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Authors: Jansen, V.S., Kolden, C.A., Schmalz, H.J., Karl, J.W., and Taylor, R.V.

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Using Satellite-Based Vegetation Data for Short-Term Grazing Monitoring to Inform Adaptive Management☆

V.S. Jansen[1,*], C.A. Kolden[1,2], H.J. Schmalz[3], J.W. Karl[1], R.V. Taylor[3]

[1] Department of Forest, Rangeland, and Fire Science, University of Idaho, Moscow, ID 83844, USA
[2] Management of Complex Systems Department, University of California, Merced, CA 95343, USA
[3] The Nature Conservancy of Oregon, Enterprise, OR 97828, USA

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A B S T R A C T

Quantifying rangeland vegetation amounts with remotely sensed satellite data is a proliferating field of study. Yet the resulting datasets are rarely related to use-based monitoring indicators (i.e., utilization or residual biomass), which are critical for adaptive management and to inform the subsequent year's grazing plans. To better assess our ability to use remotely sensed data products for grazing monitoring and adaptive management, we tested the relationships between a variety of vegetation biomass metrics derived from remotely sensed data on a bunchgrass-dominated grassland in northeast Oregon and two common indicators: stocking rate at the pasture scale (40–250 ha; a management indicator) and field-based utilization estimates at the plot scale (25–50 m; a grazing indicator). At the pasture scale, we correlated stocking rate to biomass metrics and found two metrics that had consistent relationships to stocking rate: fall mean biomass (r values range: −0.52 to −0.56; P values < 0.001) and the 10th percentile of the relative difference between summer and fall biomass (r values range: −0.47 to −0.52; P values < 0.01). Scatterplots from these correlations were then evaluated alongside managers' knowledge to interpret why some pastures deviated from the overall pattern. At the plot scale, we correlated in-field utilization estimates to biomass metrics and found consistent relationships with fall mean biomass (r values range: −0.32 to −0.47; P values < 0.001) and the relative difference between summer and fall biomass (r value: from −0.20 to −0.62; P values < 0.005). To further visualize the utilization correlations, we classified these two biomass maps into three categories guided by our utilization estimates. Significant changes in biomass due to management and interannual variation in biomass amounts stood out. The results and visualizations demonstrate how remotely sensed data relate to conventional grazing monitoring indicators and exemplify how remotely sensed data can be used to inform adaptive management.

Introduction

Temperate grassland ecosystems are threatened worldwide by conversion to crop agriculture (Hoekstra et al. 2005), livestock mismanagement (Alkemade et al. 2013), and climate change (Joyce et al. 2013; Polley et al. 2013; Tietjen et al. 2017; Souther et al. 2020). Livestock can impact the structure and function of grassland ecosystems (Milchunas and Lauenroth 1993), causing short-term effects such as reduced litter cover and compacted soils (Schmalz et al. 2013), as well as long-term effects, including reduced productivity and a shift from native perennial grasses to invasive annual grasses (Bartolome et al. 1980; Reisner et al. 2013). Over time, heavy stocking rates may reduce profitability and threaten the economic and ecological sustainability of a ranch (Holechek 1988). However, well-managed grazing has also been used to increase heterogeneity of vegetation pattern in grasslands (Fuhlendorf and Engle 2001; Fuhlendorf et al. 2012), which may have positive conservation outcomes for biological diversity (Adler et al. 2001). Wildlife and insects can have variable responses to grazing intensity; some are sensitive to grazing, while other species benefit from grazing-induced changes in vegetation structure (Severson and Urness 1994; Derner et al. 2009; Johnson et al. 2011; Kimoto et al. 2012). In native grassland systems, livestock grazing is often preferred over other land uses, such as exurban development or cul-

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* Correspondence: V.S. Jansen, Dept of Forest, Rangeland, and Fire Science, University of Idaho, Moscow, ID 83844, USA.

E-mail address: vjansen@uidaho.edu (V.S. Jansen).

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tivation, which generally result in higher degrees of alteration and impacts to natural communities (Brunson and Huntsinger 2008). Therefore, the continued presence of sustainable livestock production enterprises can prevent or slow the threat of habitat loss by fragmentation and conversion to other land uses (Brunson and Huntsinger 2008).

To avoid or mitigate the undesired effects of livestock grazing and to balance economic profitability with biologic diversity and long-term productivity, many rangeland practitioners employ adaptive management strategies (Wilmer et al. 2018; Davis et al. 2020). Effective adaptive management relies on monitoring relevant indicators (Joyce et al. 2013), translating monitoring results into information that can be used by decision makers at relevant scales, and integrating stakeholder experiences into the scientific process (Juntti et al. 2009; Bestelmeyer and Briske 2012; Wilmer et al. 2018). However, climatic variability and spatial heterogeneity make it difficult and expensive to adequately measure the ecological outcomes of grazing management decisions (e.g., setting stocking rates, animal species, or rotations) across large areas and across many years. As a result, there is a significant lack of useful quantitative monitoring data collected at the landscape scale that can be easily accessed by land managers or ranchers for adaptive decision making (Bestelmeyer and Briske 2012).

Research into remotely sensed approaches that provide estimates of commonly monitored rangeland attributes such as aboveground biomass (e.g., Anderson et al. 1993; Todd et al. 1998; Jansen et al. 2018; Jones et al. 2020); vegetation fractional cover (e.g., Marsett et al. 2006; Hagen et al. 2012; Jones et al. 2018; Allred et al. 2020); or bare ground (e.g., Guerschman et al. 2009; Jones et al. 2018; Allred et al. 2020) has increased in recent years. It is also becoming more common to attempt to isolate the impact of grazing on vegetation with remotely sensed data. For example, researchers have used single-year analysis to compare estimated vegetation amounts between pixels with different grazing levels (Todd et al. 1998; Numata et al. 2007; Jansen et al. 2016), time-series analysis to track vegetation indices over time in conjunction with land/grazing management (Archer 2004; Evans and Geerken 2004; Washington-Allen et al. 2006; Wessels et al. 2012; Tsalyuk et al. 2015) and spatial statistics to evaluate changes in spatial heterogeneity with grazing (Sankey et al. 2009; Virk and Mitchell 2015; Scarth and Trevithick 2017; Jansen et al. 2019). Recently Gillan et al. (2019) explored the use of remote sensing from an unmanned aerial vehicle (UAV) to quantify the differences in vegetation before and after grazing within a single year.

While these studies highlight the ability of remotely sensed data to quantify vegetation amounts and elucidate potential drivers of vegetation change, getting these data into the hands of rangeland managers in a consistent manner for practical applications (e.g., Butterfield and Malmstrom 2006) has been a long-sought goal (Marsett et al. 2006). In the past few years there has been a proliferation of tools based on remote sensing intended to assist in rangeland monitoring, management, and planning (e.g., https://vegmachine.net/ [Beutel et al. 2019], https://rangelands.app/ [Allred et al. 2020; Jones et al. 2020], RangeSat [https://www.rangesat.org/], GrassCast [https://grasscast.unl.edu/] [Peck et al. 2019; Hartman et al. 2020], RDMapper [Ford et al. 2017]). Although these data products are freely accessible to land managers, the potential value of intergrating these data products into grazing monitoring and adaptive management frameworks is largely still developing.

To incorporate remotely sensed monitoring indicators into adaptive management of livestock grazing, it is important to identify the types of indictors that are used in a decision-making context. Herrick et al. (2012) categorized rangeland monitoring indicators into three groups: 1) driving mechanisms (e.g., stocking rates, animal type, rotations); 2) short-term responses (e.g., residual biomass or utilization); and 3) long-term responses (e.g., species composition, soil stability). Short-term response indicators characterize direct effects of management actions on ecosystem attributes and are used to adaptively manage in a timely manner and help interpret trends detected in long-term indicators (Herrick et al. 2012). Long-term response indicators capture trends in ecosystem process and function and provide additional feedback about the influence of drivers (Herrick et al. 2012). This framework is helpful for defining monitoring objectives and clarifying the relationships between the short-term monitoring indictors and the meaningful processes or phenomena in question (Herrick et al. 2012). As with in-field monitoring data, remotely sensed monitoring data should be tested and applied within existing adaptive management objectives and decision-making cycles.

