Chesapeake Bay Program's One-meter Resolution Land Use/Land Cover Data: Overview and Production

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Contents

1. INTRODUCTION

The production of the Chesapeake Bay Program's (CBP) 1-meter resolution "land cover" data involved the identification and classification of image objects derived from the USDA's National Agriculture Imagery Program (NAIP) aerial imagery coupled with above-ground height information derived from LiDAR and local planimetric data, if available, on roads, structures, and impervious surfaces (Appendix A). Land cover represents the surface characteristics of the land with classes such as impervious cover, tree canopy, herbaceous, and barren. In contrast, "land use" represents how humans use the land with classes such as turf grass, cropland, and timber harvest. Land use data are critical for understanding the impact of human activities on the Chesapeake Bay because, for example, herbaceous vegetation can represent the highest polluting land use (e.g., corn production) or one of the lowest (e.g., natural succession). Producing land use from land cover data requires a variety of ancillary datasets combined with spatial rules that leverage the contextual information inherent in the very-high resolution land cover data. The CBP's land use/land cover (LULC) data are so named because they represent a combination of cover and use classes (e.g., extractive-barren, solar-herbaceous) to ensure the data have the broadest applicability to CBP Partner decisions.

The 1-meter resolution LULC data are foundational, authoritative, and transformative to the Bay restoration effort. They are foundational because they inform most outcomes in the 2014 Chesapeake Bay Watershed Agreement and will serve as the basis for developing the next generation of watershed and land change models. They are authoritative due to their anticipated high accuracy (i.e., 95% user's accuracy for impervious cover and tree canopy) and transparency: any person viewing the data can recognize and evaluate features and areas of interest based on their local knowledge. These data are transformative because they will ultimately change the way restoration and conservation actions are

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implemented, enabling a complete inventory of restoration and conservation opportunities, and targeting actions at a fine scale to locations where they will be most effective. Moreover, establishing accurate trends in impervious cover, forests, and tree canopy will enable the CBP Partners to improve the efficiency and effectiveness of stormwater controls, forest management, and climate resilience activities.

This document presents the LULC class definitions and methods used to create the 2013/14 and 2017/18 LULC data and change from 2013/14 to 2017/18[4]. The 2017/18 LULC was mapped first followed by the 2013/14 LULC derived from mapped changes in land cover from 2013/14 to 2017/18. By employing this method, the accuracies of the 2017/18 LULC are transferrable to the 2013/14 LULC data because ~95% of the landscape did not change over the 4 to 5-year period. This document is divided into five sections by major land use category: Development, Production, Natural (forest-related), Water, and Wetlands. The abbreviations associated with each land use type are official and used throughout the documentation and data tables. The numeration associated with each land use class represents the raster values for the 2013/14 and 2017/18 LULC datasets. Rather than combine the 2-digit LULC codes to represent change, the raster values for the 2013/14 to 2017/18 LULC change data are unique two-digit codes to minimize the bit-size of the data. Each section of this document begins with definitions for the subset of eighteen general classes in the major land use category followed by a list of the subset of fifty-four detailed classes in the category and a discussion of the technical methods employed to derive and map each of detailed class in 2017/18 and 2013/14. For classes where the LULC classes are equivalent to the land cover classes, the methods for mapping 2017/18 conditions are the same as those for mapping 2013/14 conditions. For the remaining classes, the methodologies for mapping 2017/18 and 2013/14 conditions were different and are described separately. Different methodologies were required due to the lack of comparable image segment information for 2013/14. Please note that the 2013/14 land cover and LULC data are not comparable to the CBP's original 2013/14 LULC dataset. The new 2013/14 data are more accurate and directly comparable with the new 2017/18 data compared to the original 2013/14 data produced in 2018.

2. DATA PRODUCTS AND CITATIONS

The data associated with this project cover all 206 counties that intersect or are adjacent to the Chesapeake Bay watershed, roughly 99,000 square miles (~256,000 square kilometers) in area (Figure 1). The data are publicly viewable and available for download through two websites accessible here:

Static LULC Website:

Purpose: view the complete 2013/14 and 2017/18 LC and LULC data
Downloadable data:

- GIS data viewable and downloadable: 1-meter 2013/14 and 2017/18 LC and LULC rasters, available by county, attributed with 54 detailed classes and 18 general classes. 10-meter resolution rasters representing 2017/18 impervious surfaces and tree canopy will also be available for download in July 2022.
- Tabular data: Area (acres) summaries by county and watershed for all detailed and general classes.

[4] The staggered dates for the LULC data result from the differences in the years that aerial imagery from the U.S. Department of Agriculture's National Agriculture Imagery Program was acquired for each major Bay jurisdiction: Delaware, 2013 and 2017; District of Columbia, 2013 and 2017; Maryland, 2013 and 2018; New York, 2013 and 2017; Pennsylvania, 2013 and 2017; Virginia, 2014 and 2018; and West Virginia, 2014 and 2018.

Figure 1. Mapping Area- shaded (206 counties, 99,000 square miles)

Citations:

- Chesapeake Bay Program Office (CBPO), 2022. One-meter Resolution Land Cover Dataset for the Chesapeake Bay Watershed, 2013/14. Developed by the University of Vermont Spatial Analysis Lab, Chesapeake Conservancy, and U.S. Geological Survey. [date of access], [URL]

- Chesapeake Bay Program Office (CBPO), 2022. One-meter Resolution Land Cover Dataset for the Chesapeake Bay Watershed, 2017/18. Developed by the University of Vermont Spatial Analysis Lab, Chesapeake Conservancy, and U.S. Geological Survey. [date of access], [URL]

- Chesapeake Bay Program Office (CBPO), 2022. One-meter Resolution Land Use/Land Cover Dataset for the Chesapeake Bay Watershed, 2013/14. Developed by the U.S. Geological Survey, Chesapeake Conservancy, and University of Vermont Spatial Analysis Lab. [date of access], [URL]

- Chesapeake Bay Program Office (CBPO), 2022. One-meter Resolution Land Use/Land Cover Dataset for the Chesapeake Bay Watershed, 2017/18. Developed by the Chesapeake Conservancy, U.S. Geological Survey, and University of Vermont Spatial Analysis Lab. [date of access], [URL]

Dynamic LULC Change Website:

Purpose: view the LC change and LULC change from 2013/14 to 2017/18 in a three-panel display showing the source imagery for 2013/14 and 2017/18 for reference.

Downloadable data:

- GIS data viewable and downloadable: 1-meter 2013/14 to 2017/18 LC and LULC change rasters, available by county, and attributed with 54 detailed classes and 18 general classes.
- Tabular data: LULC change matrices by county, state, watershed, and region for the detailed and general classification schemes.

Citations:

- Chesapeake Bay Program Office (CBPO), 2022. One-meter Resolution Land Cover Change Dataset for the Chesapeake Bay Watershed, 2013/14 – 2017/18. Developed by the University of Vermont Spatial Analysis Lab, Chesapeake Conservancy, and U.S. Geological Survey. [date of access], [URL]

- Chesapeake Bay Program Office (CBPO), 2022. One-meter Resolution Land Use/Land Cover Change Dataset for the Chesapeake Bay Watershed, 2013/14 - 2017/18. Developed by the University of Vermont Spatial Analysis Lab, Chesapeake Conservancy, and U.S. Geological Survey. [date of access], [URL]

All GIS data are formatted as TIFFs and projected in USA Contiguous Albers Equal Area Conic USGS, meters, NAD 1983 (WKID# 102039). When displaying unique raster values for the static LULC, a color scheme and legend corresponding to the 18 general classes will be automatically applied. When displaying unique raster values for the dynamic LULC, a color scheme and legend corresponding to the 18 general classes representing 2017/18 conditions will be automatically applied.

3. Land Use/Land Cover Modeling Process

A five-step, rule-based process model was developed to translate land cover into a LULC dataset (Figure 2). The first step in the process, called “Data Preparation”, involved developing the basic unit of analysis for the modeling process. Image segments, a by-product of the object-oriented land cover classification process were unioned with land parcels for this purpose. Parcels are important because their size and landscape context are highly indicative of land use. For example, small adjacent parcels are typically found in residential areas or commercial districts whereas large parcels are more likely to represent industrial or agricultural activities. Image segments are important because they represent variability in landscape conditions within parcels. A field in a single farm parcel may be composed of many different image segments representing variability in soil moisture, vegetation, or other surficial factors. Combined, parcels and image segments, labeled “psegs”, provided the blocks on which to build a regionally consistent land use classification (Figure 3).

The second step in the process known as the “General Land Use Model”, was designed to classify herbaceous, barren, and scrub-shrub psegs. These cover types are the most variable in terms of land use because they could represent crop fields, pasture, orchards, turf grass, natural succession, suspended succession, abandoned mine lands, or timber harvest. Ancillary data are critical for differentiating these potential uses and are integrated into the workflow using a series of rules. The third process step concerns the classification of tree canopy as forest, tree canopy over turf grass, or other tree canopy. These determinations were made largely based on context. Tree canopy with a compacted or managed understory was assumed to exist adjacent to lawns and buildings. Other tree canopy includes windbreaks and small patches of trees that do not meet the size and girth requirements of forest. Forests are contiguous patches of tree canopy at least one acre in size and 72-meters in diameter in at least one portion of the patch.

Separate workflows had to be developed for water and wetlands given the complexity of the detailed water and wetlands classes and potential confusion between the two. Most headwater ponds, for example, are classified as wetlands in the National Wetlands Inventory but all headwater ponds are classed as either riverine or terrene ponds for the purposes of this dataset. While the classification of ponds may appear simple and obvious, a confined small body of water surrounded by land, classifying them was challenging because moving upstream, rivers and streams visible in the land cover gradually become intermittently hidden beneath closures in tree canopy and appear as linear sequences of “ponds”. The final step to produce the 2017/18 LULC dataset involved a hierarchical “burning in” of water and wetland, solar, extractive, and harvested forest classes to selectively overwrite previous classifications. For example, a patch of tree canopy classed as forest in the third step might be reclassed as forested wetland in the burn in step.

What appears to be a sixth step in the modeling overview diagram, “LULC Change”, is a separate model that was developed to interpret the 2013/14 land uses based on the land cover change, the 2017/18 LULC, and additional ancillary data. The LULC Change model itself implements four separate sets of methods depending on the type of change interpreted: direct, new structure, context, and indirect. Direct methods are applied to classes where the land cover change class is equivalent to the land use change class, e.g., impervious other transitioning to impervious structures. New structure rules are particularly important for reclassifying 2017/18 turf grass and trees over turf in newly developed parcels into what they were prior to development. The context rules help determine the 2013/14 conditions based on the predominant use at the parcel scale. For example, the low vegetation in a change from low vegetation to tree canopy could be interpreted as cropland, pasture, turf grass, depending on whether it occurs within an agricultural or residential parcel. the pre-development conditions of developed parcels. The indirect rules are similar to context except that they focus on adjacency to determine the likely use of changed pseg.

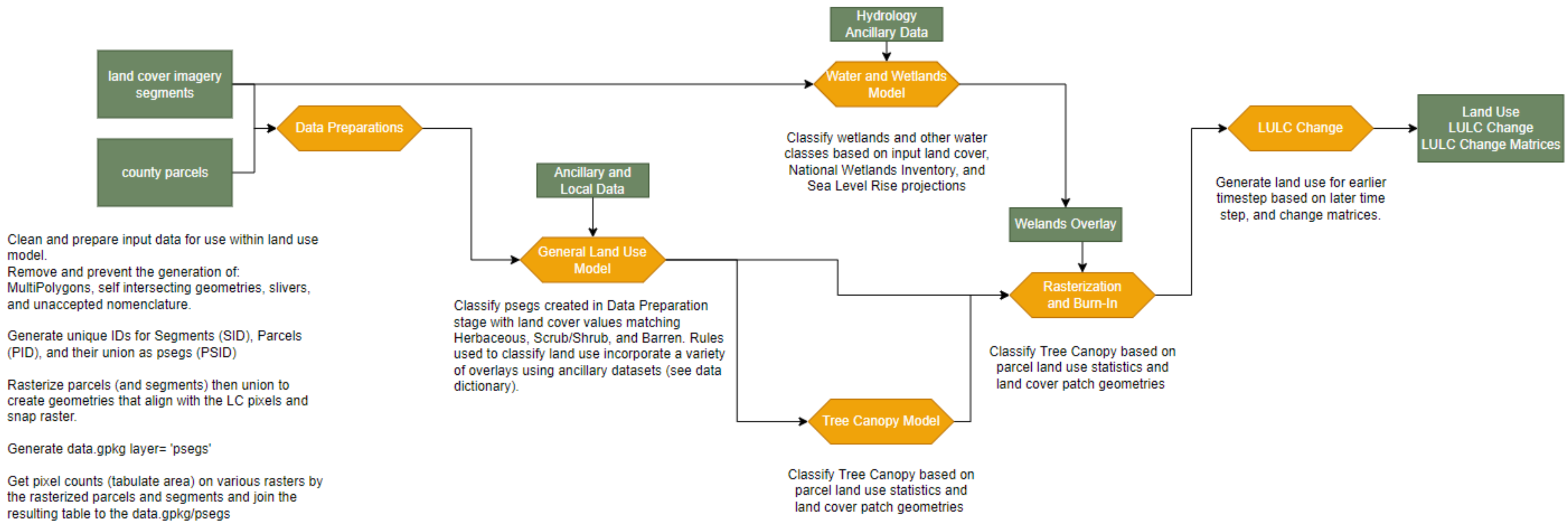

Figure 2. Land Use/Land Cover Modeling Overview

Figure 3. Parcel-Image Segments ("psegs").

4. CLASSIFICATION AND METHODS

4a. DEVELOPMENT

General Classification

Impervious Roads (ROAD) = Paved, and some unpaved, roads and bridges. Dirt and gravel roads may be mistakenly mapped as impervious depending on the spectral characteristics of the substrate (Minimum Mapping Unit (MMU) = 9 square meters).

Impervious, Structures (IMPS) = Human-constructed objects made of impervious materials that are greater than approximately 2 meters in height. Houses, malls, and electrical towers are examples of structures (MMU = 9 square meters).

Impervious, Other (IMPO) = Human-constructed surfaces through which water cannot penetrate, and that are below approximately 2 meters in height, e.g., sidewalks, parking lots, runways, field-mounted solar panels, rail lines, and some private roads. Barren, low vegetation, scrub-shrub, and emergent wetland cover types within 3 meters of rail lines were reclassed to impervious surfaces and included in this class (MMU = 9 square meters).

Tree Canopy over Impervious Surfaces (TCIS) = Tree cover that overlaps with roads, structures, or other impervious surfaces rendering them partially or completely invisible from above (MMU = 9 square meters).

Tree Canopy over Turf Grass (TCTG) = Tree cover within 30-ft of structures or adjacent turf grass and other impervious in rural wooded areas and within 60-ft of structures or adjacent turf grass and other impervious in developed areas. Developed areas include U.S. Census Bureau defined urban areas and clusters. Rural areas include all lands outside Census urban areas and clusters. The understory in all TCTG areas is assumed to be turf grass or otherwise altered through compaction, removal of surface organic material, and/or fertilization.

Turf Grass (TURF) = Low vegetation associated with residential, commercial, industrial, and recreational areas that is assumed to be altered through compaction, removal of organic material, and/or fertilization. These include low vegetation lands within small, developed parcels (≤ 5 acres with ≥ 55 m^2 of impervious cover), recreational fields, and other turf-dominated land uses (e.g., cemeteries, shopping centers, golf courses, airports, hospitals, amusement parks, etc.).

Pervious Developed, Other (PDEV) = Barren lands in developed parcels and barren or low vegetation lands that may represent the early stages of development, utility rights-of-way, portions of road rights-of-way, landfills, and the pervious portions of solar fields adjacent to panel arrays.

Detailed LULC Classification

- Developed
  - Impervious
    - 21 Roads
    - 22 Structures
    - 23 Other Impervious
    - Tree Canopy (TC) over Impervious
      - 24 TC over Roads
      - 25 TC over Structures
      - 26 TC over Other Impervious

Pervious

27 Tree Canopy over Turf Grass
28 Turf Grass
29 Transitional- barren
Suspended Succession
51 Barren
52 Herbaceous
53 Scrub-shrub

Technical LULC Mapping Methods

21 Roads

This class is directly mapped in the land cover data for both 2017/18 and 2013/14.

22 Structures

This class is directly mapped in the land cover data for both 2017/18 and 2013/14.

23 Other Impervious

This class is directly mapped in the land cover data for both 2017/18 and 2013/14.

24 Tree Canopy over Roads

This class is directly mapped in the land cover data for both 2017/18 and 2013/14.

25 Tree Canopy over Structures

This class is directly mapped in the land cover data for both 2017/18 and 2013/14.

26 Tree Canopy over Other Impervious

This class is directly mapped in the land cover data for both 2017/18 and 2013/14.

27 Tree Canopy over Turf Grass

2017/18 Methodology:

Decision rules were created and applied to three unique and mutually exclusive parcel types: agricultural, densely developed, and less densely developed.

1. Identify parcel types through a hierarchical process
    a. Agriculture parcels contain "Cropland", "Pasture/Hay", or "Orchard/Vineyard" land uses.
    b. Densely developed parcels contain a structure and are within Census Urban Areas and Clusters
    c. Less-densely developed parcels are represented by all remaining parcels with a structure
2. For agricultural parcels:
    a. Buffer "Structures" and "Other Impervious" and "Turf Grass" sharing boundary of "Structure" parcel segments by 10 meters. Reclassify "Tree Canopy" that is not surrounded by agriculture within the buffer as "Tree Canopy over Turf Grass".
3. For densely developed parcels:
    a. Buffer "Structures" and "Other Impervious" and "Turf Grass" sharing boundary of "Structure" parcel segments by 20 meters. Classify any "Tree Canopy" within the buffer as "Tree Canopy over Turf Grass".
4. For less densely developed parcels:

    a. Buffer “Structures” and “Other Impervious” and “Turf Grass” sharing boundary of “Structure” parcel segments by 10 meters. Classify any “Tree Canopy” within the buffer as “Tree Canopy over Turf Grass”.

