Use of multiple techniques for habitat area mapping

Land use and land cover data is commonly produced from satellite imagery or aerial photo interpretation. These data can be obtained at a local level from state agencies or at a federal level from the United States Geological Survey (USGS) or United States Environmental Protection Agency (EPA). The accuracy of these products varies based on a variety of factors including, type of habitat assessed, weather/atmospheric conditions, number of spectral bands, filters and algorithms utilized, and analyst experience. Most papers examined for this project concerning habitat area did not focus on techniques to derive the measures but rather noted where the (prepackaged) data was obtained. While most habitat papers were terrestrial, some addressed aquatic habitats.

Some recent papers have examined the strengths and weaknesses of different techniques. Weiers et al (2004) presented a framework to allow integration of mapping and surveys conducted at different scales for different reasons. The authors suggested that different products should be used depending upon the goals of the individual studies. For example, fine scale (local) mapping will require high accuracy and resolution, so aerial photos and ground truthing are needed. While direct use of satellite data is not appropriate for these fine scale studies, it was suggested that it could be used to target ‘changed’ areas for base map updates. For larger scale studies, some inaccuracy can be tolerated so satellite data, with its broad coverage, is appropriate. Use of different satellites (with different sensors) is possible as long as the habitat classification is harmonized and validated with other data. Mumby & Edwards (2002) demonstrated scalar dependency in shallow marine waters. At fine scales, satellite data
produced habitat maps with accuracies of ~50% while airborne sensors had ~81% accuracy. At coarse scales (only four habitat classes), both IKONOS and Landsat TM data produced accurate habitat maps, and were more cost effective than the airborne sensor data.

Several papers classified satellite data iteratively, or used other sources of data to improve satellite classification. While some papers reported classification accuracy to demonstrate that these techniques produced more accurate habitat maps, others only mentioned that ground truthing was conducted. For example, Long and Sewers (1996) used Landsat TM (blue and near-infrared bands) to map mangroves. Open water was removed from the image and mangroves mapped in zones corresponding to elevation and proximity to water. The authors mentioned that accuracy was improved using this technique but did not quantify it. Similarly, Murray et al. (2003) used a two-stage unsupervised classification of Landsat data followed by ground truthing but did not report on accuracy. Hansen et al. (2001) used a 1975 Landsat MSS and 1997 Landsat TM images as baseline data for mapping caribou habitat. The difference in brightness and greenness between the two images was used to identify disturbed areas. Undisturbed areas were classified (unsupervised), then forested areas further classified using both TM data and information on shaded relief. All areas were then combined with information on aspect and elevation. Classification accuracy using this technique was ~90%. Pearlstein et al. (2002) used Landsat TM images for Florida GAP analysis. Previously compiled land use/land cover data was used to separate natural from developed and agricultural areas. Undeveloped areas were classified from the satellite data, then overlaid with soil and wetlands data. Developed and agricultural areas were directly classified from the TM image. While aerial photos and ground truthing were utilized, classification accuracy was not reported. In contrast, Dymond & Johnson (2002) compared the accuracy of mapped vegetation using Landsat TM classification and a model utilizing moisture, temperature and solar radiation. Both models had accuracies of <70%. When both techniques were combined, accuracy increased to 83%. 

2
Other papers used multiple sources of data to map habitat for specific species. For example, Thompson et al. (2004) mapped habitat for the stone curlew using data obtained from the UK Ordnance Survey, and habitat requirements from the literature. Stone curlew habitat was identified as areas >1 km from a major road, on arable land with at least 30 ha of unimproved grassland within 1 km, on free draining soils. This model was validated against historic breeding areas, but classification accuracy was not reported. Similarly, McShae et al. (2005) modeled Eld’s deer habitat in Southeast Asia based on its ecological requirements. Large scale, low resolution data on elevation, forest type, canopy closure and human population was combined in GIS. The final model was verified by deer sightings in the modeled habitat areas. Finally, Congleton et al. (1999) modeled shellfish grow-out areas in Maine. These areas (habitat) were determined by combining data on depth, currents, and sediment type into GIS. By querying the GIS based on shellfish grow-out preferences, mariculture sites could be identified. The accuracy of this model would be verified by commercial success, but was not reported in this publication.

Although habitat area was utilized to assess biological response, or to calculate other landscape metrics, most papers did not detail how habitat was characterized or the accuracy of the classification. This is likely due to the ready availability of land use/land cover data, and the fact that the habitat composition was a small portion of the research, so more emphasis was placed on the collection of biological data and the overall analysis. Even when more detail on habitat determination was available, classification accuracy was rarely reported, although some form of ground truthing or verification was usually mentioned. The interesting most part of this project was observing the variety of habitats assessed, and different data sources utilized. The best papers detailed how they built their models or conducted their habitat classification. The worst papers (in terms of being able to tell how habitat was assessed) merely mentioned that habitat was obtained from satellite assessment or existing land use/land cover data.
For environmental monitoring, several lessons emerged. First, although ‘off-the-shelf’ land use/land cover products are available, it is important to know the strengths and weaknesses of each land use category before using them to assess habitat area. Second, habitat area assessment can be improved through use of multiple data sources, and iterative classification. Finally, with knowledge of habitat requirements for species of concern, targeted habitat area assessment can be conducted, allowing assessment of current and potential habitat area.

