

THE IMPORTANCE OF SEASONAL TEXTURAL FEATURES FOR OBJECT-BASED CLASSIFICATION OF WETLANDS: NEW YORK STATE CASE STUDY

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ABSTRACT: Seasonal variations result in hydrophytes and undrained hydric soil changes in wetland areas, which lead to a dynamic environment that makes wetland classification challenging. This study aims to explore the applicability of multi-seasonal Gray-Level Co-Occurrence Matrix (GLCM) texture-derived features for object-based wetland classification over large-extent for the first time. We attempted to enhance the performance of the random forest classifier by incorporating multi-source remote sensing data, including Sentinel-2, Sentinel-1, Alos-Palsar, and topographic features. A total of 47 features were extracted from multi-source remote sensing data. In this context, we assessed the applicability of multi- versus mono-seasonal derived features for the wetland's classes with low within-class separability. We investigated the mean decrease in the Gini impurity index for each GLCM feature. We observed that including GLCM features enhanced overall accuracy by 7.38% when using imagery from one season and 4.21% for multi-season imagery. The multi-season scenario that included GLCM measures (93.49%) attained the highest overall accuracy. For this scenario, the means of decrease in Gini impurity index suggested that Soil Adjusted Vegetation Index, Modified Normalized Difference Water Index, slope, correlation in summer (GLCM feature), and Sentinel-1 VH are the most important features in increasing the random forest's classifier performance. In looking at the GLCM features, the separability analysis suggested that Entropy, Sum of Average, and Variance calculated from the summer imagery improve the classifier's performance while other textural features from spring imagery better contributed to classifier accuracy.

1. INTRODUCTION

Wetlands are valued for their ability to recharge groundwater aquifers, support biodiversity, sequester carbon, and protect shorelines (Omernik & Griffith, 2014). However, human activities are degrading fragile wetland ecosystems. The high rate of wetlands loss during the 20th and 21st centuries has resulted in a global wetland decrease of 64–71% since 1900 (Cowardin et al., 2013). The decline of inland wetlands is estimated to be higher than coastal wetlands. With an estimated extent of 249 million hectares, North American wetlands currently account for one-third of the world's wetlands (*National Land Cover Database (NLCD) 2016 / Multi-Resolution Land Characteristics (MRLC) Consortium*, n.d.). There is a clear need to monitor these regions; however, this environment's complexity and dynamic nature make characterization difficult.

In the study of (Muñoz et al., 2019), object-based random forest classifier performance was assessed for delineating emergent wetlands in three sites in New York, Alabama, and Georgia.

They integrated Landsat imagery with Lidar-derived DEM to enhance the classification of emergent wetland. They reported an improvement for delineating wetlands compared to the 2016 National Land Cover Database.

Studies in the literature attempted to assess the influence of multi-source and multi-temporal imagery for wetland mapping. For instance, (Corcoran et al., 2013) demonstrated that the most accurate random forest model for wetland classification was obtained when including Landsat 5 TM,

topographic, PALSAR, and soils data. The pixel-level classification was conducted on the regional extent in Minnesota.

This study aims to develop an object-based classification workflow with the specific purpose of increasing the inter-class separability of wetland classes over a large extent. We assessed different scenarios for improving the classification accuracy by incorporating a different combination of multi-source and multi-seasonal input data over a large extent. In particular, the study was developed by attempting to address three main questions; 1) What textural features in what season are better able to delineate different wetland types; 2) what are the key features that contribute to increasing the classification accuracy; 3) how the classifier performance changes when including multi-seasonal textural imagery. We employ the trained model in each ecoregion of New York State to obtain a regional wetland map.

2. METHOD

2.1. Study Area

This study focuses on New York State (NYS), the largest state in the northeast United States, stretching from Lake Erie to the Atlantic Ocean with over 141,000 km². Falling within the Appalachian Mountains, NYS has distinct geologies such as the Adirondacks and the Catskills, with high rainfall supporting lakes and wetlands of varying sizes across the state. Eastern temperate and northern hardwoods cover the bulk of forested areas in the state. NYS is now termed Level III of a hierarchical scheme; NYS is divided into nine ecoregions (Omernik & Griffith, 2014) (Figure 1).

