

INTRODUCTION

Wildland fire is a pervasive disturbance agent in many forest ecosystems across the United States, causing widespread tree damage and mortality and acting as a key abiotic factor affecting forest health both positively and negatively (Agee 1998, Thom and Seidl 2016, Wade and others 2000). Wildland fire 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). In some ecosystems, wildland fires have been essential for regulating processes that maintain forest health (Lundquist and others 2011), and some forest types and tree species are adapted to fire under certain intensities and return intervals (Hanberry and others 2018, Jeronimo and others 2019). At the same time, wildland fires have created forest health (i.e., sustainability) problems in some ecosystems (Edmonds and others 2011).

Current fire regimes on more than half of the forested area in the conterminous United States 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). Fires in some regions and ecosystems have become larger, more intense, and more damaging because of the accumulation

of fuels as a result of prolonged fire suppression (Pyne 2010). In some regions, plant communities have experienced or are undergoing rapid compositional and structural changes as a result of fire suppression (Coop and others 2020, Nowacki and Abrams 2008). Additionally, changes in fire intensity and recurrence could result in decreased forest resilience and persistence (Lundquist and others 2011), and fire regimes altered by global climate change could cause large-scale shifts in vegetation spatial patterns (McKenzie and others 1996). Robust research indicates that climate change, via more common drought conditions and higher temperatures, has already resulted in increased wildfire activity (Abatzoglou and Williams 2016, Higuera and Abatzoglou 2020).

At the same time, large wildland fires also can have long-lasting social and economic consequences, which include 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, some evidence exists that 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 expose firefighters to increased likelihood of SARS-CoV-2 infection and increased COVID-19 disease severity (Navarro and others 2021).

CHAPTER 3

Broad-Scale Patterns of Forest Fire Occurrence across the 50 United States and the Caribbean Territories, 2020

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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 conterminous United States, Alaska, Hawaii, and the Caribbean territories in 2020. It also compares 2020 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 as well as the appropriate management and prescribed use 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 may be required. Additionally, 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 help us to better understand emerging spatiotemporal patterns of fire occurrence.

METHODS

Data

Annual monitoring and reporting of active wildland fire events using the Moderate Resolution Imaging Spectroradiometer (MODIS) Active Fire Detections for the United States database (USDA Forest Service 2021) allow analysts to spatially display and summarize fire occurrences across broad geographic regions (Coulston and others 2005; Potter 2012a, 2012b, 2013a, 2013b, 2014, 2015a,

2015b, 2016, 2017, 2018, 2019, 2020a, 2021). A fire occurrence is defined as one daily satellite detection of wildland fire in a 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 data are derived using the MODIS Rapid Response System (Justice and others 2002, 2011) to extract 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 (USDA Forest Service 2021). The Terra and Aqua satellites' MODIS sensors identify the presence of a fire at the time of image collection, with Terra observations collected in the morning and Aqua observations collected in the afternoon. 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). For large-scale assessments, the dataset represents a good alternative to the use of information on ignition points, which may be preferable but can be difficult to obtain or may not exist (Tonini and others 2009). More information about the performance of this product is provided by Justice and others (2011). The fire occurrence data additionally do not differentiate fires intentionally

set for management purposes (controlled burns), which are common in some parts of the United States, particularly in the South, where many prescribed fires are not detected by satellite sensors (Nowell and others 2018).

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 be counted as having 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 the course of the year. A fire detected on a single pixel for every day in the month of July, for example, would be equivalent to 31 fire occurrences.

The Terra and Aqua satellites, which carry the MODIS sensors, were launched in 1999 and 2002, respectively, and eventually will be decommissioned. An alternative fire occurrence data source is the Visible Infrared Imaging Radiometer Suite (VIIRS) sensor on board the Suomi National Polar-orbiting Partnership (Suomi NPP) weather satellite. The transition to this new data source will require a comparison

of fire occurrence detections between it and MODIS. This is because VIIRS data are available from 2014 onward (USDA Forest Service 2021), but it will be important for assessments of fire occurrence trends to be able to analyze as long a window of time as possible (i.e., from the beginning of MODIS data availability).

Analyses

These MODIS products for 2020, and for the 19 preceding full years of data, were processed in ArcMap® (ESRI 2017) to determine forest fire occurrence density (that is, the number of fire occurrences/100 km² [10 000 ha] of tree canopy cover area) for each ecoregion section in the conterminous United States (Cleland and others 2007), for ecoregions on each of the major islands of Hawaii (Potter 2020b), and for the islands of the Caribbean territories of Puerto Rico and the U.S. Virgin Islands. For the current analyses, the forest fire occurrence density metrics for the conterminous 48 States, Hawaii, and the Caribbean territories (the number of fire occurrences/100 km² of tree canopy cover area) were calculated after screening out wildland fires that did not intersect with tree canopy data. The tree canopy data had been resampled to 240 m from a 30-m raster dataset that estimates percentage of tree canopy cover (from 0 to 100 percent) for each grid cell; this dataset was generated from the 2011 National Land Cover Database (NLCD) (Homer and others 2015) through a cooperative project between the Multi-Resolution Land Characteristics Consortium and the U.S. Department of Agriculture Forest Service, Geospatial Technology and Applications

Center (GTAC) (Coulston and others 2012). For our purposes, we treated any cell with >0-percent tree canopy cover as forest. Comparable tree canopy cover data were not available for Alaska, so we instead created a 240-m-resolution layer of forest and shrub cover from the 2011 NLCD. The MODIS fire occurrence detection data were then intersected with this layer and with ecoregion sections for the State (Spencer and others 2002) to calculate the number of fire occurrences/100 km² of forest and shrub cover within each ecoregion section in Alaska. In Forest Health Monitoring national reports before 2019, the number of fire occurrences/100 km² of forest was determined for the conterminous States, Alaska, and Hawaii using a forest cover mask derived from MODIS imagery by the Forest Service GTAC (USDA Forest Service 2008).

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

The fire occurrence density value for each of the ecoregions of the States and for the Caribbean islands in 2020 was then compared with the mean fire density values for the first 19 full years of MODIS Active Fire data collection (2001–2019). Specifically, the difference of the 2020 value and the previous 19-year mean for an ecoregion was divided by the standard deviation across the previous 19-year period, assuming a normal distribution of fire density over time in the ecoregion. 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 ecoregion in 2020 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 classified as 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 (at $p < 0.025$ at each tail of the distribution).

Additionally, we used the Spatial Association of Scalable Hexagons (SASH) analytical approach to identify forested areas in the conterminous United States with higher-than-expected fire occurrence density in 2020. 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, we 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 conterminous United States 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 conterminous United States 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 are convenient and highly useful attributes for spatial neighborhood analyses. 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). We selected hexagons 834 km² in area because this is a manageable size for making monitoring and management decisions in analyses across the conterminous United States (Potter and others 2016).

Fire occurrence density values for each hexagon were quantified as the number of forest fire occurrences/100 km² of tree canopy cover area within the hexagon. The Getis-Ord G_i^* statistic was used 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 conterminous United States. As described in Laffan (2006), it is calculated as:

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

where

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

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

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

x_j = the value of neighbor j

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

n = number of samples in the dataset (the 9,644 hexagons containing tree cover)

W_i^* = the sum of the weights

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

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

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

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; a hexagon and its 18 neighbors, in other words, have a normal range of both high and low numbers of fire occurrences/100 km² of tree canopy cover area. It is worth noting that 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 considered to be 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 2020

The MODIS Active Fire database recorded 122,938 forest fire occurrences across the conterminous United States in 2020, the third highest in 20 full years of data collection and the most since 2014 (fig. 3.1). Only 2012 and 2014 saw more fire occurrences. This was a 202-percent increase from a relatively low-activity fire year in 2019, which had the fewest fire occurrences (40,657) since 2005. It was also 75 percent above the mean of the previous 19 years of data. Meanwhile, Alaska had a 98-percent drop in fire occurrences between 2019 (26,493) and 2020 (474), the fewest there since 2011. Hawaii had 22 fire occurrences in 2020, 92 percent below the 2001–2019 average and a 39-percent reduction from 2019. Finally, only four fire occurrences were detected in Puerto Rico, a decrease from 18 in 2019 and 57 percent below the average of about nine per year.

