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Forest Service Landscape Change Monitoring System Methods

Version: 2024.10

Mapping Areas: Conterminous United States, Alaska, Puerto Rico–U.S. Virgin Islands, and Hawaii

Cover image: Landscape Change Monitoring System (LCMS) Level 3 Change product depicted for all study areas.

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Executive Summary

The Landscape Change Monitoring System (LCMS) is a remote sensing-based system produced by the United States Department of Agriculture, Forest Service (Forest Service) for mapping and monitoring changes related to vegetation cover, land cover, and land use. Data produced by LCMS extend from 1985 to the most recently completed growing year. For example, LCMS version 2024.10 extends through the end of September 2024 for the conterminous United States. LCMS is intended to provide a consistent monitoring method for applications including, but not limited to, silviculture and active forest management, post-disturbance monitoring, broad-scale vegetation cover change, land cover and land use conversion trends monitoring, disaster recovery, and sensitive habitat monitoring.

This document details the methods employed to create all map products for LCMS version 2024.10. These methods will be revisited annually to ensure they reflect the best available science. Current methods involve using Landsat and Sentinel-2 data in the Landsat-based detection of Trends in Disturbance and Recovery (LandTrendr) and Landsat data in the Continuous Change Detection and Classification (CCDC) temporal segmentation algorithms. Outputs from these algorithms are used as predictor variables in random forest models that are calibrated using training data collected with the TimeSync attribution tool (Cohen et al. 2010). The broad categories of LCMS products are vegetation cover Change, Land Cover, and Land Use.

All LCMS products are freely available for download at the LCMS website.

Users can visit the LCMS Homepage to find links to data, interactive visualization & summarization tools, and more information on all things LCMS.

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Contents

Version Release Notes

Landscape Change Monitoring System Conterminous United States, Alaska, Puerto Rico–U.S. Virgin Islands*, and Hawaii* Version 2024.10 Release Notes

Any changes to the methods from Landscape Change Monitoring System (LCMS) version 2023.9 outlined below in this document will be reflected in this list. * = Fall 2025 release

- Computing platforms
  - No changes
- Model Calibration Data
  - We collected 1,050 TimeSync (Cohen et al. 2010) samples across interior Alaska for model calibration and prediction. These were combined with the Southeastern Alaska (SEAK) samples from previous SEAK production to model all of Alaska (AK) using a single model.
- Purposive sampling
  - Within regions where our model outputs had low accuracy (through qualitative evaluation), we sampled 200 random plots each for Agriculture, Developed, and Other Land Use classes, across the conterminous United States (CONUS), to use in model calibration and prediction.
  - For Developed and Other Land Use classes in AK, we sampled 50 random plots each within predetermined purposive regions to use in model calibration and prediction.
- Model predictor data

  The two Continuous Change Detection and Classification (CCDC) runs that were feathered together were the 1984–2022 CCDC run used in v2022.8 and 2014–2024.
- Modeling (Supervised Classifications)
  - To avoid including any non-mutually exclusive Land Use classes, the Land Use product no longer includes the Non-forested Wetland class.
- Map Assemblage
  - We assembled final Change maps using ancillary data to categorize modeled Change (Slow Loss, Fast Loss, Gain) into 15 cause of change classes.
  - We introduced classification levels for each product to facilitate balancing thematic detail and accuracy. The highest level for each product contains the highest number of classes and generally the lowest accuracy. This level is the only level available for download or in Google Earth Engine. Users can bin the highest-level products to lower levels to balance their needs. Change has Levels 1, 2, and 3; Land Cover has Levels 1, 2, 3, and 4; and Land Use has Levels 1 and 2.
- LCMS products
  - We released LCMS products for all of AK.

Landscape Change Monitoring System Conterminous United States, Southeastern Alaska, Puerto Rico–U.S. Virgin Islands, and Hawaii Version 2023.9 Release Notes

Any changes to the methods from LCMS version 2022.8 outlined below in this document will be reflected in this list.

- Computing platforms
    - No changes
- Model calibration data
    - No changes
- Model predictor data
    - Rather than completely rerunning CCDC for the entire time series for CONUS and SEAK, two CCDC runs were feathered together. The first run was the 1984–2022 CCDC run used in v2022.8, while the second run was 2013–2023. Between 2014 and 2021, the v2022.8 CCDC run was feathered together with the new CCDC run of 2013–2023 using a linearly weighted feathering method.
    - The Cloud Score + algorithm was used for cloud masking of Sentinel-2 data used in the annual composites used in Landsat-based detection of Trends in Disturbance and Recovery (LandTrendr).
- Modeling (Supervised Classifications)
    - The Change model is run as a multi-class probability model rather than the previous separate binary models for each Change class.
- Map Assemblage
    - Additional rulesets based on probability thresholds and ancillary datasets were introduced for the Land Use and Land Cover map assemblages to limit commission/omission of certain classes.
- LCMS products
    - The first release of the Hawaii (HI) study area (concurrently with Puerto Rico–U.S. Virgin Islands (PRUSVI) in October 2024).

Landscape Change Monitoring System Conterminous United States, Southeastern Alaska, Puerto Rico–U.S. Virgin Islands, and Hawaii Version 2022.8 Release Notes

Any changes to the methods from LCMS version 2021.7 outlined below in this document will be reflected in this list.

- Computing platforms
    - No changes
- Model calibration data
    - No changes
- Model predictor data
    - The United States Geological Survey (USGS) Landsat collection 2 data were used in generating annual composites.
    - In addition to Landsat 4, 5, 7, and 8, Landsat 9 is now included as well.
    - LandTrendr and CCDC predictor data were updated with data generated from Landsat collection 2 data.
    - Surface Reflectance data were used to run CCDC for the CONUS.
    - CCDC Normalized Burn Ratio (NBR), Normalized Difference Moisture Index (NDMI) and wetness predictors were not included.
    - No Landsat thermal data were included as predictor variables in CONUS, SEAK, PRUSVI or HI.
    - Use the USGS 3D Elevation Program (3DEP) data for our terrain predictors.

- Modeling (Supervised Classifications)
    - No changes
- LCMS products
    - Production of HI LCMS is ongoing, and the data release is upcoming.
    - For PRUSVI, low Developed probabilities were excluded to limit the commission of Developed in non-Developed classes. Through qualitative assessment of the Land Use assembled maps, we used the 70th percentile Developed raw probabilities in the highest probability classification, which excluded low Developed probabilities and allowed other Land Use class probabilities to be considered instead in classification. Excluding low Developed probabilities helped limit Developed commission in uncertain Land Use types such as Agriculture and Rangelands.

Landscape Change Monitoring System Conterminous United States, Southeastern Alaska, Puerto Rico–U.S. Virgin Islands, and Hawaii Version 2021.7 Release Notes

Any changes to the methods from LCMS version 2020.5 outlined below in this document will be reflected in this list.

- Computing platforms
    - No changes
- Model calibration data
    - Additional training locations were collected over areas of lava rock in the Southwestern U.S. and coastal wetlands in Southern Texas to help the models avoid classifying these areas as Developed.
- Model predictor data
    - To avoid masking out areas of water that were not present for the majority of the analysis period, for dark pixels only (Sum of near-infrared (NIR) and short-wave infrared band 1 (SWIR1) bands ≤0.175), the Temporal Dark Outlier Mask (TDOM) method now uses a shorter 3-year time window (one year plus and minus the year of the composite; for example, for the 2000 composite, the years 1999–2001 would be included in the TDOM statistics) to derive statistics to identify outliers. All other pixels continue to use the statistics from 1985–2020. This step helps avoid masking areas of water that were not present for most of the analysis period.
    - Landsat/Sentinel-2 composites were not used directly as predictor variables.
    - Interpolated values from LandTrendr and CCDC were included as predictor variables to allow for more complete maps (These areas can be removed by using the Quality Assessment (QA) band described below).
    - Landsat thermal data were included as predictor variables in CONUS, but not SEAK.
- Modeling (Supervised Classifications)
    - No changes
- LCMS products
    - Since Change is intended to depict vegetation cover change, Change is excluded from any pixel classified Water, Snow/Ice, or Barren for all years.
    - Ancillary information on the origin of the annual LCMS product output values is now provided as part of a QA bit layer. This layer includes whether an interpolated value was used to produce the LCMS output, the sensor, and the day of year the value came from. A postprocessing rule is now applied to Land Use maps. Since heavily treed

Developed areas are frequently erroneously classified as Forest Land Use, we now require that if a pixel has been classified as Developed it cannot subsequently change to Forest. To avoid inadvertently increasing commission errors in areas that were initially erroneously classified as Developed, we limit this ruleset to pixels that are a maximum of two pixels away from a pixel classified as built-up in the Landsat-based Global Human Settlement Layer built-up area grid (GHSL; Corbane et al. 2018) at any of the mapped GHSL years (1975, 1990, 2000, and 2014).

Background

Our landscape is continually changing. Monitoring change in vegetation cover and conversion of land cover and land use is important for making data-driven land management decisions. The Forest Service has developed the Landscape Change Monitoring System (LCMS) to consistently monitor changes in vegetation cover, land cover, and land use across the United States from 1985 to present.

The LCMS Science Team initially developed all LCMS methods (Cohen et al. 2018, Healey et al. 2018). This team evaluated the best available science about landscape change detection methods and provided guidance for the adapted operational LCMS methods employed by the LCMS Production Team described in this document.

The Science Team and Production Team jointly re-evaluate the methods annually to ensure the mapping process balances the best available science with designated resources. This document describes the methods used to create LCMS version 2024.10 products. The version naming convention is YYYY.v, where “YYYY” denotes the most recent year mapped, and the “v” denotes the version of the methods used. We recreate all map products annually from 1985 to the most recent full growing season. Annual production ensures LCMS methods can be updated when appropriate and all maps will be produced in a consistent manner.

LCMS outputs cover the conterminous United States (CONUS), Alaska (AK), Puerto Rico–U.S. Virgin Islands (PRUSVI), and Hawaii (HI). This document outlines methods used in these study areas.

The core LCMS products are annual vegetation cover Change, Land Cover, and Land Use raster maps. At its fundamental level (Level 1), Change maps areas of Disturbance, Vegetation Successional Growth, and Stable across the landscape. Level 2 and 3 Change products are intended to address needs centered around monitoring causes and types of variations in vegetation cover, water extent, or snow/ice extent that may or may not result in a transition of land cover and/or land use. Land Cover products can be used to meet more general land cover monitoring needs over time. Land Use products can be used to monitor land use conversion patterns.

Methods

Computing platforms

LCMS uses Google Earth Engine (GEE; Gorelick et al. 2017) through an enterprise agreement between the Forest Service and Google for all remote sensing raster data acquisition and processing. GEE is a parallel computing environment that provides access to many publicly available earth observation datasets, common data processing methods, and computing infrastructure to process these data. While GEE's data processing methods are extensive, it currently cannot meet the same breadth of methods available in common scientific computing platforms such as R and the Python package, Scikit-Learn (Pedregosa et al. 2011). Due to these limitations, we use the Scikit-Learn Python package for sample design, model predictor variable selection, and map validation.

Model calibration data

All supervised statistical models need a set of calibration data, such as dependent variable or training data, and predictor variables, such as independent variables, to train the model. The model is then applied to the predictor data where there are no calibration data. This section will outline how LCMS calibration data locations are selected and attributed.

Model calibration data sample design

The goal of a sample design is to efficiently sample the expected variability of the dependent variable. Since LCMS maps vegetation cover Change, Land Cover, and Land Use, the sample design needs to account for expected variability in each of these categories across the U.S.

Pilot projects we completed throughout the United States revealed that many classes, such as vegetation cover loss and impervious land cover, are relatively rare across the landscape. The simple random sample we initially used proved insufficient to capture an adequate proportion of these rare classes. To improve our sampling approach, we moved to a stratified random sample design following the guidance from Olofsson et al. (2014). Specifically, "The recommended allocation of sample size to the strata defined by the map classes is to increase the sample size for the rarer classes making the sample size per stratum more equitable than what would result from proportional allocation, but not pushing to the point of equal allocation."

Based on this guidance, we stratify the landscape using the 2016 National Land Cover Database (NLCD) land cover/land use map for CONUS, Southeastern AK (SEAK), interior AK (Interior), and HI (Yang et al. 2018; Figures 1, 2, 3 and 5), paired with Landsat-based detection of Trends in Disturbance and Recovery (LandTrendr; Kennedy et al. 2010, Kennedy et al. 2018). For PRUSVI, the sample design uses land cover data from Helmer et al. (2002) for stratification (Figure 4).

