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Where forest may not return in the western United States

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ABSTRACT

Droughts that are hotter, more frequent, and last longer; pest outbreaks that are more extensive and more common; and fires that are more frequent, more extensive, and perhaps more severe have raised concern that forests in the western United States may not return once disturbed by one or more of these agents. Numerous field-based studies have been undertaken to better understand forest response to these changing disturbance regimes. Meta-analyses of these studies provide broad guidelines on the biotic and abiotic factors that hinder forest recovery, but study-to-study differences in methods and objectives do not support estimation of the total extent of potentially impaired forest succession. In this research, we provide an estimate of the area of potentially impaired forest succession. The estimate was derived from modeling of an 18-year land cover and Normalized Difference Vegetation Index (NDVI) time series supported by an extensive ancillary dataset. We estimate an upper bound of approximately 3470 km^2 of disturbed forest that may not return or reattain prior composition and structure. Based on the data used, fire appears to be the main disturbance agent of impaired forest succession, although climatic factors cannot be discounted. The numerous field studies routinely cite distal seed sources as a factor that hinders forest recovery, and we estimate that 20 % of the upper bound estimate has no forest cover within a 4.4-ha neighborhood. Our upper bound estimate is about 0.5 % of the 2001 mapped extent of western United States forests. The estimate is cognizant of measurement and modeling uncertainties (i.e., upper bound) and uncertainties related to successional rates and trajectories (i.e., potential).

1. Introduction

Across the western United States, climate-mediated alteration of disturbance regimes has raised concerns that forests may not return or reattain prior composition and structure following disturbance (Davis et al 2019; Halofsky et al. 2020; Turner et al. 2019). Fire season length and area burned are two aspects of the western United States fire regime that appear to be increasing (Abatzoglou et al. 2017). Hicke et al. (2016) reported increases in mortality related to fire and bark beetle outbreaks beginning in the late 1990s. Numerous field-based studies following fires have reported lagging forest recovery (Chambers et al. 2016; Collins & Roller 2013; Davis et al. 2019; Haffey et al. 2018; Harvey et al. 2013; Owen et al. 2017; Tepley et al. 2017). Absence of proximal seed sources and moisture stress appear to be the two most common factors

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that hinder recovery (Korb et al. 2019; Stevens-Rumann and Morgan 2019).

The concern over the effects of changing disturbance regimes, especially fire, on forest recovery has fostered numerous field-based investigations. Meta-analyses of these studies (Korb et al. 2019; Stevens-Rumann and Morgan 2019) identify ecological factors that influence forest recovery (e.g., drought). However, because local investigations vary widely in terms of data collected and study objectives it is not possible to compile data from field investigations to estimate the areal extent of forests that may not return or reattain prior composition and structure. Field studies provide valuable information on the ecological context of forest recovery, but the information they provide cannot be used to answer the question – what is the areal extent of potential forest conversion across the western United States?

Our primary objective is to demonstrate the use of temporal synoptic data to provide an estimate of the area of potential forest conversion. For this work we adopt the definition of forest conversion offered by Coop et al. (2020, p. 660) – a disturbance causes a substantial shift in vegetation composition and structure (e.g., stand-replacing fire) and recovery agents (e.g., seed rain, precipitation) are either ineffective or absent, resulting in forest recovery that is delayed, arrested (Korb et al. 2019; Stevens-Rumann and Morgan 2019), or does not return to its prior composition and structure (Owen et al. 2017; Turner et al. 2019). We use temporal land cover data and vegetation indices spanning nearly a 20-year time frame to develop an estimate of forest conversion. To support our remote sensing-based estimate we add numerous ancillary data. The ancillary data provide measurements related to ecological context and other information that can be used to further scrutinize the base remote sensing estimate.

Our use of remotely sensed data to estimate the *potential* extent of forest conversion is an effort to monitor forest recovery. No benchmark is recognized for the amount of time needed to make confident assessments of successional outcomes (Stevens-Rumann and Morgan 2019). Succession is a conceptual model (Donato et al. 2012) that is governed by drivers that vary in space and time (Tepley et al. 2018). Field-based studies of forests indicate the pace, pathway, and ultimate successional outcome may be different for two nearby sites (Keeling et al. 2006; Yang et al. 2005). Ouzts et al. (2015) observed that recovery of ponderosa pine (*Pinus Ponderosa*), a geographically widespread, canopy-dominant species in the western United States, is not predictable. The nearly 20-year time span on which our results are based is governed by data availability and also intentionally agnostic of the time needed to make confident determinations about successional outcomes. At least three factors support our adoption of agnosticism regarding the pace and trajectory of succession. (1) Short-term successional trends can be indicators of future outcomes (Stevens-Rumann et al. 2018). Stoddard et al. (2018) measured ponderosa pine and Douglas fir (*Pseudotsuga menziesii*) regeneration prior to and 1, 10, and 15 years post fire and reported no seedlings of either species one year post fire and no seedlings of either species 15 years post fire, regardless of fire severity. (2) Monitoring is a key element of adaptive management (NRC, 2004; Williams 2011). The numerous field-based studies on forest recovery, typically collected shortly after disturbance (Korb et al. 2019; p. 14), are examples of adaptive management – data on recovery are collected so that subsequent management is more likely to produce desired outcomes (e.g., forest recovery). Meta-analysis of these field-based studies (Korb et al. 2019; Stevens-Rumann and Morgan 2019) conclude their reviews with a discussion of management options. Others have reported positive post-disturbance outcomes resulting from active management (Collins et al. 2011; Ouzts et al. 2015; Shive et al. 2013). (3) Our use of remotely sensed data to monitor forest recovery is based qualitatively on an inclusive view of commission and omission error (Foster 2001). Prescribing a successional framework in the absence of precise knowledge on rates and trajectories risks omission of locations that are indeed undergoing forest conversion simply because they are thought occur in an area where it has been accepted that succession moves slowly. We view acceptance of a potentially higher rate of commission (Type II) error as appropriate to help ensure minimization of omission of areas where forest conversion may be occurring (Type I error).

