Livestock Science 255 (2022) 104801

Contents lists available at ScienceDirect

Livestock Science

journal homepage: www.elsevier.com/locate/livsci

Can cattle geolocation data yield behavior-based criteria to inform precision grazing systems on rangeland?

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ARTICLE INFO

Keywords:
Beef cattle
GPS monitoring
Average daily weight gain
Precision grazing
Precision livestock ranching

ABSTRACT

A key challenge of precision grazing systems is identifying behavior anomalies associated with situations of reduced animal production and wellbeing. We determined typical ranges of diel variation of movement and activity patterns of steers on rangeland to identify metrics that could serve as sensitive indicators of behavior anomalies. Seventeen Raramuri Criollo or Criollo crossbred yearling steers weighing 318 ± 9.3 kg (winter; W) or 358 ± 8.4 kg (late summer; LS) were fitted with GPS collars that recorded animal location at 5-min intervals. Steers grazed a 3,215-ha rangeland pasture for approximately 67 d in W or LS of 2016 and 2017. GPS data were used to derive 22 commonly monitored behavior variables. Means and day-to-day variation (CV%) of all behavior metrics were calculated for each animal as well as linear correlations between the CV of each behavior and ADG. Daily time spent resting or grazing exhibited the least day-to-day variation in both W and LS (CV resting =10.8 and 9.9%, respectively; CV grazing =13.8 and 14.8%, respectively); predawn area explored (CV =240.8%) and time spent at drinkers (CV =336.6%) exhibited the most daily variation in W and LS, respectively. During W, increasing day-to-day variation in daytime distance traveled and area explored, as well as daily time spent traveling were associated with increasing ADG ($r = 0.56$ to 0.58; $P < 0.05$). In LS, steers with greater CV for 24-h area explored, time spent traveling, or daytime distance traveled tended to gain less weight (r =-0.77 to -0.84; $P < 0.01$), while steers with more flexible 24 hour path sinuosity tended to gain more weight ($r = 0.93$; $P <$ 0.01). Behavior metrics more closely associated with forage intake processes, such as daily time spent grazing or resting, exhibited lowest diel variation levels and could be used to diagnose non-normal behavior of cattle on rangeland.

1. Introduction

Worldwide, ranchers and herders are challenged by the need to travel daily through rugged and hard-to-access rangelands to monitor the health and wellbeing of their livestock and must do so in the face of a rapidly dwindling rural workforce. The ubiquity of modern communication tools, however, offers new opportunities to use digital technologies as a means of addressing this challenge. Increasingly sophisticated animal wearable sensors and data mining algorithms are being used to develop precision grazing tools that monitor livestock behavior in real time (Halachmi et al., 2019; Neethirajan, 2017). These technologies are key to precision livestock farming systems that seek to enable livestock producers to adjust management proactively and enhance animal wellbeing and production (Berckmans 2017). A basic challenge of precision animal agriculture, however, is identifying behavior pattern anomalies associated with situations of reduced animal wellbeing (Berckmans, 2017; Wathes et al., 2008). In heterogeneous grazing environments such as rangelands, plasticity of behavior (an animal's ability to change its behavior in response to the environment, Wong and Candolin 2014) is essential to adapt to the ever-changing forage supply (Launchbaugh and Howery, 2005; Provenza et al., 1998) which further complicates detection of atypical livestock behavior.

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1 Deceased.
2 This research was a contribution from the Long-Term Agroecosystem Research (LTAR) network. LTAR is supported by the United States Department of Agriculture. Partial support was provided by the USDA National Institute of Food and Agriculture, Hatch project 1000985 (A. Cibils) and SAS CAP grant # 12726269.

https://doi.org/10.1016/j.livsci.2021.104801
Received 7 May 2021; Received in revised form 20 September 2021; Accepted 2 December 2021
Available online 5 December 2021

Animal wellbeing is defined as the 'freedom to express normal behavior' Kilgour (2012 p.2), but determining what constitutes 'normal behavior' in grazing cattle is challenging because diel activity patterns vary considerably from herd to herd (Kilgour 2012) and individual to individual (Black Rubio et al., 2008; Nyamuryekung'e et al., 2020; Wesley et al., 2012). The use of animal wearable sensors (Neethirajan, 2017), now commonplace in livestock behavior research (Anderson et al., 2013; Knight et al., 2018; Guo et al., 2018; Vanrell et al., 2018), provides opportunities to characterize variation in diel cycles of movement and activity of grazing animals (Sarout et al., 2018) to determine what constitutes a deviation from 'normal behavior'. This definition is urgently needed if increasingly available real-time cattle movement monitoring data (Bailey et al., 2018; McIntosh et al., 2020) are to be used to develop precision grazing systems (Laca 2009) for cattle ranches in western North America.

Although ADG is insensitive to short term (transient) changes in animal wellbeing, we reasoned that it was a logical proxy for medium-term animal welfare condition since it integrates the effects of nutritional, thermal, or other environmental stressors on grazing animals (Grandin, 2016). Our objective was to characterize diel variation of movement, activity, and spatial distribution metrics derived from frequent interval geolocation readings of rangeland beef steers fitted with GPS collars during summer and winter. We also measured steer average daily gain (ADG) to determine its correlation with daily behavior variations. We hypothesized that behaviors associated with forage intake would exhibit the lowest levels of diel variation because steers would prioritize meeting daily dry matter intake requirements. We also hypothesized that metrics associated with non-forage factors (especially weather) and/or with forage search patterns would exhibit highest levels of diel and seasonal variation because ability to adapt to diel variation in weather and/or plasticity of forage search patterns are critical to thermoregulation and to composing diets that meet a steer's short term nutrient requirements. Finally, we hypothesized ADG (our proxy for animal wellbeing) would be negatively correlated with diel variation in forage intake metrics and positively correlated with diel variation in behavior metrics associated with non-forage factors and forage search patterns.

