Chesapeake Bay Agriculture

Applying Earth Observations to Monitor Marsh Migration in Maryland’s Coastal Croplands

 **Technical Report**

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# 1. Abstract

The Chesapeake Bay boasts some of the nation’s oldest farms which have continually served the greater Maryland community for centuries. Rising sea levels induced by global climate change threaten these critical coastal croplands via saltwater intrusion (SWI). The effects of SWI are widespread yet enigmatic, as crops and forests seemingly die with no apparent cause. Local farmers now face decreasing crop yields and unfavorable soil conditions that disrupt their established livelihoods. The project team partnered with the Eastern Shore Land Conservancy (ESLC) who collaborates with farmers to understand how the region may be affected by climate change, and with the Maryland Department of Planning who informs state and local policy to adapt to SWI. In response to this problem, the team applied NASA Earth observation data, which included measurements from Landsat 5 Thematic Mapper (TM) and Landsat 8 Operational Land Imager (OLI). The team created land use land cover maps of cropland and marsh migration in the Chesapeake Bay from 2001 to 2021 and forecasted maps to 2040. The project team discovered that 60,000 acres of croplands in the study area has already been lost to marsh migration since 2001, with another 58,000 acres projected to be lost within the next twenty years. These maps will inform the ESLC and the Maryland Department of Planning of vulnerable regions in the bay to aid farmers in planning for SWI and salinization.

**Key Terms**

saltwater intrusion, marsh migration, land cover change, ecological forecasting, Chesapeake Bay

**2. Introduction**

***2.1 Background Information***

Climate change poses significant economic and ecological threats to the Chesapeake Bay, as rapidly rising sea levels are introducing dangerous amounts of salt to coastal groundwater resources. Farmers are observing saltwater intrusion (SWI) on their land which alters the soil biogeochemistry and creates inhospitable growing conditions for local crops. While many ecosystems on the boundaries between land and sea are adapted to saltwater, the inward extent of SWI is a concern for saline-intolerant crops (Tully et al., 2019). Saline-tolerant coastal marshes, also called wetlands, then migrate landward due to these rising sea levels and outcompete local vegetation, resulting in “ghost forests” where terrestrial plants and crops are converted to marsh vegetation. Salt marshes are thus an important proxy to understand the scope of SWI and sea-level rise (Schieder et al., 2018; Guimond & Michael, 2021).

The influx of salts from extreme high tides, storm surges, and flooding present the most immediate threat to cropland due to the geography of the Chesapeake Bay. Maryland is divided into five physiographic provinces: Appalachian Plateau, Ridge and Valley, Blue Ridge, Piedmont, and Atlantic Coastal Plain; the Atlantic Coastal Plain is the largest province and circumscribes the entirety of the Chesapeake Bay. This province is low relief and low elevation, so a minor increase in sea level rise contributes to a large area of flooded shoreland. As a result of this low-lying topography, the Atlantic Coastal Plain is the region at greatest risk of SWI (Dubow et al., 2019). The mechanisms of SWI are complex and dependent on many factors (including sea level, coastal geomorphology, hydrologic conductivity, salinity of the soil, and soil classification). This complex causal nature results in an episodic, yet unpredictable manner of saltwater inundation. Such unpredictability proves difficult to model computationally. Remote sensing datasets are a critical means by which to understand and forecast SWI at such a scope (Ivushkin et al., 2019).

The methods used to remotely sense SWI vary depending on scope and purpose. Methods include mapping salt deposits (Rajendran et al., 2021), inferring trends from water quality data (Urquhart et al., 2012), mapping croplands using thermal imaging (Ivushkin et al., 2019), and analyzing changes in coastal land use and land cover (Schepers et al., 2017). This project implemented the lattermost method, utilizing geographic changes in land use and land cover (LULC) to map marsh migration, which demonstrated the extent of sea-level rise and SWI across the landscape.

The area affected by sea-level rise and SWI spans the Eastern Seaboard of the U.S.; however, this study chose to focus on an area that falls within Maryland borders (Figure 1). The specific region of study included all Maryland counties adjacent to the Chesapeake Bay, which provided coverage of the croplands that are most likely to be immediately affected. Areas of interest where statistical analyses were focused encompassed Dorchester, Somerset, and St. Mary’s Counties. The study period for the LULC annual mapping spanned from 2001 through 2021.

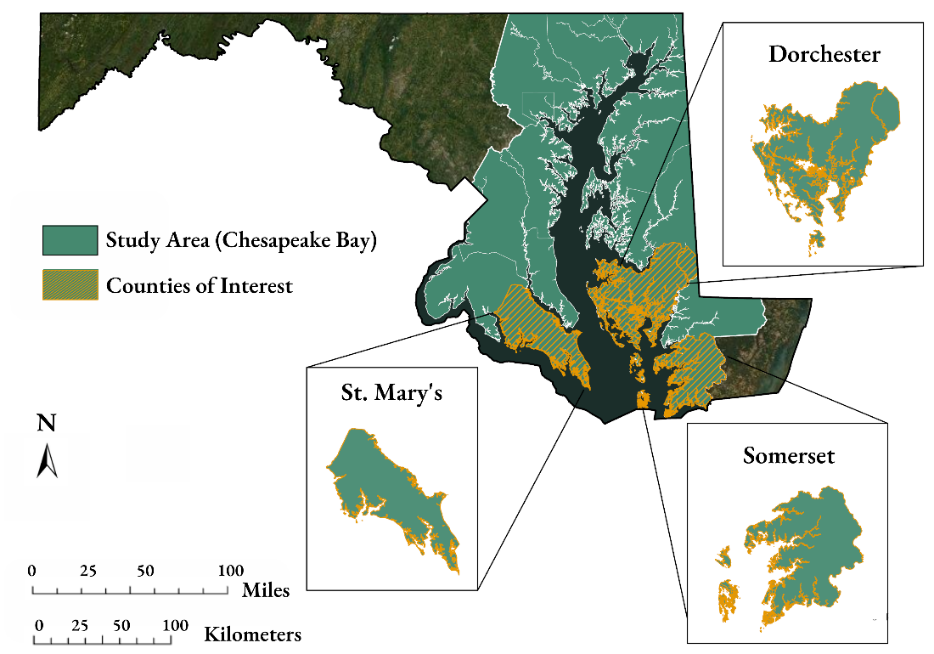


Figure 1. Study area map shows all counties immediately adjacent to the Chesapeake Bay in the State of Maryland. The highlighted area in green represents the overall area studied in this report, while the counties highlighted in marigold represent the counties of interest specified by our partner organizations.

***2.2 Project Partners & Objectives***

The Chesapeake Bay Agriculture team partnered with the Eastern Shore Land Conservancy (ESLC) and the Maryland Department of Planning, two organizations working to preserve and protect the Chesapeake Bay’s towns, lands, and waters. Through more than 300 easements, the ESLC has safeguarded over 65,000 acres of agriculture, wetlands, and forests (Eastern Shore Land Conservancy, 2021). The ESLC works closely with the Maryland Department of Planning, as they assist in providing thorough and integrated planning for the optimal use of Maryland's land (The Maryland Department of Planning, n.d.). Both partner organizations have recognized that Maryland’s croplands have changed over time due to SWI, which has led to landowners and farmers experiencing a loss of croplands and a decrease in crop productivity (Maryland Department of Planning, 2019).

