in the same phenological state from year to year, the use of imageries from the same sensor taken at the same time of day and to ensure careful registration of the images (Ozesmi & Bauer 2002).

Some of the recent studies to identify or monitor wetlands and their changes, involve the assessment of the extent and changes in the mangrove ecosystem of Niger Delta (James *et al.* 2007); the detection of change in the lower Ogun River flood Plain (Odunuga and Oyebande, 2007); monitoring of land degradation along Ondo Coastal Zone of Nigeria (Abbas, 2008); the monitoring of wetlands in the semi-arid west , USA (Neale *et al.*, 2007); the mapping of Canada's wetland with optical, radar and DEM data (Li & Chen, 2005); the inventory, monitoring of temporary and permanent wetlands of Western Cape, South Africa (De Roeck *et al.* 2008) and the spatial – temporal analysis of wetland losses in the Lagos Coastal region (Taiwo and Areola, 2009).

A change detection study was performed on the ecologically fragile lower Ogun River Flood Plan of South-Western Nigeria. Using Landsat multispectral imagery of 2005 and aerial photographs of 1965, the study assessed landuse and landcover changes from 1965 – 2005 to determine the hydrological consequences of the degradation occurring in the flood plain (Odunuga & Oyebande, 2007). The change matrix showed the extent of degradation indicating that the wetland which covered 82.45% of the area in the base year had reduced to 36.31% in 2005 mostly due to anthropogenic factors.

In the assessment of changes in the mangrove of Niger Delta, the proportion of mangrove in the baseline data in all the 3 segments of the Delta ranged from 11.43 to 23.32% while in the assessment data, it has reduced to a range of 11.01 to 22.88%. This indicated a loss over 15 - 17 year period of 1.87 to 4.53%, the highest being in the SE segment (James *et al.* 2007).

Similarly, Taiwo and Areola (2009) assessed the spatio-temporal losses in the wetlands of the Lagos coastal region based on comparative analysis of multi-date Landsat imageries (MSS, TM and ETM$^+$) between 1978 and 2006. Results showed that the total area of wetlands declined by 19% from 399.54km^2 to 323.47km^2 at annual loss of 0.6% over the 28year period. Freshwater swamps declined by 20.0% from 304.49km^2 to 240.80km^2 at an annual rate of 0.7%. Mangrove swamps declined by 13% from 95.05km to 82.67 km^2 over the same period at an annual rate of 0.43%. The losses were noted to be occurring in the previously safe rural areas. Using a Markov chain prediction technique, the trend in losses was likely to continue over 30 years if the status-quo of political/economic system was maintained.

Classification Accuracy Assessment

Although, Ozesmi & Bauer (2002) cautioned that there was no standard accuracy assessment procedure for wetland delineation because different studies employed different procedure, accuracy assessment is desirable to establish confidence level for classification results. Applicable accuracy assessment is the site-specific accuracy. Essentially, this is based on detailed assessment of agreement or error between two matching maps or images at specific locations. The common form of reporting site-specific error is the ERROR matrix, also called 'Confusion Matrix' (Campbell 1996).

Error matrix permits the identification of classes erroneously labeled or mislabeled as other classes. Two results of this matrix, User's Accuracy (Error of Omission) and Producer's Accuracy (Error of Commission) form the guide as to the reliability of the resultant maps as predictive tools. Used in conjunction with error matrices, the Kappa Index of Agreement (K or KIA) provides a quantitative assessment of the error matrix of the classification. As the K-value approaches +1.0, it implies that the score of correctly classified pixels approaches 100% while the contribution of chance agreement to the classification diminishes to zero (0). This indicates the perfect effectiveness of the classification. Similarly as the K-value decreases to 0, chance agreement increases while the percentage of correctly classified pixels decreases (Campbell 1996).

Two studies reviewed here relied on error matrix and Kappa index for assessment of their classification results (James *et al.* 2007; De Roeck *et al.* 2008). The former achieved overall accuracy of 89% - 95% while Kappa index for error matrices ranged from 0.79 – 0.95. The latter concluded that maximum likelihood had the highest mean overall accuracy (99.9%) and user's accuracy (94.3%) for wetland detection and therefore was used for all further analysis.

Relevant Ancillary or Collateral Data

Ancillary or collateral data are data acquired by other means in order to aid in the analysis of classification of remotely sensed data (Campbell 1996). Such data range from an informal, implicit application of an interpreter's knowledge and experience to explicit reference to maps, reports and other data.

Ancillary data have been found to improve classification results of multispectral imageries (Ozesmi & Bauer 2002). Such data which have been used to assist in wetland delineation include hydrographic maps, aerial photos, wetland inventory maps (where applicable), topographic data or DEM (elevation, slope, aspect), soil data or maps (soil texture, hydric soils), vegetation maps, GPS data and field sampling or ground truth data. According to Fuller *et al.* (2006), the accuracy of wetland area delineation depends not only on the quality of the imagery and the experience of the analyst, but also on the amount and quality of collateral data as well as the amount of ground truth.

Ancillary data are usable in either of two ways: either they are added to or superimposed on the spectral data or can be used in the two step layered or stratified and rule-based classifications. In layered classification, the spectral data are classified first. Then, ancillary data form another layer or layers in GIS which are used as basis for reclassification or refinement of initial results (Campbell 1996).

Layered and rule-based classifiers which incorporate ancillary data such as digital DEMs and soil maps, as opined by Ozesmi & Bauer (2002), typically result in higher classification accuracy than conventional statistical techniques such as maximum likelihood. But they equally cautioned that attention be paid to the trade-offs of time and expertise required for their use. Ultimately, for collateral data to improve wetland classification, they must be accurate and registered accurately with the imageries.

Conclusion

Wetlands ranging from marshes, swamps to coastal and inland fresh water wetlands have all been studied with remote sensing with very few reported recently from Nigeria. Featuring prominently in most of these studies is the use of Landsat imagery as the most readily available multispectral and multi-temporal imageries with global coverage.

Landsat band 5 is the most important band for wetland identification while bands 3, 4, 5 are judged usually the best combination of bands for wetland detection. Unsupervised classification or clustering is the most commonly used technique for wetland classification because of its ability to recognize natural spectral clusters with reliability. It is also the basic technique embedded in most image processing software requiring minimal expertise for usage. Supervised classification (with maximum likelihood) is the next common wetland classification technique but requires more expertise and time for utilization.

Layered and rule-based wetland classifications which incorporate ancillary or collateral data like DEMs and soil maps result in higher accuracy. Whether such data is easily available in our country is debatable. With advantages of repeat coverage over large geographic areas, satellite imageries and remote sensing have become effective tools for delineation, monitoring and change detection of large wetlands suitable for an emerging nation like Nigeria at present. Due to pixel or cell size limitations, mapping of small wetlands (i.e. < 0.081ha) may have to rely on high resolution imageries like Ikonos, Quickbird or on airborne multispectral imageries where affordable. Possibly in regional wetland delineation, high resolution imagery of selected areas can serve as part of ground truth and accuracy check. This is an area for further inquiry.

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