Spatial distribution of cattle foraging behavior on contrasting landforms in Horqin Sandy Land of northern China

(中国北部ホルチン沙地の対照的な地形における牛の採食行動分布)

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A dissertation submitted to

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Chapter 1

General introduction

Chapter 1. General introduction

1.1 Background of the study

Drylands cover more than 40% of the earth's land area, and desertification directly affects over 250 million people (Reynolds et al., 2007). Although the population density in the dryland areas is much lesser than other areas, their life and economy heavily rely on the local resources (Enfors et al., 2007). In dryland, livestock is the primary source of food and the major livelihood of the herdsman (Martin et al., 2016). And the landscape in dryland is always of grassland. Forage resources from the grassland and sustainable use of the grassland are of critical in maintaining the livelihood of local people and the stability of the ecosystem and the society (DeYoung et al., 2000; Briske et al., 2008). However, in past several decades, with the booming of population and the change in grassland management policy, the livestock has doubled/tripled, which is considered to be one of the major causes of severe desertification in the dryland. (Wang, 2002; Glindemann et al., 2009b).

Previous studies have shown that nearly 90% of the grasslands in northern China are degraded to some extent (Nan, 2005). Grassland degradation is mostly attributed to overgrazing and conversion of grassland to cropland as well as an unregulated collection of fuel and medicinal plants (Akiyama and Kawamura, 2007). The Horqin sandy land (Figure 1.1) is one of the four sandy lands in northern China. It is proved to be one of the major dust source regions that ravaged the Beijing and other northern areas of China. The land in Horqin has undergone severe desertification due to the overuse of grassland and over-exploitation and mismanagement of the grassland (Zhu and Wang, 1992). The total number of livestock increased from 2.32 million in 1970 to 9.5 million (an increase of 309.5 %) in 2010 (Duan et al., 2014). Besides the misuse of the grassland in Horqin sandy land, the climate change could also contribute to the desertification in the Horqin sandy land (Ge et al., 2015). Many field experiments and modelling studies were carried out to determine the relative contribution of climate change and livestock grazing to the desertification (Sun et al., 2019; Briske et al., 2013; Li et al., 2000; Cerdà et al., 1999). In most of the livestock grazing experiments, the number of livestock per unit areas is considered as the surrogate of grazing pressure or foraging density (Pringle et al., 2004; Butt et al., 2010). This kind of studies provides some insights on how the livestock impacts the plant community composition, productivity, and soil properties (Qu et al., 2016; Jing et al., 2014). One assumption of these studies is the even distribution of livestock grazing. However, even in areas with flat topography, the livestock grazing is uneven. In Horqin Sandy Land, the landscape is characterized by the sand dunes and interdune lowland in Figure 1.1(Zhang et al., 2012). The average size of sand dunes is around the height of 5–8 m, length of 400–600 m, and width of 20–40 m (Zhang et al., 2005). From 1980 to 2014, the annual mean temperature was 7.3 °C, and the annual mean precipitation was 318mm, with 70–80% of the precipitation occurring between June and August (Liu et al., 2014). The average annual wind speed ranged from 3.2 to 4.5 m s−1, with most windy days and windstorms occurring between March and May (Zhang et al., 2012).

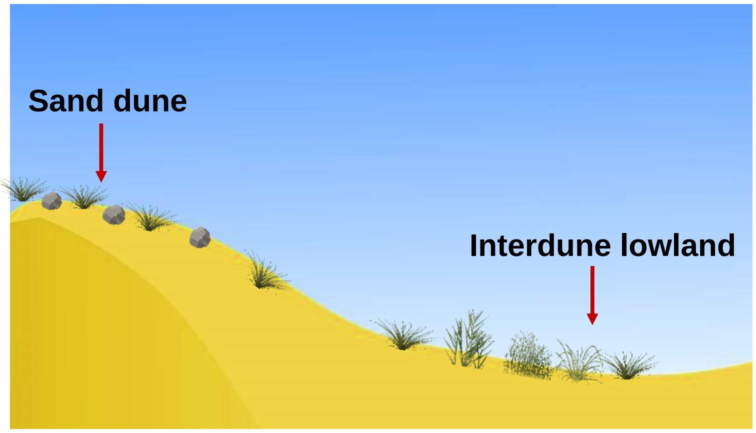

Figure 1.1 The schematic diagram of contrasting landform in Horqin Sandy Land including sand dune and interdune lowland

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Previous studies applied grazing density directly on plant communities and soil properties to these areas (Zhang et al., 2005; Li et al., 2012; Tang et al., 2016). The spatial layout of the sand dunes and inter-dune will result in the heterogeneous distribution of soil moisture, forage resources, etc., which therefore would lead to the uneven grazing of livestock. When an area of sandy land is overgrazed due to the uneven distribution of grazing pressures, the desertification may start from the over-grazed area. Moreover, it neglects the spatiotemporal dynamics of actual foraging pressure and the desertification of semiarid grassland is still ongoing (Miao et al., 2015).

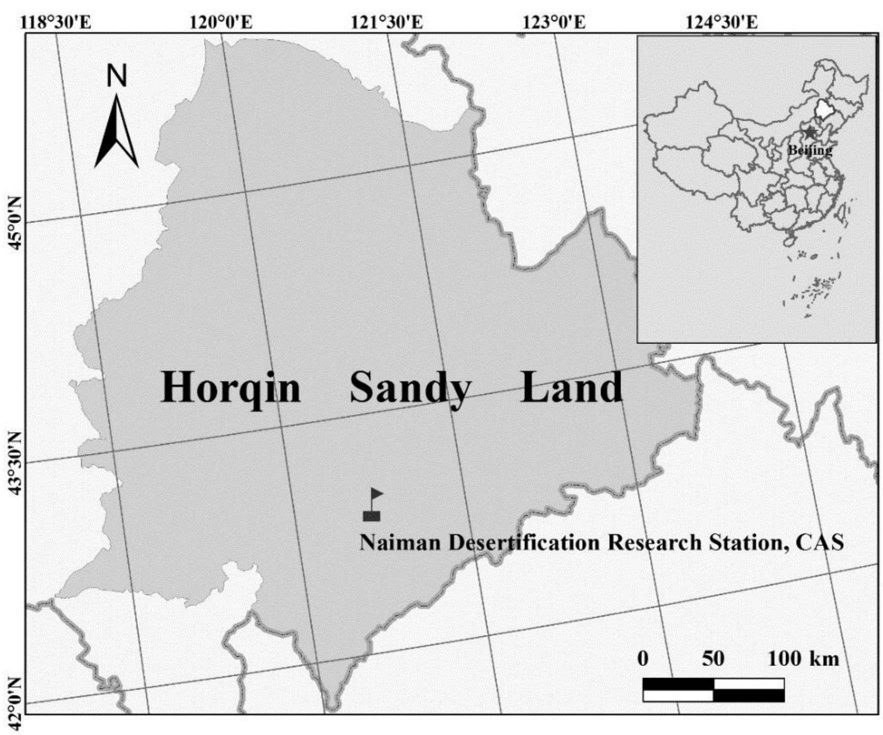


Figure 1. 2 Location map of Horqin Sandy Land in northern China

Livestock in heterogeneous landscapes often adopts different seasonal foraging strategies as a response to temporal changes in resource availability (VanderWaal et al., 2017). The critical driving factors related to the abiotic such as the settlement of watering points and topography, biotic factors such as pasture quality and quantity are strongly determined the selective distribution pattern (Coughenour et al., 1991). However, these factors are often ignored to consider in the practical management of livestock grazing, which is crucial for preventing degradation and restoration of degraded grassland by conducted fine and various types of management grazing (DeYoung et al., 2000; Briske et al., 2008; Hao et al., 2018).

Previous studies found out that different grazing behaviors have a various effect on the grassland. The walking behavior will trample and land surface and change the physical characteristics, then the hydrological cycling, and finally lead to land degradation (Jewell et al., 2001). The foraging and preferential foraging of certain species will reduce the productivity and change plant community composition, which consequently will change the biogeochemical cycling of the grassland and lead to the vegetation degradation (Bagchi et al., 2010). On the other hand, livestock is found to be able to maintain plant diversity and main productivity stability (Bagchi et al., 2010). Among the different behaviors, foraging exerts the most important influence on the grassland.

1.2 The effort to cattle foraging

1.2.1 Cattle behaviors classification

In pasture ecology, measurement of grazing behavior of livestock is an important component of many researches of grazing system. Time spent by livestock in grazing activities such as foraging, ruminating and resting reflect efficient resource use, productivity, and impacts on ecosystem functioning (Allden and Whittaker, 1970; Hasegawa and Hidari, 2001). Foraging can increase or decrease heterogeneity of vegetation, depending on pre-existing vegetation patterns and the strength of plant-soil interactions (Adler et al., 2001). Walking and trampling of animals could lead to soil compaction and is a potential source of soil erosion. Resting is often associated with deposition of excreta which can, together with herbage removal by grazing, lead to a large-scale redistribution of nutrients over the pasture area (Jewell et al., 2007). Pastoral livestock micro-mobility has been used to infer how animals cope with environmental variability by documenting seasonal patterns of forage intake and energy expenditure.

Understanding sustainable grazing systems requires modelling methods that can accurately describe the individual components of livestock behavior as they interact across space and time. Accurate behavioral models provide important information about diet selection, herbage intake and how the grazing animal modifies the environment. One such method involves applying several statistical (Bestley et al., 2012) and deep-learning (Mellone et al., 2011) models to collected data from accelerometers for classifying livestock behaviors, which have been developed by using large datasets placed on animals in managed grassland (Buho et al., 2011). These accelerometers measure the instantaneous and independent local movement of animals' legs, heads, or bodies, thus ensuring high accuracy of behavior classification (Braun et al., 2013). However, accelerometers cannot provide information regarding the location of the livestock, which is crucial for identifying the spatial distribution of animals and grassland management. Another method is to use Global Positioning System (GPS) data and machine-learning algorithms to classify livestock behaviors (Schlecht et al., 2004). Using the location records, the GPS data-based method can project the spatial distribution of various behaviors, which is crucial for herd management and the prevention of rangeland degradation. GPS data-based methods require an optimal time interval, during which metrics such as linear distance (d), cumulative distance (d), and turning angle are calculated to predict behaviors (Mellone et al., 2011). To build models for predicting livestock movement, the time intervals for metric calculation have previously been selected empirically (Anderson et al., 2012). The optimal time interval for GPS data-based methods varies with the ecosystem, livestock species, topography, and spatial distribution of available resources to evaluate (Witte et al., 2005). Therefore, the question arises how to gain behavioral information from position data alone and to what extent this is possible.

