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Beyond Inventories: Emergence of a New Era in Rangeland Monitoring

Matthew O. Jones

University of Montana, Missoula, matt.jones@umontana.edu

David E. Naugle

University of Montana, david.naugle@umontana.edu

Dirac Twidwell

University of Nebraska-Lincoln, dirac.twidwell@unl.edu

Daniel R. Uden

University of Nebraska - Lincoln, duden2@unl.edu

Jeremy D. Maestas

USDA, Natural Resources Conservation Service

See next page for additional authors

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Authors

Matthew O. Jones, David E. Naugle, Dirac Twidwell, Daniel R. Uden, Jeremy D. Maestas, and Brady W. Allred



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journal homepage: www.elsevier.com/locate/ramaBeyond Inventories: Emergence of a New Era in Rangeland Monitoring[☆]

Matthew O. Jones^{a,b,*}, David E. Naugle^a, Dirac Twidwell^c, Daniel R. Uden^{c,d}, Jeremy D. Maestas^e, Brady W. Allred^a

^a Authors are from University of Montana, W. A. Franke College of Forestry and Conservation, Missoula, MT 59812, USA

^b Numerical Terradynamic Simulation Group, University of Montana, Missoula, MT 59812, USA

^c Department of Agronomy and Horticulture, University of Nebraska–Lincoln, Lincoln, NE 68588, USA

^d School of Natural Resources, University of Nebraska–Lincoln, Lincoln, NE 68588, USA

^e US Department of Agriculture, Natural Resources Conservation Service, Portland, OR 97232, USA; and

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ABSTRACT

In the absence of technology-driven monitoring platforms, US rangeland policies, management practices, and outcome assessments have been primarily informed by the extrapolation of local information from national-scale rangeland inventories. A persistent monitoring gap between plot-level inventories and the scale at which rangeland assessments are conducted has required decision makers to fill data gaps with statistical extrapolations or assumptions of homogeneity and equilibrium. This gap is now being bridged with spatially comprehensive, annual, rangeland monitoring data across all western US rangelands to assess vegetation conditions at a resolution appropriate to inform cross-scale assessments and decisions. In this paper, 20-yr trends in plant functional type cover are presented, confirming two widespread national rangeland resource concerns: widespread increases in annual grass cover and tree cover. Rangeland vegetation monitoring is now available to inform national to regional policies and provide essential data at the scales at which decisions are made and implemented.

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Introduction

Rangelands of the United States are valuable assets that sustain biodiverse plant and wildlife populations; provide essential water, food, and fiber resources; generate recreational revenue; and are rich in cultural heritage. Covering nearly one-third of the total US land area (Reeves and Mitchell 2011), rangelands are distributed across a checkerboard of public and private land ownership. These ecosystems have experienced a wide array of use, alteration, management, and conservation, including increased fragmentation (Havstad et al. 2009), land use change for cultivation (Smith et al. 2016) and energy development (Allred et al. 2015), altered fire regimes (Miller et al. 2013), and changes in plant species

composition affecting rangeland resilience to disturbance and resistance to invasive species (Maestas et al. 2016; Chambers et al. 2017). To conserve US rangelands in the face of such changes, increasing demand has been placed on providing land managers comprehensive spatiotemporal data on the history, condition, and potential of the land surface to inform assessments and support decisions (National Research Council 1994; Toevs et al. 2011). Comprehensive spatiotemporal data of vegetation functional group continuous cover and rangeland ecological indicators are now freely available (Xian et al. 2015; Jones et al. 2018; Zhang et al. 2019; Rigge et al. 2020) and represent a paradigm shift in how we monitor US rangelands.

The rangeland profession historically focused its data collection efforts (West 2003) on inventories—plot-level quantitative measures of abiotic and biotic components and site-level qualitative ecosystem indicators (Pyke et al. 2002). Although past efforts used systematic data collection methods (Barker et al. 2018), it was not until the turn of the century, and in response to numerous reports (e.g., National Research Council 1994; SRM Task Group 1995), that nationwide standardized methods were adopted. In a major advancement, common protocols (Pyke et al. 2002) were implemented across agencies and used on public and private lands to

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* Correspondence: Matthew O. Jones, 32 Campus Dr ISB 418, Univ of Montana, W. A. Franke College of Forestry and Conservation, Missoula, MT 59812, USA. 406-370-0052.

E-mail address: matt.jones@umontana.edu (M.O. Jones).

