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Rhode Island Ecological Conservation

Methods for Monitoring Rhode Island Habitats: Contributing to a Framework for Targeted Conservation and Management

DEVELOP Technical Report

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Natasha Crater (Project Lead)
Kristen Mecke
Nancy Nthiga
Joseph Barnes

Advisors:
Joseph Spruce, Analytical Mechanics Associates, Inc. (Science Advisor)
Sylvia Reeves, NOAA National Integrated Drought Information System (Science Advisor)

Lead:
Kathryn Caruso (North Carolina NCEI)

1. Abstract
Global avian population decline since the 1970s is largely attributable to habitat loss and degradation from anthropogenic disturbances. NASA DEVELOP's Rhode Island Ecological Conservation team partnered with the Audubon Society of Rhode Island to compute land use land cover (LULC) maps of Rhode Island to aid in the conservation of the state's 140 bird species. This project aimed to support the partner's land acquisition strategies with updated and specific LULC classifications showing potential bird-habitat locations across the state. We incorporated remotely sensed data from Landsat 8 and 9 Operational Land Imager (OLI) into LULC maps using unsupervised classification techniques in ArcGIS Pro and supervised classification in Google Earth Engine. We generated six land classifications for 2023, which showed land cover dominated by upland habitats (forests, scrub/shrub, and grasslands), followed by development. We used TerrSet's Land Change Modeler to forecast LULC change through 2043, using 2011 and 2021 National Land Cover Database (NLCD) land cover maps derived from Landsat 8 and 9 data. Project results suggest that non-urban upland and wetland habitats will decrease over time, while development will continue to encroach on non-urban avian habitats. Our maps and associated data will allow for more efficient land acquisition and management efforts to support avian habitat conservation across Rhode Island. Our study shows that data acquisition and processing from open data sources is feasible and further analysis can be done through GIS classification tools. More analysis is needed beyond this study to obtain more detailed land cover maps, though Audubon can aid its targeted conservation efforts with our current, historic, and forecasted LULC maps.

Key Terms
Remote sensing; land use land cover change (LULCC); unsupervised classification; ecological forecasting; Landsat; C-CAP; NLCD; Rhode Island; Audubon Society.

2. Introduction
2.1 Background Information
Avian populations have declined globally by three billion birds since 1970 (Rosenberg et al., 2019). Most of this decline is directly related to habitat loss and degradation, as well as other anthropogenic influences such as feral domestic cats, wind turbines, glass collisions, and pesticide usage (Richard et al., 2021). Birds provide incalculable ecosystem services, including wildflower and fruit tree pollination, seed dispersal, insect population control, and scavenging (Rosenberg et al., 2019; Clarkson, 2023). Avifauna habitat monitoring is crucial as rapidly changing land covers like rocky habitats, salt marshes, seasonal pools, and shrubland affect shelter, food, and nesting availability (Berry et al., 2015; Caron & Paton, 2007; Golet et al., 2001; McKinney & Paton, 2009). Birds are often indicators of overall environmental health and integrity, so by tracking avian populations and critical habitat conditions we can ensure proper and effective ecosystem preservation (Rosenberg et al., 2019).

Situated on the Atlantic seaboard, the small U.S. state of Rhode Island is home to more than 140 bird species throughout the year (Clarkson, 2023; Berry et al., 2015; Caron & Paton, 2007; McKinney & Paton, 2009). In 2023, the Audubon Society of Rhode Island (Audubon) published a novel study titled *The State of Our Birds Parts I and II* (Clarkson, 2023). It assessed the status of bird habitat within Audubon lands, focusing on both breeding season and overwintering bird populations. With this study, Rhode Island stands as the only state in the union to possess a comprehensive report for both breeding and overwintering birds. Among the extensive list of species included within the Audubon reports, nine Responsibility Bird Species (RBS) were identified as 'umbrella species', meaning that their conservation "may indirectly lead to the conservation of other birds with similar habits" (Clarkson, 2023).

The Rhode Island RBS identified by Audubon are the Chimney Swift (*Chaetura pelagica*), Barn Swallow (*Hirundo rustica*), Common Yellowthroat (*Geothlypis trichas*), Prairie Warbler (*Setophaga discolor*), Eastern Towhee (*Pipilo erythrophthalmus*), Black-and-white Warbler (*Mniotilta varia*), Wood Thrush (*Hylocichla mustelina*), Scarlet Tanager (*Piranga olivacea*), and Red-winged Blackbird (*Agelaius phoeniceus*) (Clarkson, 2023). RBS are all experiencing nationwide declines and require additional monitoring and management. Additionally, through climatic and anthropogenic factors such as urbanization, sea level rise, and development, Rhode Island is experiencing volatile land use land cover (LULC) changes, which further degrade, alter, or shift avian habitats and populations (Berry et al., 2015; Caron & Paton, 2007; Lussier et al., 2006; Sims et al., 2013).

The National Oceanic and Atmospheric Administration (NOAA) Coastal Change Analysis Program (C-CAP) designates coastal land cover classes within the United States, including Rhode Island. C-CAP's most recent high-resolution dataset from 2021 is a reliable LULC data source utilized at a state level by wildlife biologists, conservationists, and developers. Audubon relied on standardized C-CAP land cover classification schema for its *The State of Our Birds* study. They designated the following eight C-CAP-defined habitats as the "most important" for RBS in Rhode Island: Developed High Intensity, Grassland/Herbaceous, Forested Wetlands, Scrub/Shrub Wetlands, Scrub/Shrub, Forest Edge, Deciduous Forest, and Deciduous Forest Edge.

Rhode Island, like many other jurisdictions of the United States, has witnessed significant shifts in land usage over the past several decades, with areas of "low disturbance" LULC classes like evergreen forest and pastureland transitioning into "high disturbance" classes like developed land (Mikhailova et al., 2021). Remote sensing imagery, GIS tools, and TerrSet modeling have all proven successful in conveying LULC change and predicting future LULC trends (Campbell et al., 2018; Lussier et al., 2006; McKinney & Paton, 2009; Pinos & Dobesova, 2019; Sims et al., 2013; Spruce et al. 2018; Spruce et al. 2020). Integrating remote sensing frameworks with Earth observation data into user-friendly habitat monitoring methods can enable nonprofit organizations and other conservation groups to easily highlight areas of ecological importance and more effectively set priorities for land acquisition and management. By incorporating remote sensing frameworks into current and projected LULC maps, we can support Audubon's efforts to highlight areas of conservation importance for RBS and prioritize areas for land acquisition and management.

2.2 Study Area & Study Period

Our study focused on the entire state of Rhode Island, the smallest state in the United States, which encompasses 776,960 acres (Figure 1). The study period regards 2011 to 2043. Due to the file formats used in the ecological forecasting software, TerrSet, the study area for forecast LULC change maps included some area outside of Rhode Island [geographic coordinates 42.018798, 41.146339, -71.862772, -71.120570].

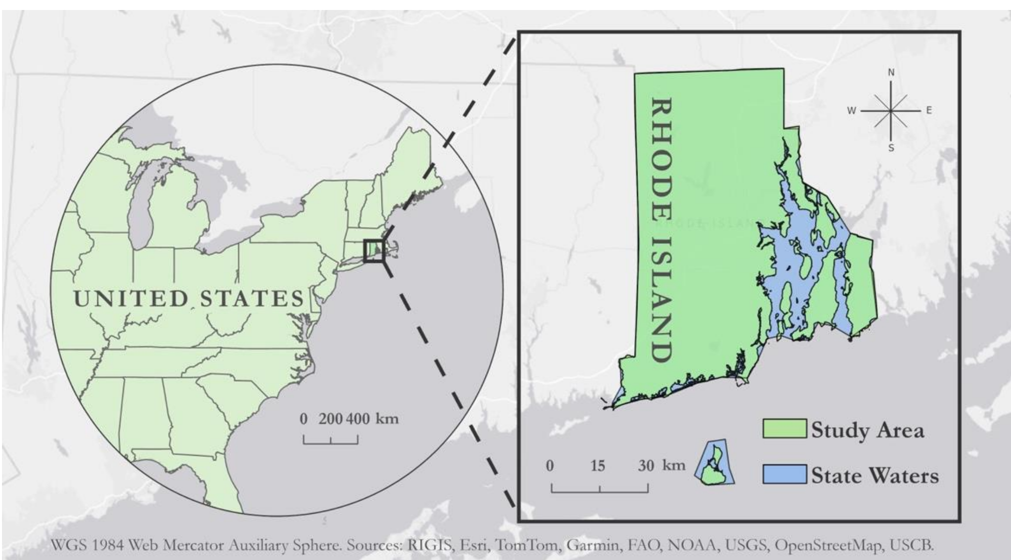

Figure 1. The study area of Rhode Island, USA.