2. Methods

2.1. Study area

The region of interest is the western United States, extending from about 102° W to 124° W and 29° N to 49° N (study area map is presented in the results). The total area of the region is about 3,465,300 km^2. Elevations range from below sea level to about 4420 m (14,500 ft). Climatic regimes (Trewartha 1961) are predominantly arid to semi-arid, except along the northern half of the Pacific Coast. Precipitation profiles are Mediterranean (winter maximum) along the Pacific coast, changing to more uniform and summer maximum profiles moving eastward (Trewartha 1961, p. 268).

2.2. Data

We used the 2016 National Land Cover Database (NLCD2016) (Homer et al. 2020; Yang et al. 2018), a U.S. Federal Geographic Data Committee (FGDC) National Geospatial Data Asset (FGDC, 2021), as our base dataset to identify potential forest conversion. NLCD2016 provided time integrated land cover (land cover at time t informs land cover at time $t - 1$) for 2001, 2004, 2006, 2008, 2011, 2013, and 2016 from the Landsat Thematic Mapper (TM) satellite at the sensor's native 30 m-x-30 m (0.09 ha pixel^{-1}) spatial resolution. We used the NLCD2016 data to create a dataset, we hereafter refer to as persistent forest loss. Persistent forest loss was defined as forest in 2001 and either shrubland or grassland only in all remaining dates of NLCD2016 land cover. Conversion of forest to other NLCD2016 land cover classes (e.g., forest to urban) were not considered persistent forest loss.

Annual summer maximum Landsat Normalized Differenced Vegetation Index (NDVI) (Holben 1986) for the years 2001 through 2019 were used to disentangle potential forest conversion from persistent forest loss by monitoring vegetation response following forest loss between 2001 and 2004. We defined summer as June, July, August, and September (JJAS). September was added to the traditional Northern Hemisphere summer months to increase NDVI data availability in cloudy areas; this exception was not extended to other data summarized over the summer. Collection 1 (top of the atmosphere) scenes requirements included L1TP processing (https://www.usgs.gov/core-science-systems/nli/landsat/landsat-levels-processing?qt-science_support_page_related_con=2#qt-science_support_page_related_con) and <20 % cloud cover. NDVI processing was done in Google Earth Engine and converted from the inherent NDVI scale (-1 to 1) to 8-bit scale (0–255) to facilitate download. Once downloaded, the NDVI data were projected (nearest neighbor) into the NLCD Alber's equal area projection and converted back to its native, −1 to 1 scale. NDVI was based on Landsat 5 for the years 2001 through 2011, Landsat 7 for 2012, and the Operational Land Imager (Landsat 8) for the years 2013 through 2019. Equations developed by Roy et al. (2016) were used to adjust NDVI from Landsat 5 and 7 to Landsat 8. Further, only persistent forest loss pixels with a complete 19-year record of NDVI were considered valid, and NDVI values < 0 were considered invalid (Myneni et al. 1998; Tucker et al. 1986). About 1.5 % of persistent forest loss area was discarded because of an incomplete temporal record or invalid data.

2.3. Potential forest conversion from persistent forest loss

K-means, time series clustering (Aghabozorgi et al. 2015) of 2001 – 2019 NDVI was used to identify persistent forest loss that may be potential forest conversion. Criteria for cluster evaluation included goodness-of-fit and cluster integrity. Performance was assessed for outcomes with 2 to 20 clusters in steps of 2. Cluster separation (Arbelaitz

Table 1
Data sources (a) and indicators (b) for examining patterns of forest disturbance and recovery.

(a) Data Sources[1]	Description
MTBS	Monitoring Trends Burn Severity - annual data (2002 – 2018) on fire severity (raster) and fire perimeters (vector); 900 m^2 resolution (https://www.mtbs.gov).
PRISM	Parameter-elevation Regressions on Independent Slopes model - climatic data; 4-x-4 km resolution (https://prism.oregonstate.edu).
NLCD2016	National Land Cover Database (2016) - land cover, tree canopy cover, impervious cover; 900 m^2 resolution (https://www.mrlc.gov) (https://data.fs.usda.gov/geodata/rastergateway/treecanopycover/).
Protected Areas	Protected Areas Database (PAD-US; version 2.1) (https://www.usgs.gov/GAP).
Togography	National Elevation Dataset (NED) - elevation, slope, aspect; 900 m^2 resolution (https://www.sciencebase.gov/catalog/item/4fcf8fd4e4b0c7fe80e81504)
LANDFIRE (LF)	Raster map of vegetation types; 900 m^2 resolution (https://www.landfire.gov).
IDS	Insect & Disease Survey (https://www.fs.fed.us/foresthealth/applied-sciences/mapping-reporting/detection-surveys.shtml)
NAFD	North American Forest Dynamics project; 900 m^2 resolution (https://daac.ornl.gov/cgi-bin/dsviewer.pl?ds_id=1799)
Indicators[1]	
Elevation	Height above mean sea level (format = integer; unit = m)
Slope	Rise/run (%)
Aspect	Solar azimuth (degrees)
nyrs	Number of years with valid NDVI values
dRng	2019 NDVI – 2001 NDVI
nFire	$\sum$ moderate severity fire occurrences (2001 – 2018)
hFire	$\sum$ high severity fires occurrences (2001 – 2018)
xFire	$\sum$ moderate + high fire occurrences (2001 – 2018)
xFire0204	$\sum$ moderate + high fire occurrences (2002 – 2004)
CumSpr	Cumulative $\sum$ of maximum vapor pressure deficit (VPD) anomalies (2001 – 2019) for MAM (hPa)
CumSmr	Cumulative $\sum$ of maximum VPD anomalies (2001 – 2019) for JJA (hPa)
fs7	Density of NLCD2016 upland forest pixels in 7- x 7-pixel (4.4 ha) window (%/100)
UrbS7	Density of NLCD2016 urban pixels in a 4.4-ha window (%/100)
AgS7	Density of NLCD2016 agriculture pixels in a 4.4-ha window (%/100)
Protected	Protected status (1 or 2 = protected; 0 = not protected)
TCC	NLCD2016 Tree Canopy Cover (0 – 100 %)
LF_EVT	LANDFIRE Vegetation class
LF_EVTr	LANDFIRE Vegetation class (aggregated)
Cluster	Output from time series cluster analysis
Dist	Euclidean distance from observation to cluster centroid
Gap	Euclidean distance from cluster centroid to nearest cluster centroid
Fit	Equals 1 if Dist < (Gap/2); otherwise = 0
PtchSz	Persistent forest loss patch size (# pixels; 1 pixel = 0.09 ha)
IDS0204	Identified tree mortality in 2002, 2003, or 2004 from Insect & Disease Survey
FDyr	NAFD year of disturbance (value + 1970)
FDtype	NAFD disturbance type (e.g., fire)
FDconf	NAFD difference between 1st and 2nd most common Random Forest result