In this paper we evaluated the utility of a remotely sensed biomass product that was created to monitor vegetation responses to cattle grazing on a grassland in northeast Oregon (Jansen et al. 2018). Our two main objectives were to determine 1) which remotely sensed biomass metrics at the pasture scale (40–250 ha) have the strongest correlations to prescribed stocking rates, a driving mechanism indictor; and 2) which remotely sensed biomass datasets are most correlated to in-field estimates of end-of-year utilization, a short-term response indicator used to monitor grazing at the plot scale (25 to 50 m^2). Guided by the results from these objectives, we then created two data visualizations to demonstrate practical use of the results for adaptive management. These visualizations consist of 1) scatterplots of biomass metrics versus stocking rates at the pasture scale and 2) maps of biomass change (i.e., the relative difference) and fall biomass data at the pixel scale, classified into three quantitative categories.

Methods

Study Area

This study took place on the Zumwalt Prairie in northeast Oregon, which is a highly valued remnant of Pacific Northwest Bunchgrass Prairie (Fig. 1). The Zumwalt Prairie is a moderately productive (1 200–1 900 kg · ha^{-1}) grassland system that is privately owned and used primarily for cattle production. The Nature Conservancy, a private landowner within the study area, has been managing livestock grazing in accordance with its conservation goals since 2006 using adaptive management principles. Across the conservation area, residual vegetation and utilization have been estimated annually to provide feedback to managers regarding livestock impacts. These measures, along with calculated grazing response indices (GRI) (Reed et al. 1999) and managers' casual observations, provide the "best available" information to interpret grazing effects and to adjust timing and stocking rates for the following year's grazing rotation. Field and management data come from pastures with a range of different grazing strategies and stocking rates due to inherent variation in productivity.

Grazing Management and Monitoring Data

Pasture Stocking Rate Data

Across the 3-yr study period (2015–2017), stocking rates (animal unit months [AUM] · ha^{-1}) were calculated by pasture for each year based on records provided by managers including dates, number, and type of grazing animal and accessible acres per pasture. Adjustments were made in animal use equivalents (AUEs) for different types of animals (e.g., bulls had 1.2 AUE, yearlings 0.75 AUE, and cow-calf pairs 1.0 AUE). Each stocking rate for each pasture in each year was categorized by season of use on the basis of the grazing timing: cool summer (May 1–June 30), hot summer (July 1–September 15), and fall (September 16–November 30).

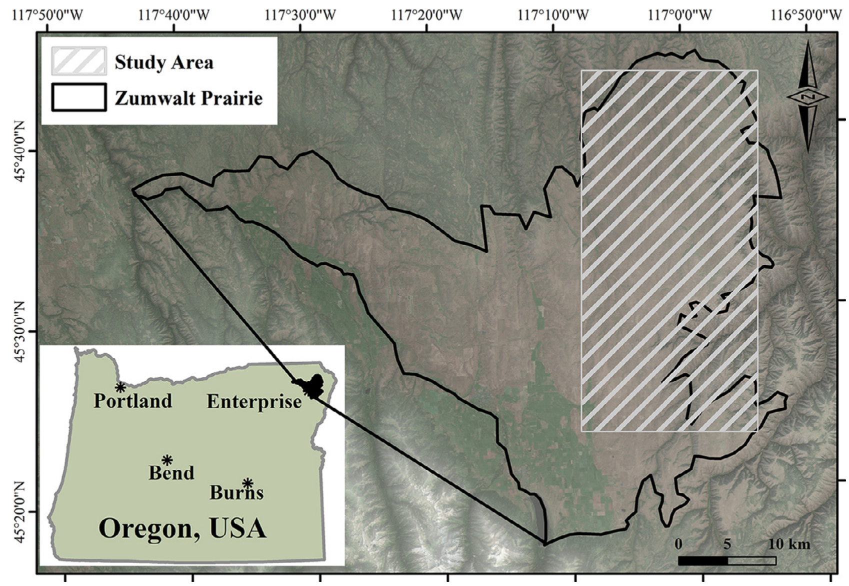

Fig. 1. Zumwalt Prairie is a Pacific Northwest bunchgrass prairie ecosystem located in northeastern Orgon. The shaded area within the map represents the general location of pastures analyzed.

Table 1
Number of plots sampled for grazing utilization using the Landscape Appearance method across the Zumwalt Prairie from two survey campaigns (2015–2017).

Yr	Survey campaign	Utilization plots (N)
2015	Upland vegetation structure	170
	Riparian stubble height	84
2016	Upland vegetation structure	125
	Riparian stubble height	92
2017	Upland vegetation structure	0
	Riparian stubble height	136

When grazing dates overlapped two seasons, the season with the majority of grazing days was used. Stocking rates across the study pastures ranged from 0 to 1.54 AUM $\cdot$ ha^{-1}.

Utilization Data

Plot-scale utilization data were collected across the 2015–2017 field seasons using the Landscape Appearance method (Coulloudon et al. 1999). In this rapid qualitative method, observers looked for evidence of grazing on key forage plants and classified the plot into one of six categories corresponding to percent utilization. In this study we used Landscape Appearance utilization data from two different monitoring surveys: one from riparian stubble height surveys (collected from 2015 to 2017) and the other from upland vegetation structure monitoring (collected only in 2015 and 2016) (Table 1). For the riparian surveys, plot locations were selected in a Geographic Information System (ESRI's ArcMap) by intersecting a 100-m grid with mapped streams. For the upland vegetation surveys, plot locations were randomly placed to represent the variety of ecological site types and management histories across the study area. Sampling plots were placed between 50 m and 1 000 m from roads and > 50 m from stock ponds and fences, and they had to be > 100 m apart. The monitoring design for both types of surveys was intended to evaluate conditions across the whole ranch, not individual pastures. Plots were revisited in the field each year with a Garmin Global Positioning System (GPS) unit but were not permanently marked. Plot selection was made without prior knowledge of typical patterns of livestock use within pastures. All utilization estimates were made at the end of the grazing season (September–November) regardless of when cattle were removed from pastures.

Landsat Remotely Sensed Data

For this study we used Landsat satellite imagery, which has a pixel resolution of 30 $\times$ 30 m. Landsat images have been collected at 16-d intervals since 1984 and are available free of charge. We downloaded the climate data record (CDR) Collection 1 Level 2 product (terrain corrected and processed to at-surface reflectance) overlapping the study area for the yr 2015–2017 from the USGS Earth Explorer website (https//earthexplorer.usgs.gov/). For each scene the pixel quality assurance band (pixel_qa) and aerosol band were used to mask clouds, cloud shadows, and smoke over the study site. We clipped the images to study area pastures, masked out nongrassland vegetation as defined by the ReGap Ecological Systems data (Kagan et al. 2006), and manually masked any tree or shrub visible with the 2014 National Agriculture Inventory Program imagery that the ReGap Ecological Systems data misclassified as grassland habitat but was actually tree or shrub cover type.

