General Information

Remote sensing of tidal wetlands using NAIP imagery and NED elevation data

Tidal marshes of the northeastern United States support the largest amount of vertebrate endemic diversity of any coastal marsh system globally. These same marshes are threatened due to significant increases in sea-level rise (SLR) in the last few decades, at a rate faster than the physical processes of marsh accretion, or vertical growth. This dissonance between SLR and local marsh accretion is resulting in a loss of tidal marsh area, specifically in high marsh communities. High marsh areas are characterized by a weekly to monthly flooding regime, and support the large majority of endemic fauna abundance in these systems. As high marsh areas shrink and disappear it is important to identify the location and size of high marsh that remains to drive conservation of these areas.

This raster layer describes salt marsh communities in the Northeast Atlantic coast of the United States, from northern Maine to Virginia in 3 X 3 m pixels. It identifies eight cover/community types:

1. **High marsh:** Area flooded by average or larger than average amplitude tide (resulting in weekly to monthly flooding) and is dominated by *Spartina patens*, *Distichlis spicata*, *Juncus gerardii* and short form *Spartina alterniflora*. In addition, *Juncus roemerianus*, *Scirpus pungens*, *Scirpus robustus*, *Limonium nashii*, *Aster tenuifolius*, and *Triglochin maritimum* are secondary cover.
2. **Low marsh:** Area flooded regularly by daily tides and dominated by tall form *Spartina alterniflora*.
3. **Salt pools/pannes:** Depressed, bare areas with sparse vegetation cover and extreme high soil salinities. Generally, pools retain water between high tides while pannes do not.
4. **Terrestrial border:** Area infrequently flooded by storm and spring tides and can include areas of marsh with fresh/brackish water due to a high water table and/or runoff from impervious surfaces. Typical plant species include *Typha angustifolia*, *Iva frutescens*, *Baccharis halimifolia*, *Solidago sempervirens*, *Panicum virgatum*, *Scirpus robustus*, and *Spartina pectinata*.
5. ***Phragmites australis*:** An exotic species mainly invading disturbed marshes that (sometimes temporarily) cause a shift to a fresh water state (Dreyer & Niering, 1995).
6. **Mudflat:** Exposed muddy areas free of vegetation.
7. **Open water:** Free-flowing water included within 500m analysis buffer
8. **Upland:** Non-marsh cover included within 500m analysis buffer

We compared several competing classification techniques and used the most efficient method (Random Forest, or RF) with the most recent National Agricultural Imagery Program (NAIP) imagery, NAIP derivatives, and National Elevation Dataset (NED) elevation data. The outcome is a detailed, continuous map layer of tidal marsh vegetation communities between coastal Maine and Virginia, subdivided by zone (Figure 1). See the Methods & Algorithms section for a detailed explanation of input datasets, pre-processing steps, algorithms and accuracies.

Layer Interpretation

Analysis assumptions

Use of this spatial layer should occur only after thoroughly understanding the intended use and inherent assumptions associated with this dataset.

Timeline
This layer was produced using 2014-2015 NAIP imagery and the most recent elevation data available through the NED. Tidal marsh communities are ephemeral, changing systems with the ability to change community composition quickly. This layer should be used with this in mind; users should consider rates of community change in the area of interest before using this layer as a prediction of the location of tidal marsh communities.

Resolution
This layer is presented at a 3 x 3 m resolution, upscaled from 1 x 1 m imagery (0.5 m for New York State imagery). Heterogeneity in tidal marsh vegetation composition can occur at a scale smaller than this; therefore, some pixels classified as high or low marsh will in reality contain a combination of several different vegetation communities. We encourage users of this product to take context of pixels into account when using this product; the use or neighborhood filters may be appropriate in some cases.

Additionally, this layer presents 8 cover types, which oversimplifies the composition of this complex system. Cover types will differ in species composition across latitudes, watersheds, and local geomorphological features.

Data sources
The salt marsh layer is based on aerial imagery, a Digital Elevation Model (DEM) layer, local tidal gauge data, and delineated polygons of high marsh, low

marsh, *Phragmites*, mudflat, pools/pannes, and open water types. This layer was produced under the following data source assumptions:

- **All data are correctly georeferenced:**
  Most data used in the production of this layer was produced by sources outside of our organization. We recognize that all spatial data layers have inherent georeferencing error.

- **Tidal gauge data correctly represents local tidal flooding regime:** We used tidal gauge data to truth DEM raster data to local flooding levels. Tidal gauges were unevenly placed along the coast, and not all gauges collect all the parameters.

- **Training and validation polygons adequately represent the community types with which they are associated:**
  Training and validation polygons were collected by a team of technicians in 2015 and 2016. Field technicians received training on identification of marsh plant communities, however error is inherent in every field-collected dataset, and there were likely differences between observer classifications in some instances.

- **Data are not sensitive to differences in tidal height during data collection:**
  This assumption is known to be false. However, since there is no known correlation between time of data collection and tidal height, we can assume equally distributed data collection across low and high tide levels.

Additionally, in limited places along the coast there are no data included in the DEM layer. In this case, we classified the marsh communities without the DEM data input. These non-DEM areas are included as separate files.