2013/14 Methodology:

1. Tree Canopy in a developed parcel in 2013/14 that was Turf Grass in 2017/18

28 Turf Grass

2017/18 Methodology:

1. Classify all low vegetation image segments intersecting developed areas as turf grass. Developed areas are those designated as: 'AIRCRAFT ROADS', 'AIRPORT', 'AMUSEMENT PARK', 'CEMETERY', 'GOLF COURSE', 'HOSPITAL', 'PARKING LOT', 'SEAPORT/HARBOUR', 'SHOPPING CENTRE', 'SPORTS COMPLEX' in the HERE LandUseA and LandUseB data layers.
2. Classify all low vegetation within small, developed parcels (<= 5 acre and contains >= $55m^2$ of impervious surface) as turf grass.

2013/14 Methodology:

1. Low Vegetation in a developed parcel (>= 55 sq. meters of structure) that is not agriculture, wetlands, or a solar field

29 Transitional- barren

Areas void of vegetation consisting of natural earthen material in developed landscapes (MMU = $25m^2$).

2017/18 Methodology:

1. All other land use methods that analyze barren lands are applied first. This includes: “Suspended Succession”, “Natural Succession”, all “Agriculture” classes, “Timber Harvest”, “Solar Fields”, “Extractive”, all “Wetland” classes, and “Bare Shore”.
2. Remaining barren land within developed parcels and barren image segments are classed as “Transitional- barren”.

2013/14 Methodology:

1. Barren land that transitioned to Structure, Other Impervious or Roads in 2017/18 and was not detected as agriculture or wetlands in 2013/14.
2. Barren land that transitioned to Tree Canopy over Turf Grass in 2017/18.

51-53 Suspended Succession

Barren, low vegetation, and scrub-shrub lands where the regrowth of woody vegetation is actively suppressed such as road and utility rights-of-way and landfills. These lands are assumed to be unfertilized.

2017/18 Methodology:

1. Classify barren, low vegetation, and scrub-shrub image segments as suspended succession if they:
    a. Intersect landfills; or
    b. Intersect impervious roads and the image segments are <= 50m2; or
    c. Intersect buffered transmission lines (25m buffer) and are <= 1000m2.

2013/14 Methodology:

1. Barren land transitioning to water or solar pervious that was not agriculture or wetlands in 2013/14 and is not a shoreline
2. Low Vegetation transitioning to Barren, development or Solar Field that was not agriculture or wetlands in 2013/14

Development Ancillary Datasets[5]:

Tax parcels, landfills, active and abandoned mines, urban areas, transmission lines, roads, rail lines, national land use/cover, national cropland cover, and wetlands.

4b. PRODUCTION

Notes: All non-agricultural land uses for barren and low vegetation land cover types except for natural succession (e.g., turf grass, suspended succession, solar pervious, extractive, etc.) take precedent over classification as cropland, pasture, or orchards. The three agricultural classes are identified based on ancillary data. The 2017, 2018, and 2019 NASS Cropland Data Layers (CDL) were used to identify cropland, pasture/hay, and orchards. Because the CDL under-classifies pasture/hay, the 2016 USGS National Land Cover Database (NLCD 2019 edition) was used to further identify pasture/hay. While solar fields are included in the production class, in the general classification they are rolled up to impervious (other) and pervious developed (other).

General Classification

Cropland (CROP) = Barren and low vegetation lands on large parcels (> 5 acres) that are mapped as cropland in the 2018 Cropland Data Layer

Pasture/Hay (PAST) = Barren, low vegetation, and scrub shrub lands on large parcels (> 5 acres) that are mapped as pasture in the 2019 National Land Cover Dataset or the 2018 Cropland Data Layer

Extractive (EXTR) = Barren lands and impervious surfaces within quarries, surface mines, and other surficial excavation sites.

Detailed LULC Classification

- Production
  - Agriculture
    - Cropland
      - 81 Barren
      - 82 Herbaceous
    - Pasture/Hay
      - 83 Barren
      - 84 Herbaceous
      - 85 Scrub-shrub
    - Orchard/vineyard
      - 86 Barren
      - 87 Herbaceous
      - 88 Scrub-shrub
    - Animal Operations (TBD)
      - Impervious (TBD)
      - Barren (TBD)
      - Herbaceous (TBD)
  - Solar fields
    - 33 Impervious
    - Pervious
      - 34 Barren

[5] A detailed description of these data can be found in the LULC Data Dictionary.

35 Herbaceous
36 Scrub-shrub

Extractive (surface mines)

37 Barren
38 Impervious

<u>Technical LULC Mapping Methods</u>

General 2017/18

1. Reclassify the CDL into five classes: 0 Non-agricultural; 1 Cropland; 2 Fallow; 3 Orchards/vineyards; and 4 Grains/Hay/Pasture.
    a. Summarize the area (hectares) of CDL cropland, orchards, and pasture within all barren, low vegetation, and scrub-shrub parcel segments (intersection of tax parcel polygons and vector image segments).
2. Reclassify the NLCD as: 0 Non-pasture/hay; 1 Pasture/hay
    a. Summarize the area (hectares) of NLCD pasture within all barren, low vegetation, and scrub- shrub parcel segments.

General 2013/14

Each parcel "type" is categorized as cropland, pasture, orchard or other using CDL 2013, NCLD 2011 and the 2017/18 land use.

a. If the majority land use in 2017/18 of a parcel is cropland, pasture or orchard, classify the parcel type as such
b. If NLCD and CDL agree a parcel is >= 50% cropland, the parcel type is cropland
c. If NLCD and CDL agree a parcel is >= 50% pasture, the parcel type is pasture
d. If CDL detects at least 20% of the parcel is cropland, pasture, or orchard, classify as such
e. Remaining parcels are classified as other (non-agricultural)

81-82 Cropland

Note: cropland is second agricultural class mapped

<u>2017/18 Methodology:</u>

1. All barren and low vegetation parcel segments with >= 1 hectare of CDL cropland
2. All barren and low vegetation parcel segments adjacent to those classed as cropland in step 1 and not adjacent to non-agricultural land use parcel segments with barren or low vegetation land cover.
3. All barren and low vegetation segments adjacent to those classed as cropland in step 2 and not adjacent to non-agricultural land use parcel segments with barren or low vegetation land cover.

<u>2013/14 Methodology:</u>

1. Neighboring parcels that are newly developed in 2017/18 whose majority type is cropland
2. Barren and Low Vegetation in a parcel whose parcel type is cropland

83-85 Pasture/Hay

Note: pasture is the first agricultural class mapped

<u>2017/18 Methodology:</u>

1. All barren, low vegetation, and scrub-shrub parcel segments with >= 1 hectare of CDL pasture
2. All barren, low vegetation, and scrub-shrub parcel segments with >= 1 hectare of, and >= 20% of their area containing, NLCD pasture

3. All barren, low vegetation, and scrub-shrub segments adjacent to those classed as pasture in steps 1 or 2 and not adjacent to non-agricultural land use parcel segments with barren, low vegetation, or scrub- shrub land cover.
4. All barren, low vegetation, and scrub-shrub segments adjacent to those classed as pasture in step 3 and not adjacent to non-agricultural land use parcel segments with barren, low vegetation, or scrub-shrub land cover.

<u>2013/14 Methodology:</u>

1. Neighboring parcels that are newly developed in 2017/18 whose majority type is pasture
2. Barren, Low Vegetation and Scrub/Shrub in a parcel whose parcel type is pasture

86-88 Orchard/vineyard

Note: orchards/vineyards are the third agricultural class mapped

<u>2017/18 Methodology:</u>

1. All barren, low vegetation, and scrub-shrub parcel segments with >= 1 hectare of, and >= 20% of their area containing, CDL orchard.
2. All barren, low vegetation, and scrub-shrub segments adjacent to those classed as orchard in step 1 and not adjacent to non-agricultural land use parcel segments with barren, low vegetation, or scrub-shrub land cover.
3. All barren, low vegetation, and scrub-shrub segments adjacent to those classed as pasture in step 2 and not adjacent to non-agricultural land use parcel segments with barren, low vegetation, or scrub-shrub land cover.

<u>2013/14 Methodology:</u>

1. Neighboring parcels that are newly developed in 2017/18 whose majority type is orchard
2. Barren, Low Vegetation and Scrub/Shrub in a parcel whose parcel type is orchard

33-36 Solar fields

Initiated after agriculture and extractive.

<u>2017/18 Methodology:</u>

1. All other impervious, structures, barren, low vegetation, and scrub-shrub parcel segments with centroids intersecting the manually-digitized, or AI-derived, solar field boundaries.

<u>2013/14 Methodology:</u>

1. Barren, low vegetation, and scrub-shrub in a parcel containing Solar Impervious in 2013/14 (solar impervious in 2017/18 that did not change)

37-38 Extractive

Note: initiated after high-confidence agriculture and suspended succession

<u>2017/18 Methodology:</u>

1. All other impervious and barren parcel segments intersecting ancillary active and abandoned mine polygons.

<u>2013/14 Methodology:</u>

1. Barren and Other Impervious that transitioned between each other and was classified as Extractive in 2017/18

<u>Production Ancillary Datasets:</u>

National cropland cover, national land use/cover data, AI-derived solar fields, active and abandoned mines, tax parcels, and wetlands.

4c. NATURAL (forest-related)

Notes: These classes are mapped after accounting for Tree Canopy over Turf Grass and Tree Canopy over Impervious Surfaces.

General Classification

Forest (FORE) = All contiguous patches of trees ≥1 acre in extent with a patch width ≥240-ft somewhere in the patch. The 240-ft girth references potential altered microclimate conditions extending inwards up to 120-ft from the patch edge. The forest understory is assumed to be undisturbed/unmanaged. Forests that are also wetlands are included in this class.

Tree Canopy, Other (TCOT) = All trees that do not qualify as "Forest" but are presumed to have an undisturbed/unmanaged understory. Such areas include narrow windbreaks adjacent to cropland and roads and tree canopy patches not qualified as "forest" that are fully surrounded by agriculture. Wetlands with "other tree canopy" are included in this class.

Harvested Forest (HARF) = Barren and low vegetation resulting from recently cleared forests and other tree canopy in association with a timber harvest permit (DE, MD, PA, VA, WV) or having a land use history of forest rotation since the mid 1980's. Timber harvest permit data were not reported to the Chesapeake Bay Program by either New York or the District of Columbia.

Natural Succession (NATS) = Barren, herbaceous, or scrub-shrub lands that are not classed as cropland, pasture, turf grass, or pervious developed. These are areas that are presumed to be undergoing either natural or managed succession and will eventually become forested although this process may take years to decades to complete. Abandoned mine lands are included in this class.

Detailed LULC Classification

Natural (forest-related)

- 41 Forest (>= 1 acre, 240-ft width)
- 42 Other Tree Canopy
- Harvested Forest (<= 3 years)
    - 31 Barren
    - 32 Herbaceous
- Natural Succession (> 3 years)
    - 54 Barren
    - 55 Herbaceous
    - 56 Scrub-shrub

Technical LULC Methods

41 Forest

2017/18 Methodology:

1. Dissolve together all "Tree Canopy" parcel segments that share < 85% of their border with cropland, pasture, or orchard/vineyard. Those with >= 85% agricultural border are assumed to be windbreaks and not dissolved.
2. Calculate the area and girth (width of widest portion) of each tree canopy patch.
3. Identify patches with ≥1 acre of tree canopy and girth ≥ 240-ft (72 meters).

2013/14 Methodology:

1. Vectorize and dissolve all 2013/2014 Tree Canopy, excluding Tree Canopy over Impervious
2. If the patch is at least an acre in area and has a width of at least 72 meters, it is forest

3. Remove areas that are Tree Canopy over Turf Grass

42 Other Tree Canopy

2017/18 Methodology:

1. Identify all patches of tree canopy that do not qualify as “forest” nor are classed as “tree canopy over turf grass” or “tree canopy over impervious surfaces”. For patches of tree canopy surrounded by agriculture, this class takes priority over “tree canopy over turf grass”.

2013/14 Methodology:

1. All tree canopy that does not meet the forest metrics

31-32 Harvested Forest

2017/18 Methodology:

1. Barren and low vegetation parcel segments that either:
    a. Intersect state timber harvest data. States that provided timber harvest polygons include Delaware, Maryland, Pennsylvania and West Virginia. The state of Virginia provided point data which was buffered by 60 meters; or
    b. Contain >=20% of LCMAP-detected forest rotation or deforestation by area and >=15% of the 20%+ portion must be LCMAP-detected forest rotation.

2013/14 Methodology:

1. Barren and low vegetation that is Natural Succession in 2017/18 due to being harvested

54-56 Natural Succession

Note: “Turf Grass”, “Agriculture”, and “Suspended Succession” methods applied first.

2017/18 Methodology:

1. Barren, low vegetation, and scrub-shrub segments with the majority area classified as natural succession based on local land use or zoning.
2. Additional low vegetation and scrub-shrub segments are classed to natural succession if
3. the parcel contains:
    a. a large percentage (~70% parcel coverage) of tree canopy and the segment area < 1000 m^2; or
    b. < 15% CDL coverage of any kind <u>and</u> < 93m^2 of road or building (opposite of "occupied parcel"); or
    c. the parcel has >70% tree cover, < 30% CDL of any kind, segment area < 150m^2, and parcel is > 4046m^2;
4. Barren, low vegetation, or scrub shrub adjacent to large tree canopy segments (>= 10,000 m^2) in large parcels (> 4046 m^2).
5. Scrub Shrub that met one of the Harvested Forest rulesets

2013/14 Methodology:

1. Barren, low vegetation, and scrub-shrub that was not agriculture, wetlands, solar fields, harvested forest or extractive

<u>Natural Ancillary Datasets:</u>

Annual land use change, timber harvest points and polygons, wetlands.

4d. WATER

Notes: Non-tidal surface waters evident in the land cover data are highly fragmented due to the large amount tree canopy and canopy-related shadows obscuring water in the 1-meter NAIP imagery. Water associated with large rivers such as the mainstems of the Susquehanna, Potomac, and James is clearly visible in aerial imagery. As streams narrow, progressing upstream towards the headwaters, they become increasingly obscured by tree canopy until they are all but invisible under the canopy. Even in open fields, narrow streams may not be clearly identifiable in the imagery. Without a very-high resolution stream dataset that aligns with the aerial imagery, it is not consistently possible to distinguish sections of daylighted stream from ponds. To partially address this issue, 1:24,000 scale National Hydrography Data channel initiation points and the USGS' Floodplain and Channel Evaluation Toolkit (FACET) (Hopkins et al., 2020) software were used to generate a stream network aligned with a 3-meter resolution Digital Elevation Model derived from LiDAR imagery.

General Classification

Water (WATR) = the Chesapeake Bay, lakes and reservoirs, riverine and terrene ponds, large rivers, and water within smaller channels visible through the tree canopy. Included with this class are NWI or state wetlands that are mapped as water in the land cover (MMU = 25m^2)

Detailed LULC Classification

Water
- 11 Estuarine/ Marine
- Lentic (fresh)
  - 12 Lakes and reservoirs
  - 13 Riverine ponds
  - 14 Terrene ponds
- Lotic (fresh)
  - 15 Channels
    - Open Channel (TBD)
    - Tree Canopy over Channel (TBD)
    - Culverted (TBD)
  - Ditches (TBD)
    - Open Ditch (TBD)
    - Tree Canopy over Ditch (TBD)
    - Culverted (TBD)

Technical LULC Methods

General 2017/18

1. Water Features
   a. Extract water from land cover
   b. Group water cells into regions based on adjacency (eight neighbor rule)
   c. Vectorize and region grouped water patches using orthogonal and diagonal connectivity
   d. For each polygon calculate the following:
      i. Perimeter-area ratio (PAR) (A measure of shape complexity: large values are less complex and smaller values are more complex)
      ii. Polsby-popper score (PPS) (A measure of shape compactness. 1 = circular/compact; and 0 = not compact and irregular.
2. Tidal overlay

a. Merge National Wetlands Inventory (NWI) tidal wetlands with NOAA's Sea-Level Rise 1-ft data.
    i. NWI tidal wetlands are created by filtering *Estuarine and Marine Wetland* and *Estuarine and Marine Deepwater* wetland types and then dissolving any adjacent (touching) *Freshwater Emergent Wetlands*
    ii. Both data sets are rasterized, merged and then vectorized to create the tidal overlay.

