

INTRODUCTION

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

At the same time, wildland fires have created forest health and sustainability problems in some ecosystems (Edmonds and others 2011). Fires in some regions and ecosystems have become larger, more intense, and more damaging because of the accumulation of fuels from prolonged fire suppression (Pyne 2010). Robust research indicates that climate change, via more common drought conditions and higher temperatures, has already played a role in increased wildfire activity (Abatzoglou and Williams 2016, Higuera and Abatzoglou 2021). Current fire regimes on more than half the forested area in the conterminous United States (CONUS) have been moderately or significantly altered from historical regimes (Barbour and others 1999), potentially altering key ecosystem components, such as species

composition, structural stage, stand age, canopy closure, and fuel loadings (Schmidt and others 2002, Stephens and others 2018). Evidence, in fact, suggests that few entirely natural fire regimes remain in North America (Parisien and others 2016). Such changes in fire intensity and recurrence could result in decreased forest resilience and persistence (Lundquist and others 2011), with plant communities in some regions undergoing rapid compositional and structural changes following fire suppression (Coop and others 2020, Nowacki and Abrams 2008).

In addition to their ecological and forest health consequences, large wildland fires also can have long-lasting social and economic consequences, including the loss of human life and property, smoke-related human health impacts, and the economic cost and dangers of fighting the fires themselves (Gill and others 2013, Richardson and others 2012). These impacts are particularly intense within the wildland-urban interface, the zone in which human development mixes with forest (Calkin and others 2015, Radeloff and others 2018). Additionally, exposure to wildfire smoke may have increased SARS-CoV-2 positivity rates among the public and thereby exacerbated the COVID-19 pandemic (Kiser and others 2021), while inhalation of wildfire smoke may have exposed firefighters to increased likelihood of SARS-CoV-2 infection and increased COVID-19 disease severity (Navarro and others 2021).

This chapter presents analyses of daily satellite-based fire occurrence data that map and quantify the locations and intensities of fire occurrences spatially across the CONUS, Alaska, Hawaii, and

CHAPTER 3

Broad-Scale Patterns of Forest Fire Occurrence Across the United States and the Caribbean Territories, 2021

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the Caribbean territories in 2021. It also compares 2021 fire occurrences, within a geographic context, to all the recent years for which such data are available. Quantifying and monitoring such large-scale patterns of fire occurrence across the United States, as described in this chapter, can help improve our understanding of the ecological and economic impacts of fire. Specifically, large-scale assessments of fire occurrence can help identify areas where specific management activities may be needed, or where research into the ecological and socioeconomic impacts of fires would be beneficial.

METHODS

Data

The Moderate Resolution Imaging Spectroradiometer (MODIS) Rapid Response System (Justice and others 2002, 2011) extracts fire location and intensity information from the thermal infrared bands of imagery collected daily by two satellites at a resolution of 1 km, with the center of a pixel recorded as a fire occurrence (NASA Fire Information for Resource Management System 2022a). The MODIS Active Fire Detections for the United States database (NASA Fire Information for Resource Management System 2022b) allows analysts to spatially display and summarize fire occurrences across broad geographic regions for monitoring and reporting of wildland fire events (Coulston and others 2005; Potter 2012a, 2012b, 2013a, 2013b, 2014, 2015a, 2015b, 2016, 2017, 2018, 2019, 2020, 2021, 2022). The Terra and Aqua satellites' MODIS sensors identify the presence

of a fire at the time of image collection by using a contextual algorithm that exploits the strong emission of mid-infrared radiation from fires (Giglio and others 2003). A fire occurrence is defined as one daily satellite detection of wildland fire in an approximately 1-km pixel, with multiple fire occurrences possible on a pixel across multiple days resulting from a single wildland fire that lasts more than 1 day. The resulting fire occurrence data represent only whether a fire was active because the MODIS data bands may not differentiate between a hot fire in a relatively small area (0.01 km², for example) and a cooler fire over a larger area (1 km², for example) if the foreground-to-background temperature contrast is not sufficiently high. The MODIS Active Fire database does well at capturing large fires during cloud-free conditions but may underrepresent rapidly burning, small, and low-intensity fires, as well as fires in areas with frequent cloud cover (Hawbaker and others 2008). The likelihood of detecting a fire beneath a tree canopy is probably low given the smaller general size of such fires and the fact that they are obscured by the canopy (Giglio and others 2018). For large-scale assessments, the dataset represents a good alternative to the use of ignition point information, which can be difficult to obtain or may not exist for many fires (Tonini and others 2009). The fire occurrence data additionally do not distinguish fires intentionally set for management purposes (controlled burns), which are common in some parts of the United States, such as the South, where many prescribed fires are smaller and/or lower severity and thus not detected by satellite sensors (Nowell and others 2018).

More information about the performance of this product is provided by Justice and others (2011).

It is important to underscore that estimates of burned area (e.g., Monitoring Trends in Burn Severity data [Eidenshink and others 2007, Picotte and others 2020]) and calculations of MODIS-detected fire occurrences are two different metrics for quantifying fire activity within a given year. Most importantly, the MODIS data contain both spatial and temporal components because persistent fire will be detected repeatedly over several days on a given 1-km pixel. In other words, a location can have a fire occurrence multiple times, once for each day a fire is detected at the location. Analyses of the MODIS-detected fire occurrences, therefore, measure the total number of daily 1-km pixels with fire during a year, as opposed to quantifying only the area on which fire occurred at some point during that timeframe. A fire detected on a single pixel every day for a week, for example, would be equivalent to seven fire occurrences.

The Terra and Aqua satellites that carry the MODIS sensors were launched in 1999 and 2002, respectively, and will be decommissioned eventually. An alternative fire occurrence data source is the Visible Infrared Imaging Radiometer Suite (VIIRS) sensors on board the Suomi National Polar-orbiting Partnership (Suomi NPP) and NOAA-20 weather satellites. The transition to VIIRS data for national and regional fire occurrence monitoring will require a comparison of fire occurrence detections between it and MODIS. This is because science-ready VIIRS fire data are available from 2015 onward (NASA Fire Information for Resource Management

System 2022a) compared to more than 20 years for the MODIS data. It would be ideal for assessments of fire occurrence trends to analyze as long a temporal window as possible (i.e., from near the beginning of MODIS data availability), encompassing the combination of older MODIS data with newer VIIRS data.

Analyses

Using ArcMap® (ESRI 2017), I processed these MODIS products for 2021 and for the 20 preceding full years of data (beginning in 2001 because of issues with data collection and processing from the Terra satellite in 2000) to determine forest fire occurrence density for (1) ecoregion sections in the CONUS (Cleland and others 2007), (2) ecoregions on each of the major islands of Hawaii (Potter 2023), and (3) the islands of the Caribbean territories of Puerto Rico and the U.S. Virgin Islands. Fire occurrence density is the number of fire occurrences per 100 km² (10 000 ha) of tree canopy cover area. I calculated forest fire occurrence density metrics for the CONUS, Hawaii, and the Caribbean territories for each year after screening out wildland fires that did not intersect with tree canopy data. The tree canopy data had been resampled to 240 m from a 30-m raster dataset that estimates percentage of tree canopy cover (from 0 to 100 percent) for each grid cell. This dataset was generated from the 2011 National Land Cover Database (NLCD) (Homer and others 2015) through a cooperative project between the Multi-Resolution Land Characteristics Consortium and the U.S. Department of Agriculture, Forest Service,

Geospatial Technology and Applications Center (GTAC) (Coulston and others 2012). I treated any cell with >0-percent tree canopy cover as forest. 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 NLCD. I then intersected the MODIS fire occurrence detection data with this layer and with ecoregion sections (Spencer and others 2002) to calculate the number of fire occurrences per 100 km² of forest and shrub cover within each ecoregion section in Alaska.

I also separately determined the total numbers of forest fire occurrences for the CONUS, Alaska, Hawaii, and the Caribbean territories after clipping the MODIS fire occurrences by the tree canopy cover or tree and shrub cover data.

I compared the fire occurrence density value for each of the ecoregions of the States and for the Caribbean territories in 2021 with the mean fire density values for the first 20 full years of MODIS Active Fire data collection (2001–2020). Specifically, I divided the difference of the 2021 value and the previous 20-year mean for the area by the standard deviation across the previous 20-year period, assuming a normal distribution of fire density over time. The result for each ecoregion was a standardized *z*-score, which is a dimensionless quantity describing the degree to which the fire occurrence density in the area in 2021 was higher, lower, or the same relative to all the previous years for which data have been collected, accounting for the variability in the previous years. The *z*-score is the number of standard deviations between the observation and the mean of the historic observations in

the previous years. Approximately 68 percent of observations would be expected within one standard deviation of the mean, and 95 percent within two standard deviations. Near-normal conditions are those within a single standard deviation of the mean, although such a threshold is somewhat arbitrary. Conditions between about one and two standard deviations of the mean are moderately different from mean conditions but are not significantly different statistically. Those outside about two standard deviations would be considered statistically greater than or less than the long-term mean ($p < 0.025$ at each tail of the distribution).

