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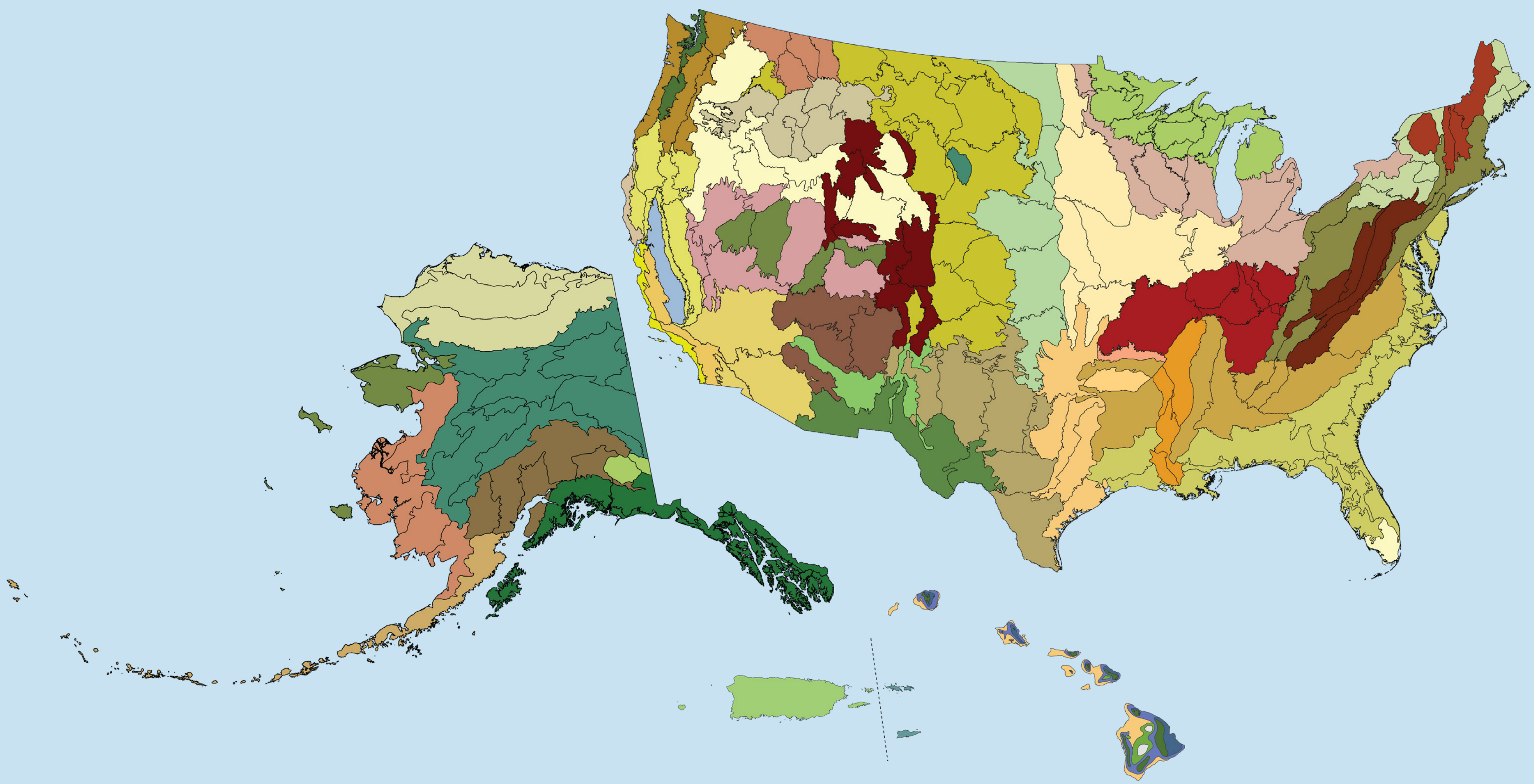
Forest Health Monitoring: National Status, Trends, and Analysis 2024

EDITORS: Karun Pandit and Simone Lim-Hing



FRONT COVER MAP: Ecoregion provinces and ecoregion sections for the conterminous United States (Cleland et al. 2007) and for Alaska (Spencer et al. 2002), and ecoregions within the islands of Hawaii, 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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ABSTRACT

The Forest Health Monitoring program of the U.S. Department of Agriculture, Forest Service produces an annual national report, which presents recent forest health status and trends from a national or multistate regional perspective and introduces new techniques to analyze forest health condition. This 24th edition of the annual report presents mapping techniques applied to investigate 2023–2024 pine mortality events in Mississippi and Louisiana based on satellite data and the national Insect and Disease Survey. A review of declines in whitebark pine (*Pinus albicaulis*) and limber pine (*P. flexilis*) is discussed based on available literature. The Forest Inventory and Analysis program's Nationwide Forest Inventory data are used to explore recent trends in American beech (*Fagus grandifolia*) demography and to compare the change in demographic variables compared to other trees in the forests. Satellite data are employed to quantify fire occurrences in 2023 in a geographical context across the conterminous United States, Alaska, Hawaii, and the Caribbean territories and in a temporal context against two decades of previously collected data.

Keywords—Demography, fire, forest health, insect and disease, pine mortality, spatial mapping, tree mortality

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EXECUTIVE SUMMARY

Forest ecosystems are considered healthy if they can maintain their vigor, organization, and autonomy over time; remain resilient to stress; and meet the desired management objectives without compromising sustainability (Costanza 1992, Kolb et al. 1994, Raffa et al. 2009, Teale and Castello 2011). Healthy forests are important for humans' current and future well-being (Edmonds et al. 2011, Trumbore et al. 2015). Long-term and large-scale monitoring via forest health indicators allows for the consistent assessment of the status, change, and trends in forest ecosystems (Riitters and Tkacz 2004). The Forest Health Monitoring (FHM) program of the U.S. Department of Agriculture, Forest Service, in cooperation with researchers within and outside the Forest Service and with State partners, assesses the status and trends of U.S. forests' health in the "Forest Health Monitoring: National Status, Trends, and Analysis" report (ch. 1). The 2024 FHM national report is the 24th edition in the annual series of reports. This report offers forest health analyses at the national and multistate regional perspective, applying analytical techniques to evaluate forest health indicators like tree mortality and forest structure, as well as assessment of recent wildfires representing national-level forest health trends.

Extreme weather events like flash droughts and hot droughts often lead to foliar damage and tree mortality, threatening overall forest health condition and resilience (Bennett et al. 2023, Christian et al. 2019, Dewez et al. 2024, Klein et al. 2022, Lawal et al. 2024). Researchers assessed a mass pine (*Pinus* spp.) mortality event across Louisiana and Mississippi in 2023–2024 following hot-drought conditions during the summer and fall of 2023 (ch. 2), which were characterized by sustained high temperature maxima, low humidity, and little precipitation for several consecutive months. Using Google Earth Engine and Sentinel-2 imagery (Gorelick et al. 2017), they identified "red-dead" pine crowns and calculated 1-year change in the Normalized Difference Vegetation Index and then applied a masking technique using the 2021 National Land Cover Database to isolate beetle-killed pines. They validated findings by comparing them with masked and resampled very-high-resolution WorldView-3 satellite imagery. Results showed 54 700 ha of large patch pine died in Mississippi and 2350 ha of pine died in Louisiana from beetles following the hot-drought event. An accuracy of 87.6 percent was achieved with the Sentinel-2-based bark beetle mortality assessment when validated against the WorldView-3-derived product. The workflow used in the study minimized typical protocol for manual delineation of beetle-killed pine.

Recent declines of whitebark pine (*P. albicaulis*) and limber pine (*P. flexilis*) in the Western United States have been attributed to abiotic stressors, pathogens like nonnative white pine blister rust (*Cronartium ribicola*), and insects (Tomback et al. 2011, 2022; U.S. Fish and Wildlife Service 2022). Researchers summarized insights into the mechanisms and indicators of whitebark and limber pine declines after reviewing previous publications including chapters from FHM national reports and peer-reviewed papers using Forest Inventory and Analysis (FIA) data published between 2005 and 2022 (ch. 3). Most of the FHM project findings suggested that limber pine was increasingly impacted by the same threats as whitebark pine (Cleaver et al. 2022) and raised a question on whether overall mortality rate in these pines will wane with the decline in mountain pine beetle epidemics (Burns et al. 2012, Eskelson and Monleon 2018, Fins and Hoppus 2013, Legg et al. 2016). Two studies based on FIA data applied indicators of mortality including (1) numbers of live and dead trees and (2) growth and mortality rates by volume to assess mortality in these pine species (Goeking and Izlar 2018, Goeking and Windmuller-Campione 2021). Low net growth rates and high mortality rates observed for both pines over the most recent decade suggest that the large number of dead trees represents recent high mortality rather than long-standing dead trees (Goeking and Windmuller-Campione 2021).

Detecting any deviations in forest demographic variables from their expected spatiotemporal patterns and identifying potential stressors associated with these trends can inform ongoing and future forest management activities (Clark et al. 2017, Jakovac et al. 2022, Sharma et al. 2022, Venturas et al. 2021). American beech (*Fagus grandifolia*), a major component of deciduous forest ecosystems in eastern North America (Stephanson and Coe 2017), has been impacted by biotic agents like beech bark disease, along with land conversions and climate conditions in recent years, causing mortality at a massive scale and a diminishment in the quality of surviving trees (Kasson and Livingston 2012, Stephanson and Coe 2017). FIA's Nationwide Forest Inventory (NFI) data were used to analyze recent trends in beech demography by comparing estimates from the current inventory period (2007–2023) to a previous inventory period (2001–2018) and by comparing these trends with that of other species in the forests (ch. 4). Current inventory revealed high live tree density and basal area of American beech in the Adirondack Mountains in New York, northern Pennsylvania, and most of New England. Beech density for small trees and seedlings increased from past inventory and was relatively stable for large trees. Results also showed a significantly higher increase in beech seedlings and small and medium-sized beech trees compared to other species.

Forest fire incidents beyond their historic range can have a long-lasting impact on forest health (Lundquist et al. 2011, Stephens et al. 2018). Detecting spatial and temporal patterns of recent forest fire incidents can help identify areas that would benefit from specific management and research (ch. 5). Satellite-detected forest fire occurrences in 2023 for the conterminous United States were the eighth lowest since complete data collection began in 2001, which was 33 percent below the mean for the previous 22 years. Alaska experienced a 69-percent decrease in forest fire occurrences compared to the 22-year average whereas fire occurrences in Hawaii were slightly fewer but not significantly different from the previous 22 years' average. In 2023, 11 forest fire occurrences were detected in Puerto Rico and the U.S. Virgin Islands, which was a 120-percent increase from the previous year. No ecoregions in 2023 had very high or higher fire occurrence densities, but 262A–Great Valley in central California (11.7 fire occurrences/100 km^2 of tree canopy cover), M261A–Klamath Mountains of northwestern California and southeastern Oregon (9.4 fire occurrences), and 251–Flint Hills in eastern Kansas and northeastern Oklahoma (7.2 fire occurrences) had high fire occurrence densities. Geographic hot spot analyses revealed very high fire occurrence density hot spots in M261A–Klamath Mountains (northwestern California and southeastern Oregon), 262A–Great Valley and M261C–Northern California Interior Coast Ranges (north-central California), and 232B–Gulf Coastal Plains and Flatwoods (southwestern Georgia).

The FHM program continues to evaluate a broad range of forest health indicators using a wide variety of data and techniques in cooperation with forest health specialists and researchers inside and outside the Forest Service. These assessments involve understanding the presence of agents and stressors and the responses of forests to these agents and stressors. 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.

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CHAPTER 1

Introduction

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FOREST HEALTH

Forests and woodlands in the United States cover approximately 36 percent (331 million ha) of the Nation's land area (Oswalt et al. 2026). These forests contribute to the health and well-being of current and future generations through a myriad of goods and services while safeguarding biological richness and ecosystem resilience (Karjalainen et al. 2010, McGinley et al. 2023). Some of these benefits include timber and nontimber forest products, soil and water resource protection, employment generation, recreation, and carbon sequestration and storage (Caldwell et al. 2023, Canham et al. 2024, McGinley et al. 2023). The amount, timing, and durability of forest benefits like these and others are dependent on forest health conditions. The socioeconomic benefits and ecological processes of these forest ecosystems are continually challenged by both long-standing and evolving stressors such as insects and disease, drought, fragmentation, and forest conversion. These stressors, as well as their effects on forest ecosystems, vary by space and time. They also interact with each other, making it challenging to establish forest health baselines and to identify departures from normal forest ecosystem functioning (Potter et al. 2024, Riitters and Tkacz 2004).

The concept of forest health has a universal appeal, but it is often viewed with different perspectives. Most of the available definitions of forest health can be grouped as representing either an ecological or a utilitarian perspective (Kolb et al. 1994, Teale and Castello 2011). The ecological perspective evaluates forest health in terms of its vigor (productivity), representation of ecosystem components (organization), functioning of inherent processes, and resilience to stressors (Costanza 1992, Edmonds et al. 2011, Kolb et al. 1994, Raffa et al. 2009). The utilitarian perspective, on the other hand, measures forest health based on how well the forest management objectives are met (Kolb et al. 1994). The latter definition is easy to apply when there is a single unambiguous management objective, such as wood production or the maintenance of wilderness; however, it can be complicated when there are multiple management objectives (Edmonds et al. 2011, Teale and Castello 2011). Teale and Castello (2011) incorporated both ecological and utilitarian perspectives of forest health into their two-component definition, wherein a healthy forest must be sustainable in terms of its size structure and observed mortality while also meeting landowner objectives without compromising the sustainability component.

THE FOREST HEALTH MONITORING PROGRAM

Forest Health Monitoring (FHM) is a national program designed to deliver actionable information on U.S. forest health through analysis, data integration, and decision support (FHM 2025). The FHM program is implemented through a partnership encompassing the U.S. Department of Agriculture, Forest Service; State foresters; other State and Federal agencies; and academic institutions. The program has three core components, which are interlinked and provide feedback to each other:

- **Analysis—**Evaluate forest health trends and project future conditions using an indicator-based approach, at various spatial and temporal scales.
- **Data integration—**Integrate a variety of high-quality data streams to build a rich dataset for forest health analyses.
- **Decision support—** Translate findings from the forest health analysis into meaningful forest health information using different tools and approaches.

The FHM program manages and coordinates its efforts through four "megaregions" (Eastern, Southern, Interior West, and West Coast) (FHM 2025). The Eastern and Southern megaregions correspond with the respective Forest Service regions. The Interior West megaregion includes four Forest Service regions (Northern, Rocky Mountain, Southwestern, and Intermountain), and the West Coast megaregion includes three Forest Service regions (Pacific Southwest, Pacific Northwest, and Alaska) and U.S. territories (fig. 1.1).

Annually, the FHM program publishes a national report characterizing the status and trends of U.S. forest health based on large-scale monitoring and reporting of key forest health indicators (Riitters and Tkacz 2004). In addition to the national report, FHM also generates reports in cooperation with 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 annual Forest Health Highlights, available on the FHM website. The FHM program and its partners also produce other publications, including peer-reviewed reports and journal articles on monitoring techniques and analytical methods. The emphases of these publications include a range of topics in forest health including regeneration (McWilliams et al. 2015); crown conditions (Morin et al. 2015; Randolph 2010a, 2010b, 2013; Randolph and Moser 2009; Schomaker et al. 2007); health condition in national forests (Morin et al. 2006); vegetation diversity and structure (Crockett et al. 2023, Schulz and Gray 2013, Schulz et al. 2009, Simkin et al. 2016); drought (Costanza et al. 2023, Vose et al. 2016); ozone monitoring (Rose and Coulston 2009); invasive plants (Guo et al. 2015, 2017; Iannone et al. 2015, 2016a, 2016b, 2018; Jo et al. 2018; Oswalt et al. 2015; Potter et al. 2023; Riitters et al. 2018a, 2018b); invasive insects and diseases (Asaro et al. 2023; Koch et al. 2011, 2014; Krist et al. 2014; Potter et al. 2019a, 2019b; Vogt and Koch 2016; Yemshanov et al. 2014); land cover change and forest fragmentation (Guo et al. 2018; Riitters 2011; Riitters and Costanza 2019; Riitters and Wickham 2012; Riitters et al. 2012, 2016, 2017); and the overall forest health indicator program (Woodall et al. 2011).

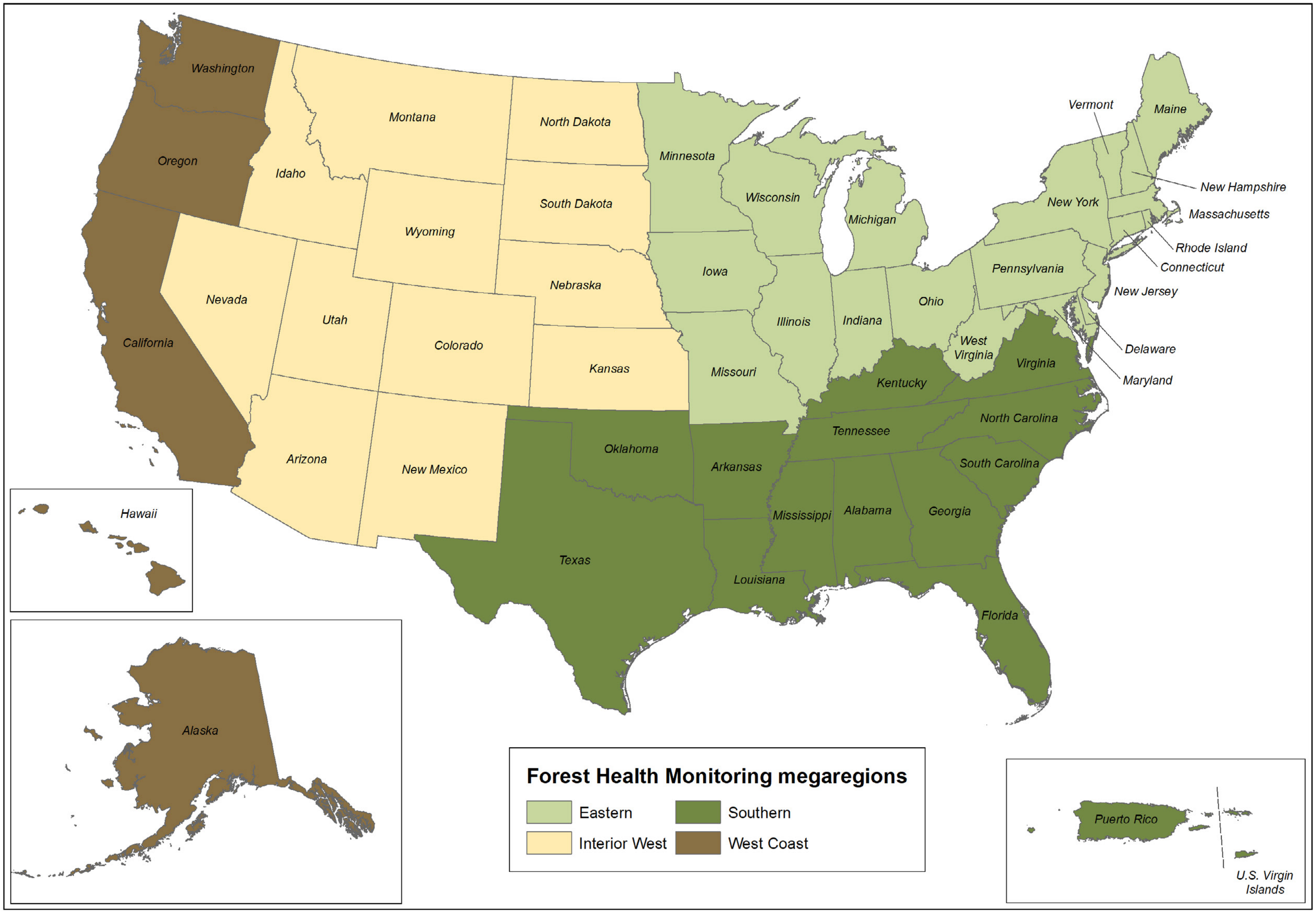


Figure 1.1—The megaregions of the Forest Health Monitoring program (Potter et al. 2024).

FHM NATIONAL REPORTING

Traditionally, the FHM national report had three objectives: (1) to present information about forest health from a national perspective, or from a multistate regional perspective when appropriate; (2) to provide analyses from various temporal scales; and (3) to present new techniques for analyzing forest health data as well as new applications of established techniques. Historically, analyses described in the national report have encompassed forest insect and disease activity, wildland fire occurrence, tree mortality, forest fragmentation, and drought, among others. Previous reports in this series are searchable on the FHM website, where links to each of these reports in their entirety and to chapters included in the reports are available. From 2008 to 2022, a section of the national report comprised Evaluation Monitoring summaries. These were compiled and published as a separate document in 2023, as they will be going forward.

Since their start in 2001, FHM national reports have followed an indicator-based framework. The Montréal Process Criteria and Indicators (Montréal Process Liaison Office 2015) provided the principal organizing framework used to produce the first iterations of the report (Conkling et al. 2005). Currently, the FHM program is developing a novel indicator-based framework for evaluating and communicating U.S. forest health status. Reporting the presence or absence of selected agents and processes in non-interacting contexts provides only a partial picture of forest health. It is important to include interactions among agents and stressors and the responses of forests to these agents and stressors when assessing forest health status. The new FHM framework will explicitly reflect that forest health is a result of complex and multifaceted processes (Castello and Teal 2011) and acknowledge a holistic view of forest health by organizing indicators into groups representing major aspects of forest health. This "Forest Health Monitoring: National Status, Trends, and Analysis 2024" report is the 24th consecutive effort in this series; the 2025 report is expected to have a scope and structure representing the new FHM framework.

The analyses presented in this report range from regional to national in spatial scale and annual to decadal in temporal scale. Chapter 2 on mapping pine (*Pinus* spp.) mortality provides results from a specific FHM megaregion whereas other chapters, like those examining recent trends in American beech (*Fagus grandifolia*) demography (ch. 4) and broad-scale forest fire patterns (ch. 5), present decadal analyses at a national scale. Some chapters in the report (ch. 2 and ch. 4) provide analytical approaches for using and interpreting forest health indicators related to tree mortality and forest demography. Likewise, a review of declines in whitebark (*P. albicaulis*) and limber pine (*P. flexilis*) mortality (ch. 3) discusses tree mortality in relation to stressors. Notably, the chapter on forest fire patterns (ch. 5) offers a continuation of many years of broad-scale reporting and also contributes to the development of the FHM program's new analytical framework for national trend monitoring.

DATA SOURCES

This edition of the FHM national report integrates data from Forest Service sources including:

- The Forest Inventory and Analysis (FIA) program's Nationwide Forest Inventory, a national network of permanent plots located in forested areas and remeasured on a 5- to 10-year cycle (Burrill et al. 2024, Westfall et al. 2022, Woodall et al. 2010)
- The Forest Health Protection program's national Insect and Disease Survey (IDS) forest mortality data for 2024 (FHP 2024)
- 2011 tree canopy cover data from the Forest Service National Land Cover Database Tree Canopy Cover dataset (2016 product suite; Ruefenacht et al. 2022) through a cooperative project between the Multi-Resolution Land Characteristics Consortium and the Forest Service (Sohl et al. 2025)

The report also includes the following data sources:

- Moderate Resolution Imaging Spectroradiometer Active Fire Detections for the United States data for 2024 (NASA Fire Information for Resource Management System 2024)
- 2021 National Land Cover Database (Dewitz and USGS 2023)
- Fire perimeter data from the National Interagency Fire Center, Wildland Fire Interagency Geospatial Services (NIFC 2023)
- Sentinel-2 enhanced true color imagery in Google Earth Engine (Gorelick et al. 2017)
- WorldView-3 imagery, 2023

Please refer to box 1.1 for more information about the FIA program, which is a major source of data for several FHM analyses.