1.2.2 The effects of biotic factor on cattle foraging behavior

Forage quality and quantity affect livestock distribution, and the time of animal spent in a plant community is proportional to the quality and quantity of forage available (Senft 1989). Livestock spends more time in areas of the pasture that are more productive and have higher levels of forage quantity and/or quality, and they spend less time in areas with less food (Duncan 1983; Taylor 1984; Owens et al. 1991). This often results in slower grazing velocity and greater residence time relative to other grazing areas available to the animal.

Moreover, the physical structure and chemical composition of forages vary greatly from the season so season (Bennett et al., 2007; Kennedy et al., 2007). While the quality specific plants community livestock preferred, which results in bite-size declines, at least partially compensatory changes in grazing time and rate of biting (Davies and Southey, 2001). Decreased forage quality also increases time spent in ingested mastication (Sahlu et al.,1989; Lachica and Aguilera, 2003). However, the interaction effects of seasonal variation and management on animal behavior have not been explored. Knowledge of this interaction can be harnessed for improving the management of grazing animals. This knowledge could be used to optimize forage allocation to different grazing ruminants and enable herders to identify vegetation attribution on which to base the rangeland restoration practices.

1.2.3 The effects of abiotic factor on cattle foraging

Quantifying spatial heterogeneity is a central focus of landscape ecology (Turner 2005) with abiotic factors (slope, elevation, distance to water) for cross-site comparisons are stable across time (Bolliger et al. 2007). The rugged terrain strongly facility the uneven grazing distribution while the livestock spent more time on gentle terrain and left other areas ungrazed (Bailey et al. 2015; Ganskopp and Vavra 1987; Mueggler 1965). For example, Gillen et al. (1984) reported cattle avoided forging in areas with slopes greater than 20%.

Moreover, elevation differences can lead to a heterogeneous distribution of available resources and differences in plant community composition and soil type (Miyasaka et al., 2011). Livestock forages longer in a nutrient-rich patch in an area with heterogeneous topographic features, but they rarely forage in the same patch for several consecutive days in a homogeneous environment (Bailey, 2005).

Spatial differences in the quality and quantity of herbage due to rugged terrain on a ranch will lead to a heterogeneous distribution of livestock (Henkin et al., 2012). Livestock prefers to spend more time in relatively flat areas where lower energy consumption is required for grazing activities (Parker et al., 1984). Few studies related to livestock grazing distribution have included slope and elevation in cattle distribution models (Bailey et al. 1996; Clark et al. 2014; Clark et al. 2016) generated model coefficients are specific to a given study pasture.

1.2.4 Water settlement on cattle foraging

Location of watering facilities on grazing system has been widely recognized as a factor restructuring the livestock grazing system and controlling foraging distribution of livestock grazing in arid and semi-arid (Western, 1975, de Leeuw et al., 2001). For example, during periods of limited water availability, livestock tends to move their water-dependent towards remaining water bodies (Western, 1975, Coppolillo, 2000, de Leeuw et al., 2001). Thus, livestock concentration may cause habitat degradation by changing plant structure and composition around these water bodies (Andrew, 1988, Johnson, 1993, Pickup et al., 1998).

Also, distance to water can have a major effect and result in a grazing gradient where overgrazing occurs near the watering point while pasture remains underutilized away from the watering point (Malan et al., 2018). Therefore, distance to water must be considered when calculating the carrying capacity of a paddock. If paddocks are stocked simply according to paddock size, areas close to the water will be over-grazed while remaining parts of the paddock will be underutilized (Dubeux et al., 2009).

1.2.5 Ranch management on cattle foraging

Poor grazing distribution within pastures has been and continues to be a major problem confronting livestock manager (Bailey et al., 2004). Therefore, the management of livestock grazing requires a sound understanding of the variation of livestock behaviors on the pasture ecosystems. As the majority of pastures are heterogeneous, there are spatial differences in the quality and quantity of pasture across the landscape (Homburger et al., 2015). Based on the logical reasoning research, the implements of rotational grazing systems subdivided pastures into several small paddocks with altering the temporal grazing density to achieve more foraging distribution (Norton et al., 2013). By doing this, overgrazing areas were avoided and allow adequate recovery time for the forages between grazing events (Teague et al., 2011).

On most range and pasture systems, the goals of management improvement were to provide more uniform grazing without reducing livestock numbers (Hunt et al., 2007). Determining the appropriate practices to implement takes a thorough appreciation for the interaction between an animal’s foraging behavior and driving factors that contribute to poor grazing distribution (Hunt et al., 2007).

1.3 The objectives of the study

The main objective of this study is to understand cattle foraging distribution and affecting factors over grazing season on the contrasting landforms of the fenced ranch. The specific objective to be perused under this study include:

- To identify cattle different behaviors by GPS recording locations and in the Random forest algorithm.
- To investigate the seasonal dynamics of spatial distribution of cattle foraging behaviors and driving factors on lowland and sand dunes.
- To understand the probability of spatial distribution of cattle foraging areas and affecting factors over the grazing season on the contrasting landforms

1.4 The structure of the thesis

The thesis is organized into five chapters (Figure 1.3). This chapter (Chapter 1) is devoted to is to understand cattle foraging distribution and driving factors over grazing season on the contrasting landforms of the fenced ranch. This is help readers to understand the extent of the problem and lay the ground to the rest of the chapters. Chapter 2 is devoted to proving cattle different behaviors by GPS recording locations in the Random forest algorithm. Thus, Chapter 3 is to investigate the seasonal dynamics of cattle grazing distribution patterns and driving factors between lowlands and sand dunes areas. In Chapter 4, we developed models to predict probability of spatial distribution of cattle foraging and driving factors over the grazing season on the contrasting landforms. The last chapter, Chapter 5, presents the main synthesis of the thesis.

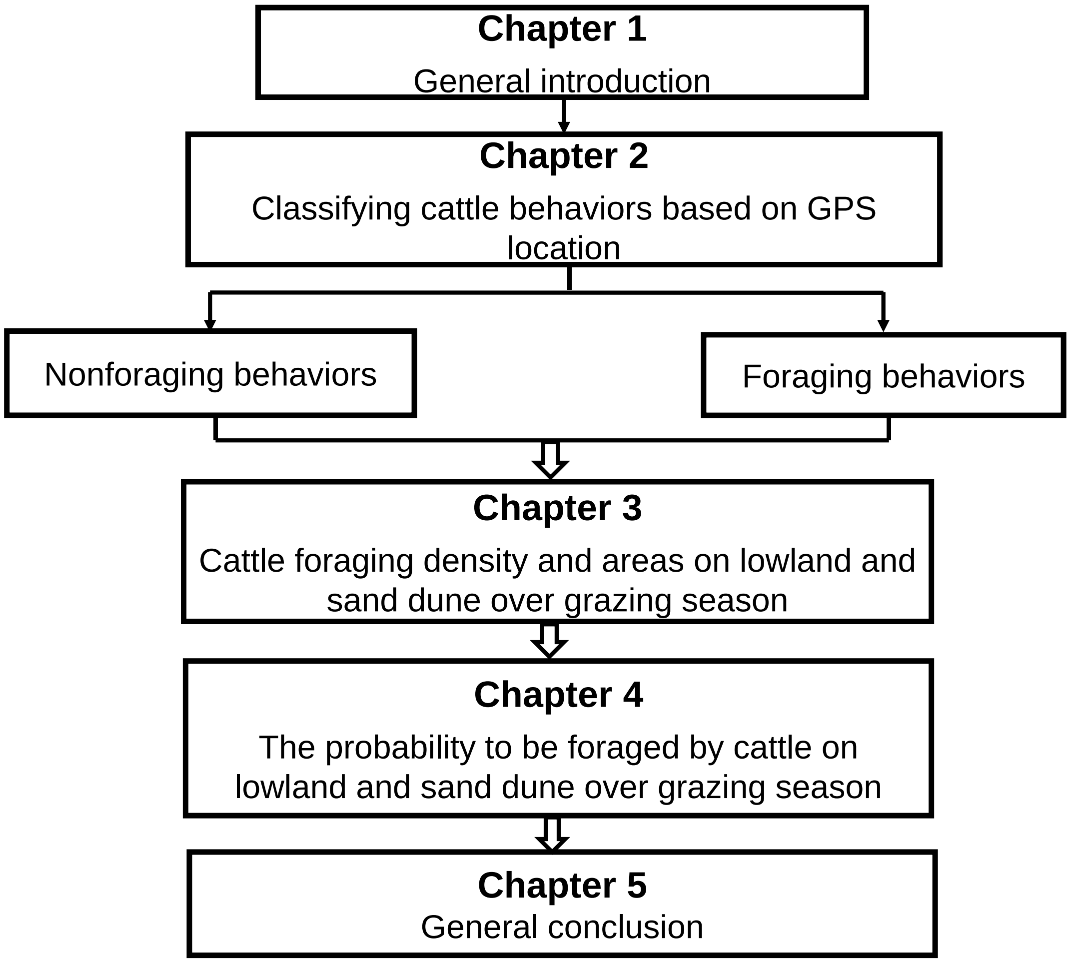


Figure 1.3 Flow chart of this thesis

Chapter 2

Method for Classifying Behavior of Livestock on Fenced Temperate Rangeland in Northern China

Sensors 19(23): 5334

Chapter 2. Method for classifying behavior of livestock on fenced temperate rangeland in northern China

2.1 Introduction

Drylands cover more than 41% of the Earth's land area, and desertification directly affects more than 250 million people (Reynolds et al., 2007). Overgrazing is considered to be the primary cause of land degradation (Massa et al., 2012). Previous studies examining overgrazing of rangeland generally used the number of livestock in a given area as the grazing intensity; this practice assumes that livestock foraging is spatially distributed evenly and that all livestock behaviors have the same influence on the rangeland (Okayasu et al., 2010). However, the livestock always shows patchy and selective grazing even in homogenous rangeland to minimize their activity range and to maximize energy use efficiency (Manthey et al., 2010). In fact, vegetation typically shows a mosaic distribution, whether induced by abiotic factors, such as elevation and slope, or by selective grazing, which aggravates the overuse of some areas of the grassland (Bailey et al., 1996).

The spatial distribution of different behavioral activities was critical for understanding the effects of grazing on ecosystem function, growth, reproduction and survival, how to make efficient use of resources (Anderson et al., 2012), and mechanisms for coping with environmental conditions (Anderson et al., 2012). In the grazing areas, the vegetation was significantly reduced by the selective foraging of livestock. Moreover, concentrated grazing depletes the soil of nutrients (Li et al., 2008) thus promotes further degradation of grassland (Fernandez et al., 2001), whereas light grazing can improve plant diversity by restraining inherent inter and intra-specific competition (Scimone et al., 2007). In comparison, nongrazing behaviors including resting and walking trample plants and compact the soil surface in overused areas, and the cumulative deposition of excreta alters various physical properties of soil, including soil bulk density, aggregate stability, aggregate size distribution and surface microrelief. Recovering rangeland from degradation due to nongrazing behaviors is considered more difficult than remediating the effects of concentrated grazing (Warren et al., 1986).

