Chesapeake Bay Watershed Historical Land Use (1985-2013) Workplan

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Overview and Background

The purpose of this document is to describe the goals, deliverables, methods, and timeline of the Chesapeake Bay Watershed Annual Historical Land Use (1985-2013), also referred to as "back-cast". The back-cast will be used in three ways for the Phase 7 Chesapeake Bay suite of water quality models. Gary Shenk describes three ways the historical land use information is used in the planning target process (personal communication, January 16, 2025).

1. Phase III planning targets and Total Maximum Daily Load (TMDL) allocations were based on necessary change in anthropogenic sources of nitrogen, phosphorus, and sediment from 1995 and so an accurate land use trend will be important for appropriate goal setting, if the partnership follows past precedent.
2. The historical land use is used as an input to CalCAST, a statistical version of Chesapeake Assessment Scenario Tool (CAST) used to estimate optimal parameters for use in CAST during the development period (Berger et al., 2024), to estimate spatially explicit loading rates from monitored loads. The resulting loading rates are input to CAST to apply Best Management Practices (BMPs) and other information to produce Nitrogen (N), Phosphorus (P), and Sediment (S) loads. An accurate land use status and trend is important for producing a model that best matches observed data.
3. The historical land use is used as inputs to scenarios run in CAST and the Dynamic Watershed Model representing those land use years. The scenarios are evaluated against monitored loads to evaluate model performance and load reduction progress in the TMDL indicator and Monitored and Expected Total Reduction Indicator for the Chesapeake (METRIC).

The methods described in this document differ from the methods used to produce the back-cast in Phase 6. The Phase 6 back-cast was built using the Decennial Census and deconstructing residential development to be farm or forest at the Land River Segment (LRSEG) scale (Claggett, 2020, p. 24). The Phase 7 back-cast has annual land cover information at 30-m resolution. It is expected that the Phase 7 back-cast will have more temporal variability than the Phase 6 back-cast, but the magnitude and spatial difference of land use change and their effects on loading rates is unknown until the analysis is complete.

Project Goals

The goal of the project is to accurately capture land use trends from 1985-2013 to inform the calibration of the Phase 7 Watershed Model. This project will utilize the spatial and categorical accuracy of 1-meter resolution Land Use/Land Cover (LULC) to represent the present and the temporal accuracy of Landsat derived products to deconstruct the landscape back through time. The land use schema, to be finalized by the Water Quality Goal Implementation Team (WQGIT), represents land uses that have unique assumptions about their sediment and nutrients loads and best management practices (BMPs). The land use classes are described in Appendix A.

Deliverables

The primary deliverable of this project is a database containing annual acres of Phase 7 land use classes by modeling segment (Modified National Hydrography Dataset Medium Resolution 1:100k Catchments), which will be posted on Chesapeake Bay Open Data Portal. The database will be shared in both tabular and vector formats. An accompanying white paper detailing methods, trends, and validation will be posted with the Phase 7 model documentation.

Additional research may result in an additional ScienceBase data release of a collection of 30-meter resolution raster datasets representing the annual land use conditions of 5 aggregate classes and a journal article detailing the methods, resulting trends, and accuracies. This deliverable is related to Part 2 of the project, in which additional modeling efforts may be used to supplement the landscape change footprint and land use classification of the annual National Land Cover Database (NLCD). These data will be produced if the evaluated temporal, spatial, and categorical trends detected by NLCD misrepresent the land use trends at the modeling scale (catchments).

Timeline

The project timeline is split into two parts. The first part will produce a database of historic land use from the annual National Land Cover Database (NLCD) to meet Phase 7 needs. The second part aims to incorporate other data and methods to improve the accuracy of the NLCD-derived product. See the Methods section for more information.

	2024			2025								
Task	OCT	NOV	DEC	JAN	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP
Develop workplan												
LUWG feedback on workplan												
Part 1												
LUWG and modeling team update - review trends of aggregate classes at county and catchment scales												
Part 2												
LUWG, FWG, Ag modeling team, and modeling team update - deliver draft Part 1 backcast; present comparison of Part 1 and initial Part 2 results; decision on final methods												
Part 2 - if necessary, scale improvements from Part 2 as needed												
Finalize and publish data, metadata, and white paper												

Methods

This section describes the methods to produce the Phase 7 land uses (Appendix A) at the catchment scale. In general, the workflow is as follows:

1. Map land use change for 5 aggregate land use classes at 30-meter resolution using the annual National Land Cover Database (NLCD), which may be supplemented with additional methods in Part 2.
2. Summarize the 5 aggregate land use change acres per year to the modeling segment scale (catchments and counties), and the CB-LULC 2013/14 acres of the Phase 7 classes.
3. Expand the 5 land use classes to the Phase 7 classes tabularly using additional data (e.g. agricultural census, Forest Inventory and Analysis (FIA)).
    a. This step will involve parallel efforts not described in this document to develop methods with CBP workgroups on how to expand specific classes at the modeling segment scale. For example, working with the Timber Harvest Task Force on incorporating clear-cut and non-clear cut timber harvests.