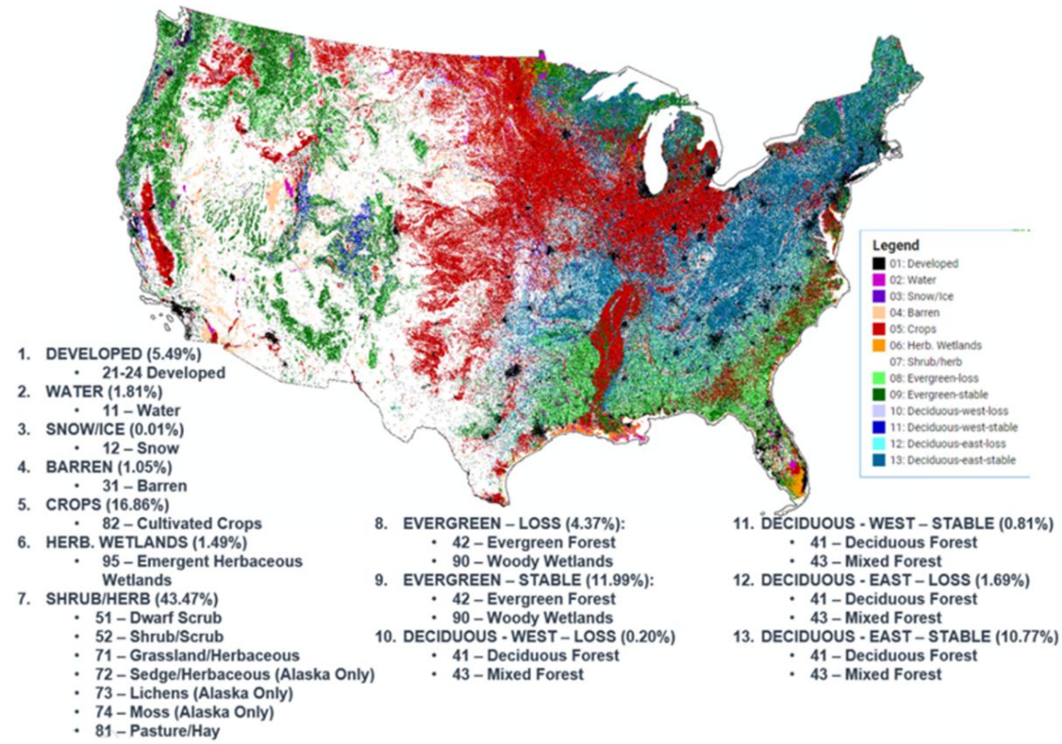


Figure 1.—Map depicting all strata used for the Landscape Change Monitoring System conterminous United States calibration/validation sample design. Final strata are listed below the map, with the percentage of total pixels represented for each stratum in parentheses, and National Land Cover Database land cover classes are sub-bulleted below their associated stratum (Yang et al. 2018).

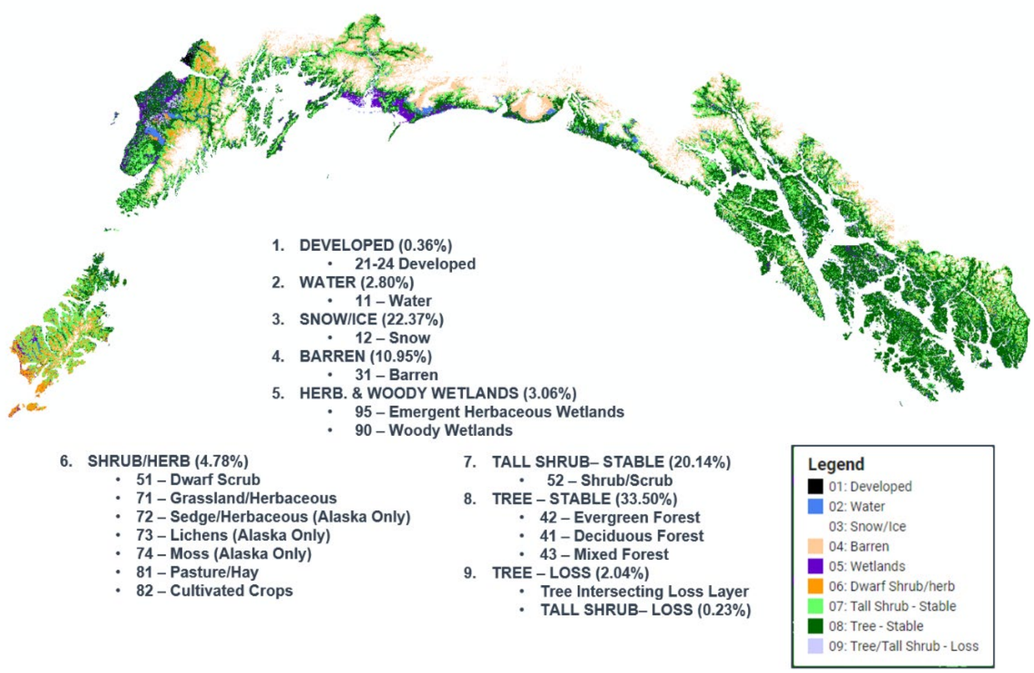
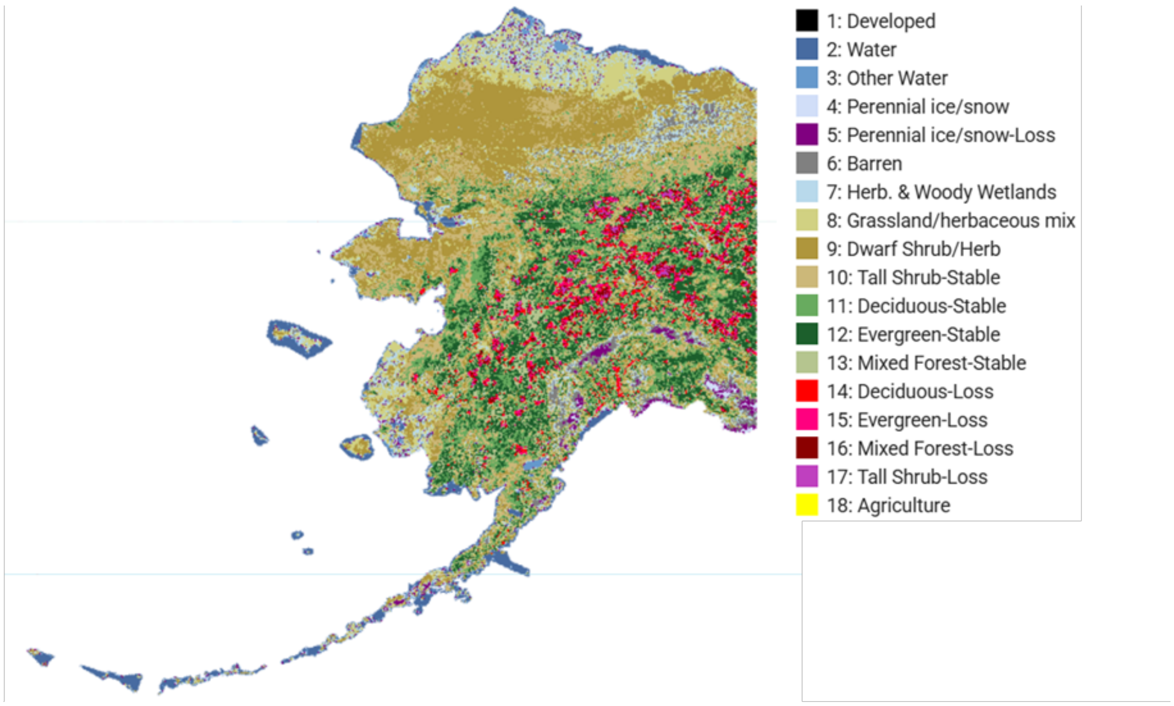


Figure 2.—Map depicting all strata used for the Landscape Change Monitoring System Southeast Alaska calibration/validation sample design. Final strata are listed below the map, with the percentage of total pixels represented for each stratum in parentheses, and National Land Cover Database land cover classes are sub-bulleted below their associated stratum (Yang et al. 2018).



Developed:	0.1%	Tall Shrub – Stable:	18.7%
Water:	10.3%	Deciduous – Stable:	2.4%
Other Water:	1.4%	Evergreen – Stable:	10.1%
Perennial ice/snow	1.6%	Mixed Forest – Stable:	2.3%
Perennial ice/snow – Loss:	0.4%	Deciduous – Loss:	1.0%
Barren:	7.7%	Evergreen – Loss:	2.1%
Herb. & Woody Wetlands:	7.1%	Mixed Forest – Loss:	0.7%
Grassland/herbaceous mix:	8.6%	Tall Shrub – Loss:	5.9%
Dwarf Shrub/Herb:	19.5%	Agriculture:	0.02%

Figure 3.—Map depicting all strata used for the Landscape Change Monitoring System interior Alaska (Interior) calibration/validation sample design. Final strata and the percentages of total pixels they represent are listed below the map and National Land Cover Dataset land cover classes are listed in the legend to the right of the map (Yang et al. 2018). Samples for Interior do not overlap geographically with Southeast Alaska samples.

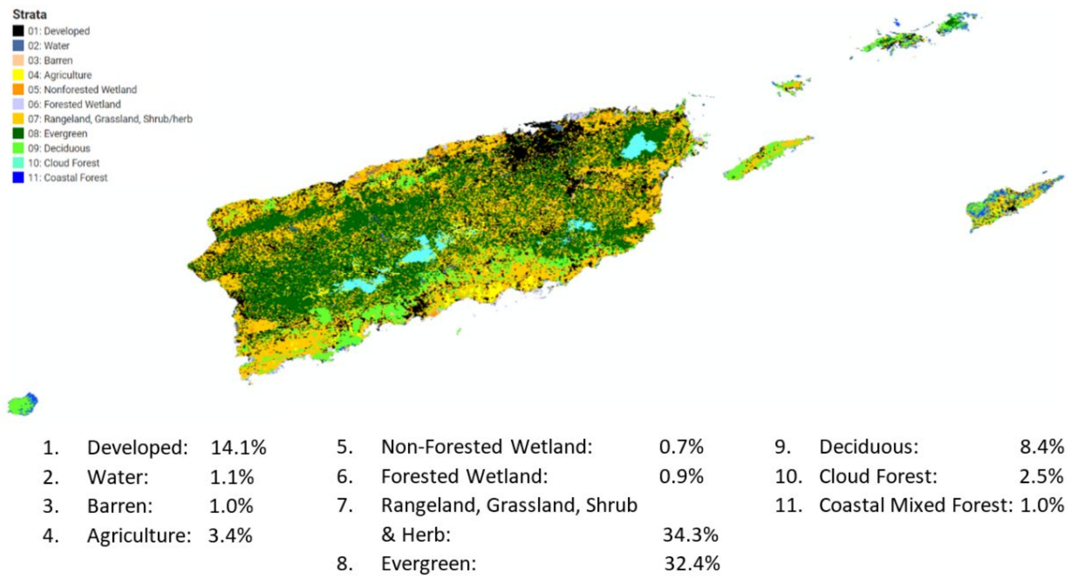


Figure 4.—Map depicting all strata used for the Landscape Change Monitoring System Puerto Rico–U.S. Virgin Islands (PRUSVI) calibration/validation sample design. Final strata and the percentages of total pixels they represent are listed below the map. PRUSVI uses land cover data from Helmer et al. (2002) for stratification.

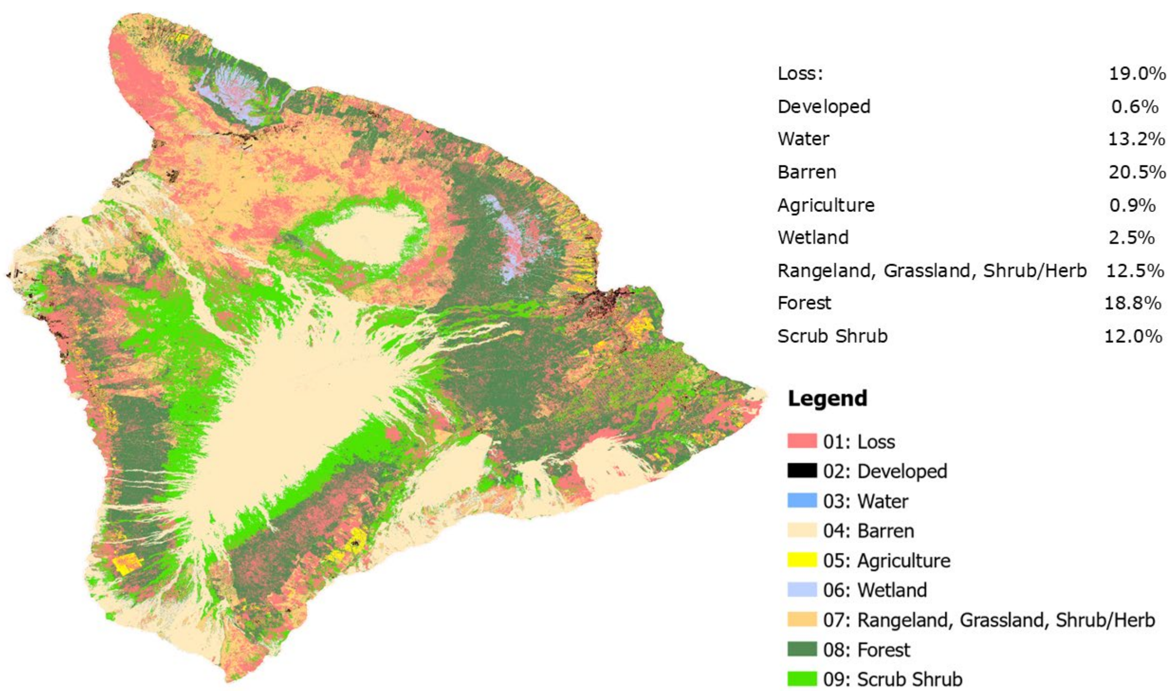


Figure 5.—Map depicting all strata used for the Landscape Change Monitoring System Hawaii (HI) calibration/validation sample design. Final strata and the percentages of total pixels they represent are listed to the right of the map. HI uses 2011 National Land Cover Database (NLCD) land cover from the 2016 NLCD land cover dataset (Yang et al. 2018) for stratification.

