Quantification of Sawgrass Biomass in the Coastal Everglades

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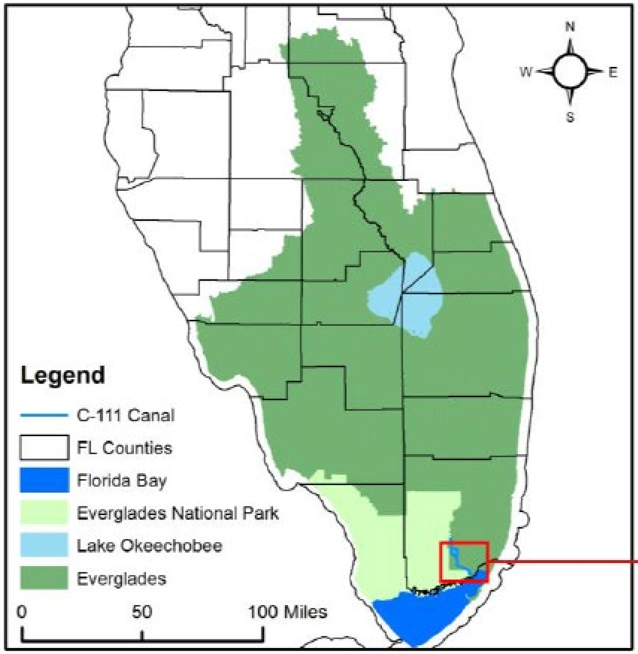
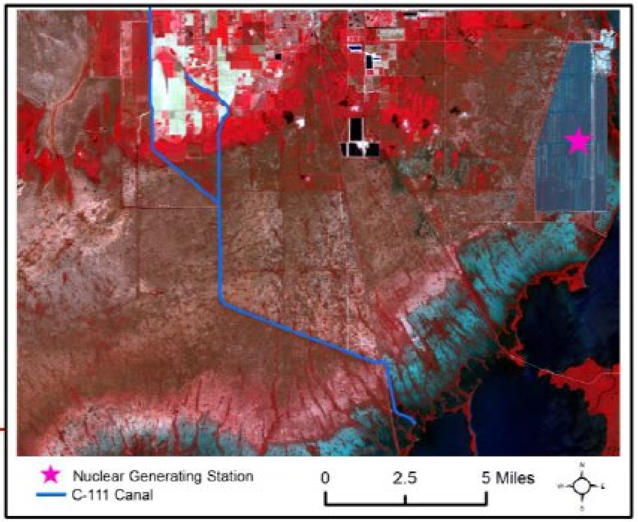
Introduction

