

## Tree regrowth duration map from LCMAP collection 1.0 land cover products in the conterminous United States, 1985–2017

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### ABSTRACT

Forest covers about one-third of the land area of the conterminous United States (CONUS) and plays an important role in offsetting carbon emissions and supporting local economies. Growing interest in forests as relatively cost-effective nature-based climate solutions, particularly restoration and reforestation activities has increased the demand for information on forest regrowth and recovery following natural and anthropogenic disturbances (e.g. fire, harvest, or thinning). However, a wall-to-wall mapping of the CONUS tree regrowth duration at an annual time interval and 30-m resolution is still challenging. In this study, we utilized the annual land cover products to develop a dataset to quantify forest regrowth duration for CONUS over 1985–2017. The land cover data used to derive the tree regrowth duration map is from the primary land cover product in the U.S. Geological Survey's Land Change Monitoring, Assessment, and Projection (LCMAP) collection. The LCMAP product used all available Landsat images to detect disturbances over forest and classify Grass/Shrub to Tree Cover transitions on an annual basis. The average regrowth duration was then calculated for each pixel. The regrowth duration map was validated using human-interpreted annual reference data that were collected independently. The validation results show 1 year of underestimation and 6-year standard deviation of error between the reference data and the regrowth duration map. In southeastern CONUS, where major tree regrowth activities have been observed, our map showed higher accuracy with less than one-year bias and 3.6 years standard deviation of error. Forest in the southeast took around 5 years to recover, which was faster than other regions of CONUS. Many pixels had multiple disturbances during the 33-year study period in the region. The spatial pattern of the tree regrowth indicated intense harvesting activities in this region. The Pacific Northwest coast region was the second main area of tree regrowth, but this region often took multiple decades to recover. Given the increasing interest in forests as nature-based climate solutions, the tree regrowth duration map can be used to assess reforestation activities as well as forest recovery following natural disturbance and harvesting.

### ARTICLE HISTORY

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Tree regrowth; Landsat; land cover; LCMAP

## 1. Introduction

In the conterminous United States (CONUS), forest covers about one-third of the land area (Marsik et al. 2018). Forest disturbances such as logging, fire, and floods can substantially affect canopy biomass and structure. Forest dynamics are important sources of information for estimating carbon accumulation (Cook-Patton et al. 2020; Pugh et al. 2019; Domke et al. 2020; Nunes et al. 2020), mitigating climate change (Qin et al. 2021; Fargione et al. 2021), understanding ecosystem services (Hansen et al. 2013; Lindenmayer 2009), and supporting the local economy (Schultz 2008) and recreation (Butler et al. 2016).

Quantitative information about tree regrowth duration at the national scale can effectively support forest management (Schultz 2008; Sloan et al. 2019; Schelhas, Brandeis, and Rudel 2021), which requires timely and accurate forest monitoring (Gillespie 1999; Kennedy, Yang, and Cohen 2010). Historical land cover information is fundamental for estimating tree regrowth duration at the national scale.

Remote sensing has long been recognized as an efficient technique for large-scale land cover mapping (Etienne and Belward 2005; Friedl et al. 2002; Collin et al. 2007; Homer et al. 2015; Loveland et al. 2000). With the history of satellite observation, the rise of

more advanced satellite data, the surge of cloud computing, and new algorithms, considerable progress has been made in large-scale land cover mapping (Yifang, Gong, and Gini 2015; You et al. 2021; Store, Copernicus Climate Data 2019; Vancutsem et al. 2020; Christelle et al. 2021; White et al. 2022). National- and global-level land cover mapping emerged, such as the Moderate Resolution Imaging Spectroradiometer (MODIS) yearly land cover (LC) dataset (Friedl et al. 2002, 2017), Climate Change Initiative LC dataset (Defourny et al. 2016), Finer Resolution Observation and Monitoring Global LC dataset (Gong et al. 2013), and 30-m resolution Global LC dataset (Globeland30) (Chen et al. 2015). These successfully developed products enable the understanding of land information and advance the environmental modeling for global land cover studies (Yifang, Gong, and Gini 2015). However, those products either mapped tree cover every few years or at coarse spatial resolutions. Other studies explored monitoring annual forest change outside the United States using long-term Landsat data (Vancutsem et al. 2020; Christelle et al. 2021; White et al. 2022). For example, Christelle et al. (2021) mapped forest cover changes at 30-m resolution in global humid tropics from 1990 to 2019 using the Landsat archive. Similarly, White et al. (2022) mapped forest recovery from 1985 to 2017 in Canada using Landsat data.

Landsat data provide 30 × 30 meter spatial resolution and a long observation history. Hansen et al. (2013) mapped global tree cover on an annual basis from 2000 onward using Landsat data, which was often used for studying forest changes in the United States. However, tree regrowth often takes several decades, so more extended tree cover monitoring can cover longer tree regrowth activities. The U.S. Geological Survey (USGS) recently released analysis ready data (ARD) that contains Landsat data from the 1980s to the present including all available surface reflectance data over the United States from the Thematic Mapper (TM) aboard Landsats 4 and 5, the Enhanced Thematic Mapper Plus (ETM+) aboard Landsat 7, and the Operational Land Imager (OLI) aboard Landsat 8 (Dwyer et al. 2018). Landsat ARD greatly enhanced monitoring of long-term tree regrowth.

The USGS Land Change Monitoring, Assessment, and Projection (LCMAP) project adopted Landsat ARD and the Continuous Change Detection and

Classification (CCDC) algorithm (Zhe and Woodcock 2014) to detect disturbances at the 30 × 30 meter scale and map land cover and land use change (LCLUC) (Brown et al. 2020) across multiple years. Capable of detecting different land cover/land use changes and of providing LCLUC maps for any given time within the dense time series, the CCDC algorithm has been extensively tested and implemented to monitor LCLUC in the United States (Brown et al. 2020; Peng and Weng 2016; Pengra et al. 2016; Vogelmann et al. 2016; Zhu et al. 2016a; Zhe and Woodcock 2014; Zhu et al. 2020) and China (Zhu et al. 2016b). LCMAP has published a suite of products to characterize annual land cover types and land surface disturbances across the CONUS since 1985 (Brown et al. 2020; Xian et al. 2022).

The main objectives of this effort were to (1) map tree regrowth duration for CONUS at 30-m spatial resolution using the LCMAP annual land cover data for 1985–2017; (2) assess the accuracy of the regrowth duration map using published validation data; and (3) characterize the spatial pattern of the map error. In this study, tree regrowth is defined as the reappearance of the Tree Cover class after cessation of previous forest disturbance (e.g. harvest or fire). The Tree Cover class definition, in LCMAP, is tree-covered land where the tree cover density is greater than 10%. Forest disturbance denotes events that cause substantial mortality or leaf-area decline within a forest stand, including harvest, thinning, and fire (Masek et al. 2013). The tree regrowth duration is defined as the number of years needed for tree cover to meet the definition again after disturbances. This study, however, does not consider land conversions such as cropland reforestation because defining the start of tree regrowth in those scenarios is challenging.