Additionally, I used the Spatial Association of Scalable Hexagons (SASH) analytical approach to identify forested areas in the CONUS with higher than expected fire occurrence density in 2021. This method identifies locations where ecological phenomena occur at greater or lower occurrences than expected by random chance and is based on a sampling frame optimized for spatial neighborhood analysis, adjustable to the appropriate spatial resolution, and applicable to multiple data types (Potter and others 2016). Specifically, it consists of dividing an analysis area into scalable equal-area hexagonal cells within which data are aggregated, followed by identifying statistically significant geographic clusters of hexagonal cells within which mean values are greater or less than those expected by chance. To identify these clusters, I employed a Getis-Ord G_i^* hot spot analysis (Getis and Ord 1992) in ArcMap® 10.5.1 (ESRI 2017).

The spatial units of analysis were 9,810 hexagonal cells, each approximately 834 km² in

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

Fire occurrence density values were calculated as the number of forest fire occurrences per 100 km² of tree canopy cover area within a hexagon. 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 (of the total 9,810) in the CONUS. As described in Laffan (2006), it is calculated as:

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

where

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

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

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

x_j = the value of neighbor j

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

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

W_i^* = the sum of the weights

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

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

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

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

via the target hexagon and its 18 first- and second-order neighbors.

RESULTS AND DISCUSSION

Trends in Forest Fire Occurrence Detections for 2021

In 2021, the MODIS Active Fire database recorded 111,416 forest fire occurrences across the CONUS. This was the fourth highest in 21 full years of data collection but a 9-percent decrease in fire activity from 2020 (122,938 fire occurrences) (fig. 3.1). It was also 53 percent higher than the mean of the previous 20 years of data. At the same time, Alaska saw a 281-percent increase in fire occurrences (1,806) from 2020 (474) but a 93-percent decrease from the extremely high fire year of 2019 (26,493). The number of fire occurrences in 2021 was about 80 percent less than the mean for the preceding 2 decades. Also in 2021, 43 fire occurrences were detected in the State of Hawaii, an increase of 95 percent from 22 in 2020 but 84 percent below the 2001–2020 average of about 273 a year. Finally, Puerto Rico and the U.S. Virgin Islands experienced 13 fire occurrences, which was a 225-percent increase from 4 in 2020 and 44 percent above the average of about 9 per year.

These results are largely consistent with official national wildland fire statistics that track the numbers of wildfires reported and area burned (National Interagency Coordination Center 2022). The area burned in 2021 decreased to 2 883 645 ha from 4 096 364 ha in 2020, about 30 percent less. The number of reported wildfires, meanwhile, stayed approximately the same: 58,985

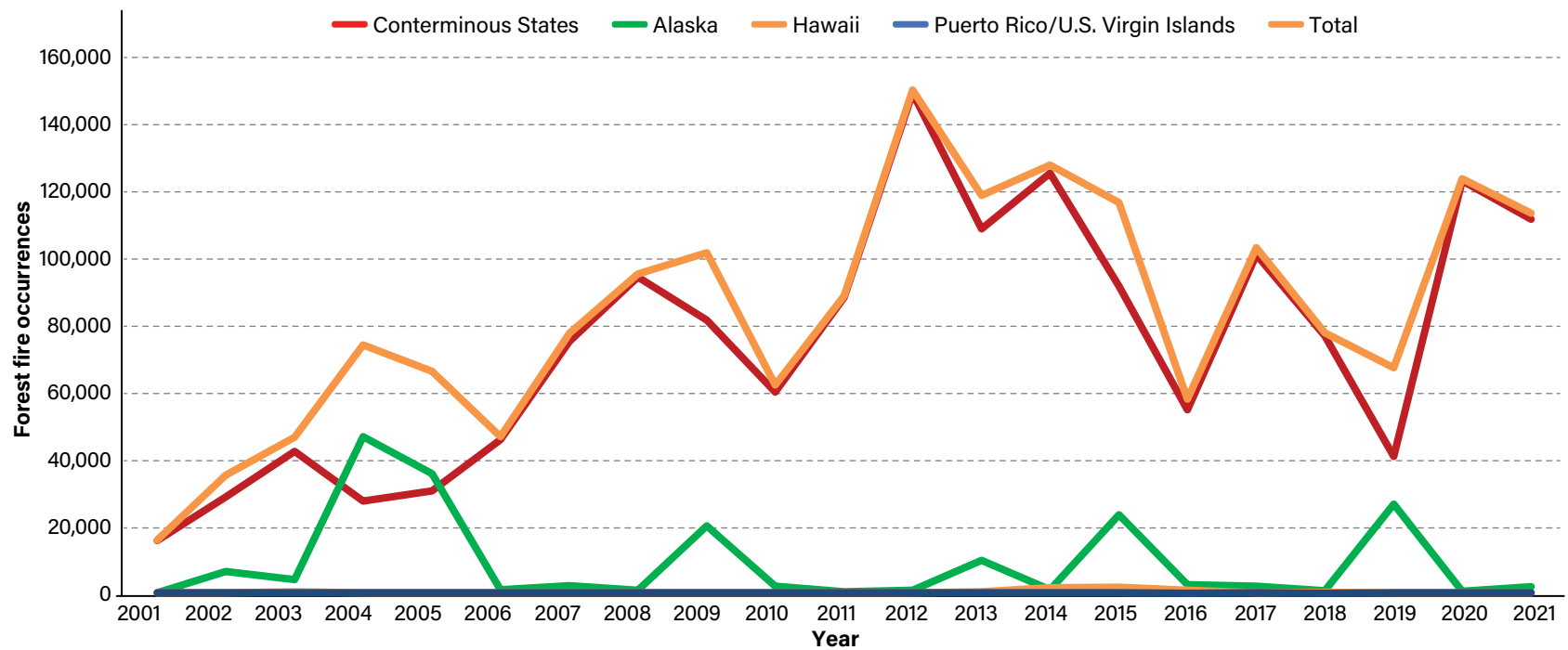


Figure 3.1—Forest fire occurrences detected by Moderate Resolution Imaging Spectroradiometer (MODIS) from 2001 through 2021 for the conterminous United States, Alaska, Hawaii, and Puerto Rico and the U.S. Virgin Islands, and for the entire Nation combined. (Data source: U.S. Department of Agriculture, Forest Service, Geospatial Technology and Applications Center, in conjunction with the NASA MODIS Rapid Response group)

compared to 58,950 the year before. Both area burned and number of fires in 2021 were similar to the 10-year average nationally but with more active years than normal for northern California, the Northern Rockies, the Pacific Northwest, and the northeastern quarter of the country (National Interagency Coordination Center 2022).

The National Interagency Coordination Center uses a benchmark threshold of 16 187 ha (40,000 acres) for tracking very large wildland fires and fire complexes. In 2021, 38 fires exceeded this threshold, compared to 50 in 2020 and 27 in 2019 (National Interagency Coordination Center 2020, 2021, 2022). Estimates of area burned and reported fires may be correlated with calculations of MODIS-detected fire occurrences, but as noted above, they are different metrics for quantifying fire activity.

The analysis of the 2021 MODIS wildland fire occurrence data indicates that, like 2020 (Potter 2022), the highest (extremely high) fire occurrence densities were present in the northwestern and Sierra Nevada regions of California, along with central Oregon and Washington (fig. 3.2). One ecoregion section in the Pacific Northwest had a very high fire occurrence density, while high densities were detected in the Pacific Northwest, the Northern Rockies, central Arizona and west-central New Mexico, and eastern Kansas.

Also as in 2020, the three specific ecoregion sections with the highest fire occurrence densities in 2021 were in California: M261D–Southern Cascades (52.2 fire occurrences/100 km² of tree canopy cover), M261E–Sierra Nevada (43.2 fire occurrences), and M261A–Klamath Mountains

(36.8 fire occurrences) (table 3.1). Other ecoregion sections of the Pacific Northwest, Northern Rockies, and California were among those with the highest fire occurrence densities: M242C–Eastern Cascades (26.5), M242D–Northern Cascades (13.6), M332A–Idaho Batholith (10.9), M332E–Beaverhead Mountains (10.7), and M261C–Northern California Interior Coast Ranges (10.6). This geographic pattern was associated at least in part with the most expansive and intense drought throughout the West in the 21st century, with more than 95 percent of the region experiencing drought conditions through August and more than half of the region in extreme or exceptional drought (National Interagency Coordination Center 2022). A heat wave of unprecedented intensity also affected the Pacific Northwest, Northern Rockies, and the Great Basin in June.

Meanwhile, Alaska had snowpack that was near or above normal during the spring but experienced high levels of lightning activity during the summer (National Interagency Coordination Center 2022). Fire occurrence densities across Alaska in 2021 were low (fig. 3.3), with only two ecoregions in the east-central part of the State exceeding 1 fire occurrence/100 km² of forest and shrub cover: M132F–North Ogilvie Mountains (1.2) and M132C–Yukon-Tanana Uplands (1.1).

