# 9

# Inland Valley Wetland Cultivation and Preservation for Africa's Green and Blue Revolution Using Multi-Sensor Remote Sensing

Murali Krishna Gumma
*International Crops Research Institute for the Semi Arid Tropics*

Prasad S. Thenkabail
*United States Geological Survey (USGS)*

Irshad A. Mohammed
*International Crops Research Institute for the Semi Arid Tropics*

Pardhasaradhi Teluguntla
*Bay Area Environmental Research Institute and U.S. Geological Survey*

Venkateswarlu Dheeravath
*World Food Program*



## Acronyms and Definitions

| | |
|---|---|
| AEZ | Agroecological zones |
| AGRA | Alliance for a Green Revolution in Africa |
| ALI | Advanced Land Imager |
| ASTER | Advanced Spaceborne Thermal Emission and Reflection Radiometer |
| AVHRR | Advanced Very High Resolution Radiometer |
| CBERS-2 | China-Brazil Earth Resources Satellite |
| CGIAR | Consultative Group on International Agricultural Research |
| CSI | Consortium for Spatial Information |
| DSS | Decision support system |
| EO | Earth observation |
| ERDAS | Earth Resources Data Analysis System |
| FAO | Food and Agriculture Organization of the United Nations |
| FORMOSAT | Taiwanis Satellite Operated by Taiwanis National Space Organization NSPO |
| Data | Marketed by SPOT |
| Hyperion | First Spaceborne Hyperspectral Sensor Onboard Earth Observing-1 (EO-1) |
| IITA | International Institute of Tropical Agriculture |
| IKONOS | High-Resolution Satellite Operated by GeoEye |
| IRS-1C/D-LISS | Indian Remote Sensing Satellite/Linear Imaging Self-Scanner |
| IRS-P6-AWiFS | Indian Remote Sensing Satellite/Advanced Wide Field Sensor |

| | |
|---|---|
| IVs | Inland Valleys |
| KOMFOSAT | Korean Multipurpose Satellite. Data Marketed by SPOT Image |
| Landsat-1, 2, 3 MSS | Multi spectral scanner |
| Landsat-4, 5 TM | Thematic Mapper |
| Landsat-7 ETM+ | Enhanced Thematic Mapper Plus |
| MODIS | Moderate Imaging Spectral Radio Meter |
| NGO | Nongovernmental organization |
| QUICKBIRD | Satellite from DigitalGlobe, a private company in the United States |
| RAPID EYE—A/E | Satellite constellation from Rapideye, a German company |
| RESOURSESAT | Satellite launched by India |
| SPOT | Satellites Pour l'Observation de la Terre or Earth-observing Satellites |
| SWIR | Shortwave Infrared Sensor |
| VNIR | Visible Near-Infrared Sensor |
| WCA | West and Central Africa |
| WORLDVIEW | |
| USGS | United States Geological Survey |

## 9.1 Introduction

Africa is the second largest continent after Asia with a total area of 30.22 million km$^2$ (including the adjacent islands). It has great rivers such as the River Nile, which is the longest in the world and flows a distance of 6650 km, and the River Congo, which is the deepest in the world, as well as the second largest in the world in terms of water availability. Yet, Africa also has vast stretches of arid, semiarid, and desert lands with little or no water. Further, Africa's population is projected to increase by four times by the year 2100, reaching about four billion from the current population of little over one billion. Food insecurity and malnutrition are already highest in Africa (Heidhues et al., 2004) and the challenge of meeting the food security needs of the fastest-growing continent in the twenty-first century is daunting. So, many solutions are thought of to ensure food security in Africa. These ideas include such measures as increasing irrigation in a continent that currently has just about 2% of the global irrigated areas (Thenkabail et al., 2009a, 2010), improving crop productivity (kg m$^{-2}$), and increasing water productivity (kg m$^{-3}$). However, an overwhelming proportion of Africa's agriculture now takes place on uplands that have poor soil fertility and water availability (Scholes, 1990). Thereby, the interest in developing sustainable agriculture in Africa's lowland wetlands, considered by some as the "new frontier" in agriculture, has swiftly increased in recent years. The lowland wetland systems include the big wetland systems that are prominent and widely recognized (Figure 9.1) as well as the less prominent, but more widespread, inland valley (IV) wetlands (Figures 9.2 through 9.8) that are all along the first to highest order river systems.

Africa's bigwetland ecosystems (Figure 9.1; MAW, 2014) are estimated to cover more than 131 million ha (4.33% of total geographic area of the continent) that vary in type from saline coastal lagoons in West Africa to fresh and brackish water lakes in East Africa. They deliver a wide range of ecosystem services that contribute to human well-being such as nutrition, water supply and purification, climate and flood regulation, coastal protection, feeding and nesting sites, recreational opportunities and increasingly, tourism (ESA, 2014). In contrast, the IV wetland systems (Figures 9.2 through 9.5) occupy roughly 6%–20% of various agroecosystems with higher percentage areas in the wetter agroecosystems and the lower percentage areas in the drier agroecosystems (Thenkabail et al., 2000b). Wetlands, with their abundant supply of fresh water, generally fertile soils, and high productivity, therefore play a central role in the economy of all river basins and coastal zones. They provide fish, water for agriculture, household uses, and transport. Additionally, many distant communities as well as entire cities and regions benefit from wetlands.

In this chapter, we will provide a focused study of wetlands of West and Central Africa (WCA) and demonstrate the richness and importance of wetlands in ensuring the food security of Africa. Throughout WCA, there is increasing pressure for agricultural development as a result of population growth and efforts to increase food security. The IV wetlands have high potential for growing agricultural crops due to (1) easy access to the river water, (2) significantly longer duration of adequate soil moisture to grow crops when compared with adjoining uplands, and (3) rich soils (depth and fertility) (FAO, 2005; WARDA, 2006; Tiner, 2009). However, 90% of WCA's current agriculture is concentrated in uplands, which have very poor soils and scarce water resources. In spite of such huge advantages over uplands, IV wetlands in WCA are highly underutilized mainly as a result of (1) waterborne diseases such as *Malaria, Bilharzias, Trypanosomiasis* (sleeping sickness), *Onchocerciasis* (river blindness), and *Dracontiasis* (guinea worm); and (2) difficulty in accessing them from roads–settlements–markets (WARDA, 2003; Lafferty, 2009). But these difficulties can be overcome with modern health care (Hetzel et al., 2007) and infrastructure (Woodhouse, 2009).

Given this background, it is increasingly felt that the best way to expedite WCA's green revolution (more crop per unit area) and blue revolution (more crop per unit of water) is to focus on its soil-water-rich and hitherto highly underutilized IV wetlands, which roughly constitute about 80% of WCA's total wetlands with the rest being river flood plains (12%) and coastal wetlands (8%) (Lyon, 2001; Mitsch and Gosselink, 2007; Thenkabail et al., 2009b). The WCA is yet to see a green revolution, so badly needed for the food security and economic progress of these countries, specifically for its subsistence farmers who constitute the overwhelming proportion of WCA's population of 350 million. The green revolution technologies developed in Asia in terms of improved agronomic, genetic traits,

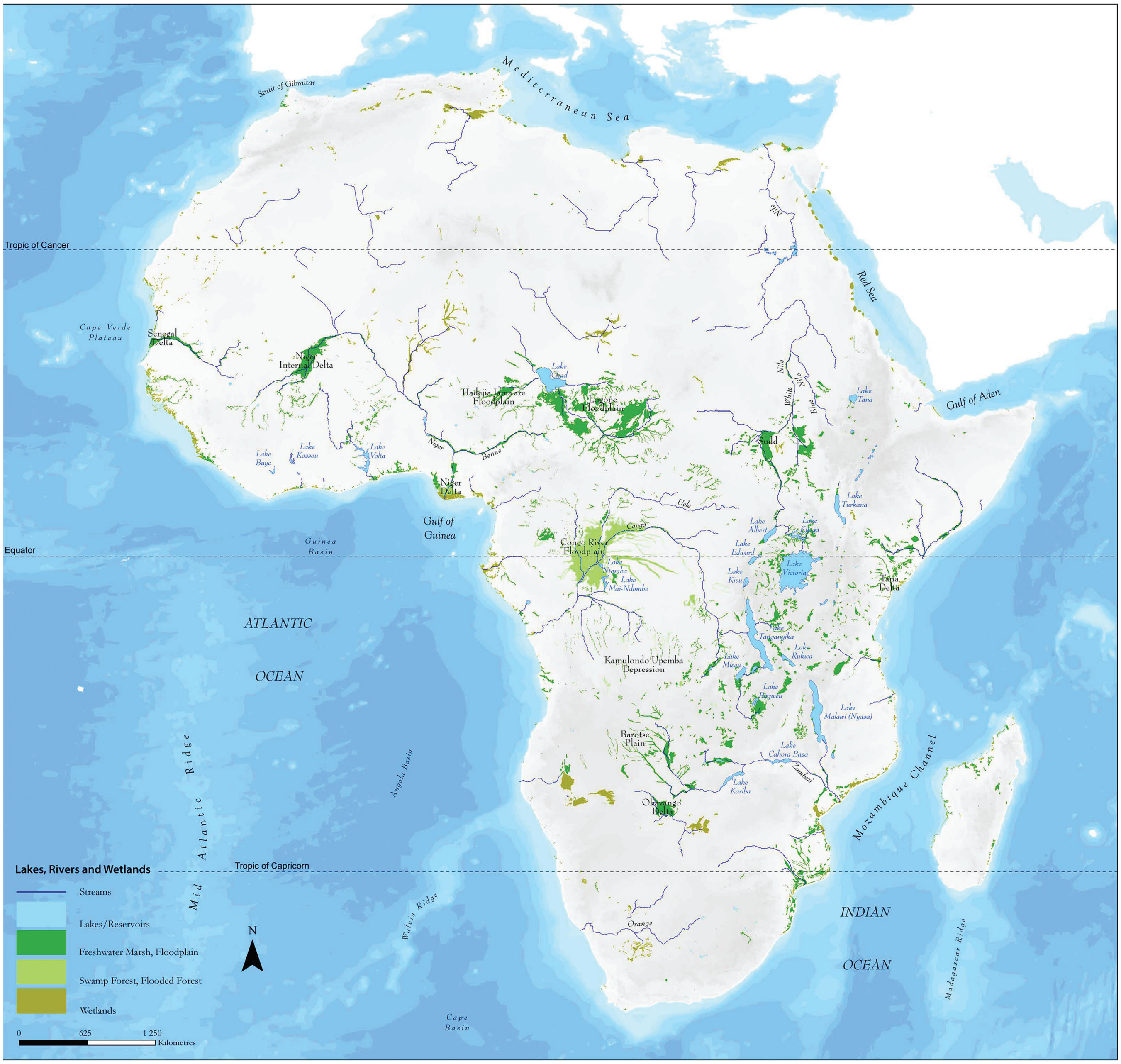



**FIGURE 9.1** African wetlands (MAW, 2014). These are: "Areas of marsh, fen, peatland or water, whether natural or artificial, permanent or temporary, with water that is static or flowing…" (RAMSAR, 2004). But, these *do not* include inland valley wetlands.

and better water management can be adopted with minor modifications to WCA's own green revolution. The importance of IV wetlands is particularly high for rice cultivation as it is becoming a major staple in WCA. Records show a rapid increase of rice consumption in West Africa from 1 million tons in 1964 to 8.6 million tons in 2004 (WARDA, 2003; FAO, 2005). IV wetlands have higher crop yields than the equivalent upland areas. For example, potential yields of rice in IVs were estimated at 2.5–4.0 ton $ha^{-1}$ compared to 1.5–2.0 ton $ha^{-1}$ on uplands (WARDA, 2006). Also, an important link in achieving food security is transportation; in these rural areas, fields nearest to the population have great value for supplying food needs and enhancing food security.

Balancing the need to bring in more land for agriculture by releasing land from other uses or natural cover are the ecological concerns about the environmental impacts of land cover such as wetland development (and the catchments that surround them) and the profound social and economic

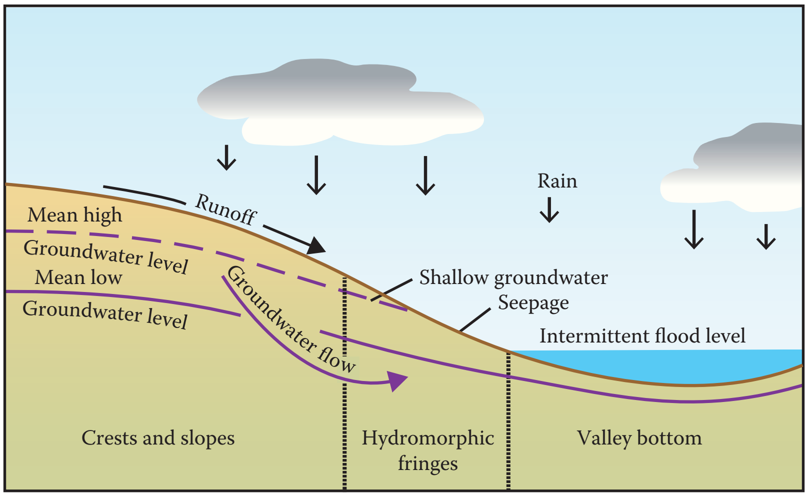



**FIGURE 9.2** Depiction of wetlands. (From WARDA, Medium Term Plan 2007–2009, Charting the Future of Rice in Africa.Africa Rice Center (WARDA), Cotonou, Republic of Benin, 2006.)

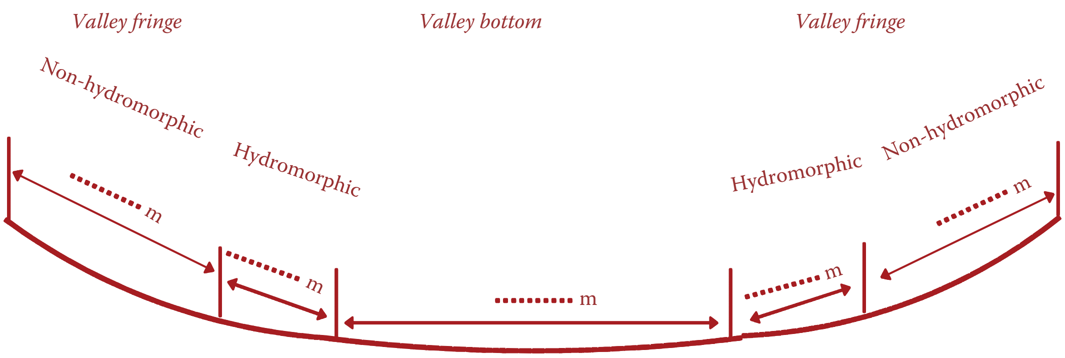



**FIGURE 9.3** Inland valley wetlands consist of valley bottoms, hydromorphic valley fringes, and non-hydromorphic valley fringes.

