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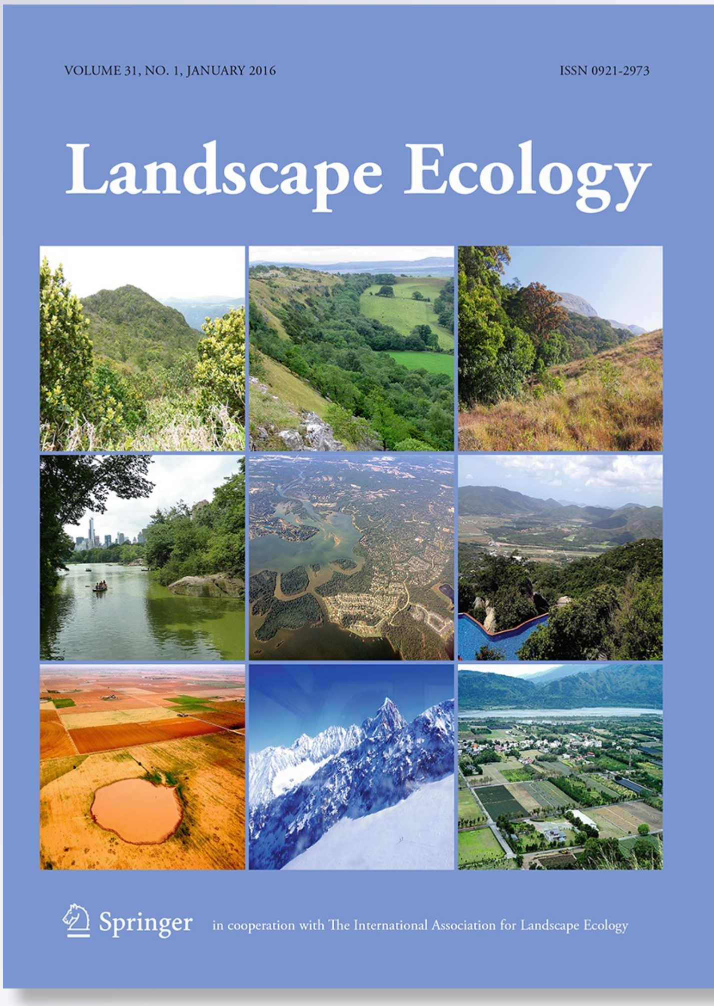

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RESEARCH ARTICLE

Data, data everywhere: detecting spatial patterns in fine-scale ecological information collected across a continent

Kevin M. Potter · Frank H. Koch · Christopher M. Oswalt · Basil V. Iannone III

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Abstract

Context Fine-scale ecological data collected across broad regions are becoming increasingly available. Appropriate geographic analyses of these data can help identify locations of ecological concern.

Objectives We present one such approach, spatial association of scalable hexagons (SASH), which identifies locations where ecological phenomena occur at greater or lower frequencies than expected by chance. This approach is based on a sampling frame optimized for spatial neighborhood analysis, adjustable to the appropriate spatial resolution, and applicable to multiple data types.

Methods We divided portions of the United States into scalable equal-area hexagonal cells and, using three types of data (field surveys, aerial surveys, satellite imagery), identified geographic clusters of forested areas having high and low values for (1) invasive plant diversity and cover, (2) mountain pine beetle-induced tree mortality, and (3) wildland forest fire occurrences.

Results Using the SASH approach, we detected statistically significant patterns of plant invasion, bark beetle-induced tree mortality, and fire occurrence density that will be useful for understanding macro-scale patterns and processes associated with each forest health threat, for assessing its ecological and economic impacts, and for identifying areas where specific management activities may be needed.

Conclusions The presented method is a "big data" analysis tool with potential application for macrosystems ecology studies that require rigorous testing of hypotheses within a spatial framework. This method is a standard component of annual national reports on

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forest health status and trends across the United States and can be applied easily to other regions and datasets.

Keywords Big data · Ecological monitoring · Hotspots · Invasive plants · Mountain pine beetle · Wildfire

Introduction

Macrosystems ecology treats the components of large areas, from regions to continents, as a system of interacting parts; within this context, it integrates fine-scaled mechanisms with broad-scale patterns and processes to help improve predictions of environmental change and to better inform environmental policy (Heffernan et al. 2014). It uses novel approaches and applies existing methods in new ways to study ecological processes interacting within and across scales, analyzing increasingly large volumes of data (Levy et al. 2014). Macrosystems ecology tools and concepts may prove particularly helpful for efforts to assess, monitor, and analyze broad-scale indicators of ecosystem health.

Healthy forested ecosystems in particular are vital to human communities (Edmonds et al. 2011), possessing the capacity to provide a wide range of goods and services, to safeguard biological diversity, and to contribute to the resilience of ecosystems, societies, and economies (United States Department of Agriculture Forest Service 2011). The 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 in the face of a long list of threats including invasive species, insect and disease outbreaks, catastrophic fire, fragmentation, and the effects of climate change (Riitters and Tkacz 2004).

For more than a decade, United States government agencies have collected standardized medium- to high-resolution forest health data that span the width and breadth of the country. These include data collected via satellite sensors, such as daily moderate resolution imaging spectroradiometer (MODIS) Active Fire Detections (Justice et al. 2002; Justice et al. 2011); by fixed-winged aircraft, especially annual aerial surveys of forest insect and disease damage (United States Department of Agriculture Forest Service 2015a); and by ground-based field crews, most prominently by the USDA Forest Service (USFS) Forest Inventory and Analysis (FIA) program across approximately 130,000 fixed-area plots (Bechtold and Scott 2005; Woudenberg et al. 2010). These datasets are vast, regularly accumulating new information from 304 million ha of forests, encompassing one-third of the terrestrial area of United States (Smith et al. 2009).

It is no small challenge to extract useful information from these extensive datasets. One common approach is to aggregate data to political units such as states or counties, or to environmentally defined ecoregions (e.g., Potter and Woodall 2012; Riitters and Wickham 2012; Potter and Koch 2014). Doing so is not always appropriate, however, and can have drawbacks (Coulston and Riitters 2003). First, units within administrative jurisdictions and ecological regions often differ considerably in spatial extent, which could result in highly inconsistent sample sizes, leading to potential biases in subsequent statistical analyses. Second, these units may be inappropriate for analyzing or displaying the fine- to moderate-scale impacts and extents of many ecological phenomena and processes because of uncertainty about the areas that exert contextual influence on a phenomenon or process under study (Kwan 2012). Third, aggregation must be done thoughtfully and cautiously because of the modifiable area unit problem (MAUP), through which aggregation of the same data to different scales can yield different results and conclusions (Jelinski and Wu 1996; Dark and Bram 2007). Fourth, phenomena that cross the boundaries of adjacent geopolitical or ecological regions may not be detected because of the dilution of the signal from the affected parts of the sampling regions (Fotheringham and Wong 1991). Finally, averaging data across broad regions may obscure extreme values that are indications of emerging problems and may conceal spatial patterns that could be important for understanding the dynamics of a given threat (Coulston and Riitters 2003).

