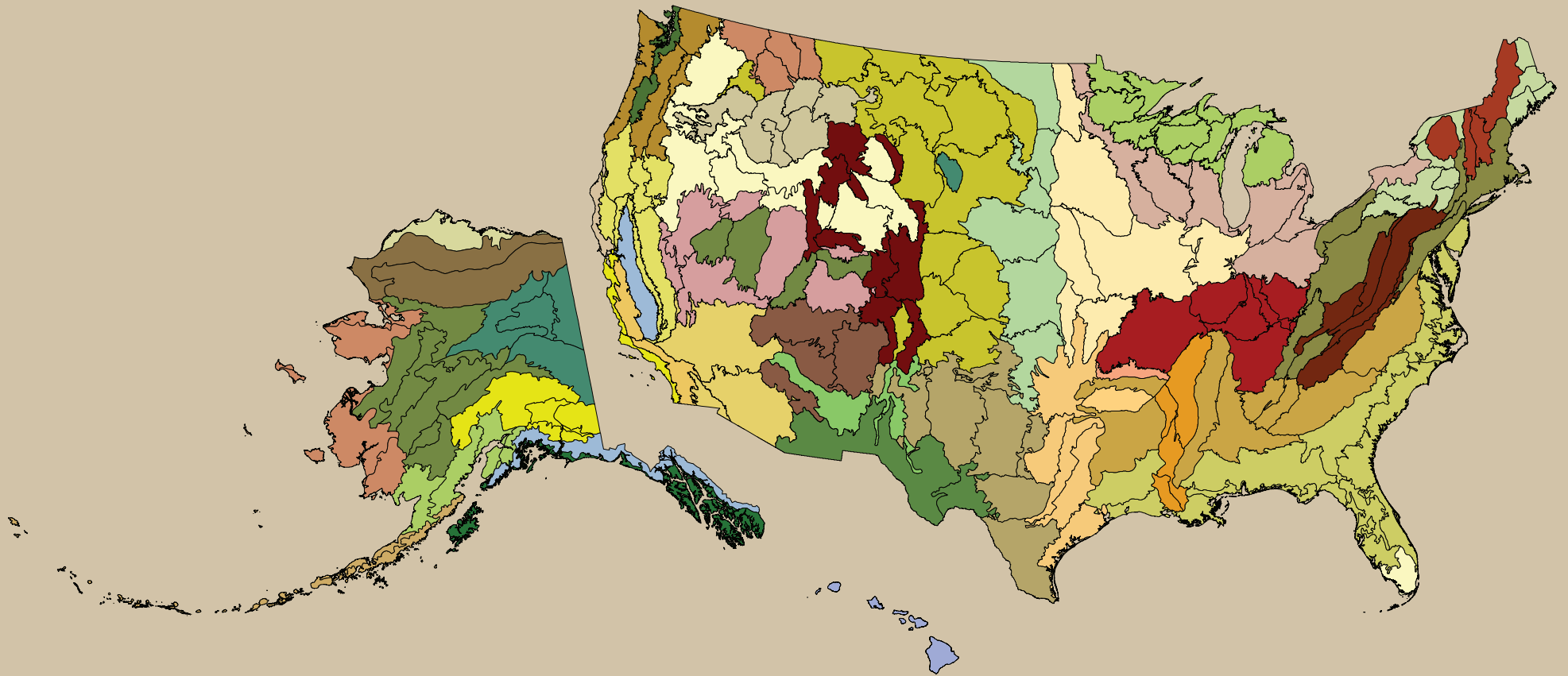




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Forest Health Monitoring: National Status, Trends, and Analysis 2017

Editors Kevin M. Potter Barbara L. Conkling



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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 Hawaii.

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:

National Status, Trends, and Analysis 2017

Editors

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ABSTRACT

The annual national report of the Forest Health Monitoring (FHM) Program of the Forest Service, U.S. Department of Agriculture, presents forest health status and trends from a national or multi-State regional perspective using a variety of sources, introduces new techniques for analyzing forest health data, and summarizes results of recently completed Evaluation Monitoring projects funded through the FHM national program. In this 17th edition in a series of annual reports, national survey data are used to identify geographic patterns of insect and disease activity. Satellite data are employed to detect geographic patterns of forest fire occurrence. Recent drought and moisture surplus conditions are compared across the conterminous United States. Data collected by

the Forest Inventory and Analysis (FIA) Program are employed to detect regional differences in tree mortality. FIA plot-level lichen data are assessed as bioindicators for large-scale monitoring of air quality across eastern U.S. forests. A national summary of crown condition across the United States is presented for 2011–15, and change over time in crown dieback is used to identify species in decline. Eight recently completed Evaluation Monitoring projects are summarized, addressing forest health concerns at smaller scales.

Keywords—Change detection, crown dieback, drought, fire, forest health, forest insects and disease, lichens, tree mortality.

LIST OF FIGURES	viii
LIST OF TABLES	xvii
EXECUTIVE SUMMARY	1
LITERATURE CITED	5
 CHAPTER 1.	
Introduction	7
KEVIN M. POTTER	
THE FOREST HEALTH	
MONITORING PROGRAM	9
DATA SOURCES.	13
FHM REPORT PRODUCTION.	15
LITERATURE CITED	15

SECTION 1.

Analyses of Short-Term Forest Health Data	21
---	----

CHAPTER 2.

Large-Scale Patterns of Insect and Disease Activity in the Conterminous United States, Alaska, and Hawaii from the National Insect and Disease Survey, 2016	23
--	----

KEVIN M. POTTER, JEANINE L. PASCHKE,
AND MARK O. ZWEIFLER

INTRODUCTION	23
METHODS.	23
RESULTS AND DISCUSSION.	29
CONCLUSION	40
LITERATURE CITED	42

CHAPTER 3.

Large-Scale Patterns of Forest Fire Occurrence in the Conterminous United States, Alaska, and Hawaii, 2016.	45
---	----

KEVIN M. POTTER

INTRODUCTION	45
METHODS.	46
RESULTS AND DISCUSSION.	49
CONCLUSION	61
LITERATURE CITED	62

CONTENTS

Contents, cont.

CHAPTER 4.

Moisture Deficit and Surplus in the
Conterminous United States for Three Time
Windows: 2016, 2014–2016, and 2012–2016 . . . 65

FRANK H. KOCH AND JOHN W. COULSTON

INTRODUCTION 65
METHODS 67
RESULTS AND DISCUSSION 71
LITERATURE CITED 80

CHAPTER 5.

Tree Mortality 85

MARK J. AMBROSE

INTRODUCTION 85
DATA 85
METHODS 86
RESULTS AND DISCUSSION 88
SUMMARY 95
LITERATURE CITED 96

SECTION 2.

Analyses of Long-Term Forest Health Trends and
Presentations of New Techniques 99

CHAPTER 6.

Lichen Species to Bioindicate Air Quality
in Eastern United States from Elemental
Composition: Lessons from the Midwest 101

SUSAN WILL-WOLF, SARAH JOVAN, AND
MICHAEL C. AMACHER

INTRODUCTION 101
METHODS 103
RESULTS AND DISCUSSION 106
CONCLUSIONS 113
ACKNOWLEDGMENTS 113
LITERATURE CITED 113

CHAPTER 7.

Crown Condition 115

KADONNA C. RANDOLPH

INTRODUCTION 115
METHODS 116
RESULTS AND DISCUSSION 118
SUMMARY 129
LITERATURE CITED 130

SECTION 3.

Evaluation Monitoring Project Summaries 133

LITERATURE CITED 133

CHAPTER 8.

Status and Trends of Whitebark Pine Distribution
and Health in California, Oregon, and Washington

(Project WC-EM-B-12-02) 135

BIANCA N.I. ESKELSON AND VICENTE J. MONLEON

INTRODUCTION 135

METHODS 135

RESULTS AND DISCUSSION 136

CONCLUSIONS 140

CONTACT INFORMATION 141

LITERATURE CITED 141

CHAPTER 9.

Monitoring Survival of Fire-Injured Trees in
Oregon and Washington (Project WC-F-08-03) 143

ROBERT A. PROGAR, LISA GANIO,
LINDSAY GRAYSON, AND SHARON M. HOOD

INTRODUCTION 143

METHODS 143

RESULTS AND DISCUSSION 148

ACKNOWLEDGMENTS 149

CONTACT INFORMATION 149

LITERATURE CITED 149

CHAPTER 10.

Wildfire and Fire Severity Effects on Post-Fire
Carbon and Nitrogen Cycling in Forest Soil

(Project NC-EM-F-14-1) 151

JESSICA R. MIESEL, RANDY KOLKA, AND
PHIL TOWNSEND

INTRODUCTION 151

METHODS 152

RESULTS AND DISCUSSION 154

ACKNOWLEDGMENTS 155

CONTACT INFORMATION 155

LITERATURE CITED 155

CHAPTER 11.

Post-Hurricane Fuel Dynamics and Implications
for Fire Behavior (Project SO-EM-F-12-01) 157

SHANYUE GUAN AND G. GEOFF WANG

INTRODUCTION 157

METHODS 157

RESULTS AND DISCUSSION 157

CONCLUSIONS 160

ACKNOWLEDGMENTS 160

CONTACT INFORMATION 160

LITERATURE CITED 160

Contents, cont.

Contents, cont.

CHAPTER 12.

Impacts of Laurel Wilt Disease on Native *Persea*
Ecosystems (Project SO-EM-B-12-05) 161

TIMOTHY M. SHEARMAN AND G. GEOFF WANG

INTRODUCTION 161
METHODS 161
RESULTS AND DISCUSSION 162
CONCLUSIONS 164
ACKNOWLEDGMENTS 164
CONTACT INFORMATION 164
LITERATURE CITED 165

CHAPTER 13.

Conventional Fire Behavior Modeling Systems
are Inadequate for Predicting Fire Behavior in
Bark Beetle-Impacted Forests
(Project INT-EM-F-11-03) 167

SHARON M. HOOD, ROBERT E. KEANE,
HELEN Y. SMITH, JOEL EGAN, AND LISA HOLSINGER

INTRODUCTION 167
MATERIALS AND METHODS 168
RESULTS 171
DISCUSSION 173
CONTACT INFORMATION 174
LITERATURE CITED 174

CHAPTER 14.

Effects of Spruce Beetle (*Dendroctonus rufipennis*)
Outbreaks on Fuels, Carbon, and Stand Structure
and Composition in Utah and Western Wyoming
(Project INT-EM-F-13-02) 177

DANIEL S. OTT, CHRISTOPHER J. FETTIG,
DARRELL W. ROSS, AND A. STEVEN MUNSON

INTRODUCTION 177
METHODS 177
RESULTS AND DISCUSSION 179
ACKNOWLEDGMENTS 182
CONTACT INFORMATION 182
LITERATURE CITED 182

CHAPTER 15.

Composition and Structure of Whitebark and
Limber Pine Stands in the Interior West and the
Silvicultural Implications (Project INT-EM-B-14-01) . . . 183

JAMES N. LONG, JOHN SHAW, AND
MARCELLA WINDMULLER-CAMPIONE

INTRODUCTION183
METHODS.183
RESULTS AND DISCUSSION.184
CONCLUSIONS186
ACKNOWLEDGMENTS186
CONTACT INFORMATION.186
LITERATURE CITED186

ACKNOWLEDGMENTS.187

AUTHOR INFORMATION188

Contents, cont.

LIST OF FIGURES

<i>Figure 1.1</i> —Ecoregion provinces and sections for the conterminous United States (Cleland and others 2007) and Alaska (Nowacki and Brock 1995). Ecoregion sections within each ecoregion province are shown in the same color. Note: no equivalent ecoregion treatment exists for Hawaii.	10
<i>Figure 1.2</i> —The design of the Forest Health Monitoring (FHM) Program of the Forest Service, U.S. Department of Agriculture (FHM 2003). A fifth component, Analysis and Reporting of Results, draws from the four FHM components shown here and provides information to help support land management policies and decisions.	12
<i>Figure 1.3</i> —The Forest Inventory and Analysis mapped plot design. Subplot 1 is the center of the cluster with subplots 2, 3, and 4 located 120 feet away at azimuths of 360°, 120°, and 240°, respectively (Woudenberg and others 2010).	14
<i>Figure 2.1</i> —The extent of surveys for insect and disease activity conducted in the conterminous United States and Alaska in 2016. Cross-hatched areas were surveyed using the new Digital Mobile Sketch Mapping (DMSM) platform, rather than the older Digital Aerial Sketch Mapping (DASM) approach, which is portrayed in green. The blue lines delineate Forest Health Monitoring regions. Note: Alaska and Hawaii are not shown to scale with map of the conterminous United States. No flight lines were recorded for Hawaii in 2016. (Data source: U.S. Department of Agriculture, Forest Service, Forest Health Protection).	25
<i>Figure 2.2</i> —Hot spots of exposure to mortality-causing insects and diseases in 2016. Values are Getis-Ord G_i^* scores, with values > 2 representing significant clustering of high percentages of forest area exposed to mortality agents. (No areas of significant clustering of low percentages of exposure, < -2, were detected.) The gray lines delineate ecoregion sections (Cleland and others 2007), and blue lines delineate Forest Health Monitoring regions. Background forest cover is derived from MODIS imagery by the U.S. Forest Service Remote Sensing Applications Center. (Data source: U.S. Department of Agriculture, Forest Service, Forest Health Protection).	32
<i>Figure 2.3</i> —Hot spots of exposure to defoliation-causing insects and diseases in 2016. Values are Getis-Ord G_i^* scores, with values > 2 representing significant clustering of high percentages of forest area exposed to defoliation agents. (No areas of significant clustering of low percentages of exposure, < -2, were detected.) The gray lines delineate ecoregion sections (Cleland and others 2007), and blue lines delineate Forest Health Monitoring regions. Background forest cover is derived from MODIS imagery by the U.S. Forest Service Remote Sensing Applications Center. (Data source: U.S. Department of Agriculture, Forest Service, Forest Health Protection).	36

Figure 2.4—Percentage of surveyed forest in Alaska ecoregion sections exposed to mortality-causing insects and diseases in 2016. The gray lines delineate ecoregion sections (Nowacki and Brock 1995). Background forest cover is derived from MODIS imagery by the U.S. Forest Service Remote Sensing Applications Center. (Data source: U.S. Department of Agriculture, Forest Service, Forest Health Protection) . . . 39

Figure 2.5—Percentage of surveyed forest in Alaska ecoregion sections exposed to defoliation-causing insects and diseases in 2016. The gray lines delineate ecoregion sections (Nowacki and Brock 1995). Background forest cover is derived from MODIS imagery by the U.S. Forest Service Remote Sensing Applications Center. (Data source: U.S. Department of Agriculture, Forest Service, Forest Health Protection) . . . 41

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). . . . 50

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). 51

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). 53

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). 55

Figures, cont.

Figures, cont.

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). 56

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). 58

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). 59

Figure 3.8—Hot spots of fire occurrence across the conterminous United States for 2016. 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). 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). 60

<i>Figure 4.1</i>—The 100-year (1917–2016) mean annual moisture index, or MI'_{norm}, for the conterminous United States. Ecoregion section (Cleland and others 2007) boundaries and labels are included for reference. Forest cover data (overlaid green hatching) derived from Moderate Resolution Imaging Spectroradiometer (MODIS) imagery by the U.S. Department of Agriculture, Forest Service, Remote Sensing Applications Center. (Data source: PRISM Climate Group, Oregon State University).	70
<i>Figure 4.2</i>—The 2016 annual (i.e., 1-year) moisture difference z-score, or <i>MDZ</i>, for the conterminous United States. Ecoregion section (Cleland and others 2007) boundaries and labels are included for reference. Forest cover data (overlaid green hatching) derived from MODIS imagery by the U.S. Department of Agriculture, Forest Service, Remote Sensing Applications Center. (Data source: PRISM Climate Group, Oregon State University).	73
<i>Figure 4.3</i>—The 2015 annual (i.e., 1-year) moisture difference z-score, or <i>MDZ</i>, for the conterminous United States. Ecoregion section (Cleland and others 2007) boundaries and labels are included for reference. Forest cover data (overlaid green hatching) derived from MODIS imagery by the U.S. Department of Agriculture, Forest Service, Remote Sensing Applications Center. (Data source: PRISM Climate Group, Oregon State University).	75

<i>Figure 4.4</i>—The 2014–2016 (i.e., 3-year) moisture difference z-score (<i>MDZ</i>) for the conterminous United States. Ecoregion section (Cleland and others 2007) boundaries are included for reference. Forest cover data (overlaid green hatching) derived from MODIS imagery by the U.S. Department of Agriculture, Forest Service, Remote Sensing Applications Center. (Data source: PRISM Climate Group, Oregon State University). . .	77
<i>Figure 4.5</i>—The 2012–2016 (i.e., 5-year) moisture difference z-score (<i>MDZ</i>) for the conterminous United States. Ecoregion section (Cleland and others 2007) boundaries are included for reference. Forest cover data (overlaid green hatching) derived from MODIS imagery by the U.S. Department of Agriculture, Forest Service, Remote Sensing Applications Center. (Data source: PRISM Climate Group, Oregon State University). . .	78
<i>Figure 5.1</i>—Forest cover in the States where mortality was analyzed by ecoregion section (Cleland and others 2007). Mortality in Eastern and Central States was analyzed using a complete remeasurement cycle; in Western States, mortality was analyzed using a partial cycle of remeasurements, and results there should be considered preliminary. Forest cover was derived from MODIS satellite imagery (USDA Forest Service 2008).	87

Figures, cont.

Figures, cont.

Figure 5.2—Tree mortality expressed as the ratio of annual mortality volume to gross annual volume growth (MRATIO) by ecoregion section (Cleland and others 2007). (Data source: U.S. Department of Agriculture, Forest Service Forest Inventory and Analysis Program). 89

Figure 5.3—Annual tree mortality expressed as a percentage of gross live tree volume by ecoregion section (Cleland and others 2007) for the Western United States. (Data source: U.S. Department of Agriculture, Forest Service, Forest Inventory and Analysis Program). Mortality was analyzed using a partial cycle of remeasurements, and results from the region should be considered preliminary 94

Figure 6.1—Approximate locations of lichen sites and instrument monitor sites for the upper Midwest study. Wisconsin, marked in the U.S. inset, is in the center with Minnesota west, Iowa southwest, and Illinois south. Full names of ecoregion provinces (Cleland and others 2007, McNab and others 2007) indicated by background shading are: 212—Laurentian Mixed Forest, 222—Midwest Broadleaf Forest, and 251—Prairie Parkland (Temperate). [Adapted with permission from Will-Wolf and others (2017a).] 103

Figure 6.2—Northeastern (A) and MidAtlantic (B) region project plots (approximate locations). For comparison,

the city of Newark, NJ, is at the bottom center of the map in (A) and near the upper right corner of the map in (B). On-frame plots are permanent FIA plots; off-frame plots are temporary plots surveyed only for each project. Full names of ecoregion provinces (Cleland and others 2007; McNab and others 2007) indicated by background shading in (A) are: 221—Eastern Broadleaf Forest, 211—Northeastern Mixed Forest, and M211—Adirondack-New England Mixed Forest - Coniferous Forest - Alpine Meadow. Full names in (B) are: M211—Adirondack-New England Mixed Forest - Coniferous Forest - Alpine Meadow, M221—Central Appalachians Broadleaf Forest - Coniferous Forest - Meadow, 221—Eastern Broadleaf Forest, 211—Northeastern Mixed Forest, and 231/232—Southeastern/Outer Coastal Plain Mixed Forest (two provinces combined, abbreviated as “Southeastern” in the legend). [(A) Adapted with permission from Will-Wolf and others (2015a); (B) adapted with permission from Will-Wolf and others (see footnote 3).] 105

Figure 6.3—Flacap and Evemes (A) original and (B) converted sample data from the upper Midwest study for nitrogen (N) in lichens vs. a Lichen Pollution Index from both N and sulfur (S) in lichens. Many symbols overlap, from both species at the same site and from sites with similar values. [Data from Will-Wolf and others (In press).] 106

Figure 6.4—(A, C) Flacap and Phyaip or (B, D) Flacap and Punrud pairs compared for the upper Midwest study. In A and B, species pairs are compared for converted nitrogen (N) concentrations vs. Pollution Index. In C and D, presence of each species is plotted by site Pollution Index and nearby forest cover. Many symbols overlap, from both species at the same site and from sites with similar values. [Data from Will-Wolf and others (In press).] 107

Figure 6.5—Presence of lichen bioindicator species in 1994–2005 compared to pollution and nearby forest cover at sites in NE and MidA regions. Northeastern and MidA Pollution Indices have the same value ranges, but indicate different levels of air pollution between regions. Many symbols overlap, from both species at the same site and from sites with similar values. [Data from Jovan and others (see footnote 2), Will-Wolf and others (2015a, footnote 3).]. 110

Figure 7.1—Regional breakdown of the United States for the crown dieback analysis corresponds to the administrative units of the U.S. Department of Agriculture, Forest Service, Forest Inventory and Analysis Program 116

Figure 7.2—Year of discovery and distribution of (A) emerald ash borer (EAB Information Network 2017), (B) beech scale (Cale and Morin 2017), and (C) hemlock woolly adelgid

(USDA Forest Service, Northeastern Area 2017) in the Eastern United States through the year 2015. 119

Figure 7.3—Percentage of trees remeasured after an interval of 10 years (Western United States) or 5 years (Eastern United States) by previous crown dieback, current tree status, and region. N=North. RM=Rocky Mountain. S=South. WC=West Coast. (Data source: U.S. Department of Agriculture, Forest Service, Forest Inventory and Analysis Program). 120

Figure 7.4—Percentage of trees in the West Coast (WC) and Rocky Mountain (RM) regions assessed with 0-percent crown dieback during 2001–2005 that were dead upon reassessment during 2011–2015, by species group. Species groups with < 200 observations are indicated with an asterisk. (Data source: U.S. Department of Agriculture, Forest Service, Forest Inventory and Analysis Program). 121

Figure 7.5—Percentage of trees in the North and South regions assessed with 0-percent crown dieback during 2006–2010 that were dead upon reassessment during 2011–2015, by species group. Species groups with < 200 observations are indicated with an asterisk. (Data source: U.S. Department of Agriculture, Forest Service, Forest Inventory and Analysis Program). 122

Figures, cont.

Figures, cont.

Figure 7.6—Mean crown dieback by duration of hemlock woolly adelgid (HWA) infestation and percentage of trees observed in each infestation class, by crown dieback class, for eastern hemlock trees assessed in the Eastern United States during 2011–2015. Bars around the mean represent one standard error. (Data source: U.S. Department of Agriculture, Forest Service, Forest Inventory and Analysis Program). 125

Figure 7.7—Mean crown dieback by duration of beech scale infestation and percentage of trees observed in each infestation class, by crown dieback class, for beech trees assessed in the Eastern United States during 2011–2015. Bars around the mean represent one standard error. (Data source: U.S. Department of Agriculture, Forest Service, Forest Inventory and Analysis Program) . . . 125

Figure 7.8—Mean crown dieback by duration of emerald ash borer (EAB) infestation and percentage of trees observed in each infestation class, by crown dieback class, for ash trees assessed in the Eastern United States during 2011–2015. Bars around the mean represent one standard error. (Data source: U.S. Department of Agriculture, Forest Service, Forest Inventory and Analysis Program). 126

Figure 7.9—Mean crown dieback for trees ≥ 12.7 cm d.b.h. in the Eastern United States, by region and inventory period. Crown dieback in the 1990s was collected by the Forest Service Forest Health Monitoring

Program and reported by Randolph (2006) for the South region and Randolph and others (2010a, 2010b) for the Northeast (NE) and North Central (NC) subregions. (Additional data source: U.S. Department of Agriculture, Forest Service, Forest Inventory and Analysis Program) 127

Figure 7.10—Distribution of crown dieback for trees ≥ 12.7 cm d.b.h. in the Eastern United States, by region and inventory period. (Data source: U.S. Department of Agriculture, Forest Service, Forest Inventory and Analysis and Forest Health Monitoring Programs). 127

Figure 8.1—Distribution of sample plots with whitebark pine (FIA plot locations are approximate). (A) Total number of plots. (B) Plots with live trees where blister rust was detected. (C) Plots with live trees where bark beetle was detected. 137

Figure 8.2—Plots where (A, B) blister rust was detected (green) and (C, D) bark beetle was detected (red), with total number of plots measured per year in Washington (left) and Oregon (right). 138

Figure 8.3—Proportions of plots (A) infected by blister rust and (B) attacked by bark beetles in Oregon and Washington combined. 139

Figure 9.1—Location of 26 wild and prescribed fires that occurred in Washington and Oregon between 1999 and 2009 from which data were collected. 145

Figure 9.2—Graphical depiction of the probability of tree mortality modeled by logistic regression indicating how changing the decision criteria can affect type of error. Y-axis is the probability of death and the x-axis is the values of a measured explanatory value like crown or cambium kill. Increasing or decreasing the value of the decision criteria changes the decision of falsely predicting a dead tree will live or falsely predicting a live tree will die 147

Figure 10.1—(A) Lake access to the 2011 Pagami Creek wildfire site in the Boundary Waters Canoe Area Wilderness showing unburned forest on the left adjacent to burned forest on the right. (B) Field personnel collecting 0–10-cm mineral soil sample after removing the organic horizon to return to the laboratory for nutrient analysis and incubation to determine *ex situ* carbon mineralization rates. (C) Field incubation tubes used to determine 90-day *in situ* nitrogen mineralization rates (tubes were loosely capped to allow soil gas exchange during the incubation). Photos by (A) Bethany Laursen, Michigan State University; (B, C) Jessica Miesel, Michigan State University 153

Figure 11.1—Location of study sites where field data were collected (Guan 2014). 158

Figure 12.1—Geographic range of redbay (dashed line) in the Southeastern United States (Brendemuehl 1990). Shaded counties represent the spread of laurel wilt disease

(LWD) as of August 2013 (USDA Forest Service, Forest Health Protection, Southern Region 2013). Darker shades indicate earlier years of reported infection 162

Figure 12.2—Location of 61 sampled plots on nine sites along the coast of South Carolina and Georgia. Laurel wilt disease infestation data obtained from Hughes and others (2015). 163

Figure 13.1—Results of the fire behavior FlamMap simulation showing the range of predicted (A) flame length, (B) fire line intensity, and (C) surface fire rate of spread by the five scenarios. Boxes denote 1st and 3rd quartiles, with lines inside boxes showing median values, and bars showing ± 1.5 interquartile range (IQR). Data points outside of 1.5 IQR not shown. Different letters denote differences between scenarios ($\alpha = 0.05$) . . . 172

Figure 13.2—Simulated area of Tenderfoot Creek Experimental Forest burned by fire type (surface fire, passive crown fire, active crown fire) by bark beetle scenario 173

Figure 14.1—Monitoring plot design with Brown’s transects. Diameter of fuels: 1-hour = 0–0.64 cm, 10-hour = 0.64–2.54 cm, 100-hour = 2.54–7.62 cm 178

Figure 14.2—Distribution of 1-, 10-, and 100-hour fuels among outbreak phases. Plots were sampled in 2013 and 2015. 179

Figure 14.3—Tree distributions by diameter at breast height (d.b.h.) class, 2013 180

Figures, cont.

Figures, cont.

Figure 14.4—Tree distributions by diameter at breast height (d.b.h.) class, 2014. Downed trees since 2013 include one in epidemic 5-year dead stands and seven in post-epidemic stands. No downed trees were found in pre-epidemic stands 180

Figure 14.5—Tree distributions by diameter at breast height (d.b.h.) class, 2015. Downed trees since 2015 include eight in epidemic 5-year dead stands and 15 in post-epidemic dead stands. No downed trees were found in pre-epidemic dead stands 181

Figure 14.6—Changes in size class distribution of epidemic sites 181

Figure 15.1—Whitebark pine density management diagram with superimposed relative density lines corresponding to mountain pine beetle (MPB) susceptibility (solid black line, after Perkins and Roberts 2003) and stocking necessary for maintenance of Clark’s nutcrackers (dashed green line, after McKinney and others 2009) 185

LIST OF TABLES

Table 2.1—Mortality agents and complexes affecting more than 5000 ha in the conterminous United States during 2016. . . 29

Table 2.2—Beetle taxa included in the “western bark beetle” group. 30

Table 2.3—The top five mortality agents or complexes for each Forest Health Monitoring region, and for Alaska and Hawaii, in 2016. . 31

Table 2.4—Defoliation agents and complexes affecting more than 5000 ha in the conterminous United States in 2016 34

Table 2.5—The top five defoliation agents or complexes for each Forest Health Monitoring region and for Alaska in 2016. 35

Table 4.1—Moisture difference *z*-score (*MDZ*) value ranges for nine wetness and drought categories, along with each category’s approximate theoretical frequency of occurrence. 71

Table 5.1—Western States from which repeated Forest Inventory and Analysis Phase 2 measurements were available, the time period spanned by the data, and the effective sample intensity (on the proportion of plots that had been remeasured) in the available datasets. 86

Table 5.2—Ecoregion sections in the Eastern and Central United States having the highest mortality relative to growth (*MRATIO*), annual growth and mortality rates, and disturbances associated with areas of mortality. 91

Table 6.1—Percentage of unique 1994–2005 FIA plots in eastern U.S. lichen regions with five target lichen elemental indicator species (names in bold) plus an additional species . . 102

Table 7.1—Year of crown dieback assessment by region and State, 2011–2015 117

Table 7.2—Mean crown dieback and number of trees ≥ 12.7 cm d.b.h. by dieback class for major species groups in the North region, 2011–2015 123

Table 7.3—Mean crown dieback and number of trees ≥ 12.7 cm d.b.h. by dieback class for major species groups in the South region, 2011–2015 124

Table 7.4—Mean crown dieback and other statistics for paired trees measured 5 years apart for major species groups in the North region, 2006–2010 vs. 2011–2015. 128

List of Tables, cont.

Table 7.5—Mean crown dieback and other statistics for paired trees measured 5 years apart for major species groups in the South region, 2006–2010 vs. 2011–2015. 129

Table 8.1—Summary of the available data, including FIA annual data (2001–2013) and spatial and temporal intensification on Pacific Southwest and Pacific Northwest Region (Regions 5 and 6, respectively) National Forest System lands 135

Table 9.1—Fire name, year of fire, fire location (latitude, longitude), and average annual rainfall for the location of the fire . . 144

Table 14.1—Analysis of Variance (ANOVA) of 1-, 10-, and 100-hour fuels measured in 2013 and 2015 179

Healthy ecosystems are those that are stable and sustainable, able to maintain their organization and autonomy over time while remaining resilient to stress (Costanza 1992). Healthy forests are vital to our future (Edmonds and others 2011), and consistent, large-scale, and long-term monitoring of key indicators of forest health status, change, and trends is necessary to identify forest resources deteriorating across large regions (Riitters and Tkacz 2004). The Forest Health Monitoring (FHM) Program of the Forest Service, U.S. Department of Agriculture, with cooperating researchers within and outside the Forest Service and with State partners, quantifies status and trends in the health of U.S. forests (chapter 1). The analyses and results outlined in sections 1 and 2 of this FHM annual national report offer a snapshot of the current condition of U.S. forests from a national or multi-State regional perspective, incorporating baseline investigations of forest ecosystem health, examinations of change over time in forest health metrics, and assessments of developing threats to forest stability and sustainability. For datasets collected on an annual basis, analyses are presented from 2016 data. For datasets collected over several years, analyses are presented at a longer temporal scale. Finally, section 3 of this report presents summaries of results from recently completed Evaluation Monitoring (EM) projects that have been funded through the FHM national program to determine the extent, severity, and/or causes of specific forest health problems (FHM 2017).

Monitoring the occurrence of forest pest and pathogen outbreaks is important at regional scales because of the significant impact insects and disease can have on forest health across landscapes (chapter 2). National insect and disease survey data collected in 2016 by the Forest Health Protection Program of the Forest Service and partners in State agencies identified 62 different mortality-causing agents and complexes on 2.99 million ha in the conterminous United States, and 63 defoliating agents and complexes on approximately 1.99 million ha. Geographic hot spots of forest mortality were associated with bark beetle infestations (mostly fir engraver, spruce beetle, mountain pine beetle, Jeffrey pine beetle, western pine beetle, and western balsam bark beetle) in the West, and with emerald ash borer in the East. Hot spots of defoliation were associated with gypsy moth, baldcypress leafroller, spruce budworm, forest tent caterpillar, browntail moth, winter moth, and white pine needle damage in the East, and with western spruce budworm in the West. Mortality was recorded on a very small proportion of the surveyed area in Alaska. The most important defoliation agents in Alaska were aspen leafminer, speckled green fruitworm, and willow leaf blotchminer. In Hawaii, approximately 9000 ha of mortality were caused by rapid ‘ōhi‘a death.

Forest fire occurrence outside the historic range of frequency and intensity can result in extensive economic and ecological impacts. The

EXECUTIVE SUMMARY

detection of regional patterns of fire occurrence density can allow for the identification of areas at greatest risk of significant impact and for the selection of locations for more intensive analysis (chapter 3). In 2016, the number of satellite-detected forest fire occurrences recorded for the conterminous States was the lowest since 2006. Ecoregions along the central coast of California, in central Oregon, and in Oklahoma experienced the most fires per 100 km² of forested area. Geographic hot spots of high fire occurrence density were detected in these same areas, as well as in the Southeast and scattered locations in the interior West. Ecoregions in the Southern Appalachians, in the Northeast, and along the central California coast experienced greater fire occurrence density than normal compared to the previous 15-year mean and accounting for variability over time. Alaska experienced low or relatively low fire occurrence densities throughout the State. The Big Island of Hawai'i experienced very high fire occurrence density as a result of an ongoing volcanic eruption.

Most U.S. forests experience droughts, with varying degrees of intensity and duration between and within forest ecosystems. Arguably, the duration of a drought event is more critical than its intensity. A standardized drought and moisture surplus indexing approach was applied to monthly climate data from 2016 to map drought conditions and surplus moisture availability across the conterminous United States at a fine scale (chapter 4). Much of the

interior of the Southeast experienced extreme drought conditions in 2016, while parts of the Northeast had extreme or severe drought. Locations of severe or extreme drought were scattered throughout the Interior West. Drought conditions were conspicuously absent throughout most of California during 2016, after several years of extreme drought. The northern Midwest, Texas, and eastern North and South Carolina experienced near-normal or moderate surplus conditions. Analyses of longer term (3-year and 5-year) conditions show that much of the West had undergone long-term drought conditions, as had coastal New England and the interior of the South. The remainder of the country generally experienced at least mild moisture surplus conditions, and much of the central part of the Nation (the Midwest south through Texas and Louisiana) had severe or extreme moisture surplus.

Mortality is a natural process in all forested ecosystems, but high levels of mortality at large scales may indicate that the health of forests is declining. Phase 2 data collected by the Forest Inventory and Analysis (FIA) Program of the Forest Service offer tree mortality information on a relatively spatially intense basis of approximately one plot per 6,000 acres (chapter 5). An analysis of FIA plots from all the Central and Eastern States found that in most areas, tree mortality is low relative to tree growth, while the areas of highest mortality occur mostly in riparian forests of the

Great Plains. Specifically, the highest ratios of annual mortality to gross growth occurred in ecoregion sections located in western South Dakota and Nebraska, in eastern North Dakota, in central Oklahoma and Arkansas, in east Texas, and in northwest Ohio and southeast Michigan. These results should be considered preliminary. For the first time, similar analyses were conducted for the Western States, where the FIA remeasurement cycle is 10 years. In much of the Interior West as well as in southern California, mortality exceeded growth, sometimes by a factor of two to four. Areas of highest annual mortality as a percentage of total live tree volume were in central Idaho and western Montana, central Colorado, northeastern Utah, and southern California. These results for the West should be considered preliminary, however.

FIA plot-level lichen data are popular and cost-effective bioindicators for large-scale monitoring of air quality across eastern U.S. forests (chapter 6). Based on upper Midwest studies and 1994–2005 species frequencies in the FIA National Lichen Database, macrolichen bioindicator species were previously recommended for Northeastern, Mid-Atlantic, and Southeastern States. This study evaluated distribution patterns of all five tested macrolichen bioindicator species with respect to pollution load and nearby forest cover in the Northeastern and Mid-Atlantic regions using FIA lichen community data. The results

support implementation of lichen elemental bioindicators in those regions. Declines in air pollution since 2005 may have increased the relative importance of nearby forest cover to predicting distribution of bioindicator lichen species in all regions. Because of this, nearby forest cover should be evaluated as a factor during implementation in all eastern U.S. regions regardless of patterns from older lichen distribution data. Reliable and cost-effective plot-level bioindicators for air quality are needed to improve assessment of the environmental health of eastern U.S. forests, especially in the absence of other reliable indicators for local air quality across a wide region.

Assessments of tree crown conditions, which are visually evaluated by the FIA program as an indicator of forest health, are useful because tree photosynthetic capacity depends on the size and condition of the crown (chapter 7). A third national summary of crown condition in the United States indicated that current crown dieback conditions appear to be within expected norms for most species in the Eastern United States. As expected, elevated levels of crown dieback were observed for ash, beech, and hemlock trees in areas affected by emerald ash borer (EAB), beech bark disease (BBD), and hemlock woolly adelgid (HWA), respectively. Crown dieback was elevated and increasing for ash trees in the East, evidence of EAB's continued spread and devastation. Crown dieback was also elevated and increasing for elm

trees, likely due to Dutch elm disease (DED) and elm yellows. In the Western United States, previous crown dieback information combined with current tree status revealed high mortality among trees previously assessed as having no crown dieback. This was particularly true for lodgepole pine, quaking aspen, and subalpine fir in the Rocky Mountain region, and is likely the result of stressors emerging during the intervening 10-year remeasurement period.

Finally, eight recently completed Evaluation Monitoring (EM) projects address a wide variety of forest health concerns at a scale smaller than the national or multi-State regional analyses included in the first sections of the report. These EM projects (funded by the FHM Program):

- Provided statistically based estimates of the distribution and of the health status and trends of whitebark pine populations in California, Oregon, and Washington (chapter 8);
- Assessed the ability of logistic regression models and other methods to predict post-fire mortality in Oregon and Washington, and identified suites of fire injury variables that discriminate between live and dead trees in that region (chapter 9);
- Evaluated wildfire effects on soil carbon and nitrogen pools and cycling along a gradient of fire severity within a 2011 wildfire site in northern Minnesota, and determined the relationships between wildfire-produced black carbon on phosphorus availability and nitrogen mineralization rates (chapter 10);
- Studied post-hurricane fuel dynamics and their effect on fire behavior by conducting field measurements and comparing fire behavior for undamaged stands and hurricane-damaged stands in southern pine forests in four States (chapter 11);
- Documented the rangewide population impacts of laurel wilt disease on redbay and swamp bay (*Persea*) populations, described community types associated with *Persea*, and characterized the patterns of mortality and regeneration of *Persea* after infestation (chapter 12);
- Simulated fire behavior before, during, and after a hypothetical mountain pine beetle outbreak in a lodgepole pine-dominated landscape in Montana to determine if FuelCalc and a fire behavior modeling system are sensitive to changes in forest structure during the red stage of a mountain pine beetle (MPB) outbreak (chapter 13);
- Documented changes in residual stand structure and composition of spruce-fir forests across monitoring plots in Utah and Wyoming spanning a temporal continuum of tree mortality attributed to spruce beetle (chapter 14); and
- Characterized the stand structure, species composition and the influence of environmental factors for whitebark and limber pine across the Interior West, and presented silvicultural recommendations addressing challenges to effective management of the species (chapter 15).

The FHM Program, in cooperation with forest health specialists and researchers inside and outside the Forest Service, continues to investigate a broad range of issues relating to forest health using a wide variety of data and techniques. This report presents some of the latest results from ongoing national-scale detection monitoring and smaller-scale environmental monitoring efforts by FHM and its cooperators. For more information about efforts to determine the status, changes, and trends in indicators of the condition of U.S. forests, please visit the FHM Web site at www.fs.fed.us/foresthealth/fhm.

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Forests cover a vast area of the United States, 304 million ha or approximately one-third of the Nation's land area (Smith and others 2009). These forests possess the capacity to provide a broad range of goods and services to current and future generations, to safeguard biological diversity, and to contribute to the resilience of ecosystems, societies, and economies (USDA Forest Service 2011). Their ecological roles include supplying large and consistent quantities of clean water, preventing soil erosion, and providing habitat for a broad diversity of plant and animal species. Their socioeconomic benefits include wood products, nontimber goods, recreational opportunities, and pleasing natural beauty. Both the ecological integrity and the continued capacity of these forests to provide ecological and economic goods and services are of concern, however, in the face of a long list of threats, including insect and disease infestation, fragmentation and conversion to other land uses, catastrophic fire, invasive species, and the effects of climate change.

Natural and anthropogenic stresses vary among biophysical regions and local environments; they also change over time and interact with each other. These and other factors make it challenging to establish baselines of forest health and to detect important departures from normal forest ecosystem functioning (Riitters and Tkacz 2004). Monitoring the health of forests is a critically important task, however, reflected within the Criteria and Indicators for the Conservation and Sustainable Management

of Temperate and Boreal Forests (Montréal Process Working Group 1995), which the Forest Service, U.S. Department of Agriculture (USDA), uses as a forest sustainability assessment framework (USDA Forest Service 2004, 2011). The primary objective of such monitoring is to identify ecological resources whose condition is deteriorating in subtle ways over large regions in response to cumulative stresses, a goal that requires consistent, large-scale, and long-term monitoring of key indicators of forest health status, change, and trends (Riitters and Tkacz 2004). This is best accomplished through the participation of multiple Federal, State, academic, and private partners.

Although the concept of a healthy forest has universal appeal, forest ecologists and managers have struggled with how exactly to define forest health (Teale and Castello 2011), and there is no universally accepted definition. Most definitions of forest health can be categorized as representing an ecological or a utilitarian perspective (Kolb and others 1994). From an ecological perspective, the current understanding of ecosystem dynamics suggests that healthy ecosystems are those that are able to maintain their organization and autonomy over time while remaining resilient to stress (Costanza 1992), and that evaluations of forest health should emphasize factors that affect the inherent processes and resilience of forests (Edmonds and others 2011, Kolb and others 1994, Raffa and others 2009). On the other hand, the utilitarian perspective holds that a forest is healthy if management objectives are met, and that a

CHAPTER 1.

Introduction

KEVIN M. POTTER

forest is unhealthy if these objectives are not met (Kolb and others 1994). Although this definition may be appropriate when a single, unambiguous management objective exists, such as the production of wood fiber or the maintenance of wilderness attributes, it is too narrow when multiple management objectives are required (Edmonds and others 2011, Teale and Castello 2011). Teale and Castello (2011) incorporate both ecological and utilitarian perspectives into their two-component definition of forest health: First, a healthy forest must be sustainable with respect to its size structure, including a correspondence between baseline and observed mortality; second, a healthy forest must meet the landowner's objectives, provided that these objectives do not conflict with sustainability.

This national report, the 17th in an annual series sponsored by the Forest Health Monitoring (FHM) Program of the Forest Service, attempts to quantify the status of, changes to, and trends in a wide variety of broadly defined indicators of forest health. The indicators described in this report encompass forest insect and disease activity, wildland fire occurrence, drought, tree mortality, understory vegetation, and regeneration, among others. The previous reports in this series are Ambrose and Conkling (2007, 2009), Conkling (2011), Conkling and others (2005), Coulston and others (2005a, 2005b, 2005c), and Potter and Conkling (2012a, 2012b, 2013a, 2013b, 2014, 2015a, 2015b, 2016, 2017).

This report has three specific objectives. The first is to present information about forest health from a national perspective, or from a multi-State regional perspective when appropriate, using data collected by the Forest Health Protection (FHP) and Forest Inventory and Analysis (FIA) programs of the Forest Service, as well as from other sources available at a wide extent. The chapters that present analyses at a national scale, or multi-State regional scale, are divided between section 1 and section 2 of the report. Section 1 presents results from the analyses of forest health data that are available on an annual basis. Such repeated analyses of regularly collected indicator measurements allow for the detection of trends over time and help establish a baseline for future comparisons (Riitters and Tkacz 2004). Section 2 presents longer-term forest health trends, in addition to describing new techniques for analyzing forest health data at national or regional scales (the second objective of the report). While in-depth interpretation and analysis of specific geographic or ecological regions are beyond the scope of these parts of the report, the chapters in sections 1 and 2 present information that can be used to identify areas that may require investigation at a finer scale.

The second objective of the report is to present new techniques for analyzing forest health data as well as new applications of established techniques, often applied to longer timescales, presented in selected chapters of

section 2. Examples in this report are chapters 6 and 7, which, respectively, assess the use of FIA plot-level lichen data as bioindicators for large-scale monitoring of air quality across eastern U.S. forests, and present a national summary of crown condition across the United States for 2011–15 and apply change over time in crown dieback to identify species in decline.

The third objective of the report is to present results of recently completed Evaluation Monitoring (EM) projects funded through the FHM national program. These project summaries, presented in section 3, determine the extent, severity, and/or cause of forest health problems (FHM 2016), generally at a finer scale than that addressed by the analyses in sections 1 and 2. Each of the eight chapters in section 3 contains an overview of an EM project, key results, and contacts for more information.

When appropriate throughout this report, authors use the Forest Service revised ecoregions (Cleland and others 2007, Nowacki and Brock 1995) as a common ecologically based spatial framework for their forest health assessments (fig. 1.1). Specifically, when the spatial scale of the data and the expectation of an identifiable pattern in the data are appropriate, authors use ecoregion sections or provinces as assessment units for their analyses. Bailey's hierarchical system bases the two broadest ecoregion scales, domains and divisions, on large ecological climate zones, while each division is broken into provinces based on vegetation macro features (Bailey 1995). Provinces are further

divided into sections, which may be thousands of square kilometers in area and are expected to encompass regions similar in their geology, climate, soils, potential natural vegetation, and potential natural communities (Cleland and others 1997).

THE FOREST HEALTH MONITORING PROGRAM

The national FHM Program is designed to determine the status, changes, and trends in indicators of forest condition on an annual basis and covers all forested lands through a partnership encompassing the Forest Service, State foresters, and other State and Federal agencies and academic groups (FHM 2016). The FHM Program utilizes data from a wide variety of data sources, both inside and outside the Forest Service, and develops analytical approaches for addressing forest health issues that affect the sustainability of forest ecosystems. The FHM Program has five major components (fig. 1.2):

- Detection Monitoring—nationally standardized aerial and ground surveys to evaluate status and change in condition of forest ecosystems (sections 1 and 2 of this report).
- Evaluation Monitoring—projects to determine the extent, severity, and causes of undesirable changes in forest health identified through Detection Monitoring (section 3 of this report).

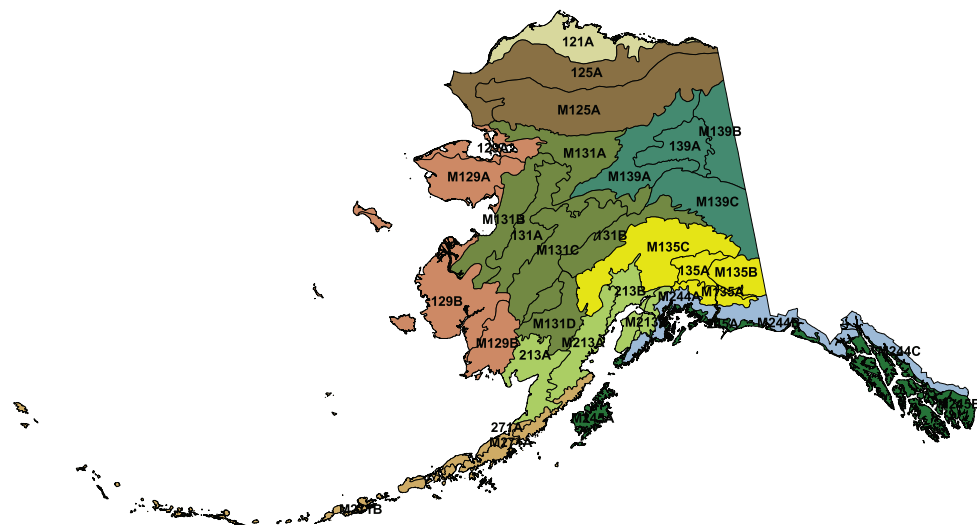
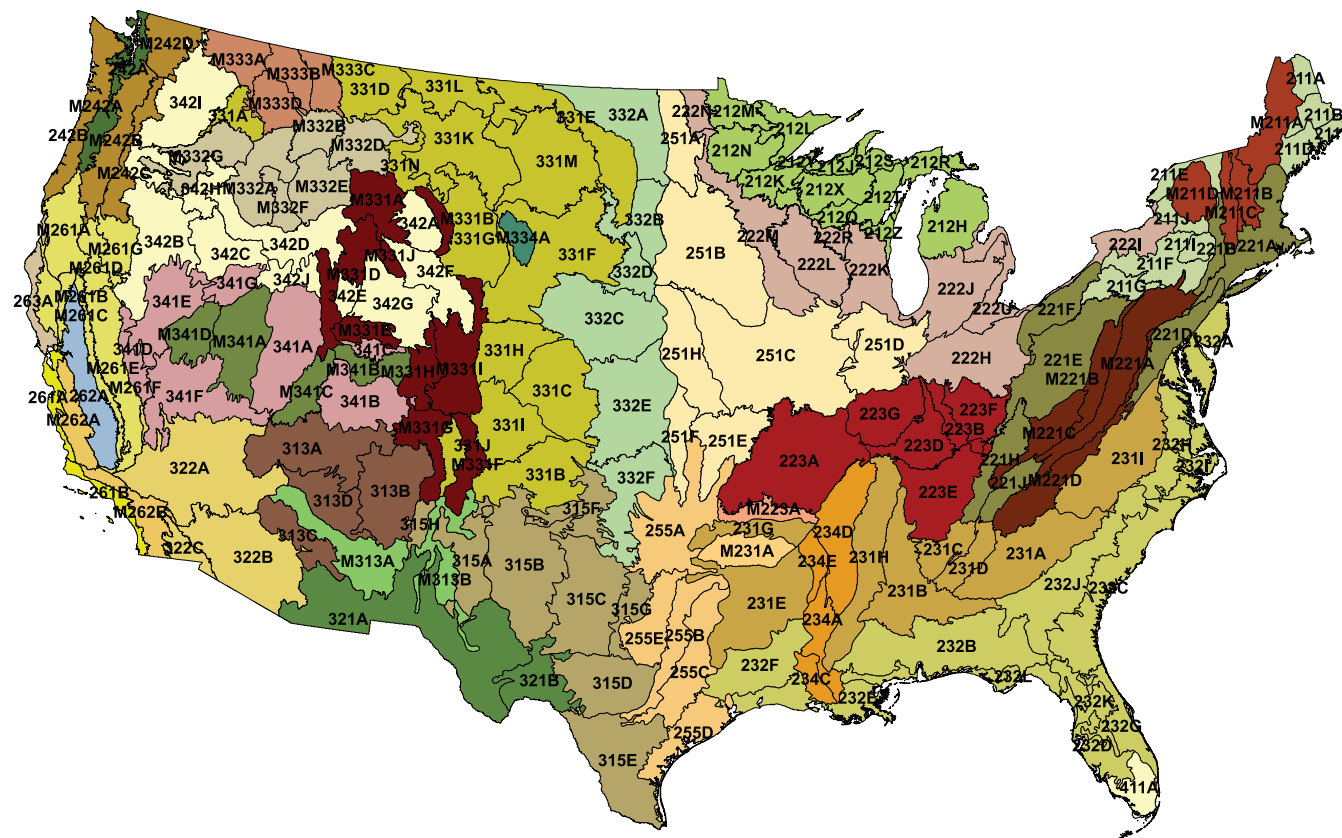


Figure 1.1—Ecoregion provinces and sections for the conterminous United States (Cleland and others 2007) and Alaska (Nowacki and Brock 1995). Ecoregion sections within each ecoregion province are shown in the same color. Note: no equivalent ecoregion treatment exists for Hawaii.