Dataset strengths and weaknesses

The out-of-bag (OOB) error estimates produced by the RF algorithm are used to measure accuracy of our classification. This allowed us to use all the training polygons to maximize accuracy of our classification while still producing an independent measure for accuracy. The OOB error estimations are known to be a consistent measure of RF accuracy, but OOB error estimates do not systematically evaluate classification accuracy outside the training polygons and should be interpreted with this in mind. All OOB estimates for DEM and non-DEM classifications are included in Appendices 2 and 3.

Phragmites proved particularly difficult to classify using these methods, as shown in the OOB error estimates. We believe this high-error classification was due to 1) a small amount of training data with which to train algorithms and 2) the confoundment of *Phragmites australis* with terrestrial border, particularly with stands of *Typha* spp. Upon visual inspection of marsh areas with local area experts we found that large stands of *Phragmites* were often misclassified as terrestrial border, and urge users of this layer to use data with this in mind.

Table 1: OOB class errors for each cover class (with DEM) estimating classification accuracy of each cover type classified using training polygons.

	Zone 1	Zone 2	Zone 3	Zone 4	Zone 5	Zone 6	Zone 7	Zone 8
High Marsh	0.0197	0.0135	0.0489	0.0167	0.0599	0.1223	0.1628	0.0229
Low Marsh	0.2607	0.2399	0.2135	0.2763	0.2961	0.1901	0.2356	0.1365
Mudflat	0.0009	0.0005	0.0009	0.0283	0.0080	0.0130	0.0053	0.0032
Phragmites	0.8020	0.0582	0.1602	0.1366	0.3309	0.1968	0.1722	0.1479
Pool/Panne	0.0454	0.0391	0.0588	0.1292	0.0449	0.0345	0.0082	0.0000
Open water	0.0009	0.0044	0.0003	0.0031	0.0026	0.0007	0.0023	0.0008

Methods & Algorithms

Study site

The final layer covers the salt marshes in the Northeast Atlantic coast of the United States, from northern Maine to Virginia. We applied a 500m buffer to all coastal, tidal marsh as delineated by the National Wetland Inventory (NWI, https://www.fws.gov/wetlands/index.html) estuarine emergent wetland (E2EM) layer. The tides affecting these marshes between Maine and Virginia are semidiurnal, creating different complexes of salt marshes, streams, pools and pannes. This large marsh complex varies substantially with latitude. In the north a preponderance of rocky or highly sloped shorelines occurs while in the south accumulated sedimentation supports larger patches of marsh. Across all latitudes, however, we divided this ecosystem into eight distinct cover/community types within the E2EM delineation: The total study site was split in different zones (Figure 1) to ease in processing and data handling.

Training and validation data

Training data was collected in the field throughout the study area during the summers of 2015 and 2016. Over 2000 training polygons were collected using a GEO 7X Trimble GPS between May and August of 2015 and 2016. We only delineated contiguous polygons with a minimum area of 250 m^2. We recorded community type (high marsh, low marsh, *Phragmites*, terrestrial border) and species cover from 10 to 100%. Besides field data we recorded stream, pools/pannes, and mudflat cover classes by manually digitizing polygons based on 2014-2015 1 m National Agricultural Imagery Program (USDA 2015) imagery using ArcGIS 10.3.