Targeted spatial analyses, rather than aggregation to large regions, are sometimes necessary to pinpoint areas of concern for operation-scale environmental research, monitoring, and management. Researchers in several fields regularly apply techniques for detecting geographic clusters, or hotspots, of a particular phenomenon for follow-up analyses,

including in epidemiology and public health (e.g., Kulldorff et al. 2009; Rogerson 2010; Netto et al. 2012), the social sciences (e.g., Lepczyk et al. 2007; Hong and O'Sullivan 2012; Johnston and Ramachandran 2014), and ecology and conservation (e.g., Kamei and Nakagoshi 2006; Hernandez-Manrique et al. 2012; Ma et al. 2012). Within the context of forest health monitoring, Coulston and Riitters (2003) used spatial scan statistics to identify clusters of forest fragmentation in the southeastern United States and of forest insect and pathogen presence in the Pacific Northwest, while Riitters and Coulston (2005) applied the same approach to detect hotspots of forest perforation. Bone et al. (2013) implemented local Moran's I_i, a local indicator of spatial association (LISA), to estimate the risk of mountain pine beetle infestation in British Columbia, while Timilsina et al. (2013) used the Getis–Ord G_i* statistic, a different LISA, to map hotspots of high forest carbon stocking in Florida.

We propose a sampling and analysis approach for pinpointing areas of ecological concern that (1) allows for the identification of locations where ecological health metrics are statistically distinct from the surrounding landscape, (2) is based on an equal-area sampling frame optimized for spatial neighborhood analysis, (3) allows the sizes of sampling units to be adjusted to the appropriate spatial resolution of analysis, and (4) is applicable to many types of fine-resolution data collected across broad extents. This spatial association of scalable hexagons (SASH) method consists of dividing an analysis area into scalable equal-area hexagonal cells within which data are aggregated, followed by the identification of 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 use a Getis–Ord (G_i*) hotspot analysis (Getis and Ord 1992), one of the most popular local indicators of spatial association. LISAs like G_i*, which quantify areas in which clusters of density or intensity are statistically distinct from patterns in the surrounding landscape (Johnston and Ramachandran 2014), are also able to assess the statistical hypothesis that observed patterns arose by chance, with the rejection of this null hypothesis used as the threshold for defining geographic hotspots and coldspots (Sokal et al. 1998; Nelson and Boots 2008).

In addition to maintaining equal areas across the analysis region, the hexagons used in SASH 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 et al. 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 or watersheds) encompassing vastly different areas. The area of hexagons used in each analysis can be determined based on ecological considerations, on sampling intensity, or on the limits of spatial dependence across the global data set.

We present three SASH example analyses using data collected in the United States (1) from ground-based surveys (USDA Forest Service inventory data of invasive plant species cover and diversity in the South), (2) from fixed-winged aircraft (aerial survey data of forest mortality caused by mountain pine beetle, *Dendroctonus ponderosae*, in the West during three separate four-year timeframes), and (3) by satellite (annual densities of MODIS fire occurrence detections). These analyses, by encompassing a variety of spatial extents, hexagon sizes, data collection timeframes, and spatial data formats, aim to illustrate the wide applicability of the SASH approach for identifying statistically significant geographic hotspots and cold spots of ecological phenomena related to environmental health. The SASH analytical approach is a standard component of annual USDA Forest Service national reports that assess forest health across broad regions (e.g., Potter 2015b; Potter and Paschke 2015), which in turn are used to inform management and policy decisions.

Materials and methods

Data

Ground-collected invasive plant data

The USDA Forest Inventory and Analysis (FIA) program is the primary source for information about the extent, condition, status and trends of forest resources in the United States (Smith 2002). FIA

applies a nationally consistent sampling protocol using a quasi-systematic design to conduct a multi-phase inventory of all ownerships; the national sample intensity is approximately one plot per 2428 ha of land (Bechtold and Patterson 2005). Forested plots, approximately 130,000 in total, are visited every 5 to 7 years in the eastern United States and every 10 years in the western part of the country. Permanent fixed-area FIA inventory plots (approximately 0.067 ha in size, consisting of four, 7.2-m fixed-radius subplots spaced 36.6 m apart in a triangular arrangement with one subplot in the center) are established in forested conditions when field crews visit plot locations that have accessible forest land. Field crews collect data on more than 300 variables, including forest type, tree species, site conditions, and the presence of nonnative invasive plant species (Smith 2002; Woudenberg et al. 2010).

FIA defines "invasive plants," in accordance with U.S. Executive Order 13112, as exotic plant species of any growth form likely to cause economic or environmental harm (Ries et al. 2004). FIA field crews collect invasive plant data based on region-specific lists of problematic forest plant invaders agreed upon by invasive plant experts (Oswalt et al. 2015). We extracted invasive plant data from the 13-state southern region, where the list of invasive forest plants encompasses 53 species (Iannone et al. 2015). It is important to note that our analyses focus on introduced plants expected by experts to cause ecological and economic problems and not on all introduced plants, which are likely to be more numerous (Schulz and Gray 2013) and to include species understood to have negligible economic and environmental effects. We conducted separate analyses for two invasion metrics: plot-level monitored invasive species richness, defined as the total number of monitored invasive plants present on a plot, and invasive percent cover, defined as the mean percent cover of all monitored invasive plants across a plot's forested subplots. These measures of plot-level invadedness (i.e., degree or level of invasion) may slightly underestimate the overall presence of nonnative invasive species because only species currently identified as problematic are recorded. The analyses encompass 38,752 FIA plots, most of which were inventoried between 2008 and 2012. Mean plot-level values for the two metrics of plant invasion were determined for each hexagonal sampling unit using ArcMap 10.1 (ESRI 2012).

Fixed-wing-aircraft-collected data of bark beetle-associated tree mortality

USDA Forest Service Forest Health Protection (FHP) national insect and disease survey data (United States Department of Agriculture Forest Service 2015a) consist of information from annual low-altitude aerial survey and ground survey efforts. These surveys identify areas of mortality and defoliation caused by insects and pathogens, providing data that can be used to identify geographic hotspots of forest insect and disease activity (Potter and Paschke 2015). Because the results are captured using aerial sketchmapping (i.e., digitization of polygons by a human interpreter aboard the aircraft), all quantities are approximate "footprint" areas for each agent, delineating areas of visible damage within which the agent is present. Unaffected trees may exist within the footprint, and the intensity of damage within the footprint is not reflected in the estimates of forest area affected.

We conducted three separate hotspot analyses, one for each of three four-year windows (2002–2005, 2006–2009, and 2010–2013). For each, the variable used in the hotspot analysis was the percent of total surveyed forest area in each hexagonal sampling unit with mortality attributed to mountain pine beetle (MPB) during at least 1 year. For each time period, we merged the 4 years of data to create a single non-overlapping footprint of mortality; areas where mortality was reported over multiple years during the period were not counted more than once. MPB is the most aggressive, persistent, and destructive bark beetle in western North America, attacking most pine species of the region as well as spruces in some situations (Rocky Mountain Region Forest Health Protection 2010). Although native to most of the west, it exhibits periodic large outbreaks that cause extensive tree mortality (Raffa et al. 2008; Meddens et al. 2012). The ongoing bark beetle epidemic has caused approximately 5.46 million ha of mortality in British Columbia and between 0.47 and 5.37 million ha of mortality in the western conterminous United States; this mortality will likely leave a long ecological legacy in these forests (Meddens et al. 2012). Data processing was conducted in ArcMap 10.1 (ESRI 2012), including use of a forest cover layer derived from MODIS imagery by the U.S. Forest Service Remote Sensing Applications Center (United States Department of Agriculture Forest

Service 2008) to determine baseline forested area within the hexagons.

