Front cover map: Ecoregion provinces and ecoregion sections for the conterminous United States (Cleland and others 2007), and for Alaska (Nowacki and Brock 1995) and the islands of Hawai‘i.

Back cover map: Forest cover (green) backdrop derived from Moderate Resolution Imaging Spectroradiometer (MODIS) satellite imagery by the U.S. Forest Service Remote Sensing Applications Center.

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Forest Health Monitoring:
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Editors

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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 fire
occurrences were concentrated spatially across the conterminous United States, Alaska, and Hawai‘i in 2015. It also compares 2015 fire occurrences, within a geographic context, to all the recent years for which such data are available. Quantifying and monitoring such medium-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 2016) allows 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). 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 2016). 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 2015 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 48 States (Cleland
and others 2007) and Alaska (Nowacki and
Brock 1995), and for each of the major islands
of Hawai‘i. 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. 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 Hawai‘i.

The fire occurrence density value for each
ecoregion and island in 2015 was then compared
with the mean fire density values for the first 14
full years of MODIS Active Fire data collection
(2001–14). Specifically, the difference of the
2015 value and the previous 14-year mean
for an ecoregion was divided by the standard
deviation across the previous 14-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 2015 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 48
States with higher-than-expected fire occurrence
density in 2015. 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 km\(^2\) 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 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 km\(^2\) 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 km\(^2\) 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 6 adjacent hexagons and the 12 additional hexagons contiguous to those 6) and the global mean of all the forested hexagonal cells in the conterminous 48
States. \(G_i^*\) 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 2 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 distance band is large enough to include several neighbors for each feature (ESRI 2012).

RESULTS AND DISCUSSION

The MODIS Active Fire database recorded 81,435 wildland forest fire occurrences across the conterminous United States in 2015, the sixth largest annual number of fire occurrences since the first full year of data collection in 2001 and the smallest number since 2011 (fig. 3.1). This was approximately 23 percent fewer than in 2014 (106,242 total forest fire occurrences), and about 25 percent more than the annual mean of 64,960 forest fire occurrences across the previous 14 full years of data collection. In contrast, the MODIS database captured 21,466 forest fire occurrences in Alaska in 2015, about 2275-percent more than the preceding year (904) and about 91-percent higher than the previous 14-year annual mean of 11,243. It was also the fourth highest annual number of fire occurrences recorded for Alaska. Meanwhile, Hawai‘i had only 904 fire occurrences in 2015, down nearly 50 percent from the previous year (1,797), but still 170-percent higher than the average 335 fire occurrences over the previous 14 years.

The decrease in the total number of fire occurrences across the United States is somewhat inconsistent with the official wildland fire statistics (National Interagency Coordination Center 2016). In 2015, 68,151 wildfires were reported nationally, compared to 63,612 the previous year. The area burned nationally in 2015 (4 097 502 ha) was 145 percent of the 10-year average, with 52 fires exceeding 16 187 ha (43 more than in 2014) (National Interagency Coordination Center 2016). The total area burned nationally represented a 182-percent increase from 2014 (1 455 092 ha) (National Interagency Coordination Center 2015). 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.

In 2015, the highest forest fire occurrence densities occurred in the interior of the Pacific Northwest States, and near the coast of northwestern California and southeastern Oregon (fig. 3.2). This area experienced a warm and dry winter and spring followed by a very hot and dry summer, which led to exceptional drought conditions and extremely dry fuels; this situation was moderated in other parts of the West by a series of tropical systems that brought much-needed rain (National Interagency Coordination Center 2016).

The five ecoregions with the highest wildland forest fire occurrence density in 2015 are all located within inland areas of the Pacific Northwest (fig. 3.2), with M333A–Okanogan Highland first on the list with extremely high fire occurrences, 59.7 per 100 km² of forest. This was the area of at least three very large fires: (1) the human-ignited North Star fire that scorched 88 277 ha between August 13 and November 30 and cost approximately $45 million to contain; (2) the lightning-caused Kettle Complex of fires that burned 30 963 ha between August 11 and September 27; and (3) the human-caused Carpenter Road fire, which burned 25 889 ha from August 14 to December 16, with a containment cost of $22.7 million (National Interagency...
Figure 3.2—The number of forest fire occurrences, per 100 km² (10 000 hectares) of forested area, by ecoregion section within the conterminous 48 States, for 2015. 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 neighboring M242D–Northern Cascades (19.4 fires per 100 km² of forest) encompassed the lightning-ignited Okanogan Complex of fires that scorched 58,794 ha between August 14 and September 29, the Chelan Complex of fires that covered 36,010 ha between August 14 and September 20 and cost $10 million to contain, and the Wolverine fire that burned 29,187 ha from June 29 until October 3 and cost $35 million to contain (National Interagency Coordination Center 2016). Other ecoregions with high fire occurrence densities in the region were 331A–Palouse Prairie (36.4 fires), M332G–Blue Mountains (20.6 fires), M333C–Northern Rockies (16.5 fires), M333D–Bitterroot Mountains (14.1 fires), and M332A–Idaho Batholith (13.1 fires).