Prior to this project, these organizations did not fully implement Earth observation data in their effort to understand the extent and impacts of SWI. Such data will play a pivotal role in their ability to adapt to the changing landscape of the Chesapeake Bay. The project objectives included using remote sensing data to provide maps quantifying the LULC changes between 2001–2021, forecasting these changes to 2040, and using marsh migration as a proxy for the distribution of sea-level rise and SWI. These maps will be used to inform the ESLC and the Maryland Department of Planning on the geographic extent of SWI to further improve their decision-making practices.

**3.** **Methodology**

***3.1 Data Acquisition***

*3.1.1. Data used for creating LULC map*

The project team selected Landsat 5 Thematic Mapper (TM) and Landsat 8 Operational Land Imager (OLI) data which were acquired via Google Earth Engine (GEE) (Table 1). Landsat 5 TM and Landsat 8 OLI are both accessible through the United States Geological Survey (USGS) and are standardized to encourage interoperability. This analysis employed Collection 2 Tier 1 data, which denotes the highest level of data quality available for these sensors. Top of atmosphere (TOA) reflectance is the light that reaches the top of Earth’s atmosphere after reflecting off the surface; this was chosen over surface reflectance because of preprocessing constraints present at the beginning of the project. These datasets served as the base imagery to be classified as they contain all of the spectral information needed to continue analysis.

Table 1

*NASA EO datasets*

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **EO** | **Source** | **Resolution** | **Years acquired** | **Product IDs** | **Website** |
| Landsat 5 Thematic Mapper (TM) | GEE | 30-meter | 2001-2011 | LANDSAT\_  LT05\_C02\_T1\_TOA | https://developers.google.com/Earth-engine/datasets/catalog/LANDSAT\_LT05\_C02\_T1\_TOA |
| Landsat 8 Operational Land Imager (OLI) | GEE | 30-meter | 2013-2021 | LANDSAT\_  LC08\_C02\_T1\_TOA | https://developers.google.com/Earth-engine/datasets/catalog/LANDSAT\_LC08\_C02\_T1\_TOA |

National Agriculture Imagery Program (NAIP) data were used for high resolution true-color images. The Cropland Data Layer (CDL) offers crop-specific land cover data created annually by the United States Department of Agriculture (USDA). Since CDL provides high accuracy crop classifications, the team used this data for identifying agricultural areas within the Chesapeake Bay region of Maryland. The Coastal Change Analysis Program (C-CAP) offers coastal land cover data created by the National Oceanic and Atmospheric Administration’s (NOAA) Office for Coastal Management. With C-CAP focusing on details for water bodies, the team used it for identifying wetland areas within the study area and detecting marsh migration in the area over time. The National Land Cover Database (NLCD) datasets offer nationally consistent land cover data created by the USGS in cooperation with the Multi-Resolution Land Characteristics Consortium (MRLC). The team used the NLCD dataset as a base map to cover the rest of the land cover classes in the study area: water, developed areas, barren land, and vegetation (Wickham et al., 2014). The project team used the Maryland Wetlands dataset from the Maryland Department of Natural resources to verify the classification of wetland class in LULC rasters created from NLCD, CDL, and C-CAP datasets. The sources and years of this land cover data are expanded upon in Appendix A.1.

*3.1.2. Data Used for Forecasting LULC Changes*

Land cover changes are driven by both natural and human causes which can differ between geographic regions (Gashaw et al., 2017). Based on the analysis of the study area and suggestions from the project advisors and partner organizations, the team chose four main explanatory variables to model land cover dynamics in the Chesapeake Bay and drive the transition from croplands to marshes: elevation, water level, salinity, and distance to water (Tully et al., 2019). Elevation data was derived from the Digital Elevation Model created by NOAA. The water level was accessed through the Mean Higher High-Water Datum (MHHW) created and maintained by the Center for Operational Oceanographic Products and Services. This dataset provides the proper sea level height in mapping applications. Chesapeake Bay Continuous Water Quality Monitoring and Assessment Data from the Eyes on the Bay was used to create the salinity layer whilst Chesapeake Bay shoreline high resolution data from Chesapeake Geoplatform was used to create the distance to water layer. These ancillary datasets are detailed in Appendix A.2.

***3.2 Data Processing***

The team used Esri ArcGIS Pro 2.9.3 to standardize projections of the collected datasets and to conduct the spatial analyses. The datasets were reprojected to Universal Transverse Mercator (UTM) Zone 18 in the Northern Hemisphere and clipped to the extent of the project study area (Figure 1). Each map was then rescaled to a 30-meter by 30-meter resolution standard in all land cover maps.

*3.2.1. LULC Map Imagery Preprocessing and Creating LULC maps*

Our team created LULC maps from two separate approaches: creating the synthesized rasters from publicly available government datasets and creating a script in Google Earth Engine editor using Landsat collections embedded in the platform. First, the team combined NLCD, CDL, and C-CAP datasets to create detailed synthesized rasters which focused on specific land cover classes (The combinations used for creating LULC maps in 5-year intervals—2001, 2006, 2011, and 2016—are displayed in Appendix A.1.). The team reclassified all the datasets to have the same number of classes. Shrubland and herbaceous vegetation types were combined in one land cover class for the analysis as these classes are spectrally similar and not a focus for the project. For the same reasons, different types of forest (including mixed, deciduous, and evergreen) were combined in one forest class. Various types of croplands and grassland were also combined into one agriculture class. The team overlayed dataset layers in order of importance using the Raster Calculator tool in ArcGIS Pro. The wetlands layer was extracted from the C-CAP dataset for all four abovementioned years, and it was first in the order of importance; therefore, it was added last in the process of creating a synthesized raster. The agricultural layer was extracted from the CDL for 2001, 2011, and 2016. Since the CDL data was not available for 2006, the team used the cropland cover class for 2006 from the C-CAP dataset. The agricultural layer came second in the order of importance. The NLCD provided the rest of the classes: open water, developed areas, barren land, and vegetation. After the three datasets were added together, there were gaps in between some of the classes with missing data. The Maryland Wetlands dataset was used to identify if the gaps were categorized as wetlands on the ground and to identify which dataset could be used to fill in the gaps of data. In most cases, the gaps were classified as wetlands and woody wetlands in the Maryland Wetlands and NLCD datasets but classified as forest in the C-CAP dataset. With Maryland Wetlands and NLCD datasets in agreement, the team decided to use the NLCD as a base layer for the mosaicked synthesized raster in order to avoid any gaps of missing data. The final land cover products included a total of seven classes: open water, developed areas, barren land, forest, shrubs, agriculture, and wetlands.