Satellite-sensor-collected data of wildfire occurrence

Annual monitoring and reporting of active wildland fire events using the moderate resolution imaging spectroradiometer (MODIS) active fire detections for the United States database (United States Department of Agriculture Forest Service 2015b) allows analysts to spatially display and summarize fire occurrences across broad geographic regions (Potter 2015b). A fire occurrence is defined as one daily satellite detection of wildland fire in a 1-km^2 pixel, with multiple fire occurrences possible on a pixel across multiple days.

The data are derived using the MODIS Rapid Response System (Justice et al. 2002; Justice et al. 2011) to extract fire location and intensity information from the thermal infrared bands of MODIS imagery collected daily by two satellites at a resolution of 1 km^2, with the center of a pixel recorded as a fire occurrence. 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 km^2, for example) and a cooler fire over a larger area (1 km^2, 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 et al. 2008). It is important to note that estimates of burned area and calculations of MODIS-detected fire occurrences are different metrics for quantifying fire activity. The MODIS data contain both spatial and temporal components because each 1-km pixel will have a frequency of daily fire occurrences during a given year since persistent fire will be detected repeatedly over several days on a pixel. Analyses of the MODIS-detected fire occurrences, therefore, measure the total number of daily fires on 1-km pixels each year, as opposed to only quantifying the area on which fire occurred at some point during the course of the year. 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 et al. 2009).

We used data from the 2012, 2013, and 2014 calendar years to separately test for statistically significant hotspots of fire occurrence within each. The MODIS products for those years were processed in ArcMap 10.1 (ESRI 2012) to determine the number of fire occurrences per 100 km^2 of forested area within each hexagonal sampling unit in the conterminous United States. This forest fire occurrence density measure was calculated after screening out wildland fires on nonforested pixels using a forest cover layer (United States Department of Agriculture Forest Service 2008).

Analysis

For each of the datasets described above, we separately employed a Getis–Ord hotspot analysis (Getis and Ord 1992) in ArcMap 10.1 (ESRI 2012) to identify forested areas with the greatest exposure to the individual forest health threat. Specifically, the Getis–Ord G_i* statistic was used to identify clusters of hexagonal cells within which the threat exposure was higher or lower than expected by chance. This statistic allows for the decomposition of a global measure of spatial association into its contributing spatial component, by location, and is therefore particularly suitable for detecting nonstationarities in a data set, such as when spatial clustering is concentrated in one subregion of the data (Anselin 1992).

The units of analysis were hexagonal cells generated in a lattice across the conterminous United States via intensification of the U.S. Environmental Protection Agency's Environmental Monitoring and Assessment Program (EMAP) North American hexagon coordinates, which are based on a truncated icosahedron (a geometric solid with 20 hexagonal and 12 pentagonal faces) fit to the globe (White et al. 1992). Briefly, these coordinates were the foundation of a sampling frame in which a hexagonal lattice was projected onto the region by centering a large base hexagon of the truncated icosahedron over the continental United States (White et al. 1992; Reams et al. 2005). This base hexagon can be subdivided into many smaller hexagons, depending on sampling needs, for instance serving as the basis of the plot sampling frame for the FIA program (Reams et al. 2005). These hexagonal cells are compactly shaped with minimal scale distortion, and are part of a hierarchical structure for sampling enhancement and reduction (White et al. 1992). The subdivision of the base hexagon, as detailed by White et al. (1992), is accomplished by

an algorithm that intensifies the number of points in a seven-point starting grid formed by the six vertices and the center point of the base hexagon. Conceptually, this intensification process works by dividing the base hexagon into six equilateral triangles defined by each side of the hexagon and each radius between the hexagon center point and a vertex. The sides of each of these triangles are then divided into equal parts determined by the sampling needs of an analysis, and the endpoints of these equal parts are connected to form a triangular lattice, with the centroid of each triangle identified. The centroids are then tessellated to generate a lattice of hexagonal cells. Notably, because this process is done using an equal-area projection, the hexagons maintain equal areas across the study region.

Determining the appropriate hexagon size for each hotspot analysis requires careful consideration because rescaling data represents a serious and often overlooked challenge in spatial analyses with few straightforward solutions (Openshaw 1977; Atkinson and Tate 2000). To resolve the variation at a given level of investigation, the intensity of sampling must relate to the scale at which most of the variation in the phenomenon of interest occurs (Oliver 2001). A general spatial data aggregation principle, therefore, is to create zonal systems which minimize intra-zonal variances and maximize inter-zonal variances (Wong 2009). At least three zone-area-selection approaches can be applied to accomplish this objective: (1) selecting zones that are as small as possible while encompassing enough data to allow for robust statistical analysis; (2) selecting zones based on the scale at which an ecological phenomenon occurs, or over which management and monitoring priorities can be decided; and (3) selecting zones based on the distance at which spatial autocorrelation is maximized across the sample data set, which can be computed using a sample variogram (Atkinson and Tate 2000; Oliver 2001) or a measure such as Moran's I, which is a weighted correlation coefficient that can detect departures from spatial randomness (Cliff and Ord 1981). For each of the three analyses described in this paper, we determined the optimal size of our hexagons using one of these approaches.

For the analysis of our invasion dataset, we determined the suitable hexagon size based on sampling considerations (option 1). Because the FIA program is designed with counties as the main focus of sampling and estimation procedures (Reams et al. 2005), we selected the hexagon size (approximately 1452 km^2) to reflect the average size of counties in the southern United States (1466 km^2). The analyses of degree of invasion encompassed 1081 hexagons with forest in the South, containing an average of 35.9 FIA plots. Hexagons with fewer than five FIA plots were excluded from analyses.

For a hotspot analysis, it is often desirable to focus on a scale of spatial variation that is associated with a process or phenomenon (Atkinson and Tate 2000). For our analyses of exposure to forest mortality associated with MPB, we therefore determined the size of the analysis hexagons based on dispersal of the organism (option 2). Specifically, most dispersal by the insect is expected to occur within a distance of 3 km, with the possibility of a smaller amount of longer-distance dispersal at varying distances (Shore and Safranyik 1992; Bone et al. 2013). We selected a hexagon size of 54 km^2, because distance from centroid to the edge is approximately 3.8 km. In the western United States, there were 38,005 hexagons of this size containing forest and for which we separately calculated the percent of total surveyed forest area exposed to MPB mortality within three four-year windows (2002–2005, 2006–2009, and 2010–13).

Often, spatial data are not collected to make statistical inferences at a particular scale, and the scale over which the ecological processes of interest occur is unclear. In such circumstances, it is possible to gain knowledge about the spatial structure of the data by generating a semivariogram, which provides an unbiased description of the scale and pattern of spatial variation (Oliver 2001). Specifically, spatial dependence exists at distances less than the range of the semivariogram (Palmer 2002); the range of the semivariogram, therefore, can be used to guide sampling, with a useful guideline being to sample at half the limit of spatial dependence, which is the interval represented by half of the range (Oliver 2001). We generated a theoretical semivariogram (i.e., a stable semivariogram model (see Waller and Gotway 2004)) in ArcMap 10.1 (ESRI 2012) of forest fire occurrence density (fire occurrences per area of forest) within 54 km^2 hexagons, based on the empirical semivariogram; the resulting range was 25,825 m. We therefore selected sampling hexagons of approximately 635 km^2, for which the distance from the centroid to each edge is approximately 13,715 m, or approximately half the range distance from the

semivariogram (option 3). The analyses of fire occurrence density encompassed 9733 forested hexagonal cells across the conterminous United States.