2. Materials and methods

2.1. Study area description

Our study was conducted at the Jornada Experimental Range (JER; 32°37′ N; 106° 40′ W) approximately 40 km north of Las Cruces, New Mexico, USA. The JER is approximately 78,104 ha and our experimental pasture was approximately 3,215 ha in size, with an average elevation of 1200 m. The JER is situated in the northern portion of the Chihuahuan Desert, where the climate is semiarid with warm summers, mild winters, and an average of 230 frost-free days. Mean annual temperature and precipitation are 16.9 °C and 248 mm, respectively. Rainfall primarily occurs during the monsoon season (July through September). Detailed weather variables for the period of this study are provided in Table 1.

Table 1
Mean, maximum, minimum, range, standard error, and coefficient of variation of four diel weather variables, daylight hours, and Normalized Difference Vegetation Indices, during two seasons in two consecutive years ($n = 25 - 35$ d).

Period	Dates	*N*	Variable	Mean	Maximum	Minimum	Range	Standard Error	Coefficient of Variation (%)
Late Summer 1	Oct 4, 2016 – Oct 28, 2016	25	Daily temperature (°C)	19.94	21.89	16.33	5.56	0.28	7.00
			Maximum daily temperature (°C)	29.03	32.22	23.89	8.33	0.48	8.32
			Minimum daily temperature (°C)	10.84	15.00	8.28	6.72	0.40	18.58
			Daily precipitation (mm)	0.00	0.00	0.00	0.00	0.00	.
			Daylight hours	11:21:14	11:45:36	11:02:24	0:43:12	0:02:58	.
			Nighttime hours	12:38:46	12:57:36	12:14:24	0:43:12	0:02:58	.
			16-d NDVI index	0.18	0.27	−0.01	0.32	0.00	.
Late Summer 2	Sep 13, 2017 – Oct 17, 2017	35	Daily temperature (°C)	22.35	26.42	15.25	11.17	0.52	13.64
			Maximum daily temperature (°C)	30.61	36.72	22.22	14.50	0.56	10.91
			Minimum daily temperature (°C)	14.08	21.11	7.78	13.33	0.59	24.69
			Daily precipitation (mm)	0.93	21.34	0.00	21.34	0.64	407.84
			Daylight hours	11:52:48	12:28:48	11:16:48	1:12:00	0:03:34	.
			Nighttime hours	12:07:12	12:43:12	11:31:12	1:12:00	0:03:34	.
			16-d NDVI index	0.19	0.27	0.08	0.31	0.00	.
Winter 1	Dec 16, 2015 – Jan 11, 2016	27	Daily temperature (°C)	4.17	9.75	−1.97	11.72	0.61	76.21
			Maximum daily temperature (°C)	10.72	20.00	3.28	16.72	0.91	44.03
			Minimum daily temperature (°C)	−2.39	2.78	−7.22	10.00	0.49	−105.52
			Daily precipitation (mm)	1.15	23.11	0.00	23.11	0.90	395.98
			Daylight hours	10:05:06	10:14:00	10:01:00	0:13:00	0:00:30	.
			Nighttime hours	13:54:54	13:59:00	13:46:00	0:13:00	0:00:30	.
			16-d NDVI index	0.09	0.21	−0.11	0.37	0.00	.
Winter 2	Dec 3, 2016 – Jan 6, 2017	35	Daily temperature (°C)	8.36	13.83	3.06	10.78	0.52	36.29
			Maximum daily temperature (°C)	15.54	24.39	8.89	15.50	0.71	26.73
			Minimum daily temperature (°C)	1.19	7.22	−3.89	11.11	0.51	250.47
			Daily precipitation (mm)	0.66	12.45	0.00	12.45	0.40	354.77
			Daylight hours	10:04:28	10:09:00	10:02:00	0:07:00	0:00:23	.
			Nighttime hours	13:55:32	13:58:00	13:51:00	0:07:00	0:00:23	.
			16-d NDVI index	0.11	0.21	−0.14	0.54	0.00	.

Pasture 1 was well watered with four permanent drinker troughs evenly spaced throughout and had six small grazing exclosures and was intersected by a series of dirt roads (Spiegal et al., 2019; McIntosh et al., 2021; Fig. 1).

Soils of the northwestern JER are predominantly sandy and vegetation of the study area is dominated by honey mesquite (*Prosopis glandulosa* Torr.) and perennial grasses such as black grama (*Bouteloua eriopoda* Torr.), dropseeds (*Sporobolus* sp.), threeawns (*Aristida* sp.), tobosa (*Pleuraphis mutica* Buckley), and burrograss (*Schleropogon brevifolius* Phil.). Soap-tree yucca (*Yucca elata* av.), broom snakeweed (*Gutierrezia sarothrae* [Pursh] Britt. & Rusby), creosote bush (*Larrea tridentate* [Pursh] Nutt.), and fourwing saltbush (*Atriplex canescens* [Pursh] Nutt.) are also common in the area. Although we did not measure forage quality, black grama (most dominant forage species) averages between 5% digestible protein for cattle when plants are immature or in early bloom (as is presumed for the late summer period of our study) and 3% digestible protein during maturity (as is presumed for the winter periods of our study; Rodgers and Box, 1967). Sixteen-day composite 250 m MODIS Normalized Difference Vegetation Index images were downloaded and projected using ArcGIS 10 (ESRI, Redlands, CA) into WGS 1984 UTM zone 13 N, and were used to compute the average pasture greenness for each study period (Table 1). Pasture greenness was used to infer relative levels of green forage available to steers during this study.