Accurately classifying different behaviors of livestock is necessary to understand rangeland degradation and to devise effective interventions to restore the degraded land. One such method involves applying several statistical (Lagarde et al., 2008) and deep-learning (Cornou et al., 2008) models to collected data from accelerometers for classifying livestock behaviors, which have been developed by using large data sets placed on animals in managed grassland (Martiskainen et al., 2009; González et al., 2015). These accelerometers measure the instantaneous and independent local movement of animals' legs, heads, or bodies, thus ensuring high accuracy of behavior classification (Fahlman et al., 2008; Gleiss et al., 2010; Green et al., 2009; Halsey et al., 2008). However, accelerometers cannot provide information regarding the location of the livestock, which is crucial for identifying the spatial distribution of animals and grassland management. Another method is to use Global Positioning System (GPS) data and machine-learning algorithms to classify livestock behaviors (Homburger et al., 2014). Using the location records, the GPS data-based method can project the spatial distribution of various behaviors, which is crucial for herd management and the prevention of rangeland degradation. However, GPS data-based methods require an optimal time interval, during which metrics such as linear distance (d), cumulative distance (d), and turning angle (t) are calculated to predict behaviors (Cornou et al., 2008). To build models for predicting livestock movement, the time intervals for metric calculation have previously been selected empirically (Schlecht et al., 2004; Homburger et al., 2014). The optimal time interval for GPS data-based methods varies with the ecosystem, livestock species, topography, and spatial distribution of available resources to evaluate (Weerd et al., 2015).

The Horqin Sandy Land in northern China has been seriously degraded since the mid-1980s, and various restoration countermeasures (e.g., fencing) have been introduced to restore the degraded land (Li et al., 2015). In Horqin Sandy Land, the average area of the fenced rangeland per household is approximately 15 to 30 ha (Zuo et al., 2009). Fencing limits the space, and thus the forage, available to animals and consequently might aggravate mosaic grazing in areas; in addition, dense walking along the fence might lead to mosaic degradation. The objectives of our study were to develop a method for classifying livestock behavior by using location information and to define the optimal time interval for a GPS data-based model for fenced rangeland.

2.2 Materials and Methods

The study was conducted in a fenced household pasture, which is located in the southwestern part (42°55′N, 120°42′E; altitude, ~360 m) of Horqin Sandy Land, China. The climate is temperate, semi-arid, continental, and monsoonal. Average annual precipitation is 360 mm, with an annual mean temperature of 6.4 °C. The minimal and maximal monthly mean temperatures are –13.1 °C in January and 23.7 °C in July, respectively.

The pasture was grazed by Simmental cattle from 1 July through 1 October 2018 (three months). During our study, the rangeland area was 20.1 ha, and herd size was 13 cattle. The stocking rate was calculated in terms of the common method (Scarnecchia et al., 1985), which the value was 0.51 Animal Unit Months per hectare. The total grazing time was approximately 3 months yearly due to the implement of ‘suspending grazing’ policy by the local government, which was for preventing grassland degradation. The availability of forage in our study area was about 53 g/m^2 in July and 243 g/m^2 in August for enclosure rangeland (Zuo et al., 2012). The vegetation was composed mainly of herbage belonging to arid grassland types (*Pennisetum centrasiaticum*, *Cleistogenes squarrosa*), with some dwarf shrubs (*Artemisia oxycephala, Artemisia halodendron*).

2.2.1 Equipment and animals

All 13 cattle in the pastured herd were fitted with GPS devices (catalog no. GT-600, i-gotU, Mobile Action Technology, Taipei, Taiwan) and tri-axis accelerometers (catalog no. UA-004-64, Hobo model, Onset, Bourne, MA, USA). GPS devices were attached on the neck only, whereas tri-axis accelerometers were placed on the neck, one leg, and the tail of each animal. The GPS device recorded cattle location at 50-s intervals throughout two consecutive days, after which the GPS devices were removed, recharged, and re-attached to the cattle; this process continued throughout the 10-d study period. The three-dimensional accelerometers recorded the anterioposterior, transverse, and superior-inferior acceleration of livestock movement. The batteries of the tri-axis devices were able to record acceleration at 50-s resolution throughout the 10-day study period without needing to be recharged.

2.2.2 Observation of livestock behaviors

Classification and criteria for animal behavior followed the method of Ganskopp and Bohnert , 2012. The direct visual behavioral observation was recorded continuously by one observer following one cattle at approximately 20 meters away from the cattle in consecutive two days (Septer 23, and 24, 2018). The observer held a timer which is synchronized with the time of the GPS. The field observation of behaviors started from 9:00 am local time. The time interval of the GPS to record each location is 50 s. The GPS will flash when recording the location of the cattle. When the GPS flashes, the observer will read the timing from the timer and record the cattle behavior. If the cattle were foraging with head down when the GPS recording the location, it is considered as grazing behavior. If the cattle were standing still, chewing, or walking it is considered as nongrazing behavior. In total, 9 hours and 539 behaviors were recorded; approximately 80% of activities were grazing behaviors, and the remaining 20% was the nongrazing activity. Detailed information regarding the behavior classification is given in Table 2.1.

Table 2. 1 Descriptions of the observed behaviors (modified from Ganskopp and Bohnert, 2012)

Behavior category	Definition	Explanation
Grazing	Foraging, Foraging–walking	Foraging: foraging continuously (head lowered) Foraging–walking: foraging while walking (head raised and lowered)
Nongrazing	Standing, Lying down, Rumination	Standing: the animal stands on all four legs, with head erect and without swinging its head from side to side Lying down: the cattle lies on the ground in any position (except flat on its side) without ruminating Ruminating: the cattle lies in a stall masticating regurgitated feed, swallowing masticated feed, or regurgitating feed with head erect

2.2.3 Movement metrics derived from GPS and tri-axis accelerometer data

Coordinates of GPS device were converted from latitude/longitude form to a Universal Transverse Mercator (UTM) format to facilitate metrics of distances and turning angle (Weerd et al., 2015). Metrics related to distances cattle moved and the turning angle were derived to classify the animal behaviors at the GPS-determined locations (Figure 2.1). In the first step, we calculated the basic two metrics over two recording positions (100s), then we extended the time interval and recalculated the metrics from 100 to 800s. The distance moved included the cumulative distance travelled and linear distances between focal locations. Distances that occurred temporally before a considered location are called backward distances, and those after a focal location are called forward distances. The distance between b3 and a1 was calculated by Eq1, and the d2, d3, d4, d5, d6, d7 and d8 was used the same equation. The accumulative distance of backward and forward was the sum of b1, b2 and b3 in Eq2 and sum of a1, a2 and a3 in Eq3. In our study, the distances were calculated at time intervals of 100 to 800 s (Figure 2.2).

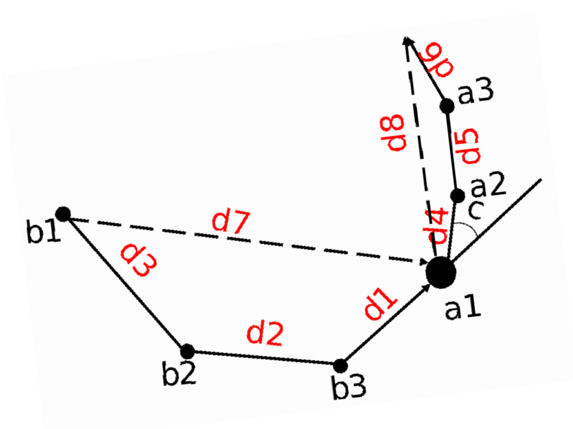


Figure 2.1 Schematic representation of movement metrics used as predictive metric in the classification. Movement metrics include backward accumulative distance (the sum of b1, b2 and b3), forward accumulative distance (the sum of a4, a5 and a6), backward linear distance (b7), forward linear distance (b8), and turning angle between GPS positions (c).

$$d1 = \sqrt{(b3_x - a1_x)^2 + (b3_y - a1_y)^2} \qquad \text{Eq 1}$$

$$b = |b1| + |b2| + |b3| \qquad \text{Eq 2}$$

$$a = |a1| + |a2| + |a3| \qquad \text{Eq 3}$$

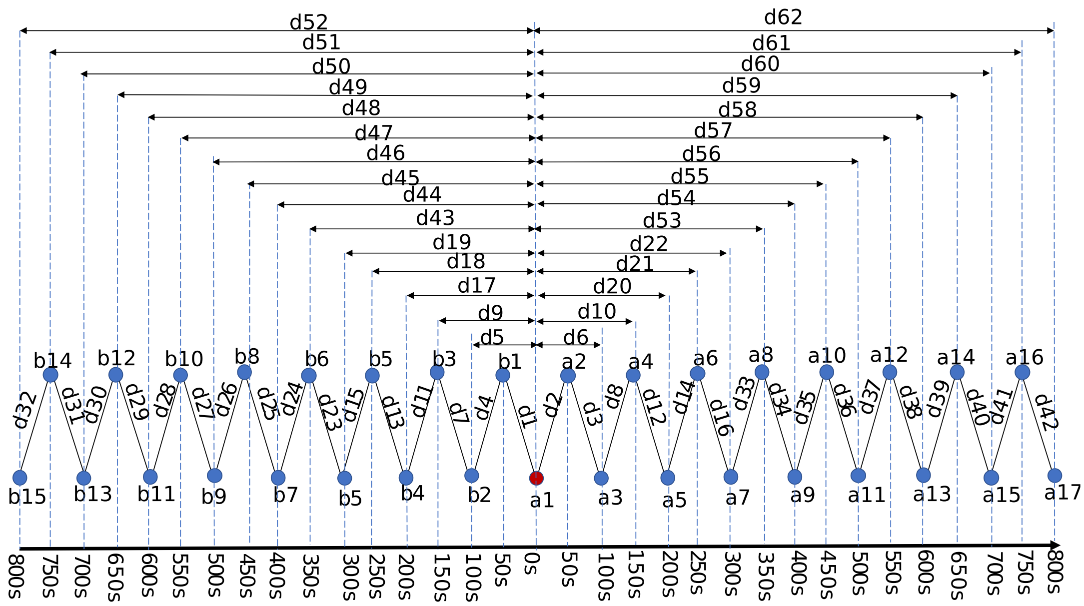


Figure 2.2 Metrics of distance extracted from GPS device were appiyed to classify livestock behaviors from 100 to 800s time interval in Random forest model. Backward and forward linear distance were showed in the figure, the metrics of accumulative were calcalated by sum of distance of segment in each time interval. (Forward accumulative distance: d63 = d2+d3; d64 = d63+d8; d65 = d64+d12; d66 = d65+d14; d67 = d66+d16; d68 = d67+d23; d69 = d68+d34; d70 = d69 + d35; d71 = d70+ d36; d72 = d71+d37; d73 = d72+d38;d74 = d73 + d39; d75 = d74+d39; d76 = d75+d41; d77 = d76+d42. Backward accumulative distance: d78 = d1+d4; d79 = d78+d7; d80 = d79+d11; d81 = d80+d13; d82 = d81+d15; d83 = d82+d23; d84 = d83+d24; d85 = d84+d25; d86 = d85+d26; d87 = d86+d27; d88 = d87+d28; d89 = d88+d29; d90 = d89+d30; d91 = d90+d31; d92 = d91+d32.)

