Check for updates

RESEARCH ARTICLE

Effects of adaptive multiple paddock and continuous grazing on fine-scale spatial patterns of vegetation species and biomass in commercial ranches

Fugui Wang · Steven I. Apfelbaum · Ry L. Thompson · Richard Teague · Peter Byck

Abstract

Context In rangelands, alterations to vegetation from grazing have potentially significant consequences for a wide variety of ecosystem structure and function.

Objectives This study measured the herbivory effects of adaptive multi-paddock grazing (AMP) and continuous grazing (CG) practices on spatial patterns of vegetation, plant community species composition, and productivity in neighboring ranches in Mississippi, USA.

Methods Assessments included on ground-measurements and remote sensing analyses using fine-scale aerial photographs and satellite images.

Results The results indicated that the spatial patterns of the classified seven vegetation species groups and biomass production were different between AMP and CG. Bahiagrass dominated the plant species in both ranches, with ~ 83% and 58% of the CG and AMP ranch vegetation cover. The AMP ranch landscape was fragmented, more diverse at a fine spatial scale, and consisted of smaller, more similar patch sizes for all seven species. A patchy mosaic of all the species was found, but no species were abundant adequately to interconnect throughout the entire landscape. In contrast, patch sizes on the CG ranch were more aggregated, with one dominant species clumped into larger compact patches. Vegetation production in the AMP ranch was higher and clustered into large patches: Hot and Cold Spots with an apparent spatial trend and configuration. In contrast, in the CG ranch, relatively smaller Spots were interspersed with no apparent spatial trend.

Conclusions The findings imply a potential change in the landscape pattern of grazing land in the Southern U.S. associated with adoption of AMP grazing.

Keywords Adaptive multiple paddock grazing · Spatial patterns · Vegetation composition · Biomass · Grazing ranches · Remote sensing · Landscape metrics

F. Wang (✉) · S. I. Apfelbaum · R. L. Thompson
Resource Environmental Solutions, LLC, 6575 West Loop South, Suite 300, Bellaire, TX, USA
e-mail: fwang@res.us

R. Teague
Texas A&M AgriLife Research, Vernon, TX, USA

P. Byck
School of Sustainability, Arizona State University, Tempe, AZ, USA

P. Byck
Walter Cronkite School of Journalism and Mass Communication, Arizona State University, Tempe, AZ, USA

Introduction

In grazing land ecosystems, different grazing management strategies affect the interaction of livestock with vegetation, soil, water, and the entire ecosystem structure and functions to varying extent and scales (Conant et al. 2017; Hewins et al. 2018; Godde et al. 2020). The grazing practices and management processes are characterized by grazing frequency and intensity, the season of use, duration, livestock stocking spatial distribution and density, paddock size and number, and forage use allocation. In general, there are three basic grazing practices: continuous grazing (CG), rotational grazing (RG), and adaptive multi-paddock grazing (AMP) (Becker et al. 2017; Park et al. 2017; Fynn et al. 2017; Teague and Barnes 2017). Each grazing practice can exert distinct effects on aboveground vegetation composition and structure (Su et al. 2017; Souther et al. 2019), aboveground plant productivity and biomass (Biondini et al. 1998; Su et al. 2017; Hillenbrand et al. 2019), belowground root productivity (Hao and He 2019), leaf litter decomposition and soil microbial communities (Wang et al. 2018; Xun et al. 2018; Kooch et al. 2020), hydrological responses at the ranch and watershed scales (Park et al. 2017), and soil carbon and nutrient cycles (Lu et al. 2017; Conant et al. 2017; Abdalla et al. 2018; Hewins et al. 2018; Wagle and Gowda 2018; Godde et al. 2020; Ritchie 2020).

AMP grazing manages livestock grazing using multiple small paddocks per herd, with only one paddock grazed at a time for a short periods, allowing other paddocks to recover before grazing again (Teague et al. 2013). It is a regenerative grazing strategy that is synonymous with Holistic Planned Grazing (HPG) management (Savory and Butterfield 2016), and aims to increase ecosystem function as the base to improving ecosystem goods and services, as well as rancher's profitability (Teague et al. 2013; Clifford 2020). AMP grazing has been found to improve available forage biomass two to three times, can increase plant diversity and decrease invasive plant dominance, and is associated with increased soil organic carbon accruals with cattle grazing in Texas (Teague et al. 2011) and bison grazing ranches in South Dakota (Hillenbrand et al. 2019). AMP grazed pastures have documented the potential to offset GHG emissions through soil carbon sequestration, with a 4-year C sequestration rate of 3.59 Mg C ha^{-1} yr^{-1}

(Stanley et al. 2018). Furthermore, soil GHG emissions monitoring indicated that AMP grazing had the highest CO_2 microbial respiration rate, but much lower N_2O and CH_4 emissions (Dowhower et al. 2020). Modeling simulations of hydrology at the ranch and watershed scales indicated that AMP could reduce surface runoff and stream flood flows, and increase infiltration for water conservation and flood risk reduction (Park et al. 2017). Currently, about 40% of surveyed ranches identified themselves as non-adopters (Wang et al. 2020), and 78% indicated they are familiar with the concept (Clifford 2020). Ranchers' adoption of AMP grazing is increasing as the awareness of the benefits of AMP has become more widely understood.

The benefits of AMP grazing may vary by ranch across over a vast landscape, or farmers may experience an up-and-down dynamic of the benefits over the years due to the inherent spatiotemporal variability of vegetation, soils, topography, and weather and the more complex response-feedback from AMP grazing. Climatic variations, in particular droughts, control major trends in plant species composition and production, as documented in a northern mixed-grass prairie where differences in grazing intensities were found to play a secondary role (Biondini et al. 1998). Precipitation alone explained ∼ 75% of the variation of plant production in mixed grasslands though the effects of grazed and ungrazed treatments were significantly different (Yang et al. 2012).

The heterogeneity of grazing benefits and patterns also depends on assessment methods and the spatial scale of the collected data. The assessment methods in general included approaches of using principals of geostatistics (Barnes et al. 2008; Lin et al. 2010; Liu et al. 2015), assessing landscape metrics of aerial imagery (Ma et al. 2019), and using cell-based simulation models (Adler et al. 2001). Samples collected from spatially distributed plots indicate that effects of grazing intensity on the plant above ground biomass, soil water content, and organic C concentration can be detected at the fine-scale (0.1–2 m); however, at the coarse-scale (1–18.7 m), spatial patterns of those variables did not respond to grazing intensities, suggesting that grazing effects were spatially homogenous at the scale (Lin et al. 2010). Though low-resolution Landsat imagery has been used to assess responses of net primary productivity (NPP) residuals and vegetation cover to grazing pressure

(Blanco et al. 2009; Chi et al. 2018), to effectively monitor the effects of grazing on the spatial heterogeneity of vegetation biomass, fine-resolution satellite data (< 10 m pixel sizes) was necessary for pastures of 40 to 745 ha (Jansen et al. 2019). Along with the technology advancement in remotely sensed image acquisition in the past decades, available sub-meter resolution aerial photos and satellite images, such as from Worldview series satellite, provided a unique opportunity to assess and monitor grassland ecosystem (Hall et al. 2012; Lopes et al. 2017; Polley et al. 2019).

To understand the influence of different grazing management practices at the ranch-scale on soil C and ecosystem goods and services, spatial patterned-response of vegetation to grazing is essential information. Without an understanding of the mechanisms and interaction between grazing and landscape structure, the design of effective grazing management that accounts for spatially explicit landscape impacts for livestock management is likely to be flawed. Spatial patterns of grazing on land need to be defined prior to evaluating how grazing alters the spatial impacts on the structure of a landscape and understanding the potentially significant consequences for a wide variety of ecosystem functions, including carbon and nutrient cycles (Adler et al. 2001; Wagner and Fortin 2005). We found only one publication that quantified landscape metrics with a high spatial resolution (1 m) using aerial imagery to study landscape dynamics with CG and RG treatments in experimental pastures (Ma et al. 2019), and it appears that spatially explicit management of spatial use intensity information has been minimally considered thus far in grassland management (Reinermann et al. 2020).