I. Part 1

Data

The Chesapeake Bay Land Use and Land Cover (LULC) Database 2024 Edition (Claggett et al., 2025) is a high-resolution land use product representing the current conditions of the landscape (2013/14, 2017/18, 2021/22). These data include 56 classes, which are aggregated to the Phase 7 land use schema (see Appendix A for a list of Phase 7 land uses).

The annual National Land Cover Database (NLCD) (USGS, 2024) includes a collection of Landsat-derived annual products, including land cover, land cover change, fractional impervious, land cover confidence, impervious descriptor, and spectral change day of year from 1985 to 2023.

The USDA National Agricultural Statistics Service (NASS) conducts the census of agriculture every five years and reports agricultural information at the county-scale. These data can be aggregated to assess acres of cropland and pasture and hay at the county scale every 5-years back to 1985.

David Helmers of the SILVIS Lab at the Department of Forest & Wildlife Ecology, University of Wisconsin-Madison, adapted the Decennial Census housing and population tables to produce a consistent census-block scale database of housing and population estimates. The housing density dataset represents 1990, 2000, and 2010.

The Maryland Department of Planning (MDP) provides tax parcel data that contains useful attributes for validation, such as “year built.”

Geographic Information Retrieval and Analysis System (GIRAS) is a 30-meter resolution Land Use/Land Cover raster dataset derived from 1970s and 1980s aerial imagery (Price et al., 2007).

Analysis

The first step of the analysis is to create a comparable classification schema between NLCD and the Chesapeake Bay LULC (CB-LULC). This analysis is focused on an aggregate classification schema for the change detection steps. The aggregate schema includes developed, forest, natural, agriculture, and water. There are three primary reasons for the aggregate schema. The first is to ensure a consistent schema between NLCD and CB-LULC in which trends from both datasets over the same time frame can be compared. The second is due to distinctions in the NLCD classification schema that are irrelevant to the Phase 7 classification, as well as classes in Phase 7 that aren’t detectable from NLCD directly. An example of the former is NLCD has four forest types, whereas Phase 7 only calls for one. An example of the latter is Phase 7 requires timber harvest and construction, which are not distinct classes in NLCD. The aggregate schema aims to simplify NLCD to a state in which it is compatible with Phase 7 and CBP can apply our own definitions of classes using region-specific data to better align with the Phase 7 schema (e.g., incorporate state-reported data, agricultural census). Thirdly, in Part 2, there is potential for additional work to supplement NLCD change detection and classification in which the aggregate 5-class schema is most feasible given the time constraints. The CB-LULC crosswalk to Phase 7 classes is being reviewed by workgroups and GITs, but can be used to create a high-resolution version of the aggregate schema. These data will be resampled from 1-meter resolution to 30-meter resolution, to match the resolution of NLCD. Cells with more than one aggregate land use will be classified as the class with the most area in the cell (i.e. the most 1-meter cells of the class). In some cases, a land use that is not the majority but meets a certain threshold may take precedence. For example, a rural house on a farm field may be majority agriculture, but could be classified as development as to not lose the impervious surfaces. In cases of a tie, the class will be assigned in a hierarchical order that is to be determined. The final rules applied in the aggregation process will be documented in the white paper. Once the 30-meter, aggregate schema version of the 2013/14 CB-LULC (2024 edition) has been created, a pivot table comparing the area of each NLCD (2013/14) land cover class by each aggregate class will be produced. Given the CB-LULC mapped dates vary by jurisdiction, the year of NLCD will be selected to match the year of CB-LULC. The results of this table will determine the crosswalk of NLCD classes to the aggregate schema.