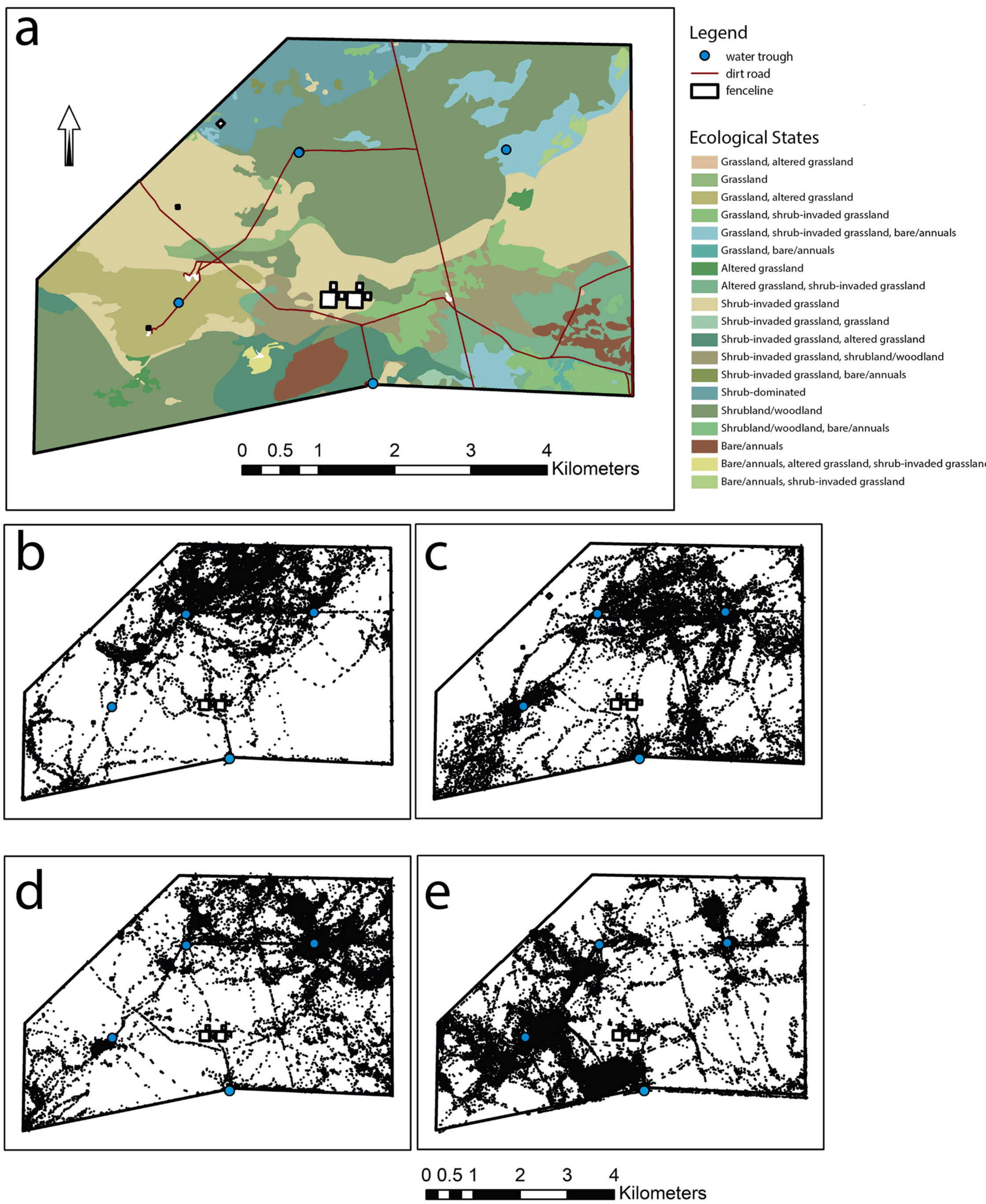

Fig. 1. Map of a) ecological states and pasture infrastructure. Maps of winter (b = cohort1; c = cohort 2) and late summer (d= cohort 1; e = cohort 2) steer GPS fix locations for all steers during study trials. Cohort 1 winter 1 n = 10; Cohort 2 winter 2 n = 8; Cohort 1 late summer 1 n = 7; Cohort 2 late summer 2 n = 9.

2.2. Animals and stocking rates

Animal handling protocols were approved by the New Mexico State University Institutional Animal Care and Use Committee (Protocol 2016–019). Two cohorts of yearling steers totaling 38 Raramuri Criollo (RC) and Criollo × beef breed crossbred (XC) animals were monitored intermittently for 25, 35, 27, and 35 days over a two year period (December 2015 – January 2017) for weight gains and grazing behavior (Table 2). Steers weighed 318 ± 9.3 kg (winter; W) or 358 ± 8.4 kg (late summer; LS) and varied in age depending on cohort and season (min age = 8 mo.; max age = 28 mo.). Crossbreds available to conduct our study were Criollo × Waguli (Cohort 1, C1) and Criollo × Brangus (Cohort 2, C2), belonging to two cooperating ranches: 47 Ranch, Bisbee, Arizona; and Evergreen Ranching, Black Hills, South Dakota.

Steers were kept on rangeland until 30 months of age. Recommended stocking rate for our study area was approximately 5.14 ha • animal unit month (AUM)$^{-1}$ (USDA-NRCS 2017). Our experimental pasture (3215 ha) stocking rate was 8.93 ha • AUM^{-1}(equivalent to a light stocking rate) and was only grazed during the periods of this study.

