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An Introduction and Practical Guide to Use of the Soil-Vegetation Inventory Method (SVIM) Data

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ABSTRACT

Long-term vegetation dynamics across public rangelands in the western United States are not well understood because of the lack of large-scale, readily available historic datasets. The Bureau of Land Management's Soil-Vegetation Inventory Method (SVIM) program was implemented between 1977 and 1983 across 14 western states, but the data have not been easily accessible. We introduce the SVIM vegetation cover dataset in a georeferenced, digital format; summarize how the data were collected; and discuss potential limitations and biases. We demonstrate how SVIM data can be compared with contemporary monitoring datasets to quantify changes in vegetation associated with wildfire and the abundance of exotic invasive species. Specifically, we compare SVIM vegetation cover data with cover data collected by BLM's Assessment, Inventory, and Monitoring (AIM) program (2011–2016) in a focal area in the northern Great Basin. We address issues associated with analyzing and interpreting data from these distinct programs, including differences in survey methods and potential biases introduced by spatial and temporal variation in sampling. We compared SVIM and AIM survey methods at 44 plots and found that percent cover estimates had high correspondence for all measured functional groups. Comparisons between historic SVIM data and recent AIM data documented significant declines in the occupancy and cover of native shrubs and native perennial forbs, and a significant increase in exotic annual forbs. Wildfire was a driver of change for some functional groups, with greater change occurring in AIM plots that burned between the two time periods compared with those that did not. Our results are consistent with previous studies showing that many native shrub-dominated plant communities in the Great Basin have been replaced by exotic annuals. Our study demonstrates that SVIM data will be an important resource for researchers interested in quantifying vegetation change through time across public rangelands in the western United States.

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Introduction

Rangelands are integral to the socioeconomic fabric of the western United States (Havstad et al., 2009; Laitos & Carr, 1999), and yet their condition and ability to sustain crucial ecosystem services are not well documented. A lack of information on long-term vegetation and soil dynamics across US rangelands is somewhat surprising given the history of monitoring by natural resource agencies (West, 2003). However, some historic datasets are being organized and analyzed. For example, a recent analysis of 10,000 plots in the US Department of Agriculture's (USDA) National Resources Inventory survey program (US Department of Agriculture, 2009) revealed that soil degradation and loss of biotic integrity are widespread on nonfederal rangelands in the western United States (Herrick et al., 2010). Similar analyses have been initiated on rangelands managed by the Department of the Interior's Bureau of Land Management (BLM; [Karl et al., 2016]), but to date, the USDA's Forest Inventory and Analysis program comprises a majority of the data available to the public and they are restricted primarily to forest and grassland ecosystems (O'Brien et al., 2003). The BLM has a long history of inventorying and monitoring soil and vegetation in the *ca.* 1,000,000 km^2 of public lands it manages, particularly in grazing allotments (US Department of the Interior, Bureau of Land Management, 2017). However, historical datasets have been stored and managed at the BLM field office, district office, or state office level, making these data difficult to compile and analyze across spatial and temporal scales of interest.

The BLM's largest inventory effort was the Soil-Vegetation Inventory Method (SVIM) program, which was implemented in 1977 across 14

states in the western US (US Department of the Interior, Bureau of Land Management, 1992) and collected varying amounts of vegetation data from more than 22,000 locations. SVIM's goal was to provide baseline data on vegetation communities and range conditions (Artz, 1984), one use of which was to estimate the carrying capacity of the surveyed area for domestic livestock and wildlife use. The SVIM program was suspended in 1983 because of funding constraints and policy changes (Menke & Miller, 1984), but some BLM field offices continued to periodically collect field data on some SVIM site write-up areas (the sampling unit for SVIM, hereafter site) to help inform local grazing management decisions. Starting in 2011, the BLM initiated a national monitoring program, the Assessment, Inventory, and Monitoring (hereafter AIM) Strategy. AIM arose in response to the need for defensible assessments of rangeland status, condition, and trend. With over 15,000 plots surveyed across 14 western states since 2011, AIM has provided the BLM and its partners with information needed to understand terrestrial resource location and abundance, condition, and trend, and to provide a basis for effective adaptive management (Herrick et al., 2016; Taylor et al., 2014; Toevs et al., 2011).

Although SVIM and AIM surveys were not conducted on the same plots, a landscape-level comparison of these datasets could provide insight into long-term changes on BLM-administered public rangelands in the western United States. SVIM and AIM programs both collected species-level data from thousands of survey localities across many of the same lands (e.g., grazing allotments and pastures). Survey localities were selected randomly across strata determined by available ecological sites defined by soil and vegetation characteristics. This inferential sampling design used by both programs provides a unique opportunity to estimate changes in plant distributions and abundances. However, there are a variety of challenges when comparing SVIM and AIM data. Researchers must account for different survey methodologies, sampling localities, and seasonal timing of surveys. Merging datasets from nonpermanent plots is not straightforward and might increase the uncertainty in interpreting emerging patterns, especially when studying vegetation changes over time (Alfonsi et al., 2017; Chytrý et al., 2014; Haveman & Janssen, 2008; Kapfer et al., 2017). Fortunately, several methods are available to reduce sources of error in merged datasets and we use those methods to illustrate their application for use of SVIM data with other datasets.

The objectives of this paper are to evaluate vegetation composition on BLM-administered public rangelands over a 35- to 40-y period using the SVIM dataset and to demonstrate its utility for understanding trends in vegetation through time. We introduce a subset of the SVIM dataset consisting of sites with vegetation cover data in a georeferenced, digital format, review how the data were collected, and summarize the SVIM data available for each state. Next, we combine SVIM and AIM data to demonstrate how SVIM can be used for comparisons with contemporary vegetation composition and environmental conditions, including changes associated with wildfire and the abundance of exotic invasive species. We evaluate issues associated with analyzing and interpreting data from disparate sources (i.e., SVIM and AIM), including differences in survey methods and potential biases introduced by spatial and temporal variation in sampling. We present and discuss solutions to these issues to facilitate use of the data by researchers and resource managers interested in quantifying vegetation change through time in the western United States. Understanding trends in the vegetation composition of rangeland ecosystems may assist their future management.