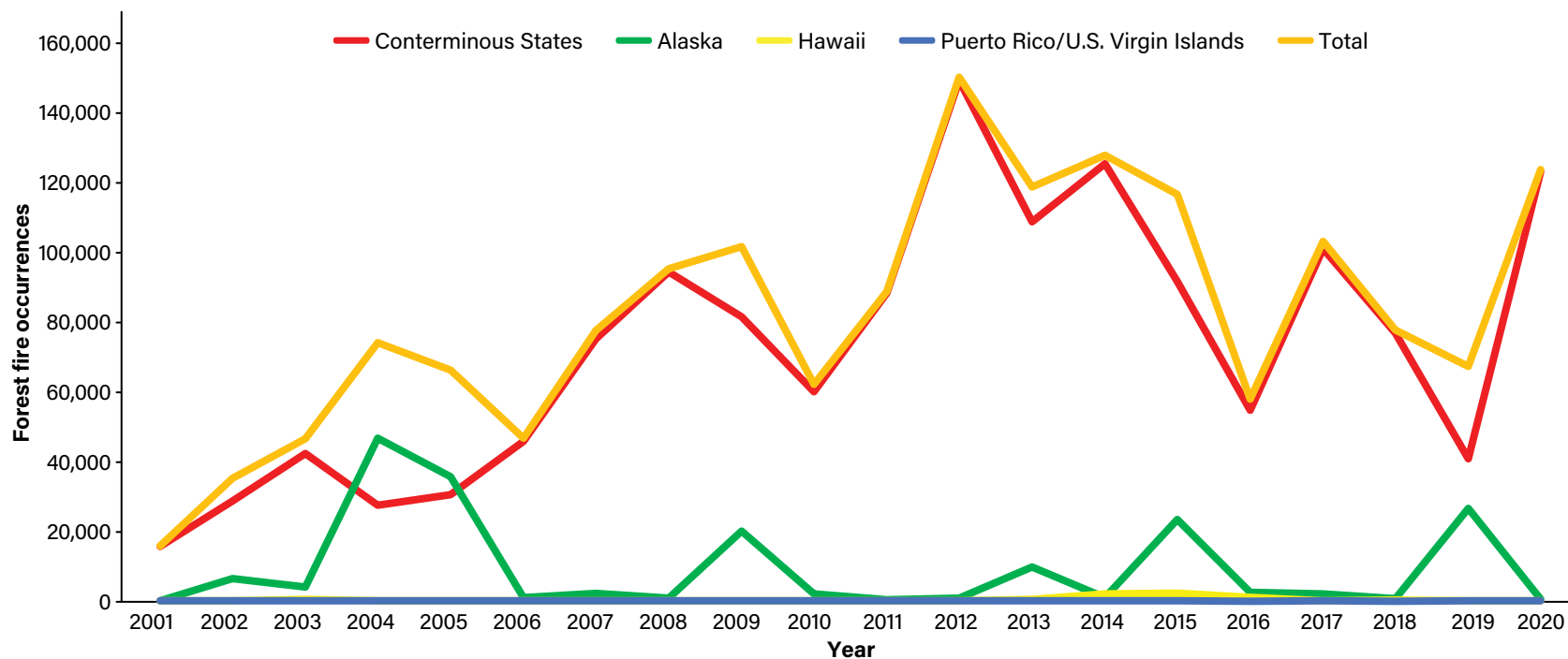


Figure 3.1—Forest fire occurrences detected by Moderate Resolution Imaging Spectroradiometer (MODIS) from 2001 through 2020 for the conterminous United States, Alaska, and Hawaii, and Puerto Rico/U.S. Virgin Islands, and for the entire Nation combined. (Data source: U.S. Department of Agriculture Forest Service, Geospatial Technology and Applications Center, in conjunction with the NASA MODIS Rapid Response group)

The dramatic increase in fire occurrences in the conterminous United States, along with the precipitous drop in Alaska fire occurrences, is consistent with official national wildland fire statistics, which track area burned and the numbers of wildfires reported (National Interagency Coordination Center 2021). These statistics indicate that the area burned more than doubled from 1 887 601 ha in 2019 to >4 046 856 ha (10 million acres) in 2020 (National Interagency Coordination Center 2020, 2021). California accounted for 38 percent of the 2020 burned area. At the same time, the number of reported wildfires increased from 50,477 in 2019 to 58,950. Beyond these general statistics, the 2020 fire season was marked by several notable and alarming superlatives (CALFIRE 2021, National Interagency Coordination Center 2021):

- The first reported fire incident exceeding 404 686 ha (1 million acres), the August Complex in northern California
- Six of the seven largest wildfire events ever recorded in California
- The three largest wildfires in Colorado history (Cameron Peak, East Troublesome, Pine Gulch)
- The first-ever tornado warning issued by the National Weather Service resulting from a wildfire, for pyrotornadoes generated by the Loyalton Fire in northeastern California

In 2020, the number of wildland fires and fire complexes exceeding 16 187 ha (40,000 acres, a benchmark threshold for the National Interagency

Coordination Center) was 50, compared to 27 in 2019 and 49 in 2018 (National Interagency Coordination Center 2019, 2020, 2021). As noted in the Methods section above, estimates of burned area and numbers of reported fires are different metrics for quantifying fire activity than calculations of MODIS-detected fire occurrences, though they are often correlated.

The areas with the highest (extremely high) fire occurrence densities in 2020 were in California (the Sierra Nevada, the northwestern part of the State, and along the central and southern coast), and in north-central Colorado and south-central Wyoming (fig. 3.2). Areas with very high fire occurrence densities included the Cascade Mountains of Washington and Oregon, southwestern Oregon and northwestern California, northeastern Utah, and south-central Idaho/northeastern Nevada/northwestern Utah. A handful of ecoregion sections in the Pacific Coast States, in the Four Corners States, in the Midwest, and in the Southeast had high fire occurrence densities.

The three specific ecoregion sections with the highest fire occurrence density in 2020 (and seven of the top eight) were in California: M261B–Northern California Coast Ranges (125.9 fire occurrences/100 km² of tree canopy cover), M261E–Sierra Nevada (50.9 fire occurrences), and M262B–Southern California Mountain and Valley (35.0 fire occurrences) (table 3.1). The fourth ecoregion on the list was M331I–Northern Parks and Ranges in Colorado and Wyoming (28.4 fire occurrences). In the previous year, the ecoregion section with the highest fire occurrence