Three ecoregions in northern California and southwestern Oregon also experienced very high fire occurrence densities: M261A–Klamath Mountains (17.6 fire occurrences), M261B–Northern California Coast Ranges (15.9 fires), and M261C–Northern California Interior Coast Ranges (15.2 fires). The first of these was the location of the River Complex of fires, which cost approximately $33 million to contain as it scorched 31,394 ha between July 30 and September 25 (National Interagency Coordination Center 2016).

Additionally, moderately high fire occurrence densities were recorded in several other Western ecoregions, both in the Northwest and in California:

- M261E–Sierra Nevada (east-central California), 11.2 fire occurrences;
- M242C–Eastern Cascades (central Oregon and south-central Washington), 9.8 fire occurrences;
- 342H–Blue Mountain Foothills (east-central Oregon), 9.3 fire occurrences;
- 342C–Owyhee Uplands (southwest Idaho and southeast Oregon), 8.0 fire occurrences; and
- M333B–Flathead Valley (northwest Montana), 6.6 fire occurrences.

Several ecoregions with moderate fire occurrence densities stretched across the Southeast, from north-central Texas and central Oklahoma east along the Gulf Coast to much of peninsular Florida as well as central Georgia and South Carolina (fig. 3.2). At the same time, fire densities were low in the Southwestern, Central Rocky Mountain, Midwestern, Mid-Atlantic, and Northeastern States.

Meanwhile, Alaska experienced drought and above-average temperatures in spring 2015, with the resulting limited snowpack leading to fire fuels being exposed earlier than usual; the fire season subsequently extended later than usual into the year (National Interagency Coordination Center 2016). Not surprisingly, much of the interior of the State had moderately high fire occurrence densities during 2015 (fig. 3.3). The ecoregions with the highest values were M131A–Upper Kobuk-Koyukuk (11.8 fire occurrences per 100 km² of forest), M139A–Ray Mountains (10.0 fire occurrences), 131A–Yukon Bottomlands (8.1 fire occurrences),...
Figure 3.3—The number of forest fire occurrences, per 100 km$^2$ (10 000 hectares) of forested area, by ecoregion section within Alaska, for 2015. 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)
and M131C–Kuskokwim Mountains (7.1 fire occurrences). The two largest U.S. fires in 2015 occurred in central Alaska, the 201,551-ha Tanana Area fire complex and the 170,621-ha Ruby Area fire complex (National Interagency Coordination Center 2016).

In Hawai‘i, lava flows from the 33-year-long eruption of Pu‘u Īō, a vent on the flank of the Kilauea volcano on the Big Island, were the cause of most forest fire occurrences; specifically, lava flowed into dense forest in the Puna district from August 2014 through March 2015 (West Hawai‘i Today 2016). As a result, fire occurrence density on the Big Island was 60.5 per 100 km² of forest in 2015 (fig. 3.4). All the other islands experienced less than one fire per 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 Hawai‘ian island, short-term (1-year) wildland forest fire occurrence densities with longer term trends encompassing the first 14 full years of data collection (2001–2014). 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 less than one fire per 100 km² of forest annually during the multiyear period (fig. 3.5A). The forested ecoregion that experienced the most fires on average was M332A–Idaho Batholith in central Idaho (mean annual fire occurrence density of 13.3). Other ecoregions with high mean fire occurrence densities (6.1–12.0 per 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 north-central Texas. Ecoregions with the greatest variation in fire occurrence densities from 2001 to 2014 were also located in central Idaho and near the California coast, with more moderate variation in north-central Washington, southwestern Oregon, northern and central California, western Montana and Wyoming, central Arizona and west-central New Mexico, and eastern North Carolina (fig. 3.5B). Less variation occurred throughout the central and northern Rocky Mountain States, northern Minnesota, 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 Northern Rocky Mountains, in the Pacific Northwest and northern California, in New England, and in the Great Lakes States experienced greater fire occurrence densities than normal in 2015, compared to the previous 14-year mean and accounting for variability over time (fig. 3.5C). Some of these areas (in New England and the Great Lakes States) had high z-scores despite a relatively low density of fire occurrences in 2015 (fig. 3.2) because
Figure 3.4—The number of forest fire occurrences, per 100 km² (10,000 ha) of forested area, by island in Hawai‘i, for 2015. 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 hectares) of forested area from 2001 through 2014, by ecoregion section within the conterminous 48 States. (C) Degree of 2015 fire occurrence density excess or deficiency by ecoregion relative to 2001–14 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, in conjunction with the NASA MODIS Rapid Response group.)
these were ecoregions that typically have very little variation over time in fire occurrence density. On the other hand, several of the northwestern ecoregions with high z-scores also had very high fire occurrence densities in 2015 (fig. 3.2), including M333A–Okanagan Highland and M242D–Northern Cascades in northern Washington, M332G–Blue Mountains in northeastern Oregon, M242C–Eastern Cascades in central Oregon and Washington, M261A–Klamath Mountains in northwestern California and southwestern Oregon, M333C–Northern Rockies in northwestern Montana, and M333D–Bitterroot Mountains in northern Idaho (fig. 3.2). Three ecoregions in the Southeast had lower fire occurrence densities in 2015 compared to the longer term: 231E–Mid Coastal Plains-Western in east Texas, southwestern Arkansas, northwestern Louisiana, and southeastern Oklahoma; 234E–Arkansas Alluvial Plains in southeastern Arkansas; and 221J–Central Ridge and Valley in eastern Tennessee. All three had low or very low fire occurrence densities in 2015: the first had a moderate annual mean fire occurrence density and variation from 2001–14, while the second two had low means and variation.