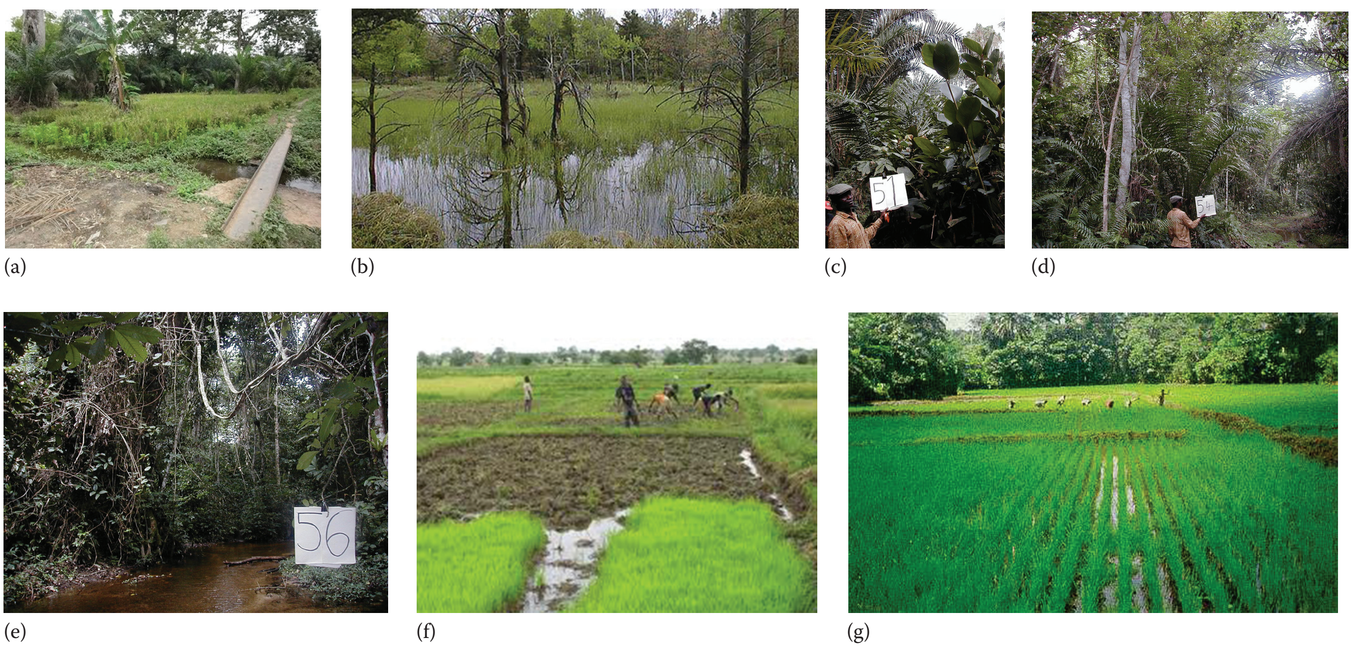



**FIGURE 9.4** Inland valley wetland illustration. The photos show valley bottoms. (From Gumma, M.K. et al., *J. Appl. Remote Sens.*, 3, 033537, 2009b.)

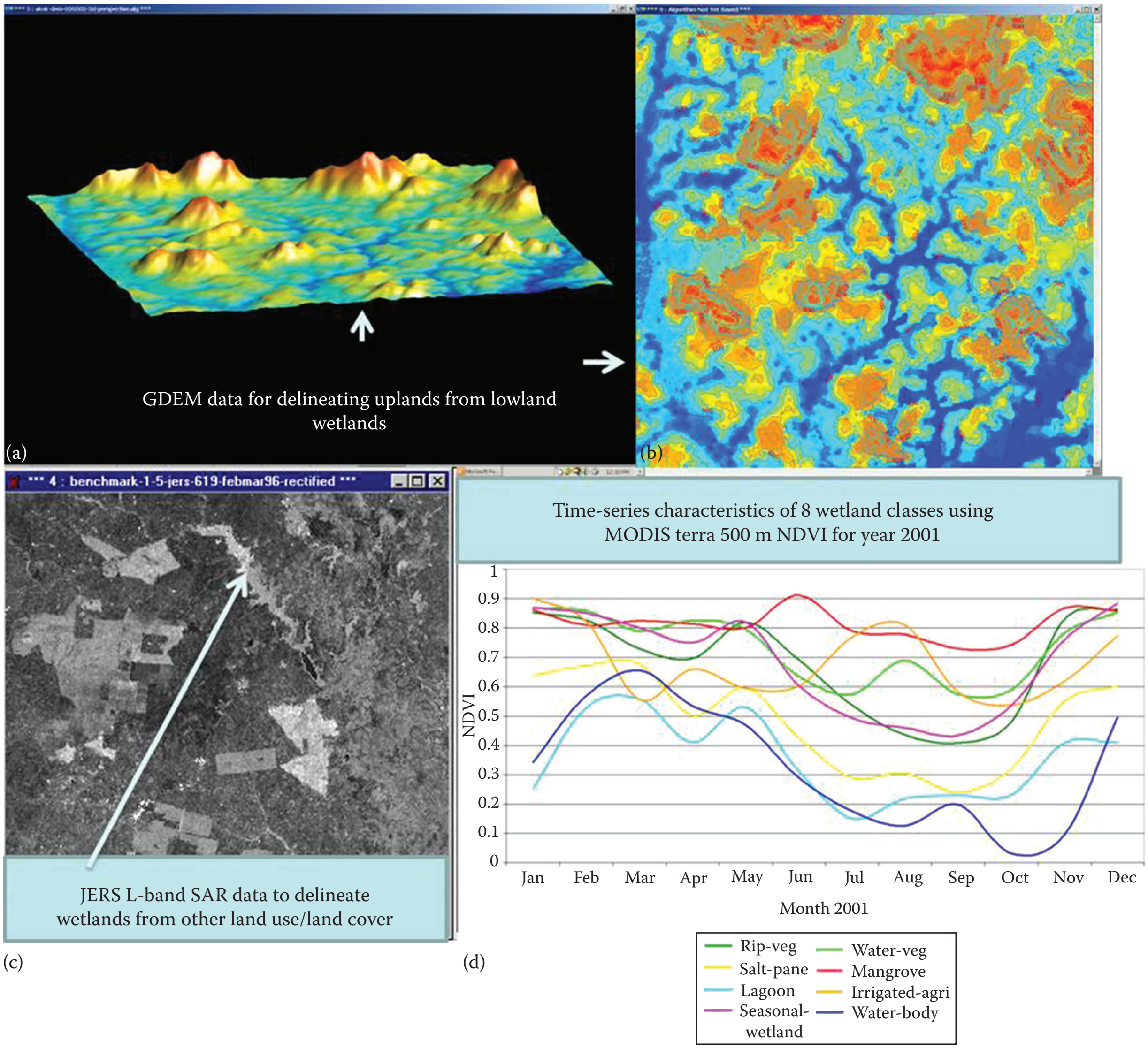



**FIGURE 9.5** Delineating uplands from lowlands using various satellite imagery: (a) IKONOS 4 m DEM data shown in 3d (top left); (b) IKONOS 4 m DEM (top right); (c) JRTS SAR data (bottom left); and (d) MODIS temporal NDVI signatures of wetland classes. Inland valleys (IV) are seen in blue color in top two images. In the bottom left (JERS SAR), very high backscatter are areas of oil palm plantations. High backscatter (see arrow pointer) shows IV wetlands.

repercussions for people dependent on their natural resources and ecosystem functions. IV wetlands play an important role in bio-geochemical cycling, flood control, and recharging of aquifers. They are considered to be one of the richest and most productive biomes, serving as cradles of biological diversity that support unique flora and fauna (RAMSAR, 2004). They serve as potential sites for breeding waterfowl and significant carbon sinks in soils and plants (Lal et al., 2002; Mitsch and Gosselink, 2007).

Clearly, it is essential to incorporate wetlands explicitly within a natural resource management framework. There is the need to not only develop technologies that are adapted to farmers' economic needs to facilitate Africa's much awaited Green Revolution and supporting its Blue Revolution, but also sustain the integrity of the globally valuable WCA ecosystems. At present, the basis for making decisions relating to wetland utilization is weak (Gliessman, 2007). Given the fact that the characteristics of wetlands are known to vary dramatically within and across agroecosystems (Andriesse et al., 1994), it is important to map, characterize, and model different wetland systems (Gumma et al., 2009a, 2011b). This will provide impetus and enable the development of appropriate technologies for maximizing food production along with transportation (food security) with minimum ecological and environmental disturbance. A pre-requisite for sustainable management of IV wetlands is greater understanding of the

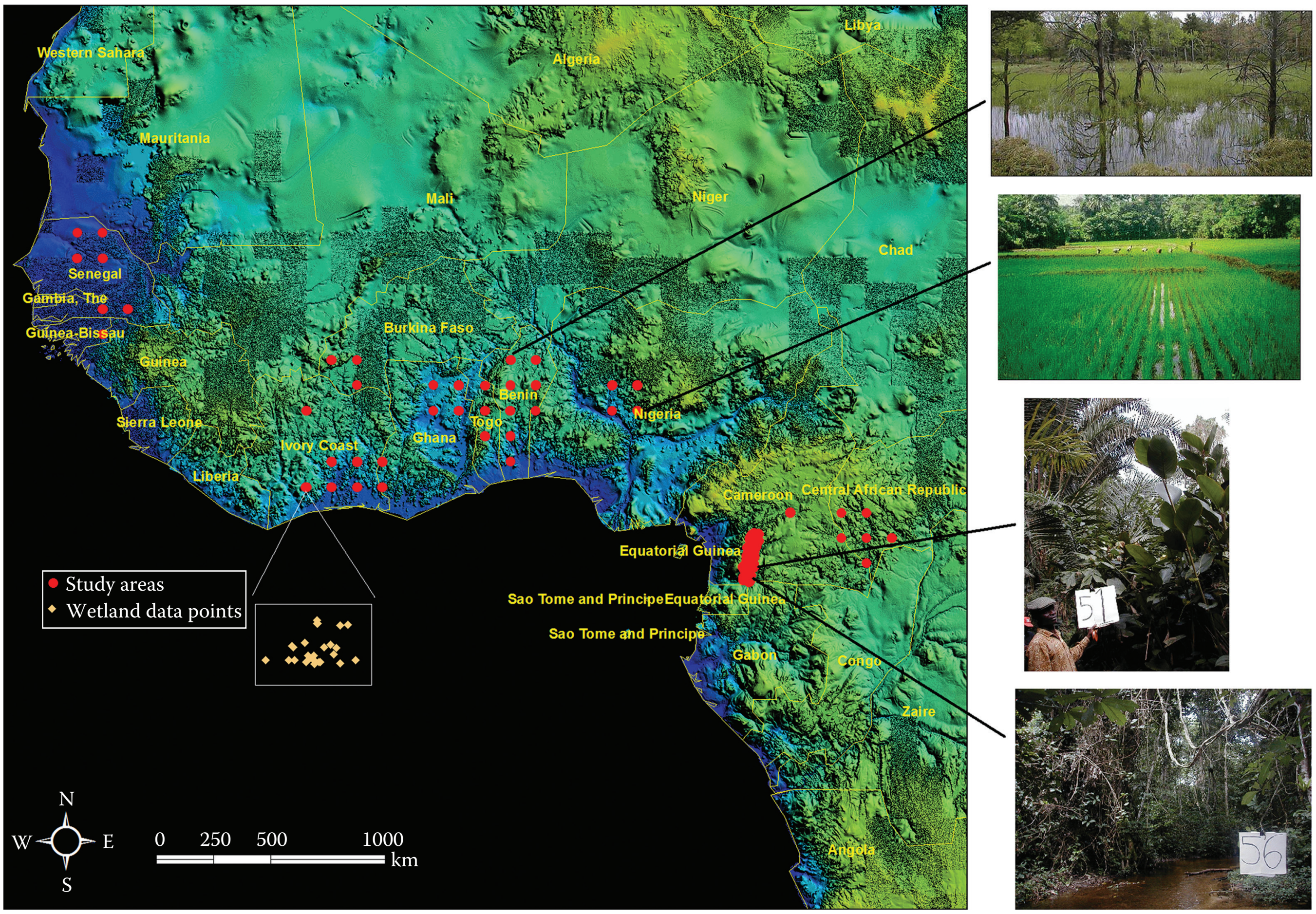



**FIGURE 9.6** Inland valley wetland study areas across West and Central Africa (WCA). *Note:* background image is GTOPO30 1 km DEM data. Red dots are study areas. Sand color shows ground data points. Photos on right show typical IV wetlands.

interaction between climate, soil, topography, water, biophysical, health, and socioeconomic factors that influence both wetland utilization and the impacts that result including societal benefits.

Given the discussion, the three key action research goals presented in this chapter are:

*First*, identify, delineate, map, classify, and characterize wetlands of the entire WCA region using data fusion involving satellite multisensor data (e.g., Landsat ETM+, JERS SAR, ALOS PALSAR, MODIS, IKONOS/Quickbird; see Tables 9.1 and 9.2), secondary data (SRTM, FAO soils, precipitation), and in situ data (e.g., Fujii et al., 2010). IV wetlands are too small to appear on most maps and therefore the wetland surveys of the world have been mostly localized (Gilmore et al., 2008; Wdowinski et al., 2008) and limit themselves to large flood plains, swamps, and water bodies with or without irrigated areas. However, recent studies (Thenkabail and Nolte, 2000; Lan and Zhang, 2006; Becker et al., 2007; Islam et al., 2008) have identified the potential of satellite remote sensing data and techniques for mapping different types of wetlands. None, however, has done so over very large areas such as nations, continents, and the world. Thereby, we propose to use multi-data fusion to best identify, map, classify, and characterize IV wetlands at high resolution (nominal 30 m) over entire WCA rapidly and accurately using automated and semiautomated methods.

*Second*, develop a decision support system (DSS) through spatial modeling to perform land suitability analysis in order to determine which of the IV wetland areas are best suited for: (1) agricultural development or (2) preservation. The goal is to balance food security-economic development with environmental conservation. Since the need is to maximize crop yields sustainably with minimal ecological and environmental impacts for the IV wetland ecosystems, we need to take into consideration climatic, soil, topographic, water, biophysical,

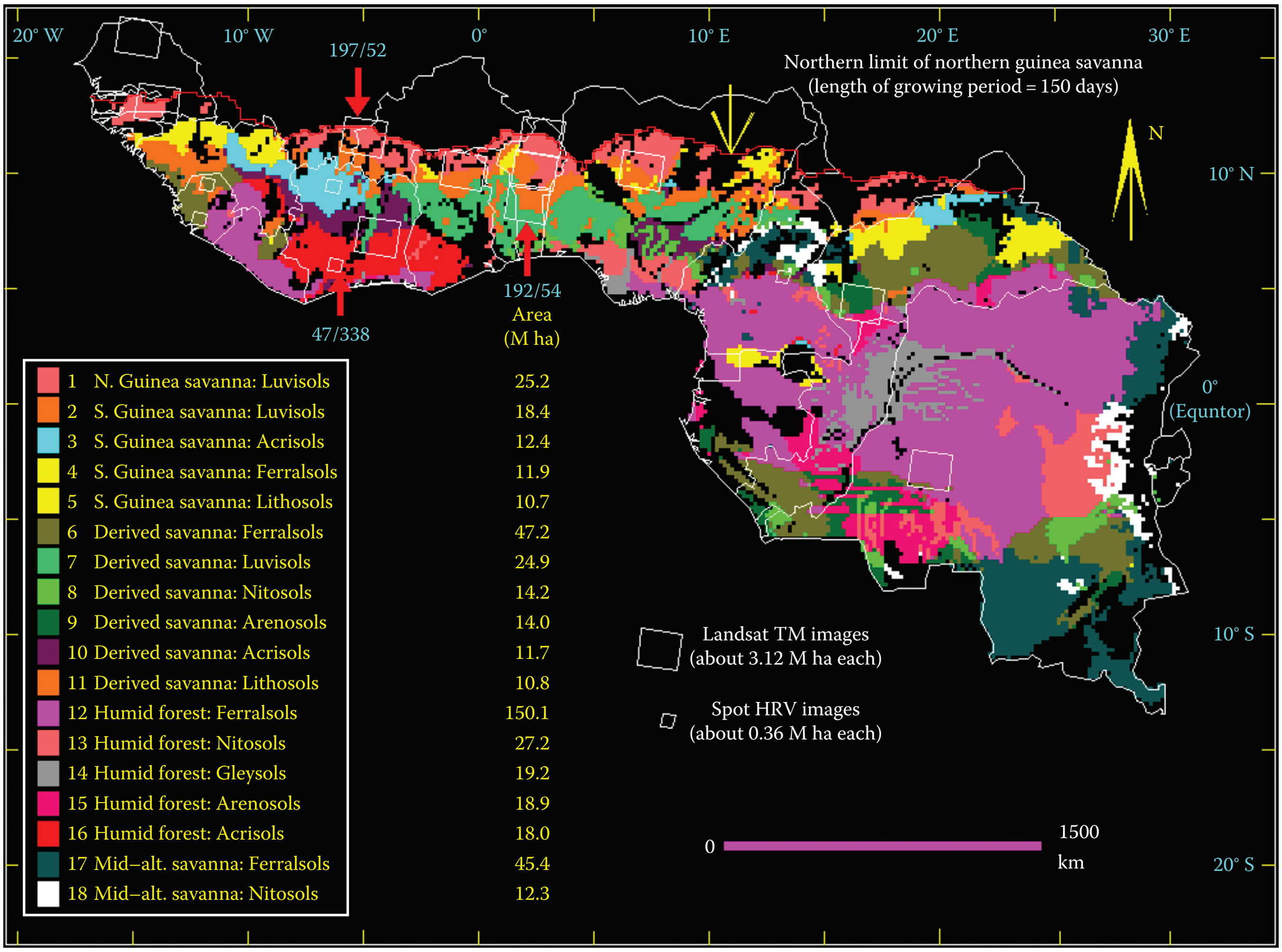
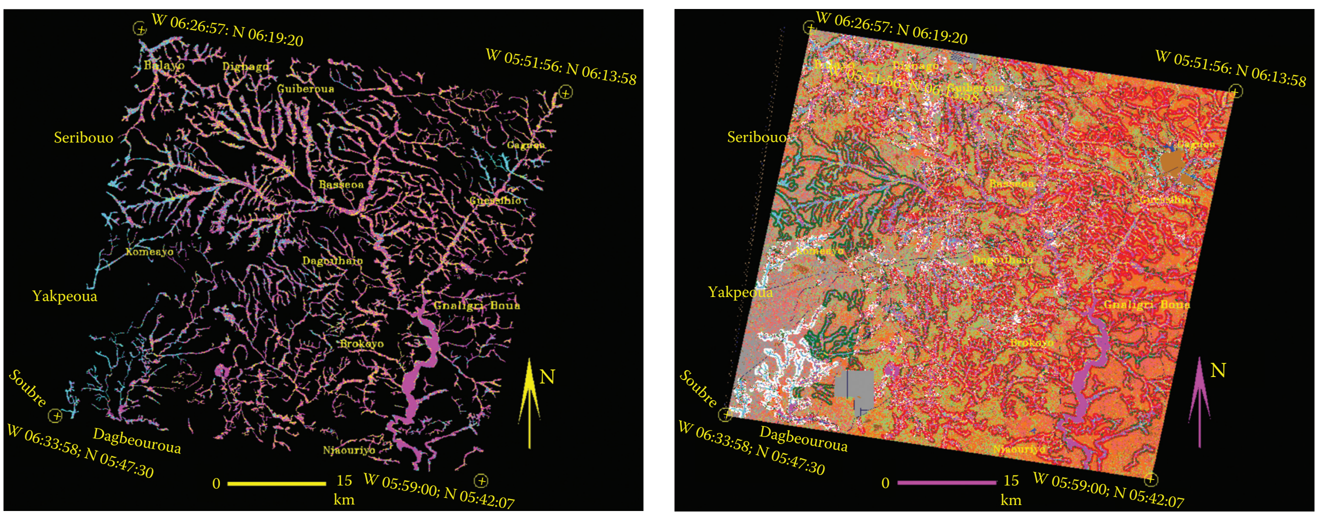