Second, satellite images from USGS, accessed through GEE, were leveraged to create a new set of LULC maps. Using an image acquisition script, NASA Earth observation data were filtered on GEE for geographic range, cloud cover, and image date. The roughly 12 to 36 images that had overlapping areas with the study area each year were kept together in an image collection for preprocessing. In addition, images were temporally filtered to the months of June through September. This range of months offered the best balance between data availability and imagery that encompassed the growing season. Imaging live plants was vital to accurately calculate vegetation indices (VI), many of which relied on the presence of green vegetation. Vegetation indices added as bands to the image in this initial image preparation phase were the Normalized Difference Vegetation Index (NDVI), the Modified Normalized Difference Water Index (MNDWI), the Brightness Index (BI), and the Modified Soil Adjusted Vegetation Index (MSAVI). NDVI excels at showing biomass and plant health by leveraging near-infrared (NIR) and red reflectance against each other (Zhu et al. 2014). The strengths of MNDWI lie in its ability to differentiate developed areas and water. (Xu 2006). BI leverages the three visible light band wavelengths (red, blue, and green) to highlight bare ground (Carabassa et al., 2020; Mathieu et al., 1998). Finally, MSAVI was chosen because it excels at identifying sparse green plant matter (Zhu et al. 2014) (The formulas for each of these VIs are found in Table 4.).

For the final mosaic, the cloud cover filter parameter had the most influence over image quality. If imagery was filtered to a value of <10% cloud cover, some maps resulted in missing data where clouds were masked out. Conversely, removing the cloud cover parameter resulted in excessive artifacts after the cloud mask was applied. A cloud cover filter of approximately 15% provided a balance between availability and quality for each year of study, but each year was slightly different. After images were filtered for general cloud cover, a cloud masking function was applied. This function utilized quality control metadata included in the Landsat images and excluded any cloud or cloud shadow from the scene. The collection of multiple processed Landsat scenes was then combined to form one scene using a mosaic function that extracted the median values of the stack of images in the collection to create one single image. This helps to smoothen any effects of fine scale temporal change like the tidal cycle. Median values offered the most consistent summarization of images in the filtered collection as opposed to a maximum or mean values; median reflectance also strengthened the classification by removing the skew effect of very bright outliers.

Table 4

*Vegetation indices (VI) used to train the classifier*

|  |  |  |
| --- | --- | --- |
| **VI** | **Bands Used** | **Equation** |
| NDVI | NIR, Red |  |
| MNDWI | SWIR1, Green |  |
| BI | Red, Green, Blue |  |
| MSAVI | NIR, Red |  |

The classifier used was a Random Forest algorithm, an out of the box analysis tool integrated into GEE which sorted each individual pixel into one of five classes: water, developed, forest, agriculture, or wetlands, based on patterns in spectral information collected by the training data (Google Earth Engine, 2020). Once a single median composited image was generated from a collection for each year, the team began the classification process by building a dataset of training points. The training data consisted of ~2000 pixels. Points were selected manually, and classes were assigned to each point based on visual assessment. These points were also used to extract the spectral information contained within the image. This process was repeated three times using imagery from 2001, 2010, and 2021 to ensure accuracy of the land cover data. The years 2001-2006 were classified using the 2001 training data, maps for 2007-2015 were generated using data from 2010, and maps for 2016-2021 used 2021 training data. This volume of points was preferred to capture within-class spectral variation and provide sufficient inputs for the classifier. Due to the manual supervised classification process, this step in the process was prone to a potential introduction of bias and human error as all land cover types were visually assessed by a team member. The classifier built 100 trees with 3 variables per split, a minimum leaf population of 1, a bag fraction of 0.5, and no maximum number of nodes. Once all pixels were assigned to a class, the map was exported for statistical analysis beginning with accuracy assessment.

The output LULC maps had to be processed in ArcGIS Pro to change the projection to UTM Zone 18N, assign the proper colormap, and clip the maps to the study area extent (Figure 1). However, residual gaps due to minor amounts of cloud cover persisted and needed to be filled. The team wanted all the LULC classifications to remain internally consistent, so instead of filling in these gaps with external datasets like NLCD or C-CAP, the team used temporally adjacent LULC maps to fill in the gaps; for example, the 2021 LULC map filled the gaps in the 2020 LULC map, then the 2020 map was used to fill the 2019 map. This process of filling in the gaps using adjacent years’ data was repeated until every LULC map was completed.

*3.2.2. Land Change Modeler in TerrSet*

The output LULC maps from supervised classification in GEE for years 2001 and 2021 were used to produce a land cover map of observed changes over 20 years in Land Change Modeler (LCM) integrated into the TerrSet Idrisi software. LCM allows users to analyze changes in land covers, model relationships between the changes and explanatory variables, and forecast future land cover dynamics (Leta et al., 2021). The map of land cover changes was analyzed to determine the transition of interest. Hence, the transition of croplands into marshes was modeled to determine the potential of this transition in the future and create forecasted LULC maps for 2025, 2030, 2035, and 2040.

Diagram

Description automatically generated

Figure 2. Flowchart displaying forecasting LULC in TerrSet Land Change Modeler.

The salinity layer was created using point data from water quality monitoring stations and interpolated into a raster using Empirical Bayesian Kriging in ArcGIS Pro. Finally, proximity to water was calculated in GIS using Euclidean distance to the Chesapeake Bay shoreline data provided by Chesapeake Geoplatform, a publicly accessible data portal. The other driver variables were obtained through the ancillary datasets listed above: NOAA DEM and NOAA MHHW. All the driver variables were preprocessed in ArcGIS Pro and assigned to the same spatial extent and resolution as mandated by LCM. The variables were congregated and added to LCM as static explanatory variables of the saltwater intrusion issue. The process of forecasting LULC is displayed in Figure 2.

***3.3 Data Analysis***

*3.3.1. LULC Map Accuracy Assessment and Validation*

Overall accuracies for NLCD 2001 and 2006 land covers were 79 and 78%, respectively (Wickham et al., 2013), while the 2011 and 2016 NLCD datasets had overall accuracies of 72% (Wickham et al., 2021). Taking in consideration that synthesized rasters were created by combining three datasets, a per class accuracy could potentially decrease after the mosaicking process.

Land cover classifications generated in GEE were given a visual inspection as an indicator of the accuracy of the maps produced; mapped areas that displayed irregular patterning or patches of a land cover class where it disagrees with visual land cover appraisal were likely erroneous. These visual verifications offered opportunities to improve the training data and reiterate the GEE classifier. A more robust statistical accuracy assessment was guided by a stratified random sample. Test points were randomly distributed across the respective geographic area covered by each class by a stratified random sample. The wetlands class, a cover type with a relatively smaller geographic extent, contained 200 test points while the other four classes had 400 test points. NAIP one meter resolution imagery was used to improve the accuracy of the visual assessment and assigning of land cover type. Classified maps were tested against this new set of test points to derive accuracy metrics including overall accuracy, kappa statistic, and user’s and producer’s accuracies (Appendix B).

With LULC maps created in GEE platform being available for each year throughout the study period, as well as the overall accuracy for those rasters being greater than 80%, the team decided to proceed with GEE LULC maps for the forecasting process instead of synthesized rasters.

