

INTRODUCTION

As a pervasive disturbance agent operating at many spatial and temporal scales, wildland fire is a key abiotic factor affecting forest health both positively and negatively. In some ecosystems, for example, wildland fires have been essential for regulating processes that maintain forest health (Lundquist and others 2011). 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). At the same time, wildland fires have created forest health problems in some ecosystems (Edmonds and others 2011). Specifically, fire outside the historic range of frequency and intensity can impose extensive ecological and socioeconomic impacts. 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, potentially altering key ecosystem components such as species composition, structural stage, stand age, canopy closure, and fuel loadings (Schmidt and others 2002). As a result of intense suppression efforts during most of the 20th century, the forest area burned annually decreased from approximately 16–20 million ha (40–50 million acres) in the early 1930s to about 2 million ha (5 million acres) in the 1970s (Vinton 2004). Understanding existing fire regimes is essential to properly assessing the impact of fire on forest health because changes to historical fire

regimes can alter forest developmental patterns, including the establishment, growth, and mortality of trees (Lundquist and others 2011).

Fire regimes have been dramatically altered by fire suppression (Barbour and others 1999) and by the introduction of nonnative invasive plants, which can change fuel properties and in turn both affect fire behavior and alter fire regime characteristics such as frequency, intensity, type, and seasonality (Brooks and others 2004). 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). Such 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). In some regions, plant communities have experienced or are undergoing rapid compositional and structural changes as a result of fire suppression (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).

This chapter presents analyses of fire occurrence data, collected nationally each day by satellite, that map and quantify where

CHAPTER 3. Large-Scale Patterns of Forest Fire Occurrence in the Conterminous United States, Alaska, and Hawaii, 2016

KEVIN M. POTTER

fire occurrences were concentrated spatially across the conterminous United States, Alaska, and Hawaii in 2016. It also compares 2016 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 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.

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 2017) 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). A fire occurrence is defined as one daily satellite detection of wildland fire in a 1-km² pixel, with multiple fire occurrences possible on a pixel across multiple days resulting from a single wildland fire that lasts more than a single 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 km², with the center of a pixel recorded as a fire occurrence (USDA Forest Service 2017). 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 do 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). 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). For more information about the performance of this product, see Justice and others (2011).

It is important to underscore that estimates of burned area 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-km² 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-km² 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 on every day of the year would be equivalent to 365 fire occurrences.

Analyses

These MODIS products for 2016 were processed in ArcMap[®] (ESRI 2012) to determine number of fire occurrences per 100 km² (10 000 ha) of forested area for each ecoregion section in the conterminous United States (Cleland and others 2007) and Alaska (Nowacki and Brock 1995) and for each of the major islands of Hawaii. This forest fire occurrence density measure was calculated after screening out wildland fires on nonforested pixels using a forest cover layer derived from MODIS imagery by the U.S. Department of Agriculture, Forest Service, Remote Sensing Applications Center (RSAC) (USDA Forest Service 2008). The total numbers of forest fire occurrences were also determined separately for the conterminous States, Alaska, and Hawaii.

The fire occurrence density value for each ecoregion and Hawaiian island in 2016 was then compared with the mean fire density values for the first 15 full years of MODIS Active Fire data collection (2001–15). Specifically, the difference of the 2016 value and the previous

15-year mean for an ecoregion was divided by the standard deviation across the previous 15-year period, assuming 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 2016 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 previous observations. 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 2016. 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® 10.1 (ESRI 2012).

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). This base hexagon can be subdivided into many smaller hexagons, depending on sampling needs, and serves as the basis of the plot sampling frame for the Forest Inventory and Analysis (FIA) program (Reams and others 2005). Importantly, the hexagons maintain equal areas across the study region regardless of the degree of intensification of the EMAP hexagon coordinates. In addition, 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 nationwide analyses (Potter and others 2016).

Fire occurrence density values for each hexagon were quantified as the number of forest fire occurrences per 100 km² of forested 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 six adjacent hexagons and the 12 additional hexagons contiguous to those six) and the global

mean of all 7,595 of the forested hexagonal cells in the conterminous United States. As described in Laffan (2006), it is calculated as

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

where

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

i is the center of local neighborhood,

d is the width of local sample window,

w_{ij} is the weight of neighbor j from location i ,

n is number of samples in the dataset,

W_i^* is the sum of the weights,

ns_{1i}^* is the number of samples within d of the central location,

$\bar{x}^*$ is the mean of whole dataset (in this case, for all hexagons), and

s^* is the standard deviation of whole dataset.

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 per 100 km² of forested 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 reliable, even with skewed data, as long as the local neighborhood encompasses several observations (ESRI 2012), in this case, the target hexagon and its 18 first- and second-order neighbors.

RESULTS AND DISCUSSION

The MODIS Active Fire database recorded 47,744 forest fire occurrences across the conterminous United States in 2016, the lowest number of annual fire occurrences since 2006 (fig. 3.1). This was approximately 41 percent fewer than in 2015 (81,435 total forest fire occurrences), and about 28 percent less than the annual mean of 66,058 forest fire occurrences across the previous 15 full years of data collection. In Alaska, meanwhile, the MODIS database captured 2,196 forest fire occurrences in 2016, about 90 percent less