[1] Data sources and indicators are described in Supplemental Information section.

et al. 2013) served as the measure of goodness-of-fit. Cluster separation was measured as the proportion of observations whose distance to its cluster centroid was < ½ of the centroid-to-centroid distance between the cluster to which the observation was assigned and the nearest cluster (Ebert et al. 2021). Observations meeting this goodness-of-fit (fit) criterion were unambiguous members of the cluster to which they were assigned. The overall NDVI trend (2019 NDVI minus 2001 NDVI) was used to assess cluster integrity. For all observations within a cluster, the overall trend should be negative, positive, or close to zero (0) (e.g., −0.05 to 0.05).

The evaluation criteria were applied to several different sets of input variables, including all 19 NDVI variables, a kernel density transformation of the 19 NDVI variables that reduced the number of inputs from 19 to 5 (i.e., kernel density estimates for histogram benchmarks of 0.00, 0.25, 0.50, 0.75 and 1.00), and reduced sets of the NDVI variables, including the overall trend (2019 NDVI – 2001 NDVI). All input variables were transformed using Euclidean distance prior to their input into K-means clustering.

2.4. Data quality

We evaluated data quality in three ways. The NDVI time series for persistent forest loss was compared to the NDVI time series from a random sample (Supplemental Information) of stable forest (upland forest in all seven land cover dates in NLCD2016). This comparison was undertaken to confirm and quantify NDVI time series differences between stable forest and persistent forest loss. We used the non-parametric L2-norm statistic ($\sum(\sqrt{(a-b)^2})$) for the comparison (Lhermitte et al. 2011). L2-norm approaches 0 as the similarity between two time series increases. The comparison was used to gauge the likelihood that a 2001 – 2019 NDVI time series for persistent forest loss could replicate a 2001 – 2019 NDVI time series for stable forest. We used the 50th percentile NDVI value for each year for the L2-norm comparisons. Comparisons were based on the persistent forest loss groups realized from time series clustering. Each persistent forest loss cluster was compared to stable forest. We used the L2-norm for the 40th and 50th percentiles of stable forest as a reference value to gauge the magnitude of the L2-norm differences between stable forest and the persistent forest loss clusters. Differences in L2-norms between persistent forest loss and stable forest larger than the reference value would indicate that the 40th percentile of stable forest more closely replicated the 50th percentile of stable forest than the 50th percentile of a persistent forest loss cluster.

A second means of data quality assessment relied on the North American Forest Dynamics (NAFD) project (Schleeweis et al. 2020). NAFD provides a Landsat-based assessment of forest change from 1986 to 2010 and assigns a cause of change to forest loss: stable (unchanged), removal (harvest), fire, stress, conversion, other, and wind. We compared results from time series clustering of persistent forest loss to NAFD loss attributions. Third, data quality was assessed by comparing persistent forest loss to the reference data collected for the NLCD2006, NLCD2011, and NLCD2016 accuracy assessments (Wickham et al. 2013, 2017, 2021) for the few locations where they were coincident (Supplemental Information). Persistent forest loss was coincident with the locations used for reference data collections from previous NLCD accuracy assessments for 130 locations. In addition, we report forest loss accuracies from previous NLCD accuracy assessments.

2.5. Ancillary data

NAFD is one component of an accompanying persistent forest loss dataset (Table 1). The ancillary data include information on topography, climate, fire, mortality from pest infestations and other disease agents, forest dynamics, and derivatives from the time series cluster analysis and NLCD. Complete descriptions of the data sources and the indicators derived from them are provided in the Supplemental Information section. These data were used to examine classification results in the context geographic patterns (e.g., topography, climate), stressors (fire, pests), and spatial factors related to the likelihood of forest regeneration, in addition to data quality.

3. Results

3.1. Time series clustering of persistent forest loss

About 10,535 km^2 were forest in 2001 and either shrubland or

Table 2
Area and output statistics from time series cluster analysis.

Cluster	Area (km^2)	Max D[1]	Near[2]	GAP[3]	Fit[4]	Min[5]	Max[5]
1	586	0.001080	2	0.000528	0.82	−0.734	−0.213
2	2,881	0.000315	3	0.000277	0.78	−0.223	−0.059
3	4,612	0.000304	4	0.000256	0.81	−0.062	0.045
4	2,298	0.001940	3	0.000256	0.71	−0.083	0.838
Overall	10,377				0.78		

[1] Max D = maximum observation-to-centroid distance.
[2] Near = Nearest cluster.
[3] GAP = centroid-to-centroid distance from cluster to nearest cluster.
[4] Fit = see methods.
[5] Cluster integrity: minimum and maximum values of 2019 NDVI – 2001 NDVI.