Material and Methods

SVIM and AIM Data

BLM conducted SVIM surveys between 1977 and 1983 within grazing allotments on BLM-administered public rangelands in 14 western states: Washington, Oregon, California, Idaho, Montana, North Dakota, South Dakota, Nebraska, Wyoming, Colorado, New Mexico, Arizona,

Utah, and Nevada. Technically, the program was named the "Site Inventory Method" in 1977 when BLM initiated the pilot studies for what became the SVIM program, but for simplicity we refer to both programs as SVIM. The sampling design of SVIM emphasized stratified randomization of sampling locations to reduce bias. For example, the SVIM site (i.e., the sampling unit), was randomly selected from a stratum of sites having the same soil and plant communities existing at the time of the survey (US Department of the Interior, Bureau of Land Management, 1992). Sites were mapped on aerial photographs and sometimes confirmed or delineated from the air (i.e., rotor-wing aircraft). Sites were constrained by administrative boundaries (e.g., allotments and pastures) and delineated on the basis of previously collected data on soils, topography, and vegetation species composition (Evans & Love, 1957; Habich, 2001; US Department of the Interior, Bureau of Land Management, 1992). Each site was at least 0.024 km^2 in size and consisted of one or more patches of relatively homogenous soil-vegetation units. Some SVIM sites were much larger.

Members of the vegetation inventory team quantified vegetation and soil surface cover within a SVIM site from one randomly placed transect located along the longest axis of the site (Appendix 1; available online at https://doi.org/10.5066/P9C3FSOC). For large sites, additional transects were sometimes added to adequately characterize existing vegetation (US Department of the Interior, Bureau of Land Management, 1992). At each transect, a starting point was chosen either randomly or conveniently (i.e. to keep the transect within the same soil-vegetation unit). Transect(s) were typically sampled at 200 equally spaced points. Overstory and ground cover data were collected using the step point method, also known as the "boot notch intercept" (BNI) method (Evans & Love, 1957). In larger sites, additional steps may have occurred between recording data to cover a larger proportion of the site. The observer used a mark placed on the notch in the toe of the boot as the sampling point. Monitoring hits were recorded by identifying whatever fell at the boot notch along the transect. Basal hits below the boot notch documented ground cover (live vegetation, litter, gravel, cobble or stone, bare ground, or bedrock) and overstory foliar hits were documented by extending the point vertically from the boot notch. Up to three foliar hits were allowed if three different species were encountered. Observers also recorded vegetation characteristics (e.g., phenology, form, and height classes) and aboveground production (plant production per species, total plant production, and seral stage per range site), as well as data on soil characteristics, fuel loads, livestock grazing levels, levels of soil erosion, and wildlife use (US Department of the Interior, Bureau of Land Management, 1992).

We gathered hardcopy and electronic SVIM files from participating BLM offices. We then either wrote custom Python scripts to extract and enter electronic SVIM files or manually entered hardcopy data into a database. Site location information for electronic SVIM files was obtained from Public Land Survey System (PLSS) data. For hardcopy data, transect location information was obtained from aerial images, 7.5 m USGS quad maps, Mylar film overlays, and site area data were used to document the location of each site. Sites were georeferenced in ArcGIS with varying degrees of precision depending on data availability and quality. Coordinate data for the sites and associated transects were not available due to an absence of GPS technology at the time. Some of the original aerial images still exist, however, and these were used to create polygons of the sampling area (Fig. S1; available online at https://doi.org/10.1016/j.rama.2018.06.003). Additional details on SVIM data extraction and processing are available online at https://doi.org/10.5066/P9C3FSOC (Barker et al., 2018).

AIM data were collected by the Terrestrial AIM Project between 2011 and 2016 and by the Landscape Monitoring Framework (hereafter LMF) Project between 2011 and 2015. Similar to SVIM, stratified-random sampling was used to choose locations for Terrestrial AIM and LMF plots (Herrick et al., 2016; Toevs et al., 2011). Terrestrial AIM plots were comprised of relatively similar plant communities, but LMF plots could be located on more than one ecological site. Plot-level species inventories were conducted using the line-point intercept method,

which records all species hit by a vertical rod placed at predetermined systematic intervals along a line (Bonham, 1989). The LMF sample design is based on quarter-quarter sections of the land with three plots within each quarter-quarter section where two 45.7 m transects form an "X" shaped plot that are sampled every 0.91 m (Natural Resources Conservation Service, 2011). Species data collected from the centroid point where the transects intersect are removed. The sampling design for Terrestrial AIM consists of either a 30-m radius circular plot composed of three 25-m transects, or a 55-m radius circular plot composed of three 50-m transects arranged in a spoke design (Herrick et al., 2016). The start of each transect is offset from the center by 5 m to minimize the effects of trampling and oversampling the center of the plot. Points are sampled every 0.5 meters in the 30-m plot, and every 1 meter in the 55-m plot. Similar to SVIM, both Terrestrial AIM and LMF documented basal and foliar hits. For simplicity, we hereafter refer to both Terrestrial AIM and LMF as AIM.

Measuring Correspondence Between Boot-Notch Intercept and Line-Point Intercept Cover Estimates

Differences in survey methodologies can potentially bias estimates of plant cover and species richness (Chytrý, 2001; Pilliod & Arkle, 2013; Winkworth et al., 1962). We compared data collected using the boot-notch intercept (BNI) and line-point intercept (LPI) sampling methods at the same plots to determine whether BNI and LPI yielded similar results. Between May and October of 2017, we surveyed 44 plots placed in sagebrush ecological sites (Fig. 1b). We first sampled

28 plots that were randomly distributed across the Great Basin using the AIM design (three 50-m transects). We sampled vegetation using both sampling methods on the same day or within 3 d of each other. To add to this initial dataset, we also surveyed 16 plots with the BNI method where LPI data had been collected 14 to18 wk previously as part of another study. These additional 16 plots, located 56 km south of Boise, Idaho (Fig. 1b), were part of long-term monitoring of vegetation with inference for the Orchard Combat Training Center (OCTC) on the Morley Nelson Snake River Birds of Prey National Conservation Area and were sampled using a single transect line of 200 points. BNI surveys in all 44 plots occurred within the same plot-area as the LPI survey but not along the same transect line(s).