Alaska ecoregion provinces

-  Alaska Mixed Forest (213)
-  Alaska Range Taiga (135)
-  Aleutian Meadow (271)
-  Arctic Tundra (121)
-  Bering Sea Tundra (129)
-  Brooks Range Tundra (125)
-  Pacific Coastal Icefields (244)
-  Pacific Gulf Coast Forest (245)
-  Upper Yukon Taiga (139)
-  Yukon Intermontaine Taiga (131)

Conterminous States ecoregion provinces

-  Adirondack-New England Mixed Forest - Coniferous Forest - Alpine Meadow (M211)
-  American Semi-Desert and Desert (322)
-  Arizona-New Mexico Mountains Semi-Desert - Open Woodland - Coniferous Forest - Alpine Meadow (M313)
-  Black Hills Coniferous Forest (M334)
-  California Coastal Chaparral Forest and Shrub (261)
-  California Coastal Range Open Woodland - Shrub - Coniferous Forest - Meadow (M262)
-  California Coastal Steppe - Mixed Forest - Redwood Forest (263)
-  California Dry Steppe (262)
-  Cascade Mixed Forest - Coniferous Forest - Alpine Meadow (M242)
-  Central Appalachian Broadleaf Forest - Coniferous Forest - Meadow (M221)
-  Central Interior Broadleaf Forest (223)
-  Chihuahuan Semi-Desert (321)
-  Colorado Plateau Semi-Desert (313)
-  Eastern Broadleaf Forest (221)
-  Everglades (411)
-  Great Plains - Palouse Dry Steppe (331)
-  Great Plains Steppe (332)
-  Intermountain Semi-Desert and Desert (341)
-  Intermountain Semi-Desert (342)
-  Laurentian Mixed Forest (212)
-  Lower Mississippi Riverine Forest (234)
-  Middle Rocky Mountain Steppe - Coniferous Forest - Alpine Meadow (M332)
-  Midwest Broadleaf Forest (222)
-  Nevada-Utah Mountains Semi-Desert - Coniferous Forest - Alpine Meadow (M341)
-  Northeastern Mixed Forest (211)
-  Northern Rocky Mountain Forest-Steppe - Coniferous Forest - Alpine Meadow (M333)
-  Ouachita Mixed Forest - Meadow (M231)
-  Outer Coastal Plain Mixed Forest (232)
-  Ozark Broadleaf Forest (M223)
-  Pacific Lowland Mixed Forest (242)
-  Prairie Parkland (Subtropical) (255)
-  Prairie Parkland (Temperate) (251)
-  Sierran Steppe - Mixed Forest - Coniferous Forest - Alpine Meadow (M261)
-  Southeastern Mixed Forest (231)
-  Southern Rocky Mountain Steppe - Open Woodland - Coniferous Forest - Alpine Meadow (M331)
-  Southwest Plateau and Plains Dry Steppe and Shrub (315)

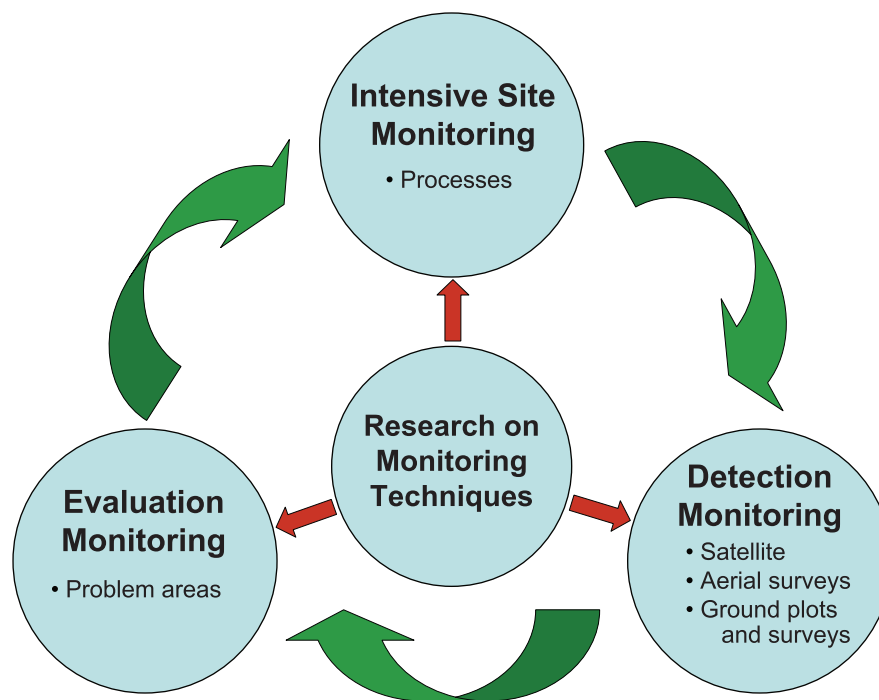


Figure 1.2—The design of the Forest Health Monitoring (FHM) Program of the Forest Service, U.S. Department of Agriculture (FHM 2003). A fifth component, Analysis and Reporting of Results, draws from the four FHM components shown here and provides information to help support land management policies and decisions.

- **Intensive Site Monitoring**—projects to enhance an understanding of cause-effect relationships by linking Detection Monitoring to ecosystem process studies and to assess specific issues, such as calcium depletion and carbon sequestration, at multiple spatial scales (section 3 of this report).
- **Research on Monitoring Techniques**—work to develop or improve indicators, monitoring systems, and analytical techniques, such as urban and riparian forest health monitoring, early detection of invasive species, multivariate analyses of forest health indicators, and spatial scan statistics (section 2 of this report).
- **Analysis and Reporting of Results**—synthesis of information from various data sources within and external to the Forest Service to produce issue-driven reports on status and change in forest health at national, regional, and State levels (sections 1, 2, and 3 of this report).

The FHM Program, in addition to national reporting, generates regional and State reports, often in cooperation with FHM partners, both within the Forest Service and in State forestry and agricultural departments. For example, the FHM regions cooperate with their respective State partners to produce the annual Forest Health Highlights report series, available on the FHM Web site at www.fs.fed.us/foresthealth/fhm. Other examples include Steinman (2004) and Harris and others (2011).

The FHM Program and its partners also produce reports and journal articles on monitoring techniques and analytical methods, including forest health data (Potter and others 2016, Smith and Conkling 2004); soils as an indicator of forest health (O'Neill and others 2005); urban forest health monitoring (Biggsby and others 2014; Cumming and others 2006, 2007; Lake and others 2006); remote sensing of forest disturbances (Chastain and others 2015, Rebbeck and others 2015); health conditions in national forests (Morin and others 2006); crown conditions (Morin and others 2015; Randolph 2010a, 2010b, 2013; Randolph and Moser 2009; Schomaker and others 2007); indicators of regeneration (McWilliams and others 2015); vegetation diversity and structure (Schulz and Gray 2013, Schulz and others 2009, Simkin and others 2016); forest lichen communities (Jovan and others 2012, Root and others 2014); downed woody materials in forests (Woodall and others 2012, 2013); drought (Vose and others 2016); ozone monitoring (Rose and Coulston 2009); patterns of nonnative invasive plant occurrence (Guo and others 2015, 2017;

Iannone and others 2015, 2016a, 2016b; Oswalt and others 2015); assessments of alien-invasive forest insect and disease risk (Koch and others 2011, 2014; Krist and others 2014; Vogt and Koch 2016; Yemshanov and others 2014); spatial patterns of landcover (Riitters 2011; Riitters and others 2012, 2016, 2017; Riitters and Wickham 2012); impacts of deer browse on forest structure (Russell and others 2017); broad-scale assessments of forest biodiversity (Potter and Koch 2014; Potter and Woodall 2012, 2014); predictions and indicators of climate change effects on forests and forest tree species (Fei and others 2017, Heath and others 2015, Potter and Hargrove 2013); and the overall forest health indicator program (Woodall and others 2010).

For more information about the FHM Program, visit the FHM Web site at www.fs.fed.us/foresthealth/fhm. Among other things, this Web site includes links to all past national forest health reports (www.fs.fed.us/foresthealth/fhm/pubs), information about funded Evaluation Monitoring projects (www.fs.fed.us/foresthealth/fhm/em), and annual State forest health highlight reports (www.fs.fed.us/foresthealth/fhm/fhh/fhmusamap.shtml).

DATA SOURCES

Forest Service data sources in this edition of the FHM national report include FIA annualized Phase 2 and Phase 3 survey data (Bechtold and Patterson 2005, Woodall and others 2010, Woudenberg and others 2010); FHP national insect and disease survey forest mortality and defoliation data for 2016 (FHP 2014); Moderate

Resolution Imaging Spectroradiometer (MODIS) Active Fire Detections for the United States data for 2016 (USDA Forest Service 2017); and forest cover data developed from MODIS satellite imagery by the Forest Service Remote Sensing Applications Center. Other sources of data include Parameter-elevation Regression on Independent Slopes Model (PRISM) climate mapping system data (PRISM Climate Group 2017) and FIA's publicly available Environmental Monitoring and Assessment Program (EMAP) hexagons (Brand and others 2000).

As a major source of data for several FHM analyses, the FIA Program merits detailed description. The FIA Program collects forest inventory information across all forest land ownerships in the United States and maintains a network of more than 130,000 permanent forested ground plots across the conterminous United States and southeastern Alaska, with a sampling intensity of approximately one plot/2428 ha. Forest Inventory and Analysis Phase 2 encompasses the annualized inventory measured on plots at regular intervals, with each plot surveyed every 5 to 7 years in most Eastern States, but with plots in the Rocky Mountain and Pacific Northwest regions surveyed once every 10 years (Reams and others 2005). The standard 0.067-ha plot (fig. 1.3) consists of four 7.315-m (24.0-foot) radius subplots (approximately 168.6 m² or 1/24th acre), on which field crews measure trees at least 12.7 cm (5.0 inches) in diameter. Within each of these subplots is nested a 2.073-m (6.8-foot) radius microplot (approximately 13.48 m² or 1/300th acre), on which crews measure trees smaller than 12.7 cm

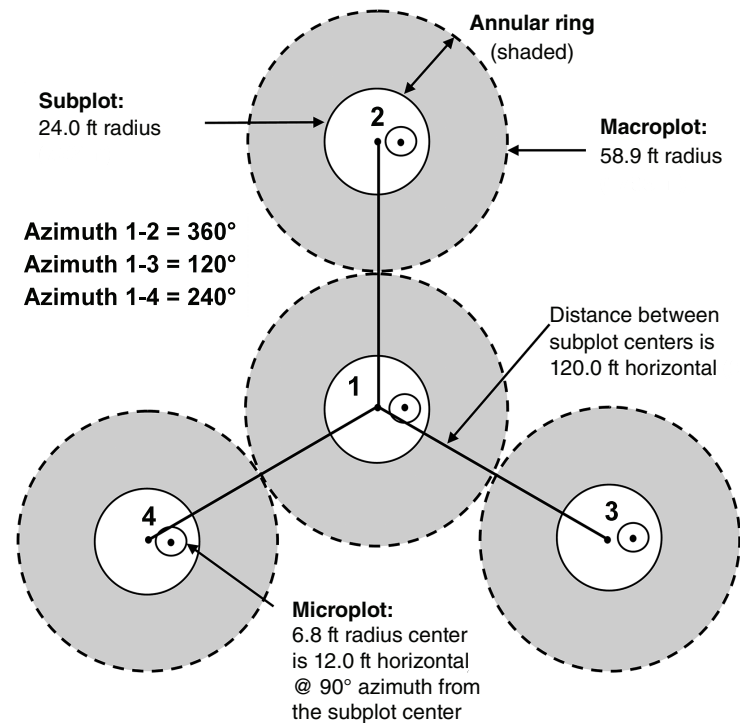


Figure 1.3—The Forest Inventory and Analysis mapped plot design. Subplot 1 is the center of the cluster with subplots 2, 3, and 4 located 120 feet away at azimuths of 360°, 120°, and 240°, respectively (Woudenberg and others 2010).

(5.0 inches) in diameter. A core-optional variant of the standard design includes four “macroplots,” each with a radius of 17.953 m (or approximately 0.1012 ha) that originates at the center of each subplot (Woudenberg and others 2010).

FIA Phase 3 plots have represented a subset of these Phase 2 plots, with one Phase 3 plot for every 16 standard FIA Phase 2 plots.

In addition to traditional forest inventory measurements, data for a variety of important ecological indicators have been collected from Phase 3 plots, including tree crown condition, lichen communities, downed woody material, soil condition, and vegetation structure and diversity, whereas data on ozone bioindicator plants have been collected on a separate grid of plots (Woodall and others 2010, 2011). Most of these additional forest health indicators were measured as part of the FHM Detection Monitoring ground plot system prior to 2000¹ (Palmer and others 1991).

FHM REPORT PRODUCTION

This FHM national report, the 17th in a series of such annual documents, is produced by forest health monitoring researchers at the Eastern Forest Environmental Threat Assessment Center (EFETAC) in collaboration with North Carolina State University cooperators. A unit of the Southern Research Station of the Forest Service, EFETAC was established under the Healthy Forests Restoration Act of 2003 to generate the knowledge and tools needed to anticipate and respond to environmental threats. For more information about the research team and about threats to U.S. forests, please visit www.forestthreats.org/about.

¹ USDA Forest Service. 1998. Forest Health Monitoring 1998 field methods guide. Research Triangle Park, NC: U.S. Department of Agriculture, Forest Service, Forest Health Monitoring Program, 473 p. On file with Forest Health Monitoring Program, 3041 Cornwallis Rd., Research Triangle Park, NC 27709.

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SECTION 1.

Analyses of Short-Term Forest Health Data

INTRODUCTION

Insects and diseases cause changes in forest structure and function, species succession, and biodiversity, which may be considered negative or positive depending on management objectives (Edmonds and others 2011). An important task for forest managers, pathologists, and entomologists is recognizing and distinguishing between natural and excessive mortality, a task that relates to ecologically based or commodity-based management objectives (Teale and Castello 2011). The impacts of insects and diseases on forests vary from natural thinning to extraordinary levels of tree mortality, but insects and diseases are not necessarily enemies of the forest because they kill trees (Teale and Castello 2011). If disturbances, including insects and diseases, are viewed in their full ecological context, then some amount can be considered “healthy” to sustain the structure of the forest (Manion 2003, Zhang and others 2011) by causing tree mortality that culls weak competitors and releases resources that are needed to support the growth of surviving trees (Teale and Castello 2011).

Analyzing patterns of forest insect infestations, disease occurrences, forest declines, and related biotic stress factors is necessary to monitor the health of forested ecosystems and their potential impacts on forest structure, composition, biodiversity, and species distributions (Castello and others 1995). Introduced nonnative insects and diseases, in particular, can extensively damage the biodiversity, ecology, and economy of affected

areas (Brockerhoff and others 2006, Mack and others 2000). Few forests remain unaffected by invasive species, and their devastating impacts in forests are undeniable, including, in some cases, wholesale changes to the structure and function of an ecosystem (Parry and Teale 2011).

Examining insect pest occurrences and related stress factors from a landscape-scale perspective is useful, given the regional extent of many infestations and the large-scale complexity of interactions between host distribution, stress factors, and the development of insect pest outbreaks (Holdenrieder and others 2004, Liebhold and others 2013). One such landscape-scale approach is detecting geographic patterns of disturbance, which allows for the identification of areas at greater risk of significant ecological and economic impacts and for the selection of locations for more intensive monitoring and analysis.

METHODS

Data

Forest Health Protection (FHP) national Insect and Disease Survey (IDS) data (FHP 2014) consist of information from low-altitude aerial survey and ground survey efforts by FHP and partners in State agencies. These data can be used to identify forest landscape-scale patterns associated with geographic hot spots of forest insect and disease activity in the conterminous United States and to summarize insect and disease activity by ecoregion in Alaska (Potter 2012, 2013; Potter and Koch 2012; Potter and Paschke 2013, 2014, 2015a,

CHAPTER 2.

Large-Scale Patterns of Insect and Disease Activity in the Conterminous United States, Alaska, and Hawaii from the National Insect and Disease Survey, 2016

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2015b, 2016, 2017) and by island in Hawaii (Potter and Paschke 2015b, 2017). In 2016, IDS surveys of the conterminous United States covered about 216.75 million ha, of which approximately 144.99 million ha were forested (about 56.9 percent of the total forested area of the conterminous States); 107.74 million ha were surveyed using the new Digital Mobile Sketch Mapping (DMSM) approach (fig. 2.1). An additional 114.03 million ha were surveyed in 2016 using the legacy Digital Aerial Sketch Mapping (DASM) approach. (These numbers exceed the total area surveyed because of overlaps in locations covered by the two methodologies.) In Alaska, roughly 11.14 million ha were surveyed in 2016, using only the DMSM approach; of this, 7.37 million ha were forested, or about 14.3 percent of the total forested area of the State. While Hawaii was surveyed for mortality agents using DMSM, the surveyed locations (and the total area surveyed) were not recorded. Additionally, some of the mortality recorded in Hawaii occurred in years previous to 2016.

DMSM includes tablet hardware, software, and data support processes that allow trained aerial surveyors in light aircraft, as well as ground observers, to record forest disturbances and their causal agents. DMSM replaces the legacy DASM approach, and will greatly enhance the quality and quantity of forest health data while improving safety by integrating with programs such as operational remote sensing (ORS), which uses satellite imagery to monitor disturbances in areas of higher aviation risk

(FHP 2016). Geospatial data collected with DMSM and DASM are stored in the national Insect and Disease Survey (IDS) database. DMSM includes both polygon geometry, used for damage areas where boundaries are discrete and obvious from the air, and point geometry, used for small clusters of damage where the size and shape of the damage is less important than recording the location, such as for sudden oak death, southern pine beetle (*Dendroctonus frontalis*), and some types of bark beetle damage in the West. Most of the points that did not overlap with a damage polygon of the same type were assigned an area of 0.809 ha (2 acres). Additionally, some damages that may be widespread and diffuse, such as those associated with gypsy moth (*Lymantria dispar*) and emerald ash borer (*Agrilus planipennis*), were recorded using grid cells (240, 480, 960, or 1920 m) in which the percent of trees affected was estimated. The entire areas of these grid cells were used in summing damage areas.

These surveys identify areas of mortality and defoliation caused by insect and disease activity, although some important forest insects [such as emerald ash borer and hemlock woolly adelgid (*Adelges tsugae*)], diseases (such as laurel wilt, Dutch elm disease, white pine blister rust, and thousand cankers disease), and mortality complexes (such as oak decline) are not easily detected or thoroughly quantified through aerial detection surveys. Such pests may attack hosts that are widely dispersed throughout forests with high tree species diversity or may cause mortality or defoliation that is otherwise

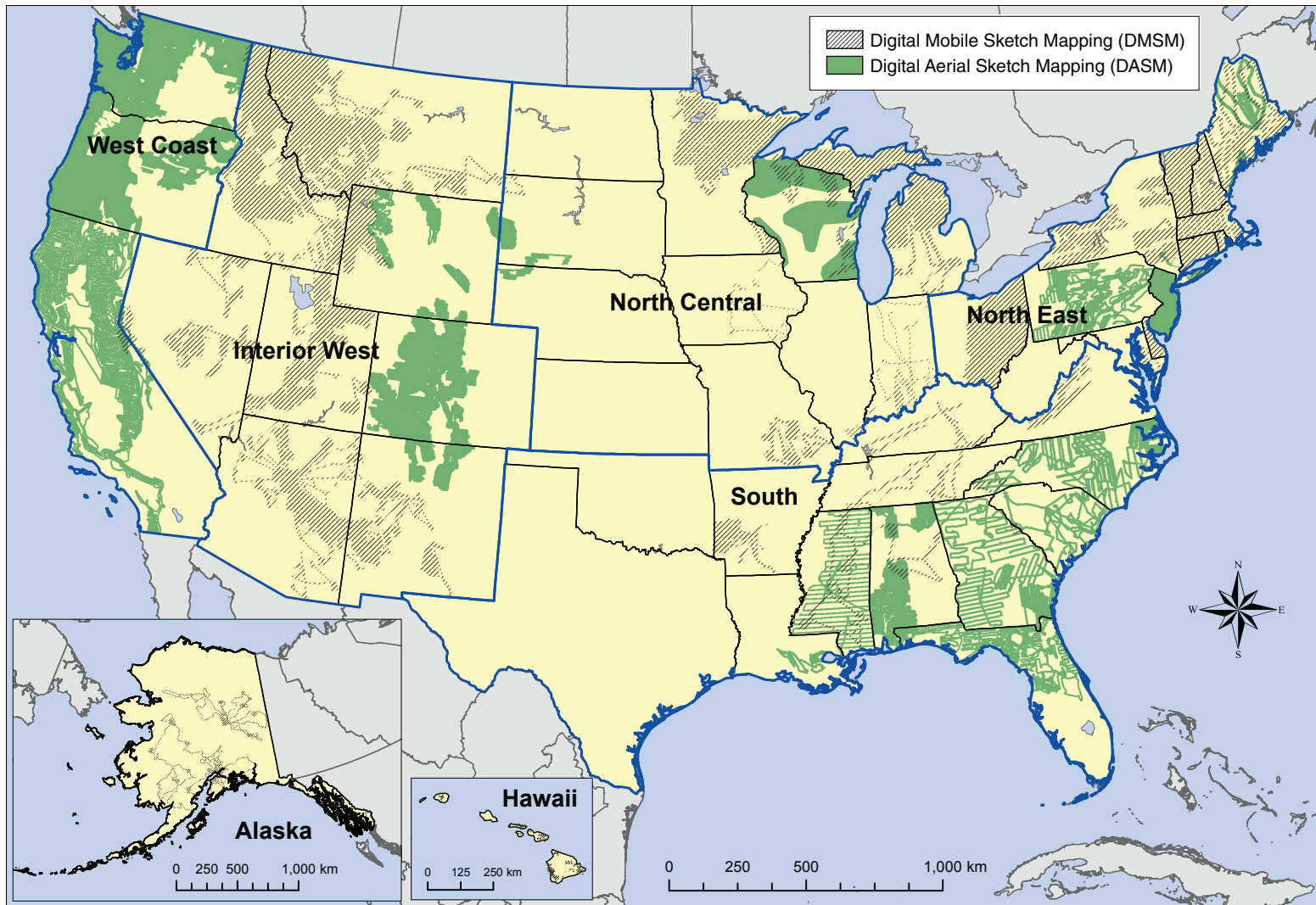


Figure 2.1—The extent of surveys for insect and disease activity conducted in the conterminous United States and Alaska in 2016. Cross-hatched areas were surveyed using the new Digital Mobile Sketch Mapping (DMSM) platform, rather than the older Digital Aerial Sketch Mapping (DASM) approach, which is portrayed in green. The blue lines delineate Forest Health Monitoring regions. Note: Alaska and Hawaii are not shown to scale with map of the conterminous United States. No flight lines were recorded for Hawaii in 2016. (Data source: U.S. Department of Agriculture, Forest Service, Forest Health Protection)

difficult to detect. A pathogen or insect might be considered a mortality-causing agent in one location and a defoliation-causing agent in another, depending on the level of damage to the forest in a given area and the convergence of other stress factors such as drought. In some cases, the identified agents of mortality or defoliation are actually complexes of multiple agents summarized under an impact label related to a specific host tree species (e.g., “beech bark disease complex” or “yellow-cedar decline”). Additionally, differences in data collection, attribute recognition, and coding procedures among States and regions can complicate data analysis and interpretation of the results.

The 2016 mortality and defoliation polygons were used to identify the select mortality and defoliation agents and complexes causing damage on more than 5000 ha of forest in the conterminous United States in that year, and to identify and list the most widely detected mortality and defoliation agents for Alaska and mortality agents for Hawaii. Because of the insect and disease aerial sketch-mapping process (i.e., digitization of polygons by a human interpreter aboard the aircraft), all quantities are approximate “footprint” areas for each agent or complex, delineating areas of visible damage within which the agent or complex is present. Unaffected trees may exist within the footprint, and the amount of damage within the footprint is not reflected in the estimates of forest area affected. The sum of areas affected by all agents and complexes is not equal to the total affected area as a result of reporting multiple agents per polygon in some situations.

Analyses

We used the Spatial Association of Scalable Hexagons (SASH) analytical approach to identify surveyed forest areas with the greatest exposure to the detected mortality-causing and defoliation-causing agents and complexes (using data collected using both DMSM and DASM). 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 employ a Getis-Ord G_i^* hot spot analysis (Getis and Ord 1992) in ArcMap® 10.1 (ESRI 2012).

The 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 analyses that are national in extent (Potter and others 2016).

The variable used in the hot spot analysis was the percentage of surveyed forest area in each hexagon exposed to either mortality-causing or defoliation-causing agents. This required first separately dissolving the mortality and defoliation polygon boundaries to generate an overall footprint of each general type

of disturbance, then masking the dissolved polygons using a forest cover map (1-km² resolution) derived from Moderate Resolution Imaging Spectroradiometer (MODIS) satellite imagery by the U.S. Department of Agriculture, Forest Service, Remote Sensing Applications Center (USDA Forest Service 2008). The same process was undertaken with the polygons of the surveyed area. Finally, the percentage of surveyed forest within each hexagon exposed to mortality or defoliation agents was calculated by dividing the total forest-masked damage area by the forest-masked surveyed area.

The Getis-Ord G_i^* statistic was used to identify clusters of hexagonal cells in which the percentage of surveyed forest exposed to mortality or defoliation agents was 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 nonstationarities in a dataset, such as when spatial clustering is concentrated in one subregion of the data (Anselin 1992).

The Getis-Ord G_i^* statistic for each hexagon summed the differences between the mean values in a local sample, determined by a moving window consisting of the 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 the forested hexagonal

cells in the conterminous United States. It is then standardized as a z-score with a mean of 0 and a standard deviation of 1, with values > 1.96 representing significant ($p < 0.025$) local clustering of high values and values < -1.96 representing significant clustering of low values ($p < 0.025$), since 95 percent of the observations under a normal distribution should be within approximately two (exactly 1.96) standard deviations of the mean (Laffan 2006). In other words, a G_i^* value of 1.96 indicates that the local mean of the percentage of forest exposed to mortality-causing or defoliation-causing agents for a hexagon and its 18 neighbors is approximately two standard deviations greater than the mean expected in the absence of spatial clustering, while a G_i^* value of -1.96 indicates that the local mortality or defoliation mean for a hexagon and its 18 neighbors is approximately two standard deviations less than the mean expected in the absence of spatial clustering. Values between -1.96 and 1.96 have no statistically significant concentration of high or low values. In other words, when a hexagon has a G_i^* value between -1.96 and 1.96, mortality or defoliation damage within it and its 18 neighbors is not statistically different from a normal expectation. As described in Laffan (2006), it is calculated as

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

where

G_i^* 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,

s_i^* is the number of samples within d of the central location,

$\bar{x}^*$ is mean of whole dataset (in this case, for all 7,595 forested hexagons), and

s^* is the standard deviation of whole dataset.

It is worth noting that the -1.96 and 1.96 threshold values are not exact because the correlation of spatial data violates the assumption of independence required for statistical significance (Laffan 2006). 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 used to define the local sample around the target observation is large enough to include several neighbors for each feature (ESRI 2012).

The low density of survey data in 2016 from Alaska and the absence of recorded survey locations in Hawaii (fig. 2.1) precluded the use of Getis-Ord G_i^* hot spot analyses for these States. Instead, mortality and defoliation data were summarized by ecoregion section in Alaska (Nowacki and Brock 1995), calculated as the percent of the forest within the surveyed areas affected by agents of mortality or defoliation. (As with the mortality and defoliation data, the flown area polygons were first dissolved to create an overall footprint.) For reference purposes, ecoregion sections (Cleland and others 2007) were also displayed on the geographic hot spot maps of the conterminous United States.

RESULTS AND DISCUSSION

Conterminous United States Mortality

The national IDS survey data identified 62 different mortality-causing agents and complexes on approximately 2.99 million ha across the conterminous United States in 2016, slightly less than the combined land area of Maryland and Delaware. By way of comparison, forests are estimated to cover approximately 252 million ha of the conterminous United States (Smith and others 2009). Twenty-two of the agents were detected on more than 5000 ha.

Fir engraver (*Scolytus ventralis*) was the most widespread mortality agent in 2016, detected on 1.19 million ha (table 2.1). Six other mortality agents and complexes were detected on more than 100 000 ha in 2016: western pine beetle (*Dendroctonus brevicomis*) on 892 000 ha, mountain pine beetle (*Dendroctonus*

Table 2.1—Mortality agents and complexes affecting more than 5000 ha in the conterminous United States during 2016

Agents/complexes causing mortality, 2016	Area
	ha
Fir engraver	1 186 692
Western pine beetle	892 023
Mountain pine beetle	626 205
Jeffrey pine beetle	331 322
Emerald ash borer	303 332
Spruce beetle	237 173
Flatheaded fir borer	124 666
Western balsam bark beetle	71 208
Unknown bark beetle	70 326
Douglas-fir beetle	56 543
Unknown	37 621
Balsam woolly adelgid	33 571
Eastern larch beetle	28 350
Flatheaded borer	18 143
Pinyon ips	14 964
Southern pine beetle	12 848
Dutch elm disease	12 440
Ips engraver beetles	9151
Gypsy moth	7886
Pine engraver	7675
Root disease and beetle complex	7523
California flatheaded borer	6996
Other (40)	32 896
Total, all mortality agents	2 990 684

Note: All values are “footprint” areas for each agent or complex. The sum of the individual agents is not equal to the total for all agents due to the reporting of multiple agents per polygon.

ponderosae) on 626 000 ha, Jeffrey pine beetle (*Dendroctonus jeffreyi*) on 331 000 ha, emerald ash borer on 303 000 ha, spruce beetle (*Dendroctonus rufipennis*) on 237 000 ha, and flatheaded fir borer (*Phaenops drummondi*) on 125 000 ha. Mortality from the western bark beetle group, which encompasses 19 different agents in the IDS data (table 2.2), was detected on approximately 2.39 million ha in 2016, representing a large majority of the total area on which mortality was recorded across the conterminous States.

The Forest Health Monitoring (FHM) West Coast region had the largest area on which mortality agents and complexes were detected, about 1.95 million ha (table 2.3). Of the 26 agents and complexes detected, fir engraver was the leading cause of mortality and was identified on about 1.15 million ha, approximately 59 percent of the entire affected area. Other bark beetles, including western pine beetle, mountain pine beetle, Jeffrey pine beetle, and flatheaded fir borer, were the other widespread causes of mortality in the region.

For the third consecutive year, a very large hot spot of extremely high and very high mortality centered on the M261E–Sierra Nevada ecoregion section in east-central California and extended north into M261D–Southern Cascades, M261A–Klamath Mountains, M261G–Modoc Plateau, and M261B–Northern California Coast Ranges in 2016 (fig. 2.2). The primary causes of mortality in the area were fir engraver in white fir (*Abies concolor*) and California red fir (*Abies magnifica*); mountain pine beetle in lodgepole

Table 2.2—Beetle taxa included in the “western bark beetle” group

Western bark beetle mortality agents	
Cedar and cypress bark beetles	<i>Phloeosinus</i> spp.
Douglas-fir beetle	<i>Dendroctonus pseudotsugae</i>
Douglas-fir engraver	<i>Scolytus unispinosus</i>
Fir engraver	<i>Scolytus ventralis</i>
Flatheaded borer	Family Buprestidae
Ips engraver beetles	<i>Ips</i> spp.
Jeffrey pine beetle	<i>Dendroctonus jeffreyi</i>
Mountain pine beetle	<i>Dendroctonus ponderosae</i>
Northern spruce engraver	<i>Ips perturbatus</i>
Pine engraver	<i>Ips pini</i>
Pinyon ips	<i>Ips confuses</i>
Root disease and beetle complex	—
Silver fir beetle	<i>Pseudohylesinus sericeus</i>
Spruce beetle	<i>Dendroctonus rufipennis</i>
Twig beetles	<i>Pityophthorus</i> spp.
Unknown bark beetle	—
Western balsam bark beetle	<i>Dryocoetes confuses</i>
Western cedar bark beetle	<i>Phloeosinus punctatus</i>
Western pine beetle	<i>Dendroctonus brevicomis</i>

— = not applicable.

pine (*Pinus contorta*), western white pine (*Pinus monticola*), and sugar pine (*Pinus lambertiana*); Jeffrey pine beetle in Jeffrey pine (*Pinus jeffreyi*); flatheaded fir borer in Douglas-fir (*Pseudotsuga menziesii*); and western pine beetle in ponderosa pine (*Pinus ponderosa*).

Meanwhile, a hot spot of very high exposure to mortality was detected in eastern Oregon, in M332G–Blue Mountains, primarily associated with mountain pine beetle mortality

Table 2.3—The top five mortality agents or complexes for each Forest Health Monitoring region, and for Alaska and Hawaii, in 2016

Mortality agents and complexes, 2016	Area	Mortality agents and complexes, 2016	Area
	ha		ha
Interior West		West Coast	
Spruce beetle	223 645	Fir engraver	1 154 268
Western balsam bark beetle	67 490	Western pine beetle	888 586
Unknown bark beetle	56 231	Mountain pine beetle	577 165
Mountain pine beetle	48 189	Jeffrey pine beetle	329 816
Douglas-fir beetle	38 094	Flatheaded fir borer	124 666
Other mortality agents (12)	75 149	Other mortality agents (21)	120 360
Total, all mortality agents and complexes	502 962	Total, all mortality agents and complexes	1 948 078
North Central		Alaska	
Emerald ash borer	288 020	Spruce beetle	76 095
Eastern larch beetle	28 350	Yellow-cedar decline	15 931
Dutch elm disease	12 341	Northern spruce engraver	5793
Unknown	6152	Spruce broom rust	109
Beech bark disease complex	4835	Western balsam bark beetle	16
Other mortality agents (12)	3390	Total, all mortality agents and complexes	97 944
Total, all mortality agents and complexes	341 600		
North East		Hawaii	
Unknown	25 047	Rapid ‘ōhi‘a death	8808
Southern pine beetle	12 147	Unknown	8748
Emerald ash borer	11 827	Total, all mortality agents and complexes	17 556
Gypsy moth	7886		
Balsam woolly adelgid	6074		
Other mortality agents (23)	8500		
Total, all mortality agents and complexes	71 217		
South			
Ips engraver beetles	5952		
Emerald ash borer	3486		
Unknown	1041		
Southern pine beetle	701		
Hemlock woolly adelgid	144		
Other mortality agents (1)	3		
Total, all mortality agents and complexes	11 327		

Note: The total area affected by other agents is listed at the end of each section. All values are “footprint” areas for each agent or complex. The sum of the individual agents is not equal to the total for all agents due to the reporting of multiple agents per polygon.

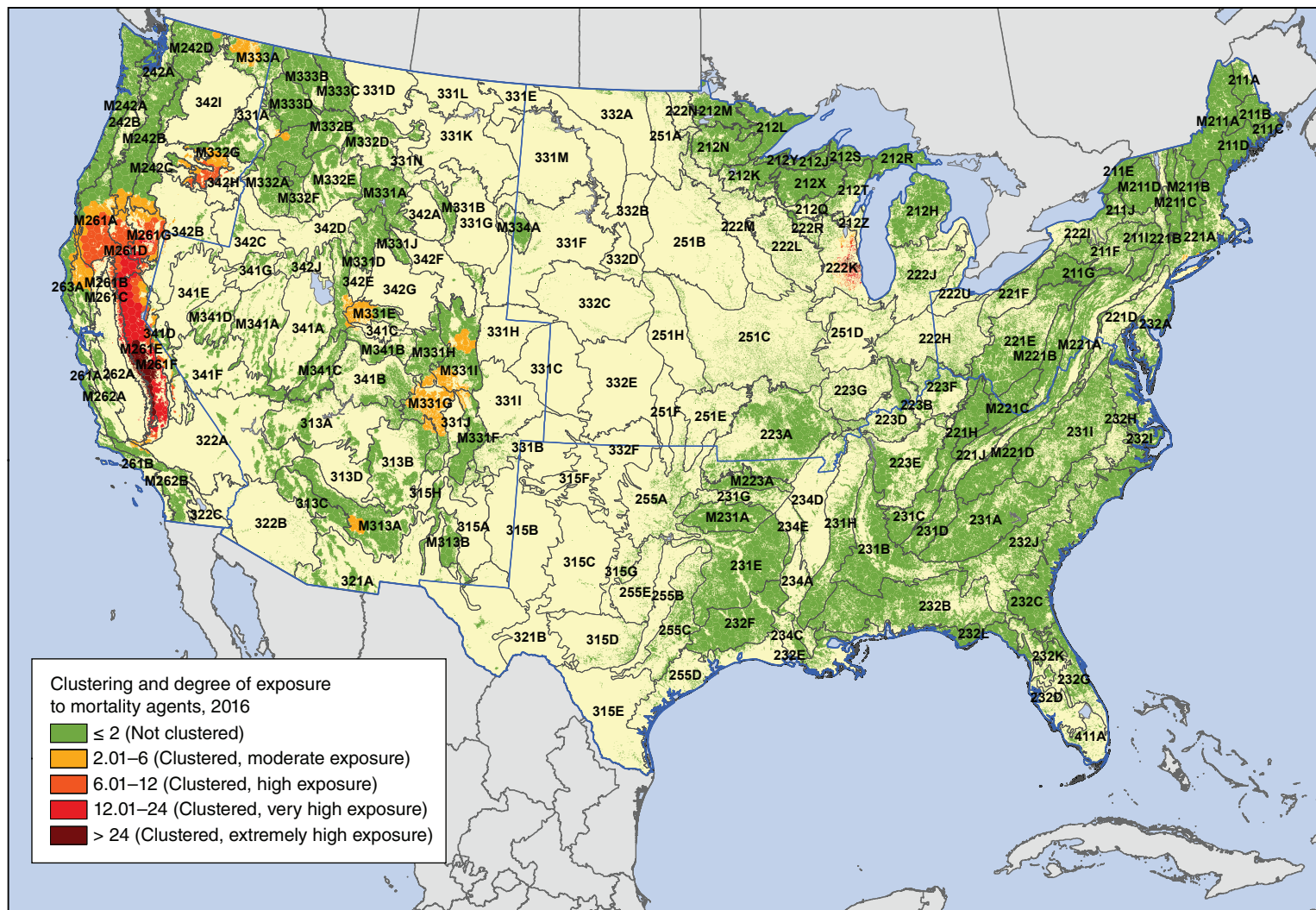


Figure 2.2—Hot spots of exposure to mortality-causing insects and diseases in 2016. Values are Getis-Ord G_i^* scores, with values > 2 representing significant clustering of high percentages of forest area exposed to mortality agents. (No areas of significant clustering of low percentages of exposure, < -2, were detected.) The gray lines delineate ecoregion sections (Cleland and others 2007), and blue lines delineate Forest Health Monitoring regions. Background forest cover is derived from MODIS imagery by the U.S. Forest Service Remote Sensing Applications Center. (Data source: U.S. Department of Agriculture, Forest Service, Forest Health Protection)

in lodgepole pine and ponderosa pine and western pine beetle mortality in ponderosa pine (fig. 2.2). The same agents caused a hot spot of moderate mortality exposure in northeastern Washington State (M333A–Okanogan Highland).

The FHM Interior West region had approximately 503 000 ha on which mortality-causing agents and complexes were detected in 2016 (table 2.3), second only to the West Coast region. About 44 percent of this was associated with spruce beetle; other agents recorded on large areas were western balsam bark beetle (*Dryocoetes confusus*) (13 percent), mountain pine beetle (10 percent), and Douglas-fir beetle (*Dendroctonus pseudotsugae*) (8 percent). A total of 17 mortality agents and complexes were detected in the region.

The Getis-Ord analysis detected four hot spots of moderate mortality exposure in the Interior West region in 2016 (fig. 2.2). A relatively extensive spruce beetle infestation in Engelmann spruce (*Picea engelmannii*) caused a mortality hot spot in south-central Colorado, centered on M331I–Northern Parks and Ranges, M331G–South-Central Highlands, and M331F–Southern Parks and Rocky Mountain Range. Similarly, a moderate-intensity hot spot in M331E–Uinta Mountains of northeastern Utah was mainly associated with spruce beetle-caused mortality in Engelmann spruce. Another hot spot in northern Colorado (M331I–Northern Parks and Ranges) was the result of both western balsam bark beetle mortality in subalpine fir and spruce beetle mortality in Engelmann spruce. Finally,

a small hot spot in M313A–White Mountains–San Francisco Peaks–Mogollon Rim in east-central Arizona was associated with fir engraver mortality in white fir stands, Douglas-fir beetle mortality in Douglas-fir stands, and unknown bark beetle mortality in ponderosa pine stands.

In the North Central FHM region, the FHP surveys recorded 17 mortality-causing agents and complexes on approximately 342 000 ha (table 2.3). Almost all of this area (288 000 ha, or 84 percent of the total) was exposed to emerald ash borer mortality. Other widespread agents and complexes were eastern larch beetle (*Dendroctonus simplex*) (8 percent of the mortality area) and Dutch elm disease (4 percent). Emerald ash borer was the cause of a hot spot of extremely high mortality exposure in 222K–Southwestern Great Lakes Morainal (fig. 2.2) along the western shore of Lake Michigan in Wisconsin.

In the North East FHM region, mortality was recorded on approximately 71 000 ha. The cause of about 35 percent of this mortality was not classified, but southern pine beetle was the most widely identified causal agent, found on 12 000 ha, or 17 percent of the total mortality area (table 2.3). Of the 28 agents and complexes detected in the region, three others affected areas exceeding 5000 ha: emerald ash borer, gypsy moth, and balsam woolly adelgid (*Adelges piceae*). One small geographic hot spot of mortality was detected in the North East FHM region, caused by southern pine beetle in pitch pine (*Pinus rigida*) stands on Long Island (221A–Lower New England).

In the South, mortality was detected on about 11 000 ha, with Ips engraver beetles the leading causal agent, on 6000 ha (53 percent of the total) (table 2.3). Emerald ash borer was associated with 3500 ha of mortality. No geographic hot spots of mortality were detected in the South FHM region.

Conterminous United States Defoliation

In 2016, the national IDS survey identified 63 defoliation agents and complexes affecting approximately 1.99 million ha across the conterminous United States (table 2.4), an area slightly less than the land area of Massachusetts. The most widespread defoliation agent was western spruce budworm (*Choristoneura occidentalis*), detected on approximately 916 000 ha. Three other insects—gypsy moth, forest tent caterpillar (*Malacosoma disstria*), and spruce budworm (*Choristoneura fumiferana*)—also affected more than 100 000 ha each (table 2.4).

The Interior West FHM region had the largest area on which defoliating agents and complexes were detected in 2016, approximately 969 000 ha (table 2.5), of which the vast majority (93 percent, or 898 000 ha) was associated with western spruce budworm (table 2.5). Unknown defoliators, Marssonina blight, and spruce aphid (*Elatobium abietinum*) were the next most widely detected defoliation agents of the 20 that were identified.

The 2016 Getis-Ord analysis detected several defoliation hot spots in the Interior West region (fig. 2.3). Most of these were associated with western spruce budworm

Table 2.4—Defoliation agents and complexes affecting more than 5000 ha in the conterminous United States in 2016

Agents/complexes causing defoliation, 2016	Area
	ha
Western spruce budworm	916 207
Gypsy moth	420 661
Forest tent caterpillar	330 362
Spruce budworm	111 714
Baldcypress leafroller	64 106
White pine needle damage	62 040
Browntail moth	28 401
Unknown defoliator	26 185
Marssonina blight	16 472
Loopers	15 786
Spruce aphid	13 041
Tamarisk leaf beetles	9178
Larch casebearer	7691
Unknown	7501
Winter moth	6981
Emerald ash borer	5085
Other (47)	43 428
Total, all defoliation agents	1 991 682

Note: All values are “footprint” areas for each agent or complex. The sum of the individual agents is not equal to the total for all agents due to the reporting of multiple agents per polygon.

Table 2.5—The top five defoliation agents or complexes for each Forest Health Monitoring region and for Alaska in 2016

Defoliation agents and complexes, 2016	Area	Defoliation agents and complexes, 2016	Area
	ha		ha
Interior West		South	
Western spruce budworm	897 507	Forest tent caterpillar	266 219
Unknown defoliator	21 477	Baldcypress leafroller	64 106
Marssonina blight	14 483	Gypsy moth	22 005
Spruce aphid	13 041	Unknown	732
Tamarisk leaf beetles	9178	Fall cankerworm	364
Other defoliation agents (15)	14 636	Other defoliation agents (3)	188
Total, all defoliation agents and complexes	969 108	Total, all defoliation agents and complexes	299 696
North Central		West Coast	
Spruce budworm	111 714	Western spruce budworm	18 700
Forest tent caterpillar	15 793	Lophodermium needle cast of pines	3371
Larch casebearer	7392	Needlecast	2652
Jumping oak gall wasp	4988	Marssonina blight	1989
Oak skeletonizer	4575	Larch needle cast	1171
Other defoliation agents (12)	11 057	Other defoliation agents (11)	2575
Total, all defoliation agents and complexes	155 520	Total, all defoliation agents and complexes	30 396
North East		Alaska	
Gypsy moth	398 354	Aspen leafminer	82 581
White pine needle damage	62 040	Speckled green fruitworm	65 521
Forest tent caterpillar	46 767	Willow leaf blotchminer	59 129
Browntail moth	28 401	Unknown defoliator	37 934
Loopers	15 786	Spruce aphid	13 971
Other defoliation agents (21)	23 575	Other defoliation agents (8)	13 310
Total, all defoliation agents and complexes	536 962	Total, all defoliation agents and complexes	272 301

Note: The total area affected by other agents is listed at the end of each section. All values are “footprint” areas for each agent or complex. The sum of the individual agents is not equal to the total for all agents due to the reporting of multiple agents per polygon.

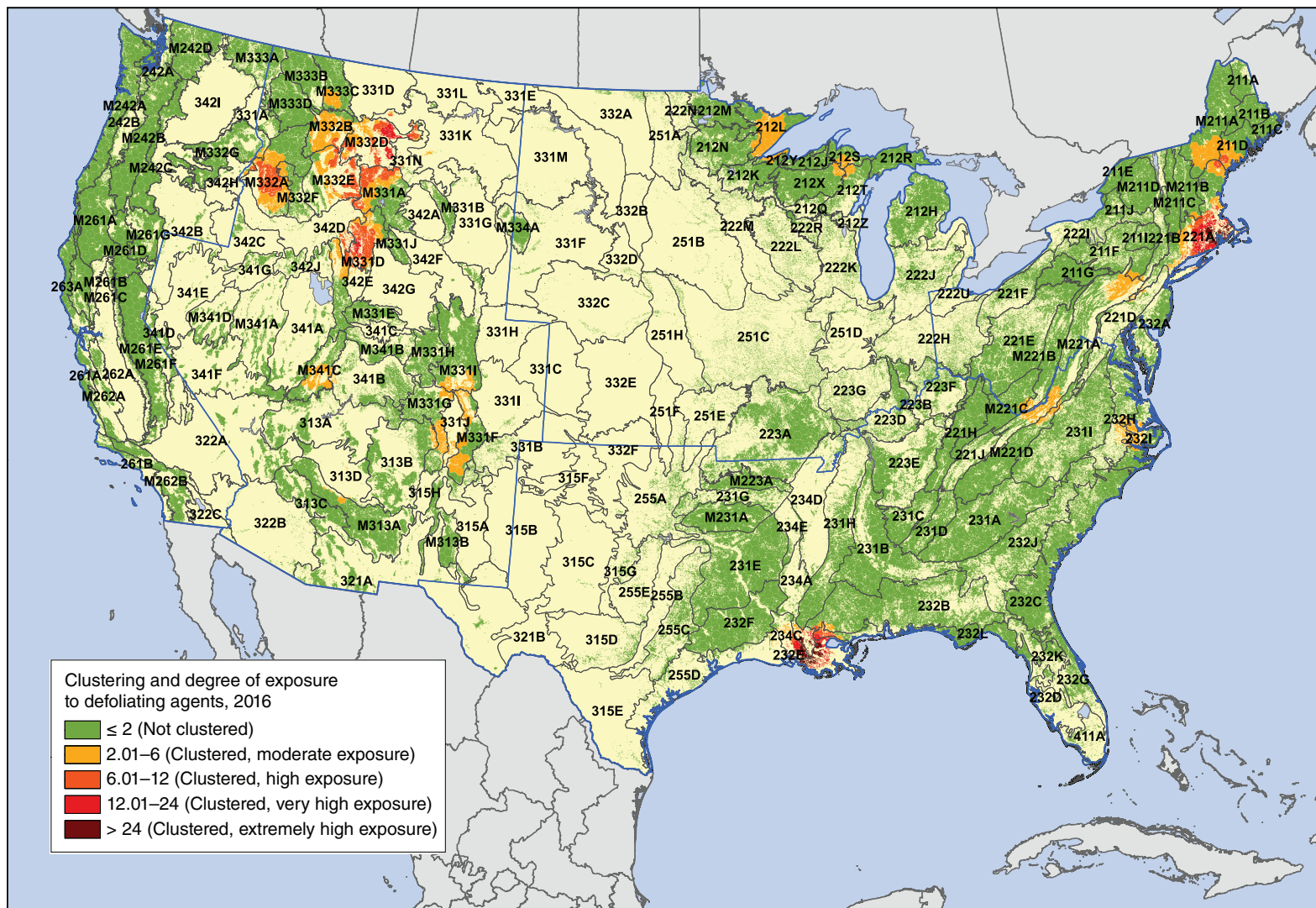


Figure 2.3—Hot spots of exposure to defoliation-causing insects and diseases in 2016. Values are Getis-Ord G_i^* scores, with values > 2 representing significant clustering of high percentages of forest area exposed to defoliation agents. (No areas of significant clustering of low percentages of exposure, < -2, were detected.) The gray lines delineate ecoregion sections (Cleland and others 2007), and blue lines delineate Forest Health Monitoring regions. Background forest cover is derived from MODIS imagery by the U.S. Forest Service Remote Sensing Applications Center. (Data source: U.S. Department of Agriculture, Forest Service, Forest Health Protection)

(along with other agents) and overlapped a similar hot spot from 2014 (Potter and Paschke 2016) and 2015 (Potter and Paschke 2017). The largest of these, of very high defoliation exposure in western Montana, was centered on M332D–Belt Mountains, M332E–Beaverhead Mountains, M332B–Northern Rockies and Bitterroot Valley, and M331A–Yellowstone Highlands, roughly corresponding to hot spots the two previous years. It was associated with western spruce budworm in subalpine fir and Douglas-fir forests. Also as in 2014 and 2015, western spruce budworm activity in Douglas-fir forests and subalpine fir resulted in a hot spot of high defoliation exposure in central Idaho (M332A–Idaho Batholith) as well as one of very high and high exposure in western Wyoming and southeastern Idaho (M331D–Overthrust Mountains).

Again, as in recent years, western spruce budworm outbreaks also resulted in hot spots of defoliation in north-central New Mexico and south-central Colorado, in M331G–South-Central Highlands, M331F–Southern Parks and Rocky Mountain Range, and M331I–Northern Parks and Ranges (fig. 2.3). Another hot spot of moderate western spruce budworm defoliation exposure appeared in M341C–Utah High Plateau.

Twenty-six defoliation agents and complexes were identified on about 537 000 ha in the North East FHM region, with gypsy moth the most widely detected on more than 74 percent of this area (more than 398 000 ha). White pine needle damage was recorded on more than 62 000 ha,

forest tent caterpillar on nearly 47 000 ha, and browntail moth (*Euproctis chrysorrhoea*) on 28 000 ha (table 2.5). One gypsy moth outbreak in Massachusetts, Rhode Island, and Connecticut resulted in a hot spot of extremely high defoliation exposure in 221A–Lower New England, while another in eastern Pennsylvania generated a hot spot of moderate defoliation exposure centered in M221A–Northern Ridge and Valley (fig. 2.3). Meanwhile, a third hot spot in the North East region was located in southern Maine and northern New Hampshire (211D–Central Maine Coastal and Embayment, 221A–Lower New England, and M211A–White Mountains), associated with white pine needle damage, browntail moth, winter moth (*Operophtera brumata*), and forest tent caterpillar.

In 2016, approximately 300 000 ha of defoliation was documented in the South FHM region. Almost 89 percent of this, or 266 000 ha, was associated with forest tent caterpillar (table 2.5). An additional seven agents and complexes were found, including baldcypress leafroller (*Archips goyerana*) on about 64 000 ha and gypsy moth on about 22 000 ha. A hot spot of extremely high exposure to defoliating agents, caused by both baldcypress leafroller and forest tent caterpillar, was located in three ecoregions of southern Louisiana, 234C–Atchafalaya and Red River Alluvial Plains, 234A–Southern Mississippi Alluvial Plain, and 232E–Louisiana Coastal Prairie and Marshes (fig. 2.3). Another hot spot of moderate defoliation exposure associated with forest tent caterpillar was detected in eastern North Carolina (in 232H–Middle Atlantic Coastal

Plains and Flatwoods and 232I–Northern Atlantic Coastal Flatwoods). Finally, a third hot spot, also of moderate exposure, was caused by gypsy moth and emerald ash borer in M221A–Northern Ridge and Valley, M221D–Blue Ridge Mountains, M221C–Northern Cumberland Mountains, and M221B–Allegheny Mountains.

Meanwhile, 17 agents and complexes were associated with about 156 000 ha of defoliation in the North Central FHM region (table 2.5). Spruce budworm was the most commonly detected defoliation agent in the region, found on a little less than 112 000 ha, or 72 percent of the defoliated area. Other widespread defoliators were forest tent caterpillar and larch casebearer (*Coleophora laricella*), affecting approximately 16 000 ha and 7000 ha, respectively (table 2.5). Our geographic hot spot analysis detected two clusters of moderate defoliation exposure in North Central FHM region (fig. 2.3). One in northeastern Minnesota (212L–Northern Superior Uplands) was associated with spruce budworm and forest tent caterpillar, and one in the Upper Peninsula of Michigan (at the intersection of 212S–Northern Upper Peninsula, 212X–Northern Highlands, and 212T–Northern Green Bay Lobe) was associated with spruce budworm and large aspen tortrix (*Choristoneura conflictana*).

Finally, western spruce budworm accounted for about 62 percent of the approximately 30 400 ha of defoliation recorded in the FHM West Coast region (table 2.5). Of the

16 defoliation agents and complexes detected in the region, the next most widely found was *Lophodermium* needle cast of pines (*Lophodermium* spp.) on 3400 ha. No geographic hot spots of defoliation were identified in the region.

Alaska and Hawaii

In Alaska, mortality was recorded on approximately 98 000 ha in 2016, attributed to five agents and complexes (table 2.3). This is a very small proportion (< 0.25 percent) of the forested area surveyed. Spruce beetle was the most widely detected mortality agent, recorded on about 76 000 ha, thereby encompassing about 78 percent of all mortality. Most of this mortality occurred in the south-central part of the State (especially in 213B–Cook Inlet Lowlands and M135C–Alaska Range). Yellow-cedar (*Chamaecyparis nootkatensis*) decline was the next most widely detected mortality agent, found on about 16 000 ha in the Alaska panhandle (M245B–Alexander Archipelago). Northern spruce engraver (*Ips perturbatus*) was detected on about 6000 ha, mostly in the east-central forested areas of Alaska.