2.3 Project Partners & Project Objectives

To undertake this project, we collaborated with The Audubon Society of Rhode Island. The Audubon's mission is to protect birds, other wildlife, and their habitats through conservation, education, and advocacy, for the benefit of people and all other life. Audubon manages approximately 10,000 acres (about half the area of Manhattan) of wildlife habitat in Rhode Island, making them the second-largest private landowners in the state. Among the lands Audubon oversees, 14 refuges are open to the public. Much of the managed land, however, has not been surveyed, and existing knowledge primarily stems from land cover usage maps dating back to 2011. In 2022, volunteers conducted wildlife surveys of the publicly accessible refuges, focusing on both breeding season and overwintering bird populations. The data collected became the basis for the *State of Our Birds* reports. Audubon has identified that its current land acquisition strategy could be improved through access to more specific information on potential bird-habitat locations throughout the state. Their current research relies upon an outdated Rhode Island LULC map from 2011. The landscape has undergone significant alteration over the last thirteen years.

Our project began with two primary objectives: [1] Use NASA Earth imagery to generate LULC change maps based on historical and contemporary land cover compositions from 2013 to 2023, to evaluate recent changes across Rhode Island and [2] based on the 2013 and 2023 LULC maps, develop a series of forecasted LULC maps projecting conditions in four equal interval time steps from 2023 to 2043. The goal of the objectives was to aid Audubon in making better informed land acquisition choices in support of avian habitat conservation. Due to the nature and scope of this feasibility study, the project's initial objectives were modified as work progressed in response to time constraints, available technological support, and partner needs.

3. Methodology

3.1 Data Acquisition

The data acquisition process for the GIS-based LULC mapping method involved locating the appropriate satellite imagery and ancillary datasets to support habitat monitoring and land cover change analysis in Rhode Island. We obtained satellite imagery from USGS Earth Explorer. We downloaded Collection-2 Level-2 Landsat 9 OLI-2 imagery for the year 2023 (Table 1). The Collection-2 Level-2 data uses surface reflectance algorithms to correct for temporally, spatially, and spectrally varying scattering and absorbing effects of atmospheric gases, aerosols, and water vapor. The May 22, 2023, date was selected based on low-to-no cloud cover for the terrestrial portion of the image.

Major ancillary datasets were obtained for 2023 (Table 1). Historic and current LULC maps, such as NLCD and C-CAP provided baseline locations for the study's six classified land uses throughout the state. We also incorporated state level vector datasets for roads, infrastructure, and hydrology into the analysis.

Table 1
List of sensors and data sources primarily utilized for this project.

Source	Product	Date(s)	Data
Landsat 9 OLI-2 Primary Source	LC09_L2SP_012031_20230522_20230524_02_T1 LC09_L2SP_012031_20231130_20231201_02_T1	5/22/23 11/30/23	Bands 2–7
Landsat 8 OLI Primary Source	LC08_L2SP_012031_20130502_20200913_02_T1	05/02/13	Bands 2–7
USGS National Land Cover Database (NLCD) Ancillary Data	NLCD 2011 Land Cover (CONUS) NLCD 2021 Land Cover (CONUS)	2011 2021	LULC

NOAA Coast Change Analysis Program (C-CAP) Ancillary Data	Hi-res (1-m resolution) Rhode Island Land Cover	2016	LULC
USFWS National Wetlands Inventory (NWI) Ancillary Data	NWI Rhode Island	2010	LULC
USDA Cropland Data Ancillary Data	Rhode Island Cropland	2022	LULC
University of Rhode Island (URI) Environmental Data Center and Rhode Island GIS (RIGIS) Ancillary Data	Lakes and Ponds 24k	2023	Single Category Vectors
	Rivers and Streams 24k	2023	
	RIDOT Roads 2016	2016	
	Building Footprints	2018	
USGS Mineral Resources	Rhode Island US Mine Features (Quarries and Open Pit Mines)	2006	Single Category Vector
Narragansett Bay Estuary Program Ancillary Data	Solarfields 2022 Clark Solarfields Cleared Land 2022	2022	Single Category Vector
US Census Bureau Cartographic Boundary Files Ancillary Data	1:500,000 National	2022	Single Category Vector

3.2 Data Processing

We used a standardized process in QGIS version 3.3.4 to clean a single, cloud-free Landsat 9 surface-reflectance scene from May 22, 2023. We selected bands 2–7 (Blue (B), Green (G), Red (R), Near Infrared (NIR), Short-wave Infrared 1 (SWIR1), and Short-wave Infrared 2 (SWIR2)) to be preprocessed to surface reflectance and applied DOS1 atmospheric corrections using the Semi-automatic Classification Plugin (SCP) (Congedo 2021).

We brought the QGIS-processed surface reflectance bands into Esri ArcGIS Pro 3.2.2 using the Composite Bands tool. Pyramid layers and statistics were automatically generated during the composite process. Bands 4 (R), 5 (NIR), and 6 (SWIR1) were added individually to calculate the Normalized Difference Vegetation Index (NDVI) and the Moisture Stress Index (MSI). We created NDVI and MSI layers to help enhance differences between wetland and upland forms of vegetated land cover.

The sequence of our 'reclassify by feature' processes was intentional. We merged ancillary data representing development first, in order from least recent and accurate to most recent and accurate. We added quarries and mines first, then roads, and building footprints, solar installations, and finally agricultural operations. Due to the inherent challenges of differentiating vegetated landcovers, we used a process of elimination approach to pull all the other readily available land cover classes out first, leaving only a broadly defined "habitat" class containing everything from forests, to grasslands, to wetlands. The classes defined prior to work on the broad habitat class included: Open Water [1], Agricultural [3], and another broad class [2] containing Developed, Open Space, and Barren pixels.

Using GIS, we processed the May 22, 2023, Landsat scene into a composite of bands 2–7 with NDVI and MSI layers that we calculated from some of the bands. We applied an offshore open water mask to the composite. We processed the composite using the Unsupervised Iso Cluster tool in ArcGIS Pro. This tool groups pixels by their spectral signatures. We used the Esri ArcGIS Pro defaults to run the clustering (classes=30, min. class size=20, sample interval=10). Our preliminary unsupervised classification computed 30 distinct classes. We carefully reviewed the results and compared them to ancillary hydrological data and red-green-blue (RGB) imagery appropriate to the subject scene's date to discern which cluster classes were associated with open water. To isolate all areas of open water within the scene, we extracted the open water clusters from our classification area. We then masked the water from the map, so it would be excluded from the clusters. This process was conducted to improve unsupervised land classification outcomes going forward. We re-ran the Unsupervised Iso Cluster routine once more using the same default parameters as before. The outcome of this operation was a preliminary LULC classification map with 26 distinct pixel classes to refine for our final map.

The 26 classes were reclassified and refined into six LULC categories using a variety of approaches. The six classes were based on pared down NLCD classifications: 1) Open Water, 2) Developed/Open Space/Barren, 3) Agricultural, 4) Upland Habitat, 5) Woody Wetlands, and 6) Non-Woody Wetlands (Table 2.) We viewed each cluster individually and started by using a 'process of elimination' or 'low-hanging fruit' approach, where we began reclassifying the clusters into organized landcover classes if it seemed only one class was present in the cluster. We spent time analyzing the pixels within each remaining class and compared the pixel groups to underlying map layers of higher resolution imagery, and to other ancillary data (Table 1). We then grouped classes together using the reclassify tool.

To 'cluster bust' or break confused cluster classes up based on the multiple landcovers each class represented, we overlaid ancillary datasets. This process involved securing data for roads, building footprints, streams, waterbodies, wetlands, agricultural land, solar energy installations, and quarries (Table 1). All ancillary data was in vector format. Each of these layers needed to be processed in a way that made the ancillary data compatible with the LULC layer we were working to create. Some extra pre-processing steps were necessary with the ancillary vectors to best use the data in a non-native raster format. For instance, we applied a 30-foot buffer to the roads vector layer. Because road layers are polylines symbolizing the street centerline, adding a 30' buffer captured the average roadbed and roadside maintenance areas of most roads. The resulting buffer layer was then dissolved into a single feature and rasterized. We adjusted the properties of the roads raster to ensure it was consistent with our working LULC raster. We merged our roads raster with our preliminary LULC layer so that any cells in the preliminary LULC intersecting the roads would have the existing class value replaced. We repeated this process on each ancillary layer, with minor modifications to accommodate the spatial needs of each layer. Rasterizing feature-specific vector data and merging it with our classification raster was especially useful for defining the entire Agricultural Lands class, Wetlands classes, and capturing all roads, building footprints, quarries, mines, and solar installations into the Developed class. The final step in this process was to vectorize the LULC layer and clip it to the same Census Bureau state outline we had used previously. We refrained from clipping the LULC to the state outline in previous steps to allow the most possible area for the iso cluster software and the reviewers to draw landscape information from. Vectorizing the raster at the end of the process also allowed us to smooth the cells into simplified shapes thereby improving aesthetics as well as making it easier to calculate the geography of each feature.

Table 2
Classifications for our six GIS LULC land cover classes.