The next step is to compare the three dates of CB-LULC with the same three dates of NCLD, at the same resolution and with the same schema. The crosswalks identified in the first step will be used to create the six raster datasets representing 2013/14, 2017/18, and 2021/22 conditions. Trends between the datasets will be compared first at the county scale. First, comparisons of area by class for 2013/14 conditions will be assessed, followed by net change per class between 2013/14 and 2021/22. Next, similar comparisons will be made at a finer scale (i.e. catchments), and at a much finer scale of 1 square kilometer hexagons (or hexes). Regressions comparing the total area and net change by class at varying scales is one method to assessing how well two datasets compare spatially across the landscape. Pivot tables representing change between classes over time at the regional and county scales will be created for both NLCD and CB-LULC, giving insight on specific land use transitions.

With the context of how NLCD and CB-LULC compare in the present, NLCD can be used to deconstruct the land use back through time. Areas with no mapped change in NLCD are equivalent to the 2013/14 CB-LULC land use. Areas with NLCD mapped change are equivalent to the 2013/14 CB-LULC back through time until the change mapped by NLCD occurs. The land use in these areas during and prior to the change detected by NLCD are classified as the land use mapped in NLCD. The fractional impervious layers from NLCD are summarized within change patches per year by catchments and counties, to allow for separation of impervious with pervious development.

The aggregate classes can be tabularly broken down to better align with Phase 7 classes once summarized by catchments and counties. The harvest class is implied (clear cuts), when forest transitions to and from natural lands is observed over time, the first 3 years after the forest is cleared is reclassified to harvest. Methods for determining harvests that are not clear-cuts (e.g., thinning) will be developed with the Timber Harvest Task Force and will likely extrapolate Forest Inventory and Analysis (FIA) proportions of clear-cuts to total harvests. Construction is also implied, where lands convert to development. The first sign of change to development is likely construction, followed by roads. The development class can be split into impervious and pervious using the fractional impervious summaries and mapped developed class. Road versus non-road impervious may be proportionally divided based on the current ratio of road and non-road impervious in the CB-LULC. The agriculture class can be proportionally divided into cropland and pasture and hay using the agricultural census data every five years and interpolated between those five years.

Validation

To validate development trends, impervious and developed land uses will be summarized by 2010 census blocks for 1990, 2000, and 2010 to be compared with SILVIS residential intensity data. A regression for all census blocks per 3 dates and change between the three dates will be evaluated. Finer temporal trends can be evaluated using the Maryland tax parcels data on the year structures were built. The parcel data will be summarized at the block scale, recording the minimum, maximum, median, mean, and standard deviation of the year built. The same statistics will be computed from the mapped data for comparison.

Since the Census of Agriculture is used to differentiate between cropland and pasture, it can’t be used to validate those numbers. It can, however, be used to validate the overall agricultural footprint. A multiple linear regression will be computed to compare county-scale estimates of agriculture that were mapped and that were reported by the census over time.

Forest Inventory and Analysis (FIA) data can be used to validate forestry trends over time. The FIA data samples plots every year, with the design that the samples can be extrapolated to the rest of the county and state.

II. Part 2

Data

Annual spectral indices from Landsat (1985 – 2023) are commonly used to characterize the landscape and detect landscape change. Some indices to be explored include the normalized difference vegetation index (NDVI), normalized difference moisture index (NDMI), normalized difference wetness index (NDWI), tasseled-cap wetness index (TCW), tasseled-cap brightness index (TCB), and tasseled-cap greenness index (TCG).

Analysis

Upon reviewing the results of Part 1, any identified pitfalls with change detection or classification using NLCD will be assessed for the feasibility of correction. The first step is to locate pilot areas that contain examples of these pitfalls. These areas will likely be at a scale that is comparable to validation data.

If the area of improvement is change detection, an alternate change detection method will be explored. This will focus on improving the footprint of change over time, potentially addressing omission (missed change) and commission (false change) errors. The Landsat-based detection of Trends in Disturbance and Recovery (LandTrendr) algorithm is designed to identify abrupt and gradual change from a single spectral band or index (Kennedy et al., 2010). Although this approach was created to assess forest disturbance, it has also been used to map urban change (Hu et al., 2024), cropland change (Zhu et al., 2019), and wetland change (Fu et al., 2022). One downside to LandTrendr is that it is designed to handle a single band or index, which provides an incomplete picture of landscape change. To address this, Cohen et al. combined the outputs from 13 individual LandTrendr runs, 6 Landsat bands and 7 indices, in a random forest stacking ensemble in an effort to test the importance of multispectral monitoring of forest disturbance (2018). A similar approach can be applied here to map a range of landscape change. In the identified pilot areas, change patches will be mapped using LandTrendr, annual cloud-free composites of the six Landsat bands and the six spectral indices in Google Earth Engine (GEE). Change segmentation is relative to the trends at each pixel, which can capture small spectral changes in places that received little changes (Kennedy et al., 2010). Filtering of small spectral changes will likely be needed to remove commission errors. Validation of the change footprints is described in the next section. In this approach, the area of change is mapped but is not classified as a unique land use.