Hawaii ecoregions also had low fire occurrence densities in 2021, with only the Mesic (MEh, 2.1) and Montane Wet-Hawai'i-Hilo-Puna (MWh-hp, 1.1.) regions on Hawai'i Island exceeding 1 fire occurrence/100 km² of canopy cover (fig. 3.4). The 16 187-ha Mana Road Fire located in the Lowland/Leeward Dry ecoregion

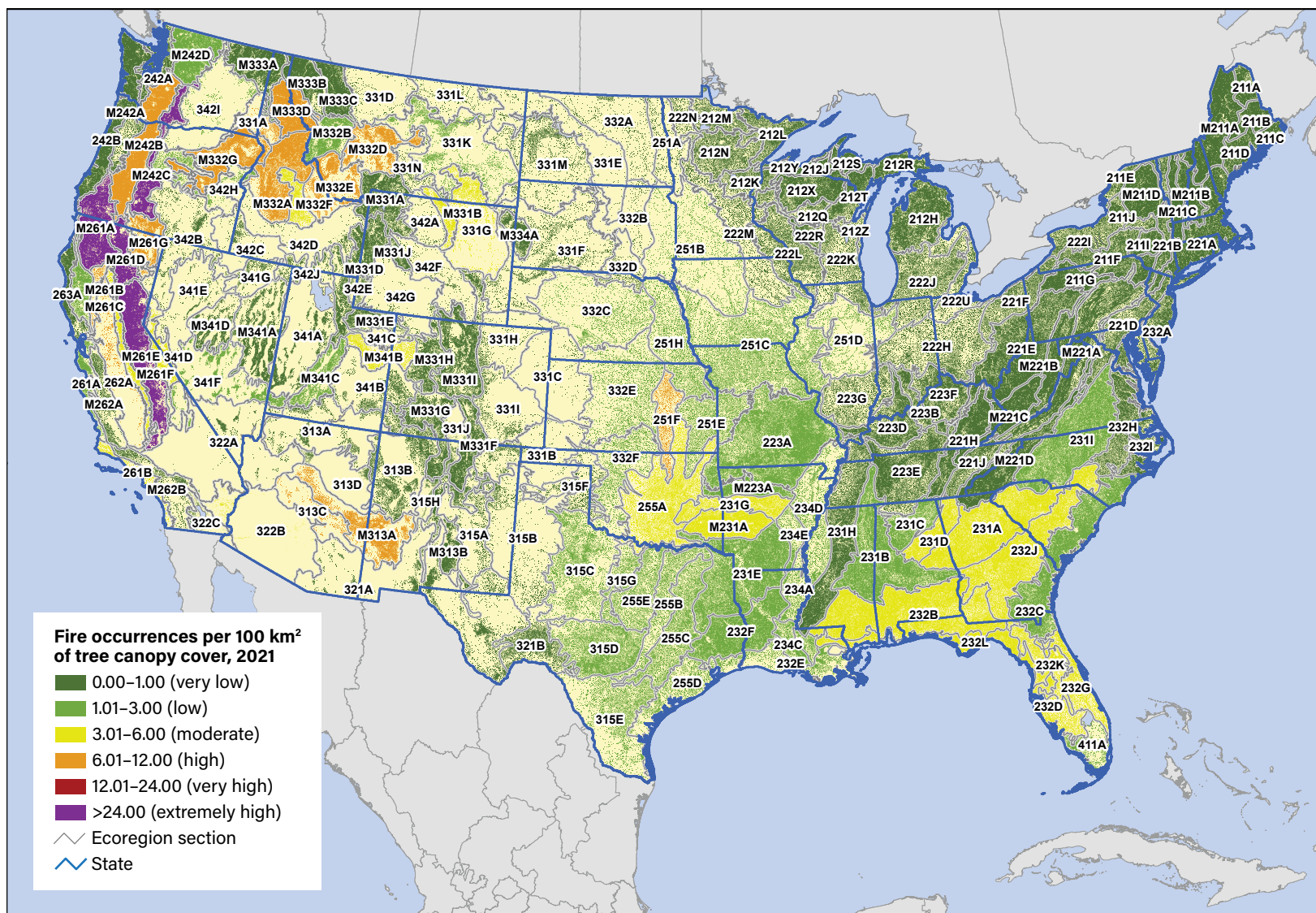


Figure 3.2—The number of forest fire occurrences per 100 km² (10 000 ha) of tree canopy coverage area, by ecoregion section within the conterminous United States, for 2021. The gray lines delineate ecoregion sections (Cleland and others 2007). Tree canopy cover is based on data from a cooperative project between the Multi-Resolution Land Characteristics Consortium (Coulston and others 2012) and the Forest Service Geospatial Technology and Applications Center using the 2011 National Land Cover Database. See figure 1.1A for ecoregion identification. (Source of fire data: U.S. Department of Agriculture, Forest Service, Geospatial Technology and Applications Center, in conjunction with the NASA Moderate Resolution Imaging Spectroradiometer Rapid Response group)

Table 3.1—The 15 ecoregion sections in the conterminous United States with the highest fire occurrence densities in 2021

Section	Name	Tree canopy area (100 km ²)	Fire occurrences (number)	Density ^a
M261D	Southern Cascades	150.6	7,862	52.2
M261E	Sierra Nevada	427.8	18,485	43.2
M261A	Klamath Mountains	338.5	12,465	36.8
M242C	Eastern Cascades	219.4	5,825	26.5
M242D	Northern Cascades	251.1	3,421	13.6
M332A	Idaho Batholith	338.9	3,680	10.9
M332E	Beaverhead Mountains	147.1	1,573	10.7
M261C	Northern California Interior Coast Ranges	18.2	193	10.6
M333A	Okanogan Highland	247.9	2,595	10.5
M332G	Blue Mountains	309.7	3,038	9.8
M332D	Belt Mountains	166.5	1,598	9.6
262A	Great Valley	19.4	185	9.5
331A	Palouse Prairie	33.4	301	9.0
M333D	Bitterroot Mountains	235.3	2,095	8.9
M242B	Western Cascades	427.9	3,591	8.4

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

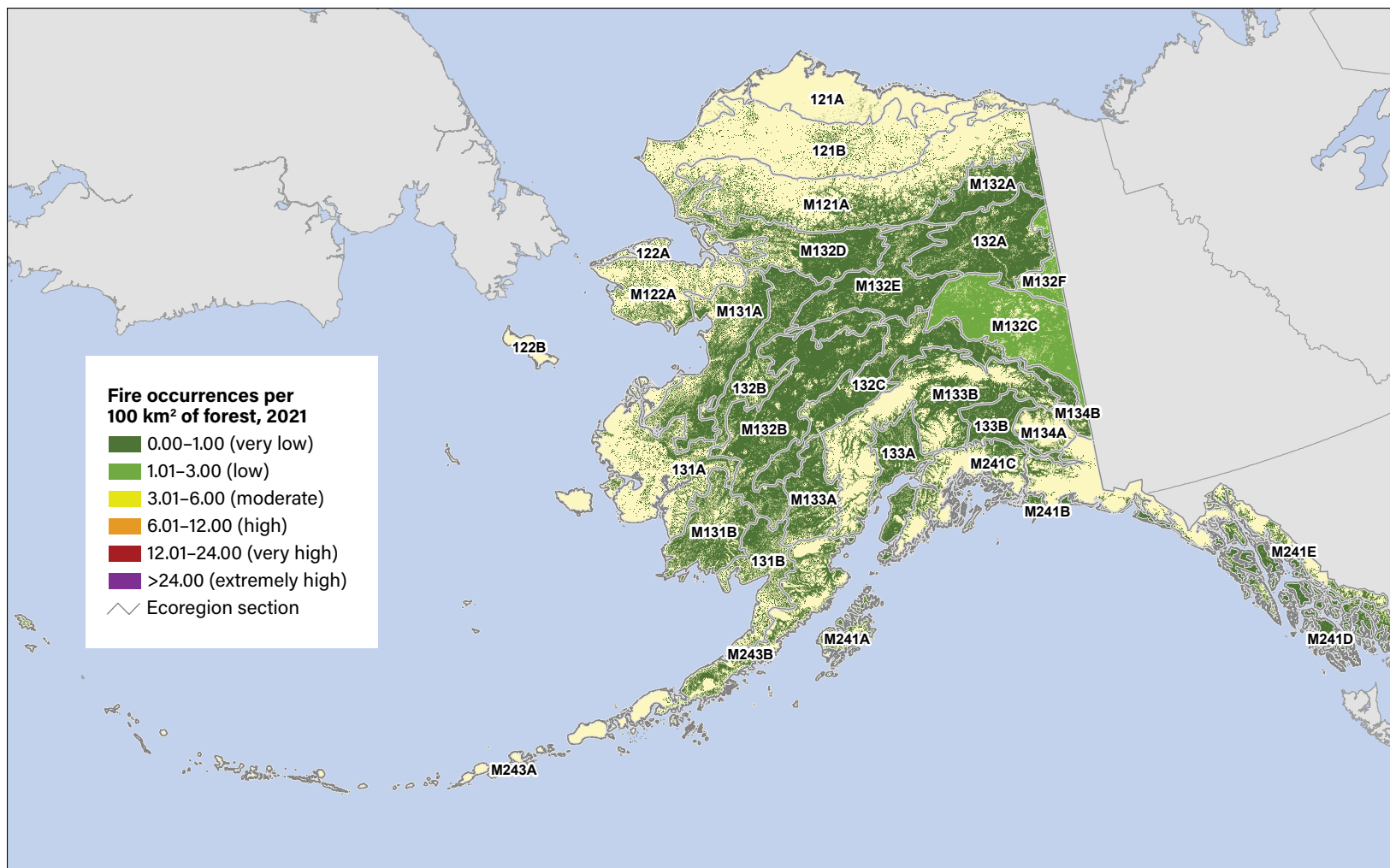


Figure 3.3—The number of forest fire occurrences per 100 km² (10 000 ha) of forest and shrub cover, by ecoregion section within Alaska, for 2021. The gray lines delineate ecoregion sections (Spencer and others 2002). Forest and shrub cover are derived from the 2011 National Land Cover Database. See figure 1.1B for ecoregion identification. (Source of fire data: U.S. Department of Agriculture, Forest Service, Geospatial Technology and Applications Center, in conjunction with the NASA Moderate Resolution Imaging Spectroradiometer Rapid Response group)