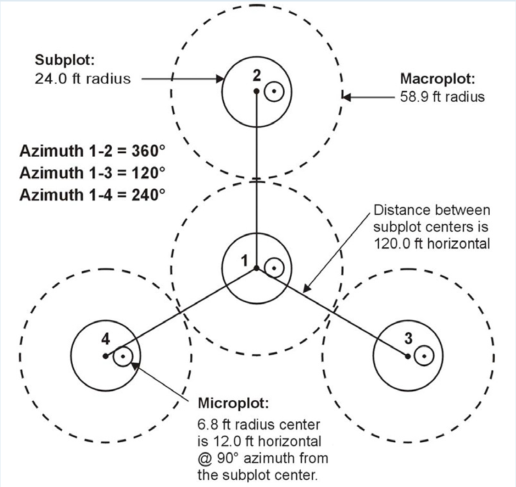
FOREST HEALTH MONITORING REPORT PRODUCTION

The FHM national report is produced annually by researchers at the Eastern Forest Environmental Threat Assessment Center (EFETAC) in collaboration with North Carolina State University cooperators in the Forest Health Monitoring Research Team, with the support of the FHM and FIA programs. 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 Forest Health Monitoring Research Team and about threats to U.S. forests, please visit the EFETAC website.

BOX 1.1

The Forest Inventory and Analysis (FIA) program delivers comprehensive and long-term information about the status of forests and forest resources in the United States by continually collecting and analyzing field-based forest inventory data. Some of the notable information includes status and trends in forest area and location; species, size, and health of trees; growth, mortality, and removals from forests; and wood production and utilization rates. Such information can be used for evaluation of biodiversity status, monitoring of forest health, assessment of forest ecosystem management practices, and support of planning and decision making (Renwick 2023). Nationwide Forest Inventory (NFI)—historically referred to as "Phase 2"—is a major component of the FIA program (Burrill et al. 2024). Plot-based field surveys are the backbone of NFI and provide unbiased estimates of forest characteristics across all ownerships. The NFI collects land use information across all areas (plots) in the United States with additional site and tree-level information on plots with forest land use. In addition, the FIA program collects information on some forest health indicators like down woody materials, vegetation profiles, invasive species, soils, etc. on a subset of NFI plots (Burrill et al. 2024).

FIA maintains a network of more than 140,000 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) (Renwick 2023). NFI encompasses the annualized inventory measured annually on a subset of plots, with each plot surveyed every 5 to 7 years in the Eastern United States and every 10 years in the Western United States (Reams et al. 2005). The standard 0.067-ha plot (see box 1.1 figure) consists of four 7.315-m (24-foot) radius subplots (approximate area of 168.6 m^2 or 1/24th 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 m^2 or 1/300th acre), on which crews measure trees between 2.5 to 12.7 cm (1 to 5 inches) in diameter and tally live seedlings smaller than 2.5 cm (1.0 inch) in diameter that are at least 15.2 cm (6 inches) in height for softwoods and 30.5 cm (12 inches) in height for hardwoods. 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 et al. 2024) and is used in highly productive sites (such as the Western Cascades) in California, Oregon, and Washington.



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 et al. 2024).

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CHAPTER 2

Mapping the 2023–2024 Pine Mortality Event in Mississippi and Louisiana Driven by an Extreme Hot Drought, Pine Bark Beetle Outbreaks, and Wildfire

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INTRODUCTION

As weather extremes increase in frequency and intensity across the United States, many forested areas are threatened with declining health and less resilience to disturbances. Among the most concerning extremes are flash droughts and hot droughts that emerge rapidly and are often associated with extreme heat (Christian et al. 2019, King et al. 2024). For example, during June 2021, a heat dome settled over the U.S. Pacific Northwest, with severe and sustained drought and extreme high temperatures leading to foliar damage and a massive die-off of mature conifers over a large area of Oregon and Washington (Bennett et al. 2023, Klein et al. 2022, Still et al. 2023). Further, an extended hot drought across Texas in 2011 killed millions of pines (*Pinus* spp.) and hardwoods (Dewez et al. 2024, Lawal et al. 2024). Herein, we describe a mass pine mortality event across Louisiana and Mississippi following hot-drought conditions that transpired during the summer and fall of 2023. As with other such events, this hot drought was characterized by sustained high temperature maxima, low humidity, and little precipitation for several consecutive months. Though periodic droughts are normal, this event broke the late season heat record. According to National Oceanic and Atmospheric Administration (NOAA) data for southwestern Mississippi (Vose et al. 2014), only in 1924 did a drier late season occur and no year since 1895 was hotter. This extreme weather contributed to the largest wildfire and worst fire season in terms of acres burned in Louisiana's recorded history. In addition, an extensive outbreak of Ips bark beetles (*Ips* spp.) developed across large sections of Mississippi and Louisiana.

In the U.S. South, several species of pine bark beetles in the genus *Ips* are known as "secondary" forest pests because they usually attack and overcome host tree defenses only when those trees are in a weakened state. For example, outbreaks of Ips bark beetles can be widespread during sustained drought conditions or after windstorms (Fettig et al. 2022). In particular, *I. avulsus*, *I. grandicollis*, and *I. calligraphus* are the three species most commonly associated with southern pines such as loblolly pine (*P. taeda*; Connor and Wilkinson 1983). In contrast to the southern Ips bark beetles, the southern pine beetle (*Dendroctonus frontalis*) is a more aggressive "primary" pest that can overcome host defenses of healthy trees using a pheromone-mediated mass attack process. Unlike Ips bark beetles, southern pine beetle outbreaks can occur during average precipitation levels or even unusually wet periods and, therefore, are not as tightly linked with sustained drought conditions (Coulson and Klepzig 2011). In fact, southern pine beetle activity is often observed to decline or "shut down" altogether during sustained high temperatures above 35 °C alongside severe and sustained drought, whereas a surge in Ips bark beetle activity is almost a certainty under such conditions (McNichol et al. 2021).

The biological differences between *Ips* and *Dendroctonus* species have implications for tree mortality patterns on the landscape. With each group, tree mortality occurs as clusters or aggregates that are loosely referred to as "spots." Most spots are small—from several dead trees to aggregates that amount to less than an acre. However, southern pine beetle spots can expand in size or merge with other nearby spots, sometimes resulting in kill zones that are hundreds or even thousands of acres in size depending on the contiguity of their host on the landscape (Coulson and Klepzig 2011). In contrast, Ips bark beetle spots generally remain small and isolated but can become highly abundant and even merge into larger dead zones during outbreaks that arise due to prevailing host stress across the landscape (McNichol et al. 2021). These differences have significant implications for management of southern pine beetle, allowing for opportunities to suppress their activity using tactics such as "cut and leave" or "cut and remove," whereby a buffer strip of infested and uninfested green trees is cut along the edge of the spot. This can help disrupt the pheromone communication system of the beetles, which then need to travel much farther distances to reinitiate the mass attack process on a new host. These tactics are mainly conserved for spots that have the greatest potential to grow and expand (Coulson and Klepzig 2011).

In contrast, during Ips bark beetle outbreaks, spot locations on the landscape are a manifestation of trees that are most stressed, usually due to sustained drought conditions (McNichol et al. 2021). Because these spots are generally small, numerous, and scattered, applying buffer strips is not a practical nor effective management tactic since spots do not actively grow and expand in predictable directions. Furthermore, downing trees would likely increase population levels of Ips bark beetles due to the lack of resistance in fresh slash. Thus, during Ips bark beetle outbreaks, the damage is done as soon as it is observed and cannot be mitigated or undone by any effective treatment, leaving only the options of salvage cutting in severely impacted stands or waiting for environmental conditions to improve (Connor and Wilkinson 1983).

Before a management response can be considered, the extent and severity of any pest or pathogen outbreaks must be adequately documented and characterized using spatially explicit data. This is a primary goal of the Forest Health Monitoring (FHM) program within the U.S. Department of Agriculture, Forest Service's division of Forest Health Protection (FHP). Forest health survey specialists within FHP or State forestry agency partners collect data for this program, with most data collected via aerial surveys (i.e., specialists in small aircrafts using digital tablets equipped with software to record various disturbances using point, polygon, or grid cell features [see USDA Forest Service 2025]). Currently, these techniques are the most practical and cost-effective ways to collect these data at the national scale. In the future, these methods will likely be supplanted, to some extent, by more unmanned remote sensing tools such as satellite imagery and fixed-wing drones.

Since the late 1990s, State and Federal partners have collected spatially explicit spot data for southern pine beetle via aerial surveys on a consistent basis such that the annual spot maps are considered a reasonable footprint of where southern pine beetle activity is concentrated across the Southern United States. Unfortunately, this is not the case for Ips bark beetle data, which have been collected sparingly and inconsistently during the last 25 years for the following reasons: (1) Spots tend to be small and widely dispersed, sometimes numbering in the many thousands during outbreaks, making mapping each individual spot impractical; (2) widespread outbreaks tend to be associated with drought-stressed trees, so Ips bark beetles have been considered less important than southern pine beetle and only inform on drought conditions; and (3) Ips bark beetle spots cannot be effectively managed or disrupted (see above), so knowing precise spot locations is often seen as unnecessary. Accurate and timely data, however, would be highly useful for understanding the population dynamics of Ips bark beetles and the conditions that facilitate eruptive outbreaks of these species. Years of anecdotal observation and some spatially and temporally limited datasets show that pine mortality due to Ips species may exceed southern pine beetle mortality by a considerable margin in some years (table 2.1). With models forecasting more episodes of severe drought, hot droughts, or flash droughts, all of which can curtail southern pine beetle activity (McNichol et al. 2021), Ips bark beetle outbreaks may become more destructive in the future as they are able to better exploit widespread host stress during more extreme conditions. Understanding these changes is critical to managing their impacts and developing new tools to characterize such outbreaks.

During the late growing season of 2023, pine trees across large swaths of Mississippi and Louisiana began fading and turning reddish-brown, and it quickly became apparent that prevailing heat and drought stress from the previous months had precipitated an Ips bark beetle outbreak on a massive scale (figs. 2.1 and 2.2). Aerial survey for documenting and characterizing the outbreak, the most common tool at FHP's disposal, was going to come up short in these circumstances due to the scale of the disturbance and the timing of the event. Late in the season, aerial survey work had wound down, pilots and surveyors were unavailable, survey contracts and budgets had expired, annual reporting and office work were in full swing, and the sketch-mapping software used for aerial survey was temporarily shut off. With these limitations in place, it was necessary to pursue other options for acquiring spatially explicit data on the pine mortality.

Change detection analysis using satellite imagery is one such alternative tool. Recent work has shown that the European Space Community's Sentinel-2 satellite, which provides 10-m spatial resolution with 5-day frequency, is adequate for detecting bark beetle spots of a few trees (Bozzini et al. 2023; Gomez et al. 2020). Obtaining cloud-free imagery can be difficult when there is a need for very rapid assessment, but the reddish-brown crown of beetle-killed pine persists for months. Further, appropriate masks or spatial filters are typically applied to reduce commission errors to acceptable levels so that any resulting map depicts the disturbance of interest (in this case, recently dead conifers) with a reasonable level of accuracy. Finally, as with data derived from aerial survey, good ground truthing is necessary to validate any spatial product derived from satellite imagery.

Table 2.1—Area of mortality attributed to the southern pine beetle (SPB) versus Ips bark beetles (*Ips avulsus*, *I. grandicollis*, *I. calligraphus*) by year or groupings of years across the 13 Southern United States

Survey year(s)	SPB mortality area (ha)	*Ips* species mortality area (ha)
2009–2016	3240	7753
2017	7626	5852
2018	3443	3806
2019	377	1465
2020	19	1844
2021	210	3611
2022	846	9417
Total	15 760	33 748

Source: USDA Forest Service (2025).

Figure 2.1—An oblique aerial photograph showing pine mortality (reddish-brown crowns) and senesced deciduous forests near Alexandria, LA, in December 2023. Forest Service photo by Jerry Groom.

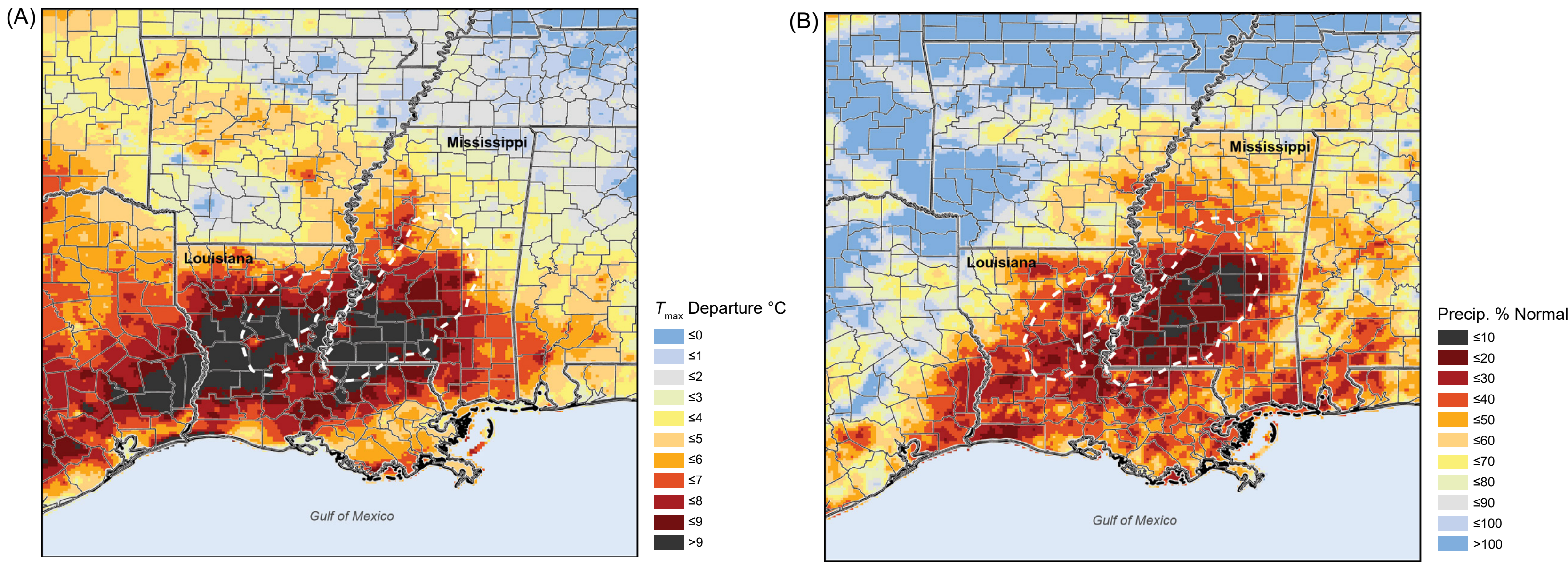

Figure 2.2— For August to October 2023, (A) maximum temperature anomaly (°C) and (B) percent of normal precipitation based on 1991–2020 mean values derived from PRISM data (Daly et al. 2008). Dotted-line polygons indicate boundaries within which pine mortality was mapped using satellite imagery and change detection analysis.

METHODS

Mapping Pine Beetle Mortality

To delineate the portions of Mississippi and Louisiana experiencing extensive pine mortality caused by bark beetles, we (the authors of this chapter) looked for the diagnostic reddish-brown crown condition of dying pines using 10-m Sentinel-2 enhanced true color imagery in Google Earth Engine (Gorelick et al. 2017) during mid-December 2023. We drew two large polygons within these two States that captured the principal areas exhibiting that condition (fig. 2.2), and then we extended the area with a 3-km buffer beyond the last observed dead pine cluster. We isolated 1 epicenter of 16 271 km^2 in central Louisiana that comprised all or part of 15 counties. A second polygon comprised 39 780 km^2 and included all or part of 30 southwestern Mississippi counties and an additional 3 counties in eastern Louisiana.

For each polygon, we calculated 1-year change in the Normalized Difference Vegetation Index (NDVI) in Google Earth Engine at 10 m using winter imagery (Norman and Christie 2022). For Mississippi, we used imagery for January 15, 2023, and January 24, 2024. For Louisiana, we used a baseline mosaic from January 23 to February 12, 2023, and compared this with January 2024. We obtained cloud-free conditions and used values that were corrected for surface reflectance. Use of anniversary dates for change-over-time analysis is a common practice for disturbance detection (Senf et al. 2017), and while this full year of change extended well before the onset of the hot drought in August, the technique provides a robust and phenologically appropriate baseline for comparison.

We used a series of masks to isolate beetle-killed pines from other causes of change and forest types. We isolated woody forest and shrub vegetation using the 2021 National Land Cover Database that used 30-m Landsat data, and we created a more updated mask for evergreen forests at 10 m by thresholding the NDVI of January 2023 imagery. We derived a threshold NDVI value of 0.725 by sampling industrial-planted and mixed pine across the most affected portion of Mississippi and calibrated results so that the mask conformed to the pattern of pine visible in true color Sentinel-2 and higher resolution imagery in Google Earth Engine (fig 2.3).

Although pine mortality was evident in both industrial-planted pine and in mixed pine-hardwood stands, the latter mortality was more difficult to isolate and validate due to adjacent senescent hardwoods. Thus, to limit commission errors, we limited this analysis to large and moderate-sized patches of pine where the majority of a 5- x 5-cell focal block was pine (i.e., at least 13 of 25 Sentinel-2 cells were pine, giving a minimum mapping area of 0.1 ha). This workflow (fig. 2.3) gave us an evergreen-only forest mask roughly 7 months prior to the onset of drought.

As the industrial pine component of this landscape is highly dynamic due to stand thinning, harvesting, prescribed fire, and southern pine beetle mortality, we applied a “pine-recency” mask in mid-September using the same NDVI evergreen threshold such that any nontargeted

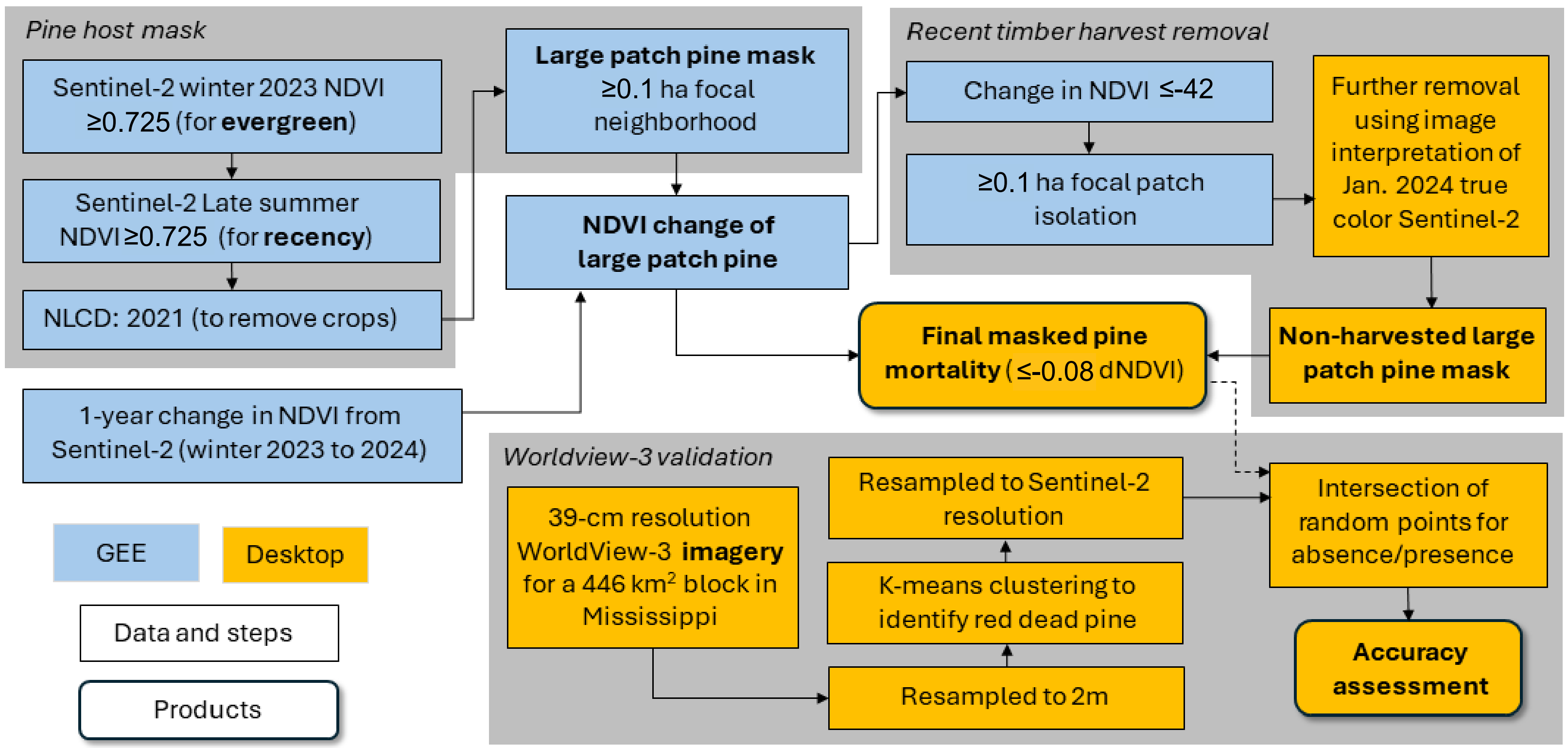

Figure 2.3—Workflow showing the steps used to isolate beetle-caused pine mortality and to conduct accuracy assessment whether in Google Earth Engine or the desktop.

pine harvest between January and September of 2023 was excluded from this analysis. For this study, only the fall and winter pine mortality that occurred after the late summer onset of drought was targeted but not the earlier southern pine beetle mortality in a few locations that caused visually similar reddish-brown-dead foliage. As nontargeted thinning and harvesting also occurred during late 2023, those units or portions of units that were not already removed by the September recency mask were isolated by identifying patches with an extreme change in NDVI (≤-42, buffered by three cells) in Google Earth Engine, and then we manually removed residual areas of lighter activity after export from Google Earth Engine with ESRI's ArcGIS Pro using visual image interpretation. With this mask in hand, the remaining areas of patchy pine that died between September 2023 and January 2024 were isolated by thresholding change in NDVI at ≤-0.08.

Validation

State and Federal partners of FHP conducted field-based validation of mortality and causal attribution as drought-associated Ips bark beetles. An accuracy assessment of our 10-m product was desired with respect to its ability to properly identify recently dead trees with reddish-brown crowns. For validation, we compared our results to 0.39-m resolution (very high resolution) WorldView-3 satellite imagery from December 10, 2023, that covered a 446-km^2 (15.3 x 28.9 km) area located northwest of Jackson, MS (fig. 2.3). This tile represented 1.12 percent of the Mississippi study area and 0.8 percent of the Louisiana and Mississippi areas combined. We masked the tile to just include the relevant large-patch pine forest under study that was generated previously. We then resampled the imagery to 2 m and then classified the imagery to isolate this recent pine mortality using k-means clustering. We verified this classification using visual interpretation of an independently evaluated set of 250 random points that were visually interpreted from the WorldView-3 imagery with an accuracy of 90.0 percent. To compare the accuracy of this WorldView-3-derived classification with the 10-m Sentinel-2 pine mortality raster, we coarsened the classified WorldView-3-derived map of mortality to 10 m using a majority threshold. As some mortality occurred between mid-December when the WorldView-3 imagery was collected and mid-January when the Sentinel-2 pine mortality product was formulated, we isolated the Sentinel-2 mortality to have just occurred by mid-December with a second recency mask at the same NDVI threshold of 0.72 used in the previous steps.

Mapping Wildfire Mortality

We downloaded large fire perimeters for Louisiana from the National Interagency Fire Center's Wildland Fire Interagency Geospatial Services (NIFC 2023). These data only included large wildfires over 121 ha. Using Google Earth Engine at 10 m, we calculated NDVI within-year change that occurred between August 16, 2023, and September 10, 2023. We used the same evergreen forest mask used for the beetle mortality step and isolated severe decline that appeared to be lethal using a threshold of -0.12.