We chose the strata shown for CONUS (Table 1), AK (Table 2), PRUSVI (Table 3), and HI (Table 4) to adequately sample rare classes that are of specific interest to LCMS applications and/or had high model error in LCMS pilot studies. These rare classes include tree loss, deciduous tree loss in the western US, wetlands, and developed areas. Areas such as water and snow/ice typically have low model error, and therefore we allocated fewer samples to those classes.

The final sample sizes were 10,010 across CONUS, 1,979 across AK, 1,100 across PRUSVI, and 1,000 across HI. We started the final sample count with an allocation halfway between equal and proportional. We set a maximum value for each stratum of 1,000 for CONUS and 200 for AK, PRUSVI, and HI. We then proportionally recursively allocated the remainder. Lastly, for CONUS we set a fixed sample number of 30 for snow/ice and 200 for water because these strata represent less variable landscapes and are thereby easier to model. For AK, we set a fixed sample number of 65 for water (across SEAK and Interior) and 60 developed (across SEAK and Interior). For PRUSVI, we set a fixed sample number of 30 for water and barren. For HI, we set a fixed sample number of 30 for water. We allocated the remaining samples equally across the three disturbance—or loss—strata. Tables 1, 2, 3, and 4 show the final sample counts by stratum for CONUS, AK, PRUSVI, and HI respectively.

Table 1.—Final sample counts by stratum for the conterminous United States calibration sample.

Stratum	Count	Percent	Proportional	Equal	Equal/ Proportiona	Min/Max	Set Values
01: Developed	472,588,767	5.5%	548	625	587	977	999
02: Water	148,583,076	1.7%	173	625	399	521	200
03: Snow/Ice	571,498	0.01%	1	625	313	313	30
03: Barren	90,344,250	1.1%	105	625	365	439	578
04: Agriculture	1,458,578,963	16.9%	1,690	625	1,158	1,055	1,007
05: Herb. Wetlands	124,067,106	1.4%	144	625	385	486	659
06: Shrub/herb	3,755,611,086	43.5%	4,350	625	2,488	1,063	1,010
05: Evergreen-loss	377,541,936	4.8%	438	625	532	841	1,280
06: Evergreen-stable	103,552,6514	12.0%	1,200	625	913	1,050	988
07: Deciduous-west-loss	17,165,119	0.2%	20	625	323	336	709
08: Deciduous-west-stable	69,803,183	0.8%	81	625	353	412	533
09: Deciduous-east-loss	146,249,349	1.7%	170	625	398	518	984
13: Deciduous-east-stable	931,577,696	10.8%	1,079	625	852	1,050	990
14: Volcanic Rocks	1,396,100	0.02%	2	625	314	315	34
15: S. Texas Coastal Wetlands	1,205,013	0.01%	2	625	314	315	33
16: S. Texas Oil & Gas	3,555,467	0.04%	5	625	315	317	33
TOTAL:	8,634,365,129	100%	10,008	10,000	10,009	10,008	10,067

Table 2.—The combined sample counts by stratum for the Southeastern Alaska (SEAK) and interior AK (Interior) calibration samples.

Stratum	**Count**	**Percent**	**Proportional**	**Equal**	**Equal/ Proportional**	**Min/ Max**	**Set Values Applied**
01: Developed (SEAK)	670,861	0.04%	4	103	54	54	30
02: Water (SEAK)	5,165,532	0.28%	26	103	65	65	30
03: Snow/Ice (SEAK)	41,313,696	2.27%	207	103	155	155	30
04: Barren (SEAK)	20,211,947	1.11%	102	103	103	103	80
05: Herb. & Woody Wetlands (SEAK)	5,642,129	0.31%	29	103	66	66	79
06: Dwarf Shrub/Herb (SEAK)	8,818,866	0.48%	45	103	74	74	87
07: Tall Shrub – Stable (SEAK)	37,192,517	2.04%	187	103	145	145	167
08: Tree – Stable (SEAK)	61,864,335	3.40%	310	103	207	207	207
09: Tree/Tall Shrub – Loss (SEAK)	3,769,700	0.21%	19	103	61	61	219
10: Developed (Interior)	1,245,790	0.07%	1	62	32	32	30
11: Water (Interior)	168,330,034	9.25%	114	62	88	88	15
12: Other Water (Interior)	23,462,639	1.29%	16	62	39	39	20
13: Perennial ice/Snow-No Loss (Interior)	26,085,831	1.43%	18	62	40	40	30
14: Perennial ice/Snow-Loss (Interior)	7,293,170	0.40%	5	62	34	34	40
15: Barren (Interior)	125,336,879	6.89%	85	62	74	74	75
16: Herb. & Woody Wetlands (Interior)	115,930,668	6.37%	78	62	70	70	90
17: Grassland/Herbaceous Mix (Interior)	140,575,720	7.72%	95	62	79	79	85
18: Dwarf Shrub/Herb (Interior)	319,377,372	17.55%	215	62	139	139	140
19: Tall Shrub-Stable (Interior)	305,652,914	16.79%	206	62	134	134	135
20: Deciduous-Stable (Interior)	39,979,708	2.20%	27	62	45	45	45
21: Evergreen-Stable (Interior)	165,941,544	9.12%	112	62	87	87	87
22: Mixed Forest-Stable (Interior)	37,334,150	2.05%	26	62	44	44	44
23: Deciduous-Loss (Interior)	16,245,946	0.89%	11	62	37	37	37
24: Evergreen-Loss (Interior)	34,232,382	1.88%	24	62	43	43	43
25: Mixed Forest-Loss (Interior)	11,767,491	0.65%	8	62	35	35	35
26: Tall Shrub-Loss (Interior)	96,489,268	5.30%	65	62	64	64	64
27: Agriculture (Interior)	290,713	0.02%	1	62	32	32	35
TOTAL:	1,820,221,802	100%	2,036	2,043	2,046	2,046	1,979

Table 3.—Final sample counts by stratum for Puerto Rico–U.S. Virgin Islands calibration sample.

Stratum	Count	Percent	Proportional	Equal	Equal/ Proportional	Min/Max	Set Values Applied
01: Developed	1,450,331	14.10%	156	100	128	157	157
02: Water	113,212	1.20%	13	100	57	59	30
03: Barren	110,101	1.10%	12	100	56	58	30
04: Agriculture	344,785	3.40%	37	100	69	76	76
05: Non-Forested Wetland	71,185	0.70%	8	100	54	55	76
06: Forested Wetland	92,958	0.90%	10	100	55	57	57
07: Rangeland	3,519,261	34.30%	378	100	239	200	200
08: Evergreen	3,325,898	32.40%	357	100	229	200	200
09: Deciduous	865,643	8.40%	93	100	97	114	114
10: Cloud Forest	258,676	2.50%	28	100	64	69	100
11: Coastal Mixed Forest	102,288	1.00%	11	100	56	58	60
TOTAL:	1,103	100%	1,103	1,100	1,104	1,103	1,100

Table 4.—Final sample counts by stratum for the Hawaii calibration sample.

Stratum	Count	Percent	Proportional	Equal	Equal/ Proportional	Min/Max	Set Values Applied
01: Developed	77,810	0.60%	6	112	152	152	80
02: Water	1,756,563	13.20%	132	112	59	59	30
03: Barren	2,742,909	20.50%	206	112	122	122	50
04: Agriculture	121,505	0.90%	10	112	159	159	70
05: Wetland	332,267	2.50%	25	112	61	61	70
06: Rangeland	1,671,666	12.50%	126	112	69	69	150
07: Forest	2,508,101	18.80%	188	112	119	119	230
08: Scrub shrub	1,602,192	12.00%	120	112	150	150	120
09: Loss	2,539,975	19.00%	191	112	116	116	200
TOTAL:	13,352,988	100%	1,004	1,008	1,007	1,007	1,000

Calibration data collection

We collected model calibration data using the TimeSync attribution tool (Cohen et al. 2010). TimeSync is a web-based application that allows users to look at a time series of Landsat images, along with available high-resolution images in Google Earth Pro and other ancillary data in the Ancillary Data Viewer web application, which is created by and hosted through the Field Services and Innovation Center—Geospatial Office (FSIC—GO), to attribute a yearly land cover, land use, and change process at each training point location (Figure 6).

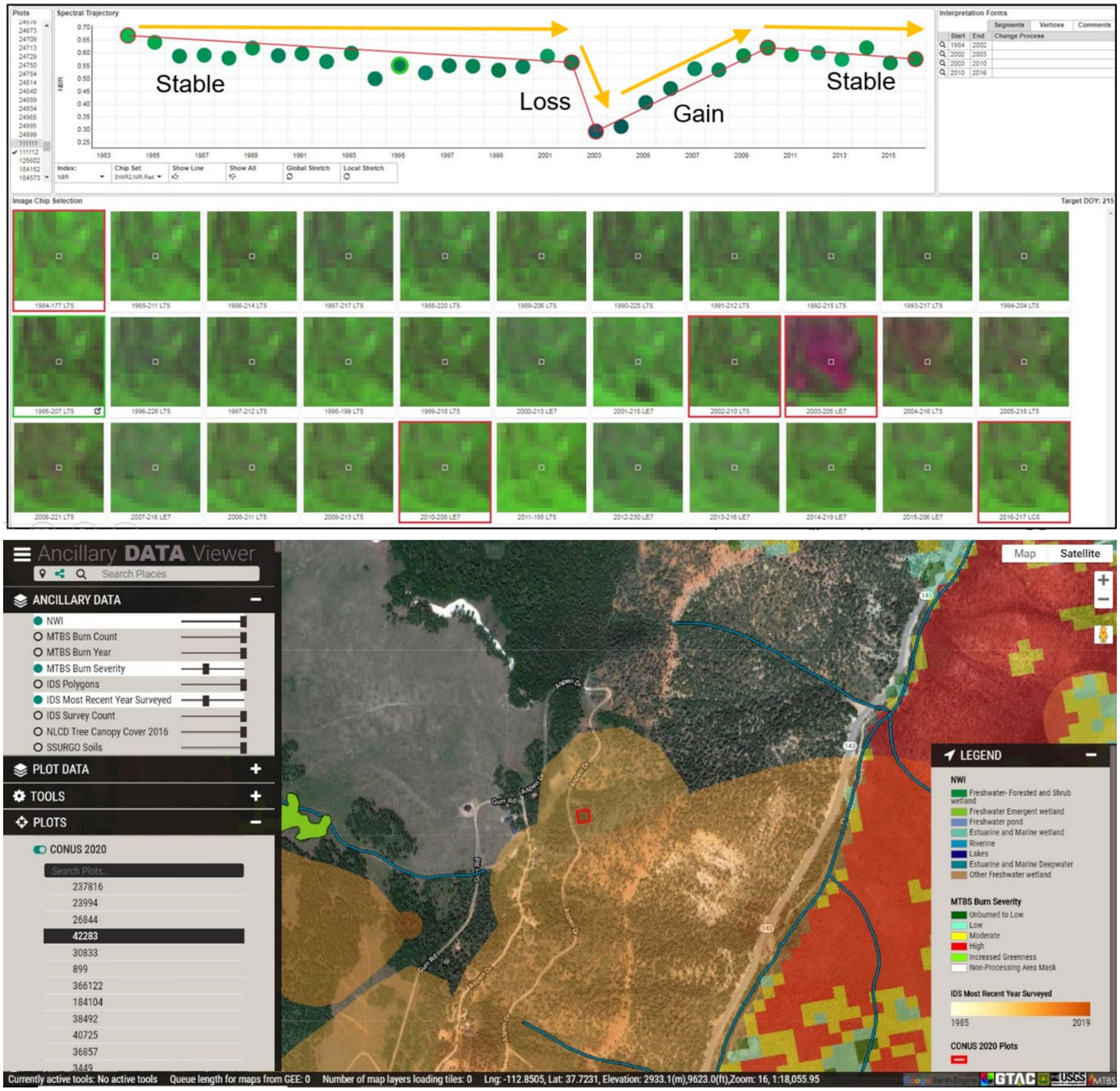


Figure 6.—Top: Example of the TimeSync tool (Cohen et al. 2010); Bottom: The Ancillary Data Viewer. These tools, along with Google Earth Pro, are used in unison to attribute change processes, land cover, and land use for each year for each model calibration plot.