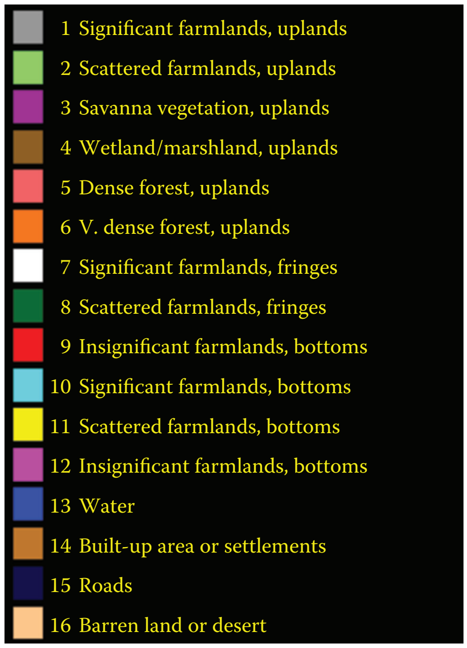

**FIGURE 9.7** Agroecological and soil zones of WCA. The datasets used in producing this map are shown in Table 9.3 and consist of International Institute of Tropical Agriculture's (IITA) agroecological zones defined by the length of growing period (LGP), and FAO soils.



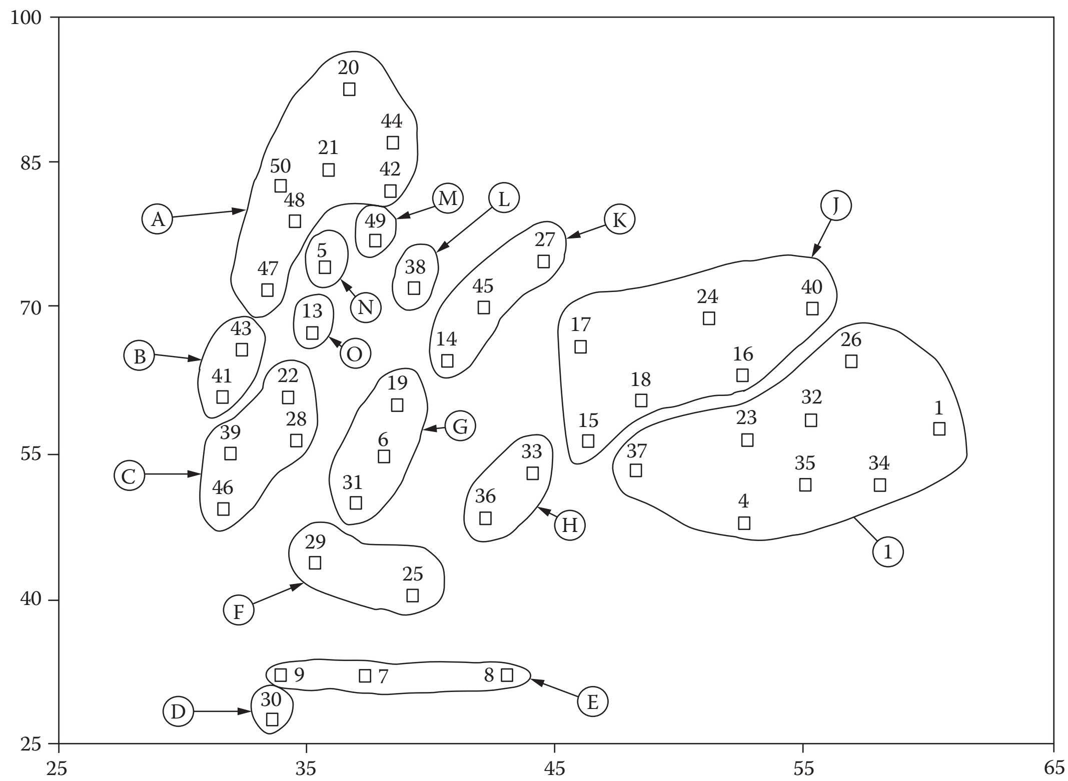

(a) (b)

**FIGURE 9.8** (a) Delineated inland valley wetlands using SPOT HRV data based on semi-automated methods (see Section 9.6.3) described in this chapter.

*(Continued)*




(c)




(d)

**FIGURE 9.8 (*Continued*)** (b) Land-use/land-cover classification of inland valley wetlands in Gaganoa, Côte d'Voire, using SPOT HRV images and semiautomated methods. (c) Land-use/land-cover class legend for (a). (d) Land-use/land-cover classes depicted in (a) and (b).

**TABLE 9.1** Wetland Delineation, Mapping, and Characterization Using Sensor Data Fusion

| Sensor | Spatial (Meters) | Spectral (#) | Radiometric (Bit) | Band Range (μm) | Band Widths (μm) | Irradiance ($W\ m^{-2}\ sr^{-1}\ \mu m^{-1}$) | Data Points (# per Hectares) | Frequency of Revisit (Days) Data Period |
|---|---|---|---|---|---|---|---|---|
| *A. Moderate resolution* | | | | | | | | |
| 1. MODIS terra/aqua | 250, 500 | 2/7 | 12 | 0.62–0.67 | 0.05 | 1528.2 | 0.16, 0.04 | 8-day reflectance |
| | | | | 0.84–0.876 | 0.036 | 974.3 | 0.16, 0.04 | 2000–present |
| | | | | 0.459–0.479 | 0.02 | 2053 | | (wall to wall—Figure 9.1) |
| | | | | 0.545–0.565 | 0.02 | 1719.8 | | |
| | | | | 1.23–1.25 | 0.02 | 447.4 | | |
| | | | | 1.63–1.65 | 0.02 | 227.4 | | |
| | | | | 2.11–2.16 | 0.05 | 86.7 | | |
| *B. High resolution on optical* | | | | | | | | |
| 2. Landsat-TM/ETM+ | 30 | 7 | 8 | 0.45–0.52 | 0.07 | 1970 | 11.1 | 16 |
| | | | | 0.52–0.60 | 0.80 | 1843 | | GLS2005 |
| | | | | 0.63–0.69 | 0.60 | 1555 | | (wall to wall—Figure 9.1) |
| | | | | 0.76–0.90 | 0.14 | 1047 | | |
| | | | | 1.55–1.74 | 0.19 | 227.1 | | |
| | | | | 10.4–12.5 | 2.10 | 0 | | |
| | | | | 2.08–2.35 | 0.25 | 80.53 | | |
| *C. Radar* | | | | | | | | |
| 3a. JERS/SAR | 100, 500 | L band | 8 | 23.5 cm | L band | — | 1, 0.04 | Consolidated 1996 |
| | | | | | | | | Two periods |
| and/or | | | | | | | | (Wall to wall—Figure 9.1) |
| 3b. ALOS PALSAR | 9–157 | L band | 8 | 23.5 cm | 14–28 MHz | — | 123, 0.4 | 2006–present |
| | | | | | | | | For benchmark areas |
| | | | | | | | | (See Figure 9.2) |
| *D. Very high resolution optical* | | | | | | | | |
| 4a. IKONOS | 1–4 | 4 | 11 | 0.445–0.516 | 0.71 | 1930.9 | 10,000, 625 | 5 |
| | | | | 0.506–0.595 | 0.89 | 1854.8 | | For benchmark areas |
| | | | | 0.632–0.698 | 0.66 | 1156.5 | | (See Figure 9.2) |
| and/or | | | | 0.757–0.853 | 0.96 | 1156.9 | | |
| 4b. QUICKBIRD | 0.61–2.44 | 4 | 11 | 0.45–0.52 | 0.07 | 1381.79 | 14,872, 625 | 5 |
| | | | | 0.52–0.60 | 0.08 | 1924.59 | | For benchmark areas |
| | | | | 0.63–0.69 | 0.06 | 1843.08 | | (See Figure 9.2) |
| | | | | 0.76–0.89 | 0.13 | 1574.77 | | |

Characteristics of data to be used in the study are listed.

health, and socioeconomic factors and potential societal benefits from the IV wetland ecosystem and use them in decision support systems. Stakeholders (e.g., Coalition for African Rice Development CARD/Alliance for a Green Revolution in Africa [AGRA] network, Consultative Group on International Agricultural Research [CGIAR] network, International Institute for Tropical Agriculture [IITA]) will be involved in assigning weights to various spatial data layers used in the models of the DSS and hence will represent the collective knowledge of experts.

*Third*, provide access to data and products through USGS/NASA as well as stakeholder (e.g., CARD/AGRA network, CGIAR Consortium of Spatial Information [CSI] network, IITA) through public domain web/data portals. This will help stakeholders to provide farmers and policy makers with sound science-based information that enables them to identify the best sites that could be developed to promote sustainable farming systems. The products will include (1) IV wetland maps, (2) wetland characteristics (e.g., phenology, land cover), (3) DSS, and (4) model outputs showing IV wetlands that are most suitable for (1) development as agricultural land and (2) conservation of biological diversity (outputs of goal 2).

**TABLE 9.2** Satellite Sensor Data That Can Potentially Used in Wetland Studies

| Sensor | Spatial (Meters) | Spectral (#) | Radiometric (Bit) | Band Range (μm) | Band Widths (μm) | Irradiance (W $m^{-2}$ $sr^{-1}$ $\mu m^{-1}$) | Data Points (# per Hectares) | Frequency of Revisit (Days) |
|---|---|---|---|---|---|---|---|---|
| *A. Coarse resolution sensors* | | | | | | | | |
| 1. AVHRR | 1000 | 4 | 11 | 0.58–0.68 | 0.10 | 1390 | 0.01 | Daily |
| | | | | 0.725–1.1 | 0.375 | 1410 | | |
| | | | | 3.55–3.93 | 0.38 | 1510 | | |
| | | | | 10.30–10.95 | 0.65 | 0 | | |
| | | | | 10.95–11.65 | 0.7 | 0 | | |
| 2. MODIS | 250, 500, 1000 | 36/7 | 12 | 0.62–0.67 | 0.05 | 1528.2 | 0.16, 0.04, 0.01 | Daily |
| | | | | 0.84–0.876 | 0.036 | 974.3 | 0.16, 0.04, 0.01 | |
| | | | | 0.459–0.479 | 0.02 | 2053 | | |
| | | | | 0.545–0.565 | 0.02 | 1719.8 | | |
| | | | | 1.23–1.25 | 0.02 | 447.4 | | |
| | | | | 1.63–1.65 | 0.02 | 227.4 | | |
| | | | | 2.11–2.16 | 0.05 | 86.7 | | |
| *B. Multi spectral sensors* | | | | | | | | |
| 3. Landsat-1, 2, 3 MSS | 56 × 79 | 4 | 6 | 0.5–0.6 | 0.1 | 1970 | 2.26 | 16 |
| | | | | 0.6–0.7 | 0.1 | 1843 | | |
| | | | | 0.7–0.8 | 0.1 | 1555 | | |
| | | | | 0.8–1.1 | 0.3 | 1047 | | |
| 4. Landsat-4, 5 TM | 30 | 7 | 8 | 0.45–0.52 | 0.07 | 1970 | 11.1 | 16 |
| | | | | 0.52–0.60 | 0.80 | 1843 | | |
| | | | | 0.63–0.69 | 0.60 | 1555 | | |
| | | | | 0.76–0.90 | 0.14 | 1047 | | |
| | | | | 1.55–1.74 | 0.19 | 227.1 | | |
| | | | | 10.4–12.5 | 2.10 | 0 | | |
| | | | | 2.08–2.35 | 0.25 | 80.53 | | |
| 5. Landsat-7 ETM+ | 30 | 8 | 8 | 0.45–0.52 | 0.65 | 1970 | 44.4, 11.1 | 16 |
| | | | | 0.52–0.60 | 0.80 | 1843 | | |
| | | | | 0.63–0.69 | 0.60 | 1555 | | |
| | | | | 0.50–0.75 | 0.150 | 1047 | | |
| | | | | 0.75–0.90 | 0.200 | 227.1 | | |
| | | | | 10.0–12.5 | 2.5 | 0 | | |
| | | | | 1.75–1.55 | 0.2 | 1368 | | |
| | | | | 0.52–0.90(p) | 0.38 | 1352.71 | | |
| 5b. Landsat-8 | 30 | 11 | 8 | 0.433–0.453 | 0.02 | 1970 | 44.4, 11.1 | 16 |
| | | | | 0.45–0.515 | 0.065 | 1843 | | |
| | | | | 0.53–0.60 | 0.07 | 1555 | | |
| | | | | 0.63–0.68 | 0.05 | 1047 | | |
| | | | | 0.845–0.885 | 0.04 | 227.1 | | |
| | | | | 1.56–1.66 | 0.1 | 0 | | |
| | | | | 2.10–2.30 | 0.2 | 1368 | | |
| | | | | 0.50–0.68 | 0.18 | 1352.71 | | |
| | | | | 1.360–1.390 | 0.03 | 1368 | | |
| | | | | 10.6–11.2 | 0.6 | 1352.71 | | |
| | | | | 11.5–12.5 | 1.0 | 1368 | | |
| 6. ASTER | 15, 30, 90 | 15 | 8 | 0.52–0.63 | 0.11 | 1846.9 | 44.4, 11.1, 1.23 | 16 |
| | | | | 0.63–0.69 | 0.06 | 1546.0 | | |

(*Continued*)