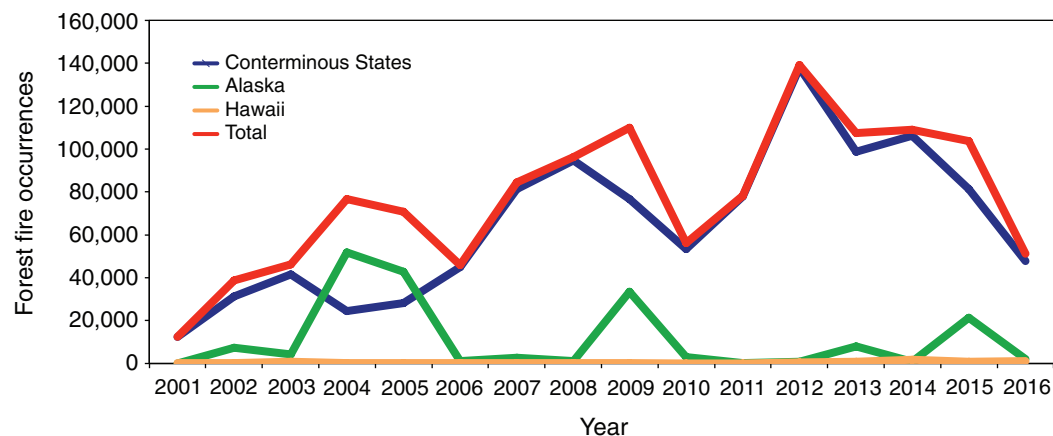


Figure 3.1—Forest fire occurrences detected by MODIS from 2001 to 2016 for the conterminous United States, Alaska, and Hawaii, and for the entire Nation combined. (Data source: U.S. Department of Agriculture, Forest Service, Remote Sensing Applications Center, in conjunction with the NASA MODIS Rapid Response group)

than the preceding year (21,466) and about 82 percent less than the previous 15-year annual mean of 11,925. Meanwhile, Hawaii had 1,210 fire occurrences in 2016, an increase of about 34 percent over the previous year (904) and 224 percent higher than the average 373 fire occurrences over the previous 15 years.

The decrease in the total number of fire occurrences across the United States is generally consistent with the official wildland fire statistics (National Interagency Coordination Center 2017). In 2016, 67,743 wildland fires were reported nationally, compared to 68,151 the previous year. The area burned nationally in 2016 (2 339 815 ha) was 79 percent of the 10-year average, with only 19 fires exceeding 16 187 ha (33 fewer than in 2015) (National Interagency Coordination Center 2016, 2017).

The total area burned nationally represented a 43 percent decrease from 2015 (4 097 502 ha) (National Interagency Coordination Center 2016). As noted in the Methods section, such estimates of burned area are different metrics for quantifying fire activity than calculations of MODIS-detected fire occurrences, though the two may be correlated.

While much of the country experienced above-normal temperatures, including many seasonal heat records, for much of 2016, wetter-than-usual conditions throughout much of the year east of the Rockies mitigated fire activity, with some exceptions (National Interagency Coordination Center 2017). Not surprisingly, forest fire occurrence densities were moderately or extremely high in only a few parts of the country (fig. 3.2). The ecoregion section with