RESULTS AND DISCUSSION

We documented pine mortality across a substantial portion of southwestern Mississippi and, to a lesser extent, central Louisiana between September 17, 2023, and January 24, 2024. By State, 54 700 ha of large patch pine in Mississippi and 2350 ha in Louisiana had bark beetle-caused tree mortality (fig. 2.4). Notably, the greatest concentration of mortality was southwest of Jackson, MS, but widespread mortality extended over multiple counties. In southwestern Louisiana, an additional 7820 ha of pine were lost in the six large wildfires that burned an 18 200-ha area. Our validation assessment of bark beetle-caused tree mortality comparing the resampled WorldView-3 classification of reddish-brown pines and the Sentinel-2 change product resulted in an accuracy of 87.6 percent (Recall = 0.513; Precision = 0.578; F-Score = 0.104). Within the 446-km^2 validation block, 15.2 percent of the pine had died. For differences in methods for imagery and changes in NDVI capture mortality, see figure 2.5.

The workflow used in this analysis reliably captured patchy tree mortality due to Ips bark beetles using a combination of high-resolution imagery, change in NDVI, and sophisticated host and temporal masking techniques. These steps minimized the need for manual delineation of beetle-killed pine. This research used a combination of 1-year change-over-time analysis and imagery classification to map beetle mortality, commonly used techniques for mapping insect disturbance (Senf et al. 2017). The anniversary-date approach used in the change-over-time analysis provides a phenologically meaningful baseline and comparable illumination. However, use of anniversary dates brings tradeoffs, and in this industrial timberland landscape, nonbeetle disturbances accumulate and require additional steps to isolate the targeted cause. Single-date classification requires a unique disturbance signature and usually masking to isolate the conifer host as drought-associated or late-season senescence of deciduous components can cause commission errors. Masking overcame problems of both approaches. We used a recency mask to minimize how much of accumulating nontargeted disturbance required analyst interpretation. We also isolated the conifer beetle host at 10 m from the most recent winter season.

In the past, tree mortality caused by Ips bark beetles has rarely been mapped in the Southern United States because it is typically of limited extent and dispersed within stands. Beetles take advantage of trees stressed from lightning, fire, or wind, but broader impacts from drought and tropical storms have also been reported (Baker 1972, McNichol et al. 2021, Palmer et al. 2024). Knowledge of historical outbreaks of Ips species in this region is largely based on anecdotal reports with limited spatial specificity (McNichol et al. 2021). The pattern of mortality is important as it may vary by cause and have implications for response (Kärvemo et al. 2023). The 2023–2024 pine mortality event in Mississippi and Louisiana killed tens of thousands of trees in just a few months with management impacts for thousands of urban, rural, and industrial forest owners. Small forest owners may have less capacity to actively manage their forests than industrial forest owners, and these forest owners may be at particularly high risk when associated wildfire fuel hazards go unmanaged. While no research has yet been conducted on fire hazards after outbreaks of southern Ips species, mortality after southern pine beetle outbreaks can increase fire hazards (Xie et al. 2020). Having firmer knowledge of the extent of impacts across ownerships can lead to a better understanding and reduction of risks at scale.

It is notable that the portion of Louisiana that experienced record large wildfires in August 2023 was outside the area of mortality attributed to Ips bark beetles. Both disturbances were triggered by late summer hot drought, although southwestern Louisiana had similar temperature stress but less of a precipitation anomaly than southwestern Mississippi (fig. 2.2). Notably, the largest of the Louisiana wildfires, the 12 663-ha Tiger Island Fire, was caused by arson, and differences in chance human ignitions can explain why some areas burned more than others. During drought, pine mortality caused by wildfire can extend drought's impact to areas beyond where Ips bark beetle-related pine mortality may occur. Such tree mortality events may reveal an emerging risk for planted pine from Ips species at a scale that may be new and extensive. As intensively managed pine has only emerged since the mid-20th century, this extreme event revealed a vulnerability to widespread Ips bark beetles that has been underappreciated in the U.S. South. New monitoring approaches, such as the workflow described here, can improve our understanding of this vulnerability for sustainable forestry.

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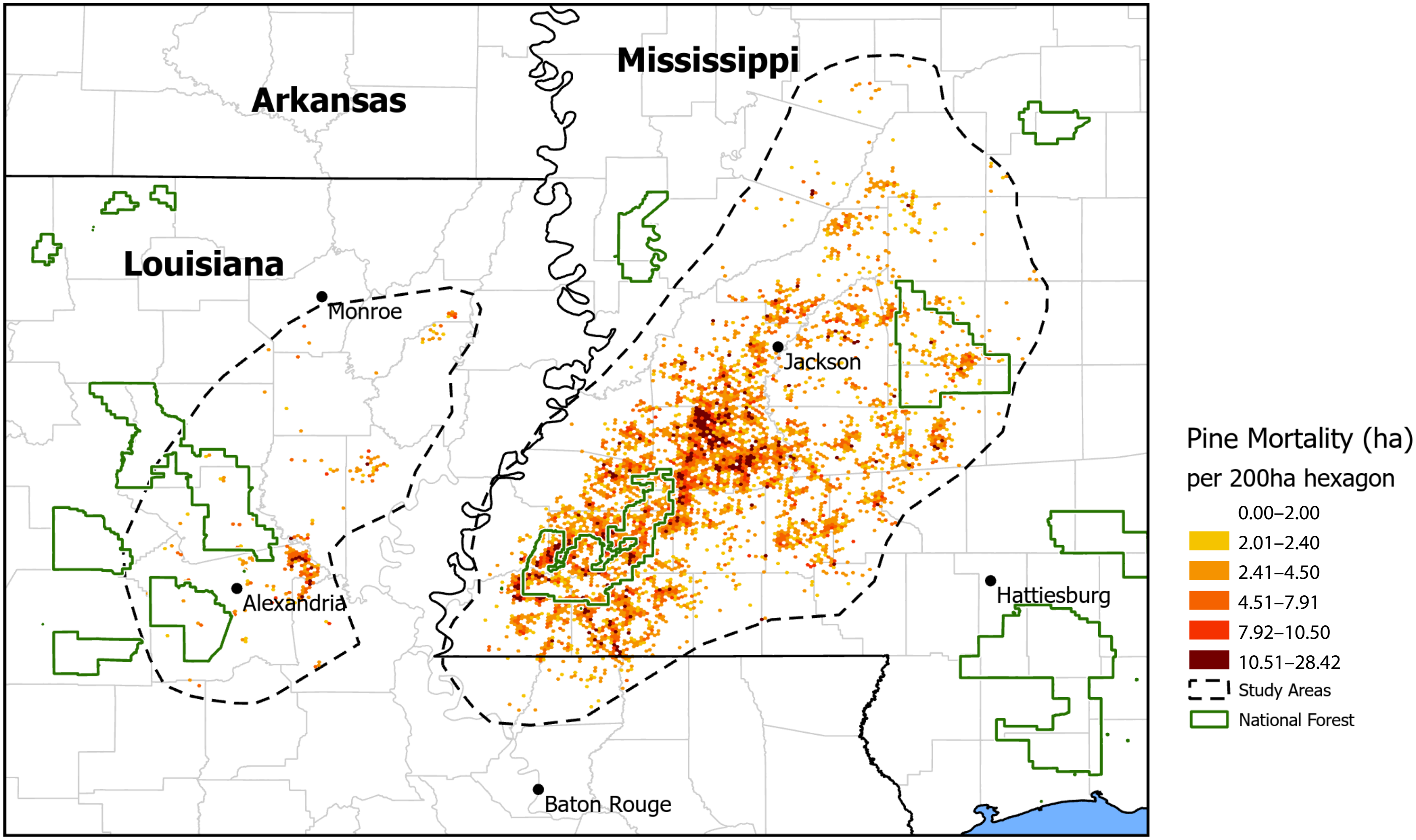

Figure 2.4—Extent of mapped pine mortality for Mississippi and Louisiana summed to 200-ha hexagons.

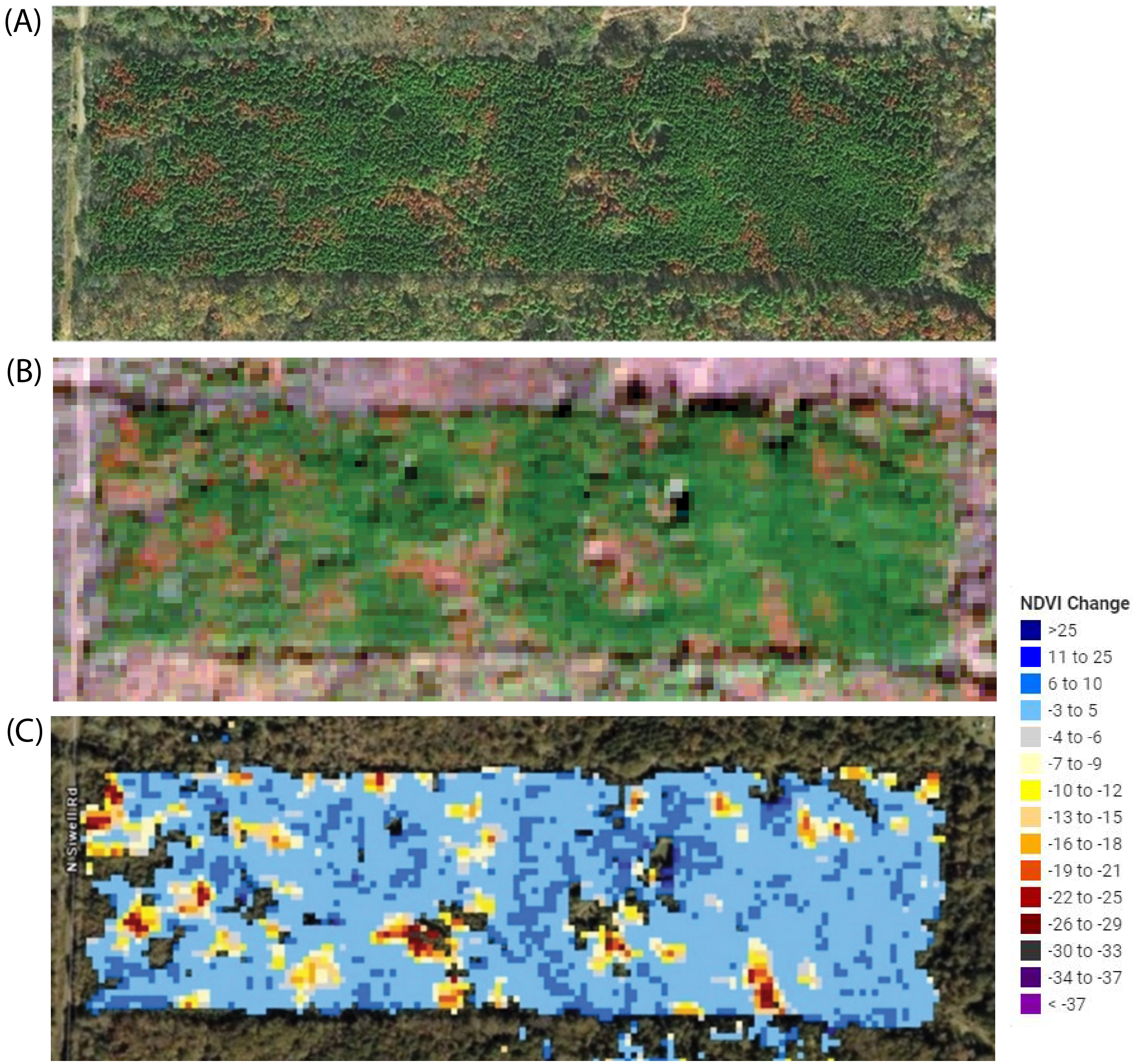

Figure 2.5— A comparison of three views of beetle mortality within a pine-dominated forest block west of Jackson, MS: (A) 0.39-m-resolution WorldView true color imagery for December 10, 2023; (B) 10-m enhanced true color Sentinel-2 imagery; and (C) 10-m change in NDVI for December 10, 2023, compared to a year earlier.

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CHAPTER 3

Complementarity of Two Forest Service Programs for Monitoring and Managing Whitebark and Limber Pines

Sara A. Goeking

INTRODUCTION

High-elevation, five-needle pines in the Western United States are focal points for multiple stressors such as drought, heat, altered wildfire regimes, pathogens such as the nonnative white pine blister rust (*Cronartium ribicola*), and insects (Tomback et al. 2011). Despite host tree species and biotic stressors having constrained geographic ranges, these stressors have contributed to widespread decline of whitebark pine (*Pinus albicaulis*), which is now listed as a threatened species in the United States (U.S. Fish and Wildlife Service 2022) and an endangered species in Canada (Government of Canada 2015). Limber pine (*P. flexilis*) is also declining throughout its range (Tomback et al. 2022). The ecological importance of these two species of concern underscores the need for greater understanding of the broad-scale consequences of their decline and possible mitigation strategies (Keane et al. 2022).

To maintain healthy populations and stands of these species, managers benefit from information that allows prioritization of restoration areas and options, as well as knowledge of how management options may mitigate or exacerbate these stressors, at a variety of spatial scales (Keane et al. 2022). Numerous projects sponsored by the U.S. Department of Agriculture, Forest Service, Forest Health Monitoring (FHM) program have investigated the interactions of these stressors and their impact on whitebark pine and limber pine. At broader scales, studies based on the probabilistic sample of Forest Inventory and Analysis (FIA) plots have tracked indicators of decline associated with these stressors and highlighted large regions where whitebark pine and limber pine populations are experiencing the most severe declines.

Analyses based on FHM projects and FIA data have previously characterized the effects of insects and white pine blister rust on whitebark pine and limber pine in terms of tree mortality. Thus, mortality is a readily available and easily scalable indicator of whitebark pine and limber pine population statuses. Mortality is typically expressed as the proportion or percentage of trees that recently died, although it can also be expressed in terms of longer term, cumulative mortality rates (i.e., numbers of dead versus live trees), as mortality rate by volume (volume per acre per year), or as net growth rate by volume (volumetric growth of surviving trees minus mortality volume per acre per year). Although whitebark pine and limber pine can be difficult to distinguish within the area where their geographic ranges overlap, particularly when cones are absent, FIA has tracked indicators for the two species separately (Goeking and Windmuller-Campione 2021) and also quantified the accuracy of species identifications on FIA plots (Williams et al. 2024). The purposes of this chapter are (1) to summarize previously published investigations based on FHM projects and FIA data and (2) to illustrate the complementarity of FHM and FIA insights into the mechanisms and indicators of whitebark pine and limber pine declines.

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METHODS

I (the author of this chapter) reviewed previously published literature from the FHM and FIA programs that focused on whitebark pine or limber pine assessment and monitoring. I summarized each paper's sampling strategy, spatial scale, and findings with particular attention to whether papers assessed drivers versus indicators of decline. Sampling strategy is related to spatial scale, both of which affect the extent to which findings can be extrapolated to other sites (Schreuder et al. 2001). The utility of characterizing drivers of demographic change versus indicators of decline is intended to illustrate that (1) drivers can provide insight into the mechanisms and causes of demographic shifts such as widespread mortality and (2) indicators of decline can spatially validate whether drivers are operating at a severity and scale that are observable throughout the species' ranges.

For this review, I included previously published chapters from national FHM reports that focused on whitebark pine or limber pine, using the search function of the FHM national report website, which included national reports from 2005 through 2022. I also included peer-reviewed papers based on FIA plot data that characterized whitebark pine or limber pine mortality from the same time period. Characteristics of the papers are summarized in table 3.1. Note that most FHM project studies assessed whitebark pine or limber pine status and stressors over a period of <5 years. FIA-based analyses, in contrast, opportunistically leveraged data collected over multiple decades (2000–2019), and they queried standard metrics across all forest types and tree species to assess whitebark pine and limber pine mortality over time.

Data

Sampling strategies in this collection of papers included both probabilistic and purposive sampling. The distinction between probabilistic and purposive sampling is important because sampling strategy influences (1) the ability to make inferences to other sites or across scales and (2) the ability to establish cause-and-effect relationships (Schreuder et al. 2001). Findings based on probabilistic studies with a random sampling component can be more readily applied to other areas, whereas findings based on purposive sampling can more readily establish cause and effect (Schreuder et al. 2001). Two studies from FHM projects established purposive monitoring plots based on random sampling, either within predefined strata (Burns et al. 2012) or within a predefined domain (Cleaver et al. 2022). Papers based on FIA data relied on FIA's probabilistic sample across all forest types and ownership categories (Burrill et al. 2023). The remaining studies' sites were purposively selected based on predetermined site characteristics (e.g., accessibility, forest type, or disturbance history).

Data collection methods in each paper followed one of three plot protocols: Greater Yellowstone Ecosystem protocols (Legg et al. 2016), Whitebark Pine Ecosystem Foundation protocols (Tomback et al. 2004), or FIA protocols (Burrill et al. 2023). All three methods included

Table 3.1—Papers included in this review from Forest Health Monitoring projects or based on Forest Inventory and Analysis data, 2005–2022

Study	Species	Percentage of trees dead	Geographic domain	Number of plots	Site selection	Measurement protocol
Burns et al. 2012	Limber pine	7	Colorado, Montana, North Dakota, and Wyoming	83	Probabilistic (stratified)	WBEF
Cleaver et al. 2022	Limber pine	27	Montana (Rocky Mountain Front)	74	Probabilistic (with constraints)	WBEF
Eskelson and Monleon 2018	Whitebark pine	24	California, Oregon, and Washington	420	Probabilistic	FIA + precursor to FIA on national forests in Pacific States
Fins and Hoppus 2013	Whitebark pine	19	Idaho (Frank Church River of No Return Wilderness Area)	119	Purposive	WBEF
Goeking and Izlar 2018	Whitebark pine	51	Western United States (California, Idaho, Montana, Nevada, Oregon, Washington, and Wyoming)	1,406	Probabilistic	FIA
Goeking and Windmuller-Campione 2021	Whitebark pine and limber pine	54 and 42	Western United States (California, Idaho, Montana, Nevada, Oregon, Washington, and Wyoming)	1,572 whitebark pine; 1,138 limber pine	Probabilistic	FIA
Legg et al. 2016	Whitebark pine	27	Idaho, Montana, and Wyoming (Greater Yellowstone Ecosystem)	176 + 8 paired burned/ unburned plots	Purposive	GYE
Long et al. 2018	Whitebark pine	NA	Western United States (California, Idaho, Montana, Nevada, Oregon, Washington, and Wyoming)	NA[1]	Probabilistic	FIA

FIA = Forest Inventory and Analysis; GYE = Greater Yellowstone Ecosystem protocols; WBEF = Whitebark Pine Ecosystem Foundation.

[1] Number of plots not specified; based on time period and use of FIA data, the number of plots is likely similar to the 1,400 plots used in Goeking and Izlar (2018).

plot- and tree-level assessments, including live versus dead status of individual trees by size class. A distinction of Whitebark Pine Ecosystem Foundation protocols is that they generally include plot- and tree-level measurements plus within-tree assessments of white pine blister rust (WPBR) location and severity as well as species-level identification of insects causing damage or mortality. Thus, the different protocols ask and answer different—and potentially complementary—questions with respect to the extent and severity of WPBR and insect attacks. Greater Yellowstone Ecosystem and FIA protocols detect presence of WPBR and insects on individual plots and trees, but they do not record the severity or location of cankers or insect effects on individual trees. Further, FIA records WPBR and insects only on trees with diameter at breast height (d.b.h.) at least 2.54 cm (1.0 inch) and not on seedlings (trees with d.b.h. <2.54 cm).

Analyses

Analysis methods varied among papers but generally quantified the proportion of the sampled whitebark pine population that was alive or dead and that was infected with WPBR, mountain pine beetle (*Dendroctonus ponderosae*), or other insects or pathogens. Other response variables included stem density (including density by size class), growth rates, and mortality rates of whitebark and limber pines. Some studies tested whether site characteristics such as aspect or elevation were correlated with WPBR incidence (number of plots or trees infected) or severity (number or extent of cankers within individual trees).

Another difference between papers using Whitebark Pine Ecosystem Foundation or FIA protocols is whether population-level inferences were possible given the sample design and available data. FIA protocols are designed specifically for making population estimates across broad scales such as counties, States, or across multiple States. However, data collected via purposively selected sites cannot be reliably interpolated or extrapolated to broader scales without carefully parameterized models (Schreuder et al. 2001). Nonetheless, those finer scale studies provide local insights into drivers of broad-scale population decline.

RESULTS AND DISCUSSION

Of the eight studies summarized in this chapter, six were FHM projects. Of these, four used Greater Yellowstone Ecosystem or Whitebark Pine Ecosystem Foundation data collection protocols and two relied on FIA data. The remaining two studies used FIA data but were not FHM projects. FHM projects were conducted between 2005 and 2018, and FIA-based studies relied on data collected between 2000 and 2019. The main findings of each study are summarized below.

FHM Project Summaries

The two earliest papers examined whitebark pine and limber pine, in 2005–2008 and 2006–2007, respectively. The objective of the earliest FHM project was to characterize baseline whitebark pine status and health in the Frank Church-River of No Return Wilderness (Fins and Hoppus 2013). The study found that 19 percent of whitebark pine trees were dead, and observers estimated that mountain pine beetle and fire were the main causes of death. The low observed incidence of WPBR-caused mortality (as low as 3 percent but could be higher as 22 percent of trees were killed by undiscernible causes) suggests that this study occurred prior to WPBR having a major impact on mortality in this area. A contemporaneous FHM project examined damage (live trees) and mortality agents (dead trees) on limber pine across several States in the Northern Rocky Mountains and Black Hills (Burns et al. 2012). The main damage and mortality agents were twig beetles and WPBR, each affecting roughly half of dying trees. About 40 percent of recently killed trees exhibited engraver damage, which included primarily mountain pine beetle as well as other engravers. Only 19 percent of mortality was attributed to WPBR. More large trees than small trees were infected with WPBR, but smaller trees tended to have a higher severity of infection (i.e., higher incidence of cankers) and thus may have been more susceptible to future mortality.

Three FHM projects in the 2010s characterized mortality in whitebark pine (Eskelson and Monleon 2018, Legg et al. 2016) and limber pine (Cleaver et al. 2022). Approximately 27 percent of whitebark pines in the Greater Yellowstone Ecosystem died between 2004 and 2014, where most mortality was due to fire or mountain pine beetle and only 3 percent was due to WPBR (Legg et al. 2016). In 2017–2018, 43 percent of limber pines sampled in Montana's Rocky Mountain Front were dead, and an additional 21 percent were declining or dying (Cleaver et al. 2022). WPBR was among the most common causes of both stressors to live trees and mortality of trees whose cause of death could be identified (Cleaver et al. 2022). Another FHM project, using FIA data collected in coastal States during the 2000s and 2010s, found a general north-south trend in whitebark pine mortality and WPBR incidence (Eskelson and Monleon 2018). The highest mortality and WPBR incidence was observed in the northern end of the study area with no WPBR observations in California (Eskelson and Monleon 2018).

FHM Findings That Generate Broader Scale Questions

The results of FHM projects in coastal States (Eskelson and Monleon 2018) highlight two questions that may be robustly answered by future FHM work or by FIA's ongoing long-term sampling: (1) Is low WPBR incidence in California due to a climatic or geographic constraint on the range of WPBR? (2) Is the higher proportion of seedlings in the northern portion of the study region a result of the recent mountain pine beetle epidemic preferentially killing larger trees? Already, a more localized study focused on constraints on the range of WPBR incidence has confirmed that WPBR may be limited by aridity or topographic gradients (Dudney et al. 2021), and another study has corroborated the finding that larger trees are more susceptible to mountain pine beetle in California (Meyer et al. 2016).

Collectively, five of the six FHM projects summarized above raise questions that could be answered using broader scale or longer term datasets. First, observations in Montana (Cleaver et al. 2022) suggest that limber pine is increasingly vulnerable to the same threats as whitebark pine. Second, the relatively low incidence of mortality caused by WPBR and high mortality caused by mountain pine beetle (Burns et al. 2012, Eskelson and Monleon 2018, Fins and Hoppus 2013, Legg et al. 2016) raises questions about whether overall mortality rates will wane as mountain pine beetle epidemics taper off. FIA data can provide verification or refutation of (1) whether limber pine mortality is tracking whitebark pine mortality and (2) whether mortality of one or both species has waned as mountain pine beetle epidemics have waned.