For the analyses of each of these three datasets, the G_i* statistic for each hexagon summed the differences between the mean values in a local sample (including the hexagon of interest) and the global mean of all the forested hexagonal cells in the analysis. Because normality for G_i* can be reasonably assumed when sample units have at least eight neighbors (Ord and Getis 1995; Nelson and Boots 2008), we defined the local sample as a moving window consisting of each hexagon and its 18 first- and second-order neighbors (the six adjacent hexagons and the 12 additional hexagons contiguous to those six) (Fig. 1). The G_i* statistic is a standardized z score with a mean of 0 and a standard deviation of 1. We assumed values greater than 1.96 represent significant ($p < 0.025$) local clustering of high values and values less than -1.96 represent significant clustering of low values ($p < 0.025$). Therefore, a G_i* value of 1.96 indicates that a value for a given hexagon and its 18 neighbors is approximately two standard deviations greater than the mean expected threat exposure in the absence of spatial clustering, while a G_i* value of -1.96 indicates a threat exposure approximately two standard deviations less than the mean expected in the absence of spatial clustering. It is worth noting that the -1.96 and 1.96 threshold values are inexact because the correlation of spatial data violates the assumption of independence required for statistical significance (Laffan 2006).

Results

Hotspots of forest plant invasion

The SASH approach revealed differing locations of hotspots for invasive species diversity and invasive species cover across the southeastern United States (Fig. 2). For example, one hotspot of moderately high invasive diversity ($z > 4$) (Fig. 2a) stretched along the Piedmont from the Virginia–North Carolina border southwest to the Alabama–Georgia border, encompassing the Raleigh–Durham, Charlotte, and Atlanta metropolitan areas. Another extended from north-central Kentucky (including Louisville, Lexington and Florence) south into the area of Nashville in north-central Tennessee. Meanwhile, a coldspot of moderately low invasive diversity ($z < -4$) extended from the western Florida panhandle coast east across the state to central peninsular Florida and north into southeastern Georgia. A smaller coldspot of moderately low invasive diversity ($z < -4$) was detected in central Oklahoma.

The SASH analysis for invasive cover, meanwhile, detected a single hotspot of very high invasive cover ($z > 8$) in north-central Alabama, centered on Birmingham (Fig. 2b). Areas of moderately high invasive cover encircle this area, extending into northeastern Mississippi. Smaller hotspots of moderate invasive cover were located in the Piedmont of North Carolina and South Carolina, in western Kentucky and northwestern Tennessee, and in southeastern Texas surrounding Houston. In all of the hotspots, only one or two species were dominant contributors to invasive cover, presenting a much different management scenario, and a markedly dissimilar geographic pattern, than invasive species diversity. Coldspots of moderately low levels of invasive cover were detected in northern Florida and southeastern Georgia, and in south-central Oklahoma.

The hotspot patterns for both invasive metrics are largely in keeping with results at the county level, which showed that large percentages of subplots were invaded in counties along a corridor from south-central Virginia southwest into northern Georgia, as well as in northern Alabama, northern and Southern Mississippi, and coastal Texas (Iannone et al. 2015; Oswalt et al. 2015). Those analyses also found counties with lower percentages of invaded subplots in northern Florida; in the Appalachian region; along the coast of Georgia, South Carolina, and North Carolina; and in central Oklahoma.

Hotspots of mortality associated with mountain pine beetle

The SASH analysis of exposure to MPB mortality across the western United States revealed the development and subsidence over time of broad-scale infestation in several locations (Fig. 3). From 2002 to 2005, 21,846.6 km^2 of surveyed forest area were exposed to MPB mortality, with hotspots of extremely high exposure ($z > 32$) occurring in north-central Idaho and north-central Colorado (Fig. 3a). Hotspots of high ($z > 8$) and very high exposure ($z > 16$) were

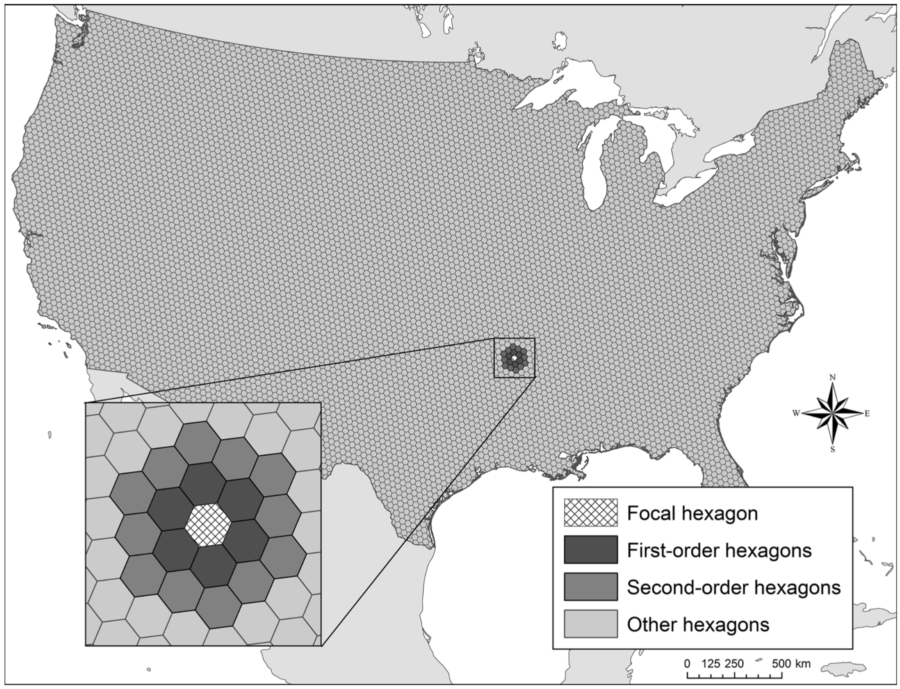

Fig. 1 A hexagonal sampling frame of the continental United States, consisting of 9810 hexagonal cells of approximately 830 km^2. The Getis–Ord G_i* statistic for each hexagon sums the differences between the mean values in a local sample and the global mean of all the hexagons in the analysis. The *inset* depicts one local sample in the moving window analysis, consisting of a focal hexagon and its six first-order and 12 second-order neighbors

detected along the cascade range in Oregon and Washington, in northern and central Idaho, in the Bitterroot and Belt Mountains of western Montana, in western Wyoming, in the Uinta Mountains of northeastern Utah, and in the Black Hills of South Dakota.

The aerial survey data indicated that the years 2006–2009 encompassed the peak of the recent MPB infestation, with 52,799.5 km^2 of surveyed Western forest exposed to MPB mortality. The SASH analysis detected no hotspots of extremely high mortality exposure, but did locate large areas with high to very high exposure, mostly in areas that had expanded past the hotspots from the previous four-year period (Fig. 3b). This included much of the forested areas of the Oregon Cascades, north-central Idaho, western Montana, western Wyoming, and north-central Colorado. Hotspots in Washington and South Dakota diminished somewhat.

From 2010 to 2013, 38,879.4 km^2 of surveyed forest area were exposed to MPB mortality. Large hotspots of high and very high mortality persisted in south-central Oregon, north-central Idaho, western Montana, western Wyoming, northeastern Utah, and north-central Colorado, but most of these areas had decreased in size (Fig. 3c). The SASH approach allowed us to detect movements of these hotspots over time. For example, hotspots shifted from the western to the eastern slope of the Front Range in Colorado. Similarly, the hotspot in western Wyoming shifted from the northern to the southern end of the Wind River Range. In Oregon, hotspots in the northern part of the cascades mostly diminished over time, while areas of high exposure increased to the south. The hotspots in Washington decreased markedly in area, and new, small hotspots of low to moderate exposure appeared in western Oregon and California.