The purpose of this study was to assess how AMP and CG on commercial ranches resulted in differences in landscape heterogeneity as measured by patterns of vegetation species composition and biomass by using fine-scale aerial photos, satellite images, and on-the-ground data collected from the ranches. This study evaluated a process within herbaceous grass and forb dominated rangelands at a fine spatial scale on one location with paired and neighboring AMP and CG ranches. Since spatial heterogeneity is scale-dependent (Wu 2004; Uuemaa et al. 2005) and the interactive effects of grazing and soil systems on plant species richness and coexistence have been predicted to vary across spatial scales (Dorrough et al. 2007), we assess these metrics using landscape metrics

quantified at both global and local scales. Unlike past studies focused on temporal land cover change by studying landscape structure and composition of a landscape over time (Griffith 2004; Gökyer 2013; Kumar et al. 2018), we compare the difference in the two adjacent landscapes on the same soil type, similar landscape position and nearly identical historical land uses that diverged with the AMP grazing beginning ~ 20 years previously. Prior to that, both areas had been managed as CG paddocks for over one hundred years or more. By use of multiple quantification approaches and different scales, our goal is to evaluate the above questions from a different perspective to better understand AMP and CG grazing at the ranch scale, and each grazing practice's potential contribution to build healthy ecosystems, soil health and biodiversity health, and replenish baseflow hydrology with a commensurate reduction in stormwater runoff, and in increasing the potential of soil to sequester more carbon for climate change mitigation.

Study area

The two ranches, a paired study design, comparing AMP and CG grazing practices were located across the fence from each other, in Woodville, Mississippi, at the approximate latitude and longitude of 31.0 North and 91.3 West (Fig. 1). The total area of each ranch is 485.1 hectares and 186.8 hectares, respectively, with a dominant land use of grazing. Both ranches occur at an elevation of 86 m above mean sea level with a standard deviation of 7–10 m. The ranches have monthly high and low temperatures averaging 25.5 °C and 12.5 °C, and monthly average precipitation of 137.4 mm.

The landscape of the two ranches is fragmented by large scattered trees with herbaceous understory (savanna), stock ponds and associated ranch roads, buildings, and the natural configurations of the forested patches. In particular, the CG ranch is smaller than the AMP ranch, but the natural spatial pattern configuration relative to the AMP ranch is slightly complicated, as indicated by the higher edge density, lower area fraction of the largest patch, and higher number of patches per hectare (Appendix 1).

The dominant herbaceous vegetation species in the AMP ranch paddocks include perennial warmer season bahiagrass (*Paspalum notatum*), Johnson grass
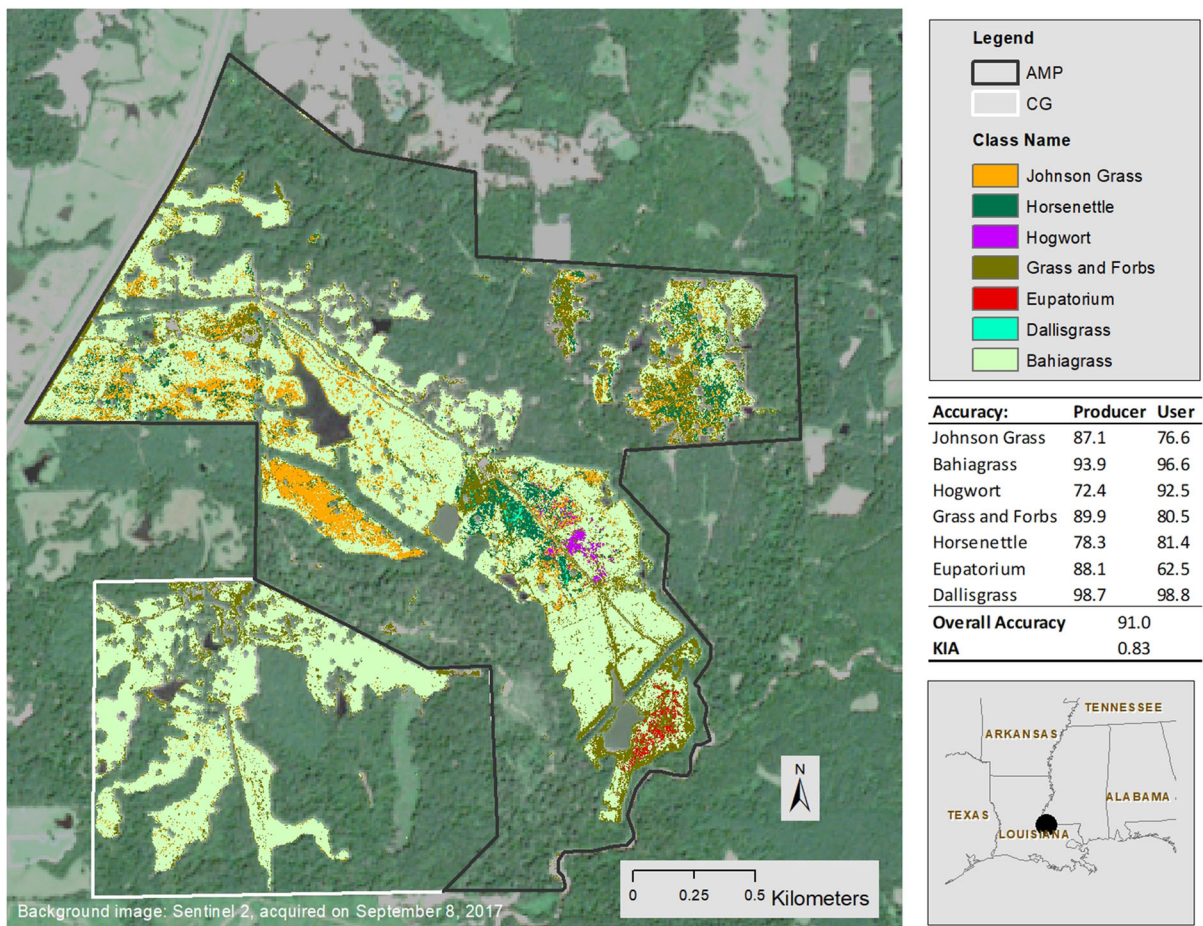
Fig. 1 Study area of the two AMP and CG ranches in Woodville, Mississippi, and classification of herbaceous vegetation using aerial photos and satellite imagery acquired in the summer of 2018 and associated accuracy assessment of the classification

(*Sorghum halapense*), and forbs of horsenettle (*Solanum carolinense*), and annual no-tilled drilled cover crop mix of annual ryegrass (*Lolium multiflorum*), various legumes, and an assortment of annual grains including oats (*Avena sativa*), grain rye (*Hordeum vulgare*), and several other species. Those cool season cover crops are planted during late summer and are grazed during the winter and spring. After they bolt in early summer, an additional no-till seeding of warm-season legumes and grasses is planted through the cool-season grass stubble. The CG ranch has primarily been left natural, and whatever forage species grow is what has been grazed over the years. There are several fields where the farmer has disked and broadcast seeded and rolled cool and warm-season grasses, including annual ryegrass. Both farms have an underlying perennial vegetation matrix, often dominated by

native and non-native weedy vegetation, through which the plantings emerge.

The AMP ranch includes small paddocks of 1–5 ha grazed for 0.5 to 2 days by approximately 225 cows and calves (personal communication with ranchers), which are then allowed to recover from 30 to 90 days, dependent on the season, before a follow-up grazing. Small paddocks are constructed daily with a temporary electric fence. During any given year, there are about 150 paddocks grazed over the entire ranch. Other than occasional mineral supplements, no supplemental feed is provided to the cattle. In contrast, the CG ranch has seven paddocks of approximately 9 ha each, and about 70 head of cattle are moved between paddocks with an average grazing period goal of 75 days, and a recovery period 90 days. After a paddock is grazed, gates separating the last from the

current paddock being grazed are allowed to remain open, so cattle can move back and forth between more than one paddock, often to access a watering point. Cattle are given supplemental feed, including round bales of hay.

Methods

Vegetation species classification

Imagery sources and preprocessing

Aerial photos acquired on August 10, 2018, and Worldview 2 satellite images acquired on July 18, 2018, were used for vegetation species classification. The spatial resolution of the aerial photos, with four spectral bands, was 0.1524 m. The satellite imagery was radiometrically corrected to reduce and minimize atmosphere effects on the spectral reflectance of the ground targets. The correction was completed by Dr. Sergii Skakun at the University of Maryland, with a Land Surface Reflectance Code (LaSRC, a generic atmospheric correction algorithm (Vermote et al. 2016) for estimating land surface reflectance, taking into account absorption by atmospheric gases and scattering by molecules and aerosols, and is based on the 6SV radiative transfer code (Vermote et al. 1997; Kotehenova and Vermote 2007). Secondly, the spatial resolution of the image was increased to 50 cm through running a pan-sharpening algorithm on the 2 m spatial resolution of the multispectral bands and 50 cm resolution of the panchromatic image (Padwick et al. 2010). Lastly, the imagery was geometrically referenced to the aerial photos with a spatial resolution of 0.1524 m. The 50 cm resolution satellite image was again resampled to 0.1524 m of resolution for final land cover classification and landscape pattern analysis.