LCMS TimeSync interpretation uses the Land Change Monitoring, Assessment, and Projection (LCMAP)/LCMS Joint Response Design. This response design provides a consistent method for attributing a common set of classes for change process, land cover, and land use (see supplementary materials in Pengra et al. 2020). The classes and their definitions are as follows:

- Change process
    1. FIRE: Land altered by fire, regardless of the cause of the ignition (natural or anthropogenic), severity, or land use.
    2. HARVEST: Forest land where trees, shrubs or other vegetation are severed or removed by anthropogenic means. Examples include clearcutting, salvage logging

after fire or insect outbreaks, thinning and other forest management prescriptions such as shelterwood/seedtree harvest.

3. MECHANICAL: Non-forest land where trees, shrubs or other vegetation are mechanically severed or removed by chaining, scraping, brush sawing, bulldozing, or any other methods of non-forest vegetation removal.
4. STRUCTURAL DECLINE: Land where trees or other woody vegetation is physically altered by unfavorable growing conditions brought on by non-anthropogenic or non-mechanical factors. This type of loss typically creates a trend in the spectral signal(s) such as Normalized Difference Vegetation Index (NDVI) decreasing, Wetness decreasing, short-wave infrared (SWIR) increasing, etc. However, the trend can be subtle. Structural decline occurs in woody vegetation environments, most commonly from insects, disease, drought, acid rain, etc. Structural decline can include defoliation events that do not result in mortality, such as in gypsy moth and spruce budworm infestations, which may recover within one or two years.
5. SPECTRAL DECLINE: A plot where the spectral signal shows a trend in one or more of the spectral bands or indices such as NDVI decreasing, Wetness decreasing, SWIR increasing, etc. Examples include cases where: a) non-forest/non-woody vegetation shows a trend suggestive of decline such as NDVI decreasing, Wetness decreasing, SWIR increasing, etc.; or b) woody vegetation shows a decline trend that is not related to the loss of woody vegetation, such as when mature tree canopies close resulting in increased shadowing, when species composition changes from conifer to hardwood, or when a dry period (as opposed to stronger, more acute drought) causes an apparent decline in vigor, but there is no loss of woody material or leaf area.
6. WIND/ICE: Land (regardless of use) where vegetation is altered by wind from hurricanes, tornados, storms, and other severe weather events, including freezing rain from ice storms.
7. HYDROLOGY: Land where woody cover or other land cover elements are significantly altered by flooding regardless of land use. For instance, this change could be new mixtures of gravel and vegetation in and around streambeds after a flood.
8. DEBRIS: Land (regardless of use) altered by natural material movement associated with landslides, avalanches, volcanos, debris flows, etc.
9. OTHER: Land (regardless of use) where the spectral trend or other supporting evidence suggests a disturbance or change event has occurred, but the definitive cause cannot be determined. Or alternatively, the type of change fails to meet any of the change process categories defined above.
10. GROWTH/RECOVERY: Land where vegetation cover increased due to growth and succession over one or more years. Applicable to any areas that may express spectral change associated with vegetation regrowth. In developed areas, growth can result from maturing vegetation and/or newly installed lawns and landscaping. In forests, growth includes vegetation growth from bare ground, as well as the overtopping of intermediate and co-dominate trees and/or lower-lying grasses and shrubs. Growth/recovery segments recorded following forest harvest will likely

transition through different land cover classes as the forest regenerates. For these changes to be considered growth/recovery, spectral values should closely adhere to an increasing trend line. For example, this change could be a positive slope that would, if extended to about 20 years, be on the order of 0.10 units of NDVI for several years.

- Land cover
    1. TREES: Live or standing dead trees.
    2. TALL SHRUBS (AK only): Shrubs >1 m in height.
    3. SHRUBS: Shrubs.
    4. GRASS/FORB/HERBACEOUS: Perennial grasses, forbs, or other forms of herbaceous vegetation.
    5. BARREN OR IMPERVIOUS: a) Bare soil exposed by disturbance such as soil uncovered by mechanical clearing or forest harvest, as well as perennially barren areas such as deserts, playas, rock outcroppings—including minerals and other geologic materials exposed by surface mining activities—, sand dunes, salt flats, and beaches. Roads made of dirt and gravel are also considered barren; or b) man-made materials that water cannot penetrate, such as paved roads, rooftops, and parking lots.
    6. SNOW/ICE: Snow and/or ice.
    7. WATER: Water.
- Land use
    1. AGRICULTURE: Land used to produce food, fiber, and fuels that is in either in a vegetated or non-vegetated state. This class includes, but is not limited to, cultivated and uncultivated croplands, hay lands, orchards, vineyards, confined livestock operations, and areas planted to produce fruits, nuts or berries. Roads used primarily for agricultural use, not used for public transport from town to town, are included in the agriculture land use class.
    2. DEVELOPED: Land covered by man-made structures such as, high density residential, commercial, industrial, mining or transportation, or a mixture of both vegetation (including trees) and structures such as low density residential, lawns, recreational facilities, cemeteries, transportation and utility corridors, etc. This class includes any land functionally altered by human activity.
    3. FOREST: Land planted or naturally vegetated and contains (or is likely to contain) 10% or greater tree cover at some time during a near-term successional sequence. This land may include deciduous, evergreen and/or mixed categories of natural forest, forest plantations, and woody wetlands.
    4. OTHER: Land perennially covered with snow and ice, water, salt flats and other undeclared classes. Glaciers and ice sheets or places where snow and ice obscure any other land cover call are included (assumed is the presence of permanent snow and ice). Water includes rivers, streams, canals, ponds, lakes, reservoirs, bays, or oceans. This class assumes permanent water, which can be in some state of flux due to ephemeral changes brought on by climate or anthropogenic.
    5. RANGELAND/PASTURE: Land that is either a) rangeland, where vegetation is a mix of native grasses, shrubs, forbs and grass-like plants arising from natural factors and processes such as rainfall, temperature, elevation and fire. Limited management may include prescribed burning as well as grazing by domestic and

wild herbivores; or b) pasture, where vegetation may range from mixed natural grasses, forbs and herbs to more managed vegetation dominated by grass species that have been seeded and managed to maintain close to monoculture status.

Calibration data finalization

Since the Change processes listed above can be too detailed to model with remote sensing data, we bin (crosswalk) them into larger classes appropriate for the LCMS modeling methods. The ten Change processes are crosswalked into three final LCMS modeling classes:

- Slow Loss
    - Structural decline
    - Spectral decline
- Fast Loss
    - Fire
    - Harvest
    - Mechanical
    - Wind/ice
    - Hydrology
    - Debris
    - Other
- Gain
    - Growth/recovery

Land Cover requires a different crosswalk approach. All TimeSync plots have a primary land cover class that makes up most of the plot (Cohen et al. 2010). Any additional land cover class that comprises 10% or more of a plot is assigned a secondary land cover class. Since a plot may have any number of secondary land cover classes, primary/secondary combinations of interest are modeled separately. We include any primary/secondary combination that is common along typical succession and have pairs where the secondary class is higher along the successional order. The expected land cover successional order is Barren to Grass/forb/herb, Grass/forb/herb to Shrub, and Shrub to Tree. Our LCMS modeled primary/secondary land cover combinations are listed in Table 5.

Table 5.—List of primary and secondary land cover classes modeled in Landscape Change Monitoring System. Shaded banding indicates successional class groupings. The Snow/Ice and Water classes do not include secondary land cover classes since they are not likely to be part of vegetation succession.

Primary	Secondary
Trees	NA
Tall Shrubs	Trees
Shrubs	Trees
Grass/forb/herb	Trees
Barren	Trees
Tall Shrubs	NA
Shrubs	NA
Grass/forb/herb	Shrubs
Barren	Shrubs
Grass/forb/herb	NA
Barren	Grass/forb/herb
Barren or Impervious	NA

We took most of the Land Use classes directly from the TimeSync plots (Cohen et al. 2010). The only exception was for the Non-forest Wetland class, which we eliminated to avoid including any non-mutually exclusive Land Use classes. The Land Use classes are as follows:

- Agriculture
- Developed
- Forest
- Other
- Rangeland or pasture

We crosswalked TimeSync (Cohen et al. 2010) plots originally assigned Non-forest Wetland dominant land use using a crosswalk into one of the other five Land Use classes according to any secondary land use designation they had or using dominant and secondary land cover designations if there was no secondary land use assigned. A summary of the crosswalk is shown in Table 6.

Table 6.—Elimination of non-mutually exclusive Non-forest Wetland class from the TimeSync (Cohen et al. 2010) plots via crosswalk to the most appropriate of the remaining five Land Use classes. Table cell colors indicate the class each color represents in the downloadable products and data viewers.

Original TimeSync Dominant Land Use	Original TimeSync SEC_LU	TimeSync Dominant Land Cover (no SEC_LU)	TimeSync Secondary Land Cover (no SEC_LU)	Crosswalked Dominant Land Use TimeSync
Non-forest Wetland	**Agriculture**	(Any)	(Any)	**Agriculture**
	Developed	(Any)	(Any)	**Developed**
	Forest	(Any)	(Any)	**Forest**
	(None)	Trees	(None)	**Forest**
	(None)	Trees	shrubs	**Forest**
	(None)	Trees	shrubs|grassForbHerb	**Forest**
	(None)	Trees	grass/forb/herb	**Forest**
	(None)	Trees	shrubs|naturalBarren	**Forest**
	(None)	Trees	naturalBarren	**Forest**
	(None)	Shrubs	trees	**Forest**
	(None)	Shrubs	trees|grassForbHerb	**Forest**
	(None)	Shrubs	trees|impervious	**Forest**
	(None)	Shrubs	trees|naturalBarren	**Forest**
	Other	(Any)	(Any)	**Other**
	(None)	Water	(None)	**Other**
	(None)	Barren	(None)	**Other**
	(None)	Shrubs	water	**Other**
	(None)	Shrubs	naturalBarren	**Other**
	(None)	Shrubs	naturalBarren|water	**Other**
	(None)	Shrubs	trees|water	**Other**
	(None)	Grass/forb/herb	water	**Other**
	(None)	Grass/forb/herb	shrubs|water	**Other**
	(None)	Grass/forb/herb	trees|water	**Other**
	(None)	Grass/forb/herb	naturalBarren|water	**Other**
	Rangeland or Pasture	(Any)	(Any)	**Rangeland or Pasture**
	(None)	Grass/forb/herb	(None)	**Rangeland or Pasture**
	(None)	Grass/forb/herb	trees	**Rangeland or Pasture**
	(None)	Grass/forb/herb	trees|shrubs	**Rangeland or Pasture**
	(None)	Grass/forb/herb	shrubs	**Rangeland or Pasture**
	(None)	Grass/forb/herb	shrubs|naturalBarren	**Rangeland or Pasture**
	(None)	Grass/forb/herb	naturalBarren	**Rangeland or Pasture**
	(None)	Grass/forb/herb	naturalBarren|water	**Rangeland or Pasture**
	(None)	Shrubs	(None)	**Rangeland or Pasture**
	(None)	Shrubs	grassForbHerb	**Rangeland or Pasture**
	(None)	Shrubs	grassForbHerb|water	**Rangeland or Pasture**

SEC_LU = secondary Land Use

Model predictor data

We use spectral information from Landsat and Sentinel-2 imagery and topographic information from the USGS 3D Elevation Program (3DEP) for modeling. Descriptions for each of these datasets are provided below.

Remote sensing spectral data

Data preparation

LCMS uses United States Geological Survey (USGS) Collection 2 Tier 1 Landsat 4, 5, 7, 8 and 9 and Sentinel-2a and -2b level 1C top of atmosphere reflectance data. We do not use surface reflectance data because Sentinel-2 surface reflectance data available within GEE are terrain-corrected. This correction makes it difficult to use the data in unison with Landsat surface reflectance data that are not terrain-corrected.

An exception is that surface reflectance data were used in the CONUS CCDC data. While v2022.8 CONUS used surface reflectance data for CCDC, it was later discovered that the surface reflectance correction algorithm does not work well over snow, ice, and water (USGS 2023). Reflectance values are frequently less than 0 or greater than 1. For this reason, CCDC uses top-of-atmosphere reflectance data in other study areas.

