

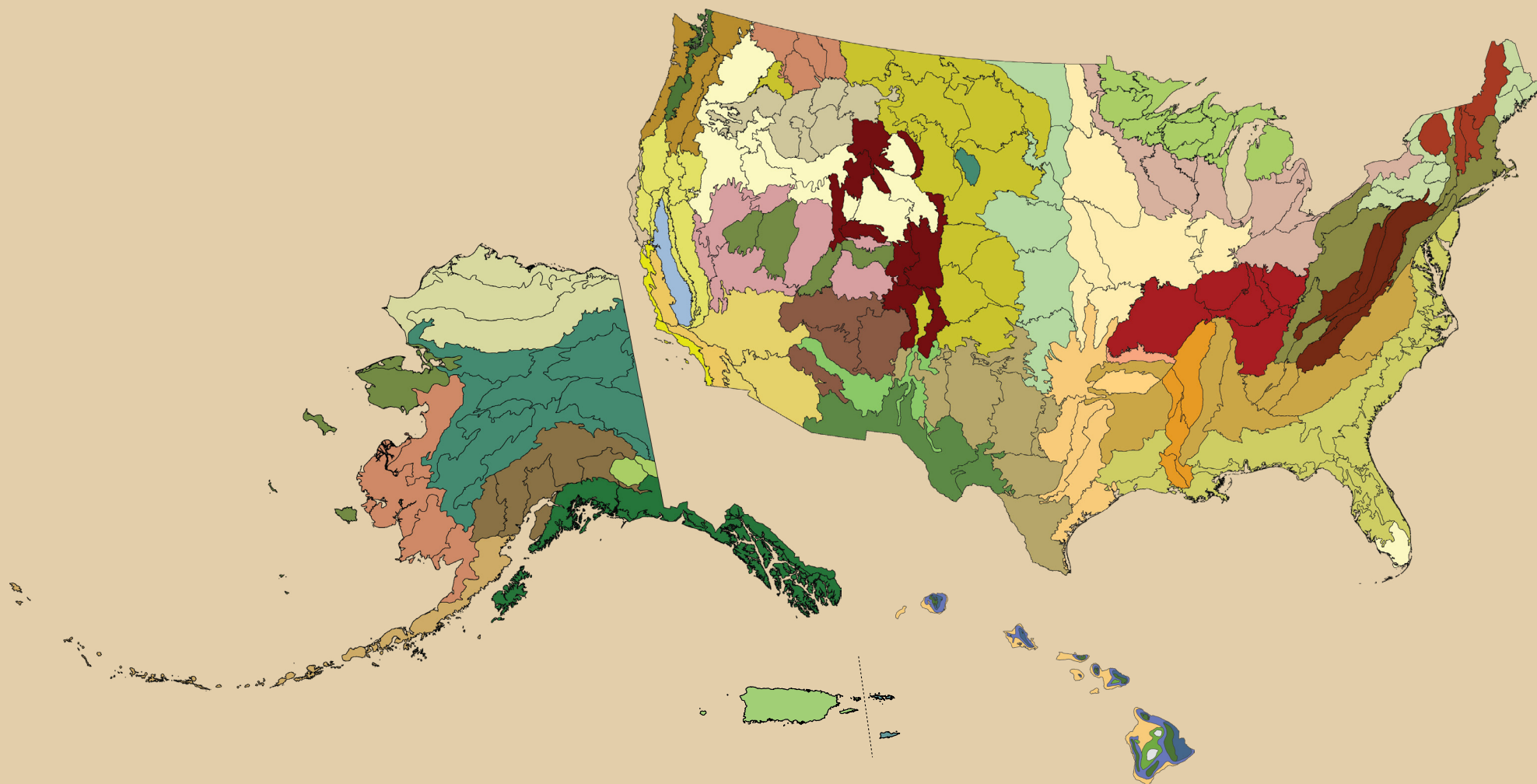


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Forest Health Monitoring: National Status, Trends, and Analysis 2023

EDITORS: Karun Pandit and Barbara L. Conkling



FRONT COVER MAP: Ecoregion provinces and ecoregion sections for the conterminous United States (Cleland and others 2007) and for Alaska (Spencer and others 2002), and ecoregions within the islands of Hawaii (Potter 2023), along with Puerto Rico and the U.S. Virgin Islands, for which no corresponding ecoregion treatments exist.

BACK COVER MAPS: Tree canopy cover (green) for the conterminous United States, Hawaii, Puerto Rico, and the U.S. Virgin Islands based on data from a cooperative project between the Multi-Resolution Land Characteristics Consortium and the U.S. Department of Agriculture, Forest Service, Geospatial Technology and Applications Center using the 2011 National Land Cover Database (NLCD). Forest and shrubland cover for Alaska derived from the 2011 NLCD.

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Forest Health Monitoring: National Status, Trends, and Analysis 2023

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ABSTRACT

The Forest Health Monitoring Program of the U.S. Department of Agriculture, Forest Service produces an annual national report that presents recent forest health status and trends from a national or multistate regional perspective and introduces new techniques to analyze forest health condition. In this 23rd edition of annual reports, national Insect and Disease Survey (IDS) data are used to identify recent spatial patterns of areas affected by insects and diseases. Satellite data are employed to detect geographic patterns of forest fire occurrence. Data collected by the Forest Inventory and Analysis (FIA) Program are used to explore regional differences in tree mortality. National Land Cover Database (NLCD) maps are used to detect trends in forest fragmentation across the conterminous United States. Exposure of forests to drought was summarized using data from the Parameter-elevation Regressions on Independent Slopes Model (PRISM) Climate Group and the FIA Program. Association of multidecadal repeat dryness with wildfire and bark beetle disturbance was explored for the conterminous United States using data from NLCD; IDS; Wildland Fire Management Research, Development, and Application; Wildland Fire Interagency Geospatial Services; Monitoring Trends in Burn Severity; and PRISM Climate Group.

Keywords—Change detection, disturbance, drought, fire, forest fragmentation, forest health, forest insects and disease, tree mortality.

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Ecosystems are healthy if they are stable and sustainable, which means that they are active and maintain their organization and autonomy over time while remaining resilient to stress (Costanza 1992). Health condition of ecosystems can be measured in terms of their vigor, organization, and resilience (Rapport and others 1998). Healthy forests are vital to current and future well-being (Edmonds and others 2011, Trumbore and others 2015). Consistent, large-scale, and long-term monitoring of key forest health indicators is necessary to assess status, change, and trends in forest ecosystems across large regions (Riitters and Tkacz 2004). The Forest Health Monitoring (FHM) Program of the U.S. Department of Agriculture, Forest Service, with cooperating researchers within and outside the Forest Service and with State partners, quantifies status and trends in the health of U.S. forests in the “Forest Health Monitoring: National Status, Trends, and Analysis” report (ch. 1). The 2023 FHM national report is the 23rd edition in the annual series of reports. The report offers a snapshot of the current condition of U.S. forests from a national or multistate regional perspective, incorporating baseline investigations of forest ecosystem health, examinations of change over time in forest health metrics, and assessments of developing threats to forest stability and sustainability. Section 1 of the report presents analyses based on short-term forest health data; section 2 covers analyses of long-term forest health trends and describes new techniques in forest health assessment. Data from 2022 were used for analyses done on an annual basis, and

datasets collected over several years were used to perform analyses at longer temporal scales.

Monitoring of forest insect and disease outbreaks at the regional scale is important to evaluate their potential impacts on forest health across the landscape (ch. 2). The national Insect and Disease Survey of 2022 identified 52 mortality-causing agents and complexes across the conterminous United States (CONUS) on approximately 3.3 million ha. Fir engraver (*Scolytus ventralis*) was the most widely detected mortality agent in 2022, identified on about 1.36 million ha and largely impacting the West Coast FHM megaregion. Emerald ash borer (*Agrilus planipennis*) was the next most damaging mortality agent nationally and the most damaging in the East. Spruce beetle (*Dendroctonus rufipennis*) is at the top of all the mortality-causing agents in Alaska, though damage was less than in recent years. Extensive mortality in Hawaii may be associated with rapid ‘ōhi’a death. Meanwhile, forest health surveyors reported damage from 59 defoliation agents and complexes affecting approximately 1.87 million ha across the CONUS in 2022. The affected area has been on an upward trend across multiple years. Like in 2021, most of this defoliation was the result of a spongy moth (*Lymantria dispar*) outbreak, primarily in the Eastern FHM megaregion. Swiss needle cast, which was not recorded as a top defoliator in the recent years, was detected as the second most prevalent defoliator in 2022. Alaska had extensive defoliation, caused mostly by western blackheaded budworm (*Acleris gloverana*) as in 2021.

Forest fire incidents outside the historic range of frequency and intensity not only impact

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forest health but can also have long-lasting socioeconomic consequences. The detection of regional patterns of fire occurrence density can allow understanding of where specific management activities or further research initiatives are needed (ch. 3). In 2022, satellite-detected forest fire occurrences in the CONUS were the fourth highest in 22 full years of data collection with a 44-percent decrease in fire activity from the 2021 fire season. New Mexico experienced the two largest forest fires in its history, and a few ecoregion sections in the Southwest had very high fire occurrence densities (fire occurrences per 100 km² of tree canopy cover area). In addition, a handful of ecoregion sections of the Pacific Northwest and the Southeast experienced high fire occurrence densities. Ecoregion sections in the Southwest, Northeast, Midwest, and Mid-Atlantic regions experienced higher-than-normal fire occurrence densities in 2022 compared to the previous 21-year mean and accounting for variability over that period. Alaska experienced a 1,000-percent jump in fire occurrences from 2021 to 2022, with the latter year tallying about 140 percent of the mean annual number of fire occurrences across the previous 21 years. This was the result of well-above normal temperatures through the early summer coupled with lightning-intense storms that sparked a rapid increase in fire activity in June. In 2022, Hawaiian forests had fire occurrence densities that were low and within expectations, except for two ecological regions on the western part of Maui Island. Parts of both Puerto Rico and the U.S. Virgin Islands had higher-than-expected fire occurrence densities. In

the Caribbean, only Great Hans Lollik Island—a tiny island near Saint Thomas in the U.S. Virgin Islands—had a higher-than-expected fire occurrence density in 2022.

In forest ecosystems, mortality is a natural process, but higher rates of mortality at broader spatial scales may be an indicator of forest health problems. Data collected by the Forest Inventory and Analysis (FIA) Program of the Forest Service (box 1.1) offer recent tree mortality information for areas where repeated plot measurements were taken using consistent sampling protocols. Ratio of annual mortality to gross growth (MRATIO) was used as a standardized mortality indicator to compare mortality across forest types and climate zones (Coulston and others 2005) (ch. 4). Analysis showed that in most of the Eastern and Central United States, mortality is low relative to tree growth. None of the ecoregion sections fell into the highest MRATIO class. In 2022, Texas had the highest mortality relative to growth, where the impacts of a record-setting drought are still apparent. Drought, combined with a variety of other biotic and/or abiotic stressors are responsible for much of the mortality observed there. In ecoregion sections 222H—Central Till Plains-Beech-Maple, 222U—Lake Whittlesey Glaciolacustrine Plain, and 223F—Interior Low Plateau-Bluegrass, ash mortality due to emerald ash borer was extremely high.

Measures of forest fragmentation have evolved substantially over three decades of international forest sustainability reporting by the Forest Service pursuant to the Montréal Process Criteria and Indicators (C&I; Montréal Process Liaison Office 2015, Riitters and Robertson 2021). Fragmentation information has been updated by incorporating new land cover data for the

year 2019 and the accompanying revisions to the earlier land cover data (ch. 5). National Land Cover Database (NLCD) maps were categorized to forest and nonforest classes and forest area density (FAD) was calculated for each pixel for five different neighborhood sizes. Between 2001 and 2019, the CONUS experienced a 2.3-percent net loss of total forest land cover area. In comparison, the net loss of interior forest was between 4.3 and 9.5 percent depending on neighborhood size. The Intermountain region exhibited the largest net area losses of total forest and interior forest, but the Pacific Southwest region exhibited the largest annual percent rates of losses. The North Central region was the only region to exhibit a net gain of interior forest area, while the Pacific Northwest region was the only region where the annual percent rate of interior forest loss was less than the rate of total forest loss. Recent results from 2016 to 2019 suggest an increase in both total forest and interior forest areas but do not indicate complete recovery to 2001 conditions.

Drought is an important stressor affecting forests. Whether alone or in combination with other disturbances, drought can reduce forest productivity, cause shifts in forest types, affect the ability of forests to regenerate, and diminish the capacity of forests to provide ecosystem services. Recent trends in drought exposure for forest land in the conterminous United States were summarized using the 36-month Standardized Precipitation Evapotranspiration Index (SPEI; Beguería and others 2014, Vicente-Serrano and others 2010) (ch. 6). SPEI was calculated for 1953–2021 using monthly precipitation and

Hargreaves' (1994) method. Exposure of different forest type groups (FIA data) and subregions (2020 Resources Planning Act Assessment subregions) of the CONUS to SPEI-based drought categories were summarized. In general, national drought exposure was more widespread than average and occurred most often in ecological sections of the Western United States, with moderate frequency in the Southeast, and least often in the Northeast. Drought exposure has been widespread in the Western United States for most of the years since 2000, especially in 2002–2004, 2009, 2013–2015, and recently in 2020–2021. Six forest type groups in the Western United States have been exposed to widespread drought (greater than the average for the CONUS) more frequently than other type groups.

Climatic conditions have amplified forest disturbances, promoted forest vulnerability, and are expected to promote increased and compounding forest disturbances as global warming intensifies. Change in precipitation from 2000 through 2021 was assessed using the Standardized Precipitation Index (SPI) relative to the long-term average from 1948 through 1999, and a new indicator, the Multidecadal Repeat-Dryness Exposure Index (MRDEI), was evaluated by assessing its spatial association with wildfire and bark beetle disturbance records from 2000 through 2022 in forested locations (ch. 7). MRDEI quantifies areas exposed to repeat dryness especially during the warm season (May–September) for long temporal scales. Annual mean SPI suggested drier conditions across the majority of the Western United States in the recent multidecadal period with significant

differences for rare and isolated locations in the Central-Eastern United States. During 2000–2021, >80 percent of forested areas in the Western United States experienced a high frequency of repeat dryness, but only 5 percent of forested areas in the Central-Eastern United States had such exposure. Significant spatial association of higher MRDEI classes was observed with increased forest disturbances (wildfire, bark beetle, and wildfire/bark beetle co-occurrence), which was even more evident for the more recent period (2017–2022).

The FHM Program, in cooperation with forest health specialists and researchers inside and outside the Forest Service, continues to investigate a broad range of issues relating to forest health using a wide variety of data and techniques. This report presents some of the latest results from ongoing national-scale detection monitoring. For more information about efforts to determine the status, changes, and trends in indicators of the condition of U.S. forests, please visit the FHM website at <https://www.fs.usda.gov/science-technology/forest-health-protection/monitoring>.

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Forests and woodlands cover an extensive area of the United States, 333 million ha or approximately 36 percent of the Nation's land area (Oswalt and others 2019). These forests provide a broad range of goods and services for current and future generations, safeguard biological diversity, and contribute to the resilience of ecosystems, societies, and economies (McGinley and others 2023). Their socioeconomic benefits include wood products, nontimber goods, reduction of air pollutants, moderation of city temperatures, recreational opportunities, and natural beauty. Their ecological roles include supplying large and consistent quantities of clean water, preventing soil erosion, and providing habitat for a broad diversity of plant and animal species. At the same time, both the ecological integrity and the continued capacity of these forests to provide ecological and economic goods and services face a long list of threats, including insect and disease infestation, drought, fragmentation and forest conversion to other land uses, catastrophic fire, invasive species, and the effects of climate change.

Natural and anthropogenic stresses vary among biophysical regions and local environments; they also change over time and interact with each other. Such variations along with other factors make it challenging to establish baselines of forest health and to detect important departures from normal forest ecosystem functioning (Riitters and Tkacz 2004). Monitoring the health of forests is a critically important task, reflected within the Criteria and Indicators for the Conservation and Sustainable Management of Temperate and Boreal Forests (Montréal Process Working

Group 1995), which the U.S. Department of Agriculture, Forest Service uses as a forest sustainability assessment framework (McGinley and others 2023; USDA Forest Service 2004, 2011). The primary objective of such monitoring is to identify ecological resources whose condition is deteriorating in subtle ways over large regions in response to cumulative stresses—a goal that requires consistent, large-scale, and long-term monitoring of key indicators of forest health status, change, and trends (Riitters and Tkacz 2004). Given the magnitude of this task, it is best accomplished through the participation of multiple Federal, State, academic, and private partners.

The concept of a healthy forest has universal appeal, but forest ecologists and managers have struggled with how exactly to define forest health (Teale and Castello 2011). No universally accepted definition exists. Most definitions of forest health can be categorized as representing either an ecological or a utilitarian perspective (Kolb and others 1994). From an ecological perspective, the current understanding of ecosystem dynamics suggests that healthy ecosystems are those that maintain their organization and autonomy over time while remaining resilient to stress (Costanza 1992), and that evaluations of forest health should emphasize factors that affect the inherent processes and resilience of forests (Edmonds and others 2011, Kolb and others 1994, Raffa and others 2009). On the other hand, the utilitarian perspective holds that a forest is healthy if management objectives are met, and that a forest is unhealthy if these objectives are not met (Kolb and others 1994). Although this definition may

CHAPTER 1

Introduction

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be appropriate when a single, unambiguous management objective exists, such as the production of wood fiber or the maintenance of wilderness attributes, it can be too narrow when multiple management objectives are required (Edmonds and others 2011, Teale and Castello 2011). Teale and Castello (2011) incorporate both ecological and utilitarian perspectives into their two-component definition of forest health: first, a healthy forest must be sustainable with respect to its size structure, including a correspondence between baseline and observed mortality; second, a healthy forest must meet the landowner's objectives, provided that these objectives do not conflict with sustainability.

This "Forest Health Monitoring: National Status, Trends, and Analysis" report, the 23rd in an annual series sponsored by the Forest Health Monitoring (FHM) Program of the Forest Service, attempts to quantify the status of, changes to, and trends in a wide variety of broadly defined indicators of forest health. The indicators described in this report encompass forest insect and disease activity, wildland fire occurrence, tree mortality, forest fragmentation, and drought, among others. The previous reports in this series are Ambrose and Conkling (2007, 2009), Conkling (2011), Conkling and others (2005), Coulston and others (2005a, 2005b, 2005c), and Potter and Conkling (2012a, 2012b, 2013a, 2013b, 2014, 2015a, 2015b, 2016, 2017, 2018, 2019, 2020, 2021, 2022, 2023). Visit <https://www.fs.usda.gov/science-technology/forest-health-protection/publications-reports/forest-health-monitoring-publications/annual-national-forest-health-monitoring-reports> for links to each of these

reports in their entirety and for searchable lists of links to chapters included in the reports.

The first objective of this report is to present information about forest health from a national perspective, or from a multistate regional perspective when appropriate, using data collected by the Forest Health Protection (FHP) and Forest Inventory and Analysis (FIA) Programs of the Forest Service, as well as from other sources that are available at a wide extent, such as subregions within the United States. Even though all the chapters in this report have a national or multistate regional perspective, they differ in their spatial extent, largely depending on the data availability for the respective kind of analysis. For example, the fire occurrence analysis (ch. 3) covers the conterminous United States (CONUS), Alaska, Hawaii, Puerto Rico, and the U.S. Virgin Islands, but the tree mortality analysis (ch. 4) is limited to the Eastern and Central United States.

The second objective of this report is to provide analyses from various temporal scales. Chapters in this report vary by their extent of temporal data. For example, the insect and disease damage (ch. 2) and tree mortality (ch. 4) chapters present analyses of forest health on an annual basis or from a short-term perspective. Such repeated analyses of regularly collected indicator measurements allow for the detection of trends over time and help establish a baseline for future comparisons (Riitters and Tkacz 2004). Other chapters, such as those about forest fragmentation (ch. 5) or drought (ch. 6 and 7), present analyses of long-term trends. Some others, like the fire occurrence analysis (ch. 3), provide forest health scenarios from both short- and long-term perspectives.

The third objective of the report is to present new techniques for analyzing forest health data as well as new applications of established techniques, often applied to longer timelines. Examples from this report include updates to sustainability indicators for forest fragmentation (ch. 5); analysis of multiyear drought trends across and within the subregions of the United States, as well as summaries of forest ecosystem exposure to droughts (ch. 6); and an evaluation of a new multiyear dryness exposure index and its association with forest disturbances (ch. 7).

Summaries of the results from recently completed Evaluation Monitoring projects funded through the national FHM Program, which generally focus on forest health problems at finer scales (FHM 2022), have been published in a section of this report since 2008. These project summaries will now be presented in a separate document.

When appropriate throughout this report, authors use the Forest Service revised ecoregions for the CONUS and Alaska (Cleland and others 2007, Spencer and others 2002) as a common ecologically based spatial framework for their forest health assessments (fig. 1.1). Specifically,

when the spatial scale of the data and the expectation of an identifiable pattern in the data are appropriate, authors use ecoregion sections, larger scale provinces, or smaller scale subsections as assessment units for their analyses. Bailey's hierarchical system bases the two broadest ecoregion scales—domains and divisions—on large ecological climate zones, while each division is broken into provinces based on vegetation macrofeatures (Bailey 1995). Provinces are further divided into sections, which may be thousands of km² in area and are expected to encompass regions similar in their geology, climate, soils, potential natural vegetation, and potential natural communities (Cleland and others 1997). Subsections are nested within sections as the smallest level in the hierarchy. This hierarchical system does not address either Hawaii or Puerto Rico beyond including each in a unique, single ecoregion province (Bailey 1995). A set of Hawaii ecoregions based on moisture and elevational characteristics was developed for use in FHM national reports (Potter 2023) because a finer scale and ecologically oriented spatial assessment framework was needed to estimate the impacts of a destructive forest disease (ch. 2) and of forest fire occurrences (ch. 3) (fig. 1.2).

(A)

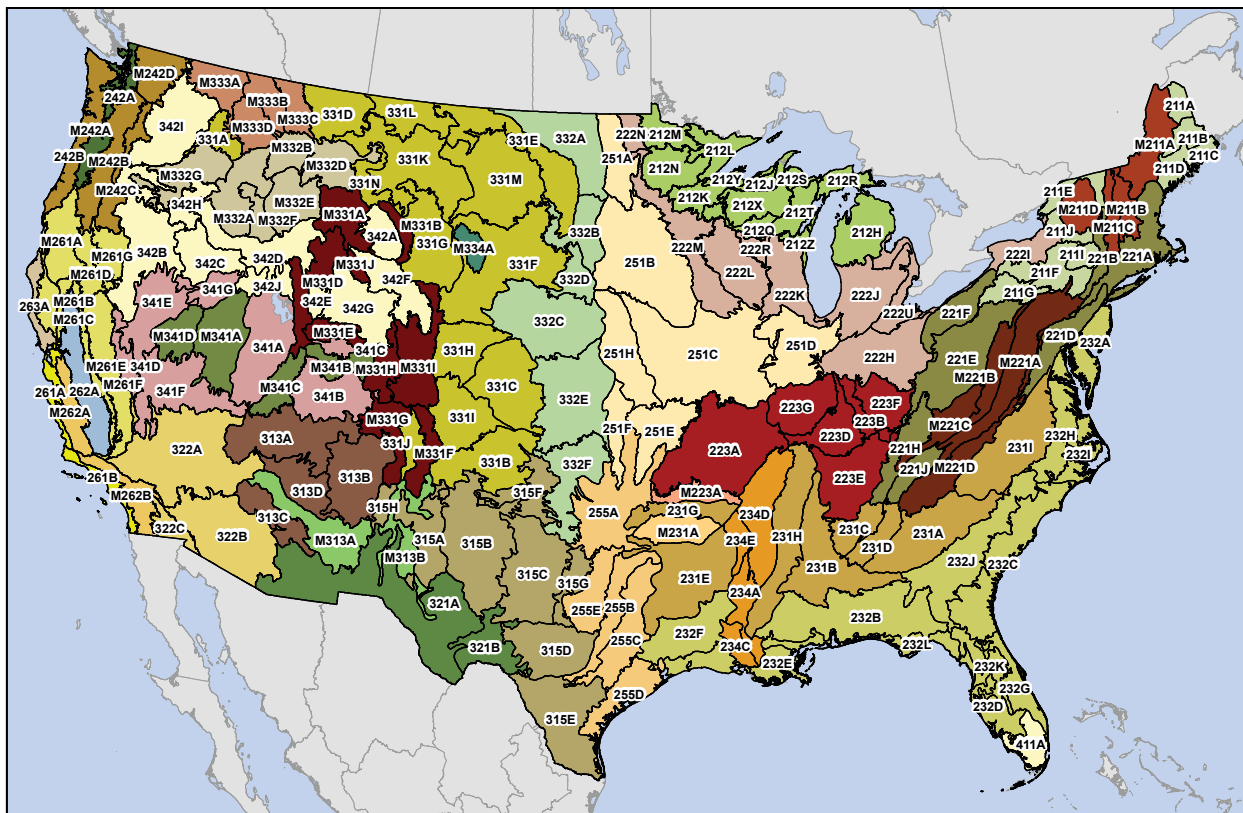
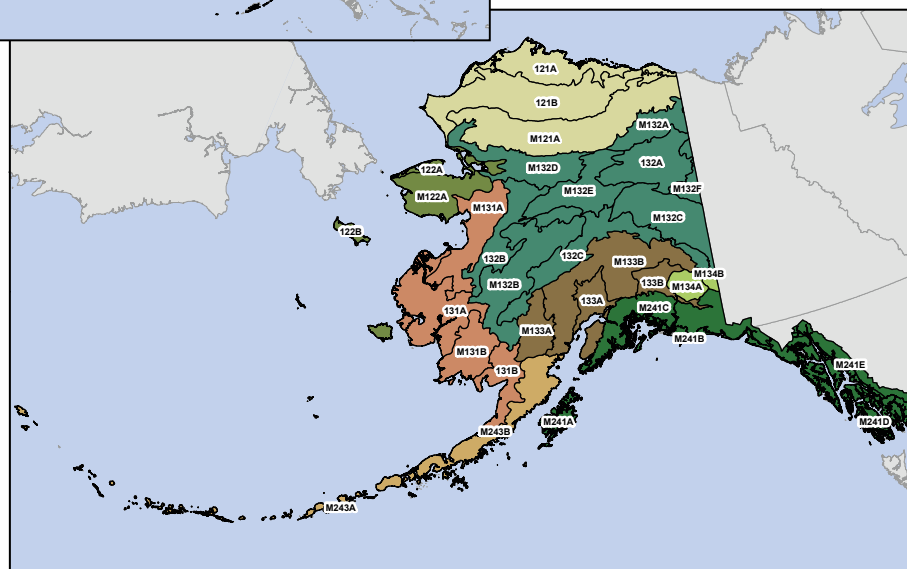


Figure 1.1—Ecoregion provinces and sections for (A) the conterminous United States (Cleland and others 2007) and (B) Alaska (Spencer and others 2002). Ecoregion sections within each ecoregion province are shown in the same color.

(B)



Conterminous States ecoregion provinces

-  211: Northeastern Mixed Forest
-  M211: Adirondack-New England Mixed Forest—Coniferous Forest—Alpine Meadow
-  212: Laurentian Mixed Forest
-  221: Eastern Broadleaf Forest
-  M221: Central Appalachian Broadleaf Forest—Coniferous Forest—Meadow
-  222: Midwest Broadleaf Forest
-  223: Central Interior Broadleaf Forest
-  M223: Ozark Broadleaf Forest
-  231: Southeastern Mixed Forest
-  M231: Ouachita Mixed Forest—Meadow
-  232: Outer Coastal Plain Mixed Forest
-  234: Lower Mississippi Riverine Forest
-  242: Pacific Lowland Mixed Forest
-  251: Prairie Parkland (Temperate)
-  255: Prairie Parkland (Subtropical)
-  M242: Cascade Mixed Forest—Coniferous Forest—Alpine Meadow
-  261: California Coastal Chaparral Forest and Shrub
-  M261: Sierran Steppe—Mixed Forest—Coniferous Forest—Alpine Meadow
-  262: California Dry Steppe
-  M262: California Coastal Range Open Woodland—Shrub—Coniferous Forest—Meadow
-  263: California Coastal Steppe—Mixed Forest—Redwood Forest
-  313: Colorado Plateau Semi-Desert
-  M313: Arizona-New Mexico Mountains Semi-Desert—Open Woodland—Coniferous Forest—Alpine Meadow
-  315: Southwest Plateau and Plains Dry Steppe and Shrub
-  321: Chihuahuan Semi-Desert
-  322: American Semi-Desert and Desert
-  331: Great Plains—Palouse Dry Steppe
-  M331: Southern Rocky Mountain Steppe—Open Woodland—Coniferous Forest—Alpine Meadow
-  332: Great Plains Steppe
-  M332: Middle Rocky Mountain Steppe—Coniferous Forest—Alpine Meadow
-  M333: Northern Rocky Mountain Forest-Steppe—Coniferous Forest—Alpine Meadow
-  M334: Black Hills Coniferous Forest
-  341: Intermountain Semi-Desert and Desert
-  M341: Nevada-Utah Mountains Semi-Desert—Coniferous Forest—Alpine Meadow
-  342: Intermountain Semi-Desert
-  411: Everglades

Alaska ecoregion provinces

-  121: Arctic Tundra
-  M122: Bering Tundra
-  M131: Bering Taiga
-  M132: Intermontane Boreal
-  133: Alaska Range Transition
-  M134: Coastal Mountains Transition
-  M241: Coastal Rainforest
-  M243: Aleutian Meadows

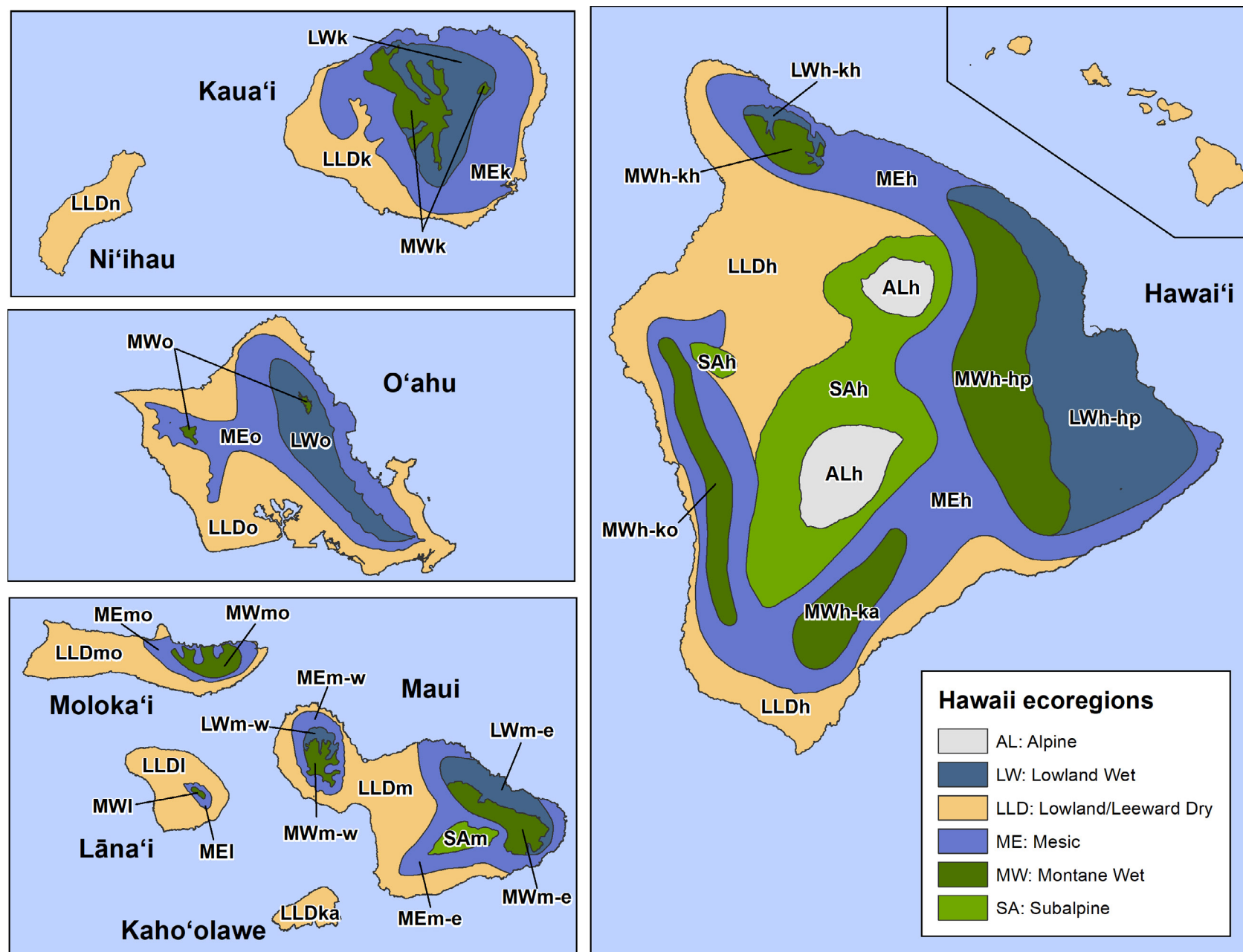


Figure 1.2—Ecoregions, and ecoregion subunits, for Hawaii (Potter 2023), developed based on moisture zones and elevation (see box 1.1). Ecoregion subunits are shown in the same color by ecoregion.

THE FOREST HEALTH MONITORING PROGRAM

The national FHM Program is designed to deliver actionable data and information on the status, trends, and future of forest conditions to land managers and decision makers. FHM implements this goal on an annual basis and covers all forested lands through a partnership encompassing the Forest Service, State foresters, and other State and Federal agencies and academic groups (FHM 2022). The FHM Program utilizes data from a wide variety of data sources, both inside and outside the Forest Service, and develops analytical approaches for addressing forest health issues that affect the sustainability of forest ecosystems. The FHM Program has three major approaches (fig. 1.3), which are interlinked and provide feedback to each other:

- **Survey and Detection**—identifying forest health challenges at local and landscape scales through nationally standardized aerial and ground surveys
- **Monitoring and Analysis**—tracking the status and trends of forest health challenges and assessing impacts on forest resources and their benefits through synthesis and evaluation of information from various data sources within and external to the Forest Service
- **Communications**—supporting decision making and communicating regional, long-term forest health trends and their implications to forest resources and their benefits

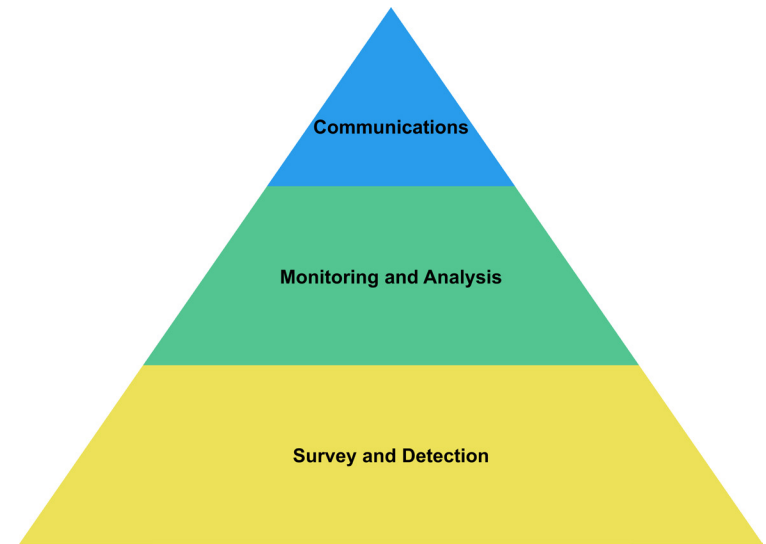


Figure 1.3—The design of the Forest Health Monitoring Program.

The FHM Program is divided into four “megaregions.” These correspond with the two Forest Service regions in the Eastern United States (Eastern and Southern) while joining four Forest Service regions into the Interior West megaregion (Northern, Rocky Mountain, Southwestern, and Intermountain) and three Forest Service regions into the West Coast megaregion (Pacific Southwest, Pacific Northwest, and Alaska) (fig. 1.4). Some analyses in this FHM national report provide results by FHM megaregion, though they separate Alaska and Hawaii from the rest of the West Coast megaregion, and Puerto Rico and the U.S. Virgin Islands from the rest of the Southern megaregion. In addition to national reporting, the FHM

Program generates regional and State reports, often in cooperation with FHM partners, both within the Forest Service and in State forestry and agricultural departments. For example, the FHM megaregions cooperate with their respective State partners to produce the annual “Forest Health Highlights” report series, available on the FHM website at <https://www.fs.usda.gov/science-technology/forest-health-protection/publications-reports/forest-health-monitoring-publications/forest-health-highlights>. Other examples include Steinman (2004) and Harris and others (2011).

The FHM Program and its partners also produce peer-reviewed reports and journal articles on monitoring techniques and analytical methods (see <https://www.fs.usda.gov/science-technology/forest-health-protection/publications-reports/forest-health-monitoring-publications/>). The emphases of these publications include forest health data (Potter and others 2016, Siry and others 2018, Smith and Conkling 2004); soils as an indicator of forest health (O’Neill and others 2005); urban forest health monitoring (Biggsby and others 2014; Cumming and others 2006, 2007; Hudgins and others 2022; Lake and others 2006); remote sensing of forest disturbances (Chastain and others 2015, Rebbeck and others 2015); health conditions in national forests (Morin and others 2006); crown conditions (Morin and others 2015; Randolph 2010a, 2010b, 2013; Randolph and Moser 2009; Schomaker and others 2007); indicators of regeneration (McWilliams and others 2015); vegetation diversity and structure (Crockett and others 2023, Schulz and Gray 2013, Schulz and others 2009, Simkin and others

2016); forest lichen communities (Jovan and others 2012, Root and others 2014); down woody materials in forests (Woodall and others 2012, 2013); drought (Costanza and others 2023, Vose and others 2016); ozone monitoring (Rose and Coulston 2009); patterns of nonnative invasive plant occurrence (Guo and others 2015, 2017; Iannone and others 2015, 2016a, 2016b, 2018; Jo and others 2018; Oswalt and others 2015; Potter and others 2023; Riitters and others 2018a, 2018b); assessments of forest risk or tree species vulnerability to exotic invasive forest insects and diseases (Asaro and others 2023; Koch and others 2011, 2014; Krist and others 2014; Potter and others 2019a, 2019b; Vogt and Koch 2016; Yemshanov and others 2014); spatial patterns of land cover and forest fragmentation (Guo and others 2018; Riitters 2011; Riitters and Costanza 2019; Riitters and Wickham 2012; Riitters and others 2012, 2016, 2017); impacts of deer browse on forest structure (Russell and others 2017); broad-scale assessments of forest biodiversity (Guo and others 2019; Potter 2018; Potter and Koch 2014; Potter and Woodall 2012, 2014); predictions and indicators of climate change effects on forests and forest tree species (Anderson and others 2021, Fei and others 2017, Heath and others 2015, Potter and Hargrove 2013); legal, institutional, and economic indicators of forest conservation and sustainable management (McGinley and Cubbage 2020); and the overall forest health indicator program (Woodall and others 2010).

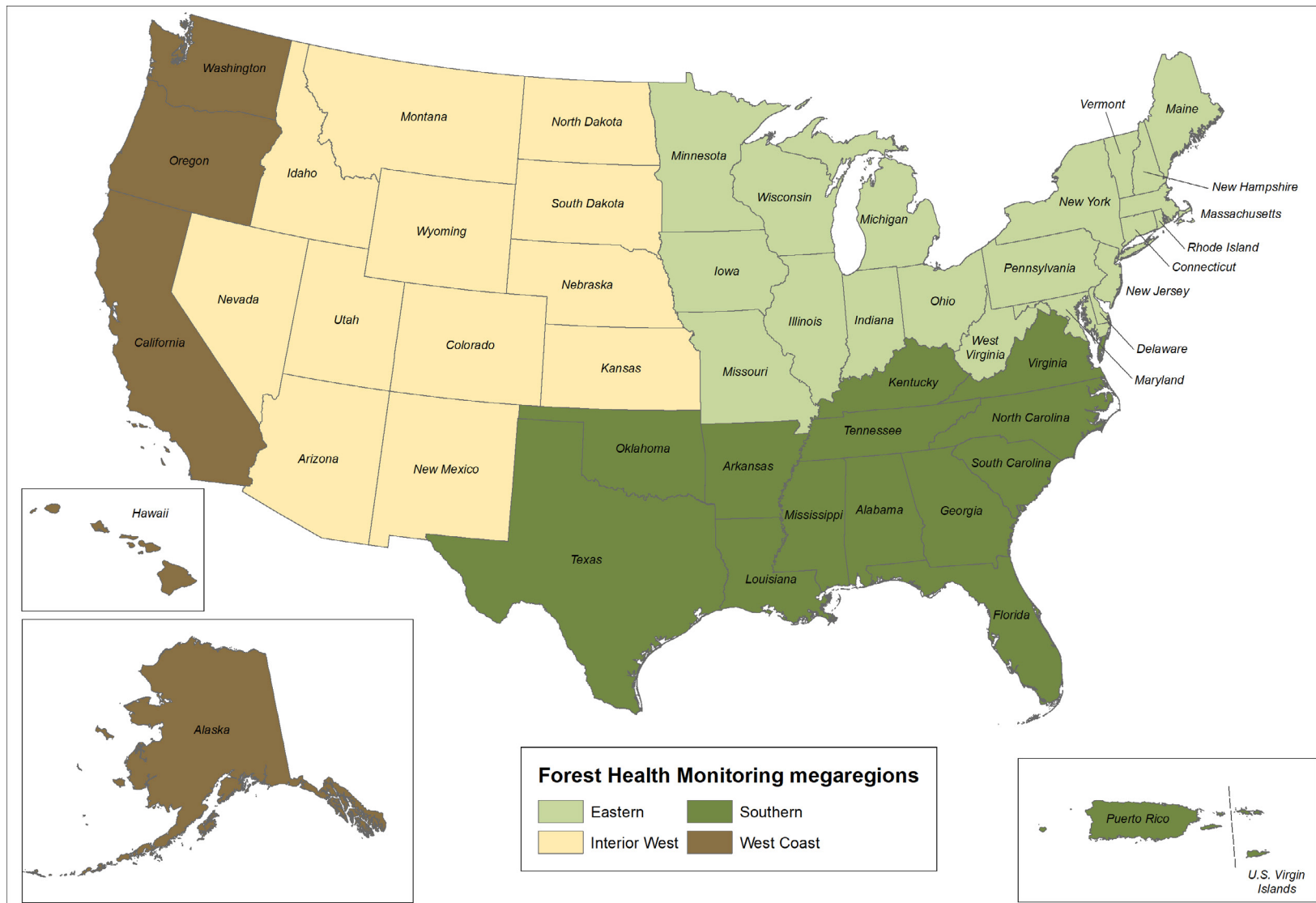


Figure 1.4—The four megaregions of the Forest Health Monitoring Program.

DATA SOURCES

Forest Service data sources in this edition of the FHM national report include FIA annualized Phase 2 survey data from a nationwide network of permanent plots located in nonurban forested areas that are remeasured on a 5- to 10-year cycle (Burrill and others 2021, Westfall and others 2022, Woodall and others 2010); FHP national Insect and Disease Survey forest mortality and defoliation data for 2022 (FHP 2023); tree canopy cover data generated from the 2011 National Land Cover Database (NLCD) (Homer and others 2015) through a cooperative project between the Multi-Resolution Land Characteristics Consortium and Forest Service Geospatial Technology and Applications Center (GTAC) (Coulston and others 2012); national Burned Area Boundaries dataset for 1984–2021 compiled within the Wildland Fire Management Research, Development, and Application (WFMRA) and wildfire incident records for 2022 from Wildland Fire Interagency Geospatial Services (WFIGS) (WFIGS 2022, WFMRA 2021); and FIA's publicly available Environmental Monitoring and Assessment Program (EMAP) hexagons (Brand and others 2000). Other sources of data include climate data from Parameter-elevation Regressions on Independent Slopes Model (PRISM) (PRISM Climate Group 2023); Moderate Resolution Imaging Spectroradiometer (MODIS) Active Fire Detections for the United States data for 2022 (NASA Fire Information for Resource Management System 2023); 2019 NLCD products (Dewitz and USGS 2021); and Alaskan forest and shrub cover derived from the 2011 NLCD. For more information about the

FIA Program, which is a major source of data for several FHM analyses, see box 1.1.

FOREST HEALTH MONITORING REPORT PRODUCTION

The FHM national report is produced annually by forest health monitoring researchers at the Eastern Forest Environmental Threat Assessment Center (EFETAC) in collaboration with North Carolina State University cooperators in the Forest Health Monitoring Research Group (<https://go.ncsu.edu/foresthealth>), with the support of the FHM Program. A unit of the Southern Research Station of the Forest Service, EFETAC was established under the Healthy Forests Restoration Act of 2003 to generate the knowledge and tools needed to anticipate and respond to environmental threats. For more information about the research team and about threats to U.S. forests, please visit <https://www.forestthreats.org/about>.