*3.3.2. Forecasting LULC in TerrSet*

The team completed a land cover change assessment of the 2001-2021 LULC maps and then forecasted the maps from 2021 to 2040 with the 5-year interval in TerrSet’s LCM. The following functions were used to process the data: Land Change Analysis, Land Transition Potential, and Change Prediction. To complete the Land Change Analysis, the team used the LULC maps for 2001 and 2021 described above. The team focused on the transitions of wetlands and agricultural areas within the study region, as this transition is the key focus of the project partners. The team also used the spatial trend of change panel with the 9th order polynomial to best fit the polynomial trend surface and detect areas of high risk for cropland cover transitioning to wetlands. For the Land Transition Potential Modeling the driving variables included elevation, water level, salinity of water and soil, and distance to water. Multi-Layer Perceptron Neural Network (MLP) technique was used for transition potential modelling. Again, the transition from croplands to wetlands only was included in the sub-model, where all other transitions were omitted. Evidence likelihood transformation was used to convert categorical data into continuous data by integrating the explanatory variables into the transition potential (Mas et al., 2014). MLP neural network parameters were chosen automatically by TerrSet to better fit the model. MLP tends to produce the most accurate change and predicted areas in comparison to other techniques, especially when looking at multiple transitions between land covers (Mozumder et al, 2016). The team was able to model the land cover changes with an accuracy of 60% and higher (Appendix C). Finally, to predict the land cover changes in the future, the changes between classes in transition potential maps were used. Markov chain analysis, embedded in the LCM module of Set, was used to predict the future land cover dynamics. Markov chain model calculates the amount of change between two dates and creates a transition areas matrix and probability images that show the potential of a land cover type to change in the future (Chisanga et al., 2022). As a result, forecasted LULC maps were created for 2025, 2030, 2035, and 2040. LULC maps from 2021 and forecasted LULC maps were used to quantify predicted net change to wetlands and agriculture in the future.

LCM provides two modes of land cover change prediction: soft and hard prediction. Hard prediction maps represent a specific scenario of land covers changing in the future. The soft prediction output is a continuous map of vulnerability to change which provides a comprehensive assessment of all plausible scenarios of change in the future (Figure 4). Within the scope of the project, the team selected only the transition from croplands to marshes to be modeled and projected in the next 20 years with the 5-year interval. Based on soft prediction maps created in LCM the team produced the risk maps highlighting the areas of agricultural land at risk due to sea-level rise and SWI by 2040. Soft prediction maps were processed and analyzed in ArcGIS Pro. The raster values showing the degree of possibility of agricultural land to change was divided in three categories using quantile classification method provided in ArcGIS Pro: low, moderate, and high risk. The transition potential values for each quantile are displayed in Table 5. Quantile method allowed each category to contain an equal number of features or pixels of potential change. Once the risk map was generated, it was overlayed with current LULC map to detect the areas where agriculture may be at hazard of transition into marshland in future.

Table 5

*The transition potential values for each quantile between counties used for creating risk categories.*

|  |  |  |  |
| --- | --- | --- | --- |
|  | Low | Moderate | High |
| Dorchester County | 0 - 0.001 | 0.001 – 0.352 | 0.353 – 0.987 |
| Somerset County | 0 - 0.001 | 0.001 – 0.411 | 0.412 – 0.962 |
| St. Mary’s County | 0 - 0.001 | 0.001 – 0.460 | 0.461 – 0.792 |

\*Low risk category covers the agricultural land and the rest of land cover classes not included in the modeling.

**4. Results & Discussion**

***4.1 Analysis of Results***

*4.1.1. LULC Map Results*

LULC maps for the observed study period show that almost 240 km2 of croplands transitioned to wetlands from 2001 to 2021 in the entire study period. Analysis of the land covers within the counties of interests demonstrate that about 29 km2, 21 km2, and 18 km2 of croplands transitioned to marshes in Dorchester, Somerset, and St. Mary’s counties, respectively (annual changes for the area of each land cover class within the entire study area as well as for three counties of interest are provided in Appendix C).

The team saw patterns in the data leading to conclusions on the mechanisms of the classifier and techniques used to make the maps. Wetland was the most difficult class to map accurately and was most often mistaken by the classifier as forest. The next most common type of error is developed areas classified as wetland. Sand is spectrally similar to concrete, likely leading to this common misclassification. For agriculture, the most common error was misclassification as the urban class. This happened more often in fields, possibly due to either spectral similarities between soil and urban land covers or not including enough cover classes in the analysis. Overall, accuracies were satisfactory for the continuation of the team’s analyses, as all LULC maps were between 81% and 87% in overall accuracy. Figure 3 exemplifies one of the final LULC maps produced. Map accuracy data from each study year was compiled into one table for simple comparison (Appendix B) are shown in Appendix B.

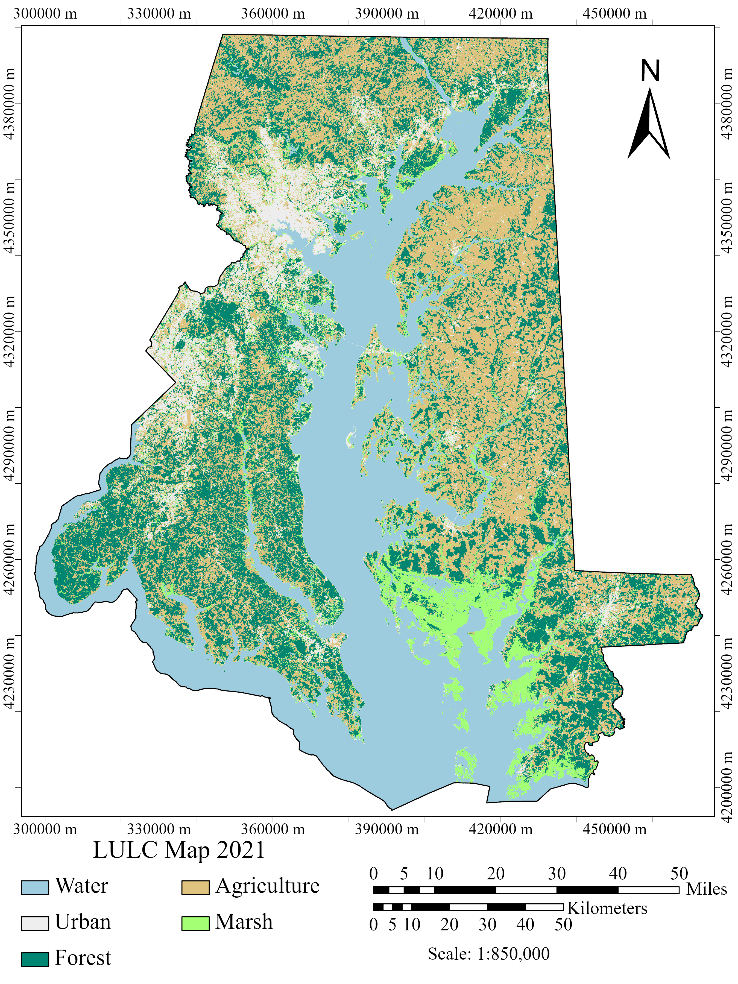


Figure 3. LULC map covering the entire study area for 2021. Maps were generated in Google Earth Engine platform.

*4.1.2. Forecasting Transitions from Agriculture to Wetlands*

Figure 4 represents the likelihood of croplands to be converted to wetlands by 2040 in the three Maryland counties of interest: Dorchester, Somerset, and St. Mary’s. Figure 5 displays the quantification of these areas at risk in these counties. About 114 km2 of the agricultural land in Dorchester County is at high risk of disappearing due to SWI. Almost the same area, 113 km2 is at danger in St. Mary’s County. Finally, about 52 km2 of croplands within Somerset County are at high risk of transitioning to wetlands. Overall, a quarter to one third of croplands in each county of interest are at high risk due to SWI.