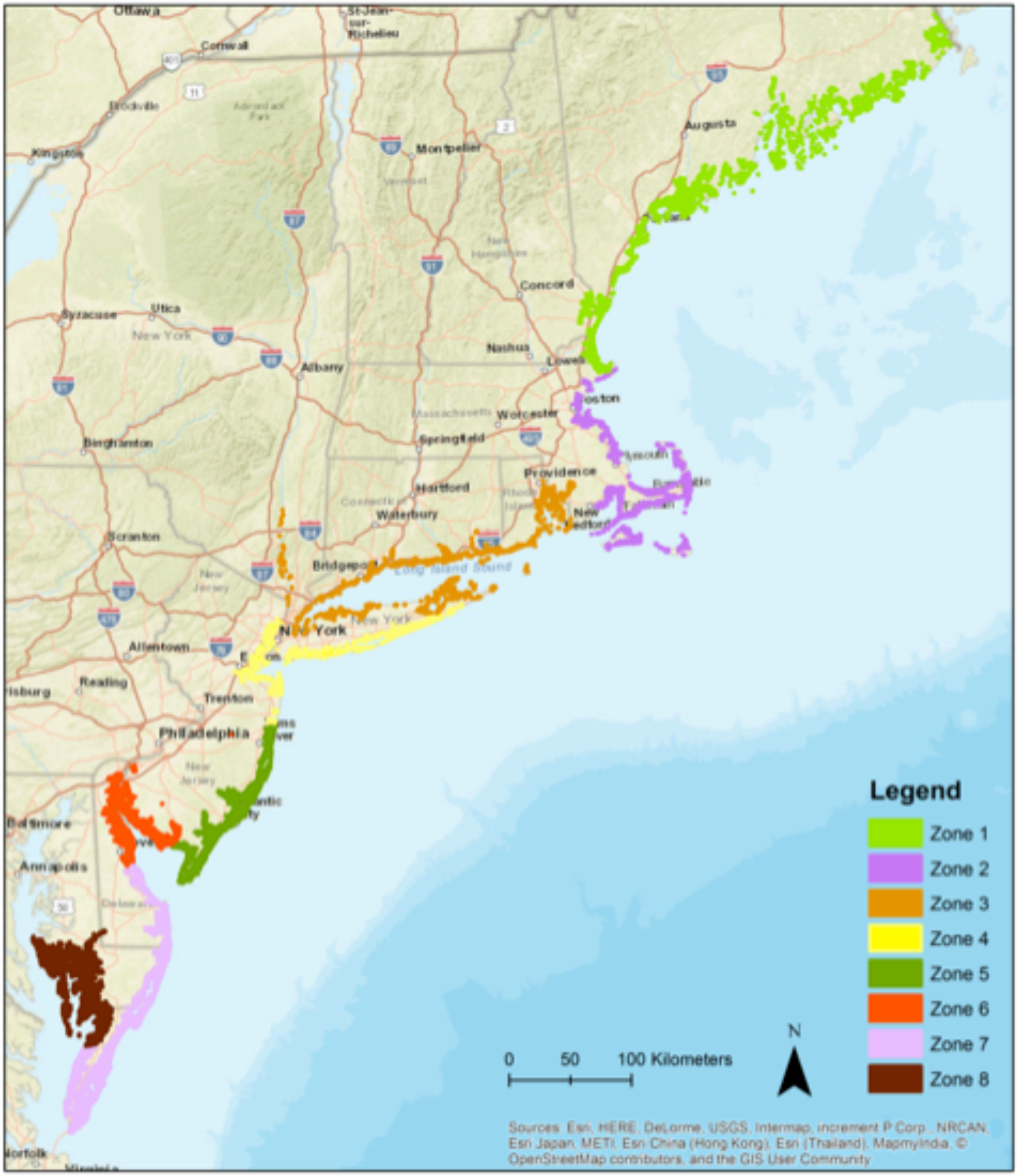

Figure 1. Study site showing the eight zones of Random Forest classification of coastal marsh communities.

Tidal amplitude data

Vast differences in local tidal amplitude exist within our study area. To account for these differences in our analysis, we split our study site into 29 zones named to the closest NOAA tidal gauge station (NOAA 2015, appendix 3). For each of these tidal gauge stations we collected the following tidal datums: HAT, MHHW, MHW, MSL, NAVD88 and Max (Table 2, Figure 2). These tidal datums are based on the national tidal datum epoch, from 1983 through 2001, the specific 19-year period adopted by NOAA as the official time segment for observations and to obtain mean values for sea level rise and related calculations (NOAA 2015).

Table 2: Datums collected. (https://www.tidesandcurrents.noaa.gov/stations.html?type=Datums)

Datum	NOAA explanation
Max	Maximum: Highest observed water level. (No datum)
HAT	Highest Astronomical Tide: The elevation of the highest predicted astronomical tide expected to occur.
MHHW	Mean Higher High Water: Average of the higher high water height of each tidal day.
MHW	Mean High Water: Average of all the high water heights.
MSL	Mean Sea Level: The arithmetic mean of hourly heights observed
NAVD88	North American Vertical Datum of 1988

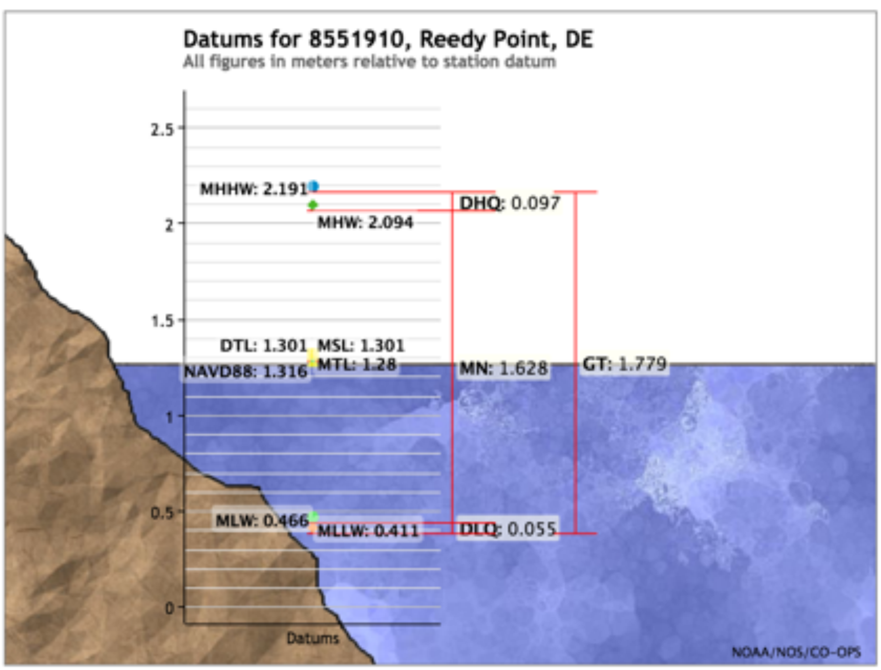

Figure 2. Graphic representation of NOAA datums collected at the tidal gauge stations, here Reedy Point, DE. (https://www.tidesandcurrents.noaa.gov/datums.html?id=8551910)

Predictor data

We used the most recent digital ortho-photography (Red (R), Green(G), Blue(B), and Near-Infrared band (NIR)) available from the NAIP that were collected during the growing season from 2014 or 2015. The year of collection, contractor, and quality varies by state (Table 3). Across all datasets, image resolution is 1 meter with a horizontal accuracy less than 6 meters. Imagery had a maximum 10% of cloud cover in order to be included in the NAIP inventory.
We resampled all NAIP 1m imagery to 3m to match the elevation data resolution and then clipped with a 500m buffer of all coastal tidal marsh as delineated by the National Wetland Inventory (NWI, estuarine emergent wetland (E2EM). All NAIP imagery derivatives were calculated in ArcMap 10.3 using the raw band values. We refer to them as 'pseudo'-vegetation indices because we use the raw band values instead of reflectance values.