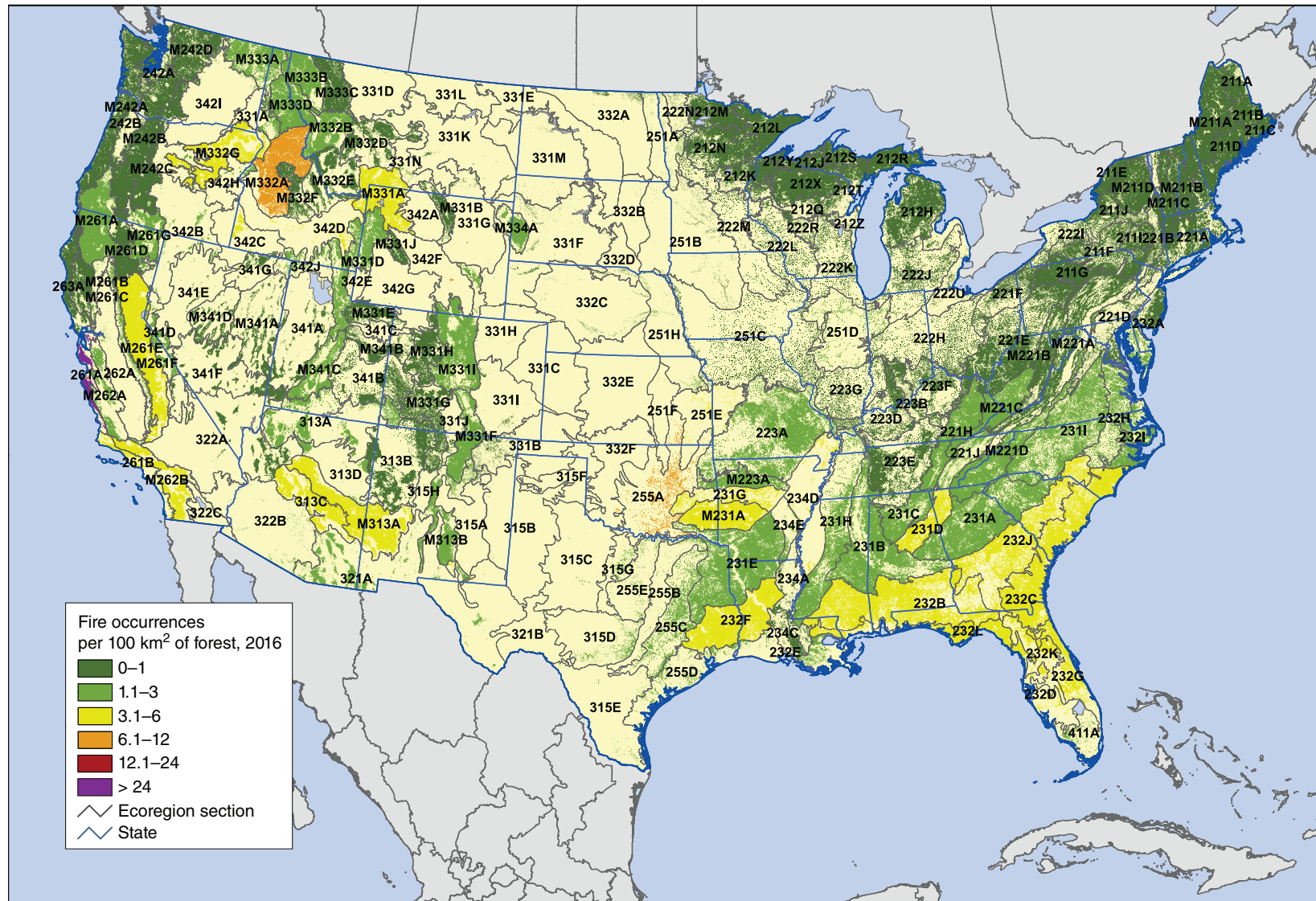


Figure 3.2—The number of forest fire occurrences per 100 km² (10 000 ha) of forested area, by ecoregion section within the conterminous United States, for 2016. The gray lines delineate ecoregion sections (Cleland and others 2007). Forest cover is derived from MODIS imagery by the U.S. Forest Service Remote Sensing Applications Center. (Source of fire data: U.S. Department of Agriculture, Forest Service, Remote Sensing Applications Center, in conjunction with the NASA MODIS Rapid Response group)

the highest fire occurrence density by far was 261A–Central California Coast, with 42.5 fires/100 km² of forest. This was the location of the Soberanes Fire, a human-ignited fire that scorched 53 469 ha between July 22 and October 23 and cost approximately \$262.5 million in damages and containment (National Interagency Coordination Center 2017). Fire occurrence densities were also relatively high in M332A–Idaho Batholith (8.2 fires/100 km² of forest) and 255A–Cross Timbers and Prairie (8.1 fires/100 km² of forest) in central Oklahoma and southeast Kansas. In the first of these, the Pioneer Fire burned 76 244 ha between July 18 and Oct. 27, costing \$90 million (National Interagency Coordination Center 2017).

Other ecoregion sections in the Southeast and scattered throughout the West had moderately high fire occurrence densities (fig. 3.2). In the Southeast, these encompassed an area stretching from eastern Texas and western Louisiana (232F–Coastal Plains and Flatwoods-Western Gulf) along the Gulf Coast (232B–Gulf Coastal Plains and Flatwoods and 232L–Gulf Coastal Lowlands) into most of peninsular Florida (232D–Florida Coastal Lowlands-Gulf, 232G–Florida Coastal Lowlands-Gulf, and 232K–Florida Coastal Plains and Central Highlands) and north along the Atlantic Coastal Plain into southeastern North Carolina (232J–Southern Atlantic Coastal Plains and Flatwoods and 232C–Atlantic Coastal Flatwoods). Fire densities were also moderately high in three adjacent ecoregion

sections in Arkansas and surrounding States: M231A–Ouachita Mountains, 231G–Arkansas Valley, and 234D–White and Black River Alluvial Plains.

Additionally, moderately high fire occurrence densities were recorded in several Western ecoregion sections, all with 3–6 fire occurrences/100 km² of forest:

- 261B–Southern California Coast, M262B–Southern California Mountain and Valley, and M261E–Sierra Nevada, all in California;
- 313C–Tonto Transition and M313A–White Mountains-San Francisco Peaks-Mogollon Rim, in central Arizona and west-central New Mexico; and
- M332G–Blue Mountains, 342C–Owyhee Uplands, 342D–Snake River Basalts and Basins, and M331A–Yellowstone Highlands, all in the northern Rocky Mountain States.

Meanwhile, the 2016 winter, spring, and summer in Alaska were among the warmest on record for that State (National Interagency Coordination Center 2016). Regardless, fire occurrence densities were almost uniformly low across the State (fig. 3.3). The ecoregion sections with the highest values were M131A–Upper Kobuk-Koyukuk (with only 2.6 fire occurrences/100 km² of forest and encompassing the 45 793-ha Alatna Complex of fires which burned for much of July) and 135A–Copper River Basin (with 2.1 fire occurrences).