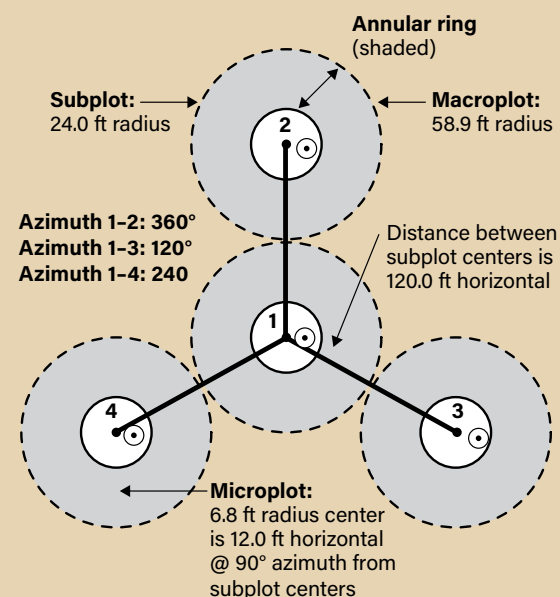
BOX 1.1

The Forest Inventory and Analysis (FIA) Program collects information on the topographic and other site characteristics, land use, trees, and vegetation occurring at plots on forest land and lands that are capable of being forested in all nonurban areas in the United States. The program maintains a network of more than 130,000 permanent forested ground plots across the conterminous United States, southeastern Alaska, Hawaii, Caribbean territories, and U.S.-Affiliated Pacific Islands with a sampling intensity of approximately one plot/2428 ha (one plot per 6,000 acres). FIA Phase 2 encompasses the annualized inventory measured annually on a subset of plots, with each plot surveyed every 5 to 7 years in the Eastern States and every 10 years in the Western United States (Reams and others 2005). The standard 0.067-ha plot (see figure) consists of four 7.315-m (24-foot) radius subplots (approximately 168.6 m² or 1/24 acre), on which field crews measure trees at least 12.7 cm (5 inches) in diameter. Within each of these subplots is nested a 2.073-m (6.8-foot) radius microplot (approximately 13.48 m² or 1/300 acre), on which crews measure trees smaller than 12.7 cm (5 inches) in diameter. An optional variant of the standard design includes four “macroplots,” each with a radius of 17.953 m or 58.9 feet (approximately 0.1012 ha or 1/4 acre) that originates at the center of each subplot (Burrill and others 2021). Macroplots are used in highly productive sites (such as the

West Cascades) in California, Oregon, and Washington.

FIA Phase 3 plots previously represented a subset of these Phase 2 plots, with 1 Phase 3 plot for every 16 standard FIA Phase 2 plots. In addition to traditional forest inventory measurements, data for a variety of important ecological indicators were from Phase 3 plots, including tree crown condition, lichen communities, down woody material, soil condition, and vegetation structure and diversity, whereas data on ozone bioindicator plants were collected on a separate grid of plots (Woodall and others 2010, 2011). Most of these additional forest health indicators were measured as part of the Forest Health Monitoring Detection Monitoring ground plot system prior to 2000¹ (Palmer and others 1991). The FIA Program recently updated its sampling techniques with flexible spatial and temporal intensities for some of these ecosystem health indicators (including down woody material, vegetation diversity and structure, and crown conditions) to improve field operation efficiency, address emerging user demands, and adjust to evolving forest health science (Castillo and Alvarez 2020). This “Phase 2 Plus Program/Ecosystem Indicator Program” (P2+) sampling scheme facilitates the collection of a national core set of indicator information on more plots for less cost than the original indicator protocols, with sampling based on a systematic subsample that can change in response to budgetary

fluctuations without compromising long-term analytical capabilities. The enhanced indicator protocols collect less-detailed information on each sampled plot than on the previous Phase 3 plots, but substantially more plots are sampled, increasing the statistical power of forest health analyses and improving the reliability of estimates in important national assessments (Castillo and Alvarez 2020).



Box 1.1 figure—The Forest Inventory and Analysis plot layout. Subplot 1 is the center of the cluster with subplots 2, 3, and 4 located 120 feet away at azimuths of 360°, 120°, and 240°, respectively (Burrill and others 2018).

¹U.S. Department of Agriculture, Forest Service. 1998. Forest Health Monitoring 1998 field methods guide. Research Triangle Park, NC: U.S. Department of Agriculture, Forest Service, Forest Health Monitoring program. 473 p. On file with: Forest Health Monitoring program, 3041 Cornwallis Rd., Research Triangle Park, NC 27709.

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SECTION 1

Analyses of Short-Term
Forest Health Data

INTRODUCTION

U.S. law authorizes the U.S. Department of Agriculture, Forest Service to “conduct surveys to detect and appraise insect infestations and disease conditions and man-made stresses affecting trees and establish a monitoring system throughout the forests of the United States to determine detrimental changes or improvements that occur over time, and report annually concerning such surveys and monitoring” (FHP 2023). Forest insects and diseases have widespread ecological and economic impacts on forests across the United States and may represent the most serious threats to the Nation’s forests (Logan and others 2003, Lovett and others 2016, Tobin 2015). Insects and diseases cause changes in forest structure and function, species succession, and biodiversity; these changes may be considered negative or positive depending on management objectives (Edmonds and others 2011).

Impacts of insects and diseases on forests vary from natural thinning to disruption of valued ecosystem processes due to tree mortality, but insects and diseases that kill trees are not necessarily the enemies of forests (Teale and Castello 2011). Disturbances such as insect and disease damage can sustain forest structures (Manion 2003, Zhang and others 2011) by facilitating a sanitation role, culling weak competitors, and releasing resources needed to support the growth of surviving trees (Teale and Castello 2011). Viewed in their full ecological context, some amount of insect- and disease-caused damage can therefore be considered “healthy.” An important task for forest managers, pathologists, and entomologists is to recognize and

distinguish between natural and excessive mortality, a task often informed by either ecologically based or commodity-based management objectives (Teale and Castello 2011).

Nearly all native tree species of the United States are affected by at least one injury-causing insect or disease agent, with native agents considerably less severe than nonnative ones (Potter and others 2019a). Additionally, the genetic integrity of several native tree species is highly vulnerable to the effects of nonnative diseases and insects (Potter and others 2019b). Introduced insects and diseases are of particular concern because they can extensively damage the biodiversity, ecology, and economy of affected areas (Brockerhoff and others 2006, Mack and others 2000). Few forests remain unaffected by invasive species, and their impacts to forest ecosystems are undeniable. These impacts can include wholesale changes in structures and function of ecosystems (Parry and Teale 2011).

Analyzing patterns of forest insect infestations, disease occurrences, forest declines, and related biotic stress factors is necessary to monitor the health of forested ecosystems and their potential impacts on forest structure, composition, biodiversity, and species distributions (Castello and others 1995). Examining insect pest occurrences and related stress factors from a landscape-scale perspective is useful, given the regional extent of many infestations and the large-scale complexity of interactions between host distribution, stress factors, and the development of outbreaks (Holdenrieder and others 2004, Liebhold and others 2013). One such landscape-scale approach is detecting geographic patterns

CHAPTER 2

Broad-Scale Patterns of Insect and Disease Damage Across the United States From the National Insect and Disease Survey, 2022

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of disturbance, allowing for the identification of areas at greater risk of significant ecological and economic impacts, and for selecting locations for more intensive monitoring and analysis. National Insect and Disease Survey (IDS) data (FHP 2023), coordinated by the Forest Service's Forest Health Protection (FHP) Program, provide an important source of information on forest disturbances and their causal agents across broad regions.

This chapter reports the area affected in 2022 by insect and disease mortality and defoliation-causing agents across all 50 States using IDS data collected by the Forest Service and its State partners. It further estimates the percentage of surveyed tree canopy cover area with insect- and disease-related mortality or defoliation within ecoregions across the United States and identifies statistically significant geographic hotspots of mortality or defoliation in the conterminous United States (CONUS).

METHODS

Data

The IDS data (FHP 2023) consist of information from low-altitude aerial survey and ground survey efforts by FHP and its partners in State agencies.¹ These data can be used to summarize insect and disease activity by regions in the CONUS, Alaska, and Hawaii (Potter 2012, 2013; Potter and Koch 2012; Potter and Paschke 2013, 2014, 2015a, 2015b, 2016, 2017, 2022, 2023; Potter and others 2018, 2019c, 2020a, 2021). IDS surveys across the CONUS in 2022 covered approximately 210.81 million ha encompassing both forested and unforested area (fig. 2.1). About 146.94 million ha of this area was forested, representing about 46.5 percent of the 315.99-million-ha tree canopy area of the CONUS. This was an increase of the tree-canopied area surveyed compared to 2020 and 2021 while similar to the amount surveyed in 2018 (46.6 percent) and 2019 (49.2 percent) (Potter and Paschke 2022, 2023; Potter and others 2020a, 2021). The 2022 data collection season, therefore, was more typical of those before the global COVID-19 (coronavirus) pandemic, which, in 2020, prevented many State partners and regional Forest Service personnel from conducting aerial survey flights because of risks posed by spending extended periods of time in the confined space of an aircraft. In Alaska, forest health specialists in 2022 surveyed 7.77 million ha across land cover types, of which about 5.85 million ha were forest and shrubland, or approximately 7.5 percent of the State's 77.78 million ha of total forest and shrubland. This was similar to the 7.2

¹ Analyses consist of data available from Forest Health Protection as of May 31, 2023.

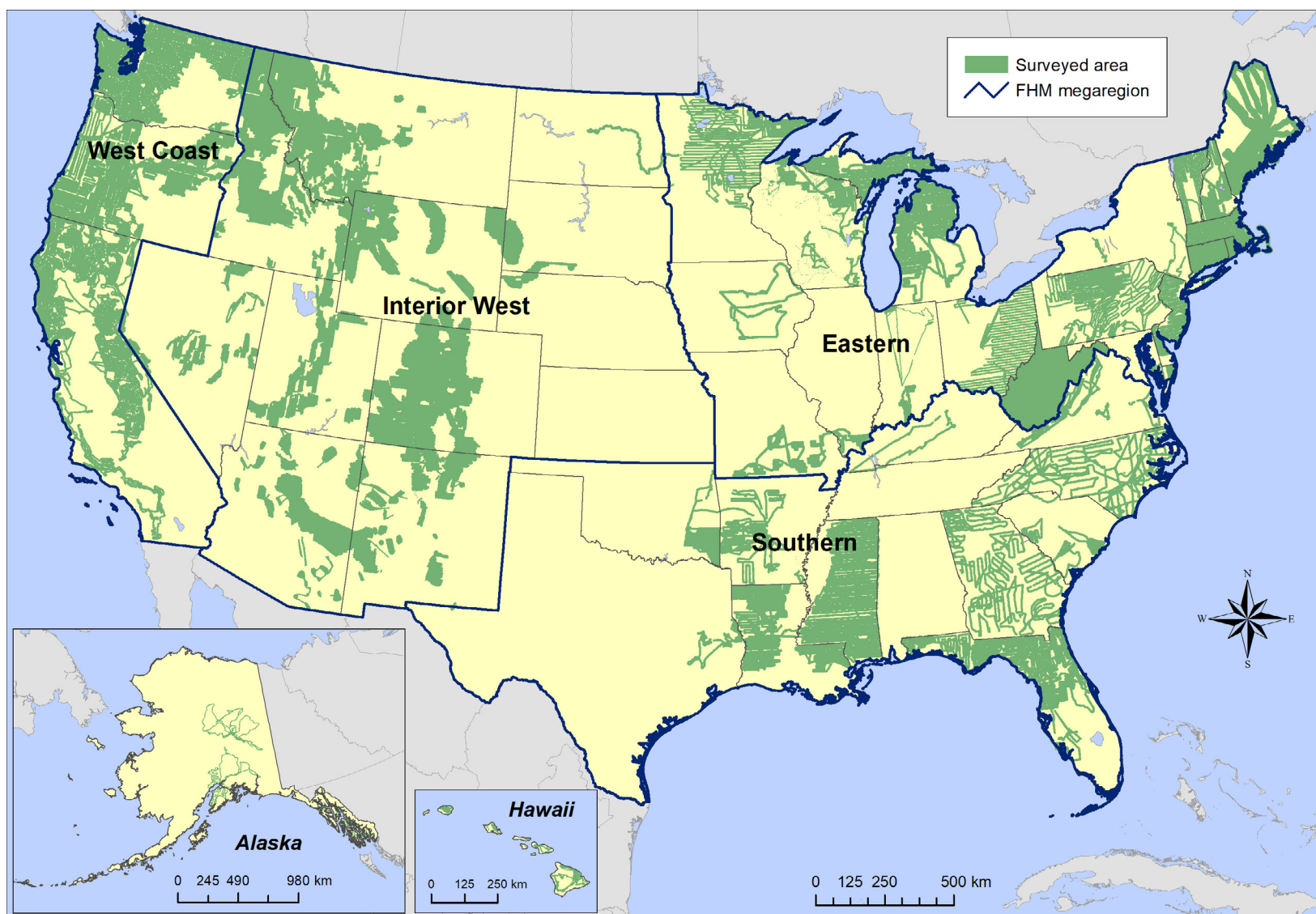


Figure 2.1—The extent of surveys for insect and disease activity conducted in the conterminous United States (CONUS), Alaska, and Hawaii in 2022. The blue lines delineate Forest Health Monitoring (FHM) megaregions in the CONUS. Note: Alaska and Hawaii are part of the West Coast megaregion, although their data are analyzed separately. Alaska and Hawaii are not shown to scale with map of the CONUS. (Data source: U.S. Department of Agriculture, Forest Service, Forest Health Protection)

percent surveyed in 2021 but more than the 2.8 percent surveyed in 2020 and less than the 12.7 percent and 10.8 percent surveyed in 2018 and 2019, respectively. In Hawaii, 2022 aerial survey efforts encompassed about 654 000 ha across all land cover types, including approximately 496 000 ha of tree canopy cover. This was about 57.6 percent of the total area of tree canopy, compared to 65.5 percent in 2021, 60.3 percent in 2020, 63.9 percent in 2019, and 69.4 percent in 2018.

The Digital Mobile Sketch Mapping (DMSM) platform includes tablet hardware, software, and data support processes allowing trained aerial surveyors in light aircraft, as well as ground observers and those using other remote sensing data, to record forest disturbances and their causal agents. DMSM enhances the quality and quantity of forest health data by integrating with remote sensing platforms (FHP 2019). Geospatial data collected with DMSM are stored in the national IDS database. DMSM includes both polygon geometry, used for damage areas where boundaries are discrete and obvious, and point geometry, used for small clusters of damage where size and shape of the damage are less important than recording the location. Good examples of insects and diseases for which point data are utilized include sudden oak death (caused by the pathogen *Phytophthora ramorum*), southern pine beetle (*Dendroctonus frontalis*), and some types of bark beetle damage in the West. For analyses in this report, these points were assigned an area of 0.8 ha (about 2 acres). Additionally, DMSM allows for the use of grid cells (240-, 480-, 960-, or 1920-m resolution) to estimate the percentage of trees affected by damages that may be widespread

and diffuse, such as those associated with spongy moth (*Lymantria dispar*), emerald ash borer (*Agilus planipennis*), and hurricanes (an abiotic disturbance not included in this chapter). When calculating the total areas affected by each damage agent, this study used the entire areas of these grid cells (e.g., 240-m cell = 5.76 ha).

The DMSM platform allows surveyors to both define the extent of an area experiencing damage and estimate the percent range of the area affected within polygons (Berryman and McMahan 2019). While additional validation is required, this relatively new method is expected to increase the accuracy of derived damage metrics because it potentially corrects for previous areal overestimation caused by “lassoing” areas of undamaged trees into large areas of damage (Coleman and others 2018, Slaton and others 2021). IDS analysis chapters in Forest Health Monitoring (FHM) reports before 2019 did not incorporate derived damage estimates beyond the areal footprint damage with mortality or defoliation polygon boundaries. However, these are now possible because of the inclusion of damage percentage estimates within polygons (see Analyses below).

The IDS database identifies areas with mortality or defoliation caused by biotic or abiotic factors, though the focus of this set of analyses is insect and disease activity. A visual interpreter might consider a pathogen or insect to be a mortality-causing agent in one location and a defoliation-causing agent in another, depending on the level of damage to the forest in an area, the specific host-pest relationship, and the convergence of other stress factors such

as drought. In some cases, identified agents of mortality or defoliation are complexes of multiple agents summarized under an impact label related to a specific host tree species (e.g., “beech bark disease complex” or “yellow-cedar decline”). In other cases, one or more agents (for example, ash yellows (caused by the *Candidatus Phytoplasma fraxini* bacterium), ash rust (*Puccinia sparganioides*), and verticillium wilt (*Verticillium albo-atrum*) in ash (*Fraxinus* spp.)) may cause stress to a tree that may ultimately increase its susceptibility to another agent to which the damage is attributed (in this example by emerald ash borer). Differences in data collection, attribute recognition, and coding procedures among States and regions can complicate data analysis and interpretation of results.

Some important mortality and defoliation agents have not been easily detected or thoroughly quantified through aerial detection and other remote sensing methods. This includes (1) insects such as emerald ash borer and hemlock woolly adelgid (*Adelges tsugae*); (2) diseases such as laurel wilt (*Harringtonia lauricola*, previously *Raffaelea lauricola*), Dutch elm disease (*Ophiostoma novo-ulmi*), white pine blister rust (*Cronartium ribicola*), and thousand cankers disease (*Geosmithia morbida*); and (3) mortality complexes (such as oak decline). (Recent efforts, however, have successfully used remotely sensed data to map damage caused by hemlock woolly adelgid, laurel wilt, and emerald ash borer in urban settings (Abdulridha and others 2018, Hanavan and others 2015, Pontius and others 2017).) Such pests may attack hosts

that are widely dispersed throughout forests with high tree species diversity or may cause mortality or defoliation that is otherwise difficult to perceive.

A comparison of aerial survey data by four aerial observers with ground presence/absence observations found the accuracy of aerial survey data exceeded 70 percent and damage type observations for tree mortality and defoliation had high levels of accuracy. However, the comparison further showed the accuracy declined for severity estimates and as specificity for observations went from the genus to the species level for tree species and damage agents (Coleman and others 2018). Recent long-term analyses of these data highlight insects as more widely detected agents of mortality compared to diseases, with bark beetles consistently the most important mortality agents across regions and time (Potter and others 2020b). (These results may be somewhat skewed toward insects because the visible signatures of insect damage are easier for IDS surveyors to detect.)

Analyses

This study generated three sets of indicators of forest insect and disease damage for 2022: (1) a series of tables reporting the most widely detected mortality and defoliation agents nationally and regionally, (2) estimates of the percentage of surveyed tree canopy cover area with insect- and disease-related mortality or defoliation within ecoregions across the United States, and (3) statistically significant geographic hotspots of mortality or defoliation in the CONUS.

The first analysis used the 2022 mortality and defoliation polygons to identify the select mortality and defoliation agents and complexes causing damage on >5000 ha of forest in the CONUS that year. Similarly, lists were generated for the five most widely reported mortality and defoliation agents and complexes within each of the four FHM megaregions in the CONUS (West Coast, Interior West, Eastern, and Southern), as well as separately for Alaska and Hawaii when data were available. Because of the insect and disease aerial sketch-mapping process (i.e., mostly digitization of polygons by a human interpreter aboard an aircraft), all quantities are approximate “footprint” areas for each agent or complex. These delineate areas of visible damage within which the agent or complex is present. Unaffected trees may exist within the footprint, and the amount of damage within the footprint is not necessarily reflected in the estimates of forest area affected. Additionally, the sum of areas affected by all individual agents and complexes is not equal to the total affected area because of overlapping polygons and because of

the reporting of multiple agents per polygon in some situations.

The second set of analyses used the IDS data for 2022 to more directly estimate the impacts of insect- and disease-related mortality and defoliation on U.S. forests within a spatial context. These results are reported in a set of figures describing, within ecoregions across the United States, the percentage of surveyed tree canopy cover area with insect- and disease-related mortality or defoliation. Specifically, as an indicator of the extent of damaging insect and disease agents, this study summarized the percentage of surveyed tree canopy cover area experiencing mortality or defoliation for ecoregions within the CONUS and Hawaii, and for surveyed forest and shrubland in Alaska ecoregions. This is a change from FHM reports before 2019, which reported the percentage of regions *exposed to* mortality and defoliating agents based only on the footprint with mortality or defoliation polygon boundaries (masked by forest cover) because information on the percentage of damage within polygons was not yet consistently available. As noted above, DMSM now allows surveyors to both define the extent of an area experiencing damage and estimate percent range of the area within the polygon affected (specifically, 1–3 percent, 4–10 percent, 11–29 percent, 30–50 percent, and >50 percent). Generating an adjusted estimate of the area affected by each mortality or defoliation agent detection is now possible by multiplying the area of damage within each polygon (after masking by tree canopy cover) by the midpoint of the estimated percent-affected range (Berryman

and McMahan 2019). These individual estimates can be summed for all polygons within an ecoregion and divided by the total surveyed tree canopy cover area within the ecoregion to generate an estimate of the percentage of its canopy cover area affected by defoliating or mortality-causing agents. (DMSM point data are also included in this estimate. Surveyors have the option to estimate the number of trees affected at a point and are required to assign an area value associated with each point, which is assumed to be 100 percent affected by its mortality or defoliation agent. For simplicity, each point was transformed into a 2-acre (0.809-ha) polygon. These areas for all the points in an ecoregion were then added to the polygon-adjusted affected area estimates for the ecoregion.)

This study calculated the percentage of surveyed tree canopy area with mortality or defoliation within each of the 190 ecoregion sections in the CONUS (Cleland and others 2007) and, similarly, summarized mortality and defoliation data for each of the 32 ecoregion sections in Alaska (Spencer and others 2002). For Hawaii, the percentage of surveyed tree canopy area affected by mortality and defoliation agents in 34 ecoregion subunits within the archipelago was calculated (Potter 2023). Statistics were not calculated for ecoregions in the CONUS and Hawaii with ≤ 5 percent of the tree canopy cover area surveyed, nor in Alaska with ≤ 2.5 percent of the forest and shrubland area surveyed.

To represent tree canopy for the CONUS and Hawaii, tree canopy data were resampled to 240 m from a 30-m raster dataset that estimates percentage of tree canopy cover (0–100 percent) for each grid cell; this dataset was generated from the 2011 National Land Cover Database (NLCD) (Homer and others 2015) through a cooperative project between the Multi-Resolution Land Characteristics Consortium and the Forest Service Geospatial Technology and Applications Center (GTAC) (Coulston and others 2012). Any cell with >0 percent tree canopy cover was treated as forest. Comparable tree canopy cover data were not available for Alaska, so a 240-m-resolution layer of forest and shrub cover was instead created from the 2011 NLCD.

Finally, the third set of analyses used the Spatial Association of Scalable Hexagons (SASH) analytical approach to identify statistically significant geographic hotspots of mortality or defoliation in the CONUS. This method identifies locations where ecological phenomena occur at greater or lower frequency than expected by random chance and is based on a sampling frame optimized for spatial neighborhood analysis, adjustable to the appropriate spatial resolution, and applicable to multiple data types (Potter and others 2016). Specifically, it encompasses two steps: first, dividing an analysis area into scalable equal-area hexagonal cells within which data are aggregated and, second, identifying statistically significant geographic clusters of hexagonal cells within which mean values are greater or less than those expected by chance. Separate Getis-Ord (G_i^*) hotspot analyses (Getis and Ord 1992) in

ArcMap® 10.3 (ESRI 2017) identified clusters of both mortality- and defoliation-causing agents across the CONUS. The low density of survey data in 2022 from Alaska and the small spatial extent of Hawaii (fig. 2.1) precluded the use of Getis-Ord G_i^* hotspot analyses in these areas.

The units of analysis were 9,810 hexagonal cells, each approximately 834 km² in area, generated in a lattice across the CONUS using intensification of the Environmental Monitoring and Assessment Program (EMAP) North American hexagon coordinates (White and others 1992). These coordinates are the foundation of a sampling frame in which a hexagonal lattice was projected onto the CONUS by centering a large base hexagon over the region (Reams and others 2005, White and others 1992). This base hexagon can be subdivided into many smaller hexagons, depending on sampling needs, and serves as the basis of the plot sampling frame for the Forest Service's Forest Inventory and Analysis (FIA) Program (Reams and others 2005). Importantly, hexagons maintain equal areas across the study region regardless of the degree of intensification of the EMAP hexagon coordinates. In addition, hexagons are compact and uniform in their distance to the centroids of neighboring hexagons, meaning a hexagonal lattice has a higher degree of isotropy (uniformity in all directions) than does a square grid (Shima and others 2010). These are convenient and highly useful attributes for spatial neighborhood analyses. These scalable hexagons are independent of geopolitical and ecological boundaries, avoiding the possibility of different sample units (such as counties, States, or watersheds) encompassing vastly different areas

(Potter and others 2016). The 834-km² hexagons are a manageable size for making monitoring and management decisions in analyses that are national in extent (Potter and others 2016).

Next, the Getis-Ord G_i^* statistic was used to identify clusters of hexagonal cells within which the percentage of surveyed tree canopy area with mortality or defoliation was higher than expected by chance. This statistic allows for the decomposition of a global measure of spatial association into its contributing factors, by location, and is therefore particularly suitable for detecting instances of nonstationarity in a dataset, such as when spatial clustering is concentrated in one subregion of the data (Anselin 1992). Hexagons were excluded if they contained ≤ 5 percent tree canopy cover or if ≤ 1 percent of the tree canopy cover was surveyed in 2022.

The Getis-Ord G_i^* statistic for each hexagon summed differences between mean values in a local sample, determined by a moving window consisting of the hexagon and its 18 first- and second-order neighbors (the 6 adjacent hexagons and the 12 additional hexagons contiguous to those 6) and a global mean. The G_i^* statistic was standardized as a z-score with a mean of 0 and a standard deviation of 1, with values > 1.96 representing significant ($p < 0.025$) local clustering of high values and values < -1.96 representing significant clustering of low values ($p < 0.025$), since 95 percent of observations under a normal distribution should be within approximately two (exactly 1.96) standard deviations of the mean (Laffan 2006). In other words, a G_i^* value of 1.96 indicates the local mean of the percentage of forest exposed to mortality- or defoliation-

causing agents for a hexagon and its 18 neighbors is approximately 2 standard deviations greater than the mean expected in the absence of spatial clustering, while a G_i^* value of -1.96 indicates the local mortality or defoliation mean for a hexagon and its 18 neighbors is approximately 2 standard deviations less than the mean expected in the absence of spatial clustering. Values between -1.96 and 1.96 have no statistically significant concentration of high or low values. In other words, when a hexagon has a G_i^* value between -1.96 and 1.96, mortality or defoliation damage within it and its 18 neighbors is not statistically different from a normal expectation. As described in Laffan (2006), it is calculated as:

$$G_i^*(d) = \frac{\sum_j w_{ij}(d)x_j - W_i^* \bar{x}^*}{s^* \sqrt{\frac{(ns_{1i}^*) - W_i^{*2}}{n-1}}}$$

where

G_i^* = the local clustering statistic (in this case, for the target hexagon)

i = the center of local neighborhood (the target hexagon)

d = the width of local sample window (the target hexagon and its first- and second-order neighbors)

x_j = the value of neighbor j

w_{ij} = the weight of neighbor j from location i (all the neighboring hexagons in the moving window were given an equal weight of 1)

n = number of samples in the dataset (the 4,178 hexagons containing >5-percent tree cover and with at least 1 percent of the canopy cover surveyed)

W_i^* = the sum of the weights

s_{1i}^* = the number of samples within d of the central location (19: the focal hexagon and its 18 first- and second-order neighbors)

$\bar{x}^*$ = mean of whole dataset (in this case, the 4,178 hexagons)

s^* = the standard deviation of whole dataset (for the 4,178 hexagons)

Note that the -1.96 and 1.96 threshold values are not exact because the correlation of spatial data violates the assumption of independence required for statistical significance (Laffan 2006). The Getis-Ord approach does not require the input data to be normally distributed because the local G_i^* values are computed under a randomization assumption, with G_i^* equating to a standardized z -score that asymptotically tends to a normal distribution (Anselin 1992). The z -scores are reliable, even with skewed data, if the distance band used to define the local sample around the target observation is large enough to include several neighbors for each feature (ESRI 2017).

RESULTS AND DISCUSSION

Conterminous United States Mortality

In 2022, surveyors identified 52 mortality-causing agents and complexes across the CONUS on about 3.33 million ha. This represents approximately the land area of Connecticut and Massachusetts combined. Of the agents in the national IDS database for the year, 19 were detected on >5000 ha. This compares to 60 agents and complexes detected on 2.21 million ha in 2021 and 45 detected on 1.17 million ha in 2020 (Potter and Paschke 2022, 2023). The 2021 and 2022 figures are more consistent with those typical of data collection before the COVID-19 pandemic, e.g., 2.69 million ha of damage associated with 58 agents and complexes in 2019 (Potter and others 2021).

The most widely detected mortality agent in 2022 was fir engraver (*Scolytus ventralis*), identified on 1.36 million ha, followed by emerald ash borer, found on about 582 000 ha, and western pine beetle (*D. brevicomis*), on approximately 303 000 ha (table 2.1). These represented, respectively, about 41, 17, and 9 percent of the total CONUS mortality area. Fir engraver was the most widely detected mortality agent in 2020, while emerald ash borer was more widely detected in 2021 (Potter and Paschke 2022, 2023). Worth noting, however, is the challenging nature of mapping emerald ash borer damage via aerial surveys, including the differentiation of damage occurrence between years and the fact that agents other than emerald ash borer damage ash species.

Table 2.1—Mortality agents and complexes affecting >5000 ha in the conterminous United States during 2022

Agents/complexes causing mortality, 2022	Area (ha) ^a
Fir engraver	1 356 411
Emerald ash borer	581 963
Western pine beetle	302 932
Flatheaded fir borer	259 722
Pinyon ips	172 475
Unknown bark beetle	136 751
Eastern larch beetle	123 122
Douglas-fir beetle ^b	116 550
Mountain pine beetle	108 575
Unknown	87 179
Balsam woolly adelgid	41 911
Western balsam bark beetle	36 681
Spruce beetle	33 988
Subalpine fir decline	26 127
Ips engraver beetles	25 844
Oak decline	25 391
Jeffrey pine beetle	16 638
Spongy moth	6632
Southern pine beetle	5635
Other (33)	15 132
Total, all mortality agents	3 326 087

^a All values are "footprint" areas for each agent or complex. The sum of the individual agents is not equal to the total for all agents due to the reporting of multiple agents per polygon.

^b In the Interior West, this is primarily damage on ponderosa pines. The group of bark beetles is known and varied but not distinguishable from the air. Regions have characterized it as "Southwest bark beetle complex" consisting mainly of damage caused by roundheaded pine beetle, western pine beetle, and ips beetles.

Six other agents were detected on >100 000 ha. These were flatheaded fir borer (*Phaenops drummondi*) on 260 000 ha, pinyon ips (*Ips confusus*) on 172 000 ha, “unknown bark beetle”² on 137 000 ha, eastern larch beetle (*D. simplex*) on 123 000 ha, Douglas-fir beetle (*D. pseudotsugae*) on 117 000 ha, and mountain pine beetle (*D. ponderosae*) on 109 000 ha (table 2.1). Meanwhile, mortality from the 15 IDS agents constituting the western bark beetle group (table 2.2) accounted for two-thirds of all the 2022 mortality area across the CONUS (2.21 million ha in the West). Six of the 10 most widely detected mortality agents and complexes belonged to this group.

The CONUS portion of the West Coast FHM megaregion had the largest area of detected mortality within the area surveyed, about 2.02 million ha linked to 22 agents and complexes (table 2.3). Almost two-thirds of this area (64.3 percent) was associated with fir engraver (1.30 million ha). Three other bark beetles also were detected on large areas: western pine beetle on 302 000 ha (15.0 percent of the total), mountain pine beetle on 90 000 ha (4.5 percent), and Douglas-fir beetle on 69 000 ha (3.4 percent). An additional 12.9 percent of the total megaregion mortality area (260 000 ha) was attributed to flatheaded fir borer.

² The unknown bark beetle agent encompasses a group of known and varied bark beetles, impossible to distinguish using IDS data, that primarily damage ponderosa pine (*Pinus ponderosa*) forests. This also has been characterized as “Southwest bark beetle complex” consisting mainly of damage caused by roundheaded pine beetle (*D. adjunctus*), western pine beetle, and ips beetles.

Table 2.2—Beetle taxa included in the “western bark beetle” group in 2022

Western bark beetle mortality agents	
Cedar and cypress bark beetles	<i>Phloeosinus</i> spp.
Douglas-fir beetle	<i>Dendroctonus pseudotsugae</i>
Douglas-fir engraver	<i>Scolytus unispinosus</i>
Fir engraver	<i>Scolytus ventralis</i>
Ips engraver beetles	<i>Ips</i> spp.
Jeffrey pine beetle	<i>Dendroctonus jeffreyi</i>
Mountain pine beetle	<i>Dendroctonus ponderosae</i>
Pine engraver	<i>Ips pini</i>
Pinyon ips	<i>Ips confusus</i>
Roundheaded pine beetle	<i>Dendroctonus adjunctus</i>
Silver fir beetle	<i>Pseudohylesinus sericeus</i>
Spruce beetle	<i>Dendroctonus rufipennis</i>
Unknown bark beetle ^a	—
Western balsam bark beetle	<i>Dryocoetes confusus</i>
Western pine beetle	<i>Dendroctonus brevicomis</i>

^a In the Interior West, this is primarily damage on ponderosa pines. The group of bark beetles is known and varied but not distinguishable from the air. Regions have characterized it as “Southwest bark beetle complex” consisting mainly of damage caused by roundheaded pine beetle, western pine beetle, and ips beetles.

Table 2.3—The top five mortality agents or complexes for each Forest Health Monitoring megaregion and for Alaska and Hawaii in 2022

Mortality agents and complexes, 2022	Area (ha) ^a	Mortality agents and complexes, 2022	Area (ha) ^a
Eastern		West Coast (CONUS)	
Emerald ash borer	581 900	Fir engraver	1 297 561
Eastern larch beetle	123 122	Western pine beetle	301 626
Unknown	27 294	Flatheaded fir borer	259 722
Oak decline	25 391	Mountain pine beetle	89 773
Spongy moth	6 632	Douglas-fir beetle	69 329
Other mortality agents (23)	15 176	Other mortality agents (17)	138 374
Total, all mortality agents and complexes	779 374	Total, all mortality agents and complexes	2 016 851
Interior West		Alaska	
Pinyon ips	171 784	Spruce beetle	19 740
Unknown bark beetle ^b	129 559	Yellow-cedar decline	4 725
Fir engraver	58 850	Northern spruce engraver	338
Douglas-fir beetle	45 845	Aspen running canker	20
Spruce beetle	33 206	Unknown	15
Other mortality agents (14)	91 387	Other mortality agents (1)	2
Total, all mortality agents and complexes	516 734	Total, all mortality agents and complexes	24 840
Southern		Hawaii	
Ips engraver beetles	9 365	Unknown ^d	36 415
Southern pine beetle	1 555	Total, all mortality agents and complexes	36 415
Douglas-fir beetle ^c	1 376		
Unknown	468		
Unknown bark beetle ^c	262		
Other mortality agents (3)	102		
Total, all mortality agents and complexes	13 128		

^a The total area affected by other agents is listed at the end of each section. All values are “footprint” areas for each agent or complex. The sum of the individual agents is not equal to the total for all agents due to the reporting of multiple agents per polygon.

^b In the Interior West, this is primarily damage on ponderosa pines. The group of bark beetles is known and varied but not distinguishable from the air. Regions have characterized it as “Southwest bark beetle complex” consisting mainly of damage caused by roundheaded pine beetle, western pine beetle, and ips beetles.

^c Personnel from Forest Service Region 3 (Southwestern Region) conducted surveys into southwestern Texas (Region 8 [Southern Region]) because of extended damage in the Guadalupe Mountains which included Douglas-fir beetle and “unknown bark beetle” damage on ponderosa pines (see note b).

^d Most of the mortality recorded in Hawaii is coded as “unknown” mortality on ‘ōhi’a lehua. Damage is likely attributed to rapid ‘ōhi’a death but has not been confirmed in all cases.

Within the CONUS portion of the West Coast megaregion, ecoregion sections in eastern and northern California and southwestern Oregon experienced high levels of mortality (2.0–5.0 percent of surveyed tree canopy cover) (fig. 2.2). Specifically, both M261E–Sierra Nevada and M261A–Klamath Mountains had 3.1 percent mortality within surveyed areas. In the former, fir engraver caused extensive mortality in California red fir (*Abies magnifica* var. *shastensis*) and white fir (*A. concolor*) stands. In the latter, flatheaded fir borer caused mortality in Douglas-fir (*Pseudotsuga menziesii*) stands, western pine beetle affected ponderosa pine stands, and fir engraver killed white fir. Meanwhile, fir engraver in white fir, California red fir, noble fir (*A. procera*), and grand fir (*A. grandis*) resulted in 2.8 percent mortality of the surveyed tree canopy cover of M261D–Southern Cascades. Neighboring ecoregion sections also had high mortality (1.0–2.5 percent of surveyed area): M261G–Modoc Plateau (2.4 percent) and M261B–Northern California Coast Ranges (1.7 percent).

Not surprisingly, the CONUS portion of the West Coast megaregion encompassed several hotspots of mortality density, including one of very high density in southwestern Oregon and four of high density across northern and eastern California (fig. 2.3). An additional hotspot of high mortality density was centered on M332G–Blue Mountains and 342H–Blue Mountain Foothills in east-central Oregon, where surveyors detected

extensive fir engraver damage in fir forests, as well as some ponderosa pine mortality attributed to western pine beetle and lodgepole pine (*P. contorta*) mortality attributed to mountain pine beetle.

With about 800 000 ha of damage, the Eastern FHM megaregion in 2022 had the second largest area on which mortality agents and complexes were detected (table 2.3). A total of 28 agents and complexes were inventoried in the megaregion. As in recent years, a large majority of the mortality (74.7 percent in 2022 and 86.2 percent in 2021) was associated with emerald ash borer, detected on 582 000 ha. Other widespread mortality agents identified in the megaregion were eastern larch beetle (123 000 ha, 15.8 percent of the total), oak decline (25 000 ha, 3.3 percent), and spongy moth (7000 ha, 0.9 percent).

Emerald ash borer caused the extremely high levels of mortality (>5.0 percent) of surveyed canopy cover area in ecoregion sections of Iowa, Minnesota, and Wisconsin: 251B–North Central Glaciated Plains (31.2 percent), 222L–North Central U.S. Driftless and Escarpment (9.5 percent), and 222M–Minnesota and Northeast Iowa Morainal-Oak Savannah (7.6 percent) (fig. 2.2). The affected host species were white, green, and black ash (*F. americana*, *F. pennsylvanica*, and *F. nigra*). These ecoregion sections, along with 251C–Central Dissected Till Plains, were the location of a hotspot of extremely high and very high mortality density (fig. 2.3).

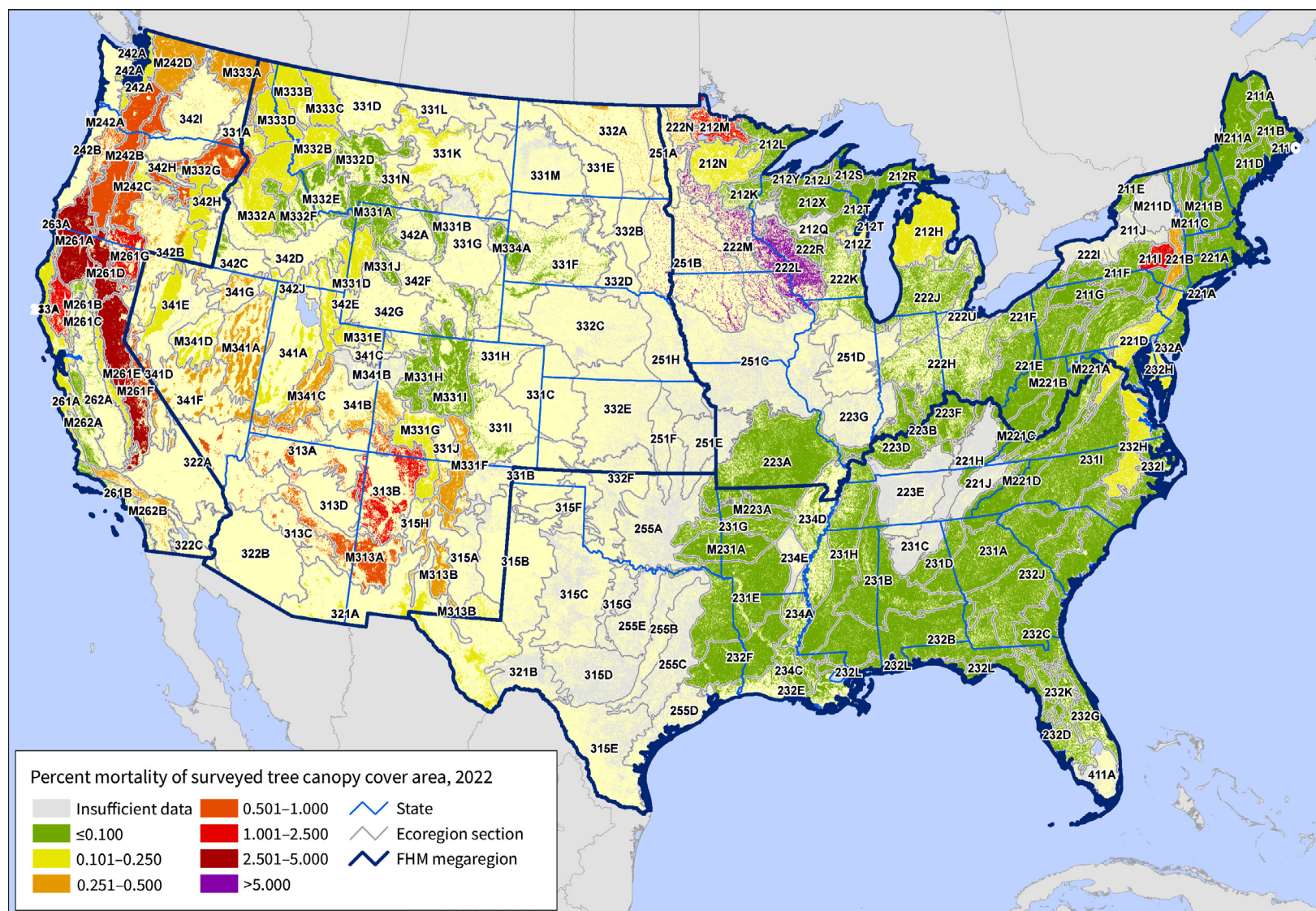


Figure 2.2—The percentage of surveyed tree canopy cover area with insect and disease mortality, by ecoregion section within the conterminous United States, for 2022. The gray lines delineate ecoregion sections (Cleland and others 2007), and dark blue lines delineate Forest Health Monitoring megaregions. The 240-m tree canopy cover is based on data from a cooperative project between the Multi-Resolution Land Characteristics Consortium (Coulston and others 2012) and the Forest Service Geospatial Technology and Applications Center using the 2011 National Land Cover Database. (Data source: U.S. Department of Agriculture, Forest Service, Forest Health Protection)

Meanwhile, the 212M–Northern Minnesota and Ontario ecoregion section experienced 2.1 percent mortality of surveyed tree canopy cover because of an ongoing eastern larch beetle outbreak in tamarack (*Larix laricina*) (fig. 2.2). This corresponded with a hotspot of high and moderate mortality density (fig. 2.3). Additionally, emerald ash borer damage in northern New York resulted in 1.2 percent mortality of surveyed canopy cover in 211I–Catskill Mountains and 0.4 percent mortality in 221B–Hudson Valley.

Surveyors in the Interior West megaregion during 2022 identified damage from 19 mortality agents and complexes across 517 000 ha (table 2.3). The most widespread was pinyon ips, detected on 172 000 ha, or 33.2 percent of all the mortality in the region. This was followed by the unknown bark beetles described above and characterized as “Southwest bark beetle complex” in ponderosa pine forests (130 000 ha, 25.1 percent of the total) and fir engraver (59 000 ha, 11.4 percent of the total). Other widespread agents were Douglas-fir beetle (46 000 ha, 8.9 percent) and spruce beetle (*D. rufipennis*) (33 000 ha, 6.4 percent).

A handful of ecoregion sections in the Four Corners region had moderately high mortality density (0.5–2.5 percent of surveyed tree canopy cover) associated with pinyon ips and Southwest bark beetle complex (fig. 2.2). These were 313D–Painted Desert (2.33 percent mortality), 313B–Navajo Canyonlands (1.29 percent), 313A–Grand Canyon (0.83 percent), M313A–White Mountains–San Francisco Peaks–Mogollon Rim (0.64 percent), 313C–Tonto Transition (0.60 percent), and 322A–Mojave Desert (0.53 percent). Several hotspots of moderate mortality density were detected in this area, along with one of high mortality density that was centered on 313B–Navajo Canyonlands in northwestern New Mexico (fig. 2.3).

Finally, surveyors in the Southern FHM megaregion recorded about 13 000 ha of mortality damage attributed to eight mortality agents and complexes in 2022 (table 2.3). Ips engraver beetles were the most widely detected agent, detected on 9000 ha (71.3 percent of the total). Other widespread agents were southern pine beetle (1600 ha, 11.8 percent) and Douglas-fir beetle (1400 ha, 10.5 percent).

Conterminous United States Defoliation

The national IDS database encompassed 59 defoliating agents or complexes across the CONUS in 2022 (table 2.4). These affected approximately 1.87 million ha, which is slightly less than the land area of New Jersey. This continued an upward trend from recent years: 1.54 million ha were attributed to 59 defoliating agents in 2020 and 1.67 million ha were associated with 56 agents in 2021 (Potter and Paschke 2022, 2023). As with 2021, spongy moth was the most widespread defoliation agent in 2022, detected on 707 000 ha or 37.9 percent of the total area of defoliation. Swiss needle cast (caused by the fungus *Nothophaeocryptopus gaeumannii*) was detected on 313 000 ha in Oregon and Washington (16.8 percent of total defoliation) as part of a periodic survey (USDA Forest Service, Pacific Northwest Region 2023). Meanwhile, spruce budworm (*Choristoneura fumiferana*) and western spruce budworm (*C. freemani*) were identified on about 216 000 and 194 000 ha, respectively, or 11.6 and 10.4 percent of the total defoliation area. Forest tent caterpillar (*Malacosoma disstria*) was the only other agent detected on >100 000 ha (114 000 ha, 6.1 percent of the total), but browntail moth (*Euproctis chrysorrhoea*; 60 000 ha, 3.2 percent) and oak leafroller (*Archips semiferana*; 53 000 ha, 2.8 percent) were also widespread.