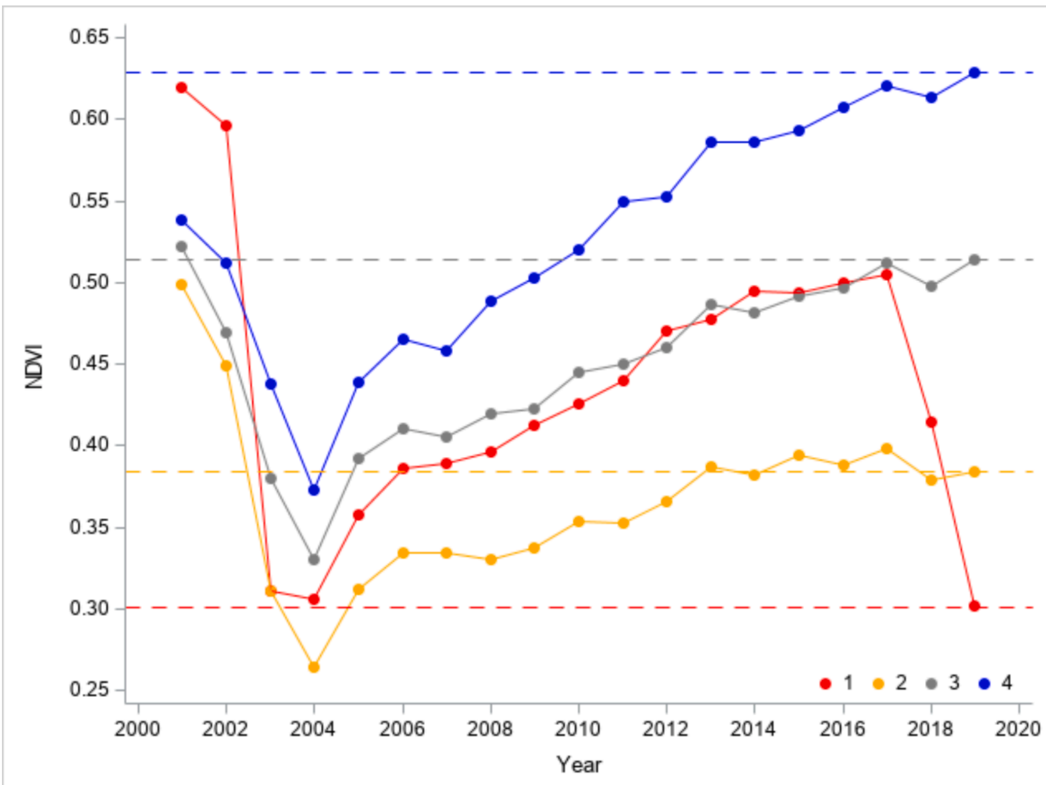

Fig. 1. Annual summer maximum NDVI means for each cluster.

grassland in 2016 (i.e., persistent forest loss). The 4-group solution provided the best performance when evaluating goodness-of-fit and cluster integrity in tandem (Fig. S1 and S2; Table S1). Goodness-of-fit for the 4-group solution was 78 % (Table 2). Groups 1 and 2 had negative overall trends and groups 3 and 4 had flat and postive overall trends, respectively. Mean 2001 NDVI and NDVI trends were distinguishing features (Fig. 1). Clusters 1 and 2 had distinctly different mean 2001 NDVI values and noticeably different mean trends from 2004 onward. Groups 3 and 4 had similar mean 2001 NDVI values but dissimilar 2004–2019 mean NDVI trends. Cluster 1 was also distinct from the other three clusters in both the abruptness and magnitude of its 2001–2004 decline in NDVI and its sharp decrease in mean NDVI after 2017. Following the mean NDVI trends, we hereafter refer to clusters 1 and 2 as potential forest conversion and clusters 3 and 4 as apparent forest recovery. The respective total areas of potential forest conversion and apparent forest recovery were 3,467 km^2 and 6,910 km^2; about 160 km^2 (1.5 %) were not evaluated due to a lack of NDVI data (see methods).

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3.2. *Geography of potential forest conversion and apparent forest recovery*

All clusters were distributed across the western United States, although clusters 1 and 2 tended for to be more concentrated in localized hotspots than clusters 3 and 4 (Fig. 2). A large portion of cluster 1 coincided with the 2002 Biscuit fire in southwest Oregon (Donato et al. 2009) and the 2002 Hayman fire in Colorado (Chambers et al. 2016). Similarly, a large portion of cluster 2 was coincident with the 2002 Rodeo-Chediski fire in east-central Arizona (Owen et al. 2017) and the Hayman fire. At a more local scale, clusters were often contagious, exhibiting both gradient and mottled patterns over more limited geographic extents (Fig. 3).

3.3. *Data quality assessment*

Persistent forest loss and stable forest temporal NDVI trends were distinctly different. L2-norms for persistent forest loss versus stable forest, regardless of cluster assignment, were larger than the reference value of 0.92 (Table 3a). The 40th percentile of the stable forest NDVI