A subset of randomly selected steers within each biotype and cohort were fitted with GPS collars (Lotek 3300, Lotek Wireless New Market Ontario, Canada) and monitored during winter (W; dormant vegetation) and late summer (LS; end of growing season). GPS collars were configured to collect data at 5-min intervals. Ten Cohort 1 (C1) steers (five RC and five XC) were tracked for 25 days in December 2015 (W). Eight C1 steers (three RC and five XC) were tracked for 27 days in October - November 2016 (LS). Seven cohort 2 (C2) steers (three RC and four XC) were tracked for 35 days in December 2016 - January 2017 (W); and nine C2 steers (six RC and three XC) were tracked for 35 days in September - October 2017 (LS). Two steers, one RC and one XC from C2 could not be retrieved upon the end of their LS trial until a later date, therefore their weight data were not incorporated into our ADG analyses.

2.3. Data processing

Steer weights were recorded to the closest half kilogram and were determined by running animals through the scale twice on each weighing day. Weights were recorded for C1 on Dec. 4, 2015, Feb. 23, 2016, Oct. 3, 2016, and Nov. 30, 2016 and for C2 on Dec. 2, 2016, Jan. 7, 2017, Aug. 31, 2017, and Nov. 8, 2017. Steers were fasted overnight and weighed on the following day. Average daily gain (ADG) was calculated for each steer by subtracting the final weight after each GPS tracking period from the weight recorded at the beginning of the GPS tracking period and dividing the difference by the total number of days in the tracking period.

GPS data collected during four periods throughout the study were used to calculate 22 behavior metrics classified into movement ($n = 9$), activity ($n = 9$) and spatial distribution ($n = 4$) variables (Table 3). Movement metrics included distance traveled (km) and path sinuosity (SI) during four daily time periods: pre-dawn hours (from midnight until sunrise); daytime hours (between sunrise and sunset); post-sunset hours (between sunset and midnight); and 24 h which were calculated using a Java program (GRAZEACT) tested by Sawalhah et al. (2016) and described by Gong et al. (2020). The ratio of day-to-nighttime distance traveled was also included in this category. Activity variables included daily (24 h) time spent traveling, grazing, or resting (h * day^{-1}) and the ratio of traveling-to-grazing time. Daily time spent at the drinker (within 15 m), close to the drinker (within 200 m) or within 1 or 2 miles from the drinker (h* day^{-1}) as well as daily number of visits to the drinker were also included in this category. Spatial distribution metrics included area of the pasture explored (ha) in each of the four daily time segments described above.

GRAZEACT uses the Pythagorean Theorem to calculate distance traveled between two consecutive GPS points. Path sinuosity was calculated using the straightness index (SI) outlined by Batschelet (1981). This index is calculated as: $SI = \frac{dE}{L}$, where dE is the Euclidean distance between the beginning and end of a path and L is the total length of the path. Minimum convex polygon (MCP) was calculated using a convex hull algorithm, which bounded the smallest possible polygon with internal angles ≤ 180° for the same four daily time periods, as listed above (Andrew, 1979). Activities including resting (velocity less than 2.34 m • min^{-1}), traveling (velocities greater than 25 m • min^{-1}), and grazing (velocities between 2.34 m • min^{-1} and 25 m • min^{-1}) were classified following Nyamureyekung'e et al. (2020) who adapted algorithms validated by Augustine and Derner (2013). Augustine and Derner (2013) identified a ~90% accurate classification rate of grazing and non-grazing locations using 5-min GPS intervals as in our study; GPS data in their study was synchronously collected with direct observations over a 4-y period.

Drinking behavior variables were calculated in ArcGIS 10 (ESRI, Redlands, CA). Cattle geolocations were tallied within defined buffered zones around water following Valentine (1947). Tallied fix locations were multiplied by 5-min to determine time spent within each area. These pasture use patterns included time spent near a drinker (within 200-m of water; h*day^{-1}), within 1.6 km of water (h*day^{-1}), and between 1.6 and 3.2 km of water (h*day^{-1}), Drinker visitation rates were calculated using another Java program (GRAZEPIX), which tallied the number of times per day an animal revisited a 30 × 30 m 'pixel'-area around each drinker water source.

2.4. Statistical analyses

We computed means daily for each of the 22 variables and each collared steer in either winter or late summer of both years and then calculated day-to-day CV of the mean for each collared animal using PROC MEANS and the CV Function in SAS 9.4 (SAS Institute, Cary, NC, USA). Winter and late summer diel means and CV of each collared steer were then averaged for the entire group of collared animals. Range of diel CV (i.e. animal-to animal variation) was also computed. To analyze the relationship between ADG and CV of all 22 variables during W and LS, we used PROC CORR in SAS 9.4 (SAS Institute, Cary, NC, USA).

Table 2
Mean and standard error weights and average daily gains and number of GPS-collared steers per biotype, cohort, season, and year of our study.

			Winter				Late Summer			
Year	Cohort	Biotype	GPS	Date	Weight	ADG	GPS	Date	Weight	ADG
2015/16	1	RC[1]	5	12/4/15	285.9 ± 12.3	−0.01± 0.23	3	10/2/2016	341.0 ± 14.4	0.33 ± 0.20
				2/23/16	285.4 ± 11.0			11/30/2016	360.3 ± 22.3	
		XC[2]	5	12/4/15	309.0 ± 9.7	−0.06 ± 0.58	5	10/2/2016	391.8 ± 10.9	0.43 ± 0.07
				2/23/16	304.4 ± 8.9			11/30/2016	417.3 ± 15.6	
2016/17	2	RC	3	12/2/16	323.2 ± 9.2	−0.27 ± 0.04	6	8/31/2017	332.3 ± 4.6	0.88 ± 0.06
				1/7/17	313.4 ± 3.7			11/30/2017	412.8 ± 11.8	
		XC	4	12/2/16	364.3 ± 17.5	−0.45 ± 0.49	3	8/31/2017	388.6 ± 19.7	1.04 ± 0.06
				1/7/17	348.1 ± 14.1			11/30/2017	483.6 ± 4.0	

[1] RC: Raramuri Criollo ($n = 18$).
[2] XC: Criollo crossbred. Waguli × Criollo ($n = 9$) and Brangus × Criollo ($n = 8$) were used for cohorts # 1 and # 2, respectively.