Landsat-Derived Aboveground Biomass Datasets

Our goal was to select images corresponding to peak biomass and postsenescence (end-of-season) timings because most of the grazing happens between this timeframe in this study area. To achieve this, for each of the downloaded and masked scenes, we computed aboveground biomass for each pixel across each of the raster images using the model developed for this study area by Jansen et al. (2018). This model relies on three vegetation indices computed from the climate data record (CDR) Collection 1 Level 2 surface reflectance products: the normalized burn ratio (NBR) for when the plants are green, the normalized tillage index (NTDI) for when the plants are brown, and the normalized difference vegetation index (NDVI) to guide which model (the green or brown model) is applied to each pixel in the scene throughout the grazing season. All green and brown models were developed as linear regressions between the vegetation indices and field data collected during both summer and fall periods over 3 yr from 2015 to 2017, which spanned both wet and dry years (**Fig. S1**, available online at ...). The resulting model for Landsat 8 was found to have a r^2 value of 0.76 and a root mean squared difference of 32.2 g/m^2 (See Jansen et al. 2018 for more details). Using this model, we created biomass datasets across the growing seasons for 2015, 2016, and

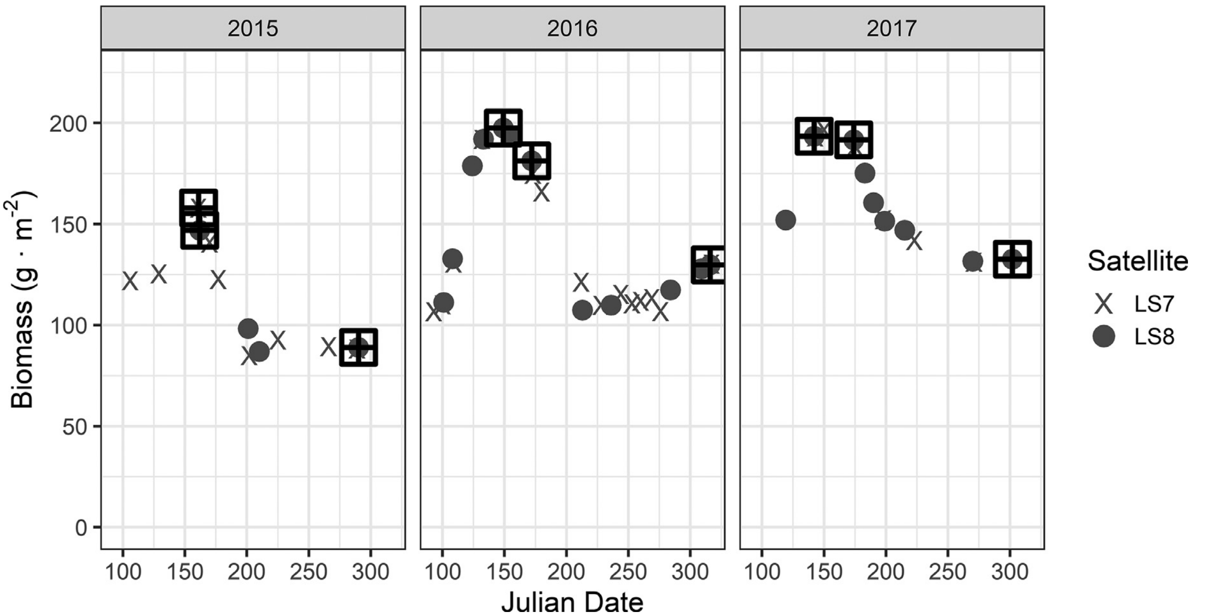

Fig. 2. Biomass estimates across the grazing season for the study area located on the Zumwalt Prairie, Oregon to guide scene selection. Scenes selected for this analysis are boxed in with black squares. Landsat 8 data (closed circles) were given preference to increase the available data used for pasture-level statistics.

Table 2
Scenes selected for the analysis and associated biomass raster datasets used for the pasture and plot scale analysis. Each of the biomass datasets were computed for each year.

Yr	Summer scene dates (sensor)	Fall scene dates (sensor)	Pasture scale—biomass raster datasets	Plot scale—biomass raster datasets
2015	6/10 (LS7), 6/11 (LS8)	10/17 (LS8)	1) $Summer_{MaxPasture}$ 2) Fall 3) $RelDif_{MaxPasture}$	1) $Summer_{MeanPixel}$ 2) $Summer_{MaxPixel}$ 3) Fall 4) $RelDif_{MaxPixel}$ 5) $RelDif_{MaxPixel}$
2016	5/28 (LS8), 6/20 (LS8)	11/11 (LS8)		
2017	5/22 (LS8), 6/23 (LS8)	10/29 (LS8)		

2017 to visualize biomass growth curves and identify scenes that represented summer (peak) biomass, as well as end-of-year residual standing crop in the fall (Fig. 2). Due to known differences in dominant plant phenology, which impacts the timing of maximum summer biomass across the study area, we selected two different scenes for data analysis that were within the peak biomass window of late May through June and had minimal cloud coverage over the study area. From these two summer scenes we created mean and maximum biomass raster composites for each year at the pixel scale. For each year, the maximum summer pixel composites ($Summer_{MaxPixel}$) were created by selecting the maximum biomass pixel value between the two summer biomass scenes, while the mean summer pixel composite ($Summer_{MeanPixel}$) took the average pixel value between the two summer scenes. At the pasture scale we created one composite image, the summer maximum pasture composite ($Summer_{MaxPasture}$). This was done by computing the average biomass across each pasture for each summer scene and then assigning the higher biomass value to each pasture. We elected to only explore maximum pasture composites to keep the biomass patterns true to one point in time and congruent with the scale of analysis for spatial statistics and interpretation purposes. For the fall, we selected the latest and clearest scene for each year that corresponded to end-of-year standing crop (Table 2).

Once the summer composites were created at the pixel and pastures scales, they were used along with the Fall biomass raster data to compute relative difference biomass datasets using the following equation:

$$RefDif_{(x,y,z)} = \left(\text{Fall Biomass} - \text{Summer Biomass}_{composite[x,y,z]}\right) / \text{Summer Biomass}_{composite(x,y,z)}) \quad (1)$$

From this equation for each year we produced three relative difference biomass datasets: $RelDif_{MaxPixel}$, $RelDif_{MeanPixel}$, and $RelDif_{MaxPasture}$ for plot and pasture scale analysis (see Table 2). The relative difference raster produces negative values when the fall biomass amount is less than peak summer biomass amount. In this case values typically range from −100% to 0, with larger negative values indicating greater change.

Pasture and Plot Scale Biomass Metrics

We created multiple statistics that have previously been used to assess grazing at pasture scales in this system, such as mean biomass, the coefficient of variation and spatial metrics (Jansen et al. 2019), as well as percentiles that can provide more information on relationships between variables that are not based solely on measures of central tendency (means and medians) (Cade and Noon 2003). Therefore, for each pasture area that had a corresponding grazing record, we used the biomass datasets from each year to compute a variety of summary and spatial statistics. The summary statistics calculated using the biomass data by pasture included the mean, the 10th, 25th, 50th, 75th, and 90th percentiles, as well as the standard deviation and coefficient of variation. To explore measures of spatial heterogeneity, we computed

Table 3
Spearman rank correlations between stocking rate (AUM · ha−1) and biomass dataset metrics at the pasture scale. This table shows only the metrics that are significant across all years of data. For the complete table, see Table S1, available online at ...

Biomass dataset metric	2015 (n = 37)		2016 (n = 60)		2017 (n = 72)	
	r	*P* value	*R*	*P* value	*r*	*P* value
$Fall_{mean}$	−0.55	< 0.001	−0.56	< 0.001	−0.52	< 0.001
$Fall_{p10}$	−0.56	< 0.001	−0.59	< 0.001	−0.49	< 0.001
$Fall_{p25}$	−0.53	< 0.001	−0.57	< 0.001	−0.50	< 0.001
$Fall_{p50}$	−0.52	< 0.01	−0.54	< 0.001	−0.50	< 0.001
$Fall_{p75}$	−0.54	< 0.001	−0.51	< 0.001	−0.51	< 0.001
$Fall_{p90}$	−0.53	< 0.001	−0.49	< 0.001	−0.56	< 0.001
$Fall_{CV}$	0.50	< 0.01	0.51	< 0.001	0.32	< 0.01
$RelDif_{mean}$	−0.32	0.05	−0.33	< 0.01	−0.54	< 0.001
$RelDif_{p10}$	−0.50	< 0.01	−0.52	< 0.001	−0.47	< 0.001
$RelDif_{p25}$	−0.44	< 0.01	−0.47	< 0.001	−0.47	< 0.001
$RelDif_{p50}$	−0.34	0.04	−0.33	< 0.01	−0.48	< 0.001

Table 4
Spearman rank correlations between pasture level metrics and stocking rate, grouped by season of use.