Platform	Aircraft
Spatial resolution	1m (rescaled to 3m)
Spectral resolution	Blue (400–580 nm) Green (500–650 nm) Red (590–675 nm) NIR (675–850 nm)/(675-940nm)
Seasonality	Growing season
State	**Year imagery**
Maine	2015
New Hampshire	2014
Massachusetts	2014
Rhode Island	2014
Connecticut	2014
New York	2015
New Jersey	2015
Maryland	2015
Delaware	2015
Virginia	2014

Table 3. National Agriculture Imagery Program (NAIP) data used for classification effort.

We created the following pseudo-vegetation indices:

- **Normalized Difference Vegetation Index (NDVI)**
  NDVI=(NIR-R)/(NIR+R)

- **Normalized Difference Water Index (NDWI)**
  NDWI=(G-NIR)/(G+NIR)

- **Difference Vegetation Index (DVI)**
  DVI=NIR-R

- **Principle Components Analysis (PCA1-3)**

We transformed the four NAIP bands in a principal component analysis to a new multivariate, uncorrelated attribute space. We used the first three out of four principal component bands because they already explain > 95% of the variance.

We used the National Elevation Dataset (NED) for all elevation data**.** The NED is derived from different and diverse source datasets and processed by the USGS to minimize artifacts, perform edge matching, and fill sliver areas of missing data (https://www.sciencebase.gov/catalog/item/4f70a58ce4b058caae3f8ddb). The NED elevation products were downloaded from http://viewer.nationalmap.gov/basic/ at the1/9-arc second (~3 meter resolution).

We resampled the NED data with 1/9-degree resolution to 3m resolution to match NAIP imagery, and similarly clipped with the 500m buffer of all coastal, tidal marsh in the NWI. We further clipped the NED by the 29 tidal gauge zones of the study area, and rescaled each zone to the NAVD88 datum using the NOAA tidal amplitude data. To create a consistent elevation dataset (hereafter named DEM) over the whole study site we used the Mean High Tide (MHT) divided by Mean Highest High Tide (MHHT) value for each tidal gauge zone.

Elevation data

Elevation can be indicative of the tidal flooding frequency and thus influences species zonation (Silvestri et al., 2005). Consequently, the different marsh zones can be defined based on their elevation. We classified the NED of each tidal gauge zone based on the tidal amplitude data for that zone (Figure 3). We rescaled NOAA tidal amplitude data to the datum used in the elevation dataset (NAVD88) and defined elevation limits for the water, high and low marsh, terrestrial border, and upland class based on flooding history. The terrestrial border and upland class is used to clip the final RF remote sensing classification(s) to the marsh areas.

When no DEM was available for an area, we used RF classification without the DEM layer and include this lower-accuracy classification as a separate file for each zone.

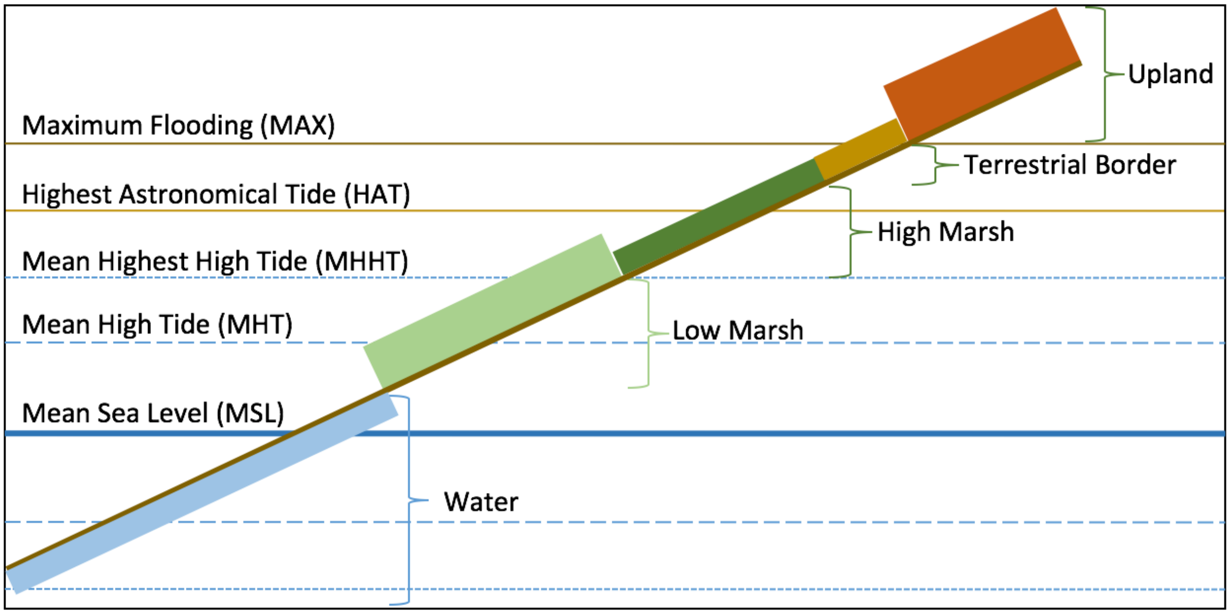

Figure 3. Salt marsh zonation based on their elevation.

