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| **Authors** | **Description** | **Study Area** | **Imagery** | **Correction** | **Pixel/Object** | **Features/Classes** | **Feature Selection** | **Classifier** | **Accuracy** |
| (Basu et al., 2015) | Mapping tree cover in USA | California – 11095 images | 4 band MS 1m aerial (NAIP) | None mentioned maybe NAIP is already corrected | Both – first pp classification then incorp spatial context using CRF | Spectral, textural, veg index (150 in ttl) – 2 classes | Ranking based on separability distance. 22 chosen | Backprop nn on pixels then conditional rabdom field on classifier output + segmented image | 88% for frag forests and 74% for urban areas |
| (Boyden et al., 2007) | Map invasive para grass in wetlands | 64km2 – single image | Quickbird 4 band ms | none | pixel | NDVI and greenness – 7 classes | none | ML | 86% |
| (De Castro et al., 2011) | Map invasive cruciferous weeds in agri fields | 7 fields – at most 7 images | Aerial 4 band 0.25m | Conducted by supplying company | pixel | Band ratios, veg index |  | ML | 63-99% |
| (Ghosh and Joshi, 2014) | Map bamboo in mixed bg of fields and natural veg | 16km2 – assume single image | WV2 – 8band 0.5m | Atcor4 | Both compared – obia best | bands, pc's and GLCM texture (32 in ttl) - 7 classes | BE/RFE down to 10 | SVM on OBIA feats with all 32 feats | PA 94% |
| (Johansen et al., 2007) | Map forest structural classes | 50km2 0 single image | Quickbird | TOA | Obia (eCognition) | NDVI, GLCM – semivariograms for win size | Z test on individual features | ? eCognition | 78.95% |
| (Kollár et al., 2013) | Veg community in riparian. 3x for 3 years | 2.5km2 study area – single image | Aerial <1.25 m/pixel | “Manual” | OBIA | Spectral, textural – 5 classes. semivariograms for win size | Jeffries-Matushita distance on class pairs (some separability measure) ranking | eCognition | 84-96% |
| (Mehner et al., 2004) | Map veg types, variable and complex veg composition | 229km2 – single image (winter and summer) | Ikonos | TOA | pixel | NDVI only? - 15 class | ? | ML | 80.28% |
| (Mirik and Ansley, 2012) | Map invasive tree in rangeland | 800km2 | Aerial 4 band 1m | ? from NAIP | ? | ? | eCognition | eCognition | 94% |
| (Mustafa and Habeeb, 2014) | Map tree species in agri and natural land | 489.63km2 – 14 scenes | WV2 – 8band, 0.5m | By the supplier DIgitalGlobe, nothing else mentioned | OBIA | shadow index, GLCM texture, NDVI veg index – 15 tree specie classes | ? | “neural network” | 76% |
| (Ouyang et al., 2011) | Mapping saltmatsh plants against herbaceous cover | Approx. 400km2 – single im | Quickbird 4 band MS 0.61m/pixel | Supplier radiometric correction | OBIA | 3 class | eCognition + some separability measure | Hierarchical + membership fn in eCognition | 87% |
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Table for GEF5 ground truth discussion

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| **Authors** | **Description** | **Study Area** | **Imagery** | **Features/Classes** | **Imagery Date** | **Ground Truth Date** | **Ground Truth Details** |
| (Basu et al., 2015) | Mapping tree cover in USA | California – 11095 images | 4 band MS 1m aerial (NAIP) | Spectral, textural, veg index (150 in ttl) – 2 classes |  |  |  |
| (Boyden et al., 2007) | Map invasive para grass in wetlands | 64km2 – single image | Quickbird 4 band ms | NDVI and greenness – 7 classes | July 2004 | within a month of image capture | ?? using helicopter survey, homogenous areas, no details on size or num of sites |
| (De Castro et al., 2011) | Map invasive cruciferous weeds in agri fields | 7 fields – at most 7 images | Aerial 4 band 0.25m | Band ratios, veg index | April 2007 | a random ground sampling procedure was carried out at the same time that the aerial images were taken | 7 fields of known crops from which “320 training points and 450 ground truth points of each plant type” |
