Earth Observation Methods for Wetlands: Overview

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Abstract

Across their range, wetlands are highly complex and dynamic and have been observed by a wide and diverse range of ground, airborne, and spaceborne sensors. The methods applied for characterizing, mapping, and monitoring mangroves are therefore diverse but have focused primarily on mapping state (i.e., water, ice, or snow) and extent as well as persistence and duration, sediment loads, substrate characteristics, and tidal fluctuations. A number of indices, algorithms, and models have been specifically developed to understand the changing states of wetlands, with these including mangroves, sea grasses, bogs, mires and fens, tropical floodplains, and semiarid wetlands. Many wetlands are also subject to anthropogenic disturbance as well as natural events and processes. Remote sensing data provide a unique opportunity to track such changes but also to classify these according to the different disturbance types. A number of international programs have also been put in place to advance the use of remote

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sensing data for wetland observations, with these including the European Space Agency's (ESA) Globwetland (I, II), the Japan Aerospace Exploration Agency (JAXA's) Kyoto and Carbon (K&C) Initiative, and the NASA's Making Earth System Data Records for Use in Research Environments (MEaSUREs) projects.

Keywords
Remote sensing · Water states · Biophysical characteristics · Human disturbance · International projects

Regions of the Electromagnetic Spectrum

At local to global scales, wetlands can be observed, characterized, mapped, and monitored using a diverse range of ground, airborne, and spaceborne sensors operating in different modes and across different spatial and temporal scales. Sensors that are generally more familiar to those involved with wetlands assessment operate in the *spectral* (reflected visible to shortwave infrared) regions of the electromagnetic spectrum, with these allowing identification of open water, determination of water state and quality, discrimination of different aquatic environments and vegetation types, and tracking of vegetation phenology and water dynamics. Sensors operating in the *thermal* regions provide information on the temperature variations of wetlands and particularly the water surface. *Microwave* sensors (on the order of cm wavelength) typically facilitate the mapping of open water and inundation and also provide information on the three-dimensional structure of wetland vegetation.

Main Sensor Types of Relevance

For wetland mapping, key sensors include the Landsat series, which has provided a global record of wetland characteristics and extent through observations at 30–80 m spatial resolution from the late 1970s onwards (Williams et al. 2006; Markham and Helder 2012). With the recent release of this archive, considerable opportunities for understanding the dynamics of wetlands are provided. Sensors operating at coarser spatial resolution have included the NOAA's Advanced Very High Resolution Radiometer (AVHRR) and the Terra-1 Moderate Resolution Imaging Spectroradiometer (MODIS), with these being particularly beneficial for mapping the dynamics of flooding over large areas through regular (at least daily) observations over several decades (Takeuchi et al. 2003; Yan et al. 2010). These and the Landsat sensors also provide observations in the thermal region. More detailed assessment of wetlands have been conducted using very high resolution (VHR) optical sensors such as Worldview, Quickbird, and IKONOS (e.g., Laba et al. 2008; Dillabaugh and King 2008; Magumba et al. 2014; Salari et al. 2014), which are increasingly available at a global level, with the constellation of five RapidEye sensors providing higher frequency (daily) observations over smaller areas. Sensors on board

Unmanned Airborne Vehicles (UAVs) are also being used more regularly for observing wetland areas in detail and on demand (Jensen et al. 2011).

Observations by many optical and also thermal sensors are limited by cloud. For this reason, Synthetic Aperture Radar (SAR) operating in the microwave region has commonly been exploited, with these also providing information on vegetation types and the extent of inundation. Different levels of information can be obtained by using data acquired at different frequencies and polarizations, with C-band (~6 cm) SAR facilitating discrimination of herbaceous vegetation and L-band SAR allowing detection of water under vegetation, including that which is woody (Hess et al. 2003; Silva et al. 2008). Airborne Light Detection and Radar (LIDAR) has also being used to provide detailed three-dimensional, high resolution representations of the terrain surface and surface features, including vegetation (Cook et al. 2009).

Remote Sensing of Water Dynamics

A wide range of remote sensing methods are available to determine the physical state of water (liquid, snow or ice) and water column characteristics and to quantify patterns of inundation and extent, persistence and duration, sediment loads, substrate characteristics, and tidal regimes.

Using spectral wavebands, water can generally be distinguished from ice and snow (Dozier 1989). Open water itself is best mapped using thresholds or classifications that utilize the near infrared and shortwave infrared bands or derived indices (e.g., the Normalized Difference Water Index). At SAR frequencies, water exhibits a relatively low backscattering coefficient allowing discrimination from nonwater surfaces. However, confusion with rough water and macrophytes often occurs (Costa and Telmer 2006).

Water column characteristics are best retrieved through spectral analysis, with the visible channels providing best opportunity for retrieval. Empirical relationships with measured properties or bio-optical models are most commonly used for retrieval (e.g., Zhang et al. 2008).