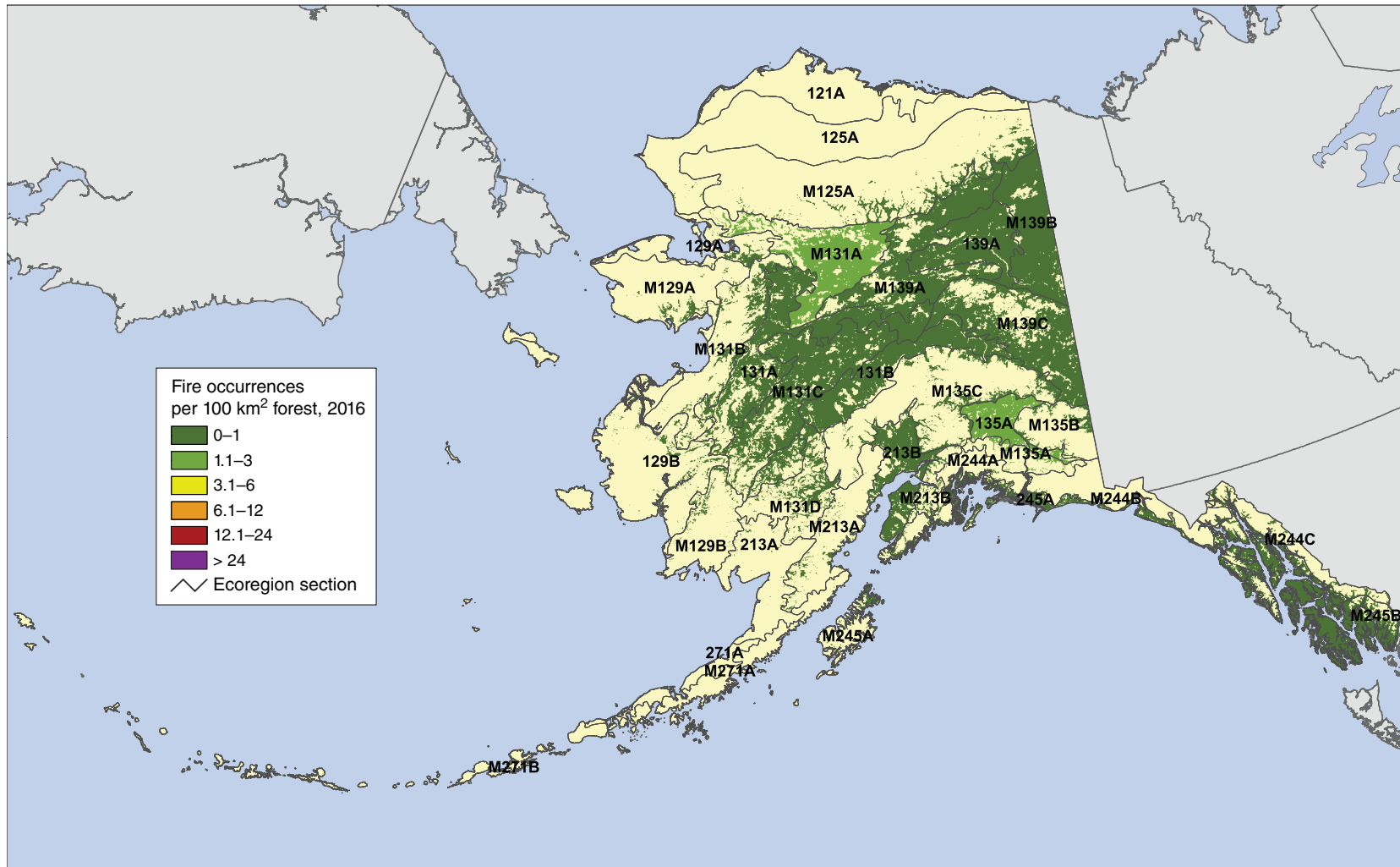


Figure 3.3—The number of forest fire occurrences per 100 km² (10 000 ha) of forested area, by ecoregion section within Alaska, for 2016. The gray lines delineate ecoregion sections (Nowacki and Brock 1995). Forest cover is derived from MODIS imagery by the U.S. Forest Service Remote Sensing Applications Center. (Source of fire data: U.S. Department of Agriculture, Forest Service, Remote Sensing Applications Center, in conjunction with the NASA MODIS Rapid Response group)

In Hawaii, lava flows from the 34-year-long eruption of Pu‘u ‘Ō‘ō, a vent on the flank of the Kilauea volcano on the Big Island, were the cause of most forest fire occurrences. Fire occurrence density on the Big Island was 29.6/100 km² of forest in 2016 (fig. 3.4), less than half the 60.5 for 2015 when a lava flow scorched dense forest in the Puna District (Potter 2017). All the other islands in the archipelago experienced < 1 fire occurrence/100 km² of forest.

Comparison to Longer Term Trends

The nature of the MODIS Active Fire data makes it possible to contrast, for each ecoregion section and Hawaiian island, short-term (1-year) forest fire occurrence densities with longer term trends encompassing the first 15 full years of data collection (2001–2015). In general, the ecoregions with the highest annual fire occurrence means are located in the Northern Rocky Mountains, the Southwest, California, and the Southeast, while most ecoregions within the Northeastern, Midwestern, Middle Atlantic, and Appalachian regions experienced < 1 fire occurrence/100 km² of forest annually during the multiyear period (fig. 3.5A). The forested ecoregion section that experienced the most fire occurrences on average was M332A–Idaho Batholith in central Idaho (mean annual fire occurrence density of 13.3), which also had one of the highest fire occurrence densities in 2016. Other ecoregions with high mean fire occurrence densities (6.1–12.0 fire occurrences/100 km² of forest) were located along the Gulf Coast and in peninsular Florida

in the Southeast, in coastal and central areas of California, in central Arizona and New Mexico, in the Northern Rocky Mountains, and in central Oklahoma. The ecoregion section with the greatest variation in fire occurrence densities from 2001 to 2015 was, again, M332A–Idaho Batholith, with more moderate variation in California, north-central Washington, southwestern Oregon, western Montana, central Arizona and west-central New Mexico, southern Idaho and northern Nevada, and coastal North Carolina (fig. 3.5B). Less variation occurred throughout the central and northern Rocky Mountain States, the Southeast, and coastal and eastern Oregon and Washington. The lowest levels of variation occurred throughout most of the Midwest and Northeast.