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Due to variation in climate and vegetation structure in each ecoregion, we defined several sites (with an approximate area of 120 km²) to train the model. The total number of sites used was fourteen.

2.2. Classification System

We will follow National Land Cover Dataset (NLCD) defined classes for categorizing upland classes, and National Wetland Inventory (NWI) maps for classifying wetland areas to ensure the greatest utility. Since the focus of the study is monitoring wetlands, we grouped three different classes of forested uplands and three classes of developed areas in two single categories. NWI follows the Cowardin classification system to impose geometrical boundaries on the deep water and wetland habitats (Cowardin et al., 2013).

2.3. Reference Data

We acquired the reference data following the Cowardin system with two different wetland classes—forested/scrub-shrub and emergent wetland—included in the reference data for the study site. We used the latest version of the NLCD to define detailed reference data for the upland classes. The reference data was verified through visual inspection using the latest high-resolution NAIP imagery (we used NAIP imagery acquired in the summer from 2016 to 2019). We used 30% of reference data for accuracy assessment and the rest for training the classifier.

2.4. Derived Features From Multi-Source Imagery

We calculated soil, vegetation, and water indices from the Sentinel-2 imagery to support the classification (Adeli et al., 2021). The span, total power, co-polarize, and cross-polarized ratio of Sentinel-1 and Alos-Palsar are generated. We also include the topographic derivative features of slope and aspect from SRTM DEM. The input features are shown in Table 1.

Sentinel-1	∂_{VV} , Vertically transmitted, vertically received SAR backscattering coefficient ∂_{VH} , Vertically transmitted, Horizontally received SAR backscattering coefficient $\frac{ S_{VV} ^2}{ S_{VH} ^2}$, $ S_{VV} ^2 - S_{VH} ^2$, $ S_{VV} ^2 + S_{VH} ^2$ Span or total scattering power
ALOS-PALSAR	∂_{HH} , Horizontally transmitted, horizontally received SAR backscattering coefficient. ∂_{HV} , Horizontally transmitted, vertically received SAR backscattering coefficient. $ S_{HH} ^2 + S_{HV} ^2$, $ S_{HH} ^2 - S_{HV} ^2$, $\frac{ S_{HH} ^2}{ S_{HV} ^2}$ Span or total scattering power
Sentinel-2	B2 (Blue), B3 (Green), B4 (Red), B8 (NIR), B11 (SWIR), normalized difference vegetation index (NDVI), Enhanced Vegetation Index (EVI), Green Soil-Adjusted Vegetation Index (GSAVI), Soil-Adjusted Vegetation Index (SAVI), Normalize Difference Build-up Index (NDBI), Normalized Difference Water Index (NDWI), Modified Normalized Difference Water Index (MNDWI), Green and Red ratio Vegetation Index (GRVI), Green Normalized Difference Vegetation Index (GNDVI)

DEM (SRTM)	Slope, Aspect
Textural features	Angular Second Moment (ASM), Contrast, Correlation, Entropy, Variance, Inverse Difference Moment (IDM), Sum Average (SAVG)

Table 1. The input features extracted from Sentinel-1, Alos-Palsar, Sentinel-2 and DEM. The textural features extracted from arithmetic ratio of Sentinel-2 imagery.

The textural features were produced using the mathematical ratio of Sentinel-2 bands.

2.5. Textural Analysis

We computed the mono and multi-seasonal GLCM textural features of the study site. GLCM measures the frequency of pair of pixels' digital numbers in a specific and pre-defined direction (Tassi & Vizzari, 2020). Since we employ object-based classification, we computed GLCM features for each segment rather than a pixel or window-based approach. We assessed the applicability of multi-temporal GLCM texture-derived features for wetland classification using four different scenarios. The first and second scenarios did not include texture features. We used them to evaluate classifier performance, with the first scenario incorporating only summer imagery and the second scenario using spring and summer imagery. The third and fourth scenarios included mono-seasonal and multi-seasonal textural features, respectively. We used seven of the 17 different GLCM features (as suggested by (Tassi & Vizzari, 2020)). These seven features were sum average (SAVG), correlation, entropy, variance, angular second moment (ASM), contrast, and inverse difference moment (IDM).

