Monitoring tree island condition in the ENP and WCA3B using bi-seasonal WorldView2 data and G-LiHT LiDAR

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Introduction

Tree islands are essential and intricate components of the Everglades ecosystem. Plant communities in tree islands are arranged along hydrologic and nutrient gradients. Compartmentalization of the Everglades and modifications of hydrologic regimes have caused changes to the vegetation structure and composition of tree islands, and even the loss of tree islands. Therefore, as a result of the implementation of the Comprehensive Everglades Restoration Plan (CERP), further impact to tree island vegetation is expected.

To understand how the structure of plant communities in tree islands respond to hydrologic change, accurate mapping techniques are needed that can detect clearly defined plant communities at a resolution that represent the scales at which change occurs along the hydrologic and nutrient gradients. When using remote sensing methods to monitor vegetation change, spectral signature extension between islands is a challenge, because vegetation structure and composition of tree islands vary throughout the Everglades landscape.

Objective: Develop a method to delineate plant communities in tree islands that allows for detection of fine scale change in vegetation communities

Study Sites

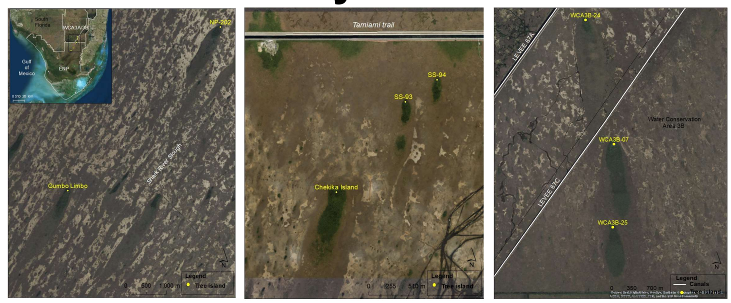


Figure 1. Gumbo Limbo (GL) and NP-202 tree islands in ENP (left). Chekika (Ch), SS-93 and SS-94 tree islands in ENP (center). WCA3B-24, WCA3B-207 and WCA3B-25 tree islands in WCA3B (right)

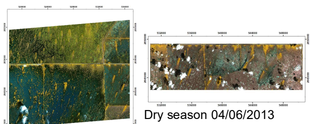
Methods

1. Establishment of classification schema

Class Code	Vegetation Class Description
blE__s	Broadleaf emergent mixed with shrubs
blFNy	Broadleaf floating mixed with nymphaea
gM	Graminoid marsh, includes short graminoids and *Typha*
gM_Clad/gMCl	*Cladium* dominated marsh
gM_sp/ gM__S	Sparse graminoid marsh
gMCl__S	Sparse *Cladium* dominated marsh
gM_Typha/ gMTy	*Typha* dominated marsh
gM_blE_s	Mixed shrub, graminoid, and emergent broadleaf, including ferns
hM	Herbaceous marsh
s_h	Scrub herbc. marsh dominated by *Cephalanthus*, ferns, *Sagittaria*
s_hM	Herbaceous marsh mixed with shrubs with heights < 4m
sB	Bayhead swamp, dominated by woody species with heights <4 m
sSa	*Salix caroliniana* shrub
tB	Bayhead forest, dominated by woody species with heights > 4 m
tH	Hardwood hammock, species that do not tolerate inundation
tB_Shin	Bayhead forest, dominated by Schinus with heights > 4m

2. Acquisition of satellite data

Worldview 2 image selection
Geometric & atmospheric correction

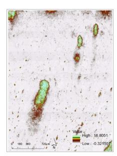


Dry season 04/06/2013

Wet season 10/20/2012

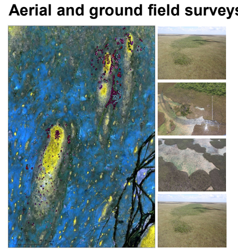
LiDAR pre-processing

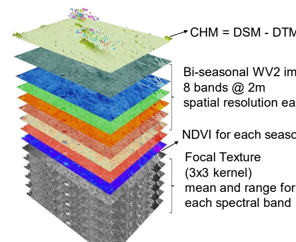
Canopy Height Model (CHM) = Digital Surface Model (DSM) – Digital Terrain Model (DTM)