The results of the MPB hotspot analyses are generally consistent with a previous analysis that showed the insect has caused extensive mortality in areas of the western conterminous United States that include western Montana and western Idaho, north-central Colorado and south-central Wyoming, northeastern Utah, and the cascade range of Washington and Oregon (Meddens et al. 2012). A separate analysis of FIA data determined that large areas of dead and salvable timber, mostly the result of mortality caused by bark beetles, exist in Montana, Idaho, Colorado, and Wyoming (Prestemon et al. 2013).

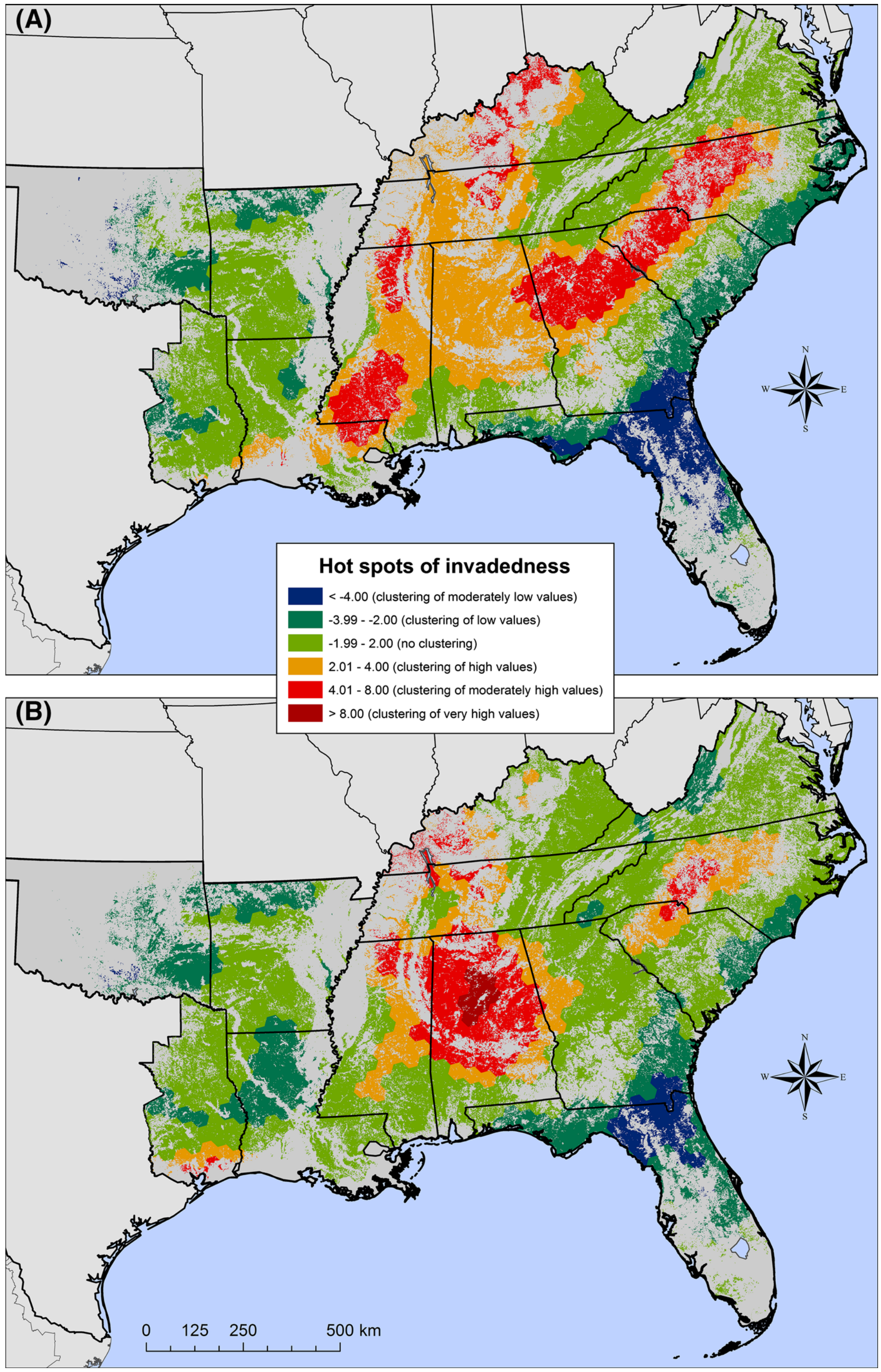

Fig. 2 Hotspots of plant invadedness across the southeastern United States, from United States Department of Forest Service Forest Inventory and Analysis data, using hexagons of approximately 1452 km^2 in area. Values are Getis–Ord G_i* scores for **a** plot-level invasive species diversity and **b** plot-level invasive species cover. Values greater than two represent areas of significant clustering of high levels of invadedness and values less than −2 represent areas of significant clustering of low levels of invadedness

Hotspots of fire occurrence density

The location and intensity of statistically significant geographic hotspots of forest fire occurrences varied for each of the 3 years of analysis (Fig. 4). The MODIS active fire database in 2012 captured the most forest fire occurrences (138,687) across the conterminous United States since the beginning of full-year data collection in 2001 (Potter 2015a). In that year, hotspots ($z > 2$) encompassed 131,035.3 km^2 of