2.6. Object-Based Random Forest Classification

We used a random forest classifier to develop the wetland maps within an object-based framework. Random forest was employed due to its ability to mitigate overfitting and handle a large number of input features. We segmented the Sentinel-2 imagery in summer using the simple non-iterative clustering (SNIC) function. SNIC uses four parameters:

1. Compactness (affects cluster shape).
2. Connectivity (influences merging of adjacent clusters).
3. Neighborhood size (avoids tile boundary artifacts).
4. Seed size (Achanta & Susstrunk, 2017).

Per object semantic segmentation of wetland, classes are assessed on both mono and multi-seasons scenarios. Selecting optimal segment size and shape is necessary for a successful object-based classification, with a preference for over-segmentation rather than under-segmentation (Adeli et al., 2021). We assessed the effect of different parameter values by visually evaluating the segmentation results to ensure segments correspond to single land cover classes. We changed one parameter in each test while holding other parameters constant (starting with neighborhood size). Once we selected the segmentation parameters, the random forest classifier was applied on the object level.

3. RESULTS

The input used imagery on one of the study sites is shown in Figure 2 (a-f). We integrated Sentinel-1 and 2 and ALOS-

PALSAR imagery. We tested four different scenarios to assess the effect of multi-seasonal textural features on classifier performance.

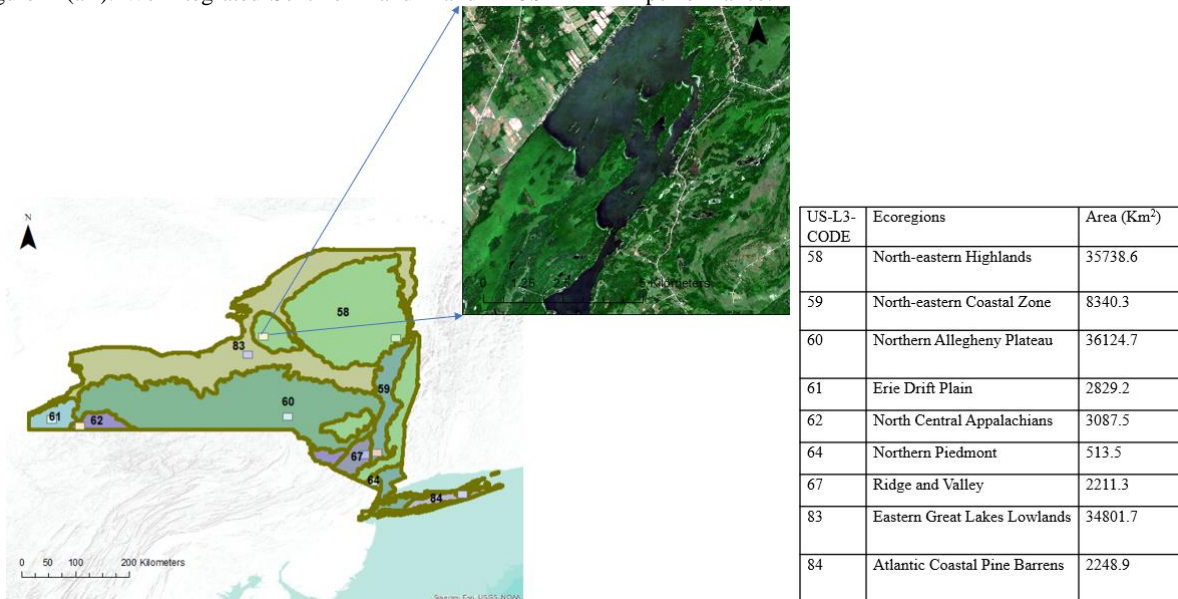


Figure 1. Nine Level III ecoregions of New York State.