The percentage of surveyed forest exposed to mortality agents in 2016 was highest in 213B–Cook Inlet Lowlands, where it was 5.9 percent (fig. 2.4) as a result of spruce beetle damage. Relatively high percentages of mortality were detected in the surveyed areas of M135C–Alaska Range (2.5 percent) and M245B–Alexander Archipelago (1.0 percent).

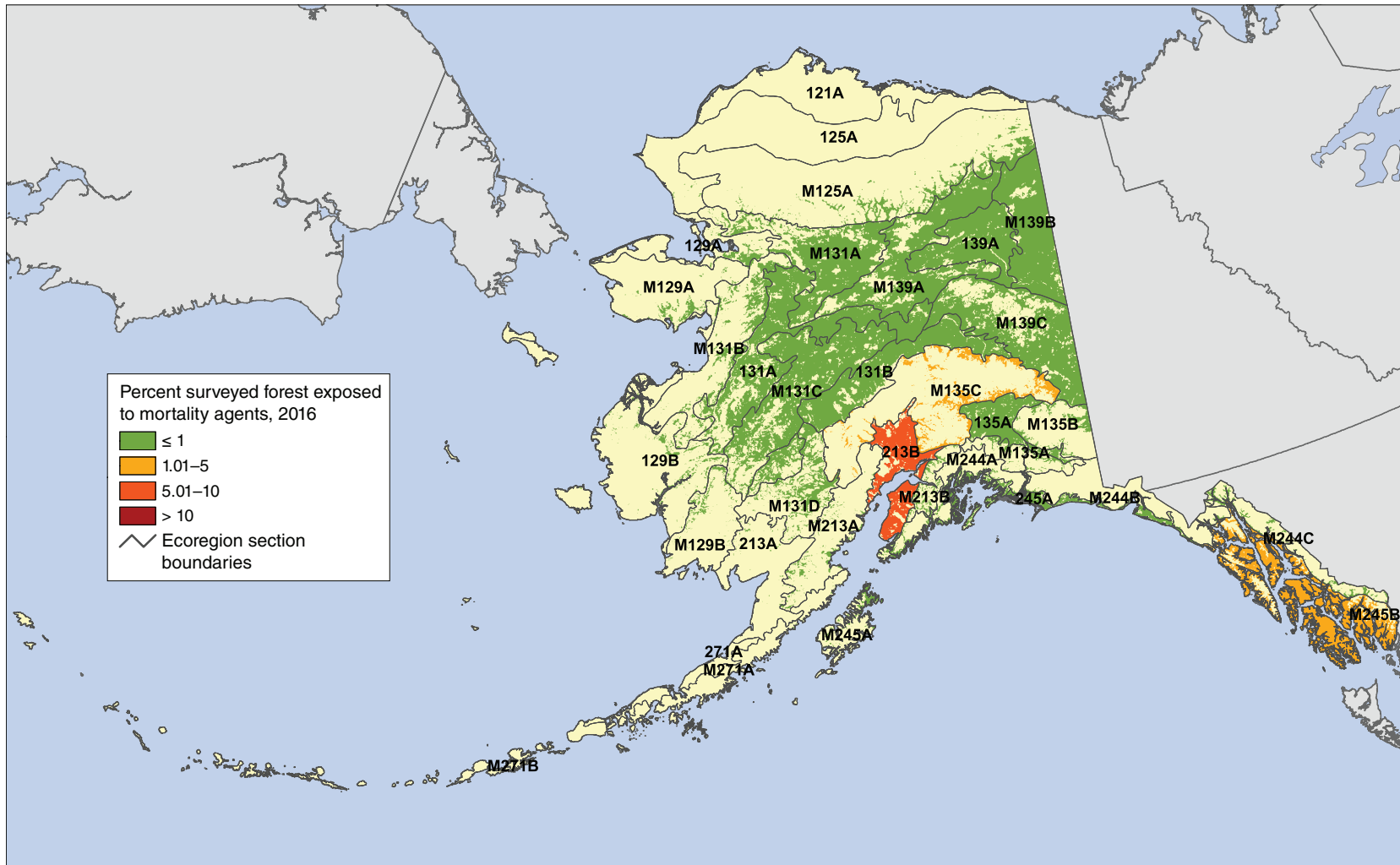


Figure 2.4—Percentage of surveyed forest in Alaska ecoregion sections exposed to mortality-causing insects and diseases in 2016. The gray lines delineate ecoregion sections (Nowacki and Brock 1995). Background forest cover is derived from MODIS imagery by the U.S. Forest Service Remote Sensing Applications Center. (Data source: U.S. Department of Agriculture, Forest Service, Forest Health Protection)

Meanwhile, defoliators in Alaska were detected on nearly three times as much surveyed area than mortality during 2016, with 13 defoliating agents recorded on approximately 272 000 ha (table 2.5). Of this area, about 30 percent (83 000 ha) was attributed to aspen leafminer (*Phyllocnistis populiella*). Meanwhile, speckled green fruitworm (*Orthosia hibisci*) was detected on about 65 500 ha, and willow leaf blotchminer (*Micrurapteryx salicifoliella*) was recorded on 59 000 ha.

The Alaska ecoregion section with the highest proportion of surveyed forest area affected by defoliators in 2016 was 139A–Yukon Flats (9.4 percent of surveyed forest) (fig. 2.5), where willow leaf blotchminer and aspen leafminer were commonly reported in willow (*Salix* spp.) and quaking aspen (*Populus tremuloides*) stands. Several ecoregion sections in the central and southwestern parts of Alaska had moderate levels of detected defoliation, including M213A–Northern Aleutian Range (6.3 percent, speckled green fruitworm in hardwood stands), M135C–Alaska Range (4.4 percent, also speckled green fruitworm), and M129B–Ahklun Mountains (4.0 percent, speckled green fruitworm and willow leaf blotchminer).

In 2016, approximately 18 000 ha of mortality was recorded in Hawaii (table 2.3), with about half of unknown cause and half attributed to rapid ‘ōhi‘a death, a wilt disease caused by the fungal pathogen *Ceratocystis fimbriata* that affects ‘ōhi‘a lehua (*Metrosideros polymorpha*), a highly ecologically and culturally important tree species in Hawaiian native forests (University of Hawai‘i 2017).

CONCLUSION

Continued monitoring of insect and disease outbreaks across the United States will be necessary for determining appropriate followup investigation and management activities. Due to the limitations of survey efforts to detect certain important forest insects and diseases, the pests and pathogens discussed in this chapter do not include all the biotic forest health threats that should be considered when making management decisions and budget allocations. However, large-scale assessments of mortality and defoliation exposure, including geographical hot spot detection analyses, offer a useful approach for identifying geographic areas where the concentration of monitoring and management activities might be most effective.

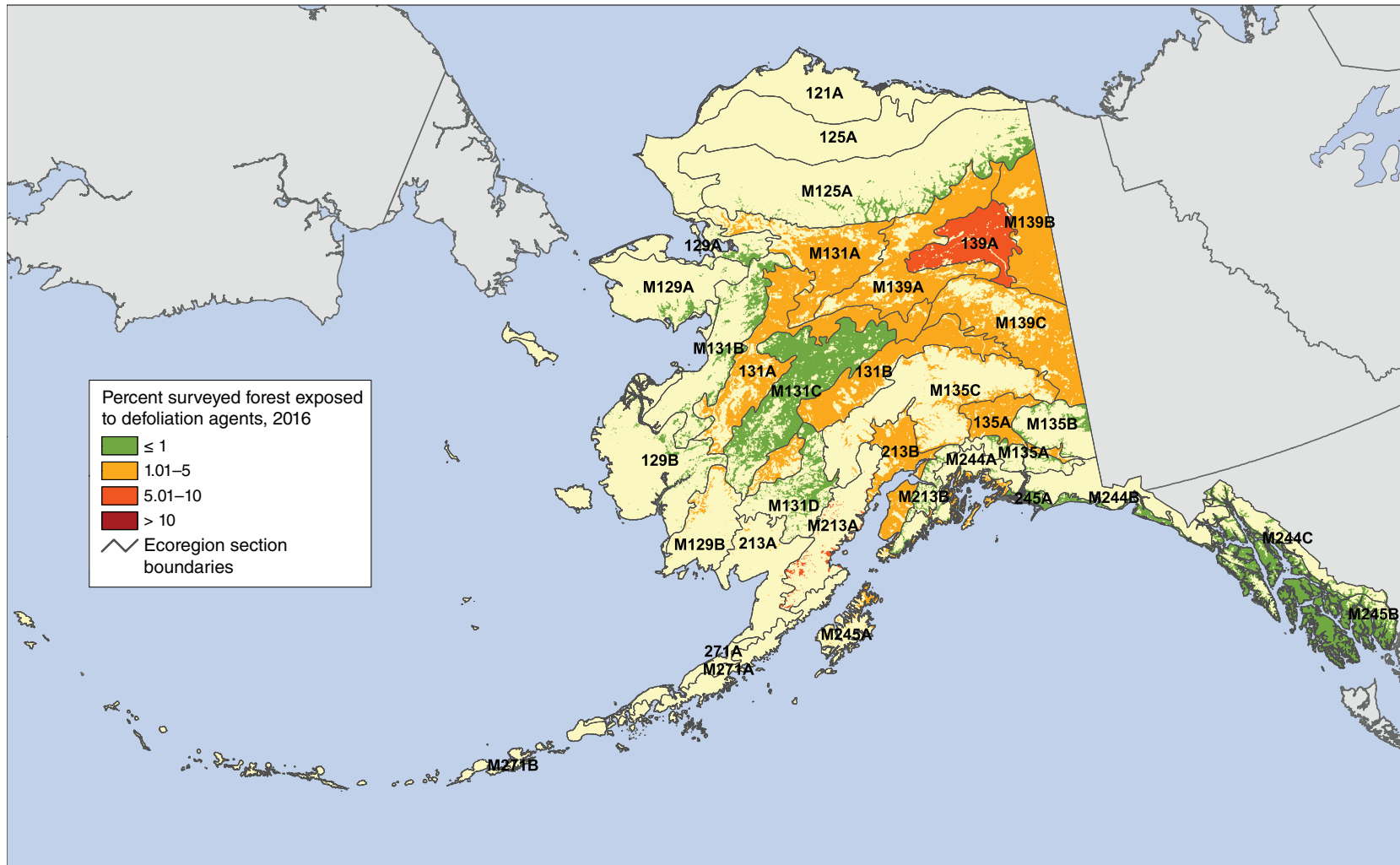


Figure 2.5—Percentage of surveyed forest in Alaska ecoregion sections exposed to defoliation-causing insects and diseases in 2016. The gray lines delineate ecoregion sections (Nowacki and Brock 1995). Background forest cover is derived from MODIS imagery by the U.S. Forest Service Remote Sensing Applications Center. (Data source: U.S. Department of Agriculture, Forest Service, Forest Health Protection)

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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

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

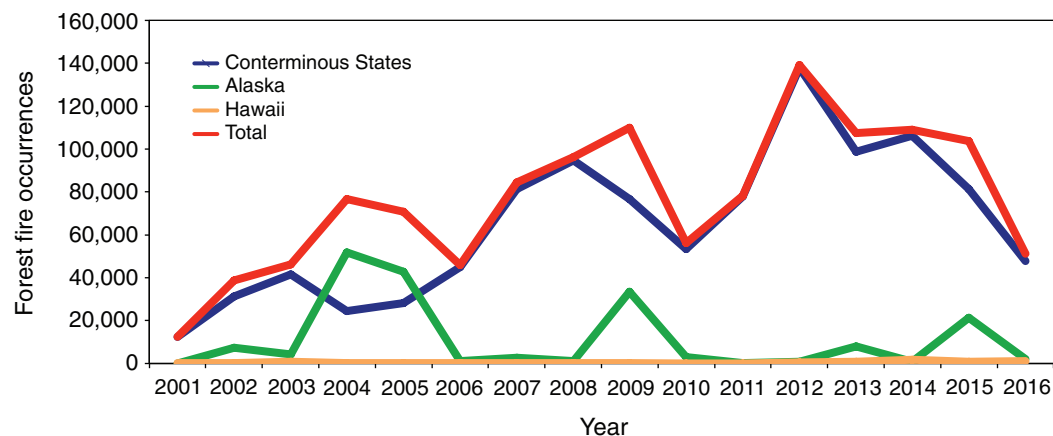


Figure 3.1—Forest fire occurrences detected by MODIS from 2001 to 2016 for the conterminous United States, Alaska, and Hawaii, and for the entire Nation combined. (Data source: U.S. Department of Agriculture, Forest Service, Remote Sensing Applications Center, in conjunction with the NASA MODIS Rapid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

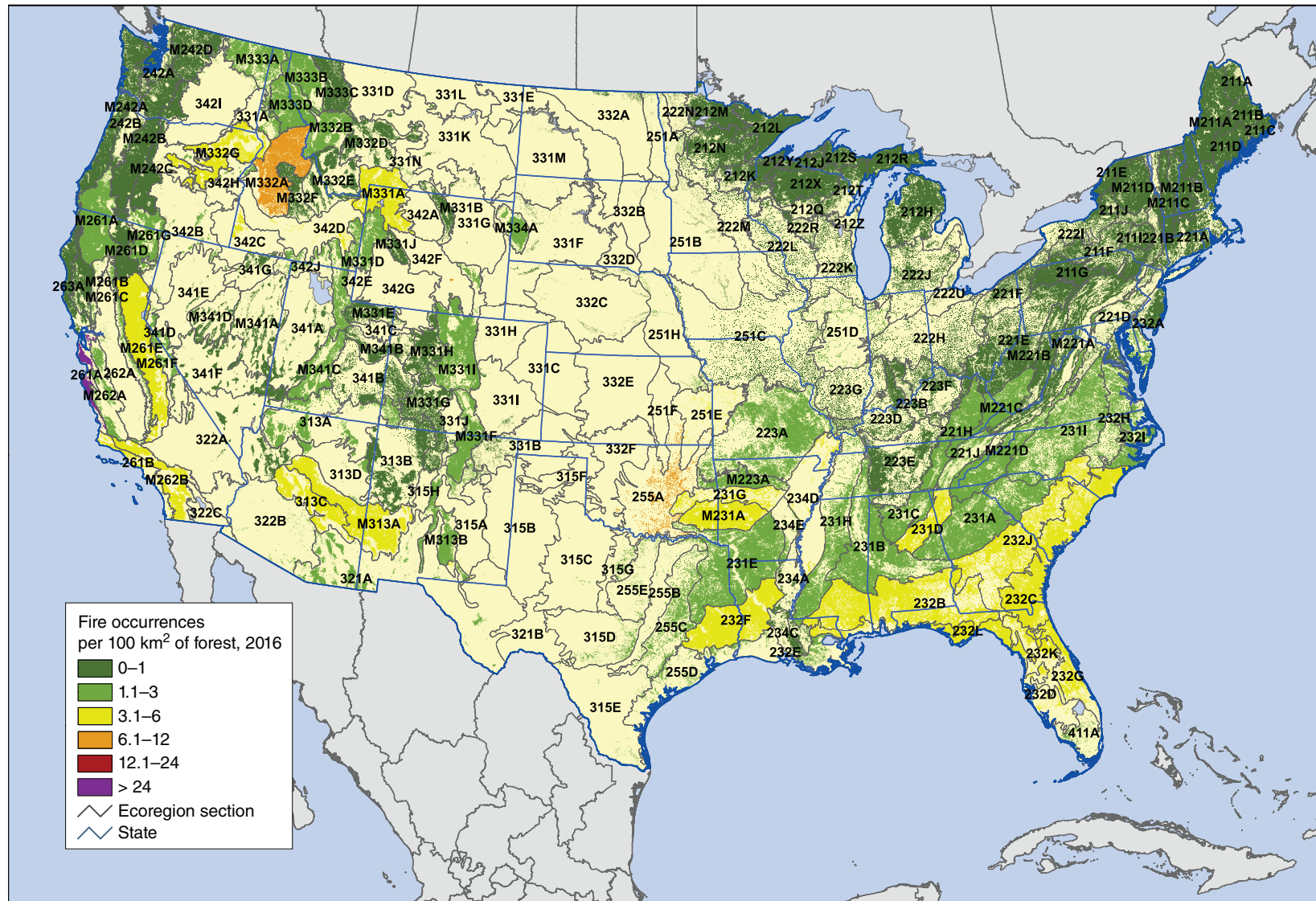


Figure 3.2—The number of forest fire occurrences per 100 km² (10 000 ha) of forested area, by ecoregion section within the conterminous United States, for 2016. The gray lines delineate ecoregion sections (Cleland and others 2007). Forest cover is derived from MODIS imagery by the U.S. Forest Service 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).

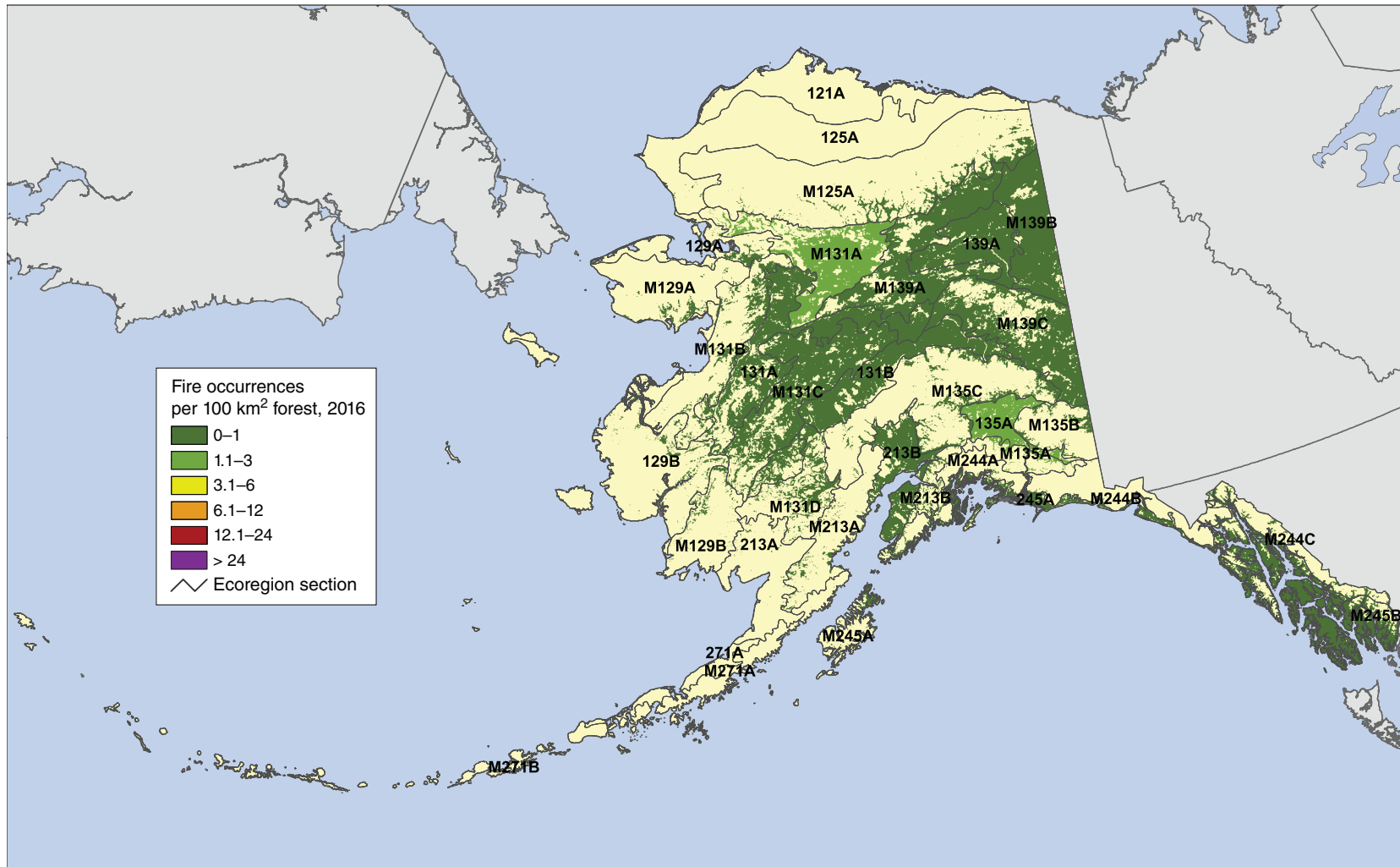


Figure 3.3—The number of forest fire occurrences per 100 km² (10 000 ha) of forested area, by ecoregion section within Alaska, for 2016. The gray lines delineate ecoregion sections (Nowacki and Brock 1995). Forest cover is derived from MODIS imagery by the U.S. Forest Service Remote Sensing Applications 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

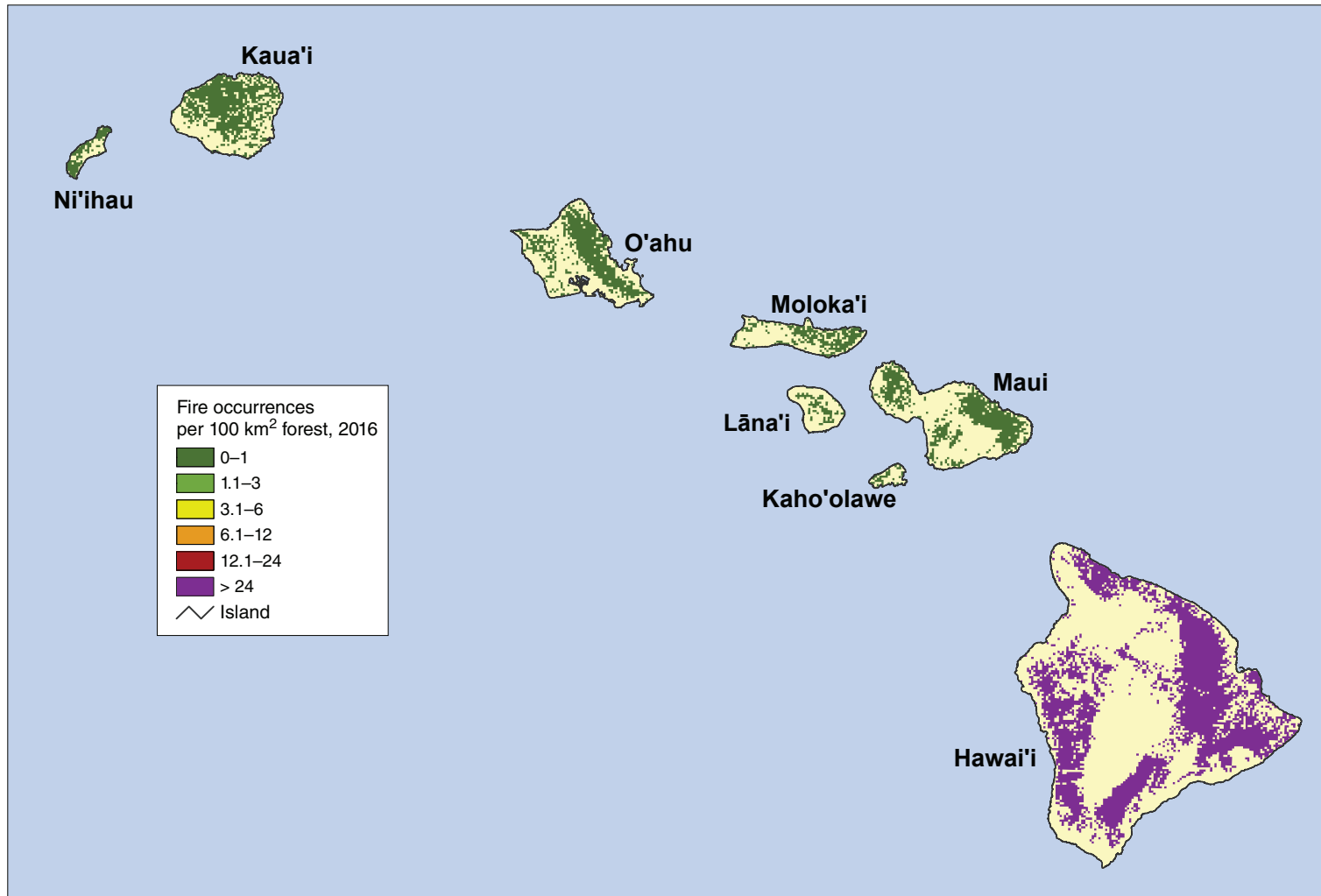


Figure 3.4—The number of forest fire occurrences per 100 km² (10 000 ha) of forested area, by island in Hawaii, for 2016. Forest cover is derived from MODIS imagery by the U.S. Forest Service Remote Sensing Applications Center. (Source of fire data: U.S. Department of Agriculture, Forest Service, Remote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

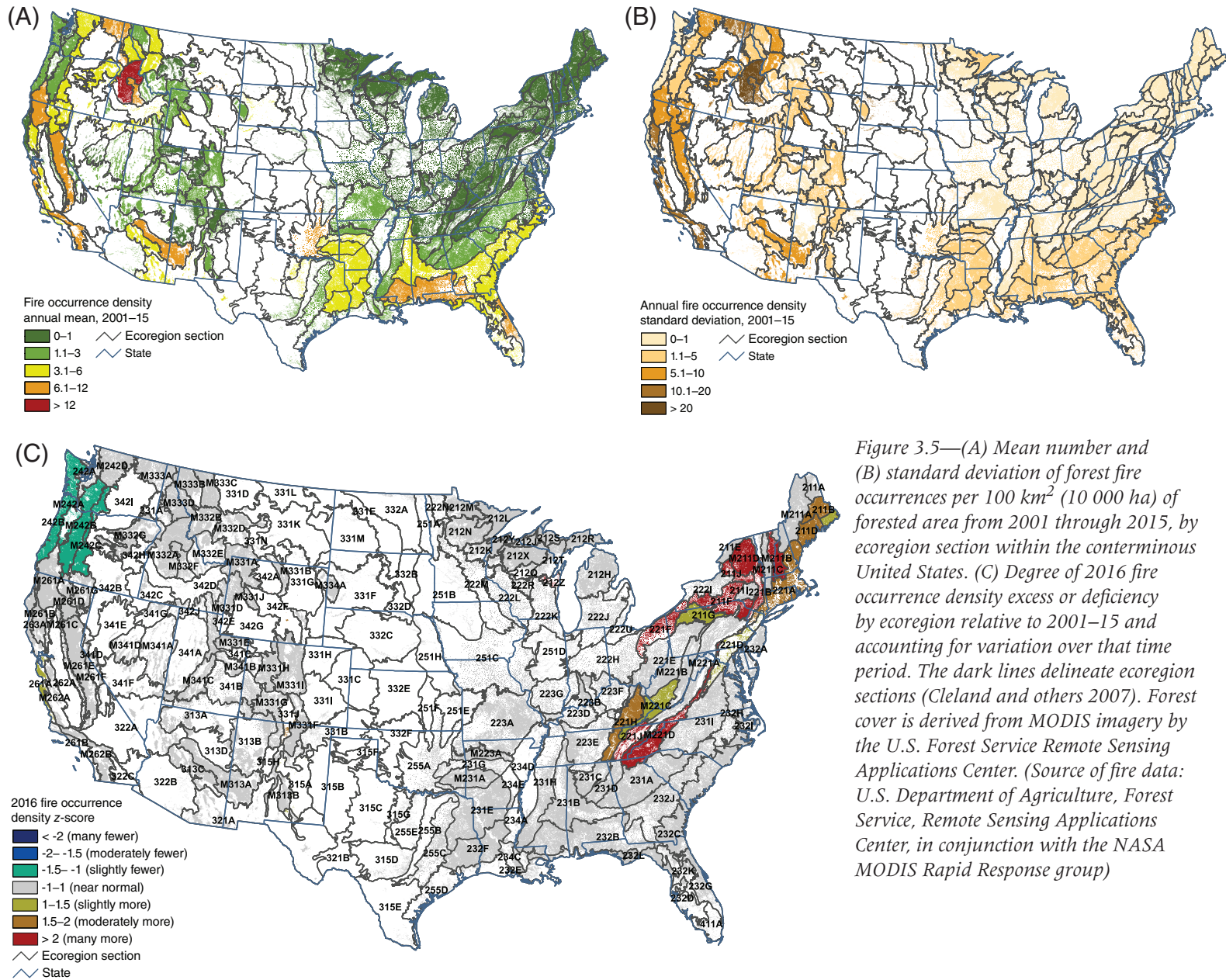


Figure 3.5—(A) Mean number and (B) standard deviation of forest fire occurrences per 100 km² (10 000 ha) of forested area from 2001 through 2015, by ecoregion section within the conterminous United States. (C) Degree of 2016 fire occurrence density excess or deficiency by ecoregion relative to 2001–15 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).

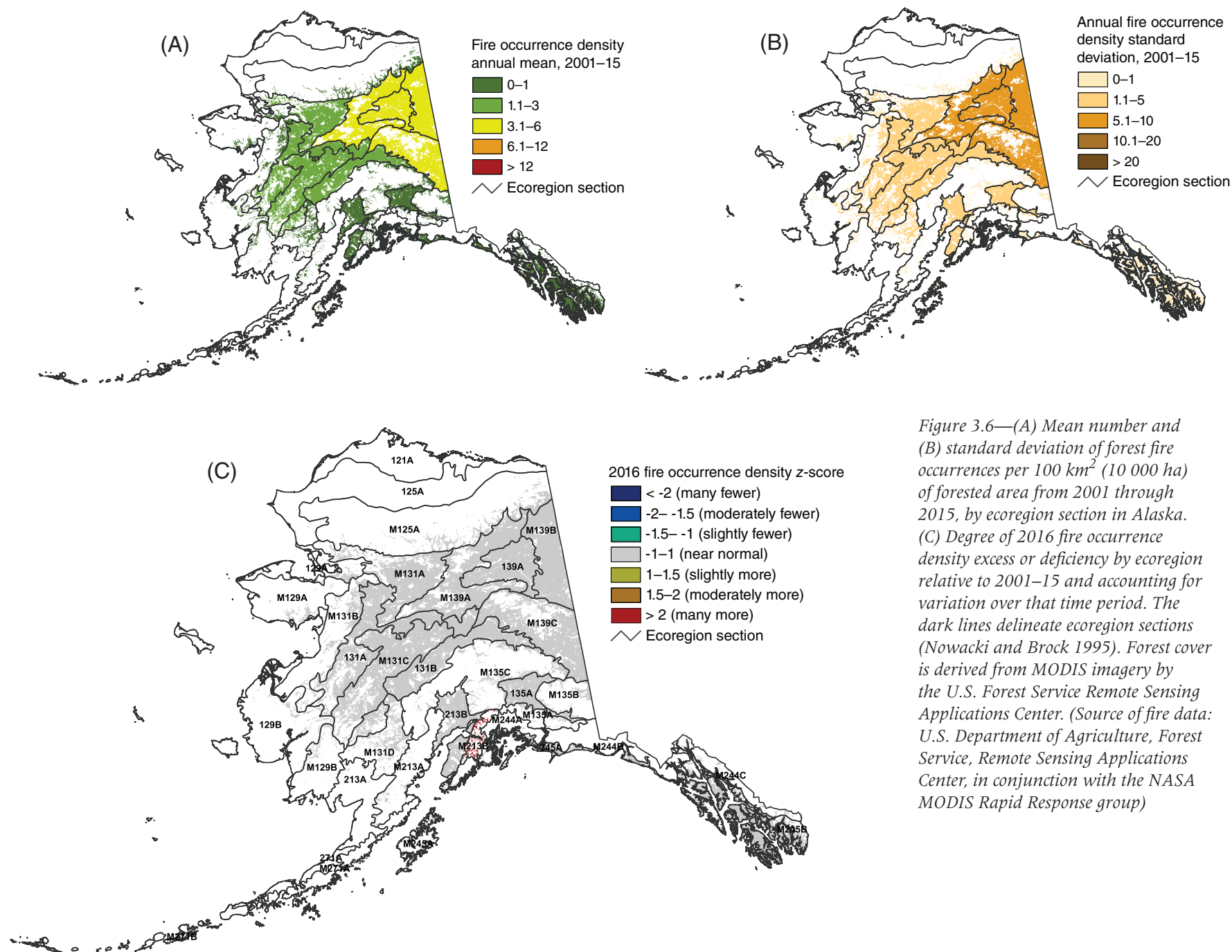


Figure 3.6—(A) Mean number and (B) standard deviation of forest fire occurrences per 100 km² (10 000 ha) of forested area from 2001 through 2015, by ecoregion section in Alaska. (C) Degree of 2016 fire occurrence density excess or deficiency by ecoregion relative to 2001–15 and accounting for variation 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)

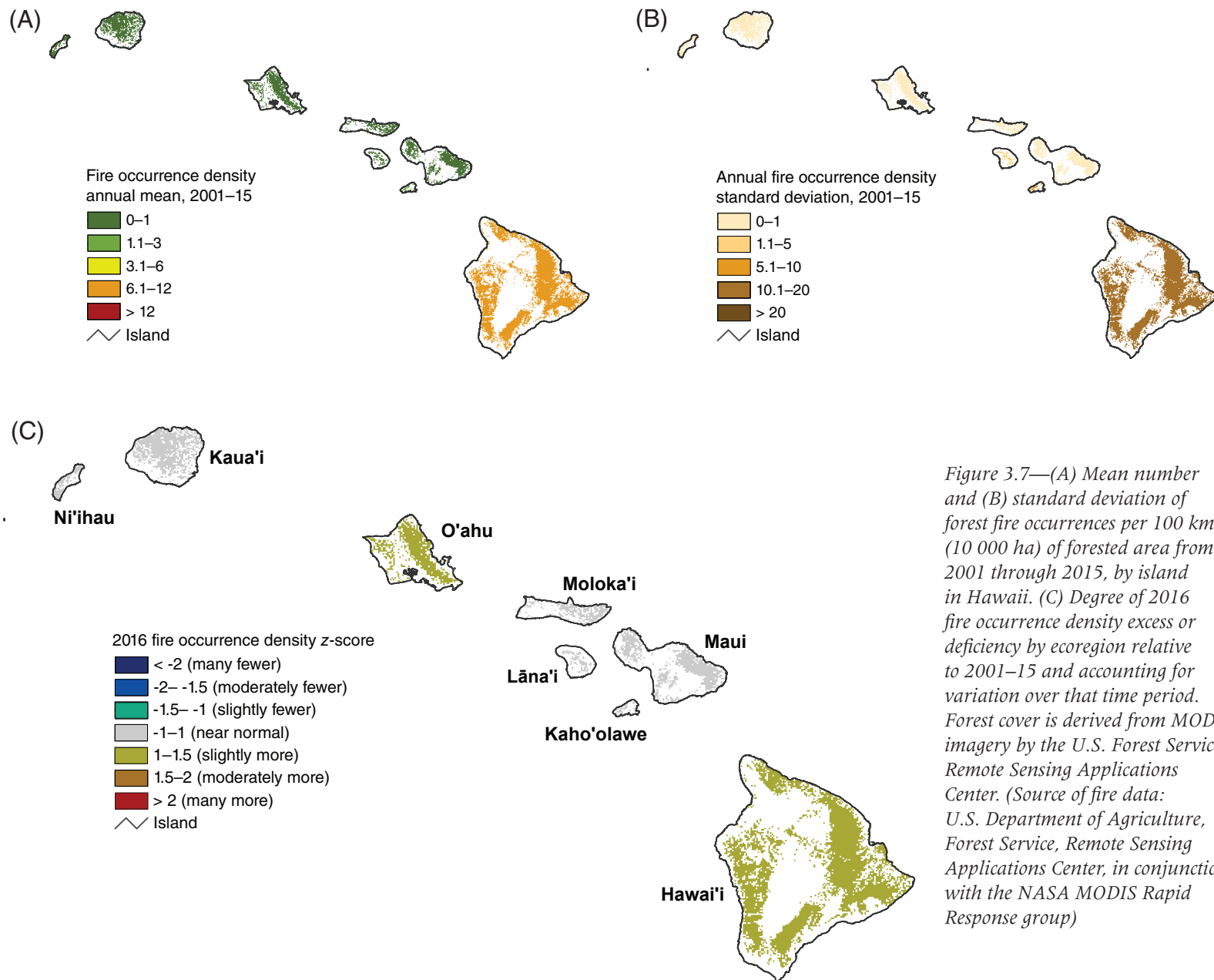
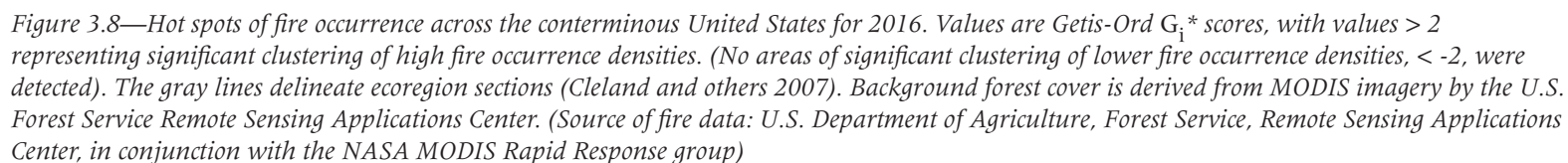


Figure 3.7—(A) Mean number and (B) standard deviation of forest fire occurrences per 100 km² (10 000 ha) of forested area from 2001 through 2015, by island in Hawaii. (C) Degree of 2016 fire occurrence density excess or deficiency by ecoregion relative to 2001–15 and accounting for variation over that 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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INTRODUCTION

Droughts affect most forested ecosystems of the United States, but they vary widely in frequency and intensity (Hanson and Weltzin 2000). Most western U.S. forests experience annual seasonal droughts, with the seasonality determined by broad-scale atmospheric circulation patterns and topography. For example, forests along the Pacific Coast usually experience dry summers and wet winters, while forests in Arizona and western New Mexico rely in part on rainfall received during a summer monsoon season (Adams and Comrie 1997, Hanson and Weltzin 2000). In contrast, eastern U.S. forests typically exhibit one of two predominant drought patterns: random (i.e., occurring at any time of year) occasional droughts, as observed in the Appalachian Mountains and the Northeast, or frequent late-summer droughts, as commonly seen in the southeastern Coastal Plain and the eastern portion of the Great Plains (Hanson and Weltzin 2000).

In forests, reduced moisture availability during droughts can cause considerable tree stress, and that stress is amplified when droughts coincide with hot conditions, especially heat waves or other extreme heat events (Allen and others 2010, L.D.L. Anderegg and others 2013, Peters and others 2015, Teskey and others 2015, Williams and others 2013). Trees, like

other plants, respond initially to drought stress by decreasing fundamental growth processes such as cell division and enlargement. Because photosynthesis is less sensitive than these fundamental processes, it decreases slowly at low levels of stress. However, as drought stress intensifies, trees and other plants close their stomata to minimize water loss, causing photosynthesis to decline more sharply (Kareiva and others 1993, Kolb and others 2016, Mattson and Haack 1987). In addition to such direct effects, drought stress often makes trees susceptible to attack by damaging insects and diseases (Clinton and others 1993, Mattson and Haack 1987, Raffa and others 2008), although this may be more of a problem in the water-limited forests of the Western United States (Kolb and others 2016). Droughts also increase wildland fire risk by inhibiting organic matter decomposition and lowering the moisture content of downed woody debris and other potential fire fuels (Clark 1989, Keetch and Byram 1968, Schoennagel and others 2004, Trouet and others 2010).

In general, forests are resistant to short-term droughts, although individual tree species differ in their levels of drought resistance (Archaux and Wolters 2006, Berdanier and Clark 2016). Because of this resistance, the duration of drought events may be more important for forests than their intensity (Archaux and Wolters 2006). For instance, forested areas subjected

CHAPTER 4. Moisture Deficit and Surplus in the Conterminous United States for Three Time Windows: 2016, 2014–2016, and 2012–2016

FRANK H. KOCH

JOHN W. COULSTON

to multiple consecutive years of drought (2–5 years) are much more likely to experience high tree mortality than areas subjected to a single year of extremely dry conditions (Guarín and Taylor 2005, Millar and others 2007). Therefore, a comprehensive evaluation of drought impact in forests should include analysis of moisture conditions over multi-year time windows.

In the 2010 Forest Health Monitoring (FHM) national report, we described a method for mapping drought conditions across the conterminous United States (Koch and others 2013a). Our objective was to generate fine-scale, drought-related spatial datasets that improve upon similar products available from sources such as the National Climatic Data Center (2015) or the U.S. Drought Monitor program (Svoboda and others 2002). The principal inputs are gridded climate data (i.e., monthly raster maps of precipitation and temperature over a 100-year period) created with the Parameter-elevation Regression on Independent Slopes (PRISM) climate mapping system (Daly and others 2002). The method utilizes a standardized indexing approach that facilitates comparison of a given location's moisture status during different time windows, regardless of their length. The index is easier to calculate than the commonly used Palmer Drought Severity Index, or PDSI (Palmer 1965), and avoids some criticisms of the PDSI (summarized by Alley 1984) regarding its underlying assumptions and limited

comparability across space and time. Here, we applied the method outlined in the 2010 FHM Report to the most currently available climate data (i.e., the monthly PRISM data through 2016), thereby providing the eighth installment in an ongoing series of annual drought assessments for the conterminous United States from 2009 forward (Koch and Coulston 2015, 2016, 2017; Koch and others 2013a, 2013b, 2014, 2015).

This is the third year in which we also mapped the degree of moisture surplus across the conterminous United States during multiple time windows. Much recent refereed literature (e.g., Adams and others 2009, Allen and others 2010, Martínez-Vilalta and others 2012, Peng and others 2011, Williams and others 2013) has tended to focus on reports of widespread, regional-scale forest decline and mortality due to persistent drought conditions, especially in conjunction with periods of extremely high temperatures (i.e., heat waves). However, surplus moisture availability can also be detrimental to forests. Abnormally high moisture can be a short-term stressor (e.g., an extreme rainfall event with subsequent flooding) or a long-term stressor (e.g., persistent wetness driven by a macroscale climatic pattern such as the El Niño-Southern Oscillation), either of which may contribute to tree dieback and mortality (Rozas and García-González 2012, Rozas and Sampedro 2013). Such impacts have

been observed in both tropical and temperate forests (Laurance and others 2009, Rozas and García-González 2012). While surplus-induced impacts in forests are probably not as common as drought-induced impacts, a single index that depicts both moisture surplus and deficit conditions provides a fuller accounting of potential forest health issues.

METHODS

We acquired grids for monthly precipitation and monthly mean temperature for the conterminous United States from the PRISM Climate Group Web site (PRISM Climate Group 2017). At the time of these analyses, gridded datasets were available for all years from 1895 to 2016. However, the grids for December 2016 were only provisional versions (i.e., finalized grids had not yet been released). For analytical purposes, we treated these provisional grids as if they were the final versions. The spatial resolution of the grids was approximately 4 km (cell area = 16 km²). For future applications and to ensure better compatibility with other spatial datasets, all output grids were resampled to a spatial resolution of approximately 2 km (cell area = 4 km²) using a nearest neighbor approach. The nearest neighbor approach is a computationally simple resampling method that avoids the smoothing of data values observed with methods such as bilinear interpolation or cubic convolution.

Potential Evapotranspiration (PET) Maps

As in our previous drought mapping efforts (Koch and Coulston 2015, 2016, 2017; Koch and others 2012a, 2012b, 2013a, 2013b, 2014, 2015), we adopted an approach in which a moisture index value is calculated for each location of interest (i.e., each grid cell in a map of the conterminous United States) during a given time period. Moisture indices are intended to reflect the amount of available water (e.g., to support plant growth) in different locations. By extension, they also depict the relative wetness or dryness of those locations (Willmott and Feddema 1992). Generally, moisture indices are computed as functions of the ratio of moisture supply to moisture demand (Willmott and Feddema 1992). In our case, the index is computed as a function of the amount of precipitation that falls on a location during the time period of interest (i.e., the moisture supply) as well as the level of potential evapotranspiration during this period (i.e., the moisture demand). Potential evapotranspiration measures the loss of soil moisture through plant uptake and transpiration (Akin 1991). It does not measure actual moisture loss, but rather the loss that would occur if there was no possible shortage of moisture for plants to transpire (Akin 1991, Thornthwaite 1948).

To complement the available PRISM monthly precipitation grids, we computed corresponding monthly potential evapotranspiration (*PET*)

grids using Thornthwaite's formula (Akin 1991, Thornthwaite 1948):

$$PET_m = 1.6L_{lm}\left(10\frac{T_m}{I}\right)^a \quad (1)$$

where

PET_m = the potential evapotranspiration for a given month m in cm

L_{lm} = a correction factor for the mean possible duration of sunlight during month m for all locations (i.e., grid cells) at a particular latitude l [see table V in Thornthwaite (1948) for a list of L correction factors by month and latitude]

T_m = the mean temperature for month m in degrees C

I = an annual heat index, calculated as

$$I = \sum_{m=1}^{12} \left(\frac{T_m}{5}\right)^{1.514}$$

where

T_m is the mean temperature for each month m of the year

a = an exponent calculated as $a = 6.75 \times 10^{-7}I^3 - 7.71 \times 10^{-5}I^2 + 1.792 \times 10^{-2}I + 0.49239$ [see appendix I in Thornthwaite (1948) regarding calculation of I and the empirical derivation of a]

Although only a simple approximation, a key advantage of Thornthwaite's formula is that it has modest input data requirements (i.e.,

mean temperature values) compared to more sophisticated methods of estimating PET such as the Penman-Monteith equation (Monteith 1965), which requires less readily available data on factors such as humidity, radiation, and wind speed. To implement Equation 1 spatially, we created a grid of latitude values for determining the L adjustment for any given grid cell (and any given month) in the conterminous United States. We extracted the T_m values for the grid cells from the corresponding PRISM mean monthly temperature grids.

Moisture Index Maps

To estimate baseline conditions, we used the precipitation (P) and PET grids to generate moisture index grids for the past 100 years (i.e., 1917-2016) for the conterminous United States. We used a moisture index described by Willmott and Feddema (1992), which has been applied in a variety of contexts, including global vegetation modeling (Potter and Klooster 1999) and climate change analysis (Grundstein 2009). Willmott and Feddema (1992) devised the index as a refinement of one described earlier by Thornthwaite (1948) and Thornthwaite and Mather (1955). Their revised index, MI' , has the following form:

$$MI' = \begin{cases} P/PET - 1 & , \quad P < PET \\ 1 - PET/P & , \quad P \geq PET \\ 0 & , \quad P = PET = 0 \end{cases} \quad (2)$$

where

P = precipitation

PET = potential evapotranspiration, as calculated using Equation 1

(P and PET must be in equivalent measurement units, e.g., mm)

This set of equations yields an index that varies between -1 and 1, with negative values indicating dry conditions and positive values indicating wet conditions. In addition, MI' is symmetric about zero. A primary advantage of this symmetry is that it enables valid comparisons between any set of locations in terms of their moisture balance (i.e., the balance between moisture demand and supply). Willmott and Feddema (1992) illustrated the index with examples where they calculated MI' values on an annual basis (i.e., using total P and PET values summed across one calendar year). In fact, MI' can be calculated for any time period using this summation approach, although the resulting values may be biased if calculated for periods of less than a year (Willmott and Feddema 1992). An alternative to summation is to calculate MI' separately for each month in a time window of interest, and then compute the mean of the MI' values for all months in the time window. This “mean-of-months” approach limits the ability of short-term peaks in either precipitation or potential evapotranspiration to negate corresponding short-term deficits, as would happen under a summation approach.

For each year in our study period (i.e., 1917-2016), we used the mean-of-months approach to calculate moisture index grids for three different time windows: 1 year (MI_1'), 3 years (MI_3'), and 5 years (MI_5'). Briefly, the MI_1' grids are the mean (i.e., the mean value for each grid cell) of the 12 monthly MI' grids for each year in the study period, the MI_3' grids are the mean of the 36 monthly grids from January of 2 years prior through December of the target year, and the MI_5' grids are the mean of the 60 consecutive monthly MI' grids from January of 4 years prior to December of the target year. Thus, the MI_1' grid for the year 2016 is the mean of the monthly MI' grids from January to December 2016, while the MI_3' grid is the mean of the grids from January 2014 to December 2016, and the MI_5' grid is the mean of the grids from January 2012 to December 2016.

Annual and Multi-Year Drought Maps

To determine degree of departure from typical moisture conditions, we first created a normal grid, $MI_{i\text{norm}}'$, for each of our three time windows, representing the mean (i.e., the mean value for each grid cell) of the 100 corresponding moisture index grids (i.e., the MI_1' , MI_3' , or MI_5' grids, depending on the window; see fig. 4.1). We also created a standard deviation grid, MI_{iSD}' , for each time window, calculated from the window's 100 individual moisture index grids as well as its $MI_{i\text{norm}}'$ grid.

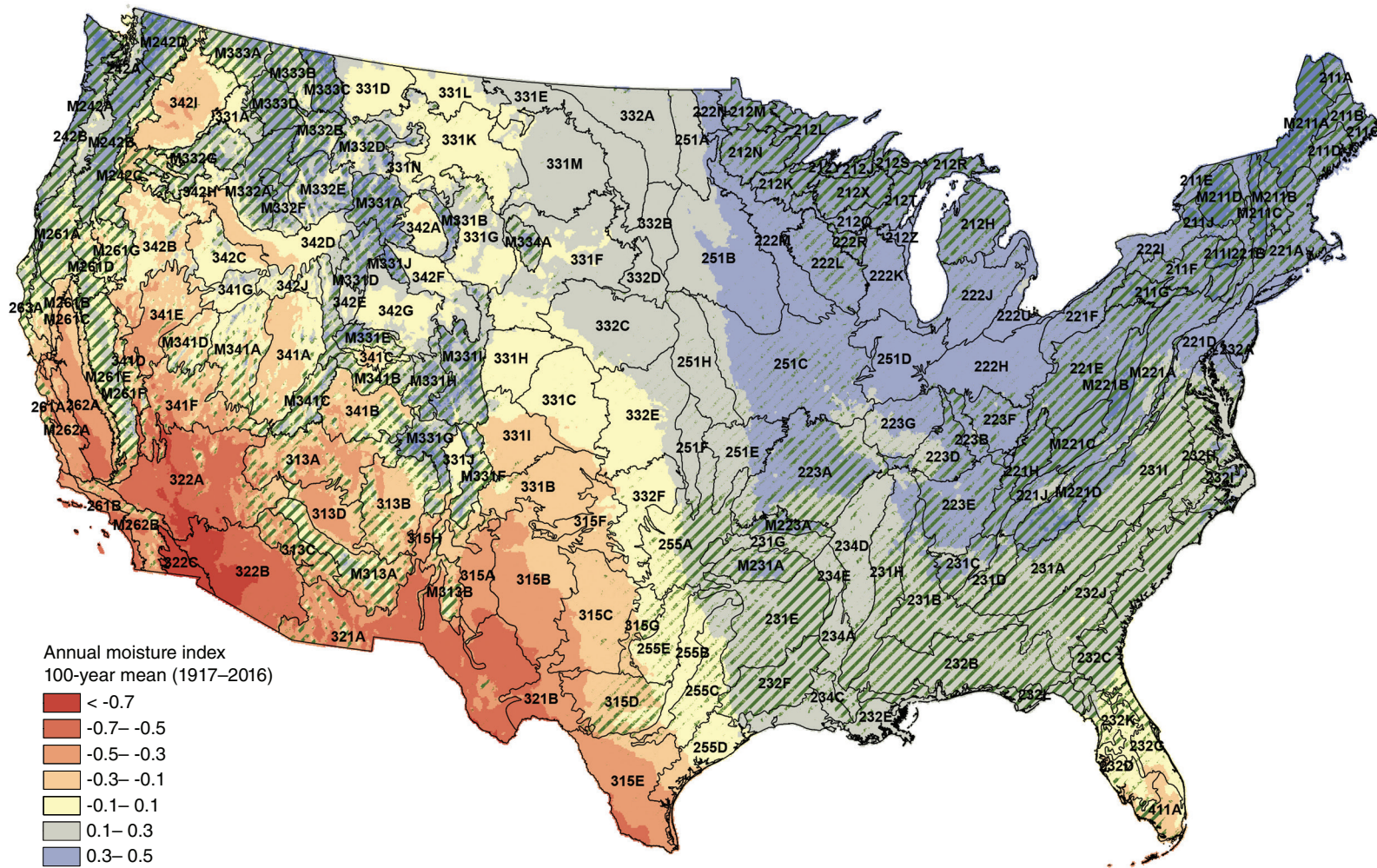


Figure 4.1—The 100-year (1917–2016) mean annual moisture index, or $MI_{100\text{yr}}$, for the conterminous United States. Ecoregion section (Cleland and others 2007) boundaries and labels are included for reference. Forest cover data (overlaid green hatching) derived from Moderate Resolution Imaging Spectroradiometer (MODIS) imagery by the U.S. Department of Agriculture, Forest Service, Remote Sensing Applications Center. (Data source: PRISM Climate Group, Oregon State University)

We subsequently calculated moisture difference z-scores, MDZ_{ij} , for each time window using these derived datasets:

$$MDZ_{ij} = \frac{MI'_i - MI'_{i \text{ norm}}}{MI'_{i \text{ SD}}} \quad (3)$$

where

i = the analytical time window (i.e., 1, 3, or 5 years) and

j = a particular target year in our 100-year study period (i.e., 1917–2016).