For cloud masking Landsat data, we apply the CFmask cloud masking algorithm (Foga et al. 2017), which is an implementation of Fmask 2.0 (Zhu and Woodcock 2012), as well as the cloudScore algorithm (Chastain et al. 2019). For Sentinel-2 data, 2016–2024, we used the cloudScore and Temporal Dark Outlier Mask (TDOM) method (Chastain et al. 2019). Starting in 2023, we use the Cloud Score + algorithm (Pasquarella et al. 2023) for masking clouds and cloud shadows. All remote sensing data preparation procedures can be accessed in the FSIC–GO GEE data processing and visualization library (FSIC–GO GEE Visualization Python Modules on PyPI, FSIC–GO GEE Visualization Python Modules on GitHub).

Annual compositing

LCMS uses cloud/cloud shadow-masked data as well as annual composites of these data to meet the needs of the temporal segmentation methods. Annual composite values are the geometric medoid of all values not masked as cloud or cloud shadow from a specified date range for each year. Due to differences in data availability and seasonality, we vary the date range across different modeling regions and time (Table 7).

Table 7.—Dates used for annual compositing of Landsat and Sentinel-2 data for the conterminous United States (CONUS), Alaska (AK), Puerto Rico–U.S .Virgin Islands (PRUSVI), and Hawaii (HI).

Study Area	Pre Sentinel-2 Start Date	Pre Sentinel-2 End Date	Post Sentinel-2 Start Date	Post Sentinel-2 End Date
CONUS	June 1	September 30	July 1	September 1
AK	June 15	September 15	June 15	September 15
PRUSVI	June 1	May 31	June 1	May 31
HI	January 1	December 31	January 1	December 31

The geometric medoid is the value that minimizes the sum of the square difference between the median value of each band’s values. This method ensures that the center-most data point in a multi-dimensional feature space is chosen. The values for all bands are from the same observation date. The bands that we include in the feature space are green, red, NIR, SWIR1, and SWIR2. Any pixel that does not have a cloud or cloud shadow-free value for a given year is left as null and excluded from any map for that year. View the 2020 composite images for CONUS and SEAK in Figure 7.

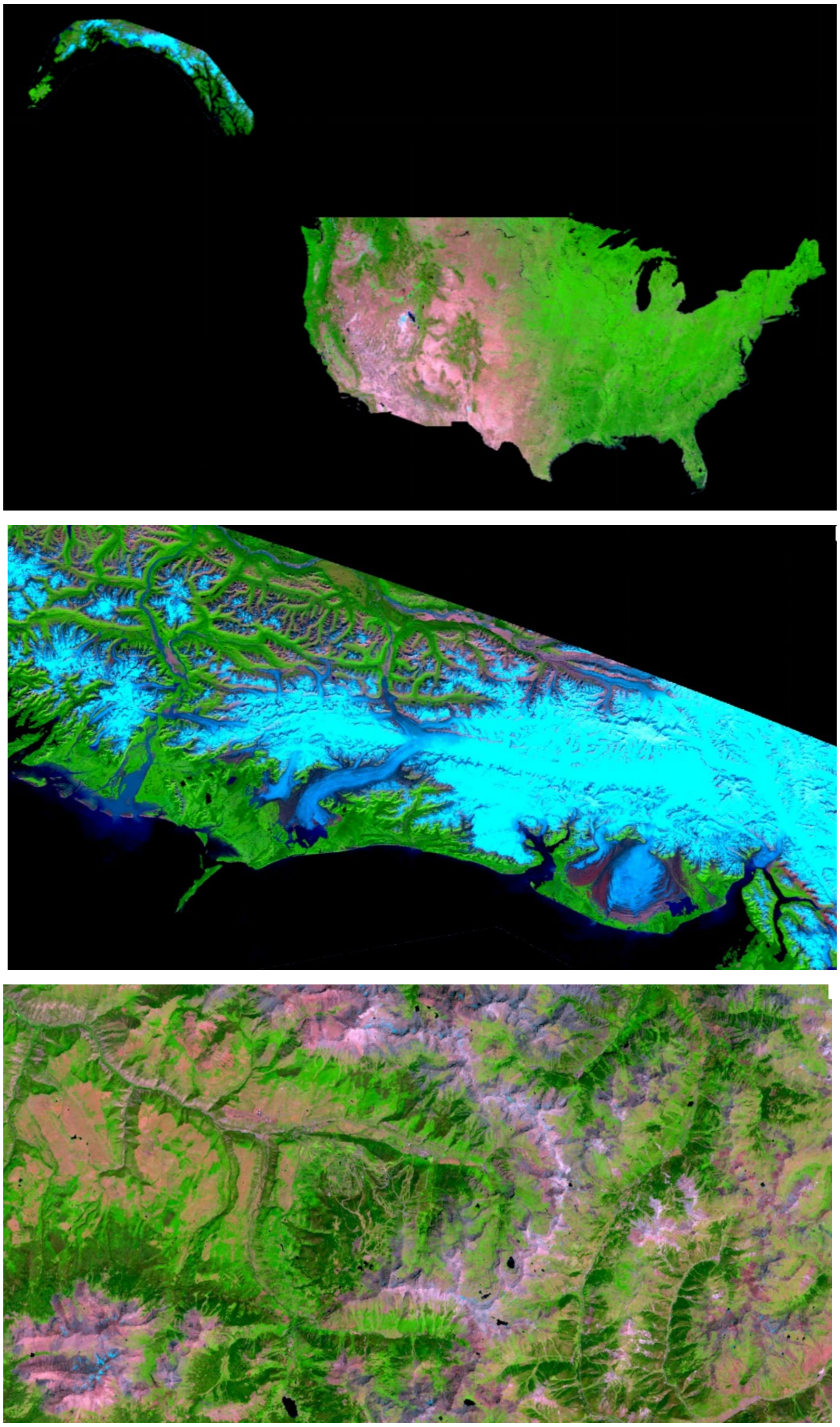


Figure 7.—Examples of the 2020 composites used in the Landscape Change Monitoring System. The red, green, and blue channels used in these composites are the second shortwave infrared, near-infrared, and red bands, respectively. The top image shows both southeast Alaska and the conterminous United States. The middle image shows a portion of coastal Alaska, while the bottom image shows a zoomed-in view of Telluride, CO.

Temporal segmentation

The goal of temporal segmentation is to identify periods of time that have similar land cover and/or change processes. Since different segmentation methods have advantages and disadvantages, LCMS uses the ensemble approach outlined in Cohen et al. (2018) and Healey et al. (2018). Currently, the operational version of LCMS uses LandTrendr (Kennedy et al. 2010, Kennedy et al. 2018) and CCDC (Zhu and Woodcock 2014) to segment the prepared time series. LandTrendr requires a maximum of one observation per year such as an annual composite made from Landsat and Sentinel-2 data. Whereas CCDC uses every available cloud and cloud shadow-free observation, specifically from the Landsat time series.

Landsat-based detection of Trends in Disturbance and Recovery (LandTrendr) methods

LandTrendr iteratively breaks the time series of annual composites and returns a set of segments. The start and end vertices of each segment have a start and end year (x-axis value in Figure 8), and a start and end fitted value (y-axis value in Figure 8), respectively.

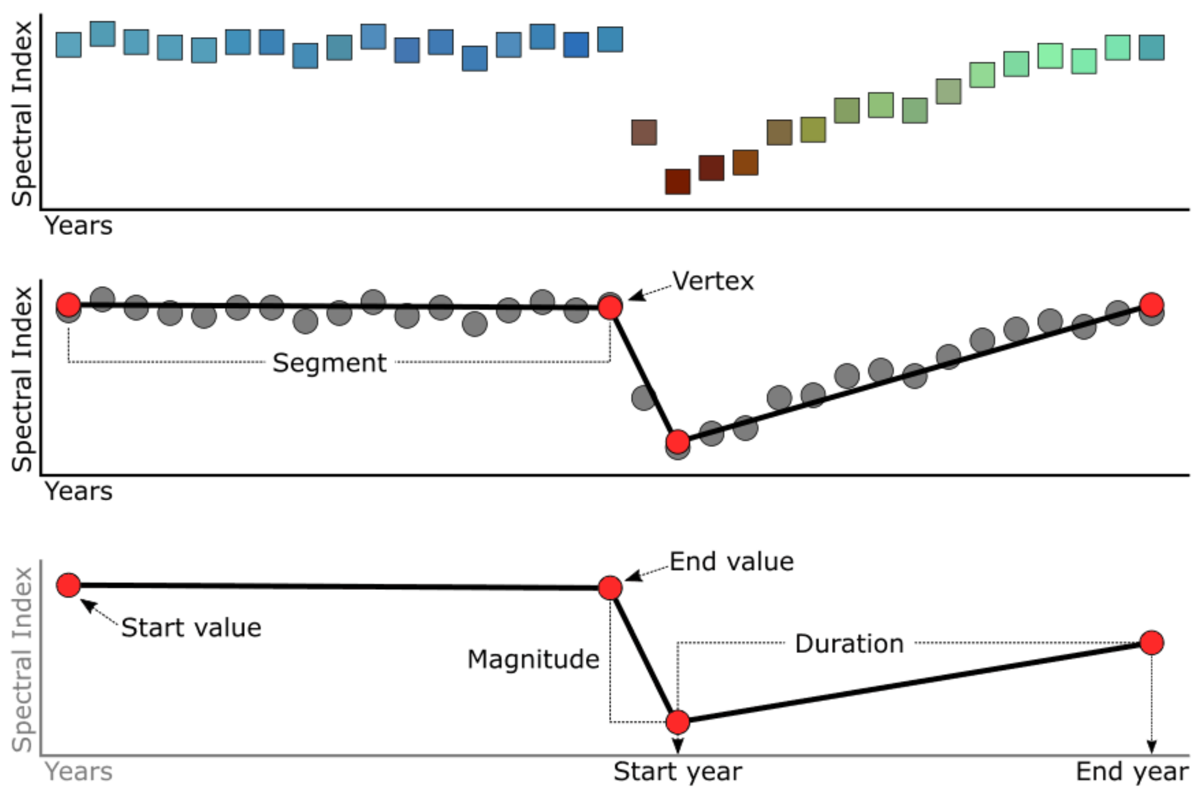


Figure 8.—Kennedy et al. (2018) illustration of how Landsat-based detection of Trends in Disturbance and Recovery breaks a time series and the information that can be taken from the output.

From the LandTrendr vertex information, we assign the following values for each band or index for each year:

- Fitted value
- Difference (magnitude) of that year's fitted value from the fitted value of the start vertex
- Difference (magnitude) between the start and end fitted values of the segment that year falls in

- The duration (length in years) of the segment each year is a member of
- The slope of the segment each year is a member of

LCMS uses the GEE version of LandTrendr outlined in Kennedy et al. (2018). The parameters that are used by LCMS are the same as those used in Kennedy et al. (2018; Table 1).

Table 8.—Parameters used when applying the Landsat-based detection of Trends in Disturbance and Recovery (LandTrendr) algorithm.

Parameter Name	**Value**	**Description**
maxSegments	9	Maximum number of segments to be fitted on the time series.
spikeThreshold	0.9	Threshold for damping the spikes (1.0 means no damping).
vertexCountOvershoot	3	The initial model can overshoot the maxSegments + 1 vertices by this amount. Later, it will be pruned down to maxSegments + 1.
preventOneYearRecovery	False	Prevent segments that represent one-year recoveries.
recoveryThreshold	0.25	If a segment has a recovery rate faster than 1/recoveryThreshold (in years), then the segment is disallowed.
pvalThreshold	0.05	If the p-value of the fitted model exceeds this threshold, then the current model is discarded, and another one is fitted using the Levenberg-Marquardt optimizer.
bestModelProportion	0.75	Takes the model with most vertices that has a p-value that is at most this proportion away from the model with lowest p-value.

Further documentation of the LandTrendr method used can be found in the GEE reference documentation.

CCDC methods

CCDC segments the time series by identifying outliers from a harmonic regression model. The idea is that different land cover and/or land use types have distinct seasonal signatures. A departure from the seasonal signature indicates a break in the time series (Figure 9).