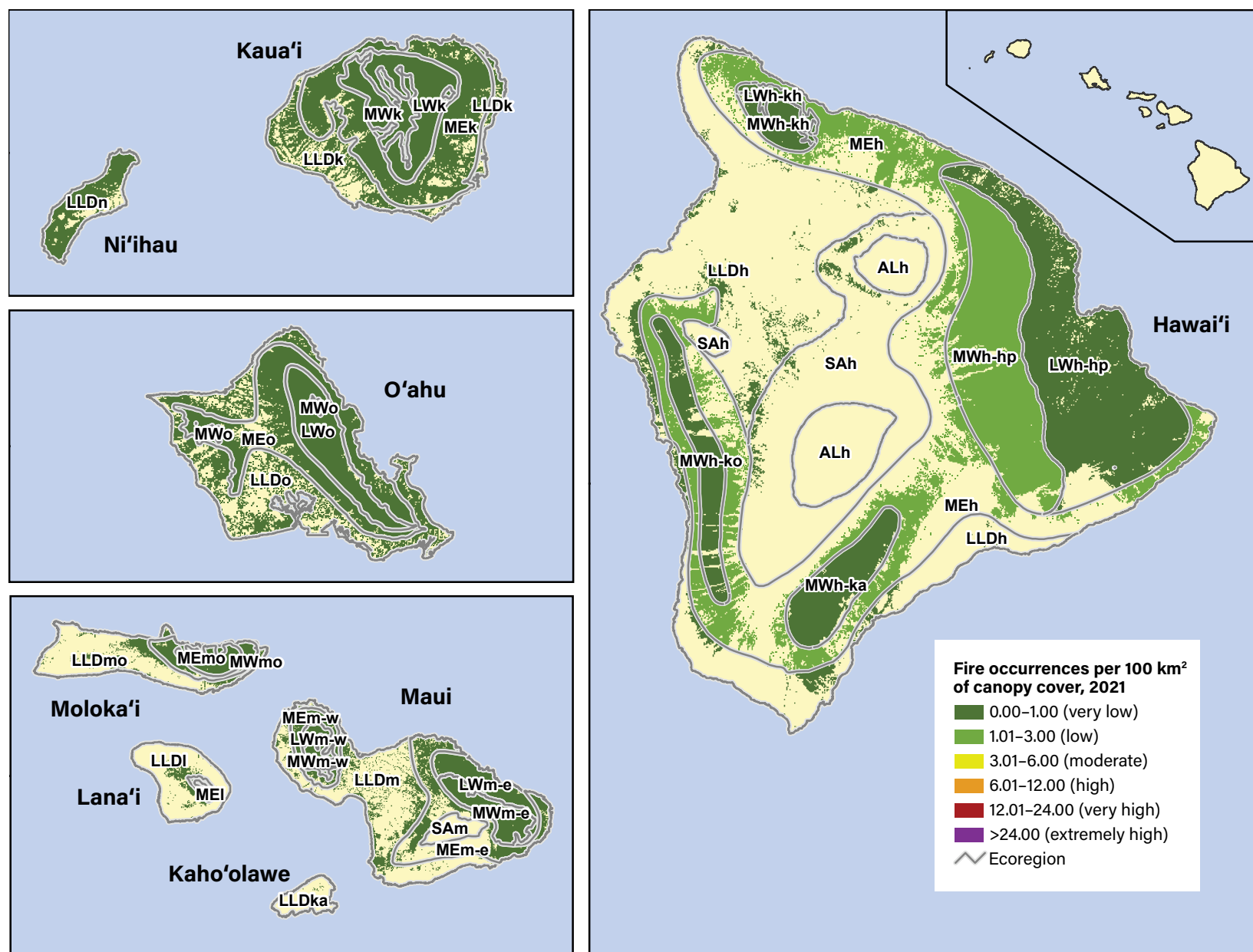


Figure 3.4—The number of forest fire occurrences per 100 km² (10 000 ha) of tree canopy coverage area, by island/ecoregion combination in Hawaii, for 2021. Tree canopy cover is based on data from a cooperative project between the Multi-Resolution Land Characteristics Consortium (Coulston and others 2012) and the Forest Service Geospatial Technology and Applications Center using the 2011 National Land Cover Database. See table 1.1 for ecoregion identification. (Source of fire data: U.S. Department of Agriculture, Forest Service, Geospatial Technology and Applications Center, in conjunction with the NASA Moderate Resolution Imaging Spectroradiometer Rapid Response group)

of Hawai'i Island (LLDh), which was one of the largest in the State's history (National Interagency Coordination Center 2022), was not reflected in the Hawaii statistics because it occurred almost entirely in brush.

Finally, fire occurrence densities in 2021 were ≤ 1 fire occurrence/100 km² of tree canopy cover for most islands of the U.S. Caribbean territories (Puerto Rico and the U.S. Virgin Islands) except for Isla de Vieques (2.2) and Saint Croix (1.8) (fig. 3.5).

Comparison to Longer Term Trends

The long-term collection of MODIS Active Fire data (more than 2 decades) makes it possible to contrast annual (2021) forest fire occurrence densities with longer term trends (2001–2020) for ecoregions in the CONUS, Alaska, and Hawaii, and for Caribbean territories. During that 2-decade period, the highest mean annual fire occurrence density (12.5 fire occurrences/100 km² of tree canopy cover annually) was in M261B–Northern California Coast Ranges (table 3.2), while several other ecoregion sections in the Pacific Coast States, Idaho, and Arizona/New Mexico, and along the Gulf Coast in the Southeast, exceeded 6 fire occurrences/100 km² of tree canopy cover (fig. 3.6A). Other ecoregion sections with high average annual fire occurrence densities included M332A–Idaho Batholith in central Idaho (11.8), M261A–Klamath Mountains of northwestern California and southeastern Oregon (10.8), M261E–Sierra Nevada in California (9.8), and M262B–Southern California Mountain and Valley near the southern

California coast (9.7) (table 3.2). Elsewhere in the West and the Southeast, ecoregion sections experienced ≤ 3 –6 fire occurrences/100 km² of tree canopy cover annually, while much of the Midwest and all the Northeast experienced ≤ 1 .

The M261B–Northern California Coast Ranges and M332A–Idaho Batholith ecoregion sections also had the greatest annual variation in fire occurrence densities from 2001 through 2020 (fig. 3.6B). High variation was also present in other mountainous ecoregion sections of California and the Pacific Northwest, while 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. These are regions with relatively high mean annual fire occurrence densities (fig. 3.6A). Other areas—including in north-central Colorado and west-central Wyoming—have relatively high variation with low mean annual fire occurrence densities, suggesting low numbers of fire occurrences most years with high numbers in others. Ecoregion sections of the Midwest and Northeast and in coastal areas of Oregon and Washington had the lowest interannual variation (standard deviation < 1), while slightly higher variation (standard deviation 1–5) was apparent across the Southeast, the central Rocky Mountains, and the Great Basin. Parts of the Southeast, especially along the Gulf Coast, had low annual variation but relatively high mean annual fire occurrence densities, suggesting consistently high numbers of fire occurrences over time.