FIA Project Summaries

Two previous studies based on FIA data (Goeking and Izlar 2018, Goeking and Windmuller-Campione 2021) applied multiple indicators of mortality to whitebark and limber pine: (1) numbers of live and dead trees and (2) growth and mortality rates by volume. For whitebark pine, the percentage of dead trees increased from 12 percent in 1999 to 51 percent in 2016 and then to 54 percent by 2019. Similarly, over the same period, the percentage of limber pine trees that were dead increased from 8 percent in 1999 to 38 percent in 2015 and then to 42 percent as of 2019 (Goeking and Windmuller-Campione 2021). Thus, mortality of both species has increased over the past two decades.

Growth and mortality rates represent trends over the most recent 10-year period. For whitebark pine and limber pine, low net growth rates and higher mortality rates over the most recent decade confirm that the large number of dead trees represents high recent mortality rather than merely long-standing dead trees (Goeking and Windmuller-Campione 2021). Growth and mortality rates over time also demonstrate that limber pine's 2019 growth and mortality mirror whitebark pine in 2015 (Goeking and Windmuller-Campione 2021). Thus, as suggested by the high limber pine mortality rates observed in a previous FHM study (Cleaver et al. 2022), mortality of limber pine is tracking whitebark pine mortality, and it is occurring at rangewide scales within the United States.

FIA Findings That Generate Finer Scale Questions

Just as finer scale FHM projects generated questions that could be tested using broad-scale probabilistic data from FIA, FIA has also generated findings that can be applied through project-scale restoration and management. Two such examples are density management diagrams and maps of mortality hot spots.

One FHM project shown in table 3.1 used FIA data, and although that project did not assess mortality, it is noteworthy because of its management applications via development of a density management diagram for whitebark pine (Long et al. 2018). The results illustrate the range of stand density indices where whitebark pine is dense enough to support Clark's nutcrackers (*Nucifraga columbiana*) but also sufficiently sparse as to presumably be resistant to mountain pine beetle attack. Because these density management diagrams are based on a probabilistic sample across the U.S. range of whitebark pine and limber pine, their value is that: (1) They are applicable to all whitebark pine and limber pine stands in the United States, and (2) they provide a management-relevant target density for specific management activities.

Maps of mortality hot spots can help prioritize strategic management activities at broad scales and also generate questions about the mechanisms and influences of stressors. For example, the geographic distribution of negative net growth rates (fig. 3.1) highlights ecoregion sections that have experienced mortality that exceeded growth over the past 10 years, and sections with more negative net growth rates represent more severe mortality regions. This map also illustrates patterns observed in previous studies (Eskelson and Monleon 2018) that have generated questions about why mortality is lower in the Sierra Nevada. Recent finer scale research has provided an explanation for this geographic pattern: that bioclimatic limits on WPBR may prevent it from having the impact in the Southern Sierra Nevada that it has already had in the Northern Rocky Mountains (Dudney et al. 2021).

Finally, broad-scale monitoring programs such as FIA are valuable only as far as the published data are reliable and of known quality. For example, FIA crews benefit from training on identification of insects and pathogens, which is often done in collaboration with FHM experts. Also, data quality of species identification is critical for monitoring these two species of interest. Because whitebark pine and limber pine have overlapping geographic ranges and are difficult to distinguish when cones are not present, additional verification of correct species identification is required. Finer scale studies can, and have (Williams et al. 2024), provided such verification.

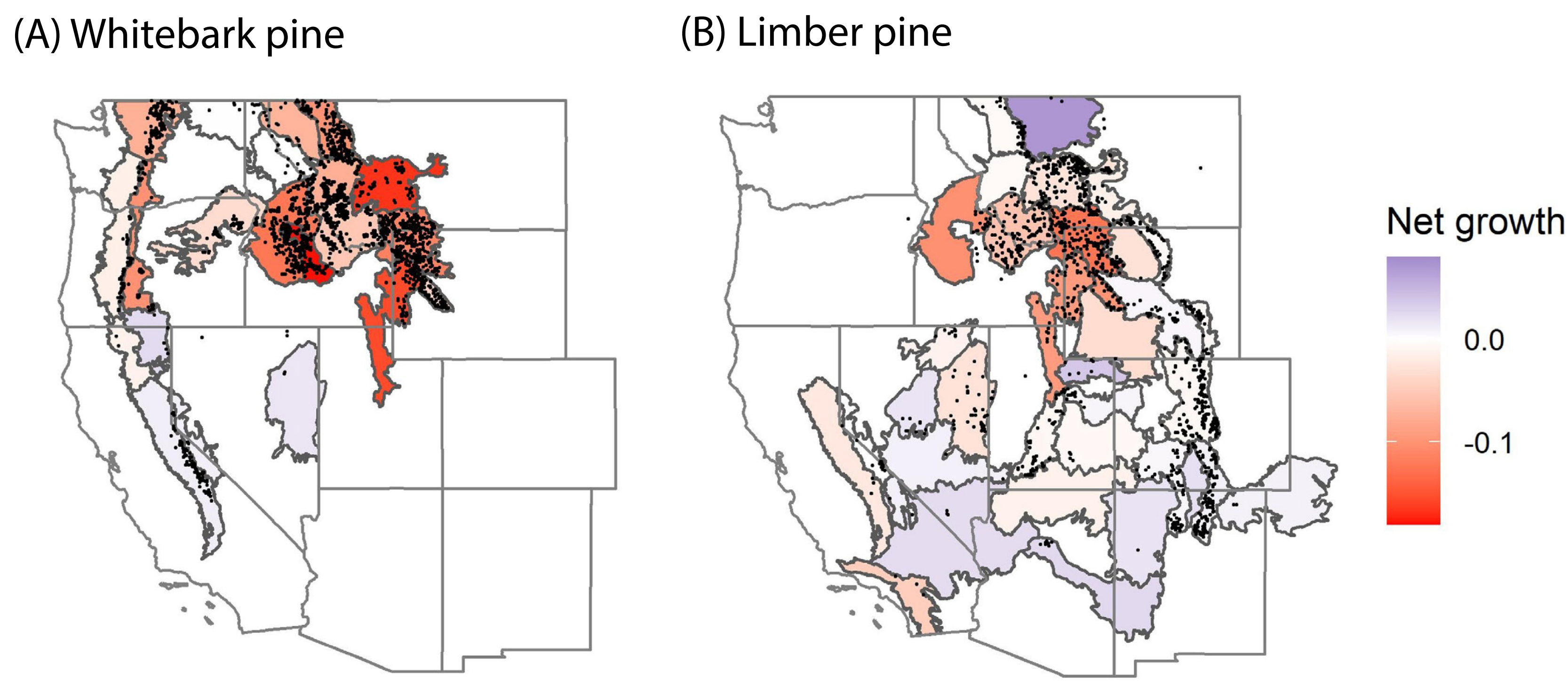

Figure 3.1—Mean annual net growth of (A) whitebark pine and (B) limber pine by ecological section. Mean annual net growth is defined as live tree growth minus the volume of trees that died, expressed as mean cubic volume per year as a proportion of live plus mortality volume (e.g., –0.1 represents negative net growth of 10 percent of live tree volume per year). Dots represent approximate locations of Forest Inventory and Analysis plots containing whitebark pine and limber pine, respectively. Source: Goeking and Windmuller-Campione (2021).

CONCLUSIONS

This chapter presented an application of tree mortality as an indicator of two tree species of concern. Possible metrics for that indicator include proportion of live versus dead trees, net growth rates, and mortality rates. Among all studies summarized here, the percentage of whitebark pine trees that were dead ranged from 19 percent for a single wilderness area in the 2000s (Fins and Hoppus 2013) to 54 percent across the species' U.S. range in 2019 (Goeking and Windmuller-Campione 2021). Dead limber pine ranged from 7 percent in the Northern Rockies in the 2000s (Burns et al. 2012) to 42 percent across the Western United States by 2019 (Goeking and Windmuller-Campione 2021). Further, growth and mortality rates confirm that the increase in mortality rates occurred during roughly the past decade (Goeking and Windmuller-Campione 2021).

The protocols used in the studies summarized here present tradeoffs related to granularity. Whitebark Pine Ecosystem Foundation protocols allow more precise, site-specific assessment of drivers (e.g., severe WPBR infection in branches versus stems), whereas FIA protocols allow more robust assessment of indicators of decline at broad scales (e.g., dead trees). At fine to medium scales, FHM projects are providing localized indicators of decline that can be aggregated across studies to suggest broad-scale drivers of population decline and mechanisms to guide hypothesis testing through probabilistic sampling designs such as FIA's. At broader scales, probabilistic assessments based on FIA data have provided robust evidence of population-scale declines as well as density management diagrams for project-scale application. Together, these programs can produce management-relevant insights on both landscape and stand characteristics and site conditions that influence forest health and resistance to stressors. Thus, purposive studies at the scale of FHM projects and probabilistic broad-scale monitoring data complement each other and can facilitate adaptive monitoring.

This chapter summarizes only one indicator from dozens of monitoring variables in the FIA dataset. Because FIA continues to collect data every year, the FIA database represents a source of accessible, consistent, and scalable information on forest health. Although such broad-scale, probabilistic sampling does not always support establishment of cause-and-effect relationships (Schreuder et al. 2001), it can confirm or refute finer scale observations on mechanisms, drivers, and extremes related to forest threats and also generate new questions that may be best addressed by localized, purposively designed investigations. Thus, FHM and FIA continue to complement each other as providers of critical information about forest health status and trends.

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CHAPTER 4

Recent Trends in American Beech (*Fagus grandifolia*) Demography

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INTRODUCTION

Tree growth, mortality, and recruitment are the key drivers of forest demography, the balance of which determines forest dynamics at any given space and time (Hara 1984, Kunstler et al. 2021, Zuidema and van der Sleen 2022). The size class distribution of a forest community (i.e., the number of individual trees within each diameter size class) provides a practical way to characterize that community; in theory, this distribution can be predicted from growth, mortality, and recruitment processes (Wang et al. 2009). In the absence of significant disturbance, the size class distribution of a forest is generally constant over time and can be represented by a steeply descending monotonic reverse J-shaped curve (Lorimer and Frelich 1984, Wang et al. 2009). However, any influence from external stressors, natural or anthropogenic, could result in disproportionate effects on forest demographic processes, potentially leading to uncertain future trajectories (Kreyling et al. 2011, Uriarte et al. 2018, van der Sleen et al. 2017). Identifying deviations from expected temporal and spatial patterns in forest demographic variables and associating them with potential stressors like fire, insects and diseases, drought, or others can inform ongoing and future forest management activities (Clark et al. 2017, Jakovac et al. 2022, Sharma et al. 2022, Venturas et al. 2021). With the rise in intensity and frequency of natural and anthropogenic stressors (Abatzoglou et al. 2021, Burgess et al. 2022, Domke et al. 2023, Ramsfield et al. 2016), regular assessment of forest demographic parameters provides promising opportunities in forest health monitoring.

The slow growth of trees and their gradual response to changes make it challenging to uncover anomalies in demographic parameters at desired temporal and spatial scales (Battison et al. 2024). Remote sensing has become a well-established method for quantifying forest dynamics regionally and continues to advance rapidly with high-resolution and robust technologies (Battison et al. 2024). Process-based models are also often used in exploring the impact of disturbances on forest demography (McDowell et al. 2020, Rüger et al. 2023). However, using forest inventory data from established plot networks is perhaps the most desirable method for quantifying forest trends and can also be used for validation of or integration with remote sensing data (Venturas et al. 2021, Yu et al. 2022).

American beech (*Fagus grandifolia*) is an important tree species, serving as a major component of deciduous forest ecosystems in eastern North America (Stephanson and Coe 2017). Its prominence in the northern hardwood forest type, along with sugar maple (*Acer saccharum*) and yellow birch (*Betula alleghaniensis*), can be attributed to its high shade tolerance and moderate longevity (Cogbill 2005, Rogers et al. 2022). In addition, it does well in most of the mesic sites in its range, especially those with fire exclusion. It is a primary food source for many animal species, with bird and mammal abundance particularly linked to beech and its nut production (e.g., Jakubas et al. 2005, Storer et al. 2005). American beech is also used as a timber product (albeit less so than other hardwood species), as well as for commercial products such as flooring and furniture (Burns 1990, Carpenter 1974).

Despite being a key species, the distribution and abundance of American beech have been reduced since European settlement, perhaps most significantly due to land use pressures, e.g., harvest or conversion of forest land to agriculture (Cogbill 2005, Suffling et al. 2003). The modern range of American beech covers the Eastern United States, going well beyond the Canadian border in the north and limited to riparian and mesic areas in the South. Its western range is largely limited by moisture availability and a strong association with river bluffs (Cogbill 2005, Little 1971).

In recent times, the biogeography of American beech has been further impacted by biotic agents like beech bark disease (BBD), along with land use and climate conditions, leading to tree mortality at a massive scale and a diminishment in the quality of surviving trees (Kasson and Livingston 2011, Stephanson and Coe 2017). BBD is a canker disease complex caused by the interaction of fungal pathogens (*Neonectria ditissima*, *N. faginata*, and *Bionectria ochroleuca*) and a nonnative insect (*Cryptococcus fagisuga*) commonly known as the beech scale (Reed et al. 2022). The first outbreaks of BBD in North America were reported in Bedford, Nova Scotia, in 1911 (Ehrlich 1934), thereafter spreading gradually through the next several decades (Cale et al. 2017, Houston 1994, Wiggins et al. 2004). The impact of the disease has been such that the species has lost its status as a valued commercial tree species in the Eastern United States (Bose et al. 2017). Another disease, beech leaf disease, was reported in northeastern Ohio in 2012 (Ewing et al. 2019) and was found to be associated with the nonnative nematode *Litylenchus crenatae* (Carta et al. 2020). While much remains unknown about beech leaf disease, it has been observed to cause rapid dieback and mortality in trees of all ages and is likely to further exacerbate the decline of American beech (Ewing et al. 2019).

In this study, we (the authors of this chapter) explored recent trends in American beech demography against the backdrop of historical factors such as BBD spread and land use change. Specifically, the study (1) characterizes the current status (for inventory period 2012–2023) of American beech in the conterminous United States, (2) assesses changes in its demographics (tree density, basal area, mortality rate, size class distribution, and proportion of standing dead) from a previous inventory period (2001–2014) to the current inventory period (2012–2023), and (3) compares such changes in demographic parameters with that observed for all other tree species (hereafter referred to as "Other species") in the forests. The findings from this analysis are expected to contribute to the development of potential forest health indicators, such that the tools and methods used in this study could be scaled to target any desired species and spatial context but also provide a quantitative benchmark for future assessments.

METHODS

This study is based on Forest Inventory and Analysis (FIA) data established and maintained by the U.S. Department of Agriculture, Forest Service's FIA program. In its Nationwide Forest Inventory (NFI), the FIA program collects information from approximately 130,000 permanent plots representing all types of land ownership with a sampling intensity of about one plot per 2428 ha (6,000 acres) (Burrill et al. 2024). Remeasurement intervals for the plots under the annualized inventory program are approximately 5 to 7 years for the Eastern United States and about 10 years in the West.

In this analysis, we used FIA data from those States with documented presence of American beech (table 4.1). The data had a temporal range spanning from 2001 to 2023, which included data from two time periods: current (2007 to 2023) and the recent past (2001 to 2018). The years that comprise a complete inventory cycle (hereafter "evaluation") differ between States, as does the most recent year for which data are available (table 4.1). We used the FIA program's web-based application EVALIDator (ver. 2.1.3), which was linked to the most recent FIA database (FIADB ver. 1.9.3.00; Burrill et al. 2024), to access and summarize inventory data for the desired variables by FIA survey units and States (USDA Forest Service, FIA Program 2024). By default, EVALIDator provides estimates for the "current" (i.e., most recently completed) evaluation. For each of the demographic variables of interest, we compared estimates from the current evaluation with estimates from a previous evaluation that, except for Texas, did not include inventory years that overlapped with the current evaluation. We conducted multiple EVALIDator runs for each demographic variable—seedling density, live tree density, live tree basal area, annual mortality rate (annual number of dead trees per hectare), and standing dead tree density—with different species filters (American beech and "All species") for current and previous evaluations (see table 4.1). Live trees (i.e., other than seedlings) were further categorized into three different size classes using diameter at breast height (d.b.h.): small trees (<12.7 cm), medium trees (≥12.7 to <25.4 cm), and large trees (≥25.4 cm). Seedlings (<2.54 cm diameter) are measured and recorded differently from larger trees in FIA; only live seedlings (i.e., no dead seedlings) are measured. While larger trees are recorded individually in the FIA data, seedlings are tallied and reported per species during inventory.

We prepared a map of FIA survey units for the conterminous United States in ArcGIS Pro 3.4. Typically, survey units are groups of counties within a State, so we used a TIGER/Line county shapefile from the U.S. Census Bureau as a foundation and grouped counties according to their FIA survey unit designations (U.S. Census Bureau 2024). Next, we prepared a map showing the current distribution of American beech in the conterminous United States at the survey unit level. For this map, we defined the broad geographic distribution of this species as all survey units with at least one plot measured during the current evaluation that had one or more live American beech trees (fig. 4.1). However, because some of these units had few American beech trees

Table 4.1—Previous and current evaluations (i.e., the inventory years included in each) for States with documented presence of American beech as analyzed in this study

States	Previous evaluation	Current evaluation
TX	2001 to 2007	2007 to 2021
TN	2005 to 2011	2012 to 2021
KY	2006 to 2013	2014 to 2020
AL	2006 to 2014	2015 to 2023
OK	2008 to 2011	2012 to 2021
FL	2009 to 2013	2014 to 2021
MD, MA, MI, WV	2009 to 2014	2015 to 2021
NC	2009 to 2015	2016 to 2022
MS	2009 to 2016	2017 to 2022
GA	2010 to 2014	2015 to 2021
CT, DE, IL, IN, MO, NH, NY, OH, PA, RI, VT, WI	2010 to 2015	2016 to 2022
NJ	2012 to 2017	2018 to 2022
SC	2012 to 2016	2017 to 2022
AR	2013 to 2018	2019 to 2023

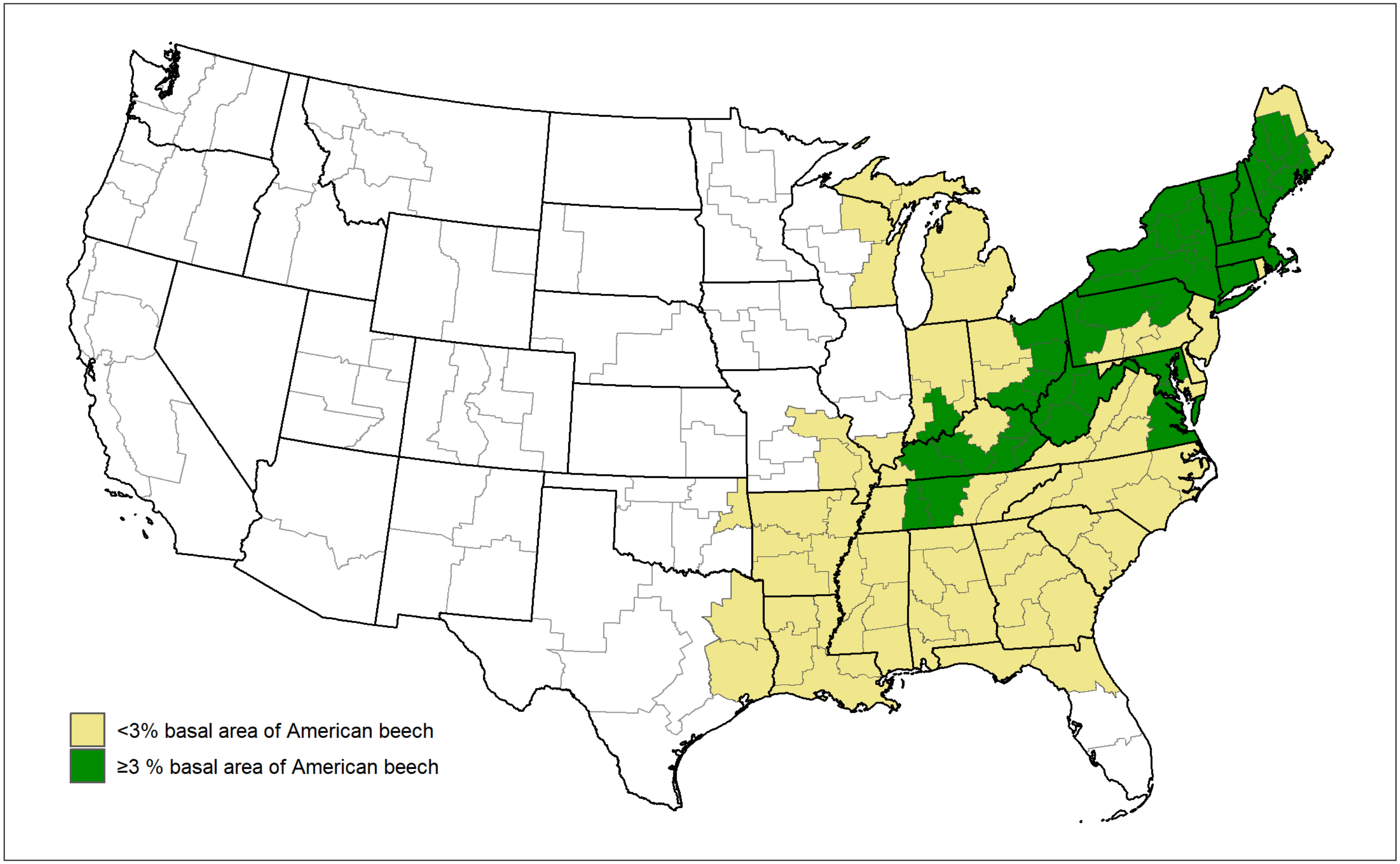

Figure 4.1—Distribution of American beech based on the current evaluation. Areas in green show survey units with ≥3 percent basal area of American beech, representing the study area selected for further demographic analysis.

present, we restricted our analyses to areas where the species is a relatively important component to achieve more interpretable results. We tried different criteria to delineate these areas and, ultimately, we adopted a threshold of 3 percent American beech basal area (i.e., as a percentage of the total basal area for all trees). Since the selected survey units were somewhat disconnected, we created a spatially contiguous study area using a concave hull function available with the sf package in R (Pebesma 2018, Pebesma and Bivand 2023). After applying this function, our study area consisted of 42 survey units (fig. 4.1).

We used percentage of American beech in the forests to describe the current status of the species and to observe any differences in its status between the two evaluations. We calculated the percentage of American beech for each evaluation and each demographic variable by dividing the estimate for beech by the corresponding estimate for all trees in the forests, including beech trees, as shown below.

$$\text{Percentage of American beech} = \frac{\text{Estimate for American beech only}}{\text{Estimate for total trees}} * 100 \qquad [1]$$

For both evaluations, we computed estimates of the variables (in terms of percentage of American beech) for each survey unit. We also created maps (fig. 4.2) showing spatial patterns (at the survey unit level) of the demographic variables for the current evaluation, represented in terms of percentage of American beech (eq. 1).

We computed 95-percent confidence intervals for the mean demographic variable estimates across the entire study area. We included a covariance term in the standard error calculation for these estimates (i.e., percentage of American beech) and all subsequent estimates at the study area level, assuming dependency between the distribution of beech and all tree species (Schreuder et al. 2004, Westfall et al. 2013). Next, we computed differences in percentage of American beech between the two evaluations for all the demographic variables, along with their associated standard errors, as mentioned above, acknowledging any dependency between the sampling efforts at two evaluations (Westfall et al. 2013). We prepared maps in R (R Core Team, 2024) showing differences in American beech percentage between the current and previous evaluations for all demographic variables at the survey unit level (fig. 4.3).

To compare the recent trends for American beech with those of the rest of the tree species ("Other species") in the forests, we used the following equation and assessed percent change in the demographic variables between the two evaluations for both groups (i.e., "American beech" and "Other species").

$$\text{Percent change} = \frac{(\text{Current mean estimate} - \text{Previous mean estimate})}{\text{Previous mean estimate}} * 100 \qquad [2]$$

We applied t-tests to assess the significance ($\alpha = 0.05$) of difference in percent change between American beech and "Other species" for any of the demographic variables (eq. 2). We also produced 95-percent confidence intervals for the percent change estimates (fig. 4.4), with adjustments made for potential dependency between the two groups (Schreuder et al. 2004).