Class	**Description** (based on pared down NLCD land use land cover classifications)
Open Water	Areas of open water generally with less than 25% cover of vegetation or soil.
Developed/Open Space/Barren	• Low-High Intensity 20-100% cover of impervious surfaces. Uses such as industrial, commercial, roadways, residential. • Open Space <20% cover of impervious surfaces. Uses such as single-family residential, parks, golf courses, landscaping. • Barren areas of bedrock, sand, other bare earthen material.
Agricultural	*Some other agricultural uses such as dairies or greenhouses will fall into the developed categories.* • Pasture/Hay Areas of cultivated grasses, legumes, or grass-legume mixtures planted for livestock grazing or the production of seed or hay crops, typically perennial. Pasture hay vegetation accounts for >20% total vegetation. • Cultivated Crops Areas used to produce annual crops such as apples, sweet corn, potatoes, vineyards, cranberries. Any land actively tilled.
Upland Habitat	• Grassland/Herbaceous Natural areas dominated by graminoid or herbaceous vegetation, generally >80%. Not subject to tilling but can be utilized for grazing. • Scrub Shrub Areas dominated by shrubs <5 meters tall/>20% cover. Includes true shrubs, tree saplings, stunted trees. • Deciduous Forest Areas dominated by trees >5 meters tall/>20% cover, >75% shed foliage seasonally. • Mixed Forest Areas dominated by trees >5 meters tall/>20% cover, neither deciduous or evergreen is >75% cover. • Commercial Timberland Primarily evergreen forest plantations, and oak (spp.) stands.
Woody Wetlands	*Areas where forest or shrubland vegetation accounts for >20% of vegetative cover and soil substrate is periodically-permanently saturated or inundated.* • Forested Wetlands • Scrub Shrub Wetlands
Non-Woody Wetlands	*Includes emergent herbaceous wetlands (areas where perennial herbaceous vegetation >80% of cover, and soil/substrate is periodically saturated/inundated with water.*

For the TerrSet modeling we processed 2011 and 2021 NLCD data. Due to modeling constraints, we had to reclassify the 15 NLCD classifications into condensed 8 class NLCD maps (Table 3). The 8 classes used in

TerrSet's projection scheme were: Open Water; Developed/Open Space; Barren; Forest/Scrub-Shrub (Upland); Grassland/Herbaceous (Upland); Agricultural Land; Woody Wetland; and Non-woody Wetland.

Table 3
Reclassification of NLCD classes, for TerrSet modeling.

<table>
<tr><th>NLCD Land Cover Classification</th><th>Reclassified Land Cover Classification</th></tr>
<tr><td>Open Water</td><td>Open Water</td></tr>
<tr><td>Developed, Open Space</td><td rowspan="4">Developed</td></tr>
<tr><td>Developed, Low Intensity</td></tr>
<tr><td>Developed, Medium Intensity</td></tr>
<tr><td>Developed, High Intensity</td></tr>
<tr><td>Barren Land</td><td>Barren</td></tr>
<tr><td>Deciduous Forest</td><td rowspan="4">Forest</td></tr>
<tr><td>Evergreen Forest</td></tr>
<tr><td>Mixed Forest</td></tr>
<tr><td>Shrub/Scrub</td></tr>
<tr><td>Grassland/Herbaceous</td><td>Grassland/Herbaceous</td></tr>
<tr><td>Pasture/Hay</td><td rowspan="2">Agricultural Lands</td></tr>
<tr><td>Cultivated Crops</td></tr>
<tr><td>Woody Wetlands</td><td>Woody Wetlands</td></tr>
<tr><td>Emergent Herbaceous Wetlands</td><td>Non-woody Wetlands</td></tr>
</table>

TerrSet's Land Change Modeler requires precise coordinate and spatial resolution matching for all uploaded files. Maps were exported from ArcGIS Pro as IMAGINE files and converted to a .rst file using TerrSet's GDAL Conversion Tool. The Rhode Island building footprints, road layer, rivers and streams, lakes and ponds, and digital elevation model variables were converted into rasters in ArcGIS Pro, then reclassified to a single object layer, so the objects had a value of one and background had a value of zero. These driver variable rasters were also exported as an IMAGINE file, converted to. rst format in TerrSet, then set with a default distance boundary using TerrSet's Distance tool. Lastly, these driver variable files were projected in TerrSet to the 2021 map data layer so that the formatting of all input spatial data to the model was consistent.

3.3 Data Analysis

To assess the agreement of our 2023 unsupervised land classification map, we conducted an accuracy assessment using a confusion matrix. The confusion matrix was created by using randomly generated accuracy assessment points in ArcGIS Pro and comparing them to reference imagery for similar dates. We used the geoprocessing tool Create Accuracy Assessment Points with the following parameters: sample size=500 and stratified random sampling method; N=507. We uploaded the accuracy assessment points to Google Earth (Imagery: Airbus, May 23, 2023) and manually classified each point into one of six land cover classes (Table 2). A confusion matrix with Cohen's Kappa statistics were created in Microsoft Excel to calculate accuracy amongst each land cover class. A land cover map can be considered acceptable if it has an overall Kappa value greater than or equal to 0.80. A Kappa value of 1 indicates perfect agreement, where a 0 indicates agreement no better than expected by chance (Detorri and Norvell 2020).

Projected 2043 land cover data were created in Terret's Land Change Modeler by analyzing historical land use change from 2011 and 2021 and using the driver variables (Table 1) to project that change to 2043 in 5.5-year intervals from 2021 to 2026, 2032, 2037, and 2043. A transition potential model showed that elevation was not a significant driver variable, so projections were run using only four variables of distance to lakes, roads, buildings, and ponds. We determined that a Weighted Normalized Likelihood (WNL) procedure was the best test to forecast the 49 possible LULC changes, as the WNL is capable of quickly calculating many changes with maximum accuracy (Eastman et al., 2019). The WNL calculates an accuracy assessment for each class to class change which was used to affirm the validity of the model (Appendix C). Land class acreage basic statistics were calculated and visualized in Microsoft Excel.

To assess estimated likelihood of our forecasted future land cover change maps to predict class specific change, we used a class-by-class accuracy for change output. This change is the likelihood that a pixel of that recorded land class change was correctly classified into the transitioned class. The change occurrence likelihood scale ranges from 0–1, with anything above a 0.5 indicating a correct, or accurate classification transition, anything under 0.5 indicating a pixel is unlikely to undergo that change, and a 0.5 represents an unchanged classification (Appendix C).

4. Results & Discussion

4.1 Analysis of Results

4.1.1. Land Use Land Cover

Unsupervised classifications for 2023 (Figure 2) were completed for six land cover classes with a Kappa statistic of 0.86. This indicates a good agreement with validation data and an accurate classification map (Appendix B). Upland forest, shrub, and grassland comprised the largest area of Rhode Island (40.7%), followed by developed, open space, and barren (38.7%), woody wetlands (11.7%), open water (4.5%), agriculture (3.8%), and non-woody wetlands (0.6%) (Figure 3). A similar land use pattern was observed when paralleled in Google Earth Engine (Appendix A).

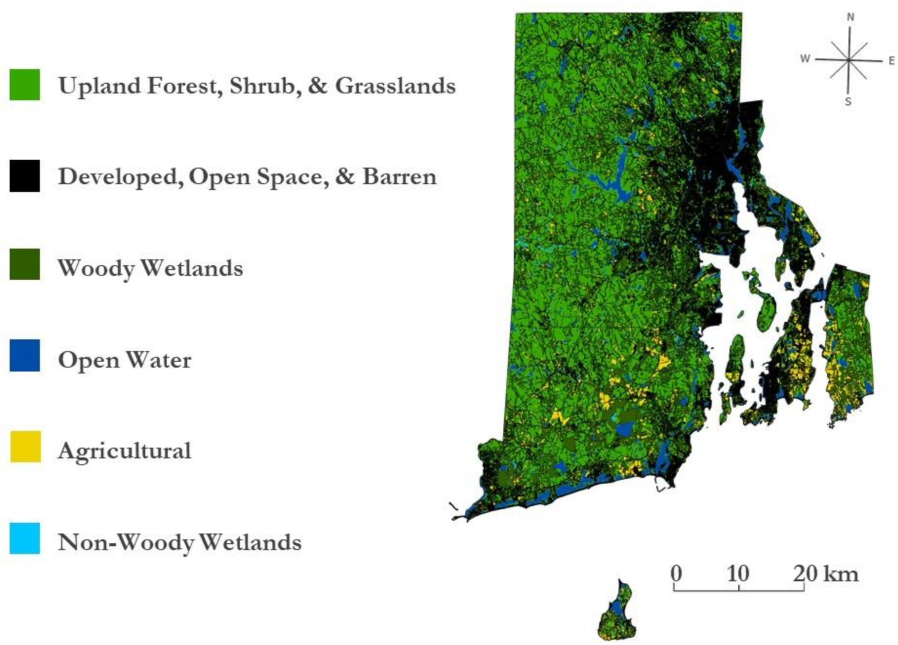

Figure 2. Land cover classification for 2023.