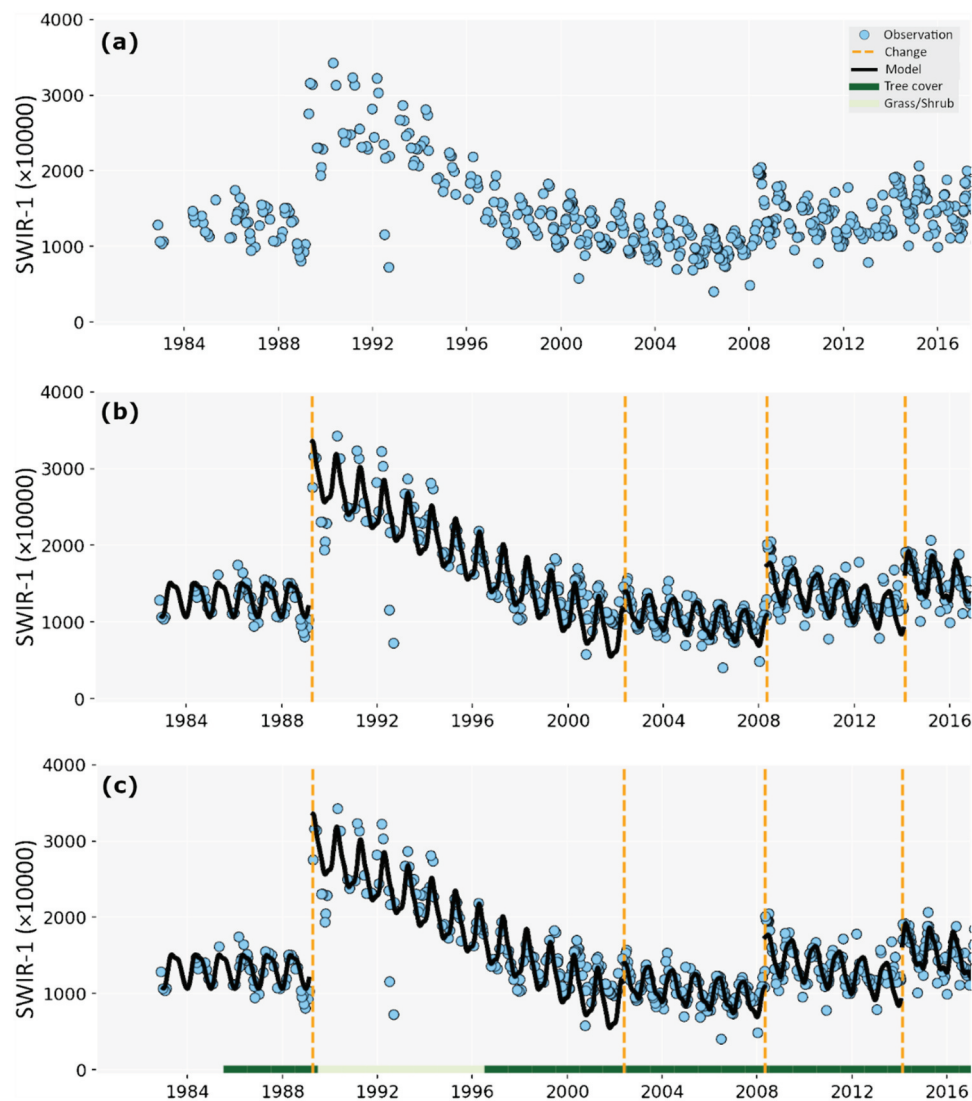
## 2. Methods and materials

The tree regrowth duration map was calculated using the annual primary land cover product (LCPRI) from LCMAP collection 1.0. In this section, we briefly describe the LCMAP primary land cover product (Section 2.1), as well as the calculation of tree regrowth duration (Section 2.2). We then evaluate the results using an independent dataset: human interpreted validation plots (Pengra et al. 2020) (Section 2.3).

## 2.1 LCMAP primary land cover product

The LCMAP product creation utilized all cloud-free Landsat ARD observations (Figure 1a) and consisted of two steps (Brown et al. 2020; Xian et al. 2022): (1) change detection of time series from 1985 to 2017 for each pixel (Figure 1b), (2) land cover classification for stable period of the time series (Figure 1c). The change detection procedure detected possible disturbances and built multi-year time-series models to represent periods with stable land covers. The multi-year time-series models were then used for classification, which effectively reduced inconsistency of land cover classification through time. The LCMAP land cover classes include Developed, Cropland, Grass/Shrub, Tree Cover, Water, Wetland, Ice/Snow, and Barren.

The LCMAP land cover product was validated for single years (Table 1) and summarized to show the average accuracy of all 33 years (Table S1) (Bruce et al. 2020). The validation was conducted for the entire CONUS as well as four mega regions (West, West Central, East Central, East) (Brown et al. 2020; Bruce et al. 2020). Because tree regrowth emerges from Grass/Shrub, we are reporting the accuracy of the Tree Cover and Grass/Shrub classes in LCMAP. For the entire CONUS, Tree Cover user accuracy (UA) ranged from 90% to 91% and producer accuracy (PA) ranged from 82% to 84% between 1985 and 2017; Grass/Shrub UA ranged from 87% to 89% and PA ranged from 79% to 81% (Table 1). Overall, the LCPRI product showed consistent land cover accuracy



**Figure 1.** Demonstration of change detection and annual land cover class production for a given pixel using all available Landsat SWIR-1 (~1.6  $\mu\text{m}$ ) surface reflectance. (a) all cloud-free observations; (b) harmonic model (black curves) and detected changes (orange dashed lines); and (c) annual land cover classes based on harmonic models (colored bars at the bottom).

**Table 1.** Classification accuracy for the conterminous United States in percentage of Tree Cover and Grass/Shrub (Gr/Sh) at every other year.

| CONUS          | 1985 | 1987 | 1989 | 1991 | 1993 | 1995 | 1997 | 1999 | 2001 | 2003 | 2005 | 2007 | 2009 | 2011 | 2013 | 2015 | 2017 |
|----------------|------|------|------|------|------|------|------|------|------|------|------|------|------|------|------|------|------|
| Tree User      | 90   | 90   | 90   | 90   | 90   | 90   | 90   | 90   | 90   | 90   | 90   | 90   | 91   | 91   | 90   | 90   | 90   |
| Tree Producer  | 83   | 83   | 84   | 84   | 84   | 84   | 84   | 84   | 83   | 83   | 83   | 83   | 83   | 82   | 82   | 82   | 82   |
| Gr/Sh User     | 87   | 88   | 88   | 89   | 89   | 89   | 88   | 88   | 88   | 88   | 87   | 87   | 87   | 87   | 87   | 87   | 87   |
| Gr/Sh Producer | 79   | 79   | 79   | 79   | 79   | 79   | 80   | 80   | 80   | 80   | 80   | 80   | 80   | 81   | 80   | 80   | 79   |

across 33 years. Tree Cover was mainly located in the East and West mega regions. The West mega region had higher Grass/Shrub accuracy (UA: 90%, PA: 91%) than the East mega region (UA: 36%, PA: 15%) (Table S1).

Most of the Grass/Shrub in the west mega region is natural vegetation, while Grass/Shrub in the east region is mostly either agricultural pastureland of domestic grasses or lands regenerating or establishing tree cover. The low PA and UA of Grass/Shrub in the east region mainly resulted from misclassification between Cropland and Grass/Shrub in the non-forest area. The accuracy assessment for all classes can be found in the LCMAP Collection 1.0 validation report (Pengra et al. 2020) (<https://doi.org/10.5066/P98EC5XR>).