**TABLE 9.2 (*Continued*)** Satellite Sensor Data That Can Potentially Used in Wetland Studies

| Sensor | Spatial (Meters) | Spectral (#) | Radiometric (Bit) | Band Range (μm) | Band Widths (μm) | Irradiance (W m$^{-2}$ sr$^{-1}$ μm$^{-1}$) | Data Points (# per Hectares) | Frequency of Revisit (Days) |
|---|---|---|---|---|---|---|---|---|
| | | | | 0.76–0.86 | 0.1 | 1117.6 | | |
| | | | | 0.76–0.86 | 0.1 | 1117.6 | | |
| | | | | 1.60–1.70 | 0.1 | 232.5 | | |
| | | | | 2.145–2.185 | 0.04 | 80.32 | | |
| | | | | 2.185–2.225 | 0.04 | 74.96 | | |
| | | | | 2.235–2.285 | 0.05 | 69.20 | | |
| | | | | 2.295–2.365 | 0.07 | 59.82 | | |
| | | | | 2.360–2.430 | 0.07 | 57.32 | | |
| | | | 12 | 8.125–8.475 | 0.35 | 0 | | |
| | | | | 8.475–8.825 | 0.35 | 0 | | |
| | | | | 8.925–9.275 | 0.35 | 0 | | |
| | | | | 10.25–10.95 | 0.7 | 0 | | |
| | | | | 10.95–11.65 | 0.7 | 0 | | |
| 7. ALI | 30 | 10 | 12 | 0.048–0.69(p) | 0.64 | 1747.8600 | | |
| | | | | 0.433–0.453 | 0.20 | 1849.5 | 11.1 | 16 |
| | | | | 0.450–0.515 | 0.65 | 1985.0714 | | |
| | | | | 0.425–0.605 | 0.80 | 1732.1765 | | |
| | | | | 0.633–0.690 | 0.57 | 1485.2308 | | |
| | | | | 0.775–0.805 | 0.30 | 1134.2857 | | |
| | | | | 0.845–0.890 | 0.45 | 948.36364 | | |
| | | | | 1.200–1.300 | 1.00 | 439.61905 | | |
| | | | | 1.550–1.750 | 2.00 | 223.39024 | | |
| | | | | 2.080–2.350 | 2.70 | 78.072727 | | |
| 8. SPOT-1 | 2.5–20 | 15 | 16 | 0.50–0.59 | 0.09 | 1858 | 1,600, 25 | 3–5 |
| SPOT-2 | | | | 0.61–0.68 | 0.07 | 1575 | | |
| SPOT-3 | | | | 0.79–0.89 | 0.1 | 1047 | | |
| SPOT-4 | | | | 1.5–1.75 | 0.25 | 234 | | |
| | | | | 0.51–0.73(p) | 0.22 | 1773 | | |
| 9. IRS-1C | 23.5 | 15 | 8 | 0.52–0.59 | 0.07 | 1851.1 | 18.1 | 16 |
| | | | | 0.62–0.68 | 0.06 | 1583.8 | | |
| | | | | 0.77–0.86 | 0.09 | 1102.5 | | |
| | | | | 1.55–1.70 | 0.15 | 240.4 | | |
| | | | | 0.5–0.75(p) | 0.25 | 1627.1 | | |
| 10. IRS-1 | 23.5 | 15 | 8 | 0.52–0.59 | 0.07 | 1852.1 | 18.1 | 16 |
| | | | | 0.62–0.68 | 0.06 | 1577.38 | | |
| | | | | 0.77–0.86 | 0.09 | 1096.7 | | |
| | | | | 1.55–1.70 | 0.15 | 240.4 | | |
| | | | | 0.5–0.75(p) | 0.25 | 1603.9 | | |
| 11. IRS-P6-AWiFS | 56 | 4 | 10 | 0.52–0.59 | 0.07 | 1857.7 | 3.19 | 16 |
| | | | | 0.62–0.68 | 0.06 | 1556.4 | | |
| | | | | 0.77–0.86 | 0.09 | 1082.4 | | |
| | | | | 1.55–1.70 | 0.15 | 239.84 | | |
| 12. CBERS-2 | 20 m pan | | 11 | 0.51–0.73 | 0.22 | 1934.03 | 25, 25 | |
| CBERS-3B | 20 m MS | | | 0.45–0.52 | 0.07 | 1787.10 | | |
| CBERS-3 | 5 m pan | | | 0.52–0.59 | 0.07 | 1587.97 | 400, 25 | |
| CBERS-4 | 20 m MS | | | 0.63–0.69 | 0.06 | 1069.21 | | |
| | | | | 0.77–0.89 | 0.12 | 1664.3 | | |

(*Continued*)

**TABLE 9.2 (*Continued*)** Satellite Sensor Data That Can Potentially Used in Wetland Studies

| Sensor | Spatial (Meters) | Spectral (#) | Radiometric (Bit) | Band Range (μm) | Band Widths (μm) | Irradiance (W $m^{-2}$ $sr^{-1}$ $\mu m^{-1}$) | Data Points (# per Hectares) | Frequency of Revisit (Days) |
|---|---|---|---|---|---|---|---|---|
| *C. Hyper-spectral sensor* | | | | | | | | |
| 1. Hyperion | 30 | 196[a] | 16 | 196 effective calibrated bands VNIR (band 8–57) 427.55–925.85 nm SWIR (band 79–224) 932.72–2395.53 nm | 10 nm wide (approx.) for all 196 bands | See data in Neckel and Labs (1984). Plot it and obtain values for Hyperion bands | 11.1 | 16 |
| *D. Hyperspatial sensor* | | | | | | | | |
| 1. World view-2 | 0.46–1.84 | 8 | 11 | 0.4–0.45 | 0.05 | 1758.2229 | 10,000, 625 | 3.7 |
| | | | | 0.45–0.51 | 0.06 | 1974.2416 | | |
| | | | | 0.51–0.58 | 0.07 | 1856.4104 | | |
| | | | | 0.585–0.625 | 0.035 | 1738.4791 | | |
| | | | | 0.63–0.69 | 0.06 | 1559.4555 | | |
| | | | | 0.705–0.745 | 0.04 | 1342.0695 | | |
| | | | | 0.770–0.895 | 0.125 | 1069.7302 | | |
| | | | | 0.860–0.900 | 0.0.4 | 861.2866 | | |
| | | | PAN | 0.860–0.900 | 0.0.4 | 1580.814 | | |
| 2. IKONOS | 1–4 | 4 | 11 | 0.445–0.516 | 0.71 | 1930.9 | 10,000, 625 | 5 |
| | | | | 0.506–0.595 | 0.89 | 1854.8 | | |
| | | | | 0.632–0.698 | 0.66 | 1156.5 | | |
| | | | | 0.757–0.853 | 0.96 | 1156.9 | | |
| 3. QUICKBIRD | 0.61–2.44 | 4 | 11 | 0.45–0.52 | 0.07 | 1381.79 | 14,872, 625 | 5 |
| | | | | 0.52–0.60 | 0.08 | 1924.59 | | |
| | | | | 0.63–0.69 | 0.06 | 1843.08 | | |
| | | | | 0.76–0.89 | 0.13 | 1574.77 | | |
| 4. RESOURSESAT | 5.8 | 3 | 10 | 0.52–0.59 | 0.07 | 1853.6 | 33.64 | 24 |
| | | | | 0.62–0.68 | 0.06 | 1581.6 | | |
| | | | | 0.77–0.86 | 0.09 | 1114.3 | | |
| 5. RAPID EYE-A | 6.5 | 5 | 12 | 0.44–0.51 | 0.07 | 1979.33 | 236.7 | 1–2 |
| RAPID EYE-E | | | | 0.52–0.59 | 0.07 | 1752.33 | | |
| | | | | 0.63–0.68 | 0.05 | 1499.18 | | |
| | | | | 0.69–0.73 | 0.04 | 1343.67 | | |
| | | | | 0.77–0.89 | 0.12 | 1039.88 | | |
| 6. WORLDVIEW | 0.55 | 1 | 11 | 0.45–0.51 | 0.06 | 1996.77 | 40,000 | 1.7–5.9 |
| 7. FORMOSAT-2 | 2–8 | 5 | 11 | 0.45–0.52 | 0.07 | 1974.93 | 2,500, 156.25 | Daily |
| | | | | 0.52–0.60 | 0.08 | 1743.12 | | |
| | | | | 0.63–0.69 | 0.06 | 1485.23 | | |
| | | | | 0.76–0.90 | 0.14 | 1041.28 | | |
| | | | | 0.45–0.90(p) | 0.45 | 1450 | | |
| 8. KOMPSAT-2 | 1–4 | 5 | 10 | 0.5–0.9 | 0.4 | 1379.46 | 10,000, 625 | 3–28 |
| | | | | 0.45–0.52 | 0.07 | 1974.93 | | |
| | | | | 0.52–0.6 | 0.08 | 1743.12 | | |
| | | | | 0.63–0.59 | 0.04 | 1485.23 | | |
| | | | | 0.76–0.90 | 0.14 | 1041.28 | | |

*Source:* Adapted from Thenkabail, P., Lyon, G., Huete, A., Advances in hyperspectral remote sensing of vegetation and agricultural croplands. CRC Press/Taylor & Francis Group, Boca Raton, FL, 2011.

[a] Of the 242 bands, 196 are unique and calibrated. These are: (A) band 8 (427.55 nm) to band 57 (925.85 nm) that are acquired by visible and near-infrared (VNIR) sensor; and (B) band 79 (932.72 nm) to band 224 (2395.53 nm) that are acquired by short wave infrared (SWIR) sensor.

*Note:* First band is panchromatic, rest multi-spectral.

### 9.1.1 Carbon Budget of Wetlands

Wetlands, globally, contain about 771 billion tons of carbon? (20% of all the carbon on earth) (Lal et al., 2002; Pelley, 2008; Tiner, 2009). This is about the same amount of carbon as is now in the atmosphere. However, they also release methane, a greenhouse gas (Pelley, 2008) which is 22 times more potent than $CO_2$, on a per-unit-mass basis, in absorbing long-wave radiation on a 100-year time horizon (Zhuang et al., 2009). Nearly 60% of the planet's wetlands have been destroyed in the past 100 years, mostly for agriculture.

In Africa, since most wetlands are still intact, there is immense pressure to develop them to ensure African food security. Indeed, many consider wetlands as the best hope for Africa's green and blue revolution (WARDA, 2006) and a far better option for food security than the alternative of building large dams that will result in greater destruction of pristine rainforests (FAO, 2005). *Given the discussions*, WCA represents an unparalleled opportunity to guide agricultural expansion while being mindful of critical conservation goals and curtail the need for future remediation.

## 9.2 Definitions and Study Areas

### 9.2.1 Definition Used for Mapping Wetlands

Wetlands are (1) "Areas of marsh, fen, peatland or water, whether natural or artificial, permanent or temporary, with water that is static or flowing…" (RAMSAR, 2004), and (2) "…Seasonally or permanently waterlogged, including lakes, rivers, estuaries, and freshwater marshes; an area of low-lying land submerged or inundated periodically…" (USGS). In this study, we will map wetlands including irrigated agriculture, fresh water bodies, salt pans, lagoons, mangroves, riparian vegetation, permanent marshes, water bodies with or without aquatic plants, and seasonal wetlands. However, we will clearly demarcate IV wetlands that occur overwhelmingly on first- to fourth-order streams and roughly constitute about 80% of all wetlands in WCA (Andriesse et al., 1994). Hydromorphism is considered as a permanent or temporary state of water saturation in the soil associated with conditions of reduction (Figure 9.3). This condition is created easily in the soil each time the water stagnates in it and is not renewed. This is, for instance, the case in clayey soils with a slow internal drainage (Aguilar et al., 2003).

## 9.3 Remote Sensing Data for IV Wetland Characterization

The availability of multiple sensors at different resolution spatially and temporally and access to the scientific community being very easy, it is now the scientists who are exploiting such data for multiple applications. The critical ecosystems services and agroeconomic services provided by the wetlands makes them more important and crucial for conservation and restoration. In this context, the identification and characterization of IV wetlands becomes a priority to sustain food production to the growing population where cultivable land is becoming scarce and water use is competed by many sectors of the society. Thenkabail and Nolte (1995a,b, 1996) and Thenkabail et al. (2000b) have used different sensors and also new techniques to map and characterize IV ecosystems in West Africa. Gumma et al. (2009) have modeled different layers of information derived from satellite imagery to identify suitable areas for cultivation of rice in the IV wetlands of Ghana. The use of remotely sensed data for such ecosystems also depends on the bio-physical characteristics of the IV wetlands, like the extent of the ecosystem. Morphometric characteristics of the river basin such as drainage network, drainage density, which in turn is dictated by the lithology and soils are also as important in the selection of remotely sensed imagery. Spatial resolution plays an important role in the IV wetland mapping, characterization, and modeling. The level of LULC classification that can be extracted is also dictated by the spatial resolution of the sensor. Especially, spatial resolution of elevation in the form of a DEM will dictate the extraction of stream order in different-sized IV wetlands. Even though water absorption bands like MIR and FIR are also useful to map such wetlands, specific sensors (Rebelo et al., 2009) have been designed to detect wetland areas like the ASTER (VNIR, SWIR and TIR subsystems).

## 9.4 Study Area and Ecoregional Approach

The 24 WCA nations are a perfect site for IV wetlands mapping and studied at nominal resolution of 30 m for the entire area (Figure 9.7, Table 9.3). The results are reported on an eco-regional basis across the WCA using the climate-length of growing period (LGP) method, FAO/UNESCO soils, and elevation (Figure 9.7). The 18 large ecoregions of 10 million ha or more (Figure 9.7) cover >90% of WCA's geographic area and are identified and mapped based on the definitions provided in Section 9.2 and Figure 9.4. Then, IV wetlands are categorized and characterized using time-series MODIS Terra/Aqua data (Figure 9.5), other temporal and spatial measures, including texture derivatives from very high resolution imagery (e.g., IKONOS, Quickbird, GeoEye; available to us from USGS sources—see data plan), along with other environmental variables derived from topography, soils, and other existing datasets. Information on habitat mapping of the species of flora and fauna that are identified for conservation is also generated. Finally, spatial models are developed to determine IV wetlands most suited for cultivation and conservation. For example, IV wetlands that form an isolated patch may be best to preserve, especially if they are part of a wildlife migration corridor, whereas wetlands near a population center, close to transportation, and with less-developed overstory vegetation may be best to cultivate.

**TABLE 9.3** Parameters Describing the Level I Agroecological and Soil Zones

| Level IAESZ[a] | Agroecological Zone According to IITA's Definition | LGP[b] (Days) | Major FAO Soil Grouping[c] | Area[d] (Million ha) |
|---|---|---|---|---|
| 1 | Northern Guinea savanna | 151–180 | Luvisols | 25.2 |
| 2 | Southern Guinea savanna | 181–210 | Luvisols | 18.4 |
| 3 | Southern Guinea savanna | 181–210 | Acrisols | 12.4 |
| 4 | Southern Guinea savanna | 181–210 | Ferralsols | 11.9 |
| 5 | Southern Guinea savanna | 181–210 | Lithosols | 10.7 |
| 6 | Derived savanna | 211–270 | Ferralsols | 47.2 |
| 7 | Derived savanna | 211–270 | Luvisols | 24.9 |
| 8 | Derived savanna | 211–270 | Nitosols | 14.2 |
| 9 | Derived savanna | 211–270 | Arenosols | 14.0 |
| 10 | Derived savanna | 211–270 | Acrisols | 11.7 |
| 11 | Derived savanna | 211–270 | Lithosols | 10.8 |
| 12 | Humid forest | >270 | Ferralsols | 150.1 |
| 13 | Humid forest | >270 | Nitosols | 27.2 |
| 14 | Humid forest | >270 | Gleysols | 19.2 |
| 15 | Humid forest | >270 | Arenosols | 18.9 |
| 16 | Humid forest | >270 | Acrisols | 18.0 |
| 17 | Midaltitudesavanna[e] | | Ferralsols | 45.4 |
| 18 | Midaltitudesavanna[f] | | Nitosols | 12.3 |

[a] AESZ, level I agroecological and soil zones.
[b] LGP, length of growing period.
[c] Names refer to the soil classification scheme of FAO/UNESCO (1974).
[d] The area figures are for West and Central Africa and were determined using the "AREA" procedure of IDRISI (Eastman, 1992).
[e] Area distribution of LGP in AEZ 17 is: 151–180 days 11%, 181–210 days 9%, 211–270 days 59%, >270 days 21%.
[f] Area distribution of LGP in AEZ 18 is: 151–180 days 2%, 181–210 days 5%, 211–270 days 53%, >270 days 40%.