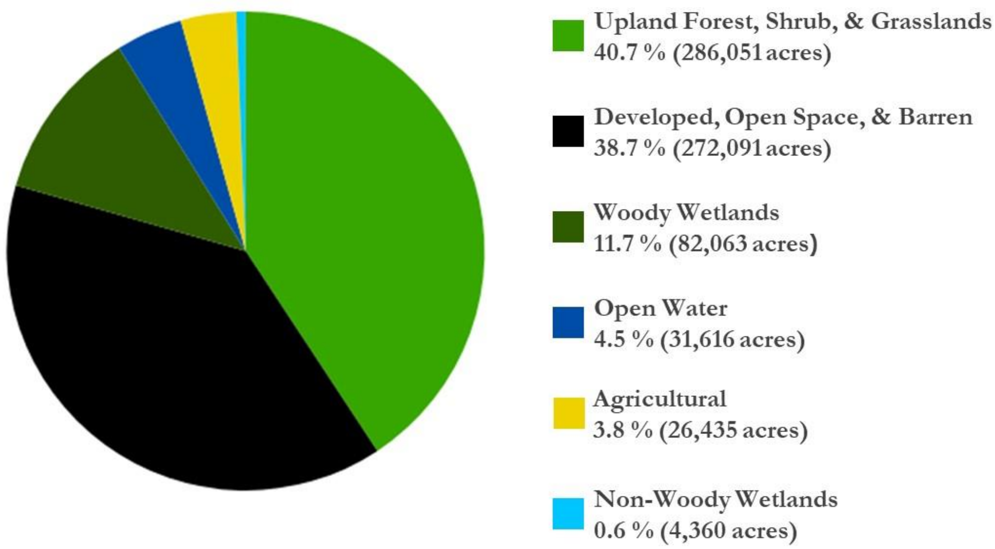

Figure 3. Land cover by percentage.

4.1.2 Land Use Land Cover Change

Based on NLCD data, the land use land cover change analysis for 2011 to 2021 revealed a decrease in non-woody wetlands, agricultural fields, and forest. Meanwhile, woody wetlands, grasslands, barren, developed, and open water classes all experienced an increase in acreage during the same time (Figure 4).

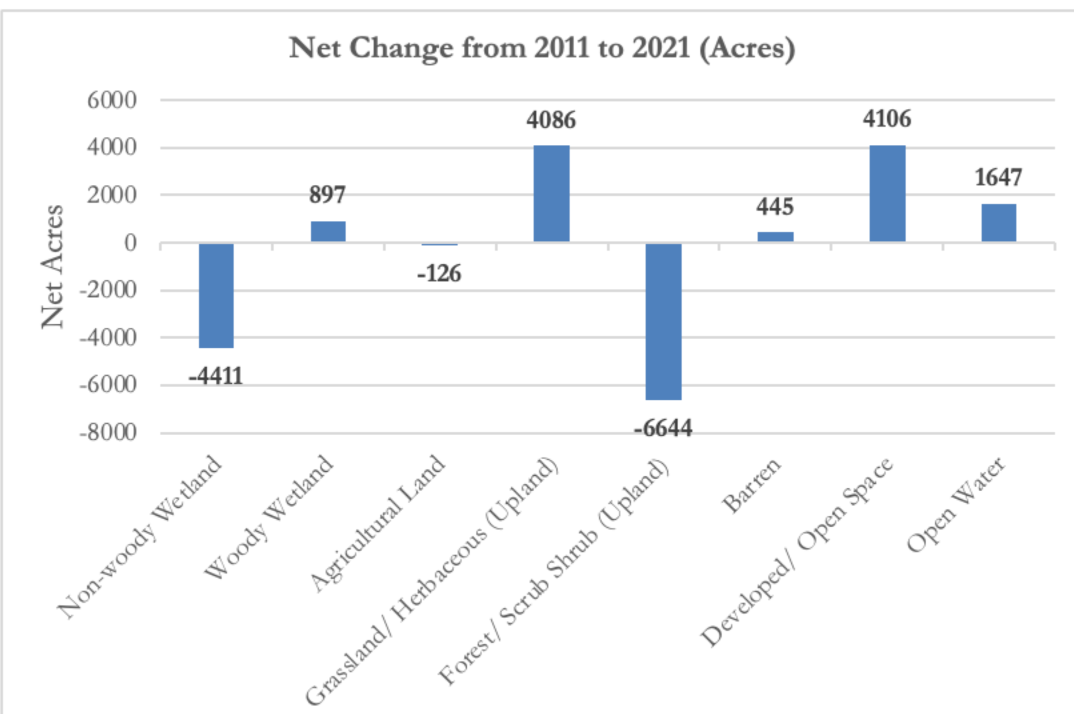

Figure 4. Net land use cover change between 2011 and 2021.

4.1.3 Forecasted Land Cover

Our forecasted land use land cover maps indicate that that the non-woody wetlands will completely disappear by 2026 with this LULC type not reappearing in any projection (Figure 6). In the projections, non-woody wetlands are lost to woody wetlands, open water, and development. The loss of non-woody wetlands is likely a forecast modeling inaccuracy, because as of 2023, we know there are approximately 4,360 acres of non-woody wetlands (Figure 3). Regardless, given concerns about sea level rise, nonwoody wetlands likely remains a priority for Audubon's conservation efforts as they are threatened by climate change and are rare compared to most other LULC types in Rhode Island.

By 2043, forest and woody wetlands show a decrease in acreage compared to 2023, while open water, development, barren, grassland, and agriculture all show an increase in acreage (Figure 5). Forests and woody wetlands are primarily displaced by forest clearing either as a forestry practice or as some kind of development. The overall trend can be observed at each 5.5-year projection (Figure 6, Appendix C).

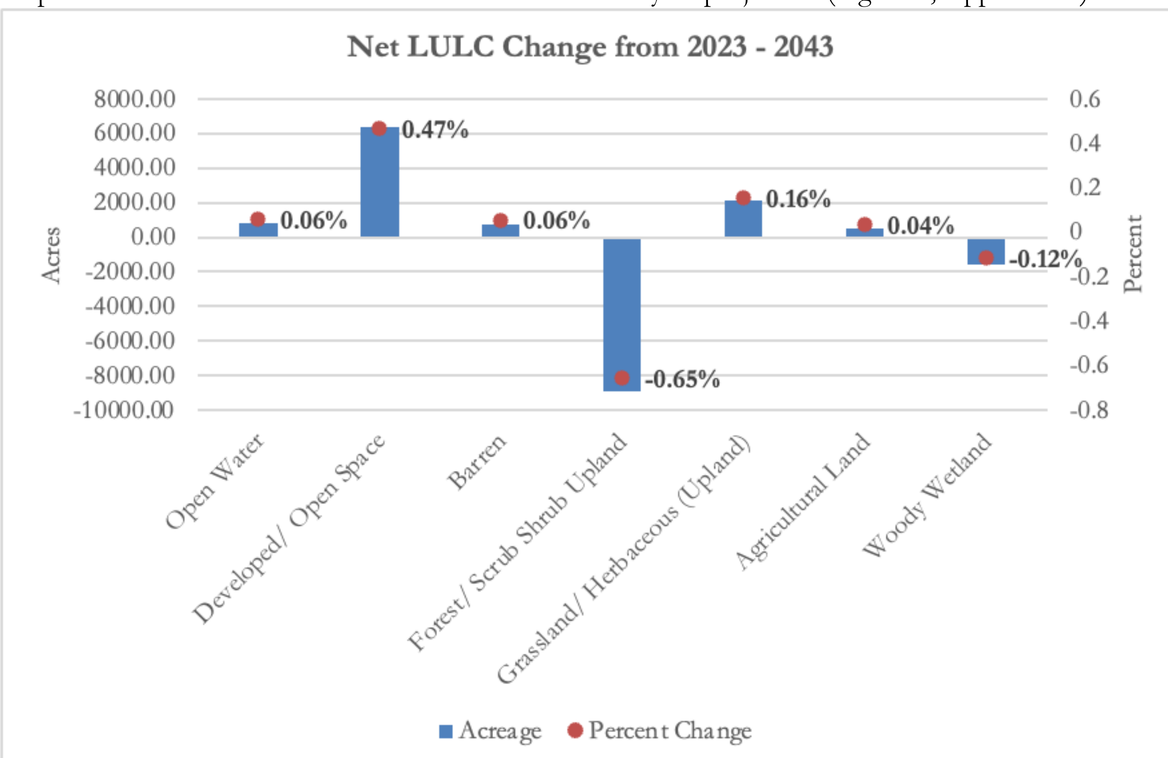

Figure 5. Net acreage and percentage change in LULC between 2023 and 2043. The bars show acreage on the primary y-axis and the points show percent change on the secondary y-axis.