Biomass dataset metric	Cool summer (*n* = 91)		Hot summer (*n* = 103)		Fall (*n* = 73)		All-season 3-yr mean
	r	*P* value	*r*	*P* value	*R*	*P* value	
$Fall_{mean}$	**−0.21**	**< 0.05**	**−0.40**	**< 0.001**	**−0.38**	**< 0.001**	−0.33
$Fall_{p10}$	−0.19	0.08	**−0.37**	**< 0.001**	**−0.36**	**< 0.01**	−0.31
$Fall_{p25}$	−0.18	0.09	**−0.39**	**< 0.001**	**−0.38**	**< 0.001**	−0.31
$Fall_{p50}$	−0.19	0.07	**−0.39**	**< 0.001**	**−0.40**	**< 0.001**	−0.33
$Fall_{p75}$	**−0.22**	**< 0.05**	**−0.41**	**< 0.001**	**−0.38**	**< 0.001**	−0.34
$Fall_{p90}$	**−0.27**	**< 0.01**	**−0.43**	**< 0.001**	**−0.33**	**< 0.001**	−0.35
$Fall_{CV}$	0.04	0.71	**0.27**	**< 0.01**	**0.33**	**< 0.001**	0.22
$Fall_{Moran's\_I}$	−0.13	0.23	**−0.46**	**< 0.001**	**−0.34**	**< 0.001**	−0.31
$RelDif_{mean}$	**−0.38**	**< 0.001**	**−0.42**	**< 0.001**	**−0.28**	**< 0.05**	−0.36
$RelDif_{p10}$	**−0.39**	**< 0.001**	**−0.52**	**< 0.001**	**−0.42**	**< 0.001**	−0.44
$RelDif_{p25}$	**−0.36**	**< 0.001**	**−0.48**	**< 0.001**	**−0.37**	**< 0.01**	−0.40
$RelDif_{p50}$	**−0.34**	**< 0.01**	**−0.39**	**< 0.001**	**−0.29**	**< 0.05**	−0.34
$RelDif_{p75}$	**−0.36**	**< 0.001**	**−0.34**	**< 0.001**	**−0.24**	**< 0.05**	−0.31
$RelDif_{p90}$	**−0.37**	**< 0.001**	**−0.34**	**< 0.001**	−0.21	0.07	−0.30

Shown are statistics that were significant in at least two out of the three seasons at the 0.05 *P* value (in bold font, *P* value < 0.05).

the sill, nugget, range, and magnitude of spatial heterogeneity from theoretical variograms. Because the pasture scale spatial heterogeneity metrics failed to produce consistent significant relationships with stocking rate, we only included these methods and results in the supplemental materials (Supplement Text A1 and Table S1, available online at…).

At the plot scale for each sample site we computed two metrics: the mean and minimum biomass values extracted across a 2×2 pixel window intersecting each in-field monitoring plot for each biomass dataset for each year (see Table 2).

Data Analysis

Pasture Scale

To identify the biomass metrics most sensitive to stocking rate at the pasture scale, we calculated Spearman rank correlation coefficients and *P* values between the pasture stocking rates (AUM · ha^{-1}) and the biomass statistics listed in Table 3. Only pastures meeting the following conditions were used for analysis: 1) the pasture contained at least 20 valid pixels, 2) valid pixels accounted for > 33% of all possible pixels within the pasture (i.e., pastures that were mostly obscured by clouds were dropped), 3) the pasture was dominated by upland grassland vegetation (i.e., exclusion of canyon grassland pastures), 4) the period of grazing in the pasture occurred between the selected summer and fall Landsat scenes, and 5) pastures could not have been used for supplemental feeding with hay. We also included ungrazed pastures that met criteria 1–3 and 5. We performed this analysis for each year individually, as well as by season of use (spring, cool summer, hot summer, fall) using all years combined. Only correlations with *P* values < 0.05 are reported here (see Table S1, available online at …, for the complete list). Following the correlation analysis, we created simple scatterplots between select biomass metrics and stocking rate to visualize these results across the management area by year.

Plot Scale

To identify the biomass metrics most sensitive to end-of-year grazing utilization, we computed Spearman rank correlations between in-field estimates of percent utilization with the mean and minimum plot-scale biomass metrics co-located with each monitoring plot. We did this for each of the biomass datasets listed in Table 2 (plot scale analysis). For plot-level analysis we used the in-field data from pastures that were grazed between the dates of the selected Landsat scenes or were ungrazed for the entire year. We also limited the in-field dataset to data collected in October and November to better match the timing of our remotely sensed fall data.

Classifying Biomass Datasets for Monitoring and Management Interpretation

To simplify the interpretation of biomass metrics relative to established conventions of acceptable utilization levels, we classified the fall biomass and relative difference maps into three categories (Low, Medium, and High), using the in-field utilization data collected each year to guide classification breakpoints. Two classification breakpoints were selected on the basis of the median pixel value associated with two landscape appearance utilization classes: the 6–20% and 41–60%. Thus, the "Low" biomass class represented 0–5% utilization class; the "Medium" biomass class represented utilization classes between 6% and 40%, and the "High" biomass class represented utilization classes > 40% (see Table 6).While the selection of breakpoints is admittedly arbitrary, the "High" class

Table 5
Spearman rank correlations between in-field utilization measures and biomass raster data at the plot scale.

Biomass dataset	2 × 2 pixel window stats	2015			2016			2017		
		R	*P* value	No.	*r*	*P* value	No.	*r*	*P* value	No.
$Summer_{meanpixel}$	Mean	**−0.17**	**< 0.01**	**250**	**−0.16**	**< 0.05**	**215**	0.03	0.7	139
$Summer_{maxpixel}$	Mean	**−0.17**	**< 0.01**	**250**	−0.09	0.20	204	−0.08	0.38	139
Fall	Mean	**−0.33**	**< 0.001**	**203**	**−0.46**	**< 0.001**	**212**	**−0.47**	**< 0.001**	**114**
$RelDif_{meanpixel}$	Mean	**−0.20**	**< 0.005**	**202**	**−0.34**	**< 0.001**	**212**	**−0.59**	**< 0.001**	**114**
$RelDif_{maxpixel}$	Mean	**−0.23**	**< 0.005**	**202**	**−0.47**	**< 0.001**	**212**	**−0.49**	**< 0.001**	**114**
$Summer_{meanpixel}$	Min	**−0.21**	**< 0.001**	**250**	**−0.20**	**< 0.01**	**215**	−0.01	0.87	**139**
$Summer_{maxpixel}$	Min	**−0.21**	**< 0.005**	**250**	−0.14	0.05	204	−0.08	0.36	139
Fall	Min	**−0.32**	**< 0.001**	**203**	**−0.44**	**< 0.001**	**212**	**−0.47**	**< 0.001**	**114**
$RelDif_{meanpixel}$	Min	**−0.26**	**< 0.001**	**202**	**−0.37**	**< 0.001**	**212**	**−0.62**	**< 0.001**	**114**
$RelDif_{maxpixel}$	Min	**−0.28**	**< 0.001**	**202**	**−0.47**	**< 0.001**	**212**	**−0.53**	**< 0.001**	**114**

Relationships with *P* values < 0.05 are shown in bold font.

Table 6
Definition of biomass class thresholds for mapping using the median biomass pixel values grouped by in-field utilization classes. Bold values were used as breakpoints for classifying biomass raster data on maps (see Fig. 4).