Five groups (Table 2.2) of metrics were calculated at 50s intervals across the dataset of cattle, including acceleration along three orthogonal axes ($\ddot{d_x}$, $\ddot{d_y}$, and$\ddot{d_z}$) which was defined as three dimensional Cartesian system; Magnitude of acceleration was calculated by Eq 4; Standard Deviation of the $\ddot{d_x}$-axes calculated by Eq 5 and $\ddot{d_y}$-axes, $\ddot{d_z}$-axes used the same equation, $\overline{\ddot{d_x}}$ is the running mean of acceleration over the previous 5 min in the equation; Standard Deviation of Magnitude was calculated by Eq 6; $\overline{M}$ is the running mean of M over the previous 5 min in the equation;

$$M=\sqrt{\ddot{d_x}^2 + \ddot{d_y}^2 + \ddot{d_z}^2} \qquad \text{Eq 4}$$

$$SD=\sqrt{\frac{\sum(\ddot{d_x}-\overline{\ddot{d_x}})^2}{n}} \qquad \text{Eq 5}$$

$$SDM=\sqrt{\frac{\sum(M-\overline{M})^2}{n}} \qquad \text{Eq 6}$$

where $\ddot{d_x}$ is acceleration (m/s^2) in the superior-inferior axis, $\ddot{d_y}$ is acceleration (m/s^2) in the anterioposterior axis and $\ddot{d_z}$ is acceleration (m/s^2) in transverse axis;

Overall dynamic body acceleration (ODBA) was measured in livestock by external attachment of a tri-axis acceleration logger. The total acceleration recorded in each axis is the result of two components; a static acceleration component, which is the result of the earth's gravitational pull across axes, and a dynamic component, which results from livestock movement and varies in magnitude according to the perceived motion (Shepard et al., 2008). ODBA uses the dynamic component, as only the dynamic acceleration is a function of the livestock's movement. The static acceleration in each axis in one recording can be calculated by applying a running mean of six accelerations in 2.5 min. before and 2.5 min. after this recording (Wilson et al., 2006). The dynamic acceleration is then determined by subtracting the static component from the acceleration recorded. The ODBA is the sum of the absolute values of the dynamic accelerations from all three axes in Eq 7 (Wilson et al., 2006).

$$\text{ODBA}= |A_X| + |A_Y| + |A_Z| \quad \text{Eq 7}$$

where Ax, Ay and Az are the derived dynamic accelerations at any point in time corresponding to the three orthogonal axes of the accelerometer

Table 2. 2 Metrics used in the Random Forest algorithm for tri-axis accelerometer data-based behavior classification

Predictors variables	Label			Definition
	Leg	Neck	Tail	
Axes	$\ddot{d}_{x1}, \ddot{d}_{y1}, \ddot{d}_{z1}$	$\ddot{d}_{x2}, \ddot{d}_{y2}, \ddot{d}_{z2}$	$\ddot{d}_{x3}, \ddot{d}_{y3}, \ddot{d}_{z3}$	X, Y, Z axes
Magnitude	M1	M2	M3	Square root of the sums of squares of the acceleration in the X, Y, and Z axes
Dynamic body acceleration	ODBA Ax1, ODBA Ay1, ODBA Az1,	ODBA Ax2, ODBA Ay2, ODBA Az2,	ODBA Ax3, ODBA Ay3, ODBA Az3,	Mean of dynamic acceleration value along X, Y, and Z axes
Overall dynamic body acceleration	ODBA1	ODBA2	ODBA3	Sum of ODBA X, ODBA Y, ODBA Z
	Leg, Neck, Tail			
Standard deviation of acceleration and magnitude	SDX SDY SDZ SDM			Standard deviation

Using the various metrics derived at intervals of 100 to 800 s, we built three types of model: one using GPS data-based metrics only (GPS model); another from the tri-axis accelerometer data only (tri-axis model); and a model combining the tri-axis accelerometer and GPS data-based metrics (GPS-tri model).

2.2.4 Livestock behavior modelling

The Random Forest algorithm classification model was used to categorize livestock behavior, with movement metrics as dependent variables and observed behaviors as independent variables (Homburger et al., 2014). Random Forest is a machine-learning algorithm that especially suits data sets with many dependent variables. Random Forest provides well-supported predictions from large numbers of dependent variables and has the ability to identify the important variables of the model (Evans and Cushman, 2009). The modelling process of Random Forest can be summarized as consisting of many decision trees (Breiman, 2001):

1. Construct bootstrap data set (bag data set) from approximate 2/3 of the original data set; the remaining 1/3 of the data set is recognized as 'out of bag' (OOB).

2. Randomly select several predictor variables to calculate nodes in the bootstrap dataset.

3. At each decision tree node, test a random subset of predictor variables, to partition the bootstrap data into increasingly homogeneous subsets. The node-splitting variable selected from the variable subset is that which results in the greatest increase in data purity (Gini) before and after the tree node split.

4. The trees are fully grown, and each tree is used to predict OOB data, compute accuracy, and average error rates over all predictions.

5. The predictions are calculated by means of the majority vote of OOB predictions of the tree, and all predictions are averaged together to determine the class for the observation. Three training parameters need to be defined in the Random Forest algorithm; these parameters then determine the model prediction power:

Our analysis is carried out with the *caret* package in R Studio (R Development Core Team 2011) by using the *Random Forest, Caret, and Plotmo packages*. When building random forest models within this package there are two main user-controlled parameters: the number of variables to try at each node (the 'mtry' argument), and the number of trees in the forest (the 'ntree' argument). We used the *train()* function from the caret package to get an optimal combination of 'mtry' and 'ntree'. The *train()* function was run for 10 ('mtry' from 1 to 10) times. To determine the optimal number of trees for our data, the approach was to create many 'caret' models for our algorithm and pass in a different value of 'ntree' while holding 'mtry' constant at the default value above. We tested models with varying numbers of trees as a function of tree number of tress approaches a flat line between 500 and 2000 trees.

Mean decrease in Gini is used to determine the importance of variables in the classification model; this parameter is based on the Gini impurity index used for the calculation of splits during training (Homburger et al., 2014). When a tree is built, the decision regarding which variable to split at each node uses the Gini parameter. For each variable, the sum of the Gini decrease across every tree of the forest is accumulated every time that variable is chosen to split a node. The sum is divided by the number of trees in the forest to give the mean decrease in Gini.

2.2.5 Performance of the Random Forest classifier

The performance of Random Forest classification models was evaluated by using two indices: overall accuracy and the κ coefficient (Mouton et al., 2010). Overall accuracy represents the proportion of the total number of correctly classified observations. The κ coefficient, which considers the agreement occurring by chance, is a statistical measure of inter-rater agreement for categorical items (Mouton et al., 2010).

To evaluate the performance of the Random Forest model, we used 10-fold (i.e., performed 5 times) cross-validation to separate the data set into different, smaller data sets as training data sets and testing data sets. This process enabled us to more precisely control the number of samples compared with the inherent bootstrap sample in the Random Forest model (Cutler et al., 2007).

2.3 Results

2.3.1 Performance of GPS, tri-axis, and GPS-tri axis models

Overall classification accuracy increased as the time interval increased: 0.844, 0.845, 0.864, and 0.876 at time intervals of 100, 150, 200, and 250 s. For all GPS models, accuracy began to plateau around 0.89 to 0.91, when the time interval was greater than 300 to 800 s. For both the GPS-tri and tri-axis models, overall classification accuracy was approximately 0.96 at all time intervals (Figure 2.2).

Compared with the relatively small change in overall classification accuracy with different time intervals, the κ coefficient for GPS models increased dramatically from 0.07 to 0.42 as the time interval increased from 100 to 250 s. The κ coefficient stabilized at 0.57 to 0.65 when the time interval exceeded 300 s (Figure 2.2). The GPS-tri and tri-axis models yielded approximately the same κ coefficient (0.91 to 0.92, 0.92) at all time intervals (Figure 2.3).

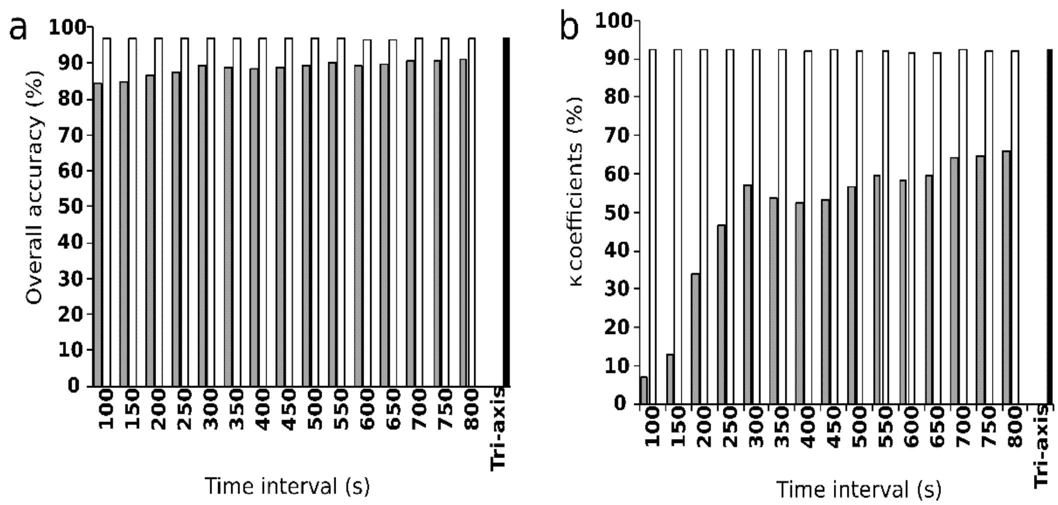


Figure 2. 3 (a) Overall accuracy and (b) κ coefficients of the GPS (gray bars) and GPS-tri (white bars) with time intervals of 100–800 s and of the tri-axis model (black bars).