Ground truth data collection

A field survey of vegetation species for training a computer to classify imagery was conducted in the ranches on July 12, 2018, with a submeter accuracy of GPS, ArcGIS Collector, and hardcopy maps. Location and spatial distribution of the dominant species with apparent spatial patch patterns were delineated as either points, polyline, or polygons. The data were then used as ground truth in the supervised classification of the vegetation species. Photos were taken at each point during all field sampling events for documentation of the status of the vegetation; these were also used as an additional source of information during image interpretation for training and verification data generation.

Vegetation species classification

Classification of vegetation species or species groups was an iterative process, including steps of image segmentation, training, classifying, and accuracy assessment. It continued until the accuracy could not be improved further. Image segmentation is a process to group pixels with similar spectral characteristics together as an object. Within each object, it is assumed that the spectral signature is homogeneous, and thereby it is identified as a single land cover type. After the procedure of image segmentation, the objects were classified into the land cover using an artificial intelligence algorithm, random forests (Ho 1995), provided in the software package eCognition for image classification (http://www.ecognition.com/). Accuracy of the final classification was assessed by creating a contingency matrix and accuracy table, with the data generated independently from the training dataset.

Vegetation biomass estimation

The biomass was estimated by using three sets of data of field biomass sampling, WorldView2 Multispectral, and Sentinel-1 SAR satellite imagery. In the field, biomass was sampled on November 27, 2018, at 40 plots that measured 1 square meter. Sample plot locations were designed to represent an approximately equal fractional area of the ranches and the cover variability of the vegetation biomass conditions across the entire two ranches. All plant materials in the plot were clipped to within 2.54 cm of the ground surface, weighed in the field, and bagged for drying and further analysis. Drying, using forced air blown through a perforated grain drying system, was terminated when constant weights were achieved.

WorldView2 multispectral satellite imagery from November 22, 2018 was acquired from Digital Globe, with a "Pre-Task Planning" approach, scheduling ahead for the satellite to acquire images during a

specific period in the future for a specific area of interest. This date was chosen as it represented the nearest cloud-free imagery that coincided with on-the-ground plot sampling. The imagery was preprocessed with the same steps of radiometric and geometric correction as we used to process the images for vegetation species classification.

The second set of satellite images, Sentinel-1 SAR image from November 25, 2018, was acquired by the European Space Agency and free for download. This imagery was processed through the customized image processing procedure—the Hybrid Pluggable Processing Pipeline—provided by the Alaska Satellite Facility (ASF) (Hogenson et al. 2016); this process corrects synthetic-aperture radar (SAR) geometric distortions, removes thermal noise, reprojects image to UTM coordinate system, and creates digital values of radar backscattering. Lastly, both sets of multispectral and radar images were rescaled to a spatial resolution of 5 m by 5 m for biomass estimation and mapping.

Multivariate regression models correlated field biomass measurements to the multispectral and SAR backscattering signatures of the vegetation biomass by using the regression analysis methods provided by software package SAS (http://www.sas.com). The model, with the highest R-square and adjusted R-square values and lowest AIC values, was selected as the final model to predict biomass in the entire ranch. The predicted extreme values, such as negative values or unreasonably high biomass, were then replaced by predictions using the model built with the multispectral image only. Any remaining extreme values were then replaced by the prediction using a model developed with SAR images alone. This model fit the data well at the lower end of the measured biomass, but large residuals appeared for the higher biomass measurements.

Quantification of spatial patterns of vegetation

Landscape configuration of the grazing land at the two ranches was distinct, with typical different natural boundaries and sizes (Fig. 1 and Appendix 1). To minimize the effects of the natural landscape configuration patterns on the comparison of the grazing effects on the spatial pattern of the vegetation itself, two approaches were implemented to quantify the landscape metrics: at a global scale for the entire ranch and a local scale at the scale of a 30.24 m by 30.24 m

grid (200 × 200 image pixels). The grids with full coverage of grazing vegetation were selected for the analysis. Any grid with one image pixel of some other land cover type, such as trails, was eliminated from further analysis.

Landscape level

At the landscape level, the landscape metrics were calculated at both the global and local levels. At the local scale, each grid was treated as an individual landscape entity; the landscape metrics computed per each grid for the entire ranch were then averaged for the comparison between the two ranches and for differentiating the performance of the metrics at the global and local levels. The three metrics of Dispersion and Interspersion, Subdivision, and Diversity were calculated using the software package "Fragstats" (McGarigal et al. 2012) and an R package, "Landscapemetrics" (Hesselbarth et al. 2019).

Dispersion and Interspersion are under the broader concept of aggregation, referred to as the tendency of patch types to be spatially aggregated. In this study, two landscape metrics, Contagion Index (CI) and Aggregation Index (AI), were selected to quantify the effects of grazing practices in the two ranches. The CI measured the aggregation from both perspectives of dispersion (the spatial distribution of the vegetation species) and interspersion (the intermixing of different vegetation species) of the vegetation patches at the landscape level. CI was a numeric value of the probability of finding a cell of type i next to a cell of type j. It was computed using raster "cell" adjacencies, not "patch" adjacencies. It was a measure of the overall landscape aggregation; the higher the value of CI, the more aggregated the vegetation species class (McGarigal et al. 2012). In contrast to CI, the AI was computed on the basis of raster "patch" or class adjacencies, and it was independent of landscape composition and map units. Therefore, AI can be compared between classes from the same or different landscapes (He et al. 2000).

Subdivision quantifies the degree to which patch types are subdivided into separate patches. Two indexes selected for this study were the Landscape Division Index (DIVISION) and Splitting Index (SPLIT). The DIVISION is the probability that two randomly chosen pixels in the landscape are not situated in the same patch, and SPLIT equals the total

squared landscape area divided by the sum of the patch area (m^2) squared, summed across all patches in the landscape (McGarigal et al. 2012). These two are typically used to measure the processes of landscape fragmentation, and had low sensitivity to tiny patches and were suitable for all fragmentation phases, as compared to indices of the number of patches and the average patch size (Jaeger 2000).

The Diversity metric measures richness and evenness, or the compositional and structural components of diversity, respectively. Shannon's Diversity Index (SHDI) was developed from information theory and is based on measuring uncertainty about the identity of an unknown individual (Shannon 1948). If a community has high diversity, the uncertainty of prediction is high because an unknown individual could belong to any species. Shannon's Evenness Index (SHEI) is merely the SHDI divided by a logarithm of the number of patch types presented in the ranches, which was the same for the both ranches. Therefore, to reduce data redundancy, only SHDI was quantified for this study.

Patch and class levels

At the class level of the vegetation species and species groups, besides the primary indices of Number of Patches, Mean Patch Area, Largest Patch Index, and Edge Density, we quantified eight indices at the global scale: DIVISION, Core Area Percentage of Landscape (CPLAND), Patch Density (PD), Clumpiness Index (CLUMPY), Interspersion and Juxtaposition Index (IJI), Perimeter-Area Fractal Dimension (PAFRAC), Mean Shape Index (SHAPE_MN), and Contrast-Weighted Edge Density(CWED). These eight indices were calculated for three out of the seven classified vegetation types created using imagery because of the very low cover of the remaining four classes in the ranches. The definition of each index is available on the Fragstats website (https://www.umass.edu/landeco/research/fragstats/fragstats.html), where readers are referred for additional details (McGarigal et al. 2012).

Quantification of spatial patterns of vegetation production

Spatial patterns and distribution of the vegetation biomass were quantified using ArcGIS (www.arcgis.com) spatial statistical tools for identifying clusters of grids with similar biomass values and the "outliers" of the grids with statistically, significantly different values as compared to the neighboring girds. Two tools, Hot Spot Analysis (HAS) and Cluster and Outlier Analysis (COA) were used. HAS generates a Gi* statistic or a z-score. The larger the statistically significant, the more positive the z-score was, and the more intense the clustering of high values (Hot Spot) was. And, vice versa, it would be the clustering of low values (Cold Spot). The COA analysis created a feature data layer with both types of clusters and outliers. The output of this analysis was similar to the HAS, but the pixels classified as "outlier" provided complementary information per the hot and cold spots identified by HAS. The "outlier" could be a useful indicator of how the grazing affected the biomass at a local scale or an indicator of the herd grazing behavior.

Results

Herbaceous vegetation species classification

The dominant six herbaceous plant species in the ranches were classified at the resolution of 0.1524 m with an overall accuracy of 91%, while species-dependent producer accuracy ranged from 0.72 to 0.99 and user accuracy ranged from 0.63 to 0.99 (Fig. 1). The six species included three grasses, Johnson grass (*Sorghum halapense*), bahiagrass (*Paspalum notatum*), dallisgrass (*Paspalum dilatatum*), and three forbs, hogwort (*Heracleum sp.*), horsenettle (*Solanum carolinense*), and Eupatorium/dogfennel (*Eupatorium capillifolium*). Classification accuracy of foxtail (*Setaria spp.*) and knotweed was too low to differentiate them from the other dominant species, though patches of these two species were observed in the ranches. Therefore, these two species were merged with other minor species into a category called "Grass and Forbs".