MDZ scores may be classified in terms of degree of moisture deficit or surplus (table 4.1). The classification scheme includes categories (e.g., severe drought, extreme drought) like those associated with the PDSI. The scheme has also been adopted for other drought indices such as the Standardized Precipitation Index, or SPI (McKee and others 1993). Moreover, the breakpoints between MDZ categories resemble those used for the SPI, such that we expect the MDZ categories to have theoretical frequencies of occurrence that are similar to their SPI counterparts (e.g., approximately 2.3 percent of the time for extreme drought; see McKee and others 1993, Steinemann 2003). More importantly, because of the standardization in Equation 3, the breakpoints between categories remain the same regardless of the size of the time window of interest. For comparative analysis, we generated and classified MDZ maps of the conterminous United States, based on all three time windows, for the target year 2016.

Table 4.1—Moisture difference z-score (MDZ) value ranges for nine wetness and drought categories, along with each category's approximate theoretical frequency of occurrence

MDZ Score	Category	Frequency
< -2	Extreme drought	2.3%
-2 to -1.5	Severe drought	4.4%
-1.5 to -1	Moderate drought	9.2%
-1 to -0.5	Mild drought	15.0%
-0.5 to 0.5	Near normal conditions	38.2%
0.5 to 1	Mild moisture surplus	15.0%
1 to 1.5	Moderate moisture surplus	9.2%
1.5 to 2	Severe moisture surplus	4.4%
> 2	Extreme moisture surplus	2.3%

RESULTS AND DISCUSSION

The 100-year (1917–2016) mean annual moisture index, or $MI'_{1 \text{ norm}}$, grid (fig. 4.1) serves as an overview of climatic regimes in the conterminous United States. (The 100-year $MI'_{3 \text{ norm}}$ and $MI'_{5 \text{ norm}}$ grids were similar to the $MI'_{1 \text{ norm}}$ grid, and so are not shown here.) Wet climates ($MI' > 0$) are common in the Eastern United States, particularly the Northeast. A noteworthy anomaly is southern Florida, especially ecoregion sections (Cleland and others 2007) 232D—Florida Coastal Lowlands-Gulf, 232G—Florida Coastal Lowlands-Atlantic, and 411A—Everglades, which appear to be dry relative to other parts of the East. This is an effect of the region's tropical climate, which has distinct wet (primarily summer months) and dry (late fall to early spring) seasons. Although

southern Florida usually receives a high level of precipitation during the wet season, it can be insufficient to offset the region's lengthy dry season (Duever and others 1994) or its high level of evapotranspiration, especially during the late spring and summer months, resulting in negative MI' values.

The comparatively dry climatic regime of southern Florida is markedly different from the extremely dry regimes seen in parts of the Western United States, especially the Southwest (e.g., sections 322A–Mojave Desert, 322B–Sonoran Desert, and 322C–Colorado Desert), where potential evapotranspiration is very high, but precipitation levels are very low. Indeed, dry climates ($MI' < 0$) are typical across much of the Western United States because of generally lower precipitation than the East. Nevertheless, mountainous areas in the central and northern Rocky Mountains as well as the Pacific Northwest are relatively wet, such as ecoregion sections M242A–Oregon and Washington Coast Ranges, M242B–Western Cascades, M331G–South Central Highlands, and M333C–Northern Rockies. This is driven in part by large amounts of winter snowfall in these regions (Hanson and Weltzin 2000).

Figure 4.2 shows the annual (i.e., 1-year) MDZ map for 2016 for the conterminous United States. Perhaps the most notable feature of the map is a large area of severe to extreme drought ($MDZ < -1.5$) extending across much of the Southeastern United States, especially sections 221H–Northern Cumberland Plateau, 221J–Central Ridge and Valley, 231A–Southern

Appalachian Piedmont, 231C–Southern Cumberland Plateau, and 231D–Southern Ridge and Valley; the southern portion of M221D–Blue Ridge Mountains; and the southwestern portion of 231I–Central Appalachian Piedmont. This area of drought developed primarily in the latter half of 2016, and expanded to occupy nearly 55 percent of the Southeast at the end of November, according to the U.S. Drought Monitor (National Climatic Data Center 2017b). During fall 2016, many locations throughout the region went more than 50 consecutive days without precipitation (National Climatic Data Center 2017b). These dry conditions have been cited as one of the main factors contributing to an unusually active fall wildfire season in the Southeastern United States, especially in the Southern Appalachian Mountains: by the end of 2016, 50 major fires had burned close to 100,000 acres in this subregion alone (Boddy 2016, Southeast Regional Climate Center 2016). However, unusually warm temperatures also played a significant role in promoting wildfire activity. In terms of average monthly temperatures, 2016 was the warmest year on record for the Southeast; in the Southern Appalachian Mountains specifically, average maximum temperatures during the July–December 2016 period were as much as 2.5 °C higher than the 20th-century averages for this period (National Climatic Data Center 2017a). Additionally, local weather conditions (e.g., high winds) facilitated the rapid expansion of some fires, thereby increasing their geographic footprints and subsequent impacts on the landscape.

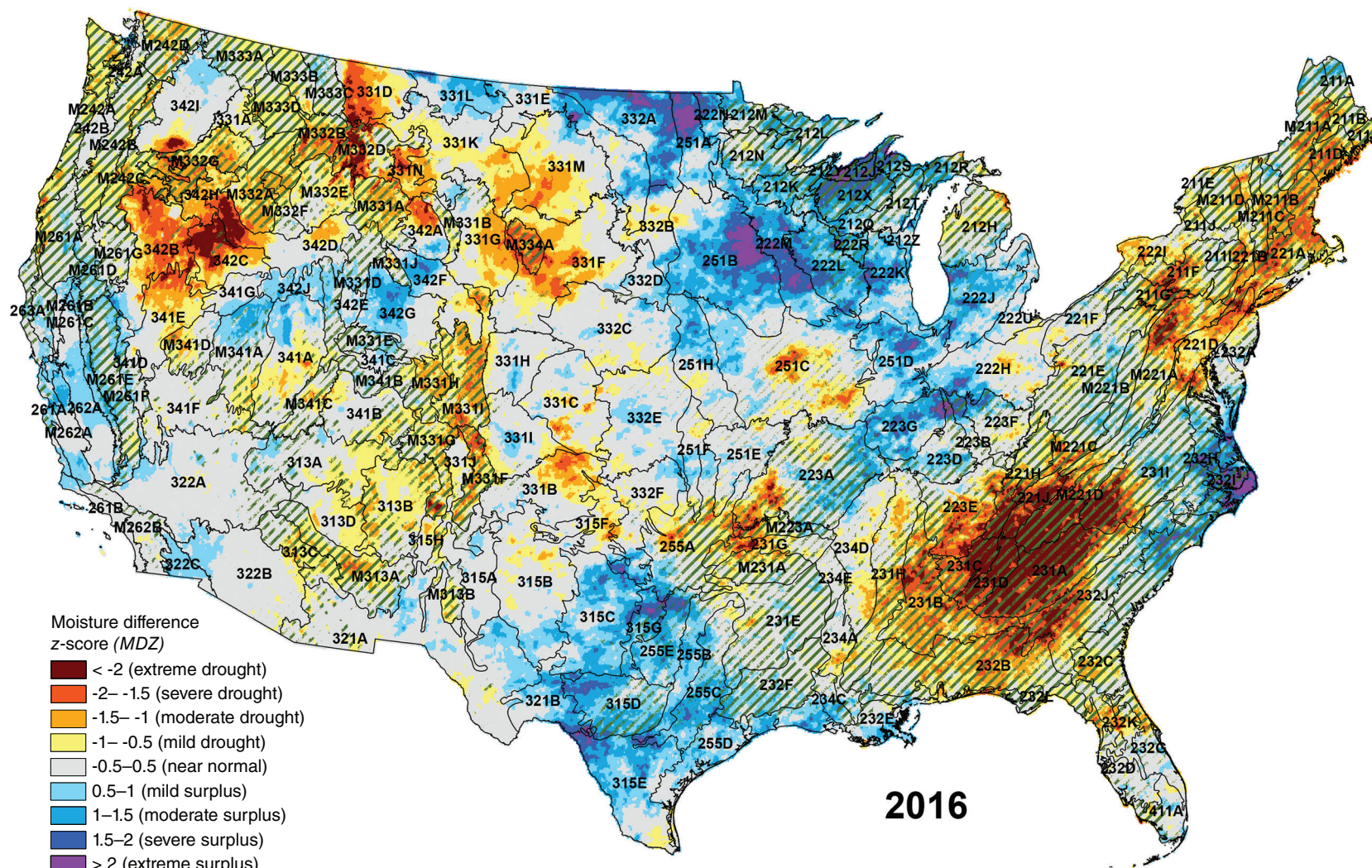


Figure 4.2—The 2016 annual (i.e., 1-year) moisture difference z-score, or MDZ, for the conterminous United States. Ecoregion section (Cleland and others 2007) boundaries and labels are included for reference. Forest cover data (overlaid green hatching) derived from MODIS imagery by the U.S. Department of Agriculture, Forest Service, Remote Sensing Applications Center. (Data source: PRISM Climate Group, Oregon State University)

Elsewhere in the Eastern United States, a contiguous area of mostly moderate to extreme drought ($MDZ < -1$) conditions extended north from the Mid-Atlantic region into New England during 2016. Among the most affected ecoregion sections were 211F–Northern Glaciated Allegheny Plateau, 211G–Northern Unglaciated Allegheny Plateau, 221A–Lower New England, and the northern portion of M221A–Northern Ridge and Valley (northern portion); much of Maine (sections M211A–White Mountains and 211D–Central Maine Coastal and Embayment) also experienced moderate to severe drought conditions. In some locations within this area, drought conditions reached historical extremes during 2016. For example, as measured by PDSI, 2016 was the driest year on record for the Connecticut coast and the second driest year on record for Long Island in New York (National Climatic Data Center 2017a).

The 2016 *MDZ* map (fig. 4.2) shows two other areas of severe to extreme drought in the northwestern portion of the United States. The larger of these, in eastern Oregon and southwestern Idaho, occurred primarily in sections 342B–Northwestern Basin and Range, 342C–Owyhee Uplands, and 342D–Snake River Basalts and Basins, all of which have little forest. The second area covered much of western Montana, but extreme drought conditions were mostly limited to section M332D–Belt Mountains. Scattered areas of moderate to extreme drought appeared elsewhere in the Western and Central United States. One such area was centered on forested section M334A–

Black Hills and extended into neighboring sections with little or no forest (e.g., 331F–Western Great Plains and 331M–Missouri Plateau). Another area extended across portions of sections 223A–Ozark Highlands, M223A–Boston Mountains, 231G–Arkansas Valley, and M231A–Ouachita Mountains. Moderate to extreme drought conditions also affected the Front Range of the Rocky Mountains in Colorado and northern New Mexico (sections M331F–Southern Parks and Rocky Mountain Range and M331I–Northern Parks and Ranges).

Drought conditions were conspicuously absent throughout most of California during 2016. As measured by PDSI, 2016 was only the 35th driest year in the State’s history, and the wettest year since 2011 (National Climatic Data Center 2017a). This is in stark contrast to 2015 (fig. 4.3), when almost all of the forested areas in California experienced severe to extreme drought conditions. Drought conditions were also much worse in the Pacific Northwest region in 2015 than in 2016. Significantly, temperature was probably the main driver of these conditions: 2015 was the warmest year on record for the Pacific Northwest, and the high temperatures increased evapotranspiration more than enough to offset the region’s relatively normal precipitation levels during 2015 (National Climatic Data Center 2017a). By comparison, 2016 was only the sixth warmest year for the region, while precipitation levels were again close to normal. Regardless, these recent circumstances in the Pacific Northwest emphasize the fact that high temperatures

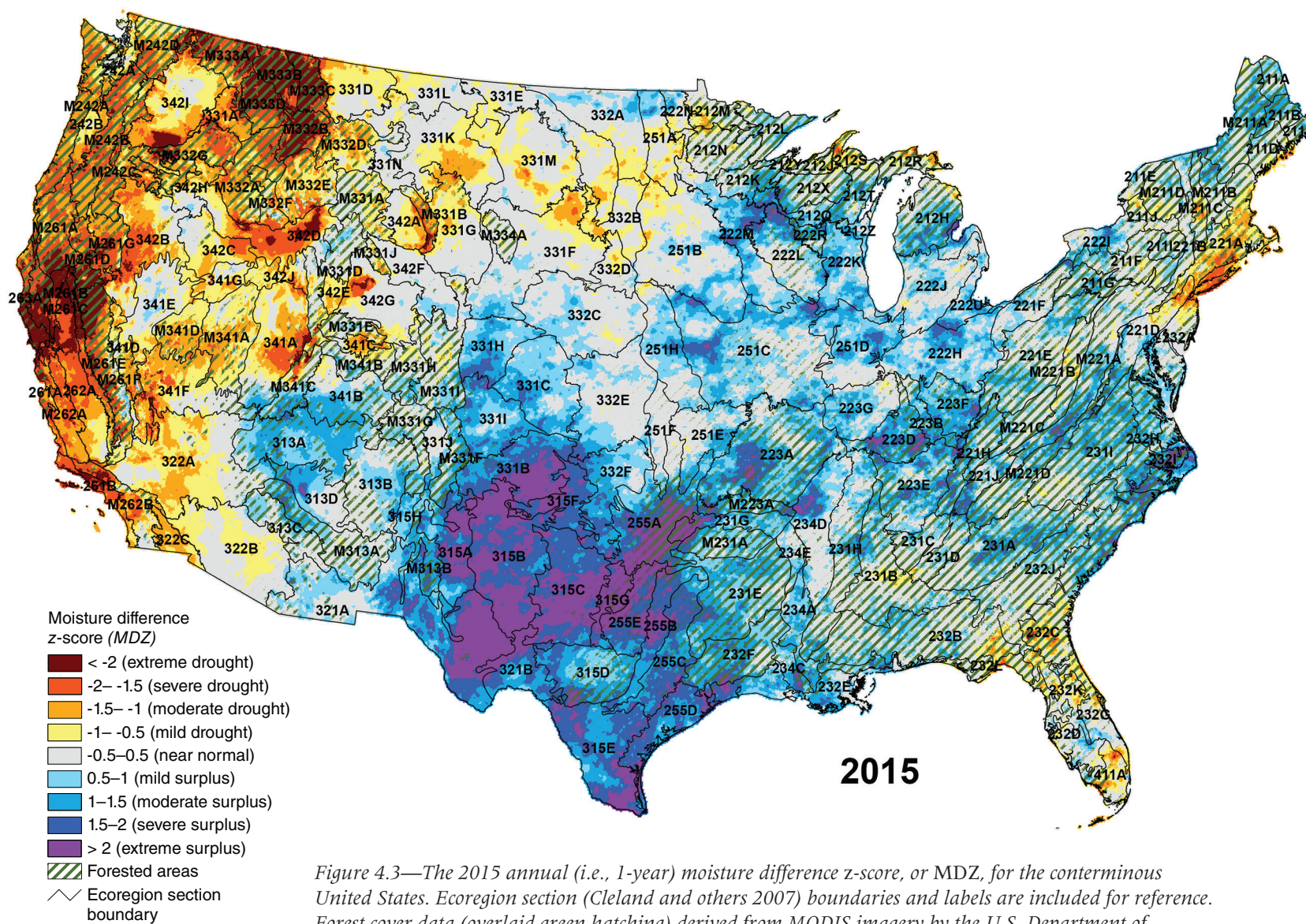


Figure 4.3—The 2015 annual (i.e., 1-year) moisture difference z-score, or MDZ, for the conterminous United States. Ecoregion section (Cleland and others 2007) boundaries and labels are included for reference. Forest cover data (overlaid green hatching) derived from MODIS imagery by the U.S. Department of Agriculture, Forest Service, Remote Sensing Applications Center. (Data source: PRISM Climate Group, Oregon State University)

(i.e., high evapotranspiration) can exacerbate moisture deficits, and in some cases overcome moisture surpluses, thereby increasing drought severity above what might otherwise be expected (Rind and others 1990). This may be especially worrisome given the continued warming trend that has been observed globally due to anthropogenic climate change (Luce and others 2016, Rind and others 1990).

Furthermore, high temperatures can prolong drought-related impacts to forests, including tree mortality, even after moisture availability returns to normal (Mitchell and others 2014), particularly if the preceding drought persisted over multiple years (Berdanier and Clark 2016). This is demonstrated by the massive-scale forest mortality that has occurred in California during the last decade. In November 2016, the Forest Service, U.S. Department of Agriculture, reported that more than 102 million trees have been killed in the State since 2010 due to primary or secondary effects (e.g., bark beetle outbreaks) of drought and extreme heat, with millions more trees expected to die in the near future (USDA Office of Communications 2016). Although California was comparatively wet during 2016 (see fig. 4.2), this came after a period of historically extreme drought conditions that lasted at least 5 years (USDA Office of Communications 2016). More to the point, temperatures remained high in California in 2016: it was the State's third warmest year on record, behind only 2014 and 2015, which were the first and second warmest years,

respectively, in terms of both average and maximum temperatures (National Climatic Data Center 2017a).

The California example also reiterates the importance of using longer time windows when assessing potential drought impacts to trees and forests. When considered as forecasts of where such impacts are most likely to emerge, the 3-year (2014–2016; fig. 4.4) and, especially, the 5-year (2012–2016; fig. 4.5) *MDZ* maps for the conterminous United States clearly show significant risk of drought impacts to forests not just in California, but throughout much of the Western United States. In contrast, the 3- and 5-year maps suggest that very few areas in the Central and Eastern United States face a similar degree of drought-related risk. For instance, the 5-year *MDZ* map shows hot spots of moderate to extreme drought in central and southern Florida (sections 232C–Atlantic Coastal Flatwoods, 232D, 232K–Florida Coastal Plains and Central Highlands, and 411A), but the 3-year *MDZ* map indicates that moisture conditions have improved in these areas in the last few years. It is also evident from the multi-year maps – especially when viewed in combination with the 1-year *MDZ* maps for 2015 (fig. 4.3) and 2016 (fig. 4.2) – that drought conditions in the Southern Appalachian Mountains did not begin to emerge until 2016. The one noteworthy case of persistent and intense drought conditions in the East is the previously highlighted area in southern New England and Long Island. In its 2016 annual summary report on drought

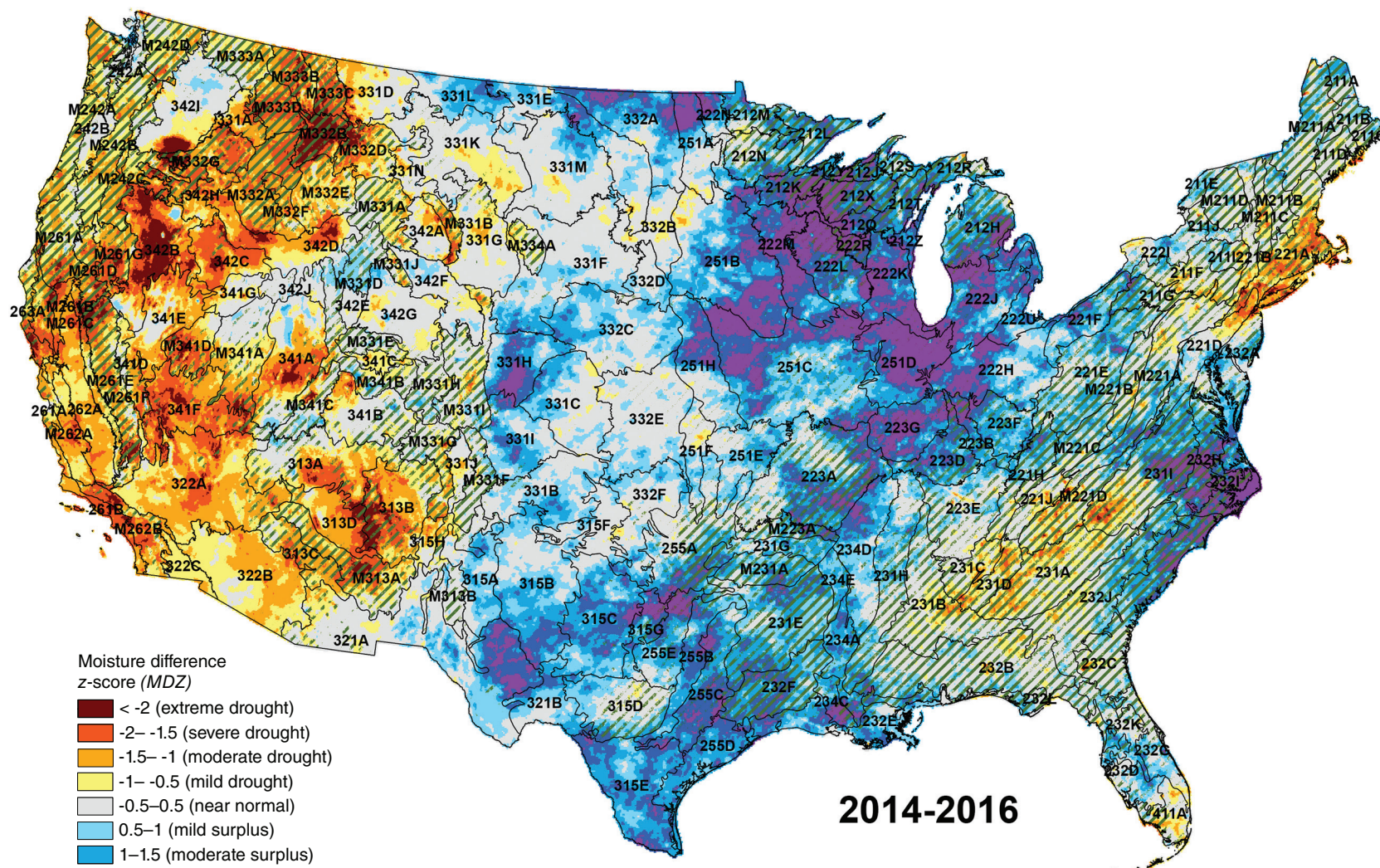


Figure 4.4—The 2014–2016 (i.e., 3-year) moisture difference z-score (MDZ) for the conterminous United States. Ecoregion section (Cleland and others 2007) boundaries are included for reference. Forest cover data (overlaid green hatching) derived from MODIS imagery by the U.S. Department of Agriculture, Forest Service, Remote Sensing Applications Center. (Data source: PRISM Climate Group, Oregon State University)

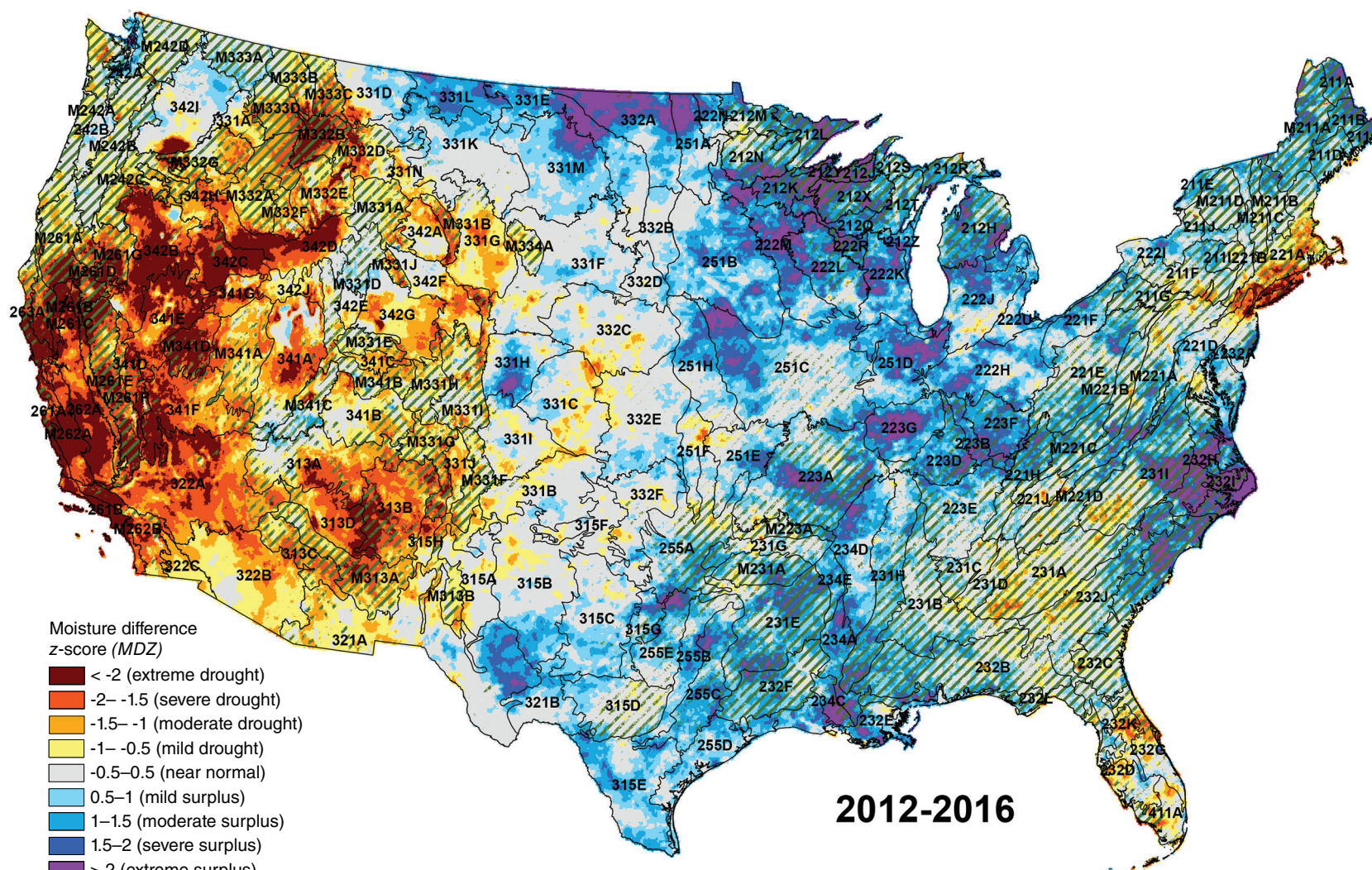


Figure 4.5—The 2012–2016 (i.e., 5-year) moisture difference z-score (MDZ) for the conterminous United States. Ecological section (Cleland and others 2007) boundaries are included for reference. Forest cover data (overlaid green hatching) derived from MODIS imagery by the U.S. Department of Agriculture, Forest Service, Remote Sensing Applications Center. (Data source: PRISM Climate Group, Oregon State University)

(National Climatic Data Center 2017b), the National Climatic Data Center compared the recent conditions in this area to a historically severe drought that persisted throughout the mid-1960s (documented in Namias 1966, 1983). Data suggest this is an apt comparison; for instance, along the coast of Connecticut, 1962–1966 was the second driest 5-year period on record as measured by PDSI, surpassed only by the 2012–2016 period (National Climatic Data Center 2017a). Although these recent conditions have not been associated with large-scale tree mortality as seen in California, they have been linked to indirect impacts such as defoliation by the European gypsy moth (*Lymantria dispar*) in Connecticut, Rhode Island, and Massachusetts at levels not seen since the 1980s (Elkinton and Boettner 2016).

As with drought, the most relevant moisture surpluses with respect to forest health are probably those that persist for several years. Areas exhibiting severe to extreme surplus conditions in both the 3-year and 5-year MDZ maps (figs. 4.4 and 4.5) may merit further attention, since the former would indicate limited recent movement toward more normal moisture conditions. Forested areas exhibiting severe to extreme surpluses over 5 years were distributed widely across the Eastern United States: in North Carolina and South Carolina (portions of 231I–Central Appalachian Piedmont, 232C–Atlantic Coastal Flatwoods, 232H–Middle Atlantic Coastal Plains and Flatwoods, and especially 232I–Northern Atlantic Coastal Flatwoods); in Kentucky

(sections 221H–Northern Cumberland Plateau, M221C–Northern Cumberland Mountains, 223B–Interior Low Plateau-Transition Hills, 223D–Interior Low Plateau-Shawnee Hills, and 223F–Interior Low Plateau-Bluegrass); in Arkansas and Louisiana (section 223A–Ozark Highlands and the northern portion of 234D–White and Black River Alluvial Plains); and in Michigan (section 212H–Northern Lower Peninsula). The area of surplus in North and South Carolina is of particular note because of its large size and contiguity, and also because its extent is nearly the same in the 2014–2016 MDZ map and the 2012–2016 MDZ map. For all Climate Divisions (see Guttman and Quayle 1996) in the eastern portion of both States, 2014–2016 was the wettest 3-year period on record, and 2012–2016 was either the wettest or second wettest 5-year period (National Climatic Data Center 2017a). For example, North Carolina Climate Division 7, which covers the central portion of the State’s Coastal Plain, averaged a 3-year precipitation total of 3.87 m during the 20th century, but received 4.72 m of precipitation during the 2014–2016 period. Likewise, this region averaged a 5-year precipitation total of 6.45 m during the 20th century, but received 7.34 m during the 2012–2016 period (National Climatic Data Center 2017a).

Future Efforts

If the appropriate spatial data (i.e., high-resolution maps of precipitation and temperature) remain available for public use, we will continue to produce our 1-year, 3-year,

and 5-year *MDZ* maps of the conterminous United States as a regular yearly component of national-scale forest health reporting. However, users should interpret and compare the *MDZ* maps presented here cautiously. Foremost, the *MDZ* approach does not incorporate certain factors that may influence a location's moisture supply at a finer spatial scale, such as winter snowpack, surface runoff, or groundwater storage. Furthermore, although the maps use a standardized index scale that applies regardless of the size of the time window, the window size may still deserve some consideration. For instance, an extreme drought that persists over a 5-year period has substantially different forest health implications than an extreme drought over a 1-year period. While the 1-year, 3-year, and 5-year *MDZ* maps may together provide a comprehensive short-term overview, it may also be important to consider a particular region's longer-term moisture history when assessing the current health of its forests. For example, in geographic regions where droughts have historically occurred on a frequent (e.g., annual or nearly annual) basis, certain tree species may be better adapted to a regular lack of available moisture (McDowell and others 2008). Because of this variability in species' drought tolerance, a long period of persistent and severe drought conditions could ultimately lead to changes in regional forest composition (Mueller and others 2005); compositional changes may similarly arise from a long period of persistent moisture surplus (McEwan and others 2011). In turn, such changes are likely to affect regional responses to future drought or

surplus conditions, fire regimes, and the status of ecosystem services such as nutrient cycling and wildlife habitat (W.R.L. Anderegg and others 2013, DeSantis and others 2011). In future work, we hope to provide forest managers and other decision makers with better quantitative evidence regarding critical relationships between moisture extremes and significant forest health impacts such as regional-scale tree mortality (e.g., Mitchell and others 2014). We also intend to examine the capacity of moisture extremes to serve as inciting factors, and thus as predictors, for other forest threats such as wildfire or pest outbreaks. For example, Westerling and others (2003) asserted that the relationship between drought and wildfire in the Western United States is strong enough to support reliable prediction of regional fire season severity as much as a year in advance. Ultimately, our goal is to be able to make these types of forecasts at the national level.

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INTRODUCTION

Tree mortality is a natural process in all forest ecosystems. High mortality can be an indicator of forest health problems. On a regional scale, high mortality levels may indicate widespread insect or disease impacts. High mortality may also occur if a large proportion of the forest in a particular region is made up of older, senescent stands. The approach presented here seeks to detect mortality patterns that might reflect changes to ecosystem processes at large scales. However, in many cases, the proximate cause of mortality may be discernable. Understanding proximate causes of mortality *may* provide insight into whether the mortality is within the range of natural variation or reflects more fundamental changes to ecological processes.

DATA

Forest Inventory and Analysis (FIA) Phase 2 (P2) data were the basis of the mortality analysis. Forest Inventory and Analysis P2 data are collected across forested land throughout the United States, with approximately one plot per 6,000 acres of forest, using a rotating panel sample design (Bechtold and Patterson 2005). Field plots are divided into spatially balanced panels, with one panel being measured each year. A single cycle of measurements consists of measuring all panels. This “annualized” method of inventory was adopted, State by State, beginning in 1999. The cycle length (i.e., number of years required to measure all plot panels) ranges from 5 to 10 years.

An analysis of mortality requires data collected at a minimum of two points in time. Therefore, mortality analysis was possible for areas where data from repeated plot measurements using consistent sampling protocols were available (i.e., where one cycle of measurements had been completed and at least one panel of the next cycle had been measured, and where there had been no changes to the protocols affecting measurements of trees or saplings). In this report, as in recent years, the repeated P2 data were available for all of the Central and Eastern States. The most recent cycle of remeasurements for each State was used in this analysis.

In addition, mortality data have become available from parts of the Western United States. In the West, plots are remeasured on a 10-year cycle. Thus, estimates of growth and mortality from the West are based on less than a complete cycle of remeasurement. Remeasurement data were available for all western States in the conterminous United States except Wyoming. However, for several States, the proportion of plots that have been remeasured is small, making the effective sampling intensity for growth and mortality estimates significantly lower than FIA’s standard of one plot per 6,000 acres (table 5.1). Therefore the percent sampling error on growth and mortality estimates tends to be large. Results are not presented for ecoregions where fewer than 50 plots had been remeasured or where the percent error was unacceptably high. Nevertheless, results presented for the West

CHAPTER 5.

Tree Mortality

MARK J. AMBROSE

Table 5.1—Western States from which repeated Forest Inventory and Analysis Phase 2 measurements were available, the time period spanned by the data, and the effective sample intensity (on the proportion of plots that had been remeasured) in the available datasets

State	Time period	Effective sample intensity
Arizona	2001–2016	1 plot: 10,000 acres
California	2001–2016	1 plot: 10,000 acres
Colorado	2002–2015	1 plot: 15,000 acres
Idaho	2004–2015	1 plot: 30,000 acres
Montana	2003–2016	1 plot: 15,000 acres
Nevada	2004–2015	1 plot: 30,000 acres
New Mexico	2005–2015	1 plot: 60,000 acres
Oregon	2001–2016	1 plot: 8,571 acres
Utah	2000–2016	1 plot: 8,571 acres
Washington	2002–2016	1 plot: 12,000 acres

should be viewed as preliminary. Because of this, results from the West are discussed separately from those from the Eastern and Central United States. The division of eastern/central vs. western States, as well as the forest cover within those States, is shown in figure 5.1.

METHODS

Forest Inventory and Analysis calculates the growth, mortality, and removal volume on each plot over the interval between repeated measurements. These values are stored in the FIA database (v. 7.0) (O’Connell and others 2017). The FIA EVALIDator (v. 1.6.0.03a) is

an online tool for querying the FIA database and generating area-based reports on forest characteristics (Miles 2015). EVALIDator was used to obtain net growth rates and mortality rates over the most recent measurement cycle for each of 97 ecoregion sections (Cleland and others 2007, McNab and others 2007) covering the Eastern and Central United States and 47 ecoregion sections in the Western United States. For most States, the most recent cycle of available data ran through 2016 (e.g., data collected 2011 through 2016).

To compare mortality across forest types and climate zones, the ratio of annual mortality to gross growth (MRATIO) was used as a standardized mortality indicator (Coulston and others 2005). Because EVALIDator does not output gross growth directly, it must first be calculated as the sum of net growth and mortality. Thus, the MRATIO was calculated from the EVALIDator output for each ecoregion section, using the formula:

$$\text{MRATIO} = m / (m + g_n)$$

where

m = annual mortality (cubic feet/year)

g_n = net annual growth (cubic feet/year).

The MRATIO has proven to be a useful indicator of forest health, but it can be a problematic indicator, especially when growth rates are very low. The MRATIO can also be difficult to interpret when there is high uncertainty to growth estimates. Both of these

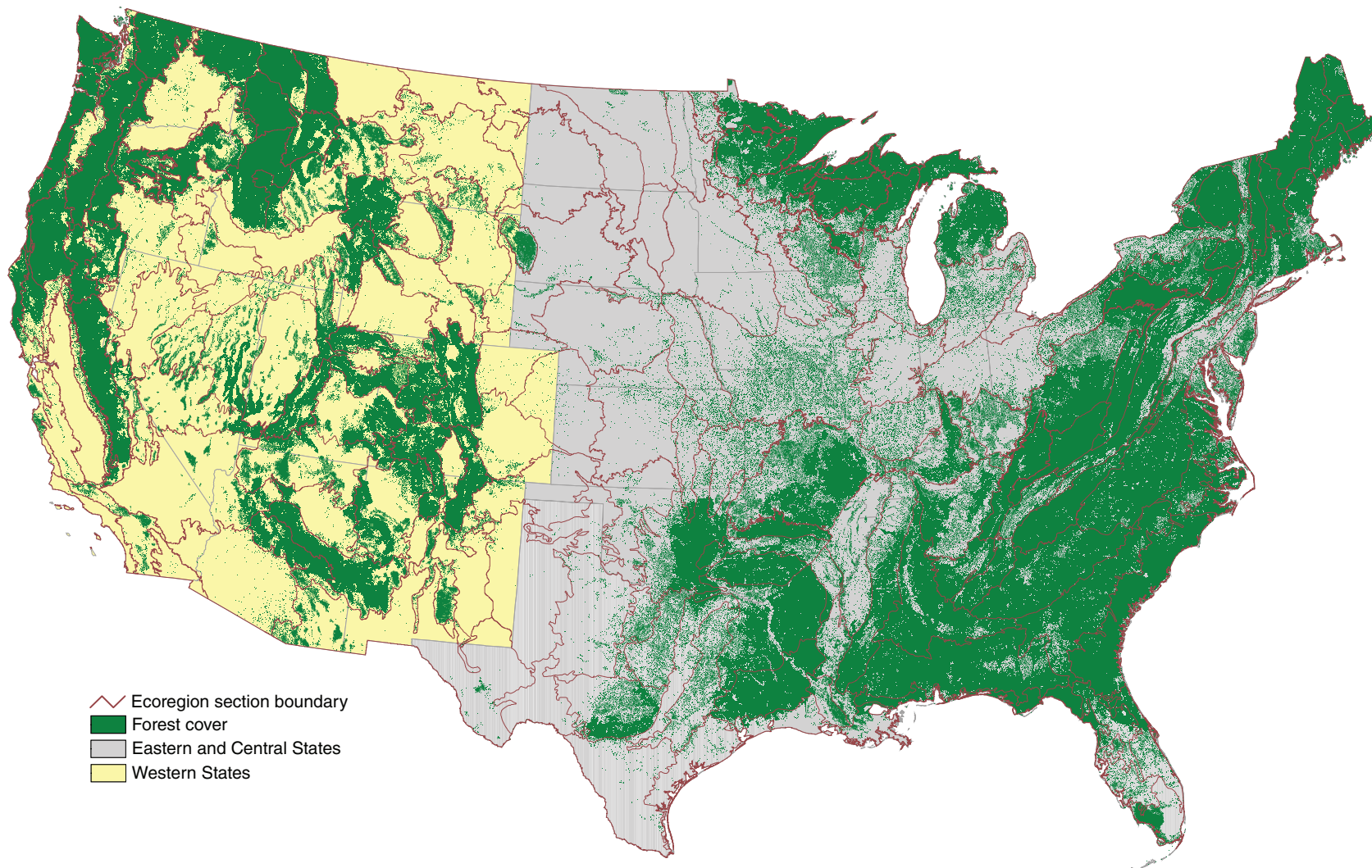


Figure 5.1—Forest cover in the States where mortality was analyzed by ecoregion section (Cleland and others 2007). Mortality in Eastern and Central States was analyzed using a complete remeasurement cycle; in Western States, mortality was analyzed using a partial cycle of remeasurements, and results there should be considered preliminary. Forest cover was derived from MODIS satellite imagery (USDA Forest Service 2008).

are the case with the data currently available from the West. Therefore, we also calculated mortality as a percentage of live growing stock volume:

$$\text{Mortality percent} = m / v_l * 100$$

where

m = annual mortality (cubic feet/year)

v_l = total live tree volume (cubic feet).

When this value is high as well as the MRATIO, it suggests a possibly serious forest health concern.

In addition, mortality rates were derived for each forest type group (USDA Forest Service 2008) for each ecoregion section. Identifying the forest types experiencing high mortality in an ecoregion is a first step in identifying what forest health issue may be affecting the forests. Although determining particular causal agents associated with all observed mortality is beyond the scope of this report, often there are well-known insects and pathogens that are “likely suspects” once the affected forest types are identified.

To identify possible causal agents for the observed mortality, EVALIDator was also used to report disturbances that were recorded on plots where mortality occurred. Care must be used in interpreting these disturbances because disturbance is a location-level variable (e.g., recorded for each stand included on a plot) rather than a tree-level variable, so a given

disturbance may not be directly related to the mortality of a particular tree. Similarly, mortality-causing agents may be present in a location but not recorded if their impact at the plot level is not significant enough to qualify as a “disturbance.” Nevertheless, such disturbances may indicate stressors that played a role in the observed mortality. Further information about the cause of mortality is provided by the aerial survey of insects and disease (see chapter 2 in this report). It is difficult to directly match aerial survey data to mortality observed on FIA plots. However, I incorporate the results of this survey into the discussion by consulting State Forest Health Highlights, which reflect in large part the results of aerial surveys.

RESULTS AND DISCUSSION

The MRATIO values are shown in figure 5.2. The MRATIO can be large if an over-mature forest is senescing and losing a cohort of older trees. If forests are not naturally senescing, a high MRATIO (> 0.6) may indicate high mortality due to some acute cause (insects or pathogens) or due to generally deteriorating forest health conditions.

Eastern and Central States

The seven ecoregion sections in the Eastern and Central States with the highest MRATIOS are labeled on the map. In the discussion that follows, I focus on the ecoregions having MRATIOS > 0.5 (i.e., where mortality was greater than half of gross growth).

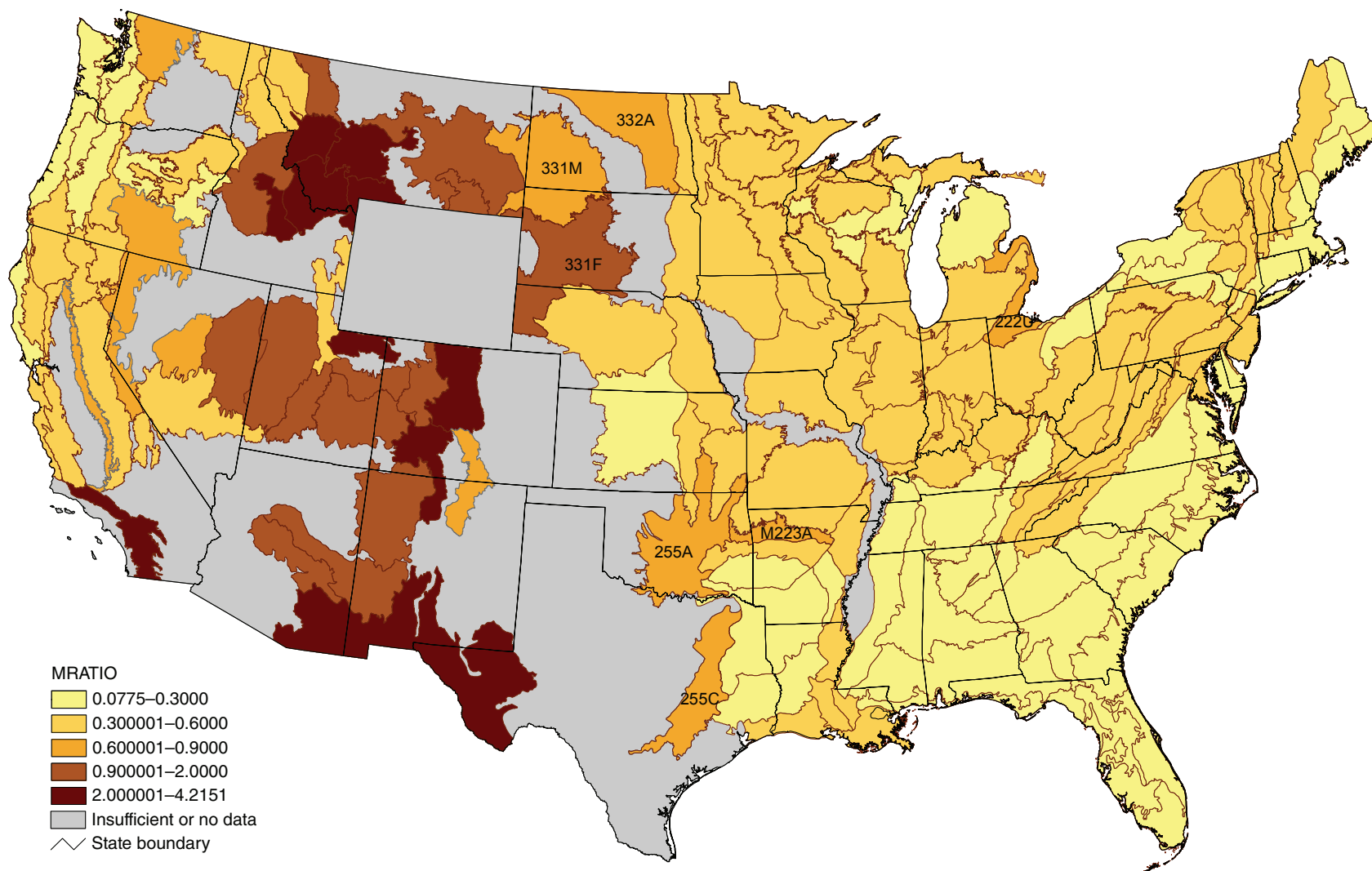


Figure 5.2—Tree mortality expressed as the ratio of annual mortality volume to gross annual volume growth (MRATIO) by ecoregion section (Cleland and others 2007). (Data source: U.S. Department of Agriculture, Forest Service Forest Inventory and Analysis Program)

The highest MRATIOS occurred in ecoregion section 331F–Western Great Plains (MRATIO = 1.32) in South Dakota and Nebraska (and Montana). Other areas of high mortality relative to growth on the Great Plains were sections 331M–Missouri Plateau (MRATIO = 0.73) in North and South Dakota and 332A–Northeastern Glaciated Plains (MRATIO = 0.62) in North Dakota. In these Great Plains ecoregions where mortality is high relative to growth, the predominant vegetation is grassland. Although the ecoregions are quite large, there was relatively little forest land to measure (e.g., 113 plots in section 331F and 93 plots in section 331M). In the Plains, tree growth is generally slow because of naturally dry conditions. Where the number of sample plots is small and tree growth is naturally slow, care must be taken in interpreting mortality relative to growth.

Both ecoregion sections 331F and 331M have had high mortality relative to growth in recent years (Ambrose 2013, 2014, 2015a, 2015b, 2016, 2017), so the observed mortality is **not a new phenomenon**. Tree growth rates in these sections (especially in 331F) are quite low, so the high MRATIOS are due to a combination of low growth and high mortality. Much of the forest in these sections is riparian, and most of the species experiencing greatest mortality are commonly found in riparian areas. The major exception was high ponderosa pine mortality in ecoregion section 331F. Ponderosa pine is not a riparian tree species, but like the riparian species, it only occurs in a relatively small area of the ecoregion, on discontinuous mountains, plateaus, canyons,

and breaks in the plains (Burns and Honkala 1990). In both of these ecoregion sections, damage from domestic animals was associated with large proportions of the mortality (table 5.2).

In ecoregion section 331F, where the MRATIO was highest, the vast majority (~83 percent) of the mortality occurred in the ponderosa pine forest type group. However, this mortality represented a relatively small proportion of the growing stock in the ponderosa pine forest type (0.47 percent) in the region. The pine mortality in this ecoregion is very likely related to mountain pine beetle (*Dendroctonus ponderosae*). There has been an ongoing pine beetle outbreak in the adjacent Black Hills region (Ball and others 2015, 2016; South Dakota Department of Agriculture 2011, 2012, 2013, 2014). Mountain pine beetle-related mortality also has been reported in western Nebraska (Nebraska Forest Service 2011, 2012), with an outbreak that began in 2009, though pine beetle-related mortality there has fallen significantly recently (Nebraska Forest Service 2014, 2015, 2016). More recently, several other agents have been reported as affecting ponderosa pine in western Nebraska, including *Ips* beetles and *Diplodia* blight (Nebraska Forest Service 2015, 2016). Drought in 2012 and 2013, affecting much of South Dakota and Nebraska (South Dakota Department of Agriculture 2012; Nebraska Forest Service 2012, 2013), may also have contributed to pine mortality, as well as that of other species, in these ecoregions.

Table 5.2—Ecoregion sections in the Eastern and Central United States having the highest mortality relative to growth (MRATIO), annual growth and mortality rates, and disturbances associated with areas of mortality

Ecoregion section	Average annual net growth	Average annual mortality	MRATIO	Major disturbances associated with areas with mortality ^a
	----- cubic feet/year -----			
331F—Western Great Plains	-3,662,068	15,227,903	1.32	Domestic animals (62%), bear (35%), fire (23%)
331M—Missouri Plateau	2,457,206	6,789,208	0.73	Weather-related (57%), domestic animals (27%), animal damage (14%)
222U—Lake Whittlesey Glaciolacustrine Plain	19,166,504	48,660,341	0.72	Insects (17%)
255C—Oak Woods and Prairies	22,472,645	53,525,386	0.70	Weather-related (11%)
255A—Cross Timbers and Prairie	8,376,354	16,526,241	0.66	Weather-related (17%), domestic animals (10%)
332A—Northeastern Glaciated Plains	4,109,748	6,668,929	0.62	Animals (26%), insects (21%), weather-related (17%), domestic animals (16%)

^a Percentages are the percent of mortality volume occurring on forested conditions that were affected by the given disturbance type.

In ecoregion section 331M—Missouri Plateau, about 64 percent of the mortality (by volume) occurred in the elm-ash-cottonwood forest type group, and about 23 percent of mortality occurred in the oak-hickory forest type group. Prior analyses identified three species: eastern cottonwood, bur oak, and green ash as suffering high mortality in this region (Ambrose 2015b). Green ash have been affected by ash/lilac borer (*Podosesia syringae*), as well as other native ash borers, in both North and South Dakota (Ball and others 2015, 2016; North Dakota Forest Service 2012; South Dakota Department of Agriculture 2012). Cottonwood canker fungi have been identified as a problem throughout North Dakota (North Dakota Forest Service 2014, 2015); these fungi may be contributing to the observed cottonwood mortality. Adverse

weather conditions, including both drought and excessively wet conditions, both of which occurred during the remeasurement cycle (North Dakota Forest Service 2012, 2013; South Dakota Department of Agriculture 2012), may have contributed to mortality by stressing trees. Adverse weather was associated with 57 percent of the observed mortality (table 5.2).

The majority of the mortality in ecoregion section 332A was split about evenly between the elm-ash-cottonwood and aspen-birch forest type groups (about 40 percent in each). As in ecoregions 331F and 331M, a large proportion of the mortality (about 16 percent) was associated with domestic animal damage (table 5.2). This ecoregion includes the Turtle Mountains, where thousands of acres of forest tent caterpillar

(*Malacosoma disstria*) and large aspen tortrix (*Choristoneura conflictana*) defoliation have occurred in recent years (North Dakota Forest Service 2014). Overmaturity of aspen stands in North Dakota has led to increasing insect and disease issues (North Dakota Forest Service 2015), and 4,000 acres of aspen decline related to over-mature stands have been identified in this ecoregion (North Dakota Forest Service 2014). The defoliation together with the aspen decline may be the cause of most of the mortality in the aspen-birch forest type. Cottonwood canker fungi have been a problem throughout North Dakota (North Dakota Forest Service 2014, 2015) and may be a cause of the mortality in the elm-ash-cottonwood forest type.

Mortality was split almost evenly between the oak-hickory and elm-ash-cottonwood forest type groups in ecoregion section 222U–Lake Whittlesey Glaciolacustrine Plain (MRATIO = 0.72). About 17 percent of the mortality in this ecoregion was associated with insects (table 5.2). Much of the mortality in the elm-ash-cottonwood group is likely due to emerald ash borer (*Agrilus planipennis*), which has produced extremely high ash mortality throughout Ohio and Michigan (Michigan Department of Natural Resources 2014, 2015, 2016; Ohio Department of Natural Resources, Division of Forestry 2014, 2015). In fact, emerald ash borer has caused the death of the “vast majority” of native ash in northwestern Ohio (Ohio Department of Natural Resources, Division of Forestry 2016). The cause of mortality in the oak-hickory forest type group is less clear. Several oak pests were reported in Ohio as well as “leaf-curl syndrome”

of unknown origin (Ohio Department of Natural Resources, Division of Forestry 2015, 2016), while in Michigan oak wilt (caused by the pathogen *Ceratocystis fagacearum*) has been confirmed in at least part of the ecoregion (Michigan Department of Natural Resources 2015, 2016).

Ecoregion section 255C–Oak Woods and Prairies in Texas had relatively high mortality (MRATIO = 0.70). About 51 percent of the mortality occurred in the oak-hickory forest type group, and another 12 percent occurred in the oak-gum-cypress forest type group. About 18 percent of mortality occurred in the loblolly-shortleaf pine type group. A record-setting drought in 2011 affected Oklahoma and Texas. It was reported as weakening both pines and hardwoods in Texas, making them susceptible to a variety of pests and pathogens (Smith 2013, 2014). This drought probably contributed to the mortality in this ecoregion. Oak wilt has been a major problem in oak woodlands in central Texas (Smith 2014; Texas A&M Forest Service 2015, 2016) and probably contributed to the mortality in the oak-hickory and oak-gum-cypress forest types. Pine engraver beetle (*Ips* spp.) has been a problem in Texas’ pine forests, and may have contributed to mortality in the loblolly-shortleaf pine forests.