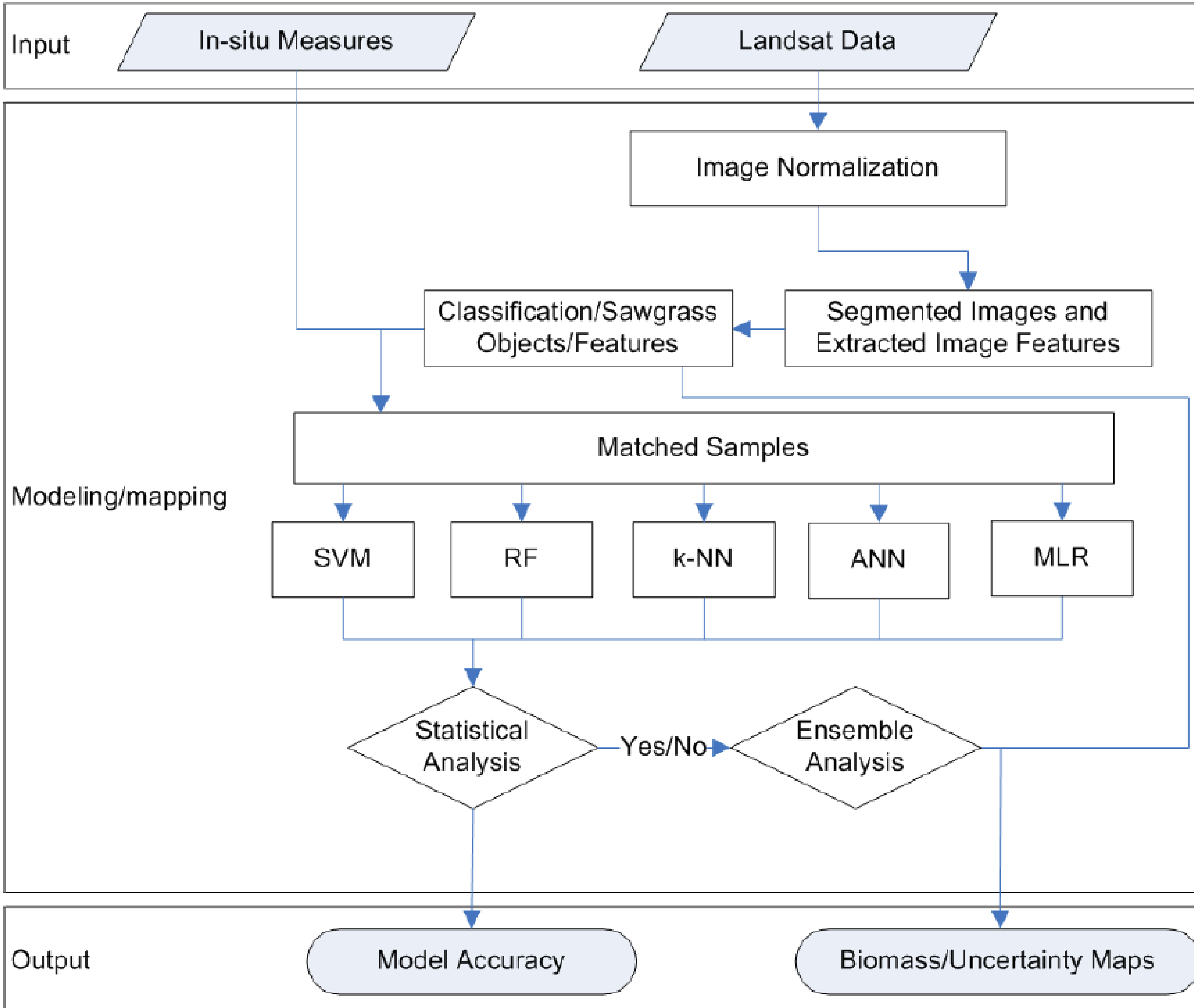
- Traditional biomass data collection
  - Labor-intensive, time-consuming, and limited plots/area
- Everglades
  - Sawgrass: cover 70% of the Florida Everglades
  - No remote sensing efforts have been made
- Objective
  - To develop remote sensing models for sawgrass biomass estimation

Study site and data





- Study site: Turkey Point Nuclear Generating Station of FPL
- Data
    - Field-based sawgrass quarterly biomass data during 2011-2014
    - Landsat imagery for model development
        - A week window of the field data: Nov. 2011, Nov. 2013, and May 2014
    - Landsat imagery for mapping
        - April 2014 and Nov. 2014
        - May 2016 and Oct. 2016


Input
In-situ Measures
Landsat Data
Image Normalization
Segmented Images and Extracted Image Features
Classification/Sawgrass Objects/Features
Matched Samples
Modeling/mapping
SVM
RF
k-NN
ANN
MLR
Statistical Analysis
Yes/No
Ensemble Analysis
Output
Model Accuracy
Biomass/Uncertainty Maps

Results: Model performance

Table 1 Model performance for live and total biomass estimation based on 4-fold cross validation.

Live Biomass Modeling					
Pixel-based					
Statistical Metrics	ANN	SVM	RF	k-NN	MLR
CC (*r*)	0.92	0.87	0.84	0.85	0.58
MAE (g/m^2)	17.21	22.15	22.93	21.28	33.82
RMSE (g/m^2)	20.79	25.87	29.97	29.17	44.07
Object-based					
CC (*r*)	0.92	0.91	0.86	0.77	0.47
MAE (g/m^2)	15.74	16.32	18.54	24.38	36.10
RMSE (g/m^2)	20.35	21.31	27.35	38.87	49.56
Total Biomass Modeling					
Pixel-based					
CC (*r*)	0.91	0.75	0.72	0.57	0.47
MAE (g/m^2)	35.96	51.2	45.85	46.23	71.23
RMSE (g/m^2)	44.52	75.46	72.88	89.46	104.19
Object-based					
CC (*r*)	0.94	0.87	0.75	0.53	0.44
MAE (g/m^2)	31.55	41.53	42.78	52.29	70.57
RMSE (g/m^2)	36.27	56.65	71.93	92.27	109.28

CC: Correlation Coefficient (*r*); MAE: Mean Absolute Error; RMSE: Root Mean Squared Error.
MLR: Multiple Linear Regression; SVM: Support Vector Machine; RF: Random Forest; k-NN: k-Nearest Neighbor; ANN: Artificial Neural Network.