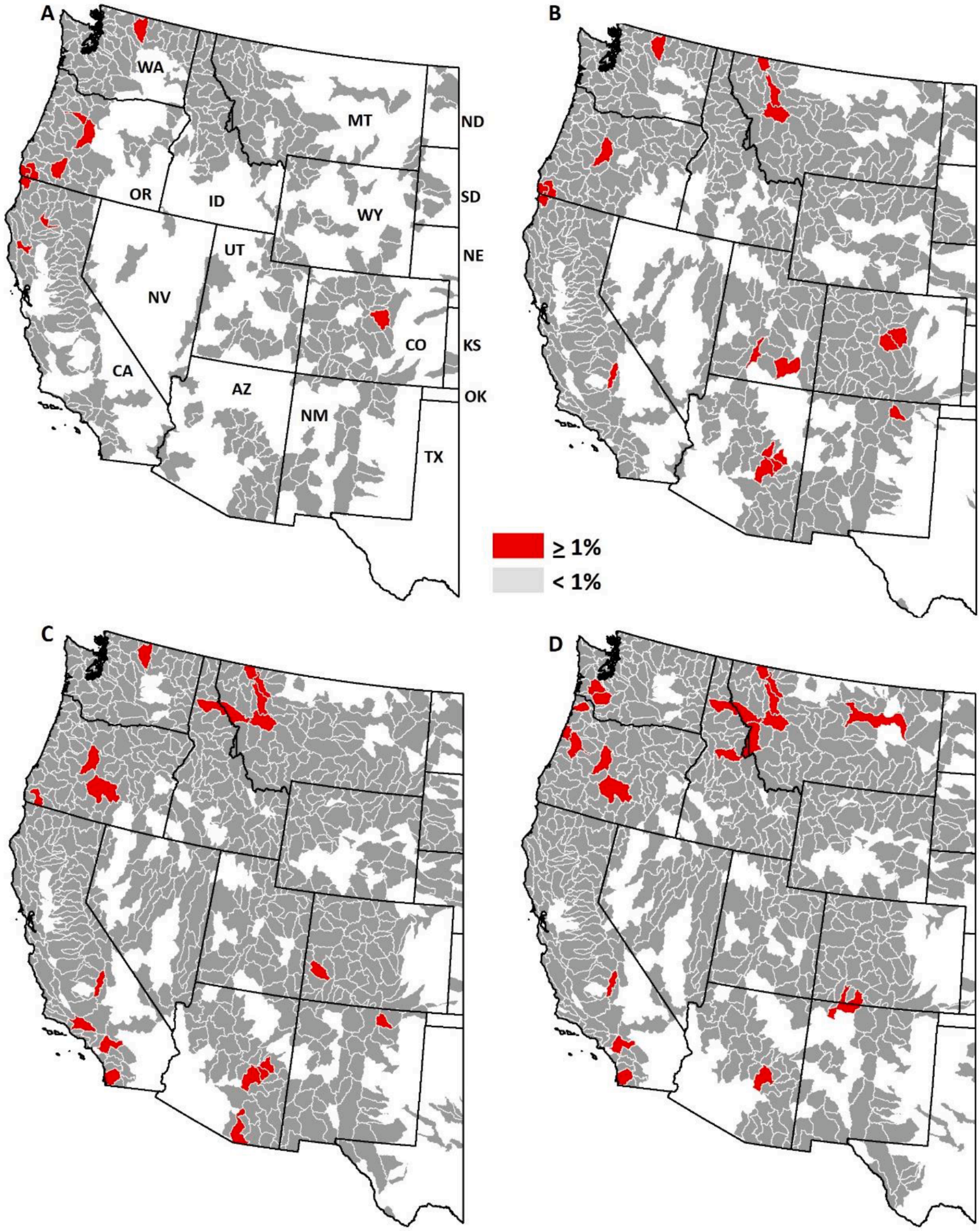

Fig. 2. Percentage[1] of cluster area by watershed for clusters (A) 1, (B) 2, (C) 3, and (D) 4. [1] About 80 % of cluster 1, 54 % of cluster 2, 41 % of cluster 3, and 38 % of cluster 4 are within watersheds shown in red. Ten (10), 18, 20, and 21 watersheds are shown in red for clusters 1, 2, 3, and 4, respectively. Clusters did not occur in watersheds not shown (white). Watersheds = 8-digit hydrologic unit codes from the U.S. watershed boundary database (https://www.usgs.gov/national-hydrography/watershed-boundary-dataset). State labels: Washington (WA); Oregon (OR), Idaho (ID), Montana (MT), Wyoming (WY), North Dakota (ND), South Dakota (SD), Nebraska (NE), California (CA), Nevada (NV), Utah (UT), Colorado (CO), Kansas (KS), Oklahoma (OK), Arizona (AZ), New Mexico (NM), Texas (TX). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

trend was more likely to reproduce the 50th percentile of the stable forest NDVI trend than the 50th percentile of persistent forest loss, regardless of cluster assignment. Greater than 90 % of persistent forest loss locations coincided with locations identified by NAFD (Schleeweis et al. 2020) as forest loss attributable to removal (harvest), fire, and stress, and<0.1 % of persistent forest loss locations were identified as conversion (e.g., forest to urban) by NAFD. Agreement between the few reference data locations from previous NLCD accuracy assessments that were coincident with persistent forest loss ranged from 80 % to 100 % (Table 3b). Accuracy of 2011 – 2016 forest loss for NLCD2016 was about 75 %. User's accuracies (1 minus commission error) of previous NLCD products were slightly higher than 75 % but producer's accuracies (1 minus omission error) were lower.

3.4. *Associations between clusters and environmental factors (ancillary data)*

Fire was more common at locations comprising the potential forest

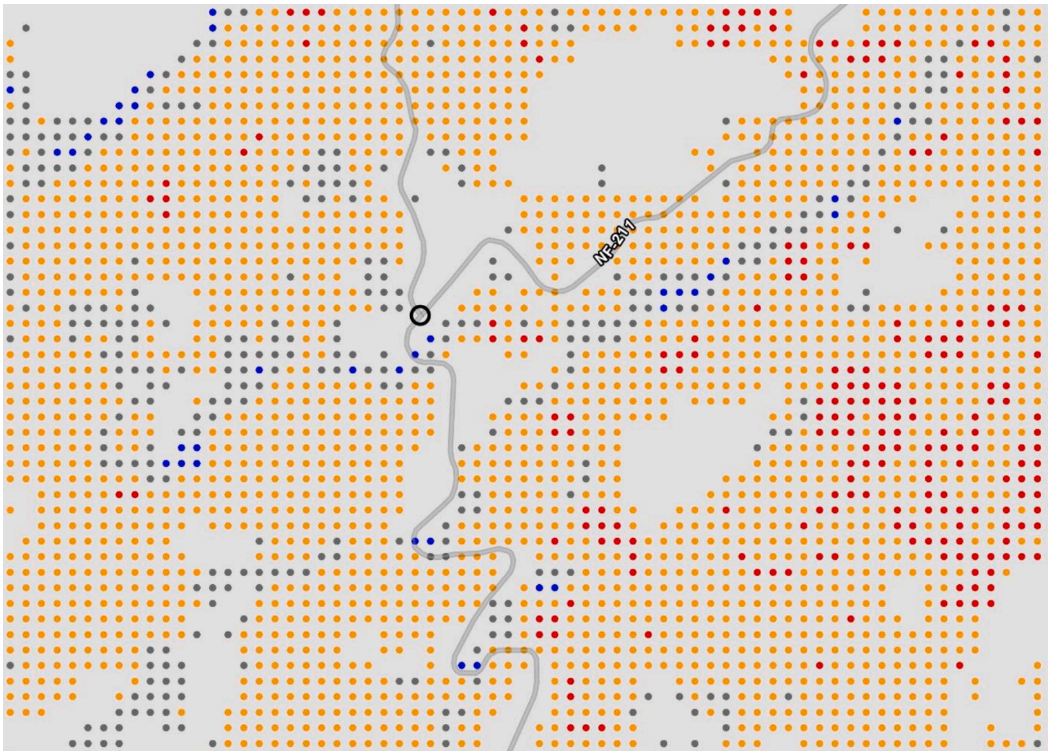

Fig. 3. Spatial pattern of persistent forest loss cluster assignment for a 3-km^2 region in Colorado, USA. Clusters: 1 (●), 2 (●), 3 (●), 4 (●); ○ = 39° 9′ 35″ N 105° 22′ 11″ W.