Remote Sensing and Machine learning classification

We compared several popular and/or promising classifiers to delineate tidal marsh systems using training and validation data. We conducted the comparison of classifiers in the center of our study area (Delaware Bay, subregion 6) to maximize utility both to the north and south. We compared the following classifiers:

Classification and Regression Trees (CART) are a set of flexible, rule-based classification methods that is computationally fast and makes no statistical assumptions regarding the distribution of the data (Otukei and Blaschke 2010). CART methods are particularly useful when integrating environmental variables with different measurement scales and are robust for large datasets.

Random Forests (RF) are decision tree ensembles that improve the accuracy and stability of a single decision tree (Breiman 2001). RFs perform well with small training sample sets, offer a cross-validation-like accuracy measure through the out-of-bag (OOB) error estimates, and assign variables' importance by assessing accuracy loss when feature values are randomly permuted (Breiman 2001).

Support Vector Machine (SVM) is a non-parametric classification method that uses risk minimization to calculate a hyperplane that separates the 2 classes with a maximum margin defined by the 'support vectors'. Success depends on how well the process is trained and if the classes are linearly separable, but a SVMkernel could be applied if the classes are not linear separable. In general, SVM offers high training performance versus low generalizing errors, but is sensitive to over-fitting, especially with noisy and unbalanced data.

Table 4. Average class error rates for the three different classification techniques. Random Forests return the lowest error rates across the three classes tested.

	High Marsh	Low Marsh	Phragmites
RF	0.1186	0.1586	0.4873
CART	0.2742	0.1878	0.4561
SVM	0.2651	0.1381	0.6829

After comparing the remote sensing techniques (Table 4), we found that Random Forests, an advanced set of machine-learning algorithms, outperformed other classifier tools when applied to the most recent National Agricultural Imagery Program (NAIP) imagery, NAIP derivatives, and elevation data. We classified a 500-m buffer around National Wetland Inventory marsh areas at a 3-m resolution creating a detailed, continuous map layer of tidal marsh vegetation communities between coastal Maine and Virginia.

For zones 1 and 6, due to low image quality and/or due to high tide during image acquisition, the water classification was altered using the RF probability scores for the Stream class to better represent the actual water cover. The RF classification was then updated with the better water classification.

Random Forest Algorithm and classification results per zone
Appendix 1: The R-code with explanatory text in between.
Appendix 2: OOB classification results per zone and class.

GIS Metadata - Final Layers

ZoneX_DEM (TIFF): RF layers are combined with the DEM-based terrestrial border and upland classes for a high-accuracy classification of tidal marsh communities (symbology below, Figure 4).

ZoneX_noDEM (TIFF): When no DEM was available, we provide RF layers with lower accuracy (symbology below, Figure 5) produced without DEM data. This layer does not include a terrestrial border or upland class. When DEM was available for the entire classified area within a Zone, we do not supply a "noDEM" file for that zone.

ZoneX_dif (.shp): This vector file for each zone indicates where DEM was and was not used for classification within each zone.

Regional_DEM (TIFF): RF layers are combined with the DEM-based terrestrial border and upland classes across all analysis zones for a high-accuracy classification of tidal marsh communities from Maine to Virginia (symbology below, Figure 4).

Regional_noDEM (TIFF): Combined RF layers with lower accuracy produced without DEM data across all analysis zones (symbology below, Figure 5). This layer does not include a terrestrial border or upland class.

Regional_dif(.shp): Combined vector file indicating where DEM was and was not used in classification across all analysis zones.

TIFF file: ZoneX_DEM	Class	Cover/Community
	1	High Marsh
	2	Low Marsh
	4	Mudflat
	5	Phragmites
	6	Pool/Panne
	7	Stream
	8	Terrestrial Border
	9	Upland

Figure 4. Symbology for all DEM-based marsh classifications

TIFF file: ZoneX_no DEM	Class	Cover/Community
	1	High Marsh
	2	Low Marsh
	4	Mudflat
	5	Phragmites
	6	Pool/Panne
	7	Stream

Figure 5. Symbology for all marsh classifications without DEM input.

Literature and Data Sources

Breiman, L. 2001 'Random Forests.' *Machine learning* 45(1):5-32.

Dreyer, G., and Niering, W. 1995 'Tidal Marshes of Long Island Sound: Ecology, History and Restauration.' The Connecticut Collage Arboretum. 30. In: Atlantic Shorelines, Natural History and Ecology, p 311.

USDA 2015. National Agriculture Imagery Program. URL: https://www.fsa.usda.gov/programs-and-services/aerial-photography/imagery-programs/naip-imagery/

USGS 2015. National Elevation Dataset. URL: https://www.sciencebase.gov/catalog/item/4f70a58ce4b058caae3f8ddb

NOAA 2015. Tides and Currents. URL: https://www.tidesandcurrents.noaa.gov/stations.html?type=Datums

Otukei, J.R. and Blaschke, T. 2010 'Land Cover Change Assessment Using Decision Trees, Support Vector Machines and Maximum Likelihood Classification Algorithms.' *International Journal of Applied Earth Observation and Geoinformation.* 12(1):27-31.