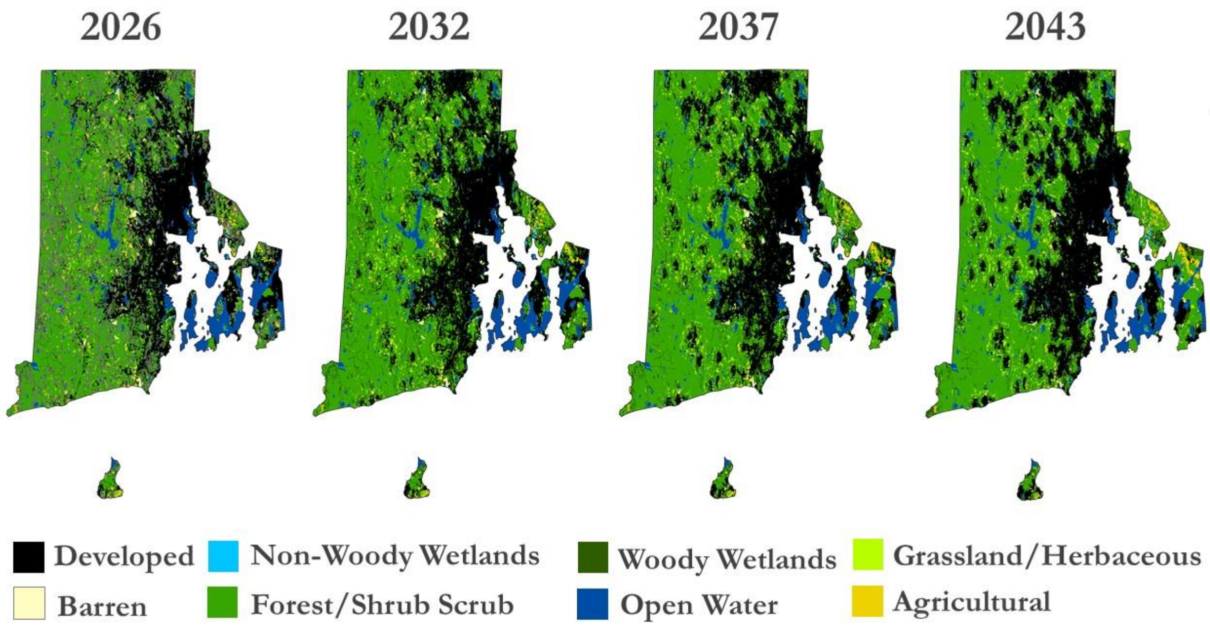

Figure 6. Projected land cover maps 2026 – 2043.

It is important to note that land class acreages between the 2023 unsupervised classification map and the forecasted maps could not be compared due to file formats; however, future work may address this issue by converting one format to another. The file formats needed by TerrSet affected the clipping extents of the projected images, resulting in inflated acreage, by including land outside of our study area. Although the land cover acreage amounts differ amongst the TerrSet and ArcGIS computed maps, the trends and accuracies are similar, lending credibility to both methods. The Weighted Normalized Likelihood (WNL) accuracy assessment showed the upper limit with moderately high agreement (i.e. likelihood of change occurrence) indicating that the projected LULC maps have a moderately high potential of being true future projections, given the driver variables (Appendix C).

The accuracy assessment of the LULC change potential yielded the following observations: The highest class change potential accuracy was from open water to barren, at 0.88. The least accurate transition potential was from forest to woody wetland at 0.322. Open water change transition potentials were the most accurate, ranging from 0.795 (change to woody wetlands) to 0.88 (change to barren). Woody wetland transitions showed moderate accuracy, ranging from 0.61 (agriculture) to 0.78 (grassland), but class transitions to woody wetlands were consistently inaccurate. The apparent inaccuracy of changes to woody wetlands falls in line with the overall loss of woody wetlands, as it would be unlikely that certain land classes are changing to woody wetlands. Woody wetlands were mostly lost to grasslands, agriculture, and development.

It is possible that non-woody wetlands were classified as woody wetlands, which would contribute to the complete loss of non-woody wetlands. We believe this also may have been a classification error when reclassifying the 2021 NLCD map. Non-woody wetlands are also quite rare across the state, so small changes may matter more for the rarely occurring classes. The class's decline would be exacerbated by the further decline of woody wetlands, especially as one of the largest transitions of both these wetland classes was to development, which had an accuracy range of 0.546 (woody wetlands) to 0.739 (barren).

4.2 Feasibility for Partner Use

4.2.1 ArcGIS and TerrSet

This project's scope was modified throughout our work to accommodate time constraints and technology gaps. In terms of using GIS to conduct land cover analysis and classification, this objective was only partially feasible within the project timeframe, with only one of two dates of LULC maps created using the unsupervised classification approach. Due to this, the second objective of using GIS to create LULC maps and analyze LULC change for the two targeted dates was also not met as far as computing new LULC maps as inputs to the change map. As far as creating accurate LULC maps that contain an acceptable level of detail, this objective was partially fulfilled with our 2023 LULC map. However, also NLCD maps for 2011 and 2021 were available and used to construct LULC change maps that were then used with TerrSet LCM to compute future LULC change maps.

Our study's large geographical extent led to increased time spent analyzing the landscape. Creating a LULC map for an entire state meant we also had to understand and identify a wide variety of land uses and covers. An additional challenge with the state-wide extent was that all ancillary data needed to be state-wide at a minimum. In our work with Landsat imagery, we encountered cloud contamination and locally evident haze in many of the scenes, which are common to coastal areas. Haze along the southern coast of the Rhode Island in the May 2023 scene selected for deriving the LULC map likely contributed to the challenges the software had with differentiating certain LULC classes (e.g., non-woody wetland areas) in the unsupervised classification.

At the project's outset, the goal was to create Landsat-based leaf-off and leaf-on LULC maps for each year. This method would have allowed us to integrate the two LULC classifications together into a holistic map, cherry-picking the most accurate landscape delineations from each into one map representing the entire year. Analysis of a leaf-off scene in addition to the leaf-on scene we chose would likely have enabled finer differentiation of forest types and woody vs. non-woody vegetation. Without the leaf-off LULC and additional analysis, we were compelled to consolidate all forest types, grassland and herbaceous areas, and shrub-scrub into one upland habitat class. We could have attempted to keep to our original nine landcover class schema but would have compromised the map's accuracy. The 2023 LULC map that we produced is accurate compared to reference data and will be useful to the partner for showing areas of development versus other kinds of habitat overall.

TerrSet's Land Change Modeler is a feasible option for projecting future LULC change, but comparison between other methods in near impossible as projection validity requires an existing map of that year, which cannot be done if the year has not come to pass yet. With more time, projecting our LULC from NLCD data to 2023 could reasonably allow for a comparison to an ArcPro-generated map, provided the file types have been converted to TerrSet-compatible files and the spatial extent of both images matches exactly. Still, TerrSet provides a useful tool for ecological forecasting and successfully generated forecasts of future Rhode Island LULC maps over the next two decades.

We provided methodologies for Audubon to conduct their own LULC analyses using Earth observations. Data acquisition and processing can be done through open-source software like USGS Earth Explorer and QGIS, but making LULC change projections in TerrSet is not feasible with the method used in the project unless Audubon pays for the yearly subscription. Audubon also now has the projected LULC maps to 2043, so they have land change data, and it may be unnecessary for the organization to purchase a TerrSet service if the maps from this project are deemed sufficient.

4.2.2. Google Earth Engine (Appendix A)

We paralleled the process for creating a land use land cover map in Google Earth Engine (GEE), using supervised classification. The GEE method is contrast to the ArcGIS unsupervised classification method also employed in the project. We found GEE to be useful in accessing and processing satellite imagery, making it feasible for computing and analyzing large-scale land use changes, with free software. GEE provided access to vast geospatial datasets and computational resources required for image processing and analysis. Additionally, GEE has a built-in Random Forest classifier which is a widely used machine learning algorithm suitable for deriving supervised land cover classification. GEE also has unsupervised classification tools.

Despite its feasibility, there are a few possible errors that might be encountered during execution. One potential error source is data availability and quality. The Landsat imagery used for classification may suffer from cloud cover or sensor errors, leading to inaccuracies in land cover classification. Moreover, mislabeling of training data or inaccuracies in the reference data used for accuracy assessment can introduce errors in the classification results. Additionally, errors may arise from parameter settings, such as the number of decision trees in the Random Forest classifier or the scale used for reducing regions, affecting the classification accuracy. The availability of reference data for training can be problematic for supervised classifications when there are several targeted classes and the image analysts are not familiar in a firsthand way with the study area. For this project, the use of NLCD data was employed for selecting training samples, though it should be noted that the NLDC LULC maps can have classification errors as well.

There are uncertainties associated with LULC classification process and the interpretation of related mapping results. Variability in land cover characteristics within the study area, such as spectral similarity between different land cover types or temporal changes not captured by the selected dates of Landsat imagery, may lead to uncertainties in classification results. Furthermore, assumptions made during the analysis, such as the consistency of land cover transitions over time or the suitability of the selected classification algorithm and parameters for the study area, contribute to uncertainties in the final land use maps. Additionally, the accuracy assessment method used in one's code, based on comparing classified maps with reference data, may not fully capture the complexity of land cover dynamics and change processes, leading to uncertainties in accuracy estimates.

4.3 Future Recommendations

Future work could include creating a historic LULC map from available 2013 Landsat data in conjunction with unsupervised classification methods. This was tried in the current project using GEE supervised classification but was not completed using the ArcGIS-based unsupervised classification method. The historic LULC map for 2013 based on unsupervised classification could then be used to generate forecasted maps, rather than using NLCD data. This would likely provide a more detailed and accurate projection of future LULC change, especially considering the loss of non-woody wetlands in our current projections. Continued work could also incorporate drought and sea-rise data into the projections since climate change is an ongoing ecological issue.

When completing the unsupervised classification, we lumped together all forests, scrub/shrub, and grassland habitats because they were hard to distinguish with the Iso Cluster tool and available time to do classification refinement was limited. Given the ecological and environmental significance of forests, we would recommend trying to distinguish different forest types (deciduous, mixed, scrub/shrub) and grasslands. By employing more advanced remote sensing techniques, using multiple seasons of Landsat data, and incorporating ancillary data sources such as vegetation indices and topographic variables, we can gain deeper insights into the composition and distribution of these different habitats. Moreover, it is also essential to refine the classification process to accurately tease out industrial developments that may overlap with certain land cover classes. For example, distinguishing features such as maintained power transmission right of ways could provide a more nuanced understanding of land use dynamics, particularly in areas undergoing rapid urbanization or industrialization.