2.3.2 Cross-validation

For GPS models with time intervals of 100 to 800 s, the accuracy for grazing behavior was 0.92 to 0.98, whereas the accuracy for nongrazing behavior increased from 0.2 to 0.47 as the time interval increased from 100 to 250 s and from 0.58 to 0.66 with time intervals of 300 to 800 s (Table 2.3). The performances of tri-axis were showed accuracy for grazing behaviors (0.98) and nongrazing (0.92) (Table 2.4).

Table 2.3 The confusion matrix for livestock behaviors classification as categorized by using GPS models with time intervals of 100 to 800 s

Observed behaviors	Predicted behaviors								
	Grazing	**Nongrazing**	**Percent accuracy**	**Grazing**	**Nongrazing**	**Percent accuracy**	**Grazing**	**Nongrazing**	**Percent accuracy**
	100s			**150s**			**200s**		
Grazing	421	35	0.92	428	28	0.94	428	28	0.94
Nongrazing	66	17	0.20	63	20	0.24	51	32	0.39
	250s			**300s**			**350s**		
Grazing	427	29	0.94	430	26	0.94	433	23	0.95
Nongrazing	44	39	0.47	30	53	0.64	34	49	0.59
	400s			**450s**			**500s**		
Grazing	447	9	0.98	440	16	0.96	446	10	0.98
Nongrazing	33	50	0.60	31	52	52	35	48	0.58
	550s			**600s**			**650s**		
Grazing	446	10	0.98	444	12	0.97	445	11	0.98
Nongrazing	35	48	0.59	33	50	0.6	32	51	0.61
	700s			**750s**			**800s**		
Grazing	442	14	0.97	440	15	0.96	435	21	0.95
Nongrazing	32	51	0.61	28	55	0.66	29	56	0.66

For each row, accuracy was calculated as the proportion of the observed class relative to the total number of behaviors.

Table 2. 4 The confusion matrix for livestock behaviors classification as categorized by using the tri-axis model

	Predicted behaviors		
Observed behaviors	**Grazing**	**Nongrazing**	**Accuracy**
Grazing	447	9	0.98
Nongrazing	7	76	0.92

For each row, accuracy was calculated as the proportion of the observed class relative to the total number of behaviors.

2.3.3 Relative importance of variables

The first four metrics in order of importance (as indicated by the mean decrease in Gini) for the GPS model with time intervals from 100 to 800 s are shown in Figure 2.3 and Figure S2.1. In most of the models, either linear or accumulated distance—rather than turning angle—was the important metric in the modelling. The time lag until the important distance metric occurred increased with the time interval from 100 to 800 s (Figure 2.4). Among all of the important metrics at different time intervals, d19 (the backward linear distance at a time interval of 300 s) and d43 (backward linear distance at a time interval of 350 s) were the most frequently used metrics in the classification of livestock behaviors. The variable d19 was the most important for the GPS models when the time interval was 300 to 600 s, and d43 was most important for time intervals from 350 to 700 s.

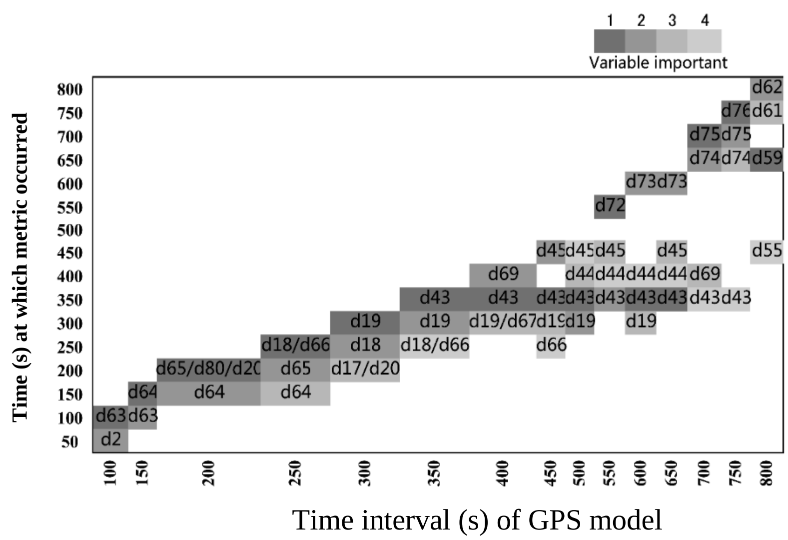


Figure 2.4 Variable importance plot generated by using the Random Forest algorithm with GPS models. The plot shows the first four important metrics of each GPS model (1, 2, 3, 4) according to the mean decrease in Gini; as this parameter increases, the variable is more important and a more accurate predictor of behavior classification.

In the tri-axis model, the variable d¨_yneck (acceleration of anterioposterior movement in the neck) had the highest mean decrease in Gini, and M_tail (square root mean of the sum of acceleration in the neck, leg, and tail) the second largest. The mean decrease in Gini gradually declined from d¨_yleg (acceleration of anterioposterior movement in the foot) to d¨_xleg (acceleration of superior-inferior movement in the foot) but then dramatically decreased from d¨_xleg to d¨_zneck (acceleration of transverse movement in the neck) (Figure 2.5).

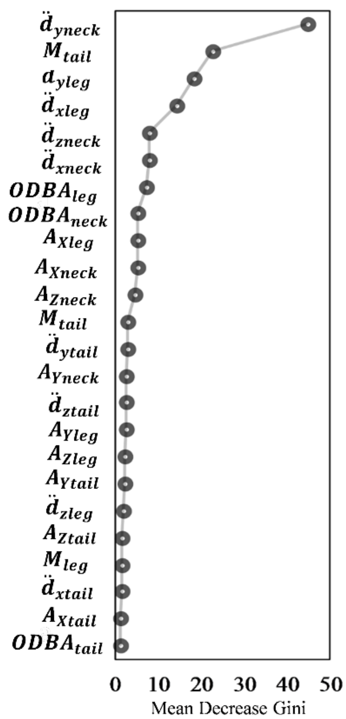


Figure 2.5 Variable importance plot generated by using the Random Forest algorithm with the tri-axis model. The plot shows the importance of each variable according to the mean decrease in Gini; as this parameter increases, the variable is more important and a more accurate predictor of behavior classification.

2.3.4 Marginal effect of the variable on livestock behavior classification

We used partial dependence plots to show the marginal effect of the metrics used in the behavior classification. For all GPS models, we generated partial dependence plots for the first four most important variables determined according to the mean decrease in Gini (Figure 2.2).

Although d19 and d43 had important roles in behavior modelling, the marginal probability of classifying a behavior as nongrazing decreased as the time interval increased. The probability of nongrazing showed a sharp decrease when d19 and d43 were greater than approximately 35 to 50 m. In the GPS model at the 300-s time interval, the marginal probability to classify a behavior as nongrazing was around 0.4 when d19, d18 (the backward linear distance at a time interval of 250 s), d17 (the backward linear distance at a time interval of 200 s), and d20 (the backward accumulative distance at a time interval of 200 s) were less than 35 to 50 m (Figure 2.6A), thus accounting for more than 80% of the total behavior in this range of distance (Figure 2.6B). The utility power of these four distances in classifying a behavior as nongrazing gradually decreased and then stabilized around 0.22 when they were greater than 50 m (Figure 6A).

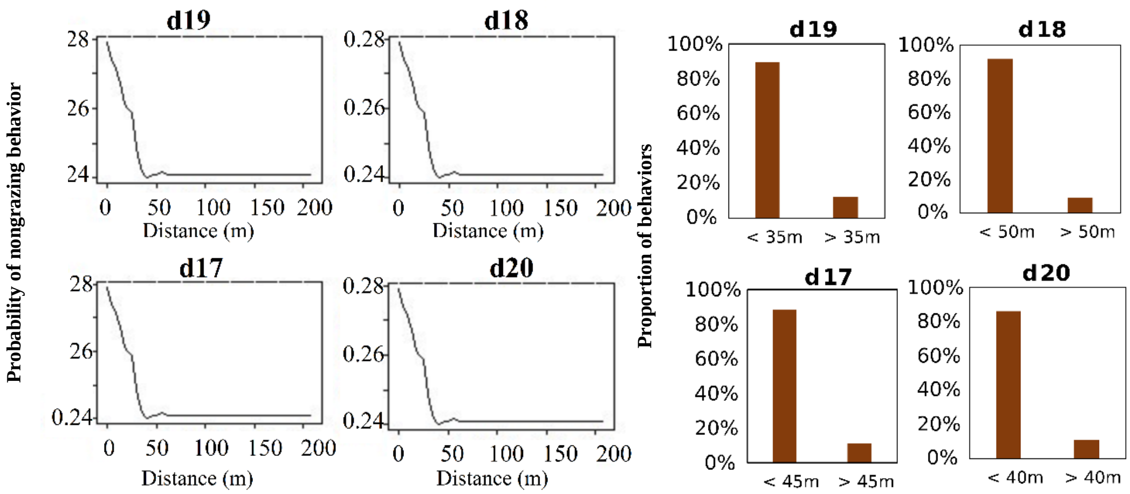


Figure 2.6 Partial dependence plots of nongrazing (A) and the proportion of behaviors corresponding to threshold in the GPS model (B). Partial plots represent the marginal effect of a single metric (d19, d18, d17, d20) of 300s time-interval included in the Random Forest model on the probability of nongrazing behavior, when the effects of all other metrics are averaged out. The criteria of threshold distance of each partial plot are recognized that the nongrazing behaviors remain same probability.

In the tri-axis model, when $\ddot{d}_{y1}$ was less than –3 m/s^2, the behavior was never classified as nongrazing, whereas the probability of a behavior being classified as nongrazing was around 0.8 when $\ddot{d}_{y1}$ was greater than –3 m/s^2. For the variable M3, the probability of a behavior being classified as nongrazing was 0.5 when M3 was 0 m/s^2 and dropped dramatically to 0.3 when M3 was 7 m/s^2. The behavior being classified as nongrazing was 0.3 when $\ddot{d}_{y2}$ was from -20 to 0 m/s^2, dropped to 0.22 when $\ddot{d}_{y2}$ was 8 m/s^2, increased to 0.25 when $\ddot{d}_{y2}$ was more than 11 m/s^2. By using $\ddot{d}_{x2}$, the highest marginal probability of determining a behavior as nongrazing was 0.31 and dropped to 0 when $\ddot{d}_{x2}$ was 11 m/s^2 (Figure 7).