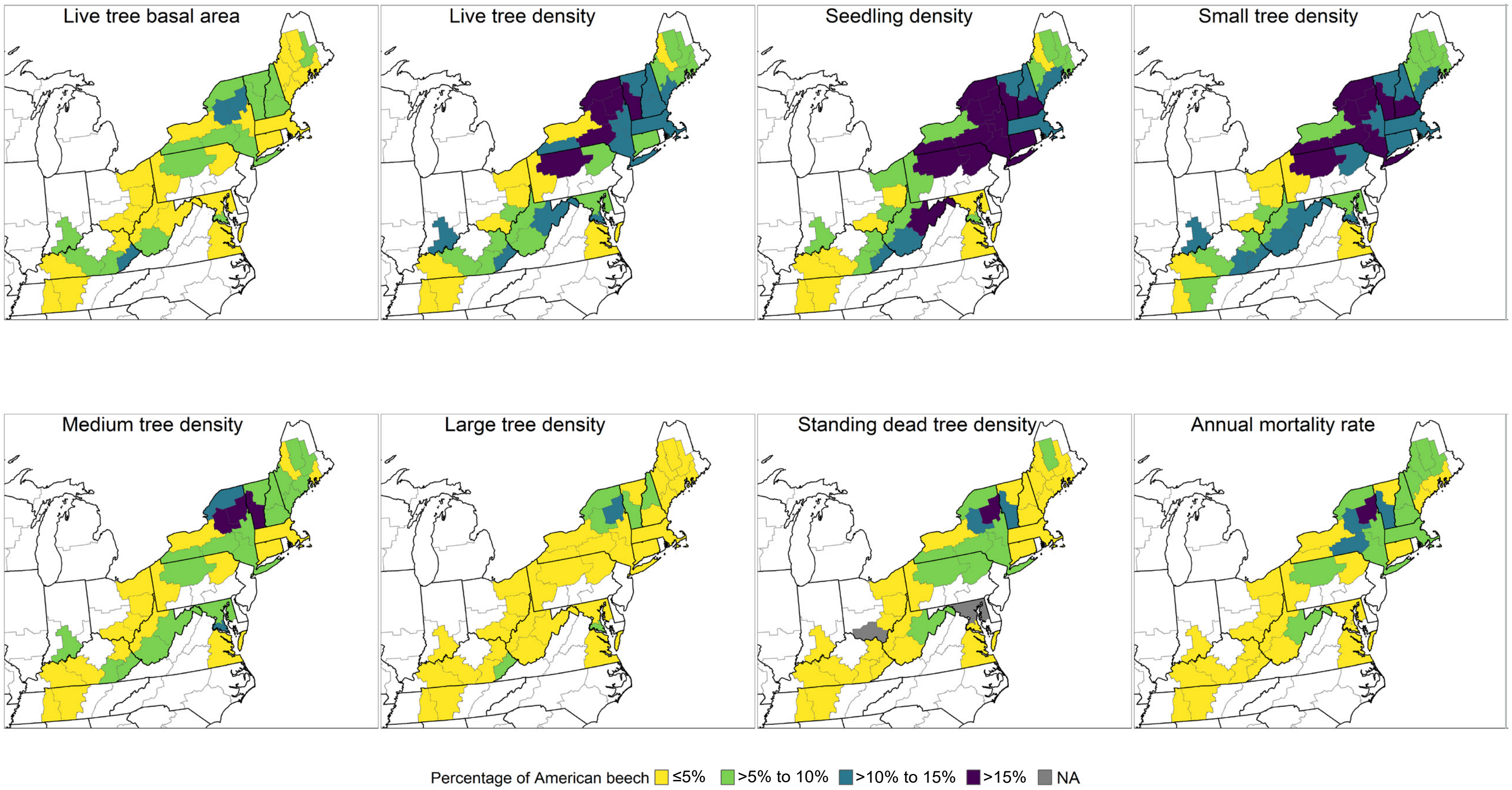

Figure 4.2—Estimates of various demographic variables in terms of the percentage of American beech out of all trees (i.e., all species including beech), summarized at the survey unit level.

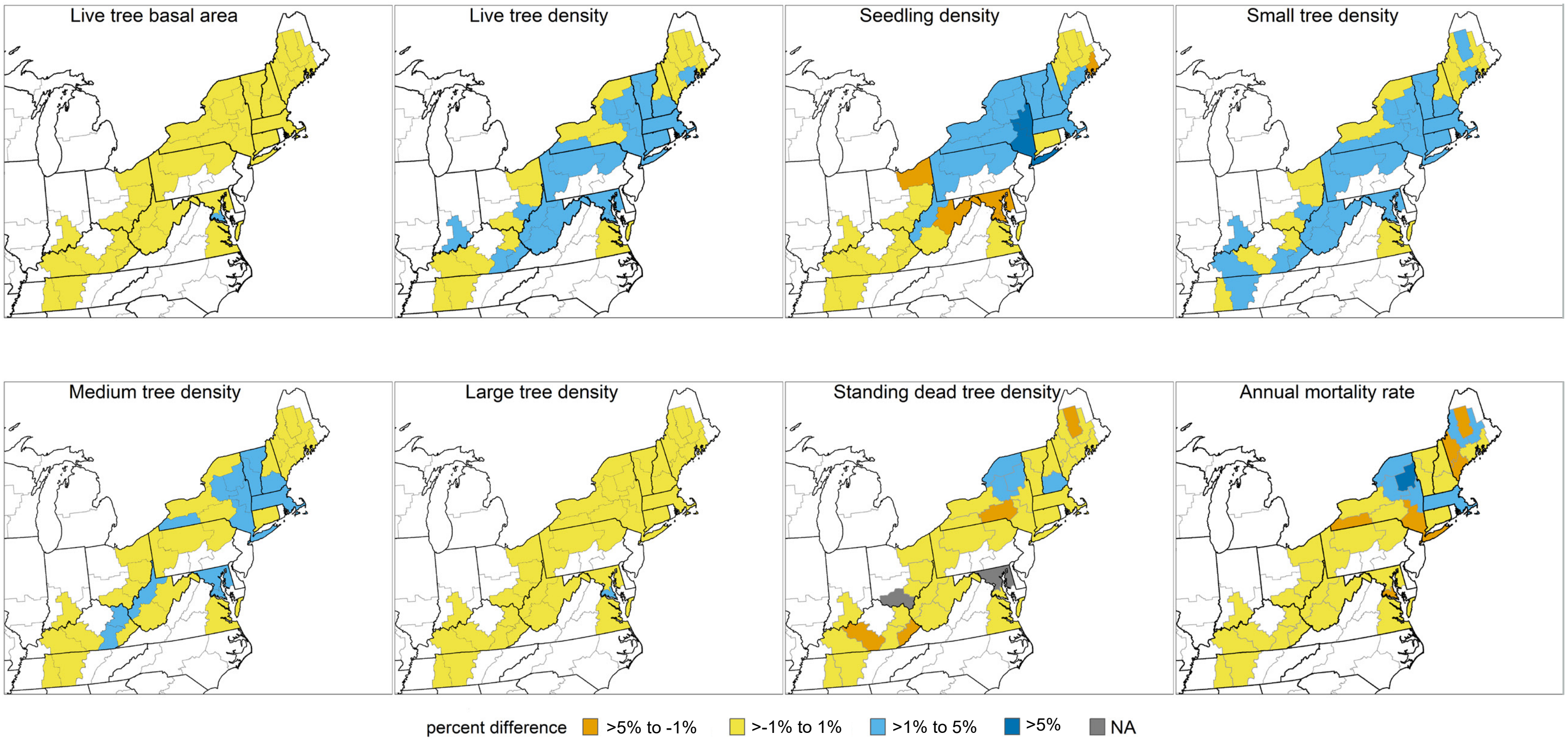

Figure 4.3—Spatial pattern of changes in various demographic variables of American beech between the current evaluation (2007–2023) and previous evaluation (2001–2018) in terms of the percentage of all the species summarized at the survey unit level.

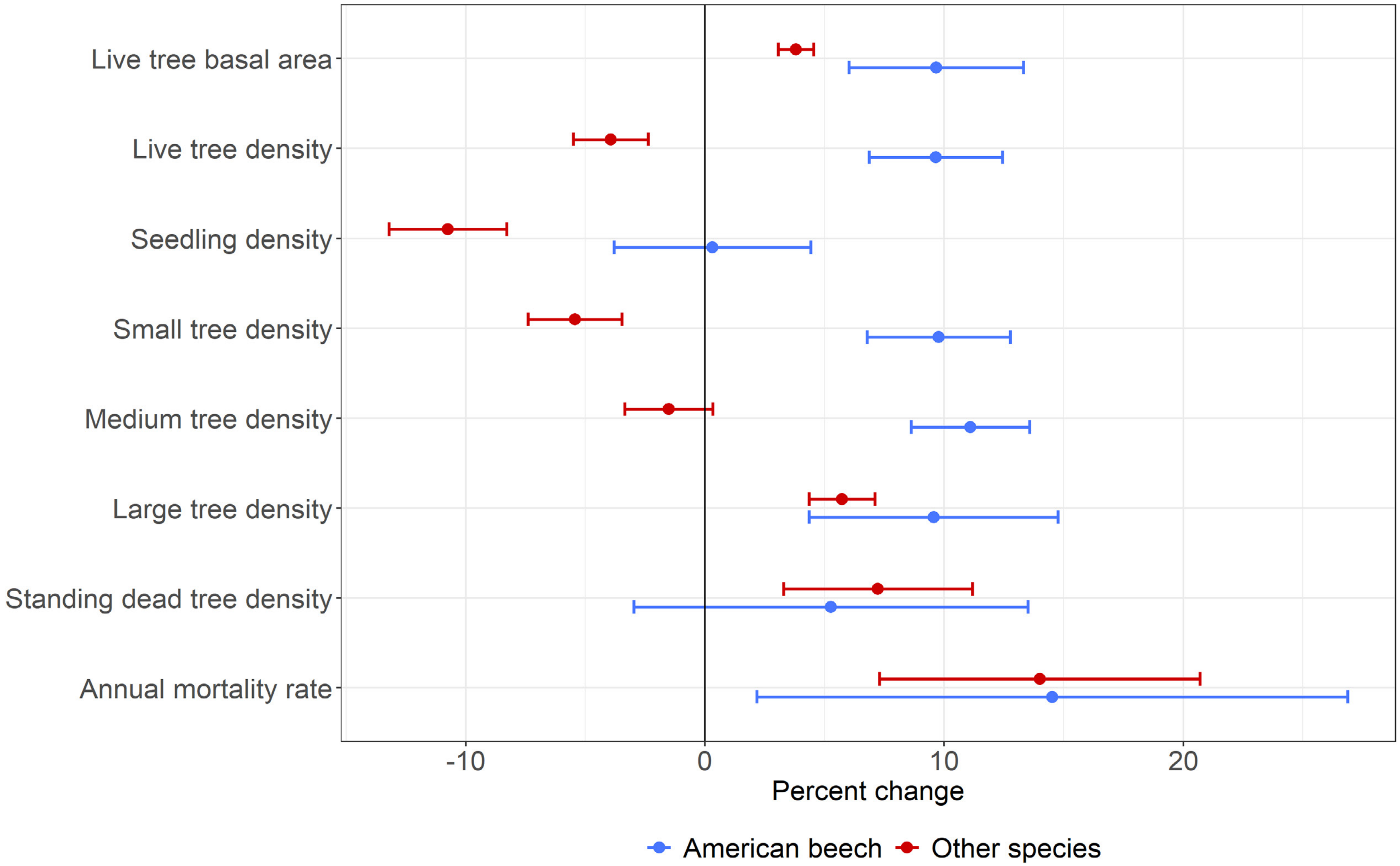

Figure 4.4—Percent change in demographic variables for American beech and other species in the study area between two evaluations. Error bars represent 95-percent confidence intervals of the estimates.

RESULTS

Current Distribution of American Beech

The current FIA evaluation shows the presence of American beech across 31 States and 113 survey units in the Eastern United States. Broadly, this represents the modern biogeographic extent of the species (Cogbill 2005, Little 1971). However, we observed substantial variation in the total number of FIA plots (1 to 496) and other parameters of American beech among these survey units. In general, the Northeastern States had greater presence of American beech as shown by the areas with ≥3 percent basal area in figure 4.1, which is consistent with areas of high importance for the species as suggested by Peters et al. (2020) and Morin et al. (2005).

Per the current evaluation, density and basal area of American beech are high in New York (particularly in the Adirondack Mountains), northern Pennsylvania, and most of New England (fig. 4.2). Beech density and basal area are also comparatively high in the Central Appalachian Mountains and the Ohio River Valley, a region that includes much of West Virginia and Kentucky as well as eastern Ohio, southern Indiana, and central Tennessee (fig. 4.2). This spatial pattern is strongly evident for seedling and small tree density but less obvious for medium and large trees. The density of standing dead trees and the annual mortality rate are also high in eastern New York and adjacent areas.

Demographic Changes in American Beech From Past Evaluation

Most demographic variables showed a positive change from the previous to the current evaluation, except for standing dead tree density, which showed some negative change, and annual mortality, with almost no change (table 4.2). Trends in small trees and seedlings suggest an increase in beech density through time in these size classes, although stable tree densities were recorded for the larger size classes. None of these average changes for any demographic variables across the study area, however, were significant at the 95-percent confidence level.

We observed some interesting spatial patterns of changes in demographic variables at the survey unit level, although these changes likewise were not statistically significant. Some positive changes were seen for seedling and small tree density in areas with high beech importance (figs. 4.2 and 4.3). Yet, some survey units in Ohio, West Virginia, and Maryland exhibited decreases in seedling density between the two evaluations. Areas in eastern New York and Massachusetts with high densities of seedlings and small and medium-sized trees also had increased mortality rates.

Table 4.2—Average values of American beech and forest demographic variables (measured in per-hectare terms) for the previous evaluation, current evaluation, and change between the two evaluations

Demographic variables[1]	Previous evaluation (2001–2018)			Current evaluation (2007–2023)			Change between two evaluations		
	AB (SE)	Total (SE)	AB % (SE)	AB (SE)	Total (SE)	AB % (SE)	AB (SE)	Total (SE)	AB % (SE)
Seedling density (ha^{-1})	613.11 (65.69)	6,501.86 (467.93)	9.43 (1.03)	615.01 (62.71)	5,870.38 (410.96)	10.48 (1.2)	1.89 (83.03)	-631.48 (631.05)	1.05 (2.12)
Live tree density (ha^{-1})	148.78 (16.62)	1,735.88 (117.08)	8.57 (0.89)	163.14 (17.18)	1,687.85 (112.58)	9.67 (0.95)	14.36 (11.92)	-48.03 (92.4)	1.09 (0.79)
Small tree density (ha^{-1})	127.26 (14.44)	1,332.76 (111.92)	9.55 (1.05)	139.68 (14.9)	1,279.69 (106.23)	10.92 (1.15)	12.42 (10.89)	-53.08 (91.12)	1.37 (1.16)
Medium tree density (ha^{-1})	15.43 (1.87)	263.13 (9.22)	5.86 (0.64)	17.14 (2)	261.11 (10.03)	6.56 (0.69)	1.71 (1.39)	-2.02 (15.17)	0.7 (0.59)
Large tree density (ha^{-1})	5.61 (0.46)	138.76 (3.89)	4.04 (0.3)	6.14 (0.51)	146.92 (4.01)	4.18 (0.32)	0.54 (0.97)	8.16 (5.77)	0.14 (0.6)
Standing dead tree density (ha^{-1})	2.23 (0.45)	41.8 (2.69)	5.34 (0.87)	2.35 (0.53)	44.78 (2.68)	5.25 (1.01)	0.12 (0.68)	2.98 (4.76)	-0.09 (1.03)
Live tree basal area ($m^2\ ha^{-1}$)	14.41 (1.25)	280.28 (4.87)	5.14 (0.41)	15.8 (1.36)	291.78 (4.51)	5.41 (0.43)	1.39 (1.82)	11.5 (5.85)	0.27 (0.5)
Annual mortality rate (ha^{-1})	0.22 (0.04)	4.96 (0.1)	4.53 (0.78)	0.26 (0.05)	5.66 (0.18)	4.55 (0.91)	0.03 (0.11)	0.7 (1.04)	0.02 (1.63)

AB = American beech; AB % = average value for American beech as a percentage of the average value for all trees in the forests (including American beech); SE = standard error associated with the estimates of corresponding demographic variables.

[1] Only areas with ≥3 percent basal area of American beech were included.

Changes in American Beech Compared to Other Species

Changes seen in American beech for most of the demographic variables, except for seedling density and standing dead tree density, were positive (fig. 4.4). In contrast, for other species, live tree density, both overall and for all size classes except large trees, showed a negative trend. Higher percent changes were observed for the demographic variables (live tree density, live tree basal area, seedling density, small tree density, and medium tree density) of American beech compared to those of the other species, as evident from non-overlapping confidence intervals between them. Indeed, paired t-tests between the estimates for American beech and other species agreed with the results from confidence intervals except for large tree density, which suggested significantly higher percent change of this variable for beech.

DISCUSSION

The general distribution of American beech documented from current FIA data resembles other contemporary range maps for the species (Cogbill 2005, Little 1971). The recent geographic center of importance of American beech in the Adirondack Mountains and neighboring areas, including New England, northern Pennsylvania, and the Southern Appalachian Mountains, is consistent with previous documentation of high beech basal area locations (Morin et al. 2005, 2007) as well as high importance value locations (Peters et al. 2020). Many of the areas where American beech is important, including the Adirondacks, are also in what is known as "aftermath forest," i.e., forests that have undergone demographic restructuring after the arrival of BBD and its subsequent impacts (Cale et al. 2017).

Higher density of standing dead American beech trees observed around the Adirondacks in New York aligns with elevated standing dead basal area in the same region reported by Morin et al. (2007). Overall, we found a slight increase in American beech density, primarily for the seedling and small tree categories. According to Garnas et al. (2011), large American beech trees have declined and have become virtually absent in the oldest BBD-infected locations, while small American beech tree densities have increased dramatically such that total beech basal area is roughly the same as before BBD. Wason and Dovciak (2016) similarly observed high proportions of smaller sized trees, especially in areas with logging. The implications of logging were further explained by Bose et al. (2017), suggesting that the practice of partial harvest in the Northeast (which targets some overstory trees) creates openings that understory American beech trees are better able to exploit than other species.

Giencke et al. (2014) reported a phenomenon of beech thicket formation that precludes the recruitment of co-occurring species such as sugar maple in the areas affected by BBD. Gravel et al. (2011) also reported higher density of beech in young age classes compared to maple trees in a study from southern Quebec spanning over a 40-year period, though they did not directly discuss the effects of BBD. Likewise, our study identified significant percent increases in densities of the small and medium size classes for American beech compared to other tree species; collectively, these other species most likely saw decreases in small and medium tree density between the two evaluations. At the same time, the observed increase in large tree density for American beech species did not differ significantly from a similar increase observed for other species. We could argue that—across a sizeable portion of the American beech range—there is still some aftereffect of BBD among large-sized trees and that recovery so far has been mainly limited to medium-sized trees and smaller.

We observed some interesting patterns for change in seedling density and mortality rates in some survey units that could give us insight into local pressures on American beech populations. Lower beech seedling density near northern Ohio and adjacent areas, for example, may be linked with the emergence of beech leaf disease, which was found in that area in 2012 (Ewing et al. 2019). The higher mortality rate in New York around the Adirondacks could be linked with BBD; however, as mentioned before, this area is also the geographic center of importance of American beech, so there could be elevated effects of intraspecies competition. Among several factors, the shade tolerance of American beech, its ability to resprout through suckers after aboveground mortality (e.g., from disease), and its ability to exploit overstory openings created by BBD or other disturbances allow the species to persist in the under- and midstory. This shift can lead to less regeneration and more competition, which may explain these trends (Bose et al. 2017).

The forest demographics of American beech in the long term remain uncertain due to the ongoing expansion of beech leaf disease into areas of high beech importance that have already experienced significant impacts from BBD. Figure 4.5 shows the expansion of both diseases since first detection. This is an area of future research, which will include finer scale analyses targeting areas where the disease extents overlap. As of now, their compounding impacts remain unresolved, but functional extinction of American beech, especially as a dominant overstory component, cannot be ruled out (Ewing et al. 2019).

This analysis provides us with some preliminary concepts on developing forest health indicators based on forest demographic patterns and trends. Some studies have identified beech shifting towards higher elevations and towards northern

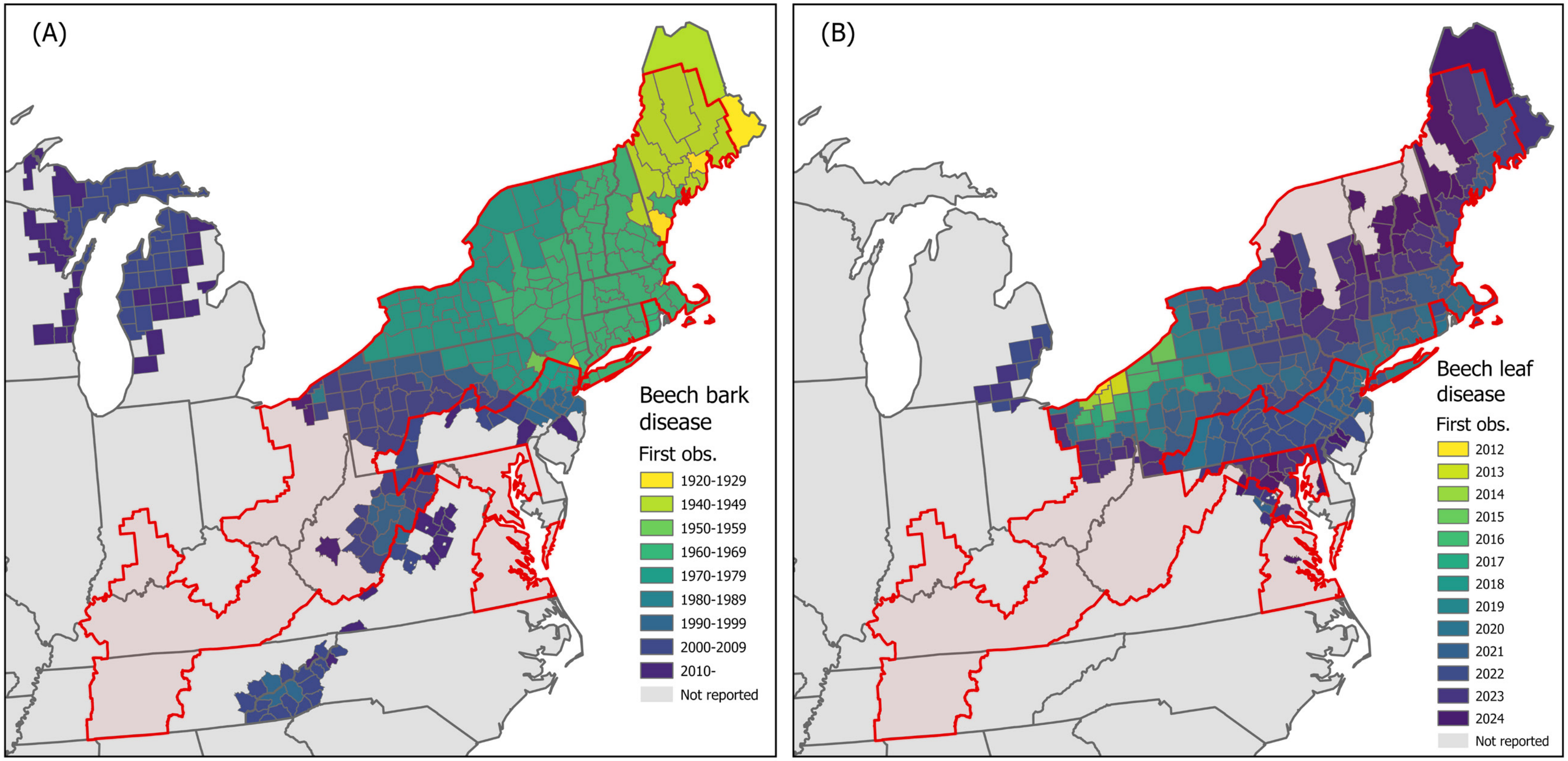

Figure 4.5—Historical range expansion of (A) beech bark disease and (B) beech leaf disease in the conterminous United States. Red outlined polygons correspond to the study area, i.e., Forest Inventory and Analysis survey units where American beech comprises ≥3 percent of live tree basal area. Data sources: Alien Forest Pest Explorer database (Fei et al. 2024), Don't Move Firewood (2025), and Cale et al. (2017).

latitudes, possibly caused in part by past climate, disease, and management events (Cale et al. 2017, Cleavitt et al. 2022, Stephanson and Coe 2017). Further work on investigating the potential impact of insects, diseases, and climate on observed patterns could provide us with better inferences. Comparing the trends of species of interest (e.g., American beech) with other codominant species (e.g., sugar maple, white oak [*Quercus alba*], etc.) in the forests would also provide us with better comparisons.