Effects of grazing on the spatial pattern of the ranches

Dispersion and interspersion

Values of AI and CI computed at both global and local scales indicated that the landscape pattern at the CG ranch was highly aggregated, though an exception of

CI at the local scale showed opposite results (Table 1 and Fig. 2). Among the six landscape metrics computed at the local and global scales for both grazing practices, CI was the only metric that showed opposite effects of grazing practices on landscape patterns between AMP and CG, with the values of − 2.9 and 20.6 at the two scales. On the global scale, the 33% lower CI measured at the AMP ranch indicated that patches of different vegetation species were well interspersed but were poorly interspersed in the CG ranch because of large and contiguous patches. The large patches with a majority of internal cells contributed to the larger value of CI, suggesting that the distribution of adjacencies among edge types is very uneven in the CG ranch.

Subdivision

Both subdivision metrics of DIVISION and SPLIT resulted in the higher values in AMP than CG ranches, indicating a more subdivided landscape in AMP (Table 1 and Appendix 2). The DIVISION measurements in the AMP ranch at both the local and global scales indicated that there was a higher chance that any two randomly selected pixels in AMP would not be the same vegetation cover type. In particularly, at local scale, there was 92% chance in CG, against 66% in AMP ranch, to find two pixels which were in the same vegetation classes. Similarly, compared to CG, AMP had 2.5 to 11 times higher SPLIT values, also revealing a decrease in patch size and a more fragmented landscape in AMP.

Diversity and richness

At both global and local scale, SHDI indicated a higher species diversity in the AMP than the CG ranch and a more equitable proportional distribution of area among the vegetation groups in the AMP ranch (Table 1 and Appendix 2). PR was the number of species groups present in the two ranches. It was the same—seven groups between the two entire ranches. However, at the local grid-scale, the richness varied by a mean of two to three, with a standard deviation of approximately 1. On average, the AMP ranch had 1.5 more species per grid than the CG ranch, with the maximum richness of six, as compared to four in the CG ranch.

Effects of grazing on spatial patterns of vegetation species

Of the classified vegetation groups, bahiagrass was the dominant species during July and August on the

Table 1 Landscape metrics at both local and global scales by AMP and CG grazing practices

| Grazing practices	Metrics	Local metrics			Global metrics	Difference between AMP and CG	
		N	Mean	STD		Local metrics	Global metrics
CG	AI	165	98.9	1.6	96.8	4.2	3.2
AMP	AI	746	94.7	3.6	93.7		
CG	CI	165	62.5	39.8	83.6	− 2.9	20.6
AMP	CI	746	65.4	19.4	63.0		
CG	DIVISION	165	0.1	0.1	0.8	− 0.4	− 0.2
AMP	DIVISION	746	0.4	0.3	1.0		
CG	SPLIT	165	1.1	0.2	4.4	− 1.8	− 44.6
AMP	SPLIT	746	3.0	2.9	49.0		
CG	SHDI	165	0.1	0.2	0.5	− 0.5	− 0.6
AMP	SHDI	746	0.7	0.4	1.2		
CG	PR	165	2.1	0.9	7.0	− 1.5	0.0
AMP	PR	746	3.6	0.9	7.0		
Mean						− 0.5	− 3.6
Std						1.0	23.9
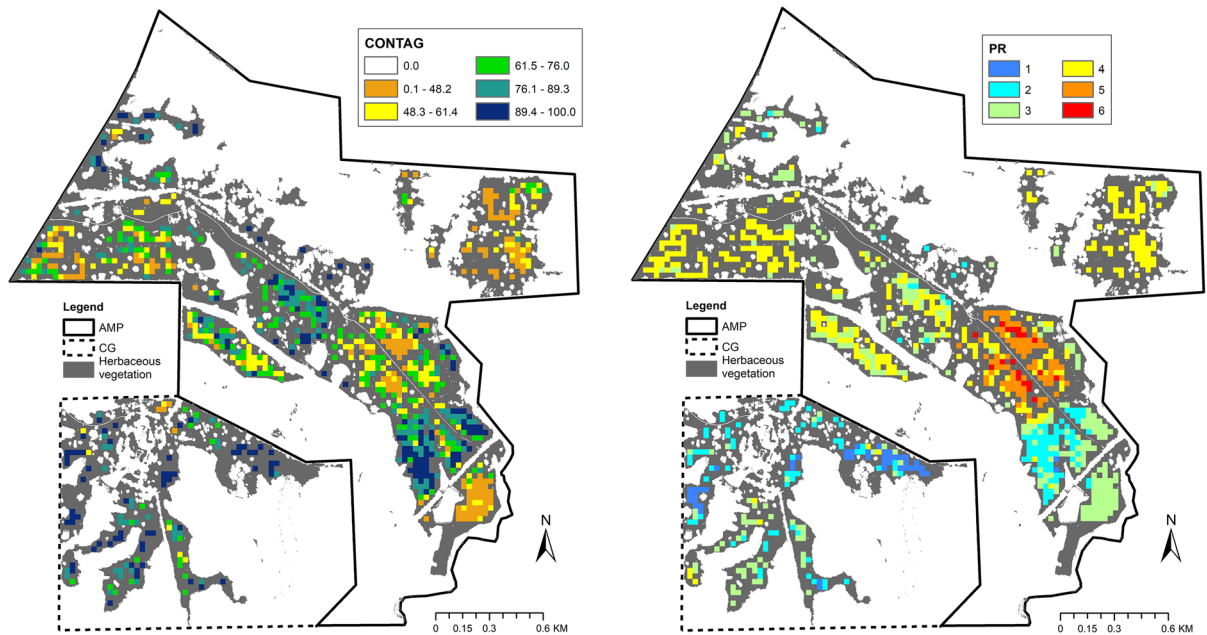
Fig. 2 Landscape metrics of Contagion Index (CONTAG) and Patch Richness (PR) per the grid of herbaceous vegetation, with a size of 30.24 m by 30.24 m

ranches (Table 2). It occupied about 83% of the CG and 58% of the AMP ranches. Many herbaceous species in the ranches were identifiable in the field by botanists, but were not identifiable using remote sensing because of the similar spectral reflectance signatures of the species. Those species were grouped into a category "Grasses and Forbs." It was the second dominant vegetation group in the ranches and it almost occupied the rest of the grazing land (15.4%) of the entire ranch in CG and 22.4% on the entire AMP ranch. Johnson grass (12%) was the third most dominant species in the AMP ranch, while horsenettle accounted for 7%; both were ∼ 1% in the CG ranch.

The number of patches and edge density of the patches of all seven groups in the AMP ranch was higher than the CG ranch, as the AMP landscape was more fragmented as indicated by the landscape level metrics (Table 1). The average patch area and the largest patch index, the percentage of the landscape comprised by the largest patch, indicated an aggregated landscape dominated by one dominant species in CG, but smaller and more similarly sized patches for all seven species in AMP (Table 2).

Eight additional landscape metrics were computed for the three dominant vegetation species of bahiagrass, the unclassified species ("Grasses and Forbs"),

and horsenettle (Table 3). Two of them, SHAPE_MN and PAFRAC, quantified complexity of patch shapes by comparing to a standard shape or based on perimeter-area relationship. Values of both the metrics revealed an irregular shape of the patches of the three vegetation classes, but the shape complexity between AMP and CG are similar (Table 3). The lower values of PD, IJI, and CWED in CG showed that the landscape of those three species had less patch density, less chance adjacent to the patch of other species evenly, and a lower amount of patch edge over the landscape. On the other hand, the small values of CLUMPY among all three vegetation groups and of DIVISION of the two groups revealed a less than 3.5% difference in pattern aggregation between AMP and CG. The large deviation of DIVISION and positive CPLAND of bahiagrass indicated that the type of herbaceous plant was likely to be more aggregated in CG, and the landscape of the unclassified species and horsenettle consisted of smaller patches and more convoluted patch shapes.