## 9.5 Field Plot Data

We adopted multiple strategies to collect field plot data. *First*, we used a large and rich collection (1023 points) of field plot data on I) wetlands spread across WCA (see distribution and source of these points in Figure 9.6). For each point, we have data on (1) type of wetlands (e.g., hydromorphic, nonhydromorphic), (2) wetland order (e.g., first, second), (3) wetland bottom width, (4) land-use type (e.g., natural or cultivated), (5) moisture level, (6) land-cover percentages (e.g., trees, shrubs, grasses, water body, cultivated), and (7) digital photos. *Second*, through collaboration with CARD/AGRA, CGIAR/CSI, and other African networks of national and international institutes that are actively involved in Africa's wetland issues. These data will be collected during the year 1 project workshop in Africa (jointly hosted with CARD/AGRA, CGIAR/CSI). These data will include IV wetland point data as well as spatial data on socioeconomics and numerous other datasets (e.g., Figure 9.6). *Third*, we will source data from our previous projects in West Africa (Gumma et al., 2009a; Fujii et al., 2010; Krishna et al., 2010). *Fourth*, very high resolution data (e.g., quickbird, IKONOS) are used as "groundtruth."

## 9.6 Methods of Rapid and Accurate IV Wetland Mapping of WCA

### 9.6.1 Existing Methods of Wetland Mapping

There are several studies that discuss methods of wetland mapping using remote sensing (Lyon and McCarthy, 1995; Lunetta and Balogh, 1999; Thenkabail et al., 2000a; Harvey and Hill, 2001; Lyon, 2001; Ozesmi and Bauer, 2002; Hirano et al., 2003; May et al., 2003; Töyrä and Pietroniro, 2005; Wagner et al., 2007; Wright and Gallant, 2007; Gumma et al., 2009; Jones et al., 2009). High levels of accuracy in delineating and mapping wetlands are feasible when multidate, multisensor, very high spatial resolution imagery are used (e.g., Lan and Zhang, 2006; Becker et al., 2007; Gilmore et al., 2008). Ramsey et al.

**TABLE 9.4** Automated Methods to Separate Wetlands, including Inland Valley Wetlands, from Non-Wetlands

| Index or Parameter | Definition | Range (−1.0 to 1.0 Dimensionless or 0%–100%) | Threshold Values That Best Delineated Wetlands |
|---|---|---|---|
| a. Slope derived from SRTM DEM | This is the percentage slope derived using spatial analyst tools available in ArcGIS | 0 to 100 | <0.5% |
| b. Normalized difference vegetation index (NDVI) (Rouse et al., 1974) | $\mathrm{NDVI} = \frac{\rho_4 - \rho_3}{\rho_4 + \rho_3}$ where $\rho_3$ and $\rho_4$ 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 = ([B1] * 0.1509 + [B2] * 0.1973 + [B3] * 0.3279 + [B4] * 0.3406 + [B5] * −0.7112 + [B7] * −0.4572) Where 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 the image data. | 0 to 100 | 0 to 30 |
| d. Normalized difference water index (NDWI) (McFeeters, 1996) | $\mathrm{NDWI} = \frac{\rho_2 - \rho_4}{\rho_2 + \rho_4}$ where, $\rho_2$ and $\rho_4$ 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) | $\mathrm{MIR} = \frac{\text{Band 4}}{\text{Band 5}}$ where bands 4 and 5 are NIR and mid infrared bands of Landsat ETM+ data respectively. | 0 to 4 | >0.25 |
| f. Ratio vegetation index (RVI) (Tucker, 1979) | $\mathrm{RVI} = \frac{\text{Band 4}}{\text{Band 3}}$ where bands 4 and 3 are NIR and red bands of Landsat ETM+ data respectively | 0 to 6 | <0.6 |
| g. Green ratio (GR) (Lo, 1986) | $\mathrm{GR} = \frac{\text{Band 4}}{\text{Band 2}}$ where bands 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 infrared band 1 of Landsat ETM + data. | 0 to 47 | <1 |

(1998) found an integrated ERS SAR-optical (TM and CIR) improved the accuracy of wetland classes by up to 20%. The SAR data are sensitive to soil moisture and are quite ideal for delineating lowlands (with high moisture) and uplands (with lower moisture) (Wagner et al., 2007). Recent research (Thenkabail and Nolte, 2000; Kulawardhana et al., 2007; Islam et al., 2008; Jones et al., 2009) demonstrated the ability to attain high levels of accuracy in delineating and mapping wetlands using multiple data. These data include (Table 9.4) (1) Global Land Survey 2005 (GLS 2005) Landsat 30 m, (2) Japanese Earth Resources Satellite Synthetic Aperture Radar (JERS SAR) 100 m, (3) MODIS 250–500 m, (4) Space Shuttle Topographic Mission (SRTM) 90 m, and (5) secondary datasets (e.g., soils).

### 9.6.2 Automated Methods of Wetland Delineation and Mapping

Automated methods of wetland delineation involve (Table 9.2; Lan and Zhang, 2006; Islam et al., 2008; Jones et al., 2009): (1) algorithms to rapidly delineate wetland streams using SRTM DEM data, (2) thresholds of SRTM-derived slopes, (3) thresholds of spectral indices and wavebands, and (4) automated classification techniques. *First*, wetlands are topographical lowlands and hence the DEM data offer a significant opportunity to delineate lowlands from uplands. Automated methods involving the SRTM-derived wetland boundaries have four known limitations (Islam et al., 2008): (1) generating non-existent or spurious wetlands, (2) providing nonsmooth alignment, (3) resulting in spatial dislocation of streams, and (4) absence of stream width. *Second*, the SRTM DEM data are used to derive local slope maps in degrees using the slope function of ArcInfo Workstation GIS. A threshold (Table 9.2) of degree slope provides areas of wetlands or low lying areas and nonwetlands. *Third*, the wetlands in the images can be highlighted by enhancing images (Lyon and McCarthy, 1995; Lunetta and Balogh, 1999). The thresholds of indices and wavebands will automatically delineate wetlands from nonwetlands (Kulawardhana et al., 2007; Schowengerdt, 2007). Numerous researchers have also attempted wetland separation through automated classification techniques on various remotely sensed data (Jensen et al., 1995; Fuller et al., 2006; Lan and Zhang, 2006) without first identifying and separating wetland areas from other land units based on their location in the toposequence. However, as Ozesmi and Bauer (2002) point out, this leads to difficulties of wetland categorization because of spectral confusion (Lan and Zhang, 2006). This is because the automated classification techniques are applied on entire image areas that include wetlands and other land units that often have significantly similar spectral properties. Classification accuracies improve when multitemporal data are used along with ancillary data such as soils and topography (Ozesmi and Bauer, 2002) in GIS modeling framework (Sader et al., 1995; Lyon, 2001; Fuller et al., 2006). Automated methods are rapid, but needs to be supplemented by semiautomated methods to increase accuracies and decrease errors of omissions and commissions.

### 9.6.3 SemiAutomated Methods of IV Wetland Delineation and Mapping

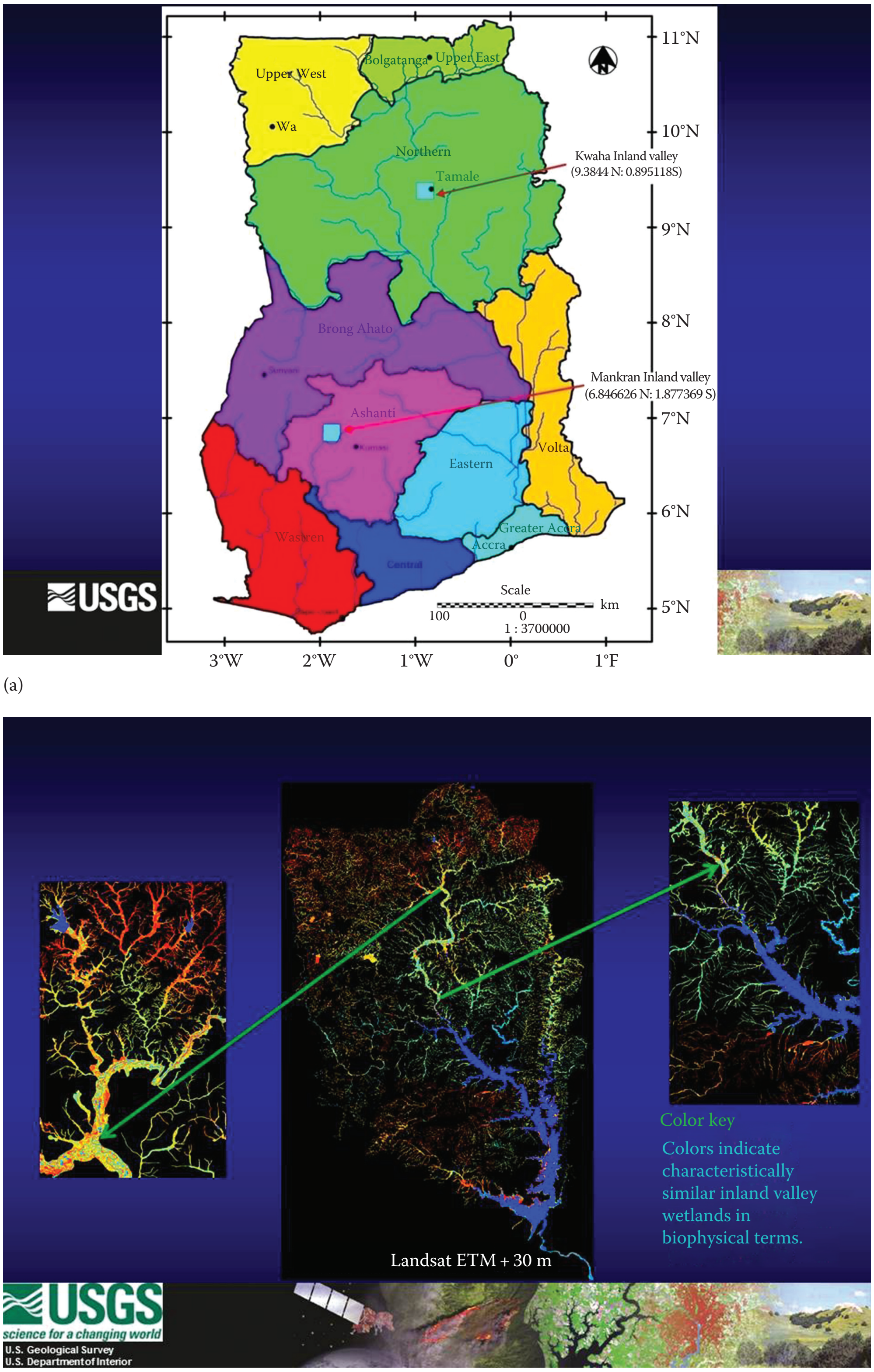
The semi-automated methods: (1) check any omissions or commissions of IV wetlands derived using automated methods, and (2) apply appropriate corrections to improve the mapping accuracies. The semi-automated methods involve (Thenkabail et al., 2000a): (1) image enhancement techniques involving ratio indices and applying simple thresholds were investigated for delineating wetlands automatically (Table 9.4; Lyon and McCarthy, 1995; Thenkabail and Nolte, 2000; Kulawardhana et al., 2007); (2) enhanced displays in red, green, blue (RGB) false color composites (FCCs) in different combinations of the ETM+ bands were also able to highlight wetland boundaries. The RGB FCCs that best highlight wetlands from other areas (Thenkabail et al., 2000a) were (a) ETM + 4/ETM + 7, ETM + 4/ETM + 3, ETM + 4/ETM + 2; (b) ETM + 4, ETM + 3, ETM + 5; (c) ETM + 7, ETM + 4, ETM + 2; and (d) ETM + 3, ETM + 2, ETM + 1; and (3) once the images are enhanced (Section 3.2.1) and displayed (Section 3.2.2), they are subjected to object-oriented image analysis using eCognition software and delineate wetlands and nonwetlands (Bock et al., 2005) and then compare the results with the IV wetland maps derived using automated methods. Studies (Kulawardhana et al., 2007; Islam et al., 2008) have established that accuracies between 88% and 97% are attainable using ETM+ and SRTM data and the automated and semiautomated methods.

## 9.7 Characterization and Classification of IV Wetlands

The IV wetland areas are highlighted using various types of remote sensing and ancillary data (e.g., Figure 9.5). Any of the images with 30 m spatial resolution or better (see Tables 9.1 and 9.2) can be used to delineate, characterize, and map IV wetlands based on methods and approaches described in Section 9.3 and its subsection (Table 9.4).

### 9.7.1 Case Studies of a Location in Côte d'Voire and Entire Ghana

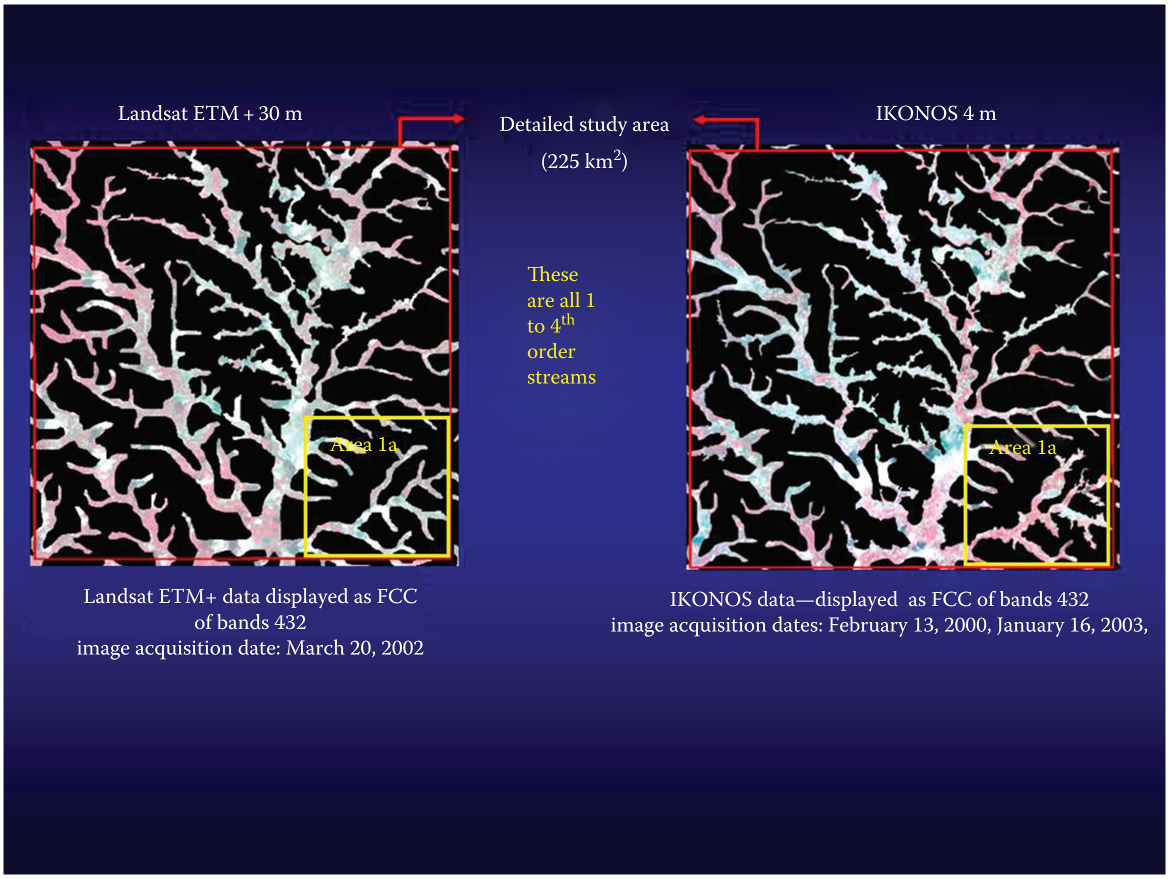
The IV wetland maps using SPOT HRV 20 m resolution image illustrated in Figure 9.8a for a location in Gagnoa, Côte d'Voire (see Figure 9.7 for the location), for the entire country of Ghana (Figure 9.9a) using Landsat ETM+ 30 m data in Figure 9.9b, and for a selected area within Ghana showing comparison between ETM+ derived versus IKONOS-derived IV wetlands (Figure 9.9c) are derived using the different methodologies explained in this chapter. These wetlands are then classified using optimized layered classification for monitoring wetland vegetation dynamics (Lan and Zhang, 2006; Wright and Gallant, 2007) using standard classification scheme such as the USGS Anderson (Table 9.5). The land-use categories derived from the imagery in this study are uplands, valley fringes, valley bottoms, and others. An equivalent level 1 class of the USGS classification systems is also compared. Since the classification systems used in this study is within the IVs and focused on agriculture as of the USGS system at different levels, it appropriately matches with the present study. It can also be seen that the toposequence followed in the classification system clearly shows the type of land-use/land-cover in the IVs. If we compare the class "significant farmland" in the uplands, it is agricultural land in the USGS system, in the valley fringes it is either agricultural land or range land due to the slope condition. Similarly in the valley bottoms, they are classified as wetlands in the USGS system, which can be potential rice cropland. A comparison to a standard classification system always helps in relating the different systems at different levels but also connects across scales. A glance at the statistics (Table 9.6) reveals the distribution of LULC in the study area. Even though the uplands occupy around 40% of the total area, the valley fringes and valley bottoms total to 58%, which can be potential rice croplands. The resulting outcome is shown for the Gagnoa, Côte d'Voire study area, in Figure 9.8b (with legend in Figure 9.8b and class bispectral plots in Figure 9.8c). Figure 9.10 shows the approach of using the tassel cap bispectral plots of the




(a)

(b)

**FIGURE 9.9** (a) Map of the Ghana. Inland valley (IV) wetlands were mapped for the entire country using Landsat ETM+ images. The Mankran and Kwaha study areas, greater details of IV wetlands, were studied using Qucikbird imagery. (b) Inland valley wetlands were delineated using Landsat ETM+ imagery based on semiautomated methods described in this chapter. Results showed that 11.4% (2,714,946 ha) of the total geographic area (23,853,300 ha) of Ghana was IV wetlands. Only 5% (130,000 ha) of IV wetlands is currently cultivated. (*Continued*)




(c)

**FIGURE 9.9 (*Continued*)** (c) Inland valley wetlands mapped for the Mankran, Kumasi, Ghana study area (225 km$^2$). The left image is derived from Landsat ETM+ 30 m and the right image using IKONOS 4 m. Total area of IV wetlands was determined as 27.72% using Landsat ETM+ and 28.50% using IKONOS.

land-use classes to define and separate various distinct classes. Table 9.7 provides the percentage land-cover types in each of the 16 land-use classes.

