This module presents remotely sensed assessment (choice of sensors and resolutions; airborne or ground-based sensors; ground truthing)
In this presentation you will be introduced to approaches for using remote sensing to map wetland extent and change.
This module includes the following sections:

Rationale
Background
Choice of sensors and resolutions
Airborne/spaceborne or ground-based sensors
Generating maps from sensor data
  • Wetlands
  • Special case: Peatlands
Ground truthing
Validation
Change detection

validation and change detection
Deforestation and forest degradation have been reported to be the 2\textsuperscript{nd} leading cause of anthropogenic greenhouse gas emissions. Wetlands, especially peatlands, represent one of the largest terrestrial biological carbon pools, and are important wildlife habitats. In particular, tropical peatlands and mangroves are being lost at high rates. Therefore, quantifying wetland type, extent, distribution and condition is vital for mitigation efforts, MRV, IPCC and related efforts. Remote sensing is a major tool in wetland mapping and so will be covered here.
Remote sensing data is the main data source for monitoring and mapping wide areas, including wetland extent and distribution; wetland type including mangrove and peat swamps because of their high carbon density, and other non-forested peatlands; and land-use/land-cover change.

Remote sensing provides human activity data, which is a critical component of estimating human impacts on wetlands. To complement the activity data, field studies provide emissions factors, which define the impact of human activity on greenhouse gas emissions. The combination of activity data and emissions factors are vital for estimating change in wetland carbon content. Baseline wetland extent maps (right) can be used to assess impacts of land use. At the top we have the national wetlands map of Indonesia, with wetlands coded dark blue. At the bottom we see the peatland map for Central Kalimantan Province, Indonesia. These maps are from Margono et al. 2014.
Selected remote sensing tools should detect some or all of the following: water presence, water temporal dynamics, landforms that are likely to retain water, and vegetation type and floristic differences. A fusion of multiple data sources often provides improved maps when compared with single sources. Digital mapping posits that water presence and dynamics, landform and vegetation type can be observed using multisource data sets.
The following describes the overall workflow for developing a wetland map from remote sensing data.

1. The goal is to map wetland characteristics (extent, type, condition) across a region of interests.

2. We obtain data at various scales to measure biological and/or physical properties. At a regional scale, combined active (e.g. radar) and passive (e.g. Landsat) sensor data represent energy and reflectance values of vegetation and hydrologic response across seasons.

3. At a localized scale, field data (direct measurements), are incorporated with aerial image interpretation to develop independent measures of site condition to aid in interpretation and validation of the remotely sensed data.

4. Landsat, PALSAR and other data are combined into a stack while field data and aerial photo interpretation data are fused, providing the foundation for a supervised data set.

5. Supervised data and the image stack are fed into Random Forest or a similar classifier.

6. Random Forest uses a series of decision trees based on the supervised data, to classify the image.

7. Specific thresholds for acceptable map accuracy should be established \textit{a priori} and then evaluated. Accuracy is a measure of how consistently the classification will correctly identify classes.
8. Users should also evaluate the map products’ precision... how close the map product is to what is really on the ground.
Spaceborne remote sensing data sources are used for mapping large regions. These include passive, multispectral data sources, e.g. Landsat TM, SPOT, MODIS; Hyperspectral, supposed to be Hyperspectral Imager (HSI) on the Lewis satellite; radar data sources, e.g. ALOS PALSAR, SRTM; and active light source LiDAR, e.g. ICESat/GLAS.

Airborne platforms can provide higher resolution data for smaller regions. These include hyperspectral, e.g. AVIRIS, AHS, HYDICE, AISA; LiDAR; Multispectral; Multiplatform, e.g. G-LiHT (LiDAR, hyperspectral, thermal).

Ground-based sensors are used primarily at the site level or to validate remote methods. For example, tripod-mounted LiDAR can be used to collect detailed information about canopy characteristics at the site level that can be compared with airborne or satellite LiDAR.
Landsat is a passive data source, i.e. it relies on incoming solar radiation. It does not see through clouds. It has multiple spectral bands.

There have been a series of Landsat satellites, most recently Landsat TM 5, Landsat 7 ETM+ and Landsat 8
Band 3, 4, 5 and 7 are commonly used and are suitable for a variety of applications, including: soil-vegetation discrimination (blue, green, red spectra); mapping biomass content (near infrared); detecting and analyzing vegetation (near infrared), contrast between different types of vegetation (short wave infrared), and measuring the moisture content of soil and vegetation (short wave infrared).