Ecoregion section 255A–Cross Timbers and Prairie experienced relatively high mortality (MRATIO = 0.66). However, the majority of the ecoregion is located in western Oklahoma, where mortality data are not yet available. Therefore, the results shown are based on

data collected in the relatively small portion of the ecoregion located in eastern Oklahoma and southeastern Kansas. About 77 percent of the mortality (in terms of tree volume) occurred in the oak-hickory forest type group; another 14 percent of the mortality occurred in the elm-ash-cottonwood forest type group. Disturbances associated with mortality included adverse weather and domestic animal damage. As mentioned above, a record drought in 2011 affected Oklahoma and Texas, stressing trees. Oklahoma has been working with Texas to monitor the impacts of drought on forest health in both States (Oklahoma Forestry Services 2014, 2015, 2016).

Western States

As mentioned above, in much of the West, only a small proportion of plots have been remeasured. Thus, the mortality results presented here should be considered preliminary. Also, one must be aware that, because of the longer 10-year measurement cycle in the West, results shown represent mortality that may have occurred any time during the period spanned by the data (see table 5.1), which may be as long as 15 years.

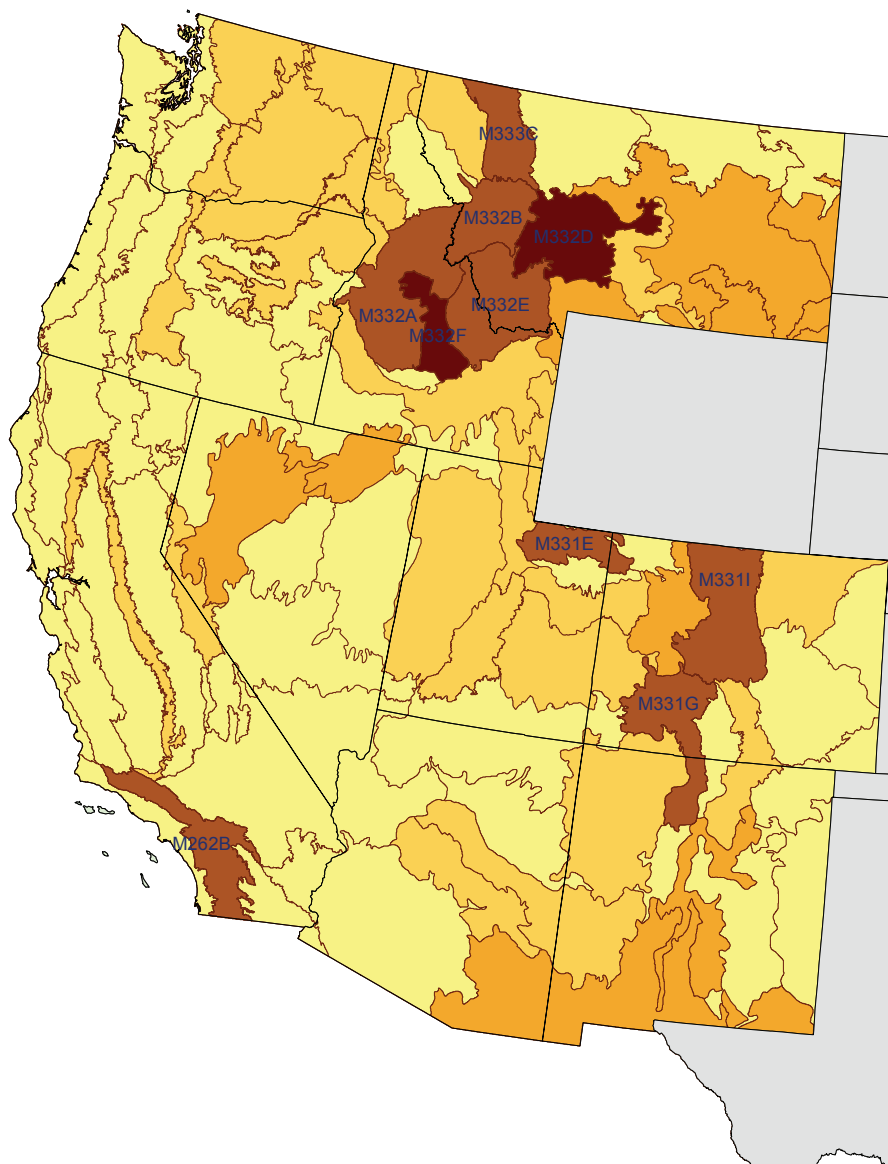
The Western United States presents a very different picture from the East in terms of mortality. For large portions of the West, no MRATIO has been calculated. This is because either (1) fewer than 50 plots had been remeasured in an ecoregion, or (2) the percent sampling error for the growth estimate was too

high (> 100 percent). One expects that as the first cycle of plot remeasurements is completed in future years, it will be possible to estimate an MRATIO for most of the West.

In much of the Interior West as well as southern California, where the MRATIO was calculated, mortality exceeded growth, sometimes by a factor of two to four (fig. 5.2). This is not surprising. In such dry regions, trees grow very slowly. Live tree volume is decreasing in regions where major mortality events are occurring. Because of the low growth rates, it will take quite a long time to recover the tree volume lost.

Figure 5.3 shows annual mortality as a percentage of total live tree volume. We see three clusters of mountain ecoregion sections where mortality is high relative to standing live volume: eastern Montana and central Idaho (M332A–Idaho Batholith, M332B–Northern Rockies and Bitterroot Valley, M332D–Belt Mountains, M332E–Beaverhead Mountains, M332F–Challis Volcanics, and M333C–Northern Rockies), the Front Range of Colorado (M331I–Northern Parks and Ranges and M331G–South-Central Highlands) together with section M331E–Uinta Mountains of Utah, and M262B–Southern California Mountain and Valley section. In all of these sections, annual mortality exceeded 3 percent of live volume.

In California, the mortality is most likely related to a combination of drought, bark beetles, and fire (California Forest Pest Council



Annual mortality as a percent of live volume

0.0%–1.0%
1.0001%–2.0%
2.0001%–3.0%
3.0001%–4.0%
4.0001%–7.16%

Figure 5.3—Annual tree mortality expressed as a percentage of gross live tree volume by ecoregion section (Cleland and others 2007) for the Western United States. (Data source: U.S. Department of Agriculture, Forest Service, Forest Inventory and Analysis Program). Mortality was analyzed using a partial cycle of remeasurements, and results from the region should be considered preliminary.

2016). In Colorado, ecoregion sections M331G and M331I include areas that have experienced major outbreaks of mountain pine beetle as well as spruce beetle (*Dendroctonus rufipennis*) (Colorado State Forest Service 2016). These same pests have been affecting ecoregion M331E (USDA Forest Service, Uinta-Wasatch-Cache National Forest [no date]; Utah Department of Natural Resources, Forestry, Fire, and State Lands 2016). The areas of high mortality in Montana and Idaho include areas suffering outbreaks of mountain pine beetle (Montana Department of Natural Resources and Conservation 2014, 2016) as well as major fires (Idaho Department of Lands 2014). However, several other insect and disease issues have been identified in this region and may have contributed to the mortality.

SUMMARY

This analysis shows that mortality is low relative to tree growth in most of the Eastern and Central United States. The areas of highest mortality occur in the mostly riparian forests of Great Plains ecoregions. A common characteristic of most of these ecoregions having high mortality is that they are on the margins of land suitable for forest growth, being very dry. Thus, they tend to be extremely vulnerable to changes in weather patterns that might produce prolonged and/or extreme drought. Drought, combined with a variety of other biotic and/or abiotic stressors, is likely responsible for much of the mortality observed.

The preliminary analysis of the Western United States shows that, almost everywhere in the Interior West, mortality relative to growth is higher than in most of the Eastern and Central United States. In several parts of the West, mortality is also very high as a percent of live volume. These areas correspond to regions where insect outbreaks (see chapter 2) as well as fire (chapter 3) and/or severe drought (chapter 4) have occurred.

It is also important to realize that the analyses presented in this chapter alone cannot tell the complete story regarding tree mortality. Mortality that is concentrated in highly fragmented forest or nonforest areas adjacent to human development may not be detected because the available FIA data do not cover most urban areas or other places not defined as forest by FIA. Also, should a particular species be dying due to a pest or pathogen in mixed-species forests where other species are growing vigorously, these analyses are unlikely to detect it. This is especially true of species (e.g., ash) that make up a relatively small proportion of many eastern forests.

To gain a more complete understanding of mortality, one should consider the results of this analysis together with other indicators of forest health. FIA tree damage data (O'Connell and others 2017) as well as Evaluation Monitoring projects that focus on particular mortality-causing agents (chapters 8–15) can provide

insight into smaller scale or species-specific mortality issues. Large-scale analyses of forest-damaging events, including insect and disease activity (chapter 2) and fire (chapter 3), are also important for understanding mortality patterns. This can be especially important in the West, where mortality data are limited.

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SECTION 2.

Analyses of
Long-Term Forest
Health Trends and
Presentations of
New Techniques

INTRODUCTION

Elemental concentration in lichens is a popular and cost-effective tool to bioindicate pollution load at plots (Donovan and others 2016, Paoli and others 2014, Root and others 2015) and to complement costly instrumented monitoring to help assess environmental health. From recent development of lichen elemental bioindicators for air pollution in the U.S. upper Midwest (Will-Wolf and others 2017a, 2017b, In press) for the U.S. Department of Agriculture, Forest Service, Forest Inventory and Analysis Program (FIA), we learned important lessons about suitability of lichen species in large-scale monitoring programs for the Eastern United States. Five macrolichen species common in Eastern North America (ENA) (Brodo and others 2001)¹ were evaluated in that study: *Evernia mesomorpha* (code Evemes; small/medium size fruticose growth form), *Flavoparmelia caperata* (code Flacap; large foliose), *Parmelia sulcata* (code Parsul; medium foliose), *Physcia aiopolia* and *P. stellaris* combined (code Phyaip; small foliose, tightly appressed), and *Punctelia rudecta* (code Punrud; large foliose). Elemental data and multi-element Pollution Indices derived from them clearly represented relative site pollution load better than did regionally modeled pollutant deposition (Will-Wolf and others 2017a), as has also been found

in other studies (e.g., Bari and others 2001, Boquete and others 2009, Geiser and Neitlich 2007, Root and others 2015). Evemes, Flacap, and Phyaip were recommended as bioindicator species for the study region (Will-Wolf and others 2017a, In press).

Based on the upper Midwest studies and 1994–2005 species frequencies in the FIA National Lichen Database (table 6.1)² Will-Wolf and others (In press) recommended bioindicator species for Northeastern (NE) region States (Connecticut, Maine, Massachusetts, New Hampshire, New York, Rhode Island, and Vermont), Mid-Atlantic (MidA) region States (Delaware, Maryland, New Jersey, Ohio, Pennsylvania, Virginia, and West Virginia), and Southeastern (SE) region States (Alabama, Georgia, North Carolina, South Carolina, and Virginia). Virginia was included in both the MidA and the SE regions to assist ecological evaluation of region boundaries.

For this study, our objective was to evaluate the recommendations of Will-Wolf and others (in press) using data from other studies. We evaluated 1994–2005 distribution patterns of all five tested macrolichen bioindicator species with respect to pollution load and nearby forest cover in the NE and MidA regions using lichen community data for subsets of FIA plots.

¹ Jovan, S.; Haldeman, M.; Will-Wolf, S. [and others]. [In management review, spring 2018]. National atlas of epiphytic lichens in forested habitats, U.S.A. Gen. Tech. Rep. PNW-GTR-XXX. Portland, OR: U.S. Department of Agriculture, Forest Service, Pacific Northwest Research Station. XX p.

² Jovan, S.; Will-Wolf, S.; Geiser, L.; Dillman, K. [In management review, spring 2018]. User guide for the national FIA lichen database (beta). Gen. Tech. Rep. PNW-GTR-XXX. Portland, OR: U.S. Department of Agriculture, Forest Service, Pacific Northwest Research Station. XX p.

CHAPTER 6.

Lichen Species to Bioindicate Air Quality in Eastern United States from Elemental Composition: Lessons from the Midwest

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SARAH JOVAN

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Table 6.1—Percentage of unique 1994–2005 FIA plots in eastern U.S. lichen regions with five target lichen elemental indicator species (names in bold) plus an additional species^a

Lichen species ^b	Species code	FIA lichen region ^c			
		NC (204p)	NE (625p)	MidA (779p)	SE (357p)
Any target species		96.6%	97.0%	91.9%	88.2%
Any of the four most common target species		95.6%	95.8%	91.9%	88.2%
Any of the three most common target species		95.1%	95.4%	91.3%	88.2%
Either of the two most common target species		90.7%	93.9%	85.1%	86.3%
<i>Evernia mesomorpha</i> Nyl. (some eastern U.S. studies, congener in Europe)	Evemes	56.4%	57.8%	3.3%	0
<i>Flavoparmelia caperata</i> (L.) Hale (several eastern U.S. studies, Europe)	Flacap	69.1%	63.0%	76.9%	60.2%
<i>Parmelia sulcata</i> Taylor (some eastern U.S. studies, Europe)	Parsul	71.6%	85.6%	52.4%	4.2%
<i>Physcia aipolia</i> (Ehrh. ex Humb.) Fűrnr. and <i>P. stellaris</i> (L.) Nyl. (no other studies)	Phyaip	78.4%	40.5%	23.1%	32.8%
<i>Punctelia rudecta</i> (Ach.) Krog (some eastern U.S. studies)	Punrud	39.2%	64.0%	58.0%	78.7%
<i>Punctelia missouriensis</i> G. Wilh. & Ladd (possible future target species; no usage)	Punmis	6.4%	0	10.8%	5.0%

^a Reprinted with permission from Will-Wolf and others (In press); data from Jovan and others (see footnote 2).

^b The three species most frequently found in each region have values in bold. Past elemental indicator use in Eastern United States and Western Europe indicated in parentheses after name.

^c FIA lichen regions are North Central (NC), Northeastern (NE), MidAtlantic (MidA), and Southeastern (SE); number of plots (p) in parentheses after lichen region code.

Comparisons of our results with those of the upper Midwest study and its recommendations for these regions support implementation of lichen elemental bioindicators in those regions. None of the NE, MidA, or SE regions currently has extensive lichen elemental data; government network instrumented monitor sites are scattered unevenly and often measure different

pollutants, and onsite instrument monitoring is very expensive (Will-Wolf and others 2017a).³ A Pollution Index from lichen elemental

³ Will-Wolf, S.; Jovan, S.; Nelsen, M.P. [and others]. [In review for The Bryologist, spring 2018]. Lichen indexes assess response to climate and air quality in the Mid-Atlantic States, USA.

analyses would greatly improve monitoring of environmental health across eastern FIA plots in most subregions.

METHODS

For the upper Midwest study (fig. 6.1), trained non-specialists (FIA field staff) collected single-species composite samples for all five target species under 20–50 percent tree canopy near permanent FIA plots using rigorous protocols [details in Will-Wolf and others (2017a, footnote 3)]. An expert collected samples of the same species from temporary plots using both rigorous protocols and several variants of relaxed (and more economical) protocols. Elemental data from combustion and ICP-OES (inductively coupled plasma optical emission spectroscopy) were validated, and then field sample quality and subsequent elemental data quality were evaluated; only the most rigorous protocols were supported [details in Will-Wolf and others (2017b)] to provide reliable data. Data were converted between species with General Linear Models (GLM) or regression [both in SPSS (2015)], then combined for analyses; two pollution indices were developed from multiple elements [aluminum (Al), cobalt (Co), chromium (Cr), copper (Cu), and iron (Fe) for one; nitrogen (N) and sulfur (S) for the other]. Estimation of relative pollution load from lichen elemental concentrations was confirmed by comparison with monitor site data (Will-Wolf and others 2017a). Lichen elemental bioindicators and protocols were recommended for implementation in other eastern U.S. regions (Will-Wolf and others, In press).

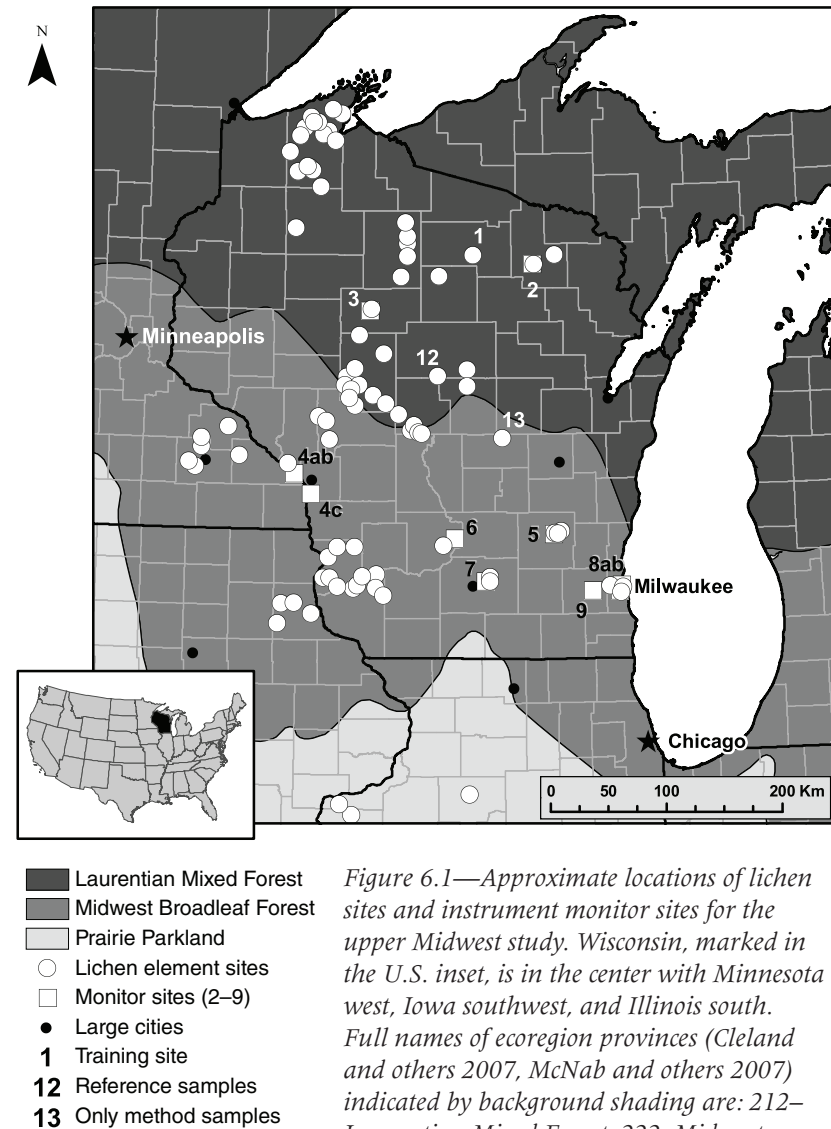


Figure 6.1—Approximate locations of lichen sites and instrument monitor sites for the upper Midwest study. Wisconsin, marked in the U.S. inset, is in the center with Minnesota west, Iowa southwest, and Illinois south. Full names of ecoregion provinces (Cleland and others 2007, McNab and others 2007) indicated by background shading are: 212—Laurentian Mixed Forest, 222—Midwest Broadleaf Forest, and 251—Prairie Parkland (Temperate). [Adapted with permission from Will-Wolf and others (2017a).]

Frequency of one or more of the five tested bioindicator species and one additional possible indicator species with respect to pollution load and proportion of nearby land in forest cover was evaluated with scatterplots for the three project areas discussed in this study (upper Midwest: Will-Wolf and others 2017a; NE: Will-Wolf and others 2015a; MidA: footnote 3). Relationships of bioindicator species abundance to pollution load and nearby landcover were evaluated for NE and MidA datasets with Pearson and Spearman rank correlations and with linear regression using original data and log10-transformed data for pollution load and nearby forest cover (SPSS 2015). For correlations, Pearson r^2 or Spearman ρ^2 , probability (p), and direction are reported; for regressions, adjusted r^2 , p , independent variables, and interpretation are reported. To account for experiment-wide error, correlations with $0.05 > p > 0.005$ were considered weak, and only correlations with r^2 or $\rho^2 \geq 0.10$ ($p < 0.00001$) were considered ecologically

important. Regression models with $0.05 > p > 0.01$ were considered weak.

Frequency of each lichen species, percent nearby forest cover, and relative pollution load were available from all three earlier studies. Nearby forest cover was the percentage of pixels with forest cover in a buffer zone around each site: $\sim 1 \text{ km}^2$ buffer for NE, $\sim 3 \text{ km}^2$ for upper Midwest, and $\sim 5 \text{ km}^2$ for MidA. Pollution load was represented by the lichen-based site Pollution Index developed independently for each of the three project areas. For the NE region, bioindicator lichen species abundance at 218 plots across all States (fig. 6.2A) was available from development of statistically independent climate and pollution indices for the region (Will-Wolf and others 2015a); species abundance at 219 plots in the MidA region (including Virginia) was available from a similar study (footnote 3). Plots were spread across most MidA States, but represented only the eastern one-quarter of Ohio (fig. 6.2B).

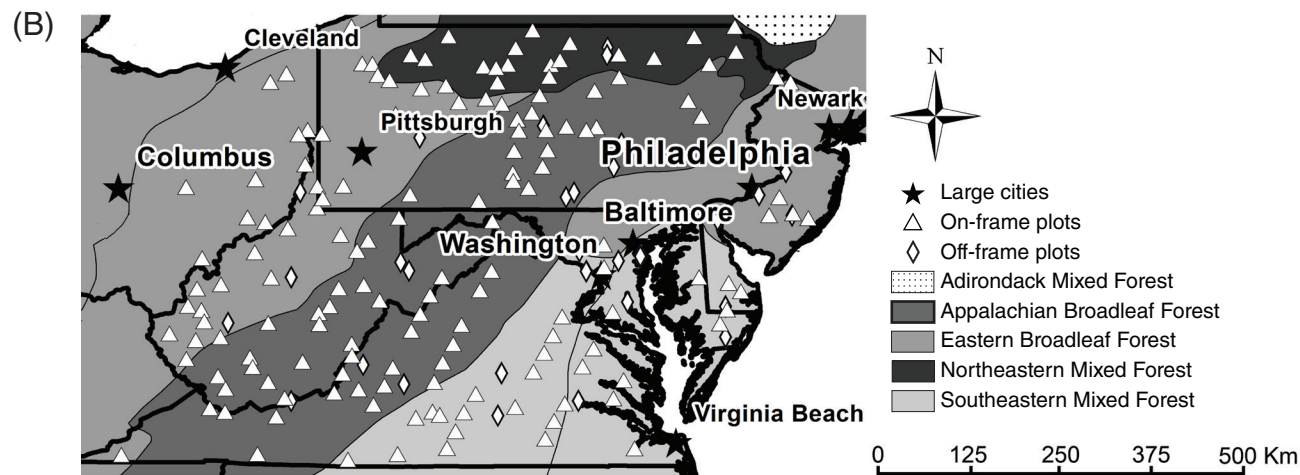
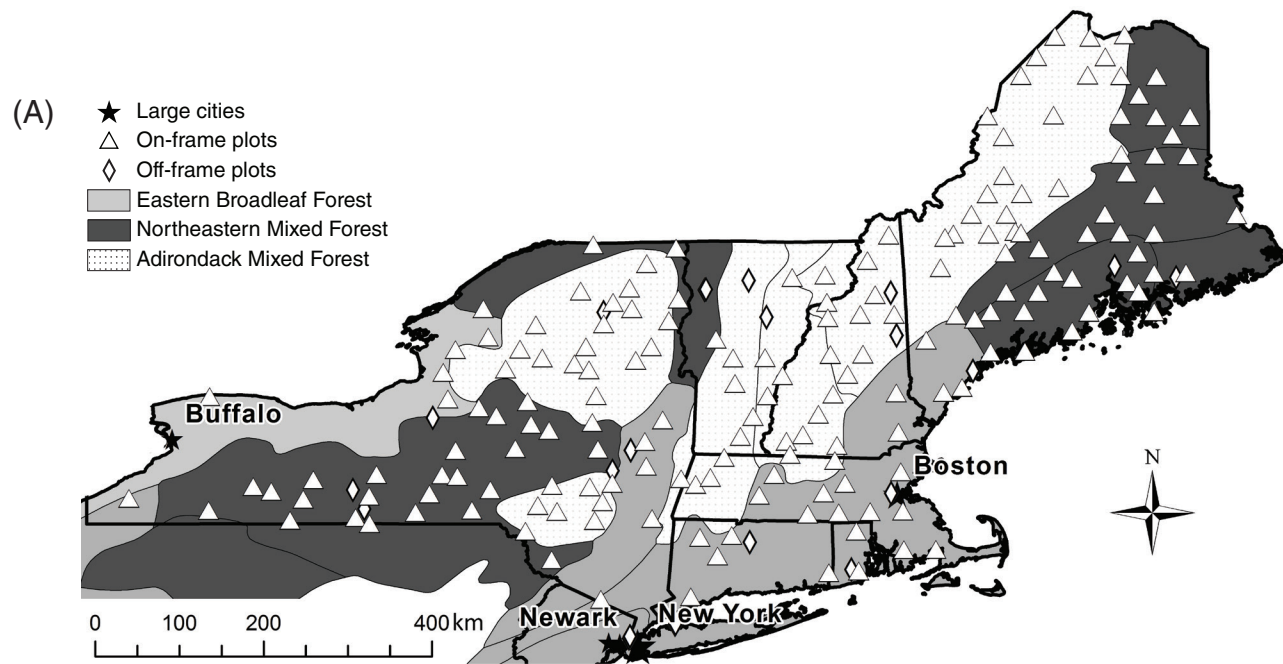


Figure 6.2—Northeastern (A) and MidAtlantic (B) region project plots (approximate locations). For comparison, the city of Newark, NJ, is at the bottom center of the map in (A) and near the upper right corner of the map in (B). On-frame plots are permanent FIA plots; off-frame plots are temporary plots surveyed only for each project. Full names of ecoregion provinces (Cleland and others 2007; McNab and others 2007) indicated by background shading in (A) are: 221—Eastern Broadleaf Forest, 211—Northeastern Mixed Forest, and M211—Adirondack-New England Mixed Forest - Coniferous Forest - Alpine Meadow. Full names in (B) are: M211—Adirondack-New England Mixed Forest - Coniferous Forest - Alpine Meadow, M221—Central Appalachians Broadleaf Forest - Coniferous Forest - Meadow, 221—Eastern Broadleaf Forest, 211—Northeastern Mixed Forest, and 231/232—Southeastern/Outer Coastal Plain Mixed Forest (two provinces combined, abbreviated as “Southeastern” in the legend). [(A) Adapted with permission from Will-Wolf and others (2015a); (B) adapted with permission from Will-Wolf and others (see footnote 3).]

RESULTS AND DISCUSSION

Relative success of lichen species as elemental bioindicators in the upper Midwest study generated several recommendations for both applications and limitations in three other eastern U.S. regions. Comparison with lichen community composition in two of those regions helped evaluate those recommendations.

Forest Inventory and Analysis field staff successfully distinguished Evemes, Flacap, and Phyaip from other lichen species (Will-Wolf and others 2017b). Flacap and Phyaip samples had good elemental data quality (203 samples of all five species at 83 sites after successful data conversion: Will-Wolf and others 2017a). Evemes samples had good data quality below a maximum relative pollution load (estimated from Pollution Index N + S and instrumented monitor site data) that reflected species sensitivity consistent with other U.S. studies (e.g., Will-Wolf and others 2015a); comparison of figures 6.3A and 6.3B illustrates exclusion of some Evemes samples from more polluted sites to achieve successful data conversion (via GLM: Will-Wolf and others 2017a) for equivalence with Flacap. Original Evemes N values (fig. 6.3A) were higher than Flacap values at the same less polluted sites. After conversion and exclusion of sites (fig. 6.3B), Evemes and Flacap values for the same sites overlap. Thus Evemes would be a reliable elemental bioindicator, but only for sites below that maximum relative pollution load, as estimated from the site Pollution Index calculated only from less sensitive lichen species. The tight correspondences between N values

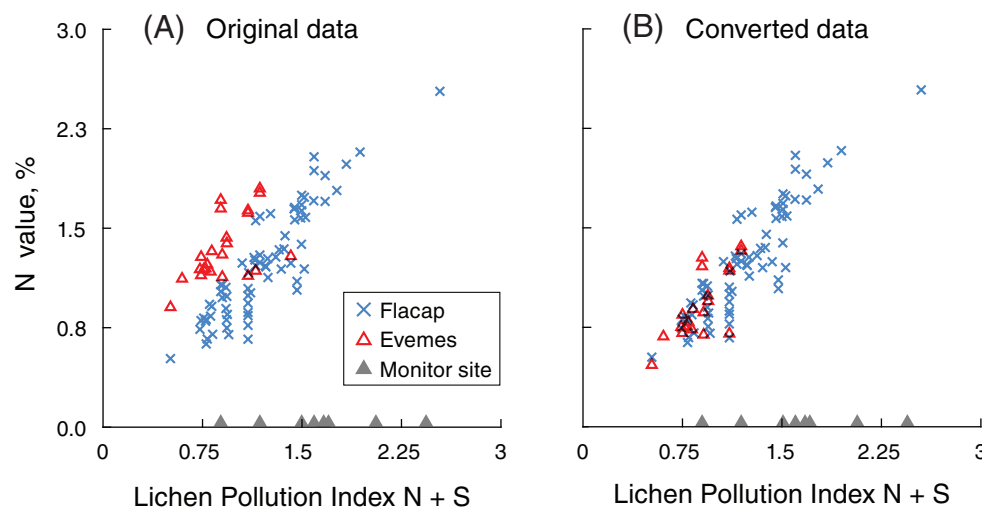


Figure 6.3—Flacap and Evemes (A) original and (B) converted sample data from the upper Midwest study for nitrogen (N) in lichens vs. a Lichen Pollution Index from both N and sulfur (S) in lichens. Many symbols overlap, from both species at the same site and from sites with similar values. [Data from Will-Wolf and others (In press).]

and the Lichen Pollution Index in figures 6.3B, 6.4A, and 6.4B reflect that converted N data for all lichen species were incorporated into the Lichen Pollution Index. Flacap (often used for lichen elemental analysis, e.g., Will-Wolf and others 2015b, 2017a, footnote 3) and Phyaip (not used before but successful in the upper Midwest study) between them covered the study area (fig. 6.4C); partitioning of sites between the species was in Will-Wolf and others (2017a) qualitatively linked as much to percentage of nearby forest cover as to site air pollution. Presence of each species was more strongly correlated with nearby forest cover than with pollution load, and logistic regression on presence of each species found nearby

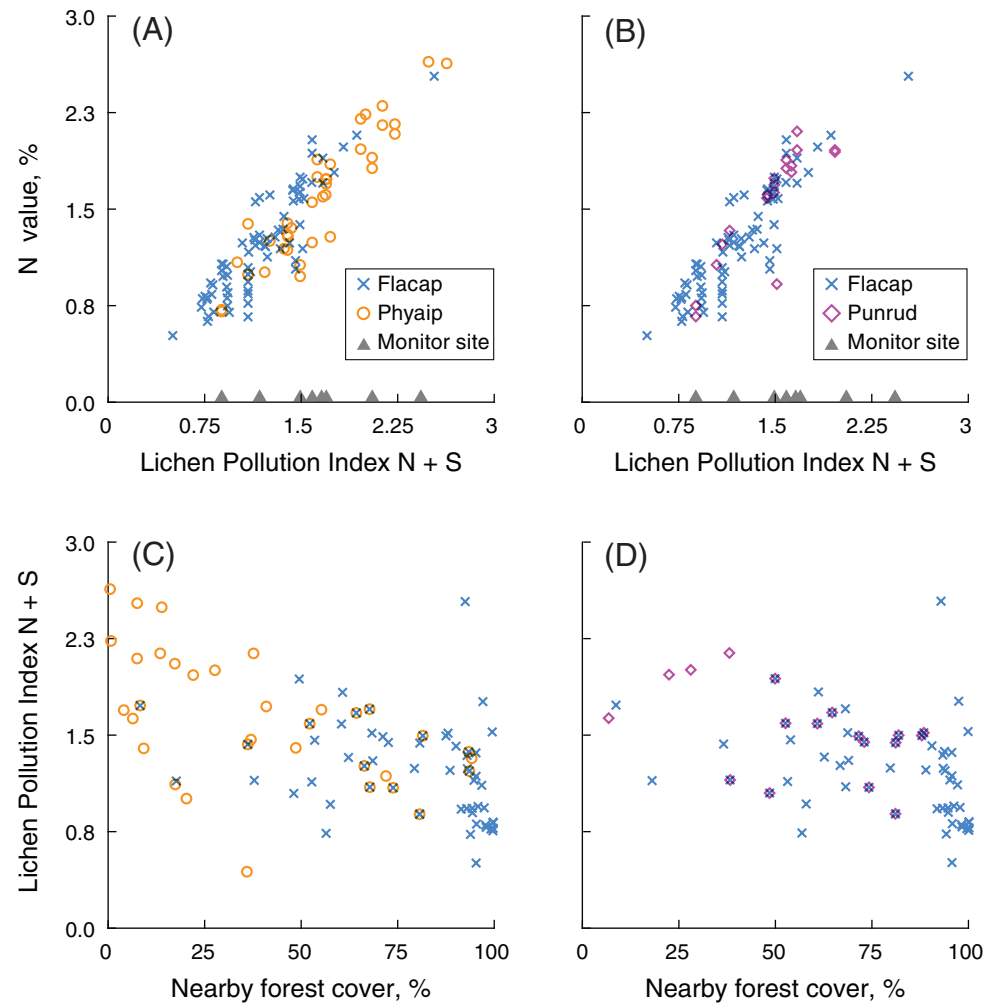


Figure 6.4—(A, C) *Flacap* and *Phyaip* or (B, D) *Flacap* and *Punrud* pairs compared for the upper Midwest study. In A and B, species pairs are compared for converted nitrogen (N) concentrations vs. Pollution Index. In C and D, presence of each species is plotted by site Pollution Index and nearby forest cover. Many symbols overlap, from both species at the same site and from sites with similar values. [Data from Will-Wolf and others (In press).]

forest cover to be the most significant predictor variable [Will-Wolf and others (in press)], an unexpected result.

Non-specialist field staff had difficulty distinguishing Parsul and Punrud [both successful in expert studies, e.g., Olmez and others 1985; reviewed in Will-Wolf and others (2017b)] from other lichen species; this led to few samples collected and poor elemental data quality in ~10 percent of samples. Parsul and Punrud identification difficulties for non-specialists were an unexpected outcome of interest particularly to large monitoring programs; the human context of a study is as important to bioindicator choice as is the scientific context. Scatterplots of Flacap and Punrud (figs. 6.4B and 6.4D) illustrate that while converted data for Punrud samples overlapped Flacap samples along most of the pollution range, they were much less frequent; Parsul had a similar pattern.

Based on these earlier studies, Flacap (in areas with less isolated forests) and Phyaip (in areas with more isolated forests) were the primary recommended lichen elemental bioindicators for the full North Central region, with Evemes a secondary recommended bioindicator in northern areas and at less polluted sites because it is so cost-effective to handle (Will-Wolf and others 2017a, in press). Based on the upper Midwest studies and on frequency of species in FIA plots (table 6.1), Will-Wolf and others (in press) recommended Flacap (widespread) and Evemes (northern and mountainous areas with less air pollution) as primary bioindicator species

for the NE region, with Phyaip as a secondary species in areas (usually with more isolated forests) where samples of a primary species were not found. For the MidA region Flacap and Punrud (both widespread) were recommended as primary bioindicators (Punrud requires intensive identification training for non-specialist field staff), with Phyaip as a secondary species at plots in less forested landscapes.

Comparisons of 1994–2005 bioindicator species distributions with pollution indices and nearby forest cover for the NE and MidA data subsets helped better predict success of recommended bioindicators in these regions. The NE dataset is ~35 percent of the available FIA plots with lichen data in those States (table 6.1); the MidA dataset is ~28 percent of the available FIA plots with lichen data. Plot distribution for the NE and MidA region projects (fig. 6.2) was more even than for the upper Midwest study (fig. 6.1), though all ecoregions were well-represented in all three studies. In the NE and MidA datasets, full lichen community composition varied strongly with both climate and air pollution represented by a Pollution Index statistically independent of climate (Will-Wolf and others 2015a, footnote 3). In each dataset, lichen composition was more weakly linked to nearby forest cover than to climate or pollution, and, in the same pattern as the upper Midwest study, Pollution Index was negatively correlated with nearby forest cover. For both NE and MidA, correlation between Pollution Index and nearby land in forest cover, while statistically strong ($p < 0.0005$), was small

enough ($r^2 = 0.28$ for NE, 0.36 for MidA) to enter both variables into the same regression model. In both these datasets, *Physcia stellaris* was more frequent at plots than was *Physcia aipolia* (from laboratory identifications; not reliably distinguishable in the field), so *Phyaip* represented the former species more, in contrast to the upper Midwest study where *Physcia aipolia* was the more frequent species in *Phyaip* based on laboratory identifications. Comparisons of indicator species pairs over the subset of plots in each dataset where at least one of them occurred helped evaluate how well suites of indicator species would represent the region. In addition, the MidA project illustrated differences between lichen species abundance at FIA plots and ability to collect a bulk lichen elemental sample within a narrow canopy range in the vicinity of an FIA plot. Flacap was recorded at 93 percent of 219 MidA plots (footnote 3), but adequate elemental samples were collected at only 85 percent of 26 temporary sites spanning the pollution gradient. Thus these analyses of lichen species abundances can at best be very general estimators for the likelihood of collecting adequate samples for elemental analyses. Indicator species not mentioned in the next two paragraphs were too uncommon in a region to consider further.

From the NE region dataset, *Phyaip* appeared to be present at more of the polluted sites than did Flacap (fig. 6.5A), but the two species overlapped across the gradient of nearby forest cover in contrast to the upper Midwest sites (compare with fig. 6.4C). *Phyaip* abundance had weak positive correlation ($\rho^2 = 0.03$,

$p = 0.011$) and Flacap abundance weak negative correlation ($r^2 = 0.052$, $p = 0.0007$) with the Pollution Index; both lacked significant correlation (not significant [NS]) with percent of nearby land with forest cover. The strongest significant ($p < 0.001$) regression model (though still weak; $\text{adj } r^2 = 0.07$) for Flacap predicted its abundance declined as Pollution Index (original values) increased. No regression model was significant for *Phyaip*. The NE Flacap and Parsul scatterplot (fig. 6.5B) showing Parsul present at more sites with high pollution and low nearby forest cover than *Phyaip* (fig. 6.5A) suggested Parsul might complement Flacap better than *Phyaip* to provide broad representation of even high-pollution FIA plots. However, Parsul abundance had weak negative correlation with pollution ($\rho^2 = 0.04$, $p = 0.005$; NS with nearby forest cover), and a weak regression model ($\text{adj } r^2 = 0.02$, $p = 0.02$) predicted the same pattern from $\log_{10}$ of Pollution Index. Thus Parsul, while present, had very low abundance at polluted sites, supporting *Phyaip* as the better complement to Flacap for NE elemental bioindication. The scatterplot of NE Flacap and Evemes (fig. 6.5C) presence shows Evemes was mostly restricted to plots with > 50 percent nearby forest cover and in the cleaner half of the Pollution Index. Evemes abundance was negatively correlated with Pollution Index ($\rho^2 = 0.54$, $p < 0.00001$) and positively correlated ($r^2 = 0.152$, $p < 0.00001$) with percent nearby forest cover; the strongest regression model ($\text{adj } r^2 = 0.56$, $p < 0.0000$) predicted Evemes decline only with increasing

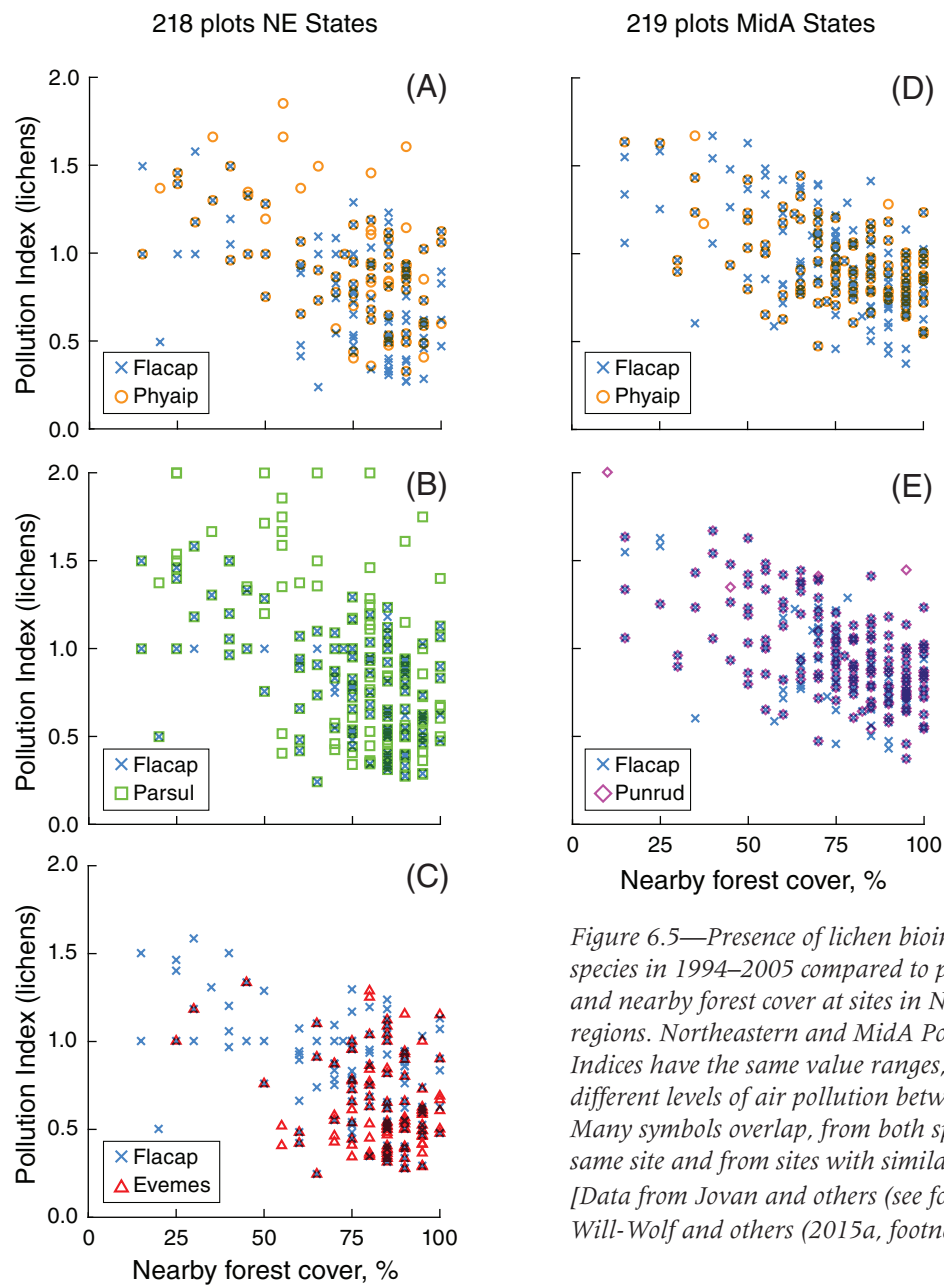


Figure 6.5—Presence of lichen bioindicator species in 1994–2005 compared to pollution and nearby forest cover at sites in NE and MidA regions. Northeastern and MidA Pollution Indices have the same value ranges, but indicate different levels of air pollution between regions. Many symbols overlap, from both species at the same site and from sites with similar values. [Data from Jovan and others (see footnote 2), Will-Wolf and others (2015a, footnote 3).]

log10 of Pollution Index. Evemes was clearly more limited in the NE region by pollution than by nearby forest cover, a reversal from the upper Midwest study (Will-Wolf and others 2017a, footnote 3); it was, however, the only NE region bioindicator species showing a statistical link with nearby forest cover. These patterns support the recommendations by Will-Wolf and others (in press) for Flacap and Phyaip plus secondary Evemes as bioindicator species in the NE region, though with little demonstrated influence of nearby forest cover on lichen distribution. Species distribution patterns should be evaluated with the full suite of NE FIA lichen plots to further refine bioindicator recommendations.

Both Phyaip and Punrud were present at more MidA plots with high pollution than was Flacap (figs. 6.5D, 6.5E). While all three species were present across the full range of nearby forest cover, response of species' abundances more strongly supported the rationale by Will-Wolf and others (in press) for recommending Flacap and Punrud as primary and Phyaip as a secondary bioindicator species in the MidA region. Flacap abundance was positively correlated with forest cover ($r^2 = 0.07$, $p < 0.0005$) and negatively correlated ($r^2 = 0.19$, $p < 0.0005$) with Pollution Index. The strongest (although still weak) regression model ($r^2 = 0.09$, $F = 23.3$, $p < 0.0005$) predicted Flacap increasing only with lower pollution. Punrud abundance had weak positive correlation with percent nearby forest cover ($r^2 = 0.03$, $p = 0.013$) but no correlation (NS) with Pollution Index; its best but weak and ecologically unimportant

regression model ($r^2 < 0.01$, $F = 5.8$, $p = 0.017$) predicted Punrud abundance increasing only with log of nearby forest cover. Phyaip abundance had weak negative correlation with Pollution Index ($r^2 = 0.02$, $p = 0.037$) and none (NS) with percent nearby forest cover. Thus Flacap appeared more pollution-sensitive as well as preferring high-forest landscapes, Phyaip appeared slightly sensitive to pollution but not to forest cover, and Punrud appeared to slightly prefer high-forest landscapes but be unresponsive to pollution. More sensitivity to forest cover might be noted in analyses including plots in low-forest landscapes of western Ohio (favors Phyaip) that were not in the 219-plot subset. Only 11 percent of the 219 MidA plots had < 50 percent local forest cover, as compared with 30 percent of the 83 upper Midwest study plots. Flacap abundance was negatively correlated ($r^2 = 0.19$, $p < 0.000001$) with Pollution Index in MidA. These analyses support recommendation of Punrud as a primary elemental bioindicator, despite its need for intensive identification training of non-specialist field staff, to complement the more environmentally sensitive Flacap and the less abundant Phyaip. Sparse MidA region lichen elemental data (footnote 3) support the recommendations and also highlight differences between species presence based on even a single individual vs. an adequate sample for elemental analysis. An adequate elemental sample is 1–2 g per species from six or more different substrates under 20–50 percent forest canopy (Will-Wolf and others 2017a, in press). For example, Flacap

was present at ~77 percent of all MidA plots (table 6.1) and 93 percent of 219 MidA subset plots, while adequate elemental samples of Flacap came from 85 percent of 26 supplemental sites (footnote 3) selected to represent the pollution gradient.

Species distribution patterns should be evaluated in the MidA region with the full suite of FIA lichen plots. *Punmis* (*Punctelia missouriensis*) (table 6.1), suggested by Will-Wolf and others (in press) as another possible bioindicator species for the MidA region in low forest landscapes (it is a Midwestern United States endemic: Brodo and others 2001), was present at only five of the 219 subset plots. However, even from those few sites, *Punmis* abundance had weak positive correlation ($r^2 = 0.02$, $p = 0.021$; regression NS) with the Pollution Index; such pollution tolerance could make it a useful elemental bioindicator there. The bioindicator potential of this species will become more apparent after evaluation with the full suite of MidA FIA lichen plots including the rest of Ohio (table 6.1), with likely most added sites in low-forest landscapes. Identification success by non-specialists has not been tested, but, based on its form and color, *Punmis* might be as difficult as *Parsul* or *Punrud* for non-specialists to distinguish from other co-occurring species.

Recommendations by Will-Wolf and others (in press) of Flacap, *Phyaip*, and *Punrud* as elemental bioindicators for the SE region

are also supported to a degree from MidA analyses, based on inclusion of Virginia in both the MidA and SE regions. Evaluation of species distribution patterns for all SE plots will be particularly important to further refine bioindicator recommendations. This region is the most likely location for recommended target species to fall short of availability at 90 percent of FIA plots, based on data in table 6.1.

Distribution of elemental bioindicator species for the NE, MidA, and SE regions may have changed somewhat from that represented by the 1994–2005 FIA lichen community data discussed here. Probably because shifts from coal to natural gas for much eastern U.S. energy production accelerated starting about 2000 from expanded fracking, recent local pollution impacts on forests (Drohan and others 2012) have been offset by regional declines in air pollution (US EPA 2017). In the NE and MidA regions since 2005, nitrogen dioxide (NO_2) has declined ~25–30 percent, sulfur dioxide (SO_2) has declined ~70–75 percent, and particulates ($\text{PM}_{2.5}$; correlated with pollution metals) have declined about 35–40 percent. So by 2017 the impact of air pollution on lichen species distribution may have declined in these regions, and the impact of nearby forest cover may have become relatively more important by default. It has long been known that forest fragmentation and distance from propagule source can affect lichen recolonization (Gilbert 1992), though such impacts were previously documented mostly on less common lichen species.

CONCLUSIONS

Distribution patterns of lichen elemental bioindicator species with respect to pollution and landcover in NE and MidA U.S. regions supported recommendations from an upper Midwest study, but also suggested the need for additional evaluations. One additional recommendation from this study is to evaluate *Punmis* as an elemental bioindicator for the MidA region. It appears from evaluation of 1994–2005 species distributions that considering nearby forest cover will be more helpful to predict bioindicator species representation at plots in the MidA region than in the NE region. Additional FIA lichen data from 1994–2005 are available for several eastern regions to conduct wider evaluations that support implementation of lichen elemental bioindicators in the NC, NE, MidA, and SE States. However, declines in air pollution since 2005 may have increased the relative importance of nearby forest cover to predicting distribution of bioindicator lichen species in all regions. Because of this, nearby forest cover should be evaluated as a factor during implementation in all eastern U.S. regions regardless of patterns from older lichen distribution data. Reliable and cost-effective plot-level bioindicators for air quality are needed to improve assessment of the environmental health of eastern U.S. forests, especially in the absence of other reliable indicators for local air quality across a wide region.

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INTRODUCTION

Tree crown conditions are visually assessed by the U.S. Department of Agriculture, Forest Service, Forest Inventory and Analysis (FIA) Program as an indicator of forest health. These assessments are useful because individual tree photosynthetic capacity is dependent upon the size and condition of the crown. In general, trees with full, vigorous crowns are associated with more vigorous growth rates (Zarnoch and others 2004); when trees undergo stress, the first symptoms are often visible in the crown. Furthermore, tree crowns form the overstory structure of the forest and directly influence the composition and structure of the understory thereby making them an integral component of the forest ecosystem.

Initially implemented by the Forest Health Monitoring (FHM) Program, crown conditions have been measured in the United States since 1990 (Randolph 2013). After a series of field tests and reviews in the early 1990s, the crown condition indicator was formalized to include a set of eight variables: vigor class, uncompact live crown ratio, crown light exposure, crown position, crown density, crown dieback, foliage transparency, and crown diameter (Schomaker and others 2007). When the FHM detection monitoring plots were incorporated into FIA in the year 2000, assessment of these and other forest health indicators was continued by FIA (Woodall and others 2011).

Due to budget uncertainties in 2011, FIA deferred collection of the forest health indicators and began reviewing its forest health monitoring protocols in light of fluctuating budgets, emergent user needs, and evolving forest health science (USDA Forest Service 2012). The review led FIA to revise the “Phase 3 (P3) Forest Health Indicators” aspect of the program into a new framework termed “Phase 2 (P2) Plus / Ecosystem Indicator Program” (USDA Forest Service 2013). When the new framework is fully implemented, FIA will collect fewer variables on a greater number of plots in an effort to improve flexibility without compromising long-term analytical capabilities. To date, updated protocols for the crown condition indicator, which, at a minimum, call for the assessment of uncompact live crown ratio and crown dieback on all P2 Plus plots, have been implemented to varying degrees by the four FIA regions (fig 7.1).

This chapter represents the third national summary of crown condition in the United States. Previous summaries were included in *Forest Health Monitoring: 2006 National Technical Report* (Randolph 2009) and *Forest Health Monitoring: National Status, Trends, and Analysis 2013* (Randolph 2015). In like manner, the objective of this report is to summarize crown conditions for major species groups for the years 2011–2015 and evaluate changes in crown condition during the last two decades with the goal of identifying species in decline. Special

CHAPTER 7. Crown Condition

KADONNA C. RANDOLPH

attention is given to species affected by three of the top mortality agents in the Eastern United States: emerald ash borer (*Agrilus planipennis*) (EAB), beech bark disease (BBD), and hemlock woolly adelgid (*Adelges tsugae*) (HWA). Due to the transition from P3 to P2 Plus, crown dieback was the only crown condition variable evaluated.

METHODS

Data

Crown dieback is the recent mortality of branches with fine twigs, which begins at the terminal portion of a branch and proceeds toward the trunk (Schomaker and others 2007). Forest Inventory and Analysis assesses crown dieback on live trees with diameter at breast height (d.b.h.) ≥ 12.7 cm by means of ocular estimation and records the values in 5-percent classes. Prior to 2011, crown dieback was collected on FIA P3 plots in all regions. In 2011 and the years following, assessment of crown dieback varied by region (table 7.1). For this summary, I obtained all crown dieback data collected by FIA from 2000 through 2015 (O'Connell and others 2017) and utilized various subsets of the data to summarize current conditions and calculate changes over time. Crown dieback assessments made by the FHM Program from 1995 through 1999 (Randolph 2006, Randolph and others 2010a, 2010b) were also incorporated. Though little to no crown dieback data were available for the Rocky Mountain and West Coast regions after 2010, information on tree status (live, dead, or cut) in those regions was incorporated into the analysis.