In Alaska, meanwhile, the highest mean annual fire occurrence density between 2001 and 2014 occurred in the east-central and central parts of the State (fig. 3.6A) in the 139A–Yukon Flats ecoregion, with moderate mean fire occurrence density in neighboring areas. As expected, many of those same areas experienced the greatest degree of variability over the 14-year period (fig. 3.6B). In 2015, several west-central ecoregions, along with one south-central ecoregion, were outside the range of near-normal fire occurrence density, compared to the mean of the previous 14 years and accounting for variability (fig. 3.6C). The ecoregions farthest outside the range of near-normal fire occurrence density were M129B–Ahklun Mountains, M245A–Gulf of Alaska Fjordlands, M131A–Upper Kobuk-Koyukuk, M131B–Nulato Hills, and 129B–Yukon-Kuskokwim Delta. All of these ecoregions had a low or very low mean annual fire occurrence density (fig. 3.6A) and variability (fig. 3.6B) over the previous 14 years.

In Hawai’i, both the mean annual fire occurrence density (fig. 3.7A) and variability (fig. 3.7B) were highest on the Big Island during the 2001–2014 period. The annual mean was less than 1 fire per 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 1 for only the Big Island (17.7), Kaho’olawe (5.2), and Lāna‘i (1.3). In 2015, the Big Island was well outside the range of near-normal fire occurrence density, controlling for variability over the previous 14 years (fig. 3.7C), with many more fires than expected.

**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
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 2014, by ecoregion section in Alaska. (C) Degree of 2015 fire occurrence density excess or deficiency by ecoregion relative to 2001–14 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 2014, by island in Hawai‘i. (C) Degree of 2015 fire occurrence density excess or deficiency by island relative to 2001–14 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)
more concentrated than expected by chance. In 2015, a geographical hot spot of extremely high fire occurrence density was located in north-central Washington, in ecoregions M333A–Okanogan Highland and M242D–Northern Cascades (fig. 3.8). As noted above, this region encompassed numerous very large wildland fires. The analysis detected a hot spot of very high fire occurrence density in east-central Oregon (M332G–Blue Mountains and 342H–Blue Mountain Foothills). This also was associated with a handful of large fires, including the Canyon Creek Complex (44,621 ha) and the Cornet-Windy Ridge fire (41,314 ha).

Hot spots of high fire density were detected in northwestern California (M261A–Klamath Mountains, M261B–Northern California Coast Ranges, and 263A–Northern California Coast), in south-central California (M261E–Sierra Nevada), and in northern Idaho (M332A–Idaho Batholith, 331A–Palouse Prairie, and M333D–Bitterroot Mountains).

Other hot spots of moderate fire density were scattered elsewhere across the Western United States (fig. 3.8), including in the following regions:

• Southwestern Idaho (342C–Owyhee Uplands).

The geographic clustering analysis detected a single moderate-density hot spot in the Southeast, in ecoregion 232B–Gulf Coast Plains and Flatwoods in southwestern Georgia and north-central Florida (fig. 3.8).

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 wildfire impacts. 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 wildland forest fire potentially outside the range of historic frequency.
Figure 3.8—Hot spots of fire occurrence across the conterminous United States for 2015. Values are Getis-Ord $G_i^*$ scores, with values > 2 representing significant clustering of high numbers of fire occurrences. (No areas of significant clustering of low numbers of fire occurrences, < -2, were detected). The gray lines delineate ecoregion sections (Cleland and others 2007). Background 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)
LITERATURE CITED