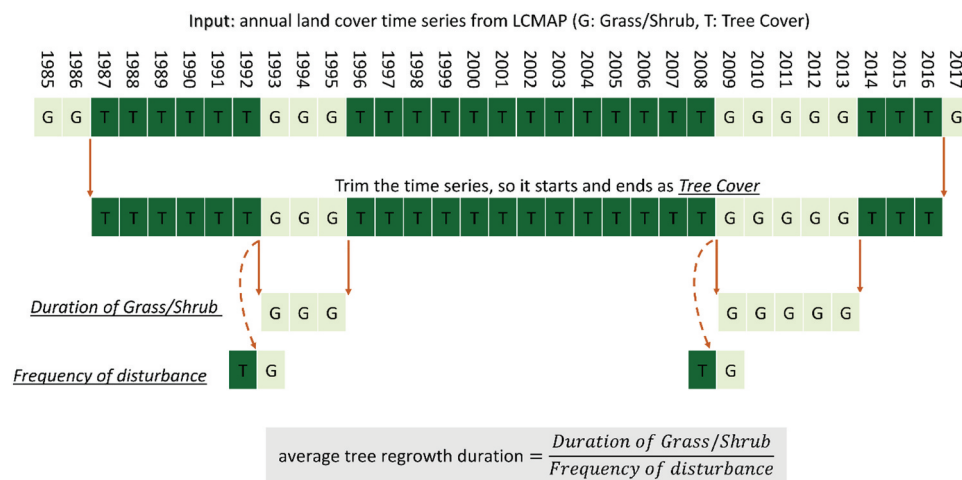
## 2.2 Calculate tree regrowth duration

We calculated the tree regrowth duration using LCMAP land cover data from 1985 to 2017. Some areas experienced multiple disturbances over 33 years associated with rapid regrowth. Those phenomena were often related to harvest and replanting

or natural regeneration. Thus, we mapped the average tree regrowth duration when multiple periods of regrowth occurred for a given pixel.

On the other hand, some of the regrowth processes were not completely captured by the 33-year land cover mapping effort, which may lead to underestimation of regrowth duration. For example, Tree Cover that was disturbed and remained Grass/Shrub in 2017 might require more time to grow enough to be classified as Tree Cover again. Similarly, if the forest was disturbed before 1985, the land cover time series would show Grass/Shrub at the beginning, later transitioning to Tree Cover. Thus, we trimmed the time series of land cover data for each pixel to ensure it started and ended with Tree Cover to eliminate incomplete tree regrowth processes (Figure 2).

Within the trimmed time series, we calculated the number of disturbances showing a land cover change from Tree Cover to Grass/Shrub, as well as the total number of years in the Grass/Shrub class as the total tree regrowth duration following disturbances. The average tree regrowth duration was calculated as the ratio between the total tree regrowth duration and the disturbance frequency. The ratio was rounded to an integer to match the time interval of the input annual land cover

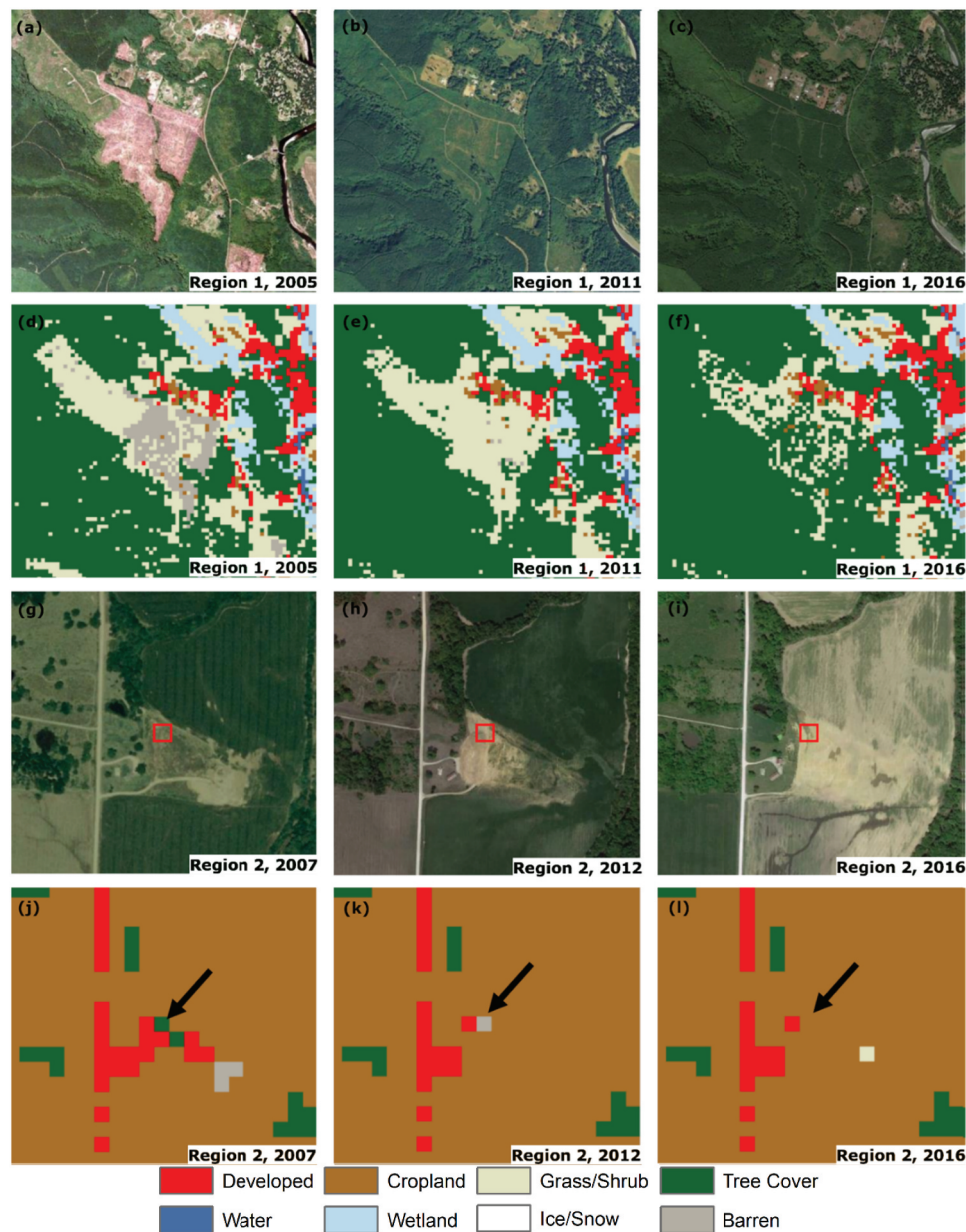
**Figure 2.** Illustration of calculating average tree regrowth duration from annual land cover data.



data. For example, Figure 2 shows two disturbances (Tree Cover to Grass/Shrub changes) and a total of 8 years of Grass/Shrub during the tree regrowth for the given pixel, which resulted in an average of 4 years of tree regrowth duration. Based on the method, if a forest pixel reported zero duration, it could indicate no disturbances for the entire 33 years or that the forest did not grow back before 2017.

In some other scenarios, the pixel was labeled as other classes during the tree regrowth. For example, in region 1 displayed in Figure 3, the area was

classified as Tree Cover from 1985 to 2003, Barren from 2004 to about 2007, then Grass/Shrub to around 2014 before the trees grew back enough to be classified as Tree Cover again. During regrowth, new roads were constructed, indicating the disturbance might persist before the tree cover started growing. In Figure 3 region 2, a scattered Landsat pixel was classified as Tree Cover 1985–1989, Cropland 1990–2000, Developed 2001–2004, Tree Cover 2005–2011, Barren 2012–2013, and Cropland 2014–2017. This pixel was frequently disturbed, and might be misclassified



**Figure 3.** Illustration of other scenarios of tree regrowth in LCMAP. (a)–(c) are Google Earth images for the region 1 example (Lon:  $-123.700514^\circ$ , Lat:  $47.013500^\circ$ ), (d)–(f) are LCMAP land cover maps. (g)–(i) are Google Earth images for the region 2 example (Lon:  $-93.862016^\circ$ , Lat:  $38.670056^\circ$ ), (j)–(l) are LCMAP land cover maps. The red squares represent the Landsat pixel pointed out in (j)–(l).

sometimes by LCMAP short time-series models. These scenarios may not reveal the actual tree regrowth duration, so in this study, we excluded Tree Cover to other classes scenarios and only considered regrowth that was immediately classified as Grass/Shrub after disturbances. This condition filtered out 3.7% of tree regrowth pixels and yielded different estimations in 0.8% of the remaining tree regrowth pixels, which affected a total of 4.4% regrowth pixels.