Compared to the previous 20-year mean and accounting for temporal variability, nine ecoregion

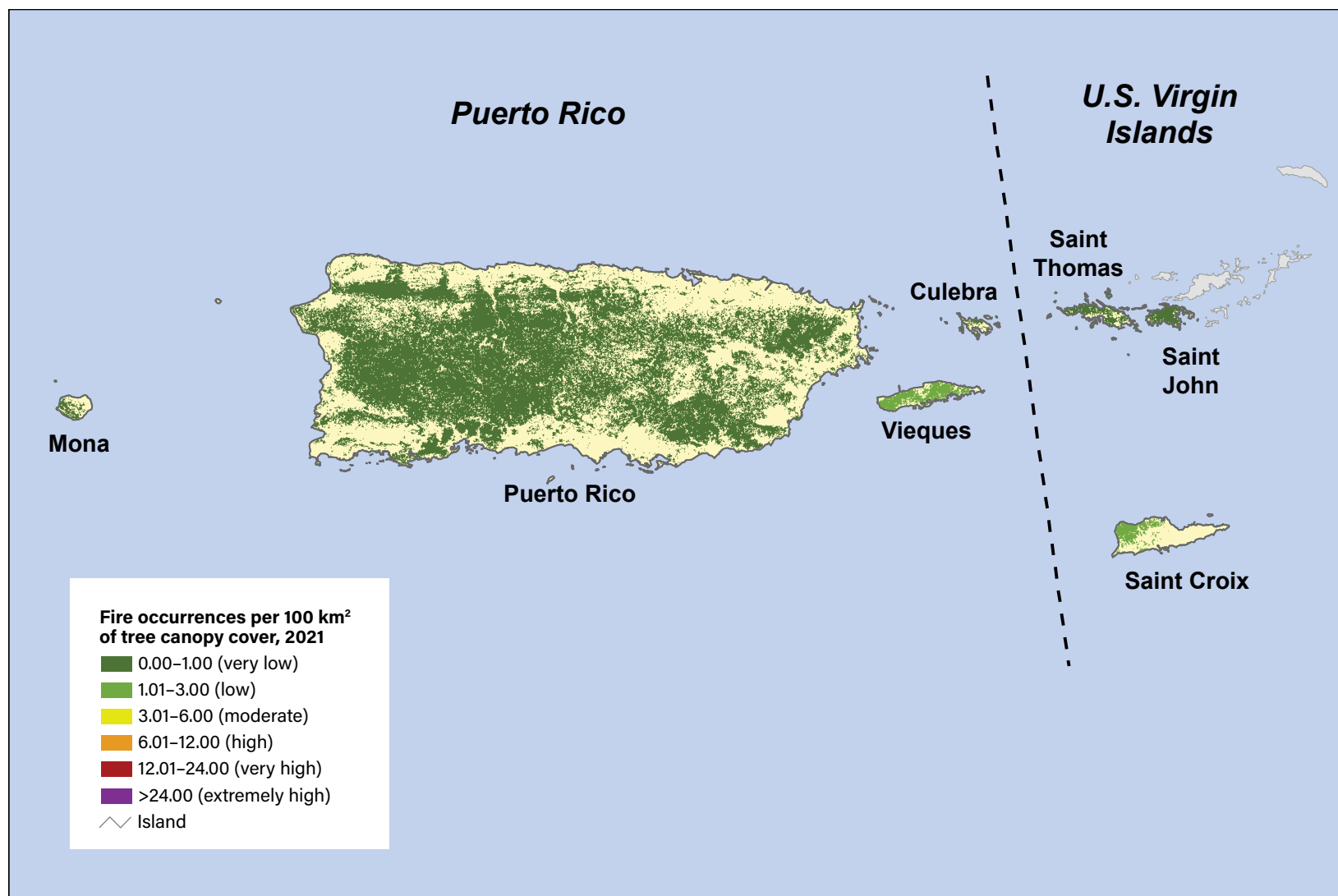


Figure 3.5—The number of forest fire occurrences per 100 km² (10 000 ha) of tree canopy coverage area, by island in Puerto Rico and the U.S. Virgin Islands, for 2021. Tree canopy cover is based on data from a cooperative project between the Multi-Resolution Land Characteristics Consortium (Coulston and others 2012) and the Forest Service Geospatial Technology and Applications Center using the 2011 National Land Cover Database. (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 3.2—The 15 ecoregion sections in the conterminous United States with the highest mean annual fire occurrence densities from 2001 through 2020

Section	Name	Tree canopy area (100 km ²)	Mean annual fire occurrence density ^a
M261B	Northern California Coast Ranges	114.1	12.5
M332A	Idaho Batholith	338.9	11.8
M261A	Klamath Mountains	338.5	10.8
M261E	Sierra Nevada	427.8	9.8
M262B	Southern California Mountain and Valley	58.1	9.7
M313A	White Mountains-San Francisco Peaks-Mogollon Rim	202.5	7.4
313C	Tonto Transition	17.5	7.2
261A	Central California Coast	66.8	7.0
251F	Flint Hills	57.8	6.9
232B	Gulf Coastal Plains and Flatwoods	888.7	6.1
M242D	Northern Cascades	251.1	6.0
331A	Palouse Prairie	33.4	5.7
M332F	Challis Volcanics	72.2	5.6
M333C	Northern Rockies	176.3	5.4
232J	Southern Atlantic Coastal Plains and Flatwoods	604.0	5.3

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

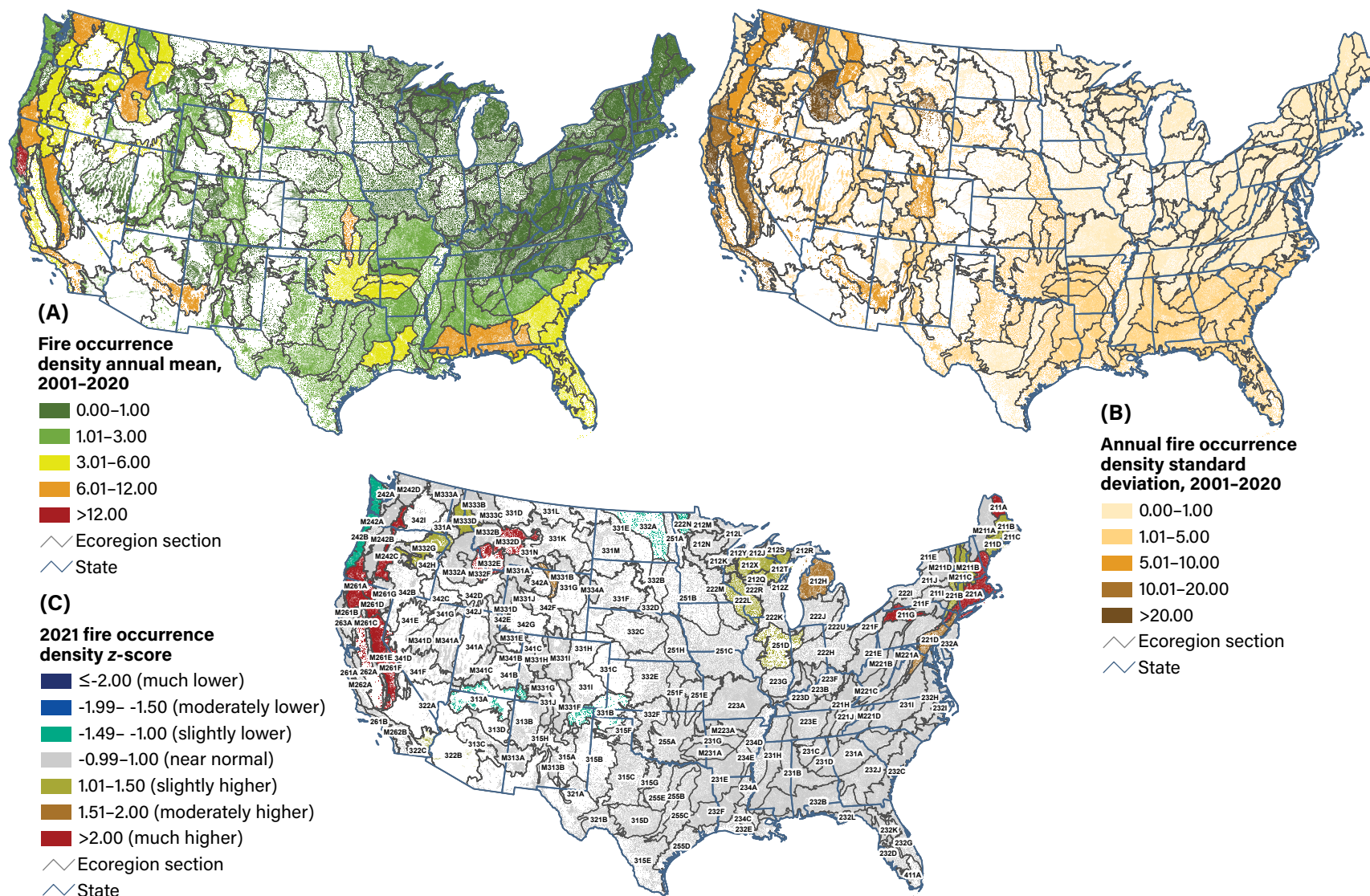


Figure 3.6—(A) Mean number and (B) standard deviation of forest fire occurrences per 100 km² (10 000 ha) of tree canopy coverage area from 2001 through 2020, by ecoregion section within the conterminous 48 States. (C) Degree of 2021 fire occurrence density excess or deficiency, by ecoregion section relative to 2001–2020 and accounting for variation over that period. The gray lines delineate ecoregion sections (Cleland and others 2007). Tree canopy cover is based on data from a cooperative project between the Multi-Resolution Land Characteristics Consortium (Coulston and others 2012) and the Forest Service Geospatial Technology and Applications Center 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)

sections in California, the Pacific Northwest, the Northern Rockies, and the Northeast had much higher fire occurrence densities in 2021 than normal (fig. 3.6C). Three of the California ecoregion sections (M261A–Klamath Mountains, M261D–Southern Cascades, and M261E–Sierra Nevada) had a high fire occurrence density in 2021 as well as a relatively high mean for the previous 2 decades. Other western ecoregion sections (M242D–Northern Cascades in northern Washington, M242C–Eastern Cascades in central Washington and Oregon, 341D–Mono in eastern California and western Nevada, and M332E–Beaverhead Mountains and M332D–Belt Mountains in southwestern Montana) had moderate average annual fire occurrence densities. Those in the Northeast, however, had much higher fire occurrence densities in 2021 relative to a very low long-term normal (211G–Northern Unglaciaded Allegheny Plateau, 221A–Lower New England, and 211A–Aroostook Hills and Lowlands). In other words, these are areas that tend to have few fires in a typical year and therefore don't require many fire occurrences to be classified as having more than normal.