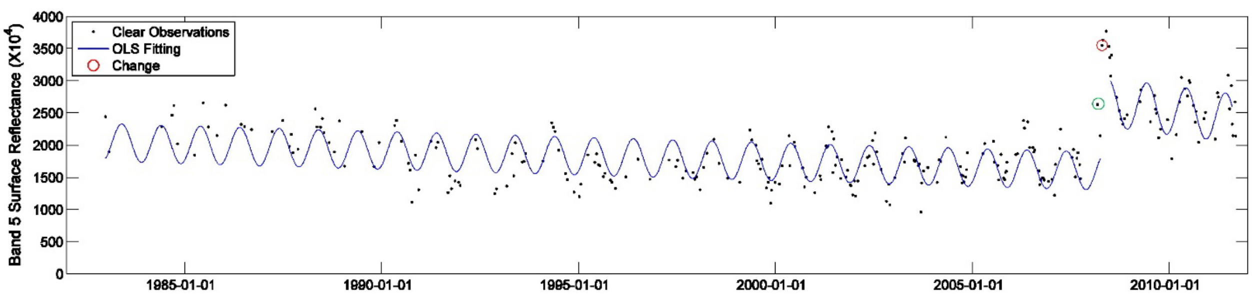


Figure 9.—Zhu and Woodcock (2014) illustration of how Continuous Change Detection and Classification (CCDC) segments a time series of data. The clear observations for band 5 (the first shortwave infrared band for Landscape Change Monitoring System) are shown as dots, while the Ordinary Least Squares (OLS) regression modeled value is shown as a blue line. Notice the dots depart from the typical values around 2008. CCDC then starts a new model following this departure when a new consistent seasonal pattern is re-established.

Input data includes all Landsat cloud and cloud shadow-free values. LCMS uses all cosine and sine coefficients from the first three harmonics (2π, 4π, and 6π; Zhu and Woodcock 2014) from the CCDC outputs. We do not use the slope and y-intercept generated by CCDC. Instead, we use the predicted value based on the harmonic model on September 1 for the intercept value (Figure 11) and the difference between that year and the previous year's fitted values for the slope value. This substitution allows the CCDC outputs to work properly within the LCMS annual ensemble framework.

To use CCDC outputs in annual LCMS modeling, the CCDC algorithm must be run annually to be consistent with the LCMS period from 1984 to the present year. Computational challenges arose by running the CCDC algorithm for the Landsat record from 1984 to the present modeling year for CONUS and AK. To overcome this challenge, the CCDC algorithm was run for the period 2014–2024 and 'feathered' into the data with the previous CCDC collection for 1984–2022 (the v2022.8 CCDC collection). Specifically, our 'feathering' method created the feathered CCDC collection by combining the previous CCDC collection data from 1984–2012 and using a linearly weighted average of the previous and updated CCDC collections from 2013–2021 (Figure 10). For each year between 2013 and 2021, the weight given to the updated collection increases linearly from 0 to 1. CCDC outputs for 2022–2024 come entirely from the updated collection.

The GEE version of CCDC is used for LCMS. The parameters used are shown in Table 9.

Figure 10.—An example time series showing the feathering of two Continuous Change Detection and Classification (CCDC) image collections. The blue line is Normalized Difference Vegetation Index (NDVI) from v2022.8 CCDC collection, and the orange line is NDVI from v2023.9 CCDC collection. The green line is the weighted average of the two CCDC collections used in our models.

Table 9.—Continuous Change Detection and Classification (CCDC) parameters used.

Parameter Name	Value	Description
breakpointBands	[“green”, “red”, “NIR”, “SWIR1”, “SWIR2”]	The name or index of the bands to use for change detection. If unspecified, all bands are used.
tmaskBands	null	The name or index of the bands to use for iterative TMask cloud detection. These are typically the green band and the SWIR2 band. If unspecified, TMask is not used. If specified, 'tmaskBands' must be included in 'breakpointBands'.
minObservations	6	The number of observations required to flag a change.
chiSquareProbability	0.99	The chi-square probability threshold for change detection in the range of 0 and 1.
minNumOfYearsScaler	1.33	Factors of minimum number of years to apply new fitting.
dateFormat	1	The time representation to use during fitting: 0 = jDays, 1 = fractional years, 2 = unix time in milliseconds. The start, end and break times for each temporal segment will be encoded this way.
lambda	0.002	Lambda for Least Absolute Shrinkage and Selection Operator (LASSO) regression fitting. If set to 0, regular Ordinary Least Squares (OLS) is used instead of LASSO.
maxIterations	10000	Maximum number of runs for LASSO regression convergence. If set to 0, regular OLS is used instead of LASSO.

NIR = near-infrared; SWIR1 = shortwave infrared band 1; SWIR2 = shortwave infrared band 2.

Further documentation of the CCDC methods used can be found in the GEE reference documentation.

Landtrendr and CCDC methods summary

Visualizing how the medoid composites and fitted LandTrendr and CCDC values relate can be quite difficult. Figure 11 attempts to illustrate how these values relate to two example pixels. The pixel depicted in the left column shows a fire event, while the right column shows insect-related tree mortality.

The first row shows the time series of the medoid composite values. Notice how each band relates to the other during the change events. The middle row shows the normalized burn ratio (NBR; a vegetation index related to moisture levels) fitted CCDC output, along with the annualized CCDC value from September 1 for each year. Notice how CCDC finds a break for the fire example but shows a single long-term declining trend of NBR for insect-related mortality. The bottom row shows the annual values of NBR from the medoid composites, LandTrendr, and CCDC. This row illustrates how all three relate to each other. Each is different but not necessarily correct or wrong. Both LandTrendr and CCDC reduce inter-annual noise but identify breaks at different points in time. LandTrendr and CCDC are used in the random forest model outlined below to produce final LCMS products.

Figure 11.—An example of predicted values from a pixel. The figures depict a pixel with a fire (left column) and insect-related tree mortality (right column). The top row shows the raw spectral bands from the annual medoid composites. The second row shows the Continuous Change Detection and Classification (CCDC) output for the normalized burn ratio (NBR) vegetation index, as well as the annualized values used in the Landscape Change Monitoring System (LCMS). The bottom row shows the raw NBR, Landsat-based detection of Trends in Disturbance and Recovery (LandTrendr; LT)-fitted NBR, and CCDC-fitted NBR values on a single graph. This figure illustrates how these data complement each other as well as how they differ. long = longitude; lat = latitude.

Terrain data

LCMS also uses terrain metrics to provide elevation, slope, aspect, and slope-position information to the model. The specific variables used are:

- Elevation
- Sine (Aspect)
- Cosine (Aspect)
- Slope
- Slope-position (circular kernel with 6-pixel window, 11-pixel window, and 21-pixel window; Weiss 2001)

For all study areas, the 10 m resolution USGS 3D Elevation Program (3DEP) data were used (USGS 2019a). All resampling to 30 m resolution used cubic convolution interpolation.

Summary

All variables covered in this section are used in the methods below. Table 10 shows a full list of all predictor variables we considered for modeling.

Table 10.—List of Landscape Change Monitoring System model predictor variables. Annual (A) values are different for each year of the analysis period, while the single-value (SV) terrain variables remain constant.

Type	LT					CCDC								Terrain
Category	**Fitted**	**Diff**	**Dur**	**Mag**	**Slope**	**Fitted**	**Fitted Slope**	**cos1**	**cos2**	**cos3**	**sin1**	**sin2**	**sin3**	**Raw**
A: Blue Band	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	
A: Green Band	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	
A: Red Band	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	
A: NIR Band	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	
A: SWIR1 Band	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	
A: SWIR2 Band	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	
A: NDVI	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	
A: NBR	✓	✓	✓	✓	✓									
A: NDMI	✓	✓	✓	✓	✓									
A: NDSI	✓	✓	✓	✓	✓									
A: TC Brightness	✓	✓	✓	✓	✓									
A: TC Greenness	✓	✓	✓	✓	✓									
A: TC Wetness	✓	✓	✓	✓	✓									
A: TC Angle Brightness/ Greenness	✓	✓	✓	✓	✓									
SV: Elevation														✓
SV: Slope														✓
SV: Cos (Aspect)														✓
SV: Sin (Aspect)														✓
SV: TPI (11 pixel)														✓
SV: TPI (21 pixel)														✓
SV: TPI (41 pixel)														✓

LT = Landsat-based detection of Trends in Disturbance and Recovery (LandTrendr); CCDC = Continuous Change Detection and Classification; Diff *= difference; Dur = duration; Mag = magnitude; A = annual; SV = single-value; NIR = near-infrared; SWIR1 = shortwave infrared band 1; SWIR2 = shortwave infrared band 2; NDVI = Normalized Difference Vegetation Index; NBR = Normalized Burn Ratio; NDMI = Normalized Difference Moisture Index; NDSI = Normalized Difference Snow Index; TC = Tasseled Cap transformation; TPI = topographic position index.*

Modeling (supervised classifications)

All supervised classifications for LCMS use the random forest modeling method (Breiman 2001). Random forest randomly selects a subset of the predictor variables and training sites in many different classification and regression trees. Each of the many trees predicts a class; these trees are then aggregated and used to determine the final modeled class.

LCMS uses the GEE instance of random forests called "smileRandomForest" for all raster-based classification. We compute variable selection and map validation via local processing using the sklearn.ensemble.RandomForestClassifier method.

LCMS uses a separate multiclass random forest model for Land Cover and Land Use products for each study area, and separate binary random forest models for each modeled Change class (Slow Loss, Fast Loss, and Gain) for each study area.

Each of these products has an annual model output, which is the proportion of trees within the random forest model that was chosen for each class. The multi-probability models output the proportion of trees for the multiple classes. For example, if the Land Use random forest model had a total of 100 classification trees in it, and 35 of those trees chose Agriculture, 10 of those trees chose Other, 55 chose Forest in 2005, and 0 chose Developed and Rangeland, that pixel would have a value of 0.35 for Agriculture, 0.10 for Other, and 0.55 for Forest in 2005. These class model confidence scores, which can also be thought of as probabilities, have values between 0 and 1 and are available for each annual model from 1985 to the most recent complete growing season. For example, LCMS version 2024.10 extends through the end of September 2024 for the CONUS. Figure 12 illustrates this concept in more detail.

Predictor variable selection

To reduce predictor variable covariance and inclusion of variables that do not improve the model, we filter predictor variables in a two-step process. The first step involves dropping variables that have a Pearson's correlation coefficient (r^2) mean greater than 0.95 (pandas.DataFrame.corr) across all predictor variable pairs. The next step is a recursive feature elimination using a 5-fold grouped cross-validation (sklearn.feature_selection.RFECV). We retain the variable combination with the highest accuracy for each model.

Hyperparameter tuning and change thresholds

We used a 10-fold grid search grouped cross-validation (sklearn.model_selection.GridSearchCV) to find the best combination of random forest hyperparameters. For example, this combination could be the number of trees, the minimum number of samples per leaf, the maximum number of features, etc. For the Change model, we determined the optimum model confidence thresholds for each class by assessing the precision and recall at every threshold (from 0–100) and selecting the threshold that maximizes both.

Map assemblage

Max probability assemblage

As explained above, each class within the Change, Land Cover, and Land Use products has a model confidence score, which represents the proportion of trees within the random forest model that classified a given pixel as that class for that model. Some examples of model confidence time series from individual pixels are shown in Figure 12. For each year, the class with the highest confidence is the initially chosen class for the given LCMS product (Change, Land Cover, and Land Use). Since the Stable class is not modeled explicitly, the class with the highest confidence must also have a value above that class's threshold.

In Figure 12, graphs of pixel time series are arranged in two columns and three rows. The pixel time series shown in the left column were affected by a fire, while the graphs shown in the right column depict long-term tree mortality from insects. Rows 1, 2, and 3 show the Change, Land Cover, and Land Use time series, respectively.

Beginning with the fire example, the Change time series (Figure 12: first row, left column) shows that the Fast Loss model confidence peaks in the year of the fire (2012) to a value that exceeds the Fast Loss threshold of 0.15. In the years following the fire (2013–2020), the Gain model confidence rose to levels above the Gain threshold of 0.29, as one might expect with growth and recovery following a fire. Complementing the Change time series, the Land Cover time series (Figure 12: second row, left column) shows that the Tree class had a remarkably high model confidence for each year until the fire in 2012. Following the fire, the Tree model confidence decreases, but it remains the most confident class. This decrease often occurs when the trees are damaged or not all burned, but the understory does burn. In the following years, we see the probability of Grass/forb/herb & Trees increase, which indicates that there are live trees in this pixel with an increased prevalence in grasses. Since a fire event generally does not indicate a land use transition, the Land Use Forest model confidence dips (Figure 12: third row, left column) but remains the highest.

The time series of long-term tree mortality caused by beetles (Figure 12: right column), is quite different. In this case, the Slow Loss model confidence is elevated for about two decades (Figure 12: first row, right column). While the Gain model confidence is elevated slightly during the second decade of this trend, the Slow Loss model remains the highest. Although there was indeed Slow Loss at this pixel, there was no transition of Land Cover or Land Use classes (Figure 12: second and third rows, right column). It is important to note that many instances of loss and gain do not result in a change of land cover or land use. This tool is important to monitor vegetation cover changes that do not result in land cover or land use change, such as forest degradation.