5. Conclusions

General trends in land cover change between 2011 and 2021 showed a decrease primarily in forests. We also observed decreases in non-woody wetlands in 2021, however we now believe these non-woody wetlands may have been miscategorized or inadvertently grouped into woody wetlands. We know from the National Wetland Inventory that there are non-woody wetlands present in Rhode Island as of 2023 and such wetlands also typically occurred on the 2021 NLCD data. Projected land cover changes to the year 2043 show a similar trend where forests and wetlands continue to decline, but this assumes that change trajectory continues at the same rate into some future specified date. The loss of forest habitats appears to be largely related to anthropogenic disturbances, such as increased urban development of buildings, leisure spaces (e.g. golf courses, open parks), and possibly also agricultural expansion. Low lying coastal marshes may also be vulnerable to sea level rise and severe hurricanes. The decrease of forest and wetlands has occurred across many areas of the United States (Cohen et al. 2016; Davidson 2016).

Although we had to reduce the specificity of our land cover classifications to six classes, we are hopeful the 2023 LULC map computed with this project will still be a valuable resource for Audubon and other conservation groups, as an aid in making decisions about land acquisition. Audubon can use this data to help assess and plan targeted land conservation areas to save the current habitat or protect the habitats that will arise. Audubon is also able to conduct further land classification analyses using open-source software, plus current and historic Landsat data. The partner knows what needs to be addressed to continue follow-on work into a second DEVELOP term if they should choose.

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7. Glossary

C-CAP – NOAA's Coastal Change Analysis Program
CDL – USDA Cropland Data Layer
Earth observations – Satellites and sensors that collect information about the Earth's physical, chemical, and biological systems over space and time
GIS – Geographic Information System
LULC – Land Use Land Cover
LULCC – Land Use Land Cover Change
MSI – Moisture Stress Index
NAIP – National Agriculture Imagery Program
NDVI – Normalized Difference Vegetation Index
NOAA – National Oceanic and Atmospheric Administration
NWI – National Wetland Inventory
OLI-2 – Operational Land Imager 2, a sensor found on Landsat 9 satellite
Remote sensing – the acquiring of information from a distance
USDA – United States Department of Agriculture
USFWS – United States Fish and Wildlife Service
USGS – United Stated Geological Survey
WNL –Weighted Normalized Likelihood

8. References

Berry, W. J., Reinert, S. E., Gallagher, M. E., Lussier, S. M., & Walsh, E. (2015). Population Status of the Seaside Sparrow in Rhode Island: A 25-Year Assessment. *Northeastern Naturalist*, *22*(4), 658–671. https://doi.org/10.1656/045.022.0403

Campbell, A., Pradhanang, S. M., Kouhi Anbaran, S., Sargent, J., Palmer, Z., & Audette, M. (2017). Assessing the impact of urbanization on flood risk and severity for the Pawtuxet watershed, Rhode Island. *Lake and Reservoir Management*, 34(1), 74–87. https://doi.org/10.1080/10402381.2017.1390016

Caron, C. M., & Paton, P. W. C. (2007). Population trends and habitat use of Harlequin Ducks in Rhode Island. *Journal of Field Ornithology*, 78(3), 254–262. https://doi.org/10.1111/j.1557-9263.2007.00110.x

Clarkson, C. (2023). *The State of Our Birds Part I: Breeding and Overwintering*. Audubon Society of Rhode Island.

Cohen, W. B., Yang, Z., Stehman, S. V., Schroeder, T. A., Bell, D. M., Masek, J. G., Huang, C., & Meigs, G.W. Forest disturbance across the conterminous United States from 1985 –2012: the emerging dominance of forest decline. Forest Ecology and Management, 360, 242–252.

Congedo, Luca, (2021). Semi-Automatic Classification Plugin: A Python tool for the download and processing of remote sensing images in QGIS. *Journal of Open Source Software*, 6(64), 3172, https://doi.org/10.21105/joss.03172

Davidson, N. C. (2016). The Wetland Book. In: Finlayson, C., Milton, G., Prentice, R., Davidson, N. (eds) The Wetland Book. Springer, Dordrecht. https://doi.org/10.1007/978-94-007-6173-5_197-1

Dettori, J. R. & Norvell, D. C. (2020). Kappa and beyond: is there agreement? *Global Spine Journal*, 10(4),499–501. https://doi.org/10.1177/2192568220911648

Eastman, J. R., Crema, S. C., Rush, H. R., & Zhang, K. (2019). A weighted normalized likelihood procedure for empirical land change modeling. Modeling Earth Systems and Environment, 5(3), 985–996. https://doi.org/10.1007/s40808-019-00584-0

Golet, F. C., Wang, Y., Merrow, J. S., & DeRagon, W. R. (2001). Relationship between habitat and landscape features and the avian community of Red Maple swamps in Southern Rhode Island. *The Wilson Bulletin*, *113*(2), 217+.

Lussier, S. M., Enser, R. W., Dasilva, S. N., & Charpentier, M. (2006). Effects of Habitat Disturbance from Residential Development on Breeding Bird Communities in Riparian Corridors. *Environmental Management*, *38*(3), 504–521. https://doi.org/10.1007/s00267-005-0088-3

McKinney, R. A., & Paton, P. W. C. (2009). Breeding birds associated with seasonal pools in the northeastern United States. *Journal of Field Ornithology*, *80*(4), 380–386. https://doi.org/10.1111/j.1557-9263.2009.00244.x

Mikhailova, E. A., Lin, L., Hao, Z., Zurqani, H. A., Post, C. J., Schlautman, M. A., Post, G. C., & Mitchell, P. I. (2021). Climate Change Planning: Soil Carbon Regulating Ecosystem Services and Land Cover Change Analysis to Inform Disclosures for the State of Rhode Island, USA. *Laws*, *10*(4), 92. https://doi.org/10.3390/laws10040092

Office for Coastal Management. (n.d.). *C-CAP Land Cover, Rhode Island, 2016 | InPort* [dataset]. Retrieved January 29, 2024, from https://www.fisheries.noaa.gov/inport/item/58101

Pinos, J., & Dobesova, Z. (2019). ATTA converter: Software for converting data between ArcGIS and TerrSet. *Earth Science Informatics*, *12*(1), 117–127. https://doi.org/10.1007/s12145-018-0359-1

Rosenberg, K. V., Dokter, A. M., Blancher, P. J., Sauer, J. R., Smith, A. C., Smith, P. A., Stanton, J. C., Panjabi, A., Helft, L., Parr, M., & Marra, P. P. (2019). Decline of the North American avifauna. *Science*, 366(6461), 120–124. https://doi.org/10.1126/science.aaw1313

Richard, F.-J., Southern, I., Gigauri, M., Bellini, G., Rojas, O., & Runde, A. (2021). Warning on nine pollutants and their effects on avian communities. *Global Ecology and Conservation*, 32. https://doi.org/10.1016/j.gecco.2021.e01898

Sims, S. A., Seavey, J. R., & Curtin, C. G. (2013). Room to move? Threatened shorebird habitat in the path of sea level rise--dynamic beaches, multiple users, and mixed ownership: a case study from Rhode Island, USA. *Journal of Coastal Conservation*, *17*(3), 339–350. https://doi.org/10.1007/s11852-013-0263-2

Spruce, J., Bolten, J., Srinivasan, R., & Lakshmi, V. (2018). Developing Land Use Land Cover Maps for the Lower Mekong Basin to Aid Hydrologic Modeling and Basin Planning. *Remote Sensing*, 10(12), 1910. https://doi.org/10.3390/rs10121910

Spruce, J., Bolten, J., Mohammed, I. N., Srinivasan, R., & Lakshmi, V. (2020). Mapping Land Use Land Cover Change in the Lower Mekong Basin From 1997 to 2010. *Frontiers in Environmental Science*, *8*. https://doi.org/10.3389/fenvs.2020.00021

9. Appendices

Appendix A. Google Earth Engine

9A.1 Data Acquisition

The data acquisition process on Google Earth Engine involved locating the appropriate satellite imagery and ancillary datasets to support habitat monitoring and land cover change analysis in Rhode Island. First, the US Census TIGER/Line dataset was loaded to delineate the boundaries of Rhode Island. We then downloaded Collection-2 Level-2 Landsat 8 Operational Land Imager (OLI) and Landsat 9 OLI-2 imagery for the years 2013 and 2023. The collection-2 level-2 data uses surface reflectance algorithms correction for temporally, spatially, and spectrally varying scattering and absorbing effects of atmospheric gases, aerosols, and water vapor. Landsat data sets from May 02, 2013 and November 30, 2023 were used as input to land cover classifications (Table 1). These dates were selected based on having acceptable low to no cloud-cover and were for a time of year in which land cover types are distinct. These two scenes represent 'leaf-on' and 'leaf-off' conditions accounting for fall and spring imagery, respectively. Imagery from both seasons helped to best distinguish land cover classes by accounting for their seasonal variation. Ancillary raster datasets were obtained for each year based on availability and included the USGS National Land Cover Database (NLCD), Historic and current LULC maps, such as those provided gathered from the NLCD.