Table 2.4—Defoliation agents and complexes affecting >5000 ha in the conterminous United States in 2022

Agents/complexes causing defoliation, 2022	Area (ha) ^a
Spongy moth	706 803
Swiss needle cast	312 770
Spruce budworm	216 426
Western spruce budworm	194 213
Forest tent caterpillar	114 404
Browntail moth	60 075
Oak leafroller	52 535
Unknown defoliator	33 000
Balsam woolly adelgid	30 875
Cytospora canker of fir	27 954
Pinyon needle scale	23 529
Unknown	15 444
Jack pine budworm	12 340
Gelechiid moths/needleminers	12 231
Larch needle cast	12 004
Large aspen tortrix	10 296
Other (43)	36 944
Total, all defoliation agents	1 867 182

^a All values are “footprint” areas for each agent or complex. The sum of the individual agents is not equal to the total for all agents due to the reporting of multiple agents per polygon.

Surveyors in the Eastern FHM megaregion detected 1.1 million ha of defoliation in 2022 (table 2.5), making this the region with the most defoliation, as in 2021. This encompassed 34 defoliation agents, with spongy moth accounting for almost two-thirds of the defoliated area (697 000 ha). Other widespread defoliators were spruce budworm (216 000 ha, 19.7 percent), browntail moth (60 000 ha, 5.5 percent), and oak leafroller (53 000 ha, 4.8 percent).

Eastern ecoregion sections with the highest levels of defoliation (0.5–10.0 percent of surveyed tree canopy cover) were concentrated in the Great Lakes region (fig. 2.4). Spruce budworm was the main defoliator in 212L–Northern Superior Uplands in northeastern Minnesota (4.8 percent) while spongy moth was the leading defoliation agent in 212H–Northern Lower Peninsula of Michigan (3.4 percent) and adjacent 222J–South Central Great Lakes (0.74 percent). Spongy moth and large aspen tortrix (*Choristoneura conflictana*) were the predominant agents in 212Y–Southwest Lake Superior Clay Plain (in northern Minnesota and Wisconsin and the Upper Peninsula of Michigan), where 9.3 percent of surveyed tree canopy area was affected by defoliation, as well as in neighboring 212J–Southern Superior Uplands (0.8 percent). These two agents, along with forest tent caterpillar, were widespread defoliators in adjacent 212K–Western Superior Uplands in Minnesota and Wisconsin (0.83 percent). Forest tent caterpillar and spruce budworm were the predominant agents in 212S–Northern Upper Peninsula in northern Michigan (2.0 percent), while these two agents along with oak leafroller were the defoliators in 212X–Northern Highlands

in northern Wisconsin (0.67 percent). Finally, multiple agents—including spruce budworm, forest tent caterpillar, Chrysomela leaf beetle (*Chrysomela* spp.), and jack pine budworm (*Choristoneura pinus*)—defoliated forests in 212R–Eastern Upper Peninsula of northern Michigan (0.51 percent).

Four of the six CONUS defoliation hotspots for 2022 were identified in the Great Lakes region (fig. 2.5). These were in northern Wisconsin (extremely high and very high defoliation density), in northeastern Minnesota (high defoliation density), and one each in the Lower and Upper Peninsulas of Michigan (moderate defoliation density).

The West Coast FHM megaregion encompassed 397 000 ha of defoliation attributed to 21 agents in 2022 (table 2.5). Most commonly detected was Swiss needle cast, on 313 000 ha, or 78.7 percent of the total defoliation in the region. Balsam woolly adelgid (*Adelges piceae*) was the next most commonly detected, on 31 000 ha (7.8 percent of the total). Cytospora canker of fir (*Cytospora abietis*) was associated with 28 000 ha of defoliation (7.0 percent) and larch needle cast (*Rhabdocline laricis*) with 12 000 ha (3.0 percent).

M242A–Oregon and Washington Coast Ranges experienced high levels of defoliation (3.3 percent of surveyed tree canopy cover), primarily because of Swiss needle cast impacts on Douglas-fir and secondarily because of balsam woolly adelgid damage to several fir species (fig. 2.4). The southern part of this ecoregion, along the coast of Oregon, constituted a hotspot of high defoliation density (fig. 2.5). Two neighboring ecoregion sections (M242B–Western Cascades (0.32

Table 2.5—The top five defoliation agents or complexes for each Forest Health Monitoring megaregion and for Alaska and Hawaii in 2022

Mortality agents and complexes, 2022	Area (ha) ^a	Mortality agents and complexes, 2022	Area (ha) ^a
Eastern		West Coast (CONUS)	
Spongy moth	696 730	Swiss needle cast	312 770
Spruce budworm	216 426	Balsam woolly adelgid	30 875
Browntail moth	60 075	Cytospora canker of fir	27 954
Oak leafroller	52 535	Larch needle cast	11 967
Forest tent caterpillar	23 869	Unknown	9835
Other defoliation agents (29)	51 465	Other defoliation agents (16)	8336
Total, all defoliation agents and complexes	1 101 090	Total, all defoliation agents and complexes	397 198
Interior West		Alaska	
Western spruce budworm	194 213	Western blackheaded budworm	277 537
Pinyon needle scale	23 335	Aspen leafminer	15 410
Unknown defoliator	23 196	Birch leafminer	8710
Gelechiid moths/needleminers	12 223	Unknown defoliator	6755
Unknown	3164	Willow leaf blotchminer	6513
Other defoliation agents (15)	7635	Other defoliation agents (2)	824
Total, all defoliation agents and complexes	263 654	Total, all defoliation agents and complexes	315 500
Southern		Hawaii	
Forest tent caterpillar	90 521	None	0
Spongy moth	10 073	Total, all defoliation agents and complexes	0
Fall cankerworm	4489		
Baldcypress leafroller	61		
Pinyon needle scale	59		
Other defoliation agents (1)	37		
Total, all defoliation agents and complexes	105 240		

^a The total area affected by other agents is listed at the end of each section. All values are “footprint” areas for each agent or complex. The sum of the individual agents is not equal to the total for all agents due to the reporting of multiple agents per polygon.

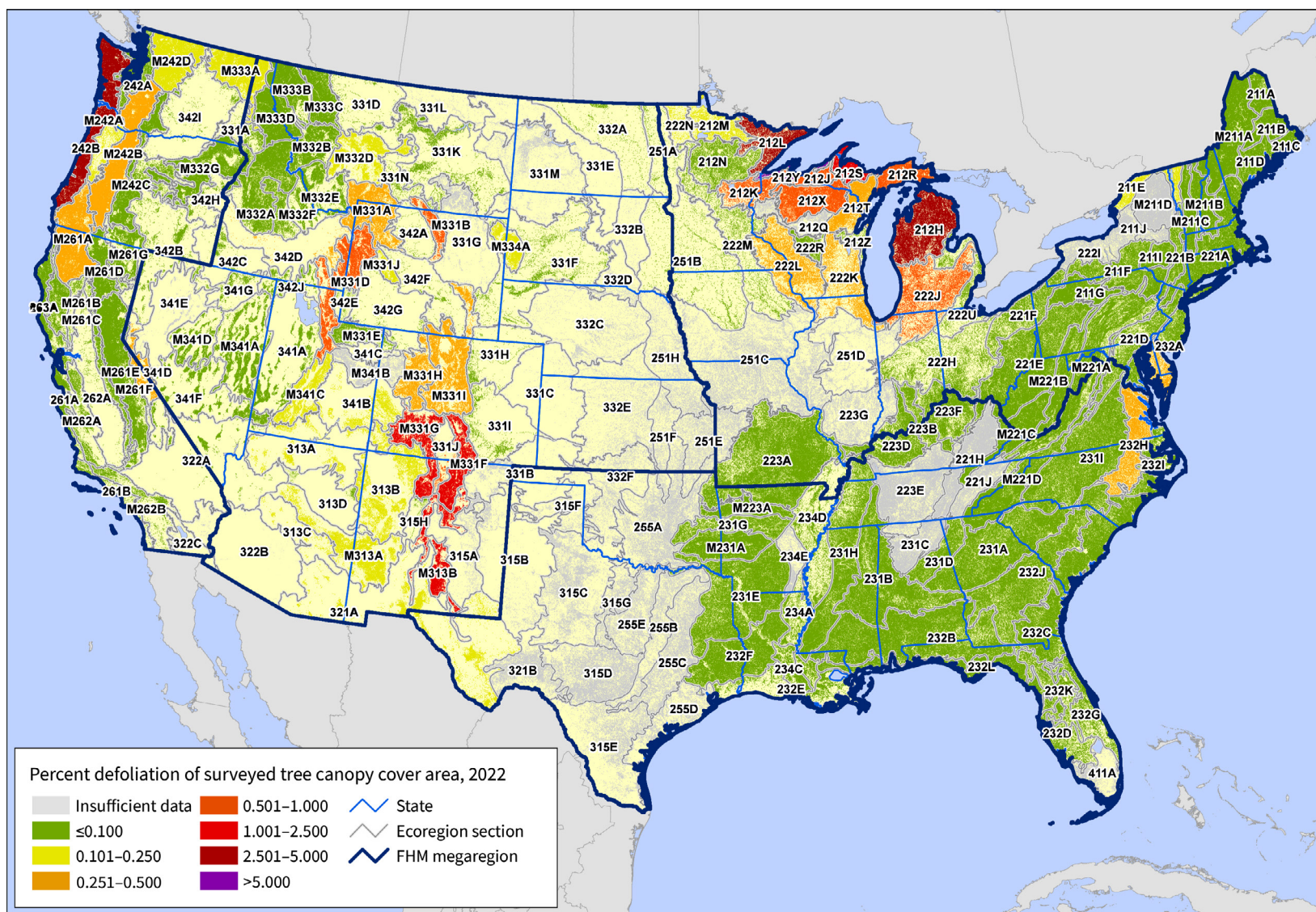


Figure 2.4—The percentage of surveyed tree canopy cover area with insect and disease defoliation, by ecoregion section within the conterminous United States, for 2022. The gray lines delineate ecoregion sections (Cleland and others 2007), and dark blue lines delineate Forest Health Monitoring megaregions. The 240-m tree canopy cover is based on data from a cooperative project between the Multi-Resolution Land Characteristics Consortium (Coulston and others 2012) and the Forest Service Geospatial Technology and Applications Center using the 2011 National Land Cover Database. (Data source: U.S. Department of Agriculture, Forest Service, Forest Health Protection)

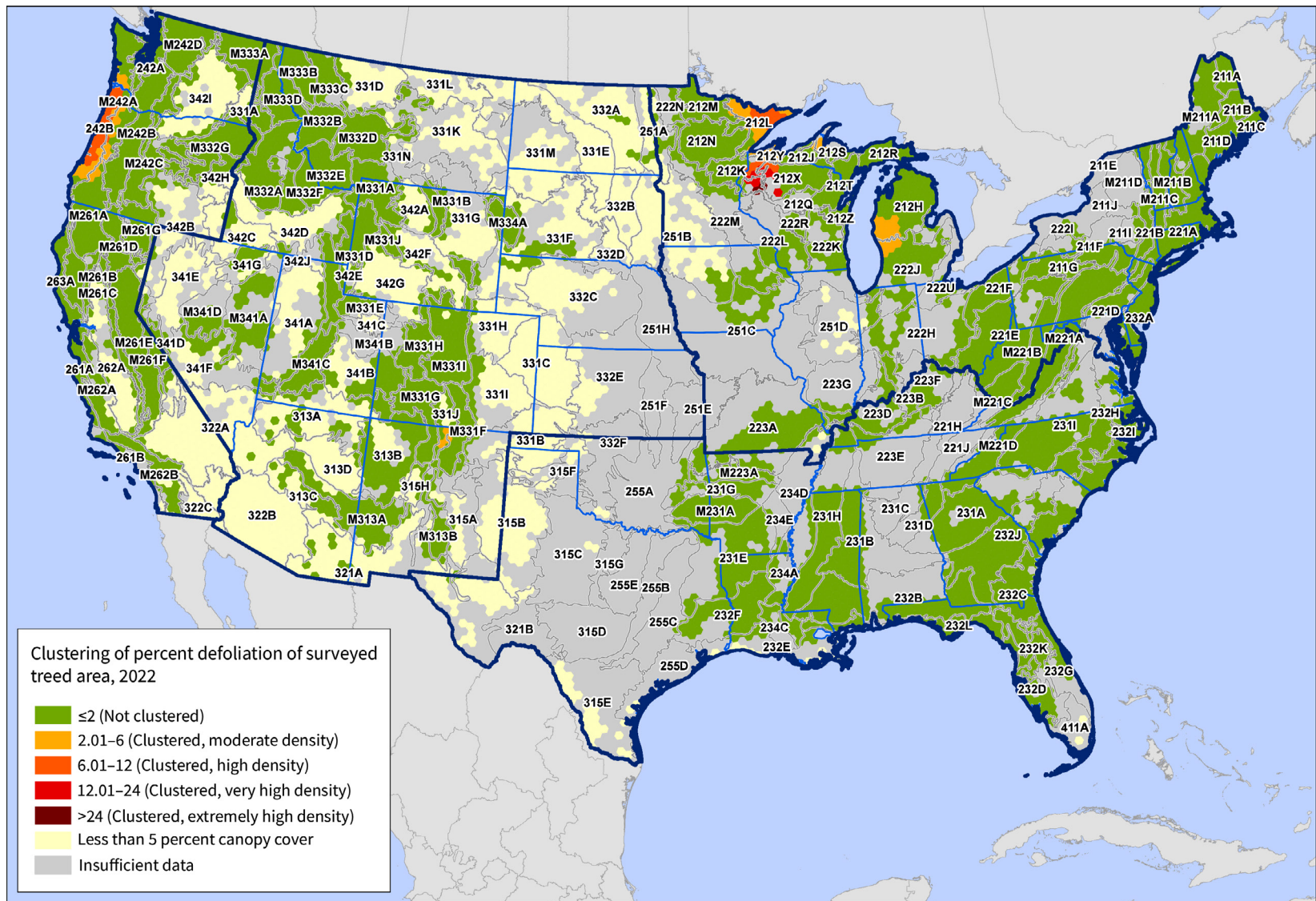


Figure 2.5—Hotspots of percentage of surveyed tree canopy cover area with insect and disease defoliation in 2022 for the conterminous United States by hexagons containing >5 percent tree canopy cover. Values are Getis-Ord G_i^* scores, with values >2 representing significant clustering of high defoliation occurrence densities. (No areas of significant clustering of low densities, <-2, were detected.) The gray lines delineate ecoregion sections (Cleland and others 2007), and dark blue lines delineate Forest Health Monitoring megaregions. Tree canopy cover is based on data from a cooperative project between the Multi-Resolution Land Characteristics Consortium (Coulston and others 2012) and the Forest Service Geospatial Technology and Applications Center using the 2011 National Land Cover Database. (Data source: U.S. Department of Agriculture, Forest Service, Forest Health Protection)

percent) and M261A–Klamath Mountains (0.27 percent)) had moderate defoliation caused by *Cytospora* canker of fir, balsam woolly adelgid, an unknown agent affecting Pacific madrone (*Arbutus menziesii*), and *Dothistroma* needle blight (*D. septosporum*) in ponderosa pine stands.

Twenty defoliation agents were detected in the Interior West FHM megaregion, affecting 264 000 ha (table 2.5). Western spruce budworm encompassed most (73.7 percent) of this area (194 000 ha), similar to recent years (Potter and Paschke 2022, 2023). Pinyon needle scale (*Matsucoccus acalyptus*) and an unknown defoliator of quaking aspen (*Populus tremuloides*) each affected about 23 000 ha (8.9 percent) while Gelechiid moths/needleminers (*Coleotechnites* spp.) were identified on 12 000 ha (4.6 percent).

The Interior West ecoregion section with the highest percent defoliation of surveyed canopy area (2.1 percent) was M313B–Sacramento–Manzano Mountains in central New Mexico (fig. 2.4), where surveyors detected Douglas-fir tussock moth (*Orgyia pseudotsugata*), pinyon needle scale on twoneedle pinyon (*Pinus edulis*), western spruce budworm, and an unknown defoliator in quaking aspen. Two neighboring ecoregion sections in north-central New Mexico and southern Colorado—M331F–Southern Parks and Rocky Mountain Range (1.9 percent defoliation) and M331G–South-Central Highlands (1.7 percent)—were affected by western spruce budworm, Gelechiid moths/needleminers in ponderosa pine, and the unknown quaking aspen defoliator. This area was the location of the single defoliation hotspot (of moderate density) in the Interior West megaregion (fig. 2.5).

Two ecoregion sections in the central Rocky Mountains of northern Colorado and southern Wyoming experienced moderate levels of defoliation by western spruce budworm and the unknown quaking aspen defoliator: M331I–Northern Parks and Ranges (0.40 percent defoliation of canopy tree cover) and M331H–North-Central Highlands and Rocky Mountains in central Colorado (0.28 percent). Meanwhile, three ecoregion sections to the north were affected by western spruce budworm defoliation:

- M331D–Overthrust Mountains in western Wyoming, southeastern Idaho, and northern Utah (0.63 percent)
- M331B–Bighorn Mountains in north-central Wyoming (0.61 percent)
- M331A–Yellowstone Highlands in northwestern Wyoming and south-central Montana (0.34 percent)

Finally, 341D–Mono in western Nevada had a moderate amount of defoliation (0.35 percent) as a result of pinyon needle scale damage in singleleaf pinyon (*P. monophylla*).

Defoliation detected in the Southern FHM megaregion totaled 105 000 ha, of which 86.0 percent (91 000 ha) was associated with forest tent caterpillar (table 2.5). Other relatively widespread agents were spongy moth (10 000 ha, 9.6 percent) and fall cankerworm (*Alsophila pomataria*; 4000 ha, 4.3 percent). Forest tent caterpillar resulted in a moderate level of defoliation in 232H–Middle Atlantic Coastal Plains and Flatwoods in eastern Virginia and North Carolina (0.33 percent defoliation of surveyed tree canopy cover) (fig. 2.4).

Alaska and Hawaii

In 2022, forest health professionals detected damage from six mortality agents across about 25 000 ha of surveyed Alaskan forest and shrubland (table 2.3). This was a decrease from the 90 000 ha detected in 2021. As in recent previous years, spruce beetle was the most commonly identified agent, detected on 20 000 ha, which represented 79.5 percent of the total mortality damage for the State. The only other relatively widespread agent was yellow-cedar (*Chamaecyparis nootkatensis*) decline, identified on 4700 ha or 19.0 percent of the total. An additional 29 762 ha of 2022 mortality attributed to an unknown defoliator were not included in table 2.3 as this resulted from defoliation that occurred before 2022.

Spruce beetle mortality resulted in moderate to high levels of mortality in ecoregion sections of south-central Alaska (0.5–2.5 percent of surveyed forest and shrubland) (fig. 2.6). In recent years, this area has also experienced a spruce beetle outbreak in stands of white spruce (*Picea glauca*) and black spruce (*P. mariana*) (Potter and Paschke 2022, 2023). This encompassed 133A–Cook Inlet Basin (2.5 percent), M241C–Chugach-St. Elias Mountains (1.0 percent), and M133B–Alaska Range (0.95 percent). Meanwhile, mortality associated with yellow-cedar decline and with an unknown and previously documented (from 2021 or earlier) defoliator in western hemlock (*Tsuga heterophylla*) stands resulted in 0.13 percent mortality of surveyed forest and shrubland of M241D–Alexander Archipelago in the Alaska panhandle.

Alaska in 2022 experienced much more defoliation (about 316 000 ha) than mortality (25 000 ha) (table 2.5). This damage—similar in extent to the previous year and a substantial increase from 2020—was attributed to seven defoliating agents, led by western blackheaded budworm (*Acleris gloverana*), detected on 278 000 ha (88.0 percent of the total damage area). Other much less widely detected defoliation agents were aspen leafminer (*Phyllocnistis populiella*) on 15 000 ha (4.9 percent of the total), birch leafminer (*Fenusa pusilla*) on 9000 ha (2.8 percent), and willow leaf blotchminer (*Micrurapteryx salicifoliella*) on 7000 ha (2.1 percent).

The western blackheaded budworm outbreak in western hemlock, mountain hemlock (*T. mertensiana*), and Sitka spruce (*Picea sitchensis*) caused high levels of defoliation in the Alaska panhandle: 6.8 percent of surveyed forest and shrubland in M241D–Alexander Archipelago and 2.2 percent in M241E–Northern Coast Mountains (fig. 2.7). Meanwhile, the minor agents listed above resulted in moderate levels of defoliation (0.25–1.0) in ecoregion sections of east-central Alaska:

- M132C–Yukon-Tanana Uplands (0.90 percent of surveyed forest and shrubland)
- 132C–Tanana-Kuskokwim Lowlands (0.61 percent)
- 132A–Yukon-Old Crow Basin (0.60 percent)
- M132E–Ray Mountains (0.41 percent)

Additionally, M241B–Gulf Coast of Alaska, along the southern coast of the State, had 0.98 percent defoliation of surveyed forest and shrubland

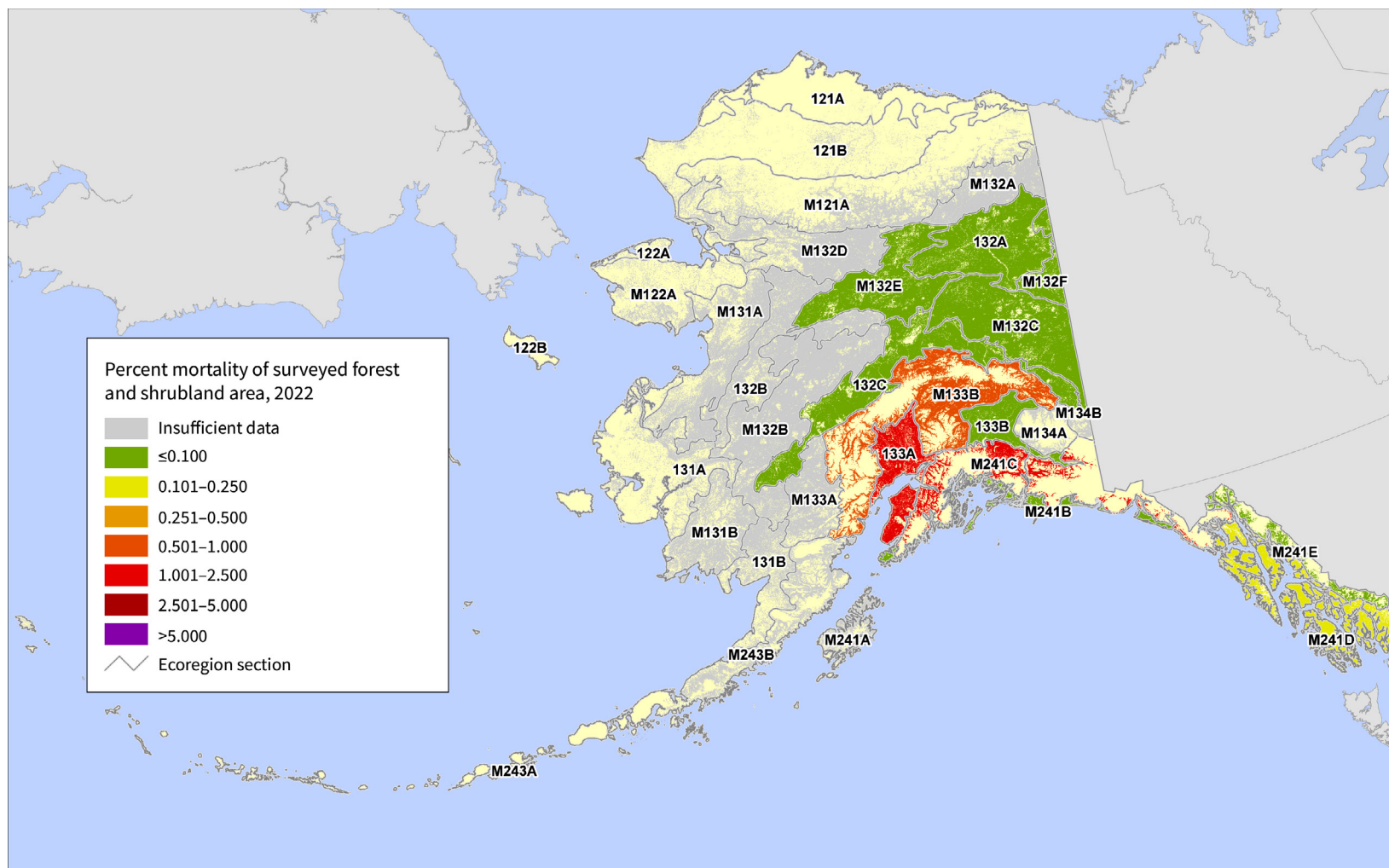


Figure 2.6—Percentage of 2022 surveyed Alaska forest and shrubland area within ecoregions with mortality caused by insects and diseases. The gray lines delineate ecoregion sections (Spencer and others 2002). Forest and shrub cover is derived from the 2011 National Land Cover Database. (Data source: U.S. Department of Agriculture, Forest Service, Forest Health Protection)

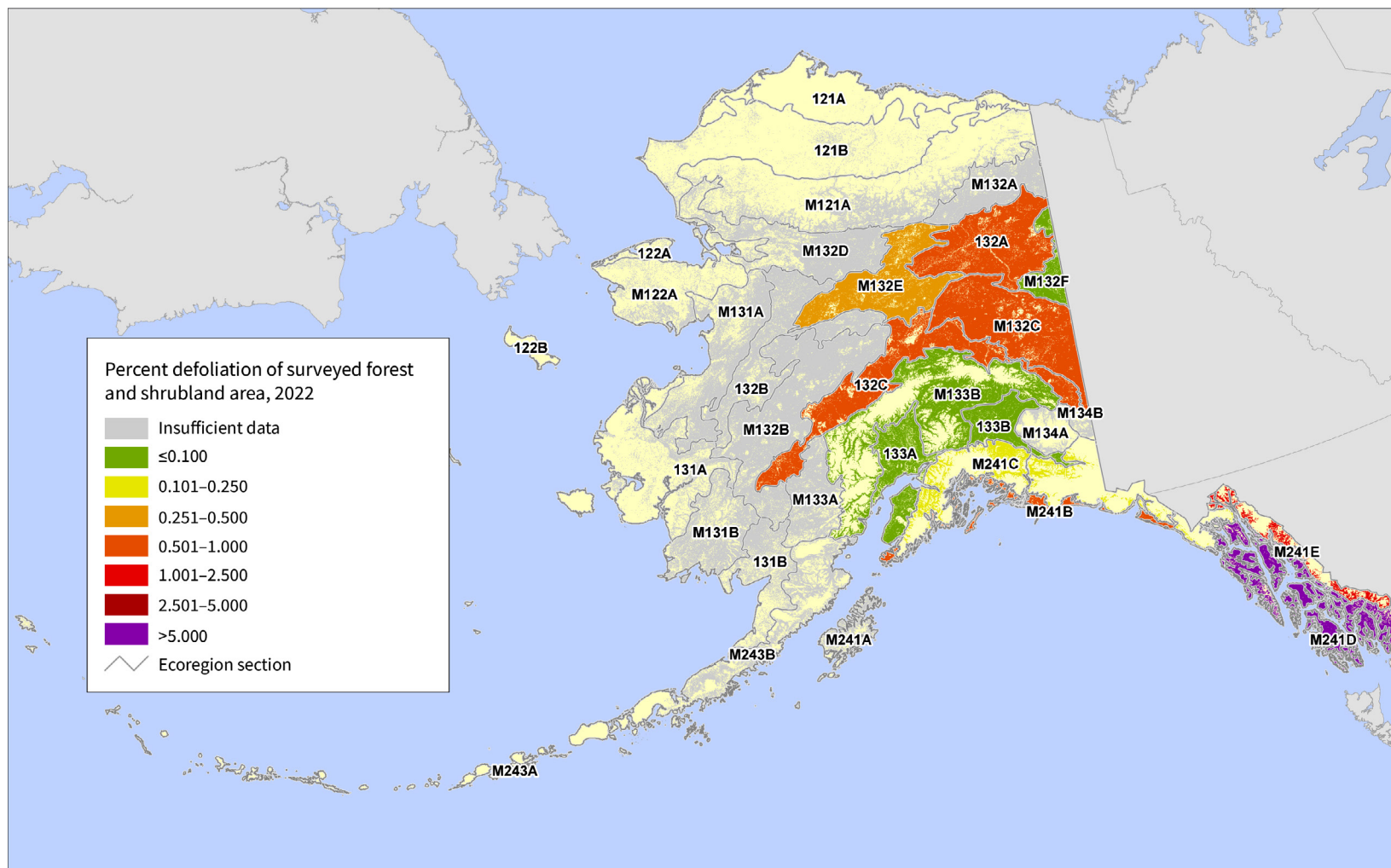


Figure 2.7—Percentage of 2022 surveyed Alaska forest and shrubland area within ecoregions with defoliation caused by insects and diseases. The gray lines delineate ecoregion sections (Spencer and others 2002). Forest and shrub cover is derived from the 2011 National Land Cover Database. (Data source: U.S. Department of Agriculture, Forest Service, Forest Health Protection)

because of an unknown defoliator of alder (*Alnus* spp.) (fig. 2.7).

Finally, in Hawaii, surveyors detected about 36 000 ha of mortality during 2022 (table 2.3), similar to 2021 and an increase compared to 2020 (32 000 ha) and 2019 (27 000 ha) (Potter and Paschke 2022, 2023; Potter and others 2021). The cause of the mortality was designated as “unknown,” but at least some of the damage may be the result of rapid ‘ōhi’a death, a wilt disease caused by two fungal pathogens—the more aggressive *Ceratocystis lukuohia* and the less aggressive *C. huliobia*—which both can kill ‘ōhi’a lehua (*Metrosideros polymorpha*) (Barnes and others 2018). This endemic tree species is the most abundant native tree in Hawaii, where it is deeply woven into Hawaiian culture (University of Hawai‘i, College of Tropical Agriculture and Human Resources 2023). Both pathogens have been confirmed on Hawai‘i Island, where most detections are of the more aggressive *C. lukuohia*, and on Kaua‘i Island (University of Hawai‘i 2023). A small single tree infested with *C. huliobia* was detected and destroyed on Maui in 2019, and about a dozen trees infested with *C. huliobia* have been identified on O‘ahu since 2019 (University

of Hawai‘i, College of Tropical Agriculture and Human Resources 2023).

In 2022, mortality was moderate to high (>0.5 percent of surveyed tree canopy cover) across the four montane wet ecoregions of Hawai‘i Island (fig. 2.8). This was highest in Montane Wet-Hawai‘i-Ka‘ū (MWh-ka, 3.3 percent of the surveyed tree canopy area), followed by Montane Wet-Hawai‘i-Kona (MWh-ko, 2.2 percent), Montane Wet-Hawai‘i-Hilo-Puna (MWh-hp, 1.9 percent), and Montane Wet-Hawai‘i-Kohala-Hāmākua (MWh-kh, 0.88 percent). Lower wet and mesic areas of the island had fairly low mortality densities (0.25–0.5 percent). Meanwhile, moderate levels of mortality were detected in the two wet ecoregions on the island of Kaua‘i: Lowland Wet-Kaua‘i (LWk, 0.74 percent of surveyed tree canopy area) and Montane Wet-Kaua‘i (MWk, 0.34 percent).

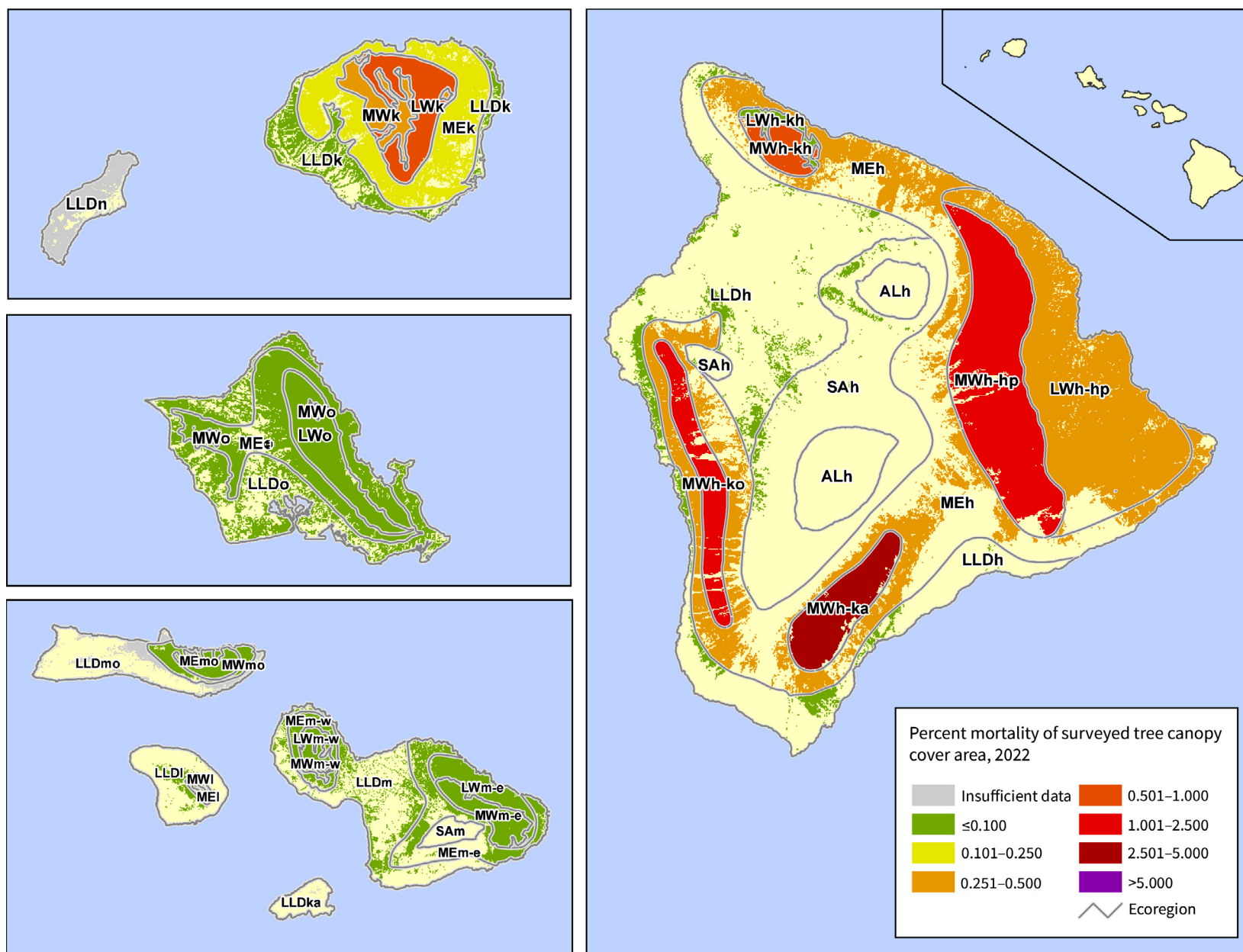


Figure 2.8—Percentage of 2022 surveyed Hawaii tree canopy area within island/ecoregion combinations with mortality caused by insects and diseases. Tree canopy cover is based on data from a cooperative project between the Multi-Resolution Land Characteristics Consortium (Coulston and others 2012) and the Forest Service Geospatial Technology and Applications Center using the 2011 National Land Cover Database. (Data source: U.S. Department of Agriculture, Forest Service, Forest Health Protection)

CONCLUSIONS

Forest health surveyors in 2022 identified 52 mortality-causing agents and complexes on approximately 3.3 million ha across the CONUS, an area similar to that of Connecticut and Massachusetts combined. Fir engraver was the most widely detected mortality agent, identified on about 1.3 million ha in the West Coast FHM megaregion and 59 000 ha in the Interior West megaregion. This is an increase from recent years (e.g., Potter and Paschke 2022, 2023). Emerald ash borer, meanwhile, was detected on about 582 000 ha, mostly in the Eastern megaregion. Alaska experienced mortality from spruce beetle, though less than in recent years, while extensive mortality in Hawaii may be associated with rapid ‘ōhi’a death.

For defoliation, meanwhile, the 2022 national IDS database listed 59 defoliation agents and complexes affecting approximately 1.87 million ha across the CONUS. This area is slightly less than that of New Jersey and continues an upward trend across multiple years (Potter and Paschke 2022, 2023). Spongy moth accounted for a plurality of this area, mostly in the Eastern megaregion but in the Southern megaregion as well. Alaskan forests experienced substantial defoliation as part of an ongoing western blackheaded budworm outbreak in the Alexander Archipelago.

Ongoing, multiple-year monitoring of insect and disease damage across the United States can guide appropriate followup investigation and management activities. The pests and pathogens discussed in this chapter do not include all the biotic forest health threats that are important to be considered when making management decisions and budget allocations, in part because of the limitations of survey efforts to detect certain important forest insects and diseases and to delineate their damage. Despite their shortcomings, large-scale assessments of mortality and defoliation severity represent a constructive approach for identifying geographic areas where monitoring and management activities are most needed and where they might be most effective.

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INTRODUCTION

Wildland fire is an important natural component of many forest ecosystems that are characterized by specific combinations of fire frequency, severity, and seasonality (Greenberg and Collins 2021). It is a widespread disturbance agent in many U.S. forest ecosystems, causing widespread tree damage and mortality and impacting forest health both positively and negatively (Agee 1998, Thom and Seidl 2016, Wade and others 2000). In some ecosystems, wildland fire has been essential for regulating processes that maintain forest health (Lundquist and others 2011). For example, it is an important ecological mechanism that shapes the distributions of species, maintains the structure and function of fire-prone communities, and acts as a significant evolutionary force (Bond and Keeley 2005, Pausas and Keeley 2019). Additionally, some forest types and tree species are adapted to fire under certain intensities and return intervals (Hanberry and others 2018, Jeronimo and others 2019).

At the same time, wildland fires have created forest health and sustainability problems in some ecosystems (Edmonds and others 2011). Fires in some regions and ecosystems have become larger, more intense, and more damaging because of the accumulation of fuels from prolonged fire suppression and past management (Pyne 2010). Robust research indicates that climate change, via more common hot droughts, has already played a role in increased wildfire activity (Abatzoglou and Williams 2016, Higuera and Abatzoglou 2021). Current fire regimes on more

than half the forested area in the conterminous United States (CONUS) have been moderately or significantly altered from historical regimes (Barbour and others 1999), potentially changing key ecosystem components, such as species composition, structural stage, stand age, canopy closure, and fuel loadings (Schmidt and others 2002, Stephens and others 2018). Evidence, in fact, suggests that few entirely natural fire regimes remain in North America (Parisien and others 2016). Such changes in fire intensity and recurrence could result in decreased forest resilience and persistence (Lundquist and others 2011), with plant communities in some regions undergoing rapid compositional and structural changes following fire suppression (Coop and others 2020, May and others 2023, Nowacki and Abrams 2008). Additionally, severe fires in combination with climate change are contributing to widespread challenges to natural regeneration, which threatens to lead to long-term conversions from forest to other vegetation types (Davis and others 2019, Stephens and others 2018).

In addition to their ecological and forest health consequences, large wildland fires also can have long-lasting social and economic consequences, including the loss of human life and property, smoke-related human health impacts, and the economic cost and dangers of fighting the fires themselves (Gill and others 2013, Richardson and others 2012). These impacts are particularly intense within the wildland-urban interface (the zone where human development mixes with forest), the area of which expanded 33 percent between 1990 and 2010 (Calkin and others 2015, Radeloff and others 2018). Additionally,

CHAPTER 3

Broad-Scale Patterns of Forest Fire Occurrence Across the United States and the Caribbean Territories, 2022

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exposure to wildfire smoke may have increased SARS-CoV-2 positivity rates among the public and thereby exacerbated the COVID-19 (coronavirus) pandemic (Kiser and others 2021).

This chapter presents analyses of daily satellite-based fire occurrence data that map and quantify the locations and intensities of fire occurrences spatially across the CONUS, Alaska, Hawaii, and the Caribbean territories in 2022. It also compares 2022 fire occurrences, within a geographic context, to all the recent years for which such data are available. Quantifying and monitoring such large-scale patterns of fire occurrence across the United States, as described in this chapter, cannot necessarily reveal whether the status and trends in wildland fire are “good” or “bad,” but they can help improve understanding of the ecological and economic impacts of fire, including those associated with changing fire regimes across the United States. Additionally, large-scale assessments of fire occurrence can help identify areas where specific management activities may be needed, or where research into the ecological and socioeconomic impacts of fires would be beneficial.

METHODS

Data

The Moderate Resolution Imaging Spectroradiometer (MODIS) Rapid Response System (Justice and others 2002, 2011) extracts fire location and intensity information from the thermal infrared bands of imagery collected daily by two satellites at a resolution of 1 km, with the center of a pixel recorded

as a fire occurrence (NASA Fire Information for Resource Management System 2022). The MODIS Active Fire Detections for the United States database (NASA Fire Information for Resource Management System 2023) allows analysts to spatially display and summarize fire occurrences across broad geographic regions for monitoring and reporting of wildland fire events (Coulston and others 2005; Potter 2012a, 2012b, 2013a, 2013b, 2014, 2015a, 2015b, 2016, 2017, 2018, 2019, 2020a, 2021, 2022, 2023). The MODIS sensors on the Terra and Aqua satellites identify the presence of a fire at the time of image collection by using a contextual algorithm that exploits the strong emission of mid-infrared radiation from fires (Giglio and others 2003). A fire occurrence is defined as one daily satellite detection of wildland fire in an approximately 1-km pixel, with multiple fire occurrences possible on a pixel across multiple days resulting from a single wildland fire that lasts more than 1 day. The resulting fire occurrence data represent only whether a fire was active because the MODIS data bands may not differentiate between a hot fire in a relatively small area (0.01 km², for example) and a cooler fire over a larger area (1 km², for example) if the foreground-to-background temperature contrast is not sufficiently high. The MODIS Active Fire database does well at capturing large fires during cloud-free conditions but may underrepresent rapidly burning, small, and low-intensity fires, as well as fires in areas with frequent cloud cover (Hawbaker and others 2008). The likelihood of detecting a fire beneath a tree canopy is probably low given the smaller general size of

such fires and the fact that they are obscured by the canopy (Giglio and others 2018). For large-scale assessments, the dataset represents a good alternative to the use of ignition point information, which can be difficult to obtain or may not exist for many fires (Tonini and others 2009). The fire occurrence data additionally do not distinguish fires intentionally set for management purposes (controlled burns), which are common in some parts of the United States, such as the South, where many prescribed fires are smaller and/or lower severity and thus not detected by satellite sensors (Nowell and others 2018). More information about the performance of this product is provided by Justice and others (2011). For this analysis, standard MODIS fire occurrence data (those that are internally consistent and well calibrated following post-collection processing) were available from January 1 through September 30, 2022. Available data from October 1 through December 31 were near-real-time fire products, for which fire occurrence locations may not be as accurate, especially for the Aqua satellite, with errors typically small (<100 m) but sometimes larger (several kilometers) (NASA Fire Information for Resource Management System 2022).

Note that estimates of burned area (e.g., Monitoring Trends in Burn Severity data (Eidenshink and others 2007, Picotte and others 2020)) and calculations of MODIS-detected fire occurrences are different metrics for quantifying fire activity within a given year. Most importantly, the MODIS data contain both spatial and

temporal components because persistent fire will be detected repeatedly over several days on a given 1-km pixel. In other words, a location can have a fire occurrence multiple times, once for each day a fire is detected at the location. Analyses of the MODIS-detected fire occurrences, therefore, measure the total number of daily 1-km pixels with fire during a year, as opposed to quantifying only the area on which fire occurred at some point during that timeframe. A fire detected on a single pixel every day for a week, for example, would be equivalent to seven fire occurrences.

The Terra and Aqua satellites that carry the MODIS sensors were launched in 1999 and 2002, respectively, and will be decommissioned eventually. An alternative fire occurrence data source is provided by the Visible Infrared Imaging Radiometer Suite (VIIRS) sensors on board the Suomi National Polar-orbiting Partnership (Suomi NPP) and NOAA-20 weather satellites. The transition to VIIRS 375-m data for national and regional fire occurrence monitoring will require a comparison of fire occurrence detections between it and MODIS. This is because science-ready VIIRS fire data are available only from 2015 onward (NASA Fire Information for Resource Management System 2022) compared to more than 20 years for the MODIS data. Ideally, assessments of fire occurrence trends would analyze as long a temporal window as possible (i.e., from near the beginning of MODIS data availability), encompassing the combination of older MODIS data with newer VIIRS data.

Analyses

Using ArcMap® (ESRI 2017), these MODIS products were processed for 2022 and for the 21 preceding full years of data (beginning in 2001 because of issues with data collection and processing from the Terra satellite in 2000). This determined forest fire occurrence density for (1) ecoregion sections in the CONUS (Cleland and others 2007), (2) ecoregions on each of the major islands of Hawaii (Potter 2020b), and (3) the islands of the Caribbean territories of Puerto Rico and the U.S. Virgin Islands. Fire occurrence density was defined as the number of fire occurrences per 100 km² (10 000 ha) of tree canopy cover area. Forest fire occurrence density metrics were calculated for the CONUS, Hawaii, and the Caribbean territories for each year after screening out wildland fires that did not intersect with tree canopy data. The tree canopy data had been resampled to 240 m from a 30-m raster dataset that estimates percentage of tree canopy cover (from 0 to 100 percent) for each grid cell. This dataset was generated from the 2011 National Land Cover Database (NLCD) (Homer and others 2015) through a cooperative project between the Multi-Resolution Land Characteristics Consortium and the U.S. Department of Agriculture, Forest Service, Geospatial Technology and Applications Center (GTAC) (Coulston and others 2012). For the purposes of this study, any cell with >0 percent tree canopy cover was treated as forest. (This would not include shrub and chaparral land cover without trees.) Comparable tree canopy cover data were not available for Alaska, so a 240-m-resolution layer of forest and shrub cover

was instead created from the 2011 NLCD. The MODIS fire occurrence detection data was then intersected with this layer and with ecoregion sections (Spencer and others 2002) to calculate the number of fire occurrences per 100 km² of forest and shrub cover within each ecoregion section in Alaska. Separately determined were the total numbers of forest fire occurrences for the CONUS, Alaska, Hawaii, and the Caribbean territories after clipping the MODIS fire occurrences by the tree canopy cover or tree and shrub cover data.