3. Lakes and Reservoirs Overlay
    a. Identify any large lakes and reservoirs in the Geographic Names Information System (GNIS) with official name designation using the FEATURE_CLASS attribute filtered by "Lake and Reservoirs"
    b. Identify Reservoirs and Lakes/Ponds in the NHD-HR Waterbody layer (FTYPE = 436 or 390)
    c. Merge GNIS and NHD-HR lakes and reservoirs.
    d. Identify NHD Area (query: FTYPE is 460 (Stream/River)) and intersect it with NWI layer (query WETLAND_TY is 'Lake').
    e. Merge all layers to create Lake and Reservoir Overlay mask
4. Non-tidal water overlays:
    a. Following overlays are applied to remaining water features once Tidal and Lake and Reservoirs overlays have been applied
    b. Elongation ratio is calculated on any remaining features that are not classified as Estuarine or Lakes and Reservoirs.
    c. Initial Lotic Overlay (only used to classify water features):
        i. Create a buffered stream network more closely aligned to the 1-meter resolution imagery using the National Hydrography Dataset - High Resolution (NHD-HR) channel initiation points and the USGS' FACET software were used to generate a stream network aligned with a 3-meter resolution Digital Elevation Model derived from available LiDAR imagery.
        ii. Buffer the aligned stream network by the average channel width attribute generated by FACET
        iii. In areas of the Bay watershed lacking LiDAR, the non-aligned NHD-HR flowlines were buffered and merged with the FACET-derived streams.
        iv. Extract following the FCodes 46000, 46003, 46006, 46007 (Stream/River) from the NHD Area.
        v. Merge all layers to create an initial lotic overlay
    d. Initial Lentic Overlay (only used to classify water features):
        i. Query NHD Waterbody for following FTYPES 361, 390 and 436 (lakes, ponds, reservoirs, playas)
        ii. Query NWI for following WETLAND_TY: Freshwater Pond
        iii. Merge both files to create an initial lentic overlay
    e. Refined lentic and lotic overlays
        i. To eliminate potentially non-lotic features from the lotic overlay, lotic features that intersect the lentic overlay are removed from the lotic overlay and classified as lentic.
        ii. Lentic features are further refined using shape, area and morphology indices to <u>exclude</u> any long segments of dammed rivers that were accidentally classified as

lentic. Query is perimeter-to-area ratio >0.01 and elongation > 0.6 and polsby-popper score < 0.1. Any features that meet these criteria are reclassified as lotic.

5. Riverine Overlay (for riverine ponds and wetlands classification only)
    a. Create a buffered stream network more closely aligned to the 1-meter resolution imagery
        i. National Hydrography Dataset - High Resolution (NHD-HR) channel initiation points and the USGS' FACET software were used to generate a stream network aligned with a 3-meter resolution Digital Elevation Model derived from available LiDAR imagery.
        ii. Buffer the aligned stream network by the average channel width attribute generated by FACET
        iii. In areas of the Bay watershed lacking LiDAR, the non-aligned NHD-HR flowlines were buffered and merged with the FACET-derived streams.
    b. SSURGO soils were split into two layers: frequently flooded soils using (*flodfreqdcd == 'Frequent'*) and hydric soils using (*hydclprs >= 1%*).
    c. FEMA 100-year floodplain from HAZUS and hydric soils were subset to identify those intersecting the aligned, unbuffered stream network.
    d. The subset FEMA 100-year floodplain and hydric soils, frequently flooded soils, and buffered stream network were merged into a single feature, rasterized and vectorized to create a seamless riverine overlay layer

11 Estuarine/Marine

2017/18 Methodology:

1. All water features intersecting the Tidal overlay.

2013/14 Methodology:

1. Water intersecting Estuary/Marine in 2017/18

12 Lakes and Reservoirs

2017/18 Methodology:

1. All water features intersecting the Lakes and Reservoirs overlay

2013/14 Methodology:

1. Water Intersecting Lakes/Reservoirs in 2017/18

13 Riverine Ponds

2017/18 Methodology:

1. All refined lentic features intersecting the Riverine overlay

2013/14 Methodology:

1. Water intersecting Riverine Ponds in 2017/18
2. Water not touching any water in 2017/18 footprint and within the riverine wetlands footprint that are not touching FACET channel buffers

14 Terrene Ponds

2017/18 Methodology:

1. All refined lentic features that do not intersect the Riverine overlay

2013/14 Methodology:

1. Water intersecting Terrene Ponds in 2017/18
2. Water not touching any water in 2017/18 footprint, not in the riverine wetland footprint and not intersecting FACET channel buffers

15 Lotic

2017/18 Methodology:

1. Refined lotic features are used (see above).

2013/14 Methodology:

1. Water intersecting Lotic water in 2017/18
2. Water not touching any water in 2017/18 footprint and intersecting FACET Channel buffers

Water Ancillary Datasets:

DEM-aligned stream network, geographic names, national hydrography data, national wetlands data, and national sea-level rise data.

References:

Hopkins, K.G., Ahmed, L., Metes, M.J., Claggett, P.R., Lamont, S., and Noe, G.B, 2020, Geomorphometry for Streams and Floodplains in the Chesapeake and Delaware Watersheds: U.S. Geological Survey data release, https://doi.org/10.5066/P9RQJPT1.

4e. WETLANDS AND WATER MARGINS

Notes: “Emergent wetlands” as a land cover class (MMU = 225 square meters) were mapped in Delaware, Pennsylvania, and the tidal portions of Maryland and the District of Columbia as low vegetation areas located along major waterways (e.g., rivers, estuary, ocean) with visually confirmed saturated ground surrounding the vegetation. Emergent wetlands were not mapped as a land cover class in New York or West Virginia. For Virginia, “emergent wetlands” as a land cover class were mapped as all barren, low vegetation, and scrub-shrub lands that substantially overlap wetland features delineated by NOAA’s C-CAP program, are non-adjacent to impervious surfaces, and within 1-ft elevation of tidal surface waters. This special approach for mapping emergent wetlands was needed because Virginia has large amounts of tidal wetlands, “emergent wetland” land cover was not mapped originally from 2014 imagery, and budget and time constraints prohibited implementation of a purely spectral-based classification.

General Classification

Tidal Wetlands, Non-forested (TDLW) = All wetlands mapped as estuarine or marine according to National Wetlands Inventory (NWI) plus any adjacent freshwater emergent wetlands, and emergent wetlands mapped from high-resolution imagery outside Virginia must be within 1-ft of adjacent tidal water elevations derived from NOAA’s Sea Level Rise dataset.
(https://www.fws.gov/wetlands/Documents/Wetlands-and-Deepwater-Habitats-Classification-chart.pdf)

Riverine Wetlands, Non-forested (RIVW) = National Wetlands Inventory (NWI) non-pond, non-lake wetlands, emergent wetlands along streams mapped from high-resolution imagery outside Virginia, state designated wetlands, and potential non-tidal wetlands (for Pennsylvania only) located within the FEMA designated 100-year floodplain, DEM-aligned 1:24,000 scale buffered stream network, SSURGO hydric or frequently flooded soils.

Terrene Wetlands, Non-forested (TERW) = National Wetlands Inventory (NWI) non-pond, non-lake wetlands, emergent wetlands mapped from high-resolution imagery outside Virginia, state designated wetlands, and state potential non-tidal, non-floodplain wetlands (for Pennsylvania only). These are spatially isolated wetlands on ridges and slopes that are most prevalent in the coastal plain where streams may originate from wetland complexes.

Detailed Classification

5000 Wetlands and Water Margins
- Tidal Wetlands
  - 91 Barren
  - 92 Herbaceous
  - 93 Scrub-shrub
  - 94 Other Tree Canopy
  - 95 Forest
- Riverine (Non-tidal)
  - 61 Barren
  - 62 Herbaceous
  - 63 Scrub-shrub
  - 64 Other Tree Canopy
  - 65 Forest
- Terrene/Isolated (Non-tidal)
  - 71 Barren
  - 72 Herbaceous

73 Scrub-shrub
74 Other Tree Canopy
75 Forest
16 Bare Shore

Technical LULC Methods:

General 2017/18

1. Build a comprehensive wetland layer
    a. Exclude “Freshwater Pond” and “Lake” from NWI wetland types and add attributes to eliminate NHD stream features which are incorporated into the latest version of NWI. Add attributes:
        i. Area
        ii. Length.
        iii. Perimeter-area ratio (PAR) (Informs shape complexity. Large values are less complex and smaller values are more complex)
        iv. Polsby-popper score (PPS) (informs shape compactness. 1 is circular/compact and 0 is not compact and irregular)
    b. Delete NWI features with PPS <= 0.1 for wetland classes that have linear features:
        i. Freshwater Emergent Wetland
        ii. Freshwater Forested/Shrub Wetland
        iii. Riverine
    c. Isolate, vectorize, and merge “Emergent Wetlands” in the land cover data with the NWI wetlands subset and any local or state wetland data to create a comprehensive wetland layer.

91-95 Tidal Wetlands

2017/18 Methodology:

1. All features from the comprehensive wetland layer intersecting the Tidal Overlay (see Water methods).

2013/14 Methodology:

1. Barren, Low Vegetation, Scrub-Shrub and Tree Canopy within tidal wetlands overlay

61-65 Riverine Wetlands (Non-Tidal)

2017/18 Methodology:

1. All features from the comprehensive wetland layer intersecting the Riverine Overlay (see Water methods).

2013/14 Methodology:

1. Barren, Low Vegetation, Scrub-Shrub and Tree Canopy within riverine wetlands overlay

71-75 Terrene Wetlands (Non-Tidal)

2017/18 Methodology:

1. All remaining features from the comprehensive wetland layer after classifying tidal and riverine wetlands.

2013/14 Methodology:

1. Barren, Low Vegetation, Scrub-Shrub and Tree Canopy within terrene wetlands overlay

16 Bare Shore

2017/18 Methodology:

1. Barren lands that are adjacent to water features but not classified as wetlands.

2013/14 Methodology:

1. Barren transitioning to Water that is adjacent to Water in 2013/14

Wetland Ancillary Datasets:

DEM-aligned stream network, 100-year floodplain, national soils data, geographic names, national hydrography data, national wetlands data, national sea-level rise data, and potential conservable (forested) wetlands in Pennsylvania.

Appendix A. Land-cover Change Mapping in the Chesapeake Bay Watershed

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1.0 Study Area

The project area encompassed 206 counties\municipalities in the Chesapeake Bay Watershed and immediately adjacent areas, including the entirety of Maryland and Delaware and parts of Virginia, West Virginia, Pennsylvania, and New York. On a north-south axis, this region extended from the Adirondack Mountains in New York to the coastal plain of southern Virginia; on an east-west axis, it stretched from the Delmarva Peninsula (Delaware, Maryland, and Virginia) to the Allegheny Mountains of West Virginia. The total study area was 258,050 km^2 (99,634 mi^2, 25,804,975 ha, 63,765,383 ac).

2.0 Analysis Period

The specific analysis of interval of interest in change detection was 2013\2014-2017\2018. A two-year range was necessary for both the beginning and ending dates because the quality of the input datasets varied in quality and availability.

3.0 Data Types

3.1 2013\2014 Land Cover

The Project Team and its collaborators previously created [1-m resolution land-cover for the 2013\2014 period.] The primary classes were: Water, Emergent Wetland, Tree Canopy, Scrub\Shrub, Low Vegetation, Barren, Impervious Buildings, Other Impervious (i.e., parking lots, driveways, sidewalks, etc.), and Impervious Roads. This scheme also included separate classes for tree canopy overhanging different types of anthropogenic surfaces: Tree Canopy Over Impervious Buildings, Tree Canopy Over Other Impervious, and Tree Canopy Over Impervious Roads. Because this first high-resolution land-cover map was developed separately for each state in the watershed, the mapping protocol varied slightly across the study area. In particular, buildings were not mapped as a separate class in Virginia, instead being combined with the Other Impervious class. Also, the Emergent Wetlands class was not included in the 2013\2014 land cover for Virginia, West Virginia, and New York, and it was restricted to tidal zones in Maryland. Despite these discrepancies, however, the 2013\2014 land cover served as the starting point for change detection, with the expectation that the mapping protocol would be standardized across all states in subsequent products and that any known errors or inconsistencies would be corrected prior to direct comparison of the two time intervals.

3.2 Imagery

The input most essential to change detection was National Agricultural Imagery Program (NAIP) imagery acquired by the USDA Farm Services Agency, a multi-temporal, national (continental United States) collection that facilitates high-resolution land-cover classification (Maxwell et al. 2017). NAIP imagery is usually acquired during leaf-on conditions at 2-3 year intervals and at a resolution of 0.6-1 m. For the Chesapeake Bay study area, all of the pertinent NAIP datasets were 4-band imagery tiles containing both the visible bands (Blue, Green, Red) and a Near Infrared (NIR) band. For the first time interval (T1), 2013 imagery was used for Delaware, Maryland, New York, Pennsylvania, and Washington, DC and 2014 imagery was used for Virginia and West Virginia. For the second time interval (T2), 2017 data were used for New York, Pennsylvania, and Washington, DC while 2018 data were used for Delaware, Virginia, and West Virginia. For Maryland, some portions of the state were covered by 2018 NAIP acquired during leaf-off conditions, limiting the imagery's utility to change detection (i.e., changes to vegetation are not as spectrally distinct as they tend to be during growing conditions). Because NAIP was acquired for Maryland in consecutive years, however, 2017 NAIP was used for this state whenever the 2018 imagery was leaf off. Portions of the 2018 NAIP for West Virginia were also acquired during leaf-off conditions but no other NAIP datasets were close enough temporally to permit substitution. Accordingly, the change detection modeling for West Virginia included routines that attempted to accommodate the leaf-off imagery to the fullest extent possible.

3.3 LiDAR

After imagery, the most useful data type was LiDAR, which permitted derivation of normalized digital surface models (nDSMs) that indicated the height of aboveground features. Where available, this feature-height information facilitated mapping and differentiation of tree canopy and buildings. It was preferable to obtain LiDAR that coincided exactly with the T1 and T2 intervals for each state but in reality the acquisition dates of LiDAR across the study area varied widely, necessitating use of datasets that were offset from the specific analysis period. In such cases, LiDAR was used more as an ancillary dataset to improve mapping rather than an exclusive input. No datasets with acquisition dates older than 2010 were used in T1 mapping while no datasets younger than 2016 were used at T2. In some cases, no LiDAR was available at T1, T2, or at either interval, necessitating complete reliance on other datasets for T1 refinement or change detection.

3.4 Thematic GIS Datasets

Thematic GIS datasets in vector format were also used to inform improvements to the original T1 land cover and subsequent analysis of change. These layers included thematic datasets developed by individual municipalities, including building footprints, roads, parking lots, sidewalks, and water bodies. Regional datasets such as the Microsoft Building Footprints v2.0 (Microsoft 2018) were also useful. However, thematic datasets were used with caution because the specific date of individual layers was not always evident, potentially complicating the chronology of land-cover change, and they also varied widely in quality. For example, footprint layers sometimes contained errors of omission and commission and in the other instances contained configuration errors (i.e., a footprint coincided with an actual structure but misrepresented its shape). Another problem was that some thematic datasets did not differentiate impervious surfaces such as buildings, roads, and parking lots, or did not attribute them adequately. Accordingly, all datasets were vetted prior to use and layers with inadequate quality or attribution were excluded from subsequent modeling. Furthermore, some thematic datasets were used more as ancillary datasets to improve existing classes rather than sources of precise feature delineation.

3.5 C-CAP Land Cover

To address the lack of an Emergent Wetlands class in the available 2013\2014 land cover for Virginia, the Project Team considered a range of possible mapping approaches. LiDAR-based topographic modeling (MacFaden et al. 2021) was one possibility but it would have required intensive manual review and correction prior to use in comprehensive land-cover mapping. This option was ultimately considered beyond the scope of the current project's timeline. An alternative approach was to use the wetlands component of NOAA's Coastal Change Analysis Program (C-CAP) land cover as a guide to modeling tidally-influenced wetlands. The most recent C-CAP dataset (NOAA 2016), with 30-m resolution, was subsequently used for this approach, facilitating addition of the Emergent Wetlands class to portions of 42 counties\municipalities in Virginia's portion of the Chesapeake Bay Watershed. Wetlands mapping for these counties was further constrained by a tidal layer produced by the Project Team (See Wetlands and Water Margins section- page 12).

4.0 Data Preparation

All input datasets necessary for land-cover mapping and change detection were publicly available from data download sites or by direct inquiry to federal, state, and local agencies. As a general rule, the best-available datasets aligning with the specific analysis period were selected for additional vetting. The Project Team then reviewed all datasets for quality, pertinence, and completeness (Appendix A), discarding any datasets that would provide little or no information in subsequent modeling or, worse, would confound change detection. If necessary, selected datasets were then re-projected to the projection of the LiDAR datasets covering an individual county\municipality, ensuring compatibility among all inputs.

4.1 2013\2014 Land Cover

The T1 land-cover maps for Pennsylvania and Delaware were obtained in their original modeling coordinate reference systems (CRS), which were zoned Transverse Mercator projections. However, the T1 land-cover datasets for the other states were available only in Albers projection, an equal-area system suitable for representing large, regional study areas. Accordingly, the T1 datasets in Albers were re-projected to the full set of different projections used in the study area. To minimize warping during re-projection, the T1 datasets in Albers were first re-sampled from 1 m to a finer resolution (0.5 m). These steps were conducted in ArcGIS Pro 2.8 (ESRI, Redlands, Colorado, USA).

4.2 Imagery

All NAIP data were obtained as uncompressed tiles in their original CRSs and cell sizes, necessitating compilation into mosaics that matched the projections and extents of individual counties or groups of counties. Mosaicking and re-projecting operations were conducted in a variety of GIS programs, including ArcGIS Pro, FME 2021 (Safe Software, Surrey, British Columbia, Canada), and ERDAS Imagine 2018 (Hexagon Geospatial, Madison Alabama, USA).

4.3 LiDAR

Whenever possible, LiDAR datasets were obtained in their original point-cloud format, which were then filtered into specific derivatives using LAStools (rapidlasso Gmbh) and exported as surface models. These models were: 1) digital elevation models (DEMs) were extracted from ground returns; 2) digital surface models (DSMs) from first returns; and 3) digital terrain models (DTMs) from last returns. In FME, the DEMs were then subtracted from DSMs and DTMs to normalize them against the ground, producing nDSMs and nDTMs, respectively. Later, during feature extraction in eCognition 10.1 (Trimble Navigation Limited, Westminster, Colorado, USA), yet another derivative was created by subtracting the DTM from the DSM (Difference DSM-DTM). The nDSMs were most useful for identifying aboveground objects while the Difference DSM-DTM layer helped differentiate trees from buildings and other structures (i.e., difference values will be consistently near zero for a consistent surface such as a building roof). Although intensity values usually accompanied the LiDAR point clouds, they were not used in any subsequent modeling because high variability within and between LiDAR collections prevented development of effective modeling rules.