Depending upon the cover of vegetation and depth of water, the extent of *inundation* can be mapped using combinations of remote sensing data, with SAR providing the best opportunity for mapping inundation beneath vegetation. The combination of satellite-derived gravity and altimetry data has also been used to quantify inundation and water dynamics (Alsdorf et al. 2007).

Detection also depends upon the frequency of coverage. By comparing maps of inundation extent, information on the *persistence and duration* of water within wetland systems has been obtained (Milne and Tapley 2004). The MODIS sensor, for example, provides excellent mapping of open water over large areas and on a frequent (i.e., daily basis). However, other sensors such as the Landsat provide observations every 16 days (cloud cover permitting) and hence temporary bodies of water may go undetected. The repeat coverage of many SAR is also relatively low (e.g., 44 days for the ALOS PALSAR).

Sediment loads and types have been mapped primarily by considering the reflectance characteristics in the visible regions (Stumpf and Goldschmidt 1992) and, when the water is optically clear, *substrate cover types* and their properties have also been retrieved (Dekker et al. 2005). Tidal regimes have often been inferred through reference to inundation detected under mangroves or maps of tidal flats (e.g., Murray et al. 2012).

Remote Sensing of Natural and Seminatural Wetlands Types

A wide range of remote sensing techniques have been developed since the beginning of earth observation from the ground and by airborne and spaceborne sensors with these often being specific to particular regions and wetland types.

In the *arctic and boreal regions*, SAR data have often been preferentially used because of the prevalence of cloud. A range of techniques has been used to differentiate wetland types, including rule-based classifications. Using Alaska as an example, elevation and slope data obtained from the Shuttle Radar Topographic Mission (SRTM) have been combined to identify areas where wetlands occur, with a Random Forests algorithm then applied to provide more detailed classifications of wetland types (Whitcomb et al. 2014). For more mapping of wetland dynamics, object-based classifications of time-series of high to moderate resolution data based on supervised methods or decision trees have been used (Tehrany et al. 2014).

In the *temperate regions* of Europe and North America, many wetlands have been fragmented through human activity and typically moderate resolution to VHR remote sensing data have provided the level of detail needed for their mapping and monitoring. In these regions, consistent mapping of seminatural and natural habitats and their differentiation from those that are cultivated, managed, or artificial is desirable. The classification schemes ideally need to be consistent within and between sites. One such taxonomy is the Food and Agricultural Organisation's (FAO) Land Cover Classification Scheme (LCCS) (Di Gregorio and Jansen 2000), which has been applied to wetland habitats in protected areas and their surrounds at sites across Europe (Lucas et al. 2014a). A particular advantage of using taxonomies such as the LCCS is that they can be applied at any scale and use a diversity of remote sensing inputs.

In the *semiarid regions*, wetlands are often periodic and water may inflow from regions within different climatic zones. In these cases, wide swath ScanSAR data and MODIS data are useful as more frequent observations of wetlands systems are obtained with these allowing better detection of inundated areas and water flows (Bartsch et al. 2009; Moser et al. 2014). Often, data from optical sensors such as MODIS and Landsat sensor data can be used to capture the vegetation response to environmental flows (Shaikh et al. 2010). Techniques used have included simple thresholding, supervised/unsupervised classifications, and machine learning (Ozesmi and Bauer 2002; Liu et al. 2008).

In the *tropical regions*, flooded forests are extensive with significant tracts occurring in the Amazon and Congo river basins (Melack and Hess 2010; Mayaux et al. 2002). Within these areas, the dynamics of flooding has a large influence on biogeochemical and nutrient cycles as well as on biodiversity distributions. To map the extent of inundation beneath the forest canopy, the use of L-band SAR has proved useful (Hess et al. 1995), with time-series allowing the changes in flooding patterns to be discerned. Through knowledge of the extent and condition of wetlands and how these have changed over time, better information on the changing distribution of energy and gaseous exchange (e.g., carbon, methane) can be obtained (Richey et al. 1997; Potter et al. 2014).

SAR data have also been integrated for mapping the extent of *herbaceous vegetation types*, including within the varzea regions of the Amazon where an object-based approach to classification has been recommended (Silva et al. 2008). By using multifrequency, polarimetric data, a greater level of discrimination can be achieved. For example, near Ankor Wat in Cambodia, NASA JPL fully polarimetric airborne SAR (AIRSAR) data have been used to differentiate macrophytes, flooded grasslands, and both trees and shrubs (Milne and Tapley 2004).

In many tropical regions, *peat swamp forests* are common and are of particular importance because of their unique biodiversity and the large amounts of carbon they contain (Jauhiainen et al. 2005). As cloud cover is persistent in these regions, data from moderate resolution optical sensors are often limited for characterizing these forests and detecting changes in their extent, although dense time-series can be used to map their extent and detect disturbance (e.g., logging). However, these peat swamps are particularly distinct within L-band SAR data and some significant changes in their state have been observed by comparing time-series of these data (Hoekman 2007).