R Core Team (2017). R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. URL: https://www.R-project.org/.

Silvestri, S., Defina, A., and Marani, M. 2004 'Tidal regime, salinity and salt marsh plant zonation.' *Estuary, Coastal and Shelf Science* 62:119-130.

Appendices

Appendix 1: R code.

```
###########################################################################################
#Step 1: Zone & Image data
###########################################################################################
# Select zone
zone <-1 #23456789
# Set workspace
getwd()
wd <- paste0("xxx/NAIP_0",zone,"_xx_3m")
setwd(wd)
#Read DEM & IMG files
files_VI <- list.files(getwd(), pattern="tif$", full.names=FALSE)
files_VI
stack_files_VI <- stack(files_VI)

###########################################################################################
#Step 2: Training data
###########################################################################################
# Read training shp-file
TData<- paste0("T_Zone",zone)
TrainingData <- readOGR("…/TrainingData", TData)
# Extract all training Pixel values for each class
img <- stack_files_VI
trainData <- TrainingData
responseCol <- "Type"
dfAll = data.frame(matrix(vector(), nrow = 0, ncol = length(names(img)) + 1))
for (i in 1:length(unique(trainData[[responseCol]]))){
  category <- unique(trainData[[responseCol]])[i]
  categorymap <- trainData[trainData[[responseCol]] == category,]
  dataSet <- extract(img, categorymap)
  dataSet <- sapply(dataSet, function(x){cbind(x, class = rep(category, nrow(x)))})
  df <- do.call("rbind", dataSet)
  dfAll <- rbind(dfAll, df)
}
dfAll$class<-factor(dfAll$class)
# Drop terrestrial border
dfAll <- droplevels(dfAll[dfAll$class!='8',])
# Drop mixed marsh
Data6 <- droplevels(dfAll[dfAll$class!='3',])
write.csv(Data6, 'Data_Z1_6.csv')
#Drop Phragmites
Data5 <- droplevels(Data6[Data6$class!='5',])
write.csv(Data5, 'Data_Z1_5.csv')
#Create subset for training & validating
trainIndex <- createDataPartition(Data6$class, p = .7, list = FALSE, times = 1)
Traindata6 <- Data6[trainIndex,]
Vdata6 <- Data6[-trainIndex,]
```

```
set.seed(1980)
trainIndex <- createDataPartition(Data5$class, p = .7, list = FALSE, times = 1)
Traindata5 <- Data5[trainIndex,]
Vdata5 <- Data5[-trainIndex,]
#########################################################################################
# If necessary, read csv's
Traindata6 <- read.csv('Traindata_Z1_6.csv')
Traindata6$class<-factor(Traindata6$class)
Traindata6$X<-NULL
Traindata5 <- read.csv('Traindata_Z1_5.csv')
Traindata5$class<-factor(Traindata5$class)
Traindata5$X<-NULL
Vdata6 <- read.csv('Vdata_Z1_6.csv')
Vdata6$class<-factor(Vdata6$class)
Vdata6$X<-NULL
Vdata5 <- read.csv('Vdata_Z1_5.csv')
Vdata5$class<-factor(Vdata5$class)
Vdata5$X<-NULL

#########################################################################################
#Step 3: RF classifications
#########################################################################################
#RF 6class
RF_DNAIP_model6C <- randomForest(class ~ ., data=Traindata6, na.action = na.omit, confusion=TRUE)
RF_DNAIP_model6C
varImpPlot(RF_DNAIP_model6C)
plot(RF_DNAIP_model6C)
predictions_DNAIP6C<-predict(RF_DNAIP_model6C,Vdata6[,1:11])
#summarizeaccuracy
table(predictions_DNAIP6C,Vdata6$class)
confusionMatrix(predictions_DNAIP6C,Vdata6$class)
#RF 5class
RF_DNAIP_model5C <- randomForest(class ~ ., data=Traindata5, na.action = na.omit, confusion=TRUE)
RF_DNAIP_model5C
varImpPlot(RF_DNAIP_model5C)
plot(RF_DNAIP_model5C)
predictions_DNAIP5C<-predict(RF_DNAIP_model5C,Vdata5[,1:11])
#summarizeaccuracy
table(predictions_DNAIP5C,Vdata5$class)
confusionMatrix(predictions_DNAIP5C,Vdata5$class)

########################################################################################
# Step 4: RF Classification and Predict Maps
#########################################################################################
#Use 8 cores for classification
beginCluster()
RF_Map_DNAIP6C <- clusterR(stack_files_VI, predict, args = list(model = RF_DNAIP_model6C,
datatype="INT1U", type="response", overwrite=TRUE))
RF_Map_DNAIP5C <- clusterR(stack_files_VI, predict, args = list(model = RF_DNAIP_model5C,
datatype="INT1U", type="response", overwrite=TRUE))
endCluster()
writeRaster(RF_Map_DNAIP6C, filename = "xxx/NAIP_01_xx_3m/Output/RF_DNAIP6C.tif", overwrite=TRUE)
writeRaster(RF_Map_DNAIP5C, filename = "xxx/NAIP_01_xx_3m/Output/RF_DNAIP5C.tif", overwrite=TRUE)
#Use all 8 cores for class predictions
beginCluster()
```

```
RF_Prob_DNAIP6C <- clusterR(stack_files_VI, predict, args = list(model = RF_DNAIP_model6C,
type="vote",index = 1:6))
RF_Prob_DNAIP5C <- clusterR(stack_files_VI, predict, args = list(model = RF_DNAIP_model5C,
type="vote",index = 1:5))
endCluster()
writeRaster(RF_Prob_NAIP6C, filename = "xxx/NAIP_01_xx_3m/Output/RF_Prob_DNAIP6C.tif",
overwrite=TRUE)
writeRaster(RF_Prob_NAIP5C, filename = "xxx/NAIP_01_xx_3m/Output/RF_Prob_DNAIP5C.tif",
overwrite=TRUE)
```

Appendix 2: Classification accuracies per class (with DEM).