## 2.3 Validation

### 2.3.1 Validation of tree regrowth duration

We used the LCMAP reference data to validate the results of tree regrowth duration (Pengra et al. 2020). The LCMAP reference data contained 25,000 random pixel samples that recorded annual land cover types from 1985 to 2017 and disturbances with the occurring year. The LCMAP reference data were interpreted by multiple land remote sensing analysts (Pengra et al. 2020). Interpreters investigated the time series of Landsat data and high-resolution images from Google Earth to identify possible disturbances and distinguish Tree Cover from Grass/Shrub or other land covers. Interpreters also identified disturbance types including harvest, thinning harvest, fire, mechanical, hydrology, wind, spectral decline, structural decline, and others (Figure S1). Because this study focused on the Tree Cover changes, 6957 forest plots were selected as reference data, including all plots that had forest to Grass/Shrub changes and stable forests. The average tree regrowth duration was calculated using the same method as described in Section 2.2.

Our resultant map relied on both accurate forest disturbance detection and land cover classification in LCMAP. Accurate disturbance detection ensured that the tree regrowth process was captured, while accurate classification ensured that the duration of the process was estimated. Thus, we evaluated our results from two aspects. (1) The accuracy of the disturbance detection was calculated using error metrics commission (Eq 1), omission (Eq 2), and the accuracy metric F1 score (Eq 3) (Zhu et al. 2020). We further evaluated the percentage of disturbance detected for each disturbance type. (2) Tree regrowth duration estimates obtained from the LCMAP land cover maps were

compared with the estimates from reference data. The error was calculated as the reference data calculated regrowth duration minus the map derivative.

$$\text{commission} = \frac{\text{detected disturbances disagree with reference}}{\text{total number of detected disturbances}} \times 100\% \quad (1)$$

$$\text{omission} = \frac{\text{reference disturbances disagree with detection}}{\text{total number of reference disturbances}} \times 100\% \quad (2)$$

$$F1\text{score} = \frac{(1 - \text{commission}) \times (1 - \text{omission})}{2 - \text{commission} - \text{omission}} \times 200\% \quad (3)$$

### 2.3.2 Identifying spatial clusters of error

We also evaluated the spatial pattern of error in the tree regrowth duration using optimized hot spot analysis (OHSA) (Arthur and Keith Ord 2010; Ord and Getis 1995). The OHSA calculates a z-value and p-value for each data point within the context of neighboring data, which indicates whether there are significantly high or low values compared to the overall average. The default *COUNT\_INCIDENTS\_WITHIN\_FISHNET\_POLYGONS* was used to automatically identify neighboring data. The z-value and p-value were automatically aggregated to a confidence level bin (Gi\_Bin) that identified statistically significant high-value and low-value spots. We applied OHSA to the absolute error of our tree regrowth duration. Thus, statistically significant low z-scores represent clustering of low errors, while statistically significant high z-scores represent clustering of high errors.

## 3. Results

### 3.1 Overview of tree cover dynamics

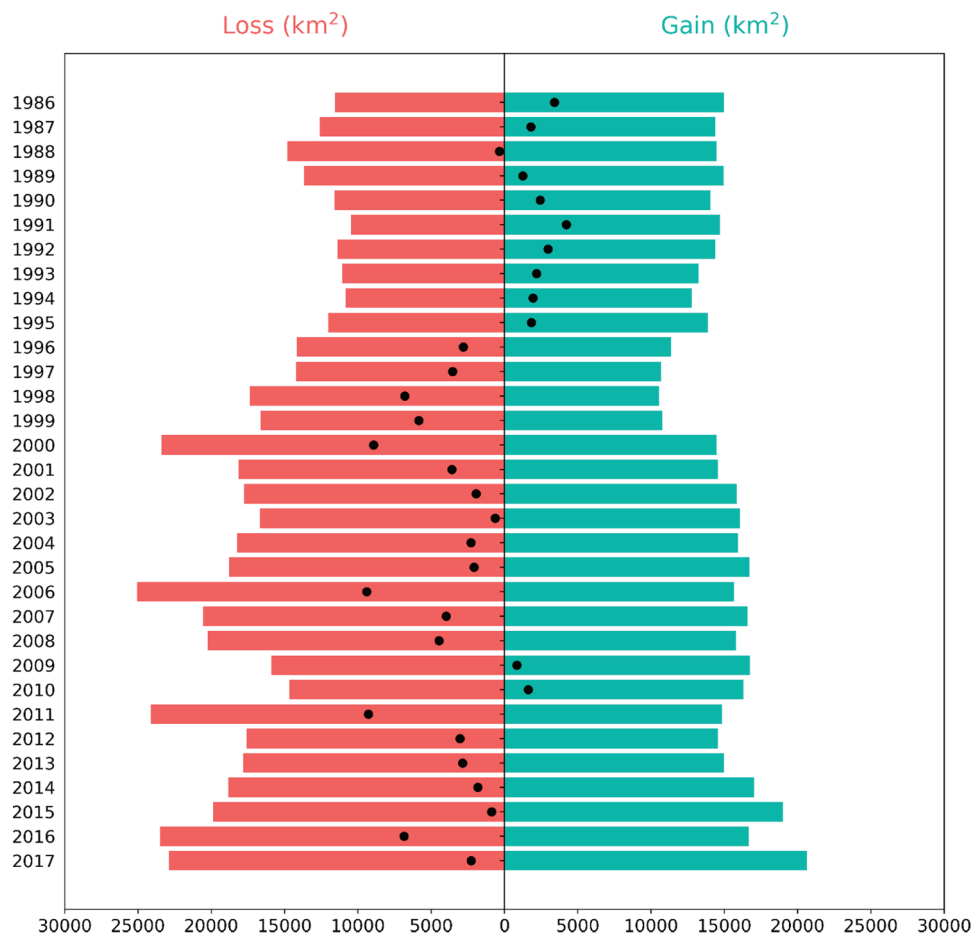
This section reports the dynamics of all Tree Cover mapped by the LCMAP land cover product, including non-disturbed and regrown forest each year. To describe the dynamics of the Tree Cover changes, we report the annual gain (non-tree classes to Tree Cover), loss (Tree Cover to non-tree classes), and net change of Tree Cover (gain – loss) from 1986 to 2017 (Figure 4). We also report the area and percentage of Tree Cover changes after forest disturbances (Figure 5). Before the year 2000, the area of loss was similar to the area of gain. The maximum total increase in Tree Cover (gain – loss) occurred in 1991

with 4228.5 km<sup>2</sup>. Since then, the loss of Tree Cover has been greater than the gain in most years. The trends in this study are slightly different from Auch et al. (2022) because their results were based on statistical estimates from LCMAP reference plots and trends from the current study are from changes in the map pixels. Figure 5b reveals that most tree losses prior to 2000 grew back (68% on average) before 2017. After 2000, the observed tree regrowth gradually declined, while more area remained as Grass/Shrub before 2017, indicating more incomplete tree regrowth process. Tree Cover was mainly converted to Grass/Shrub, Cropland, Developed, and Barren when regrowth did not occur before 2017. It is worth noting that the LCMAP land cover product in the last year has relatively low accuracy because of limited Landsat data at the end of a time series, which may explain the increasing Tree Cover to Cropland conversion (Xian et al. 2022). The years