Landsat imagery captures floristic differences that can be associated with wetland status, as well as water extent and leaf moisture content. It is available with 30 meter spatial resolution, sufficient for mapping at scale one to one hundred thousand or even one to fifty thousand. Because the sensor cannot see through clouds, many scenes are unusable, especially in humid regions such as the tropics. Therefore, timely data acquisition is limited by cloud cover and gaps can occur in temporal series.
The image to the right shows a false color composite of bands 3, 4 and 5 from Landsat 7 of a region of the Peruvian Amazon that has previously been shown to contain a peat dome (black star).
Phased Array type L-band Synthetic Aperture (PALSAR) is considered to be an active source because it sends out a microwave energy pulse and collects the returns. PALSAR uses L-band which penetrates cloud cover, thus achieving cloud-free and day-and-night land observation, a significant advantage over passive multispectral sources such as Landsat. 10–20 meter resolution data are available, but 50 meters spatial resolution is suitable for national-scale mapping exercises. Data are available in polarization mode, which enhances land-cover information. The different interactions of microwave data (PALSAR) with surface water compared to vegetation enables improved discrimination of wetlands. Comparing images from multiple dates (multi-temporal) improves our understanding of hydrology and helps us to distinguish wetlands and wetland types. Thus multi-temporal PALSAR is much more useful than single date in wetland characterization, but this increases complexity and the cost of analysis, which is an important consideration in large-scale mapping exercises.
Principal Component Analysis is a multivariate statistical technique that is used to identify the dominant spatial and temporal backscatter signatures of a landscape. PCA generates a set of new images, reducing most of the information to the first few new PC images. It has several advantages including the ability to filter out temporal autocorrelation and reduce speckle. It can be helpful in understanding moisture patterns.
Global DEM (digital elevation model, or topography map) has been derived from single-pass interferometric synthetic aperture radar (InSAR) of the Shuttle Radar Topography Mission or SRTM. These data are available globally at 90 meters spatial resolution and 30 meters resolution for some places. Spaceborne LiDAR coverage e.g. ICESat/GLAS can provide more information about the ground surface elevation vs. forest canopy elevation, but is limited to long transects with low overall coverage. Airborne LiDAR coverage varies by country. For example, LiDAR coverage for Peru is quite extensive. Using DEMs, a set of topographical indices capture landforms that are more likely to retain water.
Once data from a variety of sources is obtained, data integration (also known as data fusion) can take place. This involves combining data from different sources. For example, geospatial data integration can include information on vegetation type, generated from Landsat; information on landform derived from DEM; information on likely water presence, using topographical indices generated from DEM, such as the first derivatives of elevation (e.g. slope) and the second-order derivatives of elevation (e.g. various curvatures); and vegetation and soil wetness information, generated from ALOS-PALSAR, especially multi-temporal data if feasible. On the following slide we have an example of this.
This is an example of data integration for mapping of peatlands in Central Kalimantan, Indonesia, on the island of Borneo. The data sources include Landsat, ALOS-PALSAR, and SRTM topographic data. In (a) we have a Landsat image with band 5–4–3 spectral combination; in (b) we have a topographical index of terrain flatness derived from SRTM data; in (c) we have a topographical index with a relative elevation of 121.5 km² (medium-sized) catchments; in (d) Landsat band 5 represent soil/vegetation moisture; in (e) we see a false-color red-green-blue combination of (b), (c), and (d); and in (f) we have the initial resulting wetland map as a probability layer where blue is high wetland cover probability and white is low wetland cover probability. Single date PALSAR (data not shown) contributed a small percentage to the final wetland model.
Peatlands are wetlands that accumulate peat (partially decomposed organic matter) and so contain large reserves of carbon vulnerable to anthropogenic disturbance, for example, decomposition or fire triggered by drainage or climate change. Intentional drainage has been an important driver of change in the tropics. Drainage is sometimes combined with conversion to oil palm plantations, whereas in other regions repeated anthropogenic forest fires have suppressed forest regeneration. The image to the right shows a man-made drainage canal in an Indonesian peat swamp forest that has led to extensive peatland damage and carbon loss.
To map tropical peatlands, we can take advantage of unique vegetation, hydrology, and geomorphology. Unique vegetation can arise from known peat-forming plant associations. For example, peat swamp forests of Peru (image on top left) are characterized by the dominant palm tree, aguaje (*Mauritia flexuosa*). Peat swamp forests of Indonesia also have distinct species including ramin (*Gonystylus bancanus*) and jelutung (*Dyera costulata*). Non-forested fen peatlands in the tropical Andean mountains are characterized by distinct
plant assemblages, such as the mound-forming cushion plants in the Juncaceae pictured here (top right). Landsat can detect unique vegetation signals which is useful when unique vegetation dominates.