Table 3
Equations used to calculate 22 GPS-derived behavior metrics.

#	Movement	Equation
1	24-hour dist. traveled (km)	The Pythagorean Theorem, $c = \sqrt{a^2 + b^2}$,was used to calculate distance (c) between consecutive GPS locations (a: northing and b: easting: at 5-min intervals) which were summed for the 24-h period (between 12:00 am and 11:59 pm)
2	Daytime dist. traveled (km)	The Pythagorean Theorem, $c = \sqrt{a^2 + b^2}$,was used to calculate distance (c) between consecutive GPS locations (a: northing and b: easting: at 5-min intervals) which were summed for the daytime period (between sunrise and sunset)
3	Pre-dawn dist. traveled (km)	The Pythagorean Theorem, $c = \sqrt{a^2 + b^2}$,was used to calculate distance (c) between consecutive GPS locations (a: northing and b: easting: at 5-min intervals) which were summed for the pre-dawn period (between midnight and sunrise)
4	Post-sunset dis. traveled (km)	The Pythagorean Theorem, $c = \sqrt{a^2 + b^2}$,was used to calculate distance (c) between consecutive GPS locations (a: northing and b: easting: at 5-min intervals) which were summed for the post-sunset period (between sunset and midnight)
5	Night: Day dist. traveled ratio	Total night distance walked/total day distance walked
6	24-h path sinuosity (SI)	The straightness index: $ST = \frac{dE}{L}$, where dE is the Euclidean distance between the beginning and end of a path and L is the total length of the path for the 24-h time period.
7	Daytime path sinuosity (SI)	The straightness index: $ST = \frac{dE}{L}$, where dE is the Euclidean distance between the beginning and end of a path and L is the total length of the path for the hours between sunrise and sunset.
8	Pre-dawn path sinuosity (SI)	The straightness index: $ST = \frac{dE}{L}$, where dE is the Euclidean distance between the beginning and end of a path and L is the total length of the path for the hours between midnight and sunrise.
9	Post-sunset path sinuosity (SI)	The straightness index: $ST = \frac{dE}{L}$, where dE is the Euclidean distance between the beginning and end of a path and L is the total length of the path for the hours between sunset and midnight.
Activity		
10	Time spent traveling (h)	Total time when animal velocity was > 25 m*min. Velocity was calculated as: $v = \frac{\Delta s}{\Delta t}$, where Δs is the change in speed and Δt is the change in time. Change in speed was calculated as $\Delta s = \frac{d}{\Delta t}$, where d is distance and Δt is the change in time. Distance was calculated using the Pythagorean Theorem, $c = \sqrt{a^2 + b^2}$, where a and b represent northing and easting positions, respectively. Change in time was calculated as $\Delta t = t_2 - t_1$, where t_2 was the second time and t_1, the first in chronological order of recording.
11	Time spent grazing (h)	Total time when animal velocity was between 2.34 and 25 m*min. Velocity was calculated as: $v = \frac{\Delta s}{\Delta t}$, where Δs is the change in speed and Δt is the change in time. Change in speed was calculated as $\Delta s = \frac{d}{\Delta t}$, where d is distance and Δt is the change in time. Distance was calculated using the Pythagorean Theorem, $c = \sqrt{a^2 + b^2}$, where a and b represent northing and easting positions, respectively. Change in time was calculated as $\Delta t = t_2 - t_1$, where t_2 was the second time and t_1, the first in chronological order of recording.
12	Time spent resting (h)	Total time when animal velocity was < 2.34 m*min. Velocity was calculated as: $v = \frac{\Delta s}{\Delta t}$, where Δs is the change in speed and Δt is the change in time. Change in speed was calculated as $\Delta s = \frac{d}{\Delta t}$, where d is distance and Δt is the change in time. Distance was calculated using the Pythagorean Theorem, $c = \sqrt{a^2 + b^2}$, where a and b represent northing and easting positions, respectively. Change in time was calculated as $\Delta t = t_2 - t_1$, where t_2 was the second time and t_1, the first in chronological order of recording.
13	Traveling: grazing ratio	Time spent traveling/ time spent grazing
14	Time at drinker (h)	Tallied GPS fixes * 5-min within 15 m buffer around drinker troughs.
15	Time w/in 200 m of a drinker (h)	Tallied GPS fixes * 5-min within 200 m buffer around drinker troughs.
16	Time w/in 1 mile of drinker (h)	Tallied GPS fixes * 5-min within 1.61 km (1 mi) buffer around drinker troughs.
17	Time w/in 2 miles of drinker (h)	Tallied GPS fixes * 5-min within 3.21 km (2 mi) buffer around drinker troughs.
18	Visits to drinkers (#)	The pasture was gridded into 30 × 30 m cells using the Fishnet tool in ArcGIS 10. The Java script for GRAZEPIX tallied the number of times each steer entered each pixel associated with a drinker on a daily basis.
Spatial distribution		
19	24-h area explored (ha)	Andrew's Monotone Chain Convex Hull algorithm was used to determine area explored for the full 24-h between 12:00 and 23:59. The algorithm sorts coordinates in lexicographic order and determines the hull by encompassing any coordinate set that would produce a hull-angle <180 ° So for a polygon (v_0, v_1, …, v_{n-1}), where xy-coordinates of a vertex are deemed v_i, it is assumed that $v_n \equiv v_0$ and that $v_{-1} \equiv v_{n-1}$, and the area of the simple polygon (convex hull) is: $\frac{1}{2}\lvert\sum_{i=0}^{n-1}\delta(o, v_i, v_{i+1})\rvert = \frac{1}{2}\left\lvert\sum_{i=0}^{n-1} x_i(y_{i+1} - y_{i+1})\right\rvert$, where o = (0,0; the origin).
20	Daytime area explored (ha)	Andrew's Monotone Chain Convex Hull algorithm was used to determine area explored for the hours between sunrise and sunset. The algorithm sorts coordinates in lexicographic order and determines the hull by encompassing any coordinate set that would produce a hull-angle <180 ° So for a polygon (v_0, v_1, …, v_{n-1}), where xy-coordinates of a vertex are deemed v_i, it is assumed that $v_n \equiv v_0$ and that $v_{-1} \equiv v_{n-1}$, and the area of the simple polygon (convex hull) is: $\frac{1}{2}\lvert\sum_{i=0}^{n-1}\delta(o, v_i, v_{i+1})\rvert = \frac{1}{2}\left\lvert\sum_{i=0}^{n-1} x_i(y_{i+1} - y_{i+1})\right\rvert$, where o = (0,0; the origin).
21	Pre-dawn area explored (ha)	Andrew's Monotone Chain Convex Hull algorithm was used to determine area explored for the hours between midnight and sunrise. The algorithm sorts coordinates in lexicographic order and determines the hull by encompassing any coordinate set that would produce a hull-angle <180 ° So for a polygon (v_0, v_1, …, v_{n-1}), where xy-coordinates of a vertex are deemed v_i, it is assumed that $v_n \equiv v_0$ and that $v_{-1} \equiv v_{n-1}$, and the area of the simple polygon (convex hull) is: $\frac{1}{2}\lvert\sum_{i=0}^{n-1}\delta(o, v_i, v_{i+1})\rvert = \frac{1}{2}\left\lvert\sum_{i=0}^{n-1} x_i(y_{i+1} - y_{i+1})\right\rvert$, where o = (0,0; the origin).