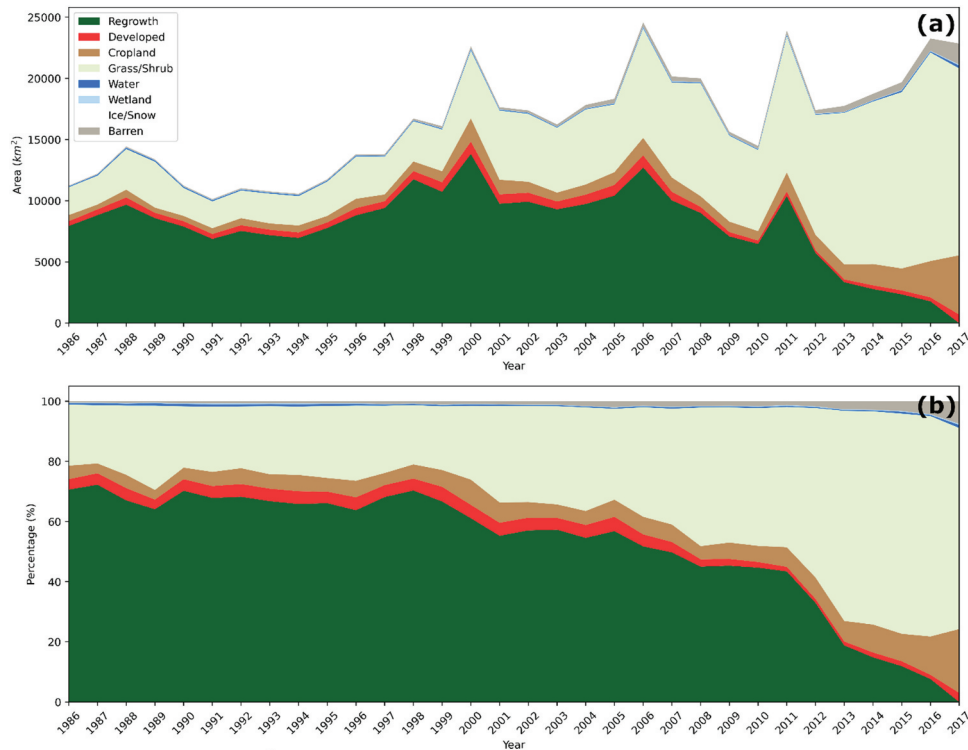
with the greatest tree loss were 2000, 2006, and 2011 (Figure 4), although more tree regrowth was also captured (Figure 5a). Correspondingly, more fire burns were observed in 2006 and 2011 (Auch et al. 2022).

### 3.2 Tree regrowth duration

The tree regrowth duration map shown in Figure 6a is aggregated to 3 × 3-km grid using the average method to represent all 30-m regrowth pixels within the grid. Figure 6b shows a forest patch in the northeast region that was disturbed in 1990 and took about 20 years to grow back. The Pacific Northwest coast region usually takes over 10 years to grow back to tree cover (Figure 6a). Figure 6c is an example of multiple harvests in the northwest region. The regrowth duration, however, has a large variance that ranges from less than 5 years to over



**Figure 4.** Area (km<sup>2</sup>) of Tree Cover gain and loss for the conterminous United States from 1986 to 2017, based on pixel count changes from the LCMAP product. The black dots are net changes (Gain – Loss) in each year. Average gain and loss are 14,922 km<sup>2</sup> and 16,768 km<sup>2</sup>, respectively. The total net change is –59,059 km<sup>2</sup>.



**Figure 5.** (a) The area ( $\text{km}^2$ ) of tree cover loss for the conterminous United States in each year. X-axis represents the disturbance year. For example, the Barren area in 2006 represents pixels that were Tree Cover in 2005; land cover changed to Barren in 2006 and did not grow back to Tree Cover before 2017. (b) The percentage area ( $\text{km}^2$ ) of tree cover loss after the most recent forest disturbance in each pixel. The color represents tree regrowth before 2017 (green) and other classes if tree cover did not grow back before 2017. Note: The last several years of the LCMAP primary land cover product have relatively low accuracy, which may influence the trend of Tree Cover changes (Xian et al. 2022).

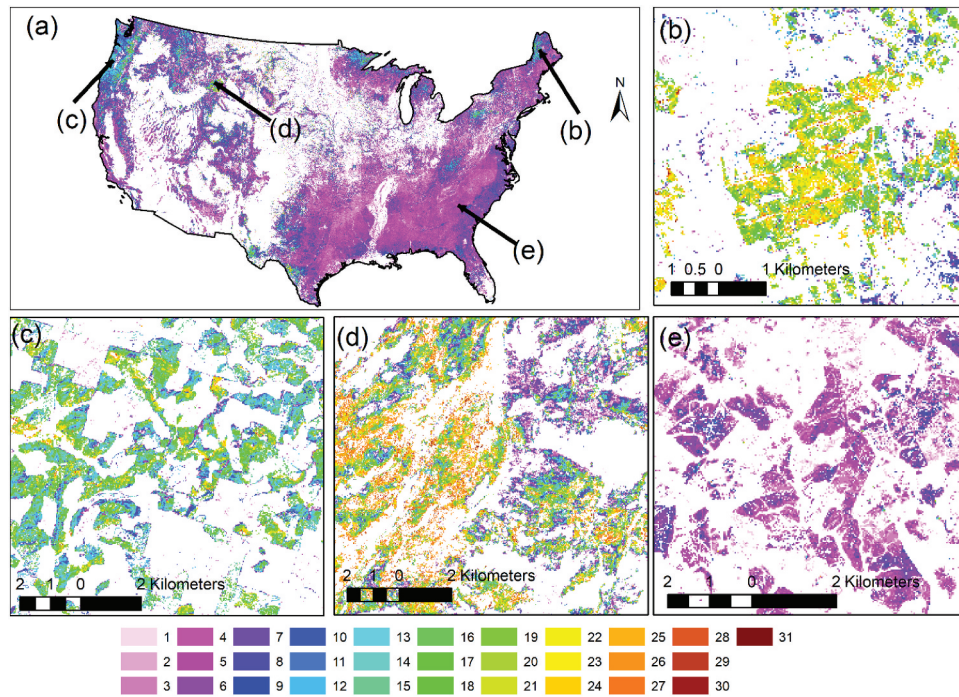
2 decades. The southeast area has an average 5-year regrowth duration. Figure 6e shows an example of regrowth from forest harvest in the southeast area. The harvest patches mostly recover in 3–8 years. The map also highlights some small regions with longer regrowth duration. For example, Figure 6d reveals tree regrowth from fire events during 1988 in Yellowstone National Park. The white color indicates the area is either not burned or remains as Grass/Shrub after the fire. For the recovered area, the west side showed a longer duration (from about 10 years to almost 30 years) than the east side.

Figure 7 tracks the tree regrowth duration after disturbance in each year. Generally, more tree regrowth starts after 1998. Overall, 64.3% of regrowth duration is less than or equal to 6 years from the disturbance, with 10.7% on average in each year. For all regrowth, 86.5% is less than or equal to 10 years, 11.7% is 11–20 years, and 1.8% is 21–31 years.