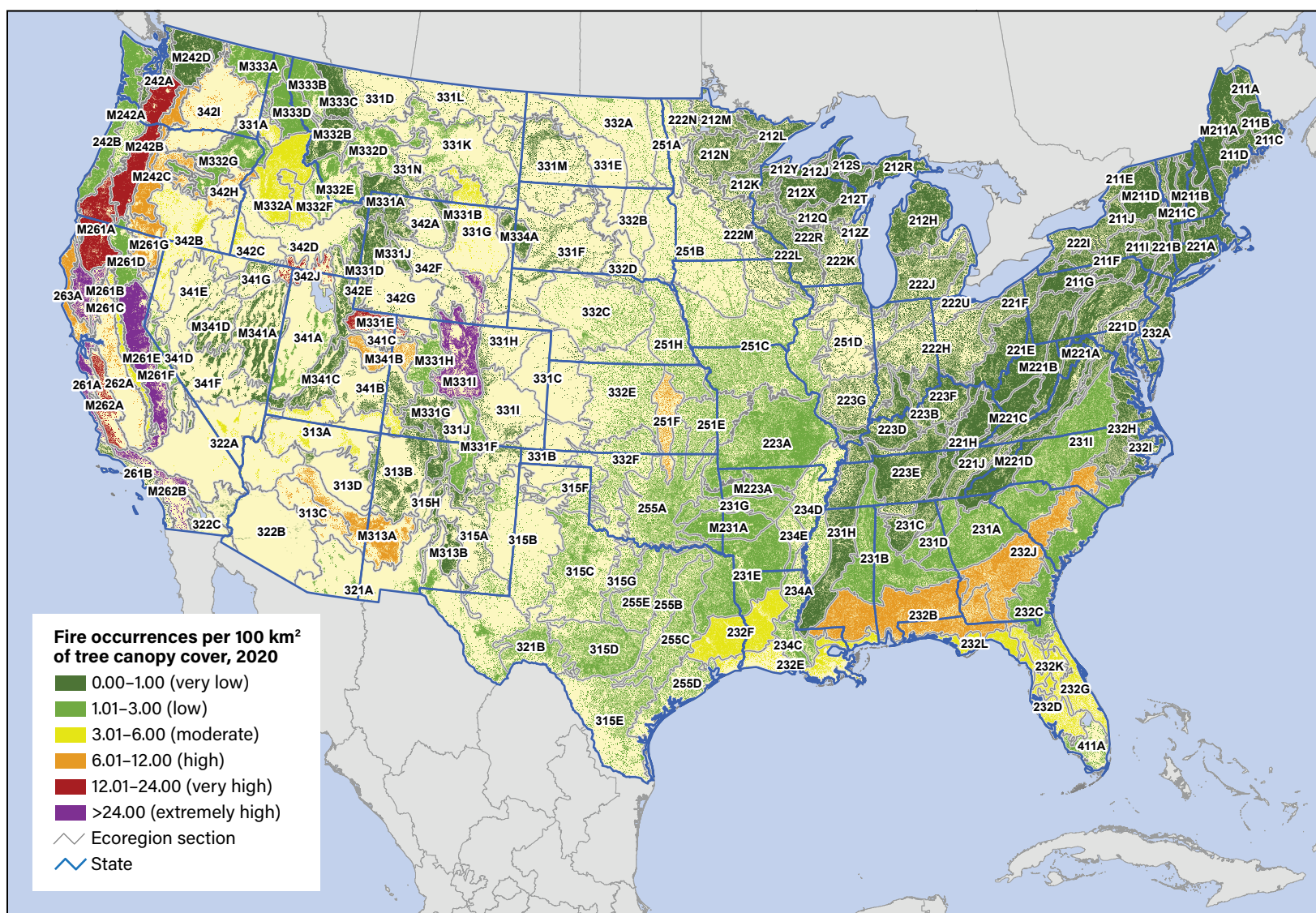


Figure 3.2—The number of forest fire occurrences, per 100 km² (10 000 ha) of tree canopy coverage area, by ecoregion section within the conterminous United States, for 2020. The gray lines delineate ecoregion sections (Cleland and others 2007). Tree canopy cover is based on data from a cooperative project 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 MODIS Rapid Response group)

Table 3.1—The 15 ecoregion sections in the conterminous United States with the highest fire occurrence densities in 2020

Section	Name	Tree canopy area <i>km²</i>	Fire occurrences <i>number</i>	Density ^a
M261B	Northern California Coast Ranges	114.1	14,362	125.9
M261E	Sierra Nevada	427.8	21,757	50.9
M262B	Southern California Mountain and Valley	58.1	2,032	35.0
M331I	Northern Parks and Ranges	302.7	8,591	28.4
M261C	Northern California Interior Coast Ranges	18.2	476	26.1
261A	Central California Coast	66.8	1,725	25.8
M262A	Central California Coast Ranges	78.9	1,846	23.4
M261A	Klamath Mountains	338.5	7,796	23.0
M242B	Western Cascades	427.9	9,704	22.7
M331E	Uinta Mountains	85.3	1,380	16.2
342J	Eastern Basin and Range	37.5	501	13.4
342H	Blue Mountain Foothills	108.6	1,302	12.0
M261G	Modoc Plateau	128.7	1,296	10.1
262A	Great Valley	19.4	183	9.4
M341B	Tavaputs Plateau	92.0	744	8.1

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

density (342C–Owyhee Uplands) experienced only 8.8 fire occurrences/100 km² of tree canopy cover (Potter 2021). In 2020, 14 of the top 15 ecoregion sections on the list of highest fire occurrence densities exceeded this number (table 3.1). The relatively high fire occurrence densities across the West in 2020 were attributable to long-term severe drought and periodic heat waves across many areas of the West that led to dry fuels that were ignited by lightning events and spread by strong wind events (Higuera and Abatzoglou 2020, National Interagency Coordination Center 2021).

Meanwhile, Alaska contributed little to the total burned area nationally in 2020 following a winter of near- or above-average snowpack (National Interagency Coordination Center 2021). As a result, fire occurrence densities across the entire State were very low (fig. 3.3), with only one ecoregion section exceeding 0.3 fire occurrences/100 km² of forest and shrub cover. This was M123E–Ray Mountains in the central interior part of the State, with 0.32 fire occurrences/100 km².

In 4 previous years, Alaska had MODIS-detected fire occurrence peaks: 2004/2005, 2009, and 2015 (fig. 3.1). Each was followed by a steep drop in Alaskan fire occurrences, and with an increase in fire occurrences in the conterminous States. That was the pattern again in 2019 and 2020: A year of many fire occurrences in Alaska was followed by a peak in the conterminous States. Such broad-scale North American patterns of wildfire result from the interaction between climate and vegetation development across a range of spatial and temporal scales

with climate influencing fine fuel moisture, ignition frequency, and rates of wildfire spread at annual to interannual timescales (Gedalof 2011). Intermediate-term patterns in wildfire occurrence in North America, meanwhile, are driven by interannual to multidecadal variability in sea surface temperatures, associated with the El Niño–Southern Oscillation (ENSO), Pacific Decadal Oscillation (PDO), and Atlantic Multidecadal Oscillation (AMO) (Kitzberger and others 2007).

Meanwhile, Hawaii had generally low fire occurrence density in 2020, with three ecoregions exceeding a fire occurrence density of 1/100 km² of tree canopy cover (fig. 3.4), Lowland/Leeward Dry-Maui (LLDm) (2.3), Mesic-Maui-West (MEM-w) (1.6), and Lowland/Leeward Dry-O‘ahu (LLDo) (1.4). There were no Big Island volcanic eruptions in 2020 that burned forests and buildings, as in 2018 (Potter 2021).

Finally, 2020 fire occurrence densities were $\leq 1/100$ km² of tree canopy cover for all the islands of the U.S. Caribbean territories (Puerto Rico and the U.S. Virgin Islands) (fig. 3.5).

Comparison to Longer Term Trends

Because the MODIS Active Fire data have been collected in a consistent fashion for 2 decades, it is possible to use the data to contrast short-term (2020) forest fire occurrence densities with longer term trends (2001–2019) for ecoregions in the conterminous States, Alaska, and Hawaii, and for Caribbean islands. The highest mean annual fire occurrences (>6 fire occurrences/100 km² of tree canopy cover annually) across that period in the conterminous States were located in ecoregions