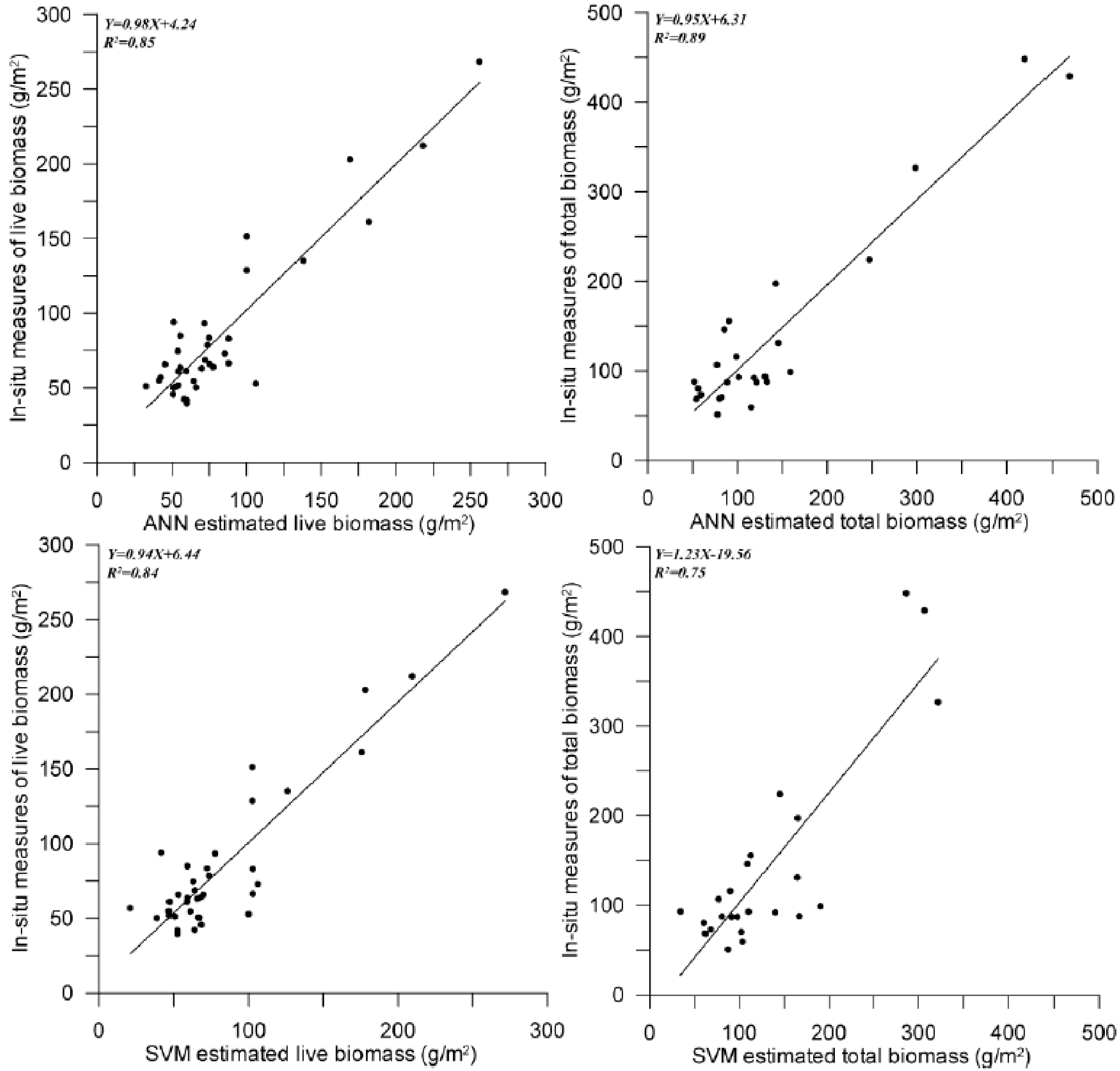


Figure 4 Scatter plots and regressions of in-situ measures, ANN and SVM estimations of live and total sawgrass biomass.