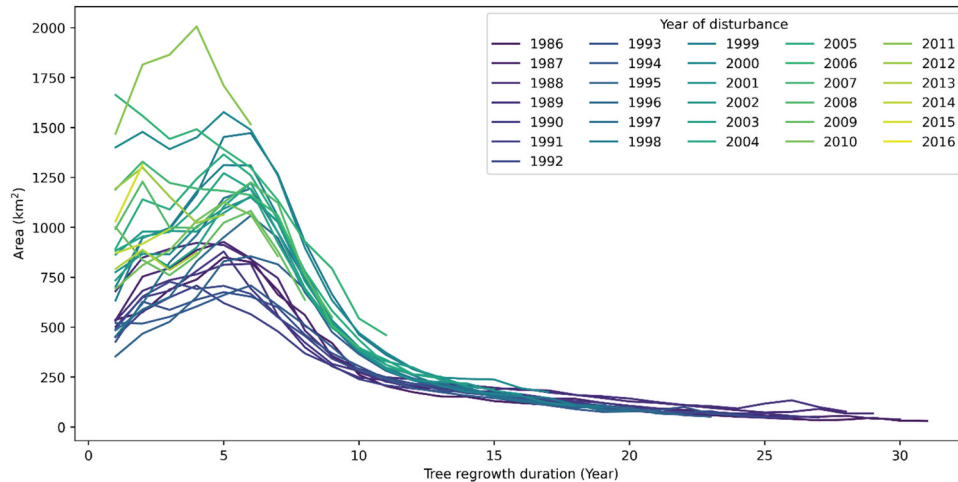
### 3.3 Validation

Among the 6957 reference plots (Figure 8a), 1048 had Tree Cover to Grass/Shrub class changes (Figure 8b) and 684 showed tree regrowth between 1985 and 2017 (Figure 8c). Within the 684 tree regrowth plots, 467 were detected by the LCMAP change detection product (SCTIME) (Brown et al. 2020), and hence had tree regrowth duration values (Figure 8d). The commission and omission errors of the disturbance detection are 0.34 and 0.44, respectively, resulting in an F1 score of 0.61. Table 2 shows the percentage of disturbances detected in each type as found in the reference plots. Harvest and fire are the most common disturbance types according to the reference data, and 65% of those events were captured by the LCMAP change detection product (SCTIME) (Brown et al. 2020). Harvest events identified as thinning harvests had a relatively lower agreement with 48% detected.





**Figure 6.** (a) The average tree regrowth duration, in years, for the conterminous United States. The 30-m resolution map was aggregated to 3-kilometer resolution using the average method for better visualization. If a  $3 \times 3$ -km grid has pixels showing no tree regrowth, the pixels are ignored in the average estimation, so the aggregated map may exaggerate the coverage of tree regrowth. Several specific locations are outlined to display the average tree regrowth durations at 30-m resolution: (b) Lon:  $-69.492243^\circ$ , Lat:  $45.980060^\circ$ ; (c) Lon:  $-123.563564^\circ$ , Lat:  $44.819984^\circ$ ; (d) Lon:  $-110.734907^\circ$ , Lat:  $44.826733^\circ$ ; (e) Lon:  $-82.497790^\circ$ , Lat:  $34.077658^\circ$ .

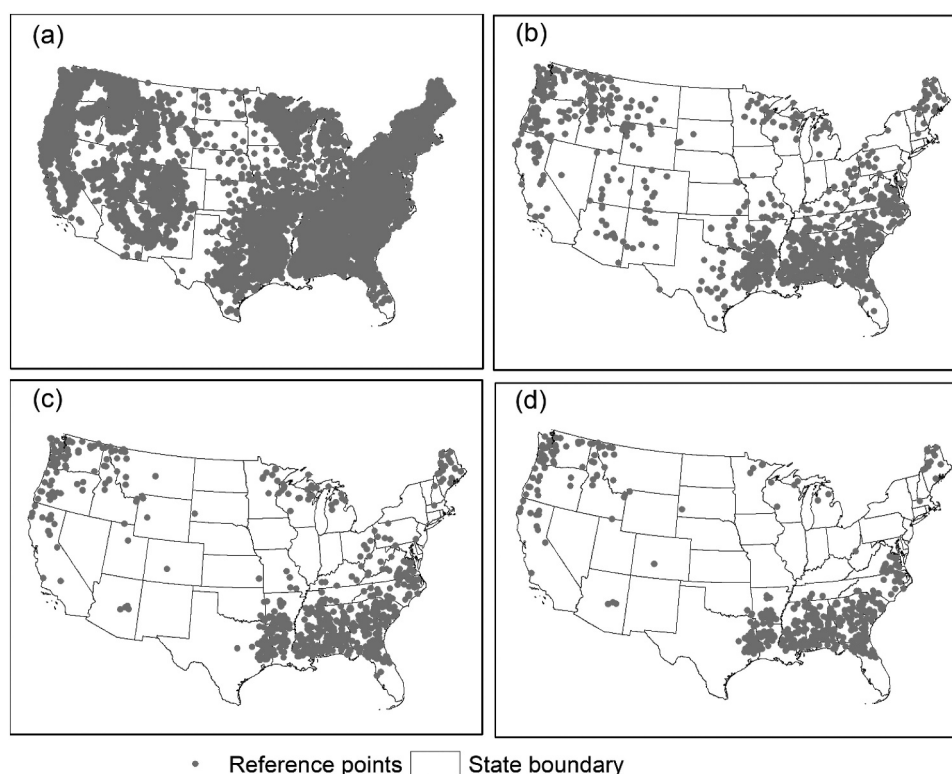


**Figure 7.** Area of tree regrowth over time.

Figure 9 shows the histogram distribution of tree regrowth duration error for the entire CONUS. The distribution (Figure 9a) shows 1-year underestimation of regrowth duration with 6 years of standard deviation error when considering all tree regrowth plots in reference data (Figure 8c). Figure 9b shows that if the

disturbance is captured by the LCMAP map products (Figure 8d), the regrowth duration estimate has zero bias with 6 years of standard deviation error.

The use of OHSA (Arthur and Keith Ord 2010; Ord and Getis 1995) provides insights on the spatial patterns of error in tree regrowth duration. OHSA was



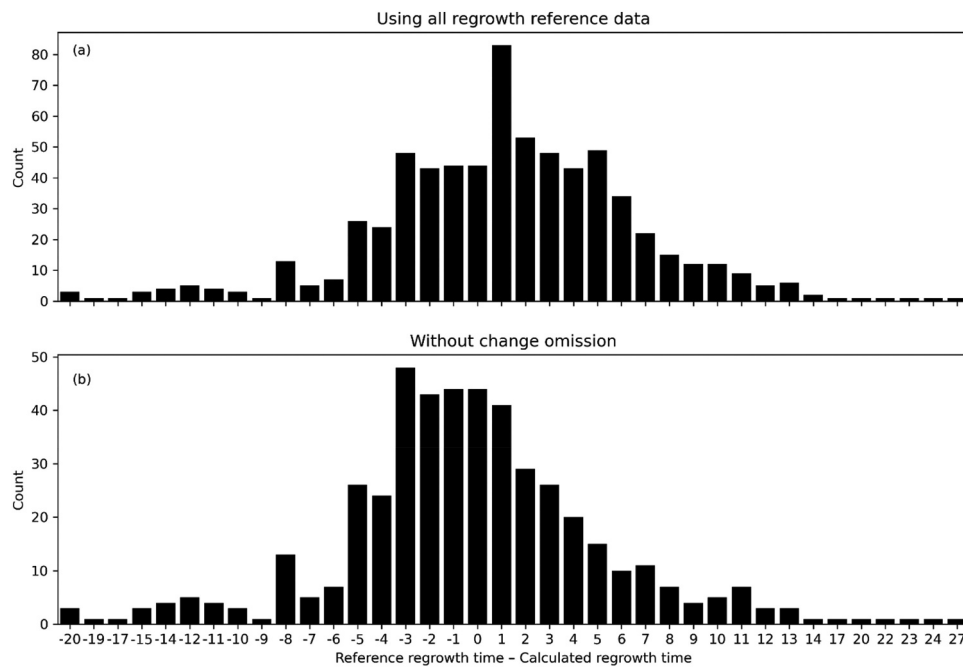
**Figure 8.** Spatial distribution of forest plots in reference data: (a) plots that either had disturbances or remained Tree Cover for all 33 years; (b) plots that had disturbances; (c) plots that had tree regrowth after disturbances; and (d) plots that had regrowth after disturbances in the reference data and was detected by the LCMAP products.