Grazing utilization range (%)	Graze class midpoint (%)	Relative difference (%) max pixel min	Fall biomass dry-yr (2015) (g/m^2)	Fall biomass wet-yr (2016–17) (g/m^2)	Raster class (degree of change)
0–5	2.5	−35.8	117.8	153.2	Low
6–20	**13**	**−40.4**	**108.8**	**152.6**	**Med**
21–40	30.5	−41.6	90.6	136.5	Med
41–60	**50.5**	**−44.0**	**78.2**	**131.4**	**High**
61–80	70.5	−47.2	63.6	122.5	High
81–94	87.8	−51.1	NA	129.0	High

breakpoint was selected on the basis of prior research, which established a 30% to 40% utilization guideline for bunchgrass vegetation to remain productive (Skovlin et al. 1976; Holechek 1988) and the knowledge that high stocking rates with utilization above 35% across a pasture can be detrimental to nesting of some select species of grassland songbirds (Johnson et al. 2011). Differences in annual production due to growing conditions compelled us to compute separate threshold values for the Fall biomass dataset for 2015 (a dry year with low annual production) and for 2016–2017 (wet years with high annual production; see Fig. S1). No such separation was made with the relative difference analysis because in theory the relative difference equation should normalize the year-to-year variation in production. Using the threshold values derived from the empirical relationship between biomass and in-field utilization, we mapped these categories across the study area to reveal patterns of end-of-season vegetation amounts and change in vegetation amounts between summer and fall.

Results

Remotely Sensed Biomass Metrics Most Correlated to Stocking Rate at the Pasture Scale

Spearman rank correlation coefficients between the pasture scale biomass metrics and pasture stocking rates revealed that the summary statistics were more consistently related to stocking rate than spatial statistics metrics derived from variogram models (see Table S1). Across all years the Fall biomass mean and percentile metrics were negatively associated with higher stocking rates, meaning that as the stocking rate increased, values for fall biomass were lower and values for relative difference were more strongly negative. The coefficient of variation (CV) was also correlated (*P* values < 0.05), but with a positive correlation to stocking rate (see Table 3). With the Relative Difference Max Pasture ($RelDif_{MaxPasture}$) dataset, the 10th percentile was most strongly correlated to stocking rate across all years, with the mean, median, and 25th percentile also having *P* values < 0.05. While most of these correlations have *P* values constantly < 0.01, none are above an absolute *r* value of 0.60, indicating a moderate to weak fit.

In general, the same metrics that had *P* values < 0.05 across the years also had small and similar *P* values for season of use when grouping all 3 yr of data. We did observe a decrease in the number of metrics with *P* values < 0.05 across the fall biomass metrics for cool summer (Table 4).

Pasture Scale Data Visualization: Stocking Rate Versus Biomass Metrics

We elected to plot two biomass metrics, one from the Fall dataset and one from the Relative Difference dataset selected based on their strength and consistency of the correlation across the years with stocking rate. These two metrics were Fall mean and Relative Difference 10th percentile ($RelDif_{p10}$) pasture metrics. Visualizing these data with scatterplots showed large variability surrounding the linear model trend line for each year (Fig. 3, blue lines), as well as the high range of values in ungrazed or rested pastures. In 2017 there were a few pastures that we noted as outliers that were either well above (highlighted with the black square) or well below (highlighted with red circles) the linear model trend line (see discussion for more details). Removing these pastures from the 2017 analysis improved the spearman rank correlations for both the RelDif 10th percentile (r = -0.61 from -0.47) and the Fall mean biomass (r = -0.64 from -0.52) metrics.

Remotely Sensed Biomass Metrics Most Correlated to Grazing Utilization at the Plot Scale

Correlation coefficients between in-field utilization data collected at monitoring plots and the spatially corresponding biomass data showed negative correlations. Similar to the pasture scale analysis results, the correlations were weak to moderate in strength, with all *r* values lower than an absolute value of 0.62 (Table 5). In most cases, the minimum pixel value in the 2 × 2-pixel window had stronger negative correlations compared with the average value across the 2 × 2 pixel window. The minimum pixel value from the Relative Difference dataset, as well as from the Fall scenes, were all related to in-field utilization with *P* values < 0.001. The $RelDif_{MaxPixel}$ dataset had only slightly stronger neg-

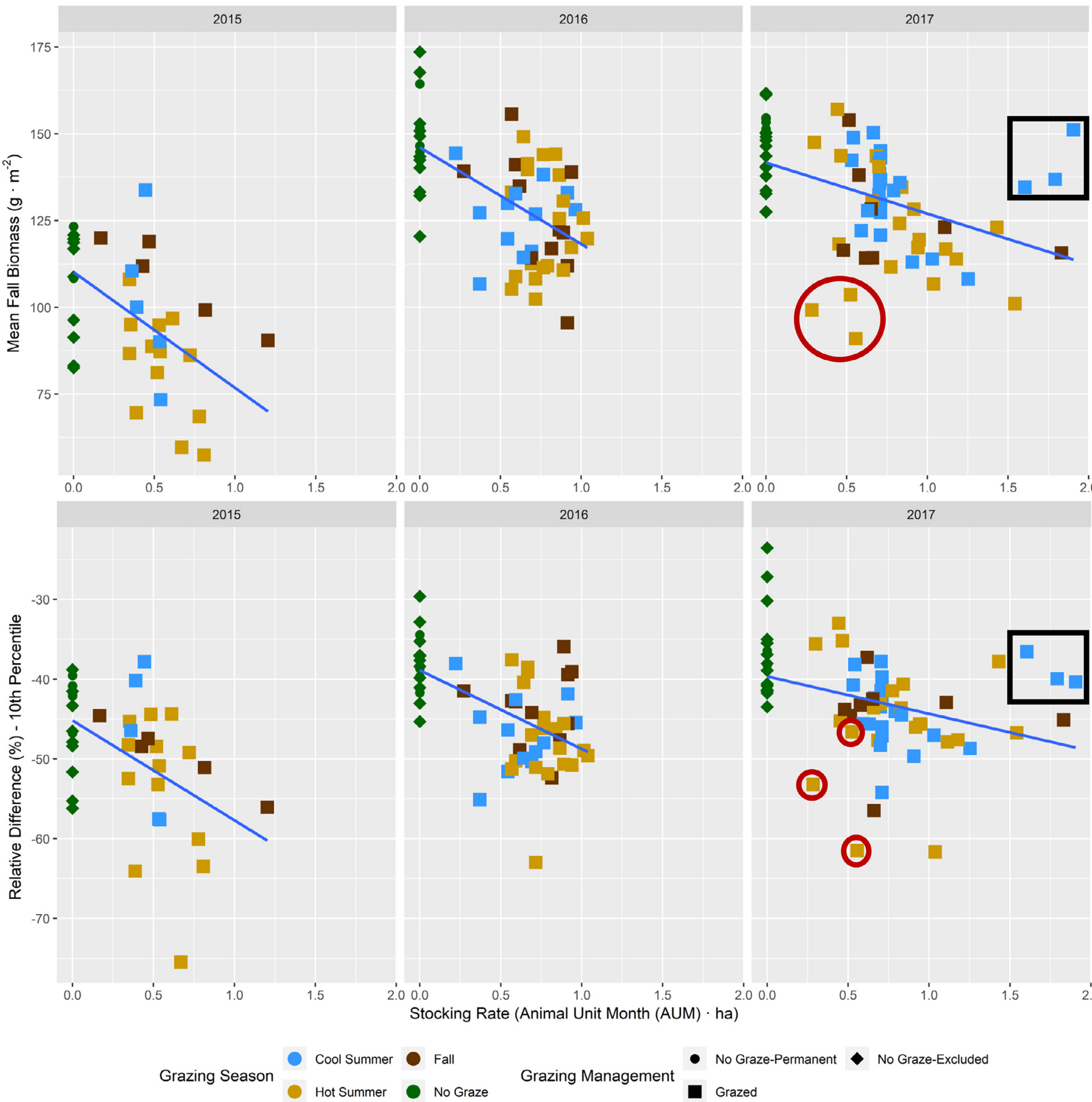

Fig. 3. Mean fall biomass and relative difference (10th percentile) across all study area pastures by grazing season and management for the yr 2015–2017. The trend line (simple linear model) in blue provides the overall relationship between the variables and helps to show the pastures that fall well above or well below the average trend. The three cool summer pastures highlighted with the black box they were grazed heavily for 5 days each from May 26th to June 9th in 2017, with adequate time for regrowth despite high stocking rates. Pastures with lower-than-expected mean fall biomass are denoted with red circles and were thought to have received grazing from trespass cattle, which would have increased the stocking rate.

ative relationships in most yr (2016 and 2017) compared with fall biomass data.