| (Ghosh and Joshi, 2014) | Map bamboo in mixed bg of fields and natural veg | 16km2 – assume single image | WV2 – 8band 0.5m | bands, pc's and GLCM texture (32 in ttl) - 7 classes | October 12, 2010 | s. The reference data (2011) was collected after one year of image acquisition (2010) but in the same month of October. This time gap can introduce some error due to dynamic land use practices observed in the study area. Care was taken to select samples from areas where no changes were observed for 2–3 years period to reduce any kind of error arising from this time gap. S | Positions of dominant LULC were recorded using GPS and corresponding polygons were defined on the maps. Training polygons were selected from all over the study area. However, we followed a random sampling without replace- ment among the polygons to select 200 sample points for each LULC class  In order to find the accuracy of the classified maps, a separate set of random reference points (around 60 for each class) were used |
| (Johansen et al., 2007) | Map forest structural classes | 50km2 0 single image | Quickbird | NDVI, GLCM – semivariograms for win size | 6 June 2005 | The TEM mapping used in this research was conducted in  2003 and 2004 | From the remaining validation data, a stratified random sample of 200 plots (pixels) was selected from both the GIS-based TEM classification and the four classified images |
| (Kollár et al., 2013) | Veg community in riparian. 3x for 3 years | 2.5km2 study area – single image | Aerial <1.25 m/pixel | Spectral, textural – 5 classes. semivariograms for win size | various | Therefore, botanical maps have been gathered, where the field survey was based on the framework of the National Biodiversity Monitoring System  Nevertheless, it has to be mentioned, that the ancillary data have been acquired in different time from the image dataset, and this brings some additional uncertainties into the image interpretation procedure |  |
| (Mehner et al., 2004) | Map veg types, variable and complex veg composition | 229km2 – single image (winter and summer) | Ikonos | NDVI only? - 15 class | February 2001 and September 2002) | sufficient ground data and a copy of the original Phase 1 Habitat Survey of the study area for comparative purposes | Ground reference data (vegetation type) were recorded during three survey campaigns, in agreement with the time of the image recording, March 2002 (one year later than acquisition, but at the same time of year)  Sample points, consisting of a 3D coordinate and the vegetation type attribute, were recorded at least every 2 m for nine different geographica transect areas (100 m × 50 m)  = 9\*(100+50)/2 ~ 700 |
| (Mirik and Ansley, 2012) | Map invasive tree in rangeland | 800km2 | Aerial 4 band 1m | ? | The 1-m image consisted of a composite of aerial images obtained by the NRCS during 26–27  September 2008 | Land cover training classes used in Feature Analyst were created by manually digitizing 50 polygons of each land cover type at identified locations on the images and on the ground. | For the accuracy assessment, 500 ground verification (i.e., “ground-truthing”) points were randomly generated on the images using the “create random points” function in ArcGIS. The verification points were then identified on the ground  At each ground-truthing location, land cover classes within a 1-m radius for the 1-m image and |
| (Mustafa and Habeeb, 2014) | Map tree species in agri and natural land | 489.63km2 – 14 scenes | WV2 – 8band, 0.5m | shadow index, GLCM texture, NDVI veg index – 15 tree specie classes | Fourteen cloud free WV2 scenes were acquired to cover the study area from 11 June to 10 July 2011.  Table | This data include the tree species name and their location (longitude, latitude, and altitude). A fieldwork carried out between June 19- July 20, 2013 | Prior to the fieldwork, false color composite images WV2 were brought to the field to directly locate and delineate tree species on the images for later use of determining training and validation (Table 1). A. In total 931 training points and 474 validation points |