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CHAPTER 5

Broad-Scale Patterns of Forest Fire Occurrence Across the United States and the Caribbean Territories, 2023

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INTRODUCTION

Wildland fire is a major 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 et al. 2000). It is an important natural component of many forest ecosystems characterized by specific combinations of fire frequency, severity, and seasonality (Greenberg and Collins 2021). Wildland fire in many situations is essential for regulating processes that maintain forest health (Lundquist et al. 2011). For example, it 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 tree species and forest types are adapted to fire under specific intensities and return intervals (Hanberry et al. 2018, Jeronimo et al. 2019).

Forest health and sustainability problems are associated with wildland fire in some ecosystems (Edmonds et al. 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). 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 et al. 1999), potentially changing species composition, structural stage, stand age, canopy closure, and fuel loadings (Schmidt et al. 2002, Stephens et al. 2018). Evidence suggests that few entirely natural fire regimes remain in North America (Parisien et al. 2016). Such changes in fire intensity and recurrence could result in decreased forest resilience and persistence (Lundquist et al. 2011), with plant communities in some regions undergoing rapid compositional and structural changes because of fire suppression (Coop et al. 2020, May et al. 2023, Nowacki and Abrams 2008). Additionally, research demonstrates that climate patterns, via more common hot droughts, are playing a role in increased wildfire activity (Abatzoglou and Williams 2016, Higuera and Abatzoglou 2021). Severe fires in combination with climate conditions are contributing to widespread challenges to natural regeneration, which could lead to long-term conversions from forest into other vegetation types (Davis et al. 2019, Stephens et al. 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 working to contain and control the fires (Gill et al. 2013, Richardson et al. 2012). These impacts are particularly intense within the expanding wildland-urban interface, the zone in which human development intermixes with forest (Calkin et al. 2015, Radeloff et al. 2018).

This chapter presents analyses of 2023 daily satellite-derived fire occurrence data that map and quantify the locations and intensities of fire occurrences spatially across the CONUS, Alaska, Hawaii, and the Caribbean territories. It also compares fire occurrences in 2023, within a geographic context, to more than two decades of previously collected data. Quantifying such large-scale patterns of fire occurrence across the United States, as described in this chapter, can improve understanding of the potential 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 that would benefit from specific management activities or research into the ecological and socioeconomic impacts of fires.

This set of analyses has been a central component of the annual "Forest Health Monitoring: National Status, Trends, and Analysis" reports for more than a decade, but its scope and use will evolve with the development of a novel indicator-based framework. The subject of this chapter fits well as one of the national trends in forest health around which Forest Health Monitoring reporting is being reorganized. National trends, such as wildfire, highlight the trajectories of large-scale agents and processes while providing context for interpreting the forest health status, trends, and future risk quantified by the indicator groups. In the case of wildfire, future analyses such as those described here may be used to better understand forest health outcomes (e.g., mortality and regeneration) that may be driven by wildfire, as well as to develop narratives that communicate why changes in forest conditions are occurring and what actions might be taken in response. The methods described below (mapping and quantifying the intensity of a forest health indicator at broad scales across the Nation, identifying geographic hot spots of that indicator, and comparing the intensity of that indicator at one time to data collected over a longer timeframe) may be applicable to the assessment of other indicators used to describe the potential causes of agents and stressors and their impacts on ecological and social systems.

METHODS

Data

The Moderate Resolution Imaging Spectroradiometer (MODIS) Active Fire Detections for the United States database (NASA Fire Information for Resource Management System 2024) allows analysts to spatially display and summarize fire occurrences across broad geographic regions for monitoring and reporting of wildland fire events (Coulston et al. 2005; Potter 2012a, 2012b, 2013a, 2013b, 2014, 2015a, 2015b, 2016, 2017, 2018, 2019, 2020a, 2021, 2022, 2023, 2024). The data are collected through the MODIS Rapid Response System (Justice et al. 2002, 2011), which 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 sensors on the Terra and Aqua satellites identify the presence of a fire by using a contextual algorithm that exploits the strong emission of mid-infrared radiation from fires (Giglio et al. 2003). A fire occurrence is defined as one daily satellite detection of wildland fire from a 1-km pixel, with multiple fire occurrences possible on that pixel across multiple days resulting from a single long-lasting wildland fire. The resulting fire occurrence data represent only whether a fire was active, and the MODIS data bands may not differentiate between a hot fire in a relatively small area (0.01 km^2, for example) and a cooler fire over a larger area (1 km^2, for example) if the foreground-to-background temperature contrast is not sufficiently high. The MODIS Active Fire Detections database records large fires well during cloud-free conditions but may underrepresent fires in areas with frequent cloud cover as well as rapidly burning, small, and low-intensity fires (Hawbaker et al. 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 et al. 2018). Despite these shortcomings, the MODIS Active Fire Detections database provides relatively fine-scale information on the occurrence of the hotter fires—those most likely to negatively impact forest health—for the longest period of time across the entire United States. 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 et al. 2009). Justice et al. (2011) provide more information about this product. Importantly, the fire occurrence data do not distinguish whether fires are intentionally set for management purposes (controlled burns). Such fires are common in some parts of the United States, such as the South, where many prescribed fires are smaller or lower severity and thus not detected by satellite sensors (Nowell et al. 2018).

Calculations of MODIS-detected fire occurrences are different metrics for quantifying fire activity within a given year than are estimates of burned area (e.g., Monitoring Trends in Burn Severity data [Eidenshink et al. 2007, Picotte et al. 2020]). Significantly, the MODIS data contain both spatial and temporal components because persistent fires are detected repeatedly over several days on a given 1-km pixel. A location therefore can have a fire occurrence multiple times, once for each day a fire is detected at the location. As a result, analyses of the MODIS-detected fire occurrences measure the total number of daily 1-km pixels with fire during a year, as opposed to only quantifying the area on which fire occurred.

After more than 20 years of service each, the Terra and Aqua satellites that carry the MODIS sensors are likely to be decommissioned soon. The Visible Infrared Imaging Radiometer Suite (VIIRS) sensors on board the Suomi National Polar-orbiting Partnership (Suomi NPP) and NOAA-20 weather satellites provide an alternative fire occurrence data source. However, science-ready VIIRS fire data are available beginning from only 2015 (NASA Fire Information for Resource Management System 2022) compared to more than two decades for the MODIS data. Any transition from MODIS to VIIRS 375-m data for national and regional fire occurrence monitoring will require a comparison of fire occurrence detections between the two datasets. Ideally, assessments of fire occurrence trends will analyze as long a temporal window as possible, encompassing the combination of older MODIS data with newer VIIRS data.

Analyses

The focus of most analyses presented in this chapter is forest fire occurrence density, which is the number of fire occurrences per 100 km^2 (10 000 ha) of area in locations with tree canopy cover. I (the author of this chapter) calculated forest fire occurrence density for (1) ecoregion sections in the CONUS (Cleland et al. 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. I made these calculations for 2023 and for the 22 preceding full years of data after screening out wildland fires that did not intersect with tree canopy data. The 2011 tree canopy data were 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 U.S. Department of Agriculture, Forest Service, National Land Cover Database Tree Canopy Cover dataset (2016 product suite; Ruefenacht et al. 2022) through a cooperative project between the Multi-Resolution Land Characteristics Consortium and the Forest Service (Sohl et al. 2025). I treated any cell with >0 percent tree canopy cover as forest, which therefore would not include shrub and chapparal land cover without trees. Comparable tree canopy cover data were not available for Alaska, so I instead created a 240-m-resolution layer of forest and shrub cover from the 2011 National Land Cover Database. I then intersected the MODIS fire occurrence detection data with this layer and with ecoregion sections for Alaska (Spencer et al. 2002) to calculate the number of fire occurrences per 100 km^2 of forest and shrub cover within ecoregion sections. I also separately determined the total number of 2023 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. Geospatial analyses were conducted in ArcGIS Pro (ESRI 2023).

I assessed whether each unit of analysis (i.e., ecoregions across the States, islands within the Caribbean territories) had a higher or lower forest fire occurrence density in 2023 relative to the previous 22 full years of MODIS Active Fire data collection (2001–2022). To do this, I divided the difference of the 2023 value and the previous 22-year mean for the area by the standard deviation across the previous period, assuming a normal distribution of fire density over time. The result for each ecoregion or island was a standardized z-score, a dimensionless quantity describing the degree to which the fire occurrence density in the area in 2023 was higher, lower, or not significantly different relative to the previous years, accounting for the variability in those 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. 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). This is because approximately 68 percent of observations are expected to occur within one standard deviation of the mean and 95 percent within two standard deviations. I also calculated 2023 forest fire occurrence z-scores for the entirety of the CONUS, Alaska, Hawaii, and the Caribbean territories.

Additionally, to identify geographic areas across the CONUS with higher-than-expected fire occurrence density in 2023, I applied the Spatial Association of Scalable Hexagons (SASH) analytical approach. 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 and adjustable to the appropriate spatial resolution (Potter et al. 2016). It consists of dividing an analysis area into scalable equal-area hexagonal cells, aggregating data within those hexagons, and then identifying statistically significant geographic clusters of hexagons within which mean values are greater or less than those expected by chance. To identify these clusters, I employed a Getis-Ord G_i^* hot spot analysis (Getis and Ord 1992) in ArcGIS Pro 3.2 (ESRI 2023). Hexagons are the unit of analysis because they have attributes that are highly useful for spatial neighborhood analyses: they 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 et al. 2010). 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 et al. 2016). This analysis encompassed 9,810 hexagonal cells, each approximately 834 km^2 in area, generated in a lattice across the CONUS using intensification of the Environmental Monitoring and Assessment Program's North American hexagon coordinates (White et al. 1992). I selected 834-km^2 hexagons because this is a manageable size for making monitoring and management decisions in analyses across the CONUS (Potter et al. 2016).

Fire occurrence density values were calculated as the number of forest fire occurrences per 100 km^2 of tree canopy cover area within each hexagon. I used the Getis-Ord G_i^* statistic to identify 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 in the CONUS. 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 have to be within approximately two standard deviations of the mean (Laffan 2006). Values between -1.96 and 1.96 are not statistically significant concentrations of either high or low values, meaning that a hexagon and its 18 neighbors have a normal range of high and low numbers of fire occurrences per 100 km^2 of tree canopy cover area. 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 2023)—in this case, the 18 first- and second-order neighbors for each target hexagon.

RESULTS AND DISCUSSION

Trends in Forest Fire Occurrence Detections for 2023

The MODIS Active Fire database for 2023 encompassed 49,951 forest fire occurrences across the CONUS, which was a 20-percent decrease in fire activity from 2022, when 62,297 fire occurrences were recorded. The 2022 number, in turn, was a 44-percent decrease from the previous year (Potter 2024). The 2023 fire occurrence total was the lowest since 2019 and the eighth lowest since complete data collection began in 2001, with all but one of those years occurring before 2007 (fig. 5.1). It was also 33 percent below the mean for the previous 22 years of data (74,187 fire occurrences), though this was not significantly different than the previous mean while accounting for variation over time (z = -0.66). Alaska experienced an even larger decrease (86 percent) in 2023 forest fire occurrences relative to 2022: a drop from 21,320 to 2,918. This number was 69 percent below the previous 22-year average of 9,494 fire occurrences but not significantly different than that mean (z = -0.49). Hawaii, meanwhile, had a 74-percent increase in fire occurrences from 46 in 2022 to 80 in 2023. This was still fewer than, and not significantly different than, the 2001–2022 average of about 252 fires per year, driven largely by active fire years during 2014–2016 as the result of an eruption of the Kīlauea volcano (Potter 2018). Finally, the MODIS Active Fire database recorded 11 forest fire occurrences in Puerto Rico and the U.S. Virgin Islands, which was a 120-percent increase from 5 in 2022 and similar to the average of approximately 9 per year for the Caribbean territories.

These results are generally in keeping with official national wildland fire statistics tracking the number of wildfires reported and the area burned (National Interagency Coordination Center 2024). Nationally, the 56,580 wildfires reported in 2023 decreased about 18 percent from the 68,988 reported in 2022, while the 1 090 187 ha burned was approximately a third of the 3 066 377 ha burned the previous year (National Interagency Coordination Center 2023). The area burned nationally was slightly lower than the 10-year average, with only the Northern United States (encompassing the Northeast and Midwest) above average. The National Interagency Coordination Center tracks very large wildland fires and fire complexes that exceed a benchmark threshold of 16 187 ha (40,000 acres). Only 10 fires in 2023 exceeded this area threshold, considerably fewer than 2022 (45), 2021 (38), and 2020 (50) (National Interagency Coordination Center 2021, 2022, 2023, 2024). Four of these 2023 fires were in Alaska, three in California, and one each in Washington, New Mexico, and Nebraska. It is important to reiterate that the official national wildland fire statistics—the number of reported fires and estimates of burned area—are different metrics for quantifying fire activity than the calculations of MODIS-detected fire occurrences that are presented in this chapter. The metrics may be correlated, however.

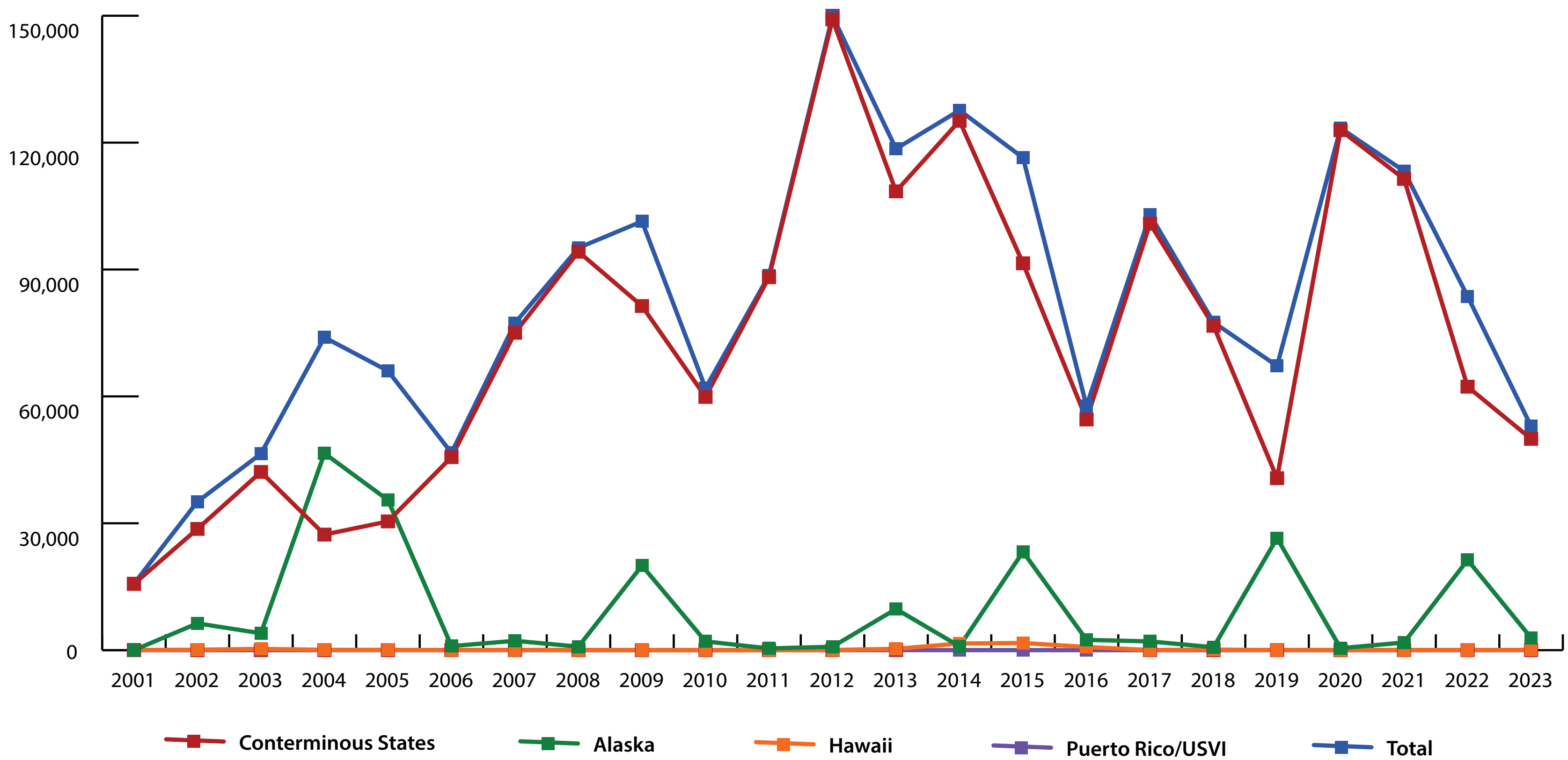

Figure 5.1—Forest fire occurrences detected by Moderate Resolution Imaging Spectroradiometer from 2001 through 2023 for the conterminous United States, Alaska, Hawaii, and Puerto Rico and the U.S. Virgin Islands (USVI), and for the entire Nation combined. Data source: U.S. Department of Agriculture, Forest Service, Geospatial Technology and Applications Center, in conjunction with the NASA MODIS Rapid Response group.

Unlike recent years, no ecoregions in 2023 had very high or extremely high fire occurrence densities (>12 occurrences/100 km^2 of tree canopy cover). Those ecoregion sections with high fire occurrence densities were 262A–Great Valley in central California (11.7 fire occurrences/100 km^2 of tree canopy cover), M261A–Klamath Mountains of northwestern California and southeastern Oregon (9.4 fire occurrences), and 251F-Flint Hills in eastern Kansas and northeastern Oklahoma (7.2 fire occurrences) (table 5.1, fig. 5.2). In 2022, no ecoregions had extremely high fire occurrence densities (>24 fire occurrences/100 km^2 of tree canopy cover), but a handful of ecoregions in the Southwest had very high fire occurrence densities (Potter 2024), while in 2020 and 2021, ecoregions in the northwestern and Sierra Nevada regions of California and in central Oregon and Washington had extremely high fire occurrence densities (Potter 2022, 2023). In 2023, seven additional ecoregions in the Southeast, Southwest, and Northwest had at least moderate fire occurrence densities (>4 fire occurrences/100 km^2 of tree canopy cover) (fig. 5.2). The year was characterized by below-normal temperatures and above-normal precipitation across much of the West, suppressing fire activity in the region, while the Southern and Plains States experienced abnormally dry conditions that were conducive to fire ignition (National Interagency Coordination Center 2024). While it was a relatively low fire activity year in the United States, Canada experienced a fire season of unprecedented severity that ended with approximately 18.5 million ha burned, 200,000 people evacuated from their homes, and abundant smoke at times pouring into the Northeastern United States (National Interagency Coordination Center 2024).

Alaska experienced an abnormally slow fire season until the end of July, when prolific lightning ignited dozens of wildfires, including several large ones (National Interagency Coordination Center 2024). Most of these fires were in the eastern interior of the State, but only one ecoregion—132C–Tanana-Kuskokwim Lowlands—had a moderate fire occurrence density (3.0 fire occurrences/100 km^2 of forest and shrub cover; fig. 5.3).

Hawaii, meanwhile, experienced the deadliest wildland fire in the United States for more than a century. This was the Lahaina fire, which killed 100 people and destroyed more than 2,300 residences on the island of Maui and was caused by extensive drought and above-normal fuel loading coupled with extremely dangerous fire weather conditions (National Interagency Coordination Center 2024). The ecological region in which it occurred—Lowland/Leeward Dry-Maui (LLDm)—had a high fire occurrence density of 6.9 fire occurrences/100 km^2 of tree canopy cover (fig. 5.4). Two other ecological regions, Lowland Wet-O‘ahu (LWo) and Mesic-Maui-East (MEm-e), had moderate fire occurrence densities, 5.3 and 4.0 fire occurrences/100 km^2 of canopy cover, respectively.

Finally, fire occurrence densities in 2023 were ≤1 fire occurrence/100 km^2 of tree canopy cover for Puerto Rico and the U.S. Virgin Islands, the two U.S. territories in the Caribbean Sea (fig. 5.5).

Table 5.1—The 15 ecoregion sections in the conterminous United States with the highest fire occurrence densities in 2023

Section	Name	Tree canopy area (100 km²)	Fire occurrences (number)	Density[1]
262A	Great Valley	19.4	227	11.67
M261A	Klamath Mountains	338.5	3,169	9.36
251F	Flint Hills	57.8	414	7.16
232J	Southern Atlantic Coastal Plains and Flatwoods	604.0	3,561	5.90
M313A	White Mountains - San Francisco Peaks - Mogollon Rim	202.5	1,140	5.63
232B	Gulf Coastal Plains and Flatwoods	888.7	4,790	5.39
232D	Florida Coastal Lowlands-Gulf	134.9	636	4.71
232K	Florida Coastal Plains Central Highlands	149.0	686	4.60
313C	Tonto Transition	17.5	78	4.47
232F	Coastal Plains and Flatwoods-Western Gulf	432.9	1,606	3.71
232G	Florida Coastal Lowlands-Atlantic	138.5	500	3.61
M333C	Northern Rockies	176.3	630	3.57
411A	Everglades	68.7	243	3.54
232C	Atlantic Coastal Flatwoods	613.1	2,129	3.47
M242B	Western Cascades	427.9	1,480	3.46

[1] Density = fire occurrences/100 km² of tree canopy coverage area.