Other classifications, not presented here, can include rule-based wetland mapping using fused MODIS, Landsat, secondary data like GDEM (e.g., Figure 9.5), and wetland change probability mapping (Nielsen et al., 2008; Wdowinski et al., 2008). Incorporating geostatistical evaluation of fine-scale spatial structure (e.g., Wallace and Marsh, 2005) will stratify wetlands based on overall canopy characteristics. Clustering algorithms, such as canonical correlation, will be used to group the wetlands into similar types based on various suites of environmental variables and their derivatives. The goal is to quantify various characteristics of the wetlands so that they can be compared for suitability given a set of criteria. For example, if two wetlands differ in total canopy cover but are otherwise similar, it may be preferable to develop the wetland with less canopy since the cost for clearing the land would be lower. It is also to be noted that even though the canopy cover decides the type of action taken on it, the amount biological diversity in that wetland needs to be considered before any action is taken.

## 9.8 Spatial Data-Weights-Models for Identifying Areas for Agriculture versus Conservation

The goal of the spatial modeling (e.g., Figure 9.10a through c) is to pin-point IV wetland areas most suited for (1) cultivation and (2) conservation using spatial data layers (Figure 9.10a) and their relative weights (Table 9.8). For example, as a result of our extensive knowledge of the wetlands of WCA (see Fujii et al., 2010), a total of 29 *biophysical, technical, socioeconomic, and eco-environmental* factors (e.g., Table 9.8, Figure 9.10b) are considered important. In this project, weights will be assigned to these spatial data layers (e.g., Table 9.8) using expert knowledge solicited from stakeholder networks (e.g., CARD/AGRA,

**TABLE 9.5** Comparison of the Land-Use/Land-Cover Classification System Used in This Study with the USGS Classification System

| Classification System Used in This Study | | This Classification of USGS | | | |
|---|---|---|---|---|---|
| | | Level I | | Level II | |
| *Upland* | | | | | |
| 1 | Significant farmlands | 2 | Agricultural land | 21 | Cropland and pasture |
| 2 | Scattered farmlands | 2 | Agricultural land, or | | |
| | | 3 | Rangeland | | |
| 3 | Insignificant farmlands | 3 | Rangeland | 32 | Herbaceous rangeland |
| | | | | 33 | Mixed rangeland |
| 4 | Wetland/marshland | 6 | Wetland | | |
| 5 | Dense forest | 4 | Forest land | 43 | Mixed forest land |
| 6 | Very dense forest | 4 | Forest land | 42 | Evergreen forest land |
| *Valley fringe* | | | | | |
| 7 | Significant farmlands | 2 | Agricultural land, or | | |
| | | 3 | Rangeland, or | 33 | Mixed range land |
| | | 4 | Forest land | 43 | Mixed forest land |
| 8 | Scattered farmlands | 3 | Rangeland, or | 33 | Mixed rangeland |
| | | 2 | Agricultural land, or | | |
| | | 4 | Forest land | 43 | Mixed forest land |
| 9 | Insignificant farmlands | 4 | Forest land, or | 43 | Mixed forest land |
| | | 2 | Agricultural land, or | | |
| | | 3 | Rangeland | 33 | Mixed rangeland |
| *Valley bottom* | | | | | |
| 10 | Significant farmlands | 6 | Wetland | | |
| 11 | Scattered farmlands | 6 | Wetland | | |
| 12 | Insignificant farmlands | 6 | Wetland | 61 | Forested land |
| *Others* | | | | | |
| 13 | Water | 5 | Water | | |
| 14 | Built-up area/settlements | 1 | Urban or built-up land | | |
| 15 | Roads | 1 | Urban or built-up land | 14 | Transportation |
| | | | | | Communication and utilities |
| 16 | Barren land or desert land | 7 | Barren land | | |

*Source:* Anderson, J.R., *A land use and land cover classification system for use with remote sensor data* (US Government Printing Office), 1976.

CGIAR CSI, IITA).The *socioeconomic factors* will include accessibility of settlements, road networks, markets, land tenure, labor force, credit systems, extension systems, social customs, gender, rice policy tariff, rice policy subsidy, and farmer's incentives. The models used algebra (e.g., coded in ERDAS modeler; Figure 9.10b) to arrive at the outputs that determined their suitability for cultivation and/or conservation. Two sets of data and four scenarios were considered to arrive at suitable areas in the IV wetlands. A 10 variable dataset where equal weights were assigned to the layers and varying weights for classes within the layers, varying weights for layers and varying weights for classes within layers produced 2 outputs, showing relatively lower area under "suitable" class. A nine-variable dataset with similar scenarios produced higher area under "suitable" class (Figure 9.10c). For example, if two wetlands differ only in their closeness to transportation and markets, it might be preferable to develop the wetland nearest to the markets. As another example, if two wetlands are similar, but one forms an isolated patch of habitat important for migratory wildlife, that wetland may be prioritized for conservation.

## 9.9 Accuracies, Errors, and Uncertainties

Thematic accuracy of the wetland maps is assessed through an error matrix analysis and a regression analysis. A number of statistical considerations including appropriate sampling scheme, sample size, and sample unit are considered (Congalton and Green, 2008). Error matrix including overall, producers,' and users' accuracies (Congalton, 2009) are reported. The study used 1023 wetland data points already available with us (e.g., Figure 9.7), as well as data sourced through our African network partners during the project (Figure 9.10c).

**TABLE 9.6** Land-Use Distribution in the Study Area[a,b]

| | | | Full Study Area | | |
|---|---|---|---|---|---|
| No. | Land-Use Category | Color | Area (ha) | Study Area (Percent of Total) | Mean NDVI |
| | *Uplands* | | 157,601 | 40.1 | |
| 1 | Significant farmlands | Gray | 22,589 | 5.8 | 0.29 |
| 2 | Scattered farmlands | Seafoam | 31,992 | 8.1 | 0.34 |
| 3 | Savanna vegetation[c] | Violet | 0 | 0 | — |
| 4 | Wetlands/marshland | Mocha | 7,024 | 1.8 | 0.25 |
| 5 | Dense vegetation | Rose | 54,619 | 13.9 | 0.34 |
| 6 | Very dense vegetation | Red-orange | 41,377 | 10.5 | 0.39 |
| | *Valley fringes* | | 158,606 | 40.3 | |
| 7 | Significant farmlands | White | 26,299 | 6.7 | 0.31 |
| 8 | Scattered farmlands | Pine-green | 39,376 | 10.0 | 0.32 |
| 9 | Insignificant farmlands[d] | Red | 92,931 | 23.6 | 0.38 |
| | *Valley bottom* | | 70,638 | 18.0 | |
| 10 | Significant farmlands | Cyan | 11,490 | 2.9 | 0.29 |
| 11 | Scattered farmlands | Yellow | 19,058 | 4.9 | 0.33 |
| 12 | Insignificant farmlands[e] | Magenta | 40,090 | 10.2 | 0.35 |
| | *Others* | | 6,268 | 1.6 | |
| 13 | Water | Blue | 358 | 0.1 | −0.07 |
| 14 | Built-up area/settlements | Tan | 2,703 | 0.7 | 0.11 |
| 15 | Roads | Navy | 2,194 | 0.5 | 0.09 |
| 16 | Barren land or desert lands | Sand | 1,013 | 0.3 | 0.13 |

[a] The study area falls entirely into agroecological zone 16 of the level I map (Figure 9.1 and Table 9.1).
[b] For the composition of land-cover types and their distribution in each land-use class see Tables 9.2 and 9.3.
[c] Class 3 occurs only in Guinea savanna zones.
[d] Spectral characteristic of vegetation in class 9 is similar to that of classes 5, 6, and 12; the difference is mainly in the toposequence position.
[e] Mainly riparian vegetation; spectral characteristics of vegetation similar to classes 5, 6, and 9; the difference is mainly in the topo sequence position.

**TABLE 9.7** Percentage Distribution of Land-Cover Types in the 16 Land-Use Classes for SPOT HRV K:44, J:338 Covering the Region of Gagnoa, Côte d'Ivoire (See the Area in Figure 9.8)

| Code of Land-Use Classesa | Code of Land-Cover Types | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
| 1 | | 4 | 14 | 12 | 58 | 12 | 0 | | | 0 |
| 2 | | 20 | 30 | 25 | 10 | 15 | 0 | | | 0 |
| 3[b] | | | | | | | | | | |
| 4 | | 21 | 31 | 27 | 4 | 7 | 1 | | | 9 |
| 5 | | 48 | 25 | 0 | 0 | 0 | 0 | | | 27 |
| 6 | | 83 | 17 | 0 | 0 | 0 | 0 | | | 0 |
| 7 | | 10 | 19 | 4 | 57 | 6 | 3 | | | 1 |
| 8 | | 19 | 39 | 6 | 13 | 6 | 2 | | | 15 |
| 9 | | 30 | 55 | 5 | 2 | 1 | 1 | | | 6 |
| 10 | | 7 | 6 | 6 | 60 | 21 | 0 | | | 0 |
| 11 | | 17 | 6 | 5 | 17 | 0 | 0 | | | 0 |
| 12 | | 32 | 52 | 11 | 5 | 0 | 0 | | | 0 |
| 13 | 100 | | | | | | | | | |
| 14 | | | | | | | | 100 | | |
| 15 | | | | | | | | | 100 | |
| 16 | | | | | | | 100 | | | |

[a] See land-use class names in Table 9.5.
[b] Class 3 (savanna vegetation) does not exist in this study area.