Table 3
Persistent forest loss data quality: (a) L2-norm statistics (Reference = 0.92) and crosstabulation of North American Forest Dynamics (NAFD) cause of forest loss by persistent forest loss cluster assignment; (b) Agreement (Agree) between persistent forest loss and coincident reference samples from the NLCD 2006, 2011, and 2016 accuracy assessments and user's and producer's accuracy (UA and PA) for NLCD forest loss and standard errors (±x%) from those assessments. Values = 0.000 are < 0.0005.

a		Cluster			
	Pfl[1]	1	2	3	4
L2-Norm	1.59	3.20	1.07	1.81	1.47
NAFD[2] class					
non-Forest		0.035	0.052	0.057	0.056
Stable Forest		0.007	0.008	0.016	0.020
Conversion		0.001	0.016	0.000	0.000
Disturbance		0.956	0.940	0.926	0.924
b	# samples	Agree(%)[3]	UA (%)	PA (%)	
NLCD 2016	7	100	74 (±5)[4]	75 (±5)[4]	
NLCD 2011	33	94	79 (±2) [5]	54 (±5)[5]	
NLCD 2006	90	80	82 (±1)[6]	30 (±3)[6]	

[1]Pfl = persistent forest loss (see methods); [2] NAFD classes are non-forest, water, stable forest, removal (harvest), fire, stress, other, wind, and conversion (https://daac.ornl.gov/NACP/guides/NAFD-NEX_Attribution.html). The label, disturbance, is an aggregation of removal (harvest), fire, stress, and other. The NAFD class, wind, did not coincide with any of the persistent forest loss locations. The NAFD class, conversion, includes forest loss that is not attributable to the other five NAFD loss classes. We interpreted conversion as forest converted to an anthropogenic land use (e.g., forest to urban; forest to agriculture). [3] See Supplemental Information for agreement definitions; [4] 2011 – 2016 forest loss (Wickham et al. 2021); [5] 2006 – 2011 forest loss (Wickham et al. 2017); [6] 2001 – 2006 forest loss (Wickham et al. 2013).

conversion group (clusters 1 and 2) and less common at locations comprising the apparent forest recovery group (clusters 3 and 4) (Table 4). The two groups were distinguished most clearly by severe fires. Locations in the potential forest conversion group were more likely to have experienced at least one severe fire than locations in the apparent forest recovery group The prevalence of fire across the clusters is consistent with their overall mean NDVI trends (Fig. 1). Moderate and severe fires were most common in cluster 1 and least common in cluster 4, and the mean 2019 NDVI minus 2001 NDVI differences for clusters 1 and 4 were the most strongly negative and positive, respectively.

Disturbance between 2002 and 2004 (i.e., xFire0204 and IDS0204 in Table 1) occurred across 72 % of the persistent forest loss locations. During this period, 69 % of persistent forest loss locations experienced fire and 15 % occurred in areas that experienced mortality (IDS0204); about 12 % of locations experienced both fire and mortality related to insect and disease infestations. The relation between fires occurring during this period and persistent forest loss clusters was, as expected, strongly similar to that reported in Table 4 – 81% of locations in the potential forest conversion group (clusters 1 and 2) and 63 % of locations in the apparent forest recovery group (clusters 3 and 4) experienced at least one moderate or severe fire during this period. However, there no relationship was apparent between persistent forest loss clusters and insects and disease mortality. Mortality related to insect and disease was distributed roughly uniformly across the persistent forest loss clusters.

Persistent forest loss clusters were not strongly associated with elevation (Fig. 4) and there was no association between persistent forest loss clusters and moisture stress (Figures S3 and S4). Cluster 1, part of the potential forest conversion group, tended to occur at lower elevations than the other three clusters, but each cluster occurred across nearly the entire range of elevations found across the western United States. The tendency for cluster 1 to occur at lower elevations was partly attributable to its concentration within the Biscuit fire. The maximum elevation within the boundary of the Biscuit fire is about 1,370 m (4,500 ft).

The relation between cluster membership and elevation was evident in the patterns of cluster membership across vegetation types (Table 5). Excluding cluster 1, which comprised only about 5 % of all persistent

Table 4
Proportions of clusters by number of moderate (nfire), severe (hFire), and moderate or severe fires (xFire).

	nFire[1]			hFire[1]			xFire[1]		
Cluster	None	≥ 1	≥ 2	None	≥ 1	≥ 2	None	≥ 1	≥ 2
1	0.524	0.476	0.090	0.292	0.708	0.197	0.077	0.923	0.547
2	0.686	0.314	0.014	0.455	0.545	0.009	0.159	0.841	0.042
3	0.652	0.348	0.005	0.639	0.361	0.003	0.297	0.703	0.014
4	0.739	0.261	0.006	0.722	0.276	0.002	0.466	0.534	0.013

[1] See Table 1 and Supplemental Information for descriptions of nFire, hFire, and xFire.