Zone 1 OOB.

	High Marsh	Low Marsh	Mudflat	Phragmites	Pool/Panne	Stream	Class error
High Marsh	**18092**	269	9	12	71	3	0.0197
Low Marsh	621	**1917**	22	1	14	18	0.2607
Mudflat	0	31	**39212**	0	2	2	0.0009
Phragmites	513	42	0	**137**	0	0	0.8020
Pool/Panne	48	9	3	1	**1535**	12	0.0454
Stream	3	6	28	0	11	**50911**	0.0009

Zone 2 OOB.

	High Marsh	Low Marsh	Mudflat	Phragmites	Pool/Panne	Stream	Class error
High Marsh	**2042**	17	3	6	2	0	0.0135
Low Marsh	60	**282**	20	0	4	5	0.2399
Mudflat	1	2	**21587**	1	0	7	0.0005
Phragmites	15	1	0	**259**	0	0	0.0582
Pool/Panne	4	4	0	0	**516**	13	0.0391
Stream	1	1	11	0	7	**4560**	0.0044

Zone 3 OOB.

	High Marsh	Low Marsh	Mudflat	Phragmites	Pool/Panne	Stream	Class error
High Marsh	**5521**	138	13	130	3	0	0.0489
Low Marsh	372	**1540**	8	38	0	0	0.2135
Mudflat	8	2	**14054**	1	1	0	0.0009
Phragmites	272	66	10	**1845**	3	1	0.1602
Pool/Panne	1	0	0	4	**624**	34	0.0588
Stream	2	0	4	1	5	**40021**	0.0003

Zone 4 OOB.

	High Marsh	Low Marsh	Mudflat	Phragmites	Pool/Panne	Stream	Class error
High Marsh	**21695**	210	24	65	65	4	0.0167
Low Marsh	852	**2391**	12	29	8	12	0.2763
Mudflat	46	11	**2098**	1	0	3	0.0283
Phragmites	232	11	3	**1561**	1	0	0.1366
Pool/Panne	49	7	5	2	**748**	48	0.1292
Stream	12	4	5	0	17	**12101**	0.0031

Zone 5 OOB.

	High Marsh	Low Marsh	Mudflat	Phragmites	Pool/Panne	Stream	Class error
High Marsh	**21636**	1184	31	60	91	12	0.0599
Low Marsh	1827	**4672**	13	62	17	46	0.2961
Mudflat	31	7	**10352**	15	7	24	0.0080
Phragmites	213	186	10	**829**	1	0	0.3309
Pool/Panne	134	21	5	5	**5142**	77	0.0449
Stream	1	1	25	0	51	**30355**	0.0026

Zone 6 OOB.

	High Marsh	Low Marsh	Mudflat	Phragmites	Pool/Panne	Stream	Class error
High Marsh	**10399**	1031	10	413	1	8	0.1233
Low Marsh	306	**1836**	11	107	0	7	0.1901
Mudflat	5	37	**43214**	0	0	529	0.0130
Phragmites	284	111	5	**1649**	2	2	0.1968
Pool/Panne	0	3	0	0	**3635**	127	0.0345
Stream	0	6	85	2	32	**171515**	0.0007

Zone 7 OOB.

	High Marsh	Low Marsh	Mudflat	Phragmites	Pool/Panne	Stream	Class error
High Marsh	**18323**	1916	14	1577	47	10	0.1628
Low Marsh	534	**2690**	1	289	1	4	0.2356
Mudflat	1	0	**749**	1	1	1	0.0053
Phragmites	625	191	3	**3995**	11	1	0.1722
Pool/Panne	0	0	1	1	**4729**	37	0.0082
Stream	3	1	1	0	46	**21838**	0.0023

Zone 8 OOB.

	High Marsh	Low Marsh	Mudflat	Phragmites	Pool/Panne	Stream	Class error
High Marsh	**4349**	59	0	41	1	1	0.0229
Low Marsh	97	**892**	0	43	0	1	0.1365
Mudflat	3	0	**949**	0	0	0	0.0032
Phragmites	79	35	0	**657**	0	0	0.1479
Pool/Panne	0	0	0	0	**6730**	0	0.0000
Stream	0	0	0	0	2	**2628**	0.0008

Appendix 3: Classification accuracies per class (without DEM only).

Zone 1 OOB.

	High Marsh	Low Marsh	Mudflat	Phrag	Pool/Panne	Stream	Class error
High Marsh	7094	321	3	78	2	96	0.066
Low Marsh	700	634	25	26	7	90	0.572
Mudflat	5	7	14817	1	0	72	0.006
Phrag	185	48	6	379	0	38	0.422
Pool/Panne	1	4	1	0	330	88	0.222
Stream	41	31	54	10	25	125650	0.001

Zone 2 OOB.