Throughout the tropics and subtropics, *mangroves and sea grasses* occur in the coastal zones and are considered as wetland habitats. For mapping mangroves, moderate resolution optical data has been advocated with several studies (e.g., Spalding et al. 2010; Giri et al. 2011) generating regional to global maps. As cloud is often persistent in mangrove regions, the use of these data for detecting change has been limited. However, time-series of JERS-1 SAR and ALOS PALSAR data can be used for monitoring losses and gains in mangrove extent and associating this with a particular cause (e.g., agriculture, aquaculture, provision of sediments; Thomas et al. 2015; Lucas et al. 2014b). Given the homogeneity of their canopies and their adjacency to the sea, the height of mangroves has been estimated using SRTM data together with ICESAT GLAS waveform data (Simard et al. 2008). For detailed mapping of mangroves (e.g., for the establishment of baseline maps of extent, height and species composition), the use of stereo aerial photography as well as airborne or spaceborne visible and near infrared data has been advocated (Lucas et al. 2002).

Remote sensing allows large areas of *sea grass* habitat to be monitored. A common approach has been to use aerial photography but the use of hyperspectral data has proved to be more effective in terms of mapping different species and determining cover and other biophysical attributes (e.g., Leaf Area Index) (Phinn et al. 2008). Time-series of moderate spatial resolution data (e.g., Landsat and SPOT) have also allowed trends in extent and condition to be described. A recent development has been the use of acoustic remote sensing for mapping seagrass extent as well as height and structure (Montefalcone et al. 2013).

For characterizing lakes in the Pantanal region of subtropical South America, a combination of spaceborne C-band and L-band data has been used in an object-based approach (Costa and Telmer 2006). Using these data, differences in backscatter between brackish and freshwater lakes have been observed. These data were also used to indicate differences in lake water geochemistry as inferred from vegetation types and amounts.

Remote Sensing of Anthropogenic Activities

Whilst many wetlands are still observed in their natural state, humans have exerted a considerable influence on their extent, condition, and dynamics. Such impacts, many of which can often be detected from remote sensing, arise from agricultural production, aquaculture, dam and reservoir construction, drainage, harvesting of aquatic resources (e.g., wood and charcoal), hydrological and sediment diversions, and salt production. However, humans also contribute to the creation and restoration of wetlands.

In many regions, aquaculture is prevalent with mangroves being the most common ecosystem within which ponds are placed. These ponds are particularly evident within SAR data with time-series of JERS-1 SAR and ALOS PALSAR data being particularly useful for discriminating aquaculture ponds that are pre-1990s and post-1990s in their formation (Lucas et al. 2014b). Rice paddies are also widespread and SAR data have often been used again for mapping extent, inundation, and cropping intensity (Rosenqvist 1999). In many regions, the SAR signal follows a distinct trend over the cropping cycle that can be used to indicate growing season length and the frequency of cycles within any one year. Coarse spatial resolution optical sensors (e.g., MODIS) have also been used for rice mapping using wavelengths and indices that are sensitive to water and vegetation (Xiao et al. 2005).

Regional to Global Wetland Mapping Programs with Remote Sensing Contributions

To ensure conservation, wise and sustainable use of mangroves, a number of regional to global initiatives have been established, with these including the European Space Agency's (ESA) Globwetland (I and II), JAXA's Kyoto and Carbon (K&C) Initiative, and the NASA's Making Earth System Data Records for Use in Research Environments (MEaSUREs) projects.

The *Globwetland projects* were designed to demonstrate the use of EO data for wetland mapping and monitoring over large areas. Globwetland I (Jones et al. 2009) was aimed at developing and demonstrating products and services based on remote sensing data for wetland managers and national authorities with Globwetland II

(Paganini et al. 2010) focusing on the provision of decision support tools for wetland management and conservation activities. In this second stage, the aim also was to generate maps of land use, land cover, change and water cycle regimes for 200 wetlands. The third Globwetland project, GlobWetland Africa, seeks to address wetland conservation and management within Africa and using specifically data from the Sentinel constellations of the Copernicus initiative.

The JAXA K&C (Rosenqvist et al. 2007) aimed to demonstrate the benefit of using data from the JERS-1 SAR and ALOS PALSAR data for conservation, international conventions, and carbon cycle science. This initiative has resulted in regional products, including maps of inundation in the Sudd Wetlands, Pantanal, and Amazon; maps of rice paddy cycles in southeast Asia and the United States; and the classifications of habitats of international importance including peat swamp forests in Indonesia. The science undertaken as part of this initiative forms the basis of applications using the ALOS-2 PALSAR-2 launched in 2014.

The NASA MEaSUREs projects aims to advance the use of earth observation data and pioneer scientific use of satellite measurements to better understand the earth system. One project is the Inundated Wetlands Earth System Data Record (IW-ESDR), which seeks to monitor wetland extent and dynamics and understand their role in, for example, greenhouse gas and water cycling, climate impacts and feedback, ecosystem health and management of water resources. For this purpose, focus is on the use of SAR data.

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