| (Ouyang et al., 2011) | Mapping saltmatsh plants against herbaceous cover | Approx. 400km2 – single im | Quickbird 4 band MS 0.61m/pixel | 3 class | 10 May 2006 | The reference data used for classification were collected at random  between April and November in 2006 | When the field investigation was performed, a portable Global Position System (GPS) was used to locate the target ground objects such as plant patches,mudflats, pools and tidal creeks. To help localization, geo-referenced color maps of QuickBird images were printed beforehand and then taken with the investigators for field checks. Some  ecause our study area is relatively small and the three targeted classes are readily distinguished visually during early summer or mid-autumn, a subset that occupies half of the area of the imagewas interpreted manually to stand for actual classes and the classification evaluation was based on the interpreted subset  [exact number of plots not mentioned] |
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Similar to above but on biomass estimation:

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| **Authors** | **Description** | **Study Area** | **Data** | **Features/Classes** | **Imagery Date** | **Ground Truth Date** | **Ground Truth Details** |
| (Singh et al., 2014) | in estimating the different forest types, their stand structure, and biomass dynamics in the context of an oil palm–tropical forest landscape |  | SPOT five bands, including one panchromatic band with 5 m spatial | Fourier-based textural ordination (FOTO) 2.3.1.  Linear regression |  |  | This study made use of the 193 vegetation plots designated previously as part of the  SAFE project. These plots, which were established using the RAINFOR protocols (see RAINFOR 2012 for more details), measure 25 m × 25 m and are distributed across all different land-use types including primary forest, various stages of degradation and logging, and OP plantations (SAFE 2011).  Riparian: Three spatially distributed riparian zones were selected per land-use type. In each of the riparian zones, an additional six plots were set up 3–5 m from the river, with the 50 m side running parallel to the river. Thus, a total of 18 plots were created for each land- use type |
| (Proisy et al., 2007) | .We assessed the  potential of Fourier-based textural ordination (FOTO) to estimate mangrove forest biomass from very high resolution (VHR) IKONOS image | The study sites, named Kaw (4° 45′ N, 52°5′ W) and  Sinnamary (5°26′ N, 53°02′ W) measure 3 km×12 km and 4 km×11 km, respectivelyThe study sites, named Kaw (4° 45′ N, 52°5′ W) and  Sinnamary (5°26′ N, 53°02′ W) measure 3 km×12 km and 4 km×11 km, respectively |  | Multiple lin regression | 2001/ 2003 | Field measure- ments were carried out from 2002 to 2005.  The problems of linking ground and remotely sensed data are  numerous. The timing of ground data collection rarely corre- sponds with that for the image acquisition. In our case, forest ground truth observations were conducted from 2002 to 2005 (Table 1) and the IKONOS images were acquired in 2001 and 2003. Although | Data were collected within areas ranging from 200 m2 for young stages with a high density of trees to 1 ha for mature and decaying lower density areas. The final forest dataset is composed of 16 and 10 plots for Kaw and Sinnamary, respectively  They use a growth model to account for year differences betw image and gt |
| (Bastin et al., 2014) | Also FOTO but across large area | 400km2 |  |  | GeoEye Jan 2012 and Quickbird July 2012 | ~Same time as imagery 2011 and 2012 | 26 plots of 1ha each – randomly located  Multiple windows within each plot are used as far as I can tell to give something like (100/25^2)\*26 = 16\*26 = 416 data points! |
| (Maack et al., 2015) |  |  | Pléiades and WorldView-2 | Random forest regression with sophisticated features including derived plant height from stereo ims and lidar DTM |  | Site1: mid-August and the beginning of September 2013  Site2: January and March 2013 | n=98 for Chile, n=101 for Germany, see  The inventory design of the field plots followed an approach of concentric rings with radii of 2 m, 3 m, 6 m and 12 m. In each of these rings trees with a Diameter at Breast Height (DBH) exceeding 7 cm, 10 cm, 15 cm and 30 cm, respectively were measured |
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