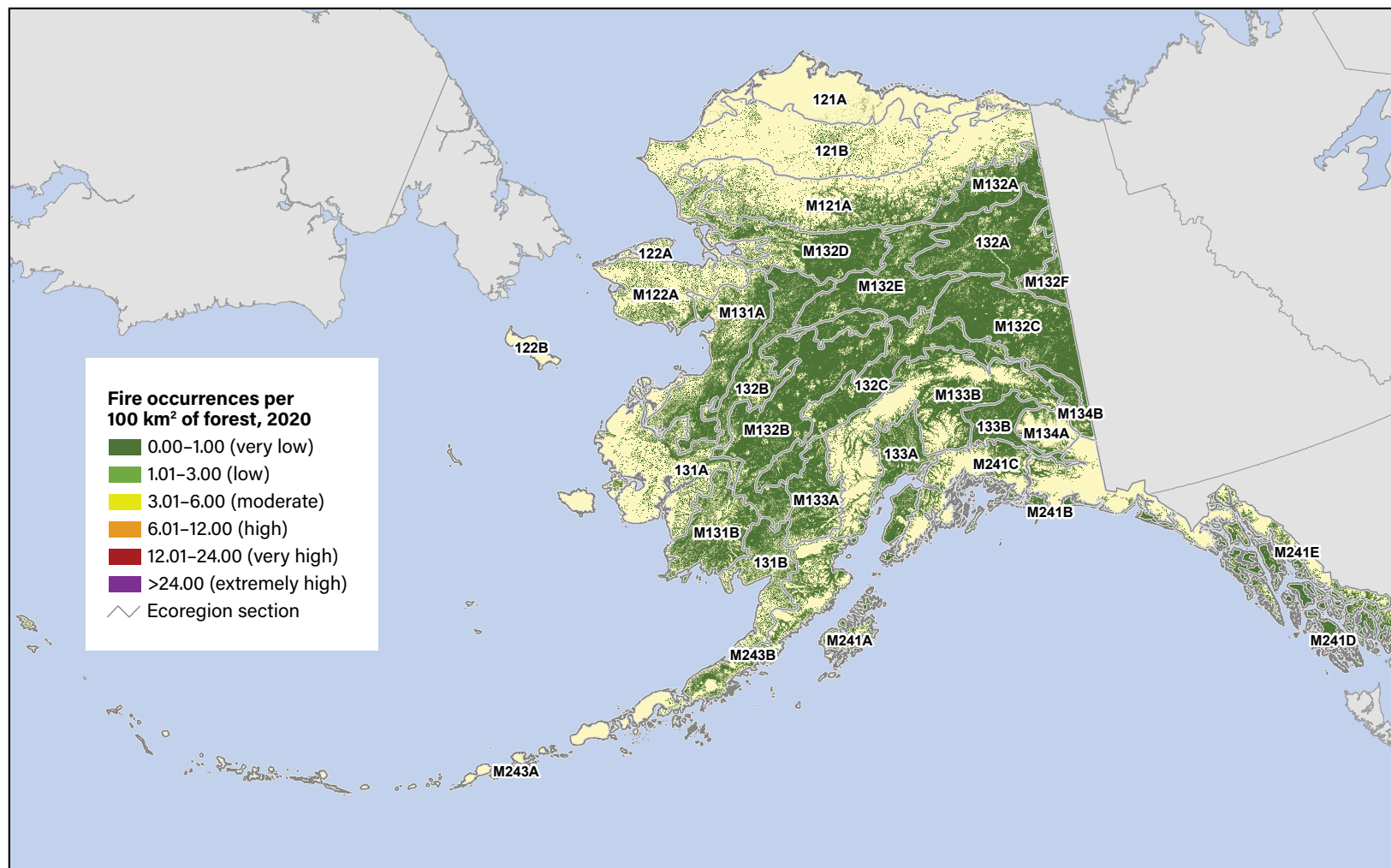


Figure 3.3—The number of forest fire occurrences, per 100 km² (10 000 ha) of forest and shrub cover, by ecoregion section within Alaska, for 2020. The gray lines delineate ecoregion sections (Spencer and others 2002). Forest and shrub cover are derived from the 2011 National Land Cover Database. See 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 MODIS Rapid Response group)

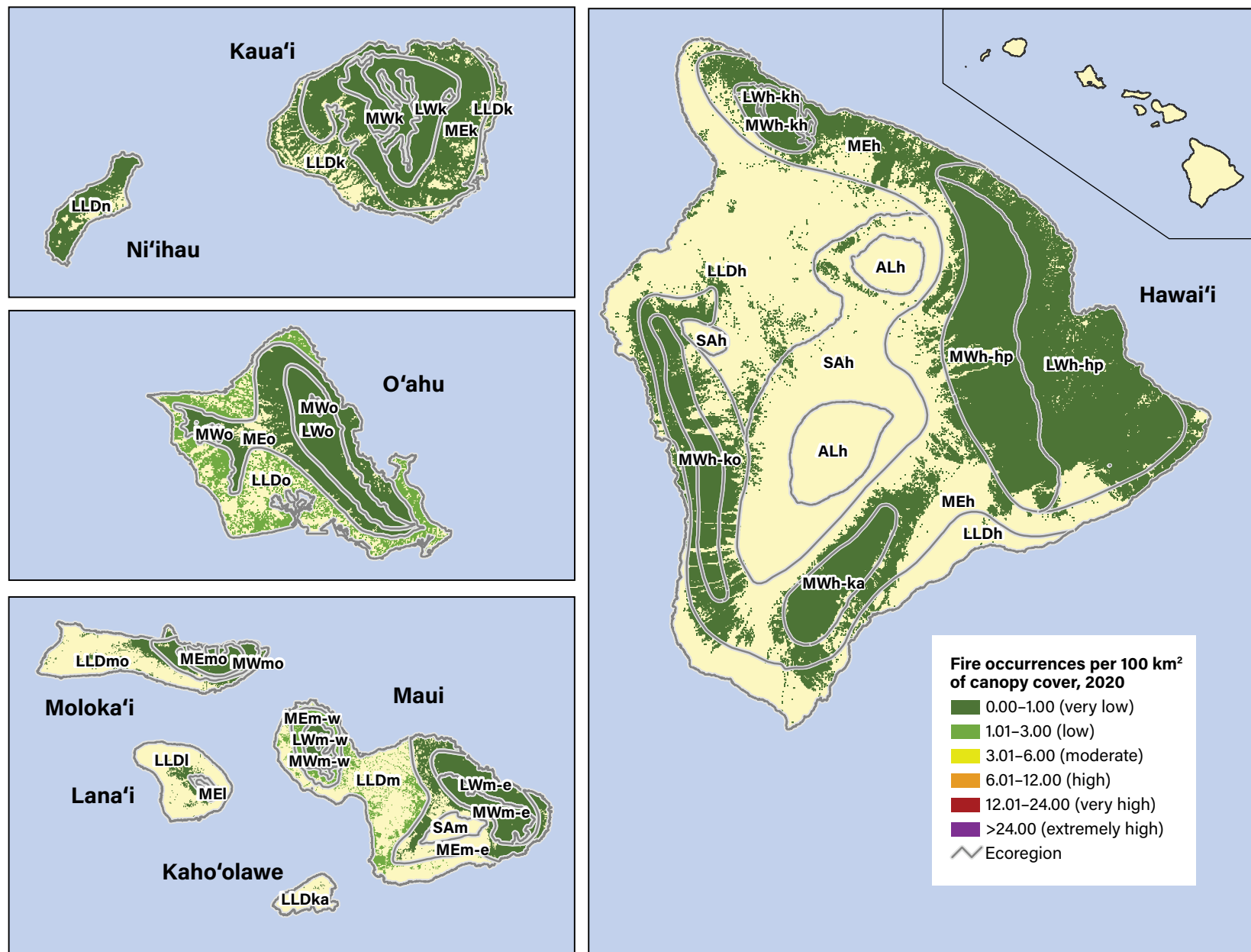


Figure 3.4—The number of forest fire occurrences, per 100 km² (10 000 ha) of tree canopy coverage area, by island/ecoregion combination in Hawaii, for 2020. Tree canopy cover is based on data from a cooperative project between the Multi-Resolution Land Characteristics Consortium (Coulston and others 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 MODIS Rapid Response group)