Table 2 Landscape metrics of the vegetation species by AMP and CG grazing practices

Grazing Practices	Vegetation	Physiognomy	Area (%)	Number of patches	Mean patch area (m^2)	Largest patch index (%)	Edge density (m/m)
CG	Johnson Grass	Grass	1.4	2633.0	3.1	0.0	583.6
CG	Bahiagrass	Grass	82.9	4046.0	119.4	38.3	3239.6
CG	Hogwort	Forb	0.0	5.0	0.9	0.0	0.3
CG	Grass and Forbs	Grass/Forb	15.4	8803.0	10.2	1.2	2987.5
CG	Horsenettle	Forb	0.3	420.0	4.0	0.0	97.1
CG	Eupatorium	Forb	0.0	4.0	1.1	0.0	0.4
CG	Dallisgrass	Grass	0.0	2.0	1.0	0.0	0.1
AMP	Johnson Grass	Grass	11.8	37,731.0	6.1	2.4	3236.0
AMP	Bahiagrass	Grass	57.7	34,391.0	33.0	8.4	5462.6
AMP	Hogwort	Forb	0.6	1169.0	10.8	0.2	146.8
AMP	Grass and Forbs	Grass/Forb	22.4	51,655.0	8.5	2.1	4874.4
AMP	Horsenettle	Forb	6.6	13,782.0	9.3	0.8	1619.7
AMP	Eupatorium	Forb	0.7	933.0	13.8	0.1	216.1
AMP	Dallisgrass	Grass	0.2	421.0	8.4	0.1	45.2

Table 3 Percentage difference of the herbaceous vegetation landscape metrics between CG and AMP, with CG as a reference

	DIVISION	CPLAND	PD	CLUMPY	IJI	PAFRAC	SHAPE_MN	CWED
Bahiagrass	− 26.55	34.42	− 152.32	− 0.12	− 127.52	− 2.55	5.73	− 60.09
Grass and Forbs	0.06	− 45.96	− 74.18	2.10	− 266.16	− 1.11	10.75	− 63.16
Horsenettle	0.01	− 2767.56	− 874.07	− 3.30	− 39.84	− 1.72	5.61	− 1600.25

Estimation and spatial pattern of vegetation biomass

Biomass sampled from 40 sites in the field indicated that AMP rather than CG resulted in more productive grazing land, with 74% higher biomass measured in the field (455.5 g/m^2 vs. 262.2 g/m^2). The AMP landscape was more heterogeneous, as indicated by the coefficients of variation for the biomass of 49% in CG and 56% in the AMP ranch.

Across both ranches, the biomass was estimated at a scale of 5 m by 5 m using regression modeling with an R-square value of 0.73 (Appendix 3 and Fig. 3). The predicted mean biomass of 417 g/m^2 in AMP was significantly higher ($p < 0.0001$) from the mean of 369.3 g/m^2 in the CG ranch. Ninety percent of the AMP ranch had predicted biomass ranging from 42.8 to 1051.5 g/m^2; while the CG ranch ranged from 67.5 to 893.3 g/m^2 (Appendix 3). The predicted spatial-explicit biomass confirmed AMP had higher biomass capable of supporting expanded enhanced biomass of grazing livestock at the field scale. The spatial variability of the biomass was apparent in both ranches, with larger clusters and scattered "outliers" on the maps of Hot Spot and Outliers (Fig. 4 and Appendix 4). In the AMP ranch, two larger clusters of both Hot and Cold Spots with 99% confidence were distributed with apparent spatial trends, and the insignificant area was occupied by a small fraction of the AMP ranch. In contrast, the clusters with 99% confidence in the CG ranch were smaller, with no apparent spatial distribution preference shown on the map, and the insignificant area was larger than in the AMP ranch (Fig. 4). More "Outliers" in the biomass distribution were identified in AMP than the CG ranch also (Appendix 4), indicating the potential effects of paddock configuration of the grazing practices.
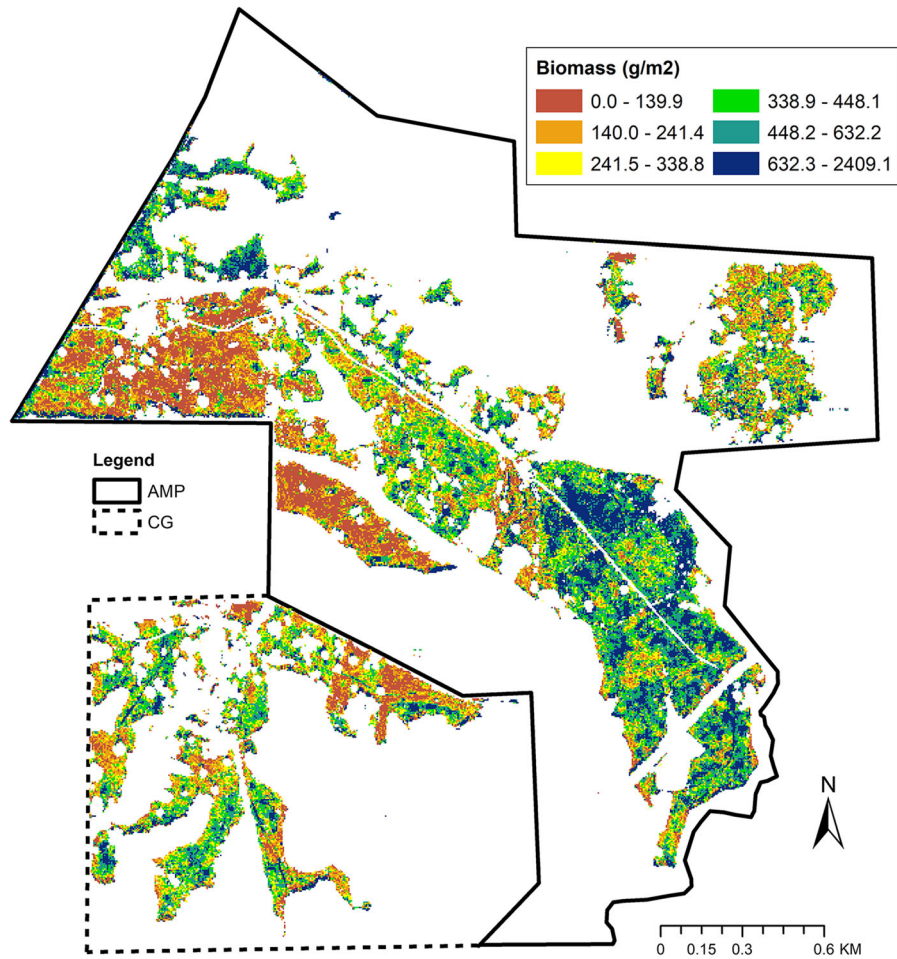
Fig. 3 Biomass of herbaceous vegetation at a grid-scale of 5 m by 5 m in the AMP and CG ranches in November 2018, estimated by using Worldview 2 and Sentinel-1 satellite imagery

Discussion

Effects on vegetation species

To our knowledge, this is the first study of how grazing land management affects spatial patterns of species and productivity of herbaceous plants at the fine grid-scale of 0.1524 m and 5 m using ground survey, aerial photos, and multispectral and radar satellite imagery. For the ranches in Mississippi in the southern U.S., there is a clear seasonality of C3 and C4 plant growth cycles ("rotations"). In this research, the vegetation pattern represented the condition of C3 in the spring and early summer, and the productivity was a result of both the C3 plant residuals and C4 new growth in later November. We found that AMP resulted in a more