Figure 3 shows classified maps for one of the sites used to train and test the classifications developed using the four different dataset combinations. Figure 3(a) shows the output from the first scenario that used only summer imagery and no GLCM texture features. Figure 3(b) illustrates the classified map from the second scenario when spring imagery is included in the classifier. The third scenario used GLCM texture-derived features for the summer season only (Figure 3(c)), and the last scenario (Figure 3(d)) used summer and spring imagery with the corresponding GLCM features. As illustrated, the delineation within the two classes of emergent and forested/scrub-shrub wetland is enhanced in the last scenario. The reason for this enhanced discrimination is the changes in the water level of wetland areas in spring compared to summer. The other reason is that the backscattering mechanism of SAR in the leaf-off season is different from leaf-on the season (Adeli et al., 2020). This can stimulate the better delineation of wetland classes from surrounding when multi-season imagery is used. The inclusion of GLCM textural features also demonstrates an enhancement in between class separability of wetland and non-wetland classes. It can be seen; some areas are not identified as wetlands when GLCM is excluded. However, the same area is identified as wetlands when GLCM features are incorporated into the classifier.

We assessed the classifier's performance in four different scenarios (Figure 4). Overall, the producer's and user's accuracy of each scenario is calculated. We observed an enhancement in the overall accuracy of mono seasonal when GLCM features were included (7.38%). The overall accuracy is increased by 4.21% when GLCM features are included in the case of multi-season. We obtained the highest overall accuracy in the last scenario (93.49%). The user's and producer's accuracy of water was highest among all the classes (98.57%, 97.36%, respectively). The user's accuracy of upland classes in the last scenario varied between 88.65% to 95.57%, corresponding to scrub/shrub upland and pasture

hey, respectively. The producer's accuracy of upland classes in the last scenario varied between 83.42% to 96.15%, corresponding to scrub/shrub upland and pasture hey, respectively. Notably, the user's accuracy of the emergent wetland class was low in the first scenario. The inclusion of multi-seasonal textural features was able to increase it.

To assess the importance of each feature, we used the Gini impurity index. The mean decrease in the Gini impurity index suggests that Soil Adjusted Vegetation Index, Modified Normalized Difference Water Index, slope derived from DEM, correlation in summer (GLCM feature) and Sentinel-1 VH is the most important in the random forest classifier. We also used the mean decrease in the Gini impurity index to analyse the importance of multi-seasonal textural features further. Three GLCM features calculated from summer imagery, entropy, SAVG, and variance, increased classifier performance, while other GLCM features from spring were more valuable. The detailed results using the mean decrease in Gini impurity to evaluate the multi-temporal texture features are shown in Figure 5.

To better understand the discrimination ability of GLCM features, we generate box-and-whisker plots for each wetland class for both the summer and spring seasons (Figure 6). The reason for choosing these three features is that they showed a higher contribution on the variable importance analysis. We plotted three different features of SAVG, Correlation, and IDM. SAVG has a good ability in discriminating water from wetland classes in both summer and spring. This feature can better distinguish forested scrub/shrub from an emergent wetland in the summertime. Correlation is better able to separate the two wetland classes in summer. IDM's box and whisker plot showing enhanced discrimination within wetland classes in spring. Once we trained the classifier in different study sites, we applied the classifier over the whole of NYS. The result is shown in Figure 6. The mean decrease in Gini impurity index of the most important features in the last scenario is shown in Table