9A.2 Data Processing

For each Landsat scene, we selected Landsat bands 2–7 Blue, Green, Red, Near Infrared (NIR), Short-wave Infrared 1 (SWIR1), and Short-wave Infrared 2 (SWIR2). The TOA function converted the raw digital numbers in Landsat imagery to top-of-atmosphere (TOA) reflectance, which corrected atmospheric effects and converted the bands to surface reflectance.

Training data for land use classification was generated by manually selecting 30 representative points across for each of the eight land use classes within Rhode Island. These points were categorized into these distinct land use land cover types: Developed, Agriculture, Grassland, Shrubs, Forest, Woody Wetland, Non-Woody Wetland, and Open Water. Each point was associated with a numeric code representing its corresponding land use class.

To facilitate classification, Landsat image pixels were matched with training data points using a reduction process. The Landsat image's spectral values were extracted at the locations of the training points, and default values were assigned for missing bands. This step ensured uniformity in input features for subsequent classification.

A Random Forest classifier was then employed for land use classification, trained using the Landsat spectral bands (B2 (as in Band 2), B3, B4, B5, B6, B7) and the associated land use labels. The classifier utilized the training data to learn patterns in spectral signatures corresponding to different land use classes.

The Landsat imageries from 2013 and 2023 were classified using the trained Random Forest classifier, assigning each pixel to one of the eight land use classes. The resulting classified 2013 (Figure A1, A2) and 2023 (Figure A3, A4) images were visualized using a predefined color palette to distinguish between different land use types.

Finally, the classified images were exported as GeoTIFFs for further accuracy assessment analyses. These images contained spatial information, enabling subsequent geospatial processing and integration with other ancillary datasets.

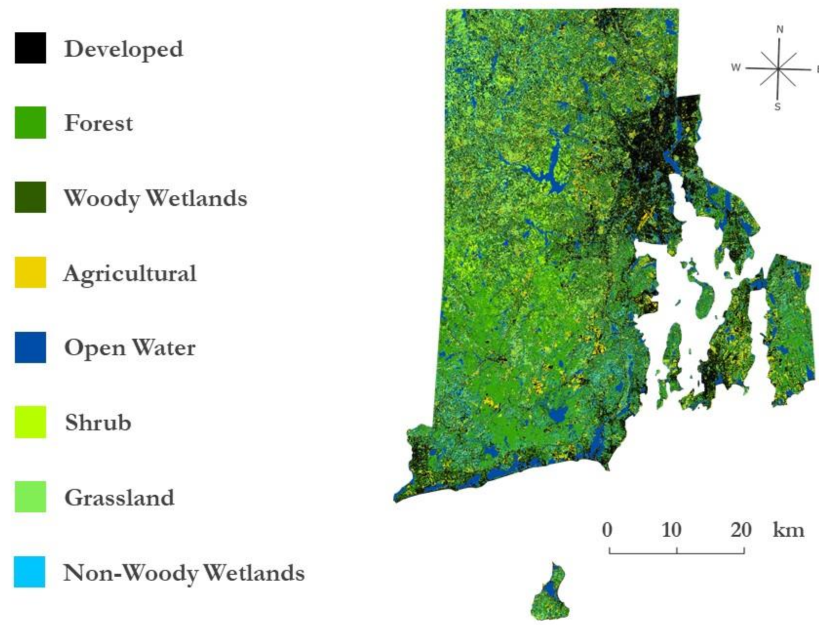

Figure A1. 2013 LULC Map created in Google Earth Engine.

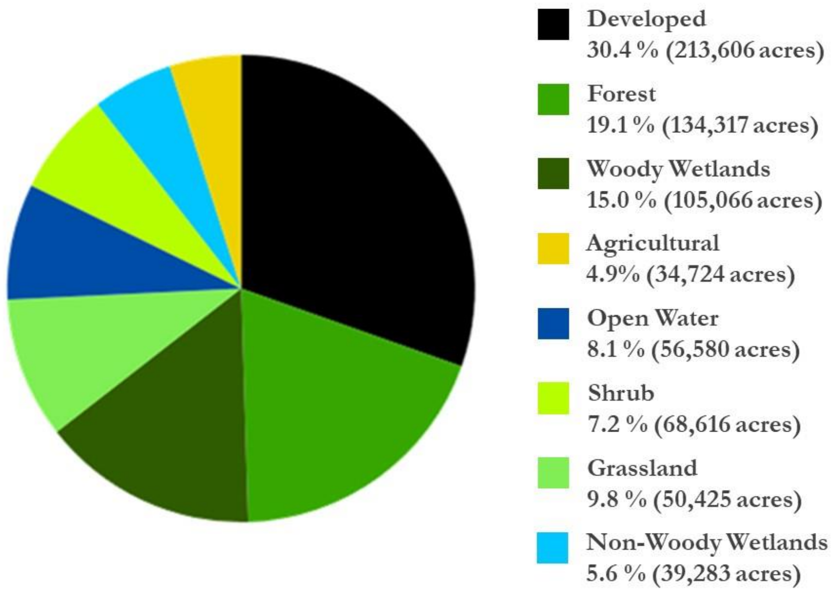

Figure A2. 2013 LULC Landcovers.

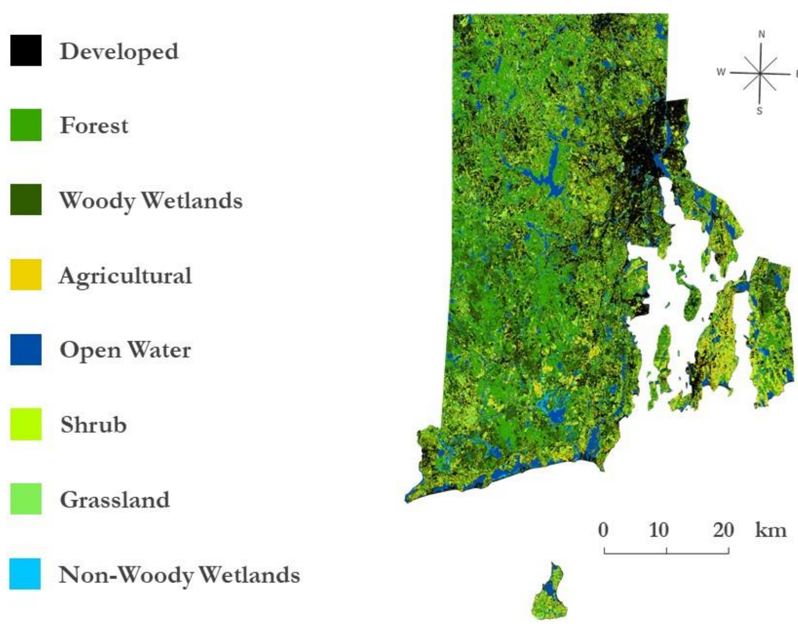

Figure A3. 2023 LULC Map created in Google Earth Engine.

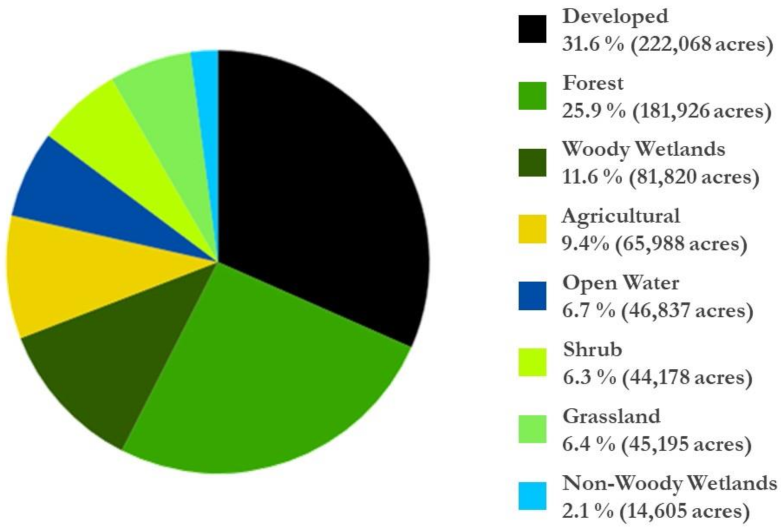

Figure A4. 2023 LULC Landcovers.