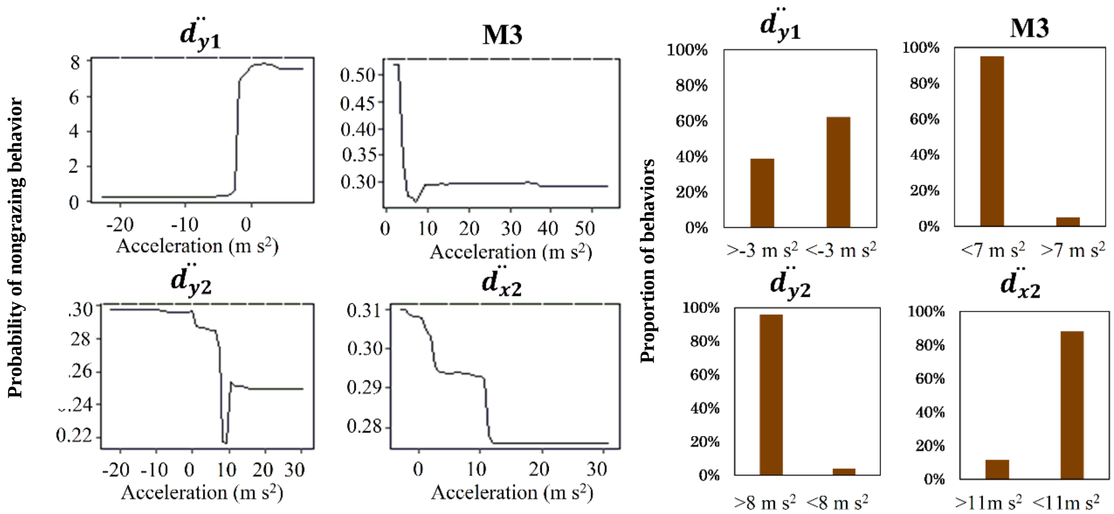


Figure 2.7 Partial dependence plots of nongrazing **(A)** and the proportion of behaviors corresponding to threshold in the tri-axis model **(B)**. Partial plots represent the marginal effect of a single metric ($\ddot{d}_{y1}$, M3, $\ddot{d}_{y2}$, $\ddot{d}_{x2}$) included in the Random Forest model on the probability of nongrazing behavior, when the effects of all other metrics are averaged out. The criteria of threshold distance of each partial plot are recognized that the nongrazing behaviors remain same probability.

2.4 Discussion

2.4.1 Optimal time interval for GPS models

GPS location data can be used to infer latent states of behavior from within individual movement trajectories (Homburger et al., 2014). The duration to complete a specific behavioral activity depends on the type of livestock and the condition of the pasture (Anderson et al., 2012). Distance and turning angle metrics extracted from GPS data over specific time intervals can be used to classify livestock behaviors, such as 1 min for beef cows on desert grassland (Anderson et al., 2012), 3 min for Brown Swiss cows in a cow shed (Schlecht et al., 2004), and 5 min (i.e., 300 s) for dairy cows on upland grassland (Homburger et al., 2014). In our study, the optimal time interval for behavior classification was approximately 300 s because the κ coefficient at this time interval was higher than for shorter time intervals and was nearly stable afterward (Figure 2.3). In addition, the most frequently used metric (d19) was the backward linear distance at the 300-s time interval (Figure 2.4).

Although overall accuracy did not vary over time intervals from 100 to 800 s, it may be a poor measure for assessing model performance, given that overall accuracy can happen just due to coincidence, especially when the data are imbalanced (Anderson et al., 2012). In contrast, the κ coefficient, which estimates accuracy beyond expectation, can correctly assess the accuracy of imbalanced data (Shoukri et al., 1992). For imbalanced data, the observed and predicted accuracies and their agreement in regard to minor behaviors determine the κ coefficient. In reality, foraging occurs more often than other behaviors. During the cross-validation, given that the accuracies for grazing behavior were relatively high and stable, the critical determinants of the κ coefficient were the accuracies for nongrazing behaviors. For the GPS models, the low accuracies of the nongrazing behaviors during cross-validation (Table 2.3) explain the low κ coefficients for the time intervals from 100 to 250 s (Figure 2.3). At time intervals of 300 s and greater, the κ coefficient stabilized around 0.5 to 0.6 because of the increase in the accuracies of nongrazing behavior (Table 2.3). In addition, the d19 (backward linear distance at 300 s) was the most frequent metric in other models when the time interval was greater than 300 s (Figure 2.4). Therefore, the optimal time interval for using the GPS location data to classify the livestock behavior in the study area was 300 s.

2.4.2 Model performance

Predicting the accuracy of models by using GPS data depends on the livestock type and the pasture condition (Weerd et al., 2015), but when using tri-axis accelerometer data it depends only on the instantaneous body posture of the animal (Fahlman et al., 2008). With the same time step to log the GPS position and the body posture by tri-axis accelerometer, models using tri-axis accelerometer data-based metrics only or combined tri-axis and GPS data-based metrics showed higher overall accuracies and κ coefficients than the models that used only GPS data-based metrics (Figure 2.3).

The distance moved by a livestock over a given time interval is expected to be an indicator of its activity. Short distances are likely to indicate static behavior (standing, ruminating), and long distances typically are associated with foraging (Augustine et al., 2013). In the current study, distance variables were the first four most important variables in most of the GPS models (Figure 2.4), thus supporting the power of using distance to classify cattle behavior.

The GPS models demonstrated several critical distances for classifying grazing and nongrazing behaviors (Figure 2.4). But the marginal probabilities of the important variables to distinguish between grazing and nongrazing behaviors were lower for the GPS models than for the tri-axis models (Figure S2.1 and Figure 2.7). Moreover, the distances tended to be within the range that ambiguously classified the two behaviors (Figure S2.1). Therefore, distinguishing between grazing and nongrazing was particularly challenging and relied on the use of multiple movement metrics, including backward and forward linear and accumulative distances (Figure 2.4). For example, for the 300-s time interval, d19 was the first most important metric to determine the two behaviors. The marginal probability for nongrazing was approximately 0.4, meaning unclear differentiation between grazing and nongrazing when d19 was less than 35 m. However, the probability of nongrazing was around 0.2, indicating that the two behaviors were clearly differentiated when d19 exceeded 35 m. Unclear classification at shorter distances than this critical distance (35 m) might reflect the condition of the specific habitat. For example, the presence of woody vegetation might have made it more difficult to distinguish between grazing and nongrazing, because the consumption of shrubs slows movement and can blur the graze signature in terms of the motion sensor counts. In addition, 89% of the d19 data were less than 35 m. Hence, the lower probability of the distance metrics to classify the two behaviors under the threshold value and the skewed distribution of these metrics could be responsible for the relatively low accuracy of the GPS models.

The tri-axis accelerometer model was based on the body posture that was simultaneously associated with a specific behavior and did not need to account for any time interval, which might lead to uncertainty regarding behavior classification (Scheibe et al., 2006). Unlike the GPS model, the tri-axis model can measure the instantaneous and independent local movement of the legs, heads, or entire bodies of animals, thus ensuring high accuracy of behavior classification (Fahlman et al., 2008; Gleiss et al., 2010; Green et al., 2009; Halsey et al., 2008). Our findings showed that the backward-and-forward movement of the neck was critical for distinguishing livestock behaviors (Figure 2.5), in agreement with the results of another study, which used *x*-axis sensor counts (González et al., 2015).

Livestock behaviors were influenced by the available forage and stocking density. With increasing stocking density, the average intake of each livestock will reduce due to the given availability forage in the rangeland (Hepworth et al., 1991). Livestock preferred to spend less time on grazing behaviors when consuming of energy was more than grain (Hepworth et al., 1991). More available forage in August (243 g/m^2) than that in July (53 g/m^2) in Horqin Sandy Land might lead to the livestock spending more time on grazing with sufficient energy of forage in August. For the behavior's classification, livestock may spend less time over a given distance for finishing grazing behavior. So, the optimal time-interval of the GPS method for classifying behaviors will decrease. Our GSP model was built over 100 to 800s to cover various situations corresponding with the change of rangeland pasture, thus the method can be applied in other sites.

2.5 Conclusions

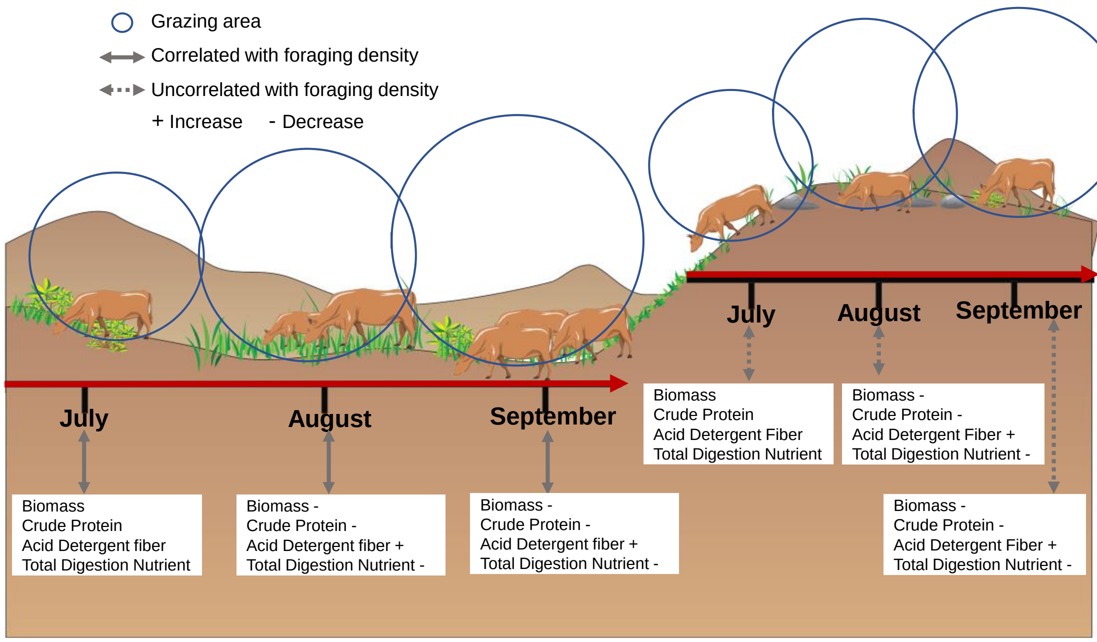
Our current study demonstrates that data from both GPS devices and tri-axis accelerometers can be applied to build reliable models for livestock behavior classification. To achieve the high and stable performance of the GPS model, we selected the optimal time interval from 300 to 800s, which is sufficient for most livestock activities associated with behaviors to be displayed. Metrics of linear distance had the most important effects on behavior classification. In addition, the marginal effects of linear distance indicated a distance of 35 to 50 m as the threshold for differentiating behaviors; at greater distances, grazing was more likely than nongrazing behavior.