Pixel Scale Data Visualization: Classifying Biomass Datasets Based on Empirically Derived Utilization Thresholds

The boxplots (see Fig. 4) of the Fall and $\text{RelDif}_{\text{MaxPixel}}$ datasets grouped by each Landscape Appearance utilization graze class revealed overlapping distributions of data across graze classes, with the median biomass value decreasing with increased grazing utilization (Table 6). The boxplots for the $\text{RelDif}_{\text{MaxPixel}}$ (minimum of 2×2 window) data grouped by utilization class, produced a small range in median threshold values from −40.4% separating the Low and Medium classes to −44.4% separating the Medium and High classes. With the Fall biomass data, there was around a 20 g · m^{-2} difference separating the Medium from the High raster classes in

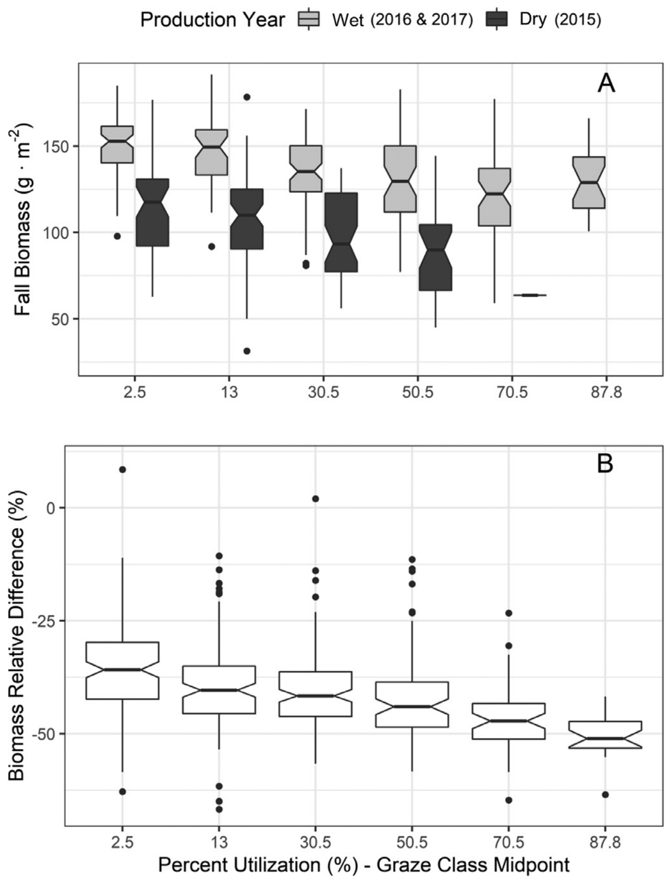

Fig. 4. Boxplots of the satellite-based raster data for a 2×2 pixel window at each of the utilization monitoring plots, grouped by graze class categories derived from utilization estimates. Panel A shows fall biomass, separated into low production (2015; $N = 203$; dark gray) and high production (2016–2017; $N = 326$; light gray). Panel B shows the biomass data (all years combined) as a computed relative difference between summer and fall biomass ($N = 528$).

the wet-years with high production compared with a 30 g · m^{-2} difference in the dry low production yr (2015). The difference in biomass values across production years (i.e., wet year–dry year for any graze class) ranged from 35.4 g · m^{-2} in the 0–5% utilization class to a high of 58.9 g · m^{-2} in the 61–80% utilization class, illustrating the importance of climate as a major influence on end-of-season residual biomass (see Table 6).

Reclassifying the biomass datasets using the above thresholds provides spatially explicit information on change in vegetation between peak summer biomass and fall residual biomass (Fig. 5). Using the different fall thresholds from wet years with high production versus dry years with low production also reveals large differences in area mapped for each class due to interannual variation of precipitation (e.g., in 2015 when comparing map B with map C). These relative difference maps also show that in 2015 (a drier yr), larger areas of the High class are mapped compared with in wetter yr (2016 and 2017).

Discussion

Biomass estimates derived from Landsat satellite data were correlated to both a driving indicator (stocking rate) at the pasture scale and a short-term response indicator (utilization) at the pixel scale, demonstrating the potential for remote sensing to inform adaptive rangeland management. The application of remote sensing to rangeland management is powerful because of its capacity to provide biomass estimates continuously across time and landscapes in ways that are not feasible to evaluate with in-field monitoring data alone. However, this source of information is relatively new to most managers, and it is necessary to build evidence based on empirical relationships to begin relating common in-field monitoring metrics to remote sensing metrics. By associating traditional management and field data used to monitor relevant vegetation indicators with remotely sensed data, an important frame of reference that increases the usefulness and application of satellite data for monitoring and management (e.g., Butterfield and Malmstrom 2006; Bradley and O'Sullivan 2011; Tsalyuk et al. 2015; Ford et al. 2017) is provided.

Pasture Scale

Before investigating the potential to use remote sensing as a tool for monitoring short-term responses, we first wanted to determine the strength of the relationship between remotely sensed data and one of the fundamental management drivers in rangelands: stocking rate. Across all the metrics explored in our study, the metrics most sensitive to pasture level stocking rate across multiple years were derived from the fall biomass and the relative difference between summer and fall biomass. Specifically, we recommend using the 10th percentile relative difference metric and the mean Fall biomass metric for monitoring applications in this system. While we explored the use of summer biomass and spatial heterogeneity metrics provided by variograms and the Moran's I, these metrics were not consistently sensitive to stocking rate across all years. The finding that spatial heterogeneity metrics are not sensitive to grazing in this grassland system aligns with a study by Jansen et al. (2019), which showed that the 30×30 m spatial resolution is too large to detect finer-scale changes in vegetation patch size and heterogeneity that grazing induces on this already highly heterogeneous landscape.

Our biomass to stocking rate relationships were weaker than Jansen et al. (2016), who found R^2 of up to 0.80 when experimentally controlling the timing and duration of livestock use in pastures that were selected on the basis of similar habitat and productivity, as well as Numata et al. (2007), who found R^2 of 0.70 and focused on one grass species and had many pasture areas with higher stocking rates. We were not surprised to find weaker relationships in our study, which was observational and therefore did not control for historical land use and management effects, timing and duration of grazing, stocking rate, or habitat types. Timing of grazing is particularly important, as revealed by the weaker relationships between Fall biomass and stocking rate for pastures grazed early in the year (cool summer) compared with pastures grazed later in the year (hot summer, fall). Also, stocking rate as a driver is not expected to be strongly related to total change in biomass as calculated between the summer and fall scenes in pastures that were grazed early in the season and had an opportunity for regrowth before the summer drought period began (typically late July). Furthermore, stocking rate does not account for reductions in biomass incurred from other herbivores (e.g., trespass cattle, elk, ground squirrels, and insects) or from senescence, all of which likely affected our correlation results. For example, elk populations in northeast Oregon have been increasing since the 1990s, with recent estimates between 1 000 and 2 500 animals on the Zumwalt Prairie (ODFW, unpublished data). Their effects on vegetation are not accounted for in our study.