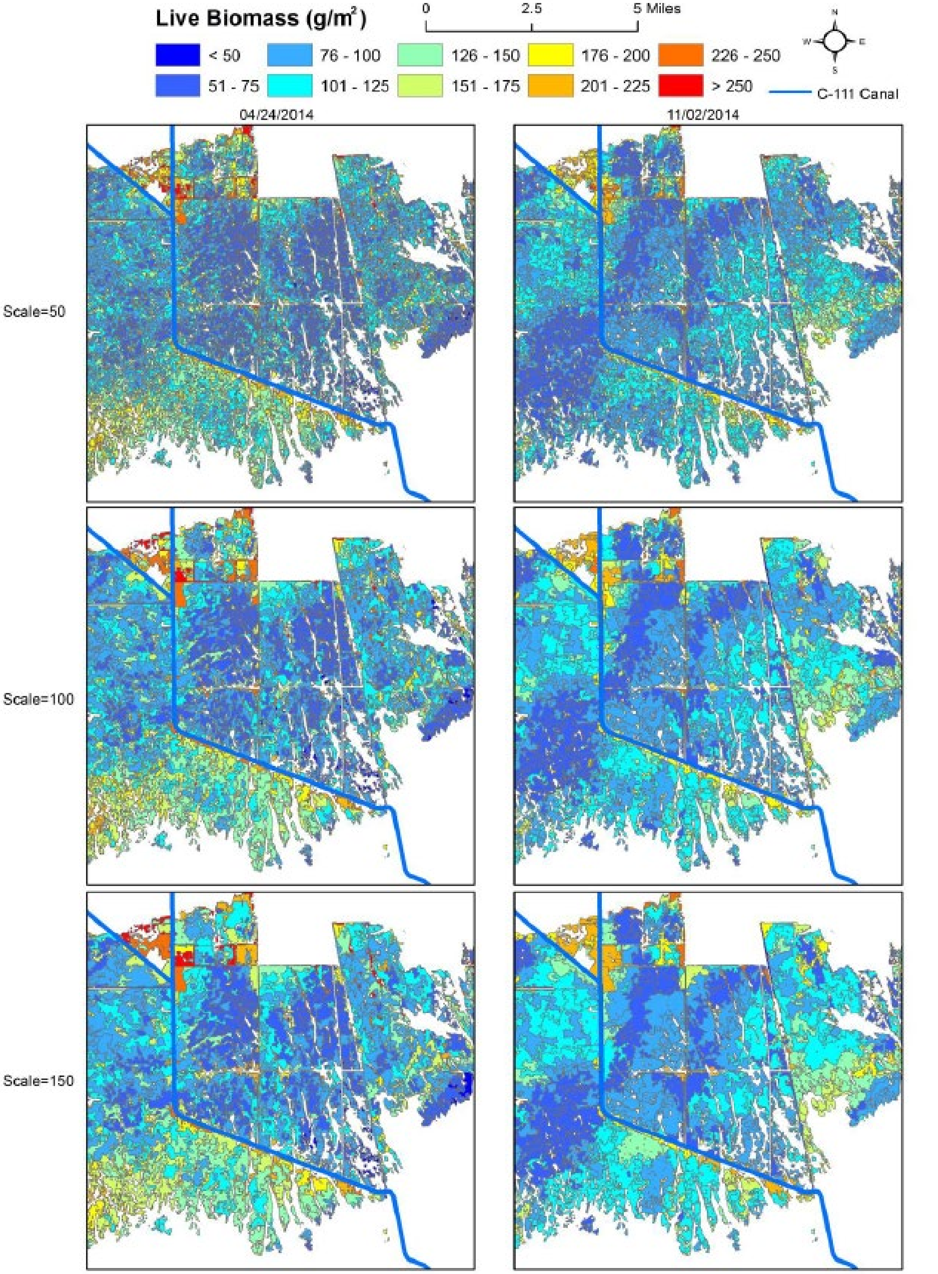


Figure 5 Live biomass maps for two harvest seasons in 2014 at scales of 50, 100, and 150, respectiv from an ensemble analysis of ANN and SVM estimations.