The fire occurrence density value for each of the ecoregions of the States and for the Caribbean territories in 2022 was compared with the mean fire density values for the first 21 full years of MODIS Active Fire data collection (2001–2021). Specifically, the difference of the 2022 value and the previous 21-year mean for the area was divided by the standard deviation across the previous 21-year period, assuming a normal distribution of fire density over time. The result for each ecoregion was a standardized *z*-score, which is a dimensionless quantity describing the degree to which the fire occurrence density in the area in 2022 was higher, lower, or the same relative to all the previous years for which data have been collected, accounting for the variability in the previous years. The *z*-score is the number of standard deviations between the observation and the mean of the historic observations in the previous years. Approximately 68 percent of observations would be expected within one standard deviation of the mean, and 95 percent within two standard deviations. Near-normal conditions are those within a single standard

deviation of the mean, although such a threshold is somewhat arbitrary. Conditions between about one and two standard deviations of the mean are moderately different from mean conditions but are not significantly different statistically. Those outside about two standard deviations would be considered statistically greater than or less than the long-term mean ($p < 0.025$ at each tail of the distribution).

Additionally, the Spatial Association of Scalable Hexagons (SASH) analytical approach identified forested areas in the CONUS with higher-than-expected fire occurrence density in 2022. This method identifies locations where ecological phenomena occur at greater or lower occurrences than expected by random chance and is based on a sampling frame optimized for spatial neighborhood analysis, adjustable to the appropriate spatial resolution, and applicable to multiple data types (Potter and others 2016). Specifically, it consists of dividing an analysis area into scalable equal-area hexagonal cells within which data are aggregated, followed by identifying statistically significant geographic clusters of hexagonal cells within which mean values are greater or less than those expected by chance. These clusters were identified through a Getis-Ord G_i^* hotspot analysis (Getis and Ord 1992) in ArcMap® 10.5.1 (ESRI 2017).

The spatial units of analysis were 9,810 hexagonal cells, each approximately 834 km² in area, generated in a lattice across the CONUS using intensification of the Environmental Monitoring and Assessment Program (EMAP) North American hexagon coordinates (White

and others 1992). These coordinates are the foundation of a sampling frame in which a hexagonal lattice was projected onto the CONUS by centering a large base hexagon over the region (Reams and others 2005, White and others 1992). The hexagons are compact and uniform in their distance to the centroids of neighboring hexagons, meaning that a hexagonal lattice has a higher degree of isotropy (uniformity in all directions) than does a square grid (Shima and others 2010). These attributes are highly useful for spatial neighborhood analyses. Importantly, these scalable hexagons also are independent of geopolitical and ecological boundaries, avoiding the possibility of different sample units (such as counties, States, or watersheds) encompassing vastly different areas (Potter and others 2016). The 834-km² hexagons are a manageable size for making monitoring and management decisions in analyses across the CONUS (Potter and others 2016).

Fire occurrence density values were calculated as the number of forest fire occurrences per 100 km² of tree canopy cover area within a hexagon. Use of the Getis-Ord G_i^* statistic identified clusters of hexagonal cells with fire occurrence density values higher than expected by chance. This statistic allows for the decomposition of a global measure of spatial association into its contributing factors, by location, and is therefore particularly suitable for detecting outlier assemblages of similar conditions in a dataset, such as when spatial clustering is concentrated in one subregion of the data (Anselin 1992).

Briefly, G_i^* sums the differences between the mean values in a local sample, determined in this case by a moving window of each hexagon and its 18 first- and second-order neighbors (the 6 adjacent hexagons and the 12 additional hexagons contiguous to those 6) and the global mean of the 9,644 hexagonal cells with tree canopy cover (of the total 9,810) in the CONUS. As described in Laffan (2006), it is calculated as:

$$G_i^*(d) = \frac{\sum_j w_{ij}(d)x_j - W_i^* \bar{x}^*}{s^* \sqrt{\frac{(ns_{1i}^*) - W_i^{*2}}{n-1}}}$$

where

G_i^* = the local clustering statistic (in this case, for the target hexagon)

i = the center of local neighborhood (the target hexagon)

d = the width of local sample window (the target hexagon and its first- and second-order neighbors)

x_j = the value of neighbor j

w_{ij} = the weight of neighbor j from location i (all the neighboring hexagons in the moving window were given an equal weight of 1)

n = the number of samples in the dataset (the 9,644 hexagons containing >5-percent tree cover and with at least 1 percent of the canopy cover surveyed)

W_i^* = the sum of the weights

s_{1i}^* = the number of samples within d of the central location (19: the focal hexagon and its 18 first- and second-order neighbors)

$\bar{x}^*$ = mean of whole dataset (in this case, the 9,644 hexagons)

s^* = the standard deviation of whole dataset (for the 9,644 hexagons)

G_i^* is standardized as a z-score with a mean of 0 and a standard deviation of 1, with values >1.96 representing significant local clustering of higher fire occurrence densities ($p < 0.025$) and values <-1.96 representing significant clustering of lower fire occurrence densities ($p < 0.025$), because 95 percent of the observations under a normal distribution should be within approximately two standard deviations of the mean (Laffan 2006). Values between -1.96 and 1.96 have no statistically significant concentration of high or low values. In other words, a hexagon and its 18 neighbors have a normal range of both high and low numbers of fire occurrences per 100 km² of tree canopy cover area. The threshold values are not exact because the correlation of spatial data violates the assumption of independence required for statistical significance (Laffan 2006). In addition, the Getis-Ord approach does not require that the input data be normally distributed, because the local G_i^* values are computed under a randomization assumption, with G_i^* equating to a standardized z-score that asymptotically tends to a normal distribution (Anselin 1992). The z-scores are reliable, even with skewed data, as long as the local neighborhood encompasses several observations (ESRI 2017): in this case, via the target hexagon and its 18 first- and second-order neighbors.

RESULTS AND DISCUSSION

Trends in Forest Fire Occurrence Detections for 2022

Across the CONUS, 62,297 forest fire occurrences were recorded in the MODIS Active Fire database for 2022. This represented a 44-percent decrease in fire activity from 2021 (111,416 fire occurrences) and was the 13th largest number of fire occurrences in 22 full years of data collection (fig. 3.1). It was also 17 percent less than the mean for the previous 21 years of data (74,753 fire occurrences). Meanwhile, Alaska experienced a >1,000-percent increase in forest fire occurrences in 2022 (21,320) compared to the previous year (1,806). The 2022 number was a 139 percent increase over the 21-year average of 8,931. It was the fifth highest number of fire occurrences in Alaska since the first full year of data collection in 2001 and repeated a trend of large fire years every few years for the State, last experienced in 2015 and 2019. Also, like 2019, the large Alaskan fire year in 2022 corresponded with a milder-than-average fire year for the CONUS. Additionally in 2022, 46 fire occurrences were detected in the State of Hawaii, a slight increase of 7 percent from 43 in 2021 but still 82 percent below the 2001–2021 average of about 262 a year. Finally, Puerto Rico and the U.S. Virgin Islands experienced 5 fire occurrences, which was a 62-percent decrease from 13 in 2021 and 45 percent below the average of about 9 per year.

These results do not correspond closely with official national wildland fire statistics tracking the number of wildfires reported and the area burned by them (National Interagency Coordination Center 2023). Nationally, the area burned increased about 6 percent from 2 883 645 ha in 2021 to 3 066 377 in 2022, and the number of individual wildfires reported climbed from 58,985 to 68,988 with higher increase in Alaska and the South (National Interagency Coordination Center 2023). The National Interagency Coordination Center uses a benchmark threshold of 16 187 ha (40,000 acres) for tracking very large wildland fires and fire complexes. More fires in 2022 (45) exceeded this threshold area than in 2021 (38), but this was fewer than the number in 2020 (50) (National Interagency Coordination Center 2021, 2022, 2023). Of these 45 very large fires in 2022, 30 were in Alaska. As noted above in Methods, the number of reported fires and estimates of burned area are different metrics for quantifying fire activity than are calculations of MODIS-detected fire occurrences, but the metrics may be correlated. The analyses described in this chapter focus on MODIS fire occurrences because they capture both the spatial and temporal components of persistent fires that are detected repeatedly over 2 or more days on a 1-km pixel, rather than quantifying only the area on which fire occurred.

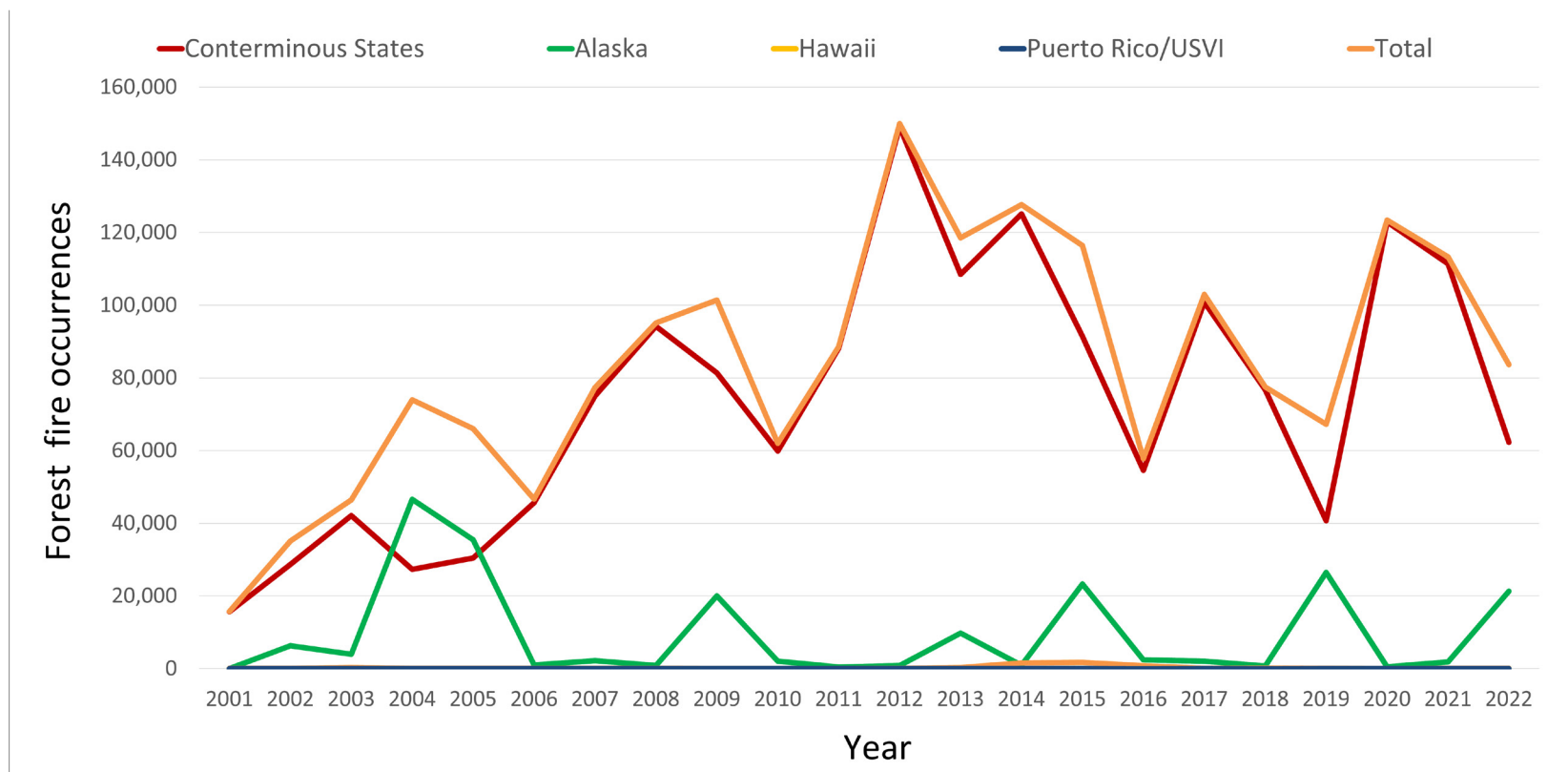


Figure 3.1—Forest fire occurrences detected by Moderate Resolution Imaging Spectroradiometer (MODIS) from 2001 through 2022 for the conterminous United States, Alaska, Hawaii, and Puerto Rico and the U.S. Virgin Islands, and for the entire Nation combined. (Data source: U.S. Department of Agriculture, Forest Service, Geospatial Technology and Applications Center, in conjunction with the NASA MODIS Rapid Response group)

The 2022 MODIS wildland fire occurrence data indicate that the areas with the highest fire occurrence densities shifted from recent years. In 2020 and 2021 (Potter 2022, 2023), ecoregions with extremely high fire occurrence densities were located in the northwestern and Sierra Nevada regions of California and in central Oregon and Washington. In 2022, no ecoregion sections had extremely high fire occurrence densities, but a handful in the Southwest had very high values (fig. 3.2). These were 315H–Central Rio Grande Intermontane in central New Mexico (20.8 fire occurrences/100 km² of tree canopy cover), M331F–Southern Parks and Rocky Mountain Range in north-central New Mexico and south-central Colorado (18.4 fire occurrences), and M313A–White Mountains-San Francisco Peaks-Mogollon Rim in southwestern New Mexico and east-central Arizona (17.2 fire occurrences) (table 3.1). (Note that the ecoregion section in 2021 with the highest fire occurrence density had 52.2 fire occurrences/100 km² of tree canopy cover (Potter 2023).) Many of the fires in this region were sparked by dry and frequently windy spring conditions that resulted in several long-duration fires, including the Hermits Peak and Black Fires in New Mexico, by the end of May (National Interagency Coordination Center 2023).

Other ecoregion sections with relatively high fire occurrence densities were located in the Pacific Northwest (M332A–Idaho Batholith, with 10.0 fire occurrences/100 km² of tree canopy cover, and M242D–Northern Cascades, 7.0 fire occurrences), central California (262A–Great Valley, 9.0 fire occurrences), and the Gulf Coast

region (232B–Gulf Coastal Plains and Flatwoods, 6.0 fire occurrences).

Alaska, meanwhile, experienced well-above normal temperatures through the early summer of 2022. This was coupled with lightning-intense storms in the southwestern and interior parts of the State that generated a rapid increase in fire activity in June, with dozens of large fires burning by the end of that month (National Interagency Coordination Center 2023). As a result, a swath of ecoregion sections from southwestern to east-central Alaska had high fire occurrence densities: M133A–Lime Hills (10.2), M132B–Kuskokwim Mountains (9.3), and 132C–Tanana-Kuskokwim Lowlands (6.2) (fig. 3.3). The fire activity in Alaska began to wane in July with the spread of cooler and wetter conditions across the State (National Interagency Coordination Center 2023).

Hawaii ecoregions had relatively low fire occurrence densities in 2022. Only three exceeded 1 fire occurrence/100 km² of canopy cover: the Mesic ecological region on Hawai‘i Island (MEh, 2.1) and the Montane Wet-Maui-West (MWm-w, 1.7) and Mesic-Maui-West (MEm-w, 1.6) on Maui (fig. 3.4). At the same time, fire occurrence densities in 2022 were ≤1 fire occurrence/100 km² of tree canopy cover for most islands of the U.S. Caribbean territories (Puerto Rico and the U.S. Virgin Islands) except for Great Hans Lollik Island north of Saint Thomas in the U.S. Virgin Islands (72.9), which is quite small and had a single fire occurrence (fig. 3.5).

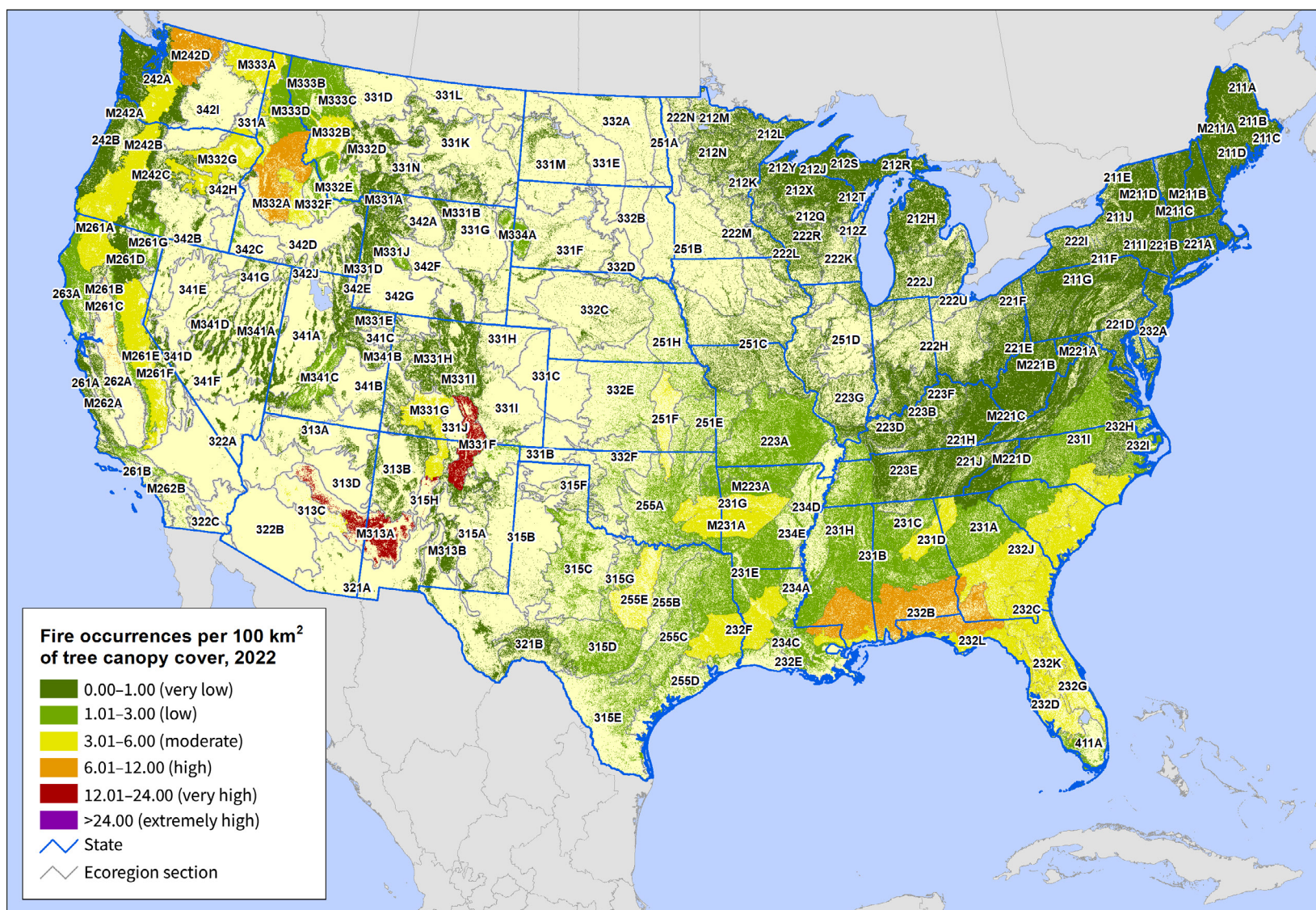


Figure 3.2—The number of forest fire occurrences per 100 km² (10 000 ha) of tree canopy coverage area, by ecoregion section within the conterminous United States, for 2022. The gray lines delineate ecoregion sections (Cleland and others 2007). Tree canopy cover is based on data from a cooperative project between the Multi-Resolution Land Characteristics Consortium (Coulston and others 2012) and the Forest Service Geospatial Technology and Applications Center (GTAC) using the 2011 National Land Cover Database. See figure 1.1A for ecoregion identification. (Source of fire data: U.S. Department of Agriculture, Forest Service, GTAC, in conjunction with the NASA Moderate Resolution Imaging Spectroradiometer Rapid Response group)

Table 3.1—The 15 ecoregion sections in the conterminous United States with the highest fire occurrence densities in 2022

Section	Name	Tree canopy area (100 km ²)	Fire occurrences (number)	Density ^a
315H	Central Rio Grande Intermontane	7.1	147	20.8
M331F	Southern Parks and Rocky Mountain Range	174.7	3,221	18.4
M313A	White Mountains-San Francisco Peaks-Mogollon Rim	202.5	3,476	17.2
M332A	Idaho Batholith	338.9	3,393	10.0
262A	Great Valley	19.4	176	9.0
M242D	Northern Cascades	251.1	1,763	7.0
232B	Gulf Coastal Plains and Flatwoods	888.7	5,355	6.0
232J	Southern Atlantic Coastal Plains and Flatwoods	604.0	3,588	5.9
M261E	Sierra Nevada	427.8	2,473	5.8
M332G	Blue Mountains	309.7	1,728	5.6
322B	Sonoran Desert	2.2	12	5.5
M332F	Challis Volcanics	72.2	374	5.2
251F	Flint Hills	57.8	286	4.9
232K	Florida Coastal Plains Central Highlands	149.0	669	4.5
M331G	South-Central Highlands	187.5	824	4.4

^a Density = fire occurrences per 100 km² of tree canopy coverage area.

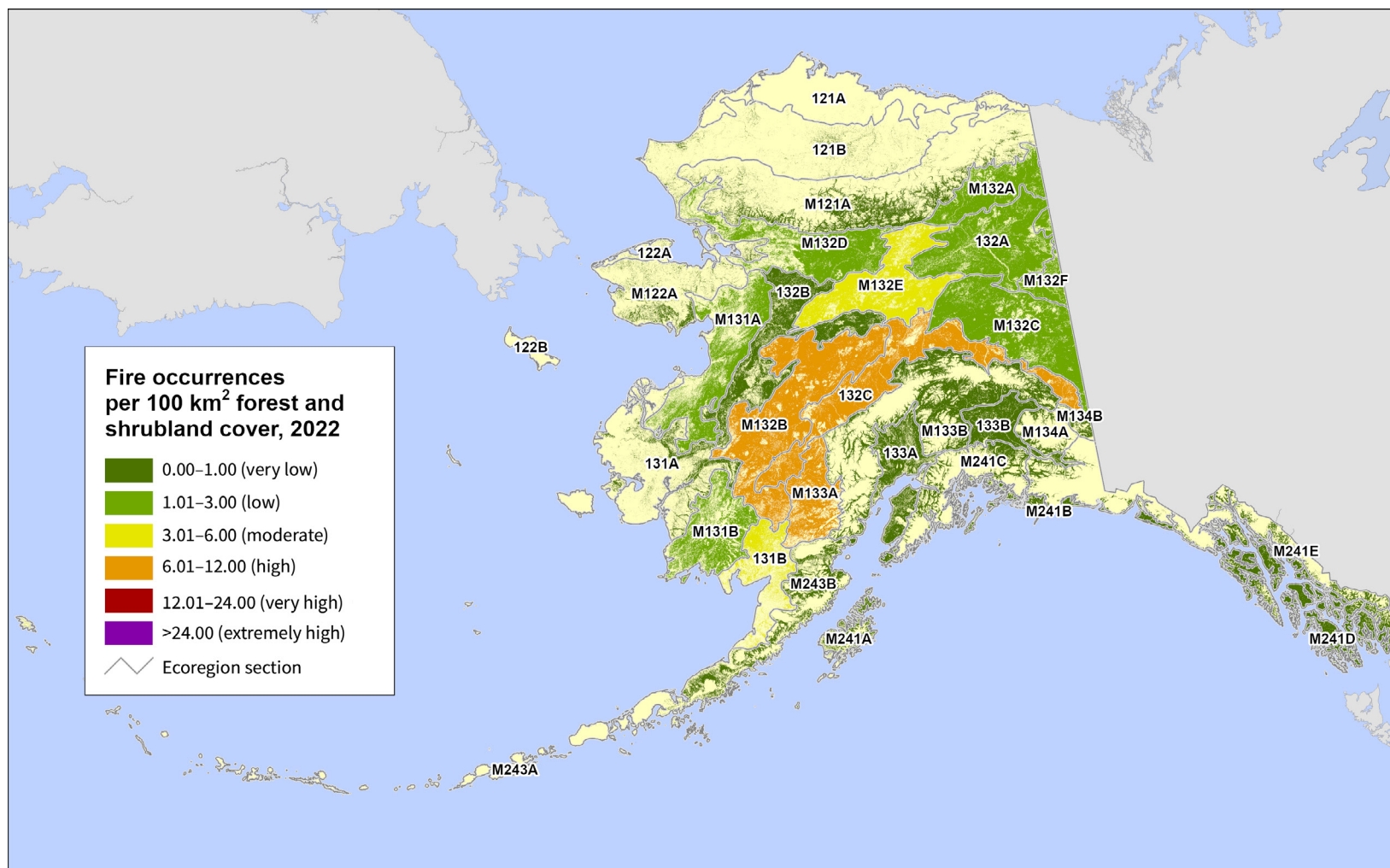


Figure 3.3—The number of forest fire occurrences per 100 km² (10 000 ha) of forest and shrub cover, by ecoregion section within Alaska, for 2022. The gray lines delineate ecoregion sections (Spencer and others 2002). Forest and shrub cover are derived from the 2011 National Land Cover Database. See figure 1.1B for ecoregion identification. (Source of fire data: U.S. Department of Agriculture, Forest Service, Geospatial Technology and Applications Center, in conjunction with the NASA Moderate Resolution Imaging Spectroradiometer Rapid Response group)

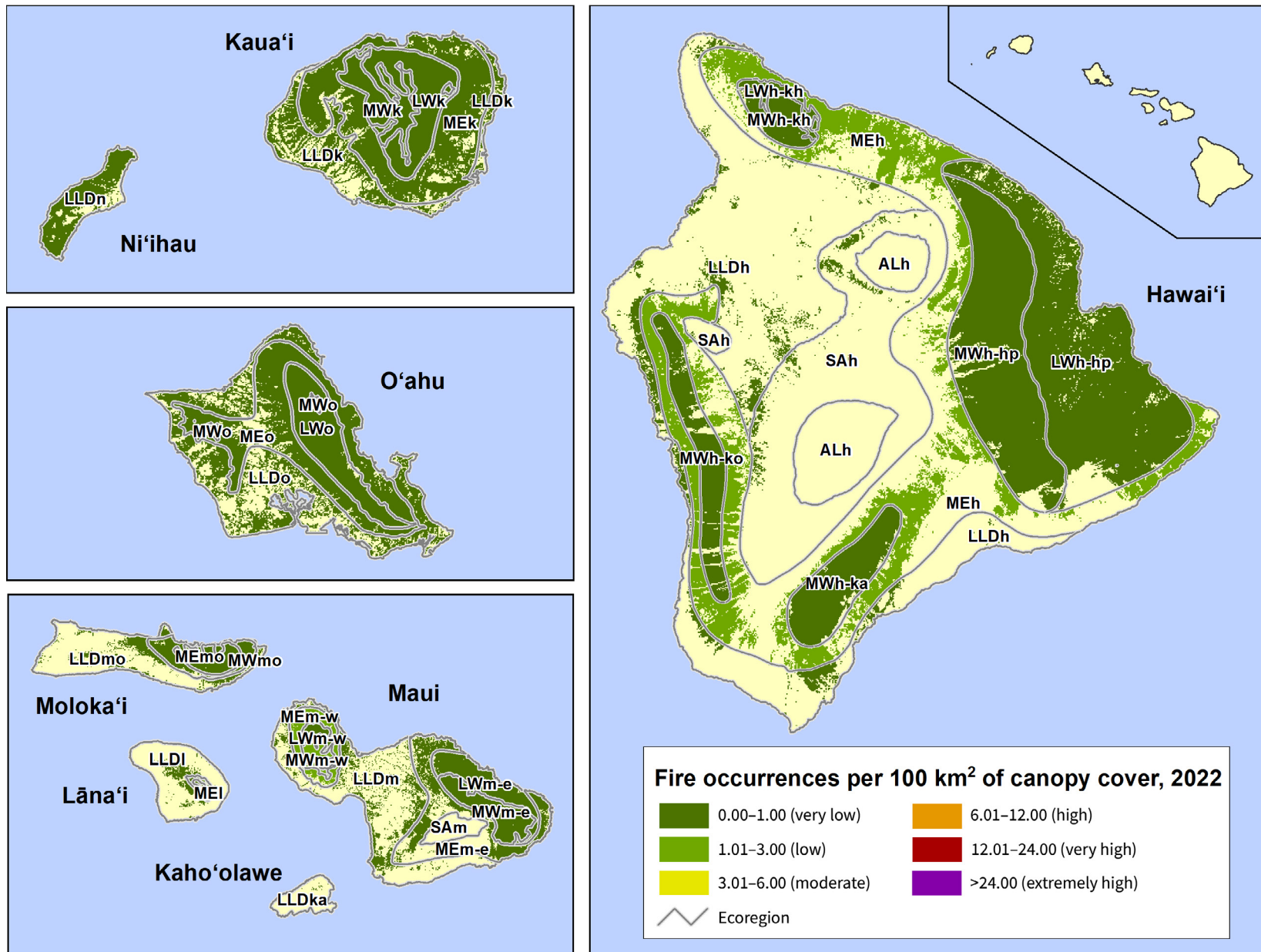


Figure 3.4—The number of forest fire occurrences per 100 km² (10 000 ha) of tree canopy coverage area, by island/ecoregion combination in Hawaii, for 2022. Tree canopy cover is based on data from a cooperative project between the Multi-Resolution Land Characteristics Consortium (Coulston and others 2012) and the Forest Service Geospatial Technology and Applications Center (GTAC) using the 2011 National Land Cover Database. (Source of fire data: U.S. Department of Agriculture, Forest Service, GTAC, in conjunction with the NASA Moderate Resolution Imaging Spectroradiometer Rapid Response group)

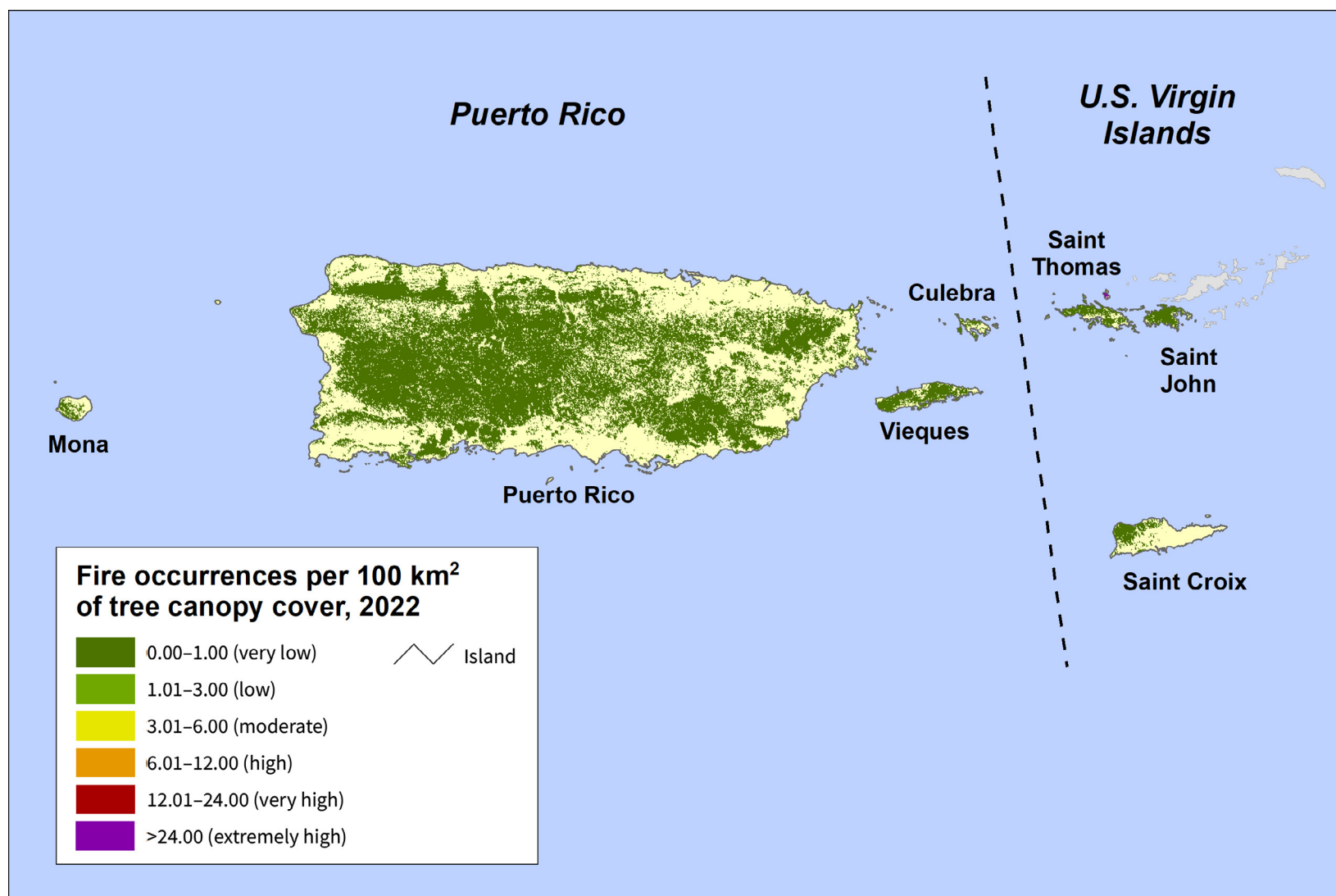


Figure 3.5—The number of forest fire occurrences per 100 km² (10 000 ha) of tree canopy coverage area, by island in Puerto Rico and the U.S. Virgin Islands, for 2022. Tree canopy cover is based on data from a cooperative project between the Multi-Resolution Land Characteristics Consortium (Coulston and others 2012) and the Forest Service Geospatial Technology and Applications Center (GTAC) using the 2011 National Land Cover Database. (Source of fire data: U.S. Department of Agriculture, Forest Service, GTAC, in conjunction with the NASA Moderate Resolution Imaging Spectroradiometer Rapid Response group)

Comparison to Longer Term Trends

The collection of MODIS Active Fire data for more than two decades allows one to contrast annual (2022) forest fire occurrence densities with longer term trends (2001–2021) for ecoregions in the CONUS, Alaska, and Hawaii, and for the Caribbean territories. During that 21-year comparison period, ecoregions in the Pacific Coast States, Idaho, Arizona/New Mexico, eastern Kansas/northeastern Oklahoma, and along the Gulf Coast in the Southeast had high mean annual fire occurrence densities (exceeding 6 fire occurrences/100 km² of tree canopy cover) (fig. 3.6A). The two specific ecoregion sections with the highest mean annual fire occurrence density (12.0 fire occurrences/100 km² of tree canopy cover annually) were M261A–Klamath Mountains of northwestern California and southeastern Oregon and M261B–Northern California Coast Ranges (table 3.2). Other ecoregion sections with high mean annual fire occurrence densities included M332A–Idaho Batholith in central Idaho (11.7), M261E–Sierra Nevada in California (11.4), and M262B–Southern California Mountain and Valley near the southern California coast (9.3). Several ecoregions in the West and Southeast had moderate mean fire occurrence densities (3–6 fire occurrences/100 km² of tree canopy cover annually), while much of the Midwest and all the Northeast had very low densities (≤ 1).

Many of the western ecoregion sections with the highest mean annual forest fire occurrence densities also had the greatest annual variation in fire occurrence densities from 2001 through 2021 (fig. 3.6B). This included M261B–Northern

California Coast Ranges, M332A–Idaho Batholith, 261A–Central California Coast, M261E–Sierra Nevada, and M262B–Southern California Mountain and Valley. More moderate variation existed in other parts of the West, including central Oregon and Washington, northwestern Montana, and central Arizona and west-central New Mexico. Other areas—including in north-central Colorado and south-central Wyoming—had moderate variation with low mean annual fire occurrence densities, suggesting low numbers of fire occurrences most years with high numbers in others. Ecoregion sections of the Midwest and Northeast and in coastal Oregon and Washington had the lowest interannual variation (standard deviation < 1), while slightly higher variation (standard deviation 1–5) was apparent across the Southeast, the central Rocky Mountains, and the Great Basin. Parts of the Southeast, especially along the Gulf Coast, had low annual variation but relatively high mean annual fire occurrence densities, indicating consistently high numbers of fire occurrences over time.

Compared to the previous 21-year mean and accounting for temporal variability, a handful of ecoregions in the Southwest, the Northeast, the Midwest, and the Mid-Atlantic States experienced 2022 fire occurrence densities that were higher than normal (fig. 3.6C). With z -scores > 2 , M331F–Southern Parks and Rocky Mountain Range, 315H–Central Rio Grande Intermontane, and 331B–Southern High Plains in the Southwest all had much higher 2022 fire occurrence densities than expected. The same was true of two ecoregion sections in Maine (211A–

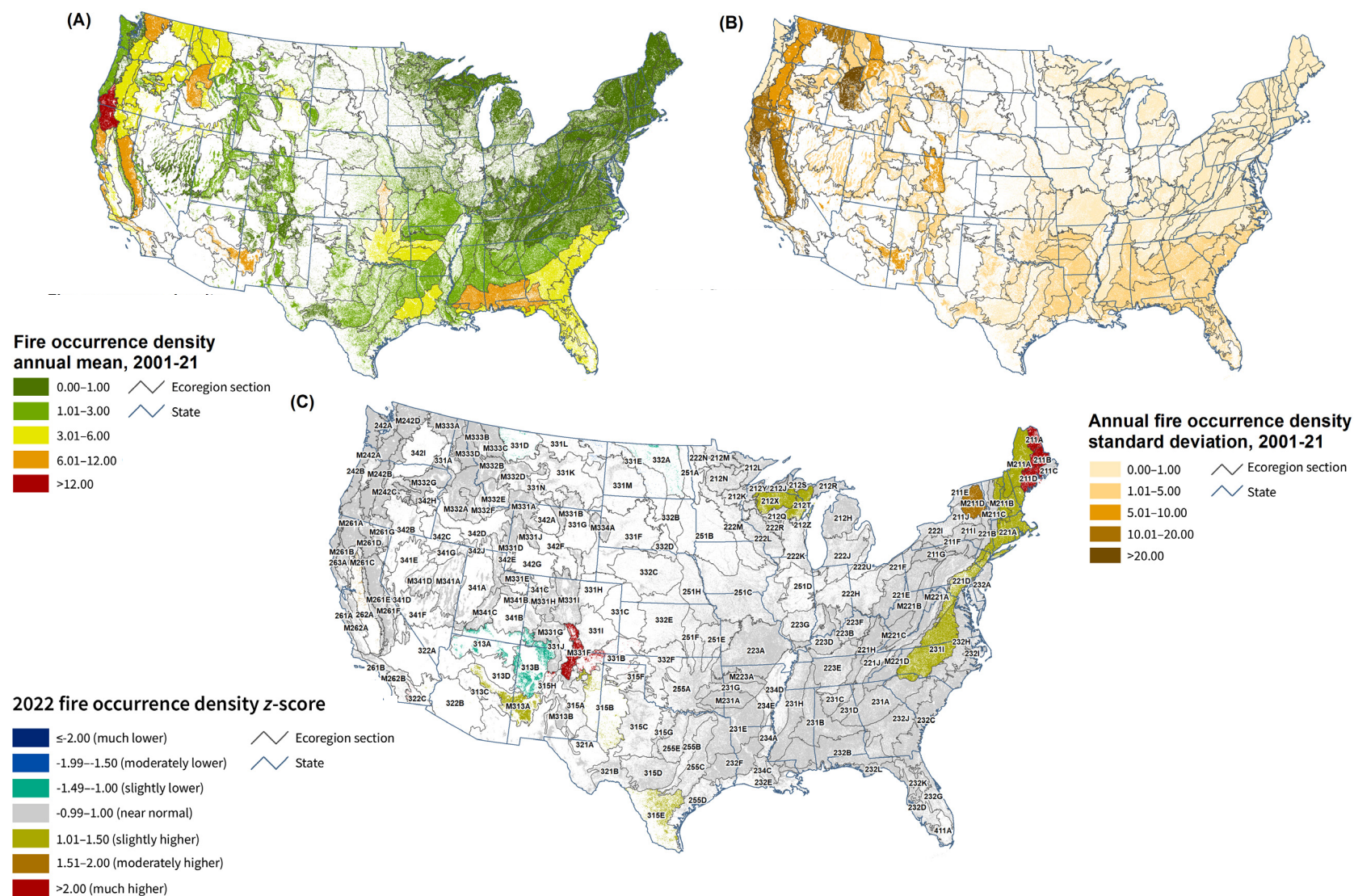


Figure 3.6—(A) Mean number and (B) standard deviation of forest fire occurrences per 100 km² (10 000 ha) of tree canopy coverage area from 2001 through 2021, by ecoregion section within the conterminous United States. (C) Degree of 2022 fire occurrence density excess or deficiency, by ecoregion section relative to 2001–2021 and accounting for variation over that period. The gray lines delineate ecoregion sections (Cleland and others 2007). Tree canopy cover is based on data from a cooperative project between the Multi-Resolution Land Characteristics Consortium (Coulston and others 2012) and the Forest Service Geospatial Technology and Applications Center (GTAC) using the 2011 National Land Cover Database. (Source of fire data: U.S. Department of Agriculture, Forest Service, GTAC, in conjunction with the NASA Moderate Resolution Imaging Spectroradiometer Rapid Response group)

Table 3.2—The 15 ecoregion sections in the conterminous United States with the highest mean annual fire occurrence densities from 2001 through 2021

Section	Name	Tree canopy area (100 km ²)	Mean annual fire occurrence density ^a
M261A	Klamath Mountains	338.5	12.0
M261B	Northern California Coast Ranges	114.1	12.0
M332A	Idaho Batholith	338.9	11.7
M261E	Sierra Nevada	427.8	11.4
M262B	Southern California Mountain and Valley	58.1	9.3
M313A	White Mountains-San Francisco Peaks-Mogollon Rim	202.5	7.4
313C	Tonto Transition	17.5	7.2
251F	Flint Hills	57.8	6.9
261A	Central California Coast	66.8	6.7
M242D	Northern Cascades	251.1	6.4
232B	Gulf Coastal Plains and Flatwoods	888.7	6.1
M261D	Southern Cascades	150.6	5.9
M242C	Eastern Cascades	219.4	5.8
331A	Palouse Prairie	33.4	5.8
M332F	Challis Volcanics	72.2	5.5

^a Mean annual fire occurrence density = fire occurrences per 100 km² of tree canopy coverage area.

Aroostook Hills and Lowlands and 211B–Maine–New Brunswick Foothills and Lowlands), though this was an area that did not have nearly as many fire occurrences in 2022 as the southwestern regions. In other words, these are areas that tend to have few fires in a typical year and therefore don't require many fire occurrences to be classified as having more than normal. Worth noting is the 2022 absence of areas with higher-than-normal fire occurrence densities in the Pacific Coast States; several ecoregions there experienced fire occurrence densities that were much higher than normal in both 2020 and 2021 (Potter 2022, 2023).

Meanwhile, a handful of ecoregion sections in the Upper Midwest and the Southwest had lower-than-expected fire occurrence densities in 2022, as indicated by z -scores ≤ -1 . This included 313A–Grand Canyon in northern Arizona and southern Utah, 313B–Navajo Canyonlands in northwestern New Mexico, 332A–Northeastern Glaciated Plains in central North Dakota, and 331D–Northwestern Glaciated Plains in north-central Montana. These are all areas with low to moderate annual fire occurrence densities on average.

Mean annual fire occurrence densities in Alaska for 2001–2021 were moderately high (3.0–6.0 fire occurrences/100 km² of tree canopy cover annually) in M132E–Ray Mountains and 132A–Yukon–Old Crow Basin of the State's central and east-central interior (fig. 3.7A). Most of the interior ecoregions around these had slightly lower mean annual fire occurrence densities, while those of northern, western, and southern Alaska (including the panhandle) were very low (≤ 1). Central and east-central interior ecoregions

exhibited moderately high variability during the 21-year period preceding 2022 (fig. 3.7B). For that year, many Alaskan ecoregions had fire occurrence densities that were much higher or moderately higher than expected compared to the previous 21 years and controlling for variability, including in the southwestern, west-central, panhandle, and far northern parts of the State (fig. 3.7C). In southwestern Alaska, the massive 350 306-ha Lime Complex of fires spanned three ecoregion sections: M133A–Lime Hills, 132C–Tanana–Kuskokwim Lowlands, and M132B–Kuskokwim Mountains. In west-central Alaska, the 111 573-ha Paradise Complex, the 92 851-ha Tatlawiksuk Fire, and the 85 997-ha Bean Complex all extended across parts of M132B–Kuskokwim Mountains and 132C–Tanana–Kuskokwim Lowlands. The number of fire occurrences was relatively small in M121A–Brooks Range of the far north and M241D–Alexander Archipelago of the panhandle, but these areas still had much higher fire occurrence density than expected because they are areas that have very few fire occurrences on average.