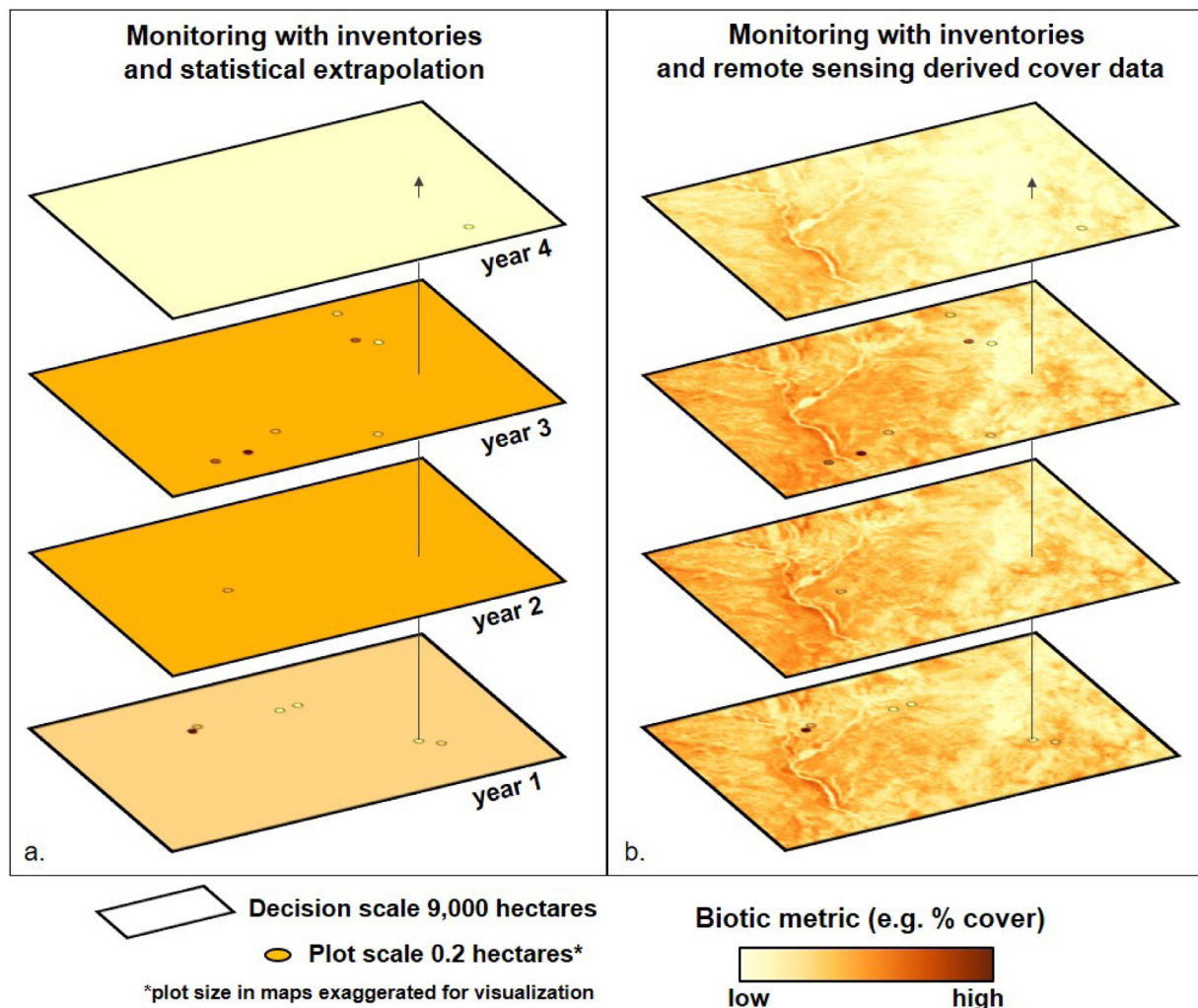


Fig. 1. Examples of monitoring 9 000 ha of rangeland in the western United States over 4 yr using (a) inventories and statistical extrapolation versus (b) inventories coupled with remote sensing–derived data. Actual Bureau of Land Management Assessment, Inventory, and Monitoring plots and their measured percent vegetation cover are shown for each yr. Solid colors within the decision scale boundary (a) are extrapolated values (mean percent cover of inventories for that yr). Color gradients within the decision scale boundary (b) are percent cover values provided by continuous land cover data (Jones et al. 2018). Arrow represents single plot location unmeasured by inventories through time but with data provided annually through remote sensing–derived monitoring data. Not shown are errors associated with both monitoring methods that must be considered.