	High Marsh	Low Marsh	Mudflat	Phrag	Pool/Panne	Stream	Class error
High Marsh	25895	341	32	26	63	4	0.018
Low Marsh	848	2788	26	0	14	28	0.247
Mudflat	17	32	74421	0	3	22	0.001
Phrag	691	50	0	247	0	0	0.750
Pool/Panne	65	14	10	0	1745	10	0.054
Stream	1	9	26	0	11	108447	0.001

Zone 5 OOB.

	High Marsh	Low Marsh	Mudflat	Phrag	Pool/Panne	Stream	Class error
High Marsh	35037	2736	153	168	12	372	0.092
Low Marsh	3792	5304	25	19	19	146	0.441
Mudflat	79	10	18690	20	60	103	0.061
Phrag	38	364	27	830		6	0.531
Pool/Panne	207	32	73	1	6364	1000	0.172
Stream	67	13	98	0	613	26624	0.005

Zone 6 OOB.

	High Marsh	Low Marsh	Mudflat	Phrag	Pool/Panne	Stream	Class error
High Marsh	15823	610	118	379	7	23	0.067
Low Marsh	1385	1458	94	286	1	17	0.550
Mudflat	121	40	62070	15	1	302	0.001
Phrag	1073	215	22	1596	7	19	0.456
Pool/Panne	11	6	9	10	4636	706	0.138
Stream	40	12	420	6	212	244510	0.003

Zone 7 OOB.

	High Marsh	Low Marsh	Mudflat	Phrag	Pool/Panne	Stream	Class error
High Marsh	25704	4338	6	561	65	587	0.178
Low Marsh	2030	2740	0	146	2	41	0.447
Mudflat	181	1	29174	0	48	4600	0.142
Phrag	2591	984	1	3205	22	90	0.535
Pool/Panne	2	1	0	1	6656	151	0.023
Stream	161	34	286	0	398	1136180	0.001

Zone 8 OOB.

	High Marsh	Low Marsh	Mudflat	Phrag	Pool/Panne	Stream	Class error
High Marsh	4318	74	3	51	0	5	0.030
Low Marsh	269	690	1	66	0	7	0.332
Mudflat	3	0	944	2	0	3	0.008
Phrag	131	44	3	585	0	8	0.241
Pool/Panne	0	0	0	0	6333	397	0.059
Stream	199	63	44	66	569	1777598	0.001

Appendix 4: NOAA datums per gauge station.

Zone	Station ID	Name	MAX	HAT	MHHW	MHW	MSL	NAVD88
Z1_1	8410140	Eastport	8.845	8.457	7.336	7.191	4.420	4.491
Z1_2	8413320	Bar Harbor	5.999	5.230	4.524	4.394	2.786	-
Z1_3	8418150	Portland	6.913	6.249	5.626	5.493	4.113	4.208
Z1_4	8419870	Seavey Island	4.478	3.922	3.411	3.286	2.068	2.126
Z2_1	8443970	Boston	5.675	4.861	4.205	4.071	2.660	2.752
Z2_2		Average						
Z2_3	8447930	Woods Hole	4.084	1.781	1.469	1.385	1.096	1.212
Z2_4	8449130	Nantucket Island	3.313	2.259	2.004	1.900	1.454	
Z3_1	8454000	Providence	6.401	3.051	2.539	2.464	1.749	1.818
Z3_2	8452660	Newport	4.633	2.148	1.751	1.676	1.106	1.199
Z3_3	8461490	New London	4.298	2.256	2.003	1.913	1.542	1.634
Z3_4	8467150	Bridgeport	4.577	3.293	2.835	2.733	1.708	1.775
Z3_5	8516945	Kings Point	8.268	6.869	6.306	6.196	5.113	-
Z3_6	8514560	Port Jefferson	4.776		3.341	3.243	2.236	2.292
Z3_7	8510560	Montauk	3.749	2.255	1.947	1.860	1.554	1.655
Z4_1		Average						
Z4_2	8518750	The Battery	5.282	2.937	2.543	2.445	1.785	1.848
Z4_3	8531680	Sandy Hook	3.840	2.777	2.359	2.258	1.551	1.624
Z5_1	8534720	Atlantic City	4.249	3.288	2.914	2.787	2.186	2.308
Z5_2	8536110	Cape May	3.448	2.784	2.398	2.265	1.521	1.658
Z6_1	8551910	Reedy Point	3.227	2.492	2.191	2.094	1.301	1.316
Z7_1	8557380	Lewes	3.658	2.620	2.266	2.138	1.528	1.649
Z7_2	8570282	Ocean City	1.954		1.625	1.557	1.236	1.362
Z7_3	8632200	Kiptopeke	3.261	2.287	2.001	1.932	1.539	1.685
Z8_1	8571892	Cambridge	2.634	1.514	1.372	1.308	1.060	1.087

Z8_2	8574680	Baltimore	3.735	1.944	1.757	1.666	1.495	1.505
Z8_2	8573927	Chesapeake City	3.600	2.135	1.936	1.877	1.432	-
Z8_4	8575512	Annapolis	3.560	1.969	1.815	1.741	1.596	1.612
Z8_5	8577330	Solomons Island	2.478	1.702	1.584	1.540	1.366	1.394