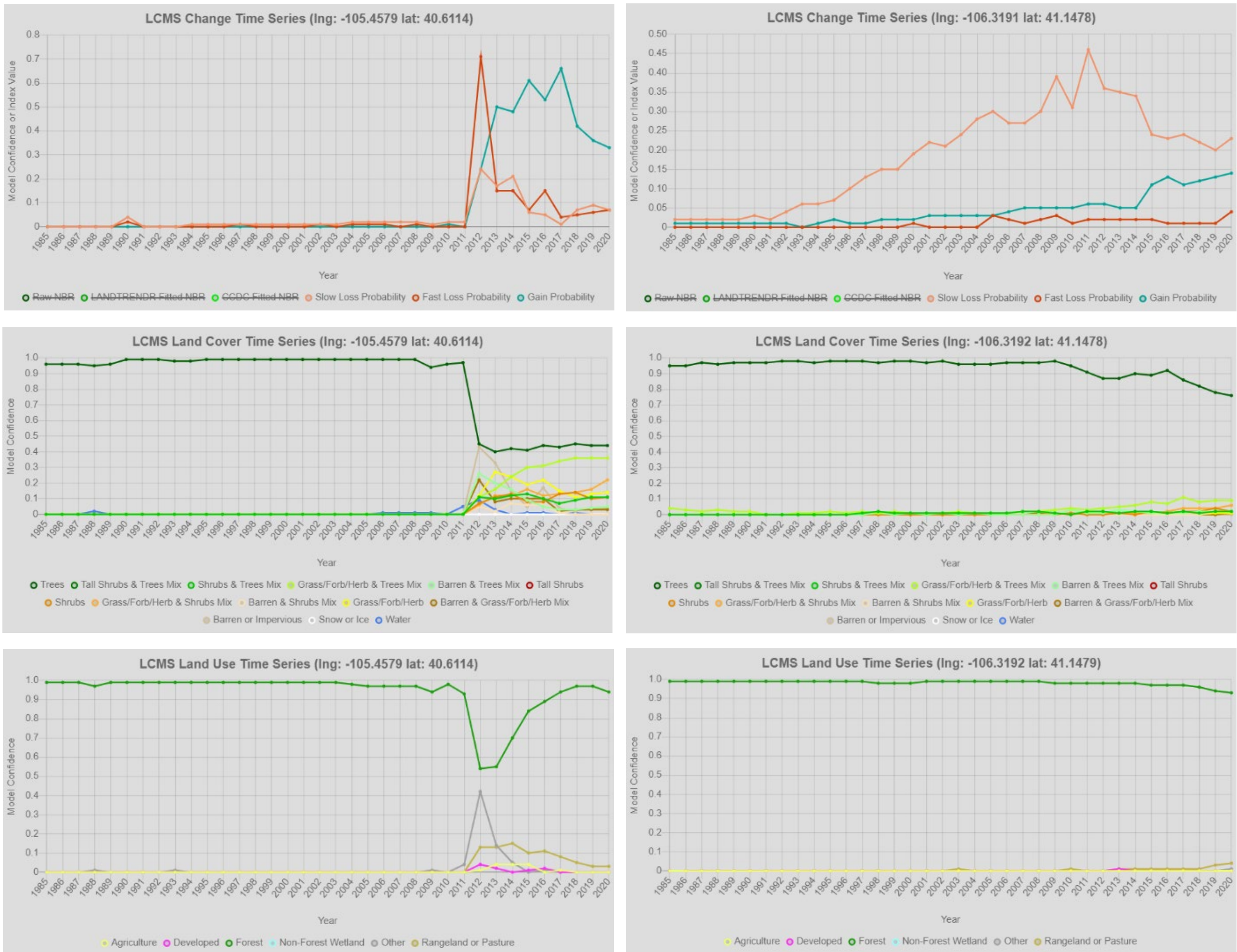


Figure 12.—Time series of Landscape Change Monitoring System (LCMS) raw modeled probabilities for each year for a fire (left column) and tree mortality due to beetles (right column). The first, second, and third rows of this figure show the Change, Land Cover, and Land Use time series respectively. The map product assumes the class with the highest confidence for each year. Notice that it is possible to have a Change event without a change in land cover or land use. long = longitude; lat = latitude.

Land Cover and Land Use ruleset and probability thresholding

To reduce commission and omission errors, we instituted a series of probability thresholds and rulesets using ancillary datasets. The ancillary datasets include (1) the Annual NLCD data (USGS 2024); (2) USDA-National Agricultural Statistics Service (NASS) Cropland Data Layer (CDL; USDA 2023) for CONUS; (3) the Global Human Settlement (GHSL) built-up surface (Pesaresi and Politis 2023) for outside the conterminous Unted States (OCONUS); and (4) the Joint Research Centre's Global Surface Water Mapping Layer (Pekel et al. 2016) for HI. We created map assemblage rules primarily for Land Use. We applied one Land Cover rule for all study areas to limit urban water commission, an additional Land Cover rule in AK to limit Tree and Snow/Ice land cover classes in intertidal zones, and an additional two Land Cover rules in HI to limit Grass class commission and limit Barren commission in reef areas in the ocean. The series of rules and associated ancillary datasets are summarized in Table 11. A pixel is finally classified according to the highest probability class that meets the minimum threshold as set forth according to the implemented rules.

Table 11.—Map assemblage rules for Land Use (LU) and Land Cover (LC) and associated ancillary datasets for the conterminous United States (CONUS), Alaska (AK), Puerto Rico–U.S. Virgin Islands (PRUSVI), Hawaii (HI), and outside the CONUS (OCONUS). Datasets include National Land Cover Database (NLCD), Cropland Data Layer (CDL), Global Human Settlement (GHSL), and Joint Research Centre (JRC).

Rule	CONUS	AK	PRUSVI	HI
Developed LU Probability Threshold	x	x	x	x
Coastal Developed LU Probability Threshold	x	x	x	x
General Agriculture LU Probability Threshold			x	x
NLCD Land Cover Cropland and Pasture mask	x			
CDL Treed Agriculture mask	x			
Alaska digitized Agriculture mask		x		
Forest in Agriculture probability threshold	x	x		
NLCD Developed class mask	x			
Coastal Tree LC Probability Threshold		x		
Probability Threshold to prevent Forest Commission in NLCD Developed (CONUS) or GHSL Builtup (OCONUS)	x	x		x
Probability Threshold to prevent Developed Omission in NLCD Developed (CONUS) or GHSL Builtup (OCONUS)	x	x	x	x
Probability Threshold to prevent Water commission in urban areas	x	x	x	x
Probability Threshold to Prevent Agriculture Commission in GHSL Builtup				x
Elevation threshold to Prevent Rangeland/Pasture Commission in Ocean using JRC Water				x
General Grass LC Probability Threshold				x
Probability Threshold to Prevent Barren Commission in Ocean				x
Probability Threshold to Prevent Other (LU) Commission in GHSL Builtup				x

Land Cover and Land Use Levels

We provide methods for users to crosswalk or bin the deliverable LCMS data products (highest level) into lower levels of thematic detail. Lower levels provide higher accuracy, while higher levels provide greater thematic detail. Most levels with higher numbers of classes exhibit lower accuracies as well. Users should use the level that best matches their error tolerance and required thematic detail. Tables 12, 13, and 14 show Land Cover, Land Use, and Change product levels, respectively.

The LCMS product levels will be included in the LCMS Data Explorer on the [LCMS Website] where users can interact with the data. In addition, we provide documentation—LCMS Levels Guidance—that includes several crosswalk methods and accuracy information for each level. The LCMS Levels Guidance documentation is an html file included in the final LCMS deliverables packaged product available to download from the [Forest Service Geodata Clearinghouse]. The geeViz Python package provides a [Jupyter notebook] that demonstrates how to programmatically crosswalk LCMS deliverables to different levels.

Table 12.—The Land Cover product classes at Levels 1, 2, 3, and 4 and their thematic colors. Level 1 reclassifies Land Cover as two classes, Vegetated and Non-Vegetated. Level 2 reclassifies Land Cover as three classes: (1) Tree Vegetated; (2) Non-Tree Vegetated; and (3) Non-Vegetated. Level 3 classes are the primary Land Cover classes (Tree, Shrub, Grass, Barren or Impervious (Imp), Snow or Ice, Water, or Non-processing area (NP)). Level 4 classes are the primary-secondary combination TimeSync (Cohen et al. 2010) Land Cover plot labels used in model calibration, prediction, and accuracy assessment. Table cell colors indicate the class each color represents in the downloadable products and data viewers.

Level 1	Level 2	Level 3	Level 4	Delivered Value
Vegetated	Tree Vegetated	Tree	Tree	1
Vegetated	Tree Vegetated	Tree	Tall Shrub & Tree Mix	2
Vegetated	Tree Vegetated	Tree	Shrub & Tree Mix	3
Vegetated	Tree Vegetated	Tree	Grass & Tree Mix	4
Vegetated	Tree Vegetated	Tree	Barren & Tree Mix	5
Vegetated	Non-Tree Vegetated	Shrub	Tall Shrub	6
Vegetated	Non-Tree Vegetated	Shrub	Shrub	7
Vegetated	Non-Tree Vegetated	Shrub	Grass & Shrub Mix	8
Vegetated	Non-Tree Vegetated	Shrub	Barren & Shrub Mix	9
Vegetated	Non-Tree Vegetated	Grass	Grass	10
Vegetated	Non-Tree Vegetated	Grass	Barren & Grass	11
Non Vegetated	Non-Vegetated	Barren or Imp	Barren or Imp	12
Non Vegetated	Non-Vegetated	Snow or Ice	Snow or Ice	13
Non Vegetated	Non-Vegetated	Water	Water	14
NP	NP	NP	NP	15

Table 13.—The Land Use product classes at Levels 1 and 2 and their thematic colors. Level 1 reclassifies Land Use classes as Anthropogenic, Non-Anthropogenic, or as Non-processing area (NP). Level 2 classes are the TimeSync (Cohen et al. 2010) Land Use plot labels used in model calibration, prediction, and accuracy assessment. Table cell colors indicate the class each color represents in the downloadable products and data viewers.

Level 1	Level 2	Delivered Value
Anthropogenic	Agriculture	1
Anthropogenic	Developed	2
Non-Anthropogenic	Forest	3
Non-Anthropogenic	Other	4
Non-Anthropogenic	Rangeland or Pasture	5
NP	NP	6

Change product cause of change ruleset

The final Change product is a reclassification of the predicted LCMS Change classes (Slow Loss, Fast Loss and Gain) that provides information on the cause of landscape change such as Tree Removal, Wildfire, or Wind damage. The LCMS science team tested several machine learning approaches to derive the Cause of Change classes. However, these tests proved less successful than a rule-set approach. We developed a ruleset based on ancillary data to further refine the Change product to 15 classes that explicitly provide information on the cause of change (Figure 13).

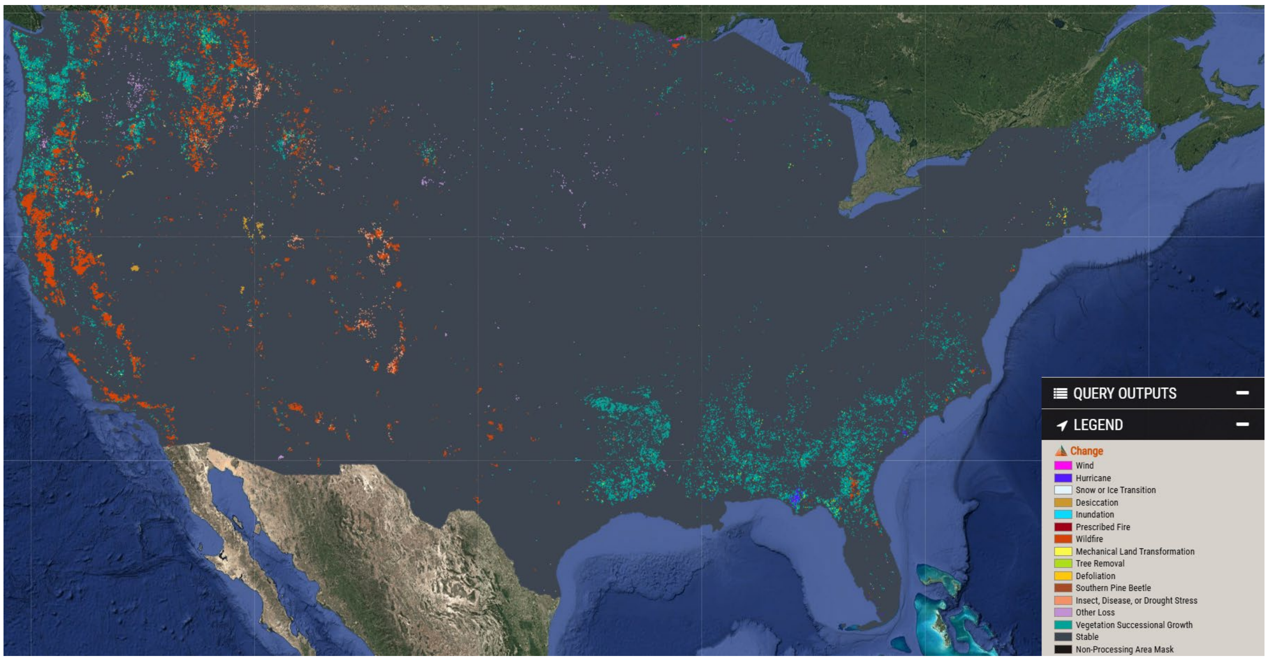


Figure 13.—Landscape Change Monitoring System Change product refined to the 15 cause of change classes (Level 3).