collect inventories (e.g., US Department of Agriculture, Natural Resources Conservation Service, National Resources Inventory (NRI)–Herrick et al. 2017; Department of Interior, Bureau of Land Management, Assessment, Inventory, and Monitoring (AIM)–MacKinnon et al. 2011). Inventory data are then often used in statistical extrapolations to estimate land surface conditions beyond the extent of measurements; this has become a standard method for monitoring US rangelands. This type of monitoring is then used for assessments–evaluations of rangeland history, condition, and potential—to aid in decision making and has been used at national scales across private (Herrick et al. 2010) and public (Karl et al. 2016) US rangelands. Using plot-level observations to make assessments, inform decisions, and guide policy requires assumptions that site-scale inventories are representative of decision-scale areas. Previous national rangeland assessments (Herrick et al. 2010; Karl et al. 2016) extrapolated field plot collections to ecoregion scales; data from 9 to 259 plots (~0.2 ha each) provided results across 657 000 to 1.7 million ha, respectively (Karl et al. 2016).

This method of monitoring was developed in recognition of resource constraints that limit the extent of plot-level data collection; it is logistically infeasible to collect inventories on more than a small fraction of US rangelands, particularly through time.

Such constraints result in spatial and temporal data gaps where variation in both space and time go unmeasured and must be filled with statistical extrapolations and assumptions of homogeneity or equilibrium. For example, within a 9 000-ha area, 16 field plots (~0.2 ha each) using standardized protocols (MacKinnon et al. 2011; Herrick et al. 2017) provided direct measures of 0.0003% of the decision extent (Fig. 1). Statistical extrapolations (e.g., the average of measurements) estimate data across the remaining area but do not capture area-wide spatial or temporal variation (see Fig. 1a). That variation is now being captured with biotic metrics and rangeland ecological indicators (Xian et al. 2015; Jones et al. 2018; Zhang et al. 2019; Rigge et al. 2020) estimated across the entire land surface, through time, via remote sensing (see Fig. 1b). These new data capture the spatial and temporal variabilities that exist across anthropogenic boundaries of management and ownership, as well as biotic and abiotic variations of the land surface.

The concept of providing spatially and temporally comprehensive data for monitoring is not new and has been implemented at limited scales since the dawn of the satellite remote sensing era (Rouse et al. 1974; Maxwell 1976; Tueller 1989; Hunt et al. 2003; Washington-Allen et al. 2006). However, long-standing barriers prevented those methods from providing data at tempo-