heterogeneous, diverse, and higher productivity landscape compared to the CG ranch. The grazing regimes also led to substantial shifts in plant composition at the landscape scale as measured by percent cover of the classified species in the AMP and paired CG ranch. The measured effects were driven by differences between the AMP and CG grazing regime itself, as the catenas sampled were selected based on matching topography, soil texture, and meteorology (Appendix 1). The two management practices primarily differed by the size of paddock, intensity and duration of grazing, stocking rate and density, and more substantial recovery periods in AMP. These, in turn, affect three factors: removal of plant tissue, animal returns, and trampling effects on vegetation and soil, and eventually, ecosystem functions and services.
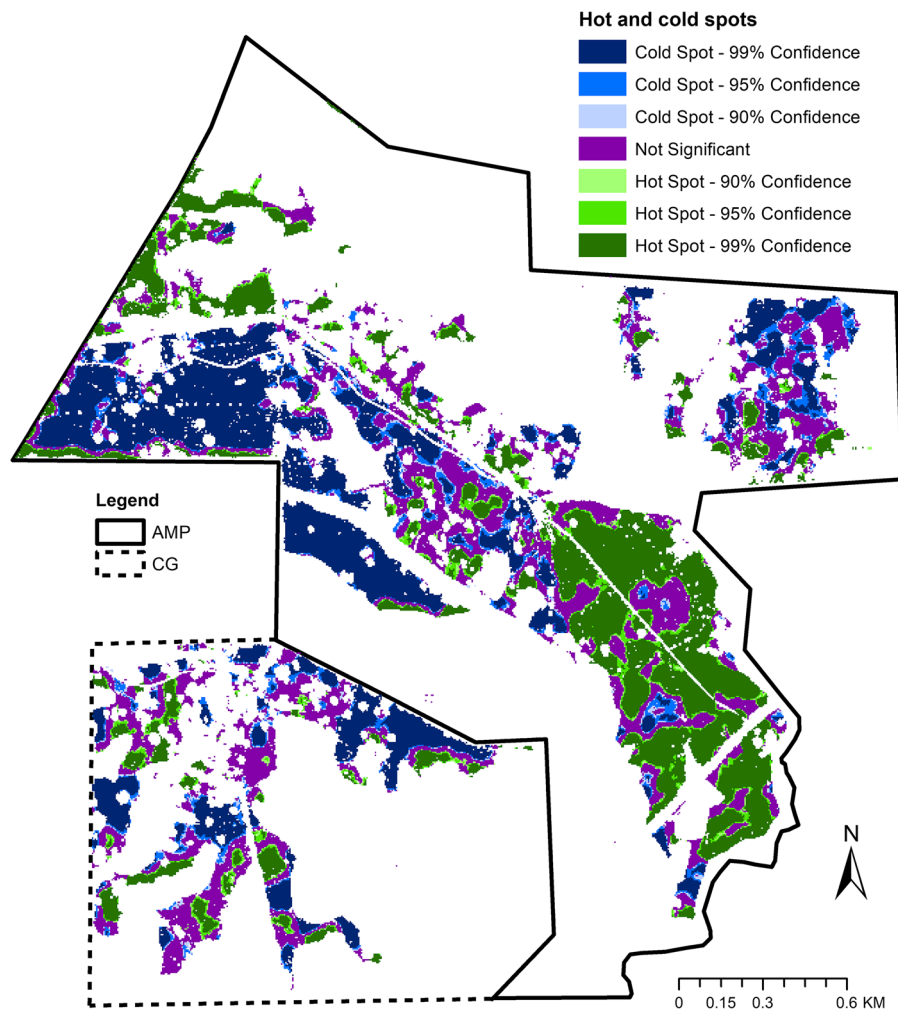
Fig. 4 Distribution of high (Hot Spots) and low biomass (Cold Spots) clusters by confidence levels. The biomass was estimated by using Worldview 2 and Sentinel-1 satellite imagery at a grid-scale of 5 m by 5 m in the AMP and CG ranches in November 2018

Through the layout of small paddocks in AMP grazing, the cattle herd is limited to a small area, which encourages more competition such that the selection of more favorable plant species is minimized or even eliminated. Thus, spatially, the effect of plant tissue (forage) removal on the ecosystem is similar across the entire paddock and measurable at the fine scale employed in this study. During each short, intense grazing episode, all plant species are exposed to grazing for a limited duration such that often, only half of the biomass is consumed. Then, during the period of recovery, because of the more evenly distributed nature of manure and livestock urine and the trampling of the remaining vegetation, the plant species have an equal chance to capture the available nutrients, water,

and sunlight resources for regrowth. This system of grazing is modeled to emulate evolution over many millennia of the vast grassland ecosystems in North America that co-evolved with immense herds of ungulates dominated by bison grazing (high intensity, short duration, long recovery).

Because both ranches have a legacy of heavy continuous grazing (as do most in the region), AMP and not CG grazing appears to regenerate evolved community composition. This suggests the recovery of ecosystem functions in the AMP grazed ranch benefits more than in the CG ranch from the short grazing episodes and significant post-grazing recovery periods. The spatial patterns of vegetation within a paddock with AMP grazing could be more

homogenous as compared to the spatial pattern in the entire ranch because the contrast between paddocks differs by grazing time and intensity, the legacy of vegetation conditions from previous grazing cycles, and land-use history. For this study, since we did not record how the paddocks were grazed, the landscape comparison was limited to the entire ranch and the grid scales.

However, the appropriate periodic length of rest of grasslands after grazing is a useful management strategy, along with the quick graze, to maintain palatable species, thereby minimizing undesirable species in the overall species composition (Zhang et al. 2018). Though the nutrient-rich patches created by animal returns generally under continuous grazing have altered plant species composition and contributes to the patchiness of the landscape (Adler et al. 2001; Steinauer and Collins 2001; Virk et al. 2014). In contrast, with AMP grazing, the enclosure of cattle in a small paddock and more uniform disturbance and nutrient enrichment from fecal material and urine would suggest a more homogenous vegetation distribution and larger, more homogenous patch sizes. Because the study found the opposite in the AMP ranch, this suggests that the combination of temporal sequencing of grazing in each paddock and the temporal recovery, at the paddock scale, affects the "whole ranch" landscape resulting in a more heterogeneous and biodiverse effect on vegetation in the paddock and the landscape scale.

Spatially, the effects of trampling in an AMP grazed paddock would be expected to be more homogeneous also. But it is dependent on the size of the paddock, stocking density, proximity to the water source, and social behavior. From the AMP ranch, we observed a spatial pattern of higher grazing intensity and trampling, with very intense trampling where cattle gathered for water, and bare soil close to the gate of a few of the paddocks where the herd gathers for the rancher to open the gate to allow them to move to an ungrazed paddock. Instead, in the CG ranch, the vegetation was grazed to a very short, lawn-like stature, with a lack of trampling effects. Overgrazing to bare soil was often observed in the CG ranch and other CG ranches in the larger southeastern U.S. study region.

The effects of trampling on vegetation composition and the spatial patterns are also related to the tolerance of existing vegetation to trampling and the establishment of new seedlings. Seeds spread after cattle trampling produced five times more seedlings ($2.5/m^2$) than seeds spread before cattle trampling ($0.5/m^2$) (Jackson 1999). Legumes, particularly *Trifolium repens*, and short forbs (especially *Veronica serpyllifolia*) were supported by intensively defoliated and trampled treatments in mesotrophic temperate Central European grassland (Ludvíková et al. 2014). In the AMP ranch, reseeding the cool-season annual ryegrass occurs annually, which adds an additional variable and uncertainty in attempting to interpret the effects of the trampling by cattle. But, the extensive trampling within a small paddock could be the reason why more forbs and more plant species diversity is present in the AMP ranch.

The spatial patterns in continuous grazing could be caused by higher grazing pressure on preferred patches. The cattle in the CG ranch are free to move around and select their preferred forage based on plant palatability and nutritive quality, which were key factors contributing to patchy vegetation patterns (Adams et al. 1996; Adler et al. 2001; Virk et al. 2014). In general, cool-season grasses (C3) have higher nutritive quality early in the season compared to warm-season grasses (C4) that grow later in the season (Adams et al. 1996). If the stocking rates were substantial, then area- and patch-selection would be more evident in the CG ranch (Teague and Barnes 2017). An increased spatial heterogeneity was expected because the grazing heightens the contrast in vegetation by affecting resource abundance between the preferred and nonpreferred landscapes (Adler et al. 2001). Collectively, from findings and theories developed from previous studies, it appears that CG would have a more patchy and heterogenous landscape than AMP (Teague and Barnes 2017). However, we found a different pattern of landscapes between the AMP and CG ranches. The key reason could be the light grazing pressure and randomly distributed grazing pressure in CG overrides the fine-scale spatial heterogeneity in vegetation created by environmental heterogeneity or neighborhood interactions (Adler et al. 2001). The scale issue in evaluating landscape pattern is always a factor to consider. However, in this study, the quantification at both the global and local scales resulted in the same findings.

Effects on biomass

From both the biomass samples collected at the plots in the field and the spatially explicit biomass estimated using remotely sensed images for the entire ranch, we found that the herbaceous productivity at the AMP ranch was significantly higher than that of the CG ranch. This conclusion was supported by other published studies as a reason for a sufficient regrowing of the grass in the paddocks in recovery and due to diverse mixtures of prairie plants (Vermeire et al., 2004). It is important to understand that the vegetative biomass measured was the recovering and remaining biomass left in each paddock after grazing, and other management practices had occurred. The measurement represents what happened in the real world, and it could give a better insight for other land managers who have not adopted AMP practices to consider adoption.

Whether AMP or CG grazing is utilized has implications on carbon cycling in the ecosystem. While this study provides one snapshot of biomass condition and not a life cycle analysis, both the field plots (measured) and modeling predicted significant increased standing crop biomass in AMP vs. CG ranches, which would suggest a significantly greater carbon turnover rate and high soil carbon accruals. While other studies of grazing effects on productivity could be offset by precipitation differences as Steiner et al. (2019) concluded that plant biomass did not differ between CG and RG systems, but that there were significant year effects, which were mainly related to the timing and amount of rainfall received.