4.4 Thematic GIS Datasets

Individual GIS datasets were re-projected in ArcGIS Pro as necessary to match the modeling CRS for each county\municipality. In some cases, hydrology and impervious surfaces layers, if adequately attributed, were filtered to separate different classes of interest (e.g., roads vs. parking lots).

4.5 C-CAP Land Cover

In ArcGIS Pro, the full 2016 C-CAP land cover layer was clipped by the Virginia boundary and then its wetland classes (13-18) within 1-ft elevation above sea level were extracted to derive an emergent wetlands dataset.

5.0 Mapping Workflow

5.1 Preliminary Roads Mapping

Discrimination of road surfaces from other impervious features can be challenging when relying primarily on imagery-based spectral criteria. Accordingly, in this project new or modified roads were digitized manually using the T1 and T2 NAIP as reference imagery. Roads removed between the analysis intervals were also mapped onscreen. Road centerlines were reviewed to help identify areas of change but were not used explicitly in mapping because the chronology of the available layers did not always match the analysis period. The digitized layer with new, modified, or removed roads was then used in subsequent modeling routines to guide change detection for the Impervious Roads class.

5.2 Object-based Image Analysis

Automated feature extraction was performed in eCognition, state-of-the-art software for performing object-based image analysis. This technique focuses on groups of pixels that form meaningful landscape objects rather than individual pixels (Benz et al. 2004), which provides a more realistic representation of features and also permits contextual analysis (i.e., how does an object relate to its neighbors?). eCognition also permits data fusion, or simultaneous use of multiple spectral, surface-model, or thematic inputs (O'Neil-Dunne et al. 2012). The Project Team has used this approach for a wide variety of high-resolution mapping applications, including tree canopy (O'Neil-Dunne et al. 2014), comprehensive land cover (MacFaden et al. 2012), and wetlands (MacFaden et al. 2021).

5.3 Modeling Scenarios

All mapping was performed by county\municipality. This narrow extent was necessitated by multiple factors: 1) the difficulty creating and working with large high-resolution imagery mosaics; 2) the patchwork availability of LiDAR in some regions; 3) the occurrence of leaf-off NAIP imagery in some regions; and 4) the limited geographic focus of most thematic vector GIS datasets (e.g., county-specific impervious surfaces). In cases where different LiDAR collections covered different portions of an individual county, the county was mapped in sections. Division of counties into sections was also necessary for regions covered by a mix of leaf-on and leaf-off NAIP imagery.

After assessing the availability and quality of the inputs for each county, a specific modeling scenario was identified and coded into an eCognition rule set that executed the complete mapping workflow (Figure 1). The optimal scenario occurred when: 1) LiDAR existed for both T1 and T2; 2) leaf-on NAIP was available at both time periods; and 3) good thematic vector datasets could help guide mapping of specific land-cover elements. For the 2013\2014-2017\2018 analysis period, this scenario rarely occurred (Appendix A), requiring alternative options for LiDAR at only one interval, LiDAR missing at both intervals, the presence of leaf-off imagery, or few if any usable thematic datasets. When sub-optimal scenarios occurred, data fusion was less comprehensive and the modeling necessarily relied more heavily on the available inputs or, later in the workflow, manual review and editing.

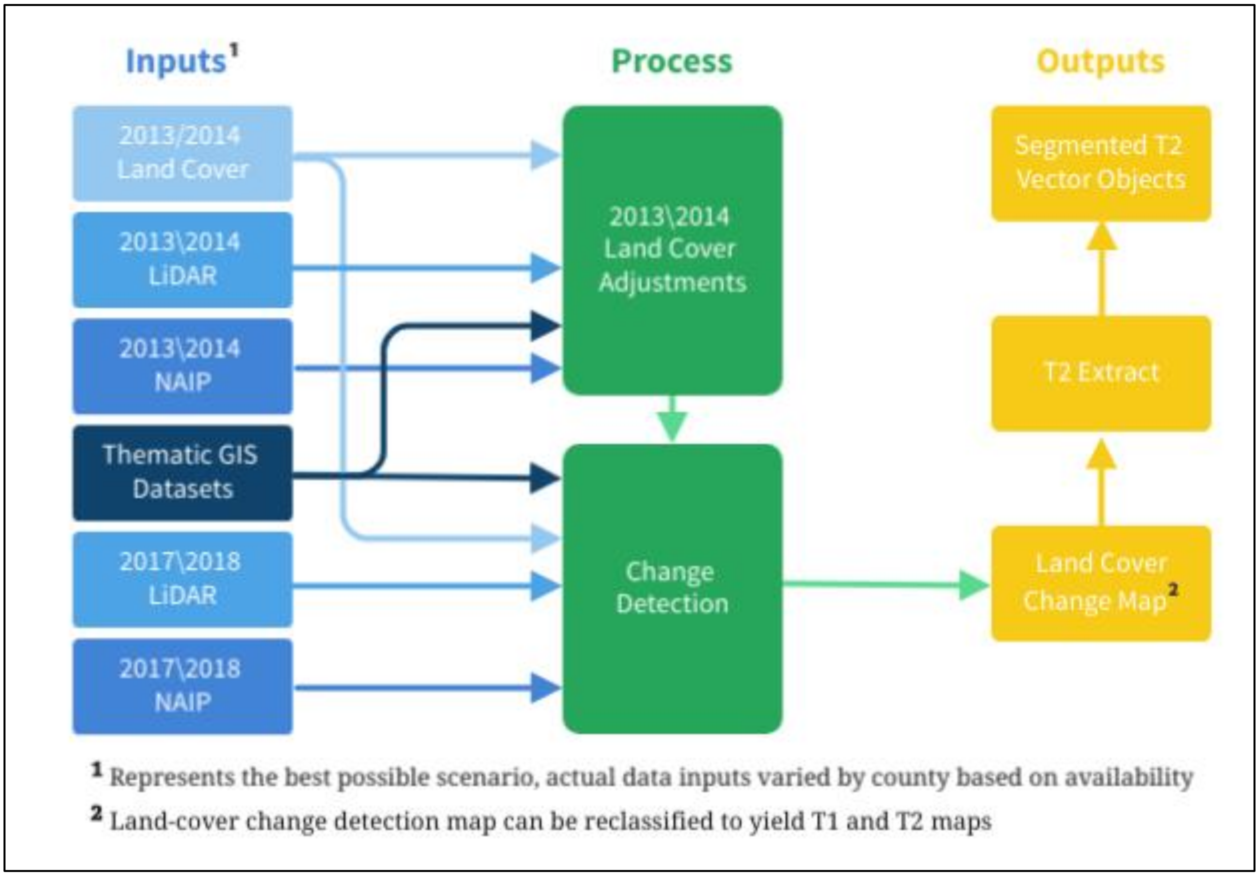

Figure 1. Workflow for land-cover change mapping in the Chesapeake Bay Watershed, 2013\2014-2017\2018. Designed to accommodate a range of data-input scenarios, the workflow first improved existing 2013\2014 maps and then performed change detection using 2017\2018 data. The output change detection map could then be used to produce T1 (revised) or T2 extracts.

5.4 Change Detection Classes

To represent change across the analysis period, the original 12-class classification scheme was expanded to include all types of change likely to occur in the Chesapeake Bay Watershed (Table 1). Change types with a low probability of occurrence or classes that could not be mapped effectively with the available data were excluded. For example, with LiDAR unavailable at T2 for many counties in the study area, no attempt was made to model expansion of the Scrub\Shrub class in old fields reverting to shrubby growth. Similarly, the available data did not permit effective mapping of incremental water-level rises in coastal zones. However, change types that might be added during manual review and editing were included in the classification, including conversion of Low Vegetation to Scrub\Shrub (change class 54). These additional classes were not systematically mapped across the entire study area; rather, they were incorporated when observed to ensure logical consistency with adjacent types of change or manual edits.

5.5 Automated Feature Extraction

A 1-m modeling resolution was used for all automated mapping, with each county divided into 2,000 x 2,000-pixel tiles to facilitate multi-thread processing. To maximize previous investments in remote-sensing data acquisition and landscape characterization, the original 2013\2014 land cover was used as starting point for all subsequent analyses. Accordingly, the mapping workflow initially focused on improving the T1 land cover, where necessary, by using the available data inputs to add features omitted from parts of the original layer (e.g., buildings) and to remove erroneous ones (e.g., Tree Canopy overestimation along forest\field edges). This harmonization step was especially important in avoiding false change estimates; if a feature existed at both time intervals, it was essential to characterize it correctly at T1. After finalizing the revised T1 map, the LiDAR, imagery, and thematic datasets available at T2 were used to perform change detection, assigning altered T1 features to one or more of the change classes to explicitly track individual land-cover conversions.

5.5.1 T1 Land Cover Adjustments

5.5.1.1 Tree Canopy

5.5.1.1.1 T1 LiDAR Available

5.5.1.1.1.1 Missing Objects

If LiDAR exited at T1, it was used to look for tree-canopy omissions in the original 2013\2014 land cover. Image objects were created from ground-level classes (e.g., Low Vegetation, Other Impervious) using a Multi-threshold Segmentation on the T1 nDSM (>0.3 m), identifying aboveground features. A combination of T1 NDVI and T1 Difference DSM-DTM was then used to evaluate the new objects with a sequence of varying thresholds (e.g., T1 NDVI >0.3 and T1 Difference DSM-DTM >0.5; T1 NDVI >0.2 and T1 Difference DSM-DTM >0.95). These routines specifically attempted to identify street trees and small clumps of small trees that may have missed during the original 2013\2014 mapping effort. The high Difference DSM-DTM also ensured that buildings were not inadvertently reclassified as Tree Canopy.

Table 1. Classification matrix for land-cover change in the Chesapeake Bay Watershed, 2013\2014-2017\2018.

		T2 Classes											
		W[a]	EW	TC	SS	LV	B	IS	OI	IR	TCIS	TCOI	TCIR
T1 Classes		1[b]	2	3	4	5	6	7	8	9	10	11	12
W	1			13	*14*	*15*	*16*	*17*	*18*	*19*			
EW	2	*21*[c]		23		25	26	27	28	29			
TC	3	*31*				35	36	37	38	39			
SS	4	*41*		43		45	46	47	48	49			
LV	5	*51*		53	*54*		56	57	58	59			
B	6	*61*		63		65		67	68	69			
IS	7	*71*		73		75	76		78	79	210[d]		
OI	8	*81*		83		85	86	87		89		211	
IR	9	*91*		93		95	*96*	*97*	98				212
TCIS	10	*101*				105	106	107	108	109			
TCOI	11	*111*				115	116	117	118	119			
TCIR	12	*121*				125	126	127	128	129			

[a]W = Water; EW = Emergent Wetlands; TC = Tree Canopy; SS = Scrub\Shrub; LV = Low Vegetation; B = Barren; IS = Impervious Structures; OI = Other Impervious; IR = Impervious Roads; TCIS = Tree Canopy Over Impervious Structures; TCOI = Tree Canopy Over Other Impervious; TCIR = Tree Canopy Over Impervious Roads.
[b]Numeric code for each land-cover or change class.
[c]Italicized classes were not mapped by modeling; manual editing only.
[d]The 8-bit raster datasets used during mapping accommodated 256 unique value; change classes 710, 811, and 912 were thus assigned alternative values.

5.5.1.1.1.2 False Objects

Where available, LiDAR was also used to check for erroneous Tree Canopy objects in the T1 map, focusing on overestimated canopy edges, false canopy over water, false canopy over buildings, utility poles, and other common sources of confusion. Image objects were created from the existing Tree Canopy class using a Multi-threshold Segmentation based on the T1 nDSM, identifying very short features (<0.1 m). After consolidating and smoothing adjacent features, the new objects were re-evaluated relative to height (<0.1 m) and short features were reassigned to a temporary placeholder class (to be evaluated later for inclusion in other classes).

5.5.1.1.2 No T1 LiDAR Available

5.5.1.1.2.2 Missing Objects

No attempt was made to automate identification of missing trees when LiDAR was unavailable; the likelihood of capturing false positives was unacceptably high using spectral criteria only.

5.5.1.1.2.1 False Objects

When no LiDAR existed at T1, NAIP imagery was the primary reference for checking the Tree Canopy class. Inevitably, spectral examination of potentially erroneous tree canopy was not as effective as LiDAR-based criteria and thus was necessarily more conservative in reassigning features. After a Multi-resolution Segmentation weighted by the four T1 NAIP bands (Scale, 25; Shape, 0.2; Compactness, 0.5; T1 Blue, Weight 1; T1 Green, Weight 1; T1 Red, Weight 1, T1 NIR, Weight 2) was used to create image objects, the Normalized Difference Vegetation Index (NDVI) calculated from the

T1 NAIP (T1 NDVI) served as the primary evaluative criterion, reassigning low T1 NDVI objects (<0.2) to a temporary class. Additional criteria with higher T1 NDVI thresholds were also combined with contextual clues (e.g., size, distance to buildings) to identify Tree Canopy likely to be false.

A second spectral routine examined objects against not only the T1 NAIP but also the T2 NAIP, identifying objects with a small (<0.2) relative difference between the two NAIP values ***and*** a low (<0.1) T1 NDVI. This type of harmonization procedure, used in many subsequent steps, helped ensure that only erroneous features were reassigned during T1 land-cover adjustments and also helped prevent identification of false land-cover conversions during change detection.

For areas with leaf-off T1 NAIP only, the Tree Canopy class was not examined spectrally; T1 adjustments relied more on later manual QA\QC. However, leaf-off T2 NAIP would be used later during change detection, albeit with much lower NDVI criteria.

5.5.5.2 Impervious Structures

5.5.5.2.1 T1 LiDAR Available

5.5.5.2.1.1 Missing Objects

The Impervious Structures class was not included in the Virginia portion of the 2013\2014 land cover but sporadic omissions also occurred elsewhere. A LiDAR-based approach similar to the one for Tree Canopy was used for buildings with the additional assistance, for most counties, of thematic vector datasets depicting building footprints. On a separate map (to avoid corrupting the initial classification), a Multi-threshold Segmentation based on the T1 nDSM (>2.4 m) identified aboveground features and then the T1 Difference DSM-DTM (<0.5) and T1 NDVI (<0) helped isolate surfaces likely to be rooftops rather than tree canopy. Additional routines incorporating size and shape (Rectangular Fit, Compactness) also helped refine the initial selection. The draft Impervious Surfaces class was then compared to thematic building footprints, where available, identifying features that overlapped substantially (>0.6). Features that strongly conformed to thematic buildings were replaced by those footprints, adopting the often-superior shape and configuration of the thematic dataset, while stand-alone LiDAR features were retained in their original form. The LiDAR-derived buildings were then smoothed with Pixel-based Object Resizing routines to ensure a reasonable geometric appearance.

5.5.5.2.1.2 False Objects

To evaluate false buildings at T1, the Impervious Structures class was segmented by the nDSM (Multi-threshold Segmentation) to identify very short (<0.2 m) draft features. These features were reassigned to a temporary class for later assignment to an alternative land-cover class.

5.5.5.2.2 T2 LiDAR Available

5.5.5.2.2.1 Missing Objects

If no T1 LiDAR existed but T2 LiDAR was available, the latter was used as a substitute for identifying draft Impervious Structures. As before, however, LiDAR-derived features were evaluated relative to T1 NAIP, minimizing the possibility that buildings constructed between T1 and T2 would be inadvertently incorporated into the revised T1 map.

5.5.5.2.2.2 False Objects

The Impervious Structures class was not evaluated for false objects when only T2 LiDAR existed. Spectral criteria could not be used because overhanging Tree Canopy could partly or wholly obscure some buildings, making NDVI unreliable.

5.5.5.2.3 No T1 or T2 LiDAR Available

5.5.5.2.3.1 Missing Objects

When no LiDAR existed, either at T1 or T2, no attempt was made to identify missing buildings; without height data, the probability of introducing further error was too high.

5.5.5.2.3.2 False Objects

For Virginia, building footprints were examined relative to spectral criteria when no LiDAR existed, reverting features with high T1 NDVI (>0.2) to a temporary class awaiting further evaluation. It was possible that small buildings wholly obscured by Tree Canopy would be removed during this step but, assuming that the building would later be identified as a type of land-cover change, it was considered the best possible compromise (i.e., change would receive more scrutiny during subsequent manual review).

5.5.1.3 Impervious Roads

The manually-produced layer containing new, modified, or removed roads was incorporated directly into the draft classification, adding corrections to existing roads and removing roads that did not actually exist at T1. In most instances, the Low Vegetation and Other Impervious classes from the 2013\2014 land cover were modified during this procedure.

5.5.1.4 Other Impervious

5.5.1.4.1 Missing Objects

Objects created when the Tree Canopy, Impervious Structures, and Impervious Roads classes were adjusted in the T1 map, but not yet assigned to other classes, were evaluated with a combination of a Multi-resolution Segmentation (Scale, 25; Shape, 0.2; Compactness, 0.5; T1 Red, 1; T1 Green, 1; T1 Blue, 1; T1 NIR, 2) and spectral criteria. First, shadows were temporarily set aside using the NIR band in the T1 NAIP, which tends to have low values in shaded areas (T1 NIR <75). After obvious impervious surfaces (T1 NDVI <0) were assigned to Other Impervious and obvious low-growing vegetated features (T1 NDVI >0.01) were assigned to Low Vegetation, the remaining unshaded objects were assigned to Other Impervious when they were mostly (>0.5) surrounded by other impervious features. Contextual criteria were also used to resolve the shaded objects, using a sequence of routines combining adjacency, size, building density (as estimated from a density layer created in eCognition with Convolution Filter Gauss Blur), and shape (i.e., Length\Width) to assign them to either Other Impervious or Low Vegetation. Another routine resolved shadows using T2 NAIP, relying on the observation that imagery datasets collected at different times may capture shadows differently (i.e., features shaded in T1 NAIP may not be shaded in T2 NAIP). When none of these routines reassigned individual shadows, a final routine grew adjacent features into the remaining shaded areas using Pixel-based Object Resizing.