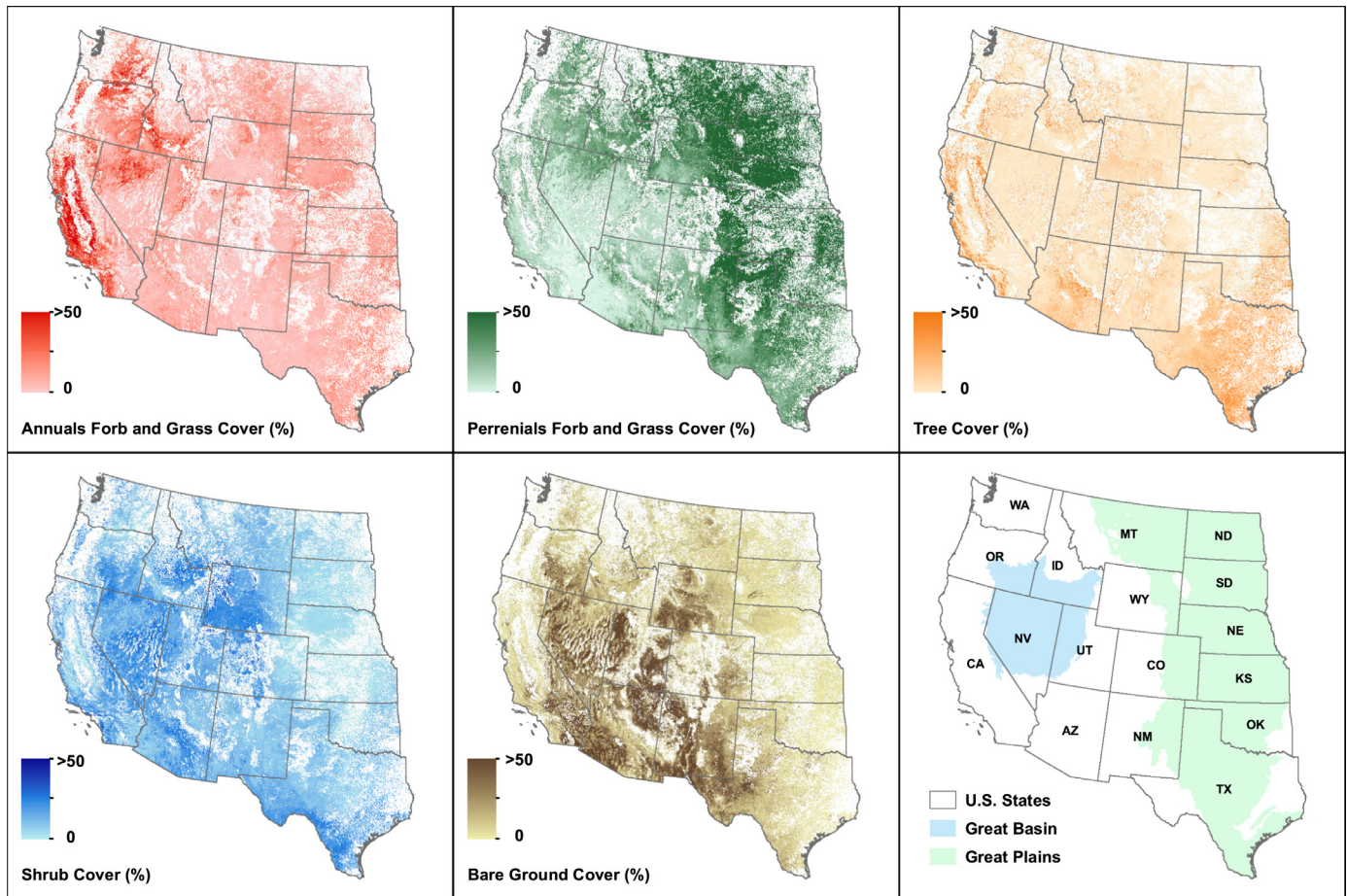


Fig. 2. Continuous land cover maps of four vegetation functional groups and bare ground for yr 2018 and a map of the study region including US state labels and two ecoregion extents, the Great Basin and the Great Plains, provided for reference. White areas in continuous cover maps are nonrangeland pixels based on a coterminous US rangelands 30 m circa 2011 product (Reeves and Mitchell 2011).

ral intervals, geographic scales, and spatial resolutions to effectively monitor and assess the ~ 3.0 million km^2 (Havstad et al. 2009; Reeves and Mitchell 2011) of US rangelands. Also, historical remote sensing–derived categorical vegetation cover classes (a pixel defined as a single cover class) did not capture the inherent heterogeneity of the land surface or provide the metrics and indicators (e.g., plant functional type composition, fractional bare ground) necessary for rangeland assessments and decisions. Over the past decade those barriers have been systematically removed with freely available preprocessed Landsat satellite data at 30-m resolution (Wulder et al. 2016), cloud-based computing and image archive platforms (Gorelick et al. 2017) to process and analyze that data, standardized field data inventories (Herrick et al. 2017; MacKinnon et al. 2011), aggregated and standardized geospatial rangeland information (Pilliod et al. 2017a), and machine learning and artificial intelligence methods to capitalize on ecological big data (Crisci et al. 2012; Lary et al. 2016). These data and technologies enabled innovative breakthroughs of spatially comprehensive (Xian et al. 2015; Zhang et al. 2019; Rigge et al. 2020) and both spatially and temporally comprehensive (Jones et al. 2018) mapping of fractional vegetation cover (percent cover of multiple plant functional types and bare ground within a single pixel) across US rangelands, with web applications (e.g., Rangeland Analysis Platform, <https://rangelands.app>) to view, analyze, and access the data. Critical monitoring data that bridge the spatial and temporal gaps between site-scale inventories and decision-scale assessments are now available nationally to guide policy, management, and conservation decisions.

We leverage these new rangeland monitoring capabilities to examine rangeland vegetation over the past 20 yr. We use an annual continuous (percent) land cover dataset (Jones et al. 2018) from 1999 to 2018 at 30-m resolution from the Great Plains to the Pacific Coast, removing the need to make spatial or temporal assumptions. The first objective is to provide a spatially comprehensive and temporally robust 20-yr view of rangeland vegetation over the western United States using pixel-wise long-term trends of four plant functional groups and bare ground. This study is not intended to be an exhaustive analysis of US rangeland vegetation but rather a demonstration of how this new monitoring capability can be applied across spatial and temporal scales. The second objective is to discuss how these new monitoring data can identify conservation and management priorities from national to local scales, help to efficiently allocate resources and quantify outcomes, and inform future inventory and data collection efforts.