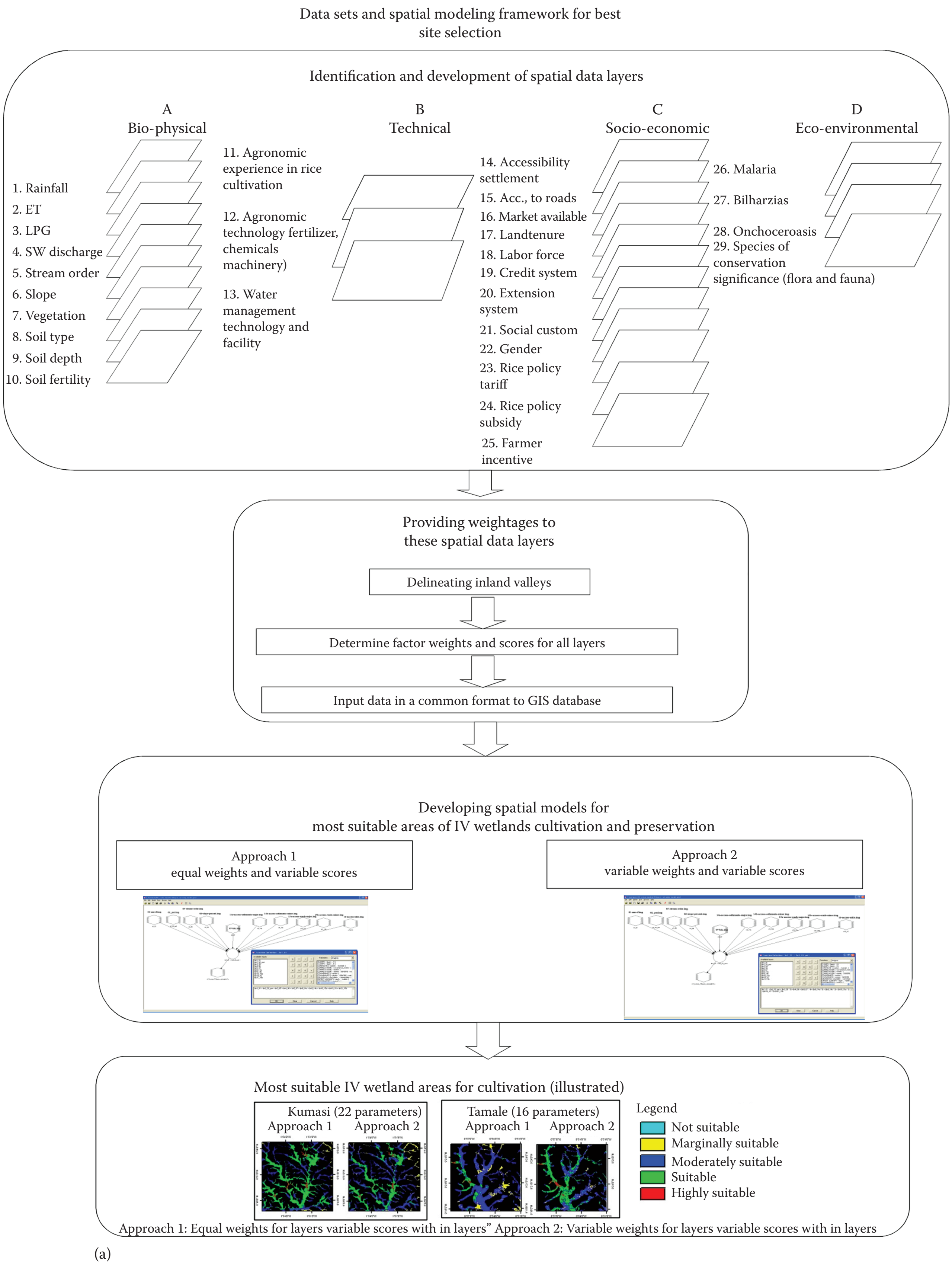
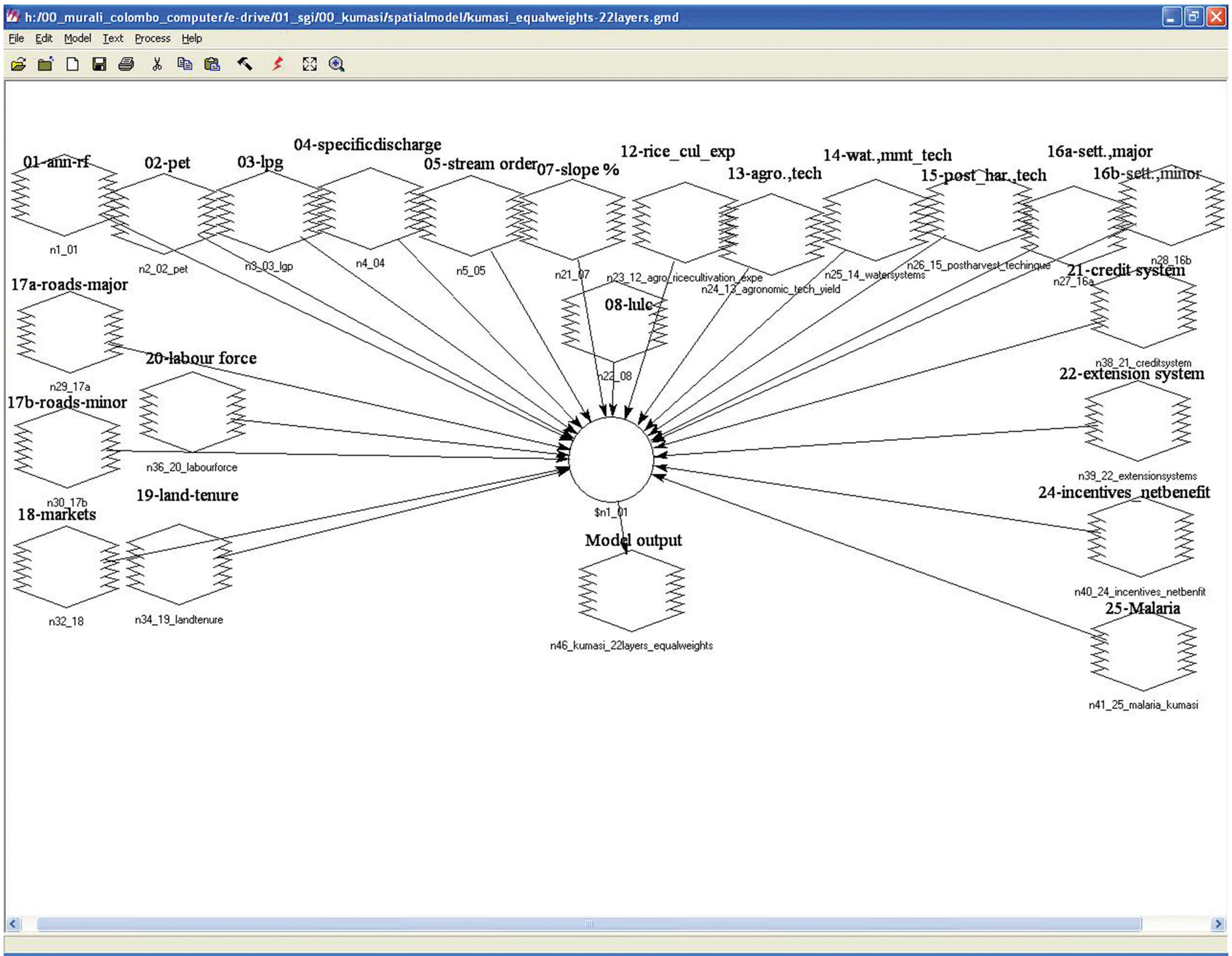
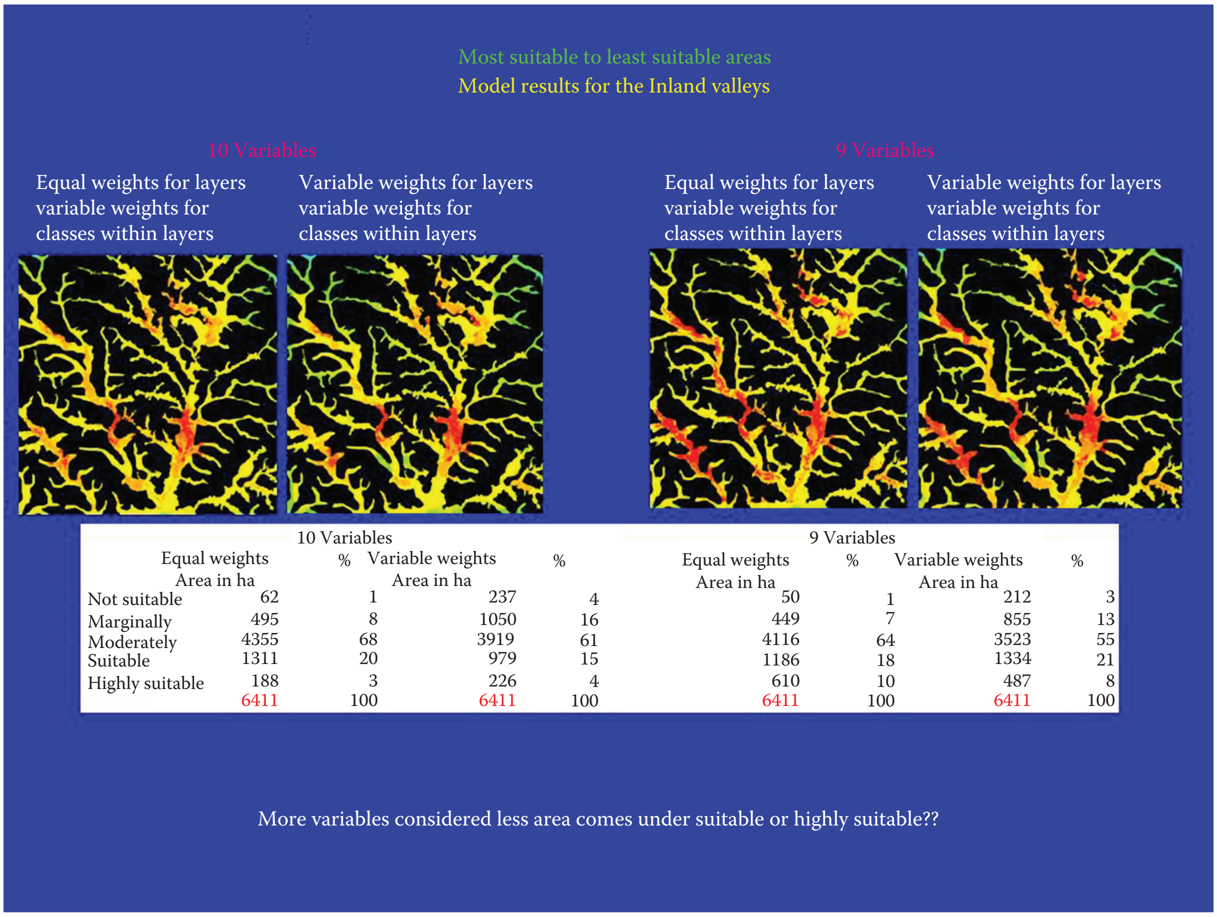



**FIGURE 9.10** (a) Spatial model steps involved in selecting the most suitable areas for rice cultivation in IV wetlands. (*Continued*)




(b)

**FIGURE 9.10 (*Continued*)** (b) Illustration of a typical spatial model built in ERDAS.




| | 10 Variables | | | | 9 Variables | | | |
|---|---|---|---|---|---|---|---|---|
| | Equal weights Area in ha | % | Variable weights Area in ha | % | Equal weights Area in ha | % | Variable weights Area in ha | % |
| Not suitable | 62 | 1 | 237 | 4 | 50 | 1 | 212 | 3 |
| Marginally | 495 | 8 | 1050 | 16 | 449 | 7 | 855 | 13 |
| Moderately | 4355 | 68 | 3919 | 61 | 4116 | 64 | 3523 | 55 |
| Suitable | 1311 | 20 | 979 | 15 | 1186 | 18 | 1334 | 21 |
| Highly suitable | 188 | 3 | 226 | 4 | 610 | 10 | 487 | 8 |
| | 6411 | 100 | 6411 | 100 | 6411 | 100 | 6411 | 100 |

**FIGURE 9.10 (*Continued*)** (c) Most suitable sites for IVs rice cultivation in (A) Kumasi (left) and (B) Tamale (right). For each location, the results and statistics are provided considering 16 variables and 2 approaches: (1) equal weight for layer, variable weight for classes within the layer; and (2) variable weight for layer, variable weight for classes within layer.

**TABLE 9.8** Process of Assigning Weightage to Spatial Data Layers and Classes within Each Spatial Data Layer Based on Expert Opinion from Stakeholders

| | | Weight | Scores |
|---|---|---|---|
| *A. Biophysical variables* | | | |
| 1 | Rainfall | 1 | |
| | <700 | | 1 |
| | 700–1,000 | | 2 |
| | 1,000–1,300 | | 3 |
| | 1,300–1,600 | | 4 |
| | >1,600 | | 5 |
| 2 | ET | 1 | |
| | <700 | | 1 |
| | 700–1,000 | | 2 |
| | 1,000–1,300 | | 3 |
| | 1,300–1,600 | | 4 |
| | >1,600 | | 5 |
| 3 | LGP | 1 | |
| | 90–120 | | 1 |
| | 120–150 | | 1 |
| | 150–180 | | 2 |
| | 180–210 | | 3 |
| | 210–240 | | 4 |
| | 240–270 | | 5 |
| | >270 | | 5 |
| 4 | Water resources: surface water unit discharge | 2 | |
| | Very high | | 5 |
| | High | | 4 |
| | Moderate | | 3 |
| | Low | | 2 |
| | Very low | | 1 |
| 5 | Water resources: stream order | 5 | |
| | 1 | | 1 |
| | 2 | | 2 |
| | 3 | | 3 |
| | 4 | | 4 |
| | 5 | | 5 |
| 6 | Slope | 1 | |
| | <0.5 | | 5 |
| | 0.5–1 | | 5 |
| | 1–1.5 | | 4 |
| | 1.5–2 | | 3 |
| | 2.0–3.0 | | 2 |
| | 3.0–5 | | 1 |
| | >5 | | 1 |
| 7 | Vegetation | 4 | |
| | Dense forest natural vegetation | | 1 |
| | Fragmented natural vegetation | | 2 |
| | Moderate natural vegetation | | 3 |
| | Sparse natural vegetation | | 4 |
| | Fallow lands and farmlands | | 5 |
| 8 | Soil type | 3 | |

(*Continued*)

**TABLE 9.8 (*Continued*)** Process of Assigning Weightage to Spatial Data Layers and Classes within Each Spatial Data Layer Based on Expert Opinion from Stakeholders

| | | Weight | Scores |
|---|---|---|---|
| | Type 1 | | 5 |
| | Type 2 | | 4 |
| | Type 3 | | 3 |
| | Type 4 | | 2 |
| | Type 5 | | 1 |
| 9 | Soil depth | 4 | |
| | <10 | | 1 |
| | 10–20 | | 2 |
| | 20–30 | | 3 |
| | 30–40 | | 4 |
| | >40 | | 5 |
| 10 | Soil fertility | 3 | |
| | Type 1 | | 5 |
| | Type 2 | | 4 |
| | Type 3 | | 3 |
| | Type 4 | | 2 |
| | Type 5 | | 1 |
| *B. Technical factors* | Water quality | | |
| 11 | Agronomic experience in rice cultivation | 2 | |
| | <2 years experience | | 1 |
| | 2–5 years experience | | 2 |
| | 5–10 years experience | | 3 |
| | 10–15 years experience | | 4 |
| | >15 years experience | | 5 |
| 12 | Agronomic technology (fertilizer, chemicals, machinery) | 3 | |
| | Very high tech | | 5 |
| | High tech | | 4 |
| | Moderate | | 3 |
| | Low tech | | 2 |
| | Very low tech | | 1 |
| 13 | Water management technology and facility | 3 | |
| | Major irrigation canal systems | | 5 |
| | Minor canal systems | | 4 |
| | Pump and lift irrigation | | 3 |
| | Dug well and manual | | 2 |
| | Rainfed | | 1 |
| *C. Socio-economic factors* | Postharvest | | |
| 14a | Accessibility settlements: major (>500 people) | 5 | |
| | <500 m | | 5 |
| | 500 m–1,000 m | | 4 |
| | 1,000–2,000 | | 3 |
| | 2,000–4,000 | | 2 |
| | >4,000 | | 1 |
| 14b | Accessibility settlements: minor (<500 people) | 3 | |
| | <500 m | | 3 |
| | 500–1,000 m | | 2 |
| | 1,000–2,000 | | 1 |
| | 2,000–4,000 | | 1 |
| | >4,000 | | 1 |

(*Continued*)

**TABLE 9.8 (*Continued*)** Process of Assigning Weightage to Spatial Data Layers and Classes within Each Spatial Data Layer Based on Expert Opinion from Stakeholders

| | | Weight | Scores |
|---|---|---|---|
| 15a | Accessibility roads: major | 3 | |
| | <500 m | | 5 |
| | 500–1,000 m | | 4 |
| | 1,000–2,000 | | 3 |
| | 2,000–4,000 | | 2 |
| | >4,000 | | 1 |
| 15b | Accessibility roads: minor | 1 | |
| | <500 m | | 3 |
| | 500–1,000 m | | 2 |
| | 1,000–2,000 | | 1 |
| | 2,000–4,000 | | 1 |
| | >4,000 | | 1 |
| 16a | Market: major (>50,000 people): define by size of settlement | 3 | |
| | <500 m | | 5 |
| | 500–1,000 m | | 4 |
| | 1,000–2,000 | | 3 |
| | 2,000–4,000 | | 2 |
| | >4,000 | | 1 |
| 16b | Market: moderate (10,000–50,000 people) define by size of settlement | 2 | |
| | <500 m | | 4 |
| | 500–1,000 m | | 3 |
| | 1,000–2,000 | | 2 |
| | 2,000–4,000 | | 1 |
| | >4,000 | | 1 |
| 16c | Market: minor (2,000–10,000 people) define by size of settlement | 1 | |
| | <500 m | | 3 |
| | 500–1,000 m | | 2 |
| | 1,000–2,000 | | 1 |
| | 2,000–4,000 | | 1 |
| | >4,000 | | 1 |
| 17 | Land tenure | 3 | |
| | Ownership individual | | 5 |
| | Ownership community/family | | 4 |
| | Lease < 80 GHC per ha | | 3 |
| | Lease 80–100 | | 2 |
| | Lease > 100 | | 1 |
| 18 | Labor force | 3 | |
| | Labor force enough | | 5 |
| | Labor force OK | | 3 |
| | Labor force shortage | | 2 |
| | Labor force extremely short | | 1 |
| 19 | Credit systems | 3 | |
| | Credit fully available | | 5 |
| | Credit available | | 4 |
| | Credit difficult | | 3 |
| | Credit very difficult | | 2 |
| | Credit not available | | 1 |

(*Continued*)

**TABLE 9.8 (*Continued*)** Process of Assigning Weightage to Spatial Data Layers and Classes within Each Spatial Data Layer Based on Expert Opinion from Stakeholders

| | | Weight | Scores |
|---|---|---|---|
| 20 | Extension system | 1 | |
| | Available | | 5 |
| | Inadequate | | 3 |
| | Not available | | 1 |
| 21 | Social customs | 1 | |
| 22 | Gender | 3 | |
| | Female gender obstacle | | 1 |
| | Female gender not obstacle | | 3 |
| | Male gender obstacle | | 1 |
| | Male gender not obstacle | | 3 |
| 23 | Rice policy tariff | 3 | |
| | No tariff | | 1 |
| | Tariff 10% | | 2 |
| | Tariff 10%–20% | | 3 |
| | Tariff 21%–30% | | 4 |
| | Tariff > 30% | | 5 |
| 24 | Rice policy subsidy | 4 | |
| | No subsidy | | 1 |
| | Low subsidy | | 2 |
| | Moderate subsidy | | 3 |
| | High subsidy | | 5 |
| 25 | Farmers' incentive | | |
| *D. Ecoenvironmental factors* | | | |
| 26 | Malaria | 2 | |
| | Very high incidence | | 1 |
| | High incidence | | 2 |
| | Moderate incidence | | 3 |
| | Low incidence | | 4 |
| | Negligible incidence | | 5 |
| 27 | Bilhazias | 1 | |
| | Very high incidence | | 1 |
| | High incidence | | 2 |
| | Moderate incidence | | 3 |
| | Low incidence | | 4 |
| | Negligible incidence | | 5 |
| 28 | Onchocercasis | 3 | |
| | Very high incidence | | 1 |
| | High incidence | | 2 |
| | Moderate incidence | | 3 |
| | Low incidence | | 4 |
| | Negligible incidence | | 5 |
| 29 | Species of conservation significance flora and fauna | | |
| | Critically endangered | | 1 |
| | Endangered species | | 2 |
| | Vulnerable | | 3 |
| | Not endangered | | 5 |

Illustrated for IV wetlands of Ghana.