Table 14 shows how the cause of change ruleset refines the LCMS Change product classification from Level 1 to Level 3. We reclassify modeled Slow Loss into 1 (all study areas) or 2 (AK) classes at Level 3: Insect, Disease, or Climate Stress (all study areas) and Defoliation (AK). Next, we reclassify modeled Fast Loss into 9 unique causes: Wind, Hurricane, Prescribed Fire, Wildfire, Mechanical Land Transformation, Tree Removal, Defoliation (CONUS), Southern Pine Beetle (CONUS only), and Other Loss. Finally, we use the LCMS Land Cover data to classify Snow or Ice Transition, Desiccation, and Inundation events. Modeled Gain is classified as Vegetation Successional Growth, and Stable remains the same across all Levels.

Table 14.—The Change product classes at Levels 1, 2, and 3 and their thematic colors. Level 1 classes most closely correspond to the Change prediction classes: (1) Disturbance (Slow or Fast Loss); (2) Vegetation Successional Growth (Gain); (3) Stable; or (4) Non-processing area (NP). Level 2 classes are the TimeSync (Cohen et al. 2010) Change Process plot labels used in model calibration, prediction, and accuracy assessment. Level 3 classes are the most refined Change classes. Table cell colors indicate the color each class represents in the downloadable products and data viewers.

Level 1	Level 2	Level 3	Level 3 Values
Disturbance	Wind	Wind	1
Disturbance	Wind	Hurricane	2
Disturbance	Other Loss	Snow or Ice Transition	3
Disturbance	Desiccation	Desiccation	4
Disturbance	Inundation	Inundation	5
Disturbance	Fire	Prescribed Fire	6
Disturbance	Fire	Wildfire	7
Disturbance	Mechanical Land Transformation	Mechanical Land Transformation	8
Disturbance	Tree Removal	Tree Removal	9
Disturbance	Insect, Disease, or Drought Stress	Defoliation	10
Disturbance	Insect, Disease, or Drought Stress	Southern Pine Beetle	11
Disturbance	Insect, Disease, or Drought Stress	Insect, Disease, or Drought Stress	12
Disturbance	Other Loss	Other Loss	13
Vegetation Successional Growth	Vegetation Successional Growth	Vegetation Successional Growth	14
Stable	Stable	Stable	15
NP	NP	NP	16

The cause of change ruleset relies on the following ancillary data:

- Tree Canopy Cover (USDA Forest Service 2025b)
- Monitoring Trends in Burn Severity (MTBS) Burn Severity Images (USDA Forest Service/USGS 2024)
- Insect & Disease Surveys (IDS; USDA Forest Service 2024)
- Manually digitized Southern Pine Beetle outbreak and defoliation event polygons
- Interagency Fire Perimeter History (IAFP; National Interagency Fire Center Open Data 2024)
- Provisional Initial Assessment Data (PIAD) MTBS fire boundaries (USDA Forest Service/USGS 2025)
- Rapid Assessment of Vegetation Condition after Wildfire (RAVG; Miller et al. 2015)
- Protected Areas Database (PAD-US) version 2.0 (USGS 2018)
- Storm Prediction Center severe report database tornado data (NOAA/NWS 2025)
- HURDAT2 hurricane track data (Landsea and Franklin 2013)
- 3D Elevation Program Digital Elevation Model (USGS 2019a)
- Global mining footprint (Tang and Werner 2023)

For the cause of change ruleset, we used the LCMS modeled Change data to identify (1) Slow Loss, Fast Loss, and Gain events; (2) LCMS Land Cover data to differentiate between vegetated and non-vegetated land; and (3) LCMS Land Cover data to identify Inundation, Desiccation, and Snow or Ice Transition. The specifics of the cause of change ruleset (Change Level 3) include:

1. Insect, Disease, or Drought Stress is the reclassification where modeled Slow Loss of vegetation occurred.
2. Wildfire is the reclassification where fire data (MTBS, RAVG, PIAD, IAFP) identified that Wildfire and Fast Loss occurred (National Interagency Fire Center Open Data 2024, USDA Forest Service/USGS 2024, Miller et al. 2015).
3. Prescribed Burn is the reclassification where fire data (MTBS or IAFP) identified that Prescribed Burn and Fast Loss occurred (USDA Forest Service/USGS 2024).
4. Tree Removal:
    a. For CONUS, Tree Removal is the reclassification where Fast Loss occurred, the LCMS Land Cover class mode of the previous three years was a Tree class, the area of connected pixels totals 1.5 ha or greater, Tree Canopy Cover loss was 30 percent or greater (USDA Forest Service 2025b), pixels were not located in protected wilderness (USGS 2018), and there was not a Wildfire or Prescribed Burn.
    b. For OCONUS, Tree Removal is the reclassification where Fast Loss occurred, the LCMS Land Cover class mode of the previous three years was a Tree class, the LCMS Land Cover class mode of the following three years was not a Tree class, the area of connected pixels totals 1.5 ha or greater, pixels were not located in protected wilderness (USGS 2018), and there was not a Wildfire or Prescribed Burn.
5. Hurricane is the reclassification where Fast Loss occurred, a Hurricane occurred (Landsea and Franklin 2013), tree damage was caused by a storm event (Gardiner et al. 2000, Gardiner et al. 2008), Inundation occurred (pixels below 3 m elevation; USGS 2019b), and there was not a Wildfire or Prescribed Burn. There is no Hurricane reclassification in AK.
6. Wind is the reclassification where Fast Loss occurred, IDS data identify a wind event (for AK) or the Storm Prediction Center severe report database or digitized Wind polygons identified a tornado or Wind event (for CONUS; NOAA/NWS 2025), and there was not a Wildfire, Prescribed Burn, or Hurricane.
7. Desiccation is the reclassification where LCMS Land Cover data identified Water in the previous year, followed by a class other than Water in the current year (USDA Forest Service 2025a).
8. Inundation is the reclassification where LCMS Land Cover data identified a class other than Water in the previous year, followed by Water in the current year (USDA Forest Service 2025a).
9. Southern Pine Beetle is the reclassification where Fast Loss occurred and the area of connected pixels total less than 1.5 ha, the LCMS Land Cover class mode of the previous three years was a Tree class, digitized polygons or insect and disease surveys (IDS) data identified southern pine beetle (USDA Forest Service 2023), and there was not a Wildfire, Prescribed Burn, Hurricane, or Wind event. There is no Southern Pine Beetle reclassification outside of the CONUS.

10. Defoliation is the reclassification where Fast Loss occurred (for CONUS) or Slow Loss occurred (for AK), the LCMS Land Cover class mode of the previous three years was a Tree class, digitized polygons or IDS data identified defoliation (USDA Forest Service 2023), Tree Canopy Cover loss was 50 percent or greater, and there was not a Wildfire, Prescribed Burn, Hurricane, or Wind event.
11. Mechanical Land Transformation is the reclassification if one of the following three scenarios occurred:
    a. Scenario 1: Fast Loss occurred outside protected wilderness, the LCMS Land Use class mode of the following three years was Developed, and there was not a Wildfire, Prescribed Burn, Hurricane, Wind, Desiccation, or Inundation event.
    b. Scenario 2: Fast Loss occurred outside protected wilderness, the LCMS Land Use class mode of the previous three years was Agriculture, LCMS Land Cover data indicates there was a Land Cover change, and there was not a Wildfire, Prescribed Burn, Hurricane, Wind, Desiccation, or Inundation event.
    c. Scenario 3: Fast Loss occurred outside protected wilderness, mining occurred (Tang and Werner 2023), and there was not a Wildfire, Prescribed Burn, Hurricane, Wind, Desiccation, or Inundation event.
12. Snow or Ice Transition is the reclassification where LCMS Land Cover data identified a change from or to Snow or Ice between the previous year and current year.
13. Other Loss is the reclassification where Fast Loss occurred and none of the other previous Change Level 3 class events occurred.
14. Vegetation Growth is the reclassification where modeled vegetation Gain occurred.
15. Stable was the reclassification where no Loss or Gain event occurred.

Accuracy assessment

To assess final map accuracy, we use the hyperparameters and thresholds chosen in the model tuning step in a stratified 10-fold cross-validation following Stehman (2014) for each Change, Land Cover, and Land Use predicted output. We use the locations for the stratified random sample of 30-by-30-m plots as the sample and group the training points by their Plot ID so that all years of training points that come from the same plot are always included in the same fold. The rules implemented in the map assemblage are mirrored in the accuracy assessment to ensure we are assessing the accuracy of LCMS' final maps rather than its models. To calculate overall and balanced accuracy for each product, we compare the final predictions (after assemblage rules) with the TimeSync class (Cohen et al. 2010) for each plot for each year and count the number of correct and incorrect predictions. For Change, accuracy is assessed using the Level 2 classes and the change process from the TimeSync interpretations; there is insufficient information in the TimeSync interpretation data to assess accuracy of Change at Level 3.

Landscape Change Monitoring System products

We package the final LCMS deliverables in annual layers. For each product (Change, Land Cover, and Land Use) we assemble annual maps, as discussed above.

Ancillary information on the origin of the annual LCMS product output values is now provided as part of a quality assessment (QA) bit layer. This layer includes whether an interpolated value was used to produce the LCMS output, the sensor, and the day of year the LandTrendr value came from. The QA bits are as follows:

- 1: Interpolated (0), not interpolated (1)
- 2–6: Which sensor the pixel came from
    - 4 = Landsat 4
    - 5 = Landsat 5
    - 7 = Landsat 7
    - 8 = Landsat 8
    - 9 = Landsat 9
    - 21 = Sentinel 2a
    - 22 = Sentinel 2b
- 7–15: Which Julian day the pixel came from (1–365)

Bitwise operations can be leveraged to unpack the QA decimal numbers to valid pixel values for the non-interpolated data, sensor, and Julian day (see the downloaded data's metadata for more detailed methods). Figure 14 shows how the bits are used in the QA Bits output image.

LCMS QA Band Bits; Read from RIGHT to LEFT, starting with Bit 1																
Bit	16	15	14	13	12	11	10	9	8	7	6	5	4	3	2	1
Description		Julian Day									Sensor					Interpolated/Non-Interpolated

Figure 14.—How bits are used in the QA Bits output image.

Known Issues

Change product known issues

- Commission of Fast Loss in early and late years:
    - Temporal segmentation is prone to over-fitting at the beginning and end of a time series. As a result, Fast Loss commission in the start year and end years in the CONUS is high. For v2024.10, the start year of 1985 and the end years of 2023 and 2024 were high. The Loss commission in 1985 is concentrated in the Pacific Northwest and in 2024, it is concentrated in the upper Midwest.
- Low Change product accuracies in HI (most notably for Slow Loss and Fast Loss classes):
    - v2023-9 is the first release of LCMS data for HI. We hope to improve our outputs in future releases by implementing different modeling techniques, additional training data, and/or calibration data sample re-design or augmentation.

Land Cover product known issues

- Open-canopy and dry deciduous tree areas are often classified as non-tree.
    - This issue is most prevalent in western CONUS pinyon-juniper, areas of AK where there are open-canopy forests, and dry deciduous forests in HI.
- Alpine, non-tree landscapes are often classified as Tree classes near tree line in the western CONUS.

Land Use product known issues

- Low Agriculture class accuracies across PRUSVI and HI:
  - We hope to improve our outputs in future releases. Some means through which we may continue to seek improvements include different modeling techniques, introduction of additional map assemblage rules and/or inclusion of additional ancillary datasets, additional training data, and/or calibration data sample re-design or augmentation.
- Agriculture omission in OCONUS:
  - Often, there is commission of non-agricultural classes in areas of agricultural land use. Our current methods address this issue for CONUS using NLCD and CDL data during the map assemblage process. However, these data are not available in OCONUS where Agriculture omission errors can be high. We are actively exploring methods to improve Agriculture omission errors, which includes using convolutional neural networks to model Agriculture independently from other Land Use classes.
- Coastal beaches and dunes in HI are often classified as Developed:
  - Many beaches and sand dunes are characterized by bright sand that is spectrally similar to concrete structures. Rules were implemented during the map assemblage to limit Developed commission in coastal beaches. However, some commission persists, particularly at elevations more than a few meters above sea level.

Useful Resources

- LCMS Homepage
- LCMS Data Explorer
- LCMS Data Download Archive
- ESRI Image Services
- LCMS GEE Collection
- Pilot Product Description
- LCMS Contact Information

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