Methods

Data

A western US land cover data set (Jones et al. 2018, Rangeland Analysis Platform, <https://rangelands.app>) provides continuous (percent cover) estimates of five cover classes (annual forbs and grasses, perennial forbs and grasses, shrubs, trees, and bare ground) at 30-m resolution annually from 1984 to 2018 (Fig. 2). The tree cover data (not included in the original data and publication [Jones et al. 2018]) were produced using the same methods

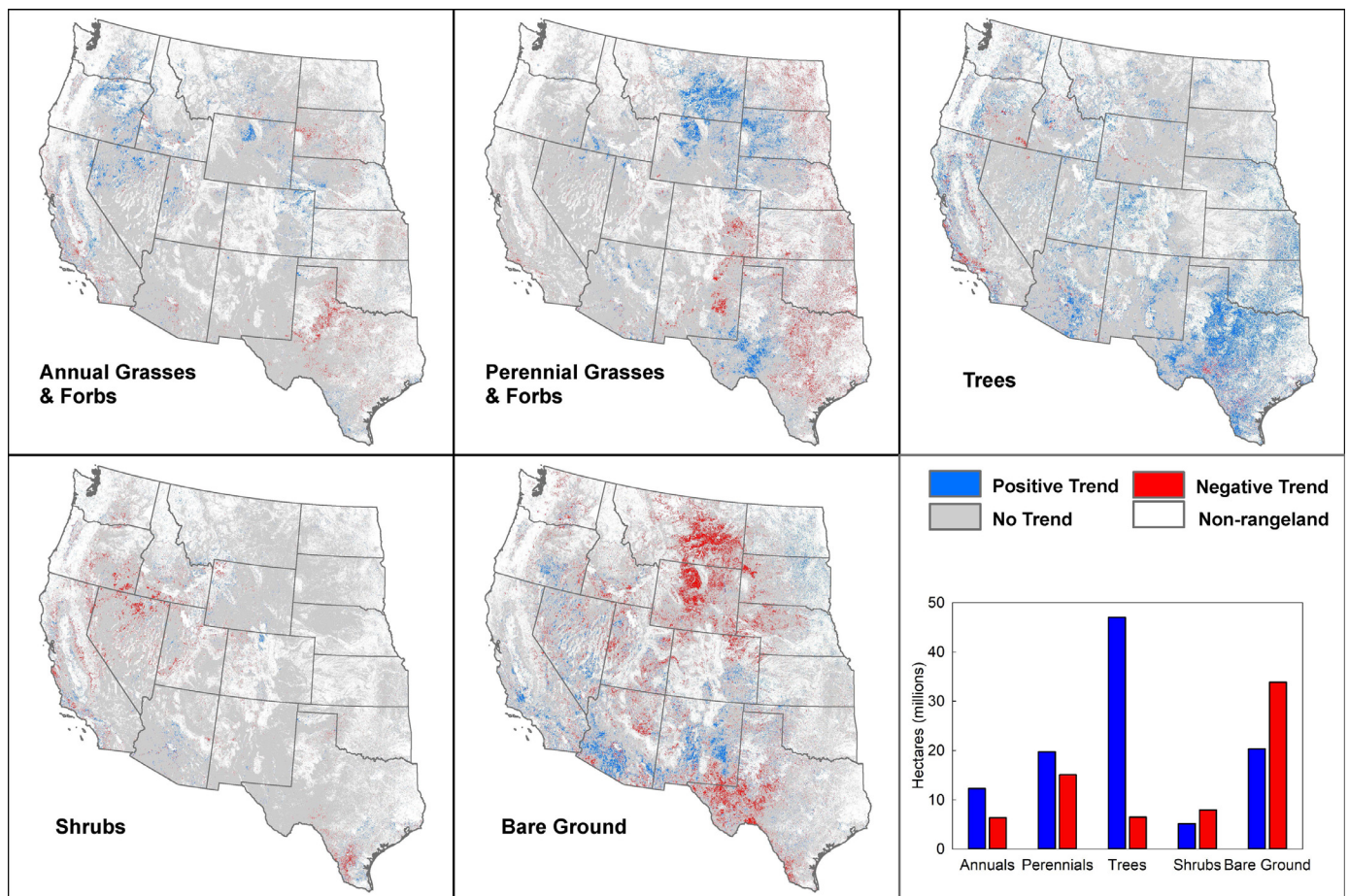


Fig. 3. Pixel-wise (30-m) trends in percent cover values for four plant functional groups and bare ground across western US rangelands (maps) using annual data from 1999 to 2018 and total hectares within each category (bar chart). Legend colors correspond to both maps and chart (hectares for no trend category not included).