2. The generated map of New York state is shown in Figure 7.

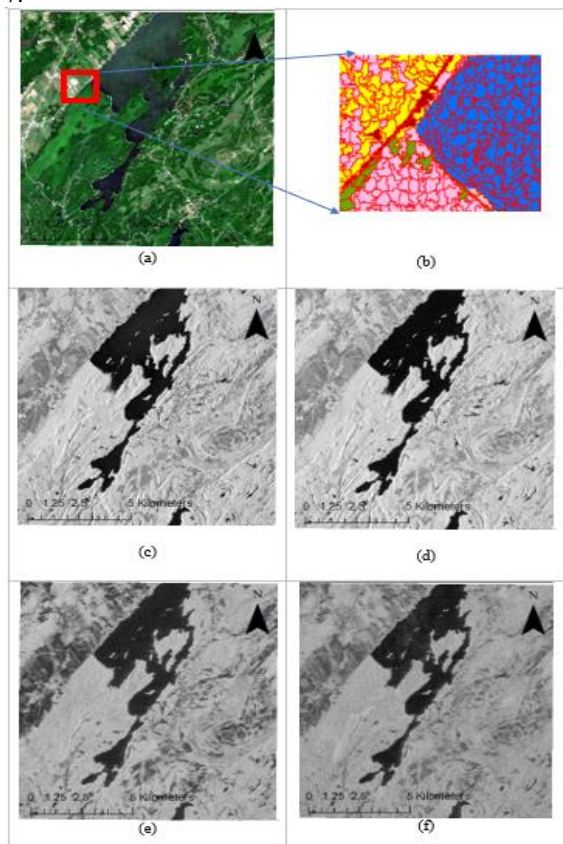
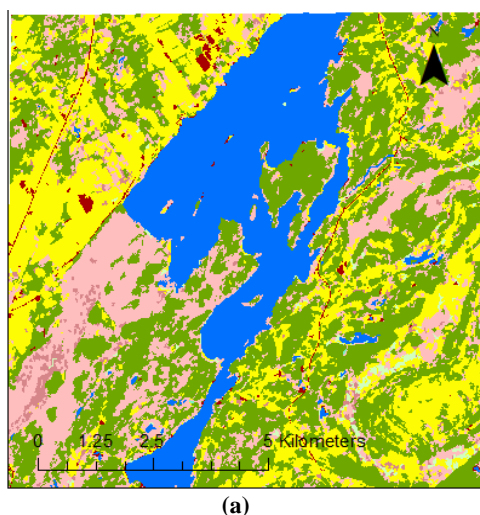
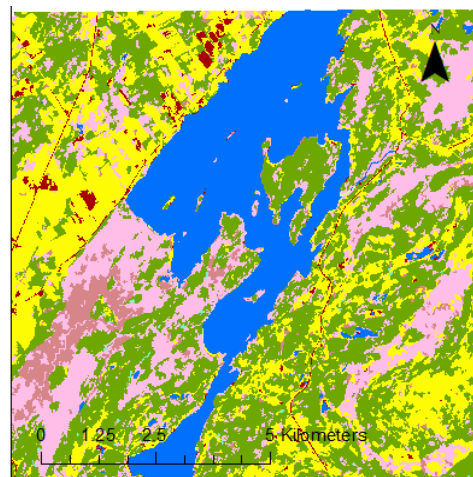


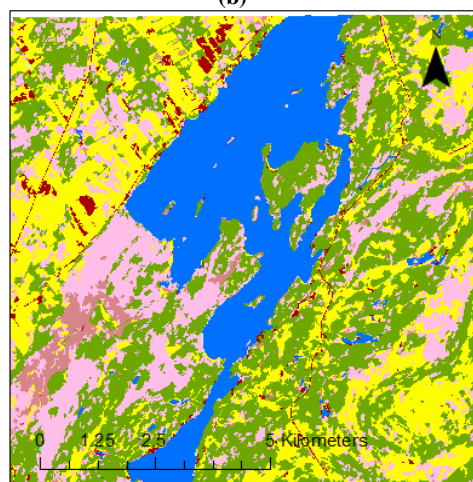
Figure 2. (a) The Sentinel-2 imagery of the study site was acquired in summer 2021. (b) The zoom-in segmentation is superimposed on the classified map. c and d) Sentinel-1 imagery of the area. e and f) Alos-Palsar imagery of the area.



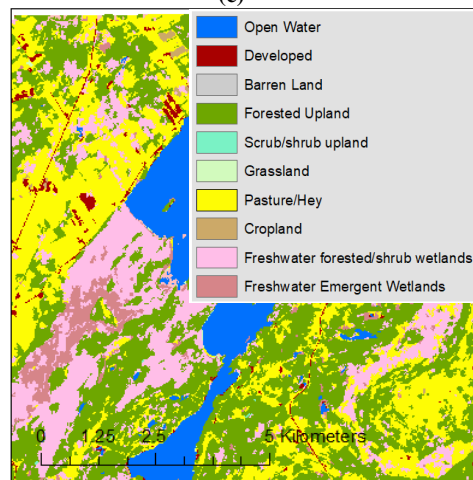
(a)



(b)



(c)



(d)

Figure 3. (a-d) The classification results in the four different scenarios. a) Mono-season and no GLCM feature is included. b) Multi-season and no GLCM features are included. c) Mono-season and seven GLCM feature is included. d) Multi-season and seven GLCM features are included.