The steps outlined in this section will be applied if the land use calls for NLCD change patches need correcting or if LandTrendr change patches need classifying. The first step is to extract the Landsat spectral signatures for each aggregate land use in the 30-meter resolution, 2013/14 CB-LULC within the pilot areas. These plots will be interpreted to determine if there are unique signatures in specific bands/indices or combination of bands/indices per aggregate class. If the class, or classes, that need improving are spectrally unique, use the spectral signatures for the class to train a Random Forest (RF) model to predict the class using Landsat back through time. The resulting back-casted data will be subset to the areas of change. The RF model will be executed in open-source Python using the scikit-learn library. The amount of training data withheld for validation will be evaluated but will likely be between 20 and 40%.

Complete the validation steps from Part 1 on the new data for the test areas. Compare the trends between both versions of the data. Assess whether the data improved, the magnitude of improvement, the effect on the trends, and where the improvements occurred. Present results to the Land Use Workgroup and other workgroups as necessary to determine if the improvements should be applied beyond the test areas.

Validation

All appropriate validation steps from Part 1 will be applied in Part 2. In addition to those in Part 1, additional validation steps will be made. First, if LandTrendr is used to identify change over time, a random sample approach of binary change versus no change, stratified over time, will be used to assess the omission and commission errors of LandTrendr change detection. In addition, a fuzzy accuracy of change will be assessed, where a change patch is considered accurate if the change occurred within a year of being mapped.

The RF accuracy will be validated using methods baked into the scikit-learn library. Some portion of the training data (the CB-LULC data) is withheld from training the RF model and is used to assess the accuracy of the model predictions. A confusion matrix of the withheld training data and the predicted values from the model is created to assess User’s and Producer’s accuracies. In addition, the precision (the number of correctly-identified members of a class divided by all the times the model predicted that class), recall (the number of members of a class that the classifier identified correctly divided by the total number of members in that class), and F1 score (a combination of precision and recall) (Kreiger, 2020).

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Appendix A: Land Use Definitions

Impervious, Roads (ROAD)

Paved roads and bridges. Dirt and gravel roads may be mapped as impervious depending on the spectral characteristics of the substrate.

Impervious, Non-Roads (IMPO)

Impervious surfaces that are not roads, including buildings (e.g. houses, malls, sheds, and warehouses), sidewalks, parking lots, and rail lines.

Tree Canopy over Impervious (TCIS)

Tree canopy overhanging roads and non-road impervious surfaces rendering them partially or completely invisible from above.

Turf Grass (TURF)

Herbaceous lands associated with residential, commercial, industrial, and recreational areas (e.g. residential lawns, sports fields, cemeteries, golf courses, and airports) that is assumed to be altered through compaction, removal of organic material, and/or fertilization.

Tree Canopy over Turf Grass (TCTG)

Tree canopy overhanging herbaceous lands in developed areas assumed to be turf grass or otherwise altered through compaction, removal of surface organic material, and/or fertilization.

Solar Infrastructure (SOLI)

Field-mounted solar panel arrays and impervious surfaces associated with solar (e.g. structures, generators)

Solar Pervious (SOLP)

Herbaceous land surrounding solar panel arrays that it assumed to be managed to prevent tree growth.

Compacted Pervious (COMP)

Herbaceous land that is assumed to be unfertilized and where the regrowth of trees is suppressed. This includes utility transmission lines, pipelines, road rights-of-way, surficial mining operations, and landfills.

Construction (CONS)

Barren lands that transition to developed lands (i.e. impervious, turf grass).

Forest (FORE)

Contiguous patches of tree canopy and herbaceous lands where the understory is assumed to be undergoing natural or managed succession.

Harvested Forest (HARF)

Herbaceous lands that are cleared tree canopy patches (i.e. clear cuts) that are undergoing succession to become forested again.

Wetlands, Riverine Non-Forested (RIVW)

Wetlands adjacent to non-tidal streams and rivers (within the floodplain or at the headwaters).

Wetlands, Terrene Non-Forested (TERW)

Wetlands that are not adjacent to non-tidal streams and rivers or tidal waters.

Cropland (CROP)

Herbaceous lands used to produce grains, legumes, vegetables, fruits and nuts, grapevines, or other agricultural crops.