For Hawaii, an ecological region on the eastern side of Hawai'i Island (Lowland Wet-Hilo-Puna (LWh-hp)) exhibited both the highest annual fire occurrence density mean (fig. 3.8A) and variability (fig. 3.8B) from 2001 through 2021 (17.8 fire occurrences/100 km² of tree canopy cover, standard deviation 40.2). This area encompasses recently active portions of the lower east rift zone of Kilauea volcano, where lava flows from intermittent eruptions have incinerated some forested areas (Andrews 2018). With the exception of the Mesic region on Hawai'i Island

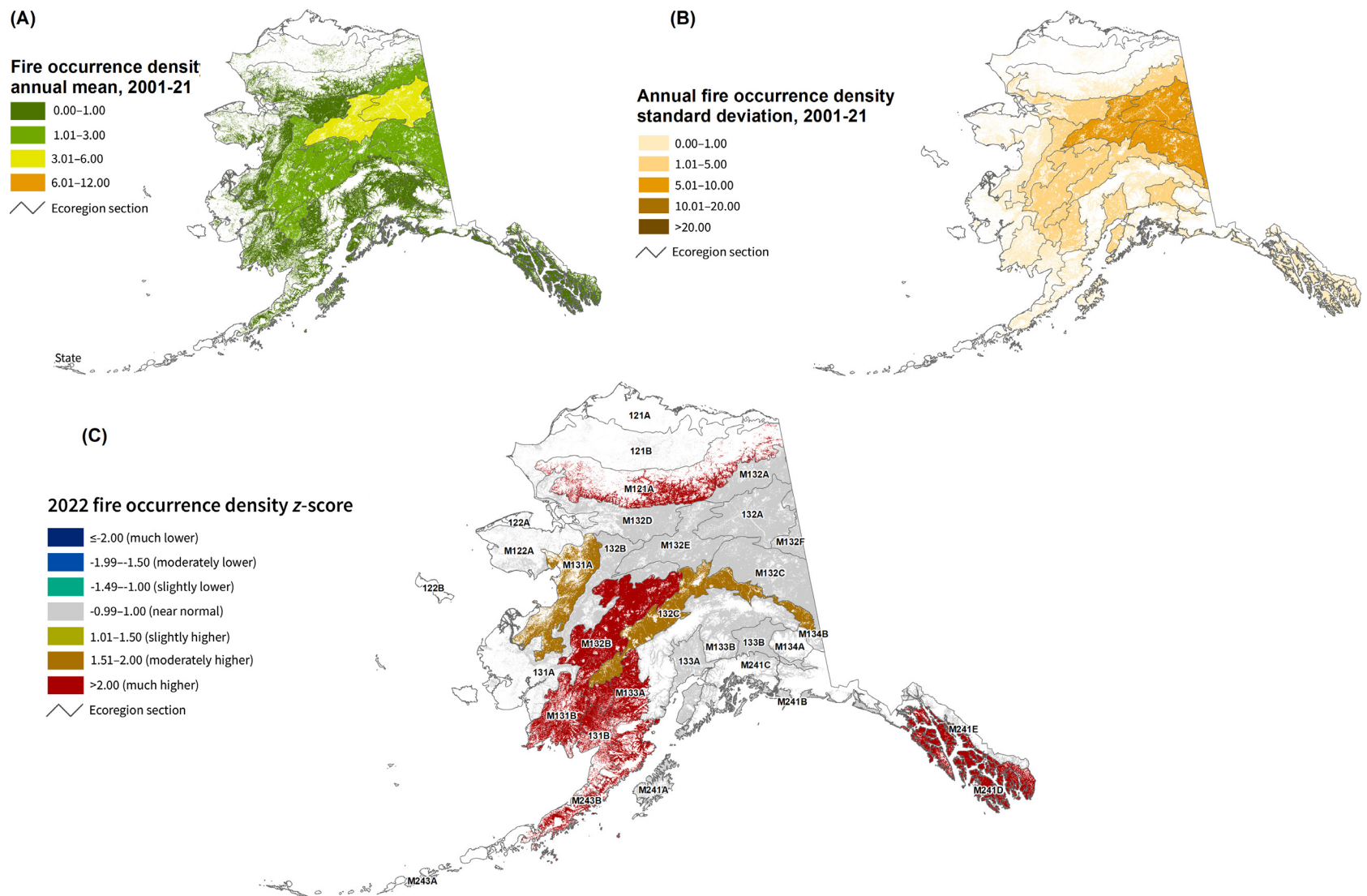


Figure 3.7—(A) Mean number and (B) standard deviation of forest fire occurrences per 100 km² (10 000 ha) of forest and shrub cover from 2001 through 2021, by ecoregion section in Alaska. (C) Degree of 2022 fire occurrence density excess or deficiency, by ecoregion section relative to 2001–2021 and accounting for variation over that period. The gray lines delineate ecoregion sections (Spencer and others 2002). Forest and shrub cover are derived from the 2011 National Land Cover Database. (Source of fire data: U.S. Department of Agriculture, Forest Service, Geospatial Technology and Applications Center, in conjunction with the NASA Moderate Resolution Imaging Spectroradiometer Rapid Response group)

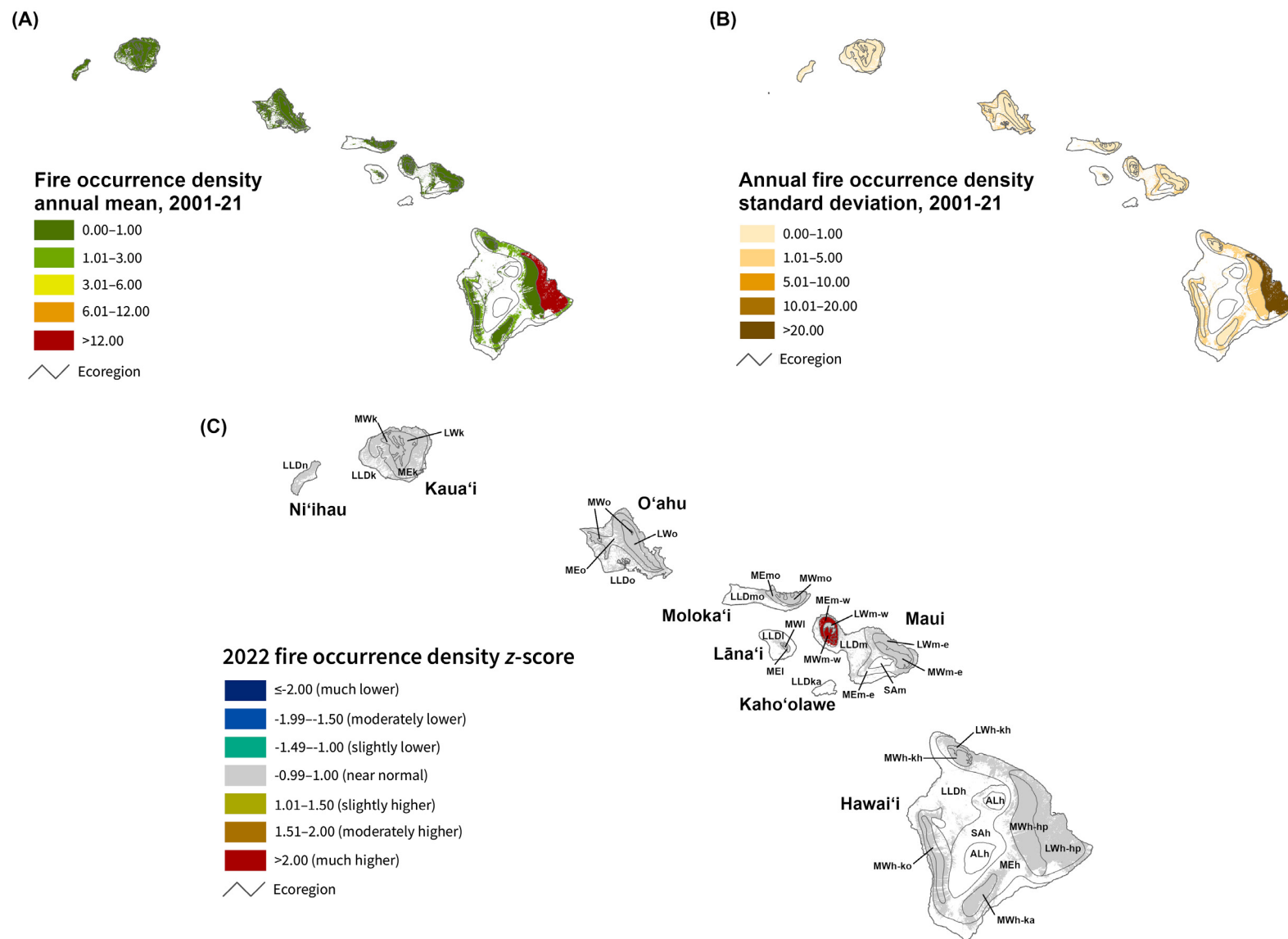


Figure 3.8—(A) Mean number and (B) standard deviation of forest fire occurrences per 100 km² (10 000 ha) of tree canopy coverage area from 2001 through 2021, by island/ecoregion combination in Hawaii. (C) Degree of 2022 fire occurrence density excess or deficiency, by island/ecoregion combination relative to 2001–2021 and accounting for variation over that period. Tree canopy cover is based on data from a cooperative project between the Multi-Resolution Land Characteristics Consortium (Coulston and others 2012) and the Forest Service Geospatial Technology and Applications Center (GTAC) using the 2011 National Land Cover Database. (Source of fire data: U.S. Department of Agriculture, Forest Service, GTAC, in conjunction with the NASA Moderate Resolution Imaging Spectroradiometer Rapid Response group)

(MEh) where it was 2.2, all other ecological regions in the State had an annual mean fire occurrence density of ≤ 1 fire occurrence/100 km² of tree cover. In 2022, two ecological regions on Maui (Montane Wet-Maui-West (MWm-w) and Mesic-Maui-West (MEm-w)) had higher-than-expected fire occurrence densities (z -score > 1), controlling for variability over the previous 21 years (fig. 3.8C).

All the islands encompassed by Puerto Rico and the U.S. Virgin Islands had fire occurrence means and standard deviations ≤ 1 for 2001–2021 (figs. 3.9A and 3.9B). Only one island, tiny Great Hans Lollok Island north of Saint Thomas in the U.S. Virgin Islands, had a higher-than-expected fire occurrence density in 2022 (z -score > 1) (fig. 3.9C).

Geographic Hotspots of Fire Occurrence Density

Most of the previous results report on fire occurrence density status and trends at the ecoregion scale. Geographic hotspot analyses using units smaller than ecoregions, meanwhile, can offer additional insights into where fire occurrences are more concentrated than expected by chance during a given year. This approach specifically identifies areas across the CONUS with higher-than-expected fire occurrence densities compared to the entire study region. Unlike the previous 2 years (Potter 2022, 2023), this SASH method did not detect any geographic hotspots of extremely high fire occurrence density ($G_i^* > 24$) in 2022. The West, however, had a

handful of hotspots of very high fire occurrence density ($G_i^* > 12$ and ≤ 24) (fig. 3.10).

One such hotspot was centered on M331F–Southern Parks and Rocky Mountain Range in north-central New Mexico, the region of the human-caused Hermits Peak Fire, the largest wildfire in the State’s history (Pietsch and Samenow 2022). It burned 138 295 ha between April and October and cost \$330 million to contain (National Interagency Coordination Center 2023). Also within the hotspot area were the Cook Fire (24 022 ha, \$13 million) and the Cerro Pelado Fire (18 456 ha, \$47 million). Another hotspot of very high fire occurrence density was detected in southwestern New Mexico in M313A–White Mountains–San Francisco Peaks–Mogollon Rim. This is the location of the human-caused Black Fire, the second largest fire in New Mexico history (Javaheri and Chinchar 2022), which scorched 131 578 ha between its May 13 ignition and its November 10 containment and cost \$60 million to control (National Interagency Coordination Center 2023).

A hotspot of very high fire occurrence density was located in M332A–Idaho Batholith of central Idaho, where the 52 692-ha Moose Fire cost \$98 million to contain between its July 17 human-caused ignition and its November 10 containment (National Interagency Coordination Center 2023). A hotspot of high fire occurrence density ($G_i^* > 6$ and ≤ 12) was detected immediately to the west in northeastern Oregon (M332G–Blue Mountains), where the lightning-caused Double Creek Fire burned 69 417 ha from August through October, with a containment cost of

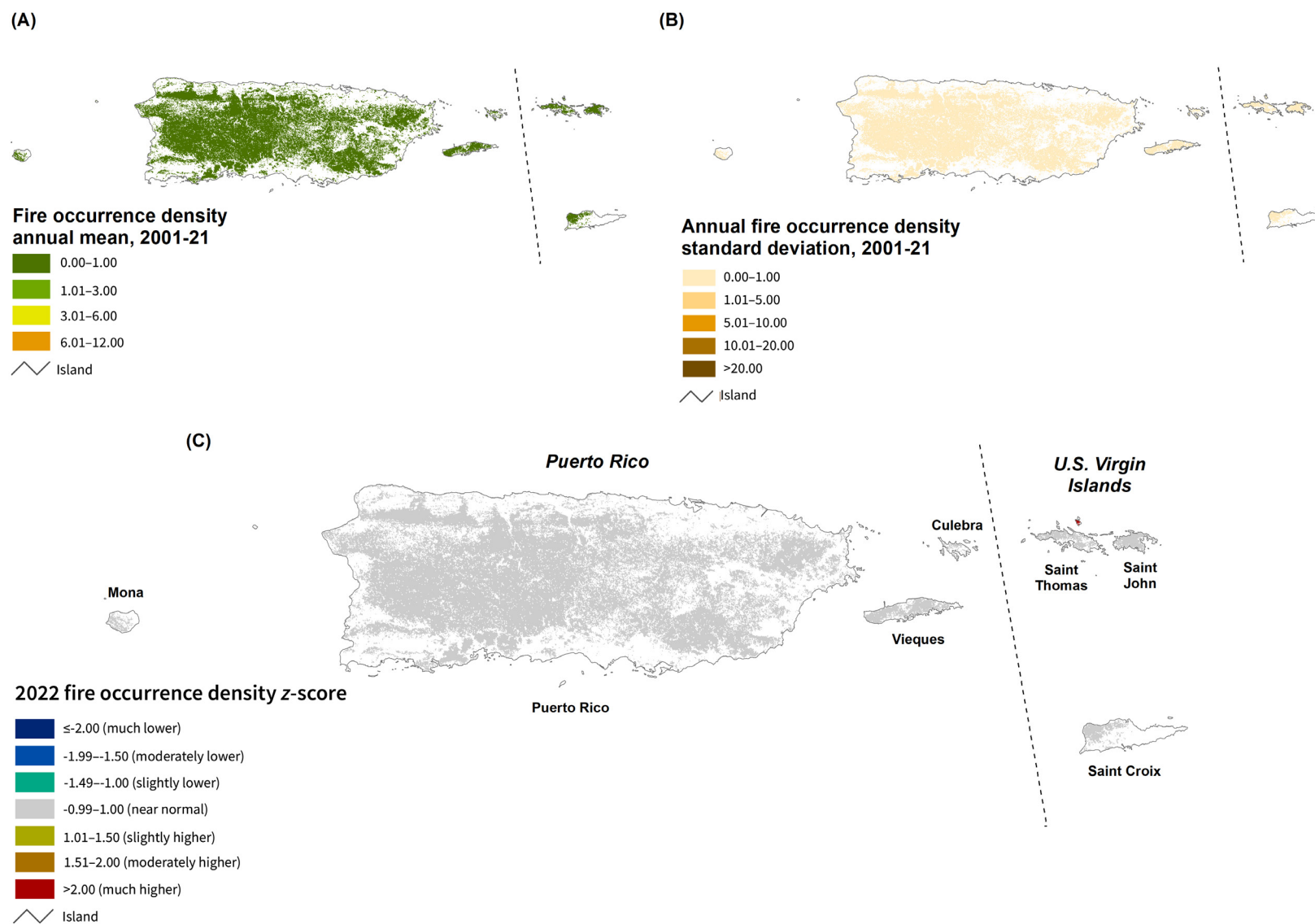


Figure 3.9—(A) Mean number and (B) standard deviation of forest fire occurrences per 100 km² (10 000 ha) of forested area from 2001 through 2021, by island in Puerto Rico and the U.S. Virgin Islands. (C) Degree of 2022 fire occurrence density excess or deficiency, by island relative to 2001–2021 and accounting for variation over that period. Tree canopy cover is based on data from a cooperative project between the Multi-Resolution Land Characteristics Consortium (Coulston and others 2012) and the U.S. Department of Agriculture, Forest Service, Geospatial Technology and Applications Center using the 2011 National Land Cover Database.

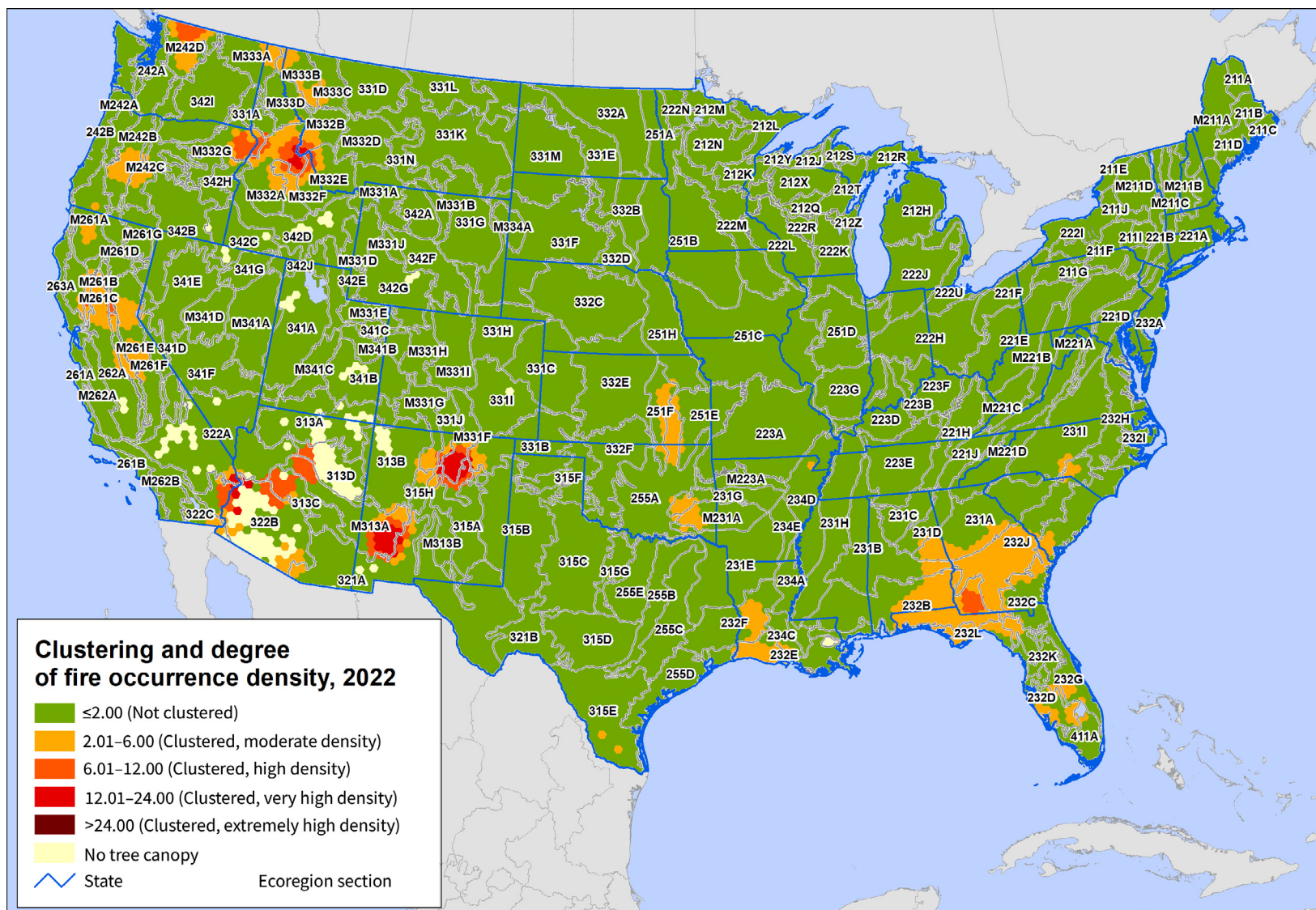


Figure 3.10—Hotspots of fire occurrence, by ecoregion section within the conterminous United States, for 2022. Values are Getis-Ord G_i^* scores, with values >2 representing significant clustering of high fire occurrence densities. (No areas of significant clustering of lower fire occurrence densities, <-2 , were detected.) The gray lines delineate ecoregion sections (Cleland and others 2007).

\$40 million (National Interagency Coordination Center 2023).

Other western hotspots in 2022 included (fig. 3.10):

- Very high occurrence density in an area of sparse forest canopy in southwestern Arizona and southeastern California (322B–Sonoran Desert)
- High occurrence density in central Arizona (313C–Tonto Transition and M313A–White Mountains–San Francisco Peaks–Mogollon Rim)
- High occurrence density in north-central Washington (M242D–Northern Cascades)
- High occurrence density in north-central California (M261E–Sierra Nevada, M261F–Sierra Nevada Foothills, 262A–Great Valley, M261C–Northern California Interior Coast Ranges), location of the \$181 million, 31 075-ha Mosquito fire
- Moderate density ($G_i^* > 2$ and ≤ 6) in west-central Oregon (M242B–Western Cascades and M242B–Western Cascades), site of the \$134 million, 51 521-ha Cedar Creek fire

Meanwhile, the SASH analysis detected one high-density and several moderate-density hotspots in the East. The single high-density hotspot was centered on 232B–Gulf Coastal Plains and Flatwoods in southwestern Georgia and extended into neighboring areas as a moderate-density hotspot.

CONCLUSIONS

In 2022, the number of MODIS satellite-detected forest fire occurrences in the CONUS decreased 44 percent from the preceding year, which was the fourth highest in 22 full years of data collection. The 2022 number was also about 17 percent below the annual mean. Despite being a relatively quiet fire year in the CONUS, New Mexico experienced the two largest forest fires in its history and a handful of ecoregions in the Southwest had very high fire occurrence densities (fire occurrences/100 km² of tree canopy cover area). Additionally, a handful of ecoregions of the Pacific Northwest and the Southeast experienced high fire occurrence densities. The fire activity in these areas resulted in geographic hotspots of very high or high fire occurrence density. Ecoregions in the Southwest, Northeast, Midwest, and Mid-Atlantic regions experienced fire occurrence densities that were higher than normal in 2022 compared to the previous 21-year mean and accounting for variability over that period. At the same time, a few ecoregion sections in the Southwest and Midwest had significantly lower fire occurrence densities than normal.

Meanwhile, Alaska experienced a 1,000-percent jump in fire occurrences from 2021 to 2022, with the latter year tallying about 140 percent of the mean annual number of fire occurrences across the previous 21 years. This was the result of well-above-normal temperatures through the early summer coupled with lightning-intense storms that sparked a rapid increase in fire activity in June. Ecoregion sections in the central

and southwestern part of the State had high fire occurrence densities for 2022, while those ecoregions and others across Alaska—including in the panhandle and far north—had higher-than-expected fire occurrence densities.

Hawaiian forests in 2022 had fire occurrence densities that were low and within expectations, with the exception of two ecological regions on the western part of Maui Island. In the Caribbean, only the tiny island of Great Hans Lollik Island near Saint Thomas in the U.S. Virgin Islands had a higher-than-expected fire occurrence density in 2022.

Rather than quantifying the severity of a given fire season, the results of these geographic analyses offer insights into where fire occurrences were concentrated spatially during a given year and compared to previous years. These products may include commission errors and may underrepresent the number of fire occurrences in some ecosystems where small and low-intensity fires are common in addition to where high cloud frequency can interfere with fire detection. At the same time, these high-temporal-fidelity products currently offer the best means for daily monitoring of forest fire occurrences.

Ecological and forest health impacts relating to fire and other abiotic disturbances are scale-dependent properties, which in turn are affected by management objectives (Lundquist and others 2011). Information about the concentration of fire occurrences may pinpoint areas of concern for aiding management activities and for investigations into the ecological and socioeconomic impacts of forest fire potentially outside the range of historic frequency. Quantifying the location and frequency of forest fire occurrences across the United States also can help to better understand emerging spatiotemporal patterns of fire occurrence in light of climate change and shifting fire regimes.

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INTRODUCTION

Tree mortality is a natural process in all forest ecosystems. High mortality can be an indicator of forest health problems. On a regional scale, high mortality levels may indicate widespread impacts of one or more factors, including insects, disease, fire, drought, or major storms. Regionally high mortality may also occur if a large proportion of the forest in a particular region is made up of older, senescent stands. The approach presented here seeks to detect mortality patterns that might reflect changes to ecosystem processes at large scales that could affect long-term forest sustainability. In many cases, the proximate cause of mortality may be discernable. Understanding proximate causes of mortality may provide insight into whether the mortality is within the range of natural variation or reflects more fundamental changes to ecological processes.

DATA

Forest Inventory and Analysis (FIA) Phase 2 (P2) data were the basis of the mortality analysis. FIA P2 data are collected across forested land throughout the United States, with approximately one plot per 6,000 acres of forest, using a rotating panel sample design (Bechtold and Patterson 2005). Field plots are divided into spatially balanced panels, with one panel being measured each year. A single cycle of measurements consists of measuring all panels. This “annualized” method of inventory was adopted, State by State, beginning in 1999. The cycle length (i.e., number of years required to measure all plot panels) ranges from 5 to 10 years.

An analysis of mortality requires data collected at a minimum of two points in time. Therefore, mortality analysis was possible for areas where data from repeated plot measurements using consistent sampling protocols were available (i.e., where one cycle of measurements had been completed and at least one panel of the next cycle had been measured, and where there had been no changes to the protocols affecting measurements of trees or saplings). The most recent cycle of remeasurements for each State was used in this analysis. Ecoregion sections were omitted from this analysis if the dataset did not have at least 50 remeasured plots.

CHAPTER 4

Tree Mortality

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Due to the COVID-19 (coronavirus) pandemic, FIA data collection slowed during 2020 and 2021. Therefore, although mortality analyses were possible for all of the conterminous United States, no new data were available from any Western States (i.e., the available datasets are the same as those used for the 2021 Forest Health Monitoring (FHM) report (Potter and Conkling 2022)). Similarly, no new data were available from most of the Great Plains States, (i.e., the available datasets are the same as those used for the 2022 FHM report). Therefore, for this report, the analysis is limited to States in the Eastern and Central United States shown in figure 4.1. That figure also shows the forested area in those States,^{1,2} which can be important for interpreting the extent of the observed mortality.

METHODS

FIA calculates the growth, mortality, and removal volume on each plot over the interval between repeated measurements. These values are stored in the FIA Database (version 9.0.1) (Burrill and others 2021). FIA's EVALIDator (ver. 2.0.6) is an online tool for querying the FIA Database and generating area-based reports on forest characteristics (USDA Forest Service, FIA Program 2023). EVALIDator was used to obtain net growth rates and mortality rates over the most recent measurement cycle for each of 96 ecoregion sections (Cleland and others 2007, McNab and others 2007) covering the Eastern and Central United States. For most States, the most recent cycle of available data ran through 2021³ (e.g., each plot was most recently measured between 2015 and 2021), and growth and mortality were calculated from the previous measurement of each plot, usually 5, 7, or 10 years prior to the most recent plot measurement.

To compare mortality across forest types and climate zones, the ratio of annual mortality to gross growth (MRATIO) was used as a standardized mortality indicator (Coulston and others 2005). The MRATIO has proven to be a useful indicator of forest health, but it can be a problematic indicator, especially when growth rates are very low. The MRATIO can also be difficult to interpret with high uncertainty to growth estimates.

¹ For the latest analysis of mortality that includes Western States, see Ambrose and others (2022).

² For the latest analysis of mortality that includes the Plains States, see Ambrose (2023).

³ Overall, the most recent data available for any State ranged from 2018 to 2022.

To identify causal agents for the observed mortality, EVALIDator was also used to summarize by the reported “cause of death” associated with the observed mortality. Causes of death are reported as general categories (e.g., insects, fire, weather). For each ecoregion with a high MRATIO, EVALIDator was used to generate a table of annual mortality volume by FIA species group (Burrill and others 2018) and cause of death. From these tables, one can make reasonable assumptions about the particular insects or diseases that may be affecting particular tree species in particular regions. Care must be used in interpreting these causes because tree mortality may actually be caused by a combination of factors such as drought and insects. Further information about the causes of mortality is provided by aerial and ground surveys of insects and disease (see ch. 2 in this report). Directly matching survey data to mortality observed on FIA plots is challenging due to both the difference in timing when mortality is recorded and difficulty matching plot locations with aerial survey mortality polygons. However, insect and disease survey information has been incorporated into the discussion by referencing State “Forest Health Highlights,” which reflect in large part the results of aerial and ground surveys of insects and diseases.

RESULTS AND DISCUSSION

The MRATIO values are shown in figure 4.2. The MRATIO can be large if an old forest is senescing and losing a cohort of older trees. If forests are not naturally senescing, a high MRATIO (>0.6) may indicate high mortality due to some acute cause (insects or pathogens) or due to generally deteriorating forest health conditions. The ecoregion sections with the highest MRATIOS are labeled on the map. In the discussion that follows, the focus is placed on the ecoregions having MRATIOS >0.6 .

Ecoregion section 321B—Stockton Plateau in western Texas (fig. 4.2), which had the highest MRATIO in the region covered in this analysis (MRATIO = 0.89), is a region of extremely low forest cover (fig. 4.1). There, about 67 percent of mortality was related to adverse weather and another 32 percent was due to fire (table 4.1). About 92 percent of mortality occurred in the western woodland softwoods species group, i.e., pinyon pines (*Pinus* spp.) and junipers (*Juniperus* spp.). About 68 percent of western woodland softwoods mortality was due to weather and 31 percent was due to fire. Most of this mortality was probably related to a record-setting drought that affected Texas and Oklahoma beginning in 2011. Note that western Texas is on a 10-year FIA remeasurement cycle, so data used in this analysis extend back up to 20 years.

Also in Texas, ecoregion section 255C—Oak Woods and Prairies had relatively high mortality (MRATIO = 0.64). About 45 percent of the mortality occurred in the red and white oak species groups, and another 11 percent occurred in the

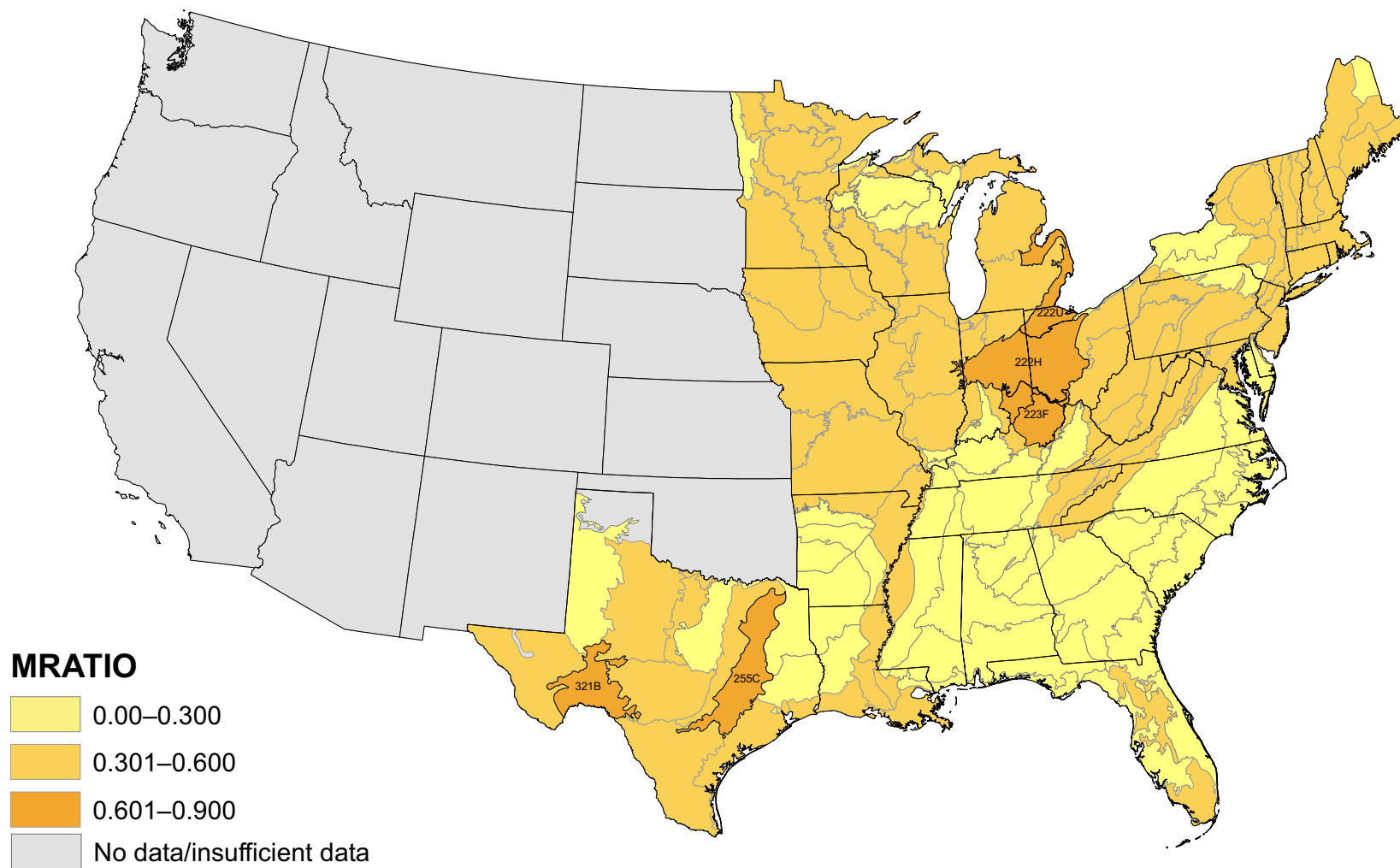


Figure 4.2—Tree mortality expressed as the ratio of annual mortality volume to gross annual growth volume (MRATIO), by ecoregion section (Cleland and others 2007). (Data source: U.S. Department of Agriculture, Forest Service Forest Inventory and Analysis program)

loblolly and shortleaf pine species group. The majority (61 percent) of mortality in this ecoregion section was identified as weather-related (table 4.1). Weather was responsible for 55 percent of mortality in the oaks and 30 percent of the loblolly and shortleaf pine species group mortality. In addition to the record-setting drought in 2011, other droughty periods occurred in following years (Oklahoma Forestry Services 2014, 2015, 2016, 2020). Drought was reported as weakening both pines and hardwoods in Texas, making them susceptible to a variety of pests and pathogens (Smith 2013, 2014). Disease was the reported cause of another 28 percent of mortality (table 4.1), responsible for 43 percent of oak mortality. Fire was responsible for 52 percent of pine mortality. Oak wilt, caused by the fungus *Bretziella fagacearum*, has been a major problem in oak (*Quercus* spp.) woodlands in central Texas (Smith 2014; Texas A & M Forest Service 2015, 2016, 2019) and probably contributed to mortality in the red and white oak species groups. Pine engraver beetle (*Ips* spp.) has been a problem in Texas' pine forests and may have contributed to mortality in the loblolly and shortleaf pine species group (Smith 2014; Texas A & M Forest Service 2015, 2016, 2017).

A cluster of ecoregions with high mortality relative to growth occurred in eastern Michigan, central Indiana, western Ohio, and northern Kentucky. Of these, mortality relative to growth was highest (MRATIO = 0.67) in ecoregion section 222U–Lake Whittlesey Glaciolacustrine Plain. There, the majority of the mortality (60

percent) was in the ash species group. About 61 percent of mortality in that ecoregion was caused by insects (table 4.1), and insects were responsible for 98 percent of ash mortality. Most of this mortality was due to emerald ash borer (*Agrilus planipennis*), which has produced extremely high ash mortality throughout Ohio and Michigan (Michigan Department of Natural Resources 2014, 2015, 2016, 2017; Ohio Department of Natural Resources, Division of Forestry 2014, 2015, 2020). Indeed, emerald ash borer has been “the most devastating forest pest in Ohio in recent years” (Ohio Department of Natural Resources, Division of Forestry 2020) and has caused the death of the “vast majority” of native ash (*Fraxinus* spp.) in northwestern Ohio (Ohio Department of Natural Resources, Division of Forestry 2016, 2017).

Similarly, in the adjacent ecoregion section 222H–Central Till Plains-Beech-Maple (MRATIO = 0.65) in Ohio and Indiana, much of the mortality (58 percent) was in the ash species group (table 4.1), and 97 percent of ash mortality was due to insects, i.e., emerald ash borer.⁴ Indeed, emerald ash borer has been confirmed throughout the ecoregion as well as throughout Indiana (Marshall 2017, 2018, 2020; Ohio Department of Natural Resources, Division of Forestry 2016, 2017).

The situation is similar in ecoregion section 223F–Interior Low Plateau-Bluegrass (MRATIO = 0.67) in southern Indiana and Ohio and north-central Kentucky. There, about 59 percent of mortality was in the ash species group. Fifty-six

⁴ Personal communication. 2022. Philip T. Marshall, Forest Health Specialist, Indiana Department of Natural Resources, Division of Forestry, 2782 W. Co. Rd. 540 S., Vallonia IN 47281.

Table 4.1—Ecoregion sections in the Eastern and Central United States having the highest mortality relative to growth (MRATIO), annual growth and mortality rates, species groups having the greatest mortality relative to growth, and associated causes of mortality

Ecoregion section	Average annual mortality	Average annual gross growth	MRATIO	Species groups ^a having the highest mortality ^b	Major causes of mortality ^c
	--- cubic feet per year ---				
321B–Stockton Plateau	7,918,664	8,929,419	0.89	Western woodland softwoods (92%)	Weather-related (67%), fire (32%)
222U–Lake Whittlesey Glaciolacustrine Plain	45,579,144	67,711,765	0.67	Ash (60%), other eastern soft hardwoods (13%)	Insects (61%), disease (10%)
223F–Interior Low Plateau-Bluegrass	105,866,216	158,460,432	0.67	Ash (59%), other eastern soft hardwoods (15%)	Insects (56%), vegetation (13%)
222H–Central Till Plains- Beech-Maple	114,530,445	175,830,480	0.65	Ash (58%), other eastern soft hardwoods (16%)	Insects (57%)
255C–Oak Woods and Prairies	103,150,455	161,311,759	0.64	Oaks ^d (45%), loblolly and shortleaf pine (11%)	Weather-related (61%), disease (28%)

^aFor the species included in each species group, see Burrill and others 2018, Appendices E and F.

^bThe value in parentheses is the proportion of average annual mortality volume in the ecoregion section occurring in the species group.

^cThe value in parentheses is the proportion of average annual mortality volume in the ecoregion section attributed to the causal agent.

^dOverall mortality of the Forest Inventory and Analysis select red oaks, select white oaks, other red oaks, and other white oaks species groups have been combined.

percent of overall mortality in the ecoregion was attributed to insects, but almost all (94 percent) ash mortality was due to insects, i.e., emerald ash borer.⁵ Emerald ash borer has been confirmed throughout the portion of the ecoregion section that is in Kentucky since at least 2016 (Kentucky Division of Forestry 2016).

The overall spatial pattern (fig. 4.2) is that MRATIOS are lowest in the Southeast and higher to the north and west. Aside from specific forest health concerns, such as those discussed above, this pattern may be due to forest management practices as well as climate patterns across the Eastern United States. In general, forests in the Southeast are more highly managed than those farther north and west. Forest management may be directly reducing the impacts of certain stressors, such as reducing the likelihood of insect outbreaks. Also, forest management means that forests in the Southeast generally tend to be younger, and younger trees tend to be more resistant to many mortality-causing agents. Finally, because these forests are younger and located in areas with longer growing seasons, they have higher growth rates. Thus, MRATIOS, being the ratios of mortality to growth, will be lower simply due to higher productivity.

CONCLUSIONS

This analysis shows that in most of the Eastern and Central United States, mortality is low relative to tree growth. No ecoregion sections fall into the highest MRATIO class (>0.9). The

areas of highest mortality relative to growth occur in Texas, where the impacts of a record-setting drought are still apparent. Drought, combined with a variety of other biotic and/or abiotic stressors, is responsible for much of the mortality observed there.

One insect pest issue does stand out in the East. In ecoregion sections 222H–Central Till Plains–Beech–Maple, 222U–Lake Whittlesey Glaciolacustrine Plain, and 223F–Interior Low Plateau–Bluegrass, ash mortality due to emerald ash borer is extremely high.

Note that the analyses presented in this chapter alone cannot tell the complete story regarding tree mortality. Mortality concentrated in highly fragmented forest or nonforest areas adjacent to human development may not be detected because the available FIA data do not cover most urban areas or other places not defined as forest by FIA. Also, these analyses are unlikely to detect a pest or pathogen attacking a particular tree species in a mixed-species forest where other species are growing vigorously. This is especially true of species (e.g., ash) that make up a relatively small proportion of many eastern forests. For example, emerald ash borer is known to have caused very high ash mortality in many Eastern and Central States in recent years (USDA APHIS 2018; Ohio Department of Natural Resources, Division of Forestry 2016). Yet, this mortality stands out only in ecoregion sections 222H–Central Till Plains–Beech–Maple, 222U–Lake Whittlesey Glaciolacustrine Plain, and 223F–Interior Low

⁵ Personal communication. 2022. Philip T. Marshall, Forest Health Specialist, Indiana Department of Natural Resources, Division of Forestry, 2782 W. Co. Rd. 540 S., Vallonia IN 47281.

Plateau-Bluegrass. Elsewhere in the East, though ash mortality is known to be extremely high, the mortality currently is masked because ash is a relatively minor component of the forest.

To gain a more complete understanding of mortality, the results of this analysis can be considered along with other indicators of forest health. FIA tree damage data (Burrill and others 2021), as well as FHM Evaluation Monitoring projects that focus on particular mortality-causing agents, can provide insight into smaller scale or species-specific mortality issues. Large-scale analyses of forest-damaging events, including insect and disease activity (ch. 2) and fire (ch. 3) are also important for understanding mortality patterns. This can be especially important in the West, where mortality data are limited.

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SECTION 2

Analyses of Long-Term
Forest Health Trends and
Presentations of New
Techniques

INTRODUCTION

International forest sustainability reporting by the U.S. Department of Agriculture, Forest Service is pursuant to the Montréal Process Criteria and Indicators (C&I; Montréal Process Liaison Office 2015). That framework includes measures of forest fragmentation that have evolved substantially over three decades of reporting (Riitters and Robertson 2021). The most recent report, for the years 2001 to 2016, indicated that fragmentation continued to increase but at a decreasing rate over that time interval (Riitters and Robertson 2021). The objective of this chapter is to update the fragmentation information by incorporating new land cover data for the year 2019 and the accompanying revisions to the earlier land cover data. Unlike the 5-year reporting of conterminous United States (CONUS) conditions in the most recent report, this chapter evaluates changes over 2- and 3-year time intervals and evaluates conditions within eight regions (fig. 5.1) and by county.

Relatively fine-scale, wall-to-wall forest maps are ideal for measuring and mapping forest fragmentation. As in earlier reports, forest is defined here by national land cover maps (see below). This definition, which is based on land cover, should be distinguished from other forest definitions that are based on land use (Nelson and others 2020). Forest land cover is more dynamic than forest land use because temporary losses of forest cover do not change the underlying forest land use. Thus, land cover data provide a more sensitive measure of fragmentation, and

fragmentation can increase or decrease with the loss or gain of forest cover over time.

The reporting is based on a metric called “forest area density” (FAD)—roughly, how much forest is surrounded by how much other forest—which is measured and mapped at multiple measurement scales. Specifically, the percentage of forest within a fixed-area neighborhood of each forest pixel is compared to minimum threshold values of 60, 90, and 100 percent to identify the forest pixels that are “dominant,” “interior,” or “core,” respectively. Measurement scales are varied by using several neighborhood sizes such that a given forest pixel could be, for example, “core” at a small scale and “dominant” at a larger scale. The reporting format thus accounts for the well-known dependence of fragmentation on scale and observer.

The FAD metric provides a transparent and sensitive indicator of the location, scale, and degree of fragmentation at a given time (Riitters 2019). If no fragmentation, then all forest pixels would meet all FAD thresholds for all neighborhood sizes. Fragmentation is therefore relative to a baseline corresponding to a completely forested condition. Scale-dependent deviations from the 100-percent-forested baseline arise from natural (and endemic) fragmentation as well as anthropogenic fragmentation, which different observers can interpret for their chosen threshold. Absent meaningful baselines describing natural (or endemic) fragmentation, the spatial and temporal changes in FAD are meaningful indicators of landscape changes. Furthermore, the same results can be interpreted in different policy contexts (e.g., forest conservation, forest biodiversity, urban sprawl) simply because wall-

CHAPTER 5

Updating the Sustainability Indicators of Forest Cover Fragmentation for the United States From 2001 to 2019

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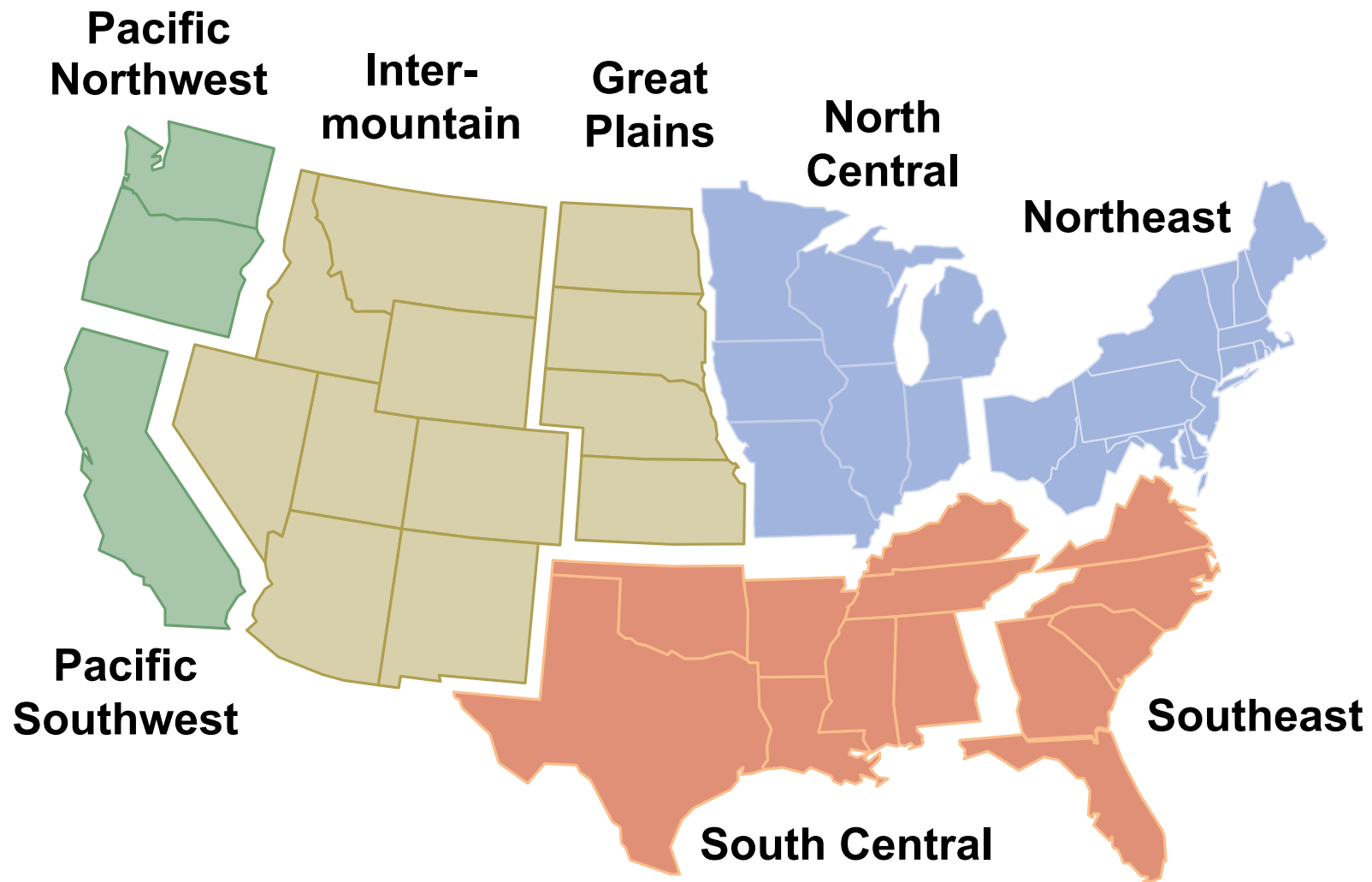


Figure 5.1—The eight geographic regions for which results are reported in this chapter. For literature comparisons, the colors indicate a set of four larger regions used in other Forest Service assessment reports. (Source: adapted from fig. 2-1 in USDA Forest Service (2023))

to-wall mapping of FAD with multiple thresholds and neighborhood sizes provides flexibility for and thus consistency among different applications. While the tension between the parsimony sought by the Montréal Process C&I approach, which comprises just one metric per indicator, and the amount of information needed to evaluate complex phenomena may never be resolved, starting with nationally consistent metrics that can be unambiguously interpreted with respect to fragmentation is essential. Subsequent interpretations can address the causes or consequences of changing fragmentation in specific circumstances.