as the other cover classes with errors reported on the data distribution web page (<https://rangelands.app/data>). The land cover data set was derived using > 27 000 Bureau of Land Management Assessment, Inventory, and Monitoring and Natural Resources Conservation Service National Resources Inventory field plots to train a random forests machine learning algorithm that incorporated > 200 geospatial data sets (Jones et al. 2018). The study region includes rangelands of the western United States from the Pacific Coast to the eastern border of Great Plains states (Fig. 2), with rangelands (inclusive of lands categorized as afforested, pasture, and barren) delineated by a coterminous US rangelands 30 m, circa 2011, product (Reeves and Mitchell 2011). Twenty yr (1999–2018) of annual continuous land cover values of each class are used to calculate trends. This recent 20-yr period provides greater satellite data coverage (both spatially and temporally) as compared with earlier years resulting in fewer data limitations that can adversely affect the land cover values (see Rangeland Analysis Platform User Guide, <https://rangelands.app>).

Trend estimation and classification

Kendall's Tau-b rank correlation (Kendall 1938) is used to test for significant trends ($P < 0.10$) and the Theil-Sen (Thiel 1950; Sen 1968) estimator (Sen's slope) to determine the slope of trends using the 20 annual percent cover values for each 30-m pixel and land cover class. These methods are nonparametric, less sensitive to outliers, and provide a robust estimate of trends and slopes when analyzing time series data. Each pixel is then classified as no

trend ($P > 0.10$) or significant positive or negative trend ($P < 0.10$). Significant trends with slopes that indicate increases or decreases in percent cover over the 20-yr period less than the mean absolute errors of the land cover data (Jones et al. 2018, Rangeland Analysis Platform, <https://rangelands.app>) are grouped into the no-trend classification.

Results

Maps provide a complete 20-yr view of the spatial extent of significant trends in plant functional groups and bare ground at 30-m resolution across all western US rangelands, and summary metrics provide hectares exhibiting trends (Fig. 3). Trends of annual grasses and forbs indicate increases in cover, particularly in the Great Basin region of Oregon, Idaho, and Nevada, where the spread of an invasive annual grass, *Bromus tectorum* (cheatgrass), is well documented (Bradley et al. 2017; Boyte et al. 2018). The same region displays the largest extent of trends that indicate decreases in shrub cover, likely a response to larger and more frequent fires fueled by the spread of annual grasses (Balch et al. 2013; Bradley et al. 2017; Pilliod et al. 2017b). Trends for perennial grasses and forbs indicate increasing cover in the northern Great Plains of Montana, Wyoming, and South Dakota, as well as a portion of southwest Texas while trends across the full eastern extent of the study area indicate decreasing cover. Trends in bare ground indicate regional patterns of increasing bare ground in the southwest (Arizona and New Mexico) and decreasing bare ground in southwest Texas and the northern Great Plains. Trees display by far