5.5.1.4.1 False Objects

Other Impervious objects unchanged by the proceeding routines were evaluated with a similar combination of a Multi-resolution Segmentation (Scale, 25; Shape, 0.2; Compactness, 0.5; T1 Red, 1; T1 Green, 1; T1 Blue, 1; T1 NIR, 2), spectral criteria, and context, with large (>100 m^2), high (T1 NDVI >0.1) objects reassigned to Low Vegetation. To avoid introducing false change during subsequent change detection, however, the identified objects were also evaluated relative to T2 NAIP, with low T2 NDVI (<0) objects reverted to Other Impervious.

5.5.1.5 Low Vegetation

5.5.1.5.1 Missing Objects

As described above for the Other Impervious class, objects created by the reassignment of other classes were evaluated relative to a combination of spectral and contextual criteria. After obvious impervious features were reassigned to Other Impervious, the remaining objects with high T1 NDVI and adjacency were assigned to Low Vegetation. Shadows were similarly assigned to Low Vegetation when they were surrounded by vegetated features.

5.5.5.5.2 False Objects

The now familiar combination of a Multi-resolution Segmentation based on T1 NAIP and spectral criteria was used to reassign Low Vegetation objects to Other Impervious when they had low (<0) T1 NDVI and were located near high building densities. As with the Other Impervious routines, however, identified objects were also compared to T2 NAIP to ensure that no actual Low Vegetation features were inadvertently reassigned. In this case, features were reverted to Low Vegetation when T2 NDVI was high (>0) and the absolute difference between T1 NDVI and T2 NDVI was also high (>0.1).

5.5.1.6 Water

5.5.1.6.1 Missing Objects

After creating objects with the standard Multi-resolution Segmentation, small water features missing from the T1 map were reassigned from the Low Vegetation and Other Impervious classes when the NIR band in the T1 NAIP was low (<50). Adjacent objects were added to the missing features when they also had low (<75) T1 NIR. Because most of these features tended to be small agricultural ponds or stormwater retention structures, identified features that were adjacent to buildings or tree canopy were reverted to their original classes.

5.5.1.6.2 False Objects

Small (<500 m^2) water features were assigned to Other Impervious when they were entirely surrounded by this class or by a combination of this class and Impervious Structures and Impervious Roads.

5.5.1.7 Barren

5.5.1.7.1 Missing Objects

Missing Barren objects were not evaluated during automated T1 adjustments because such features were easily confused with impervious surfaces, which often have similar spectral characteristics. The workflow instead relied on later manual corrections to identify and add omissions.

5.5.1.7.2 False Objects

Potential areas of false Barren were segmented by a Multi-resolution Segmentation (Scale, 25; Shape, 0.2; Compactness, 0.5; T1 Red, 1; T1 Green, 1; T1 Blue, 1, T1 NIR, 2) and then evaluated by T1 NDVI (>0.1) and size (>100 m^2). Moderate to large objects with vegetative cover were reassigned to the Low Vegetation. In a separate routine, larger objects (>500 m^2) with higher NDVI (>0.2) and surrounded by Low Vegetation were also reassigned.

5.5.1.8 Scrub\Shrub

No attempt was made to adjust Scrub\Shrub features via automated feature extraction; gaps in LiDAR coverage across the study area made this step impractical. However, this class received occasional manual corrections, when observed adjacent to other errors, during subsequent QA\QC.

5.5.1.9 Emergent Wetlands (Virginia)

In the T1 map, Emergent Wetlands were not modified in the states where they were mapped previously (Delaware, Maryland, Pennsylvania, Washington, D.C.). However, wetlands were added to 42 Virginia counties in the immediate tidal zone on or near Chesapeake Bay. In a separate eCognition modeling exercise, Low Vegetation, Scrub\Shrub, and Barren features at T1 were segmented with a Multi-resolution Segmentation and then evaluated according to the proportion of C-CAP wetland features occupying individual image objects. Objects with a majority of their area (>0.5) occupied by C-CAP wetlands were initially identified but subsequently small (<200 m^2) objects with high (>0.2) relative border to impervious features were reverted to their original classes. This provisional classification was exported as a separate output layer and then imported into the full land-cover mapping workflow.

During T1 map adjustment, the modeled wetlands derived from C-CAP were incorporated into the Low Vegetation, Scrub\Shrub and Barren classes and were then refined with adjacency and spectral criteria. Objects with high NIR (>115) at both T1 and T2 and were adjacent (>0.2) to impervious features reverted to their original classes. The wetlands classification was further constrained by the tidal-zone layer produced by the Project Team, which limited Emergent Wetlands to immediate coastal waters and major river systems.

5.5.1.10 Overhanging Tree Canopy Classes

During the T1 adjustment of buildings and ground-level classes, the modified Tree Canopy class was preserved in its entirety on a separate map. After the Impervious Structures, Other Impervious, and Impervious Roads classes were adjusted as necessary, Tree Canopy was restored to the full classification, and any features that overlapped with impervious surfaces were assigned to their respective overhanging canopy classes: Tree Canopy Over Impervious Structures, Tree Canopy Over Other Impervious, and Tree Canopy Over Impervious Roads.

5.5.1.11 Error Checking

A series of error-checking routines evaluated the adjusted T1 map and performed additional modifications as necessary. For example, the harmonization process for the Other Impervious and Low Vegetation classes, intended to minimize identification of false land-cover conversions during subsequent change detection, sometimes eliminated actual, unchanging T1 features. This was especially true for small, thin impervious features such as long suburban or urban driveways, which may have different spectral characteristics in different datasets and also may be slightly offset. To restore as many of these features as possible, the Low Vegetation class was segmented in a 2-step process that created objects with homogenous spectral characteristics: 1) Multi-resolution Segmentation on T1 NAIP (Scale, 25; Shape, 0.3; Compactness, 0.8; T1 Red, 1; T1 Green, 1; T1 Blue, 1; and T1 NIR, 2); and 2) Multiple Object Difference Conditions-based Fusion (Common Border, 0.2; T1 NDVI, 0.1). The resulting objects were then examined by the relative difference (<-0.15) in T1 NDVI between them, which identified highly-contrasting features, as well as their configuration (Length/Width >3.5), width (<10m), and relative border to vegetated classes (>0.65). Narrow with sharp spectral transitions were reverted to the Other Impervious class.

5.5.2 Land Cover Change Detection

After the T1 map was finalized, land-cover conversions that occurred during the analysis period were identified by examining the available T2 LiDAR and NAIP imagery (Figure 2). The segmentation procedures were similar to those used during T1 adjustment but the evaluation routines were more complex, with individual losses and gains assigned to a wider variety of outcomes (Table 1). Map harmonization was again a priority during change detection, with routines designed to prevent identification of false change.

5.5.2.1 Tree Canopy

5.5.2.1.1 Losses

Where T2 LiDAR was available, a Multi-threshold Segmentation based on the T2 nDSM (<1 m) first identified tree canopy that was removed between time periods. When no T2 LiDAR existed, or in case there was a chronological gap between the T2 LiDAR and T2 NAIP, Tree Canopy was also segmented with spectral criteria: 1) Multi-resolution Segmentation on T2 NAIP (Scale, 25; Shape, 0.3; Compactness, 0.8; T2 Red, 1; T2 Green, 1; T2 Blue, 1; and T2 NIR, 2); and 2) Multiple Object Difference Conditions-based Fusion (Common Border, 0.2; T2 NDVI, 0.1). After shadows were set aside, potential losses to impervious surfaces were highlighted by T2 NAIP (<0), they were further evaluated with Pixel-based Object Resizing combined with a series of shape (Length\Width), adjacency, and size criteria. This step reverted objects likely caused by an offset between the T1 and T2 NAIP datasets, which was especially relevant along tree-canopy edges. All losses, whether identified by LiDAR or spectral criteria, were then re-segmented by a Multi-resolution Segmentation with a smaller scale factor (15) to produce finer-scale objects. For final assignments, Tree Canopy was converted to Low Vegetation (change combination 35) when T2 NDVI was high (>0) or when low NDVI objects were large, distant from buildings and roads, and surrounded by other vegetation. These criteria for low NDVI objects helped prevent assignment of newly-plowed fields or forest-management operations to the Other Impervious class. All remaining candidate tree-canopy losses with low NDVI (<0) were converted to Other Impervious (change combination 38). Similar to the

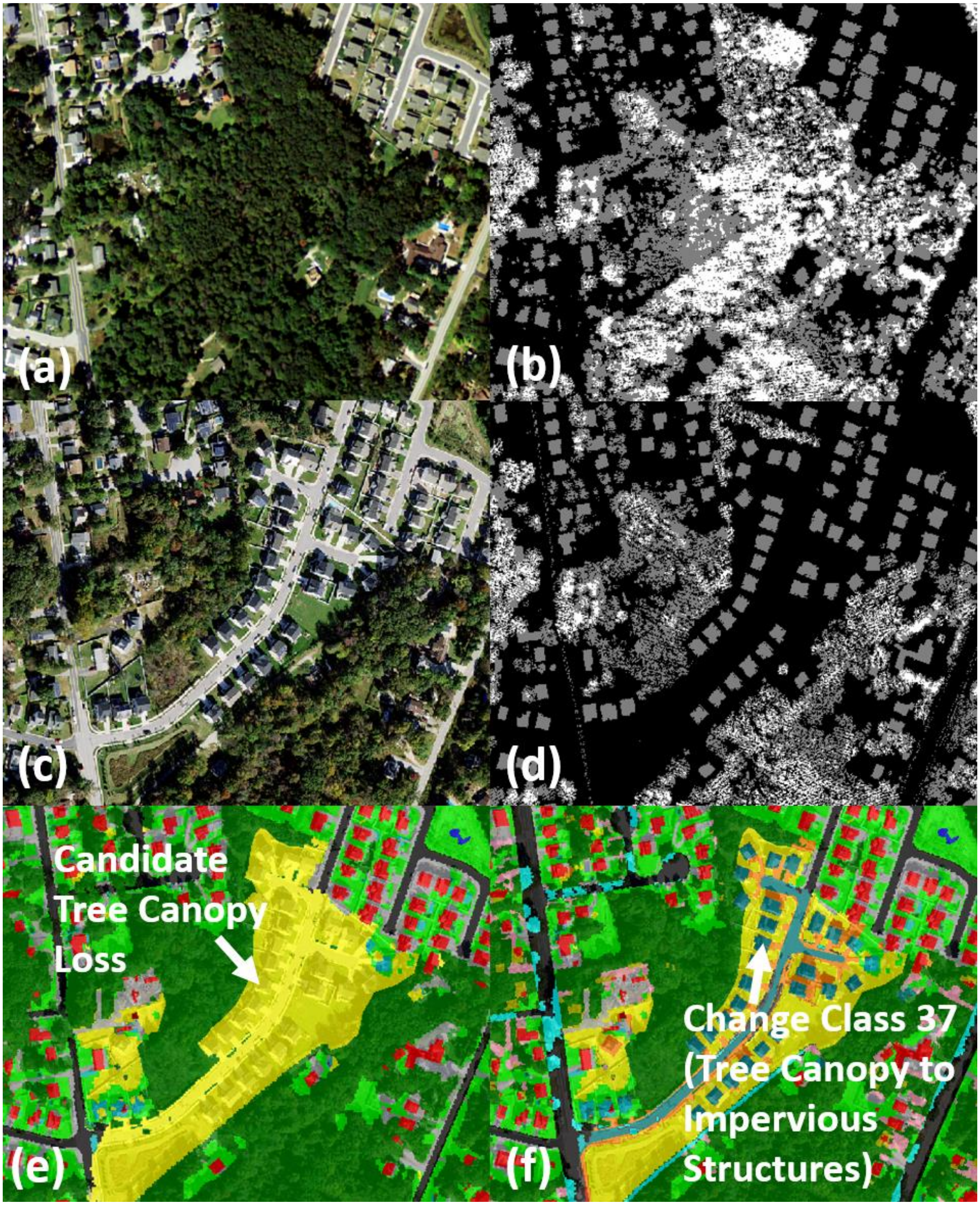

Figure 2. Land-cover change detection using a combination of NAIP, LiDAR, and thematic vector GIS layers, Chesapeake Bay Watershed. NAIP (a) and LiDAR (b) at T1 show tree canopy in the center of the frame that is missing in T2 NAIP (c) and LiDAR (d). After identifying candidate losses (e), the specific change types were assigned in the final map (f).

procedure in T1 Land Cover adjustments, shadows were then resolved with contextual criteria. Note that, when the available T2 NAIP was acquired during leaf-off conditions, a lower T2 NDVI (-0.15) threshold was used to avoid capturing erroneous losses.

Note that tree-canopy losses attributable to buildings and roads are discussed below, under Gains for Impervious Structures and Impervious Roads.

5.5.2.1.2 Gains

When T2 LiDAR existed, the addition of new, isolated trees (e.g., street trees) or small clumps of trees was provisionally identified using a Multi-threshold Segmentation on the T2 nDSM (>3 m) and then further examined by T2 DSM-DTM Difference (>0.5) and T2 NDVI (>0.2). After very small (<15 m^2) features were reverted, the remaining objects were smoothed (Pixel-based Object Resizing) and superimposed with the T1 Land Cover to identify specific change combinations (e.g., Low Vegetation to Tree Canopy, 53; Barren to Tree Canopy, 63; Other Impervious to Tree Canopy, 83). To estimate the 4-year growth of young trees, small (<50 m^2) Tree Canopy objects were expanded by a 1-m buffer using Pixel-based Object Resizing and then the buffered gains were assigned to change classes as described above. This buffering operation was also used to estimate tree growth for small trees when no T2 LiDAR existed.

5.5.2.2 Impervious Structures

5.5.2.2.1. Losses

Where available, T2 LiDAR was used to capture potential building losses by identifying features with low (<0.1 m) nDSM values. Losses with high (>0) T2 NDVI objects assumed to be vegetated features and thus were assigned to the Impervious Structures to Low Vegetation change class (75). Low (<0) T2 NDVI values were assigned to Impervious Structures to Other Impervious (78).

Without LiDAR, building losses could not be effectively mapped during automated feature extraction. In such areas, the workflow relied on manual QA\QC to identify this type of change.

5.5.2.2.1 Gains

In areas with T2 LiDAR, all non-building and non-road classes were segmented by the T2 nDSM (> 3 m) and evaluated by T2 DSM-DTM Difference (<1) and T2 NDVI (<0). After eliminating small (<25 m^2) candidate gains or small gains (<55 m^2) next to buildings (which may be caused by offsets in the input layers), the new buildings were smoothed and then superimposed with the T1 land cover to identify change combinations (e.g., Tree Canopy to Impervious Structures, 37; Low Vegetation to Impervious Structures, 57). In areas with and without T2 LiDAR, building footprint layers were also used to identify new structures, where available. After all non-building classes in the T1 Land Cover that coincided with building footprints were identified, objects that were isolated from existing Impervious Structures were set aside as possible gains. To avoid categorizing buildings that were omitted from the T1 Land Cover as gains, which could occur when such structures were heavily obscured by overhanging tree canopy, the candidate objects were also evaluated with spectral criteria, reverting features with very high T2 NDVI (>0.25) to their previous classes. Identified gains were then assigned to change classes using the same procedure as that used for LiDAR-derived buildings.

5.5.2.3 Impervious Roads

5.5.2.3.1 Losses

All losses to the Impervious Roads class were based on the manually-edited layer containing new, modified, or removed roads developed at the beginning of the mapping workflow. The Impervious Roads class was segmented by this layer and losses were provisionally identified from features labeled as T2 removals. After a 2-step segmentation process based on T2 NDVI (similar to previous operations with a Multi-resolution Segmentation followed by a Multiple Object Difference Conditions-based Fusion to consolidate homogenous objects), vegetated features were separated from impervious surfaces using spectral criteria (T2 NDVI >0) and assigned to appropriate change classes.

5.5.2.3.2 Gains

Additions to the Impervious Roads class were similarly based on the manually-edited layer of road changes, although in this case spectral evaluation was unnecessary; new roads were superimposed with the T1 Land Cover to identify individual change types.

5.5.2.4 Other Impervious

Changes to the Other Impervious class are described under Low Vegetation and other classes.

5.5.2.5 Low Vegetation

5.5.2.4.1 Losses

All remaining losses to Low Vegetation were evaluated using similar segmentation procedures (Multi-resolution Segmentation and Multiple Object Difference Conditions-based Fusion) and spectral criteria (e.g., T2 NDVI). As with Tree Canopy, shadows were first set aside to avoid overestimation of loss (i.e., shadows generally have low NDVI values) and Low Vegetation edges were examined for erroneous losses attributable to offsets between and the T1 and T2 imagery. After identifying low (<0) T2 NDVI objects, resolving shadows into adjacent objects, and re-segmenting with a second Multi-resolution Segmentation, candidate losses were further evaluated with contextual criteria (e.g., size and distance to developed features) to avoid reassigning features in actively-managed fields and forests where vegetated cover is only temporarily removed. Losses were then assigned to specific change classes, most commonly Low Vegetation to Other Impervious (38).

5.5.2.4.2 Gains

Evaluation of Low Vegetation gains focused on the Other Impervious and Barren classes. Each was segmented based on T2 NAIP and evaluated by spectral criteria, identifying features with high T2 NDVI (>0.1). To further ensure these features had truly become re-vegetated, they were also examined relative to the absolute difference in NDVI between T1 and T2 (>0.2) and T1 NDVI (<0), which indicated a sharp contrast in NDVI across the analysis period. The gains were then assigned to either Other Impervious to Low Vegetation (85) or Barren to Low Vegetation (65).