Meanwhile, a handful of ecoregion sections in the West and the Midwest had fire occurrence densities in 2021 that were lower than expected, as indicated by z -scores ≤ -1 . One was in the Pacific Northwest (M242A–Oregon and Washington Coast Ranges), and two were in the Southwestern States (313A–Grand Canyon and 331B–Southern Plains). All of these are areas that had low to moderate annual fire occurrence densities on average.

In Alaska, mean annual fire occurrence densities for 2001–2020 were relatively low except for moderate densities in the central and east-central parts of the State (M132E–Ray Mountains and 132A–Yukon–Old Crow Basin) (fig. 3.7A). These ecoregion sections, along with the neighboring M132C–Yukon–Tanana Uplands and M132F–North Ogilvie Mountains, exhibited the most variability over the 2-decade period preceding 2021 (fig. 3.7B). Only a single Alaska ecoregion section in 2021 had a fire occurrence density outside normal compared to the previous 20 years and controlling for variability: M241D–Alexander Archipelago, where there was a much higher fire occurrence density than normal (fig. 3.7C). This is an area that typically had very few fire occurrences.

In Hawaii, the area that exhibited the highest annual fire occurrence density mean (fig. 3.8A) and variability (fig. 3.8B) from 2001 through 2020 was the Lowland Wet–Hilo–Puna ecoregion (LWh-hp) on the eastern side of Hawai'i Island (18.7 fire occurrences/100 km² of tree canopy cover, standard deviation 41.1). Contained within this area are recently active portions of the lower east rift zone of Kilauea volcano, where lava flows incinerated some forested areas (Andrews 2018). With one exception, all other ecoregions in the State had an annual mean fire occurrence density of ≤ 1 fire occurrence/100 km² of tree cover. The exception was the Mesic region on the Hawai'i Island (MEh), where it was 2.2. In 2021, no Hawaiian ecoregions had fire occurrence densities outside expectations (z -score > 1), controlling for variability over the previous 2 decades (fig. 3.8C).

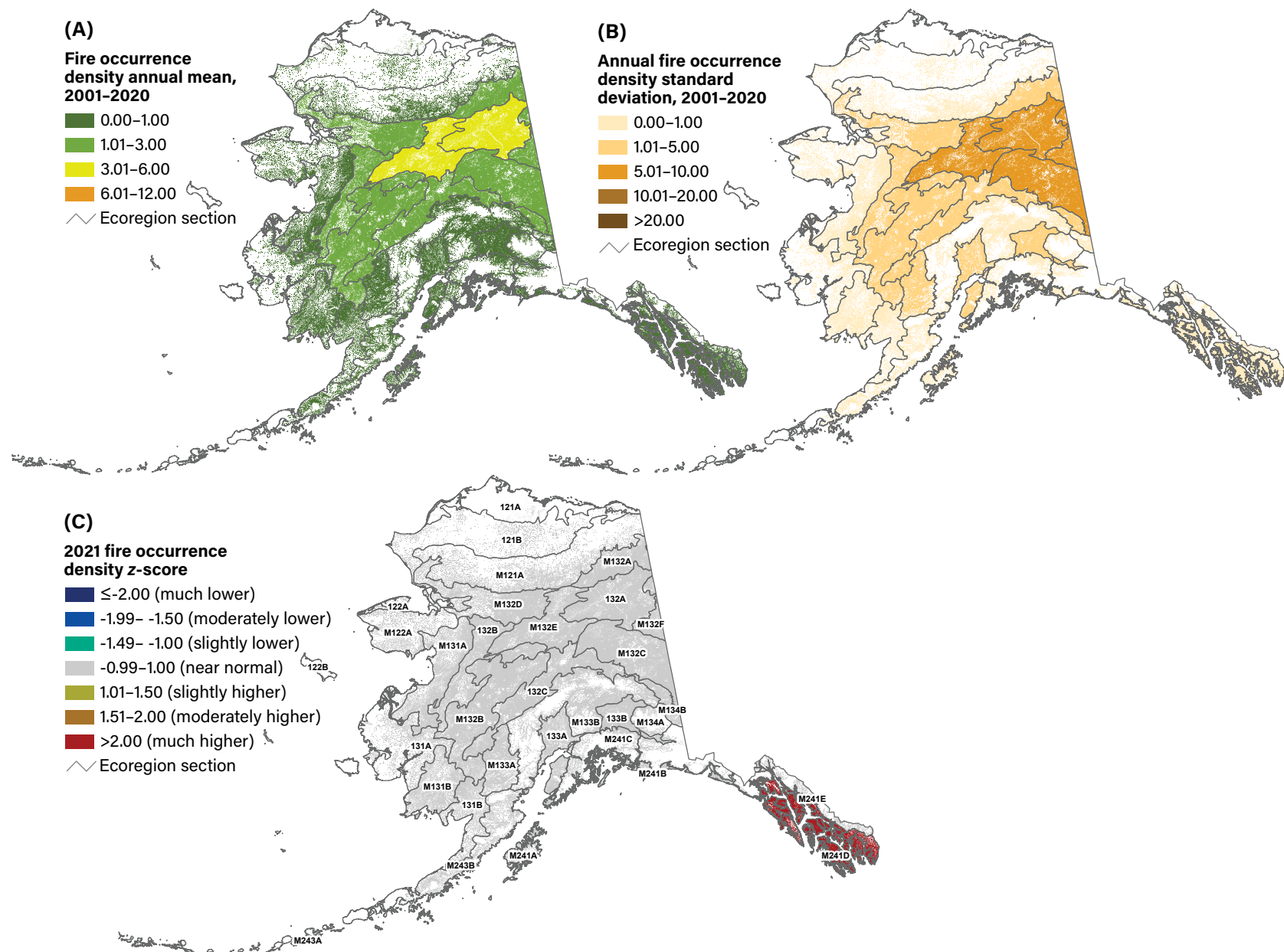


Figure 3.7—(A) Mean number and (B) standard deviation of forest fire occurrences per 100 km² (10 000 ha) of forest and shrub cover from 2001 through 2020, by ecoregion section in Alaska. (C) Degree of 2021 fire occurrence density excess or deficiency, by ecoregion section relative to 2001–2020 and accounting for variation over that period. The gray lines delineate ecoregion sections (Spencer and others 2002). Forest and shrub cover are derived from the 2011 National Land Cover Database. (Source of fire data: U.S. Department of Agriculture, Forest Service, Geospatial Technology and Applications Center, in conjunction with the NASA Moderate Resolution Imaging Spectroradiometer Rapid Response group)