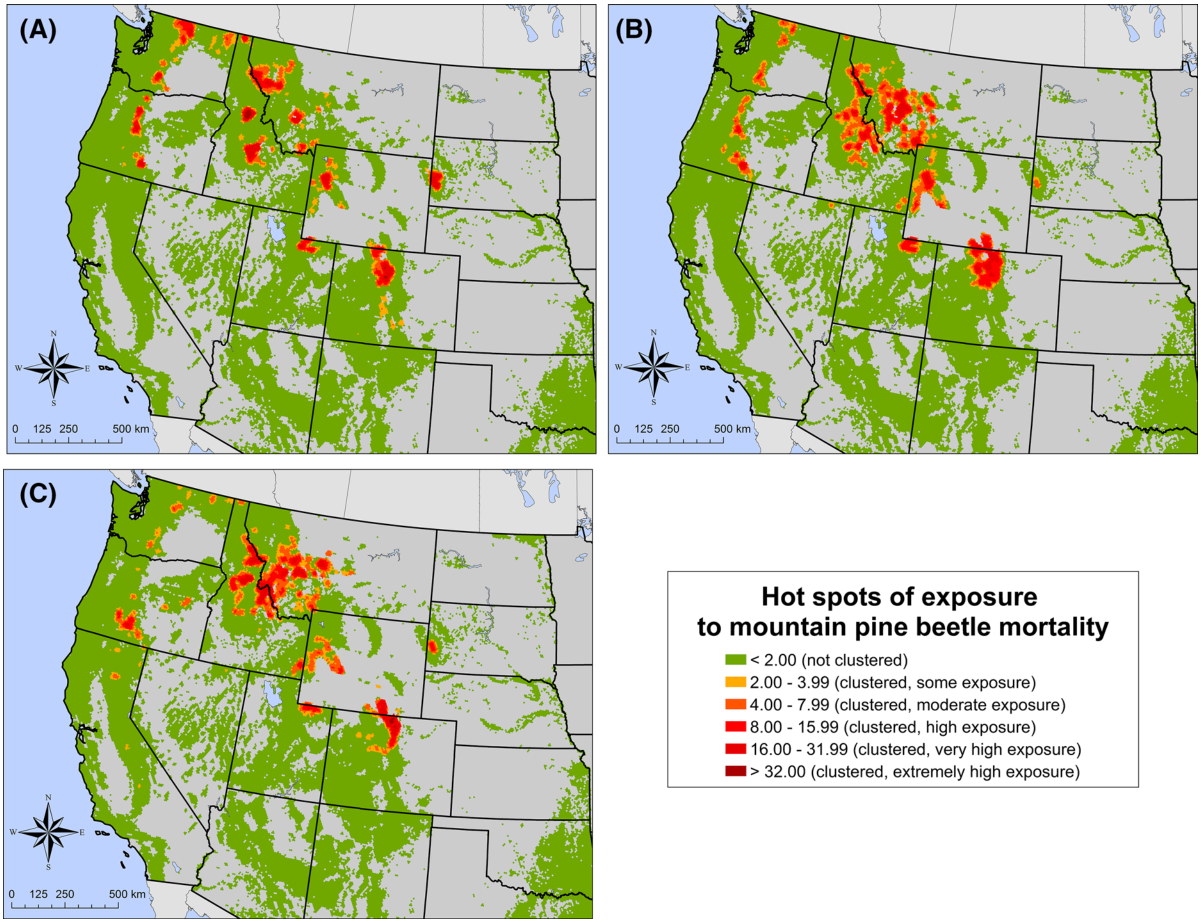

Fig. 3 Hotspots of exposure to mountain pine beetle mortality across the western United States, from United States Department of Forest Service national insect and disease survey data, using hexagons of approximately 54 km^2 in area. Values are Getis–Ord G_i* scores for **a** cumulative 2002–2005 MPB mortality footprint **b** cumulative 2006–2009 MPB mortality footprint, and **c** cumulative 2010–2013 MPB mortality footprint. Values greater than two represent areas of significant clustering of high levels of exposure to MBP mortality. (No significant areas of significant clustering of low percentages of exposure, less than −2, were detected)

forest, with 32,075.1 km^2 in hotspots of high fire density ($z > 8$) and 5197.4 km^2 in hotspots of very high fire density ($z > 16$) (Fig. 4a). The high number of fire occurrences across the conterminous states is generally consistent with the official estimates of area burned nationally in 2012 (37,742.0 km^2), which was 128 percent of the 10-year average (National Interagency Coordination Center 2013). All 2012 fire density hotspots were located in the western United States, which experienced a summer heat wave combined with record to near-record dryness following below-average winter snowpack; this situation resulted in below-normal fuel moisture and above-normal energy release component indices from Oregon, Idaho and Wyoming south to California and New Mexico (National Interagency Coordination Center 2013).

Hotspots of forest fire occurrence density were more widely dispersed across the conterminous United States in 2013 (Fig. 4b), when 98,682 fire occurrences were detected, nearly 30 % fewer than the previous year (Potter 2015b). Hotspots ($z > 2$) encompassed 154,623.4 km^2 of forest, of which 17,969.7 km^2 was in hotspots of high fire density ($z > 8$) and 7136.8 km^2 was in hotspots of very high fire density ($z > 16$). Areas of high forest fire occurrence density were located in California, Oregon, Idaho, Montana, Colorado and New Mexico. Summer drought conditions in

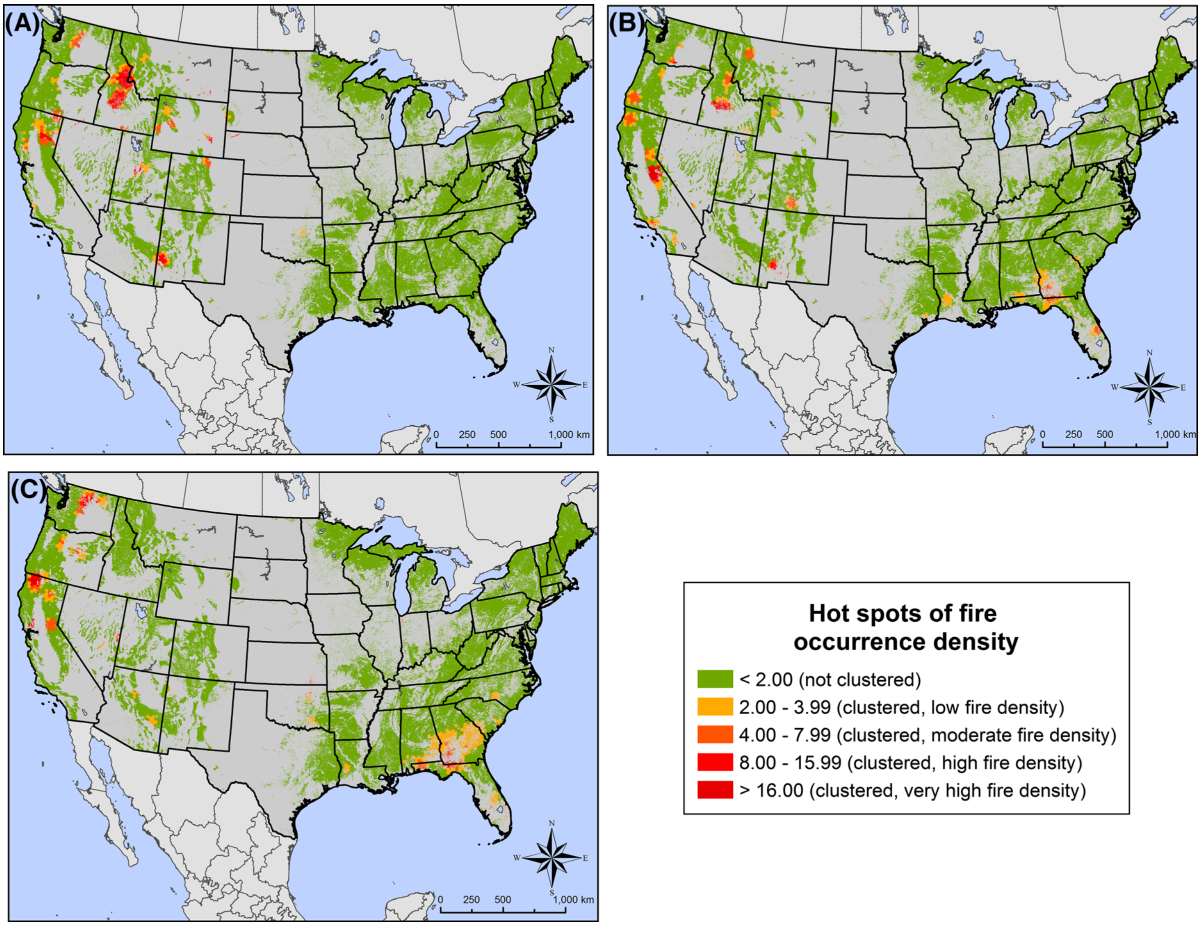

Fig. 4 Hotspots of forest wildfire occurrence across the United States, from the moderate resolution imaging spectroradiometer (MODIS) active fire detections for the United States database, using hexagons of approximately 635 km^2 in area. Values are Getis–Ord G_i* scores for **a** 2012 **b** 2013, and **c** 2014 fire occurrence densities. Values greater than two represent areas of significant clustering of high fire occurrence densities. (No significant areas of significant clustering of low fire occurrence densities, less than −2, were detected.)

the west allowed fire fuels to become extremely dry in 2013, particularly in northern California and southwestern Oregon (National Interagency Coordination Center 2014). A large hotspot of very high fire occurrence density was detected in the Sierra Nevada of California, the location of the 1041.3 km^2 rim fire, the largest in the nation that year and the third largest in California history (National Interagency Coordination Center 2014).