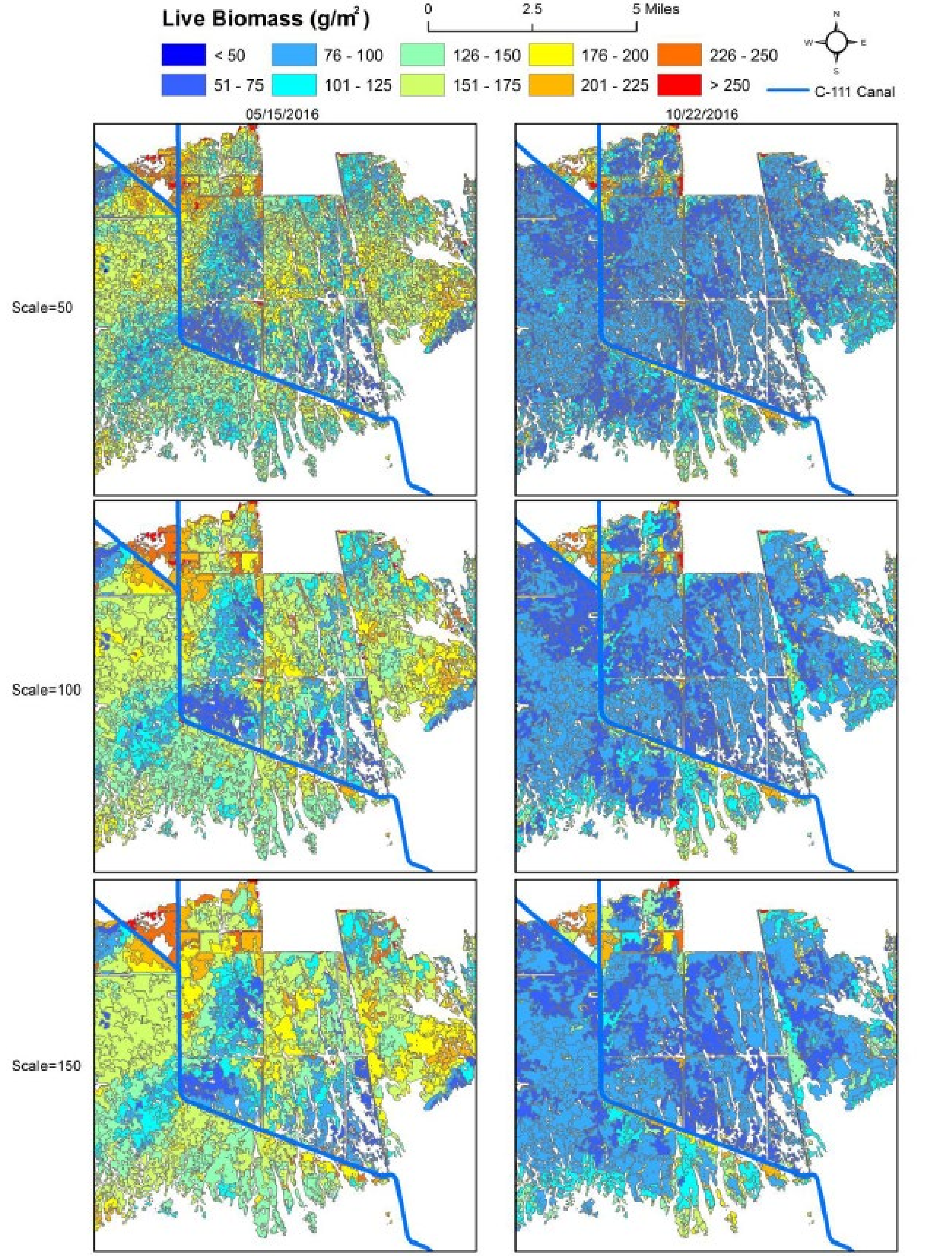


Figure 6 Live biomass maps for two harvest seasons in 2016 at scales of 50, 100, and 150, respectivel from an ensemble analysis of ANN and SVM estimations.