METHODS

CONUS forest maps were derived from the National Land Cover Database (NLCD) for the nominal years 2001, 2004, 2006, 2008, 2011, 2013, 2016, and 2019 (Dewitz and USGS 2021). The NLCD land cover maps identify 16 land cover classes at a spatial resolution of 0.09 ha/pixel (30 x 30 m). For this analysis, the 16 NLCD land cover classes were combined into two generalized classes called forest (the NLCD deciduous, evergreen, mixed forest, and woody wetlands classes) and nonforest (all other NLCD classes). The combined forest classification accuracy has not been formally evaluated for this NLCD dataset but is expected to approximate previous estimates (Nelson and others 2020) of 84 percent (producer's accuracy) and 88 percent (user's accuracy). This analysis did not address measurement errors.

FAD is defined as the percentage of forest pixels within a fixed-area neighborhood. This analysis

used five neighborhood sizes of approximately 4.41 ha (7 x 7 pixels), 15.2 ha (13 x 13), 65.6 ha (27 x 27), 590 ha (81 x 81), and 5310 ha (243 x 243). In each year, five FAD values were associated with each forest pixel by centering the five neighborhoods on their locations. For each neighborhood size, a forest pixel was labeled as “core forest” if the associated FAD equaled 100 percent, as “interior forest” if FAD was at least 90 percent, and as “dominant forest” if FAD was at least 60 percent. Note that a forest pixel that meets the “core” criterion also qualifies as “interior” and “dominant,” and one that meets the “interior” criterion also qualifies as “dominant.” Data summaries were prepared for each year by calculating the area and proportion of forest pixels that met each of the three FAD criteria, for each neighborhood size.

Temporal changes were generally calculated as net area change. Percent changes were expressed either as the net percent change over a specific time interval, or as the annual percent rate of change over N years ($N = 2, 3$, or 18) in a time interval.

$$\text{net percent change} = 100 * \frac{\text{Final area} - \text{Initial area}}{\text{Initial area}}$$

$$\text{annual percent rate of change} = 100 * \left[\left(\frac{\text{Final area}}{\text{Initial area}} \right)^{\frac{1}{N}} - 1 \right]$$

The annual percent rate of change is not available for the year 2001 because the initial area before 2001 is unknown. The two equations calculated percent changes for interior forest, and for all forest as a basis for comparison with the interior forest results.

This study also examined how the proportion of all forest that was labeled as core, interior, and dominant forest changed depending on neighborhood size for three of the NLCD map years, 2001, 2011, and 2019.

RESULTS

Because forested places tend to be clustered in proximity to one another, forest is usually the dominant land cover in these areas. Thus, for landscapes up to 5310 ha in size, >60 percent of all forest area is in forest-dominated landscapes (fig. 5.2). However, because larger blocks of forest land are increasingly subject to inclusion of at least some nonforest land (natural or anthropogenic), the percentage of forest land that is relatively unfragmented (i.e., interior) decreases rapidly as neighborhood size increases from 4.41 ha to 5310 ha (fig. 5.2). Fragmentation is so common that almost no forest qualifies as core for the two largest neighborhood sizes in all regions (fig. 5.3).

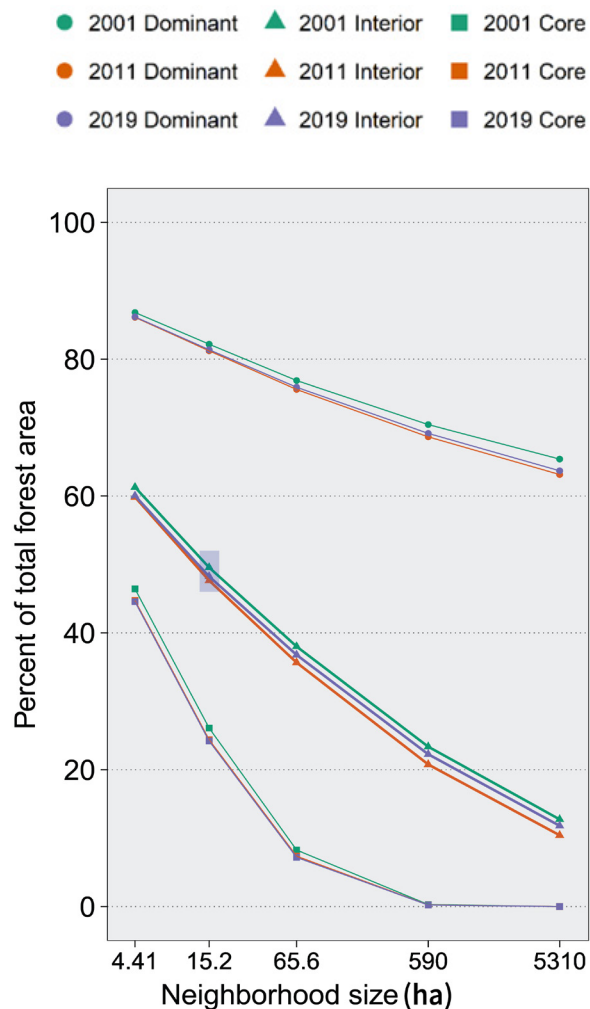


Figure 5.2—Forest fragmentation in the conterminous United States (circa 2001, 2011, and 2019) derived from measurements of forest area density. The shaded blue rectangle identifies the conditions mapped at the county level in figure 5.4. Note the logarithmic scale for neighborhood size.

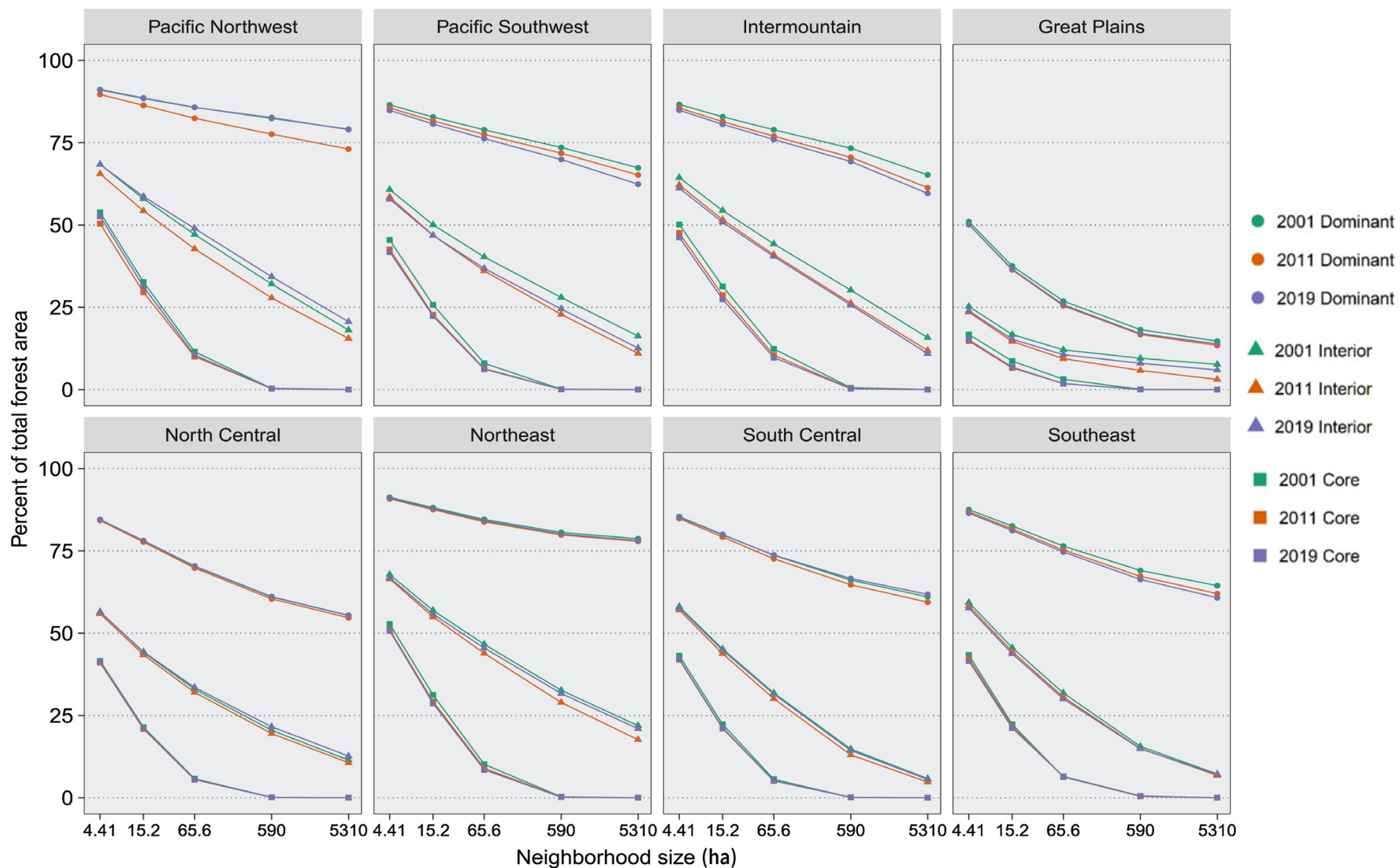


Figure 5.3—Forest fragmentation (circa 2001, 2011, and 2019) derived from measurements of forest area density, by region. Note the logarithmic scale for neighborhood size.

Between 2001 and 2019, the CONUS experienced a 2.3-percent net loss of total forest land cover area (table 5.1). In comparison, the net loss of interior forest was between 4.3 and 9.5 percent depending on neighborhood size. The net area loss of interior forest decreased with neighborhood size, consistent with the patterns of relatively local forest loss in heavily forested areas and forest gain in less-forested areas (Riitters and Wickham 2012). The percent loss of interior forest increased with neighborhood size largely due to less interior area for larger neighborhood sizes in 2001.

Shifting to a county-level analysis, changes in interior forest area for the 15.2-ha neighborhood size were used to illustrate comparisons with total forest area change. The overall geographic distribution of net percent changes (gains and losses) from 2001 to 2019 was similar for total forest area (fig. 5.4A) and interior forest area (fig. 5.4B). Except for counties within the Great Plains region, the net percent gains and losses of total forest area generally translated to larger net percent changes (gains or losses) of interior

forest area. Notable gains of interior forest area occurred along the Gulf Coast and west of the Cascade Mountains in the Pacific Northwest region. Notable losses occurred throughout most of the rest of the Western States, in the Piedmont and Coastal Plain areas in the Southeast, and elsewhere near major metropolitan areas. CONUS-level summaries are driven mainly by changes in the counties that contain most of the total forest area (fig. 5.4 inset).

The regional differences suggested by the county-level analysis are consistent with the 18-year changes in different regions (table 5.2). The Intermountain region exhibited the largest net area losses of total forest and interior forest, but the Pacific Southwest region exhibited the largest annual percent rates of losses. The North Central region was the only region to exhibit a net gain of interior forest area, while the Pacific Northwest region was the only region where the annual percent rate of interior forest loss was less than the rate of total forest loss. Net losses in terms of both area and rate were large in the Southeast region when compared to other eastern regions.

Table 5.1—Status and trend of interior forest area in the conterminous United States for five neighborhood sizes from 2001 to 2019, with change of total forest area shown for comparison

Neighborhood size (ha)	2001 (million km ²)	2019 (million km ²)	Net area change (thousand km ²)	Net percent change
4.41	1.45	1.39	-63	-4.3
15.2	1.18	1.12	-58	-4.9
65.6	0.90	0.85	-50	-5.5
590	0.55	0.52	-39	-7.0
5310	0.30	0.27	-29	-9.5
Total forest area	2.37	2.32	-55	-2.3

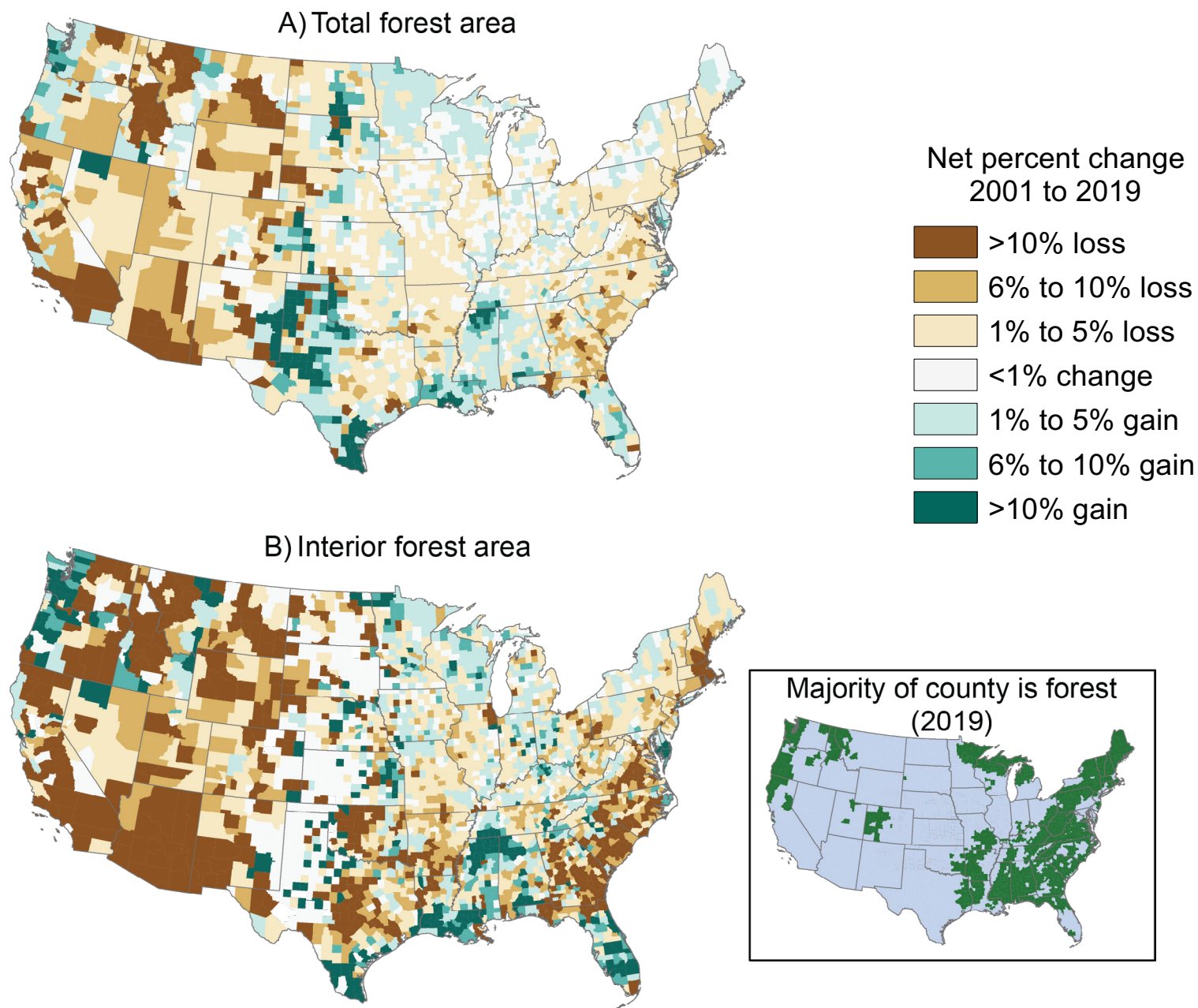


Figure 5.4—The net percent change from 2001 to 2019, by county, in (A) total forest area and (B) interior forest area (15.2-ha neighborhood). The same legend applies to both maps, and the inset map identifies counties with at least 50 percent forest area in 2019.

Table 5.2—Cumulative net changes of forest area and interior forest area (15.2-ha neighborhood) from 2001 to 2019, in the conterminous United States (CONUS) and by region

Region	Net area change (thousand km ²)		Annual percent rate of net change	
	All forest	Interior forest	All forest	Interior forest
CONUS	-55.4	-57.9	-0.13	-0.28
Pacific Northwest	-3.1	-0.6	-0.10	-0.04
Pacific Southwest	-9.2	-7.5	-0.54	-0.91
Intermountain	-30.0	-31.3	-0.38	-0.76
Great Plains	-0.5	-0.5	-0.10	-0.59
North Central	0.2	0.8	0.00	0.03
Northeast	-3.5	-6.4	-0.05	-0.16
South Central	0.1	-1.9	0.00	-0.05
Southeast	-9.5	-10.6	-0.15	-0.38

The annual percent rates of change of total forest and interior forest area between 2001 and 2019 are shown in figure 5.5. Overall, changes at the CONUS scale were generally smaller than changes in some regions. In the Intermountain and Pacific Southwest regions, annual percent rates of change were typically negative for all time periods. The Pacific Northwest region was notable because of the apparent trend of improving conditions (less loss, or more gain) there; the South Central region exhibited a similar but less apparent trend. In the Great Plains region, the relatively large annual percent rates of interior forest area change are probably related to the relatively small interior forest area in that region. Other regions showed no obvious trends, but

the annual percent rates of change in the North Central and Northeast regions appeared to be somewhat less variable over time compared to the South Central and Southeast regions. The changes after 2016 are of particular interest because the objective is to update the fragmentation statistics to incorporate the 2019 land cover data. In that regard, note that six of the eight regions exhibited net gains of total forest area, and six regions also exhibited net gains of interior forest area. The relatively large post-2016 gains in the Pacific Northwest are particularly striking.

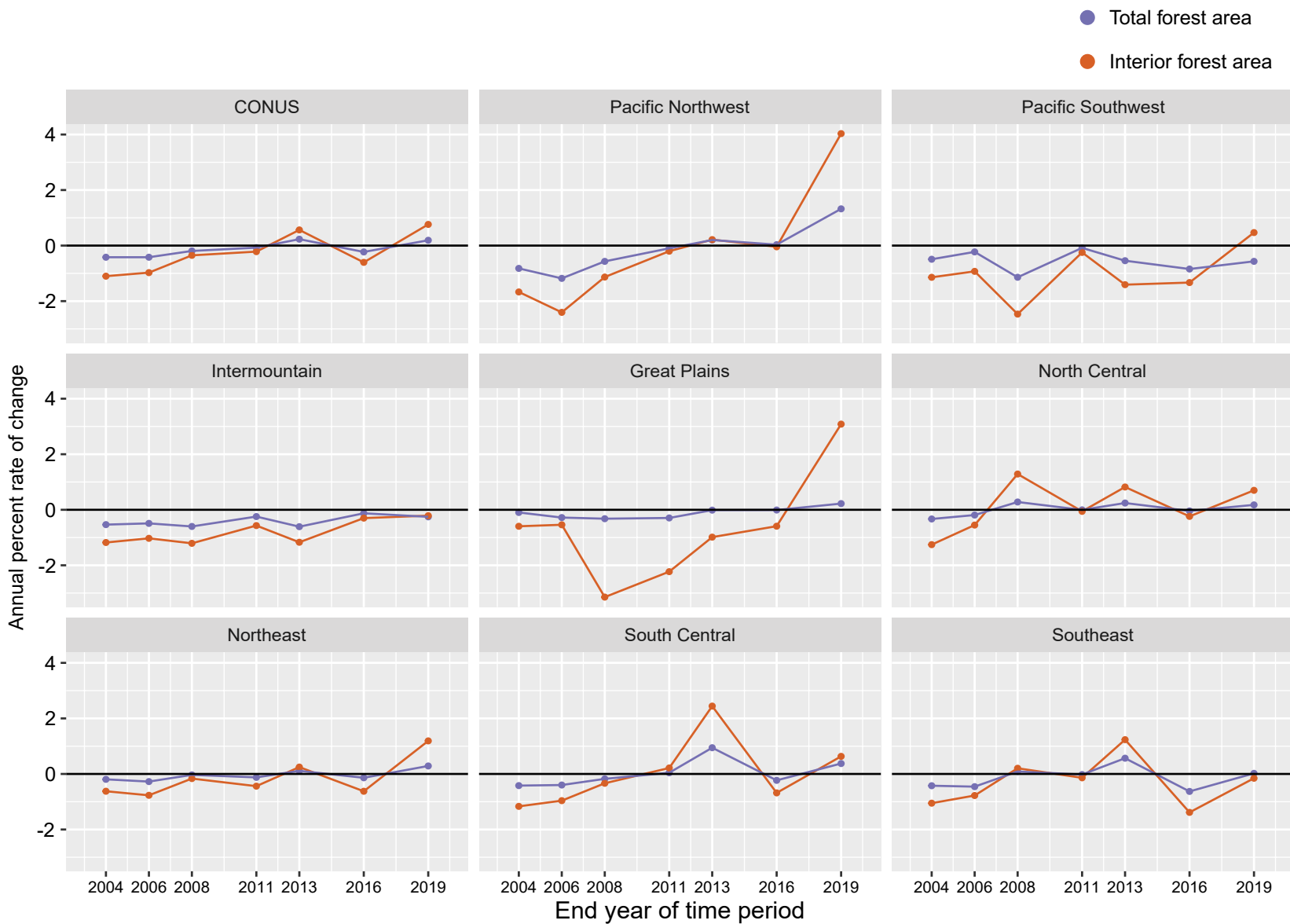


Figure 5.5—Annual percent rate of change of total forest area and interior forest area (15.2-ha neighborhood) over seven time periods from 2001 to 2019, in the conterminous United States (CONUS) and by region. Note that the interval ending in 2004 began in 2001.

DISCUSSION

Direct comparisons of these results with the results for 2001 to 2016 presented by Riitters and Robertson (2021) are not possible for several reasons. Regarding the input data for these analyses, the NLCD data for all years were updated for consistency with the release of the new data for 2019. As a result, the forest area that was newly mapped for the base year of 2001 was 17 300 km² less than the previous (2016) edition of the 2001 NLCD data. The change in base year forest area was certain to affect both the FAD calculations and the calculated rates of change of total forest and interior forest after that base year. Similarly, revisions of the NLCD data for the intervening years of 2006, 2011, and 2016 complicate comparisons with previous results presented for those years.

Considering the overall CONUS changes in dominant, interior, and core forest area, figure 5.2 indicates across the board net losses from 2001 to 2011 followed by evidence of stabilization or recovery until 2019. This contrasts with earlier reports (e.g., fig. 2 in Riitters and Robertson 2021) that indicated the same pattern of losses after 2001, with evidence of stabilization until 2016, but without much evidence of recovery. The new results presented here may reflect the widespread increase in both total forest and interior forest areas between 2016 and 2019 (fig. 5.5). The new results do not indicate complete recovery to 2001 conditions; forest loss and fragmentation have continued in most regions but at slower rates than previously reported.

Given the policy concerns related to wildfire, drought, and insect outbreaks in the Western States, this analysis supports the concerns for net loss of total forest area and increased fragmentation of the remainder in the Intermountain and Pacific Southwest regions. Similar concerns about wildfire and harvesting in the Pacific Northwest may allow speculation about the post-2016 increase in forest area and decrease in fragmentation, which may signal that relatively slow but ultimately successful regeneration was responsible for previous reports of increasing fragmentation west of the Cascade Mountains. In the Eastern States, forest area dynamics are largely driven by land use changes involving forest, agriculture, and developed land. This study's finding of decreasing fragmentation in the South Central region is generally consistent with previous reports of forest area increases due to conversion of former agricultural land (e.g., Nelson and others 2020). The finding of increasing fragmentation in the Southeast region and near major metropolitan areas elsewhere is consistent with previous reports of large expansions of urban area on former forest land in those areas (e.g., Nelson and others 2020).

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INTRODUCTION

Drought is an important stressor affecting forests and is commonly defined as a period of moisture deficit resulting from below-average precipitation, high temperatures, or both (Clark and others 2016). Alone or in combination with other disturbances, drought can reduce forest productivity, cause shifts in forest types, affect the ability of forests to regenerate, and diminish the capacity of forests to provide ecosystem services (Brodribb and others 2020, Vose and others 2016). As climate warms and many parts of the world become drier, droughts are expected to become more widespread, frequent, and severe (Ahmadalipour and others 2017, Cook and others 2015).

Measuring moisture conditions directly and determining the direct effects of drought on forests across broad geographic regions is difficult. Therefore, many scientists rely on the concept of meteorological drought (defined as a deficit in precipitation relative to a long-term mean), which can be quantified with only climate data. For forests, a meteorological drought is consequential if the period of precipitation deficit lasts long enough to deplete available soil water reserves, causing some impact to trees and other plants (Anderegg and others 2012). The magnitude of these impacts at any forested location depends on the level of drought exposure—the degree to which drought occurs at the location—as well as the sensitivities of the forest community or tree species to drought, the types and mix of surrounding land uses, and nearby human responses to drought (Crausbay and others 2017). However, such information is often lacking, as is

a comprehensive picture of how these and related factors interact to affect ecosystem function and services.

This chapter summarizes recent trends in drought exposure for forest land in the conterminous United States (CONUS) using the 36-month Standardized Precipitation Evapotranspiration Index (SPEI; Beguería and others 2014, Vicente-Serrano and others 2010), a meteorological drought index. Meteorological drought indices track relative departure from normal climate conditions for a given location and can be correlated with resulting effects on forests (Druckenbrod and others 2019). The SPEI allows for comparisons among locations and can be computed over multiple time scales, making it useful for monitoring drought in different ecological contexts (Ault 2020, Slette and others 2019). Because it considers temperature (i.e., as a determinant of potential evapotranspiration (PET)), the SPEI is deemed more suitable for research in a warming climate than precipitation-only drought metrics (Vicente-Serrano and others 2010). This study used the 36-month SPEI because prolonged droughts that persist for multiple years are more likely to cause lasting impacts to forests than shorter term droughts of equal magnitude (Archaux and Wolters 2006, Berdanier and Clark 2016, Bunting and others 2017, Guarín and Taylor 2005, Koch and others 2013, Madakumbura and others 2019, Peters and others 2015, Xu and others 2018). In this chapter, the objectives were to: (1) summarize trends in SPEI over time on forest land across the CONUS and within subregions of the CONUS, (2) examine geographic patterns of forest land

CHAPTER 6

Recent Forest Exposure to Multiyear Drought Across the Conterminous United States

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exposure to drought in forested ecoregions, and (3) summarize exposure of forest ecosystems to drought. Results show trends in SPEI for 1950–2021 and then focus on exposure of forests to drought during the most recent 30-year period: 1992–2021. A previous analysis of past drought exposure completed for the 2020 Resources Planning Act (RPA) Assessment (Costanza and others 2023a, 2023b, 2023c) was extended in several ways, including adding 3 more years of recent SPEI data (2019, 2020, and 2021), summarizing drought exposure subregionally, and mapping geographic patterns of exposure. Results are discussed in light of what is known about the sensitivity of forested regions and ecosystems to drought.

METHODS

Climate Data and Calculating SPEI

To analyze drought trends across the CONUS, this study obtained monthly gridded climate data at a spatial resolution of 2.5 arcmin (approximately 4 km) for 1950–2021 from the PRISM Climate Group website (PRISM Climate Group 2023). Calculating SPEI requires monthly precipitation (P) and potential evapotranspiration (PET) data. The PRISM dataset includes monthly precipitation (P) but does not include PET. PET estimation used Hargreaves' (1994) method, which incorporates minimum and maximum temperature, along with latitude, as proxies for radiation. While the Penman-Monteith method (Monteith 1965) is the recommended PET estimation method for SPEI calculations (Beguería and others 2014), calculation of PET

via that method was not possible because it requires data on relative humidity and wind speed, which were not available in the PRISM dataset. This study opted to use the PRISM dataset over other climate datasets that include the variables needed for the Penman-Monteith method because the PRISM dataset allowed incorporation of a longer historical period back to 1950 for calibration of SPEI, i.e., the SPEI “reference period” (see below). While several alternative methods are available for calculating PET, the method of Hargreaves (1994) has been recommended for use in SPEI when the data needed for Penman-Monteith are unavailable (Beguería and others 2014, Stagge and others 2015, Venkataraman and others 2016). The *hargreaves* function in the R package SPEI 1.7 (Beguería and Vicente-Serrano 2017) was used to calculate PET, with latitude specified, along with the option to include monthly precipitation as a proxy for insolation (i.e., incoming solar radiation).

As noted previously, this study used a time scale to calculate SPEI. At that time scale, SPEI compares the cumulative climatic water balance (P minus PET) for the previous 36 months to the same cumulative 36-month water balance for all months in a reference period. The result is a set of continuous SPEI values spanning the reference period for each pixel in the climate data, which are normally distributed with a mean of 0 and standard deviation of 1, akin to a z-score. Negative SPEI values indicate drier-than-normal conditions for a given location, while positive values are wetter than normal. Here, the reference period was defined as 1950 to

2005. Use of that reference period in this analysis allows calibration of SPEI values based on the historical conditions of each location. Because many forests are adapted to conditions at the time of tree establishment, grounding this exposure analysis in a single historical reference period is useful for determining where existing forests could experience stress from drought. This study used the historical reference period to calculate SPEI for all months in the time period (1950 to 2021). Because of the 36-month accumulation lag, the first month to have a value for SPEI in the time series was January 1953. The *spei* function in the R package SPEI 1.7 (Beguería and Vicente-Serrano 2017) was used to calculate SPEI from the monthly water balance data, with all default parameters except the reference period start and end dates, which were set to January 1950 and December 2005, respectively.

Forest Inventory Data

Monthly SPEI values were extracted for forested locations across the CONUS using geographic coordinates of plots in the U.S. Department of Agriculture, Forest Service, Forest Inventory and Analysis (FIA) Database (FIADB version 8.0; Burrill and others 2018). The FIA Program applies a nationally consistent sampling design, with one permanent plot established for every ~2428 ha of land (Westfall and others 2022). Forest Service personnel classify plots into forest types by using a decision-tree approach based on

the combination of species that comprises the highest stocking values (Arner and others 2001). Related forest types are aggregated into forest type groups (fig. 6.1). To protect sensitive plot information, especially on privately owned lands, the publicly available FIA Database contains plot coordinate information that has been altered slightly from the true coordinates. True plot coordinates were used here to extract SPEI values. Because FIA plots have fixed locations and a fixed design, a plot can straddle multiple forest type groups (Burrill and others 2018). To track those differences, multiple “conditions” can be identified within a plot, each with a unique forest type group. Each of these conditions has a corresponding area expansion factor, indicating the area of forest it represents. These expansion factors were used for all conditions to summarize the areas and proportions of forest area exposed to drought over time. Hereafter, plot conditions are simply referred to as “plots.” To ensure inclusion of the full set of plots for each State in the CONUS, this study selected a set of plots for each State that FIA used to produce an evaluation of forest conditions ca. 2016. The resulting FIA plot database consisted of 163,283 plots, representing a total forest area of 277 147 000 ha (2 771 470 km²).

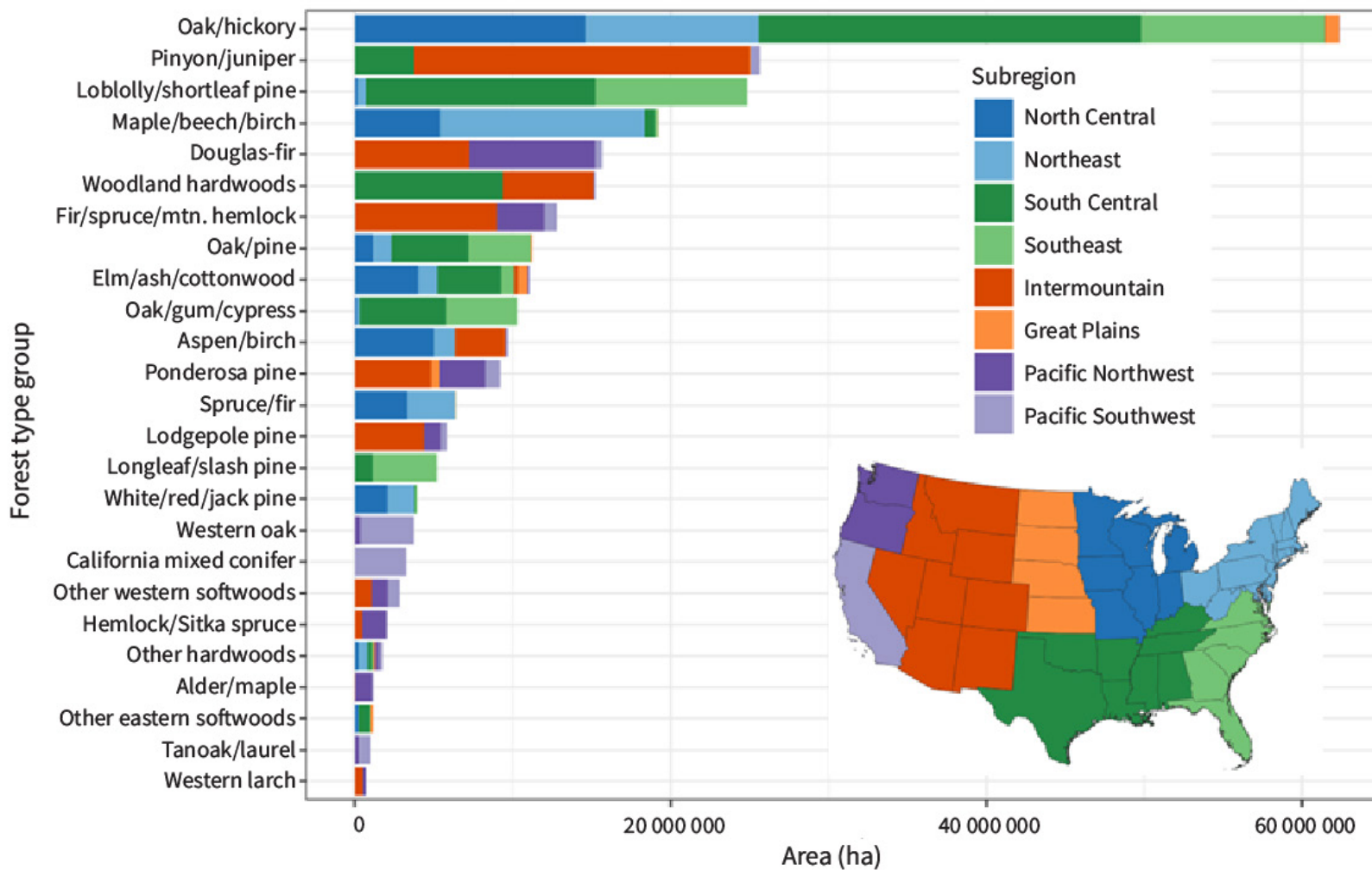


Figure 6.1—The areas of forest in each of the forest type groups included in the summary of drought exposure by type group. Inset map shows the conterminous States corresponding to each of the Forest Service Resources Planning Act (RPA) Assessment subregions used in this analysis. Colors on the bars by forest type group indicate the areas in each of the RPA Assessment subregions. (Data source: U.S. Department of Agriculture, Forest Service, Forest Inventory and Analysis Database)

Summaries of SPEI and Drought Exposure

The positive and negative values of SPEI were grouped into nine categories ranging from extreme wetness to extreme drought after Costanza and others (2023b; see table 6.1). Monthly trends were summarized in those categories of SPEI for forest land across the CONUS and within the subregions used in the 2020 Resources Planning Act Assessment (RPA subregions; fig. 6.1) for the entire time period (1953–2021). This study also specifically considered the combined categories of severe ($-2 < \text{SPEI} < -1.5$) and extreme drought ($\text{SPEI} < -2$) to be “exposed to drought” with a focus on drought exposure over the most recent 30 years in the study period: 1992–2021. Ecoregion sections (representing a moderate level of ecoregional classification; Cleland and others 2007) that contained each FIA plot location as well as the forest type group of each plot were identified. For forest land across the CONUS, by forest type group, and by ecoregion section, calculations were performed for the monthly proportion of forest with $\text{SPEI} < -1.5$ over the recent 30-year time period using the plot area expansion factors in the FIA Database. That was the principal metric of drought exposure. A metric was also developed for summarizing the frequency of forest exposure to relatively widespread drought by first calculating the overall monthly average proportion of forest across the CONUS that was exposed to drought (i.e., severe and extreme drought). Then, for ecoregion sections and by forest type group, a summary was developed for the number of months in the recent period for which the

Table 6.1—Values of Standardized Precipitation Evapotranspiration Index (SPEI) and corresponding categories, ranging from extreme wetness to extreme drought

SPEI values	Category
$\text{SPEI} > 2$	Extremely wet
$1.5 < \text{SPEI} < 2$	Severely wet
$1 < \text{SPEI} < 1.5$	Moderately wet
$0.5 < \text{SPEI} < 1$	Slightly wet
$-0.5 < \text{SPEI} < 0.5$	Near normal
$-1 < \text{SPEI} < -0.5$	Slightly dry
$-1.5 < \text{SPEI} < -1$	Moderate drought
$-2 < \text{SPEI} < -1.5$	Severe drought
$\text{SPEI} < -2$	Extreme drought

Groupings follow Costanza and others (2023b).

proportion of forest exposed to drought was greater than that average.

For analysis of drought for all forests across the CONUS and within ecoregion sections, all plots were included. For summaries of exposure for individual forest type groups, all type groups were included except nonstocked, exotic hardwoods, exotic softwoods, redwood, tropical hardwoods, and western white pine type groups (fig. 6.1). The nonstocked type group represents places with few, if any, trees. Exotic type groups were excluded because they were considered low priority with respect to drought adaptation. The other three type groups were limited in extent (<600 000 ha each, <0.2 percent of total forest land in the FIA Database). Because of their restricted distributions, this study assumed those type groups would respond more to local environmental factors and that the relatively coarse spatial resolution (~4 x 4 km) of the climate data would be less relevant. Excluded type groups accounted for a total of 3.9 percent of forest land area in the FIA Database, with nonstocked plots accounting for the majority (85 percent) of that excluded land.

RESULTS AND DISCUSSION

The major trends in observed SPEI values for forest land across the CONUS showed periods of more forest exposed to dry conditions (negative SPEI values) alternating with periods of more exposure to wet conditions (positive SPEI values; fig. 6.2). Forest land in the CONUS

was exposed to overall drier conditions in the 1950s and 1960s, the late 1980s, and the early 2000s. These past trends for the CONUS and the corresponding trends by subregion (fig. 6.3) accord with known incidence of past drought. In the 1950s, drought periods occurred across much of the Intermountain, Great Plains, North Central, South Central, and Southeast subregions (Andreadis and others 2005, Heim 2017). Drought occurred throughout the 1960s across much of the North Central and Northeast subregions (Barlow and others 2001, Namias 1966). Starting in approximately 2000 and continuing through the end of the analysis period (2021), large portions of forests in subregions of the West (Pacific Northwest, Pacific Southwest, and Intermountain subregions) were exposed to dry conditions (fig. 6.3). Other research has shown that for the Western United States, the period from 2000 to 2021 was among the driest periods in the last several centuries (Williams and others 2022). In contrast, during much of that time, forests in the eastern subregions were exposed to wet conditions (fig. 6.3; also shown for the Northeast by Krakauer and others (2019)), amounting to large proportions of extremely wet conditions across the CONUS as a whole from 2005 to 2021 (fig. 6.2). This difference between the wet conditions in the eastern subregions and the dry conditions in the western subregions over the last two decades illustrates the complexity of the recent moisture regime across the CONUS.

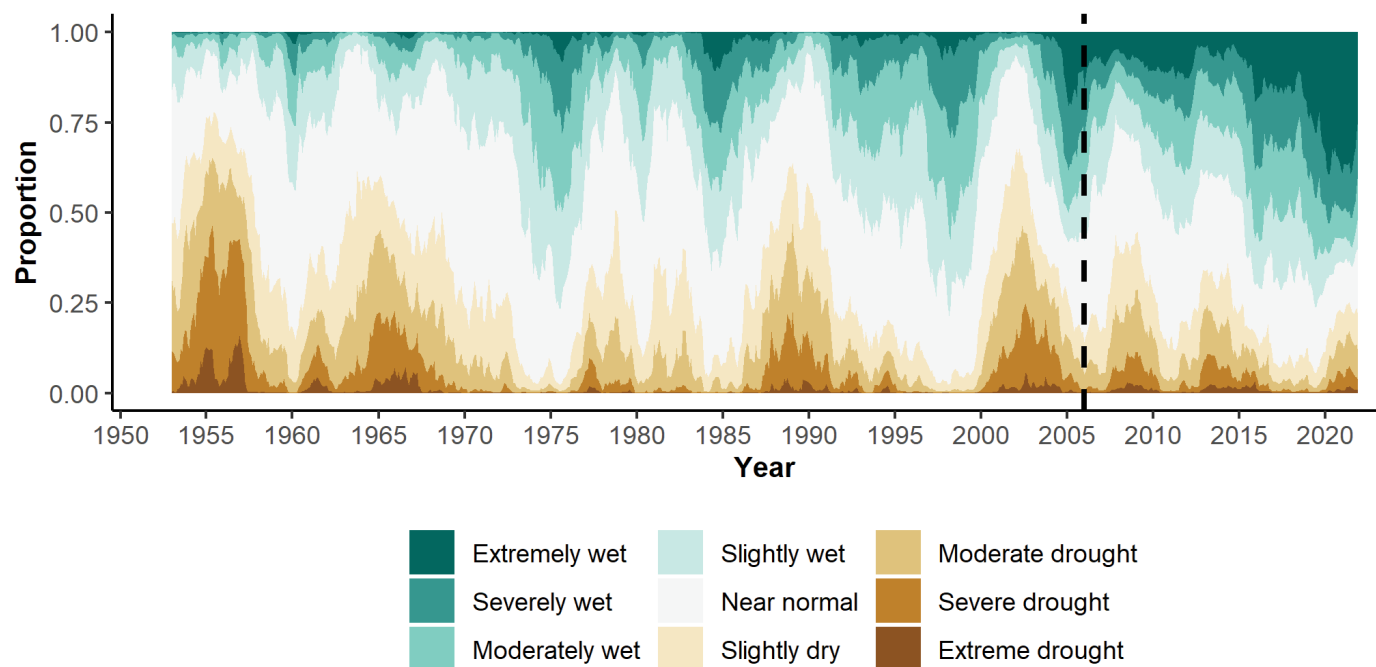


Figure 6.2—Recent and past trends in Standardized Precipitation Evapotranspiration Index (SPEI) for forest land in the conterminous United States. For each month in the time series, colors indicate the proportion of forest in each SPEI category. Values of SPEI corresponding to each category can be found in table 6.1. The period to the left of the dashed line was the reference period for calculating SPEI. (Data sources: PRISM Climate Group 2023; U.S. Department of Agriculture, Forest Service, Forest Inventory and Analysis Database)

Summaries of the proportion of forest exposed to drought (severe or extreme drought, SPEI < -1.5) for the most recent 30 years in the dataset (1992–2021) allow examination of drought in more detail than the national and subregional summaries. Maps of annual average drought exposure by ecoregion section show the geographic extent of drought over time (fig. 6.4). Over the recent period, an average of 4.5 percent of forest was exposed to drought per month.

Summaries of drought exposure by ecoregion section highlight that (1) in some years (e.g., during much of the 1990s), low levels of drought were present across the CONUS, but, in most years, drought affected >50 percent of forests in at least one ecoregion section of the country; and (2) nearly every forested region of the country was exposed to drought at some point in the last 30 years.