(*continued on next page*)

Table 3 (*continued*)

22	Post-sunset area explored (ha)	Andrew's Monotone Chain Convex Hull algorithm was used to determine area explored for hours between sunset and midnight. The algorithm sorts coordinates in lexicographic order and determines the hull by encompassing any coordinate set that would produce a hull-angle <180 ° So for a polygon ($v_0, v_1, \ldots, v_{n-1}$), where xy-coordinates of a vertex are deemed v_i, it is assumed that $v_n \equiv v_0$ and that $v_{-1} \equiv v_{n-1}$, and the area of the simple polygon (convex hull) is: $\frac{1}{2}\left|\sum_{i=0}^{n-1}\delta(o, v_i, v_{i+1})\right| = \frac{1}{2}\left|\sum_{i=0}^{n-1} x_i(y_{i+1} - y_{i+1})\right|$, where $o = (0,0$; the origin).

Because coefficients of variation can be affected by the values of the mean, we also used PROC CORR in SAS 9.4 (SAS Institute, Cary, NC, USA) to determine whether CV values and means of the variables we analyzed were related.

3. Results and discussion

Analysis to test for association between CV and means of each behavior metric showed no significant correlation in either winter or late summer. Weather variables for the study periods were within expected ranges for the Chihuahuan Desert (Table 1). Daylight hours were similar between seasons and we recorded no instances of extreme weather that could have biased our characterization of diel variation in foraging behavior. We also found no breed differences in behavior (McIntosh et al., 2021). Daily time spent resting or grazing were the behavior metrics with lowest diel variation in both summer and winter (~ 10% and 14% CV, respectively; Table 4) supporting our first hypothesis. For steers at our research site, a departure from average daily time spent resting (~ 14 h*d^{-1}) greater than 10% or a departure from average daily time spent grazing (~ 8.2 h*d^{-1}) greater than 14% in either summer or winter could signal an anomaly in foraging behavior but a controlled experiment would be needed to corroborate these thresholds. Because these metrics are closely linked to forage intake (time spent grazing) and rumination (time spent resting) we suspect that, in relative terms (i.e. similar CV values), these findings might apply more broadly to the cow herd though further corroboration is needed. Although feeding behavior in cattle is thought to be "one of the best indicators of health and welfare" (Werner et al., 2018, p. 139), contrary to what we had hypothesized, diel variation in neither time spent grazing nor resting were correlated with ADG, our proxy for steer wellbeing. The relatively small day-to-day fluctuations in time allocated to graze or rest were possibly insufficient to affect body weight dynamics. Given the low stocking rate in our study pasture, ADG was likely limited by forage quality (see below) rather than forage intake.

Two activity metrics associated with drinking behavior and three measures of area of the pasture explored by steers were the variables with highest diel CV in both summer and winter (Table 4), partially confirming our second hypothesis. Time spent at the drinker in late summer (CV = 336.6%) and area explored during pre-dawn hours in winter (CV = 240.7%) exhibited the greatest day-to-day variation (Table 4). Movement variables and foraging-related activities (time spent traveling, grazing, or resting) tended to exhibit comparable diel CV in summer and winter (Table 4). Conversely, largest seasonal differences in diel CV were observed for activities associated with drinking behaviors and area of the pasture explored (LS<*W*). Interestingly, behavior metrics with highest levels of diel or seasonal variation were variables strongly influenced by non-forage factors (thermal environment, precipitation events) that vary greatly between days and seasons.

Average daily gain of steers in summer and winter of both years combined was 0.69 ± 0.1 and −0.14 ± 0.08 kg*d^{-1}, respectively (McIntosh et al., 2021). Variation of two foraging behavior metrics (daytime distance traveled and time spent traveling) and one spatial distribution metric (area of the pasture explored) were correlated with ADG in both winter and late summer albeit with different strength (*W*<LS) and opposite signs (Fig. 2). Higher levels of diel variation in these behaviors favored ADG in winter but the opposite was true in

Table 4
Means and diel variation of 22 GPS-derived foraging behavior metrics of steers (n = 34) grazing a large Chihuahuan Desert pasture during two seasons in two consecutive years (n = 27 – 35 d). Variables were grouped into categories with similar units and ranked from least (# 1) to most (# 22) variable.