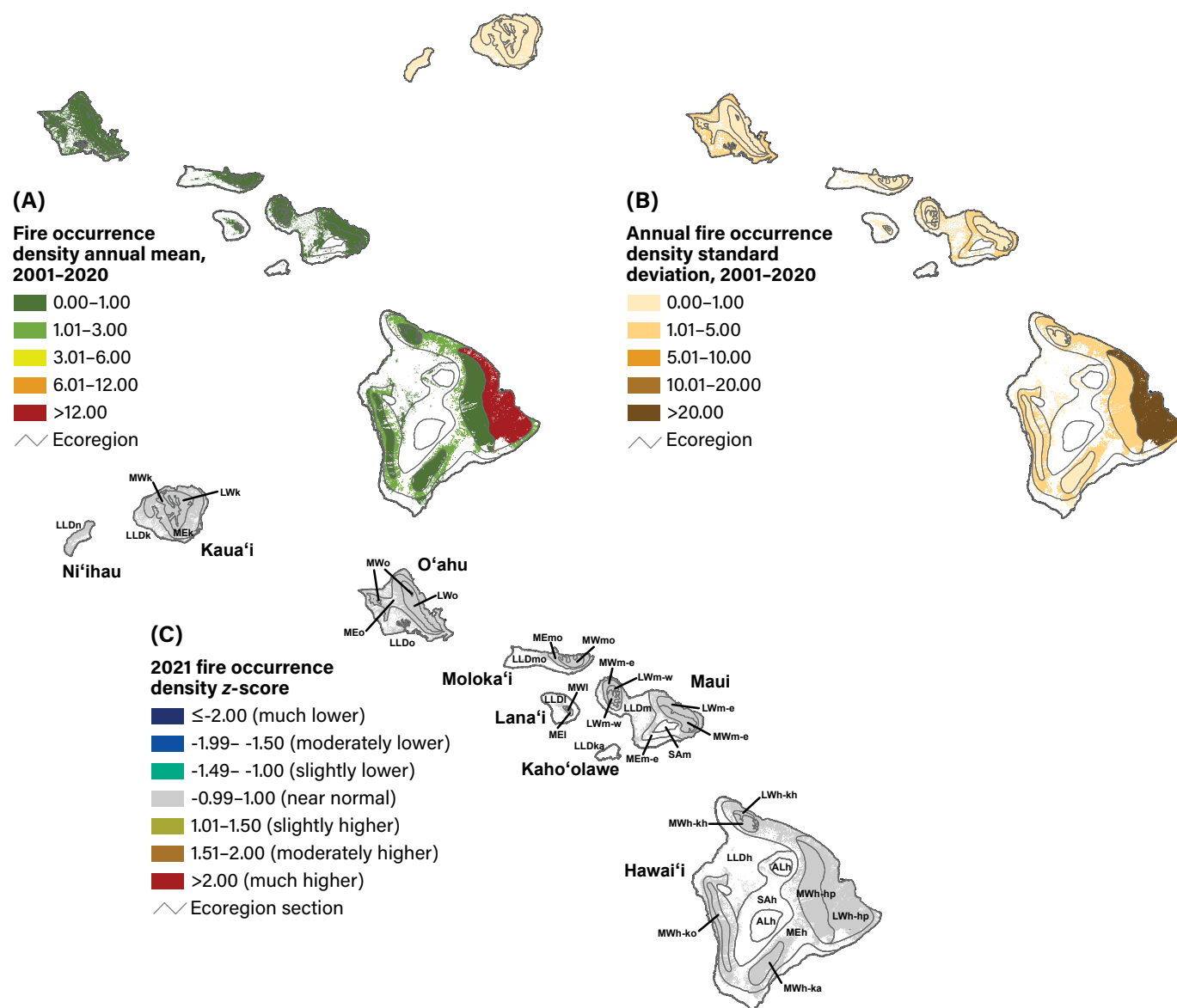


Figure 3.8—(A) Mean number and (B) standard deviation of forest fire occurrences per 100 km² (10 000 ha) of tree canopy coverage area from 2001 through 2020, by island/ecoregion combination in Hawaii. (C) Degree of 2021 fire occurrence density excess or deficiency, by island/ecoregion combination relative to 2001–2020 and accounting for variation over that period. Tree canopy cover is based on data from a cooperative project between the Multi-Resolution Land Characteristics Consortium (Coulston and others 2012) and the Forest Service Geospatial Technology and Applications Center 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)

Finally, all the islands encompassed by Puerto Rico and the U.S. Virgin Islands had fire occurrence means and standard deviations ≤ 1 from 2001–2020 (figs. 3.9A and 3.9B). Two islands had higher than expected fire occurrence densities in 2021 (z -score > 1): Isla de Vieques in Puerto Rico and Saint Croix in the U.S. Virgin Islands (fig. 3.9C).

Geographic Hot Spots of Fire Occurrence Density

Geographic hot spot analyses using analysis units smaller than ecoregions (the main unit of analysis thus far in this chapter) can offer additional insights into where, statistically, fire occurrences are more concentrated than expected by chance during a given year. Specifically, this approach can identify areas across the CONUS with higher than expected fire occurrence densities compared to the entire study region. For 2021, the SASH method detected a geographic hot spot of extremely high fire occurrence density ($G_i^* > 24$) in northern California as well as four hot spots of very high fire occurrence density ($G_i^* > 12$ and ≤ 24) elsewhere in the West (fig. 3.10).

The single hot spot with extremely high fire occurrence density spanned M261E–Sierra Nevada and M261D–Southern Cascades. This is the region of the 2021 Dixie Fire, the largest single wildfire in California history, and exceeded in area only by the August Complex of fires the previous year (CALFIRE 2022). The Dixie Fire burned 389 837 ha and destroyed more than 1,300 buildings between July 13 and October 23; it cost approximately \$637 million to

contain (CALFIRE 2022, National Interagency Coordination Center 2022). Additionally, the 42 763-ha Beckwourth Complex, which was ignited July 3, reported as contained September 21, and cost approximately \$543 million to contain, was also in this area (National Interagency Coordination Center 2022).

A very high fire occurrence density hot spot, centered in nearby M261A–Klamath Mountains of northwestern California, was caused in part by five large fires and fire complexes in 2021 (CALFIRE 2022, National Interagency Coordination Center 2022):

- Monument Fire, 90 295 ha, July 31–October 25; \$164 million containment cost, 50 structures destroyed
- River Complex, 80 678 ha, July 30–October 24; \$95 million containment cost, 122 structures destroyed
- Antelope Fire, 58 935 ha, August 1–October 14; \$75 million containment cost
- McFarland Fire, 49 636 ha, July 30–September 15; \$44 million containment cost
- McCash Fire, 38 430 ha, July 31–October 27; \$53 million containment cost

Another hot spot of similar intensity was located in the M261E–Sierra Nevada, also in California. This one was caused by the Caldor Fire west of Lake Tahoe, which scorched 89 773 ha between its ignition on August 14 and its containment on October 20. This human-caused blaze cost an estimated \$271 million to contain after burning 1,003 buildings (CALFIRE 2022, National Interagency Coordination Center 2022).

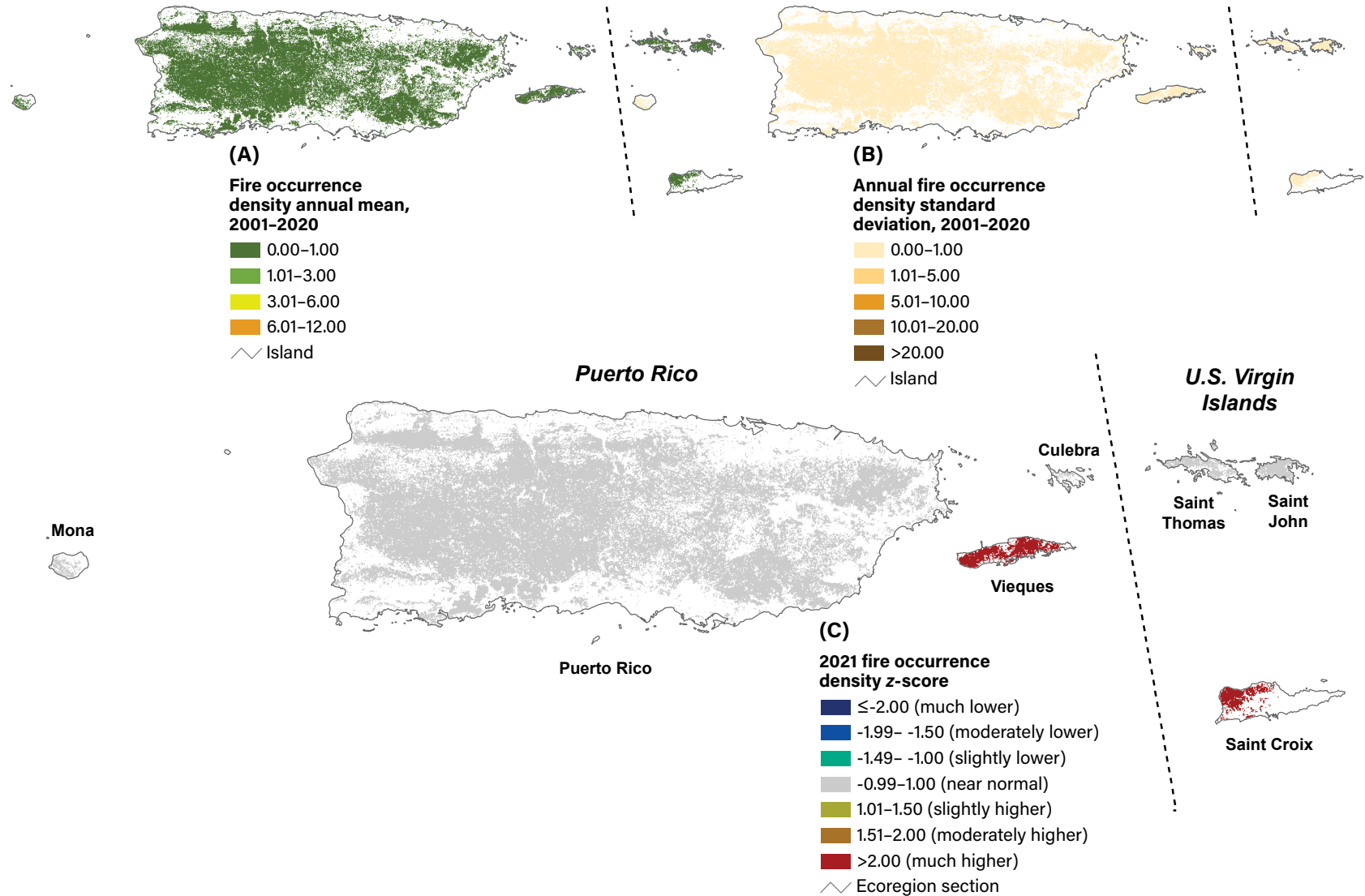


Figure 3.9—(A) Mean number and (B) standard deviation of forest fire occurrences per 100 km² (10 000 ha) of forested area from 2001 through 2020, by island in Puerto Rico and the U.S. Virgin Islands. (C) Degree of 2021 fire occurrence density excess or deficiency, by island relative to 2001–2020 and accounting for variation over that period. Tree canopy cover is based on data from a cooperative project between the Multi-Resolution Land Characteristics Consortium (Coulston and others 2012) and the U.S. Department of Agriculture, Forest Service, Geospatial Technology and Applications Center using the 2011 National Land Cover Database.