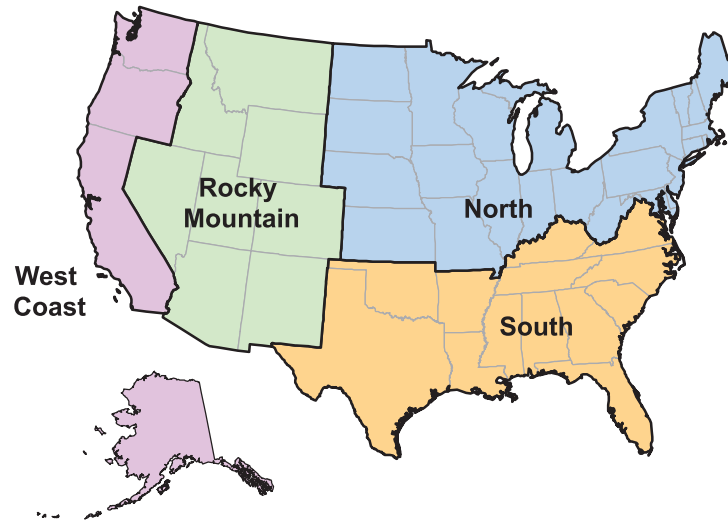


Figure 7.1—Regional breakdown of the United States for the crown dieback analysis corresponds to the administrative units of the U.S. Department of Agriculture, Forest Service, Forest Inventory and Analysis Program.

Analysis

Survivorship—The relationship between past crown dieback and current tree status, i.e., survivorship, was evaluated for all regions. For the Rocky Mountain and West Coast regions, trees with crown dieback measured from 2001 through 2005 were matched with observations made from 2011 through 2015. For the North and South regions, observations made from 2006 through 2010 were matched with observations made from 2011 through 2015. Measurement intervals for individual trees assessed during these time periods varied from 2 to 12 years; only trees with a 5-year

Table 7.1—Year of crown dieback assessment by region and State, 2011–2015

Region ^a and measurement year	State
North	
2011–2015	Illinois, Missouri, Pennsylvania
2011–2013, 2015	Delaware
2012–2015	Connecticut, Indiana, Iowa, Kansas, Maine, Maryland, Massachusetts, Michigan, Minnesota, Nebraska, New Hampshire, New Jersey, New York, North Dakota, Ohio, South Dakota, Vermont, West Virginia, Wisconsin
2013–2015	Rhode Island
Rocky Mountain	
2011–2012	Nevada, New Mexico
2012	Arizona, Colorado, Idaho, Montana, Utah, Wyoming
South	
2012–2015	Alabama, Arkansas, Florida, Georgia, Kentucky, Mississippi, North Carolina, Oklahoma, South Carolina, Texas
2012–2014	Louisiana ^b , Virginia
2012–2013, 2015	Tennessee

^a Crown dieback was not assessed in the West Coast region.

^b Crown dieback was assessed in 2015 but the data were not available at the time of analysis.

measurement interval in the North and South regions or 10-year measurement interval in the West Coast and Rocky Mountain regions were included in the survivorship analysis. The percentage of trees by past crown dieback class (0 percent, 1–10 percent, 11–20 percent, and > 20 percent) and current tree status (live, dead, or cut) was calculated for each region. To expose any species groups potentially affected by acute stressors between the most recent and previous assessments, the percentage of trees

in each current tree status class was calculated for trees with 0-percent crown dieback at the previous assessment for major species groups in each region.

Current conditions—Current (2011–2015) crown dieback conditions were summarized for the North and South regions by species class (hardwood or softwood) and species group. Mean crown dieback was calculated using the ratio of means estimator (Cochran 1977,

Woodall and others 2011). The frequency of trees in each crown dieback class (0 percent, 1–10 percent, 11–20 percent, and > 20 percent) also was calculated by species group. Infestation data (county and date of infestation discovery) were obtained for EAB (EAB Information Network 2017); beech scale (*Cryptococcus fagisuga*), the initiating agent of BBD (Cale and Morin 2017); and HWA (USDA Forest Service, Northeastern Area 2017) (fig. 7.2). These data were used to respectively subdivide ash (*Fraxinus* spp.), beech (*Fagus grandifolia*), and eastern hemlock (*Tsuga canadensis*) trees into classes based on duration of infestation. Current mean crown dieback and the frequency of trees in each crown dieback class then were calculated for each species group by infestation class.

Trends—Changes in crown condition can be evaluated by comparing crown dieback assessments on the same set of trees over time or by examining the net change in dieback for all trees measured at multiple points in time.¹ The former uses only paired trees at two (or more points) in time and necessarily includes surviving trees only. The latter includes all trees measured at each point in time and includes trees that have survived across all time periods as well as

those that died or were cut. To make the most of the crown dieback data collected to date, I made two evaluations of change in crown dieback over time. The first included only trees with crown dieback assessments made from 2006 through 2010 and 5 years later (2011–2015), i.e., surviving trees with two dieback assessments, in the North and South regions. A paired *t*-test was used to test the hypothesis that the mean change in crown dieback for the paired trees was zero. Secondly, I calculated mean crown dieback by region (North and South) for all trees assessed by FIA during three different 5-year time periods: 2001–2005, 2006–2010, and 2011–2015. Regional crown dieback means from the last FHM assessments (1995–1999 for the North region and 1996–1999 for the South region) were obtained from Randolph (2006) and Randolph and others (2010a, 2010b). The frequency of trees by crown dieback class (0 percent, 5 percent, and > 5 percent) was calculated for each time period by region.

RESULTS AND DISCUSSION

Relationship between Crown Dieback and Survivorship

Crown dieback is strongly correlated with tree survivorship such that trees with greater amounts of dieback are more likely to die within 5 years than those with little or no dieback (Morin and others 2015, Steinman 2000). Therefore, as expected, the likelihood of mortality tended to increase with increasing

¹ Bechtold, W.A.; Randolph, K.C. 2006. FIA Crown-condition indicator workshop outline and class notes. Unpublished document. 70 p. On file with: U.S. Department of Agriculture, Forest Service, Southern Forest Inventory and Analysis Program, 4700 Old Kingston Pike, Knoxville, TN 37919.

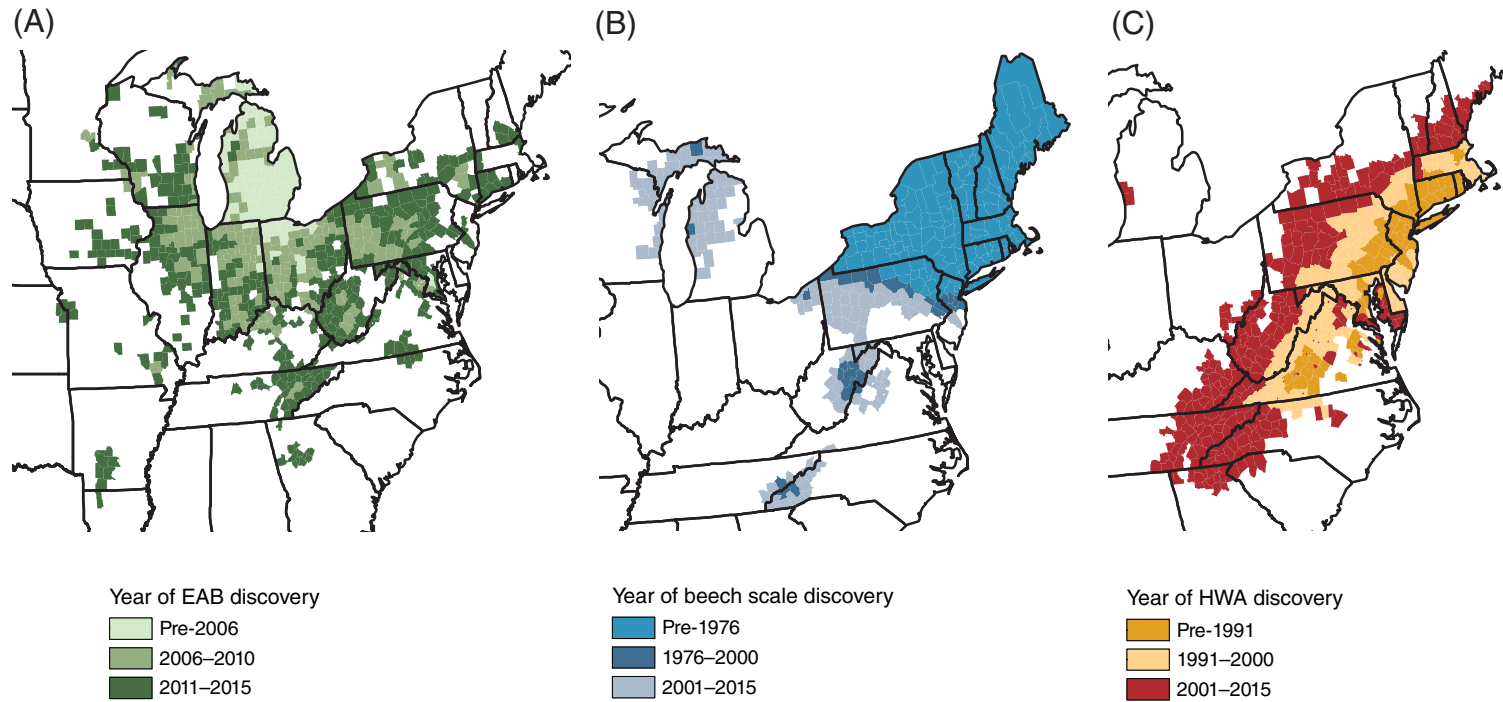


Figure 7.2—Year of discovery and distribution of (A) emerald ash borer (EAB Information Network 2017), (B) beech scale (Cale and Morin 2017), and (C) hemlock woolly adelgid (USDA Forest Service, Northeastern Area 2017) in the Eastern United States through the year 2015.

crown dieback in all regions (fig. 7.3). In the West Coast region, 50.5 percent of the trees assessed with > 20-percent crown dieback during 2001–2005 were dead by the time they were remeasured 10 years later. Likewise in the Rocky Mountain region, 43.2 percent of the trees with > 20-percent crown dieback died over the same 10-year period. Similar percentages were observed over a 5-year period in the Eastern United States where 47.2 percent and 54.0 percent of the trees assessed with > 20-percent crown dieback during 2006–2010 in the North and South regions, respectively, were dead by the time they were remeasured during 2011–2015 (fig. 7.3).

Although high levels of crown dieback are a good indicator of impending mortality, there are instances when trees with no crown dieback will die before they are reassessed. This is most likely to happen when trees die quickly as the result of an acute stressor, e.g., wildfire, or when the effects of less acute stressors coincide with a lengthy remeasurement period. Regions or species groups with high levels of mortality among trees with 0-percent crown dieback at the previous inventory prompt further investigation. Such was the case in the Rocky Mountain region where 19.2 percent of the trees observed to have 0-percent crown dieback during 2001–2005 died within 10 years (fig. 7.3). Further investigation revealed that this group of trees was composed primarily of lodgepole pine (*Pinus contorta*), quaking aspen (*Populus tremuloides*), and subalpine fir (*Abies lasiocarpa*). Considered individually, each of these species

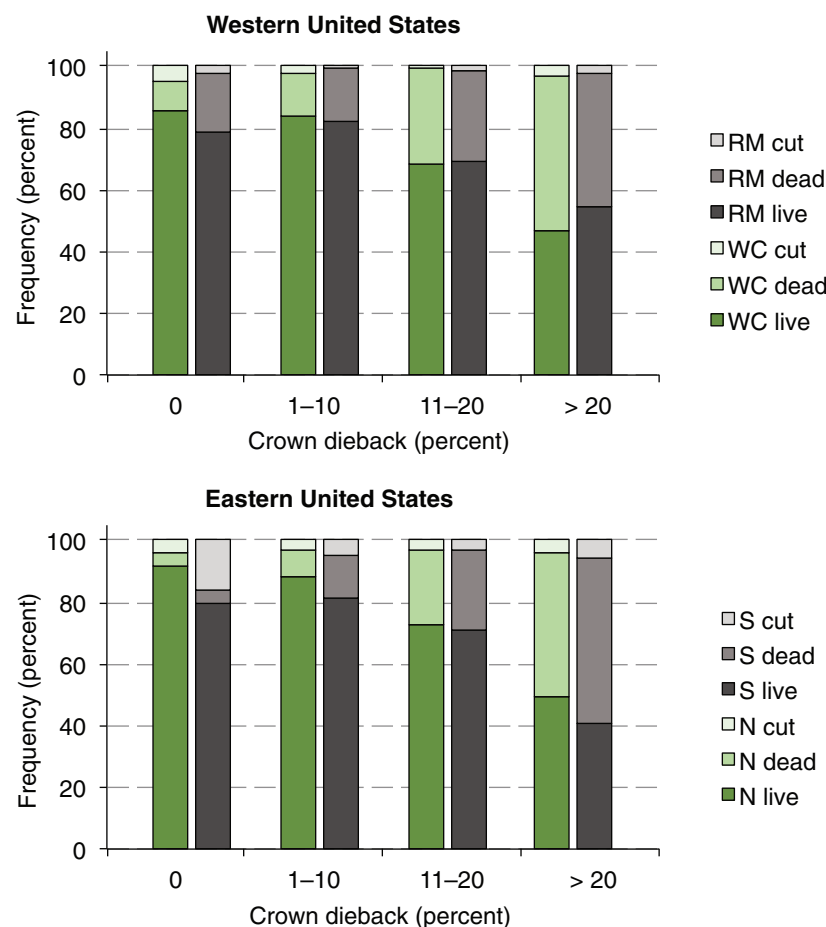


Figure 7.3—Percentage of trees remeasured after an interval of 10 years (Western United States) or 5 years (Eastern United States) by previous crown dieback, current tree status, and region. N=North. RM=Rocky Mountain. S=South. WC=West Coast. (Data source: U.S. Department of Agriculture, Forest Service, Forest Inventory and Analysis Program)

had more than 25 percent mortality among trees with 0-percent crown dieback during the 2001–2005 inventory (fig. 7.4). Lodgepole pine mortality was likely due to mountain pine beetle (*Dendroctonus ponderosae*) activity which has affected approximately 7.8 million ha of forest land in the Western United States since the year 2000 (Potter and Paschke 2016). Mountain pine beetle activity was relatively stable (< 405 000 ha annually) from 1990 through 2001 and, though increasing, remained at or below 1.2 million ha annually during the years that crown dieback was first assessed (2001–2005) (Jenkins 2015). In the intervening time period before the trees were remeasured, beetle activity increased above 1.6 million ha annually, peaking at 3.6 million ha in 2009, and incited a substantial increase in tree mortality (Jenkins 2015, Oswalt and others 2014).

The high level of quaking aspen mortality in the Rocky Mountain region among trees with 0-percent crown dieback during 2001–2005 was likely induced by a complex of interacting factors in the mid- to late-2000s termed sudden aspen decline (SAD) (Worrall and others 2013). The peak of this disease complex (2007–2008) occurred after crown dieback was first assessed during 2001–2005 (Worrall and others 2015). Similarly, mortality of subalpine fir in the Rocky Mountain region may be attributed to subalpine fir decline (SFD) which, like SAD, is a complex that involves many factors, including the western balsam bark beetle (*Dryocoetes confusus*), various fungi, and temperature and precipitation stress (Reich and others 2016).

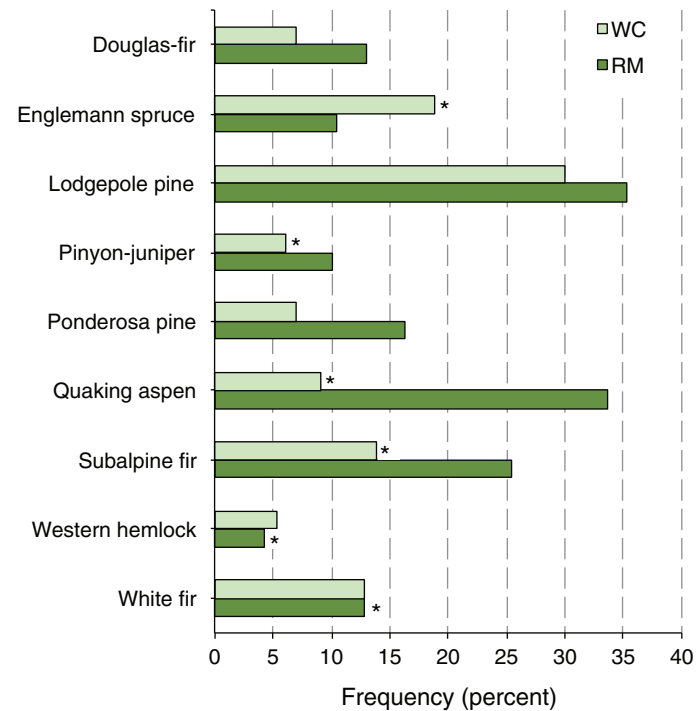


Figure 7.4—Percentage of trees in the West Coast (WC) and Rocky Mountain (RM) regions assessed with 0-percent crown dieback during 2001–2005 that were dead upon reassessment during 2011–2015, by species group. Species groups with < 200 observations are indicated with an asterisk. (Data source: U.S. Department of Agriculture, Forest Service, Forest Inventory and Analysis Program)

During 2007–2014, aerial survey data indicated that SFD mortality fluctuated yearly, affecting between 98 594 ha in 2013 (Potter and Paschke 2015) and 211 470 ha in 2007 (Potter 2012).

In contrast to the western regions, the percentage of trees assessed with 0-percent crown dieback during 2006–2010 that died prior to reassessment during 2011–2015 was < 10 percent for most species groups in the Eastern United States (fig. 7.5). One notable exception was elm (*Ulmus* spp.) in the North region, which had 17.4 percent mortality among trees with 0-percent crown dieback (fig. 7.5). Elm trees are affected by a number of insect and disease agents (Bey 1990, Penn State Extension 2017), most notably Dutch elm disease (DED) (Haugen 1998) and elm yellows (formerly called elm phloem necrosis) (Marcone 2017). Both DED and elm yellows rapidly induce mortality and are likely contributing factors to the high level of mortality.

Current Crown Dieback

Due to morphological traits or harsh growing conditions, some tree species generally maintain more crown dieback than others. Under optimal conditions, hardwoods typically have more crown dieback than softwoods. This expectation held true for the current inventory period, 2011–2015. In the North region, mean crown dieback ranged from 0.6 percent for the eastern white pine (*Pinus strobus*) and red pine (*P. resinosa*) group to 6.1 percent for elm (table 7.2) and was 2.8 percent for all species combined. In the South region, mean crown

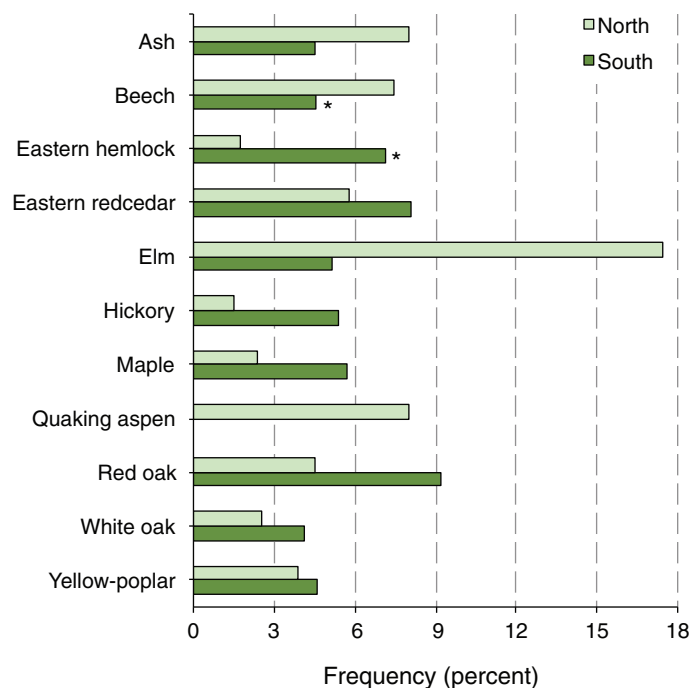


Figure 7.5—Percentage of trees in the North and South regions assessed with 0-percent crown dieback during 2006–2010 that were dead upon reassessment during 2011–2015, by species group. Species groups with < 200 observations are indicated with an asterisk. (Data source: U.S. Department of Agriculture, Forest Service, Forest Inventory and Analysis Program)

Table 7.2—Mean crown dieback and number of trees ≥ 12.7 cm d.b.h. by dieback class for major species groups in the North region, 2011–2015

Species group	Plots	Trees	Mean	SE ^a	Dieback class			
					0	1–10	11–20	> 20
			%		----- % -----			
Softwoods	1,364	18,662	1.7	0.1	15,361	2,863	226	212
Eastern hemlock	306	2,277	1.1	0.2	2,039	199	20	19
Eastern redcedar	154	800	2.4	0.5	572	201	11	16
Eastern white and red pines	432	3,249	0.6	0.1	2,950	281	9	9
Northern white-cedar	215	3,042	4.2	0.7	2,002	827	103	110
Spruce and balsam fir	630	6,609	1.1	0.1	5,554	971	55	29
Hardwoods	2,574	44,513	3.3	0.1	28,465	14,301	837	910
Ash	758	2,908	5.4	0.5	1,771	897	94	146
Basswood	267	986	2.4	0.4	754	212	5	15
Beech	453	1,991	3.2	0.3	1,362	524	65	40
Birch	832	3,750	2.9	0.2	2,563	1,053	64	70
Black cherry	519	1,671	3.7	0.3	946	653	40	32
Black walnut	218	487	3.6	0.5	255	217	8	7
Blackgum	177	410	1.8	0.4	317	87	3	3
Cottonwood and aspen	548	3,595	2.5	0.2	2,745	716	59	75
Elm	547	1,468	6.1	0.4	633	719	41	75
Hackberry	163	482	4.7	0.6	180	284	8	10
Hickory	531	1,878	2.4	0.2	1,217	637	6	18
Maple	1,703	13,437	2.6	0.1	9,459	3,510	246	222
Red oak	931	3,777	3.5	0.2	2,030	1,623	69	55
Sassafras	157	493	4.7	0.8	264	208	6	15
White oak	727	3,943	3.4	0.2	2,059	1,789	44	51
Yellow-poplar	177	768	2.9	0.6	548	201	7	12

^a Standard error.

dieback ranged from 0.1 percent for the loblolly pine (*P. taeda*) and shortleaf pine (*P. echinata*) group to 4.0 percent for black cherry (*Prunus serotina*) (table 7.3) and was 1.0 percent for all species combined. Consistent with previous observations (Randolph 2015), and with the exception of black cherry, crown dieback was higher in the North region than in the South region for species groups observed in

both regions. In particular, ash and elm had considerably higher means in the North than in the South: 5.4 percent vs. 2.7 percent and 6.1 percent vs. 1.6 percent, respectively. The disparity between the North and South regions for ash and elm may be due in part to the more northerly distribution of EAB (fig. 7.2), DED (USDA Forest Service 2017), and elm yellows (Marcone 2017).

Table 7.3—Mean crown dieback and number of trees ≥ 12.7 cm d.b.h. by dieback class for major species groups in the South region, 2011–2015

Species group	Plots	Trees	Mean	SE ^a	Dieback class			
					0	1–10	11–20	> 20
			%		----- % -----			
Softwoods	1,570	23,305	0.3	0.1	22,822	345	41	97
Eastern redcedar	245	1,010	0.7	0.2	980	17	3	10
Loblolly and shortleaf pines	1,099	17,068	0.1	0.0 ^b	16,902	126	15	25
Longleaf and slash pines	218	3,028	0.3	0.2	2,943	71	2	12
Virginia pine	113	632	1.1	0.4	603	18	2	9
Hardwoods	2,041	27,686	1.6	0.1	25,302	1,492	391	501
Ash	308	914	2.7	0.5	798	70	15	31
Beech	122	273	1.3	0.7	257	10	2	4
Black cherry	275	529	4.0	1.0	449	39	14	27
Elm	528	1,226	1.6	0.3	1,128	53	16	29
Hickory	616	1,779	1.4	0.3	1,635	92	24	28
Maple	713	2,611	1.3	0.2	2,462	73	29	47
Red oak	1,214	4,714	1.6	0.1	4,287	281	58	88
Sugarberry	107	325	1.5	0.5	307	10	2	6
Sweetgum	828	3,339	1.0	0.1	3,148	110	44	37
Tupelo and blackgum	483	1,768	0.6	0.1	1,697	52	11	8
White oak	949	4,297	1.8	0.2	3,787	357	74	79
Yellow-poplar	398	1,626	0.7	0.2	1,569	33	13	11

^a Standard error.

^b Value is >0.0 but <0.1.

Ash, beech, and hemlock—Among the ash, beech, and hemlock trees, crown dieback was greatest in counties with the known stressors (EAB, BBD, and HWA) and was highest for ash and hemlock in areas where the stressors have persisted the longest. However, the difference among the lowest and highest crown dieback means for hemlock was only 2.1 percentage points (fig. 7.6). The reason for the lack of separation among the means in counties with and without HWA may be due in part to the way hemlock trees are affected by the insect. HWA feeds at the base of the needles causing their desiccation. Defoliation follows, typically beginning at the base of the crown and moving upward even when HWA is distributed throughout the crown (McClure and others 1996). FIA procedural definitions require crown dieback to be in the “upper and outer portions of the tree” in order to be recorded (Schomaker and others 2007: 23). Therefore, full evidence of HWA infestation may not be manifested in the crown dieback assessments made by FIA. Other measures of crown condition, e.g., crown density and foliage transparency (Schomaker and others 2007), have proven useful for predicting hemlock decline individually and together with crown dieback (Eschtruth and others 2013, Rentch and others 2009).

For beech, crown dieback means and the percentage of trees with > 10-percent dieback (fig. 7.7) mirrored what might be expected in the three stages of BBD known as the advance front, killing front, and aftermath (Cale and others 2017). Counties with the latest beech

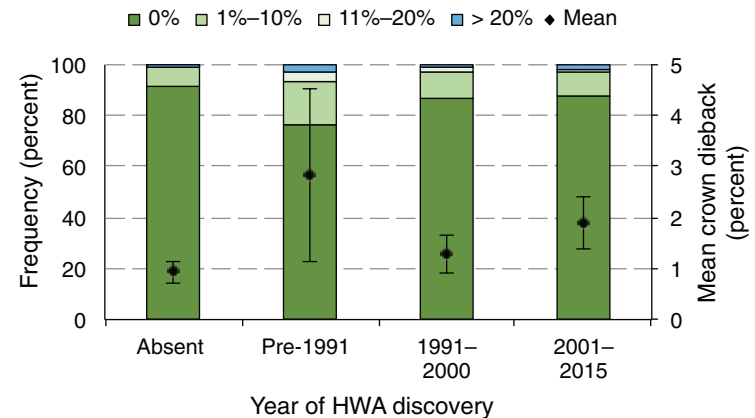


Figure 7.6—Mean crown dieback by duration of hemlock woolly adelgid (HWA) infestation and percentage of trees observed in each infestation class, by crown dieback class, for eastern hemlock trees assessed in the Eastern United States during 2011–2015. Bars around the mean represent one standard error. (Data source: U.S. Department of Agriculture, Forest Service, Forest Inventory and Analysis Program)

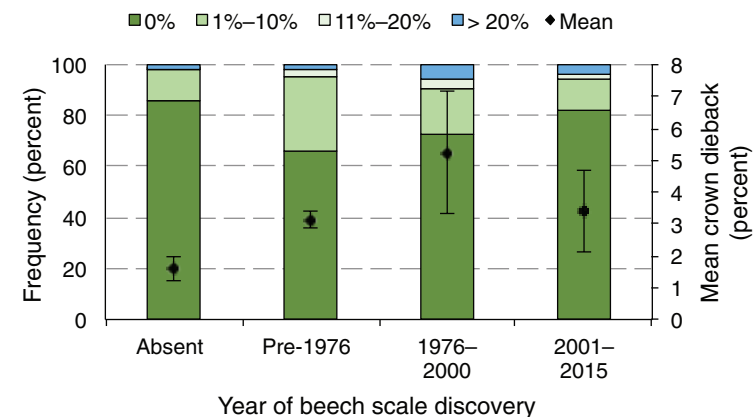


Figure 7.7—Mean crown dieback by duration of beech scale infestation and percentage of trees observed in each infestation class, by crown dieback class, for beech trees assessed in the Eastern United States during 2011–2015. Bars around the mean represent one standard error. (Data source: U.S. Department of Agriculture, Forest Service, Forest Inventory and Analysis Program)

scale detections (post-2000) are most likely in the advance front stage where beech scale populations are steadily increasing. This stage may last up to 10 years before follow-on fungal infections of *Neonectria* spp. begin to induce high levels of beech mortality, i.e., the killing front stage (Cale and others 2017). Mean crown dieback was highest (5.2 percent) in the counties presumably in the killing front stage, i.e., where beech scale was detected during 1976–2000 (fig. 7.2). Counties with the earliest beech scale detections (pre-1976) represent the aftermath stage of BBD wherein beech mortality is typically reduced due to fewer host trees and lower numbers of beech scale insects. Trees there are subject to chronic stress from BBD (Cale and others 2017), and therefore it is reasonable that mean crown dieback in these counties remains elevated above areas yet to be affected by BBD. The relatively large standard errors associated with the means for trees in counties with beech scale detections since 1976 reflect in part the degree to which stands are moving into or out of the killing front stage.

For ash, mean crown dieback increased as duration of EAB infestation increased (fig. 7.8). Mean crown dieback was highest (15.7 percent) in the counties where EAB has been present since before 2006 and lowest (3.8 percent) in counties where EAB is absent. Standard errors of the means also increased as duration of EAB infestation increased (fig. 7.8), in part reflecting variations in the distribution of the insect within the infested counties and susceptibility of individual trees. Small sample size also

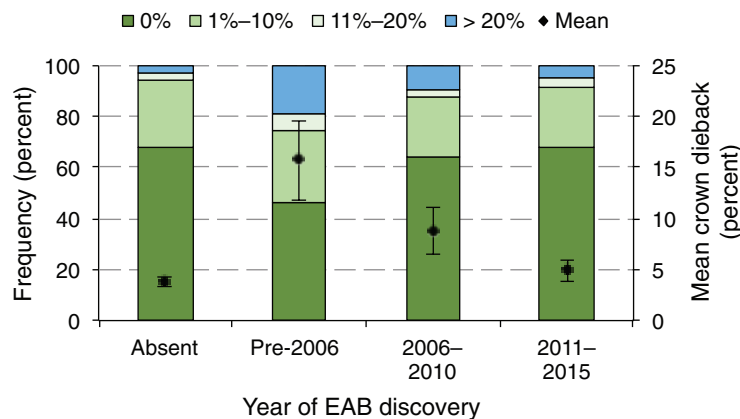


Figure 7.8—Mean crown dieback by duration of emerald ash borer (EAB) infestation and percentage of trees observed in each infestation class, by crown dieback class, for ash trees assessed in the Eastern United States during 2011–2015. Bars around the mean represent one standard error. (Data source: U.S. Department of Agriculture, Forest Service, Forest Inventory and Analysis Program)

contributed to the variability, especially in the counties where EAB was discovered prior to 2006 (only 119 trees on 25 plots).

Trends in Crown Dieback

Overall there has been a downward trend, i.e., improvement, in mean crown dieback in both the North and South regions since the late 1990s (fig. 7.9). Although the changes in mean crown dieback are small, only 1.3 percentage points in the North and 0.9 percentage points in the South, more and more trees have been observed to have 0-percent crown dieback over the last two decades, particularly in the North region (fig. 7.10). Given that the protocol for

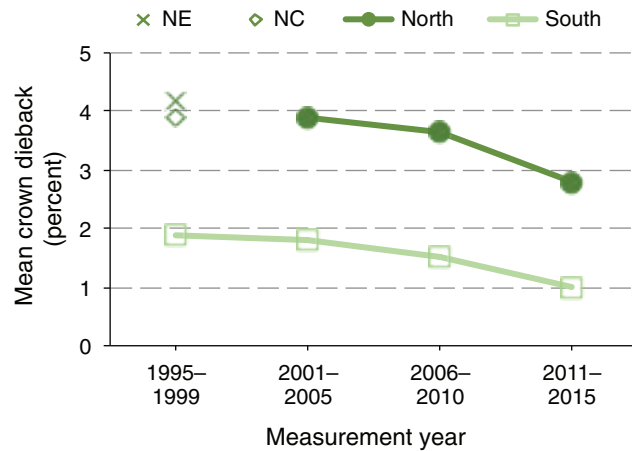


Figure 7.9—Mean crown dieback for trees ≥ 12.7 cm d.b.h. in the Eastern United States, by region and inventory period. Crown dieback in the 1990s was collected by the Forest Service Forest Health Monitoring Program and reported by Randolph (2006) for the South region and Randolph and others (2010a, 2010b) for the Northeast (NE) and North Central (NC) subregions. (Additional data source: U.S. Department of Agriculture, Forest Service, Forest Inventory and Analysis Program)

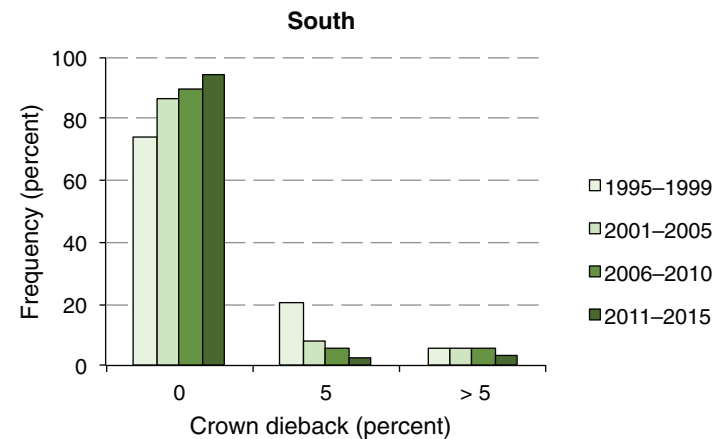
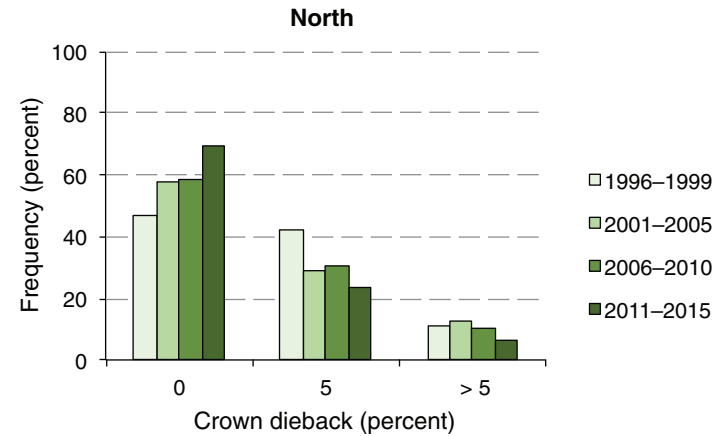


Figure 7.10—Distribution of crown dieback for trees ≥ 12.7 cm d.b.h. in the Eastern United States, by region and inventory period. (Data source: U.S. Department of Agriculture, Forest Service, Forest Inventory and Analysis Program)

assessing crown dieback has not changed over time (Randolph 2013) and that measurement quality objectives for crown dieback historically have been met (Westfall and others 2009), this small downward trend may represent an actual change in condition rather than measurement variability. Nevertheless, because the mean was < 5 percent at all time periods, the biological significance of this decrease, i.e., the effect on growth rates, is likely negligible.

Crown dieback for trees measured in the years 2006–2010 and again in 2011–2015 was stable for most species groups across the Eastern United States (tables 7.4 and 7.5). Notable exceptions were ash, elm, and yellow-poplar. In the North region, the overall increase in mean crown dieback for these three groups ranged between 1.8 and 2.9 percentage points (table 7.4). In the South region, crown dieback for ash and yellow-poplar was stable, but the mean for elm increased 2.2 percentage points (table 7.5). Further examination of the data revealed that the increase in crown dieback for yellow-poplar in the North region was largely driven by a small number of trees with changes in crown dieback from ≤ 5 percent to 99 percent. Similarly large changes in crown dieback were more common for ash trees in the North region and elm trees in both regions. Though ash yellows (Sinclair and Griffiths 1994) may play a role, EAB was likely the driving factor for the change among ash as the mean change in crown dieback was higher for ash in counties with EAB (mean = 5.4 percent, standard error = 1.8) than in counties without EAB (mean < 0.1 percent,

Table 7.4—Mean crown dieback and other statistics for paired trees measured 5 years apart for major species groups in the North region, 2006–2010 vs. 2011–2015

Species group	Plots	Trees	2006–2010		2011–2015		P-value ^b
			Mean	SE ^a	Mean	SE ^a	
			%		%		
Softwoods	577	6,797	2.1	0.2	1.9	0.2	0.25
Eastern hemlock	126	768	0.9	0.2	1.1	0.3	0.60
Eastern redcedar	64	308	2.2	0.3	2.4	0.5	0.65
Eastern white and red pines	164	1,252	0.9	0.2	0.8	0.2	0.54
Northern white-cedar	106	1,199	4.8	0.7	4.6	1.0	0.87
Spruce and balsam fir	270	2,361	2.0	0.2	1.5	0.2	0.04
Hardwoods	1,097	17,040	3.2	0.1	3.6	0.1	<0.01
Ash	299	1,140	4.3	0.4	6.1	0.8	0.01
Basswood	108	383	2.9	0.5	2.5	0.5	0.55
Beech	188	688	3.5	0.4	3.4	0.4	0.91
Birch	343	1,385	2.9	0.2	3.3	0.4	0.29
Black cherry	190	572	3.6	0.3	3.8	0.4	0.79
Black walnut	83	190	4.2	0.7	4.4	0.8	0.71
Blackgum	77	159	1.1	0.2	1.8	0.5	0.15
Cottonwood and aspen	227	1,200	2.6	0.3	3.2	0.4	0.10
Elm	211	463	3.6	0.3	6.5	0.8	<0.01
Hackberry	78	198	4.1	0.8	5.1	1.1	0.13
Hickory	214	691	2.1	0.2	2.3	0.3	0.52
Maple	714	5,452	2.8	0.1	2.8	0.2	0.65
Red oak	384	1,428	4.0	0.2	4.0	0.3	0.98
Sassafras	68	208	5.3	0.9	4.5	1.1	0.55
White oak	317	1,733	3.3	0.2	3.5	0.3	0.48
Yellow-poplar	67	288	1.7	0.3	3.5	1.0	0.03

^a Standard error.

^b The probability of obtaining a larger *t*-value under the null hypothesis that the difference between the two means equals zero.

Table 7.5—Mean crown dieback and other statistics for paired trees measured 5 years apart for major species groups in the South region, 2006–2010 vs. 2011–2015

Species group	Plots	Trees	2006–2010		2011–2015		P-value ^b
			Mean	SE ^a	Mean	SE ^a	
			%		%		
Softwoods	368	4,730	0.2	0.0 ^c	0.4	0.1	0.06
Eastern redcedar	58	258	0.6	0.3	0.4	0.2	0.52
Loblolly and shortleaf pines	255	3,242	0.1	0.0 ^c	0.1	0.1	0.16
Longleaf and slash pines	74	730	0.3	0.2	0.8	0.6	0.18
Virginia pine	28	224	0.2	0.1	0.4	0.2	0.57
Hardwoods	509	6,170	1.4	0.1	1.5	0.1	0.57
Ash	77	248	2.0	0.4	2.0	0.6	0.96
Beech	30	57	0.1	0.1	0.6	0.5	0.24
Black cherry	70	131	1.9	0.9	2.7	1.0	0.56
Elm	104	225	1.3	0.4	3.5	1.1	0.04
Hickory	159	430	1.3	0.3	1.2	0.3	0.73
Maple	175	610	1.4	0.3	1.4	0.4	0.95
Red oak	311	1,144	1.3	0.2	1.7	0.3	0.17
Sugarberry	17	35	0.3	0.3	2.9	2.8	0.37
Sweetgum	190	649	1.3	0.3	1.5	0.3	0.56
Tupelo and blackgum	135	351	2.0	1.0	0.4	0.1	0.11
White oak	248	1,065	1.6	0.3	1.1	0.2	0.03
Yellow-poplar	105	370	0.6	0.2	0.3	0.1	0.14

^a Standard error.

^b The probability of obtaining a larger *t*-value under the null hypothesis that the difference between the two means equals zero.

^c Value is >0.0 but <0.1.

standard error = 0.5). Individual-tree damage agent codes (O’Connell and others 2017) for the elm trees were examined but no single factor appeared to be driving the changes.

SUMMARY

Given the backdrop of assessments made over the last two decades, current crown dieback conditions appear to be within expected norms for most species in the Eastern United States. As expected, elevated levels of crown dieback were observed for ash, beech, and hemlock trees in areas affected by EAB, BBD, and HWA, respectively. Crown dieback was not only elevated, but also increasing for ash trees in the East, evidence of EAB’s continued spread and devastation. Crown dieback was also elevated and increasing for elm trees. This is likely due to DED and elm yellows, although followup study may be warranted to isolate any hot spots of decline and determine if there are other active causal agents, e.g., bacterial leaf scorch caused by *Xylella fastidiosa*.

In the Western United States, reduced P3 data collection prohibited an analysis of crown condition for the years 2011–2015. Previous crown dieback combined with current tree status revealed high mortality among trees previously assessed as having no crown dieback. This was particularly true for lodgepole pine, quaking aspen, and subalpine fir trees in the Rocky Mountain region, and is likely the result of stressors emerging during the intervening 10-year remeasurement period.

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Each year, the Forest Health Monitoring (FHM) Program funds a variety of Evaluation Monitoring (EM) projects, which are “designed to determine the extent, severity, and causes of undesirable changes in forest health identified through Detection Monitoring (DM) and other means” (Forest Health Monitoring 2015). In addition, EM projects can produce information about forest health improvements. EM projects have been submitted, reviewed, and selected in two main divisions: base EM projects and fire plan EM projects. More detailed information about how EM projects are selected, the most recent call letter, lists of EM projects awarded by year, and EM project poster presentations can all be found on the FHM Web site: www.fs.fed.us/foresthealth/fhm.

Beginning in 2008, each FHM national report contains summaries of recently completed EM projects. Each summary provides an overview of the project and results, citations for products and other relevant information, and a contact for questions or further information. The summaries provide an introduction to the kinds of monitoring projects supported by FHM and include enough information for readers to pursue specific interests. Five project summaries are included in this report.

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SECTION 3. Evaluation Monitoring Project Summaries

INTRODUCTION

Whitebark pine (*Pinus albicaulis* Engelm.) is a keystone species that provides a variety of ecosystem services, such as soil stabilization and protracted snowmelts. Found in many upper subalpine forests in Western North America (Arno and Hoff 1989), whitebark pine is an important high-elevation food source for grizzly bears (Bjoernlie and others 2014) and numerous other wildlife species (Tomback and others 2001, 2014). A rapid, widespread decline in whitebark pine throughout its range has been observed and reported for about 30 years (e.g., Arno 1986, Arno and Hoff 1989, Shanahan and others 2016, Tomback and others 2001). The decline in whitebark pine populations is attributed to white pine blister rust (*Cronartium ribicola*), which damages and kills five-needle white pines (Geils and others 2010); mountain pine beetle outbreaks (Tomback and Achuff 2010); altered fire regimes (Keane 2001, Keane and others 1994, Murray and others 2000); and drought (Shanahan and others 2016).

Most of the current information about whitebark pine health status and trends is based on case studies conducted in selected stands and geographic locations, predominantly in the species range in the Rocky Mountains (e.g., Fiedler and McKinney 2014, Larson and others 2009). Few studies provide information about whitebark pine populations in the Pacific Coast States (California, Oregon, and Washington) (e.g., Goheen and others 2002, Rochefort 2008, Smith and others 2011), and none of them is region-wide. The objectives of this study are

(1) to compile the available whitebark pine inventory data in the Pacific Coast States, and (2) use this rangewide inventory dataset to provide statistically based estimates of distribution and health status and trends of whitebark pine populations in California, Oregon, and Washington.

METHODS

We compiled a complete database of the available regional inventory plots in California, Oregon, and Washington that tallied whitebark pine as a seedling or live or dead tree (table 8.1). This included annual U.S. Department of Agriculture, Forest Service, Forest Inventory and Analysis (FIA) plots (Phase 2 grid) and the various National Forest System (NFS) intensifications and special studies, measured between 2001 and 2013. We also compiled data from the older Current Vegetation Survey (CVS) plots measured on Pacific Northwest Region (Region 6) NFS land (different plot design,

CHAPTER 8.
Status and Trends of
Whitebark Pine Distribution
and Health in California,
Oregon, and Washington
(Project WC-EM-B-12-02)

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VICENTE J. MONLEON

Table 8.1—Summary of the available data, including FIA annual data (2001–2013) and spatial and temporal intensification on Pacific Southwest and Pacific Northwest Region (Regions 5 and 6, respectively) National Forest System lands

	Number of plots		Number of trees		
	Plots	Plots, including remeasurements	Live	Dead	Seedlings
California	108	161	2,077	214	241
Oregon	139	177	775	299	342
Washington	173	203	686	624	303
Total	420	541	3,538	1,137	886

superseded by the FIA inventory). The FIA design consists of a probability sample of one plot every 6,000 acres (Bechtold and Patterson 2005) and up to three times that density on NFS lands outside of a wilderness area. The core sample is divided into 10 interpenetrating panels, measured annually. Thus, the data in this report include a 30 percent remeasurement of the total sample for California and Oregon (2011–2013) and 20 percent for Washington (2012–2013). For each tallied live tree, the FIA inventory collects information about tree damage agents and their location and severity. Because of their severity, both pine blister rust and bark beetles are emphasized in the data collection. For dead trees, the crews assign the cause of death, if possible. Because the main sources of insect and disease mortality are likely to be bark beetles and blister rust, we assumed that whitebark pine trees recorded as killed by insects were killed by bark beetle, and those killed by disease were killed by blister rust. This may result in a slight overestimation of the incidence of those agents if some of the mortality attributed to insects or disease was caused by a different agent. In this report, we present descriptive statistics of the species distribution, the blister rust infections, and bark beetle impact across the three Pacific Coast States.

RESULTS AND DISCUSSION

We identified 420 plots that contained whitebark pine and, as of 2013, 121 were visited more than once (table 8.1). We found

that, in the Pacific Coast States, 98 percent of the whitebark pine range is on public land, of which the Forest Service manages approximately 87 percent. Approximately 62 percent of the range is in reserved land such as congressionally designated wilderness areas and National Parks.

The proportion of mature trees that are dead is lowest in California (9 percent), intermediate in Oregon (28 percent), and highest in Washington (48 percent) (table 8.1). Lower whitebark pine mortality in California compared to other regions of Western North America has been previously reported (Millar and others 2012) and is most likely due to the lower observed disease and insect incidents in California compared to the rates in Oregon and Washington (figs. 8.1B and 8.1C). Surprisingly, white pine blister rust was not detected in any of the California inventory plots (fig. 8.1A). Blister rust has been recorded in northern California, and less so in the Southern Sierras. Maloney and others (2012) found high blister rust incidences on eight selected populations in the Lake Tahoe Basin, but Millar and others (2012) sampled the six patches of highest whitebark pine mortality in the Eastern Sierra and did not observe any evidence of blister rust. The low number of dead trees in California supports our finding that, if blister rust is present, it has not drastically increased tree mortality. In contrast, blister rust was detected in 17 percent and 49 percent of the inventory plots in Oregon and Washington, respectively, and the proportion of dead trees reflects those greater detection rates (fig. 8.1B).

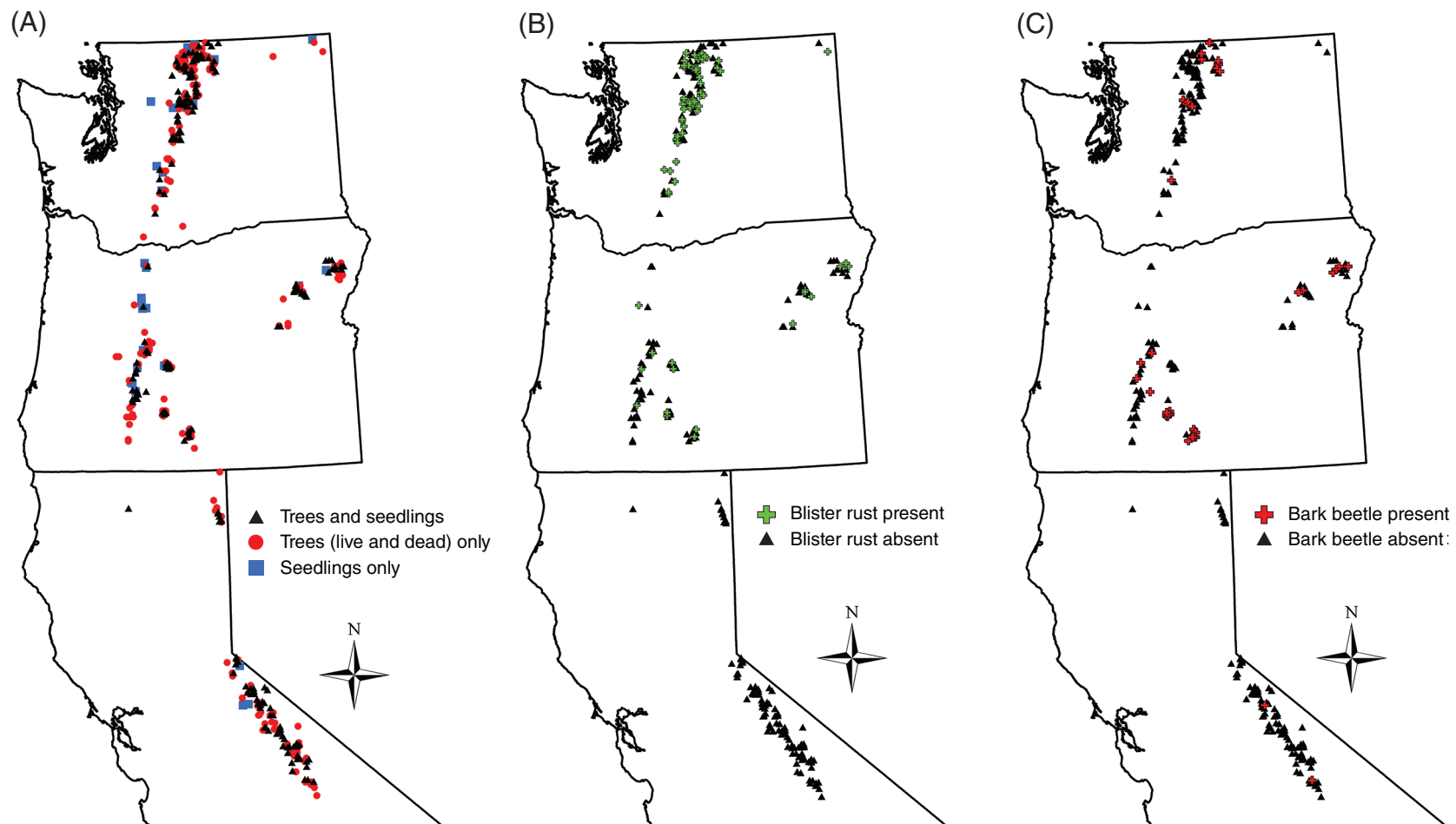


Figure 8.1—Distribution of sample plots with whitebark pine (FIA plot locations are approximate). (A) Total number of plots. (B) Plots with live trees where blister rust was detected. (C) Plots with live trees where bark beetle was detected.

Figures 8.2A and 8.2B show the number of plots measured per year in Washington and Oregon, respectively, along with the number of plots infected by blister rust. In Washington, plots measured in 2012 and 2013 were previously measured in 2002 and 2003, respectively. In Oregon, plots measured in 2011 to 2013 were previously measured in 2001 to 2003, respectively. An increase in blister rust incidences in these sets of plots occurred in the 10-year period between remeasurements in both States (figs. 8.2A and 8.2B). Because the number of plots measured per year differs, and different plots were measured each year for the first 10 years of the presented data, we also present the proportion of plots that had blister rust incidents, which increased over time (fig. 8.3A). Smith and others (2008) found increases in blister rust infection levels between 1996 and 2003/2004 in the 170 plots that they established in British Columbia and Alberta, Canada, with highest infection levels close to the U.S. border. Our results show an increase in blister rust incidences from 2001 to 2013 with incidents being most pronounced close to the Canadian border. Our study looks at a fairly short time period (12 years) and tree mortality can vary over time due to a large number of stressors other than insect and disease (e.g., precipitation, temperature). Yet, our reported regional increases in blister rust incidences in Oregon and Washington confirm what other case studies have previously reported at smaller scales.