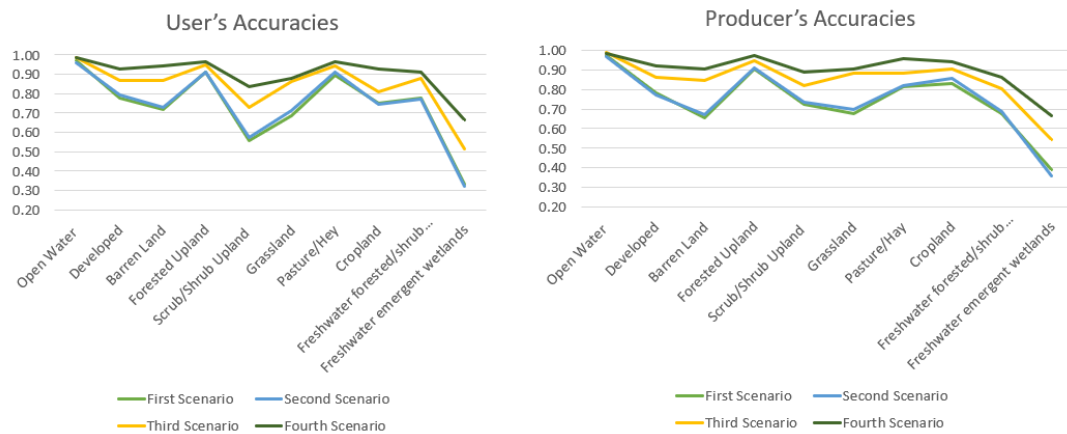


Figure 4. User's and producer's accuracies of defined scenarios.

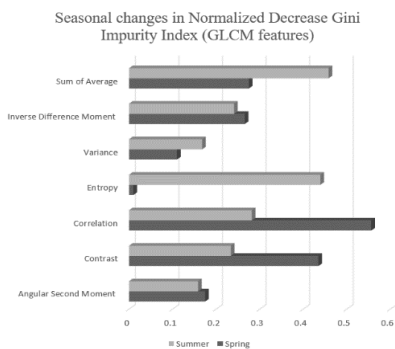


Figure 5. Mean decrease in Gini impurity index of multi-seasonal GLCM features.

4. DISCUSSION AND CONCLUSION

Dynamic monitoring of wetlands is crucial since we are losing them at an increasing rate. Our results showed the importance of multi-seasonal object-oriented textural features for increasing the predictive ability of a random forest classifier. Some studies in the literature used multi-seasonal imagery for vegetation mapping. For instance, (van Deventer et al., 2019) investigated the role of multi-seasonal Rapid eye imagery for the delineation of drylands and wetlands. Their results showed the highest overall accuracy when all four seasons were included. However, the question of what season provides the highest separation of vegetation in dryland and wetland is not investigated. In another study, (Lu et al., 2018) explored the use of an object-oriented classification model to monitor the dynamic of mangrove forests in China. They demonstrated that the inclusion of leaf-on and leaf-off imagery leads to better delineation of the transitional zone because of the tidal state. This study assessed the importance of multi-seasonal textural features for wetland delineation on the object level. The