5.5.2.7 Water

Given the difficulty of evaluating the Water class across multiple time periods, when variable precipitation inland and tides along coastal zones can affect water levels, water-related conversions identified by automated feature extraction were limited to Tree Canopy gains (i.e., trees growing out over water). However, other conversion types involving water were added during manual QA\QC.

5.5.2.8 Scrub\Shrub

Losses to the Scrub\Shrub class were modeled, as described above, for the developed-feature classes (e.g., Impervious Structures, Other Impervious, Impervious Roads). With T2 LiDAR unavailable for many counties in the study area, gains were not modeled but were added occasionally during subsequent manual corrections.

5.5.2.9 Emergent Wetlands

Similar to Scrub\Shrub features, losses to the Emergent Wetlands class were modeled for the developed-feature classes. No gains were mapped.

5.5.2.10 Overhanging Tree Canopy Classes

Changes to the overhanging tree canopy classes were mapped with the same routines as used for Tree Canopy. These included estimated growth of small trees out over underlying impervious surfaces (e.g., Other Impervious to Tree Canopy Over Other Impervious, or change class 211).

5.5.2.11 Error Checking

After all possible land-cover conversions were incorporated, a final round of error-checking routines improved not only selected change classes but also unchanged T1 classes. First, any impervious features represented in available thematic vector datasets (e.g., parking lots and sidewalks) but not in the near-final map were burned into the classification as Other Impervious. By design, only unchanged T1 features were affected by this step because the chronology of many thematic datasets could not be precisely determined. Similarly, waterbodies in county-specific hydrology layers were incorporated into unchanged T1 classes (mostly Low Vegetation) as Water when the layers were deemed, during the initial vetting process, to provide more and better detail than the existing classification.

Additional improvements to the Water class were also performed by segmenting the Low Vegetation class with the T2 NAIP (Multi-resolution Segmentation; Scale, 15; Shape, 0.3; Compactness, 0.8; T2 Red, 1; T2 Green, 1; T2 Blue, 1; T2 NIR, 2) and examining T1 NIR and T2 NIR simultaneously. When both were low (T1 NIR <20 and T2 NIR <60, or vice versa), Low Vegetation was reassigned to Water. This data-fusion step helped add stable, unchanging details that could not be reliable extracted from the T1 NAIP alone. Similar NDVI-based procedures reassigned unchanged but erroneous Low Vegetation to Other Impervious (and vice versa) and reverted change class 85 (Other Impervious to Low Vegetation) to Low Vegetation in densely-developed areas where sparsely-vegetated lawns were incorrectly classified as Other Impervious at T1.

5.5.3 Initial Post-processing

All 2,000 x 2,000-pixel tiles processed in eCognition were exported as individual raster files and then mosaicked into county-specific layers, in GeoTiFF format, using FME. These layers were then re-projected from the original CRS into Albers Contiguous Equal Area projection (meters) using ArcGIS Pro. Pyramids, statistics, and raster attribute tables were also added in ArcGIS Pro.

The change classes in the land-cover map for each county encoded both T1 and T2 conditions, meaning that the map for either interval can be extracted as separate product, if necessary. For use in subsequent land-use analyses, the Low Vegetation, Scrub\Shrub, and Barren classes at T2 were re-segmented in eCognition to capture sub-class variability (e.g., fields captured by the Low Vegetation class may include a mix of plowed, bare soil, crops, hayfield, and pasture). For all three classes, a 2-step segmentation was used to highlight spectrally-diverse features: 1) Multi-resolution Segmentation (Scale, 25; Shape, 0.3; Compactness, 0.8; T2 Red, 1; T2 Green, 1; T2 Blue, 1; T2 NIR, 2); and 2) Multiple Object Difference Conditions-based Fusion (Common Border, 0.1; T2 NDVI, 0.05). The objects were then exported as vector objects, in ESRI Geodatabase format, and re-projected to Albers using ArcGIS Pro.

5.5.4 Quality Assurance\Quality Control (QA\QC)

Two rounds of manual QA\QC were conducted to provide an additional increment of quality to the draft change-detection layers created via automated feature extraction. Previous work by the Project Team has shown that manual editing does not necessarily change the output statistically but does help remove non-systematic errors and modeling glitches that might diminish end-user confidence in the final product (O'Neil-Dunne et al. 2012). To maximize the benefit of local knowledge, draft versions of the T2 extract were first submitted to each county for review (the change-detection layer was not submitted to outside reviewers because the multitude of change classes would be difficult to display and interpret efficiently). Reviewers were instructed to focus specifically on omitted areas of change but other comments were also accepted. Comments received from reviewers were compiled by the Project Team and evaluated for pertinence; suggestions implying a scale finer than the modeling resolution (1 m) were ignored. In ArcGIS Pro, the Project Team then drew polygons representing necessary changes at either T1 or T2, specifically coding "To" and "From" change classes. For each round, automated feature extraction was re-run for each county, incorporating the suggested edits and producing revised output. The first round of editing (V1) focused on errors that were observable at a moderate zoom level, appropriate for changes at 10-m resolution. The second round (V2) examined and addressed corrections at a finer scale, down to the 1-m modeling resolution.

5.5.5 Final Post-processing

Although all mapping was performed on a county-by-county basis, seamless mosaics at the state and watershed scales were also needed for use by stakeholders. To eliminate small gaps that could occur between adjacent counties, usually no more than a pixel or two, a preliminary mosaic was created by combining all county layers using FME. The preliminary mosaic was then smoothed in eCognition using filling routines (Pixel-based Object Resizing) that consolidated unclassified pixels in adjacent ones with the longest common border, and output tiles were again mosaicked in FME to produce final state-specific and watershed layers.

5.5.6 Accuracy Assessment

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5.5.7 Final Output

The final map provides a comprehensive representation of not only landscape change but also of land-cover conditions at two different time periods. Conditions at either T1 or T2 can be extracted from the map by reassigning the change classes to their original or subsequent states. When evaluating change, either at individual locations or across the entire study area, it is important to remember that the T1 and T2 maps have been harmonized to avoid capturing cross-period discrepancies that are attributable to methodological differences or variable data inputs rather than bona fide land-cover conversions. Accordingly, the new change product should not be compared to the original T1 map or any other previous products. With constantly evolving mapping technologies and ever-present variability in remote-sensing data, future change-detection maps will require similar harmonization to ensure valid cross-period analysis.

5.5.8 References

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Appendix A. Specific analysis period and data inputs for 206 counties\municipalities in the Chesapeake Bay Watershed.

		Analysis Period		NAIP		LiDAR		
County	State	T1	T2	T1	T2	T1	T2	Thematic Vector
District of Columbia	DC	2013	2017	2013	2017	2015	2015	building footprints, roads, impervious surfaces
Kent	DE	2013	2018	2013	2018	2013/ 2014	none	building footprints
New Castle	DE	2013	2018	2013	2018	2013/ 2014	none	building footprints (Microsoft Buildings 2018)
Sussex	DE	2013	2018	2013	2018	2013/ 2014	none	building footprints (Microsoft Buildings 2018)
Allegany	MD	2013	2018	2013	2017	2012	none	building footprints
Anne Arundel	MD	2013	2018	2013	2017/ 2018	2011	2017	building footprints, road polygons
Baltimore	MD	2013	2018	2013	2017/ 2018	2014	none	building footprints, road polygons, parking lots, driveway lines, bridges
Baltimore City	MD	2013	2018	2013	2017/ 2018	2014	none	building footprints, road polygons, other paved, railroads
Calvert	MD	2013	2018	2013	2018	2011	2017	building footprints, road polygons, other paved, bridges
Caroline	MD	2013	2018	2013	2018	2013	none	none[a]
Carroll	MD	2013	2018	2013	2017/ 2018	2014	none	building footprints
Cecil	MD	2013	2018	2013	2018	2014	none	building footprints
Charles	MD	2013	2018	2013	2017/ 2018	2014	none	building footprints
Dorchester	MD	2013	2018	2013	2018	2013	none	none
Frederick	MD	2013	2018	2013	2017/ 2018	2012	none	building footprints, road polygons, other paved polygons, railroad polygons
Garrett	MD	2013	2018	2013	2017/ 2018	2014	none	building footprints
Harford	MD	2013	2018	2013	2018	2013	none	road polygons, parking lots
Howard	MD	2013	2018	2013	2017/ 2018	2011	none	building footprints, road polygons, driveways, sidewalks, pools, tennis courts, basketball courts, sand

								traps
Kent	MD	2013	2018	2013	2018	2014	none	building footprints, driveway lines
Montgomery	MD	2013	2018	2013	2017/ 2018	2014	2018	building footprints, roads, railroads, cultural features (pads, pools), hydrology
Prince George's	MD	2013	2018	2013	2018	2014	2018	building footprints, bridges, impervious surfaces, hydrology
Queen Anne's	MD	2013	2018	2013	2018	2013	none	building footprints
Somerset	MD	2013	2018	2013	2017/ 2018	None	none	building footprints (Microsoft Buildings 2018)
St. Mary's	MD	2013	2018	2013	2017/ 2018	2014	2018	building footprints, transportation (roads), transportation (driveways, sidewalks, parking lots, air strips)
Talbot	MD	2013	2018	2013	2018	2014	none	building footprints
Washington	MD	2013	2018	2013	2017/ 2018	2012	none	building footprints, hydrology
Wicomico	MD	2013	2018	2013	2018	2011	none	building footprints, road polygons, driveways, sidewalks, decks and patios, concrete pads
Worcester	MD	2013	2018	2013	2018	2011	none	building footprints
Allegany	NY	2013	2017	2013	2017	None	2016/ 2017	building footprints (Microsoft Buildings 2018)
Broome	NY	2013	2017	2013	2017	2015[c]	none	building footprints (Microsoft Buildings 2018)
Cayuaga	NY	2013	2017	2013	2017	None	2018	building footprints (Microsoft Buildings 2018)
Chemung	NY	2013	2017	2013	2017	None	none	building footprints (Microsoft Buildings 2018)
Chenango	NY	2013	2017	2013	2017	2015	none	building footprints (Microsoft Buildings 2018)
Cortland	NY	2013	2017	2013	2017	None	none	building footprints (Microsoft Buildings 2018)
Delaware	NY	2013	2017	2013	2017	None	none	building footprints (Microsoft Buildings 2018)
Herkimer	NY	2013	2017	2013	2017	2015[c]	none	building footprints

								(Microsoft Buildings 2018)
Livingston	NY	2013	2017	2013	2017	2011	none	building footprints (Microsoft Buildings 2018)
Madison	NY	2013	2017	2013	2017	2015[c]	none	building footprints (Microsoft Buildings 2018)
Oneida	NY	2013	2017	2013	2017	2015[c]	none	building footprints (Microsoft Buildings 2018)
Onondaga	NY	2013	2017	2013	2017	None	none	building footprints
Ontario	NY	2013	2017	2013	2017	None	none	building footprints
Otsego	NY	2013	2017	2013	2017	2015	none	building footprints (Microsoft Buildings 2018)
Schoharie	NY	2013	2017	2013	2017	2014	none	building footprints (Microsoft Buildings 2018)
Schuyler	NY	2013	2017	2013	2017	2014[c]	none	building footprints (Microsoft Buildings 2018)
Steuben	NY	2013	2017	2013	2017	none	2016[c]	building footprints
Tioga	NY	2013	2017	2013	2017	none	none	building footprints (Microsoft Buildings 2018)
Tompkins	NY	2013	2017	2013	2017	none	none	building footprints
Yates	NY	2013	2017	2013	2017	2014	none	building footprints (Microsoft Buildings 2018)
Adams	PA	2013	2017	2013	2017	none	2017	building footprints
Bedford	PA	2013	2017	2013	2017	none	none	none[a]
Berks	PA	2013	2017	2013	2017	none	none	building footprints, hydrology (lakes, ponds, basins, rivers)
Blair	PA	2013	2017	2013	2017	none	none	building footprints
Bradford	PA	2013	2017	2013	2017	none	none	building footprints
Cambria	PA	2013	2017	2013	2017	none	none	building footprints
Cameron	PA	2013	2017	2013	2017	none	none	building footprints (Microsoft Buildings 2018)
Carbon	PA	2013	2017	2013	2017	none	none	building footprints (Microsoft Buildings 2018)
Centre	PA	2013	2017	2013	2017	none	none	building footprints, road polygons, parking lots, driveway lines
Chester	PA	2013	2017	2013	2017	2014	none	building footprints

Clearfield	PA	2013	2017	2013	2017	none	none	building footprints
Clinton	PA	2013	2017	2013	2017	none	none	building footprints
Columbia	PA	2013	2017	2013	2017	none	2017	building footprints (Microsoft Buildings 2018)
Cumberland	PA	2013	2017	2013	2017	none	2017	none
Dauphin	PA	2013	2017	2013	2017	none	2016	building footprints, sidewalk lines
Elk	PA	2013	2017	2013	2017	none	none	building footprints (Microsoft Buildings 2018)
Franklin	PA	2013	2017	2013	2017	none	2017	building footprints
Fulton	PA	2013	2017	2013	2017	none	none	building footprints (Microsoft Buildings 2018)
Huntingdon	PA	2013	2017	2013	2017	none	none	building footprints (Microsoft Buildings 2018)
Indiana	PA	2013	2017	2013	2017	none	none	building footprints (Microsoft Buildings 2018)
Jefferson	PA	2013	2017	2013	2017	none	none	building footprints (Microsoft Buildings 2018)
Juniata	PA	2013	2017	2013	2017	None	2017	building footprints
Lackawanna	PA	2013	2017	2013	2017	None	none	building footprints (Microsoft Buildings 2018)
Lancaster	PA	2013	2017	2013	2017	2014	none	building footprints
Lebanon	PA	2013	2017	2013	2017	None	2017	building footprints
Luzerne	PA	2013	2017	2013	2017	None	none	building footprints (Microsoft Buildings 2018)
Lycoming	PA	2013	2017	2013	2017	None	2017	building footprints (Microsoft Buildings 2018)
McKean	PA	2013	2017	2013	2017	None	none	building footprints (Microsoft Buildings 2018)
Mifflin	PA	2013	2017	2013	2017	None	none	building footprints, sidewalks, driveways, roads, parking lots, miscellaneous impervious
Montour	PA	2013	2017	2013	2017	None	2017	building footprints (Microsoft Buildings 2018)
Northumberland	PA	2013	2017	2013	2017	None	2017	building footprints

Perry	PA	2013	2017	2013	2017	None	2017	building footprints (Microsoft Buildings 2018)
Potter	PA	2013	2017	2013	2017	None	none	building footprints (Microsoft Buildings 2018)
Schuylkill	PA	2013	2017	2013	2017	None	none	building footprints
Snyder	PA	2013	2017	2013	2017	None	2017	building footprints, airports, hydrology polygons
Somerset	PA	2013	2017	2013	2017	None	none	building footprints (Microsoft Buildings 2018)
Sullivan	PA	2013	2017	2013	2017	None	none	building footprints (Microsoft Buildings 2018)
Susquehanna	PA	2013	2017	2013	2017	None	none	building footprints (Microsoft Buildings 2018)
Tioga	PA	2013	2017	2013	2017	None	none	building footprints
Union	PA	2013	2017	2013	2017	None	2017	building footprints, hydrology polygons
Wayne	PA	2013	2017	2013	2017	None	none	building footprints
Wyoming	PA	2013	2017	2013	2017	None	none	building footprints
York	PA	2013	2017	2013	2017	2014	none	none
Accomack	VA	2014	2018	2014	2018	2015	none	building footprints, road centerlines
Albemarle	VA	2014	2018	2014	2018	None	2016	building footprints, road centerlines, driveway polygons
Alexandria	VA	2014	2018	2014	2018	2014	none	building footprints (Microsoft Buildings 2018), road centerlines, driveway polygons, parking lots
Alleghany	VA	2014	2018	2014	2018[b]	none	2017	building footprints (Microsoft Buildings 2018), road centerlines, driveways, hydrology
Amelia	VA	2014	2018	2014	2018	2014	none	building footprints (Microsoft Buildings 2018), road centerlines
Amherst	VA	2014	2018	2014	2018	none	2017	building footprints (Microsoft Buildings 2018), road centerlines
Appomattox	VA	2014	2018	2014	2018	none	2016	building footprints (Microsoft Buildings 2018), road centerlines