## 9.10 Conclusions

The chapter provides a comprehensive overview of mapping inland valley (IV) wetlands of Africa using remote sensing and GIS. Wetlands are in cusp of development *versus* preservation debate in Africa. Africa's food security, especially given that its population is projected to be four times (reaching about four billion) by the year 2100 relative to its present population of little over one billion, calls for urgent need to utilize inland valley wetlands for agriculture. At the same time, preserving the unique flora and fauna and the carbon sequestered in the wetlands is of utmost importance.

*First*, the chapter provides a roadmap for consistent IV wetland characterization and mapping at various spatial resolutions using a multitude of remote sensing data. For this, the chapter uses West and Central African (WCA) nations as case studies. *Second*, the chapter demonstrates wetland land-use/land-cover classification and study of their time-series phenological characteristics (Gumma et al., 2011a, 2014). *Third*, the remote sensing-derived products along with secondary data (e.g., length of growing period, soils, slope, elevation, temperature, agroecological zones), as well as a number of other data such as the biophysical data, socioeconomic data were assigned weights by experts for their importance and then harmonized, standardized, and built into a decision support spatial model that pin-pointed IV wetland areas that are (1) best suited for cultivation and (2) prioritized for conservation.

The chapter shows approaches and methods of utilizing EO for the purposes of (1) understanding inland valley wetlands as land units for Africa's green and blue revolution, and (2) balancing inevitable developmental activities with environmental/ecological solutions that inform which areas to preserve and which areas to develop. The outputs and outcomes of such a study is expected to benefit: (1) farmers to make decisions on where to focus their IV wetland agriculture based on pin-pointed areas most suitable for cultivation; (2) national governments to make decisions on promoting IV wetland cultivation and conservation; (3) financial institutions (e.g., African Development Bank) to make educated decisions on where to invest to fast forward Africa's green and blue revolution; and (4) researchers and NGOs working in Africa.

## References


Aguilar, J., Fernandez, J., Dorronsoro, C., Stoops, G., Dorronsoro, B. 2003. Hydromorphy in soils. http://edafologia.ugr.es/hidro/indexw.

Anderson, J.R. 1976. *A land use and land cover classification system for use with remote sensor data* (US Government Printing Office).

Andriesse, W., Fresco, L., Van Duivenbooden, N., Windmeijer, P. 1994. Multi-scale characterization of inland valley agro-ecosystems in West Africa. *NJAS Wageningen Journal of Life Sciences* 42, 159–179.

Becker, B.L., Lusch, D.P., Qi, J. 2007. A classification-based assessment of the optimal spectral and spatial resolutions for Great Lakes coastal wetland imagery. *Remote Sensing of Environment* 108, 111–120.

Bock, M., Xofis, P., Mitchley, J., Rossner, G., Wissen, M. 2005. Object-oriented methods for habitat mapping at multiple scales—Case studies from Northern Germany and Wye Downs, UK. *Journal for Nature Conservation* 13, 75–89.

Congalton, R.G. 2009. Accuracy and error analysis of global and local maps: Lessons learned and future considerations. *Remote Sensing of Global Croplands for Food Security*, 441. In Chapter 19, *Remote Sensing of Global Croplands for Food Security*. CRC Press, 441p.

Congalton, R.G., Green, K. 2008. *Assessing the Accuracy of Remotely Sensed Data: Principles and Practices*. CRC Press, Boca Raton, FL.

Eastman, J.R. 1992. IDRISI: Version 4.0, March 1992. Clark University, Graduate School of Geography, Worcester, MA.

ESA. 2014. Europian Space Agency. http://www.esa.int/Our_Activities/Observing_the_Earth/World_Wetlands_Day_focuses_on_agriculture (accessed in May 6, 2014).

FAO. 2005. Limpopo Basin Profile report. http://www.arc.agric.za/limpopo/profile.htm (accessed in May 1, 2014).

Fujii, H., Gumma, M., Thenkabail, P., Namara, R. 2010 August. Suitability evaluation for lowland rice in inland valleys in West Africa. *Transactions of the Japanese Society of Irrigation, Drainage and Rural Engineering* 78(4), 47–55.

Fuller, L.M., Morgan, T.R., Aichele, S.S. 2006. Wetland delineation with IKONOS high-resolution satellite imagery, Fort Custer Training Center, Battle Creek, Michigan, 2005 (accessed in March 3, 2006). Scientific Investigations Report. United States Geological Survey, Reston, VA, p. 20.

Gilmore, M.S., Wilson, E.H., Barrett, N., Civco, D.L., Prisloe, S., Hurd, J.D., Chadwick, C. 2008. Integrating multi-temporal spectral and structural information to map wetland vegetation in a lower Connecticut River tidal marsh. *Remote Sensing of Environment* 112, 4048–4060.

Gliessman, S.R. 2007. *Agroecology: The Ecology of Sustainable Food Systems*. CRC Press, Boca Raton, FL.

Gumma, M.K., Nelson, A., Thenkabail, P.S., Singh, A.N. 2011a. Mapping rice areas of South Asia using MODIS multitemporal data. *Journal of Applied Remote Sensing* 5, 053547.

Gumma, M.K., Thenkabail, P.S., Fujii, H., Namara, R. 2009. Spatial models for selecting the most suitable areas of rice cultivation in the Inland Valley Wetlands of Ghana using remote sensing and geographic information systems. *Journal of Applied Remote Sensing* 3, 033537.

Gumma, M.K., Thenkabail, P.S., Hideto, F., Nelson, A., Dheeravath, V., Busia, D., Rala, A. 2011b. Mapping irrigated areas of Ghana using fusion of 30 m and 250 m resolution remote-sensing data. *Remote Sensing* 3, 816–835.

Gumma, M.K., Thenkabail, P.S., Maunahan, A., Islam, S., Nelson, A. 2014. Mapping seasonal rice cropland extent and area in the high cropping intensity environment of Bangladesh using MODIS 500 m data for the year 2010. *ISPRS Journal of Photogrammetry and Remote Sensing* 91, 98–113.

Harvey, K., Hill, G. 2001. Vegetation mapping of a tropical freshwater swamp in the Northern Territory, Australia: A comparison of aerial photography, Landsat TM and SPOT satellite imagery. *International Journal of Remote Sensing* 22, 2911–2925.

Heidhues, F., Atsain, A., Nyangito, H., Padilla, M., Ghersi, G., Vallée, L. 2004. Development strategies and food and nutrition security in Africa: An assessment. International Food Policy Research Institute, Washington, DC.

Hetzel, M.W., Iteba, N., Makemba, A., Mshana, C., Lengeler, C., Obrist, B., Schulze, A., Nathan, R., Dillip, A., Alba, S. 2007. Understanding and improving access to prompt and effective malaria treatment and care in rural Tanzania: The ACCESS Programme. *Malaria Journal* 6, 83.

Hirano, A., Madden, M., Welch, R. 2003. Hyperspectral image data for mapping wetland vegetation. *Wetlands* 23, 436–448.

Islam, M.A., Thenkabail, P., Kulawardhana, R., Alankara, R., Gunasinghe, S., Edussriya, C., Gunawardana, A. 2008. Semi-automated methods for mapping wetlands using Landsat ETM+ and SRTM data. *International Journal of Remote Sensing* 29, 7077–7106.

Jensen, J.R., Rutchey, K., Koch, M.S., Narumalani, S. 1995. Inland wetland change detection in the Everglades Water Conservation Area 2A using a time series of normalized remotely sensed data. *Photogrammetric Engineering and Remote Sensing* 61, 199–209.

Jones, K., Lanthier, Y., van der Voet, P., van Valkengoed, E., Taylor, D., Fernández-Prieto, D. 2009. Monitoring and assessment of wetlands using Earth Observation: The GlobWetland project. *Journal of Environmental Management* 90, 2154–2169.

Krishna, G.M., Prasad, T.S., Bubacar, B. 2010. Delineating shallow ground water irrigated areas in the Atankwidi Watershed (Northern Ghana, Burkina Faso) using Quickbird 0.61–2.44 meter data. *African Journal of Environmental Science and Technology* 4, 455–464.

Kulawardhana, R.W., Thenkabail, P.S., Vithanage, J., Biradar, C., Islam, M.A., Gunasinghe, S., Alankara, R. 2007. Evaluation of the Wetland Mapping Methods using Landsat ETM+ and SRTM Data. *Journal of Spatial Hydrology* 7(2), 62–96.

Lafferty, K.D. 2009. The ecology of climate change and infectious diseases. *Ecology* 90, 888–900.

Lal, R., Hansen, D.O., Uphoff, N. 2002. *Food Security and Environmental Quality in the Developing World*. CRC Press, Boca Raton, FL.

Lan, Z., Zhang, D. 2006. Study on optimization-based layered classification for separation of wetlands. *International Journal of Remote Sensing* 27, 1511–1520.

Lo, T.H.C., Scarpace, F.L., and Lillesand, T.M. 1986. Use of multitemporal spectral profiles in agricultural land-cover classification. *Photogrammetric Engineering and Remote Sensing* 52, 535–544.

Lunetta, R.S., Balogh, M.E. 1999. Application of multitemporal Landsat 5 TM imagery for wetland identification. *Photogrammetric Engineering and Remote Sensing* 65, 1303–1310.

Lyon, J. 2001. *Wetland Landscape Characterization: Techniques and Applications for GIS Mapping, Remote Sensing, and Image Analysis*. CRC Press, Boca Raton, FL, 135pp.

Lyon, J., McCarthy, J. 1995. *Wetland and Environmental Applications of GIS*. CRC/Lewis Publishers, Boca Raton, FL, 368pp.

MAW. 2014. Map of African wetlands, African wetlands. http://africa.wetlands.org/Africanwetlands/ (accessed in May 6, 2014).

May, D., Wang, J., Kovacs, J., Muter, M. 2003. Mapping wetland extent using IKONOS satellite imagery of the O'Donnell point region, Georgian Bay, Ontario. *Proceedings, 25th Canadian Symposium on Remote Sensing, Canadian Aeronautics and Space Institute*, Kanata, Ontario, Canada, CD-9pp.

Mitsch, W.J., Gosselink, J.G. 2007. *Wetlands*. John Wiley & Sons, New York, 582pp.

Nielsen, E.M., Prince, S.D., Koeln, G.T. 2008. Wetland change mapping for the US mid-Atlantic region using an outlier detection technique. *Remote Sensing of Environment* 112, 4061–4074.

Ozesmi, S.L., Bauer, M.E. 2002. Satellite remote sensing of wetlands. *Wetlands Ecology and Management* 10, 381–402.

Pelley, J. 2008. Can wetland restoration cool the planet? *Environmental Science and Technology* 42, 8994–8994.

RAMSAR. 2004. RAMSAR convention. www.ramsar.org (accessed in May 1, 2014).

Ramsey III, E.W., Nelson, G.A., Sapkota, S.K. 1998. Classifying coastal resources by integrating optical and radar imagery and color infrared photography. *Mangroves and Salt Marshes* 2, 109–119.

Rebelo, L.-M., Finlayson, C.M., Nagabhatla, N. 2009. Remote sensing and GIS for wetland inventory, mapping and change analysis. *Journal of Environmental Management* 90, 2144–2153.

Sader, S.A., Ahl, D., Liou, W.-S. 1995. Accuracy of Landsat-TM and GIS rule-based methods for forest wetland classification in Maine. *Remote Sensing of Environment* 53, 133–144.

Scholes, R. 1990. The influence of soil fertility on the ecology of southern African dry savannas. *Journal of Biogeography* 17, 415–419.

Schowengerdt, R. 2007. *Remote Sensing: Models and Models for Image Processing*. Elsevier, New York.

Thenkabail, P., Biradar, C., Noojipady, P., Dheeravath, V., Li, Y., Velpuri, M., Gumma, M. et al. 2009a. Global irrigated area map (GIAM) for the end of the last millennium derived from remote sensing. *International Journal of Remote Sensing* 30(14), 3679–3733.

Thenkabail, P., Hanjra, M., Dheeravath, V., Gumma, M. 2010. A holistic view of global croplands and their water use for ensuring global food security in the 21st century through advanced remote sensing and non-remote sensing approaches. *Remote Sensing* 2, 211–261.

Thenkabail, P., Lyon, G., Huete, A. 2011. Advances in hyperspectral remote sensing of vegetation and agricultural croplands. CRC Press/Taylor & Francis Group, Boca Raton, FL.

Thenkabail, P., Lyon, J.G., Turral, H., Biradar, C. 2009b. *Remote Sensing of Global Croplands for Food Security*. CRC Press, Boca Raton, FL.

Thenkabail, P.S., Nolte, C. 1995a. Regional characterization of inland valley agroecosystems in Save, Bante, Bassila, and Parakou Regions in south-central Republic of Benin. Inland Valley Characterization Report 1. Resource and Crop Management Division. International Institute of tropical Agriculture, Ibadan, Nigeria, 60pp.

Thenkabail, P.S., Nolte, C. 1995b. Mapping and characterizing inland valley agroecosystems of west and central Africa: A methodology integrating remote sensing, global positioning system, and ground-truth data in a geographic information systems framework. RCMD Monograph No.16. International Institute of Tropical Agriculture, Ibadan, Nigeria, 62pp.

Thenkabail, P.S., Nolte, C. 1996. Capabilities of Landsat-5 Thematic Mapper (TM) data in regional mapping and characterization of inland valley agroecosystems in West Africa. *International Journal of Remote Sensing* 17, 1505–1538.

Thenkabail, P.S., Nolte, C. 2000. Regional characterisation of inland valley agroecosystems in West and central Africa using high-resolution remotely sensed data. In: *GIS Applications for Water Resources and Watershed Management* (John G. Lyon, eds.). Taylor & Francis, New York, Book Chapter #8, pp. 77–100, 266.

Thenkabail, P.S., Nolte, C., Lyon, J.G. 2000a. Remote sensing and GIS modeling for selection of a benchmark research area in the inland valley agroecosystems of West and Central Africa. *Photogrammetric Engineering and Remote Sensing* 66, 755–768.

Thenkabail, P.S., Smith, R.B., De Pauw, E. 2000b. Hyperspectral vegetation indices and their relationships with agricultural crop characteristics. *Remote Sensing of Environment* 71, 158–182.

Tiner, R.W. 2009. Global distribution of wetlands. *Encyclopedia of Inland Waters*. pp. 526–530.

Töyrä, J., Pietroniro, A. 2005. Towards operational monitoring of a northern wetland using geomatics-based techniques. *Remote Sensing of Environment* 97, 174–191.

Tucker, C.J. 1979. Red and photographic infrared linear combinations for monitoring vegetation, *Remote sensing of Environment*, 8(2), 127–150.

Wagner, W., Bloschl, G., Pampaloni, P., Calvet, J.-C., Bizzarri, B., Wigneron, J.-P., Kerr, Y. 2007. Operational readiness of microwave remote sensing of soil moisture for hydrologic applications. *Nordic Hydrology* 38, 1–20.

Wallace, C.S., Marsh, S. 2005. Characterizing the spatial structure of endangered species habitat using geostatistical analysis of IKONOS imagery. *International Journal of Remote Sensing* 26, 2607–2629.

WARDA. 2003. Strategic Plan 2003–2012. WARDA—The Africa Rice Center, Bouaké, Côte d'Ivoire, 56pp.

WARDA. 2006. Medium Term Plan 2007–2009. Charting the Future of Rice in Africa.Africa Rice Center (WARDA), Cotonou, Republic of Benin.

Wdowinski, S., Kim, S.-W., Amelung, F., Dixon, T.H., Miralles-Wilhelm, F., Sonenshein, R. 2008. Space-based detection of wetlands' surface water level changes from L-band SAR interferometry. *Remote Sensing of Environment* 112, 681–696.

Woodhouse, P. 2009. Technology, environment and the productivity problem in African agriculture: Comment on the World Development Report 2008. *Journal of Agrarian Change* 9, 263–276.

Wright, C., Gallant, A. 2007. Improved wetland remote sensing in Yellowstone National Park using classification trees to combine TM imagery and ancillary environmental data. *Remote Sensing of Environment* 107, 582–605.

Zhuang, Q., Melack, J.M., Zimov, S., Walter, K.M., Butenhoff, C.L., Khalil, M.A.K. 2009. Correction to "Global methane emissions from wetlands, rice paddies, and lakes". *EOS Transactions* 90, 92.