The spatial pattern of the productivity did show higher-lower spots both in AMP and CG ranches. However, in the AMP ranch, the spots were aggregated into big patches instead of small, interspersed spots, as documented in the CG ranch. In the AMP ranch, the pattern was supposed to relate to the pattern of the paddocks, reseeding, and seasonality. Based on our in-field observations from the AMP ranch, paddock size was slightly larger than a few other AMP ranches we saw in the southern U.S., but there were many more paddocks in the entire ranch. The cattle stocking rate was 200–300 animals for a grazing duration of a day or two. This grazing pressure, along with the longer recovery period, appears sufficient to prevent multiple hot and cold spots. The cold spots (lower biomass) in the AMP ranch is believed to result

from the lull after reseeding cool-season grass. In the majority of those cold spots, the vegetation was green in the November satellite images. In contrast, it was brown vegetation residuals in the hot spots. Therefore, the productivity pattern is the combined effects of grazing and other management practices coupled with management seasonality. Additional imagery from the growing (and dormant) seasons would be required to measure seasonally changing plant productivity and biomass to provide more evidence of how grazing affects productivity. In the CG ranch, the broadly interspersed pattern of cold and hot spots of productivity revealed the effects of the patchiness created by grazing, though we found a lesser extent of spatial heterogeneity in the vegetation species composition as compared to the AMP ranch. The interspersed patterns of the spots should result from the free movement of the cattle and preference of palatability and response of productivity to animal returns in the entire ranch. Additionally, the difference in the proportion of grasses and forbs between AMP and CG could also contribute to the patterns in productivity.

Potential effects on soil carbon

Climate primarily generates global patterns of soil carbon. However, other ecological processes, including rainfall infiltration, soil erosion, sediment deposition, and soil temperature and texture vary on the local scale due to landscape heterogeneity, all of which also affect the carbon sequestration capacity of the soil at the different landscape and field scales. Soil organic carbon (SOC) input rates are primarily determined by the root biomass of a plant and associated soil microbial mass and composition, but also include litter deposited from plant shoots (Ontl and Schulte 2012), modified by climate. In grazing lands, belowground root productivity, available litter inputs to soil, and vegetation species diversity are all affected by the grazing regime.

For this study, the higher measured plant biomass production, more heterogeneous patches, and more diverse landscape in the AMP ranch would be expected to result in heterogeneous soil properties and carbon sequestration potential at the ranch scale. The increased aboveground plant productivity could result in more litter C inputs to the soil, and the increased living and dead plant litter, would decrease soil erosion and also preserve higher levels of carbon

on the land and in the soils, encouraging carbon stocks to accumulate more rapidly, and at higher rates, than in CG managed ranches. These results have been reported in other studies (Teague et al. 2011; Hillenbrand et al. 2019) and are supported by the larger AMP grazing study impacts on soil carbon in the southeastern U.S. (Mosier et al. 2021). This paper documented that AMP grazing sites had on average 13% (i.e., 9 Mg C ha^{-1}) more soil C compared to the CG sites over a 1 m depth.

Conclusions

AMP and CG grazing resulted in different spatial patterns of vegetation species and production. The findings do not refute the hypothesis that AMP grazing is a promising grazing practice for achieving the goal of managing rangeland for the health of the ecosystem and long-term soil carbon sequestration potential. Rather than making such a conclusion from a study in test plots at experimental sites, our findings at the ranch scale are essential to understand how these different grazing practices affect the fundamental properties, components, and process of a rangeland ecosystem, and the interactions among the processes under heterogeneous landscapes. The landscape pattern heterogeneity and the difference between AMP and CG revealed that the grazing effects varied both within a ranch and across the grazing practices. The effects could be measured as positive or negative, depending on the spatial scale of the sampling and data used to support the analysis, such as was conducted in this study. Field and ranch scale mapping is a useful tool for ranchers to evaluate the effects of adaptively managed grazing over time. If AMP grazing is appropriately scaled and deployed, fine-scale and larger landscape-scale mapping to monitor vegetation changes is an important management tool for restoring degraded rangeland or maintaining rangeland ecological function.

The study focused on understanding grazing practices at paired, neighboring ranches. More detail on the paddock size, stocking density, and length of grazing and recovery periods have been recorded, but have not been evaluated quantitatively as covariates in this paper and will be addressed in subsequent analyses and publications. These added variables are unlikely to affect the broader outcomes, but may be essential to further understand the underlying ecological processes and mechanisms, so as to not oversimplify and generalize the conclusions from one pair of ranches to the regional scale.

References

Abdalla M, Hastings A, Chadwick DR, Jones DL, Evans CD, Jones MB, Rees RM, Smith P (2018) Critical review of the impacts of grazing intensity on soil organic carbon storage and other soil quality indicators in extensively managed grasslands. Agric Ecosyst Environ 253:62–81

Adams DC, Clark RT, Kloptenstein TJ, Volesky JD (1996) Matching the cow with forage resources. Rangelands 18:57

Adler P, Raff D, Lauenroth W (2001) The effect of grazing on the spatial heterogeneity of vegetation. Oecologia 128:465–479

Barnes MK, Norton BE, Maeno M, Malechek JC (2008) Paddock size and stocking density affect spatial heterogeneity of grazing. Rangel Ecol Manag 61:380–388

Becker W, Kreuter U, Atkinson S, Teague R (2017) Whole-ranch unit analysis of multipaddock grazing on rangeland sustainability in north central Texas. Rangel Ecol Manag 70:448–455

Biondini ME, Patton BD, Nyren PE (1998) Grazing intensity and ecosystem processes in a northern mixed-grass prairie, USA. Ecol Appl 8:469–479

Blanco LJ, Ferrando CA, Biurrun FN (2009) Remote sensing of spatial and temporal vegetation patterns in two grazing systems. Rangel Ecol Manag 62:445–451

Chi D, Wang H, Li X, Liu H, Li X (2018) Assessing the effects of grazing on variations of vegetation NPP in the Xilingol Grassland, China, using a grazing pressure index. Ecol Indic 88:372–383

Clifford ME (2020) Beef producers' motivations, perceptions and willingness to adopt adaptive multi-paddock grazing. Michigan State University, Thesis

Conant RT, Cerri CEP, Osborne BB, Paustian K (2017) Grassland management impacts on soil carbon stocks: a new synthesis. Ecol Appl 27:662–668

Dorrough JW, Ash JE, Bruce S, McIntyre S (2007) From plant neighbourhood to landscape scales: how grazing modifies native and exotic plant species richness in grassland. Plant Ecol 191:185–198

Dowhower SL, Teague WR, Casey KD, Daniel R (2020) Soil greenhouse gas emissions as impacted by soil moisture and temperature under continuous and holistic planned grazing

in native tallgrass prairie. Agric Ecosyst Environ 287:106647

Fynn RWS, Kirkman KP, Dames R (2017) Optimal grazing management strategies: evaluating key concepts. African J Range Forage Sci 34:87–98

Godde CM, de Boer IJM, zu Ermgassen E, Herrero M, van Middelaar CE, Muller A, Röös E, Schader C, Smith P, van Zanten HHE, Garnett T (2020) Soil carbon sequestration in grazing systems: managing expectations. Clim Change 161:385–391

Gökyer E (2013) Understanding landscape structure using landscape metrics. In: Ozyavuz M (ed) Advances in landscape architecture. InTech, Janeza Trdine 9, 51000 Rijeka, Croatia, pp 663–676

Griffith JA (2004) The role of landscape pattern analysis in understanding concepts of land cover change. J Geogr Sci 14:3–17

Hall K, Reitalu T, Sykes MT, Prentice HC (2012) Spectral heterogeneity of QuickBird satellite data is related to fine-scale plant species spatial turnover in semi-natural grasslands. Appl Veg Sci 15:145–157

Hao Y, He Z (2019) Effects of grazing patterns on grassland biomass and soil environments in China: A meta-analysis. PLoS ONE 14:e0215223

He HS, DeZonia BE, Mladenoff DJ (2000) An aggregation index (AI) to quantify spatial patterns of landscapes. Landsc Ecol 15:591–601

Hesselbarth MHK, Sciaini M, With KA, Wiegand K, Nowosad J (2019) landscapemetrics: an open-source R tool to calculate landscape metrics. Ecography (cop) 42:1648–1657

Hewins DB, Lyseng MP, Schoderbek DF, Alexander M, Willms WD, Carlyle CN, Chang SX, Bork EW (2018) Grazing and climate effects on soil organic carbon concentration and particle-size association in northern grasslands. Sci Rep 8:1–9

Hillenbrand M, Thompson R, Wang F, Apfelbaum S, Teague R (2019) Impacts of holistic planned grazing with bison compared to continuous grazing with cattle in South Dakota shortgrass prairie. Agric Ecosyst Environ 279:156–168

Ho TK (1995) Random decision forests. In: Proceedings of 3rd international conference on document analysis and recognition. vol 1, pp 278–282

Hogenson K, Arko SA, Buechler B, Hogenson R, Herrmann J, Geiger A, Hogenson K, Arko SA, Buechler B, Hogenson R, Herrmann J, Geiger A (2016) Hybrid pluggable processing pipeline (HyP3): A cloud-based infrastructure for generic processing of SAR data. Abstract [IN21B-1740] presented at 2016 AGU Fall Meeting, San Francisco, CA, 12-16 December