For our survey methods comparison, we calculated percent cover values that reflect foliar, basal, and ground cover hits for plants and biotic or abiotic objects on the soil surface (hereafter "cover"). We calculated percent cover for each plant species and then assigned the plant species into one of eight functional groups on the basis of morphology and life history: native shrub, native annual forb, native perennial forb, native perennial grass, exotic shrub, exotic annual forb, exotic annual grass, and exotic perennial grass. We calculated percent cover measured at ground level for bare ground, gravel (2–75 mm minimum diameter), and rock (≥75 mm minimum diameter). This is consistent with Herrick et al. (2016) who defined fine gravel as 2–5 mm and gravel as 5–75 mm and slightly different than the SVIM protocol that classified gravel as <76.2 mm (US Department of the Interior, Bureau of Land Management, 1992). Bare ground included lichen and moss because few SVIM surveys recorded lichen and moss. Percent cover was
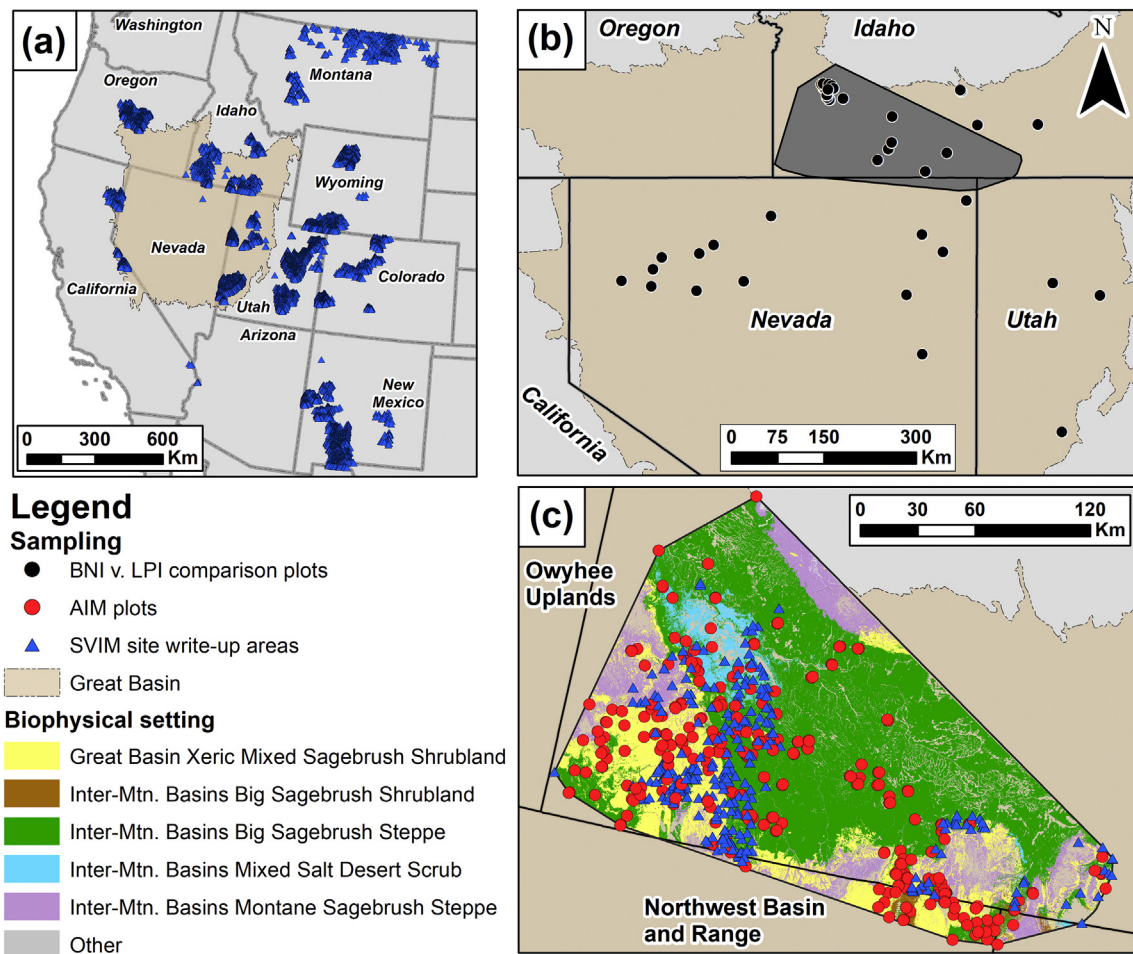
Figure 1. Maps showing the approximate (a) locations of SVIM sites for which both locality and vegetation data are available, (b) the locations of 44 plots in the Great Basin that were surveyed with line-point intercept (LPI) and boot-notch intercept (BNI) methods (focal area is in dark gray), and (c) the locations of subsampled SVIM sites and AIM plots in our focal area in relation to ecoregions and biophysical settings. AIM, Assessment, Inventory, and Monitoring; SVIM, Soil-Vegetation Inventory Method.

quantified as the number of LPI or BNI sampling points where a given functional group was contacted out of the total number of points at a plot. If two or more hits of different species within the same functional group were encountered at a single point, then only one hit counted for that point within the functional group. Therefore, no individual functional group could exceed 100% cover. We excluded native annual forbs and exotic shrubs because these groups were detected by both LPI and BNI at fewer than 10 plots, which makes accurate comparisons difficult.

We conducted Deming regression and correlation analyses to quantify the correspondence of percent cover estimates between BNI and LPI methods for each functional group. Deming regression is often used to test for systematic differences between two measurement methods because it accounts for random measurement error in both the response and predictor variables (Linnet, 1993; Linnet, 1999). BNI and LPI survey methods would likely both be subject to random error (e.g., not observing species actually present, plant species misidentification error, and estimation error; Morrison, 2016). We generated scatterplots with a Deming regression fit line and calculated Deming regression equations and Pearson's correlation coefficients using R version 3.3.3 (R Development Core Team, 2017). When within-plot cover estimates based on LPI and BNI were strongly associated, the slope term (β) and Pearson's correlation coefficient (r) both approached one.

We converted SVIM's BNI cover estimates into LPI cover estimates using the Deming regression equations to reduce measurement bias when comparing data collected using the two methods (c.f., Fiala et al., 2006; Moeser et al., 2014). To prevent adding cover estimates for undetected functional groups at a plot (i.e., those with 0% cover), we only applied the correction equation when the functional group was detected. Any resulting negative cover estimates were changed to zero.

A Demonstration of Change in Occupancy and Cover of Plant Functional Groups in the Northern Great Basin

We estimated the vegetation change that has occurred in the 35 to 40 y since SVIM surveys occurred in a focal area in the northern Great Basin (Fig. 1b and 1c). We chose this focal area because it is a region where many SVIM sites ($N = 771$) and AIM plots ($N = 367$) occurred in close geographic proximity (≤20 km) to each other. Low elevations there support Wyoming big sagebrush (*Artemisia tridentata* Nutt. ssp. *wyomingensis* Beetle & A.L. Young), low sagebrush (*A. arbuscula* Nutt.), black sagebrush (*A. nova* A. Nelson), green rabbitbrush (*Chrysothamnus viscidiflorus* [Hook] Nutt.), bluebunch wheatgrass (*Pseudoroegneria spicata* [Pursh] A. Löve), western wheatgrass (*Pascopyrum smithii* [Rydb.] Á. Löve), Thurber's needlegrass (*Achnatherum thurberianum* [Piper] Barkworth), bottlebrush squirreltail (*Elymus elymoides* [Raf.] Swezey), Great Basin wildrye (*Leymus cinereus* [Scribn. & Merr.] A. Löve var. Magnar), Sandberg's bluegrass (*Poa secunda* Presl.), Indian ricegrass (*Oryzopsis hymenoides* [Roem. & Schult.] Barkworth), cheatgrass (*Bromus tectorum* L.), and medusahead (*Taeniatherum caput-medusae* [L.] Nevski) (Miller & Eddleman, 2001). At higher elevations, mountain big sagebrush (*Artemisia tridentata* Nutt ssp. *vaseyana* [Rydb] Beetle), serviceberry (*Amelanchier alnifolia* Nutt), mountain snowberry (*Symphoricarpos oreophilus* A. Gray), Idaho fescue (*Festuca idahoensis* Elmer), mountain brome (*Bromus marginatus* Nees ex Steud), bluegrass (*Poa* sp.), and bluebunch wheatgrass are common.