**Annotated Bibliography:**


Shellfish grow-out habitat was delineated using a GIS to integrate data. Elevation was calculated by combining NOAA depth values supplemented with GPS heights at low tide to create a triangular irregular network. Currents were modeled using a modified Princeton Ocean Model with vertical averaging, producing outputs every 10 minutes through three simulated tidal cycles. Aerial photos at low and flood tide were obtained from USGS and input into GIS. Data layers were input over these maps. Sediment type from USGS was input and delineated to form discrete polygons. Depth and currents were also placed into the GIS. By querying bottom type (clams prefer muddy sand or firm mud), elevation between -1.22 and -1.83 m msl, mean current velocity between 9 and 10 cm/s, and flood tide velocity <20 cm/sec, the location and area of shellfish grow-out habitat can be identified.


This study investigated improving vegetation maps by using biophysical models. Two watersheds in the Canadian Rockies were mapped using Landsat TM, giving an overall accuracy of 68.3%. A model was developed associating species abundance with modeled moisture, temperature and solar radiation. This model had classification accuracy of 67.4% and was also able to identify some communities not detectible using remote sensing. Combining remote sensing data and the biophysical model increased classification accuracy to 83.2%. The authors suggested that species-habitat relationships be used to improve remote sensing products.

This paper assessed habitat suitability for caribou based primarily on satellite data. Landsat MSS imagery from 1975 was used to visualize baseline timber conditions. A 1997 Landsat TM image was used to visualize the current landscape. The 1975 image was transformed to produce ‘brightness’ and ‘greenness’ components. The 1997 image was transformed to produce ‘brightness,’ ‘greenness,’ and ‘wetness’ components. To classify the 1997 image, brightness differences were identified between the 75 and 97 images. Where differences were seen, the area was classified as disturbed. For undisturbed areas, an unsupervised classification was performed based on the three TM components. Forested areas were further classified using brightness, greenness, wetness, and shaded relief (from a DEM). Finally, the disturbed, forested and non forested habitat were merged and combined with aspect and elevation rules to produce the final habitat. The 1997 habitat map was used to backcast onto the 1975 image to produce previous habitats. The classification accuracy of both maps was checked using field verification and aerial photos. Accuracy of the 1997 TM map was 91.8% while the 1975 MSS was 89.6%. Data from these maps were input into a habitat suitability model.


The authors used the blue band and near-infrared bands to map shallow water mangrove areas. Open water was removed looking at near-infrared densities. The ‘mangrove’ areas were divided into zones corresponding to elevation and proximity to water. The accuracy of the mapping improved when dividing into zones and using photo-interpretation for smaller mixed vegetation zones.


Global data sets were used to model habitat areas suitable for Eld’s deer in Southeast Asia. USGS Global land cover provided areas of broadleaf deciduous forest. USGS arc second elevation data was used to exclude forest >400 m in elevation. Canopy cover was from the University of MD’s continuous fields tree cover. Only forests with cover between 15 and 45% were retained. Oak Ridge laboratory’s landScan data was used to exclude areas with >10 people/pixel. All datasets were combined in GIS. A logistic (not GIS) model was also examined.

Mapping accuracy for shallow water reef and seagrass mapping was compared using IKONOS images and imagery from Landsat (TM & MSS) and SPOT (XS & Pan) satellites, and with the airborne Compact Airborne Spectrographic Imager (CASI). Mapping was done at coarse (four habitat classes), medium (8 classes) and fine (13 classes) resolution. All imagery was geometrically corrected and the effects of depth compensated for. For IKONOS, CASI and Landsat TM, texture algorithms were developed using depth invariant bands to increase classification accuracy. For coarse classification, CASI produced the most accurate maps but was also the most expensive. SPOT Pan and Landsat MSS were the least accurate. IKONOS was not significantly different than Landsat TM and SPOT. Landsat TM was the most cost effective. At the finest classification, IKONOS was more sensitive than Landsat TM but still had low accuracy (~50%). In comparison, CASI had classification accuracies of ~81%.


Landsat TM (bands 3,4,5) was used to map mangroves using a 2-stage classification. The first stage classification differentiated between mangroves and non-mangroves. Once mangroves are identified, the second stage classifies types of mangroves. Smaller areas had to be identified using aerial photos. The classification was verified using aerial flights and ground truthing. The accuracy of the mapping was not reported. The data was organized and georeferenced in GIS.


Land cover classes were based on the Nature Conservancy’s National Vegetation Classification Scheme. Data was obtained from 1992-94 Landsat TM imagery. The data was georeferenced in relation to the land use/land cover from the Water Management District. Haze was removed from the images, and the brightness in winter/spring images compensated for. Based on the Water Management District LULC, the ‘natural areas’ were separated from developed areas and agricultural areas. The developed and agricultural areas were then directly classified. The natural areas were classified, then overlaid with a stratified image based on soils and wetlands coverage. These subscenes were then reclassified and named based on other data including ground truthing and aerial photography.
Habitat for the stone curlew was mapped by assembling data on its abiotic habitat requirements. The base maps were obtained from the UK Ordnance Survey (OS). Slope was calculated from a DEM built using a triangular irregular network. Road location was obtained from the OS. Arable land and unimproved grassland were obtained from a land use database. Free draining soils were identified from the national soil map. These layers were combined in GIS. Stone curlew areas were identified as this greater than 1 km from a major road, on arable land with at least 30 ha of unimproved grassland within 1 km, and on free draining soils.


The authors suggested that a framework be devised to allow integration of mapping and surveys done at different scales for different reasons. Use of a common habitat key will allow comparison of different studies. There will always be a need for 'base' maps based on aerial photography and field investigations, but satellite change analysis might be used to target areas to update base maps. Data from different satellites can be used as long as their habitat classification are harmonized and validated with other data (aerial photos, ground truthing). In general, more large scale studies, aggregation of data is useful and allows for some inaccuracy in the base (satellite or GIS) data. For fine-scale (local) studies however, high accuracy and resolution are necessary.