Jackson LL (1999) Establishing tallgrass prairie on grazed permanent pasture in the upper midwest. Restor Ecol 7:127–138

Jaeger JAG (2000) Landscape division, splitting index, and effective mesh size: New measures of landscape fragmentation. Landsc Ecol 15:115–130

Jansen BVS, Kolden CA, Greaves HE, Eitel JUH (2019) Lidar provides novel insights into the effect of pixel size and grazing intensity on measures of spatial heterogeneity in a native bunchgrass ecosystem. Remote Sens Environ 235:111432

Kooch Y, Moghimian N, Wirth S, Noghre N (2020) Effects of grazing management on leaf litter decomposition and soil microbial activities in northern Iranian rangeland. Geoderma 361:114100

Kotehenova SY, Vermote EF (2007) Validation of a vector version of the 6S radiative transfer code for atmospheric correction of satellite data. Part II. Homogeneous Lambertian and anisotropic surfaces. Appl Opt 46:4455–4464

Kumar M, Denis DM, Singh SK, Szabó S, Suryavanshi S (2018) Landscape metrics for assessment of land cover change and fragmentation of a heterogeneous watershed. Remote Sens Appl Soc Environ 10:224–233

Lin Y, Hong M, Han G, Zhao M, Bai Y, Chang SX (2010) Grazing intensity affected spatial patterns of vegetation and soil fertility in a desert steppe. Agric Ecosyst Environ 138:282–292

Liu M, Liu G, Zheng X (2015) Spatial pattern changes of biomass, litterfall and coverage with environmental factors across temperate grassland subjected to various management practices. Landsc Ecol 30:477–486

Lopes M, Fauvel M, Girard S, Sheeren D (2017) Object-based classification of grasslands from high resolution satellite image time series using Gaussian mean map kernels. Remote Sens 9:688

Lu X, Kelsey KC, Yan Y, Sun J, Wang X, Cheng G, Neff JC (2017) Effects of grazing on ecosystem structure and function of alpine grasslands in Qinghai-Tibetan Plateau: a synthesis. Ecosphere 8:e01656

Ludvíková V, Pavlů VV, Gaisler J, Hejcman M, Pavlů L (2014) Long term defoliation by cattle grazing with and without trampling differently affects soil penetration resistance and plant species composition in Agrostis capillaris grassland. Agric Ecosyst Environ 197:204–211

Ma S, Zhou Y, Gowda PH, Chen L, Starks PJ, Steiner JL, Neel JPS (2019) Evaluating the impacts of continuous and rotational grazing on tallgrass prairie landscape using high-spatial-resolution imagery. Agronomy 9:238

McGarigal K, Cushman S, Ene E (2012) FRAGSTATS v4: Spatial pattern analysis program for categorical and continuous maps. Computer software program produced by the authors at the University of Massachusetts, Amherst. http://www.umass.edu/landeco/research/fragstats/fragstats.html. Accessed 24 January 2020

Mosier S, Apfelbaum S, Byck P, Calderon F, Teague R, Thompson R, Cotrufo MF (2021) Adaptive multi-paddock grazing enhances soil carbon and nitrogen stocks and stabilization through mineral association in southeastern U.S. grazing lands. J Environ Manag 288:112409. https://doi.org/10.1016/j.jenvman.2021.112409

Ontl TA, Schulte LA (2012) Soil carbon storage. Nat Educ Knowl 3:35

Padwick C, Deskevich M, Pacifici F, Smallwood S (2010) WorldView-2 pan-sharpening. In: ASPRS 2010 Annual Conference. San Diego, California

Park JY, Ale S, Teague WR, Dowhower SL (2017) Simulating hydrologic responses to alternate grazing management practices at the ranch and watershed scales. J Soil Water Conserv 72:102–121

Polley H, Yang C, Wilsey B, Fay P (2019) Heterogeneity predicts local-scale gamma and beta diversity of mesic grasslands. Remote Sens 11:458

Reinermann S, Asam S, Kuenzer C (2020) Remote sensing of grassland production and management—a review. Remote Sens 12:1949.

Ritchie ME (2020) Grazing management, forage production and soil carbon dynamics. Resources 9:49.

Savory A, Butterfield J (2016) Holistic management: A commonsense revolution to restore our environment. Island Press, Washington, DC

Shannon CE (1948) A mathematical theory of communication. Bell Syst Tech J 27:623–656

Souther S, Loeser M, Crews TE, Sisk T (2019) Complex response of vegetation to grazing suggests need for coordinated, landscape-level approaches to grazing management. Glob Ecol Conserv 20:e00770

Stanley PL, Rowntree JE, Beede DK, DeLonge MS, Hamm MW (2018) Impacts of soil carbon sequestration on life cycle greenhouse gas emissions in Midwestern USA beef finishing systems. Agric Syst 162:249–258

Steinauer EM, Collins SL (2001) Feedback loops in ecological hierarchies following urine deposition in tallgrass prairie. Ecology 82:1319–1329

Steiner JL, Starks PJ, Neel JPS, Northup B, Turner KE, Gowda P, Coleman S, Brown M (2019) Managing tallgrass prairies for productivity and ecological function: a long-term grazing experiment in the southern Great Plains, USA. Agronomy 9:699

Su R, Cheng J, Chen D, Bai Y, Jin H, Chao L, Wang Z, Li J (2017) Effects of grazing on spatiotemporal variations in community structure and ecosystem function on the grasslands of Inner Mongolia. China Sci Rep 7:40

Teague R, Barnes M (2017) Grazing management that regenerates ecosystem function and grazingland livelihoods. African J Range Forage Sci 34:77–86

Teague R, Provenza F, Kreuter U, Steffens T, Barnes M (2013) Multi-paddock grazing on rangelands: Why the perceptual dichotomy between research results and rancher experience? J Environ Manage 128:699–717

Teague WR, Dowhower SL, Baker SA, Haile N, DeLaune PB, Conover DM (2011) Grazing management impacts on vegetation, soil biota and soil chemical, physical and hydrological properties in tall grass prairie. Agric Ecosyst Environ 141:310–322

Uuemaa E, Roosaare J, Mander Ü (2005) Scale dependence of landscape metrics and their indicatory value for nutrient and organic matter losses from catchments. Ecol Indic 5:350–369

Vermeire L, Mitchell R, Fuhlendorf S, Gillen R (2004) Patch burning effects on grazing distribution. J Range Manag 57:248–252

Vermote E, Roger JC, Justice CO, Franch B, Claverie M (2016) A generic approach for inversion of surface reflectance over land: Overview, application and validation using MODIS and LANDSAT8 data. 2016 IEEE International Geoscience and Remote Sensing Symposium (IGARSS). Institute of Electrical and Electronics Engineers Inc., Beijing, China, pp 1958–1961

Vermote EF, Tanré D, Deuzé JL, Herman M, Morcrette JJ (1997) Second simulation of the satellite signal in the solar spectrum, 6s: an overview. IEEE Trans Geosci Remote Sens 35:675–686

Virk RS, Mitchell WW (2014) Effect of different grazing intensities on the spatial-temporal variability in aboveground live plant biomass in north American mixed grasslands. Can J Remote Sens 40:423–439

Wagle P, Gowda P (2018) Tallgrass prairie responses to management practices and disturbances: a Review. Agronomy 8:300

Wagner HH, Fortin MJ (2005) Spatial analysis of landscapes: concepts and statistics. Ecology 86:1975–1987

Wang T, Jin H, Kreuter U, Feng H, Hennessy DA, Teague R, Che Y (2020) Challenges for rotational grazing practice: views from non-adopters across the Great Plains, USA. J Environ Manage 256:109941

Wang Z, Yuan X, Wang D, Zhang Y, Zhong Z, Guo Q, Feng C (2018) Large herbivores influence plant litter decomposition by altering soil properties and plant quality in a meadow steppe. Sci Rep 8:9089

Wu J (2004) Effects of changing scale on landscape pattern analysis: Scaling relations. Landsc Ecol 19:125–138

Xun W, Yan R, Ren Y, Jin D, Xiong W, Zhang G, Cui Z, Xin X, Zhang R (2018) Grazing-induced microbiome alterations drive soil organic carbon turnover and productivity in meadow steppe. Microbiome 6:170

Yang X, Guo X, Fitzsimmons M (2012) Assessing light to moderate grazing effects on grassland production using satellite imagery. Int J Remote Sens 33:5087–5104

Zhang C, Dong Q, Chu H, Shi J, Li S, Wang Y, Yang X (2018) Grassland community composition response to grazing intensity under different grazing regimes. Rangel Ecol Manag 71:196–204