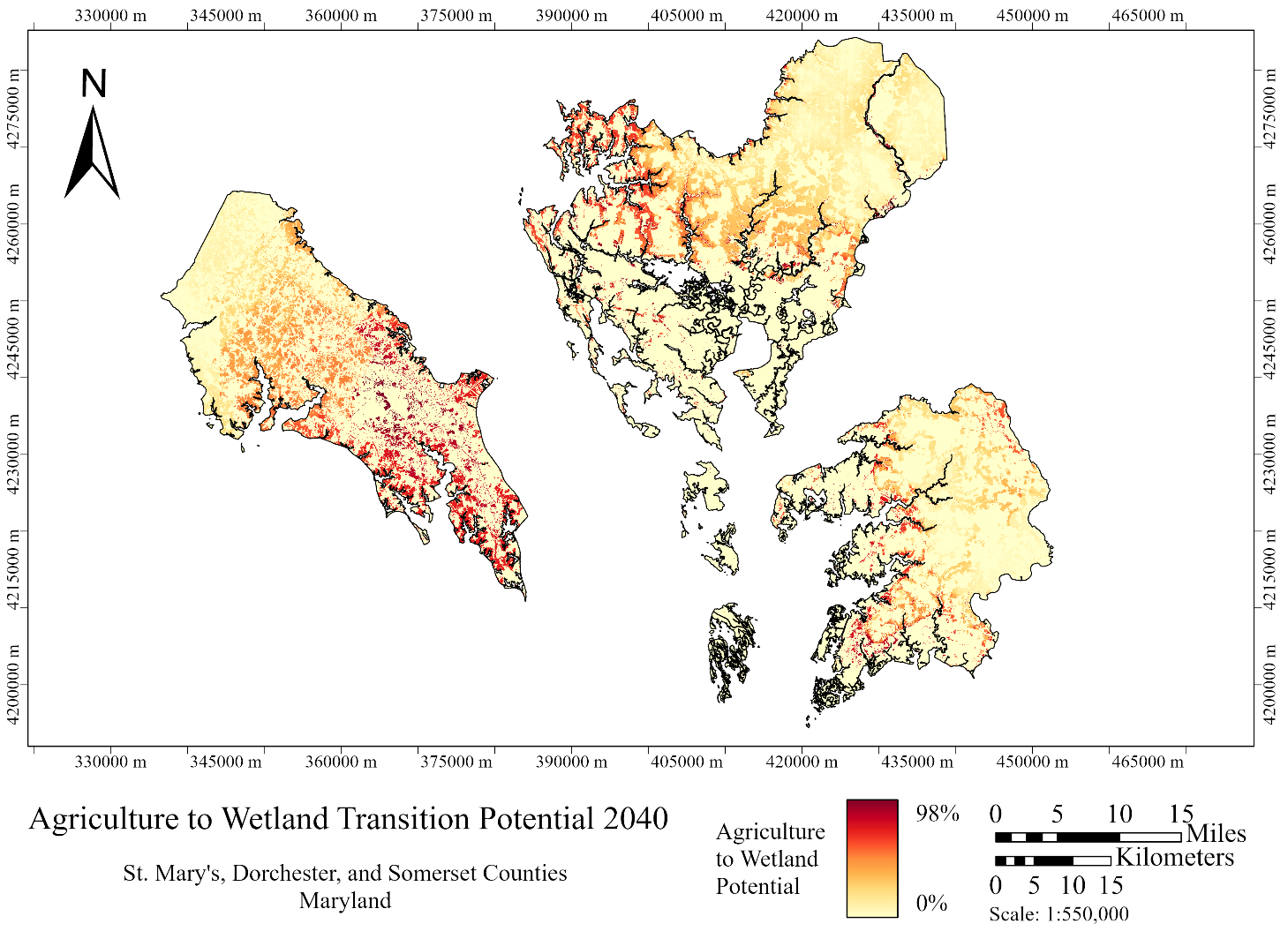


Figure 4. Soft prediction maps generated in Land Change Modeler for St. Mary’s, Dorchester, and Somerset counties in Maryland.

|  |  |  |  |
| --- | --- | --- | --- |
|  | Dorchester | Somerset | St Mary’s |
| Med | 359.4 | 132.8 | 199.2 |
| High | 114.4 | 52.3 | 112.8 |

Figure 5. Quantified agricultural areas at risk for Dorchester, Somerset, and St. Mary’s counties in square kilometers.

In addition to the three counties of interest, the team produced soft and hard prediction maps and quantified the agricultural areas at risk and transitions of croplands to wetlands for the entire study area (Appendix C.1). In contrast to a soft prediction output, hard prediction is a representation of a specific scenario of land covers changing in the future. The hard prediction maps include the same land cover classes as the input maps. The hard predicted land cover classes are based on the historical change of agriculture within the observed time period (from 2001 to 2021) with consideration of driving forces of that specific change. Approximately 25 km2, 14 km2, and 17 km2 of cropland is forecasted to convert to wetland by 2040 in Dorchester, Somerset, and St. Mary's counties, respectively (Figure 6). Considering the entire study area, approximately 236 km2 of croplands is projected to transition to marshes by 2040.

Map

Description automatically generated

*Figure 6. Areas of potential conversion of croplands to marshes for three key counties by the year 2040.*

***4.2 Limitations***

One of the first limitations the team faced was with the Landsat data used to generate the LULC maps. These datasets are 30-meter resolution. For the scope of the study area, this offers ample granularity, but when looking at individual plots of land there may be smaller or more incremental landcover changes that are not recognized. Training data for the LULC maps were collected manually to include the greatest amount of spectral variation, but such methods could have introduced human factor biases. Accuracy was higher around the Chesapeake Bay which could be due to sampling bias towards the center of the study area. Future studies can avoid this bias by using a stratified random sampling method to choose training points. Including more classes would also allow for a more fine-scale analysis of land cover change, as five classes limit the range for land cover types present in a certain landscape. Visual inspection of the finished maps indicated that there is classified cropland in urban areas. These land covers were not agriculture, but rather green lawns and parks that the classifier had no other option to map apart from agriculture. Adding a class for urban vegetation and other interstitial cover types would increase the accuracy of the analyses presented. Furthermore, the testing dataset was created using imagery from 2021 and was used to test the accuracy of the LULC maps through the entire study period; land cover types certainly changed during that time period, so the testing data’s ability to assess the maps may be diminished. Although spatial biases may have been removed, temporal limitation were introduced. This dynamic would have a downward pressure on accuracy in earlier years so the true accuracy of those maps may be higher. The final limitation was that surface reflectance products were not used in the creation of the LULC maps. Inexperience with GEE at the beginning of the project led to errors when trying to perform preprocessing on the surface reflectance images. The team decided to continue with TOA data in the name of time management. With the practice the team has with GEE now, classification could be run again with surface reflectance as a base to get a more accurate final classification. Testing the difference showed that improvement could range from 0.05% - 0.10% if this change were made.