We found distinctive differences in the combination of elevation and survey ordinal date of SVIM sites and AIM plots (Fig. S2; Table S1; available online at https://doi.org/10.1016/j.rama.2018.06.003), a result that is potentially problematic because over-representing certain elevational zones and seasons in one survey compared with another may obscure real changes in vegetation over time (Haveman & Janssen, 2008). AIM surveys occurred primarily from May through September across various elevations, whereas SVIM surveys occurred at higher elevations as the year progressed, and more surveys occurred during August, September, and October. We mitigated this sampling bias by resampling the two

datasets to create an equal number of SVIM sites and AIM plots across eight different ordinal date and elevation bins. Bins were defined using the cut function in R version 3.3.3. A single survey data point was randomly chosen for SVIM sites and AIM plots that were surveyed on multiple dates. Finally, we retained only SVIM sites and AIM plots that occurred in one of the five dominant biophysical settings in our focal area (Fig. 1c). Biophysical setting data were extracted from the LANDFIRE database at a 30 m resolution (LANDFIRE, 2008). This resulted in 278 data points each for AIM and SVIM.

We compared spatial variations in plant communities within each dataset (SVIM vs. SVIM and AIM vs. AIM) with temporal variations (SVIM vs. AIM) because estimating vegetation change through time with data from nonpermanent plots may produce misleading evidence for temporal changes in vegetation if there is high spatial variability among plots, a phenomenon known as spatial pseudo-turnover (Cannone & Pignatti, 2014; Keeley, 2004; Ross et al., 2010). We measured temporal and spatial variability among SVIM sites and AIM plots as the difference in their functional group composition according to the abundance-based Bray-Curtis dissimilarity metric, as calculated in the R ecodist package (Goslee & Urban, 2007) in R version 3.3.3. The Bray-Curtis metric ranges from zero to one, where a zero indicates that the communities have exactly the same functional group composition, and a one indicates no sharing of functional groups (Bray & Curtis, 1957). In this and all subsequent analyses, we included the following functional groups: native shrub, native perennial forb, native perennial grass, exotic annual forb, exotic annual grass, and exotic perennial grass.

Averaging cover data across a large sample of sites may reduce erroneous inferences due to spatial pseudo-turnover (Kapfer et al., 2017; Keeley, 2004), so we quantified changes in occupancy and cover for individual functional groups based on cover data that was averaged across all 556 SVIM sites and AIM plots. Occupancy of a functional group was estimated as its frequency in occurrence across the focal area, where occurrence is indicated by a cover value greater than zero at any given SVIM site or AIM plot. This is a naïve estimate of occupancy (i.e., it assumes perfect detection), because we lacked data necessary to correct for imperfect detection. We conducted a chi-square test of independence to test the null hypothesis that the proportion of SVIM sites and AIM plots occupied by each functional group is equal. We tested whether the average percent cover of each functional group significantly differed between SVIM and AIM surveys with a Welch's t-test, which does not assume equal variances and sample sizes. These analyses were done in R version 3.3.3.

We explored the relationship between plant cover and both annual precipitation and wildfires because these factors are important drivers of vegetation change in Great Basin sagebrush ecosystems (Anderson & Inouye, 2001; Balch et al., 2013; Chambers et al., 2014b; Pilliod et al., 2017). We analyzed a wildfire dataset consisting of over 57,000 wildfires that occurred in the United States between 1878 and 2015 (Welty et al., 2017) to identify which AIM plots burned at least once between the end of SVIM surveys in 1981 and their survey date. High resolution (800 m) monthly precipitation data for 1977 to 2015 were derived from the LT71m Parameter-elevation Relationships on Independent Slopes Model (PRISM) dataset (PRISM, 2015), and data for 2016 were from the LT81m PRISM dataset (PRISM, 2016). For each survey year, we plotted average percent cover of each functional group in SVIM sites, unburned AIM plots, and burned AIM plots together with average precipitation. SVIM data for 1977 were excluded because of low sample size ($N = 2$).

Results

SVIM Data

The timing, number, and geographic coverage of SVIM surveys that collected vegetation cover data varied widely across states (Fig. 1a; Table 1). Three to 10 BLM field offices per state collected vegetation

Table 1

Summary of Soil-Vegetation Inventory Method (SVIM) vegetation data for each state, including the number of Bureau of Land Management (BLM) field offices, sites surveyed, and years when surveys occurred.

State	Field offices	Sites	Years surveyed
California	3	672	1979–1980
Colorado	6	2 149	1978–1980
Idaho	7	2 155	1977–1983
Montana	6	1 928	1978–1981
Nevada	2	47	1979
New Mexico	6	3 934	1977–1980
Oregon	4	1 315	1979–1980
Utah	7	7 160	1977–1981
Wyoming	5	3 220	1977–1980
Total	46	22 580	

cover data for a total of 22 578 SVIM sites surveyed in nine states (California, Colorado, Idaho, Montana, Nevada, New Mexico, Oregon, Utah, and Wyoming). Spatial data were available for 20 636 (91%) of the sites. Of these, 16 036 were at a geographic resolution of a section (2.6 km^2), 3 449 were at a geographic resolution of a quarter-quarter section (0.16 km^2), and 1 151 had point coordinate data estimated from aerial photos or PLSS grids that were drawn on SVIM data sheets. An average of 2 509 sites were sampled per state (range = 47 − 7 160). SVIM vegetation cover data and geospatial data are available online at https://doi.org/10.5066/P9C3FSOC (Barker et al., 2018).

A Comparison of SVIM and AIM Survey Methods

Percent cover estimates obtained with LPI and BNI had high correspondence for all measured functional groups (Table 2; Fig. S3; available online at https://doi.org/10.1016/j.rama.2018.06.003). The β value ranged from 0.73 (rock) to 1.06 (native perennial grass). We found high and significant correlations ($r \geq 0.8$) between percent cover estimates from the two methods for bare ground, gravel, rock, native perennial grass, native shrub, exotic annual forb, exotic annual grass, and exotic perennial grass.