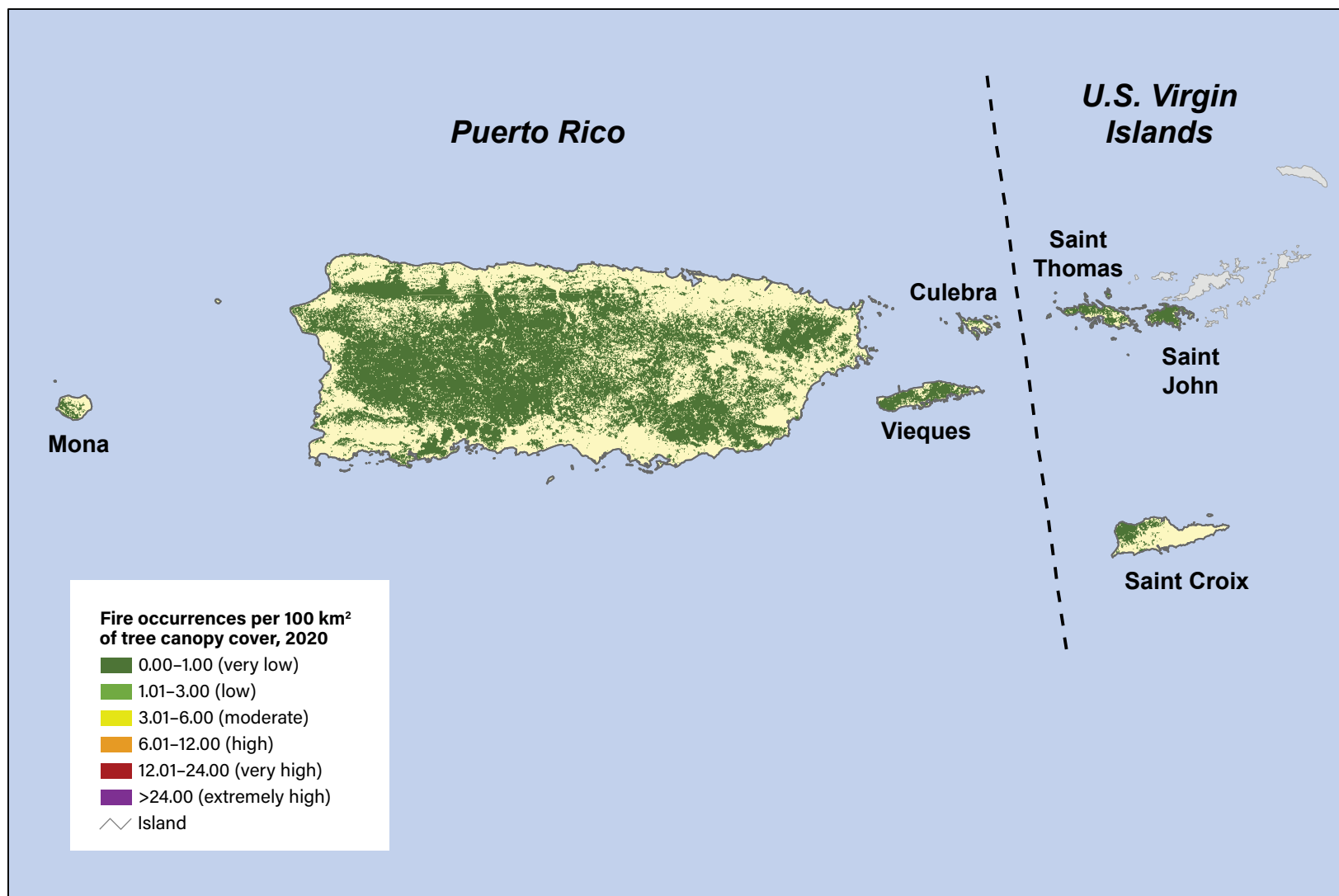


Figure 3.5—The number of forest fire occurrences, per 100 km² (10 000 ha) of tree canopy coverage area, by island in Puerto Rico and the U.S. Virgin Islands, for 2020. Tree canopy cover is based on data from a cooperative project between the Multi-Resolution Land Characteristics Consortium (Coulston 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 MODIS Rapid Response group)

along the Gulf Coast in the Southeast; in coastal, northern, and central areas of California; in north-central Washington; in central Arizona and west-central New Mexico; in the northern Rocky Mountains; and in central Kansas and northeastern Oklahoma (fig. 3.6A). Elsewhere outside of the West and the Southeast, ecoregions experienced ≤ 3 fire occurrences/100 km² of tree canopy cover annually, with much of the Midwest and all the Northeast experiencing ≤ 1 . The ecoregion section with the highest fire occurrence density on average was M332A–Idaho Batholith in central Idaho (12.8), followed by M261A–Klamath Mountains of northwestern California and southeastern Oregon (10.7), and M262B–Southern California Mountain and Valley near the southern California coast (8.9) (table 3.2). The M332A–Idaho Batholith ecoregion was also the one with the greatest annual variation in fire occurrence densities from 2001 to 2019 (fig. 3.6B). More moderate variation was apparent in California, southern Oregon, northeastern Washington and northwestern Idaho, western and southeastern Montana, west-central Wyoming, and central Arizona and west-central New Mexico. Meanwhile, the interannual variation was the lowest in the Midwest and Northeast and in coastal areas of Oregon and Washington (standard deviation < 1), with slightly higher variation (standard deviation 1–5) across the Southeast, the central Rocky Mountains, the Great Basin, and central Oregon and Washington.

Several ecoregions in California, Washington, and Oregon, as well as four in northwestern Colorado and northeastern Utah, had many more fire occurrences in 2020 than normal, compared to the previous 19-year mean and accounting for variability over time (fig. 3.6C). Several of these

are ecoregions that both had a high fire occurrence density in 2020 and a relatively high mean for the previous years. The ecoregion section with the highest z -score in 2020, however, was M331E–Uinta Mountains in northeast Utah, an area with typically very few fire occurrences. A handful of ecoregions in the Northeast also had moderately or much higher fire occurrence density than normal, though these are areas that tend to have few fires in a typical year, so they don't require many fire occurrences to be classified as having more than normal.

A few ecoregion sections, mostly in the eastern half of the United States, had 2020 fire occurrence densities that were lower than expected, as determined by z -scores that were ≤ -1 . Four of these were in the Great Lakes States: 212H–Northern Lower Peninsula and 212R–Eastern Upper Peninsula in Michigan, 212X–Northern Highlands in Wisconsin, and 212K–Western Superior Uplands in Minnesota and Wisconsin. Three were in the South: M231A–Ouachita Mountains in southeast Oklahoma and west-central Arkansas, 221H–Northern Cumberland Plateau in eastern Tennessee and Kentucky, and 411A–Everglades in southern Florida. One was in the West: 341B–Northern Canyonlands in eastern Utah and western Colorado. Most of these are ecoregion sections that have low annual fire occurrence densities on average, but two were exceptions that have moderately high mean fire occurrence densities (M231A–Ouachita Mountains and 411A–Everglades).

In Alaska, meanwhile, mean annual fire occurrence densities for 2001–2019 were relatively low except for in M132E–Ray Mountains and

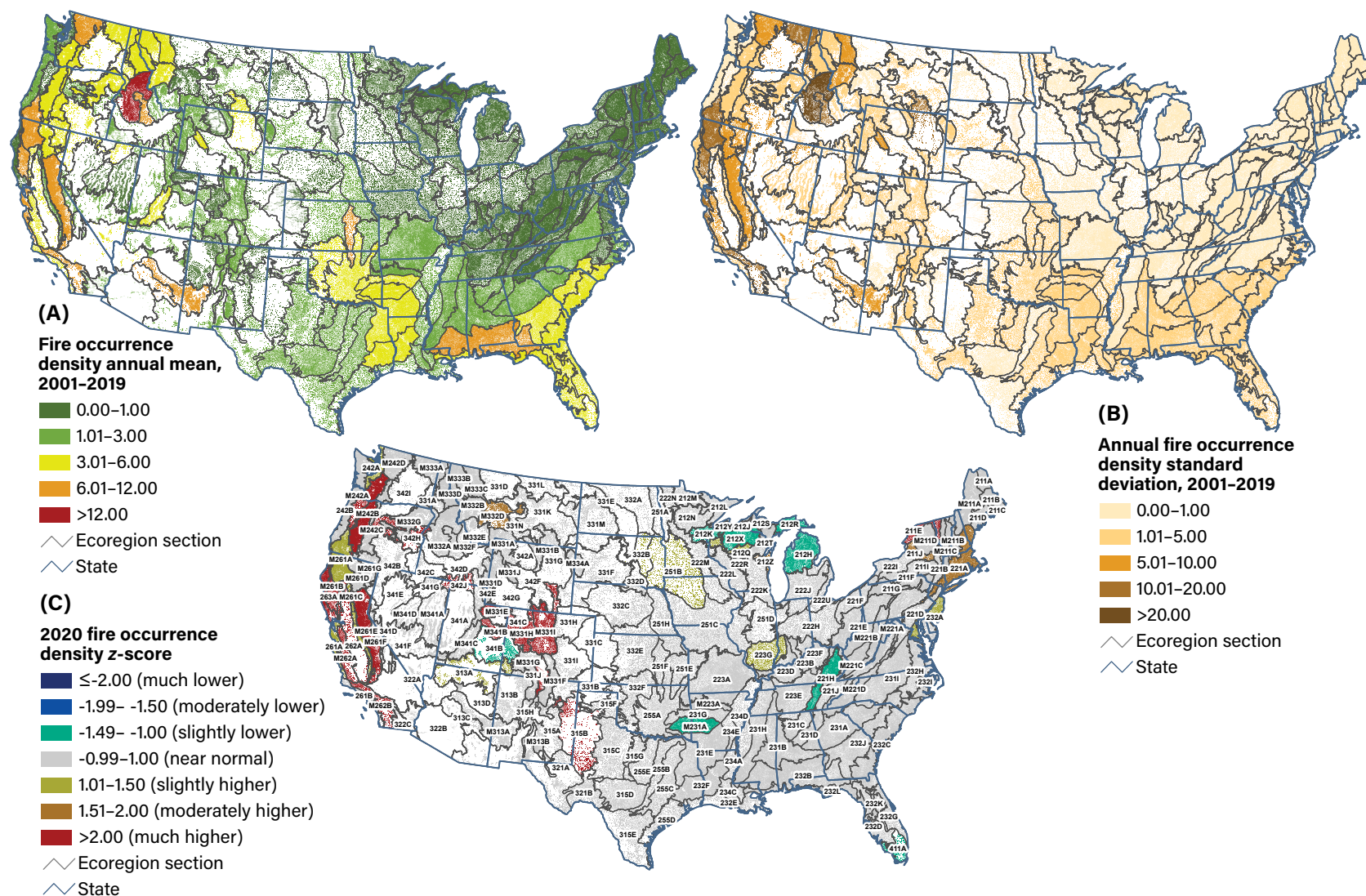


Figure 3.6—(A) Mean number and (B) standard deviation of forest fire occurrences per 100 km² (10 000 ha) of tree canopy coverage area from 2001 through 2019, by ecoregion section within the conterminous United States. (C) Degree of 2020 fire occurrence density excess or deficiency by ecoregion relative to 2001–2019 and accounting for variation over that time 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 MODIS 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 to 2019