It is also important to note that the underlying model can influence the relationships observed. While the goal of the biomass model was to be general across years and habitat types, it is known that the biomass model tends to underestimate vegetation amount in areas with high perennial grass cover (Jansen et al. 2018), which in turn will translate reduced accuracy and underestimation of change (i.e., the relative difference metric) and residual vegetation amount (i.e., fall biomass) across pastures composed

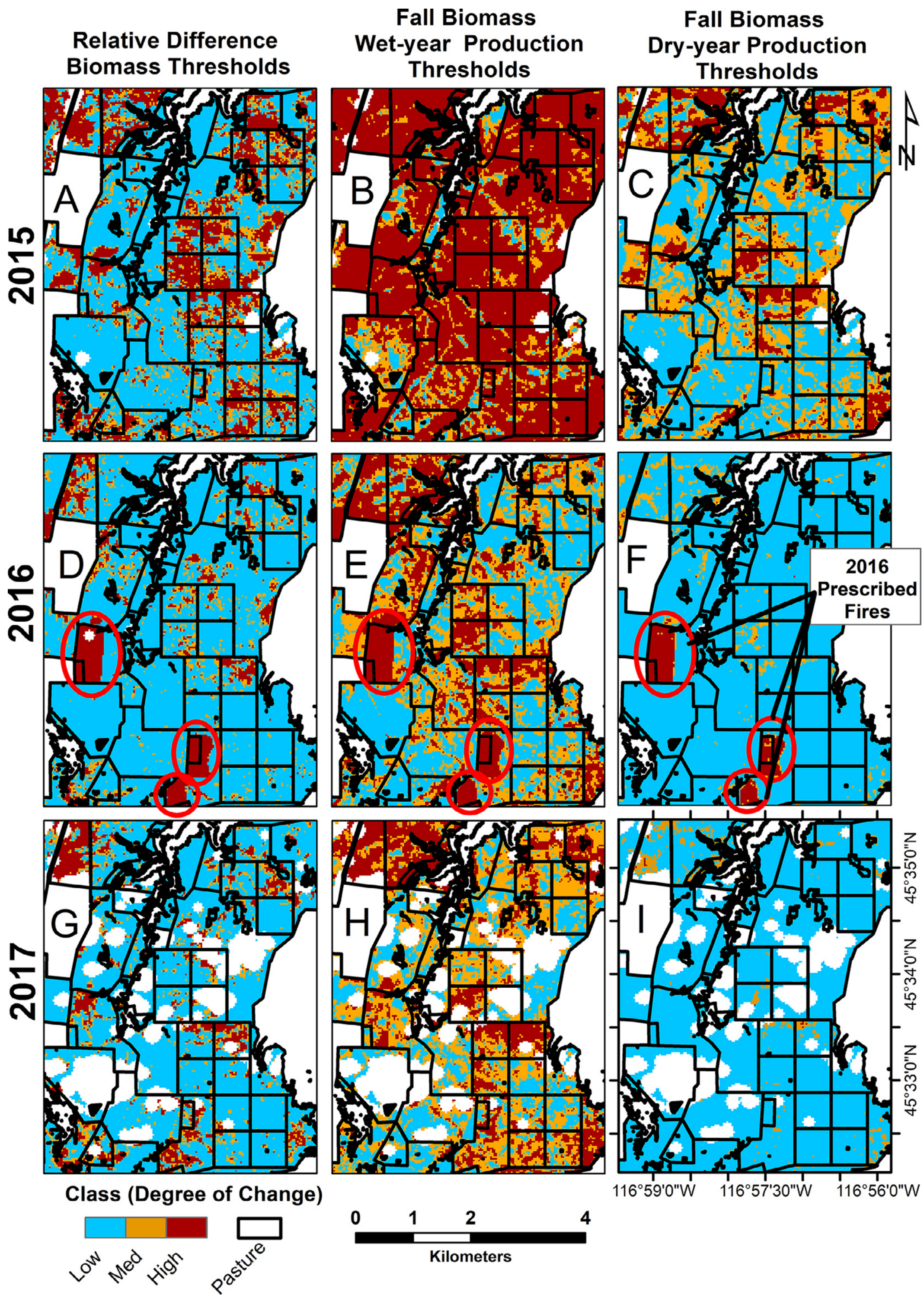

Fig. 5. Classified relative difference and fall biomass maps using both dry-year (i.e., low production) and wet-year (i.e., high production) thresholds across 2015–2017. The three classes of change are high (red), medium (orange), and low (blue) with 2016 fires circled with red ovals. The white areas are masked data due to clouds.

largely of continuous and dense vegetation cover and years where growing conditions tend to increase vegetation cover. Also, the model performs better when vegetation is green (Landsat 8 validation $r^2 = 0.81$, relative root mean square error (rRMSE) = 16.86%) as opposed to brown (Landsat 8 validation $r^2 = 0.70$, rRMSE = 26.69%) (Jansen et al. 2018). This introduces more uncertainty with the fall biomass metrics as compared with estimates in summer.

Although the pasture scale results showed moderate to weak relationships, we believe management insight can be gleaned from these data. For example, plotting fall biomass and relative difference data at the pasture scale and categorizing individual pastures by their management history and season of use (see Fig. 3) allows for examination of the overall relationships and draws attention to pastures that deviate from the prevailing pattern (i.e., far above or below the trend line). In this example, scatterplots of fall biomass by year at the pasture scale revealed several pastures in 2017 that had unexpectedly high fall biomass corresponding with high stocking rates. Further examination of the management records revealed that these pastures were each grazed for 5 d early in the season (late May to early June). Coupled with the facts that 2017 was above normal for production and these pastures have inherently high productive potential, it can be reasoned that there was significant regrowth between the grazing event and the time the fall scene was acquired. Using the satellite data in this way improves a managers' knowledge of pasture-specific responses to management, such as potential for regrowth under specific circumstances, which may lead to adjustments in timing or intensity of grazing in the subsequent year. A second example of interpreting these plots lies at the other end of the stocking rate scale. Plotting the 10th percentile of the relative difference by pasture revealed several pastures in 2017 that had abnormally large relative difference values despite having low stocking rates. When reviewing this with the land manager, we learned that these pastures had high use by trespass cattle, which was not accounted for in the manager's records. Highlighting pastures with greater-than-desired changes in biomass could allow a manager to investigate reasons for the patterns and, if necessary, reduce stocking rates, rest the pasture entirely for a year, or graze at a different time to ameliorate the conditions. The subsequent years' relative difference map and plots could then provide feedback about the management adjustments.

Plot and Pixel Scale

Relating the remotely sensed biomass data to in-field grazing utilization data collected at the plot scale produced similar correlation values as our analysis with stocking rates at the pasture scale. The moderate to weak results between plot scale data and the biomass raster data were likely due to several reasons. In-field utilization estimation is subjective and can have high observer variability (Smith et al. 2007). Also, geographic coregistration and the spatial size of the field plot to the Landsat pixel can lead to spatial mismatches between what the observer is estimating and what the satellite is estimating. Furthermore, as mentioned earlier, the underlying model affects our ability to accurately and precisely estimate a change in vegetation amount or fall biomass at any given pixel, which also influences the correlation results. For example, biomass in sample plots located in meadows and areas with dense vegetation cover are likely to be underestimated, while biomass at sample plots having extensive moss and lichen cover may be overestimated (see Jansen et al. 2018 for more). Previous studies have shown that stratifying the landscape by vegetation type (e.g., meadow vs. upland) can improve statistical relationships (Kawamura et al. 2005) and is generally helpful when making inferences from sample data (Elzinga et al. 1998). Here we combined utilization data that were collected across sites with a variety of dominant species (i.e., rhizomatous grasses and bunchgrass species). We did this to produce a generalized dataset that could be easily applied across the study area and interpreted for management decisions but acknowledge that combining all data across vegetation types may have resulted in a weaker relationship. As with stocking rate, the timing of grazing relative to the opportunity for regrowth within the growing season may have also contributed variability to the relationship between in-field utilization and biomass raster data.