As determined by the calculation of standardized fire occurrence z-scores, ecoregions in the Southern Appalachian region, the Northeast, and coastal California experienced greater fire occurrence densities than normal in 2016, compared to the previous 15-year mean and accounting for variability over time (fig. 3.5C). The ecoregion section with the highest fire occurrence density in 2016 (261A–Central California Coast, fig. 3.2) also had a high z-score. At the same time, the ecoregions in the Appalachians and the Northeast had high z-scores despite a relatively low density of fire occurrences in 2016 (fig. 3.2) because these ecoregions typically have few fire occurrences on average and very little variation over time in fire occurrence density. Two of these, M221D–Blue Ridge Mountains and 221J–Central Ridge and

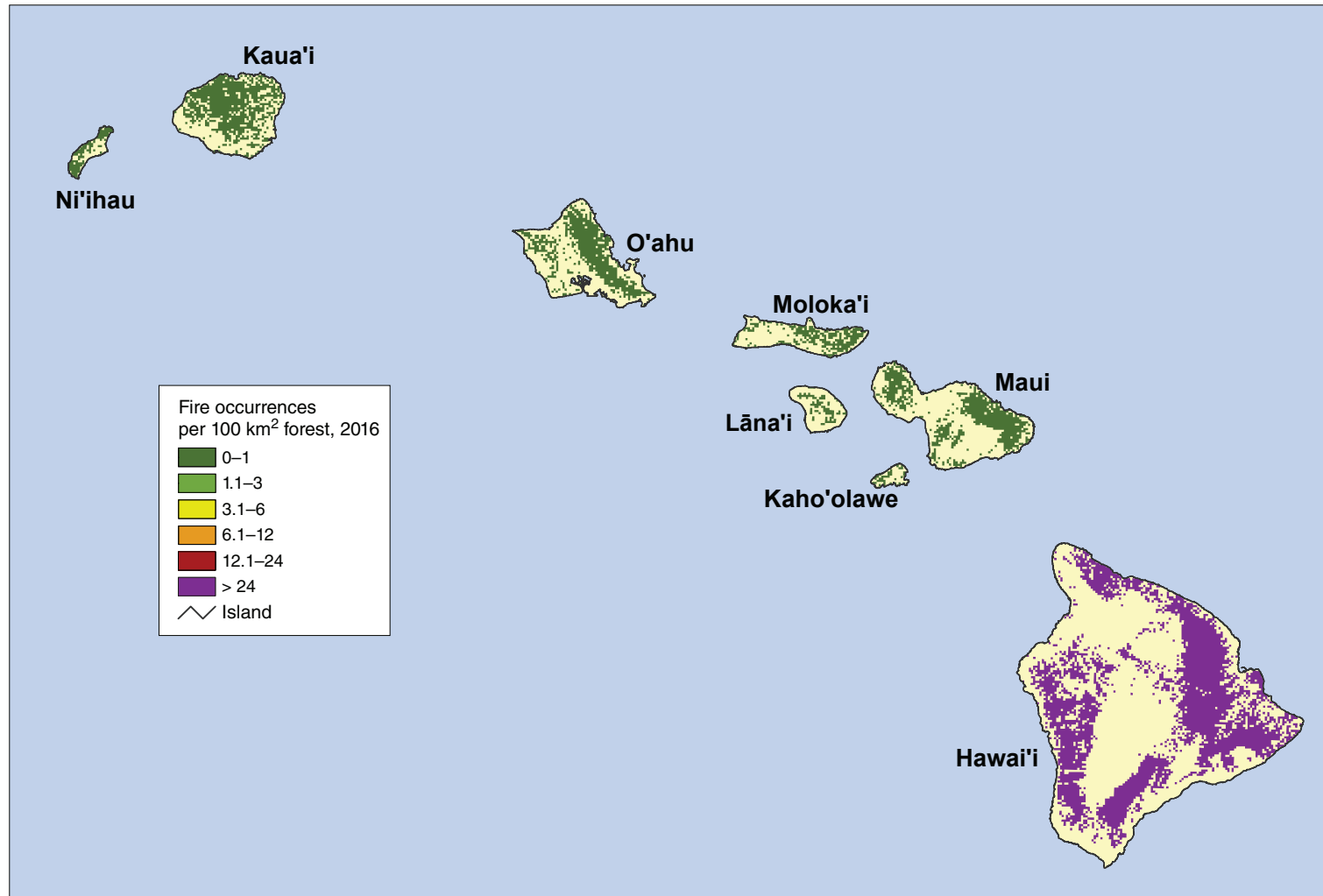


Figure 3.4—The number of forest fire occurrences per 100 km² (10 000 ha) of forested area, by island in Hawaii, for 2016. Forest cover is derived from MODIS imagery by the U.S. Forest Service Remote Sensing Applications Center. (Source of fire data: U.S. Department of Agriculture, Forest Service, Remote Sensing Applications Center, in conjunction with the NASA MODIS Rapid Response group)