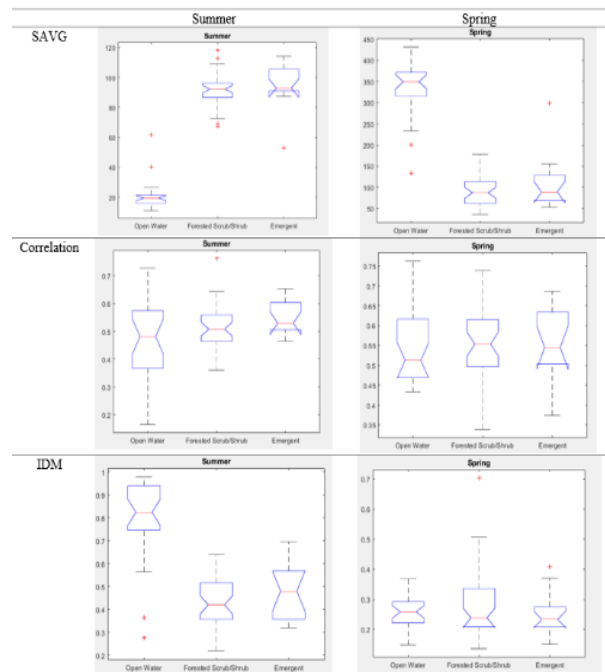


Figure 6. The box and whisker plots of important GLCM features for different wetland classes in summer and spring.

results demonstrated an enhancement when we included multi-seasonal textural features in delineating emergent and forested wetland classes. Such an investigation may facilitate a more accurate mapping of wetlands, leading to better preservation and management of these fragile lands. This study demonstrated that delineation of wetland classes is more challenging among different landcover types due to their high variability in their hydrology and hydric soil. The use of multi-seasonal textural features enhanced wetland classes discrimination. For future studies, accurate elevation models derived from Lidar data are expected to increase the delineation of wetland classes.

Features	Gini impurity index
SAVISENT	1
MNDWISENT	0.611
Slope	0.563
Correlation in spring	0.556
VH	0.550
B8 in spring	0.534
GSAVI	0.467
Sum of Average in summer	0.458
GRVI	0.441
Entropy in summer	0.439
Contrast in spring	0.434

Table 2. The mean decreases in Gini impurity index for the first eleven important features.

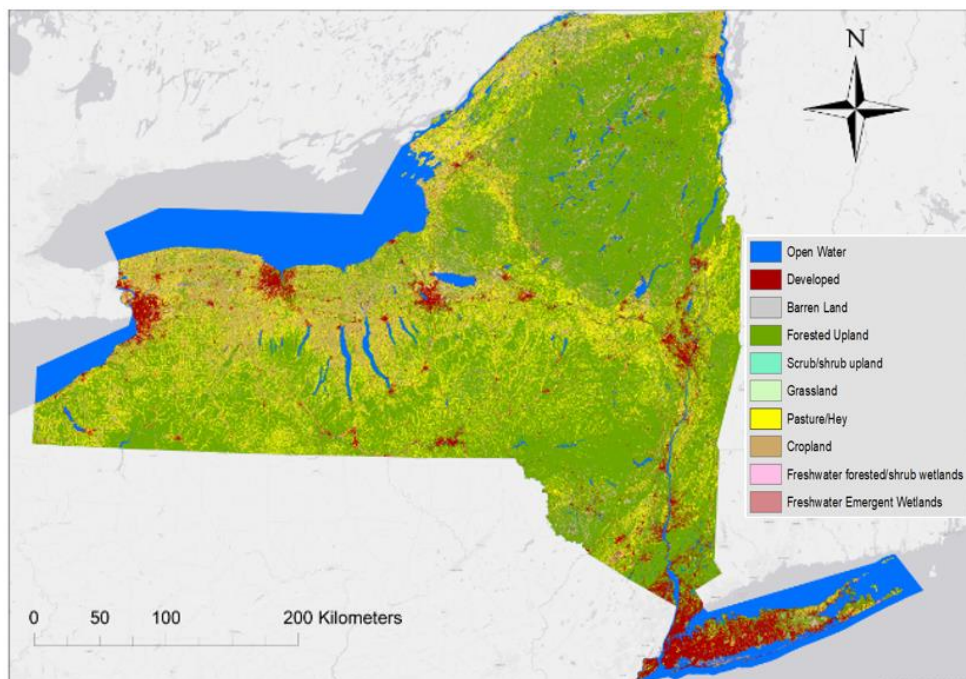


Figure 7. The generated classified map over NYS.

5. ACKNOWLEDGMENT

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