Arlington	VA	2014	2018	2014	2018	2014	none	building footprints, roads (polygons), impervious surface polygons (driveways, airports, parking lots, sidewalks)
Augusta	VA	2014	2018	2014	2018[b]	2011[c]	none	building footprints, road centerlines
Bath	VA	2014	2018	2014	2018[b]	none	2017	building footprints (Microsoft Buildings 2018), road centerlines
Bedford City	VA	2014	2018	2014	2018	none	2017	building footprints, road centerlines, driveway lines, sidewalk lines, hydrology (small ponds, lakes only)
Bedford County	VA	2014	2018	2014	2018	none	2017	building footprints, road centerlines, driveways, hydrology (small lakes and ponds)
Botetourt	VA	2014	2018	2014	2018[b]	none	2017	building footprints, road centerlines
Buckingham	VA	2014	2018	2014	2018	none	2016	building footprints (Microsoft Buildings 2018), road centerlines
Buena Vista	VA	2014	2018	2014	2018	none	2017	building footprints, road centerlines
Campbell	VA	2014	2018	2014	2018	none	2017	building footprints (Microsoft Buildings 2018), road centerlines
Caroline	VA	2014	2018	2014	2018[b]	2014	none	building footprints (Microsoft Buildings 2018), road centerlines
Charles City	VA	2014	2018	2014	2018	2011	none	building footprints (Microsoft Buildings 2018), road centerlines
Charlotte	VA	2014	2018	2014	2018	none	2017	building footprints (Microsoft Buildings 2018)
Charlottesville	VA	2014	2018	2014	2018	none	2016	building footprints, road centerlines
Chesapeake	VA	2014	2018	2014	2018	2013	none	building footprints (Microsoft Buildings 2018), road centerlines
Chesterfield	VA	2014	2018	2014	2018	2014	none	building footprints, impervious surfaces (roads, other impervious surfaces)
Clarke	VA	2014	2018	2014	2018[b]	2011	none	building footprints, road centerlines, sidewalk

								lines
Colonial Heights	VA	2014	2018	2014	2018	2014	none	building footprints (Microsoft Buildings 2018), road centerlines
Covington	VA	2014	2018	2014	2018[b]	none	2017	building footprints (Microsoft Buildings 2018), road centerlines, driveway lines, hydrology (small ponds and lakes only)
Craig	VA	2014	2018	2014	2018[b]	none	2016/ 2017	building footprints, road centerlines
Culpeper	VA	2014	2018	2014	2018[b]	2014	none	building footprints (Microsoft Buildings 2018), road centerlines
Cumberland	VA	2014	2018	2014	2018	none	2016	building footprints (Microsoft Buildings 2018), road centerlines
Dinwiddie	VA	2014	2018	2014	2018	2014	none	building footprints (Microsoft Buildings 2018), road centerlines
Essex	VA	2014	2018	2014	2018	2011	none	building footprints (Microsoft Buildings 2018), road centerlines
Fairfax City	VA	2014	2018	2014	2018	2014	none	building footprints, road centerlines
Fairfax County	VA	2014	2018	2014	2018[b]	2014[c]	none	building footprints, road centerlines, sidewalk lines
Falls Church	VA	2014	2018	2014	2018	2014	none	building footprints, road centerlines
Fauquier	VA	2014	2018	2014	2018[b]	2012	none	building footprints, road centerlines
Fluvanna	VA	2014	2018	2014	2018	2014[c]	2016[c]	building footprints (Microsoft Buildings 2018), road centerlines
Frederick	VA	2014	2018	2014	2018[b]	2012[c]	none	building footprints, road centerlines
Fredericksburg	VA	2014	2018	2014	2018[b]	2011	none	building footprints (Microsoft Buildings 2018), road centerlines
Giles	VA	2014	2018	2014	2018[b]	none	2016	building footprints, road centerlines
Gloucester	VA	2014	2018	2014	2018	2010	none	building footprints, road centerlines
Goochland	VA	2014	2018	2014	2018	none	2016[c]	building footprints (Microsoft Buildings 2018), road centerlines
Greene	VA	2014	2018	2014	2018	2014/	none	building footprints, road

						2016		centerlines
Hampton	VA	2014	2018	2014	2018	2013	none	building footprints (Microsoft Buildings 2018), road centerlines
Hanover	VA	2014	2018	2014	2018	2014	none	building footprints, road centerlines, hydrology (lakes, ponds, rivers)
Harrisonburg	VA	2014	2018	2014	2018	2011[c]	none	building footprints, road centerlines
Henrico	VA	2014	2018	2014	2018	2014	none	building footprints, road centerlines
Highland	VA	2014	2018	2014	2018[b]	none	2017	building footprints (Microsoft Buildings 2018), road centerlines
Hopewell	VA	2014	2018	2014	2018	2014	none	building footprints (Microsoft Buildings 2018), road centerlines
Isle of Wight	VA	2014	2018	2014	2018	none	none	building footprints (Microsoft Buildings 2018), road centerlines
James City	VA	2014	2018	2014	2018	2010	none	building footprints, road centerlines, water polygons
King and Queen	VA	2014	2018	2014	2018	2010	none	building footprints (Microsoft Buildings 2018), road centerlines
King George	VA	2014	2018	2014	2018[b]	2011	none	building footprints (Microsoft Buildings 2018), road centerlines
King William	VA	2014	2018	2014	2018	2011	none	building footprints (Microsoft Buildings 2018), road centerlines
Lancaster	VA	2014	2018	2014	2018	none	none	building footprints (Microsoft Buildings 2018), road centerlines
Lexington	VA	2014	2018	2014	2018	none	2017	building footprints, road centerlines
Loudon	VA	2014	2018	2014	2018[b]	2012	none	building footprints, road centerlines
Louisa	VA	2014	2018	2014	2018	2012/ 2014	none	building footprints (Microsoft Buildings 2018), road centerlines
Lunenburg	VA	2014	2018	2014	2018	none	2018	building footprints (Microsoft Buildings 2018), road centerlines
Lynchburg	VA	2014	2018	2014	2018	none	2018	building footprints (Microsoft Buildings 2018), roads, impervious surfaces

								(driveways, parking lots), hydrology (lakes, rivers, streams)
Madison	VA	2014	2018	2014	2018[b]	2014	none	building footprints, road centerlines
Manassas	VA	2014	2018	2014	2018[b]	2011	none	building footprints (Microsoft Buildings 2018), road centerlines
Manassas Park	VA	2014	2018	2014	2018[b]	2011	none	building footprints (Microsoft Buildings 2018), road centerlines
Mathews	VA	2014	2018	2014	2018	2010	none	building footprints (Microsoft Buildings 2018), road centerlines
Middlesex	VA	2014	2018	2014	2018	2010	none	building footprints (Microsoft Buildings 2018), road centerlines
Montgomery	VA	2014	2018	2014	2018	none	2018	building footprints, road centerlines, hydrology
Nelson	VA	2014	2018	2014	2018	none	2016	building footprints, road centerlines, driveway lines
New Kent	VA	2014	2018	2014	2018	2011	none	building footprints, road centerlines, driveway lines
Newport News	VA	2014	2018	2014	2018	2013	none	building footprints, road centerlines
Norfolk	VA	2014	2018	2014	2018	2013	none	building footprints, road centerlines, water polygons
Northampton	VA	2014	2018	2014	2018	2015	none	building footprints, road centerlines
Northumberland	VA	2014	2018	2014	2018	none	none	building footprints (Microsoft Buildings 2018), road centerlines
Nottoway	VA	2014	2018	2014	2018	2014	none	building footprints (Microsoft Buildings 2018), road centerlines
Orange	VA	2014	2018	2014	2018	2014	none	building footprints (Microsoft Buildings 2018), road centerlines
Page	VA	2014	2018	2014	2018[b]	2014	none	building footprints, road centerlines
Petersburg	VA	2014	2018	2014	2018	2014	none	building footprints (Microsoft Buildings 2018), road centerlines
Poquoson	VA	2014	2018	2014	2018	2013	none	building footprints (Microsoft Buildings 2018), road centerlines

Portsmouth	VA	2014	2018	2014	2018	2013	none	building footprints (Microsoft Buildings 2018), road centerlines
Powhatan	VA	2014	2018	2014	2018	none	2016	building footprints, road centerlines
Prince Edward	VA	2014	2018	2014	2018	2014	none	building footprints (Microsoft Buildings 2018), road centerlines
Prince George	VA	2014	2018	2014	2018	2011	none	building footprints (Microsoft Buildings 2018), road centerlines
Prince William	VA	2014	2018	2014	2018[b]	2011	none	building footprints (Microsoft Buildings 2018), road centerlines
Rappahannock	VA	2014	2018	2014	2018[b]	2014	none	building footprints (Microsoft Buildings 2018), road centerlines
Richmond City	VA	2014	2018	2014	2018	2014	none	building footprints (Microsoft Buildings 2018), road centerlines
Richmond County	VA	2014	2018	2014	2018	2011	none	building footprints (Microsoft Buildings 2018), road centerlines
Roanoke City	VA	2014	2018	2014	2018	none	2018	building footprints
Roanoke County	VA	2014	2018	2014	2018[b]	none	2018	building footprints
Rockbridge	VA	2014	2018	2014	2018[b]	none	2017	building footprints, road centerlines
Rockingham	VA	2014	2018	2014	2018[b]	2011[c]	2017[c]	building footprints, road centerlines
Salem	VA	2014	2018	2014	2018	none	2018	building footprints
Shenandoah	VA	2014	2018	2014	2018[b]	none	2017[c]	building footprints, road centerlines
Spotsylvania	VA	2014	2018	2014	2018[b]	2014	none	building footprints, road centerlines, other impervious (parking lots, driveways lines), water polygons
Stafford	VA	2014	2018	2014	2018[b]	2011	none	building footprints, road centerlines, road centerlines
Staunton	VA	2014	2018	2014	2018	2011	none	building footprints, road centerlines
Suffolk	VA	2014	2018	2014	2018	none	none	building footprints (Microsoft Buildings 2018), road centerlines
Surry	VA	2014	2018	2014	2018	none	none	building footprints (Microsoft Buildings 2018), road centerlines

Virginia Beach	VA	2014	2018	2014	2018	2012	2018	building footprints, roads, parking lots, driveways, sidewalks, bike paths
Warren	VA	2014	2018	2014	2018[b]	2011/ 2014	none	building footprints
Waynesboro	VA	2014	2018	2014	2018	2011	none	building footprints, road centerlines
Westmoreland	VA	2014	2018	2014	2018[b]	2011	none	building footprints (Microsoft Buildings 2018), road centerlines
Williamsburg	VA	2014	2018	2014	2018	2010	none	building footprints, road centerlines
Winchester	VA	2014	2018	2014	2018[b]	2012	none	building footprints, road centerlines
York	VA	2014	2018	2014	2018	2013	none	building footprints, road centerlines
Berkeley	WV	2014	2018	2014[b]	2018[b]	2012	none	building footprints (Microsoft Buildings 2018)
Grant	WV	2014	2018	2014	2018[b]	none	2016[c]	building footprints (Microsoft Buildings 2018)
Greenbrier	WV	2014	2018	2014[b]	2018[b]	none	2016	building footprints (Microsoft Buildings 2018)
Hampshire	WV	2014	2018	2014[b]	2018[b]	none	2016	building footprints (Microsoft Buildings 2018)
Hardy	WV	2014	2018	2014[b]	2018[b]	none	2016	building footprints (Microsoft Buildings 2018)
Jefferson	WV	2014	2018	2014[b]	2018[b]	2012	none	building footprints
Mineral	WV	2014	2018	2014[b]	2018[b]	none	2016[c]	building footprints (Microsoft Buildings 2018)
Monroe	WV	2014	2018	2014[b]	2018[b]	none	2016	building footprints (Microsoft Buildings 2018)
Morgan	WV	2014	2018	2014[b]	2018[b]	2012	none	building footprints (Microsoft Buildings 2018)
Pendleton	WV	2014	2018	2014[b]	2018[b]	none	2016	building footprints (Microsoft Buildings 2018)
Pocahontas	WV	2014	2018	2014[b]	2018[b]	none	2016[c]	building footprints (Microsoft Buildings 2018)
Preston	WV	2014	2018	2014[b]	2018[b]	none	none	building footprints

								(Microsoft Buildings 2018)
Randolph	WV	2014	2018	2014[b]	2018[b]	none	none	building footprints (Microsoft Buildings 2018)
Tucker	WV	2014	2018	2014[b]	2018[b]	none	none	building footprints (Microsoft Buildings 2018)

[a]Where no plainimetrics were used, the structures were based on the original 2013\2014 land cover, LiDAR (if available) and manual QA\QC.

[b]Leaf-off NAIP imagery, all or in part.

[c]Partial coverage.

Appendix B. Interpreting LULC Change Matrices

Data on LULC change represent transitions of LULC between two time periods: an early date (e.g., Time 1, 2013 or 2014) and a late date (e.g., Time 2, 2017 or 2018). A concise way of illustrating such changes is to construct a cross-tabulation, aka "pivot table", between the two datasets. The result is a LULC change matrix that shows all observed changes in LULC in a single table with the early date values (acres of land use X) represented in rows and the late date values represented in columns. Values along the diagonal are absent because they would represent no change and are not included in the LULC change raster data. LULC change matrices have been produced for each of the 206 counties and incorporated cities (those with unique 5-digit FIPS codes) within and adjacent to the Chesapeake Bay watershed and separately for the portions of each county in the watershed. An aggregated pivot table for the 206-county region and one for just the Bay watershed have also been produced. For these different geographies, LULC change matrices have been produced for the 18-class general classification and the 54-class detailed classification[6]. A crosswalk relating these two classifications is provided below (Figure 1) and can be referenced to understand the composition of the general classes. Note that the LULC change matrices for the detailed classification include greater amounts of overall change than the matrices for the general classification. This is because detailed class changes that occur within the same general class are not recognized as change at the general aggregation level. For example, changes from herbaceous to barren cover within the general cropland class do not represent a change to or from cropland at the general level. LULC change matrices are available for download via the dynamic LULC change website, http://lulc-1718.cicapps.org/.

The general LULC change matrix for Charles County, Maryland is shown below (Table 1). The values in the table are in units of acres and restricted to areas of change. LULC codes are defined below the table. The "Decrease" column represents the total acreages of 2013 LULCs (row labels) that transitioned to a different 2018 LULC (column labels). The "Increase" row represents the total acreages of 2017 LULCs that transitioned from a different 2013 LULC. The "Net" row represents overall net change in a particular LULC from 2013 to 2018. To facilitate interpretation, changes among the seven developed LULC classes are colored beige, changes among the four forest-related LULC classes are colored green, changes among agricultural and extractive LULC classes are colored orange, and changes among the wetlands and water classes are colored shades of blue. From 2013 to 2018, 6,892 acres of land in Charles County changed from one to another of the 18 general LULC classes.

Forest Change

The largest LULC increase in Charles County was from natural succession to forest (1,329 acres) while the largest decrease was from forest to natural succession (879 acres). Note that this decrease should not be considered a permanent loss of forest. These types of changes are often indicative of timber harvest activities and mostly represent resulting in a temporary loss of tree canopy. Forests transitioning to the five non-tree developed classes (ROAD, e.g., Roads (ROAD), Impervious Structures (IMPS), Impervious Other (IMPO), Turf Grass (TURF), and Pervious Developed, Other (PDEV)) represent a change in use coupled with a change in cover. Forests transitioning to the two developed classes with trees, Tree Canopy over Impervious Surfaces (TCIS) and Tree Canopy over Turf Grass (TCTG), represent only a change in use meaning no trees were cut down. These formerly forest trees are now adjacent to buildings or other impervious surfaces and are assumed to no longer function as forest trees because their understory was likely compacted or otherwise altered as part of the

[6] Change matrices for the 13 mapped land uses informing the Phase 6 Watershed Model and CAST are available upon request.

development process. Forests (FORE) transitioning to Tree Canopy, Other (TCOT) are an indicator of fragmentation due to a reduction in forest patch size or division of forest patches.

Tree Canopy Change in Developed Areas

Increases in tree canopy in developed areas are most apparent in the transition from Turf Grass (TURF to either) to Tree Canopy over Turf Grass (TCTG), Forest (FORE), or Tree Canopy, Other (TCOT). Decreases in tree canopy in developed areas are evident in the transition from Tree Canopy over Impervious Surfaces (TCIS) and/or TCTG to one of the five non-tree developed classes.

Agricultural Change

These data show both increases and decreases in cropland and pasture. The decreases are associated with development or afforestation, both of which represent obvious and actual declines. in cropland and/or pasture. The increases, however, are suspect as they are either are associated with lands becoming undeveloped or the clearing of forests and other tree canopy. With just two dates of imagery covering a 4–5-year timespan, it is not always possible to know the ultimate use of forest lands that was recently cleared. were cleared during this period. Context and ancillary data are therefore used to infer potential use of the land. Cleared forests adjacent to agricultural fields or in parcels dominated by agriculture are assumed to cropland or pasture. This may or not be the case and cannot be verified until the 2021/22 mapping is complete.

Extractive Change

The development or expansion of quarries, sand and gravel mines, and other surficial mining operations are evident as gains particularly from forests (FORE) and pervious developed, other (PDEV).

Wetland Change

Changes between forests and wetlands are misleading because all types of forested and other tree canopy wetlands were included in the Forest (FORE) and Tree Canopy, Other (TCOT) general classes. Therefore, changes from FORE to Wetlands, Riverine (RIVW) and RIVW to FOREvice versa represent tree removal or tree growth in a wetland, not a decrease or increase in wetlands. This interpretation applies to the following change categories:
Forest (FORE) to/from Wetlands, Tidal (TDLW)
Forest (FORE) to/from Wetlands, Riverine (RIVW)
Forest (FORE) to/from Wetlands, Terrene (TERW)
Tree Canopy, Other (TCOT) to/from Tidal Wetlands
Tree Canopy, Other (TCOT) to/from Wetlands, Tidal (TDLW)
Tree Canopy, Other (TCOT) to/from Wetlands, Riverine (RIVW)
Tree Canopy, Other (TCOT) to/from Wetlands, Terrene (TERW)

Besides tree removal and tree growth, the only substantial change in wetlands evident in these data are changes from wetlands to water which either represent actual changes associated with sea level rise and/or marsh subsidence or could represent ephemeral change due to differences in tidal stages when the 2013 and 2018 imagery were acquired. All other wetland changes are minor because wetlands were defined and mapped using static ancillary data (e.g., National Wetlands Inventory) and changes in hydrology and hydrophytic vegetation are not readily detectable in aerial imagery.