Because it is based on the instantaneous acceleration of livestock body movement, the tri-axis model achieves higher performance regarding livestock behavior classification than does the GPS model. The anteroposterior movement of the animal's neck was the most important metric for the tri-axis model. The marginal effects showed that acceleration of -3 m/s^2 was the threshold for differentiation of behaviors; at greater values, nongrazing was more likely than grazing.

In summary, compared with GPS models, a tri-axis model can better support livestock behavior classification, which is advantageous for assessing the detailed activities associated with investigating livestock physiology. But the main disadvantage of a tri-axis model is its lack of location information. A GPS model is sufficient for livestock behaviors classification and provides information regarding an animal's location; this feature is associated with the interaction between livestock activities and the rangeland ecosystem. These findings may improve our understanding of how the selection of the time interval influences the process of distinguishing livestock activities in a GPS model and provide insight into selecting an optimal time interval when using GPS data only to classify livestock behaviors.

Chapter 3

Seasonal dynamics of cattle grazing behaviors on contrasting landforms of a fenced ranch in northern China



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Chapter 3. Seasonal dynamics of cattle grazing behaviors on contrasting landforms of a fenced ranch in northern China

3.1 Introduction

The total desertified land area is estimated to be 3.6 billion ha in arid and semi-arid regions around the world (Daily, 1995). Overgrazing is believed to be one of the primary driving forces of degradation (Schlesinger et al., 1990; Van De Koppel and Rietkerk, 2000). Overgrazing can lead to marked reductions in nutritive value and yield of herbage (Chaneton et al., 1988; Ayantunde et al., 1999; Gutman et al., 1999) and result in severe grassland degradation. With the surging numbers of livestock in arid and semi-arid lands, understanding how to manage livestock grazing both temporally and spatially is crucial for preventing degradation and restoration of degraded grassland as well as for maintaining livestock production (DeYoung et al., 2000; Briske et al., 2008; Hao et al., 2018).

Many field grazing experiments have been carried out (Lunt et al., 2007; Hanke et al., 2014; Eldridge et al., 2016) to clarify how livestock grazing affects grassland productivity (Huang et al., 2016), species diversity (Pour and Ejtehadi, 1996), soil quality (Hiernaux et al., 1999), and desertification (Weber and Horst, 2011). In these experiments, researchers used different grazing density gradients indicated by the number of livestock per unit area (Okayasu et al., 2010; Wang and Wesche, 2016). The effects of different livestock behaviors such as foraging and resting were ignored across space. However, grazing density varies temporally and spatially with the availability of resources and the changing environments across a grassland (Chillo and Ojeda, 2014). Therefore, monitoring and modeling different livestock behaviors and investigating the seasonal dynamics of the spatial distribution of livestock would improve the management of livestock grazing and help to prevent grassland degradation (Bailey et al., 1996; Kohler et al., 2006).

Estimating the spatial distribution and temporal dynamics of grazing density is difficult because of the spatial heterogeneity and temporal dynamics of resource availability and differences in livestock energy consumption across various landforms (Butt, 2010). Grazing activities, including foraging and non-foraging activities, comprise various interactions between livestock and the environment (Baumont et al., 2004). Complex interactions among biotic factors, such as forage quantity and quality, and abiotic factors, such as elevation and distance to a watering point (Von Müller et al., 2017), determine the spatial distribution of different livestock behaviors on a ranch (Hirata et al., 2010). In a ranch with abundant vegetation and flat terrain, livestock generally concentrate in several areas that have good-quality forage at the beginning of the grazing season and then expand over a broader area to achieve an even spatial distribution with relatively low grazing density late in the season (Evans et al., 2004; Pelster et al., 2004). On a ranch with spatially homogenous resources, the livestock’s use of herbage resources also shows selective grazing and a mosaic pattern that balances the nutrient demand and energy supply for livestock (Andrew, 1988; Barnes et al., 2008, Okayasu et al., 2010). The spatial expansion across a ranch is moderated by the trade-off between the area’s forage quality and productivity. Livestock instinctually avoid walking long distances to save energy given abundant herbage resources (Sejian et al., 2012). Otherwise, the spatial range of livestock movement will be constrained by the energy gained at the expense of energy consumption (Fierro and Bryant, 1990).

Spatial differences in the quality and quantity of herbage due to rugged terrain on a ranch will lead to a heterogeneous distribution of livestock (Henkin et al., 2012). Livestock prefer to spend more time in relatively flat areas where lower energy consumption is required for grazing activities (Parker et al., 1984). As compared to that on flat terrain, grazing capacity was 30% lower in areas with slopes between 11% and 30%, and 60% lower in areas with slopes between 31% and 60% (Holechek, 1988). Moreover, elevation differences can lead to a heterogeneous distribution of available resources and differences in plant community composition and soil type (Miyasaka et al., 2011). Livestock forage longer in a nutrient-rich patch in an area with heterogeneous topographic features, but they rarely forage in the same patch for several consecutive days in a homogeneous environment (Bailey, 2005).

The Horqin Sandy Land of northern China has suffered from serious desertification (Chen and Su, 2008). Despite many national and regional restoration projects, such as fence construction and the provision of cash subsidies to reduce the livestock number per household, desertification of grasslands in the Horqin Sandy Land is still ongoing (Miao et al., 2015). Several researchers have investigated plant communities under different grazing densities in the Horqin Sandy Land (Zhang et al., 2005; Li et al., 2012; Tang et al., 2016). The direct application of grazing density to arid and semi-arid pastoral systems has been criticized, however, because it neglects the spatiotemporal dynamics of actual foraging pressure (Bailey et al., 1996). Understanding these spatiotemporal dynamics may help ranchers to improve the efficiency of resource use and to respond effectively to the actual environmental conditions on a ranch (Anderson et al., 2012). Given the landform characteristics of the Horqin Sandy Land and the ongoing land degradation (Li et al., 2012), we expect that livestock should preferentially use low-land areas and that temporal patterns of grazing pressure should differ in areas with contrasting landforms.

The objectives of our study were (1) to quantify the ratio of foraging to non-foraging behaviors of livestock on a ranch in the Horqin Sandy Land; (2) to explore the spatial distribution of livestock grazing and its temporal dynamics on contrasting landforms (i.e., low-land vs. sand-dune); and (3) to understand the biotic factors determining the grazing spatial distribution.

3.2 Material and methods

3.2.1 Study site

The study was conducted in the western part of the Horqin Sandy Land (42°00'N, 119°39'E), Naiman County, Inner Mongolia, northern China (Fig. 1A). The area is characterized by interspersed low-land areas, fixed and semi-fixed sand dunes with an average height of 5–8 m, length of 400–600 m, and width of 20–40 m (Zhang et al., 2005). The fixed and semi-fixed dunes account for 70% of the total area (Zhang et al., 2012). From 1980 to 2014, the annual mean temperature was 7.3 °C, and the annual mean precipitation was 318 mm, with 70–80% of the precipitation occurring between June and August (Liu et al., 2014). The average annual wind speed ranged from 3.2 to 4.5 m s^{-1}, with most windy days and windstorms occurring between March and May (Zhang et al., 2012).

Sheep, goats, and cattle have been grazed in this region in recent decades. However, the carrying capacity of pasture has decreased from 1.81 to 0.19 sheep unit ha^{-1} owing to the continuously increasing number of livestock in the region (Jiang et al., 2003; Li et al., 2012). For this reason, a livestock exclusion policy has been extensively implemented in the Horqin Sandy Land (Li et al., 2012) since the mid-1980s to prevent grassland degradation (Baxter, 2007).

Before monitoring livestock movement and conducting the plant survey, we visited and inspected ranches of several households in this region and selected one (42°51'24.59" N, 120°55'50.34" E) of them as the research site (Fig. 1) for the following reasons. First, consistent with the prevailing management practices in this region, livestock grazing at this ranch occurred without herdsman interventions, such as supplemental feed supplies. Second, landforms on the range included both fixed dunes and low-land areas, which are typical landforms in the Horqin Sandy Land (total area is 20.1 ha, with 8.04 ha of lowland and 12.06 ha of sand dunes; Figure 3.1). Third, the ranch's use history was clear; low-land areas were used to grow corn and millet from 1995 until 2007, when fencing was erected and livestock grazing began across the ranch. Finally, the owner of the ranch communicated well with us, and good communication was essential for this experiment to be completed.

At the research site, livestock grazing usually occurs from early July to late September. The vegetation is typical of a temperate desert steppe; the dominant species are *Pennisetum centrasiaticum, Cleistogenes squarrosa*, and some dwarf shrubs (*Artemisia oxycephala* and *Artemisia halodendron*).

The low-land area characterized by Kastanozems, and sand-dune by Ustic Sandic Entisols (FAO, 2006). The Ustic Sandic Entisols are with a loose structure, and they are particularly susceptible to wind erosion (Li et al., 2009). Soils in the low-land areas have more nutrients and higher soil moisture level, as compared with soil property in dunes (Li et al., 2009).

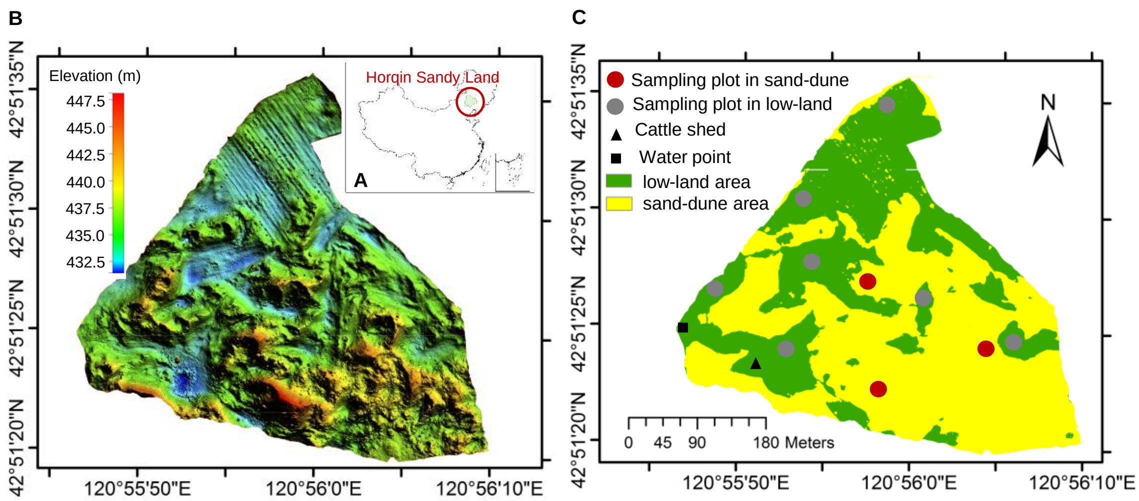


Figure 3.1. (A) Location of the Horqin Sandy Land, (B) digital surface model of the study ranch, and (C) landform classification into low-land and sand-dune areas and sampling plot locations.