Unique hydrology is also evident because of the properties of the peat that regulate the movement of water across the landscape. Given the extensive peat accumulations and their distinct high water-holding capacity, seasonal hydrologic dynamics of peatlands differ from other wetland classes. As noted earlier, multi-temporal PALSAR can be used to characterize hydrologic dynamics and hence distinguish peatlands that exhibit distinct hydrology.

Unique geomorphology can also be used in identifying and estimating carbon content of some peatlands. Many peatlands have convex geomorphology (dome formation) arising from peat accumulation.
SRTM or LiDAR-derived DEMs can be used to characterize and identify domes
Peatland hydrology is driven by exogenous and endogenous factors. Doming, which is common in Indonesian peat swamp forests and is being quantified elsewhere, regulates water flux patterns.

The SAR multi-temporal image to the right reveals divergent hydrology across the width of a peat dome, with the flat top of this peat dome (light blue areas, A) exhibiting a different time course of flooding than the edges and stream channels (redder areas, B).
Peat accumulates over thousands of years where production outpaces decomposition. In some places, peat rises above the local water table, creating domes. Doming can be observed as regular, rounded topographic features sometimes many kilometers across. These features can be recognized when analyzing topographic relief, especially in conjunction with wetland mapping. Quantifying dome morphology can improve estimation of peatland carbon storage. The example at the right (Ballhorn et al. 2011) illustrates the use of satellite-based LiDAR (ICESat/GLAS) to determine dome morphology and forest structure on a peatland in Indonesia. In image B the blue points delineate the dome height in meters over a horizontal distance of about 100 km. The green points represent canopy height. The method was validated using airborne LiDAR and ground sampling.
In addition to the remotely sensed data, it is important to collect independent data to help in classification and validation of created maps. These data can come from field surveys and image interpretation. For field surveys, plot selection is critical, because sampling should be statistically valid, ideally stratified over putative wetland classes from initial unsupervised classification or other preliminary data. Logistical constraints on plot selection should be included in sampling design. Plot characteristics are also critical. Sampling plots should be sized and oriented to stay within a single map class.

In addition to field surveys, image interpretation can derive data from aerial imagery, e.g. urban areas, lakes and other distinct features. If reliable data from these sources are available, they will greatly reduce the cost of field activities.
Based on field surveys, image interpretation, or other independent data, a supervised classification can be run using a portion of the data to generate an initial map. This map is then subject to validation. Using plots not included in supervised classification the quality of the classification can be evaluated. Results can be presented as an accuracy assessment matrix in which correct and incorrect assignments to land classes are evaluated. Quality thresholds established in advance should be used to determine if the map is of sufficiently high quality for operational use.
In addition to developing static maps of wetland distribution and type, we also must develop maps of wetland change. Remote sensing can be used to quantify change in land use/land cover of wetlands. This can be accomplished by performing a change detection analysis using remote sensing data (e.g. Landsat) collected over time, known as a multi-temporal dataset.

Change analysis involves change from one class to another (e.g. conversion to agriculture), or change within a class (e.g. thinning of forest). To the right we give a broad outline of the steps involved in change detection.

Initial steps typically include: image registration to align images to each other; calibration or normalization to minimize artifacts arising from differences in conditions during image capture; selection for same spatial/spectral resolution; and mosaicking (stitching) images together for work at larger spatial scales.

There are many possible change detection approaches. These include algebra-based, transformation-based, classification-based, advanced models, GIS-based, and a variety of other methods. Once a method is chosen, there are steps followed that are specific to that method, involving direct comparison of spectral data, or some sort of image processing (transformation, classification, etc.) followed by comparison. As with
approaches describe previously, some form of accuracy assessment is necessary. This requires field-based reference data, e.g., forest inventory, followed by the use of accuracy assessment matrix/ error matrix.
The image here depicts a typical generic work flow for change detection.
The future of change detection using remote sensing will be transformed by a number of key developments. First, the Landsat archive is available with free access to terrain-corrected data for many regions. Second, automated image preprocessing and land-cover characterization methods will soon be standard practice. Combined with advances in computing speed, this will enable automated change detection using freely available resources, which will greatly enhance the scope and speed of change analyses. The images on the right show change detection results for the expansion of bare ground on a national scale from the US (top) and a close-up of a localized region, from the Web-Enabled Landsat Data (WELD) project. Blue areas are newly bare ground (Hansen and Loveland 2012). Third, these large-scale automated methods should greatly accelerate change analysis in wetlands.
References


References


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