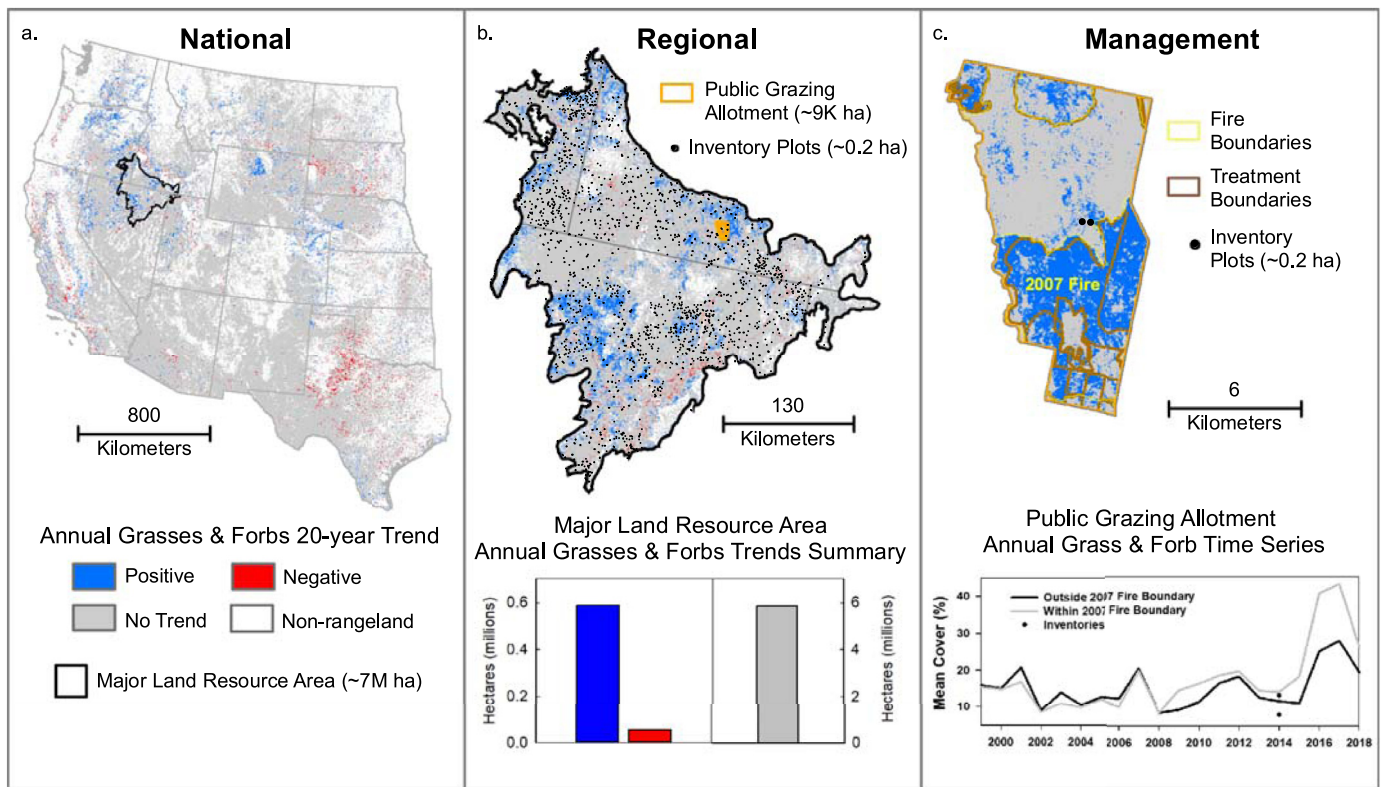


Fig. 4. Comprehensive monitoring data can inform policy and decisions from national to regional to management scales (legend in [a] also applies to [b] and [c]). Twenty-yr trends in annual grasses and forbs at the national scale (a) allow the extent of resource concerns to be visualized, its area quantified (see Fig. 2 bar chart), and highly affected regions (e.g., Major Land Resource Area) prioritized for management. Regional scale assessment (b) can quantify the extent of area affected (bar chart) and prioritize management units (e.g., public grazing allotments) for conservation. Within a management unit (c), resources can be efficiently allocated and targeted to address the resource concern. For example, within the public grazing allotment the time series (graph) of average percent cover for annual grasses and forbs (Jones et al. 2018; <https://rangelands.app>) provides temporally relevant data to accompany the two inventory plots measured in 2014 (graph points). Further implementation of complementary geospatial layers (Fire Boundaries/Eidenshink et al. 2007; Treatment Boundaries/Pilliod et al. 2013) allows within-management unit spatial and temporal variability (plot lines) to be evaluated in terms of historical treatments and fires.

the greatest extent of positive trends in cover, indicative of large-scale woody encroachment into rangelands, an issue of significant concern (Van Auken 2000; Davies et al. 2011) due to noticeable losses in ecosystem services (Twidwell et al. 2013).

Discussion

The newfound ability to monitor all western US rangeland vegetation annually at 30-m resolution while capturing continuous change in functional group vegetation cover, allows for the identification of national scale priorities that can guide policy, and inform regional to local management. National vegetation cover trends can be easily identified, their acreage quantified, and the most vulnerable regions and resources prioritized for management. The 20-yr national trend maps provide evidence supporting current national priorities addressing two major concerns on rangelands: 1) the threat of invasive annual grasses coupled with decreases in native shrub cover and 2) the massive expansion of trees into grass and shrub systems, both of which have well-established negative effects on rangeland resources and ecosystem services (Knapp 1996; Van Auken 2000). With monitoring data that span complete geographies, these national priorities can be translated into regional initiatives and efforts where common data sets can inform shared practices. Such initiatives using these comprehensive geospatial data are already under way as agencies and partners are developing strategies to counter invasive annual grass expansion in the Great Basin (Brown 2019; NRCs 2020) and eastern red cedar encroachment in the Great Plains.

These new monitoring data also inform regional management efforts to more efficiently allocate resources and target practices. With spatial variability captured, the extent of area requiring treatment within a region can be quantified and specific locations prioritized for treatment. Examination of temporal variability can identify areas undergoing transitions and the degree of that transition, informing the extent of management needed and whether goals can be met with the resources available. Further capitalizing on 30-m resolution data, resources can be efficiently applied within individual management units (e.g., differential herbicide or seeding application resulting in cost savings and production increases) instead of blanket area-wide applications. Furthermore, with monitoring data that are historical and produced annually, outcome assessment of management and conservation efforts past and present is possible, with utility for identifying successful practices and informing future decisions.