In 2014, hotspots of forest fire occurrence density were generally limited to three areas: the Pacific Coast states, the Southeast, and the southern plains states (Fig. 4c). In that year, the MODIS satellites recorded 106,242 forest fire occurrences. Hotspots ($z > 2$) encompassed 173,018.8 km^2 of forest; of this, 15,512.7 km^2 consisted of hotspots of high fire density ($z > 8$) and only 3629.6 km^2 consisted of hotspots of very high fire density ($z > 16$). The distribution of fire density hotspots reflects the severe to exceptional drought conditions that continued from previous years and extended from the Pacific coast to the western slope of the Rocky Mountains, and that existed across the southern plains; areas east of the Rocky Mountains, meanwhile, generally received abundant precipitation that reduced fire potential (National Interagency Coordination Center 2015). The southeastern region had the greatest area burned in 2014 (National Interagency Coordination Center 2015), but this was mostly from small, short-duration fires occurring in the spring or autumn. Hotspots of low-

($z > 2$) to moderate ($z > 4$) fire occurrence density were detected in southwestern Georgia, the western panhandle of Florida, and southern peninsular Florida (Fig. 4c).

Discussion

Broad-scale ecological monitoring efforts fall within the realm of macrosystems ecology because they occur at regional to continental extents while incorporating biological, geophysical and social components occurring at smaller scales (Heffernan et al. 2014). As such, they present the "big data" challenges of macrosystems ecology, including data collection and management, analytical complexity, and appropriate handling of scale issues (Heffernan et al. 2014; Levy et al. 2014; Ruegg et al. 2014). Broad-scale ecological monitoring requires flexible approaches that are quantitative, scalable, and applicable to many types of data, while allowing for the rigorous testing of hypotheses within a spatial framework. The spatial association of scalable hexagons (SASH) method described here consists of three steps (1) division of the analysis extent into equal-area hexagons of the appropriate size (scaling), (2) aggregation of the data within these hexagons, and (3) completion of a Getis–Ord hotspot analysis (Getis and Ord 1992) to identify statistically significant geographic clusters of hexagons.

Scaling and aggregation

The equal-area sampling frame that underpins the SASH approach is optimized for spatial neighborhood analysis, and can be adjusted to the appropriate spatial resolution based on sampling considerations, ecological processes, or the spatial structure of the data. Specifically, a hexagonal lattice is highly useful and convenient for spatial neighborhood analysis because the hexagons are compactly shaped (nearly circular), maintain equal areas across a study region, are independent of geopolitical boundaries, and are uniform in their distance to the centroids of their neighboring hexagons. The selection of the appropriate size for the hexagons is a critically important step, given that the existence of scale-dependent spatial variation can make re-scaling and data integration problematic (Atkinson and Tate 2000). While there is no consistent approach for determining proper hexagon size, a reasonable guideline is to base it on the properties of the phenomenon of interest, whether related to ecological processes, sampling size, or spatial dependence in the data. In general, the goal is to minimize within-zone variability while selecting zones that are as small as possible yet encompass enough information for robust statistics; this can be a challenging task, however, and sometimes may need to rely on heuristics (sensu Wong 2009). We recommended three possible approaches for selecting hexagon size, and applied each in a separate analysis, choosing a size at which hexagons (1) are as small as possible while encompassing enough data to allow for robust statistical analysis, (2) reflect the scale over which an ecological phenomenon occurs or over which management and monitoring priorities can be decided, or (3) encompass the distance at which spatial autocorrelation is maximized across the sample data set. When in doubt about appropriate hexagon size, researchers also can vary sizes based on reasonable estimates (such as those defined by expert knowledge) to ensure the robustness of spatial patterns across a sensible range.

While data aggregation will cause some loss of information, it is a necessary step to generate meaningful results when assessing fine-scale data collected across a broad area. Selecting the appropriate hexagon size should help minimize the loss of important information. Depending on the type of data analyzed, it may be necessary to standardize data within hexagons to avoid biasing the results; not standardizing data based on the amount of forest, for example, could miss large proportional problems in areas with small amounts of forest or mistakenly identify small proportional problems as large problems in areas with much forest. We standardized both the MODIS satellite fire detection data and the mountain pine beetle aerial survey detection data. Similarly, the aggregation of data collected across time requires careful consideration, and may depend on management needs, on environmental patterns and processes, or on data collection considerations. For example, although beyond the scope of this paper, analyses of invasive species metrics during different five-year FIA measurement cycles could offer a sense of areas where nonnative species have recently become more problematic. We were able to detect such temporal patterns in mortality caused by MPB within three four-year periods.

Geographic clustering approaches

Multiple geographic clustering approaches are used in ecology (Coulston and Riitters 2003; Hernandez-Manrique et al. 2012; Bone et al. 2013; Timilsina et al. 2013). All have advantages and disadvantages, and most could be applied as cluster-detection tools within the SASH framework. We used the Getis–Ord G_i*statistic (Getis and Ord 1992) for the SASH analyses presented here because, as a local indicator of spatial association (LISA) (Anselin 1995), it is generated by a relatively robust approach that is fairly easy to use and allows users to test for a given level of statistical significance while identifying hotspots and coldspots (Nelson and Boots 2008; Johnston and Ramachandran 2014). It also is integrated into geographic information system packages like ArcMap (ESRI 2012) and assigns a value to all hexagons in the domain of analysis. Local Moran's I_i, a different LISA approach (Anselin 1995), has similar advantages to G_i* while additionally offering the ability to identify statistically significant outliers, e.g., high values surrounded by low values. This feature was not needed for our analyses, however. Positive values of local Moran's I_i indicate spatial autocorrelation in values that are extremely positive relative to the mean, while negative values indicate spatial autocorrelation in values extremely negative relative to the mean; at the same time, it is impossible to tell whether values near zero have no spatial autocorrelation or have autocorrelation in values close to the mean (Nelson and Boots 2008), which is a potential disadvantage.

One caveat for both LISAs is that testing for local measures of spatial autocorrelation can be affected by the potential presence of global spatial autocorrelation (i.e., across the analysis extent) or by the statistical problems associated with conducting multiple comparisons (Nelson and Boots 2008; Johnston and Ramachandran 2014). Both G_i* and local Moran's I_i are relatively robust to the size of the local neighborhood, with the same general areas of significance detected regardless of how the local neighborhood is defined, although larger spatial neighborhoods tend to result in a greater number of hotspots (Nelson and Boots 2008). Meanwhile, it is important to note that the regional extent of an analysis can strongly affect LISAs. The selection of the appropriate regional extent is therefore critical, and should be based on data considerations (e.g., the FIA program's use of a consistent list of problematic invasive species across the southern United States), the extent of the phenomenon (e.g., MPB occurring only in the western United States), or the extent at which regional policy and/or management decisions are made (e.g., fire occurrence densities across the entire United States).