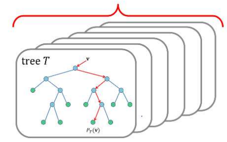


3. Model-Based Classifier Evaluation and Selection

Training point digitization. Aerial and ground field surveys → **Spectral value extracted from 51 layer data cube** → **Recursive partitioning algorithm (randomForest) in R**



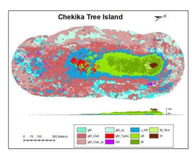




model name	variable set
wetSeason	8 refl. Bands, 16 text. and NDVI
drySeason	8 refl. Bands, 16 text. And NDVI
biSeason	16 refl. Bands, 32 text. and 2 NDVI
biSeasonLiDAR	16 refl. Bands, 32 text., 2 NDVI, CHM

Select classifier with highest overall accuracy (OA)

← **Classify full data set** ←

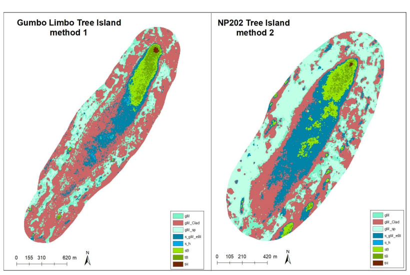


Visual inspection of classified map

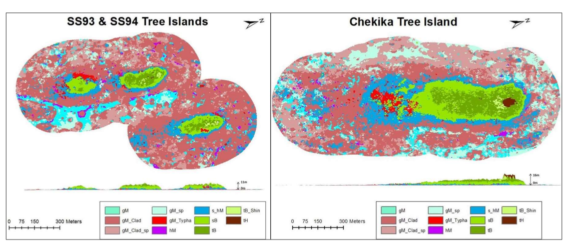
4. Design-Based Post-classification Accuracy Assessment

Stratified random sampling design: number of samples/class determined by multinomial probability distribution. Goal was to test for a map accuracy of 95% with a 95% confidence.
Confusion matrices constructed from reference and predicted data, include: overall accuracy, class specific accuracies and class specific omission and commission errors extracted from the confusion matrices.

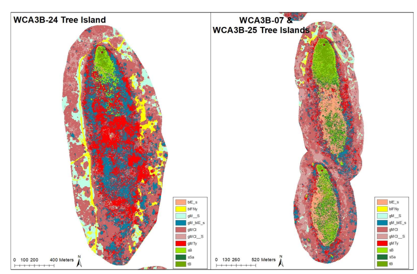
Results



Using a classifier trained only on GL: OA of 95.1 ± 2.2% (estimated standard error (ESE)) for GL and 92.7 ± 2.5% for NP202. OA of both islands increased to 97.3 ± 0.97% and 94.9 ± 1.6% for GL and NP202 respectively when training sample points on NP202 were included.



Models that used bi-seasonal data (bi-seasonal: 91% and bi-seasonal plus LiDAR: 92%) presented higher accuracy.
LiDAR data improves the classification of shrubs and trees, with a decrease of 3% in the omission error for shrub classes and 6% for tree classes.
OA of 93.3 ± 2.2%
gM_Clad was the most abundant class, covering approximately 40%



Models that used bi-seasonal data (78% and 84%) presented highest accuracy.
OA of 97.1% ± 2.2%

Conclusions

- Differentiation between tree islands and their tails and marsh communities is very reliable and given the spatial resolution of 2 m for WV2 data, expansion or contraction of tree islands could be detected as they occur.
- Spectral signature extension across islands was limited due to class variability between islands. Signatures were successfully extended across islands with similar structure and class compositions.
- Hardwood hammocks on tree islands are relatively small areas in the heads of the islands and are therefore limited to a small subset of species of the regional pool on any given island. In order to reliably detect hardwood hammock it seems that a larger training sample than can be provided by a single island is necessary for consistent mapping at high accuracy.
- Differentiating short shrub / herbaceous vegetation mixes poses a challenge for their rare occurrences across the mapped tree islands.

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