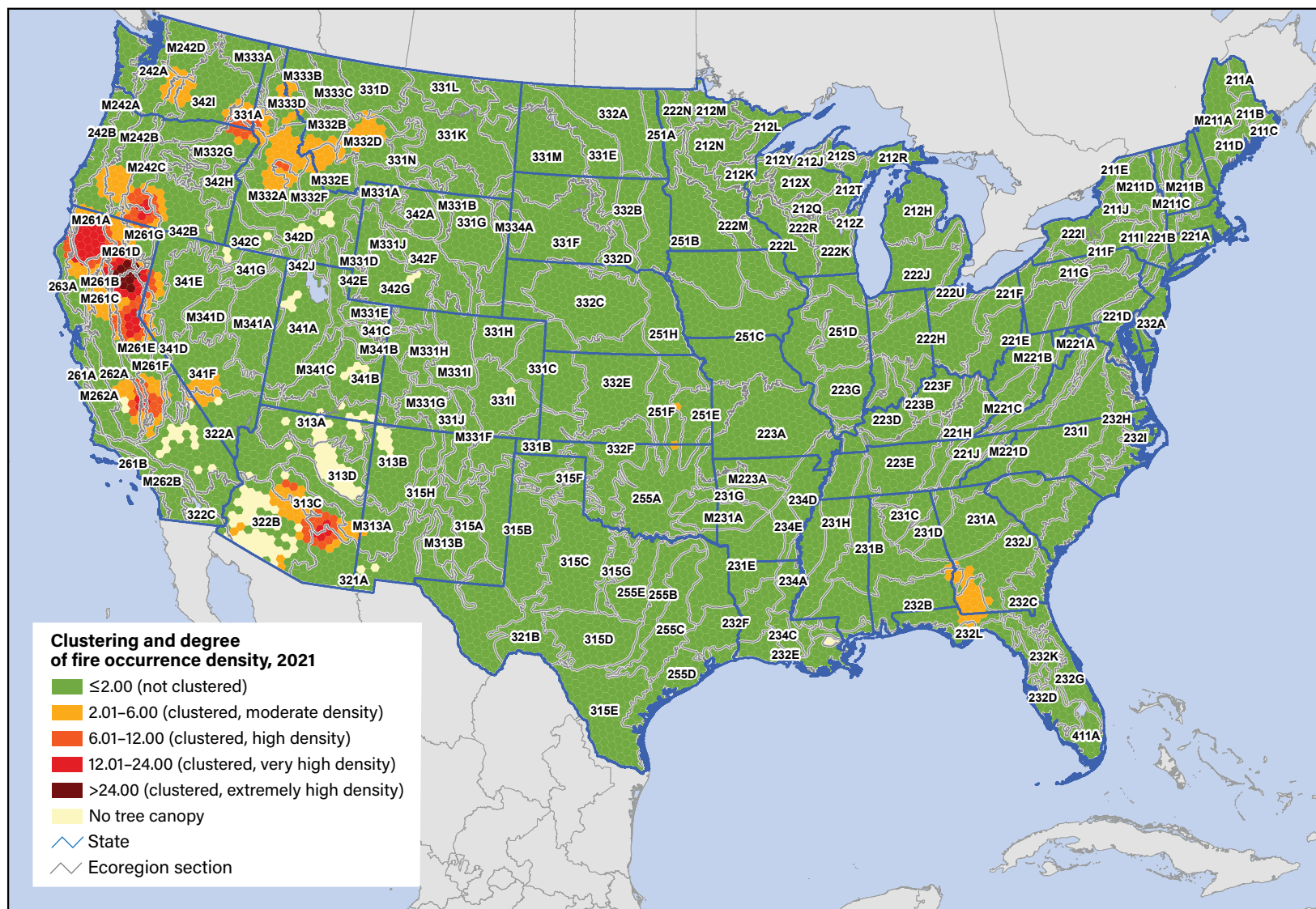


Figure 3.10—Hot spots of fire occurrence, by ecoregion section within the conterminous United States, for 2021. Values are Getis-Ord G_i^* scores, with values >2 representing significant clustering of high fire occurrence densities. (No areas of significant clustering of lower fire occurrence densities, <-2, were detected.) The gray lines delineate ecoregion sections (Cleland and others 2007).

To the south, also in M261E–Sierra Nevada as well as in M261F–Sierra Nevada Foothills, a very high fire occurrence density hot spot was associated with the Windy Fire (39 468 ha, \$78 million) and the KNP Complex (35 737 ha, \$170 million), which burned from September through November and December, respectively (National Interagency Coordination Center 2022).

One additional hot spot of very high fire occurrence density in 2021 was detected outside of California (fig. 3.10) and was also associated with a megafire:

- 313C–Tonto Transition and 321A–Basin and Range of southeastern Arizona, location of the human-caused Telegraph Fire, which burned 73 150 ha between June 4 and July 2 and cost \$36 million to contain, and the nearby human-caused Mescal Fire, which burned 29 239 ha (National Interagency Coordination Center 2022)

Additionally, four hot spots of high fire occurrence density ($G_i^* > 6$ and ≤ 12) were identified in the West during 2021 (fig. 3.10):

- In south-central Oregon (M242C–Eastern Cascades and M261G–Modoc Plateau), where the Bootleg Fire—the third largest fire in recorded Oregon history (Sutton and others 2021)—burned 167 425 ha between July 6 and August 13, costing approximately \$101 million to contain (National Interagency Coordination Center 2022) and destroying more than 400 structures (InciWeb 2021)

- In north-central Washington (M242D–Northern Cascade and M333A–Okanogan Highland)
- In southeastern Washington and northeastern Oregon (331A–Palouse Prairie)
- In central Idaho (M332F–Challis Volcanics)

A hot spot of moderate fire occurrence density ($G_i^* > 2$ and ≤ 6) occurred in the southwestern corner of Georgia and the panhandle of Florida (232B–Gulf Coastal Plains and Flatwoods and 232L–Gulf Coastal Lowlands). One additional small moderate fire occurrence density hot spot was detected in southeastern Kansas (255A–Cross Timbers and Prairie).

CONCLUSIONS

In 2021, the number of MODIS satellite-detected forest fire occurrences in the CONUS was the fourth highest in 21 full years of data collection but still represented a 9-percent decrease in fire activity from the extremely active 2020 fire season. The year included the largest single fire event in California history as well as the third largest in Oregon's. Parts of California and the Pacific Northwest in 2021 had extremely high fire occurrence densities (fire occurrences per 100 km² of tree canopy cover area), while areas of the Northern Rockies, Pacific Northwest, and Southwest had very high or high densities. The extensive fire activity in these regions resulted in geographic hot spots of extremely high or very high fire occurrence density. Not surprisingly, these areas experienced fire occurrence densities that were much higher than normal in 2021 compared to the previous 20-year mean and

accounting for variability over time. Parts of the Northeast also had fire occurrence densities that exceeded normal, although these areas tend to have few fires in a typical year and therefore don't require many fire occurrences to be classified as outside expectations. At the same time, a few ecoregion sections in the Southwest and Pacific Northwest had significantly lower fire occurrence densities than normal.

Meanwhile, Alaska in 2021 experienced a 281-percent increase in fire occurrences from 2020, but this was a 93-percent decrease from the extremely high fire year of 2019 and about 80 percent less than the mean for the preceding 2 decades. An ecoregion section within the panhandle of Alaska was the only part of the State that had a higher than normal fire occurrence density. Hawaiian forests in 2021 also had fire occurrence densities that were low and within expectations. Parts of both Puerto Rico (Isla de Vieques) and the U.S. Virgin Islands (Saint Croix) had higher than expected fire occurrence densities in 2021.

The results of these geographic analyses are intended to offer insights into where fire occurrences have been concentrated spatially during a given year and compared to previous years; they are not intended to quantify the severity of a given fire season. Given the limits of MODIS active fire detection using 1-km-resolution data, these products may underrepresent the number of fire occurrences in some ecosystems where small and low-intensity fires are common, and where high cloud frequency can interfere with fire detection. These products can also have commission errors. At the same

time, these high-temporal-fidelity products currently offer the best means for daily monitoring of forest fire occurrences.

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

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