For the LULC prediction, the team utilized only four variables: elevation, water level, distance to water, and salinity. There may have been other variables that would have aided the forecasting process and enabled a more accurate prediction of future agricultural changes. In addition, any errors in the explanatory variables’ datasets likely propagated through the forecasting. Finally, modeling in LCM focused on agricultural loss due to SWI and did not forecast the transitions in the rest of land cover classes, which could potentially affect modeling accuracy and outcomes.

***4.3 Future Work***

Given how salt marshes are vital for sustainability of shoreline ecosystems, future studies would benefit from focusing on the evolution of these marshes through space and time in new study areas. Such investigations would validate the data presented in this study, providing conclusive evidence for the correlation between SWI and marsh migration. A continuation project would also find success in expanding on the number of classes selected to derive the LULC maps. This study area was highly varied in its hydrogeomorphology and having more land cover classes will help model this landscape more accurately. Including classes on the type of wetlands and specific crops would enhance impact statistics, allowing partners to quantify the financial burden of the observed cropland lost due to marsh migration.

**5. Conclusions**

The project team defined three main objectives to assist the partners: creating annual LULC maps from 2001 to 2021, extracting wetlands to map the extent of marsh migration, and forecasting land cover changes to the year 2040. The 2001 to 2021 annual LULC maps demonstrated 240 km2 of cropland lost solely to wetland conversion in the study area; this measured area translates to a loss of 60,000 acres which introduces economic losses in the region in the form of productivity decreases and diminished yields (Figure 3)­. These maps will provide partners with additional information about land cover dynamics on the coasts to quantify their observations.

The marsh migration maps (Appendix D) indicated a 610 km2 increase of wetlands in the study area since 2001. These maps functioned as a proxy to understand the inland extent of sea-level rise and SWI. Visualizing the extent of SWI is a difficult undertaking, so these marsh migration maps are important to map the impacts of salt in the soil. The partners will use these maps to identify regions where SWI is present and implement their conservation measures.

The forecasted maps had two outputs: hard prediction and soft prediction maps. (Figure 5). Estimates from the hard prediction map suggest a continued decrease of approximately 235 km2 of cropland to wetland. Based on this analysis, the land cover trends of the next twenty years will follow the trends of the past twenty years. Soft prediction maps entailed a risk percentage of agriculture to wetland loss, encompassing multiple possible land cover change scenarios (Figure 4). The soft prediction maps will enable the partners to identify regions at high risk for conversion to wetland; with the predicted maps extending twenty years into the future, the partners should have ample time to anticipate such forecasted scenarios. The results of this study will provide the project partners with the means to aid in the assessment, conservation, mitigation, and restoration of these vital wetlands.

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Any opinions, findings, and conclusions or recommendations expressed in this material are those of the author(s) and do not necessarily reflect the views of the National Aeronautics and Space Administration.

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**7. Glossary**

**Brackish Water** **–** Intermediate mixture of freshwater and saltwater

**C-CAP –** Coastal Change Analysis Program, a nationally standardized land cover and land change data product for the coastal regions of the US, developed and maintained by NOAA

**CDL –** Cropland Data Layer, hosted on USDA-NASS CropScape; provides a raster, geo-referenced, crop-specific land cover map for the contiguous US

**DEM** **-** Digital Elevation Model representing the bare ground topographic surface of the Earth excluding trees, buildings, and any other surface objects

**EO** **–** Earth observations; Satellites and sensors that collect information about the Earth’s physical, chemical, and biological systems over space and time

**GEE** **–** Google Earth Engine platform combines a multi-petabyte catalog of satellite imagery and geospatial datasets with planetary-scale analysis capabilities

**Marsh Migration** **–** The inland movement of marshes as increased salinity replaces the predeceasing plants with marsh-type flora

**MHHW Datum –** Mean Higher High-Water Datum, the average of the higher high water height of each tidal day observed over the National Tidal Datum Epoch, provided by NOAA

**MRLC** **–** Multi-Resolution Land Characteristics Consortium. A group of federal agencies that collaborate on creating and collecting land cover data at a national scale

**NAIP –** National Agriculture Imagery Program, a program to acquire peak growing season imagery and deliver this imagery to USDA County Service Centers, in order to maintain the common land unit (CLU) boundaries and assist with farm programs

**NLCD –** National Land Cover Database, a comprehensive land cover product based on decadal Landsat imagery and other supplementary datasets, available from the Multi-Resolution Land Cover Characteristics (MRLC) Consortium

**NOAA –** National Oceanic and Atmospheric Administration, a US government agency

**OLI –** Operational Land Imager, a multispectral sensor aboard the Landsat 8 satellite

**TerrSet** **–** Geospatial Monitoring and Modeling Software for monitoring and modeling the Earth system for sustainable development

**TM –** Thematic Mapper, a multispectral sensor aboard the Landsat 5 satellite

**Salinization –** Another term for saltwater intrusion. Refers to the increase in salinity of soils and seawater

**USDA-NASS –** United States Department of Agriculture National Agricultural Statistics Service, a branch of a US government agency

**USGS –** United States Geological Survey, a US government agency

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**9. Appendices**

***Appendix A.1: Ancillary Datasets Synthesized into Landcover Rasters***

|  |  |  |
| --- | --- | --- |
| **Map Year** | **Dataset** | **Land Cover Classes** |
| 2001 | 2001 C-CAP | Wetlands/Water |
| 2002 CDL | Agriculture |
| 2001 NLCD | Other classes/base layer |
| 2006 | 2006 C-CAP | Wetlands/Water |
| 2006 C-CAP | Agriculture |
| 2006 NLCD | Other classes/base layer |
| 2011 | 2010 C-CAP | Wetlands/Water |
| 2011 CDL | Agriculture |
| 2011 NLCD | Other classes/base layer |
| 2016 | 2016 C-CAP | Wetlands/Water |
| 2016 CDL | Agriculture |
| 2016 NLCD | Other classes/base layer |

***Appendix A.2:* Ancillary Data Acquired by the Chesapeake Bay Agricultural Team**

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Ancillary Data** | **Source** | **Description** | **Years acquired** | **Website** |
| National Land Cover Database (NLCD) | USGS | Base layer | 2001, 2006, 2011, 2016 | https://www.mrlc.gov/ |
| Cropland Data Layer (CDL) | USDA | Agriculture layer | 2002, 2011, 2016 | https://www.nass.usda.gov/Research\_and\_Science/Cropland/Release/ |
| Coastal Change Analysis Program (C-CAP) | NOAA | Wetland layer | 2001, 2006, 2011, 2016 | https://coast.noaa.gov/htdata/raster1/landcover/bulkdownload/30m\_lc/ |
| Maryland Wetlands | Department of Natural Resources | Wetland layer validation | 2017 | https://data.imap.maryland.gov/datasets/maryland::maryland-wetlands-wetlands-polygon-department-of-natural-resources/about |
| Digital Elevation Model | NOAA | Elevation | 2021 | https://coast.noaa.gov/dataviewer/#/lidar/search/ |
| Mean Higher High Water Datum | NOAA | Water Level | 2019 | https://coast.noaa.gov/htdata/Inundation/TidalSurfaces/NOAA\_OCM\_MHHWInterpolatedSurface.zip |
| Chesapeake Bay Continuous Water Quality Monitoring & Assessment | Eyes on the Bay | Salinity | 2021 | https://eyesonthebay.dnr.maryland.gov/bay\_cond/LongTermData.cfm |
| Chesapeake Bay shoreline high resolution | Chesapeake Geoplatform | Distance to water | 2020 | https://data-chesbay.opendata.arcgis.com/datasets/17e8587747434f95b16aede1ed134e9b\_0/about |
| NAIP | GEE | 10-meter resolution composite images | 2003, 2009, 2012, 2015, 2018 | https://developers.google.com/earth-engine/datasets/catalog/USDA\_NAIP\_DOQQ |