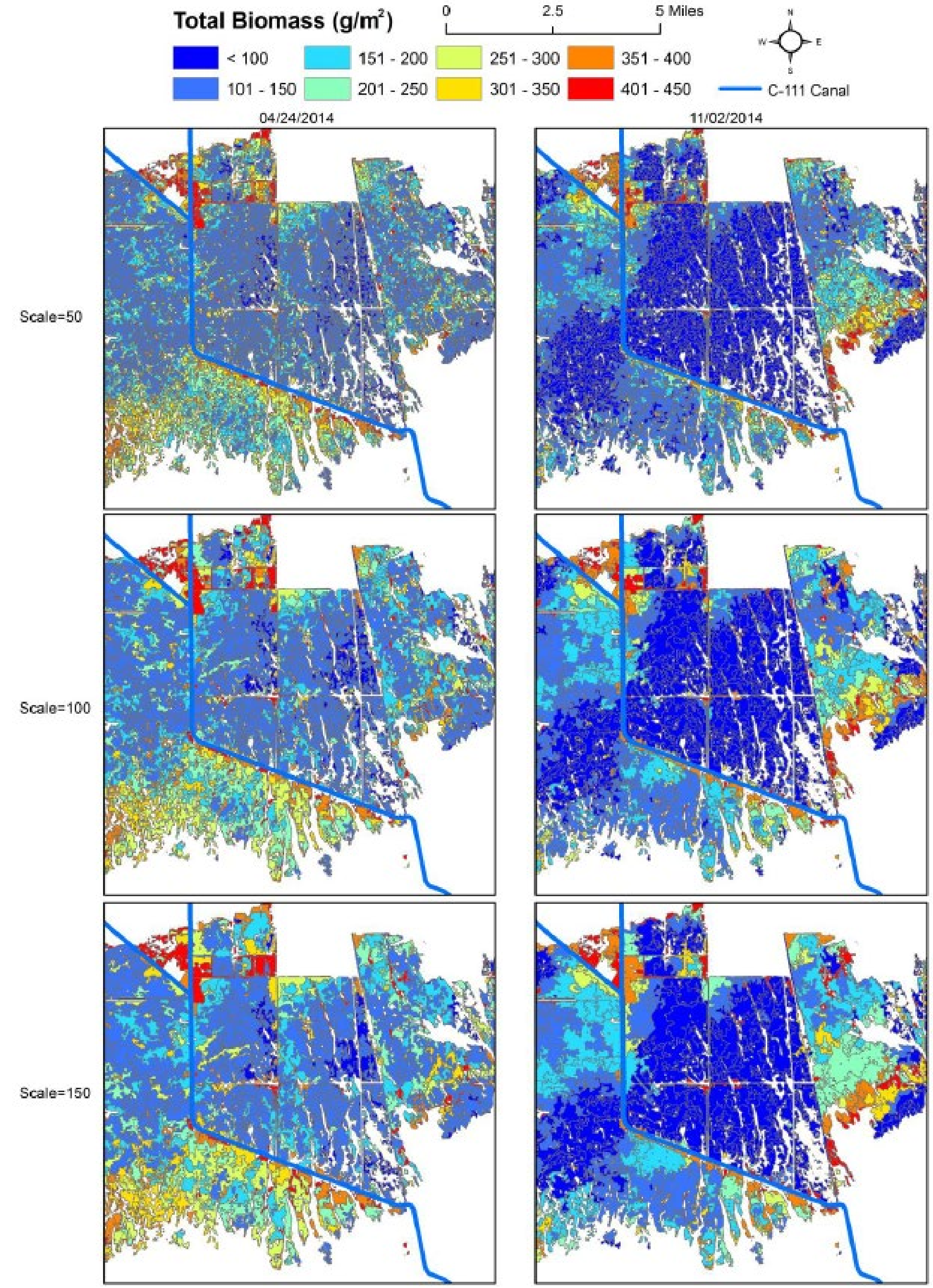


Figure 7 Total biomass maps for two harvest seasons in 2014 at scales of 50, 100, and 150, respe
from ANN estimation