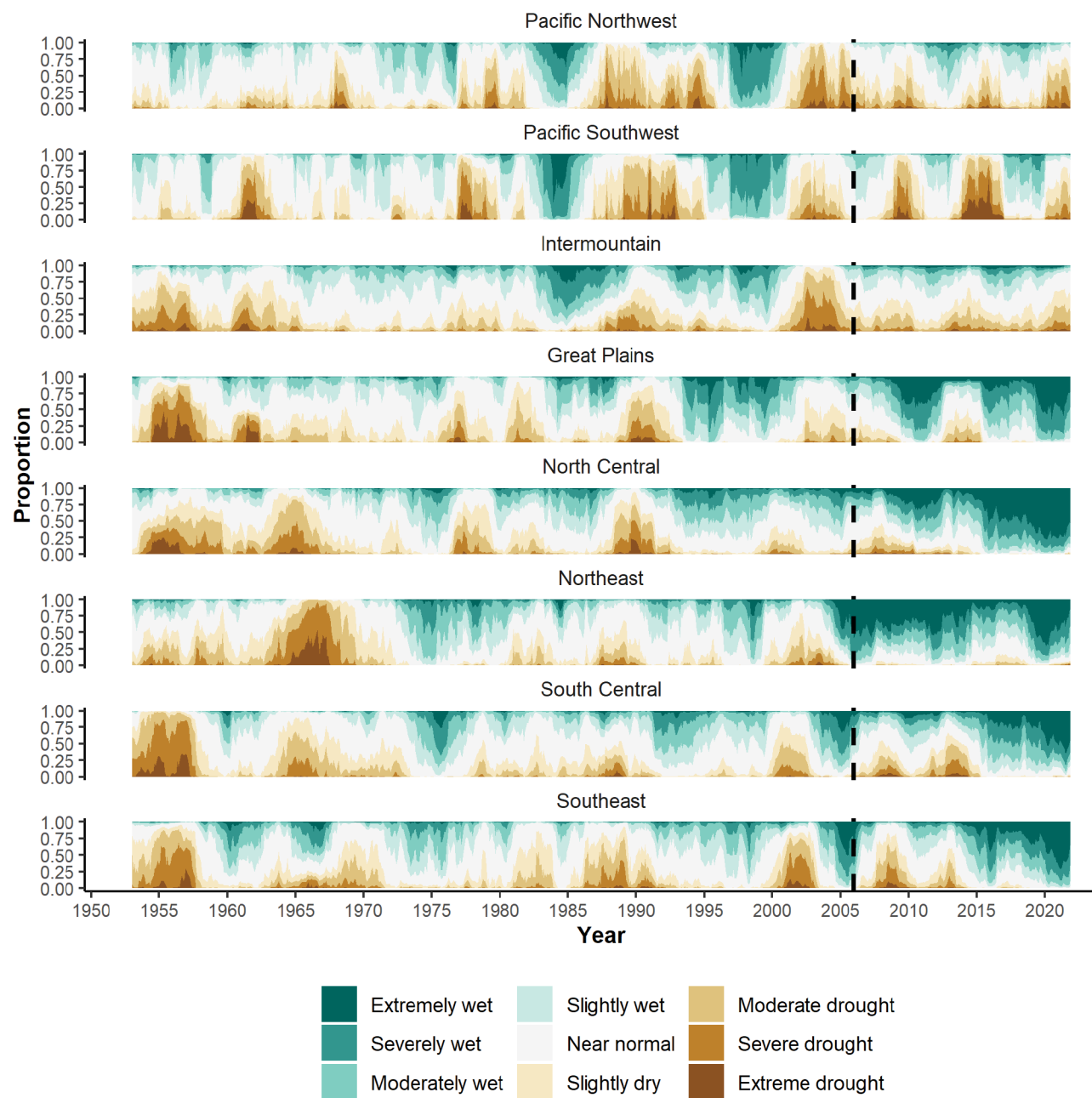


Figure 6.3—Recent and past trends in Standardized Precipitation Evapotranspiration Index (SPEI) for forest land by Resources Planning Act Assessment subregion. For each month in the time series, colors indicate the proportion of forest in each SPEI category. Values of SPEI corresponding to each category can be found in table 6.1. The period to the left of the dashed line was used as the reference period for calculating SPEI. (Data sources: PRISM Climate Group 2023; U.S. Department of Agriculture, Forest Service, Forest Inventory and Analysis Database)

In general, more widespread than average drought exposure (greater than the national average of 4.5 percent of forest exposed per month) occurred most often in ecoregion sections of the Western United States, with moderate frequency in the Southeast, and least often in the Northeast (fig. 6.5). For many ecoregion sections in the Northeast, 10 percent of months in the recent period had >4.5 percent of the forests exposed to drought, in contrast with sections in western California and other parts of the West, where >40 percent of the months in the recent period had >4.5 percent of the forests exposed to drought (fig. 6.5). One ecoregion section in western Montana had >4.5 percent of the forests exposed to drought for 50 percent of the months in the recent period (fig. 6.5). Since 2000, drought exposure has been widespread in the Western United States during most years, especially in 2002–2004, 2009, and 2013–2015, and has returned recently in 2020–2021 (fig. 6.4). The persistent drought in the Western United States since 2000 has been called a “megadrought” because it has been more intense and long lasting than any observed drought in the region (Cook and others 2022, Williams and others 2020). Within the Western United States, forests in ecoregion sections in California were exposed to drought during the mid-2010s, a period that has been shown to be drier than any historical precedent in California (Robeson 2015). The period corresponded with high wildfire activity and insect outbreaks in the region, and widespread forest tree mortality during that time has been attributed to drought in combination with those other disturbances (Fettig and others 2019,

Goulden and Bales 2019, Halofsky and others 2020, Steel and others 2023). Forests in the Southwestern United States and near the Four Corners area of Utah, Colorado, New Mexico, and Arizona have also experienced frequent widespread drought exposure over the past 30 years (figs. 6.4 and 6.5). A multiyear drought there in 2002–2004 led to wildfire and bark beetle outbreaks, causing extensive tree mortality (Breshears and others 2005), and dry conditions have been present there frequently in the past two decades (Lisonbee and others 2022).

In Texas and other parts of the Central United States, widespread exposure to drought in 2011–2014 (fig. 6.4) reflects one of the worst droughts on record in 2011, which occurred in conjunction with a heat wave (Fernando and others 2016, Grigg 2014, Hoerling and others 2013, Nielsen-Gammon 2012). A combination of drought and historically high temperatures killed an estimated 301 million trees in Texas, or >6 percent of trees statewide (Hoerling and others 2013, Moore and others 2016). In the Southeastern United States, many ecoregion sections experienced relatively widespread exposure to drought between 10 and 20 percent of the time over the last 30 years (fig. 6.5). Some notable droughts in the Southeast occurred in 2001–2002, 2007–2009, and 2012–2013 (fig. 6.4). While those droughts were not associated with widespread, acute tree mortality as in many Western and Central U.S. subregions, evidence suggests that prolonged exposure to drought events in the Southeastern United States has led to growth declines and eventual mortality (Berdanier and Clark 2016).

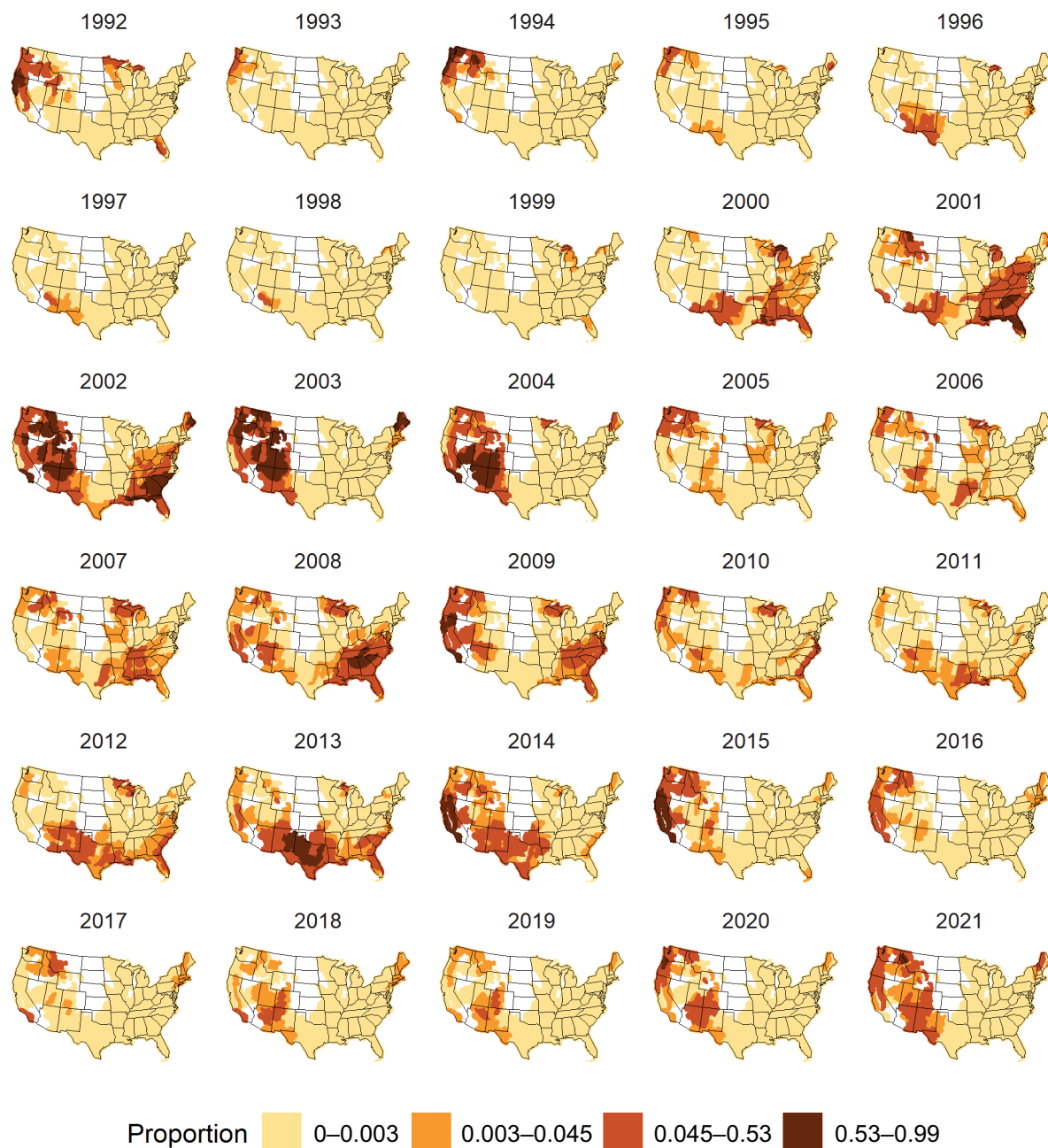


Figure 6.4—Average monthly proportion of forest in each ecological section exposed to severe or extreme drought (36-month SPEI ≤ -1.5) in the recent 30-year period summarized annually. Ecological sections containing <10 percent forest land are not shown. (Data sources: Cleland and others 2007; PRISM Climate Group 2023; U.S. Department of Agriculture, Forest Service, Forest Inventory and Analysis Database)

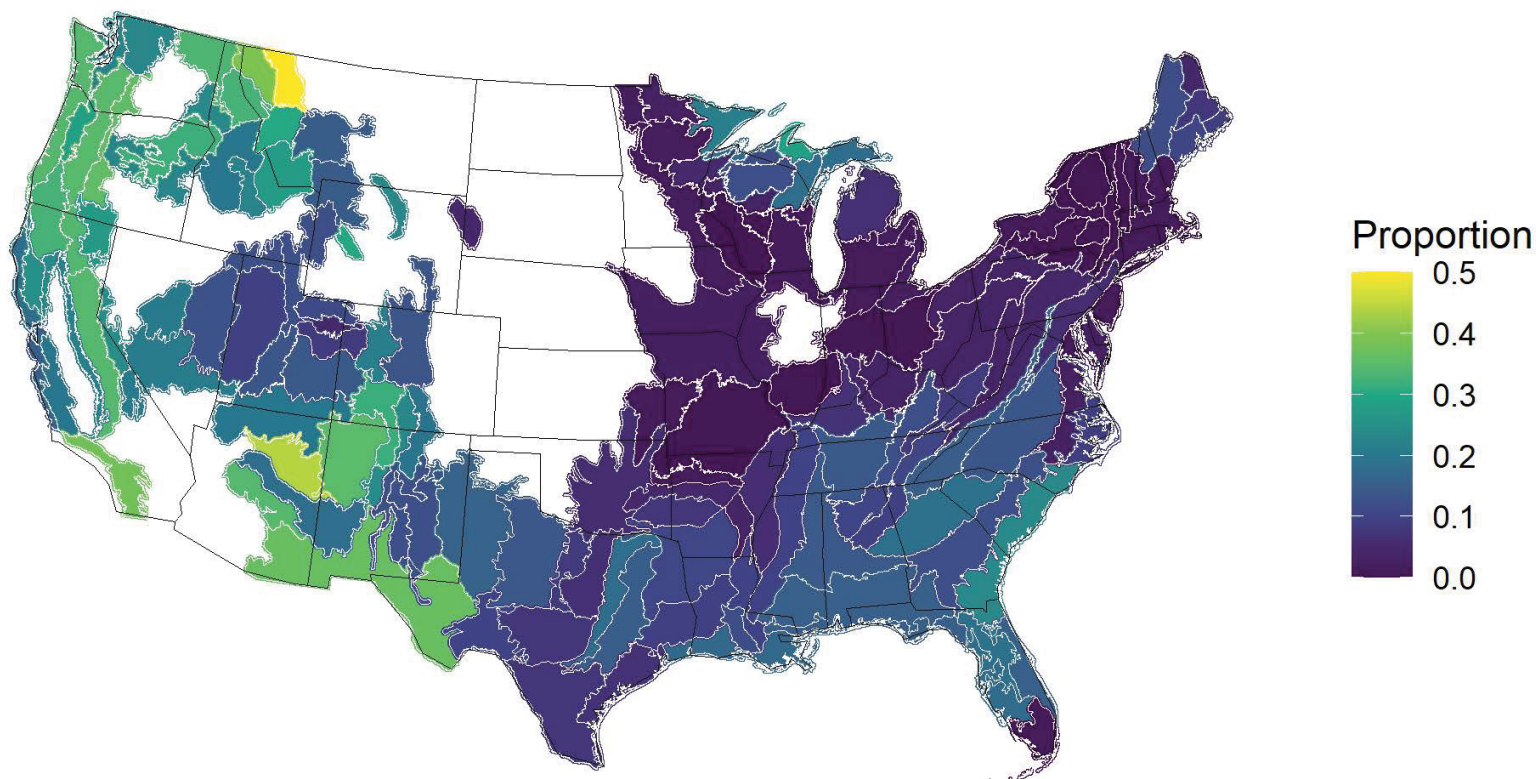


Figure 6.5—Proportion of months in the recent 30-year period (1992–2021) during which exposure to drought in each ecological section was more widespread than average (greater than the national average of 4.5 percent of forest exposed per month). Ecological sections containing <10 percent forest land are not shown. (Data sources: Cleland and others 2007; PRISM Climate Group 2023; U.S. Department of Agriculture, Forest Service, Forest Inventory and Analysis Database)

Summaries of drought exposure by forest type group reflect the geographic ranges of those type groups, and thus mirror the trends seen in the previous (i.e., subregional) summaries. However, together with existing information on the sensitivities and adaptive capacities of tree communities and species, the type group summaries can provide insights into the vulnerabilities of forest ecosystems to drought. The six forest type groups that have experienced the highest exposure on average all occur in the Western United States: fir/spruce/mountain hemlock, lodgepole pine, Douglas-fir, other western softwoods, western larch, and ponderosa pine (fig. 6.6A). Those type groups also have been exposed to widespread drought (greater than the national average of 4.5 percent of forest exposed per month) more frequently than other type groups (fig. 6.6B). These six type groups can be found in a variety of conditions throughout the West, but most have relatively wide distributions and occur especially in the Pacific Northwest and Intermountain subregions (fig. 6.1). The wide distributions of some type groups mean that the sensitivities of forests to drought exposure can vary considerably across their ranges. For example, recent mortality of Douglas-fir (*Pseudotsuga menziesii*) associated with drought stress and subsequent insect infestations has been higher in forests growing on hotter and drier sites compared with other sites (Bennett and others 2023). The ponderosa pine type group also occurs across a broad range. In the Southwestern United States, widespread drought-induced mortality of ponderosa pines (*Pinus ponderosa*) has been followed by limited regeneration (Minott and

Kolb 2020). Other forest and woodland types in the region, including pinyon/juniper forests, have experienced widespread mortality due to dry conditions, followed by limited recruitment of constituent species (Minott and Kolb 2020, Redmond and others 2015, Shriver and others 2022). In ponderosa pine forests in California, drought has led to widespread mortality from bark beetle outbreaks, and research has shown that carbon storage, an important ecosystem service in those forests, may not return to pre-drought levels before the end of the 21st century (Robbins and others 2023).

Several type groups experienced widespread drought exposure several times in the recent 30-year period (fig. 6.6B), even though when averaged across the 30 years, the monthly proportion exposed to drought was lower than other type groups (fig. 6.6A). Those include western oak, California mixed conifer, and tanoak/laurel. Those forest type groups occur in California, where drought exposure has varied greatly in recent years, with widespread exposure in some years and little to none in others (fig. 6.4; Swain and others 2018). Climate projections for California suggest even more variability in precipitation by the end of the 21st century, with extreme dry and wet precipitation events becoming more common as mean precipitation undergoes only modest changes (Swain and others 2018).

Forest type groups occurring predominantly in the East have been less exposed to severe or extreme drought than western type groups in general, having lower median monthly exposures and lower numbers of months with widespread exposure than most western type groups (figs.

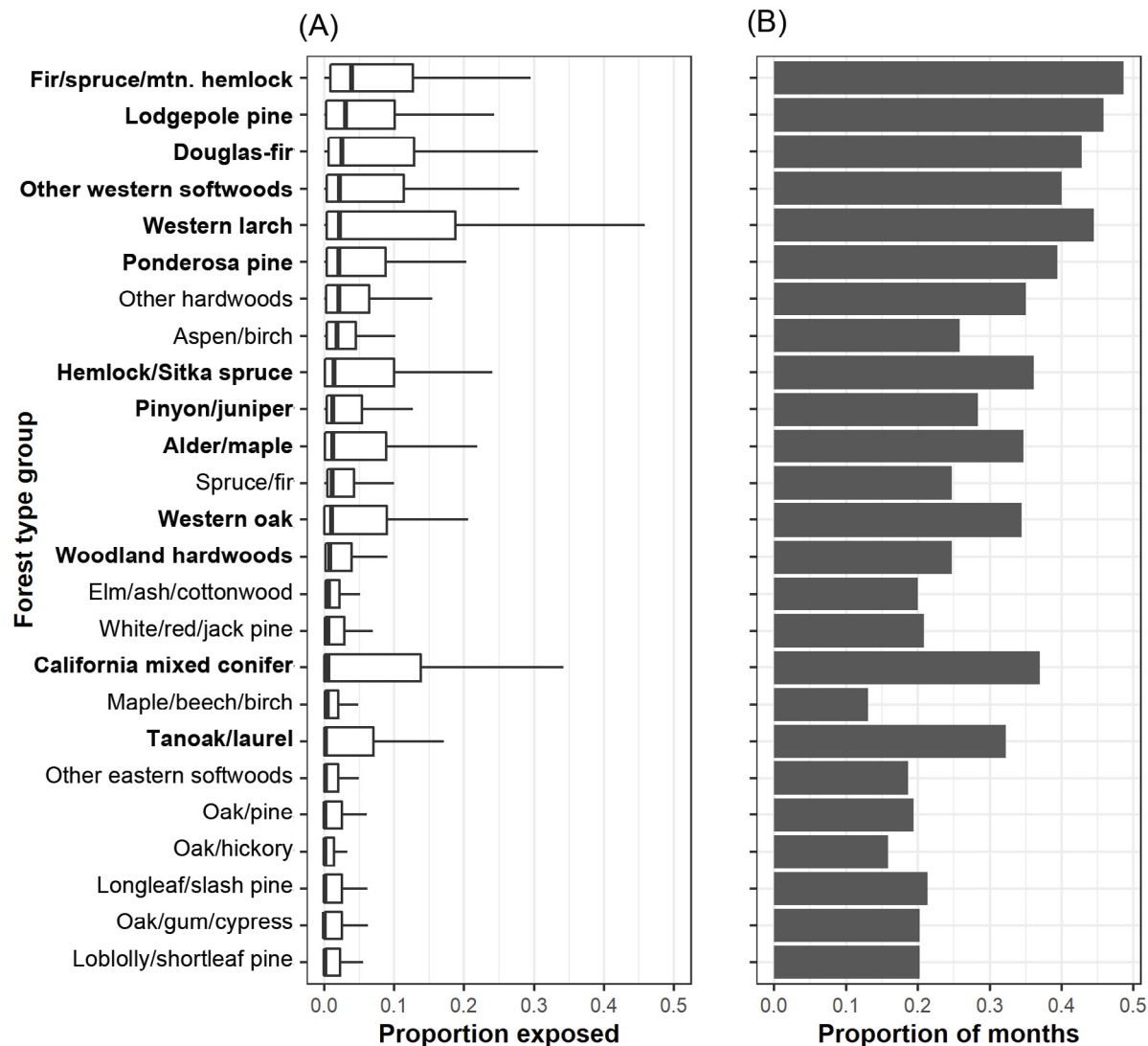


Figure 6.6—Exposure of forest type groups to drought (severe or extreme drought, 36-month Standardized Precipitation Evapotranspiration Index (SPEI) ≤ -1.5) in the recent 30-year period (1992–2021). (A) shows boxplots of monthly proportion exposed and (B) is the proportion of months during which the proportion of each forest type group exposed to drought was more widespread than average (greater than the national average of 4.5 percent of forest exposed per month). In the boxplots, the dark line within the box represents the median monthly proportion exposed, and forest type groups are listed in descending order according to that value. Left and right edges of the box represent the first and third quartiles, respectively, and the whiskers extend to 1.5 times the interquartile range of the data. Outliers extending beyond that range were omitted from the figure for readability, but many forest type groups had >50 percent exposure in a few months. Bold indicates forest type groups primarily distributed in the Western United States. (Data sources: PRISM Climate Group 2023; U.S. Department of Agriculture, Forest Service, Forest Inventory and Analysis Database)

6.6A and B). Worth noting, however, is that although spruce/fir forests had moderate exposure overall, that type group had one of the highest exposure rates of all eastern type groups (figs. 6.6A and B). Those forests occur at relatively high elevations and are adapted to cool and moist conditions, so they are likely to be sensitive to drought conditions. In addition, drought exposure for oak/hickory forests has been low in the recent period, but future drought impacts in those forests are less certain (Novick and others 2022), so further investigations of future drought impacts may be needed.

Results emphasize that over the past 30 years, while forests in some regions of the CONUS have been more exposed to drought than others, widespread forest exposure to drought somewhere in the CONUS has been commonplace rather than an exception. Drought events are already being attributed to anthropogenic climate trends (Williams and others 2020), and research suggests that drought will become even more common and more severe in many places as climate warms (Seidl and others 2017, Ullrich and others 2018). In fact, some of the forested portions of the CONUS as well as some forest type groups that have had the highest rates of drought exposure in the recent past (figs. 6.4, 6.5, and 6.6) may be among the most exposed in the future, including the Southwestern United States and associated forest type groups like ponderosa pine and pinyon/juniper (Costanza and others 2023b). Assessments of forest exposure to meteorological drought in the future compared with recent past exposure are important for prioritizing which forests need mitigation, increasing adaptive

capacity, and determining where further research into potential future drought impacts is necessary (Costanza and others 2023b). Although this study focuses on drought exposure, by linking the FIA Database to recent SPEI, this study, along with recent work on future forest exposure (Costanza and others 2023b) can set the stage for further investigations of drought impacts on forests nationwide using the observed trends in forest conditions from the forest inventory.

Studies of forest responses to recent droughts have produced some evidence that management can help ameliorate the worst effects of drought in some cases and may facilitate resilience to future drought. In ponderosa pine and pinyon/juniper forests, thinning to lower stand density has helped mitigate impacts and may be one management action for helping those forests adapt to future climate (Bottero and others 2017, Bradford and Bell 2017, Bradford and others 2022). Thus, examining forest exposure to past droughts alongside drought's effects on forests can be a critical first step toward informing management and policy that help forests be more resilient in the future.

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INTRODUCTION

Forest disturbances have occurred throughout the conterminous United States (CONUS) within the 20th and 21st centuries in conjunction with dry multidecadal time periods (Clarke and others 2016, Danneyrolles and others 2021, Hicke and others 2020, Morgan and others 2008, Pernin 1971, Wickman 2005). These dry periods are influenced by the long-term dynamics of Pacific Decadal Oscillation, Atlantic Multidecadal Oscillation, and Northern Hemisphere temperatures (McCabe and others 2004).

In the Western United States (defined as conterminous States including and west of Montana, Wyoming, Colorado, and New Mexico), climatic conditions promote coniferous vegetation primarily found within the Dry Domain ecological classification, with coastal areas falling into the Humid Temperate Domain. These conditions influence species distributions across ecological divisions while also excluding trees across substantial areas that are too arid to support forested vegetation (Perry and others 2022). In these domains, dry periods have commonly reoccurred throughout the Western United States, often with numerous multiyear droughts occurring each century from 800 A.D. to 2021 (Williams and others 2020, 2022). Multidecadal dry periods, referred to as “megadroughts,” have been associated with widespread, synchronized wildland fire and bark beetle disturbances. These disturbance periods occurred in the early 20th century (1917–1940) as well as in the early 21st century (2000–2022) when exposure to dry conditions promoted widespread vulnerability to

disturbance in forests across the Western United States (Hicke and others 2020, Iglesias and others 2022, Jenne and Egan 2019, Morgan and others 2008, Wickman and others 2005). Dry periods reduce fuel moisture and soil moisture conditions, resulting in increased vegetation flammability while promoting physiological stress within trees as carbon assimilation, water conductivity, tree vigor, and synthesis of chemical defensive compounds that protect trees from bark beetle attacks are compromised (Kolb and others 2016, Nolan and others 2020). Interactions between wildfire and bark beetles can be amplified with dry conditions as bark beetles can colonize fire-injured trees after wildfire incidents and, conversely, wildfire behavior can be impacted by the changes in fuel structure and moisture content resulting from bark beetle attacks that induce tree mortality (Fettig and others 2022c, Hood and Bentz 2007, Jolly and others 2012, Moriarty and others 2019).

For wildland fire incidents, precipitation wetting days during the warm season (May–September) have been identified as a primary driver that influenced the spatial extent of wildfire area burned, along with lesser contributions of vapor pressure deficit (Holden and others 2018). Similarly, numerous studies of bark beetle outbreaks in the Western United States identified that reduced precipitation, especially during spring and/or summer months, affects physiological tree stress by reducing defensive capacity and can increase overall forest vulnerability to severe and widespread bark beetle outbreaks (Egan and others 2010, 2016; Fettig and others 2022a, 2022b; Lestina and others 2019).

CHAPTER 7

Association of Multidecadal Repeat Dryness With Wildfire and Bark Beetle Forest Disturbances in the Conterminous United States, 2000–2022

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Differing from dry periods, wet multidecadal periods can reduce potential for widespread, synchronized, and compounding wildfire and bark beetle disturbances while promoting tree recruitment, biomass growth, forest densification, and shade-tolerant species expansions (Brown 2006, Brown and Wu 2005). A multidecadal wet period occurred throughout the Western United States from the 1940s through the 1990s during warm season months (May–September) that interacted with anthropogenic fire suppression activities to mute spatially widespread and synchronized wildfire and bark beetle disturbances (Bollenbacher and others 2014, Iglesias and others 2022, Morgan and others 2008, Westerling and others 2016). As an example, the fire-prone forests of the Northern Rocky Mountains in Idaho and western Montana had no regional-fire years (i.e., years when numerous wildfire events are spatially synchronized by climate over a broad region) between 1935 and 1987. This contrasts to regional-fire years frequently occurring during the modern (2000–2022) and historic (1917–1940) periods when the Northern Rocky Mountains were exposed to repeated years of dry conditions during the warm season (Morgan and others 2008).

In the Central and Eastern United States (hereafter referred to as Central-Eastern United States, defined as conterminous States excluding and east of Montana, Wyoming, Colorado, and New Mexico), climatic conditions are generally wetter relative to the West. These conditions have promoted forests with a majority of deciduous species with areas of coniferous tree species across a Humid Domain that is further refined

by primarily Hot Continental and Subtropical ecological divisions (Perry and others 2022). Typically, these conditions are not conducive to synchronized and widespread wildfire or bark beetle disturbances to the extent observed in the Western United States (Fettig and others 2022a); however, severe wildfires and bark beetle outbreaks still occur in conjunction with dry conditions (Clarke and others 2016, Danneyrolles and others 2021, Pernin 1971).

Across the CONUS, human development has expanded since the 20th century with communities and their surrounding ecosystems being directly impacted by spatially widespread wildfire and bark beetle outbreaks (Hicke and others 2020, Strader 2018). Climatic conditions have amplified forest disturbances and promoted forest vulnerability and are anticipated to promote increased and compounding wildfire and bark beetle disturbances as global warming intensifies (Allen and others 2015, Barbero and others 2015, Bentz and others 2010, Heeter and others 2023, UNEP 2022, Wion and others 2022).

To address changed conditions with climate-amplified disturbances, the U.S. Department of Agriculture (USDA), the USDA Forest Service, and other USDA agencies completed Climate Adaptation Plans (CAPs) that identify climate risks and mitigation activities needed to meet agency missions and continued delivery of services to the public. The Forest Service CAP Action 3 identified risk of chronic climate-amplified stressors on ecosystem function and recommended integrating climate vulnerability assessments into land management planning activities across all land ownerships (Action 3b; USDA Forest

Service 2022). Similarly, the USDA's Office of the Secretary released Memorandum 1077-004, which requires the Forest Service to provide spatially explicit climate data to identify where climate-based exposure and vulnerability to disturbance is elevated across the Nation for management support (Action 2a; USDA 2023). This chapter presents a spatially explicit climate-based indicator derived by the Forest Service's Forest Health Monitoring Program to support these mandates.

The goals of this study were to (1) identify, across 481,631 site-specific locations in the CONUS, whether precipitation conditions changed during 2000–2021 relative to the long-term average for 1948–1999 and (2) to evaluate a new indicator, the Multidecadal Repeat-Dryness Exposure Index (MRDEI), by assessing spatial association with wildfire and bark beetle disturbance records for 2000–2022 in forested locations. Specifically, objectives were to:

1. Assess site-specific forested locations for changed precipitation, by season, that occurred during 2000–2021 relative to a long-term average.
2. Determine whether annual, spring, or warm season periods had changed precipitation conditions at a scale associated with recently widespread forest disturbances for indicator development.
3. Identify differences in site-specific dryness dynamics across the Central-Eastern United States and Western United States since 1980.

4. Validate the MRDEI indicator by evaluating whether forest disturbances increased in conjunction with elevated repeat-dryness exposure rates during multidecadal (2000–2022) and recent (2017–2022) timescales.

METHODS

Geospatial Data for the Conterminous United States

Multiple spatial datasets were geospatially compiled for analysis across the CONUS using ArcGIS Pro 2.8.8. These included forested area locations, Standardized Precipitation Index (SPI), bark beetle spatial records for 2000–2022, and certified wildland fire perimeters for 2000–2022. Each dataset was geospatially attributed across the CONUS through a network of 16-km² grid cells that contained >10 percent forested vegetation as indicated by 2019 National Land Cover Database (NLCD) classification groups that included deciduous, evergreen, and mixed forest designations (Dewitz and USGS 2021). Bark beetle disturbance records, operationally collected by the Forest Service's Forest Health Protection Program and State partners, were aggregated from the national Insect and Disease Survey (IDS) by filtering annual geospatial datasets for the CONUS to include all damage causal agents (DCAs) identified as bark beetles (coded as 11000–11999). Then, records from all DCAs were dissolved or combined into a single record where spatial overlap occurred within ESRI ArcGIS Pro across 2000–2022 and 2017–2022 time periods to produce a bark beetle indicator feature class

(McConnell and others 2000, USDA Forest Service 2005).

Wildfire footprint records for all certified fire perimeters >100 acres were aggregated from the national Burned Area Boundaries dataset compiled within the Wildland Fire Management Research, Development, and Application (WFMRDA) data for 1984–2021 and the Wildland Fire Interagency Geospatial Services (WFIGS) data for 2022 wildfire incident records (WFIGS 2022, WFMRDA 2021). Fire perimeter footprints were dissolved to erase yearly records that overlapped in 2000–2022. Then, the wildfire footprint derived layer was cross-referenced with the Monitoring Trends in Burn Severity (MTBS) geospatial fire data for 2000–2022, which is limited to >500- or >1,000-acre incidents depending on location, to cross-validate WFMRDA and WFIGS data to ensure wildfire records were not missing any large wildfire perimeters (Eidenshink and others 2007). Footprint data were intersected to identify overlapping co-occurrence of wildfire and bark beetle disturbance data. Finally, all three disturbance footprint layers built were stratified to represent the 2000–2022 multidecadal period as well as a recent 2017–2022 period, with acres impacted summed across individual 4-km² grid cells to match climatic data indicated below.

All disturbance footprint datasets were compiled from best-available datasets and were considered authoritative at the time accessed for this study. However, limited cases of incomplete disturbance records are possible. The national IDS does not survey every forested acre annually due to capacity and logistic limitations (McConnell and

others 2000). Similarly, the national WFMRDA and WFIGS wildfire datasets may have occasional missing records and are often updated when additional wildfire records become available.

Standardized Precipitation Index (SPI)

The SPI (Guttman 1999, McKee and others 1993) is a widely used drought index that represents the deviation between measured precipitation and the long-term climatological average for precipitation at the same location. This metric is beneficial for site-specific, long-term comparisons over multiyear periods (Hoylman and others 2022). Site-specific standardization allowed for consistency to assess changed precipitation conditions and disturbance associations across vastly different Dry and Humid ecological domains found throughout the CONUS (Perry and others 2022).

SPI was calculated for each of the 481,631 grid cells across the CONUS through an iterative process. First, the monthly Parameter-elevation Regressions on Independent Slopes Model (PRISM) precipitation values for 1948–2021 were partitioned to calculate spring (March–May), warm season (May–September), and calendar year (January–December) totals (Daly and others 1994, PRISM Climate Group 2023). Using the PRISM data, SPI anomalies were calculated for each seasonal time window relative to the 1948–2021 average and normalized across each year in the 1948–2021 period by fitting gamma distribution, using observations to compute Cumulative Distribution Function (CDF), and then evaluating CDF with inverse

Gaussian function to derive final SPI anomaly values (Holden and Hoylman 2023). Data were only summarized back to 1948 because weather measurement stations, which serve as the base input data for PRISM, had sparse occurrence and were limited to valley bottoms in some locations prior to that year.

SPI, which represents precipitation relative to local baseline conditions, was specifically selected to calculate repeat dryness spatially without temperature influences for various reasons. First, PRISM records suggest temperatures trended higher ubiquitously across respective Western and Central-Eastern U.S. regions with limited within-region spatial variation in the modern (2000–2021) dry period (fig. 7.1; Daly and others 1994). Warming trends are anticipated to continue and co-occur with cyclic precipitation events that have a level of repeatability due to the influence of static terrain and topographic complexity (Daly and others 1994, Heeter and others 2023, IPCC 2022, Johnson and Hanson 1995). This repeatability is evident with reoccurrence of severe and widespread wildfire and bark beetle disturbances across the Western United States where forest conditions were susceptible during the 1917–1940 and 2000–2022 dry periods (Jenne and Egan 2019; Morgan and others 2008). Thus, identification of forested areas prone to repeat dryness when combined with increased temperature assumptions can highlight forested areas with potential for aridification, especially in the Western United States. Second, temperature and precipitation variables have dependency with each other. This dependance can compound errors when these variables are combined, especially in

mountainous areas of the Western United States and where monitoring stations were limited across the 1948–2021 period of normalization. For these areas, greater reliance on spatial interpolation is needed to derive PRISM site-specific variable estimates (Daly and others 1994, Trenberth and Shea 2005, Wazneh and others 2020).

Multidecadal Repeat-Dryness Exposure Index (MRDEI)

The MRDEI is a climate-based indicator that represents locations exposed to repeat dryness during the warm season (May–September) throughout long-term time periods of interest. The SPI data were used to parameterize the MRDEI through a severity-weighted area statistic that combines years of dry conditions with severity of dryness. Index values represent the percentage of the timescale evaluated during which multiyear dry exposure was equivalent to a severe dry SPI (<-3 standard deviation) baseline by applying a scaling factor. Scaling factors (table 7.1) were applied to grid cell acres that were summed across respective multidecadal time periods (1948–1959, 1960–1979, 1980–1999, and 2000–2021) and divided by the total (nonscaled) grid cell acres multiplied by the total years within the time period. In effect, the frequency of SPI <0 substantially influences the final multidecadal index statistic. The magnitude of SPI values <0 provides for limited influence as the index was designed to identify where forested areas are prone to repeated occurrence of dry conditions rather than estimate site-specific impacts of cumulative dryness. Overall, a value of 100 percent represents baseline conditions and would indicate every

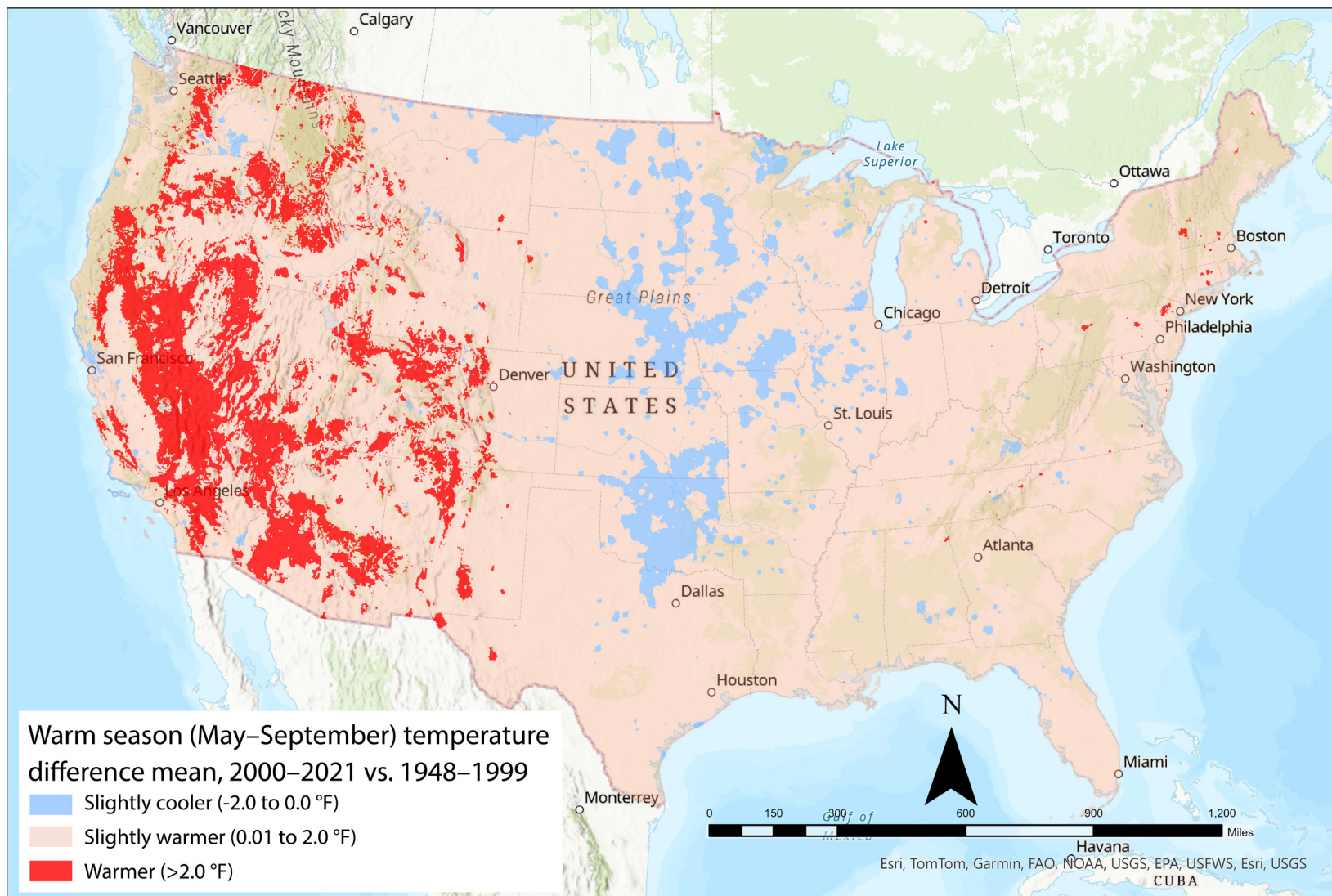


Figure 7.1—Magnitude of warm season (May–September) mean temperature differences during 2000–2021 relative to the long-term average for 1948–1999.

Table 7.1—Weighting factors utilized to scale area within grid cells based on Standardized Precipitation Index (SPI) magnitude of dry anomaly for cumulative analysis

SPI category	Scaling factor to represent severe dry (percent)
$SPI \geq 0$	0
$0 > SPI \geq -1$	65.90
$-1 > SPI \geq -2$	86.40
$-2 > SPI \geq -3$	97.90
$SPI < -3$	100

year during 2000–2021 was exposed to severe conditions during the warm season. With the temporally cumulative assessment, wet years (>0 SPI) do not reduce, nor contribute further, to MRDEI index values. This methodology was designed to reflect multiyear soil moisture trends reconstructed for the warm season that identified progressive reductions in soil moisture since 2000 across the Western United States without upward changes to that trajectory during individual wet years (Martin and others 2020; Williams and others 2020, 2022).

Statistical Assessment

All statistical analyses were performed in R software (version 4.3.1; R Core Team 2021). Precipitation was evaluated by assessing whether average SPI conditions changed through time within each respective 4-km² grid cell within various seasons and annually. Specifically, spring, warm season, and annual periods were evaluated to assess whether mean SPI differed during the recent (2000–2021) multidecadal period relative to the previous period (1948–1999). Analyses

in R used two-sample Welsh t-tests under the normality assumption with the *t.test* function (Student 1908). MRDEI was evaluated for spatial association with forest disturbances across the CONUS with descriptive and inferential approaches. First, the percentage of forested area impacted by wildfire, bark beetles, and wildfire-bark beetle co-occurrence, for 2000–2022 and 2017–2022, were classified by MRDEI exposure class and descriptively evaluated to see if disturbance increased with the increasing MRDEI exposure classes. Then, MRDEI was statistically evaluated for spatial association with respective wildfire, bark beetle, and wildfire-bark beetle co-occurrence footprints for 2000–2022 and 2017–2022. For this, the proportion of grid cells with each disturbance was assessed for equivalency or deviation relative to the baseline proportion of forested area grid cells that had lower (1–3) or higher (4–5) MRDEI classes. This statistical assessment occurred in R using a two-sample test for proportions with the *prop.test* function (Newcombe 1998).

RESULTS AND DISCUSSION

Assessment of Precipitation Exposure Changes to Forested Areas by Season

Forested areas across the CONUS were assessed for site-specific precipitation differences, across 228,581 forested 4-km² grid cells, by assessing mean spring, warm season, and annual SPI for the 2000–2021 and 1948–1999 multidecadal periods (table 7.2). Spring mean SPI was significantly different between periods for only 5 percent of CONUS forested areas, with drier conditions identified during the 2000–2021 period primarily within the Southwest and limited areas in the Southeast (fig. 7.2, table 7.2). Warm season mean SPI was significant between periods for 16 percent of the CONUS with differences being primarily in the Western United States where nearly half (48 percent) of forests were exposed to drier conditions during 2000–2021 (fig. 7.3, table 7.2). A minimal (<1 percent) of Central-Eastern

U.S. forests, limited to forested areas near the Great Lakes, were exposed to drier conditions. Similarly, annual mean SPI values indicated exposure to dry conditions was elevated across a substantial portion of the Western United States in the recent multidecadal period with significant differences being detected only in rare, isolated locations in the Central-Eastern United States. Assessments of warm season and annual SPI changed conditions found that locations with significant warm season precipitation differences also had annual precipitation changes. Thus, warm season SPI changes were depicted and used for indicator development as this season heavily influenced the annual changed precipitation results. Additionally, the locations with warm season SPI changes appeared spatially correlated with wildfire and bark beetle disturbance indicators, which suggested utility for climate-based indicator development.