***Appendix B.1: Map Accuracies***

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Year | OA | Kappa | Class | User's Accuracy | Producer's Accuracy |
| 2021 | 0.869772366 | 0.835824555 | 1 - Water | 0.982543641 | 0.968058968 |
| 2 - Developed | 0.893129771 | 0.839712919 |
| 3 - (4) Forest | 0.971153846 | 0.768060837 |
| 4 - (6) Agriculture | 0.77970297 | 0.931952663 |
| 5 - (7) Wetlands | 0.650909091 | 0.895 |
| 2020 | 0.818728092 | 0.771000095 | 1 - Water | 0.985074627 | 0.949640288 |
| 2 - Developed | 0.744639376 | 0.848888889 |
| 3 - (4) Forest | 0.948849105 | 0.708015267 |
| 4 - (6) Agriculture | 0.72183908 | 0.773399015 |
| 5 - (7) Wetlands | 0.671875 | 0.86 |
| 2019 | 0.858145363 | 0.820593924 | 1 - Water | 0.985 | 0.940334129 |
| 2 - Developed | 0.781818182 | 0.875565611 |
| 3 - (4) Forest | 0.957013575 | 0.80418251 |
| 4 - (6) Agriculture | 0.826196474 | 0.803921569 |
| 5 - (7) Wetlands | 0.689655172 | 0.9 |
| 2018 | 0.848049281 | 0.807182245 | 1 - Water | 0.98687664 | 0.969072165 |
| 2 - Developed | 0.776180698 | 0.849438202 |
| 3 - (4) Forest | 0.949425287 | 0.797297297 |
| 4 - (6) Agriculture | 0.787439614 | 0.779904306 |
| 5 - (7) Wetlands | 0.688311688 | 0.888268156 |
| 2017 | 0.84810757 | 0.807917883 | 1 - Water | 0.975609756 | 0.959232614 |
| 2 - Developed | 0.788793103 | 0.818791946 |
| 3 - (4) Forest | 0.929787234 | 0.830798479 |
| 4 - (6) Agriculture | 0.828644501 | 0.775119617 |
| 5 - (7) Wetlands | 0.644688645 | 0.88 |
| 2016 | 0.853830645 | 0.815396146 | 1 - Water | 0.985074627 | 0.972972973 |
| 2 - Developed | 0.875 | 0.774193548 |
| 3 - (4) Forest | 0.95631068 | 0.75047619 |
| 4 - (6) Agriculture | 0.738229755 | 0.937799043 |
| 5 - (7) Wetlands | 0.690196078 | 0.88 |
| 2015 | 0.848031888 | 0.808667154 | 1 - Water | 0.973170732 | 0.966101695 |
| 2 - Developed | 0.934097421 | 0.729306488 |
| 3 - (4) Forest | 0.948356808 | 0.768060837 |
| 4 - (6) Agriculture | 0.773076923 | 0.954869359 |
| 5 - (7) Wetlands | 0.566225166 | 0.855 |
| 2014 | 0.848813209 | 0.808998016 | 1 - Water | 0.98034398 | 0.977941176 |
| 2 - Developed | 0.883008357 | 0.780788177 |
| 3 - (4) Forest | 0.921052632 | 0.746124031 |
| 4 - (6) Agriculture | 0.747514911 | 0.921568627 |
| 5 - (7) Wetlands | 0.669322709 | 0.84 |
| 2013 | 0.838323353 | 0.796080693 | 1 - Water | 0.975247525 | 0.940334129 |
| 2 - Developed | 0.891472868 | 0.785876993 |
| 3 - (4) Forest | 0.905529954 | 0.747148289 |
| 4 - (6) Agriculture | 0.765182186 | 0.9 |
| 5 - (7) Wetlands | 0.596491228 | 0.85 |
| 2012 | NO DATA | NO DATA | 1 - Water |  |  |
| 2 - Developed |  |  |
| 3 - (4) Forest |  |  |
| 4 - (6) Agriculture |  |  |
| 5 - (7) Wetlands |  |  |
| 2011 | 0.83407849 | 0.790847449 | 1 - Water | 0.975429975 | 0.945238095 |
| 2 - Developed | 0.904371585 | 0.742152466 |
| 3 - (4) Forest | 0.937027708 | 0.707224335 |
| 4 - (6) Agriculture | 0.715789474 | 0.96912114 |
| 5 - (7) Wetlands | 0.626373626 | 0.855 |
| 2010 | 0.80942928 | 0.76030809 | 1 - Water | 0.977667494 | 0.940334129 |
| 2 - Developed | 0.904153355 | 0.628888889 |
| 3 - (4) Forest | 0.906392694 | 0.756190476 |
| 4 - (6) Agriculture | 0.724264706 | 0.935866983 |
| 5 - (7) Wetlands | 0.514195584 | 0.815 |
| 2009 | 0.836724566 | 0.79401683 | 1 - Water | 0.975062344 | 0.933174224 |
| 2 - Developed | 0.867374005 | 0.728285078 |
| 3 - (4) Forest | 0.922902494 | 0.773764259 |
| 4 - (6) Agriculture | 0.764132554 | 0.93111639 |
| 5 - (7) Wetlands | 0.597173145 | 0.845 |
| 2008 | 0.83986118 | 0.796799842 | 1 - Water | 0.975429975 | 0.945238095 |
| 2 - Developed | 0.8525 | 0.757777778 |
| 3 - (4) Forest | 0.893246187 | 0.779467681 |
| 4 - (6) Agriculture | 0.73012939 | 0.93824228 |
| 5 - (7) Wetlands | 0.719047619 | 0.755 |
| 2007 | 0.814851485 | 0.765909729 | 1 - Water | 0.980246914 | 0.945238095 |
| 2 - Developed | 0.889908257 | 0.642384106 |
| 3 - (4) Forest | 0.895196507 | 0.779467681 |
| 4 - (6) Agriculture | 0.678756477 | 0.933491686 |
| 5 - (7) Wetlands | 0.61752988 | 0.775 |
| 2006 | 0.848935116 | 0.808602573 | 1 - Water | 0.9875 | 0.94047619 |
| 2 - Developed | 0.866995074 | 0.778761062 |
| 3 - (4) Forest | 0.872651357 | 0.794676806 |
| 4 - (6) Agriculture | 0.788617886 | 0.921615202 |
| 5 - (7) Wetlands | 0.665289256 | 0.805 |
| 2005 | 0.833167331 | 0.788667703 | 1 - Water | 0.982278481 | 0.92601432 |
| 2 - Developed | 0.851758794 | 0.75 |
| 3 - (4) Forest | 0.863829787 | 0.771863118 |
| 4 - (6) Agriculture | 0.73870334 | 0.914841849 |
| 5 - (7) Wetlands | 0.694915254 | 0.82 |
| 2004 | 0.817821782 | 0.769430711 | 1 - Water | 0.985037406 | 0.94047619 |
| 2 - Developed | 0.857142857 | 0.688741722 |
| 3 - (4) Forest | 0.862745098 | 0.752851711 |
| 4 - (6) Agriculture | 0.702166065 | 0.923990499 |
| 5 - (7) Wetlands | 0.661157025 | 0.8 |
| 2003 | 0.824317618 | 0.777281815 | 1 - Water | 0.982630273 | 0.942857143 |
| 2 - Developed | 0.812339332 | 0.703786192 |
| 3 - (4) Forest | 0.863445378 | 0.782857143 |
| 4 - (6) Agriculture | 0.736943907 | 0.904988124 |
| 5 - (7) Wetlands | 0.682608696 | 0.785 |
| 2002 | 0.828217822 | 0.78170575 | 1 - Water | 0.984848485 | 0.928571429 |
| 2 - Developed | 0.8515625 | 0.721854305 |
| 3 - (4) Forest | 0.830985915 | 0.785171103 |
| 4 - (6) Agriculture | 0.714285714 | 0.914489311 |
| 5 - (7) Wetlands | 0.774509804 | 0.79 |
| 2001 | 0.814356436 | 0.76467679 | 1 - Water | 0.984924623 | 0.933333333 |
| 2 - Developed | 0.800480769 | 0.735099338 |
| 3 - (4) Forest | 0.837606838 | 0.745247148 |
| 4 - (6) Agriculture | 0.715976331 | 0.862232779 |
| 5 - (7) Wetlands | 0.714285714 | 0.825 |