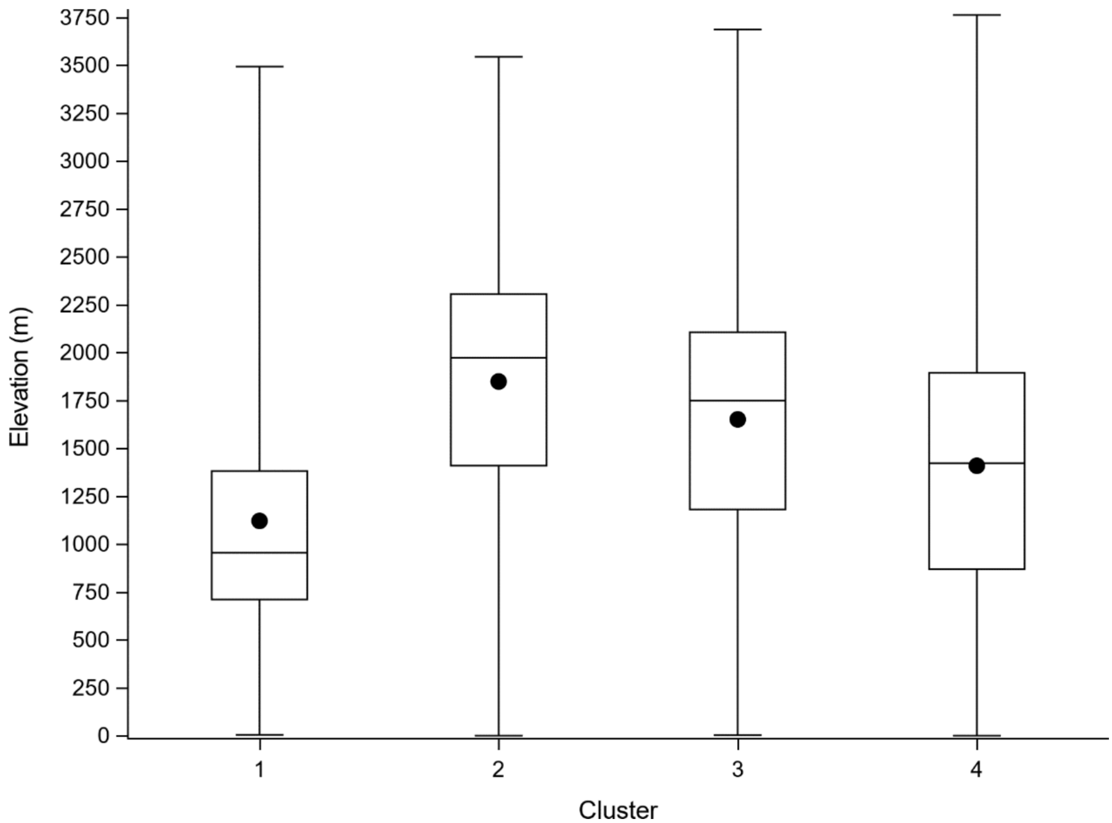

Fig. 4. Cluster elevation ranges (whiskers (⊥) extend to minimum and maximum from lower and upper quartiles; mean (●); median (-)).

forest loss locations, vegetation classes tended to occur in all clusters in roughly even distributions. The ponderosa pine class, for example, comprised nearly 20 % of cluster 2, part of the potential forest conversion group, but also comprised a large share of the apparent forest recovery group (clusters 3 and 4). Eight vegetation classes comprised at least 5 % of cluster 2, ranging from low elevation woodlands (e.g., pinyon-juniper) to high elevation forests (e.g., spruce-fir). Given that cluster 1 was predominantly located within the boundaries of the Biscuit and Hayman fires, it follows that two vegetation classes comprised 60 % of its area.

Variables in the ancillary dataset such as tree canopy cover (TCC) (Coulston et al. 2012) and surrounding forest (fs7) can be used as ecological context surrogates, which may be useful for further examination of locations in the potential forest conversion group. The area estimate for the potential forest conversion group, 3,470 km^2, can be combined with TCC and fs7 to determine a location's proximity to seed sources, an important determinant of recovery (Stevens-Rumann and Morgan 2019). If TCC is zero (0), seed sources are lacking in the immediate neighborhood and if fs7 is 0 there is no forest cover within a 4.4-ha neighborhood surrounding the location. About 20 % of the locations in the potential forest conversion group have no tree canopy cover (TCC) in its immediate vicinity and no forest cover (fs7 = 0) within a 4.4-ha neighborhood surrounding the location (Table 6).

3.5. Discussion

We estimated that 3,467 km^2 of 2001 forest loss may not return or reattain prior structure and composition. Our estimate of potential forest conversion is about 0.5 % of the 2001 total mapped upland forest extent in the NLCD2016 database (Homer et al. 2020) for the western United States. Our results complement *meta*-analyses of the ecological patterns of forest regeneration following disturbance (Korb et al. 2019; Stevens-Rumann and Morgan 2019) by adding geographic context and identifying specific locations where ecological conditions may not support forest recovery from disturbance.

Concern over potential forest conversion has focused on ponderosa pine and Douglas fir because of their widespread occurrence throughout the western United States and their tendency to occupy on warmer, drier sites (Davis et al. 2019; Korb et al. 2019). Our results are consistent with this concern but also highlight that potential forest conversion may not be limited to sites characterized by these species (Stevens-Rumann and Morgan 2019). Sites in the potential forest conversion group included many other vegetation classes covering a wide range of elevations.

About 72 % of persistent forest loss co-occurred with fire or mortality

Table 5
Proportion of cluster area occupied by LANDFIRE (LF) vegetation system groups.[1]

LF Code[3]	Description[4]	P[5]	Cluster[2] 1	2	3	4
631	PIPO F, W, S	0.158	0.027	0.194	0.175	0.113
625	PSME-PIPO-PICO F, W	0.137	0.146	0.164	0.121	0.133
639	Spruce-Fir F,W	0.095	0.045	0.095	0.091	0.116
626	CA Mixed Evergreen F, W	0.079	0.445	0.079	0.054	0.033
643	PSME-ABAL-ABCO F, W	0.074	0.067	0.064	0.071	0.095
630	Pinon-Juniper W	0.066	0.004	0.076	0.088	0.023
614	PSME F, W	0.064	0.017	0.056	0.066	0.080
615	PSME-TSHE F, W	0.060	0.024	0.017	0.058	0.129
610	Conifer-Oak F, W	0.047	0.034	0.039	0.039	0.012
622	Juniper W	0.028	0.014	0.032	0.025	0.031
640	Subalpine W, P	0.024	0.013	0.041	0.020	0.011
629	Western Oak W, S	0.020	0.012	0.011	0.026	0.022
603	Aspen Mixed Conifer F, W	0.020	0.004	0.019	0.020	0.025
635	Western riparian W, Sh	0.019	0.005	0.016	0.021	0.021
999	NLCD land cover[6]	0.015	0.022	0.008	0.012	0.024
696	Juniper-oak	0.014	0.001	0.015	0.021	0.004
645	Western Red-cedar F	0.014	0.051	0.018	0.007	0.011

[1] LF vegetation system group = attribute LF_EVTr in Table 1; [2] Proportions are based on cluster area; [3] LF classes shown comprise 92 % of all persistent forest loss locations; [4]F = forest; W = woodland; S = savanna; P = parkland; Sh = shrubland; PSME = Douglas fir (*Pseudotsuga menziesii*); PIPO = ponderosa pine (*Pinus ponderosa*); TSHE = western hemlock (*Tsuga heterophylla*); PICO = lodgepole pine (*Pinus contorta*); ABAL = silver fir (*Abies alba*); ABCO = white fir (*Abies concolor*); [5] proportion of persistent forest loss (i.e., all clusters); [6] LF assigned NLCD land cover to areas that could not be confidently labeled as a designated vegetation class.