Table 7.2—Forested area with significantly drier Standardized Precipitation Index mean values in 2000–2021 relative to the long-term average for 1948–1999

Season	Western United States		Central-Eastern United States		Conterminous United States	
	Area (millions of acres)	Percent of forested acres	Area (millions of acres)	Percent of forested acres	Area (millions of acres)	Percent of forested acres
Spring (March–May)	18.7	12	4.4	1	23.0	5
Warm season (May–September)	75.8	48	1.4	0.5	77.2	16
Annual (January–December)	59.3	37	0.6	0.2	59.9	13
Total acres	159.0		309.8		468.8	

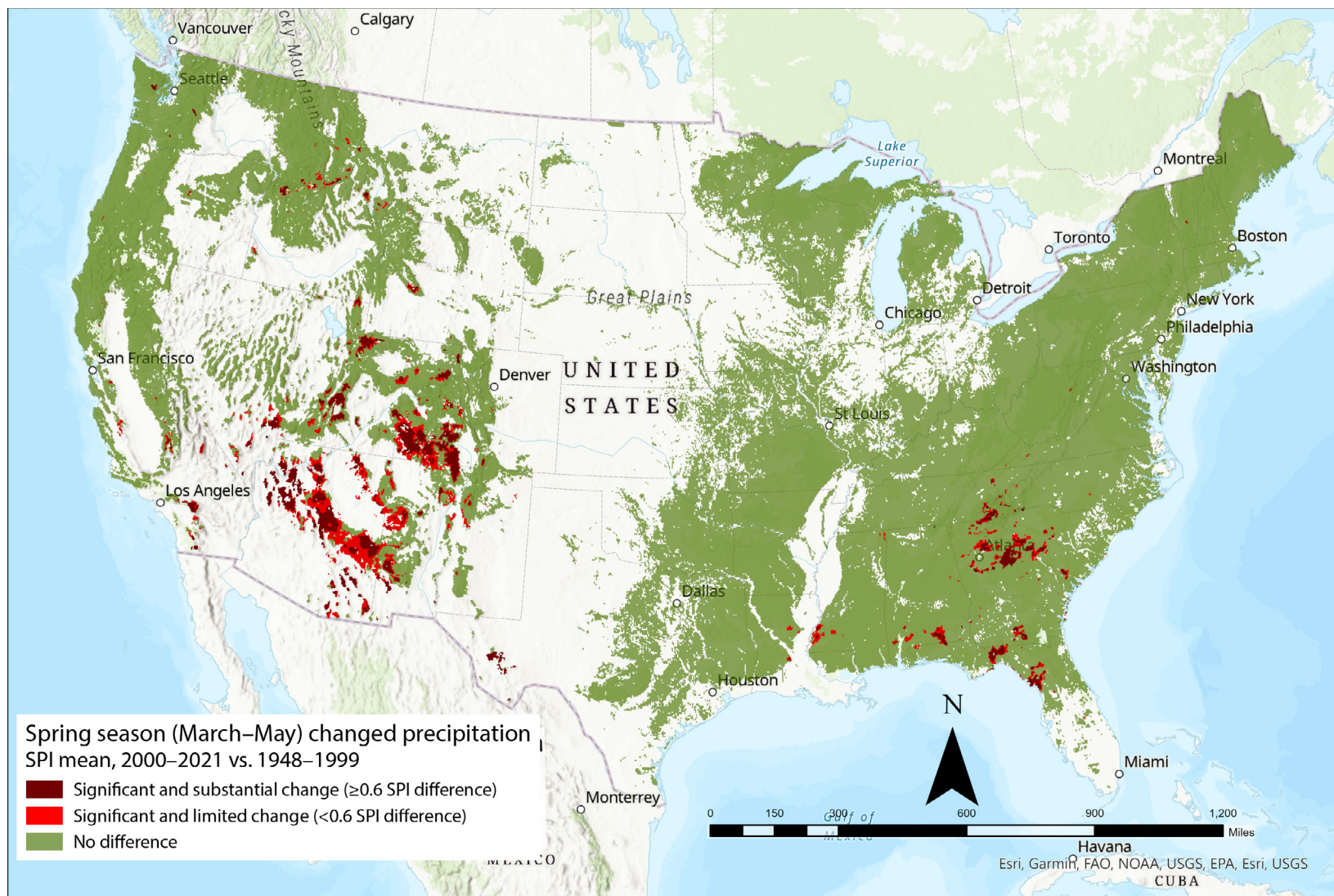


Figure 7.2—Forested areas with significantly drier mean Standardized Precipitation Index (SPI) values for spring (March–May) during 2000–2021 relative to the long-term average for 1948–1999.

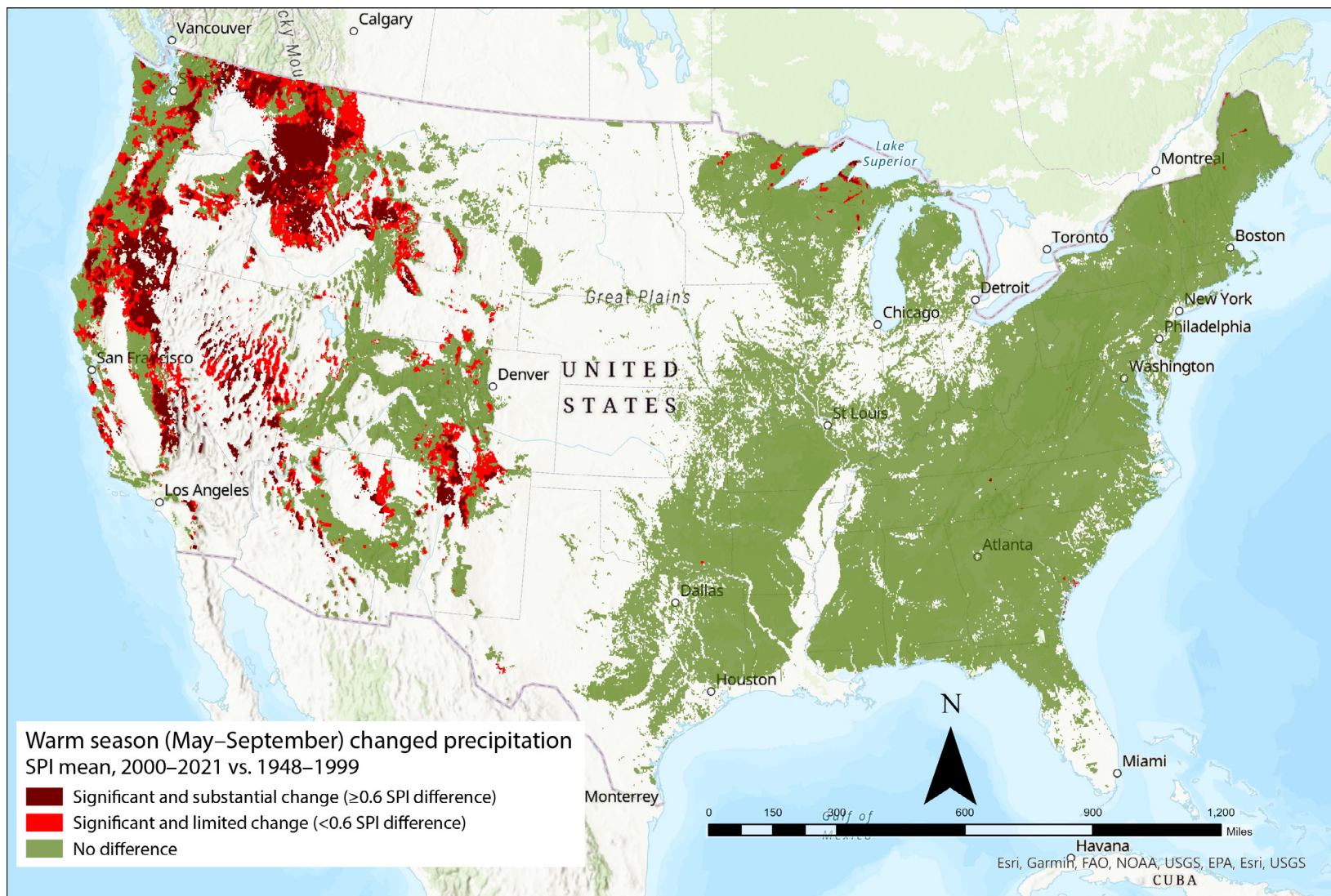


Figure 7.3—Forested areas with significantly ($p < .0001$) drier mean Standardized Precipitation Index (SPI) values for the warm season (May–September) during 2000–2021 relative to the long-term average for 1948–1999.

Assessment of Wildfire, Bark Beetle, and Disturbance Co-Occurrence in Forested Areas, 2000–2022

Wildfire and bark beetle disturbances, respectively, impacted 12 percent of CONUS forested area in 2000–2022 and co-occurred across 3 percent of this area (table 7.3). These disturbances occurred extensively across the Western United States, where approximately one-third of forested area had respective wildfire and bark beetle disturbances with a 7-percent forested area having both disturbances documented (fig. 7.4). Bark beetle agents that contributed most to the bark beetle footprint layer included mountain pine beetle (*Dendroctonus ponderosae* Hopkins; 26.2 million acres) and fir engraver (*Scolytus ventralis* LeConte; 15.4 million acres) (table 7.4). In the Central-Eastern United States, wildfire and bark beetle disturbances were rare and only impacted 2 percent of total forested area. During 2017–2022, forest disturbance was observed primarily in Western U.S. forested areas while Central-Eastern U.S. forested areas had substantially less impact (fig. 7.5). Other forest disturbances beyond the scope of this analysis, such as native and nonnative insect defoliators and pathogens were commonly recorded in Central-Eastern U.S. forests.

Forested areas with wildfire and bark beetle disturbances were documented across similar magnitude of area in the Western United States; however, bark beetle records include live and dead trees within damaged areas as disturbance being mapped is commonly spatially discontinuous. After adjustment (see Egan and others 2019), calculations that include the severity of bark beetle-caused tree mortality were reduced to 15.2 million acres of aggregate tree mortality from bark beetles, which totaled only one-third of the wildfire disturbance area footprint. Forested areas that experienced both disturbance agents primarily had bark beetle activity initially followed by subsequent wildfire (table 7.3).

Forest disturbances occurred across the Western United States at a similar scale as warm season changes in SPI conditions were identified during the recent 2000–2021 period relative to the long-term average during 1948–1999 (figs. 7.2 and 7.3). Similarly, disturbances rarely occurred in the majority of Central-Eastern U.S. forested areas that did not exhibit exposure to reduced precipitation conditions. This confirmed that the season Holden and others (2018) identified as being important for wildfire area burned was also important for bark beetle disturbances and the co-occurrence of bark beetles and wildfire. Thus, warm season was selected for creation and analysis of the MRDEI indicator variable.

Table 7.3—Forested area with wildfire and bark beetle disturbances documented in 2000–2022 and 2017–2022

Disturbance (period)	Western United States		Central-Eastern United States		Conterminous United States	
	Area (millions of acres)	Percent of forested acres	Area (millions of acres)	Percent of forested acres	Area (millions of acres)	Percent of forested acres
Bark beetles (2000–2022)	54.9	35	2.5	1	57.4	12
Wildfire (2000–2022)	48.8	31	7.4	2	56.2	12
Bark beetle and wildfire overlap (2000–2022)	11.6	7	0.3	0	11.8	3
Bark beetles (2017–2022)	16.6	10	1.2	0.4	17.8	4
Wildfire (2017–2022)	23.1	15	5.1	2	28.3	6
Bark beetle and wildfire overlap (2017–2022)	2.2	1	0	0	2.2	0.5

Table 7.4—Top five bark beetle mortality agents recorded through the national Insect and Disease Survey (IDS) across the conterminous United States, 2000–2022

Bark beetle common name	Bark beetle scientific name	Number of IDS records	IDS impacted area ^a (millions of forested acres)
Mountain pine beetle	<i>Dendroctonus ponderosae</i> Hopkins	1,281,233	26.2
Fir engraver	<i>Scolytus ventralis</i> LeConte	337,659	15.4
Western pine beetle	<i>D. brevicomis</i> Hopkins	274,859	6.4
Pinyon ips	<i>Ips confusus</i> LeConte	60,833	5.2
Douglas-fir beetle	<i>D. pseudotsugae</i> Kirby	443,792	5.0
Total		2,398,376	58.2

^a Does not adjust for overlap between species or severity of mortality in impacted forest areas.

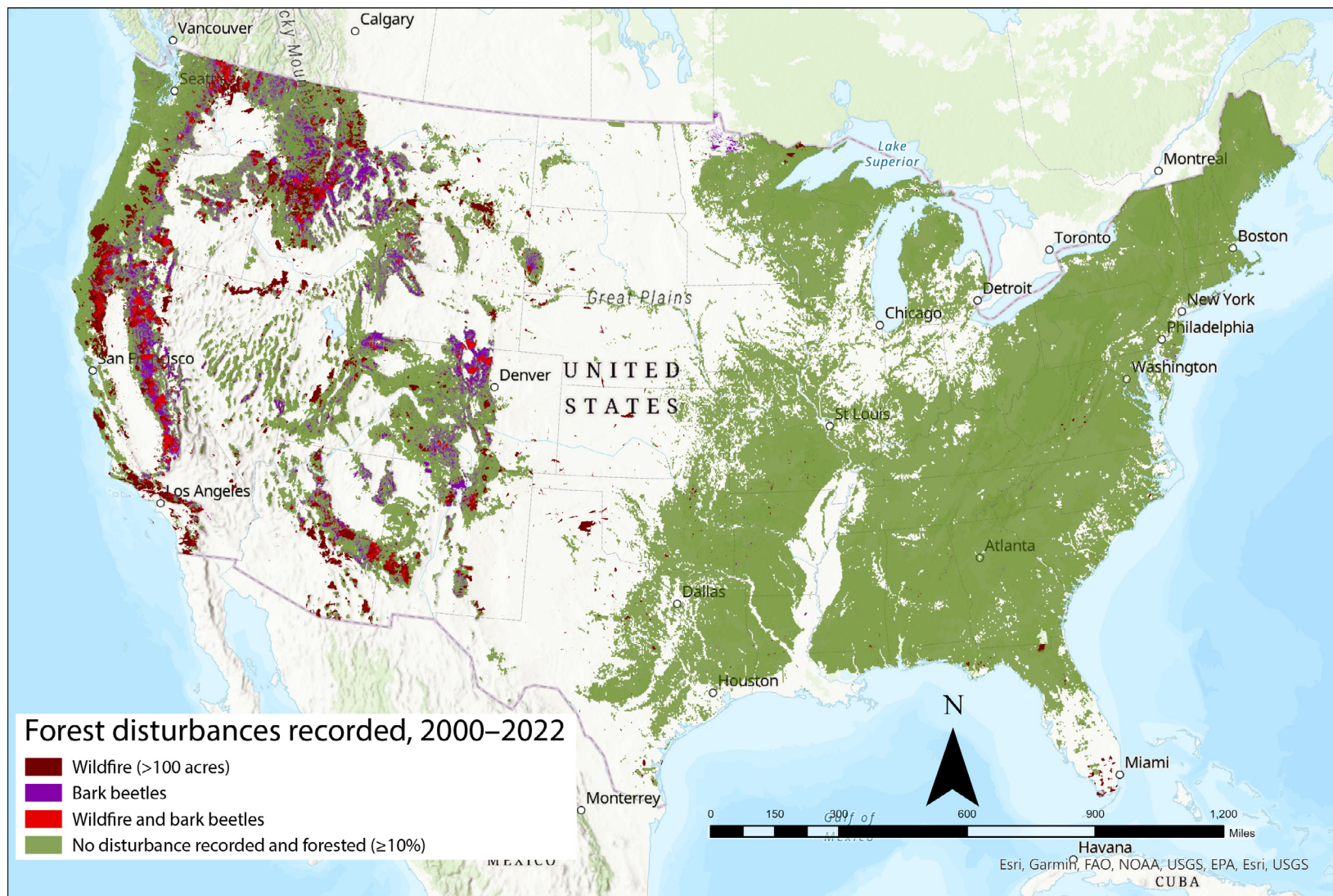


Figure 7.4—Wildfire and bark beetle forest disturbances recorded across the conterminous United States, 2000–2022.

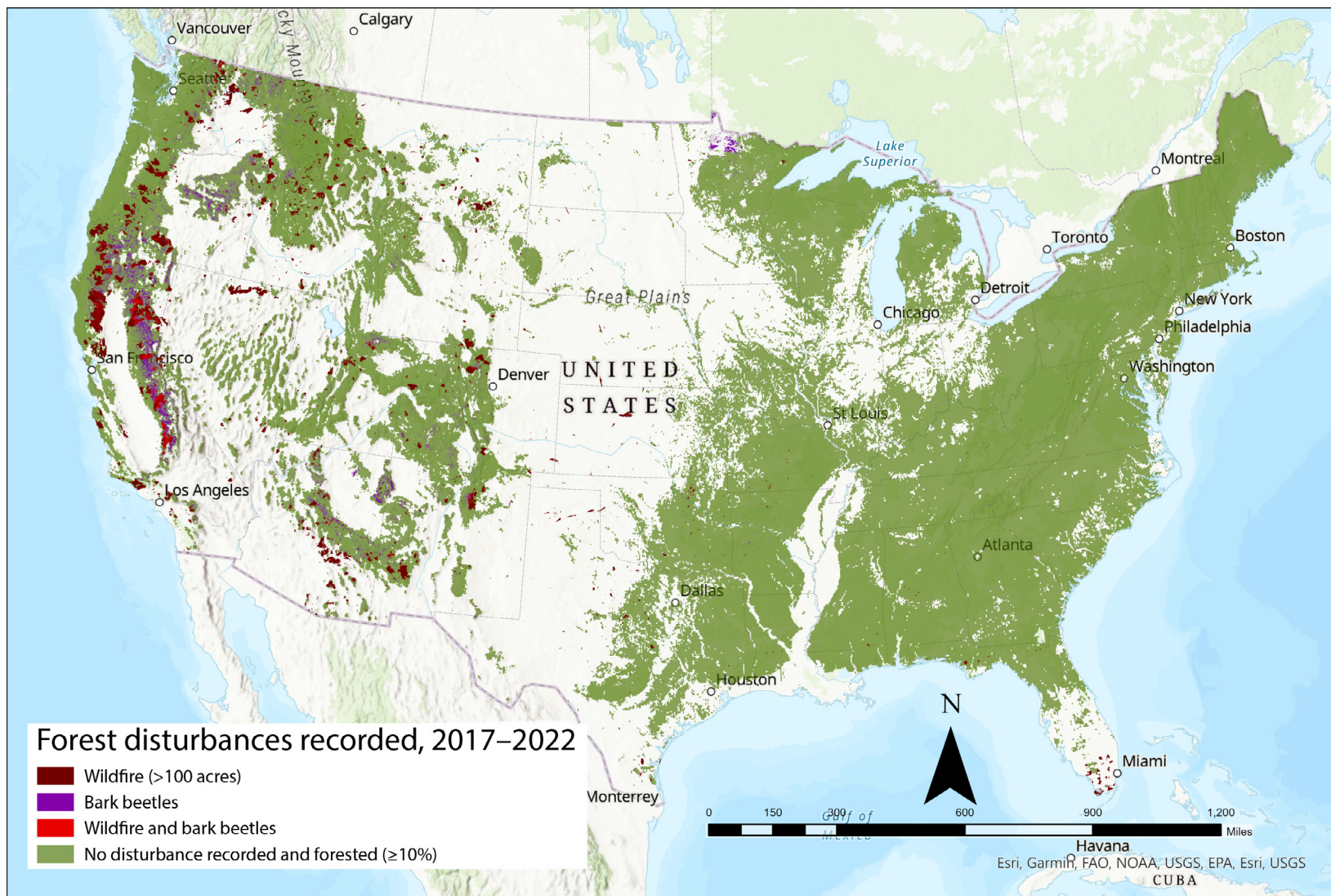


Figure 7.5—Wildfire and bark beetle forest disturbances recorded across the conterminous United States, 2017–2022.

Multidecadal Repeat-Dryness Patterns Across the Conterminous United States, 1980–2021

The MRDEI represents the frequency of repeat dry, warm season conditions across multidecadal time periods for the CONUS. During the most recent period (2000–2021), >80 percent of forested areas in the Western United States experienced >40 percent frequency of repeat dryness, whereas the Central-Eastern United States had only 5 percent exposure (table 7.5, fig. 7.6). Interestingly, the MRDEI for the multidecadal period of 1980–1999 shows that climatic conditions were opposite relative to 2000–2021 as repeat-dryness exposure during the warm season occurred throughout the Central-Eastern United States and rarely in the Western United States (table 7.5, fig. 7.7). As such, MRDEI based on multidecadal dry conditions in 2000–2021 is most appropriate for the Western United States while assessment of Central-Eastern U.S. locations prone to repeat-dryness conditions could be informed by the 1980–1999 MRDEI. However, formal validation to assess association between the 1980–1999 MRDEI with forest disturbances is still needed, and disturbance records from that period were not standardized nationwide.

Validation of MRDEI Spatial Associations with Wildfire, Bark Beetle, and Co-Occurring Forest Disturbances

MRDEI was first evaluated for spatial association with forest disturbances for 2000–2022 and 2000–2017 by assessing whether the percentage of forest area impacted by wildfire, bark beetle, and wildfire/bark beetle co-occurrences increased across the higher MRDEI classes that depicted greater exposure to warm season dry conditions. The data for the CONUS suggest this (fig. 7.8A); however, the majority of forested areas in the CONUS are found within the Central-Eastern United States, which were only minimally exposed to repeat-dryness conditions during 2000–2021 (table 7.5, fig. 7.6). Considering only the Western United States where the vast majority of disturbance occurred, each forest disturbance group had the percentage of forested area impacted increase in conjunction with increased MRDEI classes (fig. 7.8B). This included >35 percent of all forested area exposed to MRDEI classes 4 and 5 being impacted by respective wildfire or bark beetle disturbances (fig. 7.8B). Similarly, the co-occurrence of wildfire and bark beetle disturbances was prevalent in forested areas exposed to MRDEI classes 4 and 5 (fig. 7.8).

While disturbances were proportionally greater in the highest MRDEI exposure classes, they occurred in all MRDEI classes in 2000–2022, with ample bark beetle activity documented in classes 1 and 2 (fig. 7.8B). This showcases that extreme weather and shorter repeat-dryness durations were associated with disturbance, such as for bark beetle activity that occurred at the

Table 7.5—Multidecadal Repeat-Dryness Exposure Index (MRDEI) class distribution across forested areas, 2000–2021 and 1980–1999

MRDEI classes	Western United States		Central-Eastern United States		Conterminous United States	
	Area (millions of acres)	Percent of forested acres	Area (millions of acres)	Percent of forested acres	Area (millions of acres)	Percent of forested acres
2000–2021						
Class 1: <30% exposure	2.0	1	191.2	62	193.2	41
Class 2: 30–39.9% exposure	28.9	18	101.6	33	130.5	28
Class 3: 40–49.9% exposure	78.9	50	16.1	5	95.0	20
Class 4: 50–59.9% exposure	46.0	29	0.7	0	46.7	10
Class 5: ≥60% exposure	3.2	2	0.0	0	3.2	1
1980–1999						
Class 1: <30% exposure	127.6	80	24.0	8	151.6	32
Class 2: 30–39.9% exposure	26.8	17	99.8	32	126.6	27
Class 3: 40–49.9% exposure	4.5	3	122.0	39	126.5	27
Class 4: 50–59.9% exposure	0.1	0	57.7	19	57.8	12
Class 5: ≥60% exposure	0	0	6.2	2	6.2	1

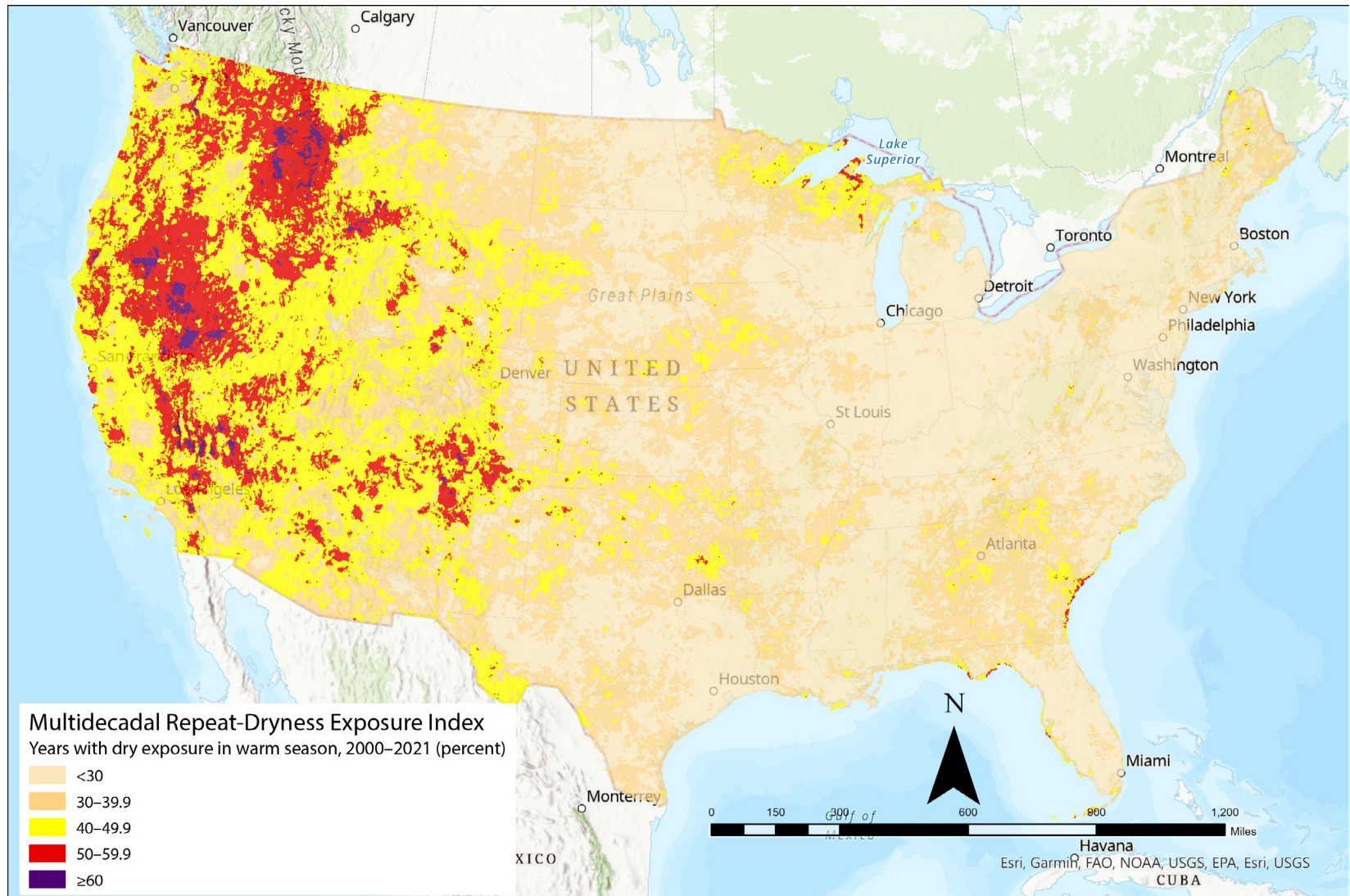


Figure 7.6—Multidecadal Repeat-Dryness Exposure Index showcasing recurring dry conditions for the warm season (May–September) across the conterminous United States, 2000–2021.

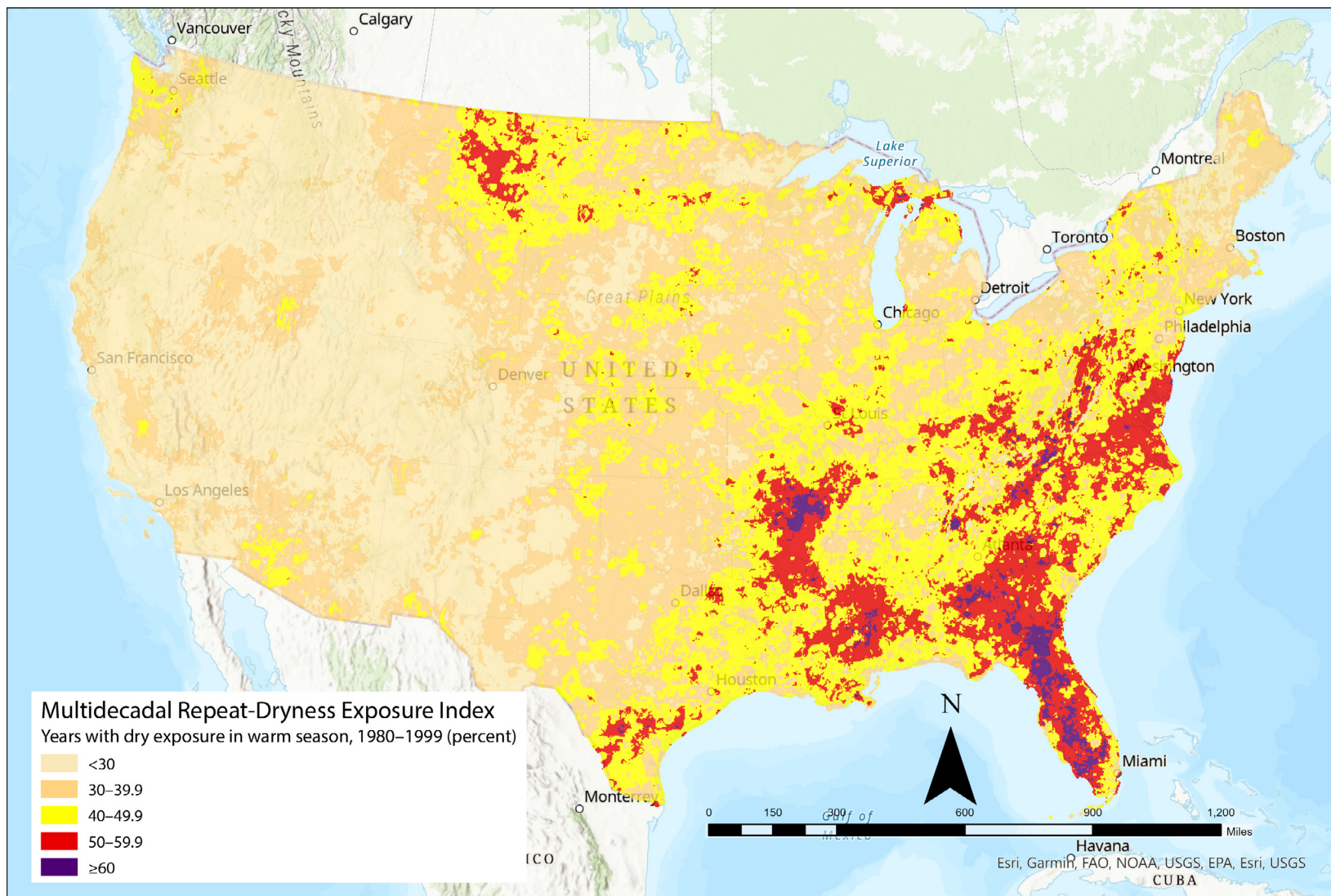


Figure 7.7—Multidecadal Repeat-Dryness Exposure Index showcasing recurring dry conditions for the warm season (May–September) across the conterminous United States, 1980–1999.

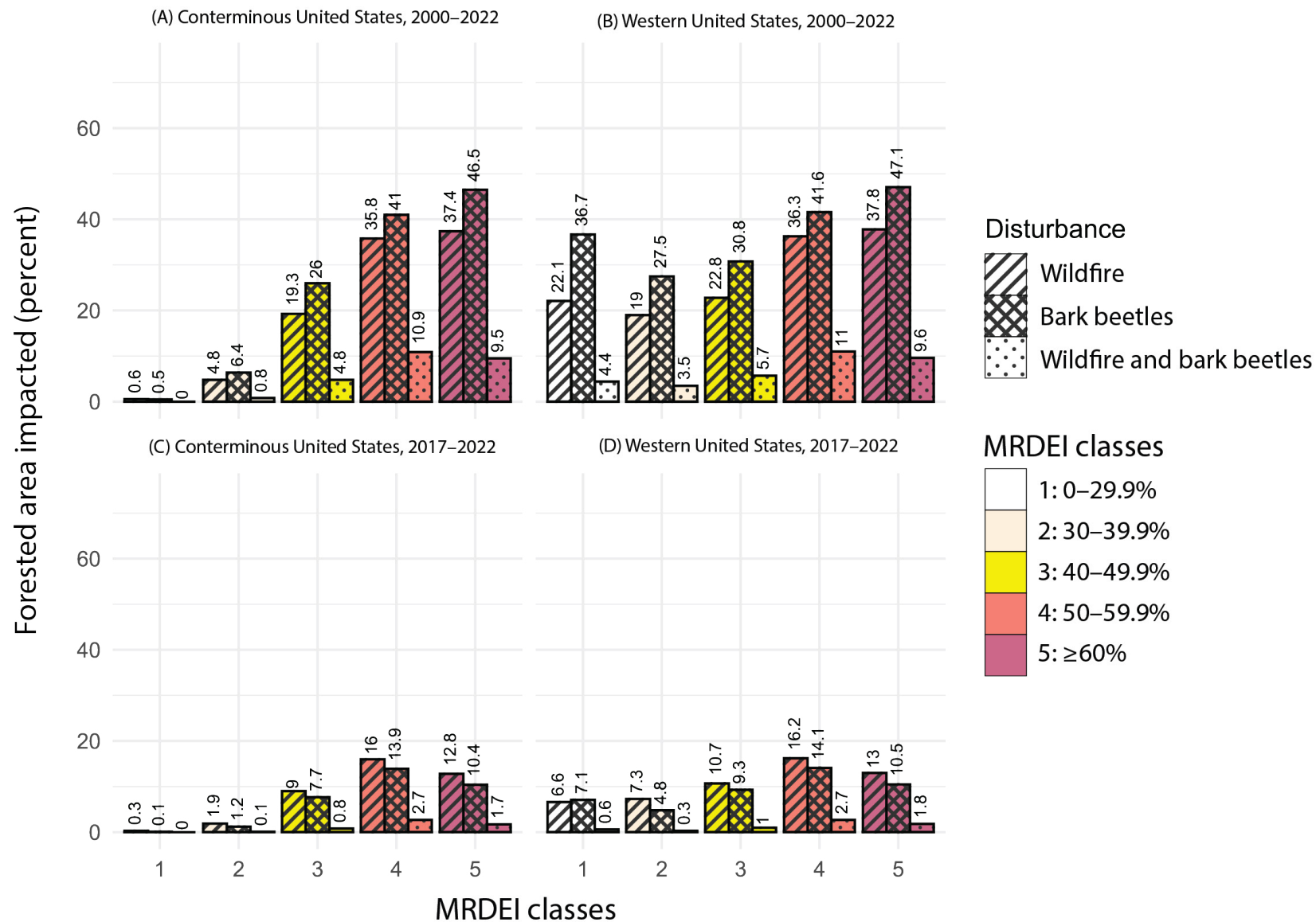


Figure 7.8—Percentage of forested area, stratified by Multidecadal Repeat-Dryness Exposure Index (MRDEI) classes, impacted by disturbance across 2000–2022 (A and B) and 2017–2022 (C and D) periods for conterminous U.S. (A and C) and Western U.S. (B and D) forested areas.

beginning of the multidecadal period in early 2000s. More recent disturbance records for 2017–2022 provide a more reasonable timespan for MRDEI assessment as it represents disturbance proportions in MRDEI classes that had sufficient time for repeat-dryness exposure. For 2017–2022, bark beetle and wildfire disturbances increased with increasing MRDEI classes. When aggregated, forested areas across the Western United States exposed to MRDEI classes 4 and 5 had twice the percentages of area impacted than those with reduced exposure rates in classes 1 and 2 (fig. 7.8D).

MRDEI was next evaluated for spatial association with forest disturbances by statistically evaluating whether the proportion of grid cells with disturbance deviated from a baseline proportion of forested area that was exposed to either lower (1–3) or higher (4–5) MRDEI classes (fig. 7.9). All disturbance types, for both 2000–2022 and recent 2017–2022 time periods, occurred at significantly ($p < .0001$) lower proportions than the forested area baselines

within lower exposure MRDEI classes and at significantly higher proportions than baselines within the higher exposure MRDEI classes for the Western United States and the CONUS (fig. 7.9). Interestingly, the co-occurrence of wildfire and bark beetle footprints in the Western United States had the greatest deviation from the forested baseline in MRDEI classes 4 and 5, suggesting disturbance co-occurrence was heavily impacted by forest exposure to repeat dryness represented by MRDEI (figs. 7.9B and D).

Overall, both the general and the statistical assessment of MRDEI classes with forest disturbances confirmed higher MRDEI classes were spatially associated with increased disturbance occurrence. These efforts validate that MRDEI is a useful tool for identifying areas predisposed to repeat-dryness occurrence during the warm season and can assist forest managers by highlighting areas with climate-induced vulnerability to wildfire, bark beetle, and co-occurring forest disturbances.

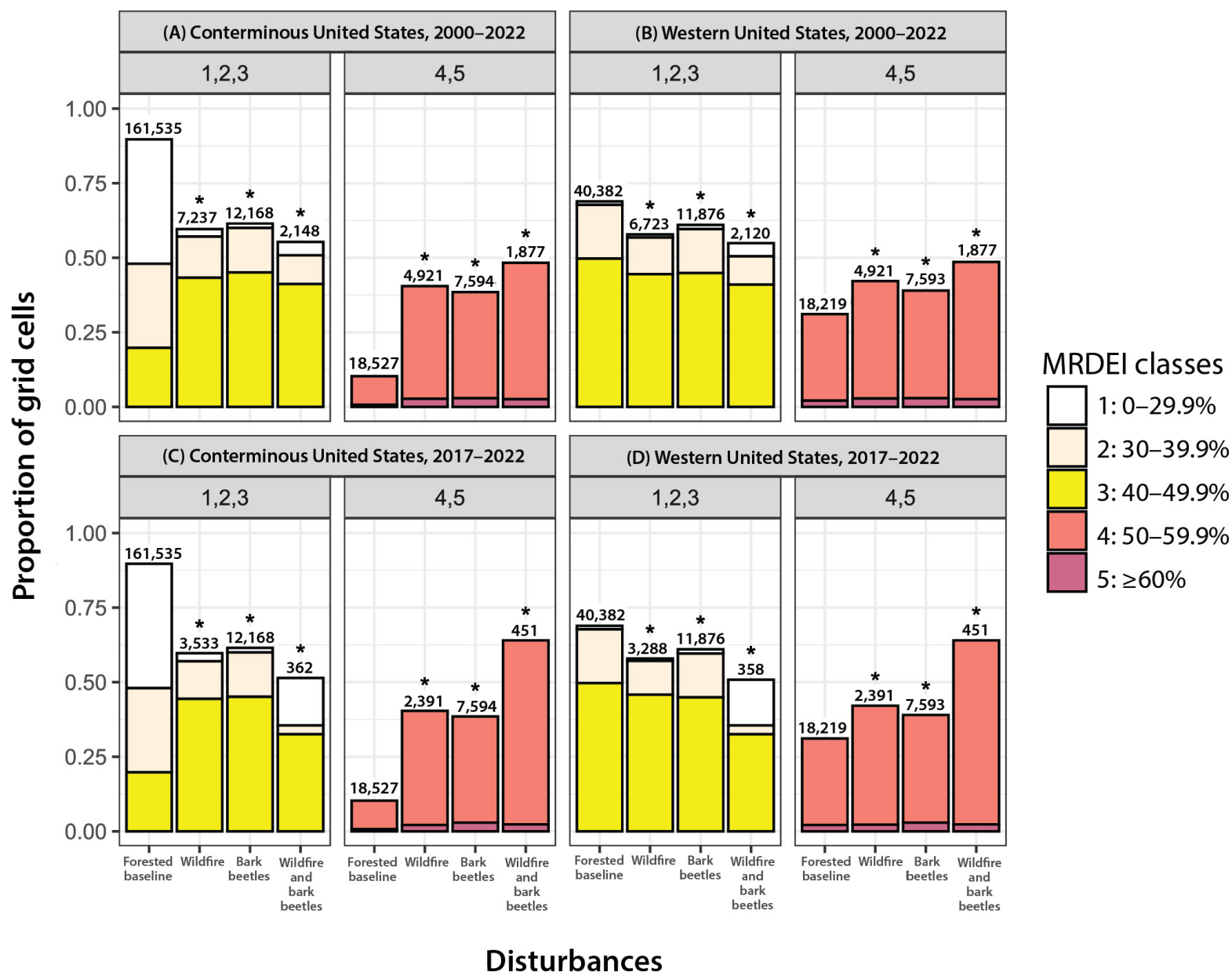


Figure 7.9—The proportion of forested area baseline and disturbance grid cells that had Multidecadal Repeat–Dryness Exposure Index (MRDEI) class exposure of <50 percent (classes 1–3 based on 2000–2021 MRDEI) and proportion of grid cells that had MRDEI class exposure of ≥50 percent (classes 4–5) impacted by disturbance during 2000–2022 (A and B) and 2017–2022 (C and D) for the conterminous United States (A and C) and Western United States (B and D). * = significant deviation from baseline forested conditions for disturbance type while numbers underneath indicate the total number of grid cells within disturbance categories.

CONCLUSIONS

Often, forest health assessments focus on a temporally discrete disturbance event in limited spatial forested area to identify absolute weather and climatic thresholds that were catalysts and/or facilitators of disturbance occurrence and severity. This study's approach was the opposite. For all forested areas in the CONUS, this study identified whether a spatial association existed between wildfire and bark beetle records with repeated exposure to dry warm season climatic conditions represented by MRDEI classes. This approach identified site-specific locations in the CONUS that experienced chronic exposure to reduced precipitation during the warm season and demonstrated that wildfires, bark beetles, and co-occurrence of these disturbances are associated with the rate of dry exposure.

With this effort, the MRDEI has been validated by independent disturbance records to showcase areas in the CONUS with repeat exposure to warm season dryness and, where vegetation has composition and structure susceptible to disturbance, areas that are more vulnerable to wildfire and bark beetles due to this exposure. This information is critical for strategic resource management planning efforts to prioritize forested areas because it identifies locations prone to repeat dry exposure where climate adaptation management tactics may be needed to adjust forest density, structure, and/or composition in response to reduced precipitation (Fettig and others 2022b). Specifically, MRDEI was built as a climate-based indicator to be used as an overlay for mid-, broad-, and national-level assessments

including the National Insect and Disease Forest Risk Assessment, Climate Risk Viewer tool, regional out-year planning efforts, and forest plan revision assessments, as well as State and Tribal forest action plans (Krist and others 2014, USDA Forest Service 2023).

Finally, this study identified that compounding wildfire and bark beetle disturbances co-occurred in numerous locations across the Western United States with higher MRDEI classes during 2000–2022. Most areas with disturbance co-occurrence experienced bark beetle activity prior to wildland fire incidents. Standing-dead fuels associated with prior bark beetle-caused tree mortality, under certain fire weather conditions, have been associated with unexpected and extreme fire behavior (Fettig and others 2022c, Moriarty and others 2019). This suggests there may be further utility for the aggregated bark beetle records as an indicator of prior disturbance. This indicator may provide useful information related to the risk of wildfire occurrence or potential for extreme fire behavior. Further investigation into the associations between bark beetle disturbances and wildland fire behavior is warranted.

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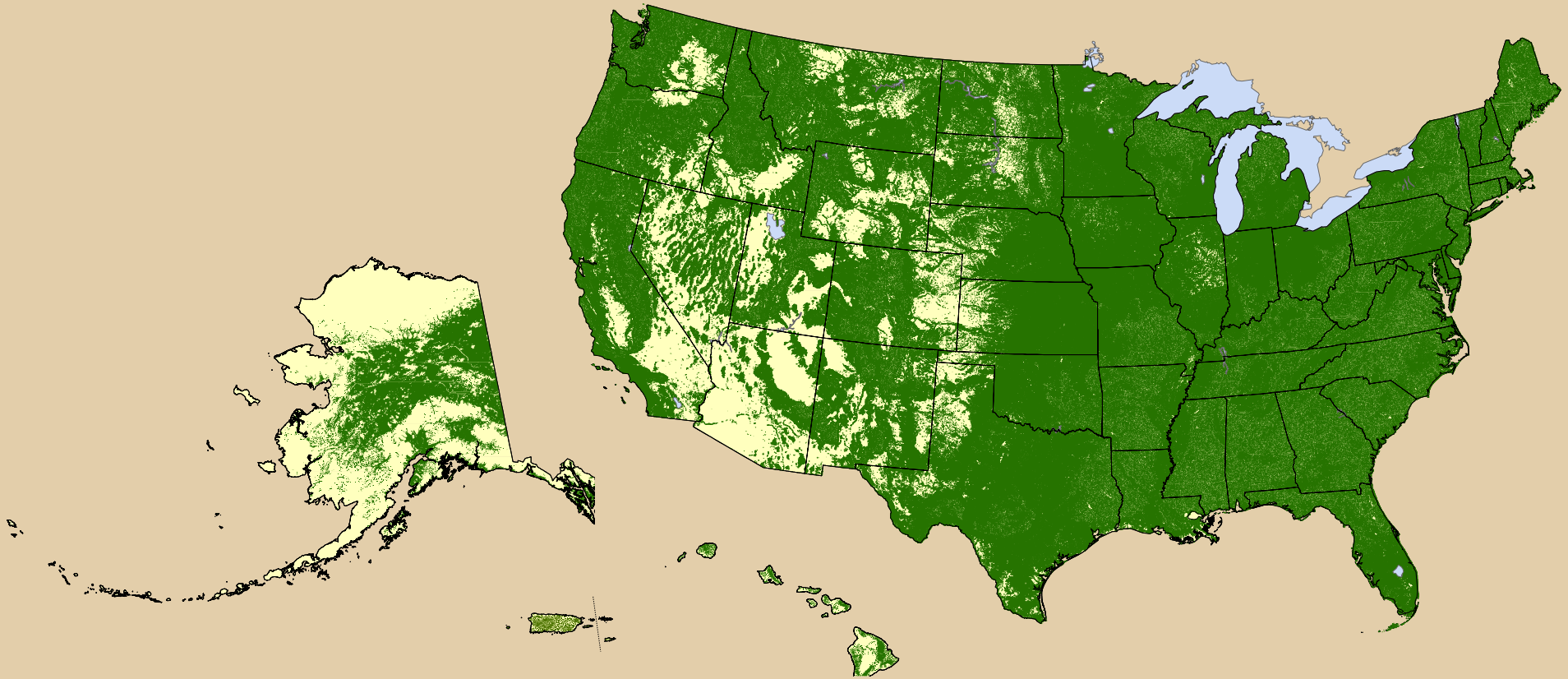
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The Forest Health Monitoring Program of the U.S. Department of Agriculture, Forest Service produces an annual national report that presents recent forest health status and trends from a national or multistate regional perspective and introduces new techniques to analyze forest health condition. In this 23rd edition of annual reports, national Insect and Disease Survey (IDS) data are used to identify recent spatial patterns of areas affected by insects and diseases. Satellite data are employed to detect geographic patterns of forest fire occurrence. Data collected by the Forest Inventory and Analysis (FIA) Program are used to explore regional differences in tree mortality. National Land Cover Database (NLCD) maps are used to detect trends in forest fragmentation across the conterminous United States. Exposure of forests to drought was summarized using data from the Parameter-elevation Regressions on Independent Slopes Model (PRISM) Climate Group and the FIA Program. Association of multidecadal repeat dryness with wildfire and bark beetle disturbance was explored for the conterminous United States using data from NLCD; IDS; Wildland Fire Management Research, Development, and Application; Wildland Fire Interagency Geospatial Services; Monitoring Trends in Burn Severity; and PRISM Climate Group.

Keywords—Change detection, disturbance, drought, fire, forest fragmentation, forest health, forest insects and disease, tree mortality.



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