**Table 2.** Disturbance detection agreement by type.

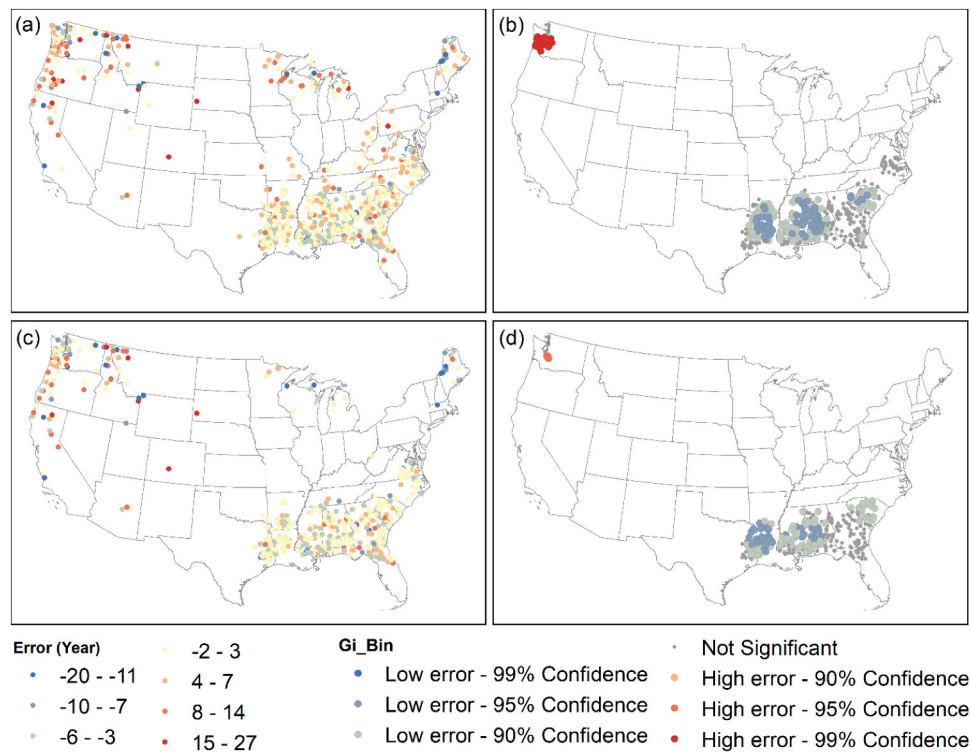
| Disturbance Type   | Description                                                                                                                                                                                                                             | Reference count | LMCAP detected count | Lcmap detected percentage |
|--------------------|-----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|-----------------|----------------------|---------------------------|
| Harvest            | Forest lands where trees, shrubs, or other vegetation have been removed by anthropogenic means.                                                                                                                                         | 808             | 525                  | 65%                       |
| Harvest thinning   | Forest lands where partial removal of trees/vegetation occurred by anthropogenic means but with some proportion of residual trees/vegetation left behind.                                                                               | 88              | 42                   | 48%                       |
| Fire               | Land altered by fire, regardless of the cause of ignition (natural or anthropogenic), severity, or land use.                                                                                                                            | 123             | 80                   | 65%                       |
| Mechanical         | Non-forest land where trees, shrubs, or other vegetation have been mechanically severed/removed (chaining, scraping, bulldozing, etc.).                                                                                                 | 13              | 5                    | 38%                       |
| 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 such as insects or disease.                                                | 11              | 4                    | 36%                       |
| Spectral Decline   | Plot where the spectral signal shows a trend in one or more spectral indices indicating a possible loss of vegetation vigor, but the trend is not associated with a visible loss of leaves or woody vegetation.                         | 2               | 2                    | 100%                      |
| Hydrology          | Land where flooding has significantly altered land cover elements regardless of land use.                                                                                                                                               | 1               | 0                    | 0%                        |
| Wind               | Land where vegetation is altered by wind from hurricanes, tornadoes, etc.                                                                                                                                                               | 1               | 1                    | 100%                      |
| Other              | Land where the evidence indicates a disturbance or change event occurred, but the definitive cause cannot be determined, or the type of change fails to meet any of the change process categories defined by the Joint Response Design. | 1               | 0                    | 0%                        |

applied to the absolute value of all tree regrowth errors (Figure 10a) as well as the disturbance detected tree regrowth errors (Figure 10c). Statistically significant ( $p$ -value < 0.1, 0.05, and 0.01 for 90%, 95%, and

99% confidence, respectively) low z-scores represent clustering of low errors, while statistically significant high z-scores represent clustering of high errors. The corresponding results of OHSa are shown in Figure 10



**Figure 9.** Histogram of tree regrowth error: tree regrowth duration from reference data minus the calculated regrowth duration. (a) All tree regrowth reference data (total 684 plots) were used. (b) Only included reference points that had disturbance detected by the LCMAP product (467 plots remaining).



**Figure 10.** Spatial patterns of tree regrowth error (year) (a) using all reference data that showed regrowth, or (c) using reference data that showed disturbances detected. Error is defined as the tree regrowth duration from reference data minus this study's estimates. Hot spot analysis on the right showing the spatial cluster (in terms of the confidence level Gi\_Bin) of high and low error in panel (b) and (d), respectively.

b and d. Because the approach indicated that results are not reliable if results were calculated using fewer than 30 neighbors, Figure 10 b and d only showed plots with 30 or more neighbors. Figure 10b shows that the southeast region has overall low error, but a cluster of high error shows in the northwest region. If disturbances are detected, most of the high errors disappear (Figure 10d). The result indicates that if the regrowth process is captured, the tree regrowth duration estimation tends to have less error. Figure 11 shows the histogram of significant ( $p$ -value < 0.1) clustered low errors (mean = 0.6, standard deviation (STD) = 3.6) and high errors (mean = 2.7, STD = 7.1) when all errors are used, as well as significant clusters of low errors (mean = -0.39, STD = 3.5) and high errors (mean = 4.3, STD = 9.2) when disturbances are detected.

#### 4. Discussion

In this study, we mapped and validated tree regrowth duration using LCMAP primary land cover product from 1985 to 2017. Quantifying tree regrowth duration after disturbance will improve carbon budget estimates and lead to better parameterization of forest carbon cycle models (Stephen et al. 2009). The tree regrowth duration map can be used to evaluate the carbon accumulation related to tree regrowth and assess potential drivers at the national level (Cook-Patton et al. 2020). The dataset can also be used to support related studies on ecological processes, such as erosion/sedimentation, nutrient and water cycling, and wildlife habitat (Schroeder, Cohen, and Yang 2007).