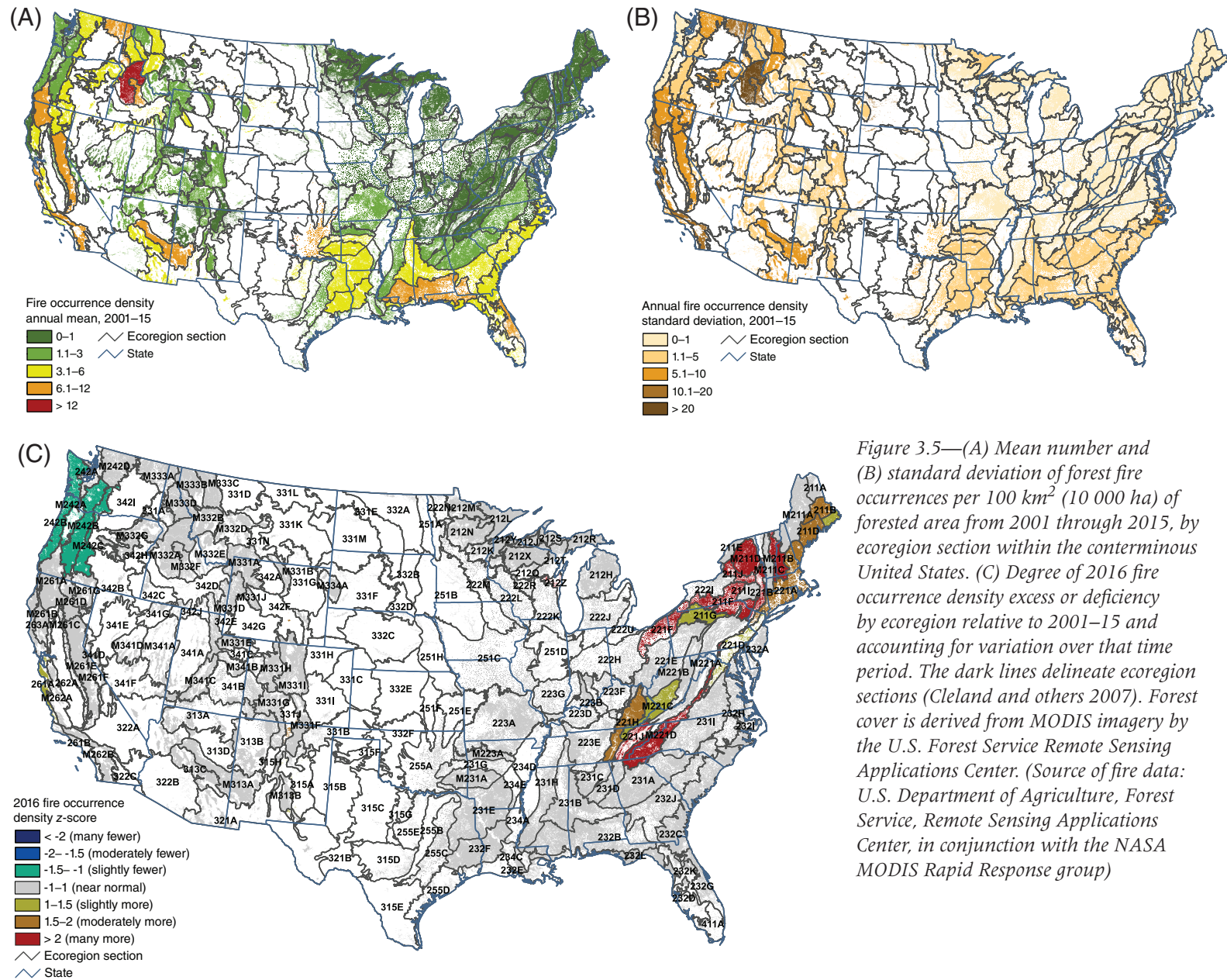


Figure 3.5—(A) Mean number and (B) standard deviation of forest fire occurrences per 100 km² (10 000 ha) of forested area from 2001 through 2015, by ecoregion section within the conterminous United States. (C) Degree of 2016 fire occurrence density excess or deficiency by ecoregion relative to 2001–15 and accounting for variation over that time period. The dark lines delineate ecoregion sections (Cleland and others 2007). Forest cover is derived from MODIS imagery by the U.S. Forest Service Remote Sensing Applications Center. (Source of fire data: U.S. Department of Agriculture, Forest Service, Remote Sensing Applications Center, in conjunction with the NASA MODIS Rapid Response group)

Valley, were the site of the large and destructive fires in late November 2016 following a period of intense drought (National Interagency Coordination Center 2016). One of those fires, the Chimney Tops 2 fire, killed 14 people in Gatlinburg, TN, and destroyed or damaged 1,684 structures (Gabbert 2016).

Four ecoregion sections on or near the coast in Oregon and Washington had lower fire occurrence densities in 2016 compared to the longer term: M242A–Oregon and Washington Coast Ranges, 242B–Willamette Valley, M242B–Western Cascades, and M242C–Eastern Cascades. All had very low fire occurrence densities in 2016, and low annual mean fire occurrence density and variation from 2001–15.

In Alaska, meanwhile, there were no areas of high mean fire occurrence density between 2001 and 2015, but moderate mean fire occurrence density existed in the east-central and central parts of the State centered on the 139A–Yukon Flats ecoregion (fig. 3.6A). These same areas experienced the greatest degree of variability over the 15-year period (fig. 3.6B). In 2016, only one ecoregion section, M213B–Kenai Mountains, was outside the range of near-normal fire occurrence density, having many more fire occurrences compared to the mean of the previous 15 years and accounting for variability (fig. 3.6C).

In Hawaii, both the mean annual fire occurrence density (fig. 3.7A) and variability (fig. 3.7B) were highest on the Big Island during the 2001–2015 period. The annual mean

was < 1 fire occurrence/100 km² of forest for all islands except the Big Island (11.6) and Kaho‘olawe (1.8). The annual fire occurrence standard deviation exceeded one for only the Big Island (17.7), Kaho‘olawe (5.2), and Lāna‘i (1.3). In 2016, the Big Island and O‘ahu were slightly outside the range of near-normal fire occurrence density, controlling for variability over the previous 15 years (fig. 3.7C).

Geographical Hot Spots of Fire Occurrence Density

Although summarizing fire occurrence data at the ecoregion scale allows for the quantification of fire occurrence density across the country, a geographical hot spot analysis can offer insights into where, statistically, fire occurrences are more concentrated than expected by chance. In 2016, a geographical hot spot of very high fire occurrence density was centered on 261A–Central California Coast (fig. 3.8), location of the Soberanes Fire (see above).

Two hot spots of high fire occurrence density were detected near each other in west-central Idaho (M332A–Idaho Batholith) and east-central Oregon (M332G–Blue Mountains and 342H–Blue Mountain Foothills). Another such hot spot was located in the West, in central Arizona (313C–Tonto Transition and M313A–White Mountains-San Francisco Peaks-Mogollon Rim); one was detected in the South, in southwestern Georgia and the Florida panhandle (232B–Gulf Coastal Plains and Flatwoods); and one was in the Midwest, in southeastern Kansas (255A–Cross Timbers and Prairie and 251E–Osage Plains).