Case Study: Change in Occupancy and Cover of Plant Functional Groups in the Northern Great Basin

The subsampled dataset consisted of 36% of SVIM sites (278/771) and 76% of AIM plots (278/367) from the full dataset (Fig. 2a; Table S2; available online at https://doi.org/10.1016/j.rama.2018.06.003). Point coordinates were estimated for all 278 SVIM sites. SVIM surveys occurred in 1977, 1979, 1980, and 1981, with most (93%) taking place in 1979 and 1980 (Table S2; available online at https://doi.org/10.1016/j.rama.2018.06.003). On average, SVIM sites were 4.5 km from the nearest AIM plot (range: 0.44–20 km). Of the AIM plots, 122 were from the Terrestrial AIM Project and 156 were from the LMF Project.

Table 2

Deming regression slopes (β) and Pearson's correlation coefficients (r; with P value, P) for the relationships between percent cover of different functional groups as measured with the use of line-point intercept (LPI) and boot-notch intercept (BNI) methods. The number of data points (N) for each functional group (i.e., number of plots where it was detected by both LPI and BNI) out of a total of 44 plots is indicated. Data from both methods were collected concurrently in 2017.

Functional group	N	β	Pearson's r	P
Bare ground	44	1.01	0.91	<0.0001
Gravel	18	1.01	0.93	<0.0001
Rock	23	0.73	0.80	<0.0001
Native perennial forb	10	0.78	0.78	<0.0001
Native perennial grass	37	1.06	0.93	<0.0001
Native shrub	32	0.93	0.90	<0.0001
Exotic annual forb	34	0.94	0.83	<0.0001
Exotic annual grass	30	0.95	0.98	<0.0001
Exotic perennial grass	15	0.90	0.96	<0.0001

AIM surveys occurred in 2011, 2013, 2014, 2015, and 2016 (Table S2; available online at https://doi.org/10.1016/j.rama.2018.06.003). Thirty six percent of the AIM plots (100/278) burned at least once between the end of SVIM surveys and their survey date.

The Bray-Curtis analysis revealed a broad range of dissimilarity estimates in functional group composition across space and between time periods. The median estimate of the Bray's D metric in the temporal comparison (SVIM vs. AIM = 0.52) was only slightly higher than the median estimate in the spatial comparison (SVIM vs. SVIM = 0.50, AIM vs. AIM = 0.50; Fig. 2b). Spatial differences in functional group composition among some SVIM sites and AIM plots were equivalent to or even higher than differences between time periods, which suggests the possibility of making erroneous inferences of temporal change due to spatial pseudo-turnover (Chytrý et al., 2014; Fischer & Stöcklin, 1997). Therefore, we only inferred temporal change from cover data that were averaged across all SVIM sites and AIM plots, because differences between plots in a heterogeneous area should even out as sample size increases (Keeley, 2004).

Our analyses of cover data that were averaged across all SVIM sites and AIM plots revealed that the occupancy (Fig. 3) and cover (Fig. 4) of some plant functional groups changed significantly from the 1970s to present conditions (2011–2016), whereas others were more stable. The occupancy of native shrubs has decreased by 10.1% and native perennial forbs has decreased by 11.9%, whereas native perennial grass remained unchanged. Cover of native shrubs and native perennial forbs also decreased (−3.4% and −2.8%, respectively), whereas native perennial grasses increased by 5.1% through time. Exotic annual forbs appear to have proliferated with occupancy increasing by 10.8% and cover increasing (+1%) as well.

The relationship between plant cover and both annual precipitation and wildfires varied across functional groups (Fig. 5). When examining whether functional group cover corresponded with fluctuations in precipitation, exotic annual forb was the only functional group to have estimates of cover that tracked average annual precipitation across all survey years. Exotic annual grass cover appeared to track average annual precipitation in most survey years. When examining the effects of wildfire, native shrub cover in AIM plots that had not burned since 1981 (when SVIM surveys ended) were within the range of those found during SVIM surveys, whereas native shrub cover in burned plots were markedly lower across all AIM survey years. Exotic annual forbs and exotic annual grass had higher cover in burned plots than in unburned plots across all AIM survey years. Native perennial grass and exotic perennial grass had higher cover in burned plots than in unburned plots across some AIM survey years.

Discussion

Merging SVIM and Contemporary Field Plot Datasets: Challenges and Approaches

Using historic vegetation datasets, such as SVIM, to assess changes in vegetation relative to contemporary field data presents several challenges, but practical solutions exist. For example, preliminary assessments of our data revealed that overrepresentation of certain elevational zones and seasons in SVIM compared with AIM influenced estimates of occupancy and cover for certain functional groups in our focal area (Fig. S4; available online at https://doi.org/10.1016/j.rama.2018.06.003). This finding was somewhat expected, because of the elevational and seasonal changes in soil temperature and moisture that can strongly influence the types and amount of vegetation in Great Basin sagebrush ecosystems (Anderson & Inouye, 2001; Bates et al., 2006; Chambers et al., 2014b; Pilliod et al., 2017). We attempted to minimize overrepresentation by subsampling the two datasets by ordinal date and elevation, an approach similar to those used in previous studies that measured vegetation change through time with data from nonpermanent plots (Kapfer et al., 2011; Kapfer et al., 2017; Schei et
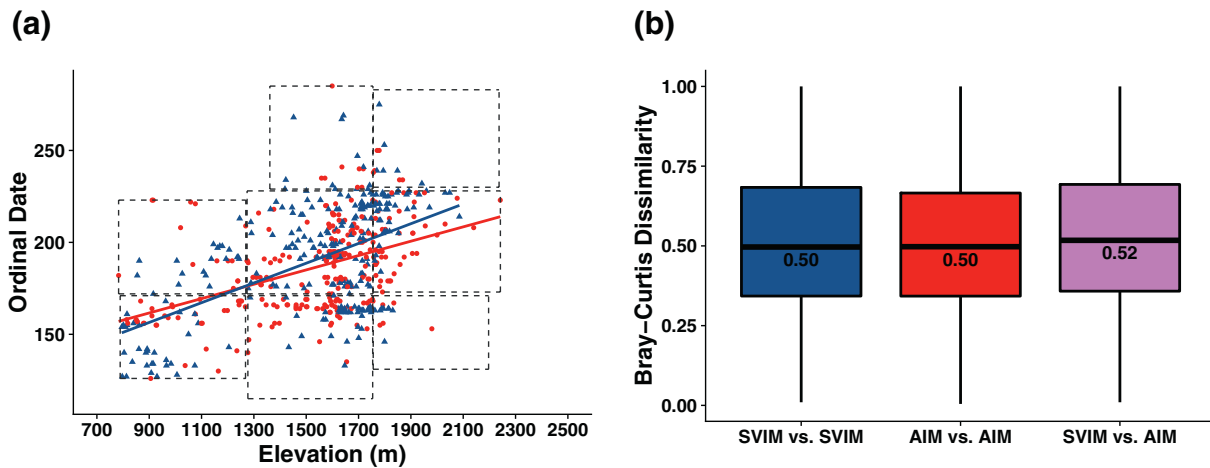
(a)