Scalability of information provided by this national to local management-unit monitoring potential is exemplified herein for annual grasses and forbs (Fig. 4). At the national scale (see Fig. 4a), the geographic extent of the resource concern can be visualized, its area quantified (see Fig. 2, bar chart), and highly affected regions (e.g., Major Land Resource Area) prioritized for management. Then at the regional scale the extent of area affected and the scale of management required can be quantified (see Fig. 4b). The most imperiled areas, as well as intact core areas with stable or decreasing annual grass cover in the region, can be identified. Then with input from regional and local stakeholders, management units can be selected to apply practices that maintain intact areas or increase

regional resilience and resistance. And finally, using the same data that informed the initial national and regional-scale priorities, spatial and temporal variability of the resource concern within the management unit (see Fig. 4c) can be assessed and areas can be targeted to achieve the greatest return on investment. With the inclusion of other geospatial data sets (e.g., fire and treatment boundaries), the land's history (see Fig. 4c) can be incorporated into the assessment and decision.

Although these data represent a powerful new tool, they do not replace the need for rangeland professionals' boots on the ground and continued plot-level inventories, which remain integral to the decision-making framework. Indeed, the comprehensive spatiotemporal monitoring data rely on plot-level inventories for their creation. However, plot data and local knowledge no longer need to be extrapolated with assumptions; rather, they can be used to inform and verify the remote sensing-derived monitoring data and assessments and decisions that follow. In turn, the monitoring data can then inform future inventory efforts including plot placement and sampling intensity to focus resources on areas of concern or areas undergoing or susceptible to transitions. Extensive local knowledge of the area under examination is still critical as a myriad of interacting landscape factors (treatments, fire, climate, livestock utilization, etc.) must be incorporated in any assessment along with ecological indicators beyond vegetation cover and bare ground (e.g., edaphic attributes). Just as a farmer with the advantage of precision agriculture technology still walks the field and digs into the soil, it is essential that local knowledge of the land's history (see Fig. 4c) and utilization are incorporated. Some of these factors can be accounted for using readily available geospatial data sets, such as the US Geological Survey Land Treatment Digital Library (Pilliod & Welty 2013), Monitoring Trends in Burn Severity (Eidenshink et al. 2007), and surface meteorological data (GRIDMET/Abatzoglou 2013; DayMET/Thornton et al. 2017), further informing the assessment process and supporting data-driven decisions.

Implications

This new era of monitoring and assessment has the potential to take rangeland ecosystem management beyond the reactive realm of diagnosis and treatment of undesirable conditions to the proactive realm of screening and prevention. Similar to practices in the medical community, where new technologies provide detection of malignant conditions before the manifestation of symptoms or adverse effects, so too can rangeland managers screen for the presence of undesirable vegetation conditions or transitions before the manifestation of state changes (Uden et al. 2019). We can also now test theoretical concepts in rangeland ecology and management that have been difficult to verify at broad scales. These include the existence of large-scale persistent transitions driven by disturbance (Turner 2010), the utility of early warning and regime shift metrics for identifying transitions (Roberts et al. 2018), and the incorporation of resilience and resistance concepts for managing landscapes (Chambers et al. 2019). Further analysis can test the effectiveness of common management practices and policies, such as rotational grazing (Briske et al. 2008), brush and woody removal (Archer et al. 2011), and herbicide treatments (Pilliod et al. 2017a, b), not only tracking effectiveness and outcomes at individual management scales but also determining comprehensively (in both space and time) whether such practices and policies are worth their resource investments.

The concerted effort within the rangeland profession to align inventory collection protocols across agencies coupled with the rise in technological advancements and computing resources has ushered in a new era of rangeland monitoring. Comprehensive western US rangeland vegetation monitoring data are now available (Xian

et al. 2015; Jones et al. 2018; Zhang et al. 2019, Rigge et al. 2020) to bridge the inventory to assessment gap that until now was dependent on statistical extrapolations. The scale mismatch among the biotic, abiotic, and ecological data available to decision makers and the scale at which those processes manifest is being resolved, providing the capacity for data-driven rangeland conservation and management. Overcoming this mismatch has the potential to increase rangeland resources and ecosystem services with cascading benefits to the socioecological resilience of these vital systems (Cumming et al. 2006). This new approach will aid in identifying national priorities for conservation and management, result in more efficient resource allocation to achieve desired outcomes, provide a means to track and quantify those outcomes, inform future inventory and data collection efforts, and spur the development of new tools and data sets to advance management of these complex systems.

Declaration of Competing Interest

None.

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