***Appendix B.2: Confusion Matrices***

|  |  |
| --- | --- |
| **Classification Year** | **Matrix** |
| 2001 |  |
| 2002 |  |
| 2003 |  |
| 2004 |  |
| 2005 |  |
| 2006 |  |
| 2007 |  |
| 2008 |  |
| 2009 |  |
| 2010 |  |
| 2011 |  |
| 2012 | No Data |
| 2013 |  |
| 2014 |  |
| 2015 |  |
| 2016 |  |
| 2017 |  |
| 2018 |  |
| 2019 |  |
| 2020 |  |
| 2021 |  |

***Appendix C.1: Observed and Forecasted Land Cover Areas in square kilometers***

*C.1a: Study Area*

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
|  | 2001 | 2021 | 2025 | 2030 | 2035 | 2040 |
| Water | 6030.33 | 6057.04 | 6057.04 | 6057.04 | 6057.04 | 6057.04 |
| Developed | 2325.32 | 1772.66 | 1772.66 | 1772.66 | 1772.66 | 1772.66 |
| Vegetation | 5745.81 | 5461.23 | 5461.23 | 5461.23 | 5461.23 | 5461.23 |
| Agriculture | 6025.05 | 6224.24 | 6171.8 | 6108.25 | 6047.14 | 5988.4 |
| Wetlands | 1298.96 | 1910.29 | 1962.74 | 2026.28 | 2087.39 | 2146.13 |
| Sum | 21425.47 | 21425.46 | 21425.47 | 21425.46 | 21425.46 | 21425.46 |

*C.1b: Dorchester County, MD*

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| Classes | 2001 | 2021 | 2025 | 2030 | 2035 | 2040 |
| Water | 8.31 | 12.84 | 12.84 | 12.84 | 12.84 | 12.84 |
| developed | 52.05 | 52.07 | 52.07 | 52.07 | 52.07 | 52.07 |
| vegetation | 425.52 | 376.02 | 376.02 | 376.02 | 376.02 | 376.02 |
| agriculture | 523.84 | 474.17 | 469.36 | 463 | 456.24 | 449.1 |
| wetlands | 394.94 | 489.56 | 494.37 | 500.74 | 507.49 | 514.63 |
| sum | 1404.66 | 1404.66 | 1404.66 | 1404.67 | 1404.66 | 1404.66 |

*C.1c: Somerset County, MD*

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| Classes | 2001 | 2021 | 2025 | 2030 | 2035 | 2040 |
| water | 9.54 | 11.3 | 11.3 | 11.3 | 11.3 | 11.3 |
| developed | 37.66 | 34.37 | 34.37 | 34.37 | 34.37 | 34.37 |
| vegetation | 282.46 | 333.12 | 333.12 | 333.12 | 333.12 | 333.12 |
| agriculture | 259.04 | 185.28 | 182.22 | 178.44 | 174.72 | 171.07 |
| wetlands | 238.75 | 263.37 | 266.44 | 270.21 | 273.93 | 277.58 |
| sum | 827.45 | 827.44 | 827.45 | 827.44 | 827.44 | 827.44 |

*C.1d: St. Mary’s County, MD*

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| Classes | 2001 | 2021 | 2025 | 2030 | 2035 | 2040 |
| water | 5.39 | 5.57 | 5.57 | 5.57 | 5.57 | 5.57 |
| developed | 55.47 | 71.09 | 71.09 | 71.09 | 71.09 | 71.09 |
| vegetation | 493.31 | 467.7 | 467.7 | 467.7 | 467.7 | 467.7 |
| agriculture | 324.96 | 312.28 | 307.97 | 303.13 | 298.89 | 295.26 |
| wetlands | 52.44 | 74.93 | 79.24 | 84.08 | 88.32 | 91.95 |
| sum | 931.57 | 931.57 | 931.57 | 931.57 | 931.57 | 931.57 |

*C.1e: Transition from Agriculture to Wetland by County*

|  |  |
| --- | --- |
| Location | Area of Forecasted Transition from Agriculture to Wetland |
| Study Area | 239.38 |
| Dorchester County | 29.33 |
| Somerset County | 20.9 |
| St. Mary’s County | 18.39 |

***Appendix C.2: Accuracies for the forecasting models in Terrset LCM***

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | Chesapeake Bay​ | | Dorchester​ | | Somerset​ | | St. Mary's​ | |
| Variables in model​ | Order of  Influence​ | accuracy %​ | Order of Influence​ | accuracy %​ | Order of Influence​ | accuracy %​ | Order of Influence​ | accuracy %​ |
| With all variables​ | ​ | 60.5​ | ​ | 69.8​ | ​ | 63.3​ | ​ | 63.8​ |
| Excluding  DEM​ | 1​ | 50.3​ | 1​ | 50.1​ | 1​ | 50​ | 3​ | 63.6​ |
| Excluding  Distance to Water​ | 3​ | 60.7​ | 2​ | 68.8​ | 3​ | 62​ | 2​ | 63.6​ |
| Excluding MHHL​ | 2​ | 60.4​ | 3​ | 69.7​ | 2​ | 61.2​ | 1​ | 57.4​ |
| Excluding  Salinity​ | 4​ | 61.2​ | 4​ | 70.1​ | 4​ | 64.4​ | 4​ | 63.8​ |

***Appendix D.1: Dorchester County Marsh Migration Extent Maps 2001 and 2021***

Map

Description automatically generatedMap

Description automatically generated

***Appendix D.1: Dorchester County Forecasted Marsh Migration Extent Map 2040***