(b)

Figure 2. a, Scatterplot showing the relationship between elevation (m) and ordinal date of surveys of SVIM sites (blue triangles) and AIM plots (red triangles) after subsampling datasets across eight different date and elevation bins (gray dashed boxes). The solid lines represent the best-fitting line calculated with linear regression for SVIM (blue) and AIM (red). An ordinal date ranges from 1 to 366 and starts on 1 January. b, Box plots depict spatial variability (i.e., SVIM vs. SVIM and AIM vs. AIM) and temporal variability (i.e., SVIM vs. AIM) in plant communities in the subsampled dataset, measured as the difference in their functional group composition according to the Bray-Curtis dissimilarity metric. The solid black line and value below are the median and the "whiskers" below and above the box show the location of the minimum and maximum, respectively. AIM, Assessment, Inventory, and Monitoring; SVIM, Soil-Vegetation Inventory Method.

al., 2015; Vymazalová et al., 2012). We chose elevation because of its high correlation with soil temperature and moisture (Chambers et al., 2014b); however, plant species richness and composition in the western United States can be influenced by additional factors like topography (e.g., slope and aspect), hydrology, and soil properties (e.g., texture, nutrients, and water availability; Bansal & Sheley, 2016; Pennington et al., 2017). Future research that incorporates SVIM data may want to take these additional factors into account when defining environmental gradients from which to stratify SVIM sites and contemporary plot data. However, the coarse resolution of many SVIM sites may prevent obtaining meaningful estimates of factors that can vary widely across small spatial scales. In addition, researchers may wish to stratify datasets by the major plant community or vegetation types in their focal area to account for unequal sampling intensity in different vegetation types (e.g., Alfonsi et al., 2017; Schei et al., 2015).

Spatial pseudo-turnover can result in erroneous estimates of temporal vegetation change when analyzing data sets originating from nonpermanent plots, particularly those collected from areas with high vegetation heterogeneity (Chytrý et al., 2014; Fischer & Stöcklin, 1997;

Keeley, 2004). We found that differences in functional group composition across our focal area (SVIM vs. SVIM and AIM vs. AIM) could be equivalent to or higher than differences between time periods (SVIM vs. AIM), which suggests the presence of high vegetation heterogeneity. We therefore did not infer temporal change from analyses based on single or just a few SVIM sites and AIM plots because confidence in interpreting patterns of vegetation change is low if temporal variability is not significantly greater than spatial variability (Cannone & Pignatti, 2014; Keeley, 2004; Ross et al., 2010).

We suggest that researchers maximize the geographic proximity and sample sizes of SVIM sites and contemporary plots in their focal area to avoid making erroneous inferences of temporal change because of spatial pseudo-turnover. Focusing on areas where SVIM sites and contemporary plots occur in close geographic proximity to each other increases the likelihood that similar plant communities are being compared. Geographic and temporal sampling bias can be easier to remove when the numbers of both old and new plots are sufficiently large (Haveman & Janssen, 2008). Larger datasets also increase the reliability of estimates of temporal change, particularly for areas with high vegetation heterogeneity (Chytrý et al., 2014; Kapfer et al., 2017; Keeley, 2004). Nevertheless, spatial pseudo-turnover can affect results even
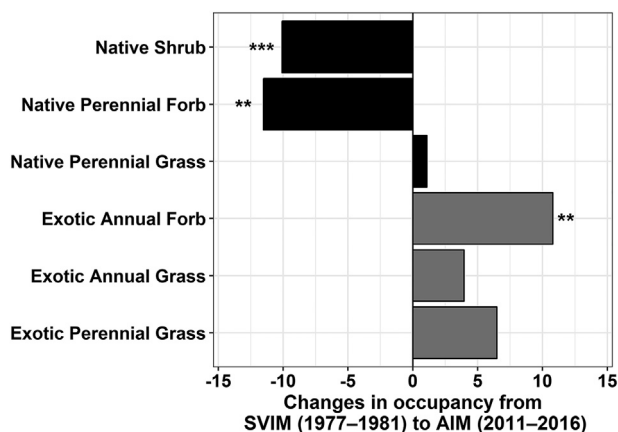

Figure 3. Changes in occupancy of plant functional groups in a focal area in the northern Great Basin from 1977 to 1981 (SVIM) to 2011 to 2016 (AIM), measured as the percent change in the frequency of occurrence from SVIM to AIM. Negative values indicate fewer detections in AIM plots compared with SVIM sites and positive values indicate more detections. Significant changes are indicated (***$P \le 0.001$; **$P \le 0.01$; *$P \le 0.05$). AIM, Assessment, Inventory, and Monitoring; SVIM, Soil-Vegetation Inventory Method.
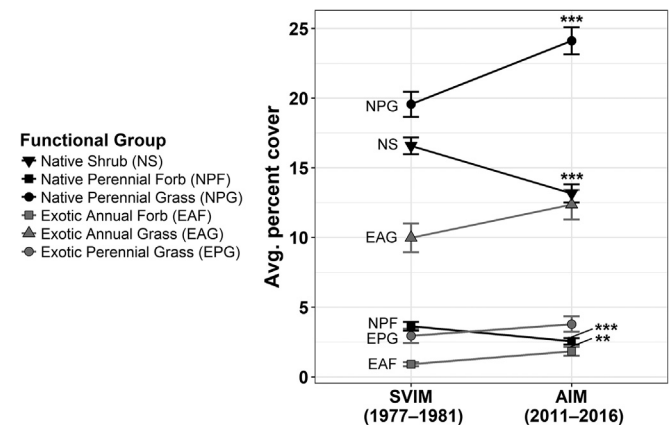