Section	Name	Tree canopy area <i>km²</i>	Mean annual fire occurrence density ^a
M332A	Idaho Batholith	338.9	12.8
M261A	Klamath Mountains	338.5	10.7
M262B	Southern California Mountain and Valley	58.1	8.9
M261E	Sierra Nevada	427.8	8.1
M313A	White Mountains-San Francisco Peaks-Mogollon Rim	202.5	7.9
313C	Tonto Transition	17.5	7.6
251F	Flint Hills	57.8	7.3
M261B	Northern California Coast Ranges	114.1	6.9
M242D	Northern Cascades	251.1	6.7
232B	Gulf Coastal Plains and Flatwoods	888.7	6.4
261A	Central California Coast	66.8	6.3
M332F	Challis Volcanics	72.2	6.1
331A	Palouse Prairie	33.4	6.0
M333C	Northern Rockies	176.3	6.0
M332B	Northern Rockies and Bitterroot Valley	154.9	5.8

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

132A–Yukon–Old Crow Basin in the central and east-central parts of the State (fig. 3.7A). Along with the neighboring M132C–Yukon–Tanana Uplands and M132F–North Ogilvie Mountains, these ecoregion sections exhibited the most variability over the 19-year period preceding 2020 (fig. 3.7B). All Alaska ecoregions in 2020 had fire occurrence densities that were near normal compared to the previous 19 years and accounting for variability (fig. 3.7C).

In Hawaii, the area exhibiting the highest annual fire occurrence density mean (fig. 3.8A) and variability (fig. 3.8B) from 2001–2019 was the Lowland Wet–Hilo–Puna ecoregion (LWh–hp) on the eastern side of the Big Island (19.6 fire occurrences/100 km² of tree canopy cover, standard deviation 42.0). This ecoregion contains recently active portions of the lower east rift zone of Kilauea volcano, where lava flows have incinerated some forested areas. For all other ecoregions in the State, the annual mean was ≤ 1 fire occurrence/100 km² of tree cover, with the exception of the Mesic region on the Big Island (MEh), where it was 2.3. In 2020, two ecoregions on Maui had fire occurrence densities higher than expected, controlling for variability over the previous 19 years (z -score >1): the Mesic–Maui–West ecoregion (ME_m–w) and the Maui Lowland/Leeward Dry ecoregion (LLD_m) (fig. 3.8C).

Finally, all the islands of the Caribbean territories of Puerto Rico and the U.S. Virgin Islands had fire occurrence means and standard deviations ≤ 1 for the 2001–2019 period (figs. 3.9A and 3.9B). None of the islands was outside

the range of near-normal fire occurrence density (z -score ≤ -1 or >1) in 2020 (fig. 3.9C).

Geographic Hot Spots of Fire Occurrence Density

Geographic hot spot analyses, conducted across the conterminous United States using analysis units smaller than ecoregions (the main unit of analysis thus far), can offer additional insights into where, statistically, fire occurrences are more concentrated than expected by chance. Even in a year marked by high fire activity for much of the conterminous United States, this analysis identifies areas that have higher-than-expected fire occurrence densities compared to the entire study region. For 2020, the SASH method detected two geographic hot spots of extremely high fire occurrence density ($G_i^* > 24$), both in California, and several of very high fire occurrence density ($G_i^* > 12$ and ≤ 24) throughout the West (fig. 3.10).

One of the hot spots of extremely high fire occurrence density was centered in M261B–Northern California Coast Ranges in the northwestern part of the State. This was the location of the August Complex of fires, which burned from August 17 to November 11 across 417 898 ha (the largest in the United States in 2020), costing approximately \$116 million to contain (National Interagency Coordination Center 2021). It was the largest recorded fire complex in California history (CALFIRE 2021), encompassing 1 percent of the State—an area larger than Rhode Island. The second extremely high fire density hot spot was in the central part of M261E–Sierra Nevada, caused by the 153 738-ha Creek Fire. Ignited on September 4

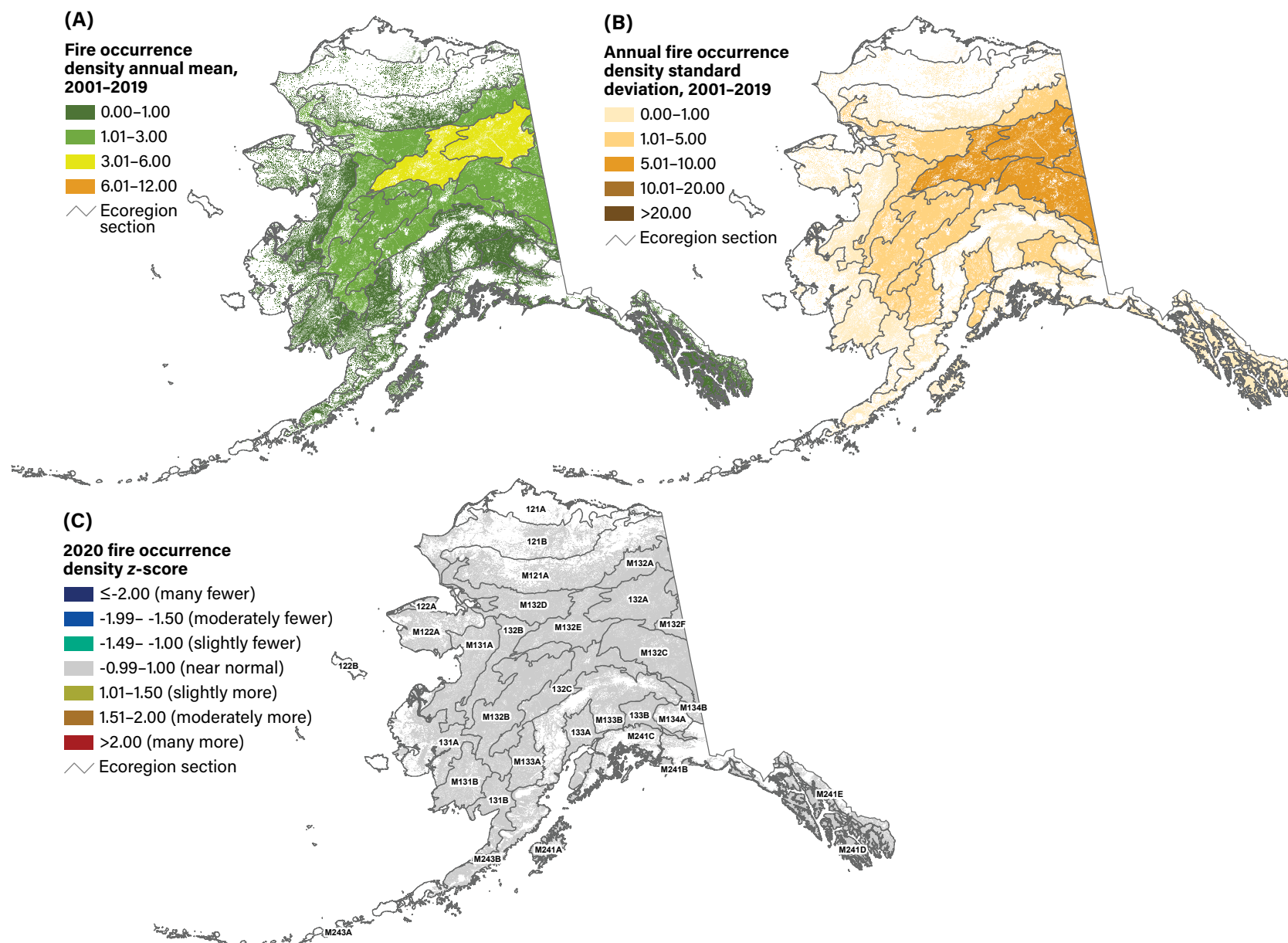


Figure 3.7—(A) Mean number and (B) standard deviation of forest fire occurrences per 100 km² (10 000 ha) of forest and shrub cover from 2001 through 2019, by ecoregion section in Alaska. (C) Degree of 2020 fire occurrence density excess or deficiency by ecoregion relative to 2001–2019 and accounting for variation over that time 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 MODIS Rapid Response group)