We first evaluated the dynamics of tree cover, which showed similar gain and loss of trees in most years, except several years of extensive loss associated with fire (Figure 4). Likewise, Auch et al. (2022) evaluated annual tree gain and loss using pixel samples in the LCMAP reference data, which found an overall smaller net change in tree cover. A major difference was that our study found more evident tree loss in larger wildfire years than Auch et al. (2022). A possible reason is that our result is derived from the LCMAP annual land cover product, while Auch et al. (2022) used pixel samples to estimate. The latter approach may not accurately capture increasing fire disturbances. Meanwhile, our study also found that most of the trees that were lost before

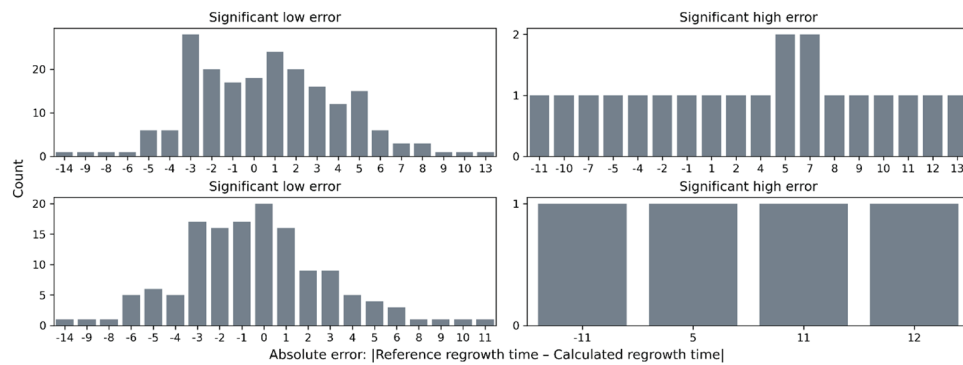
2000 grew back before 2017, and the declining area of tree regrowth may indicate an incomplete regrowth process (Figure 5).

We then mapped the tree regrowth duration at the 30-m scale using the LCMAP CONUS land cover product. The tree regrowth duration map was validated based on human interpretation of time-series pixels at randomly selected plots. The reference data indicated that most tree regrowth occurred in southeastern CONUS and the second highest regrowth region was in the northwest (Figure 8b). The overall error distribution implied an average 1-year underestimation and 6-year standard deviation error across the nation based on the reference data. The error might come from the omission of disturbance detection or classification in LCMAP. The omitted disturbance detection often had short regrowth duration (1–2 years) in the reference data. Figure 9b indicates that if disturbance was detected, the classification procedure tended to find regrowth duration with less than 1-year bias. Figure 10d shows most of the high error clusters were gone when disturbances were detected, which indicates that most of those high errors might also be related to the omission of disturbance detection. However, most regrowth plots were in the southeast region of CONUS with a few in the northwest region, which could limit the OHSA results as there are not enough neighbors to estimate the significance of error in the northwest region.

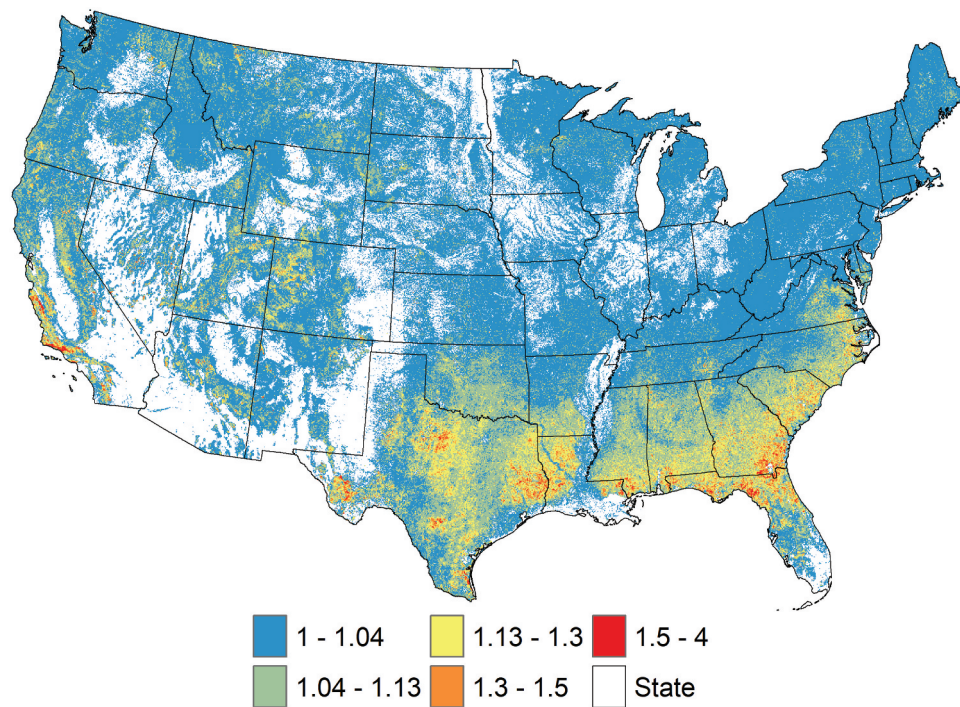
Most tree regrowth occurred in the southeast region, with higher accuracy reflected in the less than 1-year bias and 3.6 years standard deviation of error (Figure 10 and Figure 11). The average regrowth duration was about 5 years. This region has intense logging activities typically followed by replanting. Forest in the southeast recovered faster than other regions of CONUS and often had multiple cycles of harvesting and regrowth (Figure 12).

The Pacific Northwest region is another main area of tree regrowth. Although this region generally takes longer to grow (about 12 years on average), the area of tree regrowth is much smaller than the southeast. Unlike the southeast, both harvesting and fire were common causes of tree regrowth in the northwest. Although the estimated regrowth duration has a larger difference with the reference data, the overall classification accuracy of Tree Cover and Grass/Shrub is high in western CONUS (tree: UA = 90%, PA = 84%; Grass/Shrub: UA = 90%, PA = 91%) (Table S1) (Bruce





**Figure 11.** Histogram of clustered low and high errors when using all reference data that showed regrowth (top row) or using reference data that showed disturbances detected by the LCMAP product (bottom row).



**Figure 12.** Forest disturbance frequencies from 1985 to 2017. The colors show average times (1–4) of changes at the  $3 \times 3$ -km scale. If a  $3 \times 3$ -km grid has pixels showing no tree regrowth, the pixels are ignored in the average estimation, so the aggregated map may exaggerate the coverage of tree regrowth.

et al. 2020). Possible reasons for the large errors include the sparse reference plots due to less widespread areas of forest disturbances and a relatively long regrowth duration. Reference data are based on the interpretation of high-resolution images and rely on visualizing the tree canopy for Tree Cover classification. On the other hand, the LCMAP map products are produced by time-series models through characterizing Landsat data. The tree cover characterization depends on the information about the seasonality of spectral bands. The different classification

mechanisms might disagree with each other, especially when the tree density is close to the 10% threshold, which defines land cover type as tree if the tree cover density is greater than 10%. The disagreement could be larger in the northwest than the southeast because trees generally grow slower in the northwest and have longer period at the margin of the class definition. On the other hand, stable Tree Cover and Grass/Shrub were classified well, which might lead to the high tree regrowth duration error, but high classification accuracy in the northwest.

## 5. Conclusion

Monitoring and mapping tree regrowth are essential for understanding carbon storage potentials and effectively managing tree resources across the nation. The dataset described in this study provides a tree regrowth duration map for CONUS at 30-m resolution from 1985 to 2017. The regrowth duration map was validated with annual reference samples collected independently across CONUS, showing an average of 1-year underestimation and 6-year standard deviations of error. Southeast CONUS is a major tree regrowth region where our map shows higher accuracy with less than 1-year bias and 3.6 years standard deviation. This map is the first attempt, to our knowledge, to quantify tree regrowth duration at a national extent in the CONUS. Continued monitoring of tree regrowth duration can be accomplished by utilizing updated Collections of LCMAP products now available through 2020 (<https://www.usgs.gov/special-topics/lcmap/lcmap-data-access>). The results offer new insights to support mitigating the impacts of climate change and to guide natural resource decision makers in creating management policies for sustainable development.

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## Data availability statement

The regrowth duration map and the script are available at the USGS ScienceBase repository in GeoTIFF format (<https://doi.org/10.5066/P9IYK5YW>). The LCMAP products are available at <https://doi.org/10.5066/P9SW95Z0>

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