Figure 4. Changes in average percent cover (and standard error) of plant functional groups in a focal area in the northern Great Basin from 1977 to 1981 (SVIM) to 2011 to 2016 (AIM). Significant changes are indicated (***$P \le 0.001$; **$P \le 0.01$; *$P \le 0.05$). AIM, Assessment, Inventory, and Monitoring; SVIM, Soil-Vegetation Inventory Method.
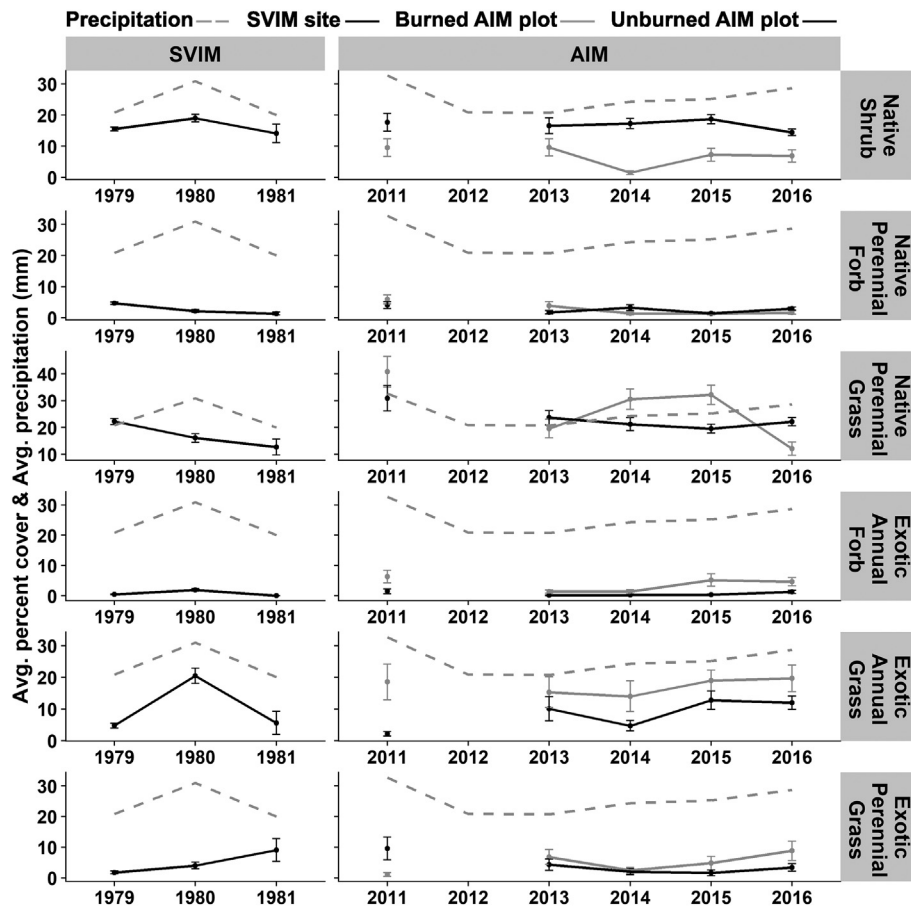
Figure 5. Average percent cover (and standard error) of plant functional groups during each year of SVIM (1977–1981) and AIM (2011–2016) surveys in a focal area in the northern Great Basin in relation to average annual precipitation. AIM plots that burned in a wildfire between the end of SVIM surveys in 1981 and their survey date are depicted separately from those that did not burn. Cover data were collected from different SVIM sites and AIM plots each year (i.e., they are not from repeated surveys of the same SVIM site/AIM plot). SVIM cover data for 1977 were excluded because of low sample size ($N = 2$), and cover data for 1978 and 2012 were absent. AIM, Assessment, Inventory, and Monitoring; SVIM, Soil-Vegetation Inventory Method.

after subsampling, and the relative magnitude of its effects on the results will remain unknown (Chytrý et al., 2014).

Ideally, the assessment of vegetation change using datasets collected from different time periods and localities should be complemented with independent data sources (Chytrý et al., 2014). In particular, integrating historic and contemporary field plot datasets with remote sensing datasets can yield important insights into the patterns and drivers of plant distributions and vegetation dynamics (Franklin et al., 2016). Remotely sensed Landsat images that have been collected across large areas of the western United States since 1984 provide an excellent supplemental data source for quantifying vegetation change through time in US rangelands (McCord et al., 2017). In particular, the percent cover of certain functional groups can be compared with the fractional amounts of various ground cover components (e.g., bare ground, herbaceous, and shrub cover) that have been characterized from Landsat images throughout much of the Great Basin (Shi et al., 2017; Xian et al., 2015).

Additional challenges when combining SVIM data with contemporary field plot datasets include SVIM's distinct survey methodology (i.e., boot-notch intercept), the varying number of transects and sampling points used in surveys, and differences in field personnel and training across BLM field offices. Comparing cover estimated from studies with different sampling designs or sampling intensity without accounting for imperfect detection of species can result in erroneous inferences of species richness, abundance, and distributions (Zhang et al., 2014), and could potentially bias estimates of functional group composition and diversity as well (Roth et al., 2018). The inability to account for imperfect detection when comparing estimates of occupancy

measured from SVIM and contemporary datasets could therefore bias results. We used Deming regression equations to reduce measurement bias when comparing data collected using BNI and LPI methods, but our sample sizes were modest ($N = 10$–44). The precision of slope and intercept estimations generated by Deming regression analysis depends in part on the number of samples (Linnet, 1999). Nonetheless, our regression-based adjustment of SVIM cover estimates is likely preferable to not accounting for systematic biases at all. Future work could potentially improve the precision of SVIM cover estimates by conducting rigorous comparative analyses of different methods.

Limitations of SVIM Data and Additional Caveats

A limitation of the SVIM data is the absence of coordinate data for most sites, which prevents extracting accurate data from georeferenced biophysical datasets and Landsat images. However, a polygon feature of the section or quarter-quarter section exists for most sites. With these data, the average or most frequently occurring value (i.e., mode) of a biophysical attribute can be calculated. Nevertheless, the coarse spatial resolution of most sites prevents making vegetation change estimations at small spatial scales. Future work that quantifies changes in occupancy using SVIM and contemporary datasets may want to use SVIM data that were collected from sites at the scale of a quarter-quarter section, because their smaller area is likely to be more similar in size to most plots. More accurate site locations may exist on paper datasheets within some BLM field offices, however, additional resources are required to identify, extract, and digitize any data that may exist.

Researchers who are interested in exploring dynamics of individual plant species should account for changes in scientific names and species codes that have occurred since SVIM surveys ended (i.e., 1983) to avoid biasing estimates of temporal change for certain taxa. For example, *Artemisia arbuscula longicaulis* (Lahontan sagebrush) was not recognized as a distinct subspecies until the mid-1990s, and it was apparently recorded as *A. tridentata* ssp. *wyomingensis* by SVIM crews at certain BLM field offices. We used a cross-walk table to update or modify species names and codes for our focal area (available online at https://doi.org/10.5066/P9C3FSOC; Barker et al., 2018), a strategy that we recommend to mitigate naming inconsistencies elsewhere. The crosswalk table can also be used to assign individual species to functional groups, as we did. In addition, caution should be taken when analyzing data for plant species that can be difficult to identify (e.g., those in the genus *Poa*), because some were recorded at the genus level more frequently in SVIM surveys than in contemporary surveys like AIM. Despite the potential issues when working with SVIM data, researchers can gain meaningful insights into vegetation change through time by carefully considering the SVIM dataset's limitations and reducing potential sources of error when merging it with contemporary datasets.