Another family of cluster detection methods scan a study area to find subregions with atypical values (Rogerson 2010). One of the most widely used, especially in epidemiological studies, applies a likelihood ratio test to examine spatial and/or temporal windows of different size and length to assess the randomness of phenomena (e.g., Kulldorff and Nagarwalla 1995; Kulldorff et al. 2009). This approach, which also has been used in forest health monitoring applications, is able to detect geographic clusters with significantly high rates of a phenomenon and to rank the clusters according to the statistical likelihood that the observed rate is higher than the background rate; it does so regardless of the actual spatial pattern of the clusters and without having to specify cluster sizes and regions in advance (Coulston and Riitters 2003; Riitters and Coulston 2005). At the same time, users must choose from among many scan statistic parameters and probabilistic models based on the needs of a given application (Costa and Kulldorff 2009), which requires a thorough understanding of the relatively complicated approach. Additionally, computationally intensive spatial scan tools do not currently incorporate strong cartographic capabilities, and therefore are inefficient for making easily interpretable maps.

Kernel estimation is a third approach for identifying spatial variability in a phenomenon of interest, by portraying local values that are weighted by the values of other observations in a neighborhood, with closer locations having greater weights (Rogerson 2001; Nelson and Boots 2008). Kernel-estimated surfaces can easily depict locations of abundance and scarcity of a phenomenon, as well as spatial variability (Nelson et al. 2006). Although a useful data exploration technique, kernel estimation is not able to determine the statistical significance of locations with higher or lower values (Rogerson 2001), and is only applicable to point data. Additionally, the amount of smoothing used in kernel estimation, which is determined by the neighborhood from which values are averaged, has a large impact on kernel results (Kelsall and Diggle 1995). Small neighborhoods will reveal small-scale

features of the data, while larger neighborhoods will reveal more general features, requiring a degree of subjectivity in choosing an appropriate neighborhood size (Nelson and Boots 2008).

Example analyses

The flexibility of the SASH approach is demonstrated by three examples, which encompassed a variety of data types, spatial extents, hexagon sizes, and data collection timeframes. Furthermore, each of these analyses highlighted a different aspect of forest health, illustrating the utility of the SASH approach across a wide range of ecological phenomena.

Nonnative invasive plant species

Invasions by nonnative plant species may cause severe and long-term impacts on forested ecosystems (Martin et al. 2009) and ecosystem services (Pejchar and Mooney 2009). Because nonnative species continue to be introduced via trade and transportation, and because their impacts will likely increase with ongoing expansion of global commerce (Lodge et al. 2006; Hulme 2009), it is critically important to synthesize existing data on nonnative species abundance and distributions (Crall et al. 2006) and to be able to understand the spatial context of these data (as illustrated here) in order to detect regions of particular concern. Using the SASH approach, we located geographic hotspots and coldspots of nonnative invasive plant species diversity and cover across the southeastern United States. The analysis illustrates a way to identify locations where nonnative invasive plant species are concentrated and where they potentially have the greatest ecological impact, i.e., where invasive cover is greatest (Hillebrand et al. 2008). Such information may be useful in understanding macroscale invasion patterns and for targeting activities to detect and control nonnative invasive plant species. The SASH approach may also represent a new cost-effective diagnostic technology that can be used to increase active surveillance and sharing of information about invasive species so responses to new invasions can be more rapid and effective (Lodge et al. 2006). Datasets, such as in the FIA plot system, that are collected consistently and in a standardized fashion at relatively high density across broad scales may not be available in other parts of the world, but similar analyses are possible at a coarser scale (i.e., using larger hexagons) for other data sources.

Mountain pine beetle

Diseases and insects cause changes in forest structure and function, species succession, and biodiversity, all of which may be considered negative or positive depending on management objectives (Edmonds et al. 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 for understanding the potential impacts of these stressors on forest structure, composition, biodiversity, and species distributions (Castello et al. 1995). Using the SASH approach, we analyzed exposure to forest mortality associated with the MPB epidemic across the western United States during three four-year analysis windows. Such large-scale assessments offer a useful approach for identifying geographic areas where the concentration of management activities might be most effective (e.g., Potter and Paschke 2015) or where risk of future outbreaks is highest (e.g., Bone et al. 2013). Furthermore, the SASH approach provides a straightforward framework for continued monitoring of outbreaks, which is necessary for determining appropriate follow-up investigations. Specific examples with respect to MPB include efforts to understand the interaction between beetle-associated mortality and other forest disturbances such as climate change, wildland fire, and harvest; to quantify impacts to timber, wildlife, recreation, and water; and to construct ecosystem models that evaluate impacts on biochemical and biophysical processes (Meddens et al. 2012).

Fire occurrence

As a key agent of disturbance operating at many spatial and temporal scales, wildland fire affects forest health both positively and negatively (Edmonds et al. 2011; Lundquist et al. 2011). 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 et al. 2011). Quantifying and monitoring large-scale patterns of fire occurrence also may help improve understanding of the ecological and economic impacts of fire, as well as the appropriate

management and prescribed use of fire. Specifically, spatially explicit assessments of fire occurrence could help identify relatively compact areas where specific management activities may be necessary, or where research into the ecological and socioeconomic impacts of fires may be required (e.g., Tonini et al. 2009; Potter 2015b). Using the SASH approach, we present analyses of high-temporal-fidelity fire occurrence data, collected by satellite, that map where fire occurrences have been concentrated spatially across the conterminous United States during three recent years. Similar analyses are possible in other areas of the world, such as Australia (Oliveira et al. 2015), Latin America (Portillo-Quintero et al. 2013), Russia (Krylov et al. 2014), and India (Vadrevu et al. 2008), where MODIS and other satellite data have been applied in broad-scale analyses of fire detections.

Conclusions

Fine-scale ecological data are becoming increasingly available across broad regions. Presenting this information in ways that are relevant for policy and management decisions is critically important (e.g., Hooper et al. 2005), but poses a major challenge. Specifically, doing so requires a framework that aggregates information to a spatial scale at which ecological processes occur or at which decisions can be made, and that can help to discern which areas need the most attention. We propose a flexible approach that identifies statistically significant geographic clusters of ecological phenomena after aggregating fine-scale data into scalable hexagonal cells across broad extents. The SASH method described here is based on an equal-area sampling frame that is optimized for spatial neighborhood analysis and that can be adjusted to the appropriate spatial resolution.

Because creative geographic analyses of broad-scale data are necessary to identify places where indicators suggest the existence of relatively poor forest health conditions (Coulston and Riitters 2003), the SASH analytical approach has become a foundational element of annual USDA Forest Service national reports on the status and trends of forest health across the nation (e.g., Potter 2015b; Potter and Paschke 2015). The results of these analyses are used by researchers and managers to select finer-scale locations for follow-up research activities. For the analyses described here and in the Forest Service reports, it is fortuitous that the United States is data-rich, with the existence of several fine-scale standardized ecological datasets that span the extent of the country. The SASH method is not limited to North America, however, and is a "big data" analysis tool that, regardless of region, has potential application for a broad range of macrosystems ecology studies requiring the rigorous testing of hypotheses within a spatial framework. The North American hexagon that was the foundation of the analyses presented here is, in fact, a single face of a truncated icosahedron fit to the globe (White et al. 1992). That global truncated icosahedron can be configured to position a hexagon over any area of interest, which can then be subdivided into multiple hexagons of appropriate area. Tools also can be imported into Geographic Information Systems programs to generate hexagons of desired size for a given study region. Additionally, while it is desirable to use fine-scale data collected in a standardized fashion and at a high sampling intensity, the lack of such data is not necessarily a limitation. In such cases, the flexibility of the SASH method allows for the aggregation of data to larger hexagons and, therefore, to coarser scales of analysis.

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