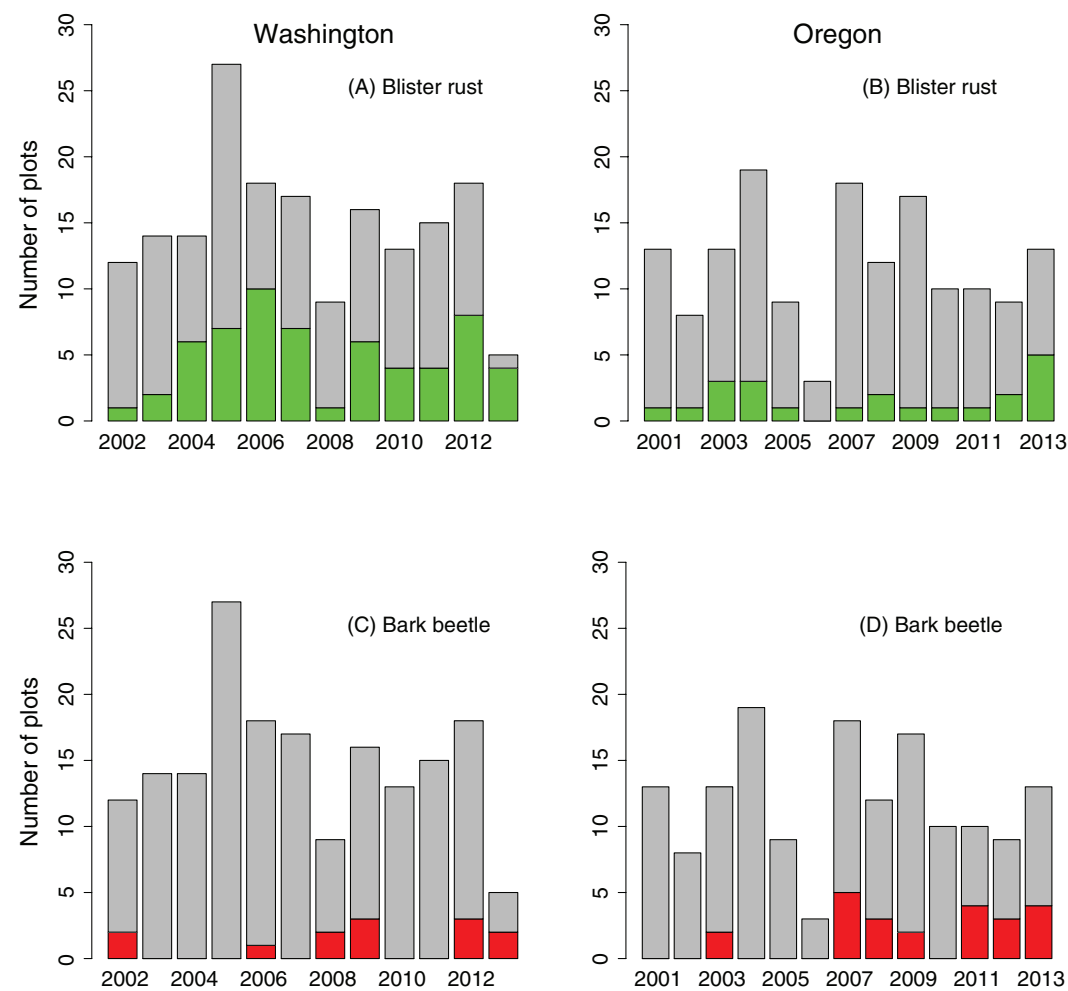


Figure 8.2—Plots where (A, B) blister rust was detected (green) and (C, D) bark beetle was detected (red), with total number of plots measured per year in Washington (left) and Oregon (right).

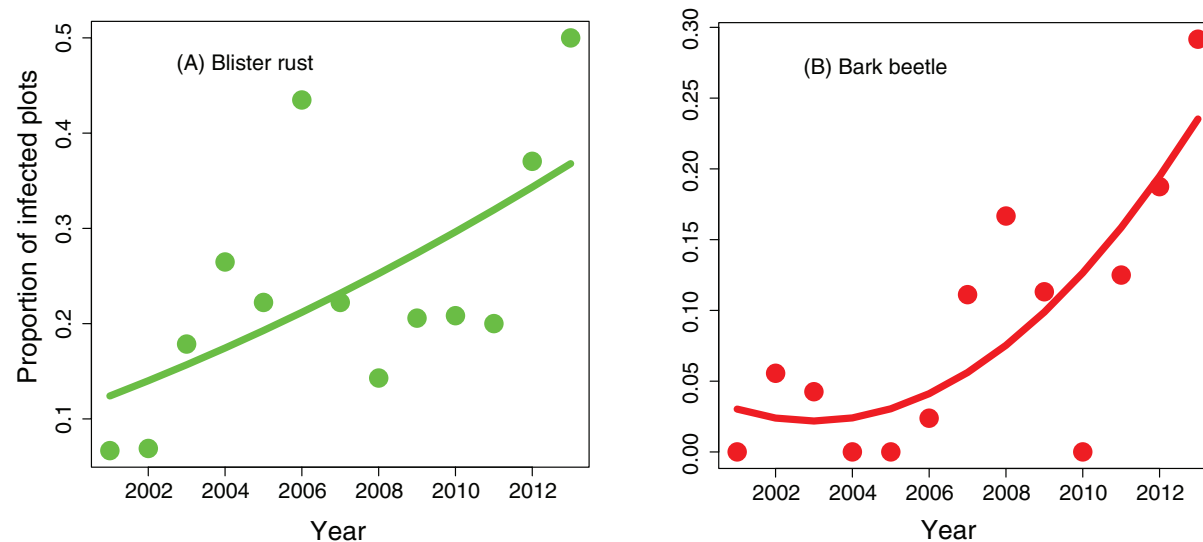


Figure 8.3—Proportions of plots (A) infected by blister rust and (B) attacked by bark beetles in Oregon and Washington combined.

Bark beetle attacks were detected in only 2 percent of the California inventory plots, while 21 percent and 10 percent of the Oregon and Washington inventory plots were attacked by bark beetles, respectively (fig. 8.1C). Millar and others (2012) report extensive bark beetle infestations, which seems to contradict the low observed bark beetle incidents in this study. However, Millar and others (2012) focused their analysis on the ‘largest patches of tree mortality in the study region,’ which suggests that they selected their study sites based on bark beetle presence. The plots that were remeasured in Washington and Oregon show no or a smaller number of plots with bark beetle attack at the initial measurement and higher numbers

of bark beetle plots at the remeasurements (figs. 8.2C and 8.2D). Over time, the proportion of plots attacked by bark beetle increased even more drastically than the proportion of plots with blister rust incidents (fig. 8.3B). Increases in acres with mountain pine beetle-killed whitebark pine have been reported by Gibson and others (2008) based on aerial detection surveys. They reported very low levels of bark beetle-killed areas in California from 1998–2005 and observed slight increases in 2006 and 2007. For Oregon, they observed moderate levels up to 2005 with large increases in 2006 and 2007. In Washington, the amount of acres with beetle-killed whitebark pine has been at high levels since 2001.

The number of tallied seedlings and live or dead mature trees (table 8.1, fig. 8.1A) shows that the proportion of seedlings is higher in the northern portion of the whitebark pine species range in the Pacific Coast States. Shanahan and others (2016) found that bark beetles preferentially attacked larger whitebark pine trees and that smaller trees with white pine blister rust exhibited higher mortality than larger trees. Their findings suggest a shift from large to smaller-sized trees as large, mature trees are attacked and killed by bark beetle. The current distribution of seedlings and mature trees may be used as a surrogate for range shift. However, the difference between the mean temperature of the range of seedlings and that of mature trees was not statistically significant (Monleon and Lintz 2015), which suggests that the population shift may be due to causes other than warming climate. This coincides with findings in British Columbia, Canada, where local climate variables showed weak or no relationship with whitebark pine mortality (Campbell and Antos 2000).

Inventory plots sample the entire range of whitebark pine and, therefore, are well suited to provide region-wide estimates of the conditions and status of its population. However, as the inventory plots in the compiled regional whitebark pine database were measured with various sampling intensities, with varying remeasurements and measurement periods, standard design-based approaches cannot easily be applied. Therefore, we are working on developing spatio-temporal models that account for these varying spatial and temporal

dependencies in the dataset. Specifically, we are developing spatial copula models (e.g., Madsen 2009) that allow the incorporation of spatial and temporal dependence structures as well as non-normally distributed response variables. The application of these new models allows us to make use of all available inventory data instead of the base grid FIA plots without temporal intensification. Therefore, we will be able to provide information on the status and trend of whitebark pine health at a finer spatial and temporal scale than would be possible with the base grid FIA plots.

CONCLUSIONS

There is a clear north-south trend in blister rust incidence, with most incidences observed in Washington and none in the southern whitebark pine range in California. The least amount of bark beetle attacks was observed in California. The higher incident rate of bark beetle attacks in Oregon and Washington may be due to already weakened whitebark pine trees due to blister rust infections. The proportion of plots infected by blister rust as well as the proportion of plots attacked by bark beetles increased over time. Washington showed the largest proportion of dead trees. Because there is considerable variability in spatial and temporal sampling intensity, it is impossible to use design-based sampling estimation. Spatio-temporal models have to be employed to account for the complexity of the sampling design, the different number of measurements, and variable time between measurements when temporal

trends and regional variation in mortality, recruitment, and incidence of insect and disease are estimated.

CONTACT INFORMATION

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INTRODUCTION

Wild and prescribed fire injury to trees can produce mortality that is not immediately apparent, and environmental stress subsequent to a fire may also contribute to tree mortality in the years after a fire (Hood and Bentz 2007). In order to predict post-fire tree mortality from fire injury variables before tree mortality is clearly apparent, dozens of statistical logistic regression models have been developed (see Woolley and others 2012 for a review), and some are incorporated within larger fire behavior and effects models and computer models used to support land management decisions (Hood and others 2007, Reinhardt and others 1997). In the Wallowa and Blue Mountains of northeastern Oregon, a polychotomous field key has been developed to predict tree mortality (Scott and others 2002). For this project, post-fire tree mortality and fire injury variables were collected for 26 wild and prescribed fires across Oregon and Washington, providing an opportunity to test specific published models for 16 species of conifers. Our objectives with these data are (1) to assess the ability of previously published logistic regression models and other guidelines or methods to predict 3-year post-fire tree mortality in Oregon and Washington State and (2) to identify suites of fire injury variables that best discriminate between live and dead trees in that region.

METHODS

Field Sampling

Twenty-six wild and prescribed fires that occurred between 1999 and 2009 and ranged over a wide geographical area from southwest Oregon to northeastern Washington were identified by local U.S. Department of Agriculture, Forest Service, Forest Health Protection offices in cooperation with Forest Service National Forest and District offices (table 9.1, fig. 9.1). Survival and a suite of fire injury metrics were monitored for approximately 13,000 trees representing 16 species that burned in fires in the Pacific Northwest. Tree species included Douglas-fir (*Pseudotsuga menziesii*), Pacific silver fir (*Abies amabilis*), white fir (*A. concolor*), Grand fir (*A. grandis*), subalpine fir (*A. lasiocarpa*), incense cedar (*Calocedrus decurrens*), Port Orford cedar (*Chamaecyparis lawsoniana*), Alaska-cedar (*C. nootkatensis*), Western redcedar (*Thuja plicata*), Ponderosa pine (*Pinus ponderosa*), lodgepole pine (*P. contorta*), sugar pine (*P. lambertiana*), western white pine (*P. monticola*), Engelmann spruce (*Picea engelmannii*), Western larch (*Larix occidentalis*), and western hemlock (*Tsuga heterophylla*). Existing logistic models adequately described post-fire mortality of *A. concolor*, *A. lasiocarpa*, *C. decurrens*, *C. lawsoniana*, *L. occidentalis*, *P. engelmannii*, *P. contorta*, and *P. lambertiana*. Field crews selected trees for measurement if

CHAPTER 9.

Monitoring Survival of Fire-Injured Trees in Oregon and Washington (Project WC-F-08-03)

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Table 9.1—Fire name, year of fire, fire location (latitude, longitude), and average annual rainfall for the location of the fire

Fire	Year	Latitude, longitude	Average annual rainfall <i>inches</i>
Apple	2002	43.2763389, -122.5235750	54.33
B & B Complex	2006	44.4971418, -121.7626360	52.76
Biscuit	2002	42.32976479, -123.6620449	105.91
Blossom	2006	42.7794056, -123.9528139	96.46
Bonanza	2004	44.9913944, -122.0388583	94.49
Bull Spring	2003	44.8367667, -118.9231056	21.65
Clark	2003	43.9882806, -122.5755944	59.06
Columbia Complex	2007	46.2700556, -117.7109472	33.86
Davis Lake	2003	43.5981028, -121.7084917	38.58
Egley	2007	43.7369389, -119.4225611	20.08
Fischer	2004	47.5804671, -120.5646950	24.80
Grapple	2007	44.0447111, -118.7549306	23.23
Griff	2003	48.0234694, -123.4155472	58.27
Herman Creek	2003	45.6503472, -121.9022778	101.57
Hud2	2005	48.3854722, -119.2580028	12.60
Monument	2007	45.2517500, -119.3753389	14.96
Nile	2004	46.8574822, -121.0049832	27.95
Pearrygin Creek	2005	48.5053843, -120.1336373	15.75
Quartz	2001	42.3622750, -122.1094167	51.97
Rancheria Creek	1999	42.5597889, -122.3755806	51.18
School	2005	42.3622750, -122.1094167	20.47
Shake Table	2007	42.5597889, -122.3755806	21.65
Sharps Ridge	2007	44.8611361, -118.9621972	24.80
Sisters	2006	46.27249585, -117.603965	14.57
Squaw Creek	2005	44.2963639, -119.2479639	22.44
Tiller Complex	2009	44.8611361, -118.9621972	50.79

any green needles were present on the tree and fire injury was present; the goal was to sample at least 500 trees in each fire. Fire severity variables were measured for models addressed in the current literature. Initial assessments of tree condition and fire injury variables were completed during the summer of the year of the fire or in the following spring after budbreak if the burn occurred early- to mid-summer, or during the following summer if the fire occurred in late summer or early fall. The variables that were collected were chosen so as to match, or to calculate, variables collected in previous studies of post-fire tree mortality.

The following data were collected in the initial field assessment for each tree:

- Tree species
- Diameter at breast height (d.b.h.) measured to the nearest 0.25 cm on the uphill side of the tree at 1.37 m above mineral soil
- Dwarf mistletoe rating recorded using the 6-class dwarf mistletoe rating system (Hawksworth 1977)
- Percent of pre-fire crown volume that was killed relative to the space occupied by the pre-fire crown volume to the nearest 5 percent (Ryan 1982)
- The distance from the ground to the following points on the tree recorded using an Impulse 200 Laser hypsometer (Laser Technologies, Englewood, CO) with measurements taken on the uphill side of the tree perpendicular to the slope at a distance sufficient to obtain an accurate value:

- Top of tree – Tree height (m)
- Base of pre-fire tree crown (m)
- Base of post-fire tree crown (m)
- Upper limit of post-fire bole-blackening (scorch) (m)

The following measurements were also made on four quadrants of each tree, numbered in clockwise order beginning with the downhill quadrant or with the south-facing quadrant on flat ground:

- Cambium, close to the ground-line, assessed as dead or alive in each bole quadrant with bark removed to within 0.25 to 0.50 cm of the cambium and a bark punch drilled into the cambium, if necessary
- Bole scorch scored as 0, 1, 2, or 3 in each quadrant of the tree bole following methods in Ryan (1982)

After the initial assessment, every year, for up to 5 years, each tree was visually evaluated for mortality and evidence of bark beetle or wood borer infestation. Trees were recorded as dead in each year if no green foliage was visible or if the tree had fallen or broken off since the previous year. No bark was removed from living trees to determine the success of the beetle infestation to avoid injury that could have been detrimental to its survival. If the tree subsequently died, bark beetle galleries were examined to determine the species present.

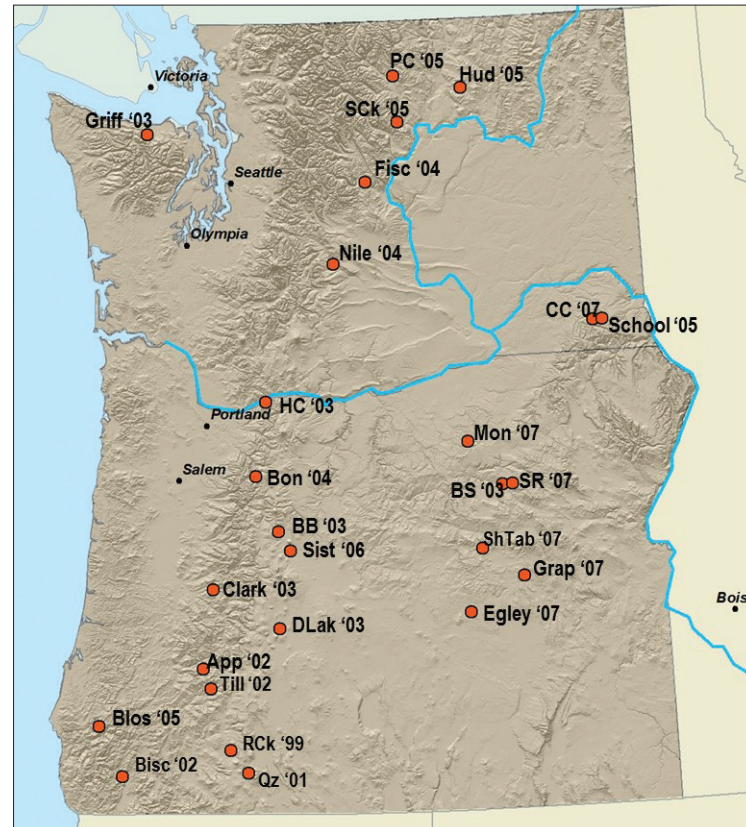


Figure 9.1—Location of 26 wild and prescribed fires that occurred in Washington and Oregon between 1999 and 2009 from which data were collected.

Data Analysis

In the process of building new models for our Oregon and Washington data, we selected suites of potential variables based on the examination of the distributions of the explanatory variables, the discriminatory ability of the previously published models, and our desire for a simple but broadly applicable model. We built new regression models in two ways and followed the same strategy for each tree species. First, we included the suites of variables used in each of the previously published models we tested. In an effort to identify parsimonious models for our dataset, we also tested suites of variables with related but simpler terms. The Akaike information criterion (AIC) is a measure of the relative quality of statistical models for a given set of data. Given a collection of models for the data, AIC estimates the quality of each model, relative to each of the other models. Hence, AIC provides a means for model selection. In both approaches, we calculated the change in the AIC (Δ AIC) between the model in question and the model with the lowest AIC statistic as a measure of the support in the data for each model. Models with Δ AIC statistics between 0 and 2–7 are considered to be equally well supported by the data (Burnham and others 2011). To summarize the predictive ability of each model, we computed 95 percent confidence intervals for a tenfold cross-validated AUC (Area Under the Curve) statistic (James and others 2013) to reduce the bias that is known to occur when assessing predictive ability using data from which the model was built. All *P. ponderosa* and

P. menziesii analyses were carried out using PROC GENMOD and PROC LOGISTIC in SAS® v. 9.4 (SAS Institute, Cary, NC, USA). Analyses of all other species were performed using R Studio® v. 3.3.1 (R Development Core Team).

Trees with probability of mortality (P_m) values higher than the chosen cutoff are predicted to die, and those with values lower than the cutoff are predicted to survive. A tree is classified as dead if the predicted probability of death from the regression model is greater than a predetermined decision criterion. For a chosen decision criterion, two types of misclassification errors can occur: dead trees predicted as live [false negative rate (FNR); trees predicted to live that died] or live trees predicted as dead [false positive rate (FPR); trees predicted to die that survived] (fig. 9.2). These two types of errors are inversely related. As the decision criterion increases, for example from 0.5 to 0.95, the number of live trees that are predicted to be dead decreases but the number of dead trees that are predicted to be live increases. That is, changing the decision criterion decreases one type of error but the other type must increase. Most studies report these accuracies using cutoff values at P_m of 0.5 or 0.6 (Ganio and Progar 2017; Grayson and others 2017; Hood and others 2007, 2010; Thies and others 2006). Typically, here, classification rates are estimated for a decision criterion of 0.5 where mistakenly predicting dead trees as live is minimized and mistakenly predicting live trees as dead is maximized. The decision criterion allows continuous P_m values to be converted to

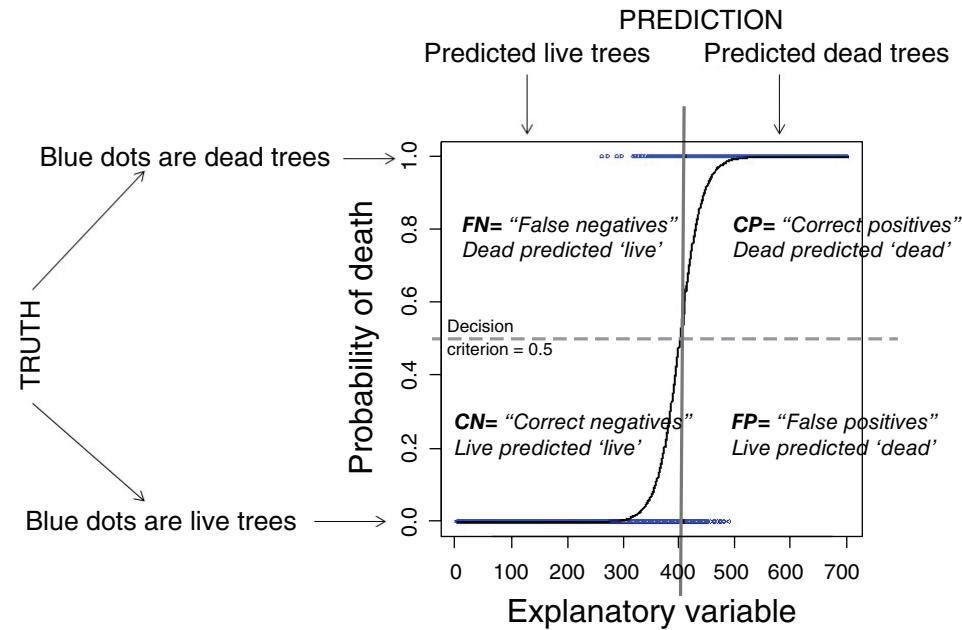


Figure 9.2—Graphical depiction of the probability of tree mortality modeled by logistic regression indicating how changing the decision criteria can affect type of error. Y-axis is the probability of death and the x-axis is the values of a measured explanatory value like crown or cambium kill. Increasing or decreasing the value of the decision criterion changes the decision of falsely predicting a dead tree will live or falsely predicting a live tree will die.

binary values in order to calculate true positive rate [(TPR); trees predicted to die and observed dead], true negative rate [(TNR); trees predicted to live and observed live], and the total percent of trees correctly classified (%C).

The Receiver Operating Characteristic (ROC) curve evaluates the specificity and sensitivity of the model over the range of decision criteria (0–1). In essence, AIC measures how well the model fits the data, while ROC describes how

well the model predicts the outcome. Area under the ROC curve (AUC) is then taken as a measure of overall accuracy. When the units are normalized, the AUC is equivalent to the probability that the model will assign a higher score to a randomly chosen positive observation than to a negative one. That is, AUC is a measure of the chance that the model will predict a higher probability of mortality for a tree that was observed dead than to a tree that was observed live. We followed the

rating system for AUC outlined by Hosmer and Lemeshow (2000). They report that ROC values equal to 0.5 suggest no discrimination from a 50-50 chance, values between 0.7 and 0.8 are acceptable discrimination (fair or adequate), values between 0.8 and 0.9 are excellent discrimination, and values > 0.9 are considered outstanding discrimination. Models with AUC values < 0.7 were considered poor, and those < 0.6 considered very poor.

RESULTS AND DISCUSSION

Validation of Previously Published Logistic Regression Models

In Ganio and Progar (2017), we assessed the discriminatory ability of 22 existing logistic regression models and a polychotomous key. We also built new models for each tree species, and identify fire injury variables that consistently produce accurate mortality predictions. The prediction of post-fire mortality of *P. menziesii* and *P. ponderosae* using previously developed models for specific fire types was not consistently better than prediction for all trees of each species regardless of the fire type (wild or prescribed burn). The overlap in 95 percent confidence intervals for AUC calculated from the subset and from all trees indicates similar average discriminatory ability. The distributions of fire injury variables for live and dead trees in our dataset are similar for both prescribed and wild fire and thus models will discriminate between live and dead trees to the same degree regardless of fire type. Our new models for Oregon and Washington and the validation of

existing models for Douglas-fir and ponderosa pine suggest that the percent of the crown volume scorched and the cambium kill rating are good predictors of post-fire tree mortality for both tree species. The presence of beetles in year 3 improves the average predictive ability and is present in our recommended model. For *P. menziesii*, models that included these variables had average predictive ability above 80 percent, but, for ponderosa pine, average predictive ability is not above 80 percent, suggesting that it can be more difficult to identify dying ponderosa pine trees.

In Grayson and others (2017), we validated 54 logistic regression tree mortality models from seven published articles and two sets of mortality guidelines from two sources. We developed new logistic regression models for species with adequate sample size and which had no existing species-specific model (*A. amabilis*, *A. grandis*, *P. monticola*, and *T. heterophylla*). Most of our recommended models contained a crown scorch term and either a cambium injury term or a bark beetle infestation term. As many of these species have never been validated before, this paper provides users with previously unknown expected accuracy of mortality equations and identifies areas where additional data are needed. New thresholds of post-fire mortality were developed for *A. amabilis*, *A. concolor*, *A. grandis*, *P. contorta*, *P. lambertiana*, *P. monticola*, *P. engelmannii*, *L. occidentalis*, and *T. heterophylla*. We were not able to develop acceptable logistic mortality models or thresholds for *C. nootkatensis* or *T. plicata* because of small sample sizes. Injury

to cambium and crown were both significant predictors in all but one set of new thresholds. The validation of existing models and guidelines allows managers to determine which models will likely perform best and identifies knowledge gaps where no adequate models exist to predict post-fire tree mortality. The new logistic regression models and threshold guidelines provide improved accuracy, with simpler application for fire and forest management.

The two types of errors that can occur (i.e., falsely predicting a dead tree will live and falsely predicting a live tree will die) come with different costs to land managers that depend on the application. Land managers, when using a model to predict mortality, may wish to change the decision criterion for a particular application from the typical 0.5 to something higher to control the particular error that is most costly in their application.

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INTRODUCTION

Fire is a key ecological driver in determining vegetation composition, biomass, and ecosystem dynamics in coniferous forests of the Laurentian Mixed Forest in the Great Lakes region (Cleland and others 2004, Frelich 1995). Regional projections of future climate conditions indicate warmer temperatures, more variable precipitation patterns, and greater moisture stress (Handler and others 2014). These conditions are likely to increase the occurrence of drought that in turn influences fire risk and severity (Clark 1989, Neary and others 2008). For example, a recent modeling investigation of relationships between future climate and wildland fire risk in the Great Lakes region showed that the expected changes in precipitation and temperature are associated with increased duration of conditions of high fire risk and earlier timing of the peak wildland fire season (Kerr and others 2016). Further, the 2011 Forest Health Monitoring Program's national report identified a pattern of persistent and/or severe to extreme drought in recent previous years across the Laurentian Mixed Forest of the western Great Lakes region (Potter and Conkling 2013), and the 2011 Pagami Creek wildfire in northern Minnesota resulted from a lightning strike during these conditions.

Fire has direct impact to forest carbon (C) stocks by releasing C via combustion, including partial to complete consumption of the organic horizon of forest soil (Jain and others 2012; Kolka and others 2014, 2017). However, indirect effects on forest C may also occur via changes to the rate of C sequestration by the regenerating forest, as well as by affecting the composition and quality of the soil organic matter, which stores and provides nutrients to the soil ecosystem (Miesel and others 2015). For example, pyrogenic C (PyC) may be a component of soil organic matter and is produced via thermal decomposition (pyrolysis) of biomass, which occurs under oxygen-limited conditions during wildfires (Bird and others 2015, Santín and others 2015). Pyrogenic C is characterized by a polyaromatic chemical structure, which contributes to resistance to decomposition and a long residence time in soil (Bird and others 2015). An earlier study in this region reported PyC concentrations of up to 70 percent of total C in the soil organic horizon and up to 30 percent in the upper 10 cm of mineral soil, and PyC was present even in areas unburned since 1864 (Miesel and others 2015). Pyrogenic C has been positively correlated with soil pH, total C and nitrogen (N), phosphorus (P) availability, and conifer seedling regeneration (MacKenzie and others 2008, Makoto and

CHAPTER 10.

Wildfire and Fire Severity Effects on Post-Fire Carbon and Nitrogen Cycling in Forest Soil

(Project NC-EM-F-14-1)

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others 2011), suggesting that PyC may play an ecologically important role in post-fire forest recovery. Efforts to evaluate ecosystem response to gradients of burn severity are relatively recent, and widely available estimates of aboveground burn severity derived from remote sensing approaches may not accurately reflect soil burn severity (e.g., Kolka and others 2014, 2017). Information about how fire and burn severity affect soil and soil ecosystem processes in the Great Lakes region is particularly limited but important to understand, given the potential for future drought to influence fire risk and severity (e.g., Handler and others 2014, Kerr and others 2016). The direct and indirect effects of fire therefore have potential for long-term impacts to forest health via effects on soil properties and nutrient cycling.

The overarching goal of our study was to investigate the impacts of fire on post-fire carbon and nutrient cycling in forest soil and to determine whether the magnitude of effect differs across a gradient of burn severity level. This information is important for understanding the potential ecological impacts that may result from increasingly extreme wildfire disturbance events, as anticipated in future climate scenarios. The specific objectives of this project were to evaluate wildfire effects on soil C and N pools and cycling along a gradient of fire severity within the 2011 Pagami Creek wildfire site, and to determine the relationships between wildfire-produced black C on P availability and N mineralization rates.

METHODS

The 2011 Pagami Creek wildfire was a late summer lightning-ignited fire that burned through diverse vegetation and resulted in areas of varying fire severity across a range of forest types in the Boundary Waters Canoe Area Wilderness (BWCAW) in northern Minnesota. Heinselman (1996) reported a fire frequency of 4.3 years in the BWCAW for the 1727–1868 presettlement time period and 6.1 years for the 1911–1972 time period following the initiation of U.S. fire suppression policy. Therefore, the 2011 Pagami Creek fire occurred after a historically unprecedented fire-free interval, and although the Lake States region (Michigan, Minnesota, and Wisconsin) has experienced an average of 3,787 wildfire ignitions annually over the past decade (https://www.nifc.gov/fireInfo/fireInfo_statistics.html), the 38 000 ha Pagami Creek fire was among the largest in the past century. A previous study at this site used advanced remote sensing technology and intensive field measurements to characterize pre-fire forest attributes as well as post-fire severity, aboveground forest structure and composition, and total soil C and N (Kolka and others 2014) across forest composition types previously investigated by Wolter and Townsend (2011). We used these existing data on forest structure and composition and burn severity level to select a subset of the study plots established by Kolka and others (2014) for our July 2014 field sampling. These sites included areas dominated by jack pine (*Pinus banksiana*)

or aspen (*Populus tremuloides*) prior to the fire for the full range of soil burn severity levels as determined in the original severity assessment. The original study by Kolka and others (2014) and our study included control plots for each forest cover type in unburned reference areas adjacent to the Pagami Creek fire perimeter. We collected forest floor and 0–10 cm mineral soil samples at locations < 1 m from the original sampling locations, following the protocol described in Kolka and others (2014). We measured *in situ* nitrogen mineralization rates using a 90-day field incubation (Robertson and others 1999), and we performed a 12-month laboratory incubation to measure soil respiration rates. We also measured concentrations of soil total C and N, extractable P, and PyC. Photos of the study area are shown in figure 10.1. Here we present summary information from our study; detailed results will be presented in forthcoming publications in the scientific literature.



Figure 10.1—(A) Lake access to the 2011 Pagami Creek wildfire site in the Boundary Waters Canoe Area Wilderness showing unburned forest on the left adjacent to burned forest on the right. (B) Field personnel collecting 0–10-cm mineral soil sample after removing the organic horizon to return to the laboratory for nutrient analysis and incubation to determine *ex situ* carbon mineralization rates. (C) Field incubation tubes used to determine 90-day *in situ* nitrogen mineralization rates (tubes were loosely capped to allow soil gas exchange during the incubation). Photos by (A) Bethany Laursen, Michigan State University; (B, C) Jessica Miesel, Michigan State University.

RESULTS AND DISCUSSION

We found that fire caused major decreases in the rates at which C and N are mineralized in forest soil for soil samples collected 3 years after fire. Soil respiration rate (C mineralization) in burned areas decreased between 8 percent and 50 percent in burned coniferous sites and between 8 percent and 20 percent in burned deciduous sites, relative to soils from unburned coniferous or deciduous forest reference areas, respectively. Nitrogen mineralization rates in coniferous areas were between 78 percent and 115 percent slower in low- and high-severity burned areas, respectively, relative to soils from the unburned reference areas. In contrast, N mineralization rates in deciduous areas increased by 171 percent in low-severity areas and decreased by 154 percent in high-severity areas, relative to soils from reference sites.

Extractable P concentrations increased between 56 percent and 63 percent relative to reference area soils in low- to moderate-severity burned areas in coniferous sites, whereas the relative increase in high-severity areas was only 10 percent. Changes in P concentrations in the deciduous sites were both much greater (110 percent increase in low-severity areas and 77 percent increase in high-severity areas) as well as more variable than in the coniferous sites.

In general, PyC concentrations decreased across the severity gradient in coniferous sites, showing 36 percent to 12 percent lower concentrations than unburned coniferous

reference areas. In contrast, PyC concentrations in deciduous forest decreased by 25 percent in low-severity areas and between 15–17 percent in moderate- and high-severity areas. However, the contribution of PyC to soil total C increased in all burned areas. We observed a weak positive relationship between PyC and extractable P concentrations ($r^2 = 0.10$) and a moderately strong relationship between PyC concentration and initial C mineralization rates ($r^2 = 0.46$). Relationships between PyC and net N mineralization rates were not statistically significant.

Nutrient availability and the rates of nutrient cycling provide insight into important ecosystem processes associated with post-fire forest recovery. Fire can alter nutrient concentrations and supply rates by combusting the organic horizon of soil; volatilizing nutrients such as N; and affecting the size, composition, and activity of the soil microbial community (Neary and others 2008). Our study shows that the effects of fire on soil nutrients and C and N mineralization rates persist 3 years after fire. We observed large differences in burned areas compared to unburned reference areas, although differences among severity levels within burned areas were variable and did not consistently increase or decrease across the severity gradient. In general, we observed a different pattern of effect between the two forest cover types, suggesting that the effects of fire on soil nutrients differs among contrasting forest cover types within a single wildfire.

This study extends the original post-fire dataset on soil C and N concentrations and stocks (Kolka and others 2014) to provide an assessment of intermediate-term (3-year) ecosystem response to a wildfire across contrasting soil burn severity levels classified nearly immediately (1 month) after fire in a designated Wilderness Area. This study also provides critically needed information on PyC concentrations in soils from contrasting forest types and as affected by fire and burn severity. Additional results will be presented in forthcoming publications and will include an assessment of fire effects on the soil microbial community. Future studies are needed to quantify how pre-fire forest heterogeneity influences effects observed on soil properties and ecosystem processes and how fire effects interact with other potential future impacts to soil processes likely to result from changes to soil temperature and moisture regimes. For example, a recent study in temperate conifer forest soils showed that soil warming of only 4 °C increases C release from older C pools and increases soil respiration by up to 37 percent (Hicks Pries and others 2017). Information that allows identification of the primary drivers that control the direct and indirect effects of fire on forest soil will be particularly valuable for anticipating potential short- and long-term impacts of fire on forest ecosystems, especially as forests in the Great Lakes and many other regions have experienced disruptions of historical fire regimes.

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INTRODUCTION

Hurricanes have long been a powerful and recurring disturbance in many coastal forest ecosystems. Intense hurricanes often produce a large amount of dead fuels in their affected forests. How the post-hurricane fuel complex changes with time, due to decomposition and management such as salvage, and its implications for fire behavior remain largely unknown. Therefore, the primary objective of the project was to study post-hurricane fuel dynamics and its effect on fire behavior by conducting field measurements and comparing fire behavior for undamaged stands and hurricane-damaged stands in southern pine forests. In addition, the project also examined the effect of post-hurricane salvage logging and the response of tree regeneration.

METHODS

We investigated four major hurricanes that occurred within the last 25 years, including Hurricanes Hugo (1989), Opal (1995), Katrina (2005), and Ike (2008) (fig. 11.1). We originally attempted to sample only areas without other major disturbances since the studied hurricane, but disturbances from prescribed fire could not be avoided because it is routinely applied to achieve multiple management goals in southern pine forests. As a result, among all sampled stands affected by hurricanes, only eight stands damaged by Hurricane Hugo were not burned after the hurricane, and the rest were periodically burned. To assess the

impact of salvage, we also sampled three types of stands in the forests affected by Hurricane Katrina: damaged and salvaged, damaged and unsalvaged, and undamaged stands. Analysis of variance was used to test the differences in fuel loading and tree regeneration between hurricane-damaged and undamaged stands; among stands affected by hurricanes in different years; and among damaged and salvaged, damaged and unsalvaged, and undamaged stands (for Hurricane Katrina only). Based on the post-hurricane fuel dynamics observed in the study, we modeled potential fire behavior using BehavePlus (Andrews 2009).

RESULTS AND DISCUSSION

Fuel Loading and its Dynamics

After a hurricane, fuel accumulates drastically over a short period of time, then drops as time progresses and eventually stabilizes. Post-hurricane fuel loads were significantly elevated in the damaged stands when compared to undamaged stands. Although downed woody debris (all size classes) decreased over time, litter and duff depth remained relatively stable due to prescribed burning. The higher fuel loads in all size classes for Hurricane Hugo, the oldest hurricane investigated in the study, were likely caused by the absence of prescribed burning. Fine fuels (< 7.5 cm in diameter) declined through time, and stabilized after 8 years. Coarse fuels took longer to decompose and their decomposition was greatly facilitated by periodic prescribed burning. Direct consumption

CHAPTER 11.

Post-Hurricane Fuel Dynamics and Implications for Fire Behavior

(Project SO-EM-F-12-01)

SHANYUE GUAN
G. GEOFF WANG

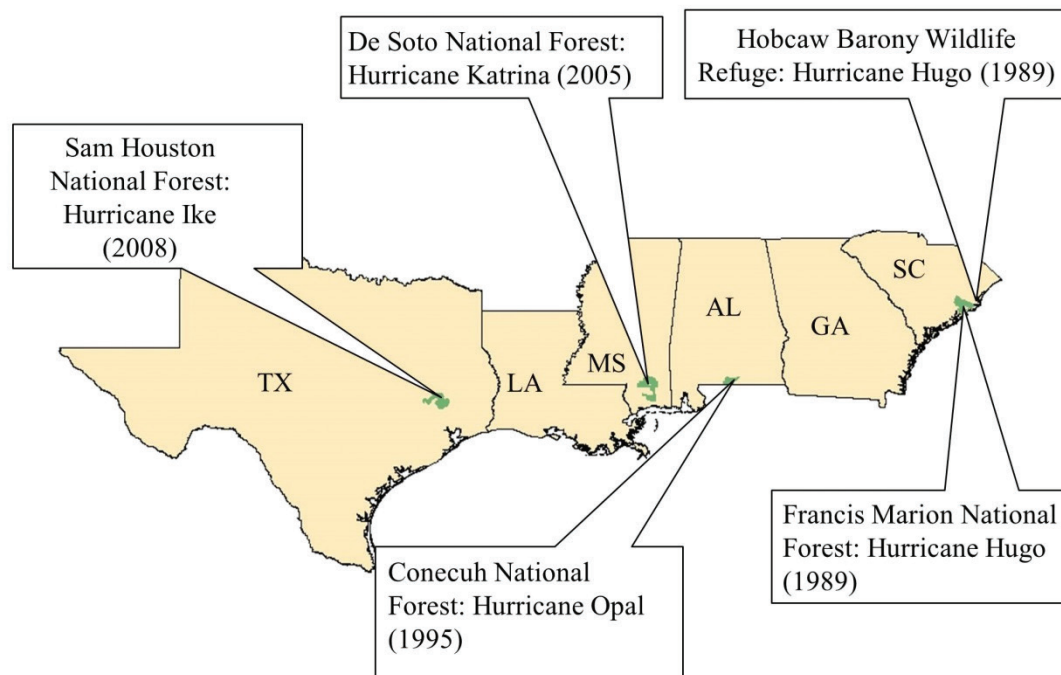


Figure 11.1—Location of study sites where field data were collected (Guan 2014).

of coarse fuels by fire is also possible depending on fuel moisture. It was estimated that the heavy fuel loading produced by hurricanes will require several decades to decompose without the addition of fire. With prescribed fire, heavy fuel loads will be consumed and decomposed within 18 years except for 1,000-hour fuels. Salvaging downed trees greatly reduced the fuel load and affected fuel dynamics. In salvaged stands, 1-hour (< 0.64 cm in diameter), 10-hour (0.64 to 2.54 cm in diameter), and 1000-hour (> 7.62 cm in diameter) fuel loads were significantly lower than those in unsalvaged

stands. Even though prescribed fire consumed most of the fine fuels, additions from coarse woody debris decomposition likely act as a source of fine fuels. There was no difference in 100-hour (2.54 to 7.62 cm in diameter) fuels, which may be the result of periodic prescribed burning reducing fuel size.

Post-Hurricane Forest Regeneration

Intense hurricanes destroyed many trees in the forest canopy, and the resulting canopy gaps promoted forest regeneration. However, periodic prescribed fires after hurricane disturbance

significantly suppressed the regeneration of those tree species susceptible to fire. For stands that were subjected to periodic prescribed burning, there were no significant differences in the density of small seedlings between damaged and control stands. Significant differences in large seedlings were observed between damaged and control stands for Hurricanes Ike and Katrina but not for Hurricane Opal. Given its fire adaptation, it was not surprising that significantly more longleaf pine regeneration was found in stands damaged by Hurricane Katrina. With the absence of prescribed fire after Hurricane Hugo, more tree regeneration was observed in damaged stands which led to elevated loblolly pine recruitment. Salvage in hurricane-damaged longleaf pine stands greatly reduced fuel loads and thus fire hazard, but did not impact the regeneration of longleaf pine.

Post-Hurricane Fire Behavior

Due to periodic prescribed fires, modeled fire intensities were mild regardless of the hurricane studied. Predicted fire behavior did not differ between damaged and control stands for Hurricanes Opal and Katrina, but it did for Hurricanes Ike and Hugo, where damaged stands had a higher rate of spread and a longer flame length than control stands. Lack of prescribed burning (Hurricane Hugo) and being the most recent disturbance (Hurricane Ike) were likely the causes of the observed differences in predicted fire behavior between damaged and undamaged stands. To evaluate our predictions from BehavePlus, fire behavior data from prescribed fires conducted after Hurricane Hugo

were acquired. With comparable fuel loads, we found that the modeled fire behaviors were similar to those observed. Although we could not test the modeled fire behaviors for other hurricanes due to a lack of data, the low fire intensity that resulted from our modeling would be expected given that those stands were subjected to periodic prescribed burning. Our modeling study also suggested that, if some variables required in the model were not available from measurements, the fire model Southern Rough (Anderson 1982) could be appropriately applied to predict the fire behavior in most coastal pine stands, and especially in well-managed longleaf pine stands.

Effect of Mitigation Treatments

Mitigation treatments after a hurricane, such as salvaging and prescribing fire, reduce fuel load and thus fire hazard. Because of significantly lower 1-hour and 10-hour fuel loads, fires in salvaged stands were not predicted to be as intense as those in unsalvaged stands. However, fires in unsalvaged stands were also predicted as low intensity, probably due to periodic prescribed burning. Therefore, with periodic prescribed burning, salvaging hurricane-damaged stands may not be necessary for the purpose of reducing fire hazard. However, our data did not allow us to evaluate the immediate impact of salvage on fire hazard. Unlike other studies which found that mitigation impacted the regeneration of local climax species, mitigation treatments in our study did not compromise the regeneration of desired canopy species. In fact, we found more longleaf pine

seedlings in salvaged stands than in unsalvaged stands. It is possible that there were enough longleaf pine seed trees left after the hurricane, and salvaging increased seed germination and establishment.

CONCLUSIONS

Our results indicated that the elevated fuel loadings from hurricane damage diminished gradually over time, and mitigation measures such as salvage operations, especially when combined with prescribed fire, greatly reduced the potential fire hazard while promoting the regeneration of longleaf pine. Therefore, salvage in combination with prescribed burning can be used as an effective strategy to restore longleaf pine forest after a hurricane while reducing fire risk at the same time.

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INTRODUCTION

Although mostly occurring as associate tree species in forest communities, *Persea* has a wide native distribution in southeast coastal plains (Shearman and others 2015). Laurel wilt disease (LWD) is a lethal vascular infection of trees in the laurel family (Lauraceae) caused by the fungus *Raffaelea lauricola* (Fraedrich and others 2008). The fungus is vectored by a nonnative ambrosia beetle (*Xyleborus glabratus*), which was first recorded in the United States in 2002 (Rabaglia and others 2006). Laurel wilt disease was first reported in 2003 in redbay (*P. borbonia*), and has since spread throughout *Persea* populations in South Carolina, Georgia, and Florida, as well as parts of North Carolina and small pockets of Mississippi and Alabama (fig. 12.1) (Shearman and others 2015). Laurel wilt disease infestation often causes near 100 percent mortality of *Persea* stems, but it also affects sassafras and avocado. The objectives of this project were to document the rangewide population impacts of LWD, to describe community types associated with *Persea*, to characterize the patterns of mortality and regeneration of *Persea* after infestation, and to quantify changes in fuel and invasive plants.

METHODS

We used Forest Inventory and Analysis (FIA) data (Reams and others 2005) from the Forest Service, U.S. Department of Agriculture, to estimate *P. borbonia* populations from 2003 to 2011 to see if any decline could be observed since the introduction of the LWD causal agent. We developed a logistic regression model to predict the probability of redbay mortality due to LWD.

To document the stand characteristics of redbay and swamp bay (*P. palustris*) communities, we analyzed data collected from 1988–2012 by the Carolina Vegetation Survey (Peet and others 1998). We used cluster analyses and species indicator analyses to group 388 plots into distinct communities.

To study the response of communities after LWD, we surveyed 61 plots from 1 to 10 years post-LWD on nine sites in South Carolina and Georgia (fig. 12.2). On each plot, we also sampled woody fuels to see if LWD had any implications on fire behavior. However, because LWD kills nearly all *Persea* in a stand and spreads rapidly from stand to stand, we did not have adequate control plots in the same stands as

CHAPTER 12.

Impacts of Laurel Wilt Disease on Native *Persea* Ecosystems

(Project SO-EM-B-12-05)

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G. GEOFF WANG

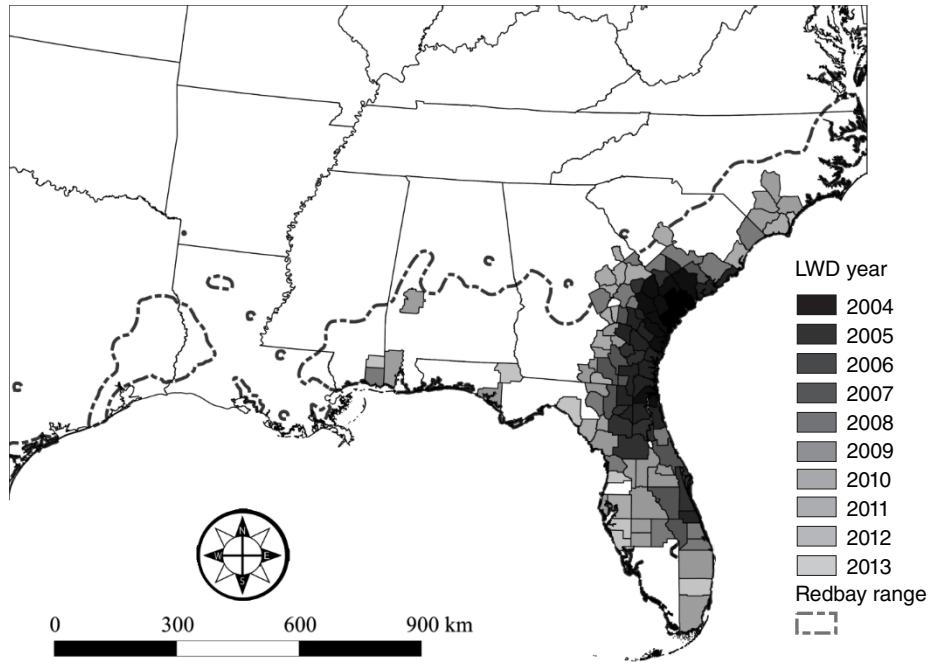


Figure 12.1—Geographic range of redbay (dashed line) in the Southeastern United States (Brendemuehl 1990). Shaded counties represent the spread of laurel wilt disease (LWD) as of August 2013 (USDA Forest Service, Forest Health Protection, Southern Region 2013). Darker shades indicate earlier years of reported infection.

infected plots. We therefore focus on comparing fuel loading among recovery years using analysis of variance.

RESULTS AND DISCUSSION

The trend line for the rangewide population estimates from 2003–2011 showed significant negative curvature, suggesting that the redbay population is declining. The population

in Georgia significantly decreased from approximately 241.1 ± 11.9 million stems in 2003 to 150.3 ± 7.9 million in 2011. Redbay densities decreased significantly in plots surveyed before and after the reported infection by an average of 89.6 live redbay stems/ha. Number of years since LWD infection was the most significant variable, with every increase in 1 year resulting in a 153.7 percent increase in

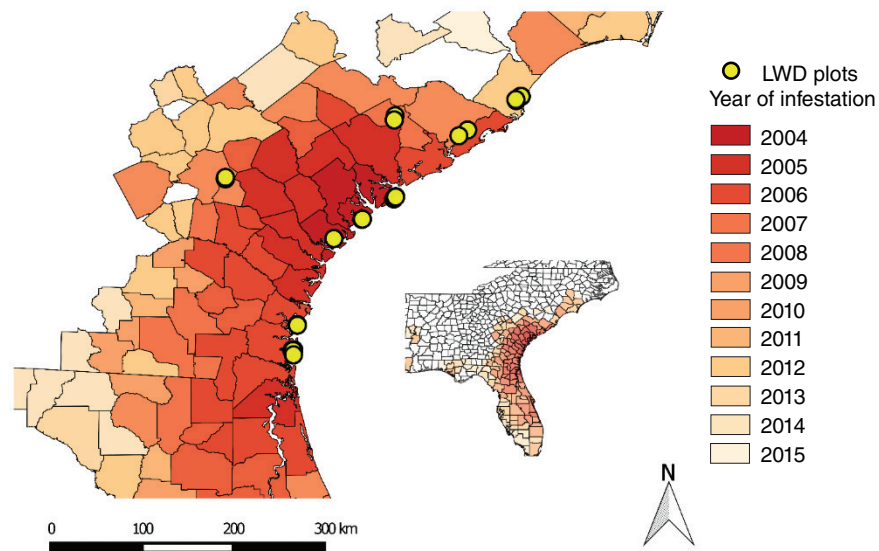


Figure 12.2—Location of 61 sampled plots on nine sites along the coast of South Carolina and Georgia. Laurel wilt disease infestation data obtained from Hughes and others (2015).

odds of death. Diameter was also a significant predictor, with an increase of 1 cm diameter at breast height (d.b.h.) resulting in a 5.0 percent increase in odds of death.

Our community analysis indicated that redbay and swamp bay communities were significantly different in species composition. In addition, redbay was almost exclusively limited to maritime coastal forests, whereas swamp bay had a significantly larger geographical range, extending from near coastal settings inland through the fall-line sandhills.

We did not find evidence of invasive species abundance increasing after LWD. Nearly all *Persea* in a plot are killed within the first two years of LWD, with the exception of smaller stems < 2.5 cm in diameter. After 10 years, *Persea* had regained much of the basal area prior to infection; however, the structure of the stands was predominantly composed of small diameter stems (1–5 cm d.b.h.). Seedling densities remained relatively the same throughout all recovery years. Although we detected differences in 1-hour fuels, litter, and duff among recovery years, it is likely that these differences are due

to factors other than LWD. Initial attempts at preventing the spread of the disease, such as removing and burning symptomatic stems, have also likely impacted the fuel loadings in our study. We therefore cannot conclude that LWD has increased the risk of high intensity fires.

CONCLUSIONS

Contrary to initial fears, this study suggests that the native *Persea* species in the United States are not on the immediate verge of extinction from LWD at this time. However, it is still too early to say whether these species will fully recover from the disease. Whether *Persea* recovers completely hinges on the ability of *X. glabratus* to maintain low populations in the long term. We predict one of four possible futures for *Persea* species: (1) the species will continue to decline, failing to regenerate, to the point of extinction; (2) both species will recover, either by *X. glabratus* populations declining due to lack of sufficient host material or by the propagation (natural or assisted) of wilt-resistant individuals; (3) *X. glabratus* will maintain small populations resulting in *Persea* occurring perpetually as small diameter stems; or (4) a cyclical pattern will emerge as *Persea* recover,

are attacked and decimated, and recover again. Future long-term studies that monitor recovery in *Persea* species as well as beetle populations will be able to test these hypotheses.