Changes in Occupancy and Cover of Plant Functional Groups in the Northern Great Basin

Comparisons of SVIM and AIM survey data suggest that the occupancy and cover of native shrubs and native perennial forbs decreased since the late 1970s in our focal area, whereas exotic annual forbs increased. AIM plots spanned a smaller area than SVIM sites and had fewer sampling points per plot, which could be problematic when comparing differences in occupancy, particularly for species with clumped distributions. Nonetheless, the changes that we documented in both occupancy and cover are consistent with previous studies showing that many native shrub-dominated plant communities in the Great Basin have been replaced by exotic annuals in recent decades (Beever et al., 2004; Brooks & Pyke, 2001; Peters & Bunting, 1994). Prominent native plants that declined in cover included Wyoming big sagebrush (*Artemisia tridentata* spp.), green rabbitbrush, and forbs in the genera *Cryptantha*, *Phlox*, and *Astragalus.* Conversely, exotic plants that exhibited particularly large increases included tall tumblemustard (*Sisymbrium altissimum* L.), bur buttercup (*Ceratocephala testiculata* Crantz), and tumbleweed (*Salsola tragus* L.). An increased frequency of wildfire, past management practices, and conversion of sagebrush steppe to cropland have resulted in the decline of sagebrush and corresponding increase in non-native grasses and forbs (Davies et al., 2009; Haubensak et al., 2009; Whisenant, 1990). However, determining whether the changes we detected represent long-term trends or short-term fluctuations would require supplemental data sources like Landsat images, because exotic annual forbs and native perennial forbs can exhibit large annual fluctuations in density and cover (Anderson & Inouye, 2001; Pilliod et al., 2017). Native shrub cover can also fluctuate from year to year, but in the absence of a major disturbance like wildfire, changes in shrub cover are generally less substantial than those of annual and biennial herbaceous plants (Anderson & Inouye, 2001). The decline in occupancy and cover of native shrubs therefore likely represents a multiyear trend, which is consistent with similar patterns documented throughout the northern Great Basin (Beever et al., 2004; Davies et al., 2011; Shi et al., 2017).

We did not detect significant changes in the occupancy and cover of exotic annual grass and exotic perennial grass over a 35- to 40-y period between 1979 and 2016. Interestingly, analyses of a full dataset that included all available SVIM and AIM data (i.e., data that had not been subsampled) revealed significant increases in cover of exotic annual grass (Fig. S4; available online at https://doi.org/10.1016/j.rama.2018.06.003). This contrasting finding may be due to a failure to reject the null hypothesis because of the smaller size of the subsampled dataset (Haveman & Janssen, 2008; Kapfer et al., 2017). Conversely, a lack of

significant increase in the occupancy and cover of exotic annual grass and exotic perennial grass in the subsampled dataset may suggest that these functional groups were already well established by the late 1970s. Indeed, exotic annual grasses and exotic perennial grasses were detected in 59% and 19% of SVIM sites in the subsampled dataset, respectively. One of the most widespread exotic grass species in our focal area, cheatgrass, was established in southern Idaho at least three decades before SVIM surveys occurred (Stewart & Hull, 1949), and was detected in 57% of sites there.

Native perennial grass cover increased since the late 1970s. In addition, the cover of this functional group was higher in burned AIM plots than in unburned AIM plots and in the older SVIM sites across some AIM survey years. Interpreting this result in the absence of supplemental data is difficult, because native grass cover can vary widely across sites depending on vegetation type, history of disturbance, seeding efforts, and precipitation trends. For example, Anderson and Inouye (Anderson & Inouye, 2001) reported an increase in native perennial grass over a 50-y period in southeastern Idaho, but their plots had not been grazed or burned since at least 1950, which is in contrast to many AIM plots in our focal area. Native perennial grass cover did not significantly differ between burned and unburned sites in salt desert shrublands in northwestern Nevada (Haubensak et al., 2009), whereas an experimental treatment in southeastern Oregon found that it was greatest in areas that had been both grazed and burned (Davies et al., 2009). An investigation of the mechanisms influencing the distribution and abundance of native perennial grasses in the Great Basin is warranted, especially because of its importance as forage for livestock and wildlife, and influence on soil stability, resistance to invasive species invasion, and resilience from disturbance.

We detected clear differences between the cover of some plant functional groups in AIM plots that had burned since SVIM surveys ended compared with those that did not burn, which points to wildfire as an important driver of vegetation change in our focal area. Across all surveyed years, native shrub cover was substantially lower in AIM plots that had burned, whereas exotic annual forb and exotic annual grass cover were higher. This finding is consistent with the expectation that fires in cold desert shrublands of western North America are associated with high native shrub mortality and postfire plant invasions (Chambers et al., 2014a). Substantial increases in the distribution and abundance of non-native plants in western North America during the 20th century, particularly cheatgrass, have resulted in an increase in the number, size, and frequency of wildfires in this region (Balch et al., 2013; Brooks et al., 2004). A shorter fire return interval prevents or greatly retards the reestablishment of native shrubs, and facilitates the dominance of non-native grasses and forbs (D'Antonio & Vitousek, 1992). The cover of native shrubs, exotic annual forbs, and exotic annual grass in unburned AIM plots was similar to their cover in SVIM sites, which suggests relatively little temporal change in the absence of fire. Similarly, remote sensing studies in the northern Great Basin have shown substantially greater declines of native shrubs in areas that had burned since the 1980s compared with those that did not burn (Shi et al., 2017; Vogelmann et al., 2012).

The cover of most plant functional groups did not consistently fluctuate with annual precipitation. Exotic annual forb was the only functional group with cover estimates that fluctuated with annual precipitation across all survey years, a finding consistent with a study that showed a strong association between annual variation in exotic forb cover and seasonal precipitation over a 26-y period in southwestern Idaho (Pilliod et al., 2017). Inconsistent associations between plant cover and annual precipitation for the other functional groups may be in part explained by analyzing cover data from different SVIM sites and AIM plots each year. Ideally, cover should be estimated from the same plot each year because it removes the confounding effects of factors like biophysical settings and disturbances. Nevertheless, estimates of average annual precipitation were similar during SVIM and AIM surveys, which suggests that this factor cannot fully explain differences in plant functional group cover between the two time periods.

Implications

When combined with contemporary field plot datasets such as AIM or remote-sensing information, the publicly available SVIM dataset will provide a useful resource for quantifying patterns and drivers of vegetation change on public rangelands in the western United States. This information may help improve studies that aim to forecast changes in plant community composition and species distributions under future climate and land use conditions. A greater understanding of vegetation dynamics is critical because future climate change is expected to favor the spread of exotic invasive plant species, increase the frequency and extent of wildfires, increase the length of the fire season, lower ecosystem productivity, and reduce the quality and amount of forage (Bansal & Sheley, 2016; Boyte et al., 2016; McCollum et al., 2017; Polley et al., 2013). Ultimately, knowledge gained from studies that incorporate SVIM data may help resource managers document and understand the ecological changes happening across longer time scales, such as decades.

Acknowledgments

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.rama.2018.06.003.

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