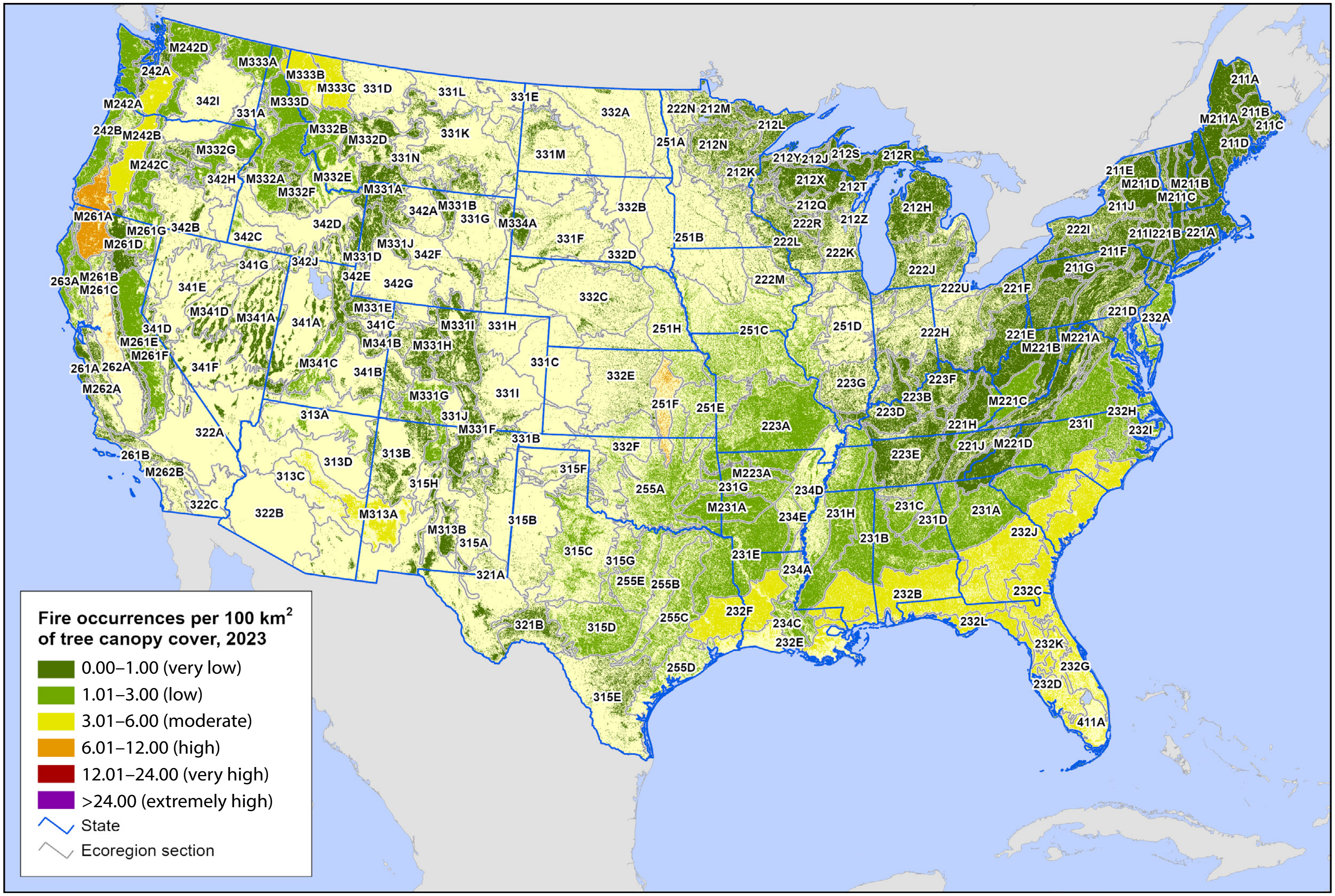

Figure 5.2—The number of forest fire occurrences per 100 km² (10 000 ha) of tree canopy coverage area, by ecoregion section within the conterminous United States, for 2023. The gray lines delineate ecoregion sections (Cleland et al. 2007). Tree canopy cover is based on data from a cooperative project between the Multi-Resolution Land Characteristics Consortium (Sohl et al. 2025) and the Forest Service Geospatial Technology and Applications Center using 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.

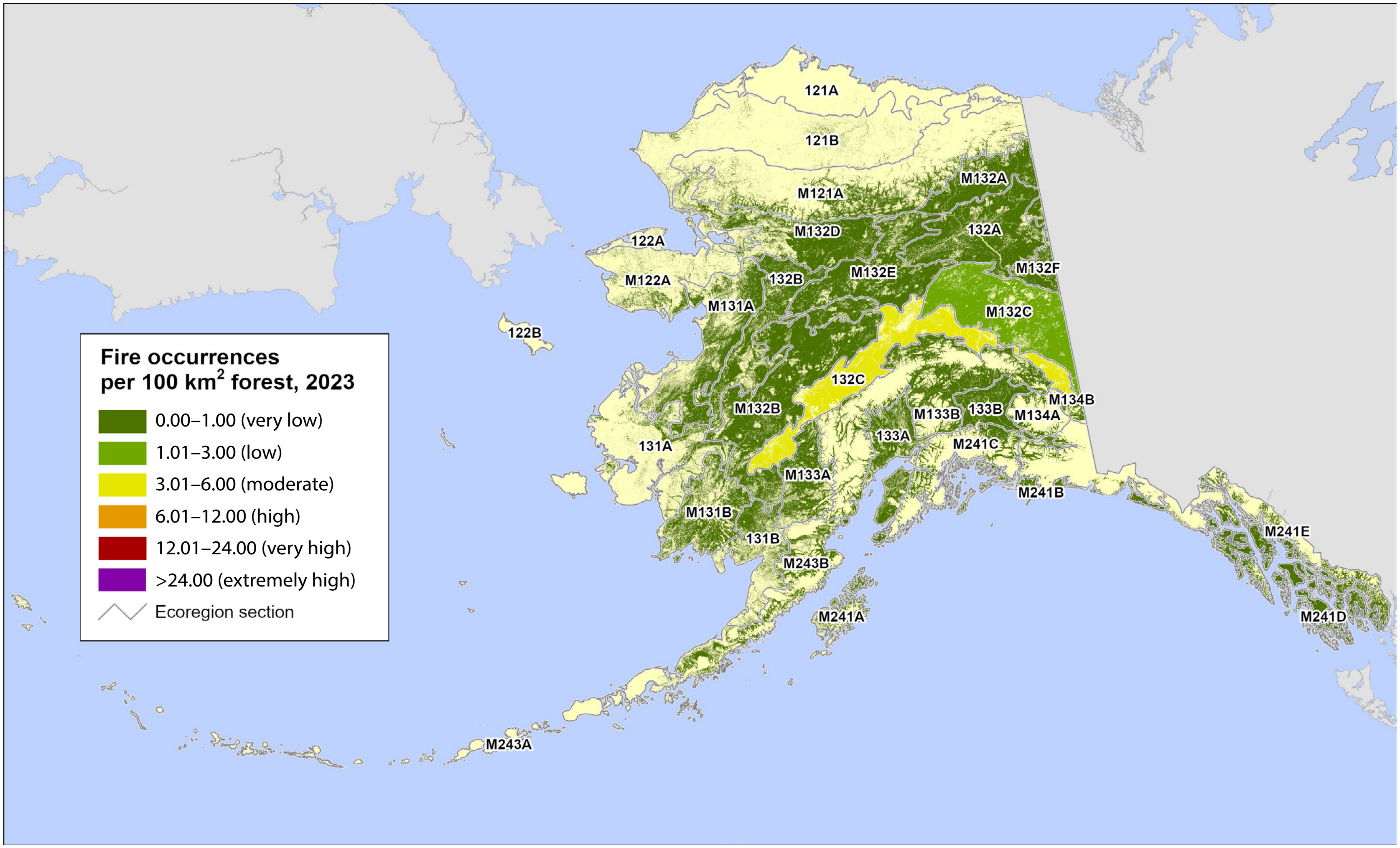

Figure 5.3—The number of forest fire occurrences per 100 km² (10 000 ha) of forest and shrub cover, by ecoregion section within Alaska, for 2023. The gray lines delineate ecoregion sections (Spencer et al. 2002). Forest and shrub cover are derived from the 2011 National Land Cover Database. Source of 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.

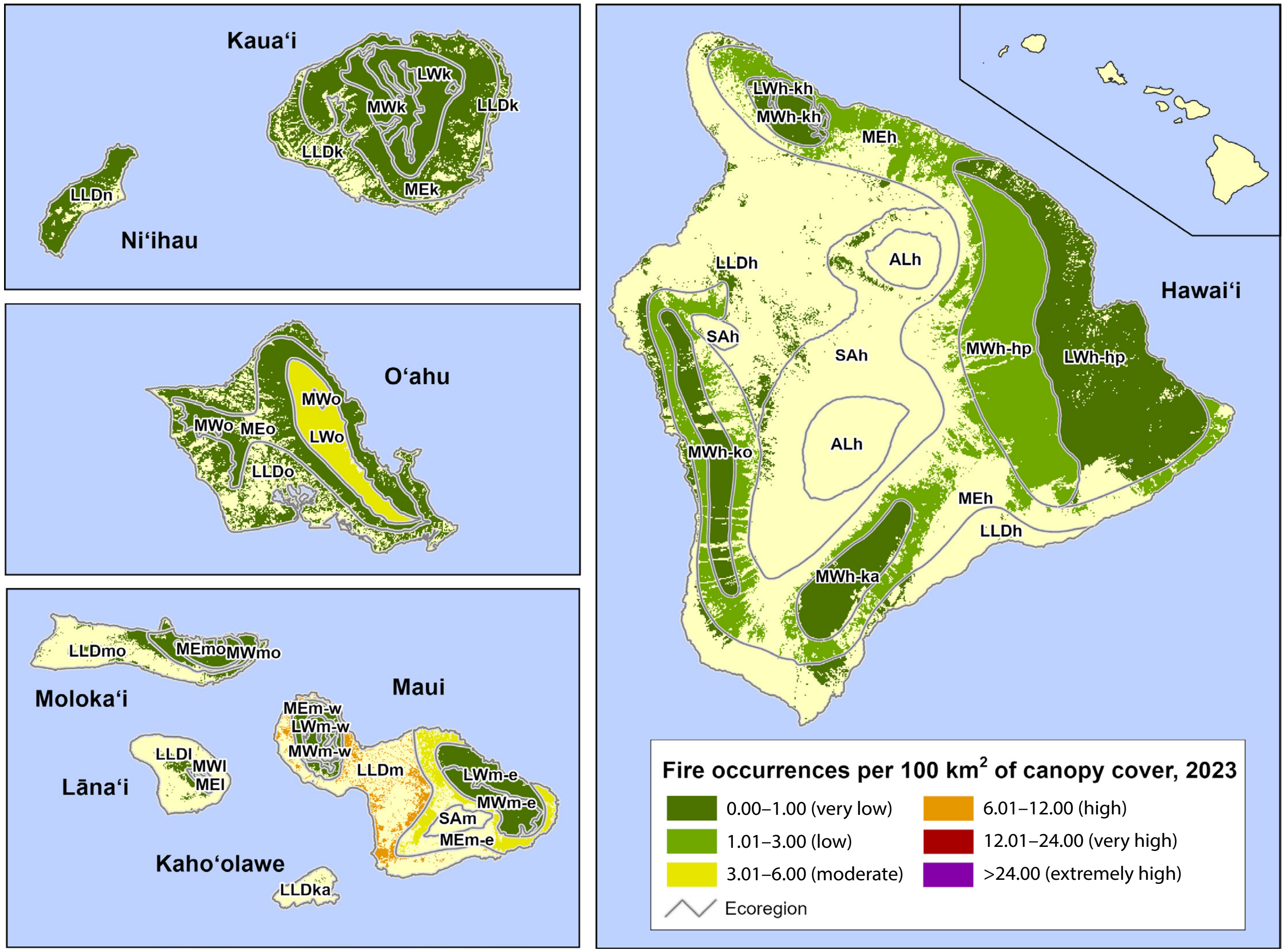

Figure 5.4—The number of forest fire occurrences per 100 km² (10 000 ha) of tree canopy coverage area, by island/ecoregion combination in Hawaii for 2023. Tree canopy cover is based on data from a cooperative project between the Multi-Resolution Land Characteristics Consortium (Sohl et al. 2025) and the Forest Service Geospatial Technology and Applications Center using 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.

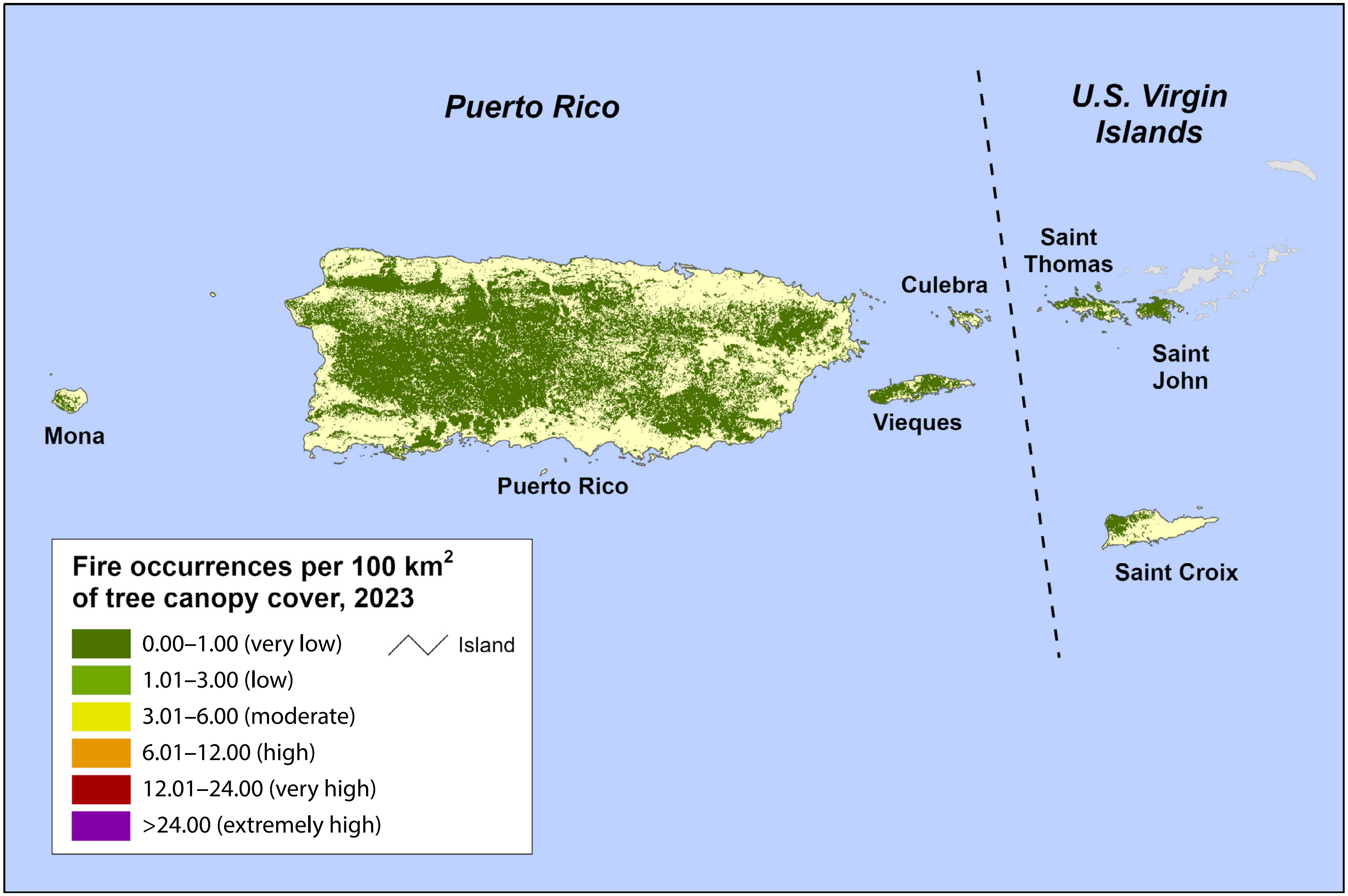

Figure 5.5—The number of forest fire occurrences per 100 km² (10 000 ha) of tree canopy coverage area, by island in Puerto Rico and the U.S. Virgin Islands, for 2023. Tree canopy cover is based on data from a cooperative project between the Multi-Resolution Land Characteristics Consortium (Sohl et al. 2025) and the Forest Service Geospatial Technology and Applications Center using 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.

Comparison to Longer Term Trends

The collection of MODIS Active Fire data for 23 years makes it possible to contrast annual (2023) forest fire occurrence densities with longer term trends (2001–2022) for ecoregions in the CONUS, Alaska, and Hawaii, as well for the islands that make up the Caribbean territories. During that 22-year comparison period, ecoregions in the Pacific Coast States, Idaho, and Arizona/New Mexico and along the Gulf Coast in the Southeast had high mean annual fire occurrence densities (exceeding 6 fire occurrences/100 km^2 of tree canopy cover) (fig. 5.6A). Four ecoregion sections exceeded 11.0 fire occurrences/100 km^2 of tree canopy cover annually: M261A–Klamath Mountains of northwestern California and southeastern Oregon, M332A–Idaho Batholith in central Idaho, M261B–Northern California Coast Ranges, and M261E–Sierra Nevada in California (table 5.2). Other ecoregion sections with high mean annual fire occurrence densities were M262B–Southern California Mountain and Valley near the southern California coast, M313A–White Mountains-San Francisco Peaks-Mogollon Rim in Arizona and New Mexico, 313C–Tonto Transition in Arizona, 251F–Flint Hills in eastern Kansas and northeastern Oklahoma, M242D–Northern Cascades in Washington, 261A–Central California Coast, and 232B–Gulf Coastal Plains and Flatwoods. Other ecoregions in the West and Southeast had moderate mean fire occurrence densities (>3–6 fire occurrences/100 km^2 of tree canopy cover annually), while much of the Midwest and all the Northeast had very low densities (≤1).

Many of the western ecoregions with the highest mean annual forest fire occurrence densities also had the greatest annual variation in fire occurrence densities from 2001 through 2022, especially in the West (fig. 5.6B). 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 west-central Wyoming—had moderate variation with low mean annual fire occurrence densities, suggesting high numbers of fire occurrences in some years but low numbers in most. Ecoregion sections of the Midwest and Northeast and in coastal Oregon and Washington had the lowest interannual variation (standard deviation <1), while ecoregions across the Southeast and the central Rocky Mountains had slightly higher variation (standard deviation 1–5). Parts of the Southeast, especially along the Gulf Coast, had low annual variation in conjunction with relatively high mean annual fire occurrence densities, indicating consistently high numbers of fire occurrences over time.

Several ecoregions in the Northeast, the Great Lakes States, and the Mid-Atlantic States—along with one ecoregion each in California and the Pacific Northwest—experienced 2023 fire occurrence densities that were higher than normal, compared to the previous 22-year mean and accounting for temporal variability (fig. 5.6C).

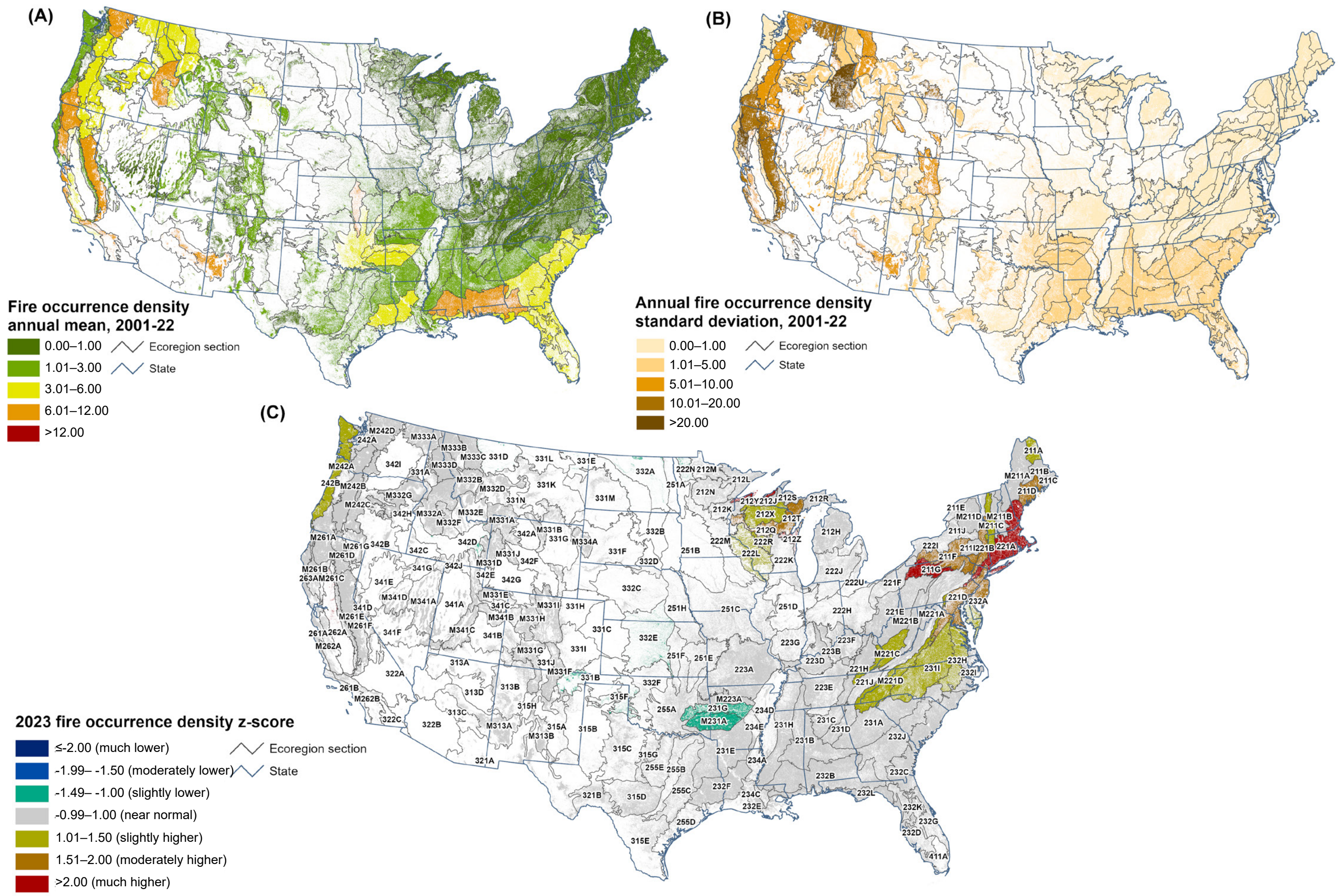

Figure 5.6—(A) Mean number and (B) standard deviation of forest fire occurrences per 100 km^2 (10 000 ha) of tree canopy coverage area from 2001 through 2022, by ecoregion section within the conterminous 48 States. (C) Degree of 2023 fire occurrence density excess or deficiency, by ecoregion section relative to 2001–2022 and accounting for variation over that period. The gray lines delineate ecoregion sections (Cleland et al. 2007). Tree canopy cover is based on data from a cooperative project between the Multi-Resolution Land Characteristics Consortium (Sohl et al. 2025) and the Forest Service Geospatial Technology and Applications Center using 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.

Table 5.2—The 15 ecoregion sections in the conterminous United States with the highest mean annual fire occurrence densities from 2001 through 2022

Section	Name	Tree canopy area (100 km^2)	Mean annual fire occurrence density[1]
M261A	Klamath Mountains	338.5	11.69
M332A	Idaho Batholith	338.9	11.67
M261B	Northern California Coast Ranges	114.1	11.48
M261E	Sierra Nevada	427.8	11.15
M262B	Southern California Mountain and Valley	58.1	8.90
M313A	White Mountains-San Francisco Peaks-Mogollon Rim	202.5	7.83
313C	Tonto Transition	17.5	7.03
251F	Flint Hills	57.8	6.81
M242D	Northern Cascades	251.1	6.42
261A	Central California Coast	66.8	6.41
232B	Gulf Coastal Plains and Flatwoods	888.7	6.07
331A	Palouse Prairie	33.4	5.63
M261D	Southern Cascades	150.6	5.62
M242C	Eastern Cascades	219.4	5.61
M332F	Challis Volcanics	72.2	5.48

[1] Mean annual fire occurrence density = fire occurrences/100 km^2 of tree canopy coverage area.

With *z*-scores >2, two ecoregion sections in the Northeast (221A–Lower New England and 211G–Northern Unglaciated Allegheny Plateau), two in the Great Lakes region (212Y–Southwest Lake Superior Clay Plain and 212Z–Green Bay-Manitowoc Upland), and one in California (262A–Great Valley) had much higher 2023 fire occurrence densities than expected. With the exception of 262A–Great Valley, all these areas had very low fire occurrence densities for the year (fig. 5.2) but were still higher than the very low long-term average. In other words, these ecoregions 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.

At the same time, a few ecoregion sections in the Southeast and in the Plains States had lower-than-expected fire occurrence densities in 2023—that is, they had *z*-scores ≤-1. These included M231A–Ouachita Mountains and 231G–Arkansas Valley in Arkansas and eastern Oklahoma; 332A–Northeastern Glaciated Plains in central North Dakota; 222N–Lake Agassiz-Aspen Parklands in northern Minnesota; 332E–South-Central Great Plains in Kansas and Nebraska; 331B–Southern High Plains in New Mexico, Colorado, Oklahoma, Texas, and Kansas; and 315F–Northern Texas High Plains. With the exceptions of M231A–Ouachita Mountains and 231G–Arkansas Valley, these areas have low to moderate annual fire occurrence densities on average.