		Winter				Late Summer			
GPS - derived behavior metrics	GPS - derived behavior metrics	Mean	CV (%)	CV Range (%)	Rank	Mean	CV (%)	CV Range (%)	Rank
Movement									
1	24-hour dist. traveled (km)	10.5	33.3	24.5 - 41.9	7	9.3	34.9	19.7 - 53.8	6
2	Daytime dist. traveled (km)	5.6	42.7	34.0 - 54.4	8	5.4	39.3	27.6 - 52.2	7
3	Pre-dawn dist. traveled (km)	1.5	53.5	53.7 - 128.8	10	1.6	64.2	38.7 - 101.7	12
4	Post-sunset dis. traveled (km)	3.4	86.5	31.0 - 67.8	14	2.3	70.4	36.7 - 98.5	15
5	Night: Day dist. traveled ratio	0.9	21.3	17.8 - 32.7	3	0.7	17.5	22.2 - 37.2	3
6	24-h path sinuosity (SI)	0.2	65.5	54.9 - 87	12	0.2	65.3	39.3 - 87.3	13
7	Daytime path sinuosity (SI)	0.4	47.5	38.5 - 59.8	9	0.4	48.9	30.9 - 63.2	8
8	Pre-dawn path sinuosity (SI)	0.4	73.2	55.0 – 132.0	13	0.4	66.1	40.0 - 78.4	14
9	Post-sunset path sinuosity (SI)	0.6	86.5	28.4 – 41.0	15	0.4	52.5	37.5 - 66.8	10
Activity									
10	Time spent traveling (h)	2.2	60.8	45.1 – 77.0	11	1.8	60	39.1 - 86.9	11
11	Time spent grazing (h)	8.2	13.8	10.2 - 18.3	2	8.2	14.8	10.9 – 20.0	2
12	Time spent resting (h)	13.6	10.8	8.2 - 17.8	1	14	9.9	6.9 – 15.0	1
13	Traveling: grazing ratio	0.3	21.5	32.2 - 64.7	4	0.2	21.7	34.0 - 74.6	5
14	Time at drinker (h)	1.1	182.9	124.8 - 255.9	21	0.2	336.6	262.8 - 472.5	22
15	Time w/in 200 m of a drinker (h)	2.7	98.9	58.6 - 144.4	18	2	119.9	62.3 - 177.7	17
16	Time w/in 1 mile of drinker (h)	18.3	27.5	20.6 - 34.9	6	21.2	19	7.7 - 33.9	4
17	Time w/in 2 miles of drinker (h)	5.6	90.7	68.2 - 131.6	16	2.7	180.5	94.6 - 286.4	20
18	Visits to drinkers (#)	1.0	21.6	0.0 - 42.5	5	0.8	52.2	13.6 - 93.1	9
Spatial distribution									
19	24-h area explored (ha)	188.7	93.2	57.2 - 103.4	17	116	113.1	59.6 - 146	16
20	Daytime area explored (ha)	91.8	120.6	76.9 - 171.3	19	64.1	131	116.4 - 146.6	18
21	Pre-dawn area explored (ha)	14.4	240.8	198.0 - 324.4	22	9.1	179.3	102.0 - 295.7	19
22	Post-sunset area explored (ha)	42.9	125.4	92.2 - 171.5	20	19.7	184.6	120.9 - 298.3	21