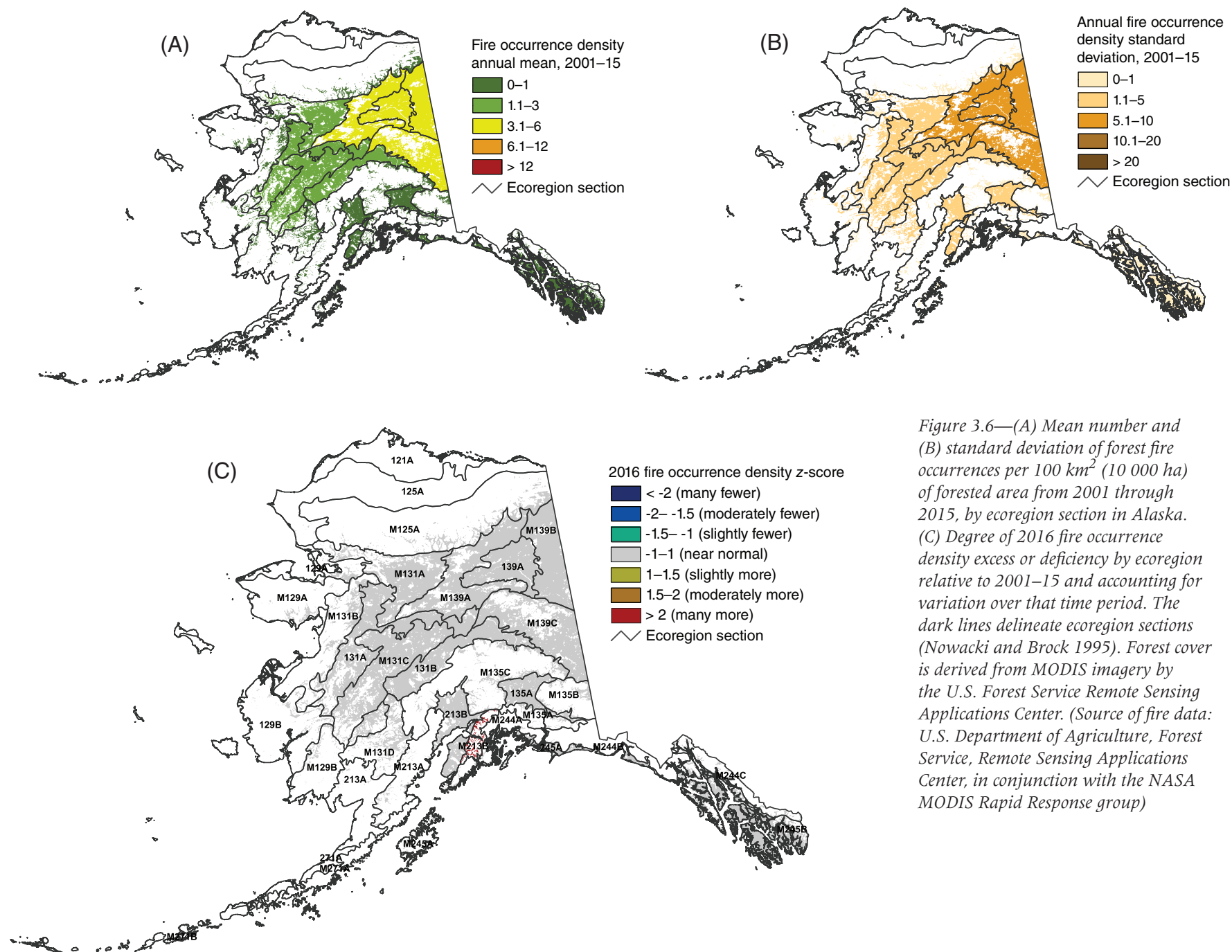


Figure 3.6—(A) Mean number and (B) standard deviation of forest fire occurrences per 100 km² (10 000 ha) of forested area from 2001 through 2015, by ecoregion section in Alaska. (C) Degree of 2016 fire occurrence density excess or deficiency by ecoregion relative to 2001–15 and accounting for variation over that time period. The dark lines delineate ecoregion sections (Nowacki and Brock 1995). Forest cover is derived from MODIS imagery by the U.S. Forest Service Remote Sensing Applications Center. (Source of fire data: U.S. Department of Agriculture, Forest Service, Remote Sensing Applications Center, in conjunction with the NASA MODIS Rapid Response group)