In Alaska, mean annual fire occurrence densities for 2001–2022 were highest (moderately high >3–6 fire occurrences/100 km^2 of tree canopy cover annually) in 132A–Yukon-Old Crow Basin and M132E–Ray Mountains of the State's central and east-central interior (fig. 5.7A). Several neighboring interior ecoregions around these had slightly lower mean annual fire occurrence densities, while those of the rest of Alaska were very low (≤1). Central and east-central interior ecoregions exhibited moderately high variability during the 22-year period preceding 2023 (fig. 5.7B). No Alaskan ecoregions in 2023 had fire occurrence densities that were either higher or lower than expected compared to the previous 21 years and controlling for variability (fig. 5.7C).

For Hawaii, an ecological region on the windward (eastern) side of Hawaiʻi Island had both the highest annual fire occurrence density mean (fig. 5.8A) and variability (fig. 5.8B) from 2001 through 2022. This ecological region (Lowland Wet-Hilo-Puna [LWh-hp]) encompasses recently active portions of the lower east rift zone of the Kīlauea volcano, where lava flows from intermittent eruptions burn forested areas (e.g., Andrews 2018). In 2023, three ecological regions had higher-than-expected fire occurrence densities (fig 5.8C). Two were on Maui, Lowland/Leeward Dry-Maui (LLDm; site of the catastrophic Lahaina fire) and Mesic-Maui-East (MEm-e), and one was on Oʻahu, Lowland Wet-Oʻahu (LWo).

All the islands encompassed by Puerto Rico and the U.S. Virgin Islands had fire occurrence means and standard deviations ≤1 for 2001–2022 (figs. 5.9A and 5.9B), with the exception of the small Great Hans Lollik Island north of Saint Thomas in the U.S. Virgin Islands. No islands in 2023 had a higher- or lower-than-expected fire occurrence density (*z*-score >1 or <1) (fig. 5.9C).

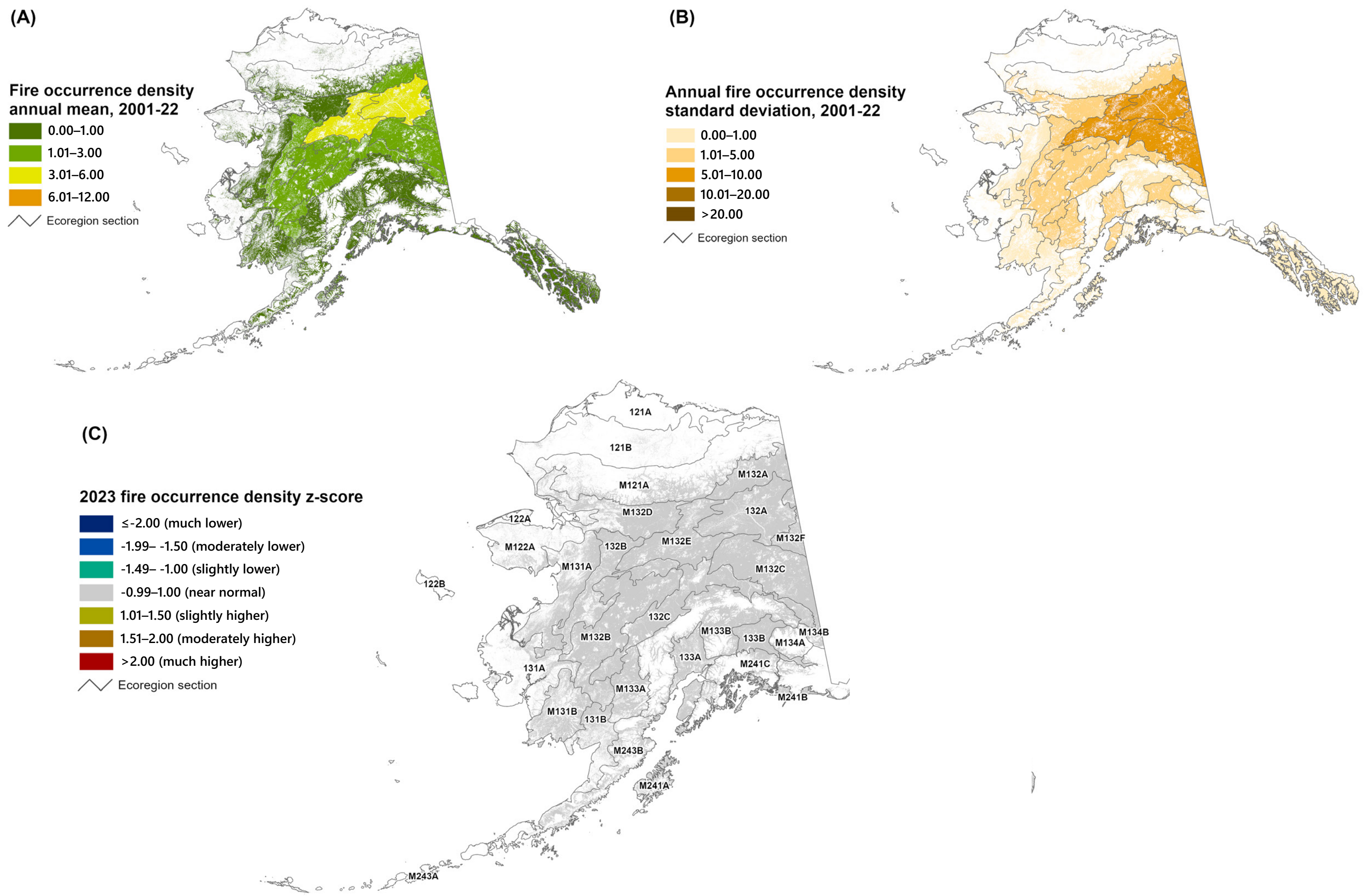

Figure 5.7—(A) Mean number and (B) standard deviation of forest fire occurrences per 100 km² (10 000 ha) of forest and shrub cover from 2001 through 2022, by ecoregion section in Alaska. (C) Degree of 2023 fire occurrence density excess or deficiency, by ecoregion section relative to 2001–2022 and accounting for variation over that period. The gray lines delineate ecoregion sections (Spencer et al. 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.

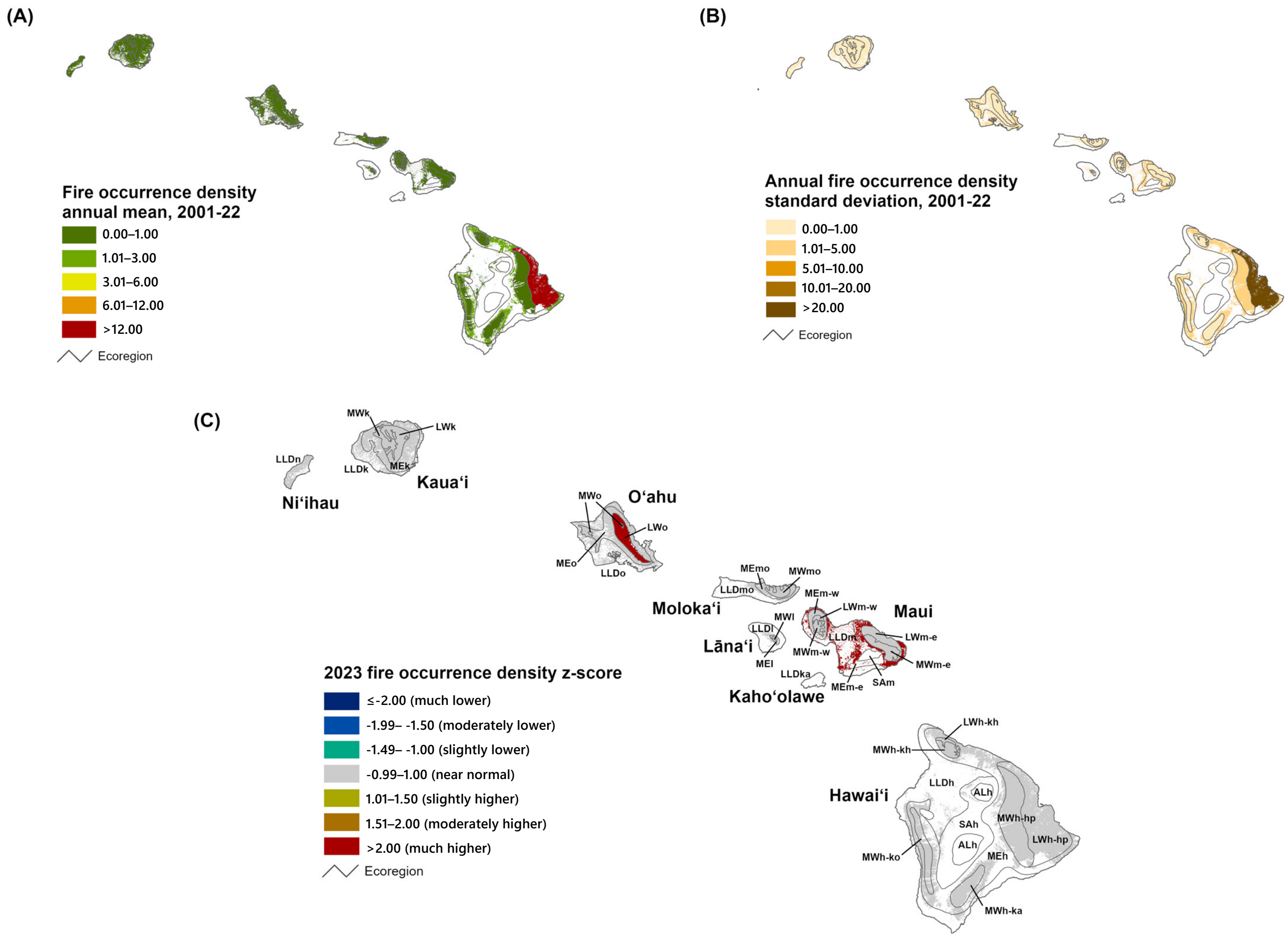

Figure 5.8—(A) Mean number and (B) standard deviation of forest fire occurrences per 100 km² (10 000 ha) of tree canopy coverage area from 2001 through 2022, by island/ecoregion combination in Hawaii. (C) Degree of 2023 fire occurrence density excess or deficiency, by island/ecoregion combination relative to 2001–2022 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 (Sohl et al. 2025) and the Forest Service Geospatial Technology and Applications Center using 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.

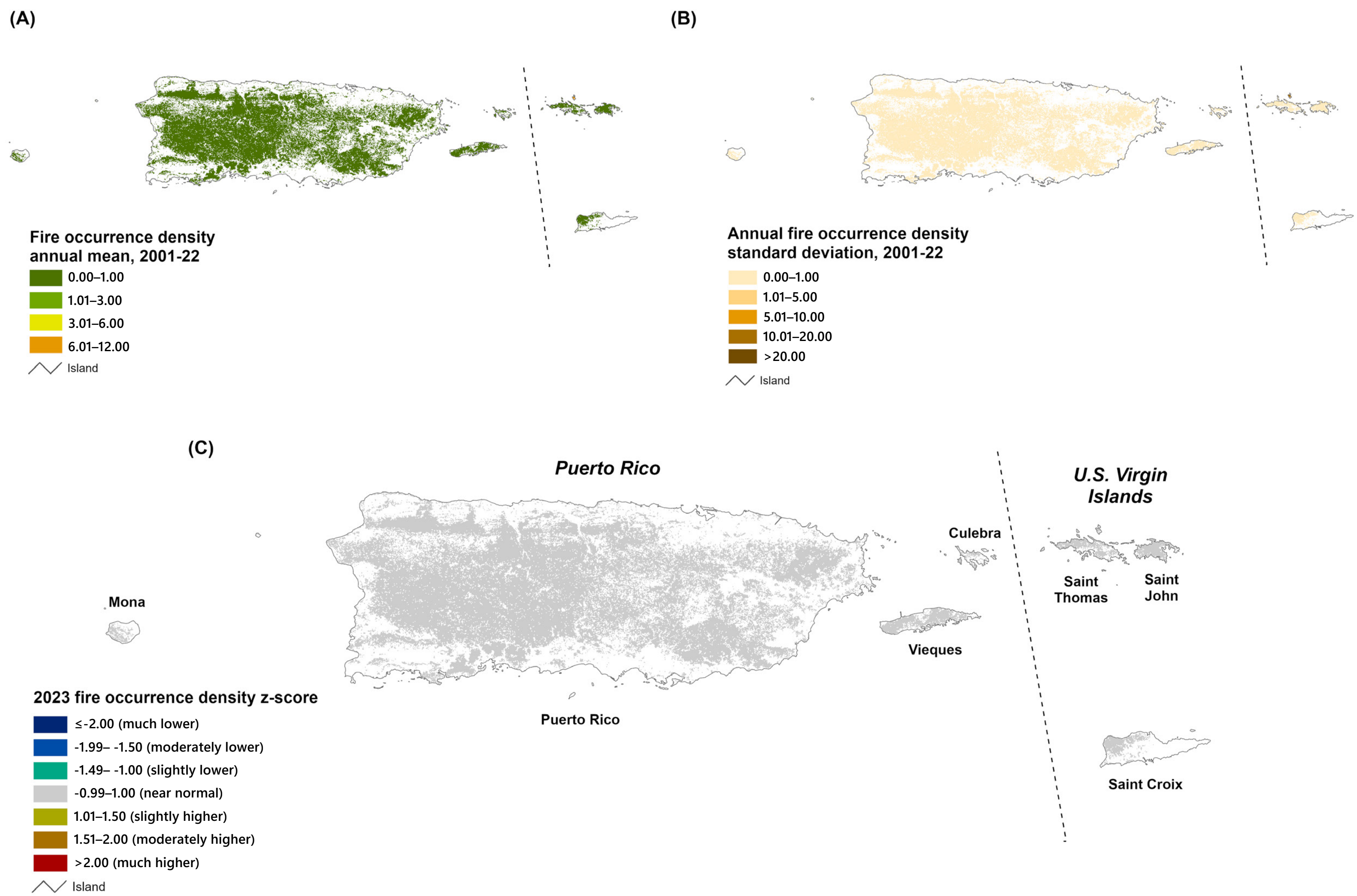

Figure 5.9—(A) Mean number and (B) standard deviation of forest fire occurrences per 100 km^2 (10 000 ha) of forested area from 2001 through 2022, by island in Puerto Rico and the U.S. Virgin Islands. (C) Degree of 2023 fire occurrence density excess or deficiency, by island relative to 2001–2022 and accounting for variation over that period. Tree canopy cover is based on data from a cooperative project between the Multi-Resolution Land Characteristics Consortium (Sohl et al. 2025) and the U.S. Department of Agriculture, Forest Service, Geospatial Technology and Applications Center using the 2011 National Land Cover Database.

Geographic Hot Spots of Fire Occurrence Density

Geographic hot spot analyses using units smaller than ecoregions can offer additional insights into where fire occurrences are more concentrated than expected by chance during a given year. Specifically, this approach identifies areas across the CONUS with higher-than-expected fire occurrence densities compared to the entire study region. As for 2022 (Potter 2024), but unlike 2020 and 2021 (Potter 2022, 2023), the 2023 analysis did not detect any geographic hot spots of extremely high fire occurrence density (G_i^* >24) (fig. 5.10). At the same time, there were three hot spots of very high fire occurrence density (G_i^* >12 and ≤24) and several more of high density (G_i^* >6 and ≤12).

One of the very high fire occurrence density hot spots was detected in M261A–Klamath Mountains of northwestern California and southeastern Oregon. This region was the location of the Smith River Fire Complex and the SRF Lightning Fire Complex, which respectively burned 38 488 ha and 20 314 ha from mid-August through mid-November and late October (National Interagency Coordination Center 2024). The other very high density hot spots were detected in north-central California (262A–Great Valley and M261C–Northern California Interior Coast Ranges) and in southwestern Georgia (232B–Gulf Coastal Plains and Flatwoods).

As shown in figure 5.10, other 2023 hot spots of high fire density were in:

- West-central Oregon (M242B–Western Cascades and 242B–Willamette Valley)
- North-central Oregon and south-central Washington (342I–Columbia Basin and M242C–Eastern Cascades)
- Northwestern Montana (M333B–Flathead Valley, M333C–Northern Rockies, and M333D–Bitterroot Mountains)
- Southwestern Arizona (322B–Sonoran Desert and 322C–Colorado Desert)
- North-central Arizona (M313A–White Mountains-San Francisco Peaks-Mogollon Rim)
- Southwestern New Mexico (also M313A–White Mountains-San Francisco Peaks-Mogollon Rim)
- Eastern Kansas (251F–Flint Hills, 251E–Osage Plains, and 251H–Nebraska Rolling Hills)
- Southeastern Texas and southwestern Louisiana (232E–Louisiana Coastal Prairie and Marshes)
- South-central Alabama and western Florida panhandle (232B–Gulf Coastal Plains and Flatwoods)

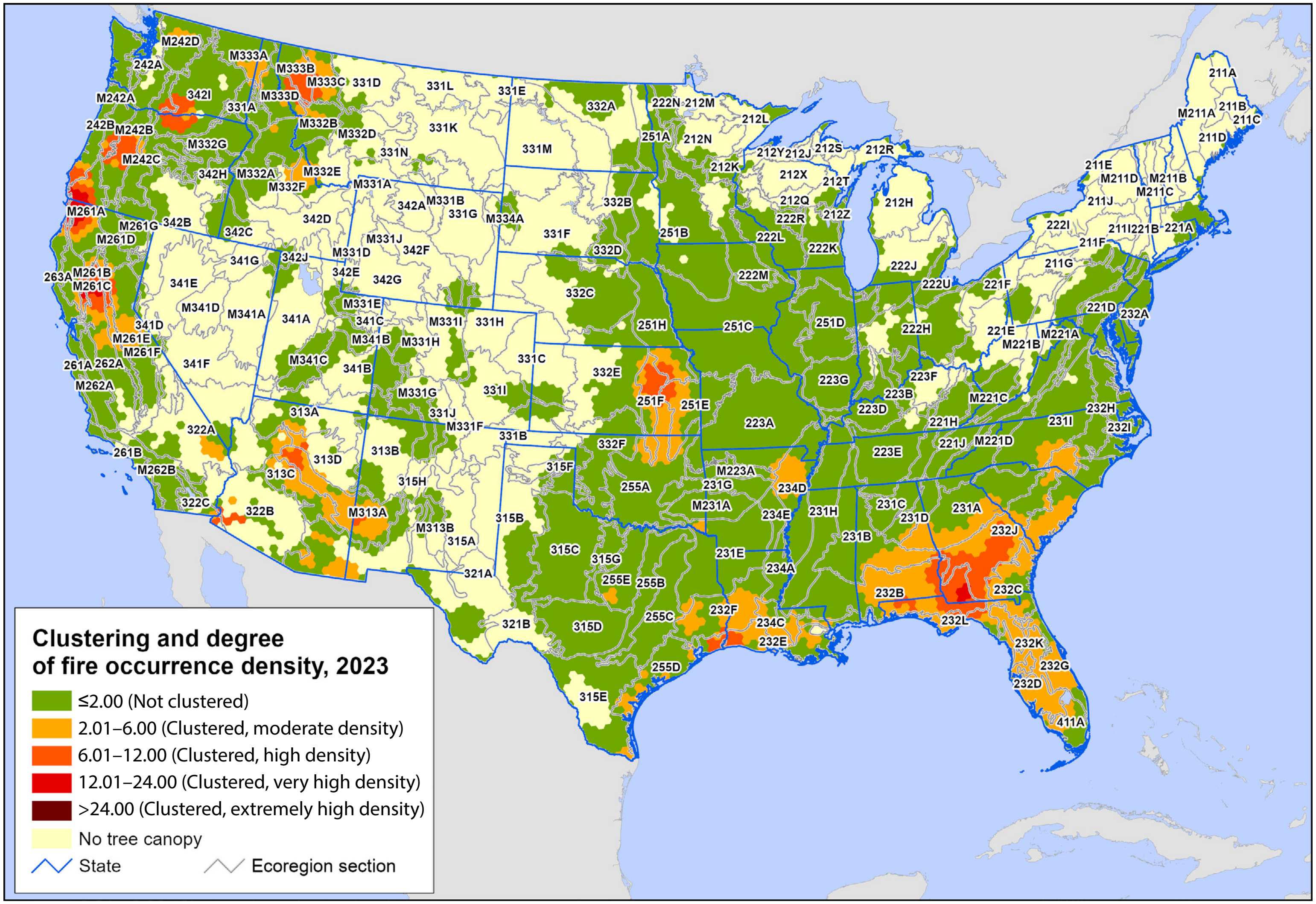

Figure 5.10—Hot spots of fire occurrence, by ecoregion section within the conterminous United States, for 2023. Values are Getis-Ord G_i^* *scores, with values >2 representing significant clustering of high fire occurrence densities. (No areas of significant clustering of lower fire occurrence densities, <–2, were detected.) The gray lines delineate ecoregion sections (Cleland et al. 2007).*

CONCLUSIONS

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 et al. 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. These results can also inform understanding of the forest health indicator groups in the context of interactive effects of agents and processes on multiple aspects of forest ecosystem structure and dynamics. Specifically, information from mapping and quantifying wildfire occurrence density at broad scales across the Nation, identifying geographic hot spots of wildfire occurrence density, and comparing recent wildfire occurrence density to longer term trends can be used to better understand forest health indicator dynamics affected by wildfire, as well as to develop forest health narratives about why changes in forest conditions occur and what the appropriate management responses may be.

The number of 2023 MODIS satellite-detected forest fire occurrences decreased 20 percent across the CONUS from the preceding year and was the eighth lowest since complete data collection began in 2001, with all but one of those years occurring before 2007. Despite being a relatively quiet fire year in the CONUS, three ecoregions—one each in California, the Pacific Northwest, and the Midwest—had high fire occurrence densities. Unlike recent years, no ecoregion had very high or extremely high fire occurrence densities. Three geographic hot spots of very high fire occurrence density were detected, two in the Pacific Northwest and one in the Southeast, along with several hot spots of high fire occurrence density. Some ecoregions in the Northeast, Great Lakes, Pacific Northwest, and Mid-Atlantic experienced fire occurrence densities that were higher than normal in 2023 compared to the previous 22-year mean and accounting for variability over that period. Many of these areas typically have very few fire occurrences. Meanwhile, a handful of ecoregion sections in the Southeast and Plains States had lower-than-expected fire occurrence densities.

Alaska experienced an even larger decrease in 2023 forest fire occurrences relative to 2022. The number was 69 percent below the previous 22-year average. Only one ecoregion, in central Alaska, had a moderate fire occurrence density level (>3 fire occurrences/100 km^2 of forest and shrub cover); the rest had low or very low densities. No ecoregions had higher- or lower-than-expected fire occurrence densities.

Hawaii had a disastrous wildfire year in 2023 because of the Lahaina fire, which was the deadliest U.S. wildfire for more than a century. The ecological region where it occurred on Maui had a high fire occurrence density (>6–12 fire occurrences/100 km^2 of tree canopy cover), while two other ecological regions, one each on Maui and O‘ahu, had moderate fire occurrence densities. The 2023 fire occurrence densities for these regions were higher than expected compared to the previous 22 years of data. Finally, the Caribbean islands had low fire occurrence densities that were neither higher nor lower than expected.

The results of these geographic analyses offer insights into where fire occurrences were concentrated spatially during a given year and compared to previous years. They are not designed to quantify the severity of a given fire season. These research 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.

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The Forest Health Monitoring program of the U.S. Department of Agriculture, Forest Service produces an annual national report, which presents recent forest health status and trends from a national or multistate regional perspective and introduces new techniques to analyze forest health condition. This 24th edition of the annual report presents mapping techniques applied to investigate 2023–2024 pine mortality events in Mississippi and Louisiana based on satellite data and the national Insect and Disease Survey. A review of declines in whitebark pine (*Pinus albicaulis*) and limber pine (*P. flexilis*) is discussed based on available literature. The Forest Inventory and Analysis program's Nationwide Forest Inventory data are used to explore recent trends in American beech (*Fagus grandifolia*) demography and to compare the change in demographic variables compared to other trees in the forests. Satellite data are employed to quantify fire occurrences in 2023 in a geographical context across the conterminous United States, Alaska, Hawaii, and the Caribbean territories and in a temporal context against two decades of previously collected data.

Keywords—Demography, fire, forest health, insect and disease, pine mortality, spatial mapping, tree mortality