Artifactual Change

While great effort was invested to minimize potential errors when translating land cover change to land use change, a few transitions in the change matrices are likely artifacts associated with the mapping protocols rather than actual change on the ground. Artifactual changes include:

Tree canopy over Turf Grass (TCTG) to Tree Canopy, Other (TCOT)
Pervious Developed, Other (PDEV) to/from Natural Succession (NATS)
Natural Succession (NATS) to Pervious Developed, Other
Natural Succession (NATS) to Harvested Forest (HARF)
Cropland (CROP) to/from Pasture (PAST)
Pasture (PAST) to Cropland (CROP)

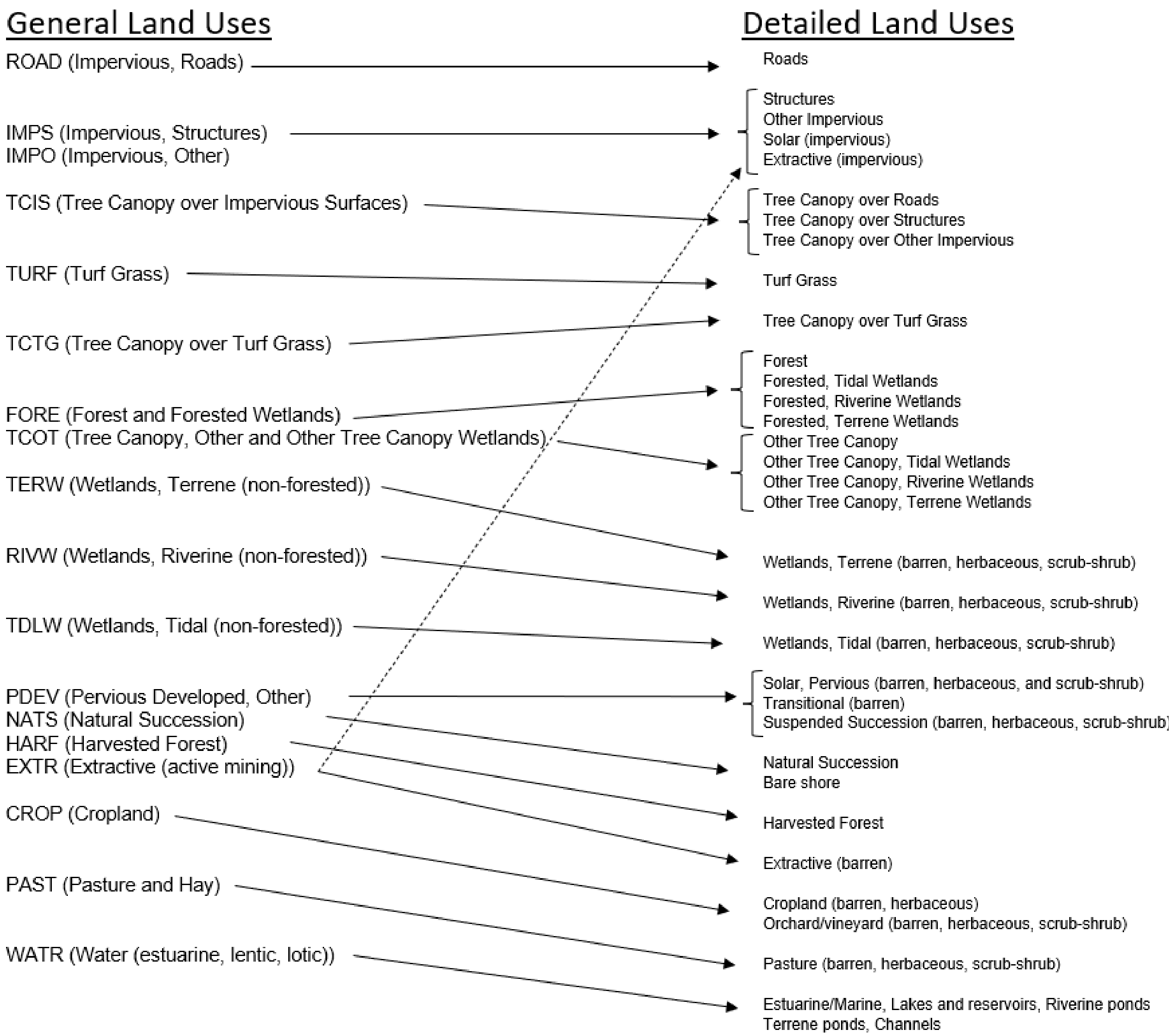

Figure 1. Crosswalk between the 18 general and 54 detailed LULC class.

Table 1. LULC Change Matrix, 2013 to 2018 for Charles County, Maryland.

2018 LULC

2013 LULC

	ROAD	IMPS	IMPO	TCIS	TURF	TCTG	PDEV	FORE	TCOT	HARF	NATS	CROP	PAST	EXTR	TDLW	RIVW	TERW	WATR	Decrease
ROAD	-	0.0	0.2	0.6	0.2	0.5	0.1	1.4	0.4	-	-	0.1	0.2	-	-	-	-	-	3.8
IMPS	-	-	4.2	0.2	2.2	0.8	0.1	0.4	0.0	-	0.4	0.2	0.5	-	-	-	-	0.1	9.0
IMPO	8.6	18.9	-	2.7	9.8	2.8	3.8	2.0	0.5	-	1.8	1.0	1.1	-	-	0.2	0.0	1.1	54.3
TCIS	0.0	3.6	14.0	-	38.1	-	14.4	-	-	0.0	2.4	0.8	1.4	0.0	0.0	0.2	0.0	-	74.9
TURF	-	19.7	96.1	-	-	56.6	53.8	5.8	3.1	0.0	8.1	1.1	0.7	8.9	-	-	-	-	254.0
TCTG	0.1	38.0	39.4	0.3	192.0	-	10.7	-	69.3	0.0	6.0	2.1	4.9	0.1	-	-	-	0.1	363.1
PDEV	62.9	133.4	113.6	-	438.7	3.2	-	16.1	4.1	-	22.6	5.2	0.3	26.2	-	-	-	3.8	830.0
FORE	32.2	52.0	127.9	7.0	213.1	635.4	409.8	-	218.3	23.2	879.2	52.5	60.7	158.9	9.5	45.5	2.8	7.5	2,935.3
TCOT	1.5	11.5	20.1	-	37.5	26.6	18.6	-	-	0.0	28.9	13.0	18.8	2.1	2.1	1.9	0.6	0.1	183.1
HARF	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
NATS	0.3	0.8	2.0	-	188.2	25.6	42.9	1,328.8	116.0	1.7	-	8.3	17.4	14.7	-	-	-	35.6	1,782.3
CROP	-	5.1	15.0	-	6.4	0.6	11.8	56.4	10.3	-	12.4	-	1.7	-	-	0.1	0.7	9.0	129.5
PAST	0.7	5.6	16.6	-	20.2	1.5	8.0	20.0	21.1	-	6.0	1.2	-	0.1	-	-	1.2	2.5	104.8
EXTR	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
TDLW	-	0.0	0.4	-	-	-	-	22.1	3.7	-	-	-	-	-	-	-	-	19.6	45.8
RIVW	-	0.0	0.4	-	2.1	-	-	54.3	6.9	-	-	-	-	0.3	-	-	-	1.4	65.4
TERW	-	0.1	0.7	-	1.6	0.1	1.8	35.6	4.8	-	-	0.9	-	0.1	-	-	-	1.8	47.5
WATR	-	0.0	-	-	0.0	0.0	-	1.0	0.8	-	2.1	0.3	0.1	4.0	-	0.2	0.0	-	8.6
Increase	106.3	288.8	450.8	10.7	1,150.1	753.6	575.7	1,543.9	459.3	24.9	969.7	86.7	107.8	215.4	11.6	48.1	5.4	82.5	6,891.5

TotIncr	**106.3**	**288.8**	**450.8**	**10.7**	**1,150.1**	**753.6**	**575.7**	**1,543.9**	**459.3**	**24.9**	**969.7**	**86.7**	**107.8**	**215.4**	**11.6**	**48.1**	**5.4**	**82.5**
TotDecr	**3.8**	**9.0**	**54.3**	**74.9**	**254.0**	**363.1**	**830.0**	**2,935.3**	**183.1**	**-**	**1,782.3**	**129.5**	**104.8**	**-**	**45.8**	**65.4**	**47.5**	**8.6**
Net	**102.6**	**279.9**	**396.5**	**(64.2)**	**896.1**	**390.5**	**(254.3)**	**(1,391.4)**	**276.1**	**24.9**	**(812.6)**	**(42.8)**	**3.0**	**215.4**	**(34.2)**	**(17.3)**	**(42.1)**	**74.0**

ROAD = Impervious, Roads
IMPS = Impervious, Structures
IMPO = Impervious, Other
TCIS = Tree Canopy over Impervious Surfaces
TURF = Turf Grass
TCTG = Tree Canopy over Turf Grass
PDEV = Pervious Developed, Other
FORE = Forest and Forested Wetlands
TCOT = Tree Canopy, Other

NATS = Natural Succession
HARF = Harvested Forest
RIVW = Wetlands, Riverine (non-forested)
TERW = Wetlands, Terrene (non-forested)
TDLW = Wetlands, Tidal (non-forested)
CROP = Cropland
PAST = Pasture and Hay
EXTR = Extractive (active mining)
WATR = Water (estuarine, lentic, lotic)

* Transitions in red text represent values that should be interpreted with caution for all counties. Please read the interpretation above for an explanation.

Appendix C

2013/14 and 2017/18 Land Cover Classification

1 Water: All areas of open water. This includes ponds, rivers, lakes and boats not attached to docks. It also includes small, anthropogenic features such as farm ponds and storm-water retention structures. MMU[7] = 25 square meters

2 Emergent Wetlands: Low vegetation areas located along marine or estuarine regions that are visually confirmed to have the look of saturated ground surrounding the vegetation and that are located along major waterways (i.e. rivers, ocean). For Virginia tidal zones, this class includes low vegetation, woody vegetation, and barren features that overlap substantially with wetland features delineated by the NOAA C-CAP program and within 1-ft of tidal waters. MMU = 225 square meters

3 Tree Canopy: Deciduous and evergreen woody vegetation of either natural succession or human planting that is over approximately >3 meters in height. Stand-alone individuals, discrete clumps, and interlocking individuals are included. MMU = 9 square meters

4 Scrub/Shrub: Heterogeneous area of both/either deciduous and/or evergreen woody vegetation. Characterized by variation in height of vegetation through patchy coverage of shrubs and young trees interspersed with grasses and other lower vegetation. Discrete clumps and small patches of interlocking individuals are included, as are true shrubs, young trees, and trees or shrubs that are small or stunted because of environmental conditions, when intermingled in a heterogeneous landscape with low vegetation. MMU = 225 square meters

5 Low Vegetation: Plant material less than approximately 3 meters in height. Includes lawns, tilled fields, nursery plantings with or without tarp cover, recently cut forest management areas, and natural ground cover. MMU = 9 square meters

6 Barren: Areas void of vegetation consisting of natural earthen material regardless of how it has been cleared. This includes beaches, mud flats, and bare ground in construction sites. MMU = 25 square meters

7 Impervious Structures: Human-constructed objects made of impervious materials that are greater than approximately 2 meters in height. Houses, malls, and electrical towers are examples of structures. MMU = 9 square meters

8 Other Impervious: Human-constructed surfaces through which water cannot penetrate, and that are below approximately 2 meters in height. MMU = 9 square meters

9 Impervious Roads: Impervious surfaces that are used and maintained for transportation. MMU = 9 square meters

10 Tree Canopy over Impervious Structures: Forest or Tree Cover that overlaps with impervious surfaces rendering the structures partially or completely not visible to plain sight. Note: impervious

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[7] Minimum Mapping Unit (MMU) in this instance is the minimum size, dimensions, or threshold for features to be mapped or classified within a specific 2013/14 and 2017/18 land cover class.

surfaces and tree canopy were mapped independently, overhanging tree canopy was identified by superimposing these classes to isolate areas of overlap. MMU = 9 square meters

11 Tree Canopy over Other Impervious: Forest or Tree Cover that overlaps with impervious surfaces rendering the impervious surface partially or completely not visible to plain sight. Note: impervious surfaces and tree canopy were mapped independently, overhanging tree canopy was identified by superimposing these classes to isolate areas of overlap. MMU = 9 square meters

12 Tree Canopy over Impervious Roads: Forest or Tree Cover that overlaps with impervious surfaces rendering the roads partially or completely not visible to plain sight. Note: impervious surfaces and tree canopy were mapped independently, overhanging tree canopy was identified by superimposing these classes to isolate areas of overlap. MMU = 9 square meters

254 Aberdeen Proving Ground: No source imagery or ancillary data were available for this area. This class only exists in Harford, County Maryland.

2013/14 and 2017/18 General LULC Raster Classification

11-15 Water (WATR) = the Chesapeake Bay, lakes and reservoirs, riverine and terrene ponds, large rivers, and water within smaller channels visible through the tree canopy. Included with this class are NWI or state wetlands that are mapped as water in the land cover (MMU = $25m^2$)

21 Impervious Roads (ROAD) = Paved, and some unpaved, roads and bridges. Dirt and gravel roads may be mistakenly mapped as impervious depending on the spectral characteristics of the substrate (Minimum Mapping Unit (MMU) = 9 square meters).

22 Impervious, Structures (IMPS) = Human-constructed objects made of impervious materials that are greater than approximately 2 meters in height. Houses, malls, and electrical towers are examples of structures (MMU = 9 square meters).

23 Impervious, Other (IMPO) = Human-constructed surfaces through which water cannot penetrate, and that are below approximately 2 meters in height, e.g., sidewalks, parking lots, runways, field-mounted solar panels, rail lines, and some private roads. Barren, low vegetation, scrub-shrub, and emergent wetland cover types within 3 meters of rail lines were reclassed to impervious surfaces and included in this class (MMU = 9 square meters).

24-26 Tree Canopy over Impervious Surfaces (TCIS) = Tree cover that overlaps with roads, structures, or other impervious surfaces rendering them partially or completely invisible from above (MMU = 9 square meters).

27 Tree Canopy over Turf Grass (TCTG) = Tree cover within 30-ft of structures or adjacent turf grass and other impervious in rural wooded areas and within 60-ft of structures or adjacent turf grass and other impervious in developed areas. Developed areas include U.S. Census Bureau defined urban areas and clusters. Rural areas include all lands outside Census urban areas and clusters. The understory in all TCTG areas is assumed to be turf grass or otherwise altered through compaction, removal of surface organic material, and/or fertilization.

28 Turf Grass (TURF) = Low vegetation associated with residential, commercial, industrial, and recreational areas that is assumed to be altered through compaction, removal of organic material, and/or fertilization. These include low vegetation lands within small, developed parcels (≤ 5 acres with ≥ 55 m^2 of impervious cover), recreational fields, and other turf-dominated land uses (e.g., cemeteries, shopping centers, golf courses, airports, hospitals, amusement parks, etc.).

29; 35; 51-53 Pervious Developed, Other (PDEV) = Barren lands in developed parcels and barren or low vegetation lands that may represent the early stages of development, utility rights-of-way, portions of road rights-of-way, landfills, and the pervious portions of solar fields adjacent to panel arrays.

32 Harvested Forest (HARF) = Barren and low vegetation resulting from recently cleared forests and other tree canopy in association with a timber harvest permit (DE, MD, PA, VA, WV) or having a land use history of forest rotation since the mid 1980's. Timber harvest permit data were not reported to the Chesapeake Bay Program by either New York or the District of Columbia.

37-38 Extractive (EXTR) = Barren lands and impervious surfaces within quarries, surface mines, and other surficial excavation sites.

41; 65; 75; 95 Forest (FORE) = All contiguous patches of trees ≥1 acre in extent with a patch width ≥240-ft somewhere in the patch. The 240-ft girth references potential altered microclimate conditions extending inwards up to 120-ft from the patch edge. The forest understory is assumed to be undisturbed/unmanaged. Forests that are also wetlands are included in this class.

42; 64; 74; 94 Tree Canopy, Other (TCOT) = All trees that do not qualify as "Forest" but are presumed to have an undisturbed/unmanaged understory. Such areas include narrow windbreaks adjacent to cropland and roads and tree canopy patches not qualified as "forest" that are fully surrounded by agriculture. Wetlands with "other tree canopy" are included in this class.

16; 54-56 Natural Succession (NATS) = Barren, herbaceous, or scrub-shrub lands that are not classed as cropland, pasture, turf grass, or pervious developed. These are areas that are presumed to be undergoing either natural or managed succession and will eventually become forested although this process may take years to decades to complete. Abandoned mine lands are included in this class.

61-63 Riverine Wetlands, Non-forested (RIVW) = National Wetlands Inventory (NWI) non-pond, non-lake wetlands, emergent wetlands along streams mapped from high-resolution imagery outside Virginia, state designated wetlands, and potential non-tidal wetlands (for Pennsylvania only) located within the FEMA designated 100-year floodplain, DEM-aligned 1:24,000 scale buffered stream network, SSURGO hydric or frequently flooded soils.

71-73 Terrene Wetlands, Non-forested (TERW) = National Wetlands Inventory (NWI) non-pond, non-lake wetlands, emergent wetlands mapped from high-resolution imagery outside Virginia, state designated wetlands, and state potential non-tidal, non-floodplain wetlands (for Pennsylvania only). These are spatially isolated wetlands on ridges and slopes that are most prevalent in the coastal plain where streams may originate from wetland complexes.

81-82; 87-88 Cropland (CROP) = Barren and low vegetation lands on large parcels (> 5 acres) that are mapped as cropland in the 2018 Cropland Data Layer

83-85 Pasture/Hay (PAST) = Barren, low vegetation, and scrub shrub lands on large parcels (> 5 acres) that are mapped as pasture in the 2019 National Land Cover Dataset or the 2018 Cropland Data Layer

91-93 Tidal Wetlands, Non-forested (TDLW) = All wetlands mapped as estuarine or marine according to National Wetlands Inventory (NWI) plus any adjacent freshwater emergent wetlands, and emergent wetlands mapped from high-resolution imagery outside Virginia must be within 1-ft of adjacent tidal water elevations derived from NOAA's Sea Level Rise dataset.
(https://www.fws.gov/wetlands/Documents/Wetlands-and-Deepwater-Habitats-Classification-chart.pdf)