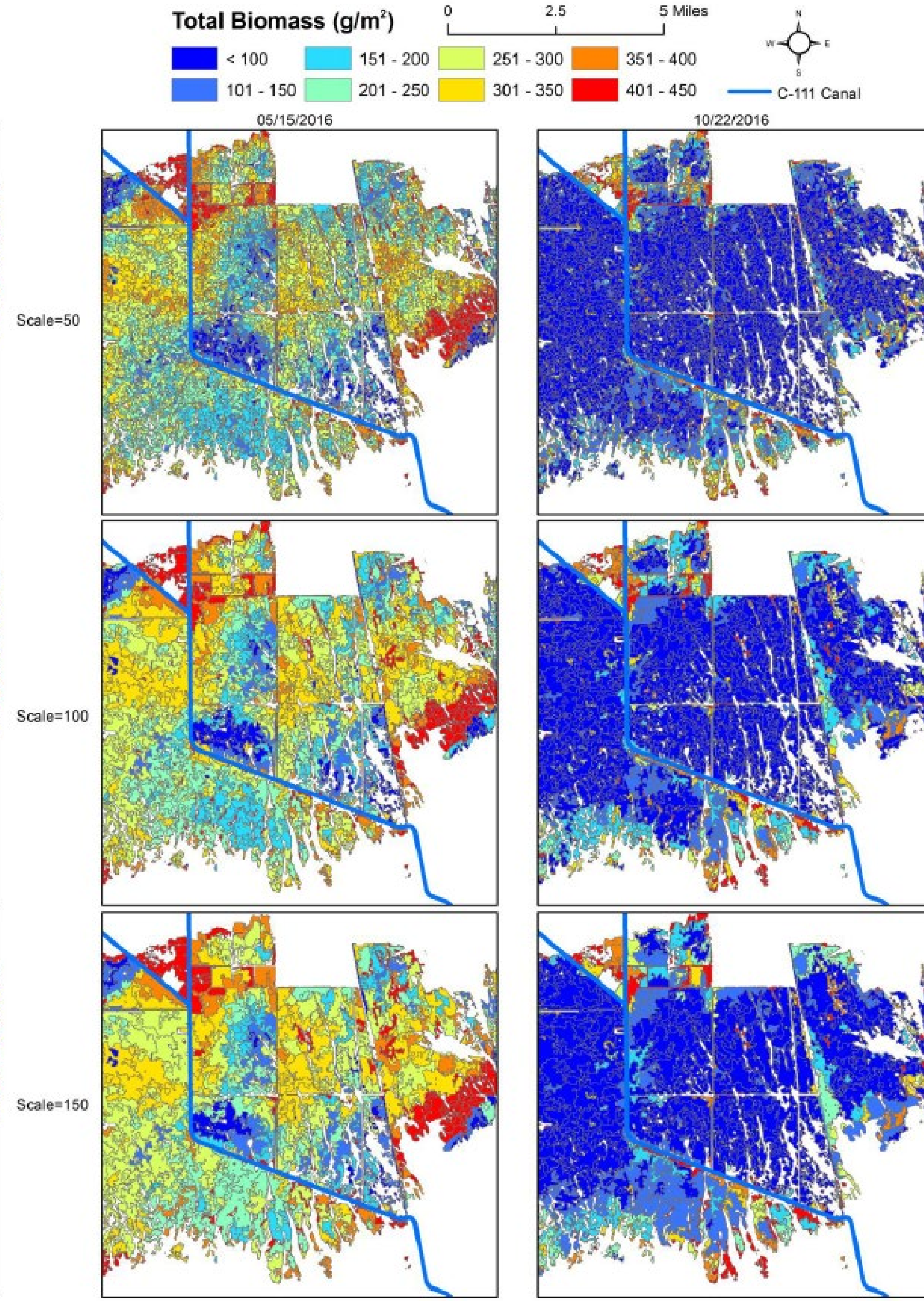


Figure 8 Total biomass maps for two harvest seasons in 2016 at scales of 50, 100, and 150, resp
from ANN estimation