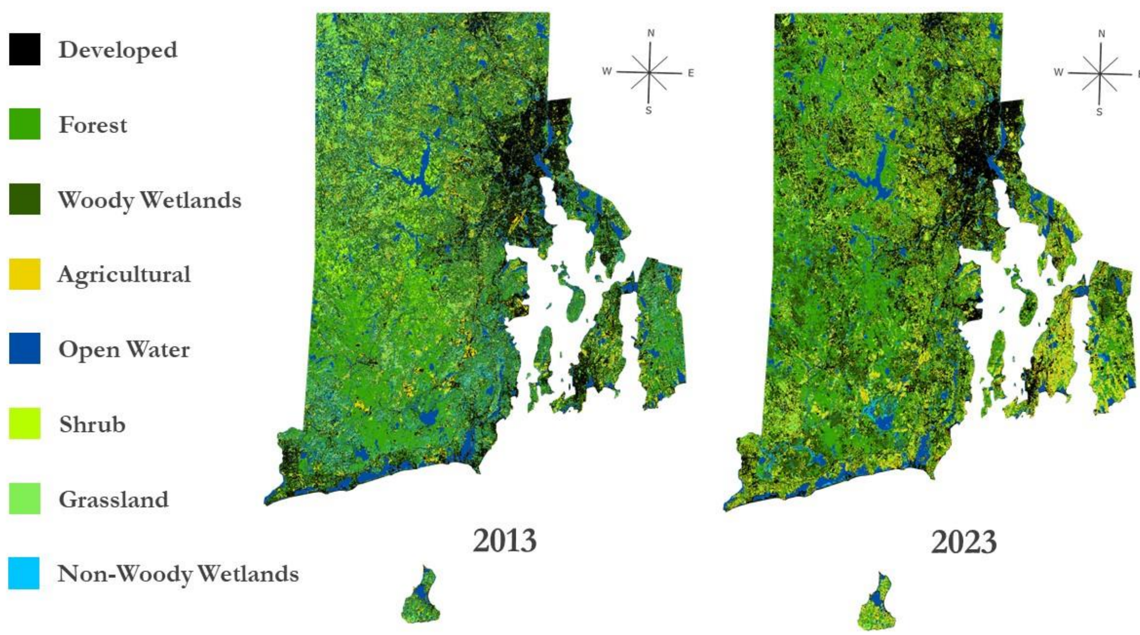

Figure A5. 2013 and 2023 LULC Maps Compared.

Data Analysis

To assess accuracy of the 2023 supervised land classification LULC map, we conducted an accuracy assessment using a confusion matrix. Firstly, a reference dataset, the NLCD (National Land Cover Database) 2021, was loaded to compare against the 2023 LULC map. The NLCD data was sampled at a scale of 30 meters and within the same region of interest (ROI) as the 2023 map. The geometry and projection of the 2023 map was reprojected to match the NLCD projection.

Next, 240 sample points were extracted from both NLCD 2021 and the same points were extracted from the 2023 map within the ROI i.e Rhode Island. These samples were combined into one Feature Collection and a tolerance value was defined to allow for matching between land cover classes. A tolerance threshold was set to account for potential discrepancies between the NLCD classes and the 2023 classes. The accuracy assessment calculates the accuracy for each sample point by comparing the assigned land cover class from NLCD with the 2023 land cover class. Points with matching classes within the defined tolerance were considered correctly classified.

The accuracy calculation was based on comparing the absolute difference between the NLCD and 2023 land cover classes to the defined tolerance. The resulting accuracies were filtered to remove null values and then used to construct a confusion matrix. The diagonal elements of the confusion matrix represent the correct classifications.

Overall accuracy (i.e., agreement) of the derived LULC map was calculated by dividing the number of correct classifications by the total number of classifications. This generated an overall accuracy value of 81.43 % which meets the minimum accuracy requirement. Next, we calculated accuracy metrics for each land use class by comparing the assigned class labels from the classification results with those from the NLCD 2021 dataset. We employed a confusion matrix approach to quantify correct classifications for each land use class. This generated accuracy percentages for each land use category as follows: Developed (92.4%), Agriculture (80.25%), Grasslands (80.64%), Shrubs (67.73%), Forests (84.38%), Woody Wetlands (85.19%), Non-Woody Wetlands (40.47%), and Open Water (98.92%) (Table A1). The accuracy calculated here was the producer's accuracy since we measured the probability that a pixel classified as a certain class on the classified map is correctly classified with respect to the 2021 NLCD reference data.

Table A1
Classifier accuracy assessment for 2023 Google Earth Engine LULC map.

Accuracy Assessment	
Agriculture	80.25%
Developed	92.40%
Forests	84.38%
Grassland	80.64%
Non-woody Wetland	40.47%
Open Water	98.92%
Shrubs	67.73%
Woody Wetland	85.19%
Overall	81.43%

Appendix B. Confusion Matrix for 2023 LULC Map

Table B1

Confusion matrix for 2023 Unsupervised land classification map.

Validation Data								
Classified Data		Water	Developed /barren	Agricultural	Upland forests/ shrub/ grasslands	Woody wetlands	Nonwoody wetlands	Total
	Water	126	0	0	0	0	0	126
	Developed /Barren	2	105	3	23	1	1	135
	Agricultural	0	0	15	1	0	0	16
	Upland forests/ shrub/ grasslands	3	11	0	159	1	2	176
	Woody wetlands	0	2	0	7	35	0	44
	Nonwoody wetlands	1	0	0	3	3	3	10
	Total	132	118	18	193	40	6	507
	Accuracy (K)	0.955	0.889	0.833	0.823	0.875	0.5	
	Total Accuracy (K)	0.875						

Appendix C. Land Use Projection Data

Table C1

Total acreage per class for each year. 2011 and 2021 were NLCD classifications, the rest of the numbers were projected values using TerrSet Land Change Modeler.

	2011	2021	2023	2026	2032	2037	2043	Difference (2043 – 2023)
Open Water	345095.40	346742.17	346855.55	346966.97	347191.41	347418.04	347643.71	788.17
Developed/ Open Space	303243.69	307342.41	308067.52	309077.94	310850.07	312639.76	314427.71	6360.19
Barren	8680.37	9122.54	9196.66	9329.61	9537.59	9746.05	9956.13	759.46
Forest/ Scrub Shrub Upland	499942.78	493313.38	492054.15	490797.11	488259.23	485693.54	483121.54	-8932.60
Grassland/ Herbaceous (Upland)	18514.63	22593.44	23078.00	23245.18	23896.93	24547.41	25197.36	2119.36
Agricultural Land	41165.67	41041.83	41045.09	41173.29	41294.60	41415.91	41532.30	487.21
Woody Wetland	144162.28	145059.34	144918.15	144625.00	144185.27	143754.39	143336.35	-1581.80
Non-Woody Wetland	4410.30	0*	0*	0*	0*	0*	0*	0*
Total	1365215.11	1365215.11	1365215.11	1365215.11	1365215.11	1365215.11	1365215.11	

*Non-woody wetlands completely disappeared in the 2021 NLCD reclassification and the projections. We believe this was a processing error and we did not have a chance to explore where the error originated.

Table C2

Weighted Normalized Likelihood (WNL) statistics for forecasted LULC maps.

Transition	Accuracy	Transition	Accuracy	Transition	Accuracy	Transition	Accuracy
Open Water to Developed/ Open Space	0.81	Developed/ Open Space to Open Water	0.686	Barren to Open Water	0.789	Forest/ Scrub Shrub Upland to Open Water	0.64
Open Water to Barren	0.88	Developed/ Open Space to Barren	0.739	Barren to Developed/ Open Space	0.842	Forest/ Scrub Shrub Upland to Developed/ Open Space	0.716
Open Water to Forest/ Scrub Shrub Upland	0.812	Developed/ Open Space to Forest/ Scrub Shrub Upland	0.597	Barren to Forest/ Scrub Shrub Upland	0.343	Forest/ Scrub Shrub Upland to Barren	0.671
Open Water to	0.819	Developed/ Open Space	0.593	Barren to Grassland/	0.468	Forest/ Scrub	0.737

Transition	Accuracy	Transition	Accuracy	Transition	Accuracy	Transition	Accuracy
Grassland/ Herbaceous (Upland)		to Grassland/ Herbaceous (Upland)		Herbaceous (Upland)		Shrub Upland to Grassland/ Herbaceous (Upland)	
Open Water to Agricultural Land	0.8	Developed/ Open Space to Agricultural Land	0.622	Barren to Agricultural Land	0.399	Forest/ Scrub Shrub Upland to Agricultural Land	0.493
Open Water to Woody Wetland	0.795	Developed/ Open Space to Woody Wetland	0.546	Barren to Woody Wetland	0.43	Forest/ Scrub Shrub Upland to Woody Wetland	0.322
Grassland/ Herbaceous (Upland) to Open Water	0.643	Agricultural Land to Open Water	0.632	Woody Wetland to Open Water	0.644	Grassland/ Herbaceous (Upland) to Developed/ Open Space	0.494
Agricultural Land to Developed/ Open Space	0.747	Woody Wetland to Developed/ Open Space	0.685	Grassland/ Herbaceous (Upland) to Barren	0.589	Agricultural Land to Barren	0.77
Woody Wetland to Barren	0.68	Grassland/ Herbaceous (Upland) to Forest/ Scrub Shrub Upland	0.429	Agricultural Land to Forest/ Scrub Shrub Upland	0.577	Woody Wetland to Forest/ Scrub Shrub Upland	0.73
Grassland/ Herbaceous (Upland) to Agricultural Land	0.503	Agricultural Land to Grassland/ Herbaceous (Upland)	0.735	Woody Wetland to Grassland/ Herbaceous (Upland)	0.752	Woody Wetland to Agricultural Land	0.61
Grassland/ Herbaceous (Upland) to Woody Wetland	0.384	Agricultural Land to Woody Wetland	0.384	NA	NA	NA	NA