Pasture and Hay (PAST)

Herbaceous lands used for grazing livestock (e.g., cattle, goats, sheep) or producing fodder (e.g., hay and alfalfa).

Water (WATR)

Tidal waters (e.g. Chesapeake Bay), lakes and reservoirs, riverine and terrene ponds, large rivers, and water within smaller channels visible through the tree canopy.

Appendix B: Workplan Review Feedback

The draft workplan was circulated via email to Land Use Workgroup for review between January 2nd through 31st, 2025. Below is a table of the feedback received.

Reviewer(s)	Question/Comment
Maryland Department of Planning (MDP) - Jason Dubow, Michael Haxel, Deborah Herr Cornwell, Deborah Sward	MDP assumes the final product will be tabular due to interpolations that aren't spatially allocated (e.g. impervious vs. pervious development). Can the Bay Program clarify what the "additional 30-meter resolution raster datasets" would include? For example, the aggregate classes vs. the phase 7 classes? What factor(s) would determine whether these spatial deliverables would be produced?
	Through resampling, MDP assumes certain types of development would be generalized out, such as rural and very low-density residential development on parcels > 5 acres with very little turf grass and/or impervious surface. The proposed validation efforts using CAMA and Census information could potentially identify this phenomenon, and it may be something to consider addressing as part of the Part 2 effort.
	MDP requests clarification on whether the 2013 vintages of CB-LULC and NLCD be used for this pivot table.
	The deliverable is a database of land use at the segment scale - but it also sounds like the method would be applied to smaller scales (HUCs? Hexes?); would this be watershed-wide, or only for pilot areas? If it's watershed-wide, MDE and MDP would like to see these smaller scales also available in the database for state or local policy-making decisions.

Reviewer(s)	Question/Comment
Maryland Department of Agriculture (MDA) - Alisha Mulkey Maryland Department of Planning (MDP) - Jason Dubow, Michael Haxel, Deborah Herr Cornwell, Deborah Sward	MDA requested clarification on how nursery (indoor) and greenhouse structures be captured and categorized. Also, urban agriculture, which may include smaller parcels with raised beds? MDP assumes classifications could vary depending on whether urban agriculture is classified as agricultural in the CB-LULC or meets criteria for turf grass (small parcel w/ structure). MDP assumes agriculture would need to comprise the majority of a 30-meter pixel to be "backcast" as agriculture. Has CBP observed any other patterns related to how urban greenhouses, nurseries, agriculture, raised beds may appear in the high-resolution and backcast efforts?
Maryland Department of Environment (MDE) - Shannon McKenrick	MDE requested clarification on the necessity of reclassing both the NLCD and the model LU into an "aggregate schema" for Part 1 of the methodology. Is this only to do a statistical analysis on their comparability? It seems like the bulk of the method relies on identifying areas of change in the NLCD and then using fractional land uses to reclass those areas into the equivalent model land use. I can't seem to work out a reason to create a third classification in this case -- unless its for the potential 30m "annual conditions" rasters.
U.S. Forest Service – Katie Brownson	Is there a need for a more explicit consideration of how to back-cast non-clearcut acres that aren't being captured in the NLCD data? I know we had discussed using the FIA-derived estimates of % clearcuts (as a function of total harvest) to extrapolate out an estimate of total harvest acres from the NLCD data. And also potentially piloting this approach with a state where we have good historic reporting data to gauge accuracy. Is that something you are still considering?
Hampton Roads Planning District Commission – KC Filippino	Can you provide examples of land use changes that will impact and or advise calibration? Also, what model segmentation will you be using? Will the final data set from

Reviewer(s)	Question/Comment
	1985-2013 be much different from what it is currently? If so, how will that be communicated and how will it translate into loads? Will the P7 model will have these actual acres in it? It will include the backcast 1985- 2013, and the new data 2013/14, 2017/18, ad 2021/22. But what about the years in between? Will that still just be change data or will you be modeling it like the back-cast?
Carroll County Government, Department of Planning & Land Management – Andrew Gray	Why does “Bare Developed” under CB-LULC correlate to “Construction” under Phase 7? Why does “Riverine Wetlands Harvested Forest”, “Harvested Forest Barren”, “Harvested Forest Herbaceous”, “Terrene Wetlands Harvested Forest”, and “Tidal Wetlands Harvested Forest” under CB-LULC correlate to “Natural” under Aggregate Schema? Why does “Bare Shore” under CB-LULC correlate to “Water” under Phase 7? Why would “Rail Lines” be under Impervious, Non-Roads (IMPO) in the Appendix. Would the ballast be pervious?