Using threshold values to classify biomass maps is a straightforward way to visualize remote sensing data for quick interpretation. When we used data from the landscape appearance method to classify maps of the Fall and Relative Difference biomass datasets, it was easy to see areas with different amounts of vegetation change and locations of lower and higher residual biomass amounts and to interpret interannual variability due to climate (see Fig. 5). Variability in production that is driven by climate is well known in grassland systems (Briske et al. 2015), and an understanding of interannual variation is important for the management of these systems (Chapin et al. 1996; Joyce et al. 2013), as well as analysis of data spanning multiple years (e.g., Archer 2004; Evans and Geerken 2004; Brinkmann et al. 2011; Wessels et al. 2012). This is exemplified and easily visualized when applying threshold values derived from a dry year with lower biomass to a wetter year with higher biomass and vice versa. For example, when we applied the dry-year (i.e., Low) production thresholds (derived from 2015 data) to the 2016 Fall biomass data, the places that appear in the High change category are the patches that had received prescribed burns that year (see Fig. 5). Conversely, when applying the wet-year (i.e., high) production thresholds (derived from 2016–2017 data) to the 2015 fall biomass data, the majority of the map is classified within the High class and the pixels with Low and Medium change fall mostly in places with the greatest productivity over time, such as old fields, pastures that have been rested for multiple years, and areas close to stream channels (**Fig. S2**, available online at …). Using the relative difference biomass metric instead of the absolute value of fall biomass helps to overcome the difficulty of interpreting interannual variability (see Fig. 5). Mapping the relative difference biomass data across 2015–2017 shows a pattern aligned with management (grazing and fire), as well as past land use history such as cultivated fields. The small range (< 4%) between the Medium and High categories (see Table 6) indicates weak sensitivity of this algorithm to quantifying in-field measures of moderate grazing as estimated by the Landscape Appearance method. Current research is being performed to address this sensitivity by 1) increasing the size of the in-field utilization sampling plot to better match the size of a Landsat pixel; 2) exploring different selections of pregrazing and postgrazing scenes with relation to grazing events; and 3) scaling up both the in-field and remote sensing data to determine which scales are most reliable to provide estimates of livestock use within pastures. Further research could also seek to use classification and machine learning approaches to estimate in-field utilization data with a variety of remotely sensed and geographic data layers.

Thresholds for classifying biomass maps could be derived from various sources for different purposes. For example, managers could derive thresholds from normal rainfall years and apply these thresholds to drier yr (i.e., 2015) to locate areas that have the capacity to remain above ecologically relevant residual biomass thresholds even in low-production years (i.e., drought refugia). Results such as these are important conservation tools that help to focus management on areas that have greater production or conservation potential (e.g., Wiens et al. 2009), since the greatest difficulty may lie in maintaining the higher range of biomass quantity as climate variability continues to increase (Joyce et al. 2013; Briske et al. 2015). By mapping locations of biomass that stay above important habitat thresholds in most years, managers can try to maintain those areas by removing management drivers that reduce vegetation amounts. User-defined thresholds based on current-year conditions could provide a customized visualization. For example, managers who have spent time surveying pastures could choose a particular pasture to represent “moderate” use and that biomass pasture average could be used as the breakpoint for classifying other pastures.

Integrating Remotely Sensed Data with In-field Monitoring and Adaptive Management

Integrating vegetation information provided by satellites into field-based monitoring has the potential to improve sampling designs and thus increase the efficiency and interpretation of field-based data. For example, if the goal is to monitor grazing utilization efficiently and effectively, stratifying the landscape using the relative difference raster could potentially improve pasture or ranch-wide estimates compared with a simple random sampling design. Also, the fall and relative difference maps could be used as an initial screening tool to identify critical and key areas to monitor for signs of overuse or trends in plant composition. The thresholds listed in this study should be continuously improved with new monitoring and research data and tested for applicability when land managers define new objectives. Ideally, these remotely sensed data can advance the adaptive management cycle in an iterative process whereby the remotely sensed data improves in-field grazing monitoring efforts by providing better stratification for increased efficiency. In turn, yearly monitoring data would provide feedback to improve the remotely sensed classification of the fall and relative difference biomass monitoring products.

It is also important to understand how remotely sensed data relates to in-field monitoring data and how this relationship affects interpretations for adaptive management. First, utilization and relative difference in biomass are estimates of two different things: utilization is an estimation of what percentage of forage plants have been removed, while relative difference in biomass is an estimate of the change in total biomass between two points in time, including losses due to senescence. Although the two indicators are both expressed as percentages and are expected to coincide in a relative way, many methodological factors (i.e., the accuracy of the biomass model) and ecological factors (i.e., regrowth, summer decomposition) impact the strength of this relationship. Further development and study between this relationship are needed to help managers transition to using remote-sensing indicators. At present, we do not consider relative difference to be a direct proxy for utilization. Second, because stocking rate does not account for reductions in biomass incurred from other herbivores (trespass cattle, elk, ground squirrels, and insects) or from senescence, we advise caution when interpreting patterns of total biomass change across a pasture; some of these changes were caused by livestock, but not all. For this reason, we refrain from interpreting relative difference maps strictly as indicators of livestock use patterns. We are currently addressing these issues by placing GPS collars (e.g., Karl and Sprinkle 2019) on a large percentage of cattle within herds to narrow down where livestock use is happening within each pasture and relating those GPS location data to both in-field utilization measures and remotely sensed vegetation measures to provide a more complete understanding of the strengths, weakness, and relationships between field and remotely sensed data. Lastly, while many sources of satellite data are freely available (e.g., Landsat, Sentinel, MODIS), and there are various platforms that use these data for management-oriented tools (see Introduction), the “on-the ground” relevance and effectiveness of such data products are not necessarily guaranteed.

In our study we tested the relationship between a previously developed biomass model specific to a grassland type with limited geographic extent and two grazing-related indicators. While there are costs associated with data collection, model development and online tool development (i.e., RangeSAT.org) methods for model development and similar tests can be performed in other rangeland systems. For example, we are currently working on creating and testing models in sagebrush steppe habitat following similar workflows described by Jansen et al. 2018. However, this degree of model specificity may not be necessary in all places or for other management-related questions, and existing broad-scale datasets (Allred et al. 2020; Jones et al. 2020) may be sufficient for improving in-field sampling designs, monitoring rangeland vegetation amounts over time, or helping to set stocking rates (see Hudson et al. 2020). Regardless of the spatial extent (i.e., local vs. global models) of the underlying data, additional work is necessary to test and inform remote-sensing products for livestock management and short-term use-based monitoring. To unlock the potential of remote sensing for monitoring and management, collaboration among scientists, land managers, and ranchers will be important. Such collaborations should include direct input from land managers and ranchers regarding the relevance of data products for decision making, along with education about both the uncertainty associated with the underlying model but also the most applicable ways to integrate these data into monitoring and adaptive management. Future work aimed at comparing multiple remotely sensed vegetation products with various management actions and or disturbances would provide guidance to end users regarding the most applicable uses, as well as provide valuable information to scientists who seek to improve these tools over time.

Conclusion

While many remote-sensing studies seek to understand how stocking rate or grazing intensity change the aboveground estimates of vegetation or vegetation indices (Todd et al. 1998; Kawamura et al. 2005; Jansen et al. 2016), few have related estimates of grazing utilization with satellite-based remotely sensed data from pregrazing and postgrazing scenes or with estimates of end-of-season residual biomass. In performing the analysis in such a way, we hope that this technology will be more easily adopted and understood for short-term monitoring and adaptive management. The ability to monitor large landscapes with satellite data is an important step in improving in-field data collection efforts, the adaptive management cycle, and conservation outcomes at meaningful scales. In this study we attempted to move beyond the statistics of modeling of vegetation amounts with remotely sensed data and demonstrated how remotely sensed vegetation data can directly inform adaptive management.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.rama.2021.01.006.

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