Table 6
Area estimates of potential forest conversion from classification (A) and adjusted using indicators in ancillary dataset (C).

Assumption (A) & Criteria (C)	Area (km^2)
A: Potential forest conversion (clusters 1 & 2)	3,467
C: Potential forest conversion & TCC ≤ 9[a]	2,188
C: Potential forest conversion & TCC ≤ 9[a] & fs7 = 0	642

[a] Use of TCC ≤ 9 % rather than TCC = 0 % is explained in supplement information section.

attributable to insect and disease agents between 2002 and 2004. Some portion of the remaining 28 % is probably attributable to timber production, which is common in the Pacific Northwest and likely captured in the apparent forest recovery group (clusters 3 and 4). Drought may also be a factor. Although there was no association between the persistent forest loss clusters and moisture stress, cumulative vapor pressure deficit (VPD) anomalies were greater than the 30-year normal for more than 75 % of all locations for spring and summer.

Unexpectedly, there was no difference in VPD across the potential forest loss and apparent forest recovery groups. Moisture stress impedes forest recovery (Davis et al. 2019; Korb et al. 2019; Stevens-Rumann and Morgan 2019). Our results may be at least partly attributable to the coarse resolution of the PRISM data (4- x 4-km). For example, a 4- x –4 km pixel centered on the peak of Mt. Hood in Oregon would have an elevation of 3,430 m (11,250 ft) at its center and an elevation of about 2,285 m (7,500 ft) at its edge. Despite PRISM's widespread use and documented data quality (Spangler et al. 2019), the higher resolution (800- x 800-m) PRISM dataset likely would have provided a better assessment of the influence of moisture stress. The financial resources needed to acquire the higher resolution PRISM data were not available.

Cluster membership was most strongly associated with fire exposure and severity. Insect outbreaks and drought were not associated with cluster membership. Notwithstanding the potential effects of the coarse resolution of the climatic data used, our results are consistent with field observations of potential forest conversion. Several case studies of management activities aimed at addressing potential forest conversion cite fire as the main agent of vegetation change (Guiterman et al. 2022). Observations by Guiterman et al. (2022) are consistent with observations reported in many of the field-based studies we cite, which also often point out the importance of post-fire moisture availability to recovery (e.g., Chambers et al. 2016; Collins and Roller 2013; Haffey et al. 2018; Harvey et al. 2016; Rodman et al. 2020; Shive et al. 2013; Stoddard et al. 2018). The IDS data itself indicated a limited association with potential forest conversion (i.e., cluster membership) because only 15 % of persistent forest loss locations coincided with pest infestations and the average area of the 2002 – 2004 outbreaks was only about 3 ha. Additionally, much of the available literature suggests forests recover from pest infestations, although relative canopy composition may change somewhat (Collins et al. 2011; Négron and Cain 2019; Pelz et al. 2018).

TCC and fs7 were included in the dataset because they can be used as ecological surrogates for distance to a seed source. Existence of proximal seed sources is perhaps the most often cited factor promoting forest re-establishment (Korb et al. 2019; Steven-Rumann and Morgan 2019). Use of TCC and Fs7 together is an example of a weight-of-evidence approach, which is often applied in risk assessment (Linkov et al. 2009). Professional judgement may ascribe greater likelihood of potential forest conversion to those locations where Fs7 was zero (0) and TCC was effectively zero (0) than locations where neither criteria or just one was met.

3.6. Summary and conclusion

We estimated an upper bound of the area of potential forest conversion to be 3,467 km^2. Others have raised concern regarding the potential effects of changing disturbance regimes (Abatzoglou et al. 2017; Allen et al. 2015; Coop et al. 2020; Halofsky et al. 2020), estimated disturbance extent (Hicke et al. 2016), and summarized factors that promote recovery following disturbance (Korb et al. 2019; Stevens-Rumann and Morgan 2019). To our knowledge, this is the first attempt to estimate the areal extent of potential forest conversion. The estimate is cognizant of measurement error and ecological context (i.e., upper bound) and uncertainties related to determination of successional outcomes (i.e., potential). Concern over adverse ecological effects of changing disturbance regimes highlights that additional monitoring would be beneficial. Our results indicated that NLCD (Homer et al. 2020; Yang et al. 2018), other allied datasets (Wickham et al. 2014), and additional geographic data, as used here, are useful for monitoring potential forest conversion. Future releases of NLCD can be used to extend the time span reported herein. The approach used herein can be applied to all locations that have a time series of land cover data.

4. Data availability

Data are posted as a csv-formated file on EPA's Environmental Dataset Gateway (https://gaftp.epa.gov/EPADataCommons/ORD/EnviroAtlas/PotentialForestConversionNLCD2016.zip). The X,Y coordinates in the csv file can be used to reconstitute in a GIS. The coordinates are based on the USA Contiguous Albers Equal Area Conic USGS projection (WKID = 102039).

Author contributions

JW conceived and led the research and writing. AN recommended and advised on statistical analyses. KH advised on data quality analysis and wrote and edited the paper. MN advised on statistical analyses. JD and SJ recommended ancillary data and advised on analytical considerations. MVF and DR assisted with code development for NDVI processing.

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Declaration of Competing Interest

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Data availability

Data will be made available on request.

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Appendix A. Supplementary data

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