ACKNOWLEDGMENTS

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INTRODUCTION

Understanding the impacts of mountain pine beetle (MPB; *Dendroctonus ponderosae* Hopkins) on fire behavior is important from both an ecological and land management viewpoint. However, numerous uncertainties exist in the linkages of MPB-caused tree mortality to changes in canopy and surface fuels (e.g., fuel loading, arrangement, and availability) and the effects on simulated and observed fire behavior in MPB-attacked forests. Current fuel inputs to fire behavior models may be poorly suited to predict fire behavior in these disturbed forests because of inappropriate assumptions, resolutions, and design. Spatial patterns of recent beetle mortality are difficult to realistically represent in fire models, and it is virtually impossible to determine model output accuracy in a planning scenario. The numerous stages of tree condition (green-infested, red, and gray phases) due to time since attack further complicate modeling. MPB-killed foliage is more flammable than green needles (Jolly and others 2012); however, it is unknown if this increase in flammability scales up to entire canopies to result in higher-intensity crown fires (Alexander and Cruz 2013).

In spite of the complexities in predicting fire in MPB-killed stands discussed above, the greatest limitation likely lies in our ability to accurately describe the fuel complex for simulating resultant fire behavior because of

model reliance on fire behavior fuel models (FBFMs) (Anderson 1982, Scott and Burgan 2005). Most fire behavior prediction systems are point models using the Rothermel (1972) surface fire spread model applied at the stand or landscape levels with generalized surface fuel inputs or FBFMs. These surface fuel classifications are often insensitive to fine-scale changes in fuels after MPB outbreaks (Keane 2013). FBFMs are chosen to match a set of observed or expected fire behavior under a range of environmental conditions rather than to actually describe surface fuel characteristics (Burgan 1987). As a result, we are constrained in accurately representing the true tree-to-stand-level heterogeneity of fuels over the spatial scales used by fire behavior modeling systems because the FBFMs in Scott and Burgan (2005) or Anderson (1982) are too coarse to represent the subtle changes in fuels resulting from MPB outbreaks, leading to inaccuracies in model outputs.

We simulated fire behavior before, during, and after a hypothetical MPB outbreak using an intensively sampled subalpine lodgepole pine-dominated (*Pinus contorta* Douglas ex Loudon) landscape in central Montana to determine if FuelCalc (Reinhardt and others 2006) and the fire behavior modeling system FlamMap (Finney 2006) are sensitive to changes in forest structure during the red stage of a MPB outbreak. Previous studies have used plot data to assess fire hazard

CHAPTER 13.

Conventional Fire Behavior Modeling Systems are Inadequate for Predicting Fire Behavior in Bark Beetle-Impacted Forests

(Project INT-EM-F-11-03)

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using non-spatial fire behavior models (see Hicke and others 2012 for review, Schoennagel and others 2012) or used simulated input values based on broad, stand-level mapping to predict spatially explicit fire behavior (McMahan and others 2008). This study is one of the first to model potential fire behavior spatially across a MPB-affected landscape using an extensive plot-level fuel and tree data grid as model inputs. Results of this study are intended to highlight how model inputs change predicted fire behavior in MPB-affected stands to increase understanding of appropriate model applications and limitations.

MATERIALS AND METHODS

Field Methods

The Tenderfoot Creek Experimental Forest (TCEF) is a high-elevation (1850 to 2441 m) lodgepole pine-dominated forest in the Little Belt Mountains of central Montana (Hood and others 2012). We used a network of permanent plots established in 1997 on a 330-m² grid across the entire TCEF to sample vegetation and fuel loading. We collected surface and canopy fuel data on three hundred 0.04-ha circular plots during the summers of 2011 and 2012, which appeared to be the start of a MPB outbreak. We estimated fine downed, dead woody surface fuel loading using the planar-intercept method (Brown 1974). Duff and litter depths were measured at two points along each transect

(Lutes and others 2006). For coarse woody fuel (> 8 cm diameter), we measured small- and large-end diameter, length, and numerical decay classification (Maser and others 1979) of every log within the 0.04-ha plot. We used FIREMON sampling methods and classes (Lutes and others 2006) to collect vegetation data. We visually estimated canopy cover class and height of each plant species or genera, if species was unknown on eight 1-m² microplots placed along each fuel transect. We tallied tree seedlings (< 1.37 m) by height class and species on a 0.01-ha plot nested in the larger 0.04-ha plot. Saplings [< 12.7 cm diameter at breast height (d.b.h., measured at 1.37 m above ground)] and trees (≥ 12.7 cm d.b.h) were recorded individually on the 0.04-ha circular plot. For each sapling, we recorded diameter class, species, height, and crown base height. For each living tree, we recorded d.b.h., species, height, crown base height, and crown class (dominant, codominant, intermediate, and suppressed). For *Pinus* species, we also assessed each tree for signs of MPB attack and assigned an estimated attack year. For standing dead snags, we recorded diameter, species, and height. For standing dead *Pinus*, we also assigned a snag class.

Mountain Pine Beetle Severity Scenarios

We first created three MPB attack scenarios to compare effects of bark beetle severity on potential fire behavior at endemic, incipient,

and epidemic population stages. We used the field-measured tree and attack data to represent the incipient scenario and created the other scenarios by changing sampled tree characteristics in the input data. To create the endemic scenario, we changed the status of trees recorded as recently attacked to alive and unattacked and assigned crown base height (CrBH) and crown class using estimates obtained from regression modeling of live trees. To create the epidemic scenario, we used the MPB rate-of-loss model by Cole and McGregor (1983) over a 10-year period, using our actual field data of recently attacked trees to initialize the model. This model predicts the probability of a tree being attacked within a given time based on host tree characteristics, stand conditions, and MPB population pressure.

Currently, most fuel and fire behavior modeling system inputs do not explicitly include dead trees with needles remaining in the crown (Hicke and others 2012). We addressed this possible shortcoming by creating two additional scenarios based on the incipient and epidemic scenarios (red-incipient and red-epidemic). For these scenarios we changed tree status for currently attacked trees from dead to healthy to allow crown base height values. Red needles have lower foliar moisture contents and ignite more easily than green needles (Jolly and others 2012), which can increase crown flammability and affect the likelihood of torching and crown

initiation (Jolly and others 2012, Scott and Reinhardt 2001). To reflect potential increased flammability of recently attacked trees, we used a recently proposed method (USDA Forest Service 2011) that substitutes an effective crown base height ($\text{CrBH}_{\text{effective}}$) for the measured CrBH value. The $\text{CrBH}_{\text{effective}}$ lowers the crown base height of trees based on foliar moisture content of green and red needles. For green needles we used a foliar moisture content ($\text{FMC}_{\text{green}}$) of 108.5 percent and a FMC_{red} of 11.7 percent for red needles as suggested by Jolly and others (2012) to calculate $\text{CrBH}_{\text{effective}}$. For example, a tree with a pre-attacked live CrBH of 6 m has a $\text{CrBH}_{\text{effective}}$ of 1.3 m to reflect the increased flammability of the red or fading needles due to bark beetle attack. We reduced tree height by the same amount as crown base height to keep crown bulk density estimates unchanged.

Crown class and CrBH were not recorded for dead trees. Therefore, for the endemic, red-incipient, and red-epidemic scenarios, we estimated CrBH for dead trees based on regression analysis of healthy lodgepole pine trees ≥ 12.7 cm d.b.h. We assigned crown classes for dead trees using the crown class distribution of living pine trees and then assigned a class using a random number generator. These changes were made to individual trees prior to any estimation of canopy fuel variables.

Fuel Calculations and Fire Behavior Simulation

We used FuelCalc v. 1.1.1.0 (Reinhardt and others 2006) to calculate canopy fuel characteristics and FBFM by plot for each of the bark beetle attack scenarios. FuelCalc computes canopy bulk density, canopy base height, and stand height based on species-specific allometric equations relating individual tree, sapling, and seedling diameter; crown base height; tree height; and crown class to crown biomass and keys these values to a FBFM (Lutes 2014). Ground fuel and woody surface fuel loadings were calculated in FIREMON v. 2.1.2 (Lutes and others 2006).

We used FlamMap v. 5.0.1.3 (Finney 2006) to simulate fire behavior at 30 x 30-m pixel resolution for the five scenarios across the entire TCEF. FlamMap computes rate of spread, fire line intensity, and flame length using constant weather and live fuel moisture conditions to assess potential fire behavior for a given scenario on a landscape. We used the Scott and Reinhardt (2001) crown fire calculation method. For non-spatial inputs to FlamMap, we applied the following parameters: initial fuel moisture scenario of 1-hour = 4 percent, 10-hour = 5 percent, 100-hour = 7 percent, herbaceous = 60 percent, live woody = 90 percent, and live crown fuels = 80 percent. We conditioned fuels based on topography and weather from nearby weather stations (Finney 2006). The

conditioning period was 12 August 2007 at 1300 to 16 August 2007 at 1500, and elevation was modified to 2134 m to reflect the lower elevation at TCEF compared to the weather station location. We assumed no cloud cover during the conditioning period. We chose this conditioning period because it was when recent fires in the area had experienced large growth and therefore represented realistic extreme burning conditions. We used a wind speed of 32 km/hour at 227° based on August wind speed gusts and average direction recorded at the Onion Park SNOTEL station (#1008).

We compared FuelCalc average stand characteristics by attack scenario using general linear mixed model analysis with plot as a random factor (SAS® v. 9.4, SAS Institute, Cary, NC, USA). Predicted fire behavior response from FlamMap (fire line intensity, rate of spread, and flame length) for each pixel by attack scenario was modeled as a generalized additive model (GAM) with a northing x easting interaction component included using a thin plate regression spline basis (R v. 3.0.1 packages mgcv, multcomp, and gstat), followed by multiple comparisons adjusted for family-wise Type I error. The lack of effect of spatial dependence on the standard errors of parameter estimates was confirmed by increasing the number of spline knots until the residual variograms indicated no spatial correlation.

RESULTS

Bark Beetle Severity

Recent MPB activity was generally low across TCEF in 2012 based on field evaluations, with only 4 percent of host trees (pines ≥ 12.7 cm d.b.h.) recorded as recently attacked. However, 36 percent of the plots contained at least one recently attacked tree suggesting the potential for increased MPB activity in the future. Attacks were more concentrated along portions of the TCEF boundary, with up to 50 percent of the host trees attacked in these areas. The simulated epidemic scenario dramatically increased recent MPB attacks to 47 percent of host trees and 56 percent total host mortality (lodgepole pine and whitebark pine only).

Surface Fuel Characteristics

TCEF litter loadings ranged from 0 to 4.3 kg/m² (mean = 0.7 kg/m²; median = 0.5 kg/m²), while duff loadings ranged from 0 to 13 kg/m² (mean = 2.7 kg/m²; median = 2.3 kg/m²). Herbaceous and shrub loadings were quite low across the study area with maximum loads of 0.06 and 0.08 kg/m², respectively. Mean and median seedling loadings were also low, with values of 0.07 and 0.03 kg/m², respectively, and were fairly uniform across the experimental forest. Fine woody fuels (1-, 10-, and 100-hour size classes) ranged from 0 to 13.7 kg/m² (mean

= 3.2 kg/m²; median = 2.9 kg/m²). Coarse woody fuels (1,000-hour sound and rotten) ranged from 0 to 9.4 kg/m², with the maximum for sound wood being 7.1 kg/m² and that for rotten wood being 5.7 kg/m². Total surface fuel load ranged from 0.3 to 21.1 kg/m² (mean = 6.1 kg/m²; median = 5.7 kg/m²).

FuelCalc assigned 10 FBFMs, and these did not change with scenario. Over 62 percent of the plots were assigned to the Timber Litter (TL) group. The majority of these (77 percent) were TL6, which represents a moderate fuel load with a less compacted fuelbed, moderate spread rate, and low flame length. The next most common FBFM category (22 percent) was Slash-Blowdown (SB) with SB2 being predominant. Fires burning in SB FBFMs are predicted to have high spread rates and flame lengths. Ten percent of the remaining plots were defined as Timber-Understory (TU), which is represented by low grass and/or shrub loading with litter. Low spread rates and flame lengths are predicted in the TU1 FBFM, which comprised 9 percent of the landscape. The FBFMs associated with more intense fire behavior (e.g., TU4, 10, SB2, and SB3) were concentrated in the steeper slopes of the Tenderfoot Creek drainage, while fuels represented by the TL6 FBFM were generally on the flatter portions of the forest.

Canopy Fuel Characteristics

Based on our field measurements (incipient scenario), average canopy fuel loading was 1.06 kg/m^2 , canopy base height was 1.7 m, canopy bulk density was 0.12 kg/m^3 , and canopy cover was 66 percent. Average overstory tree ($\geq 12.7 \text{ cm d.b.h.}$) density was 813 trees/ha. Average stand density (seedlings, saplings, and trees) was 1,972 trees/ha, reflecting the many areas of dense seedlings and saplings. Most stand attributes among the endemic, red-incipient, and red-epidemic scenarios were identical due to the assumptions used to create these scenarios. Increasing beetle-killed trees with red needles using the $\text{CrBH}_{\text{effective}}$ values decreased canopy base height, but did not affect predicted torching and crowning indices in the FuelCalc predictions, as fuel moisture is not an input into this model. The epidemic scenario lowered canopy base height, canopy bulk density, tree density, quadratic mean diameter, and basal area.

Simulated Fire Behavior

There was relatively little difference in median simulated fire behavior variables among scenarios (fig. 13.1), but the epidemic and red-epidemic had more variability and higher flame lengths, fire line intensities, and rates of spread in some areas. Flame length values for the majority of the TCEF ranged from 0.5 m to 1.3 m (1^{st} to 3^{rd} quantiles) for the endemic, incipient, and red-incipient scenarios, but

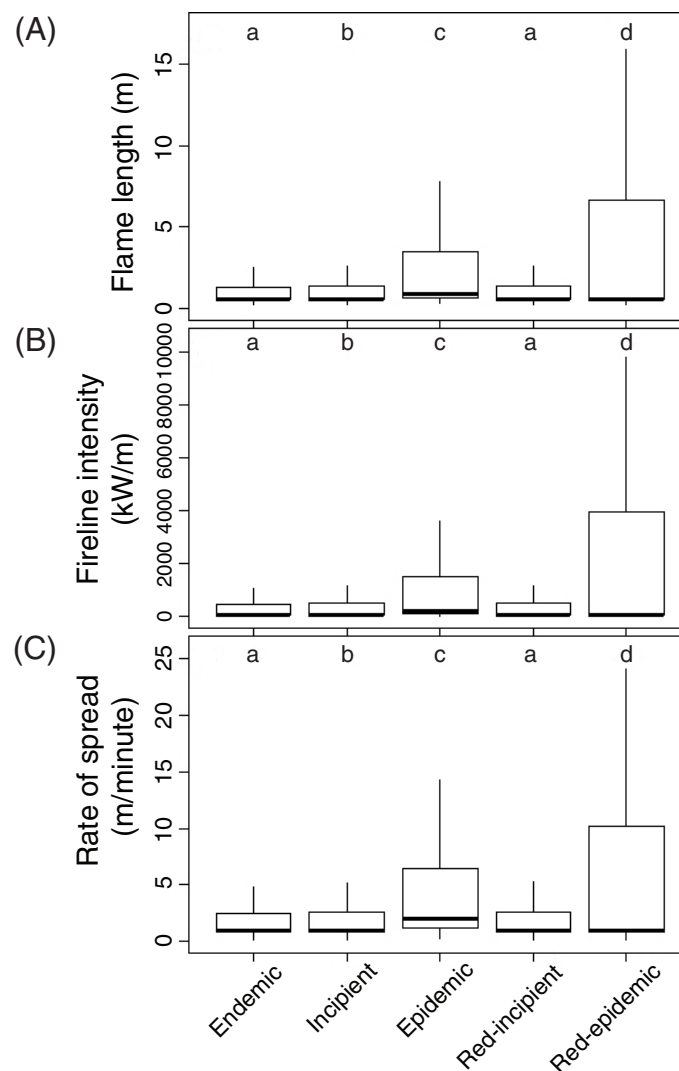


Figure 13.1—Results of the fire behavior FlamMap simulation showing the range of predicted (A) flame length, (B) fire line intensity, and (C) surface fire rate of spread by the five scenarios. Boxes denote 1^{st} and 3^{rd} quartiles, with lines inside boxes showing median values, and bars showing ± 1.5 interquartile range (IQR). Data points outside of 1.5 IQR not shown. Different letters denote differences between scenarios ($\alpha = 0.05$).

ranged up to 3.5 m for the epidemic scenario and 6.7 m for the red-epidemic scenario. Fire line intensity variability was greatest for the red-epidemic scenario, ranging from 68 kW/m to almost 4000 kW/m. Median rate of spread was double for the epidemic scenario at 2 m/minute compared to 1 m/minute for the other scenarios.

Surface fire was the dominant fire type simulated for all scenarios (51–78 percent of total area; fig. 13.2). Passive crown fire was highest for the epidemic (49 percent) and red-epidemic (33 percent) scenarios, compared to 20–23 percent for the other scenarios (fig. 13.2). This increased passive crown fire activity was

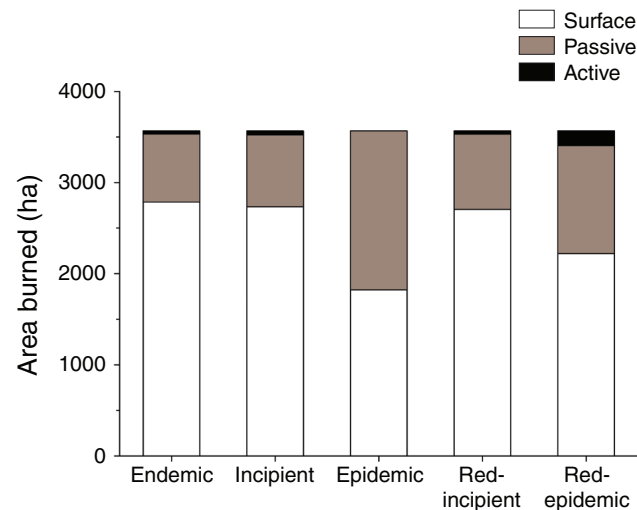


Figure 13.2—Simulated area of Tenderfoot Creek Experimental Forest burned by fire type (surface fire, passive crown fire, active crown fire) by bark beetle scenario.

driven by reduced canopy base height and canopy cover values, especially in the epidemic scenario, which increased midflame windspeeds, thereby fostering more crown fire activity. This was also reflected in the torching index for the epidemic scenario, which was lower (52 km/hour) than all other scenarios (79–87 km/hour). Active crown fire activity increased slightly for the red-epidemic scenario to 5 percent of the area, compared to approximately 1 percent for the other scenarios, but crowning index was the same for all scenarios except the epidemic scenario (65 km/hour vs. 101 km/hour). Unlike the red-epidemic scenario, the epidemic scenario did not increase active crown fire due to the reduction in canopy bulk density and canopy fuel load after trees died from beetle attack and no needles were left in the tree crowns, making it much more difficult for active crown fire to propagate.

DISCUSSION

Our results highlight the limitations of predicting fire hazard in red-stage MPB-affected forests due to a mismatch of scales and resolution between canopy fuels, surface fuel FBFMs, and fire behavior prediction systems. We show that large changes in crown fuels due to a simulated MPB outbreak did not translate into large changes in predicted fire behavior. This is likely because the surface fuel model did not change. Moreover, MPB-mediated differences

were not detected by FuelCalc to change fire behavior fuel models, and FlamMap's 30-m² resolution was not sufficient to capture the subtle changes in canopy fuel characteristics during the simulated MPB outbreak.

Increased efforts to collect tree and fuel data at finer scales will likely not improve efforts to simulate fire behavior in MPB-affected forests with the current suite of models. Fire behavior fuel models were originally developed to help managers predict fire behavior based on a current fire incident. They were designed as a guide to match current fire behavior observations with predicted fire behavior, rather than to describe actual fuel characteristics. Modeling fire behavior in bark beetle outbreaks will undoubtedly continue to be challenging because there is limited opportunity to validate model predictions with actual fire behavior. Therefore, we rarely can know accuracy levels of these models.

Our goal was to evaluate the differences in fuels and fire behavior across MPB scenarios, but the design of the fuel and fire behavior modeling systems did not have the sensitivity to detect the subtle differences across bark beetle scenarios. We feel that the fire behavior predictions simulated in this study likely do not reflect expected fire behavior in the event the TCEF burns. In reality, wildfires burning in lodgepole pine forests in the red stage will likely have

higher intensities, rates of spread, and crown fire activity compared to unattacked lodgepole pine (Hicke and others 2012, Jenkins and others 2014, Page and others 2014, Perrakis and others 2014). Current fire behavior models have shown a consistent under-prediction of surface and crown fire rate of spread in unattacked forests (Cruz and Alexander 2010); therefore, it is not surprising that attempting to use these models outside of their originally intended use may lead to dubious predictions. It will always be difficult to address all the factors that impact fire hazard after MPB outbreaks because of the complex biophysical feedbacks that influence the fire and fuel environment at multiple scales. Even so, improving fire behavior simulation accuracy will continue to be limited without a better understanding of the basic physical processes of fire ignition and spread.

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INTRODUCTION

Spruce beetle (*Dendroctonus rufipennis*) is the primary mortality agent of mature spruce species in Western North America (Jenkins and others 2014a, Schmid and Frye 1977). The species preferentially colonizes hosts with reduced defenses, including diseased trees or downed material produced by wind events, snow avalanches, and landslides, as well as trees affected by abiotic stressors, such as high temperature, drought, and/or fire. The majority of colonization of live spruce occurs following downed tree disturbances in mature spruce forests. Outbreaks modify stand structure and composition by causing tree mortality and impact timber and fiber production, fuel conditions, fire risk and severity, water quality and quantity, fish and wildlife populations, recreation, grazing capacity, real estate values, human safety, biodiversity, carbon pools, aesthetics, endangered species, and cultural resources, among other factors (Jenkins and others 2014a). These impacts have been frequently observed in Engelmann spruce (*Picea engelmannii*) forests of the Intermountain West (Hebertson and Jenkins 2008, Holsten and others 1999). Describing and quantifying these changes provide land managers guidance for future management actions.

The objectives of our study (INT-EM-F-13-02) were to document changes in residual stand structure and composition associated with ground, surface, and aerial fuel loads; tree age, size, and species diversity; regeneration; invasive plants; and snag demography. To achieve this,

we established monitoring plots in forest stands in Utah and Wyoming spanning a temporal continuum of tree mortality attributed to spruce beetle [i.e., prior to epidemic (pre), during epidemic or incipient epidemic (epidemic), and post-epidemic (post)] (Jenkins and others 2008). This summary focuses on a subset of data collected, namely changes in fine surface fuels (1-, 10-, and 100-hour fuels) and tree size as complete data analyses are ongoing. Our scope of inference is spruce-fir forests in the Intermountain West.

METHODS

In 2013, we established eight 0.08-ha circular plots in each of five National Forests (N = 40) of the Intermountain Region (Region 4) in Utah and Wyoming [Uinta-Wasatch-Cache (UWC), Fishlake (FL), Manti-La Sal (MLS), Dixie (Dixie), and Bridger-Teton (BT)]. Uinta-Wasatch-Cache, FL, and BT each contained plots representing the three different outbreak stages. Plots on the Dixie were all post-epidemic. Plots on the MLS consisted of four that were post-epidemic and four that were epidemic.

In 2013, at each plot, we established three 16.1-m modified Brown's transects (Brown and others 1982, Brown and Roussopoulos 1974, Woodall and Williams 2005) at 0°, 120°, and 240° from plot center where we counted surface fuels by size class and measured litter and duff depth (fig. 14.1). We estimated forest floor composition of herbaceous vegetation in 1-m² subplots at the beginning of each transect on the outer edge of each plot. We also used

CHAPTER 14.

Effects of Spruce Beetle (*Dendroctonus rufipennis*) Outbreaks on Fuels, Carbon, and Stand Structure and Composition in Utah and Western Wyoming (Project INT-EM-F-13-02)

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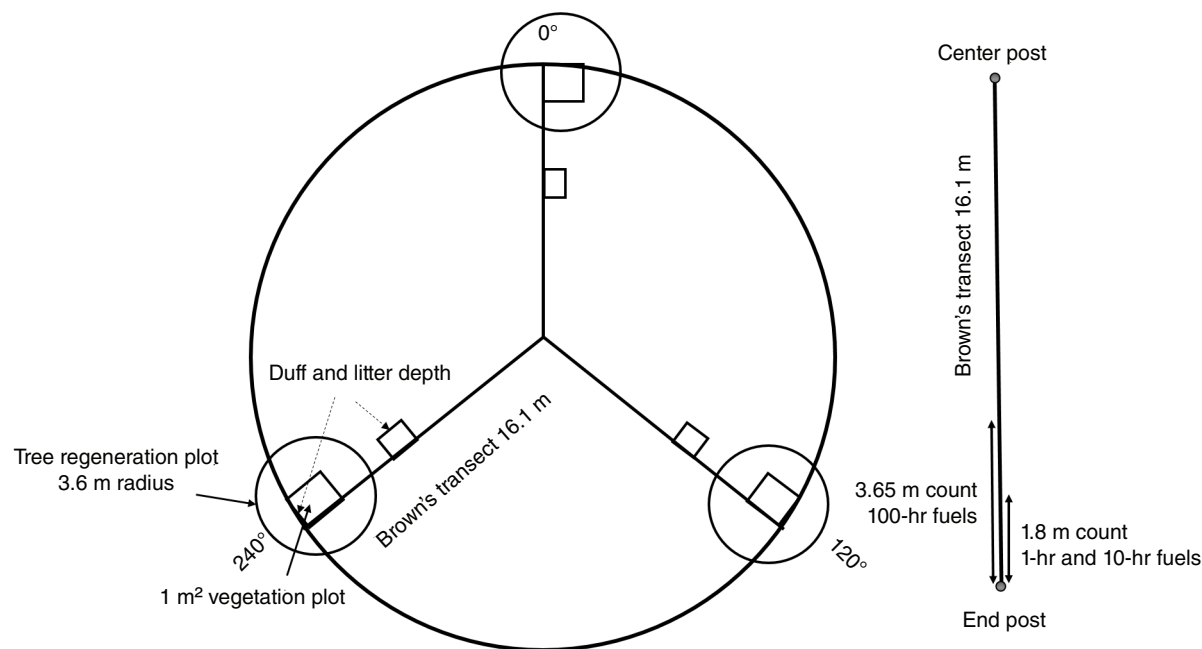


Figure 14.1—Monitoring plot design with Brown's transects. Diameter of fuels: 1-hour = 0–0.64 cm, 10-hour = 0.64–2.54 cm, 100-hour = 2.54–7.62 cm.

3.6-m radius subplots at the beginning of each transect to count tree regeneration by species and seedling (< 7.6 cm in diameter and < 30 cm in height) or sapling (< 7.6 cm in diameter and > 30 cm in height) class. We recorded tree diameter at breast height (d.b.h., 1.37 m), total height, species, status (live or dead), and spruce beetle presence. The year of spruce beetle colonization was determined to be: (1) current year attack (presence of boring dust and immature brood, occasional fresh pitch tubes, green needles); (2) previous year attack [symptoms ranging from fading needles to some or most needles fallen, possible presence

of live beetles (especially at the root collar)]; (3) second year attack (fine twigs attached, most or all needles fallen, no live brood present); or (4) older attack (no needles, some or many fine twigs missing). Related to aerial fuels, we quantified height-to-crown and determined ladder fuels for each tree. On each plot, three of the largest trees based on d.b.h. and tree height were cored to determine stand age and site productivity (10-year growth increment). Ongoing changes in tree mortality, spruce beetle colonization, and tree fall rates were recorded in 2014 and 2015. In 2015, we remeasured surface fuels using modified Brown's transects.

RESULTS AND DISCUSSION

In 2013, significant differences were measured in fine surface fuels for 100-hour fuels among outbreak phases, but not for 1- or 10-hour fuels (table 14.1, fig. 14.2). Following remeasurement in 2015 significant differences in 10- and 100-hour fuels were observed, which indicates the current epidemic may be winding down since no differences were measured in 1-hour fuels as seen in other systems [e.g., mountain pine beetle (*Dendroctonus ponderosae*) in lodgepole pine (*Pinus contorta*)] (Jenkin and others 2008, 2014b).

Between 2013 and 2015, analyses showed consistent d.b.h. distribution in pre- and post-epidemic stands (figs. 14.3–14.5), while increases in standing dead and decreases in standing live

Table 14.1—Analysis of Variance (ANOVA) of 1-, 10-, and 100-hour fuels measured in 2013 and 2015

ANOVA	1-hour 2013	10-hour 2013	100-hour 2013	1-hour 2015	10-hour 2015	100-hour 2015
F-value	1.08	2.7	7.59	0.79	10.16	4.97
Pr > F	0.35	0.08	0.002	0.46	0.001	0.01

trees occurred. Figure 14.6 illustrates spruce beetle-caused tree mortality was initiated in the largest study trees and then shifted to smaller diameters, but caused very little mortality in trees ≤ 20 cm d.b.h. Preliminary observations indicate that subalpine fir (*Abies lasiocarpa*) regeneration is dominant, perhaps indicative of a future shift in tree species composition.

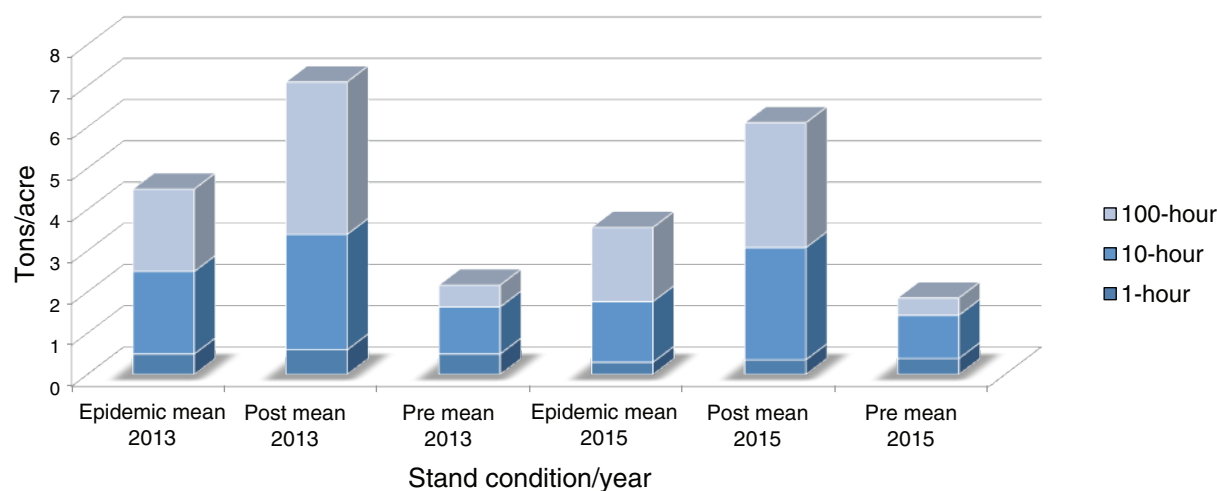


Figure 14.2—Distribution of 1-, 10-, and 100-hour fuels among outbreak phases. Plots were sampled in 2013 and 2015.

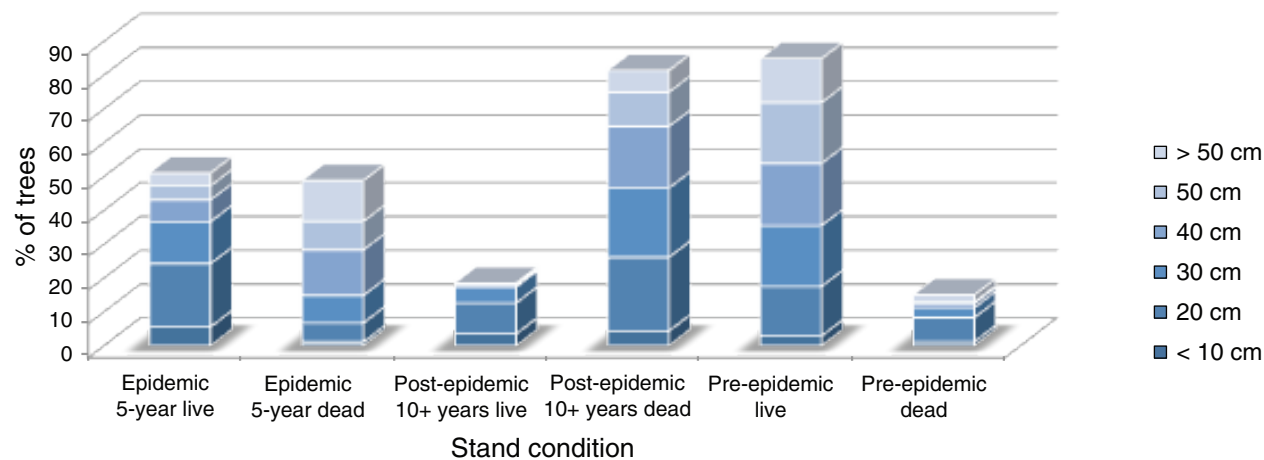


Figure 14.3—Tree distributions by diameter at breast height (d.b.h.) class, 2013.

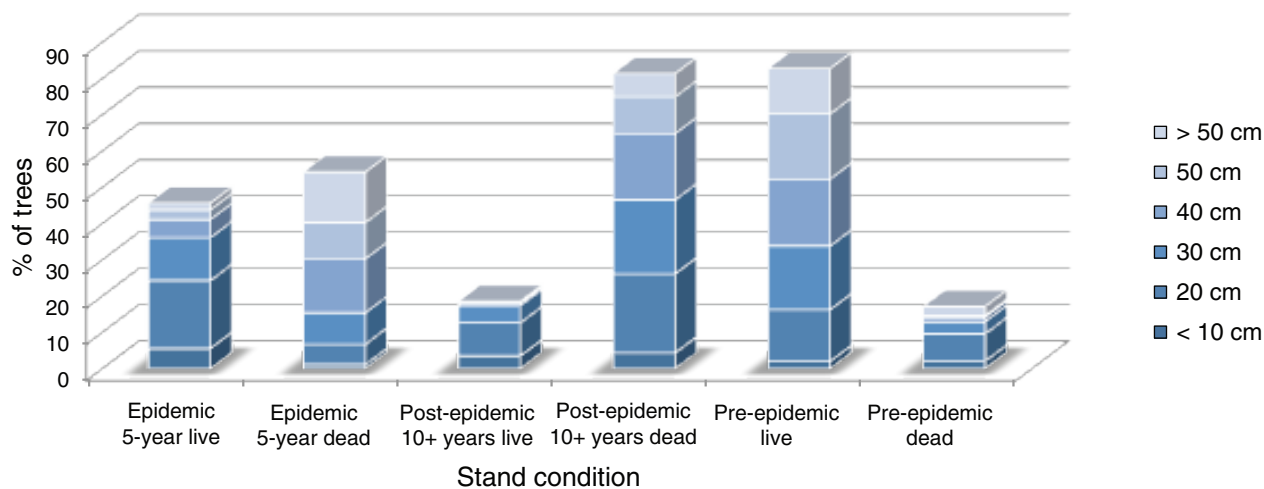


Figure 14.4—Tree distributions by diameter at breast height (d.b.h.) class, 2014. Downed trees since 2013 include one in epidemic 5-year dead stands and seven in post-epidemic stands. No downed trees were found in pre-epidemic stands.

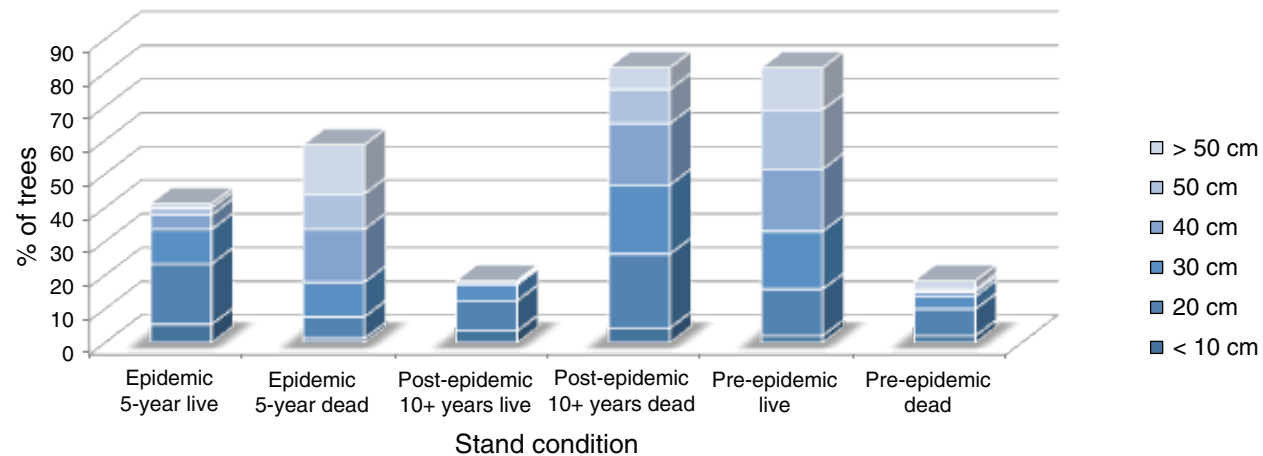


Figure 14.5—Tree distributions by diameter at breast height (d.b.h.) class, 2015. Downed trees since 2013 include eight in epidemic 5-year dead stands and 15 in post-epidemic dead stands. No downed trees were found in pre-epidemic dead stands.

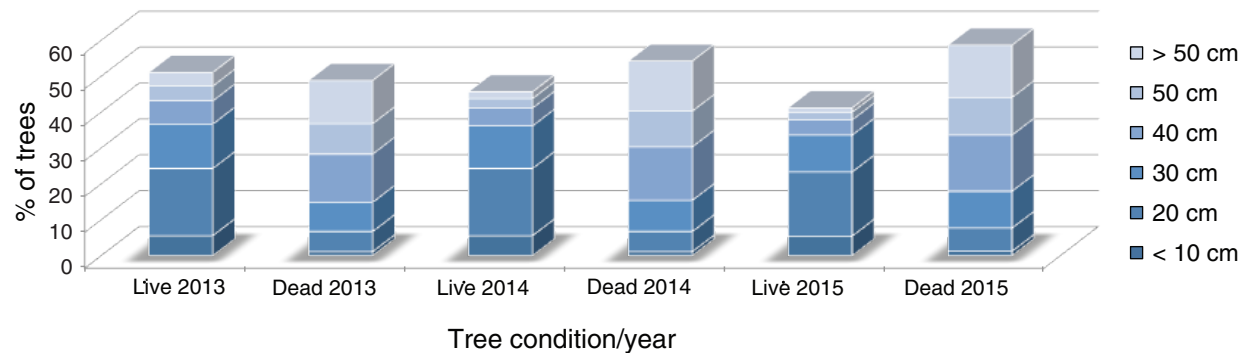


Figure 14.6—Changes in size class distribution of epidemic sites.

In summary, changes in fuel loading and stand structure were consistent with other studies, where fine fuels increase during epidemics, standing live trees decrease, and standing dead trees increase (Jenkins and others

2014b). Changes in regeneration were consistent with DeRose and Long (2007) with subalpine fir regeneration dominating and Engelmann spruce regeneration low.

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INTRODUCTION

As forest communities continue to experience interactions between climate change and shifting disturbance regimes, there is an increased need to link ecological understanding to applied management. Whitebark pine (*Pinus albicaulis*) and limber pine (*P. flexilis*) are important high-elevation five-needle pines in the central and northern Rocky Mountains. Populations of both species face considerable challenges from mountain pine beetle (*Dendroctonus ponderosae*), white pine blister rust (*Cronartium ribicola*), and successional displacement resulting from altered natural disturbance regimes.

Many studies of these pines have focused on relatively narrow portions of what are, in fact, considerable ranges in stand structure and species composition. Both of these species occupy sites in addition to the “high and dry” habitats with which they are typically associated. In addition, both species are represented in stands ranging from pure to mixed-species and from single- to multi-cohort.

This project has contributed to our understanding of the complexity of whitebark and limber pine stand dynamics, including successional trajectories and age-class distributions. This insight is key to the development of effective management strategies and silvicultural prescriptions. The objectives of the study were (1) to characterize stand structure, species composition, and the influence

of important environmental factors (e.g., elevation, aspect, temperature, and precipitation) for whitebark and limber pine across the Interior West, including important variations in stand dynamics for the two species; and (2) to develop silvicultural recommendations addressing the challenges to effective management of whitebark pine and limber pine.

METHODS

The data used in our analysis of whitebark pine were drawn from a database of U.S. Department of Agriculture, Forest Service, Forest Inventory and Analysis (FIA) surveys (Woudenberg and others 2010) conducted across the range of whitebark pine in the Western United States (California, Nevada, Oregon, Washington, Idaho, Montana, and Wyoming). For our analysis of limber pine, a query of the FIA Database located all FIA plots containing limber pine in the overstory and regeneration layer within the Intermountain West.

The current FIA sampling design is approximately 0.067 ha and includes four 7.32-m radius subplots. On each subplot, overstory trees > 12.7 cm d.b.h. (diameter at breast height) were measured. Each subplot contains a 2.073-m radius circular microplot where saplings (trees between 2.4 cm and 12.7 cm d.b.h.) and seedlings (trees < 2.4 cm d.b.h.) were measured. Only Phase 2 (annual inventory) data were used in our analyses. Some States were in the process of beginning their second round of annual inventories resulting

CHAPTER 15.

Composition and Structure of Whitebark and Limber Pine Stands in the Interior West and the Silvicultural Implications (Project INT-EM-B-14-01)

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in 2 years of data. The most recent sampling year was used so there were no repeated measurements within the dataset.

FIA plots measured since 2000 follow a mapped-plot design, meaning that a plot footprint can sample forest and nonforest, or stands of differing composition. The contrasting units are referred to as “conditions,” and they are uniquely identified within a plot in the FIA database. Characteristics normally attributed to stands in other inventories, such as forest type or site index, are assigned to FIA conditions. Among condition-level variables is the proportion of the plot footprint that the condition occupies, and the sum of all condition proportions on a plot equals 1.0.

For all conditions with a whitebark or limber pine component, we obtained the following variables for trees > 1.0 inch (2.54 cm) d.b.h.: species, diameter, height, and individual tree cubic-foot volume. FIA data include volume on a per-tree basis that is calculated using local volume equations (Woudenberg and others 2010). We calculated basal area on a per-acre (0.4047 ha) basis separately for the two target species and all species combined and computed the target species composition on a basal area basis.

RESULTS AND DISCUSSION

Whitebark Pine

Whitebark pine is both a keystone and a foundational species that is a candidate for protection under the Endangered Species Act. Threats to whitebark pine include mountain pine beetle and white pine blister rust. A density management diagram was constructed for whitebark pine and used to assess density-related aspects of this complex system. There are tradeoffs in managing stand relative density with the objectives of maintaining resistance to attack by the mountain pine beetle, maintaining resilience with respect to the potential for Clark’s nutcracker-mediated (*Nucifraga columbiana*) natural regeneration, and maintaining genetic resistance to white pine blister rust.

The density management diagram allows the graphical display of stand relative densities thought to be critical for maintaining resistance and resilience of whitebark pine stands (fig. 15.1). While the relative density thresholds are based on only two studies, they are conservative and appear reasonable. Relative density needs to be low enough to maintain resistance to attack by the mountain pine beetle (Perkins and Roberts 2003), yet high enough to maintain resilience with respect to

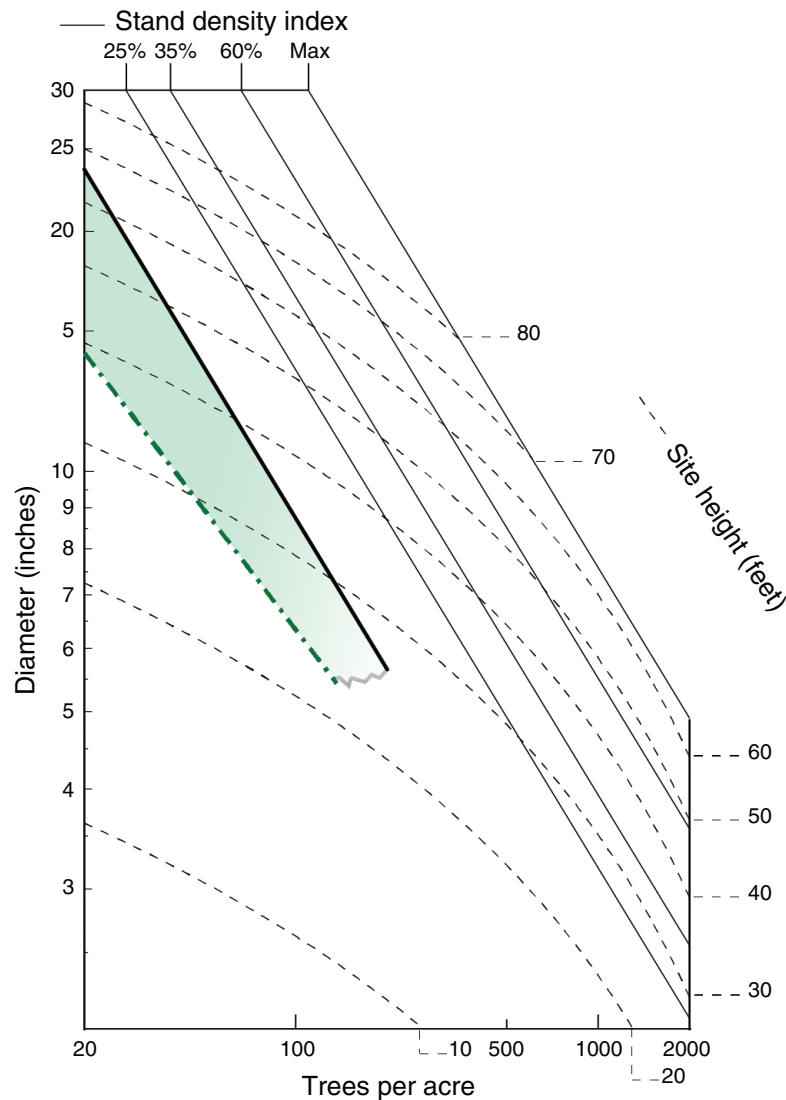


Figure 15.1—Whitebark pine density management diagram with superimposed relative density lines corresponding to mountain pine beetle (MPB) susceptibility (solid black line, after Perkins and Roberts 2003) and stocking necessary for maintenance of Clark's nutcrackers (dashed green line, after McKinney and others 2009).

the potential for Clark's nutcracker-mediated natural regeneration (McKinney and others 2009). Density management plans also need to be developed in the context of white pine blister rust. Thinning to increase resistance to mountain pine beetle attack will ideally be done so that whatever genetic resistance to white pine blister rust exists in the population will not be negatively affected (Keane and others 2012: 80).

Limber Pine

Limber pine has been described as a harsh environment specialist, competitively excluded from mesic environments. We used the FIA database to test the competitive exclusion hypothesis across a broad elevational and geographic area within the Intermountain West. We anticipated that competitive exclusion would result in limber pine's absence from mid-elevation forest communities, creating a bimodal distribution, i.e., high and low elevations. Using the FIA database, limber pine was observed to occur with 22 different overstory species, which represents a surprising number of the woody, overstory species commonly observed in the Intermountain West. There were no biologically significant relationships between measures of annual precipitation, annual temperature, or climatic indices (i.e., Ombrothermic Index) and limber pine dominance. Limber pine was observed to be a consistent component of forest communities across elevation classes. Of the plots that contained limber pine regeneration, nearly half did not have a live or dead limber pine in the overstory. However, limber pine regeneration was greater in plots with higher

live limber pine basal area and higher average annual precipitation. Our results suggest limber pine may be better described as a habitat generalist instead of a specialist (Windmuller-Campione and Long 2016).

CONCLUSIONS

Goals for the management of whitebark pine include maintaining resistance to attack by the mountain pine beetle, maintaining resilience with respect to Clark's nutcracker-mediated natural regeneration, and maintaining genetic resistance to white pine blister rust. Achieving these goals will require careful attention to critical tradeoffs in stand relative density. If relative density is too high, a stand has limited resistance to mountain pine beetle attack. If relative density is too low, cone production may be insufficient to support the Clark's nutcracker on which natural regeneration depends. And finally, any thinning must be done so as to not compromise existing genetic resistance to white pine blister rust.

Generalists like limber pine may be increasingly important as managers are challenged to build resistance and resilience to future conditions in western forests. Additional research is needed to understand how different silvicultural systems can be used to maintain multi-species forest communities.

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Potter, Kevin M.; Conkling, Barbara L., eds. 2018. Forest health monitoring: national status, trends, and analysis 2017. Gen. Tech. Rep. SRS-233. Asheville, NC: U.S. Department of Agriculture, Forest Service, Southern Research Station. 190 p.

The annual national report of the Forest Health Monitoring (FHM) Program of the Forest Service, U.S. Department of Agriculture, presents forest health status and trends from a national or multi-State regional perspective using a variety of sources, introduces new techniques for analyzing forest health data, and summarizes results of recently completed Evaluation Monitoring projects funded through the FHM national program. In this 17th edition in a series of annual reports, national survey data are used to identify geographic patterns of insect and disease activity. Satellite data are employed to detect geographic patterns of forest fire occurrence. Recent drought and moisture surplus conditions are compared across the conterminous United States. Data collected by the Forest Inventory and Analysis (FIA) Program are employed to detect regional differences in tree mortality. FIA plot-level lichen data are assessed as bioindicators for large-scale monitoring of air quality across eastern U.S. forests. A national summary of crown condition across the United States is presented for 2011–15, and change over time in crown dieback is used to identify species in decline. Eight recently completed Evaluation Monitoring projects are summarized, addressing forest health concerns at smaller scales.

Keywords—Change detection, crown dieback, drought, fire, forest health, forest insects and disease, lichens, tree mortality.

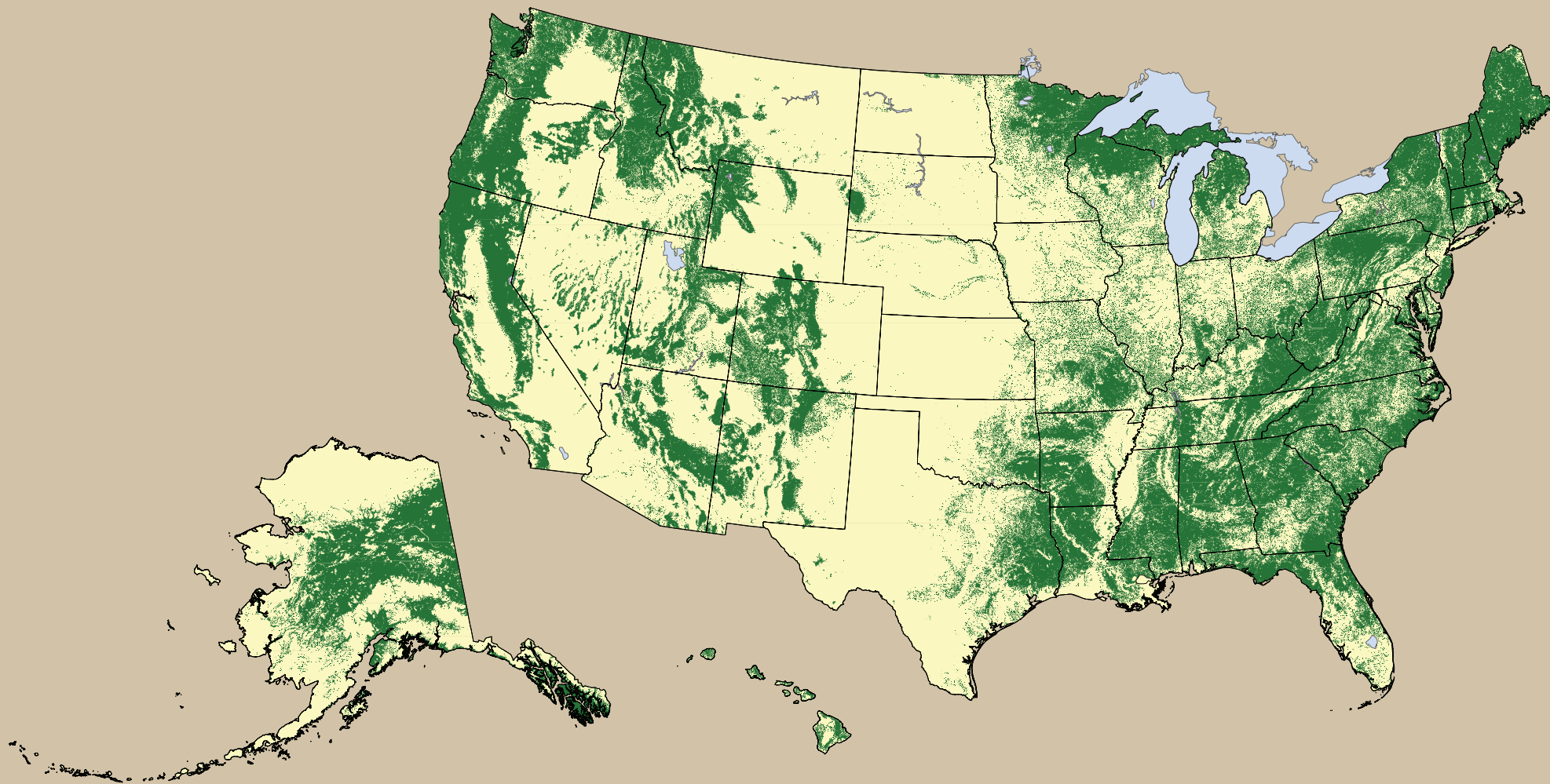


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