- Uncertainty map for live biomass estimation using ANN and SVM

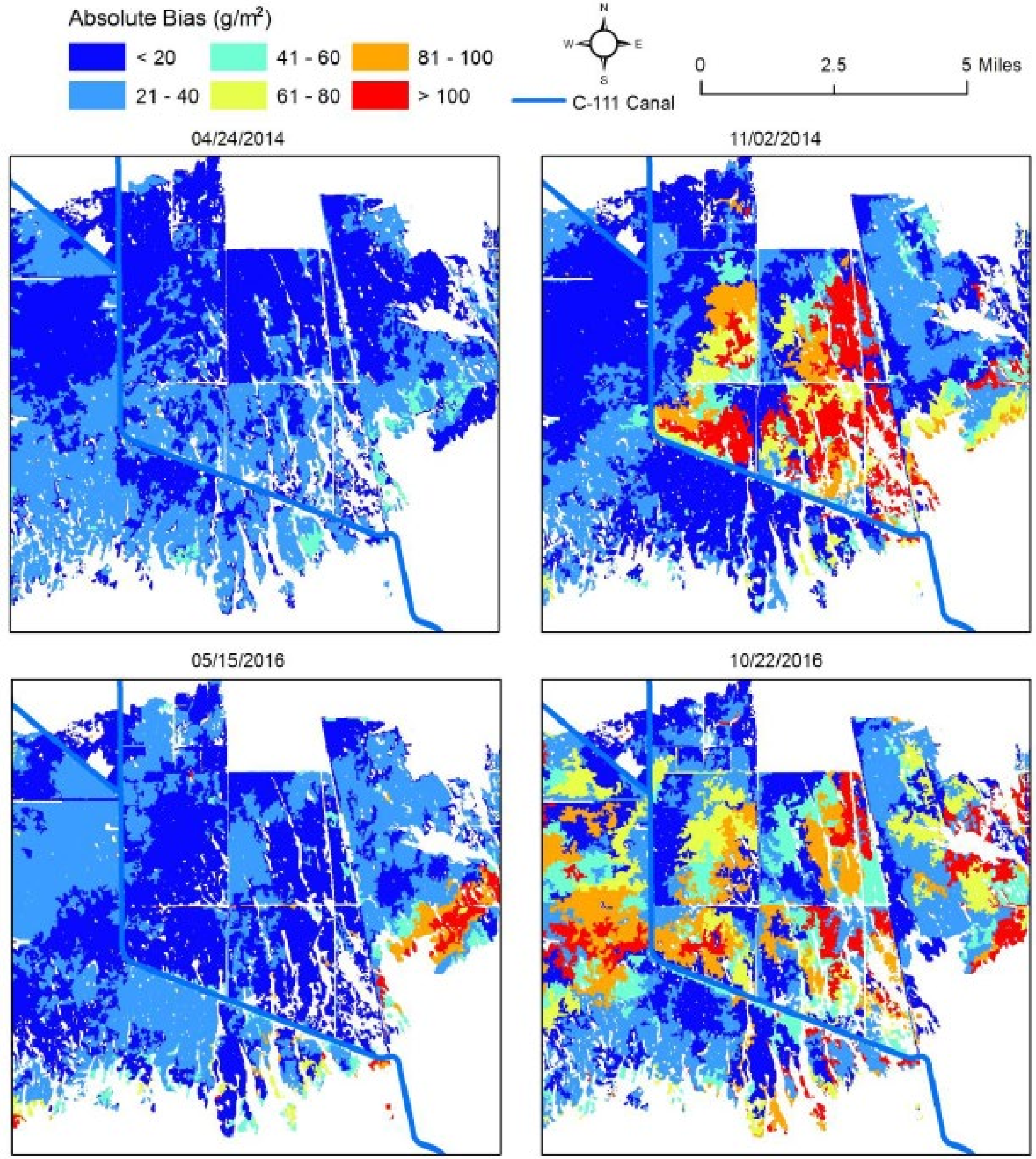


Figure 9 Uncertainty maps for live sawgrass biomass estimation derived from ANN and SVM models for two harvest seasons in 2014 and 2016, respectively.

Summary and Conclusions

- Developed object-based ensemble approach for biomass modeling
- Non-parametric modeling is better than parametric modeling
- Object-based modeling is a good alternative to the pixel-based modeling
- Ensemble modeling is promising in biomass estimation

The End

Zhang, C., S. Denka, H. Cooper, and D. R. Mishra, 2018. Quantification of Sawgrass Marsh Aboveground Biomass in the Coastal Everglades Using Object-Based Ensemble Analysis and Landsat Data. *Remote Sensing of Environment*, 204, 366-379.

Thanks for your attention!

Questions or comments?