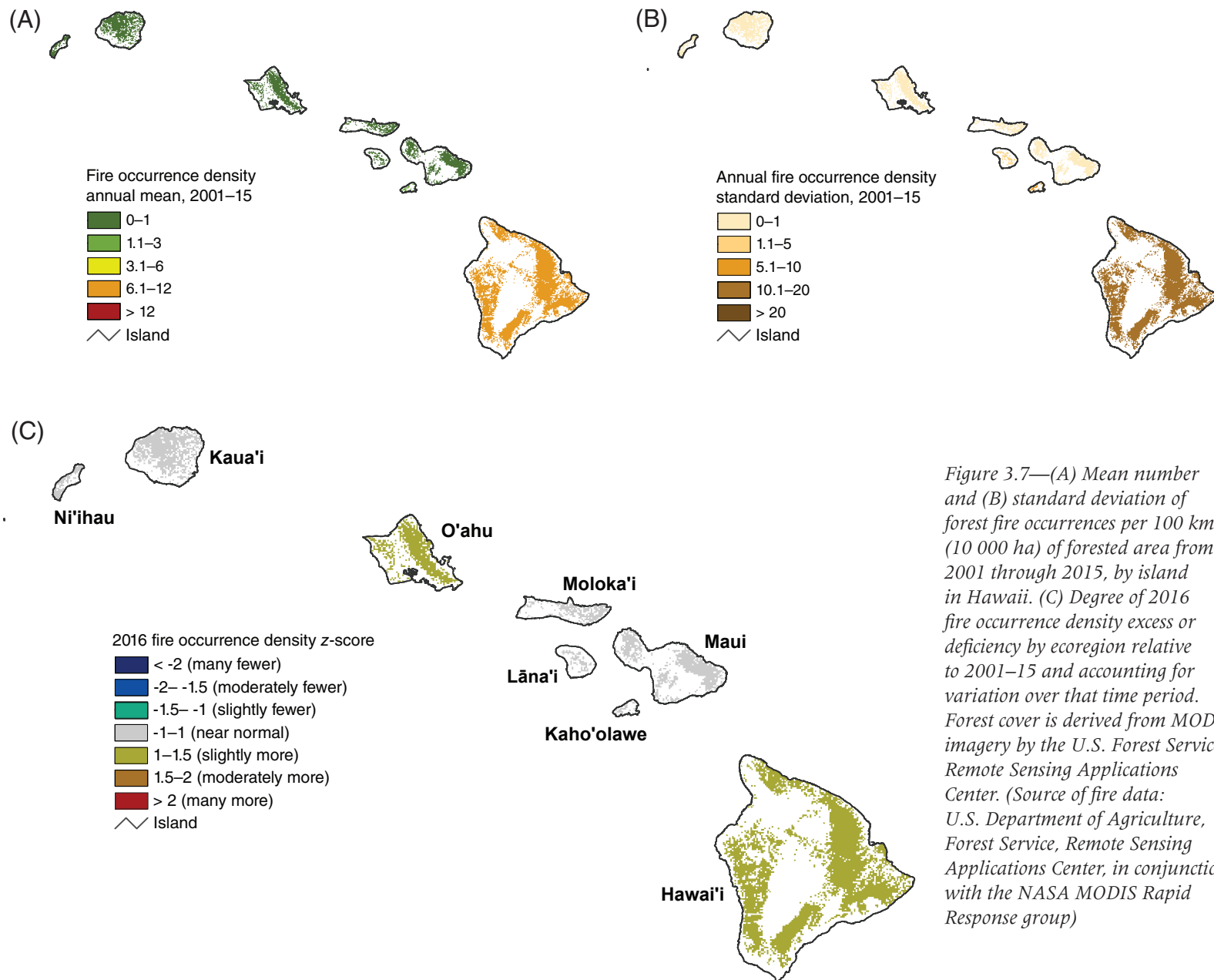
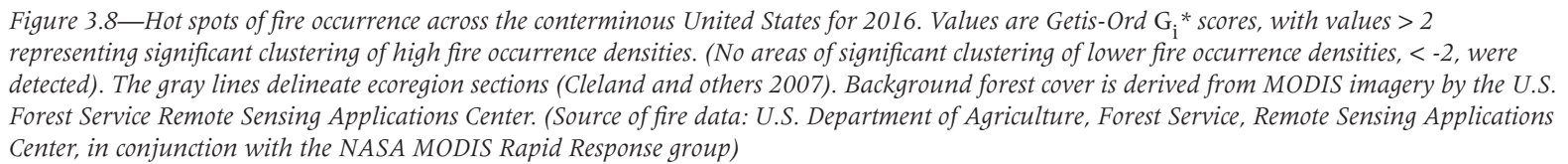


Figure 3.7—(A) Mean number and (B) standard deviation of forest fire occurrences per 100 km² (10 000 ha) of forested area from 2001 through 2015, by island in Hawaii. (C) Degree of 2016 fire occurrence density excess or deficiency by ecoregion relative to 2001–15 and accounting for variation over that time period. Forest cover is derived from MODIS imagery by the U.S. Forest Service Remote Sensing Applications Center. (Source of fire data: U.S. Department of Agriculture, Forest Service, Remote Sensing Applications Center, in conjunction with the NASA MODIS Rapid Response group)



Hot spots of moderate fire density in 2016 were scattered elsewhere across the Southeastern United States (fig. 3.8), including in the following regions:

- Eastern Oklahoma (255A–Cross Timbers and Prairie, 231G–Arkansas Valley, and M231A–Ouachita Mountains),
- Central and eastern Texas (315D–Edwards Plateau and 232F–Coastal Plains and Flatwoods-Western Gulf),
- South-central Louisiana (234C–Atchafalaya and Red River Alluvial Plains and 232E–Louisiana Coastal Prairie and Marshes),
- Southern Florida (232D–Florida Coastal Lowlands-Gulf, 232G–Florida Coastal Lowlands-Gulf, 232K–Florida Coastal Plains and Central Highlands, and 411A–Everglades), and
- The Coastal Plain of Georgia, South Carolina, and North Carolina (232C–Atlantic Coastal Flatwoods and 232J–Southern Atlantic Coastal Plains and Flatwoods).

Hot spots of moderate fire density were also identified in the Western United States, including:

- Northeastern Idaho/northwestern Montana (M333D–Bitterroot Mountains),
- Northwestern Wyoming (M331A–Yellowstone Highlands and M331D–Overthrust Mountains),
- North-central Colorado/south-central Wyoming (M331I–Northern Parks and Ranges),

- Northern Arizona (313A–Grand Canyon and 313D–Painted Desert), and
- Southern California (261B–Southern California Coast, M262B–Southern California Mountain and Valley, and M261E–Sierra Nevada).

CONCLUSION

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-km² resolution data, these products also may underrepresent the number of fire occurrences in some ecosystems where small and low-intensity fires are common. 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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