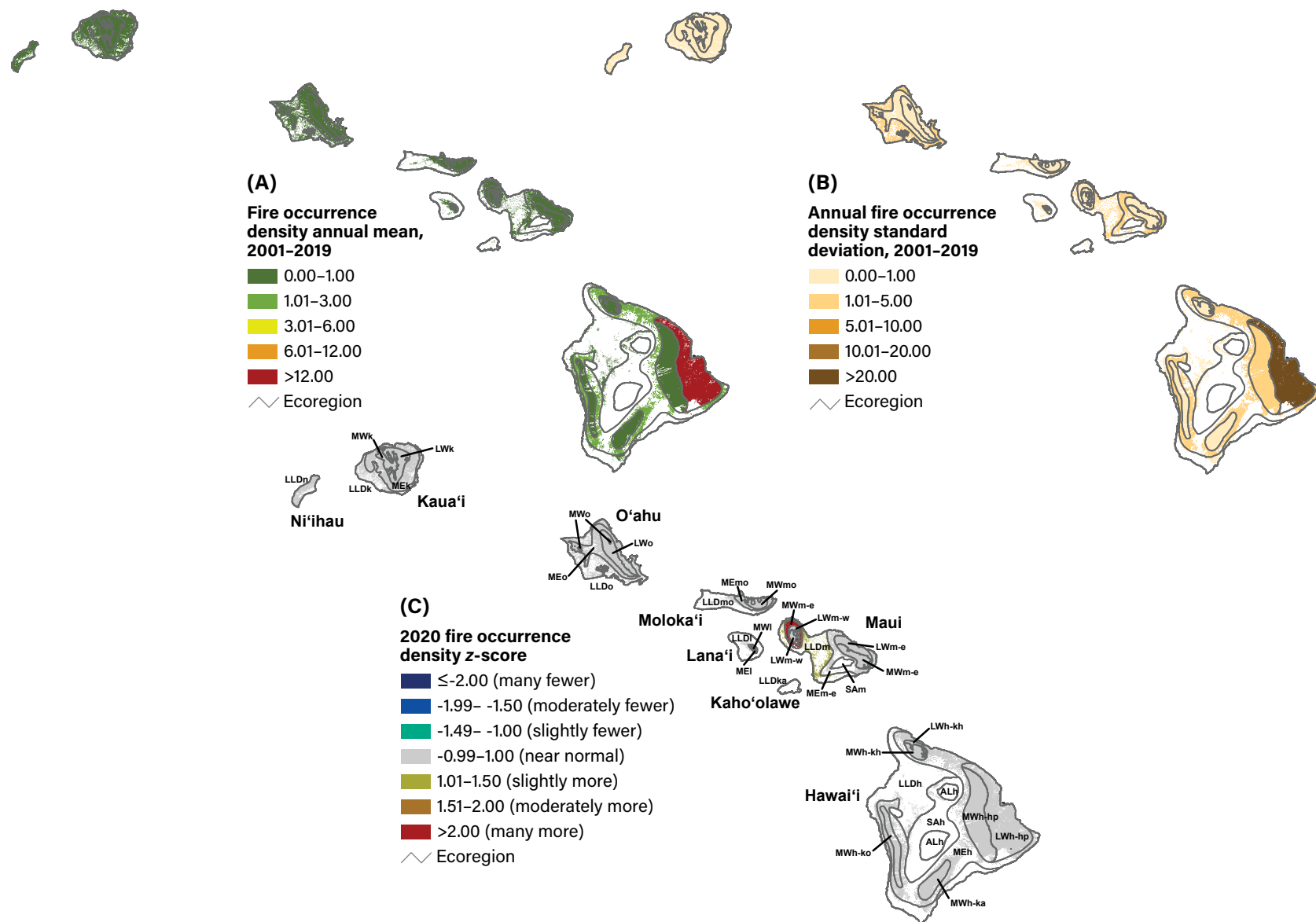


Figure 3.8—(A) Mean number and (B) standard deviation of forest fire occurrences per 100 km² (10 000 ha) of tree canopy coverage area from 2001 through 2019, by island/ecoregion combination in Hawaii. (C) Degree of 2020 fire occurrence density excess or deficiency by ecoregion relative to 2001–2019 and accounting for variation over that time 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 MODIS Rapid Response group)

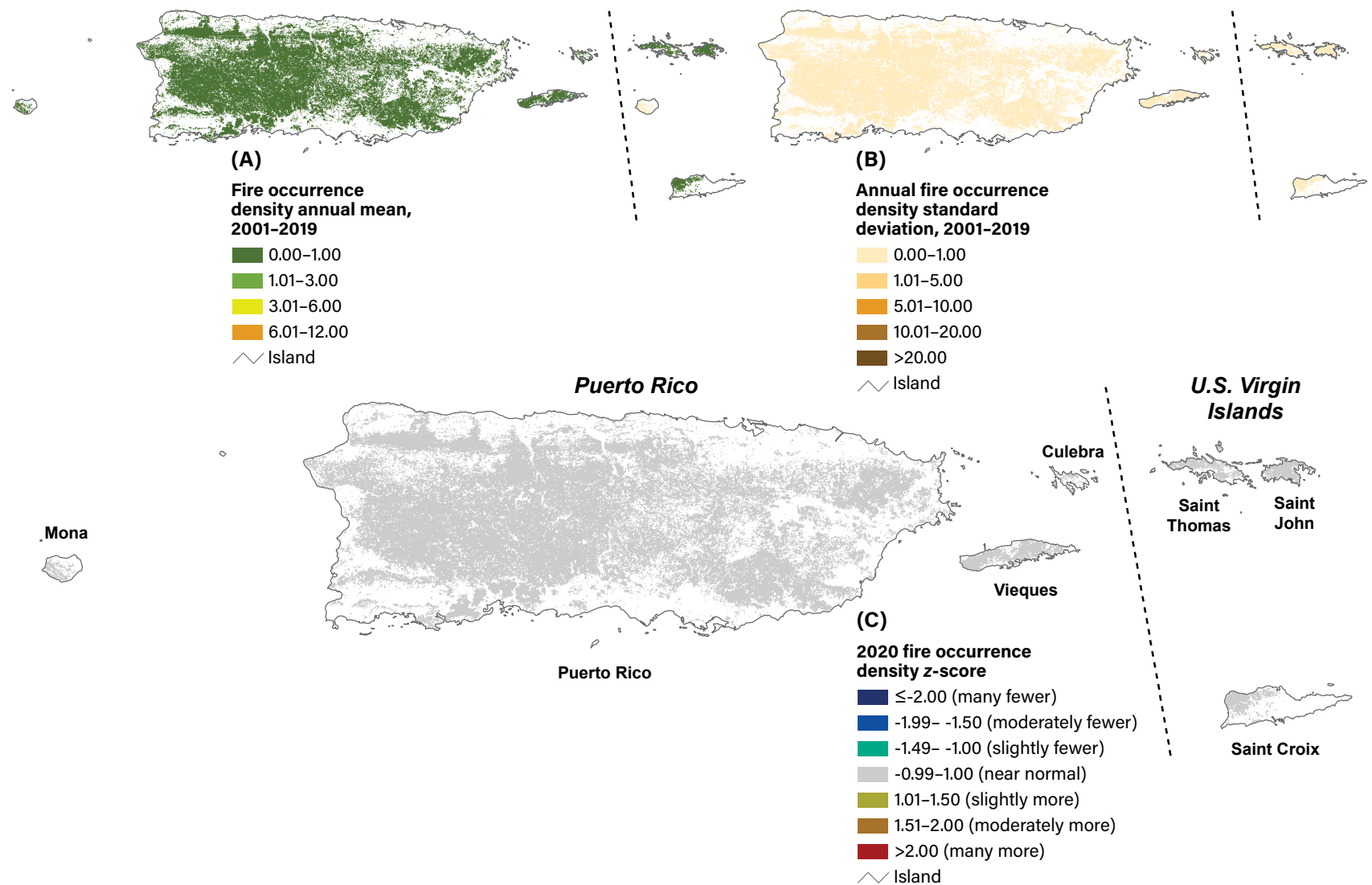


Figure 3.9—(A) Mean number and (B) standard deviation of forest fire occurrences per 100 km² (10 000 ha) of forested area from 2001 through 2019, by island in Puerto Rico and the U.S. Virgin Islands. (C) Degree of 2020 fire occurrence density excess or deficiency by ecoregion relative to 2001–2019 and accounting for variation over that time 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. (Source of fire data: U.S. Department of Agriculture Forest Service, Geospatial Technology and Applications Center, in conjunction with the NASA MODIS Rapid Response group)