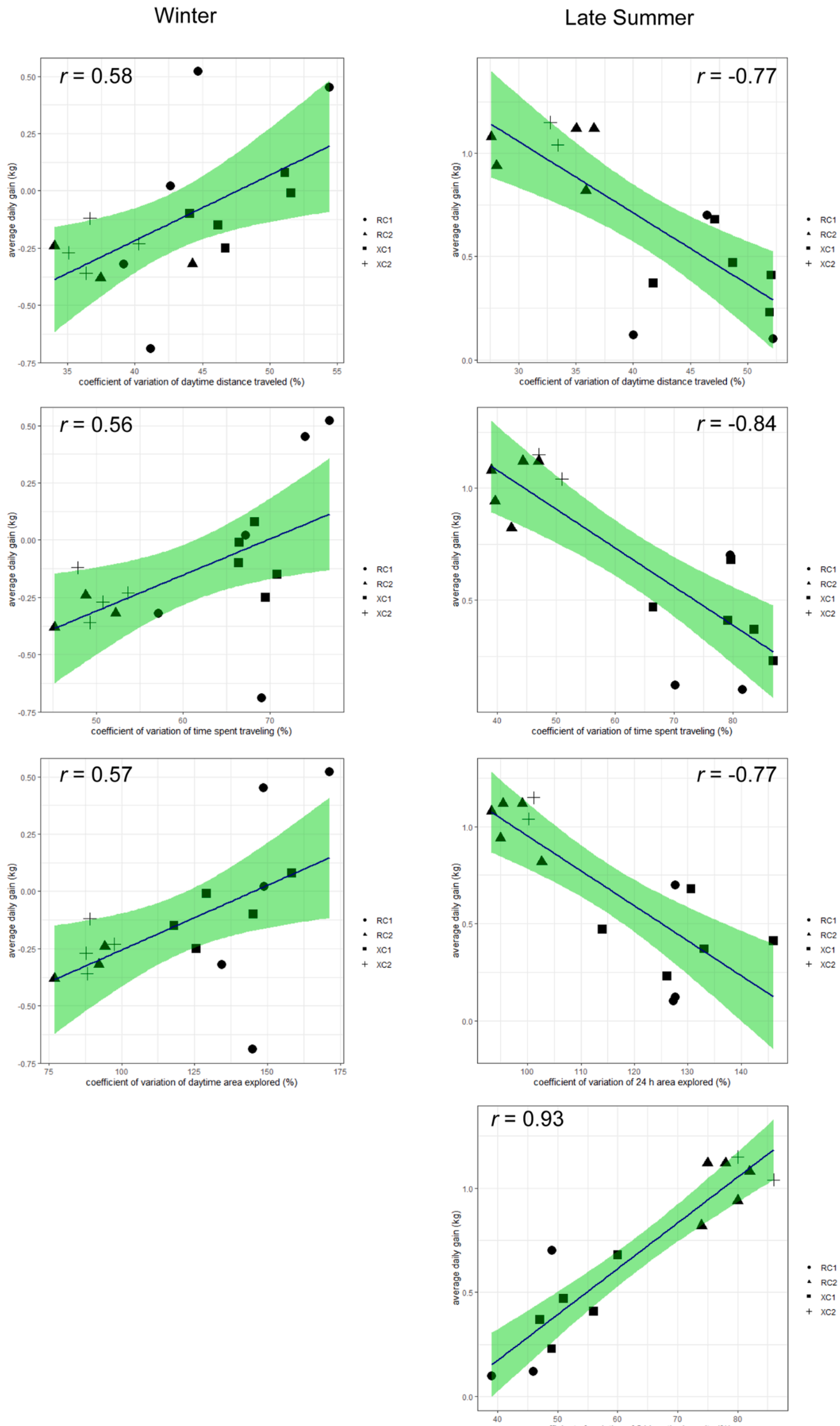

Fig. 2. Pairwise correlations between diel variation in selected GPS-derived foraging behavior metrics and ADG of steers in winter ($n = 17$) and late summer ($n = 15$) grazing a large Chihuahuan Desert pasture for 25 to 35 day in winter and 27 to 35 days in late summer in two consecutive years. We did not track the same animals in winter and late summer. Symbols on each graph represent a collared steer. Different symbols were used for Raramuri Criollo steers in cohorts 1 and 2 (circles and triangles, respectively) and crossbred steers in cohort 1 (Waguli × Raramuri Criollo, squares) and cohort 2 (Brangus × Raramuri Criollo, crosses).

summer (Fig. 2). This contrast may have reflected the stark difference in seasonal patchiness of forage quality (*W*>LS; see NDVI indices in Table 1).

In winter, behaviors correlated with ADG exhibited intermediate to high levels of diel variation (rankings 8 to 19; Table 4). Increased diel variation in daytime travel (both in terms of distance and time invested in this activity) and daytime area covered were associated with greater ADG, partially supporting our third hypothesis. This variation was perhaps associated with more plasticity in searching behaviors, a pattern that could reflect greater selectivity at the patch and plant community scales (Bailey et al., 1996) and a trait that is likely advantageous in heterogeneous grazing environments (Allred et al., 2014). Low diel variation in average daytime distance traveled (< 40%), time spent traveling (< 60%) or daytime area explored (< 120%) could signal unfavorable grazing conditions (as well as imminent welfare challenges) for steers grazing desert rangeland during winter.

In late summer, increasing diel variation in daytime distance traveled, time spent traveling, and 24 h area explored (i.e. day-to-day changes in search behavior) were all associated with declining ADG ($r = -0.77$ to -0.84; $P < 0.05$; Fig. 2), contrary to what we had predicted. Conversely, increasing diel variation in path sinuosity (i.e. possible plasticity in patch selection) was strongly correlated with increasing ADG ($r = 0.93$; $P < 0.05$; Fig. 2). Thus, day-to-day consistency in time and effort allocated to search for forage, but flexibility in movement trajectory (search patterns) were correlated with increasing ADG, likely due to the collective influence of these behavior metrics on intake levels and diet quality. Interestingly, diel variation in search behavior metrics were correlated with patterns of drinker visitation. Steers that gained the most weight tended to exhibit greatest flexibility in search behaviors and least day-to-day variation in number of visits to water (i.e. they visited the drinker only once on most days). The straightness index we used to assess path sinuosity is strongly influenced by the physical structure of vegetation (Benhamou 2004); therefore, diel variation in sinuosity may have been associated with a steer's ability to either selectively forage in different vegetation types (shrub-dominated = more sinuous path vs. grass-dominated = less sinuous path) or to opportunistically hone in on more nutritious forage patches or feeding stations along its daily foraging trajectory. Overall, high diel variation in daytime distance traveled (> 39%) or time spent traveling (> 60%) or 24 h area explored (> 113.1%) or low diel fluctuation in path sinuosity (< 65%) during late summer could signal unfavorable conditions that could lead to reduced weight gains and potential animal wellbeing challenges.

4. Management implications

Behavior metrics more closely associated with forage intake processes, such as daily time spent grazing or resting, exhibited lowest diel variation levels and could be used to diagnose non-normal behavior of cattle on rangeland. Monitoring diel variation in search behaviors (summer and winter) or path sinuosity (summer) could provide further criteria to identify imminent weight gain challenges and prevent potential animal wellbeing problems. Researchers in the United States and elsewhere have gathered massive amounts of livestock geolocation data over the past 25 years (see references cited in Anderson et al., 2013, (Millward et al., 2020); Raynor et al., 2021). Our results suggest that an interdisciplinary coordinated effort to mine these data sets with cutting-edge methods used for big data analytics would accelerate the development of precision grazing tools for western US ranches.

Acknowledgments

We wish to dedicate this manuscript to our dear collaborator, mentor, and friend, Alfredo Gonzalez who selflessly dedicated himself to this and many other studies that evaluated Criollo cattle which he was endlessly passionate about investigating and preserving. We wish to thank Guadalupe Continanza for her contributions to our Java software and Dr. Jerry L. Holechek for comments on an earlier version of this manuscript.

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