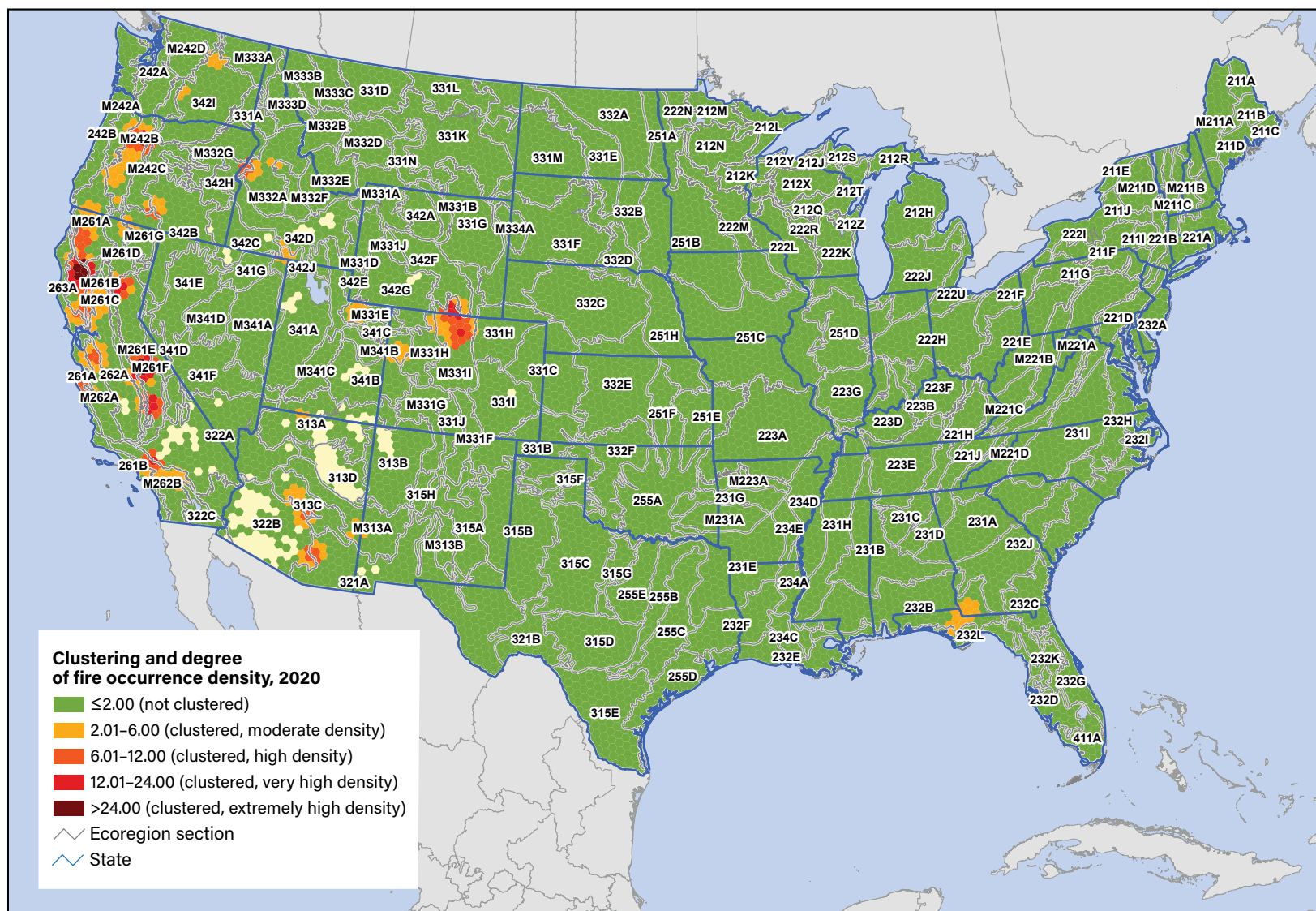


Figure 3.10—Hot spots of fire occurrence across the conterminous United States for 2020. Values are Getis-Ord G_i^* scores, with values >2 representing significant clustering of high fire occurrence densities. (No areas of significant clustering of lower fire occurrence densities, <-2 , were detected). The gray lines delineate ecoregion sections (Cleland and others 2007). (Source of fire data: U.S. Department of Agriculture Forest Service, Geospatial Technology and Applications Center, in conjunction with the NASA MODIS Rapid Response group)

and reported as contained on December 17, it cost in the neighborhood of \$193 million to contain (National Interagency Coordination Center 2021) and was the largest single fire (i.e., not a complex) in California history, destroying 853 structures (CALFIRE 2021).

The five hot spots of very high fire occurrence density in 2020 (fig. 3.10) were also each associated with megafires:

- In the northern part of M261E–Sierra Nevada in California, where the North Complex fire burned 129 068 ha between August 17 and December 2, killing 15 people, destroying 2,352 structures, and costing approximately \$113 million to contain (CALFIRE 2021, National Interagency Coordination Center 2021)
- In the southern part of M261E–Sierra Nevada in California, location of the SQF Complex fire, which burned 70 487 ha between August 24 and December 24, destroying 228 structures (CALFIRE 2021, National Interagency Coordination Center 2021)
- In the M262B–Southern California Mountain and Valley in the southwestern part of the State, where the Bobcat Fire cost approximately \$100 million to contain between September 6 and November 27, burning 46 942 ha (National Interagency Coordination Center 2021)
- In the M242B–Western Cascades in northwestern Oregon, location of the 82 746-ha Lionshead Fire; the 78 336-ha Beachie Creek

Fire, and the 55 868-ha Riverside Fire, ignited between mid-August and early September and contained by late-November at a combined cost of about \$115 million (National Interagency Coordination Center 2021). The Beachie Creek Fire killed five people and destroyed 500 homes (Templeton 2020).

- In M331I–Northern Parks and Ranges in north-central Colorado and south-central Wyoming, where three fires burned across large areas in the autumn: Cameron Peak (84 544 ha) and East Troublesome (78 433 ha) in Colorado, and Mullen (71 580 ha) in Wyoming and Colorado. Together, they cost roughly \$191 million to contain (National Interagency Coordination Center 2021). Cameron Peak and East Troublesome were the largest fires in recorded Colorado history, and the East Troublesome Fire grew by 48 562 ha in a single day, by far the most rapid fire expansion ever seen in the State, and then jumped the Continental Divide despite a lack of fuels above treeline (Brasch 2021).

Additionally, hot spots of high fire density in 2020 ($G_i^* > 6$ and ≤ 12) were identified in scattered locations throughout much of the West, including California, Oregon, and Arizona (fig. 3.10). Unusually, a single 2020 hot spot occurred in the Eastern United States, and it was of only moderate fire density ($G_i^* > 2$ and ≤ 6), in the panhandle of Florida and the southeastern corner of Georgia (232B–Gulf Coastal Plains and Flatwoods and 232L–Gulf Coastal Lowlands).

CONCLUSIONS

During a year marked by several worrying wildfire superlatives, the number of MODIS satellite-detected forest fire occurrences recorded for the conterminous States in 2020 was among the highest in 20 full years of data collection. Only 2012 and 2014 had more fire occurrences. The year included the first-ever fire incident that exceeded 404 686 ha (1 million acres), six of the seven largest wildfire events in California history, and the three largest wildfires ever recorded in Colorado. Areas with the highest forest fire occurrence densities were almost entirely limited to the West, attributable to long-term severe drought and periodic heat waves across much of the region.

In particular, ecoregions in California, Colorado, Oregon, Washington, and Utah had the highest forest fire occurrence densities (fire occurrences/100 km² tree canopy cover area) in 2020. Geographic hot spots of extremely high fire occurrence density were detected in California and Colorado, while areas of very high forest fire occurrence density were identified in California, Oregon, and Arizona. Not surprisingly, these areas experienced much higher than normal fire occurrence densities in 2020 compared to the previous 19-year mean and accounting for variability over time. At the same time, a few ecoregions scattered across the East had significantly lower fire occurrence densities than normal.

Alaska, meanwhile, experienced a quiet fire season compared to 2019 and to the conterminous States, with the fewest fire

occurrences since 2011. Similarly, most Hawaiian forests had low fire occurrence densities in 2020, although two ecoregions on the island of Maui had fire occurrence densities that were higher than expected, controlling for variability over the previous 19 years. All the U.S. islands in the Caribbean had near-normal fire occurrence densities.

The results of these geographic analyses are intended to offer insights into where fire occurrences have been concentrated spatially in a given year and compared to previous years but 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 also 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. However, 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 help 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.

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