3.2.2 Land survey

An elevation map of the study ranch was generated by using drone photogrammetry. A drone (DJI Phantom 4 Pro, https://www.dji.com/jp/phantom-4-pro) was used to capture photos covering the whole ranch by using an autopilot flight paths program. Since the total area of the study ranch was 20.1 ha, the fixed height and horizontal speed were set to 80 m and 3 m s^{-1} and the forward overlap (flying direction) and side lap (between adjacent flight lines) were set to 80%. With these parameters applied to the flight autopilot, the program was designed to obtain 400 images over a target area of 700 m × 700 m (Fig. 3.1B).

Pix4Dmapper Pro software (version 2.0) was used to process the acquired photographs and to automatically generate orthoimages, a 3D point cloud, and a digital surface model (DSM) with 2 cm × 2 cm ground resolution (Car et al., 2016). To refine the geolocation of the drone photographs and to assess the accuracy of the DSM, eight ground control points were evenly positioned across the study ranch. Geographic coordinates and elevation of the eight ground control points were measured with a Trimble RTK GPS (Real-Time Kinematic) within 1 m accuracy (UTM Zone 51 N, WGS84 horizontal datum). We then evaluated the spatial accuracy by comparing digitized and known coordinates from the ground and calculating the root mean square error (RMSE). Finally, we generated a DSM with a vertical resolution of 5 cm.

Landforms at the study site were classified as low-land or sand-dune by using field observations. We selected an elevation threshold of 438 m to distinguish the two landforms; if the pixel elevation was higher than 438 m, that DSM pixel was classified as sand-dune; otherwise it was classified as low-land (Fig. 3.1C).

3.2.3 Grazing behavior analysis

During the grazing season of 2018 (1 July to 30 September), 13 adult Simmental cattle (3 to 6 years old) grazed the ranch. Each animal had a GPS device (precision ± 3 m; catalog no. GT-600, i-gotU, Mobile Action Technology, Taipei, Taiwan) attached to a collar around its neck with a battery that allowed the GPS device to operate for more than 5 days. The GPS device continuously recorded the animal's location at 50-s intervals for five consecutive days; then it was removed, recharged, and re-attached. This procedure was followed throughout the grazing season.

During the grazing season, we observed cattle activities for around 15 days (09:00 to 17:00 UTC+8) per month and found that the 13 animals moved together around the ranch. However, the number of available GPS devices declined through the sampling period due to rainfall damage and loss. Because the objective of the study was to compare cattle behaviors and distribution patterns among three grazing periods in both the low-land and sand-dune areas, the GPS recordings should have the same time length, a fixed date-interval corresponding to the timing of the herbage survey (15th of each month), and the same number of cattle among the 3 months. In September, GPS recordings were available only for two cattle on 5 consecutive days (11 to 15 September). Therefore, we calculated the foraging density for 5 consecutive days in each month using the GPS recordings of two cattle, and the GPS data of two cattle were used for the following analysis.

Every 5 days, there were around 8550 GPS position data for each animal. The predicted metrics of distance (linear distance, cumulative distance) and turning angle were calculated by using the focal locations from 100- to 800-s time intervals. We applied the random forest algorithm to classify livestock behaviors by using predicted metrics and field-observed behavioral data. To evaluate the performance of the random forest model, we used 10-fold (i.e., performed 5 times) cross-validation to separate the data into smaller training data sets and testing data sets. The overall accuracy of the random forest model was 87% (95% CI = 85–90%), and the accuracy of foraging behaviors was 95% (95% CI = 92–98%) in the model. Then, we randomly selected two cattle for each grazing period and imported these data into the constructed algorithm to classify foraging and non-foraging behaviors (Gou et al., 2019). The few and similar precipitation occurred during these periods; 1.2 mm of rain fell in July, 5.6 mm in August, and 0.2 mm in September (Fig. S1). The mean air temperature was 25.6 °C in July, 23.8 °C in August, and 20.7 °C in September (Fig. S2). Few precipitation events occurred in the 3 months.

As explained in section 2.4, we surveyed plant communities and collect biomass in mid-July, mid-August, and mid-September of 2018. Thus, only the GPS recordings covering 11–15 July, 11–15 August, and 11–15 September 2018 were used for further analysis.

3.2.4 Herbage production and quality measurement

For the plant community surveys and biomass collection, we selected seven low-land sites that were evenly distributed and three typical sand dunes on the ranch. As there were small variations in the species composition across the low-land areas, we selected three small and four large low-land sites to investigate the herbage community. Most sand-dunes on the ranch were distributed along the edges of ranch fences, and we selected three sand dunes evenly distributed in the center of the ranch to investigate the sand dune plant community.

On 15 July, 15 August, and 15 September 2018, three (1 m × 1 m) quadrats were randomly established at each selected low-land site along the diagonal of a 10 m × 10 m plot, and three quadrats were established on each sand-dune, one at the top, one on the leeward slope, and one on the windward slope (i.e., 21 low-land quadrats and 9 sand-dune quadrats in each month). We recorded every species that occurred in the quadrats, cut the aboveground part of each plant, and put the material in envelopes separated by species. The plant samples were dried to constant weight (55 °C for 48 h) and then weighed to obtain the biomass of each species. The biomass of each quadrat is the summed biomass of all plants in the quadrat. Then the same species from different low-land or sand-dune quadrats were mixed. The crude protein (CP), neutral detergent fiber (NDF), acid detergent fiber (ADF), and total digestible nutrients (TDN) of each species per month were determined by chemical analyses performed by Cumberland Valley Analytical Services (Tongzhou District, Beijing, China). The CP, NDF, ADF, and TDN of each quadrat were the means of CP, NDF, ADF, and TDN of each species in the quadrat weighted by the relative abundance of each species.

3.2.5 Cattle density

The boundary of the study ranch was recorded by a real-time differential hand-held GPS (GPS PRO XR, Trimble Navigation Ltd., Sunnyvale, CA, USA), which we moved along the fence boundary while recording GPS position at 10-s intervals. The DSM was clipped by the boundary data to cover the study ranch. The GPS position data of the two selected cattle were classified as foraging or non-foraging behaviors by using a random forest algorithm (Gou et al., 2019). In our study, 80% of the moving distance in the 50-seconds interval was less than 10m (Fig. S3). Thus, to examine the spatial distribution of cattle behaviors, we analyzed the foraging density at the 10×10 grid. Thus, each livestock behavior at each point had position information. Then, the summed number of foraging behaviors in each 10 m × 10 m grid was considered as the foraging density of the grid. The average foraging densities in the low-land and sand-dune areas each month were the means of the foraging density of the low-land and sand-dune grids, respectively.

3.2.6 Data analysis

The foraging density at each elevation was the average of foraging densities at that elevation throughout the 3 months of grazing. The foraging area was the sum of grids in which foraging occurred in low-land and sand-dune areas, respectively. The proportional low-land foraging area was the ratio of low-land grids in which foraging occurred to the total number of ranch grids. The same method was used to calculate the proportional sand-dune foraging area.

The number of GPS points was considered to represent the total time that cattle stayed on the ranch every 5 days. The number of foraging behaviors in the same period was considered to represent the foraging pressure on the ranch. The ratio of summed foraging behaviors to the total number of GPS points was the proportion of foraging during the period. This way of calculating proportional foraging is the same as using the ratio of foraging time to the total time cattle stayed on the ranch because the time interval for each GPS point is the same. The calculation of the proportion of non-foraging behavior was done in the same way.

After log-transformation, the foraging densities in all 10 m × 10 m grids in low-land and sand-dune areas during the 3 months were tested for normal distribution and variance equality by using the *Kolmogorov–Smirnov* and Levene’s tests, respectively; data normal distribution and homogeneity of the variances were considered at a $P > 0.05$. The foraging densities during this period were not normally distributed, and heteroscedasticity was observed in both low-land and sand-dune areas. Therefore, differences in foraging density between the two landforms during the 3 months were tested by using the non-parametric Kruskal–Wallis test (*rstatix* package in R). Log-transformation of the raw data does not affect the results of the Kruskal–Wallis test. Thus, the log-transformed foraging density data were used in the following analyses. For multiple comparisons of foraging densities among the 3 months in both low-land and sand-dune areas, the Kruskal–Wallis test and Dunn's post hoc test were used to analyze the differences between pairs of months and between the landforms. The foraging density in all grids during the 3 months was used to assess the frequency distribution in low-land areas and in sand-dune areas. Two-way ANOVA (*ANOVA.TFNs* package in R) was used for comparing the herbage quality (CP, NDF, ADF, TDN) and quantity (biomass, species diversity) among the 3 months between low-land and sand-dune areas; significance levels were set a $P < 0.05$. Species diversity was calculated by using the Shannon diversity index in the *vegan* package in R.

A multiple linear regression model (*lme4* package in R) was used to analyze the relationships between foraging density and herbage quality and quantity in the study. First, the data from both low-land and sand-dune areas were included. The dependent variable in the model was the foraging density in grids of field plots where biomass and forage quality had been determined. The independent variables in the model were herbage quality and quantity at plots on the ranch. In the analysis, the "period of July" was a dummy reference category compared with the "period of August" and "period of September" for effects of seasonal grazing density.

Also, to evaluate the effects of landform on the cattle behaviors and distribution pattern, the variable "sand-dune" was a dummy reference category compared with "low-land". In the second step, two multiple linear regression models were calculated to assess the relationship between cattle density and herbage conditions in low-land and sand-dune separately; significance levels were set at $P < 0.05$. In both analyses, the independent variables were the same as in the first step except for the variable of "landform". All analyses were conducted in RStudio v.1.2.1335 with R 3.6.1 and ArcGIS 10.2 (Environmental Systems Research Institute, Olympia, WA, USA).

3.3. Results

3.3.1 Dynamics of the spatial distribution pattern of livestock behavior

We observed a significant difference ($P < 0.05$) in the summed log-transformed foraging density in July, August, and September (number of total foraging behaviors in 5 days measured at 50-s intervals per grid cell of 10 m × 10 m) between low-land and sand-dune areas (Figure 3.2A). The average log-transformed foraging density ranged from 1.5 to 2.8 in low-land areas during the grazing season and from 1.2 to 2.0 in sand-dune areas (Figure 3.2B). The average foraging density decreased with increasing elevation (Figure 3.2C).

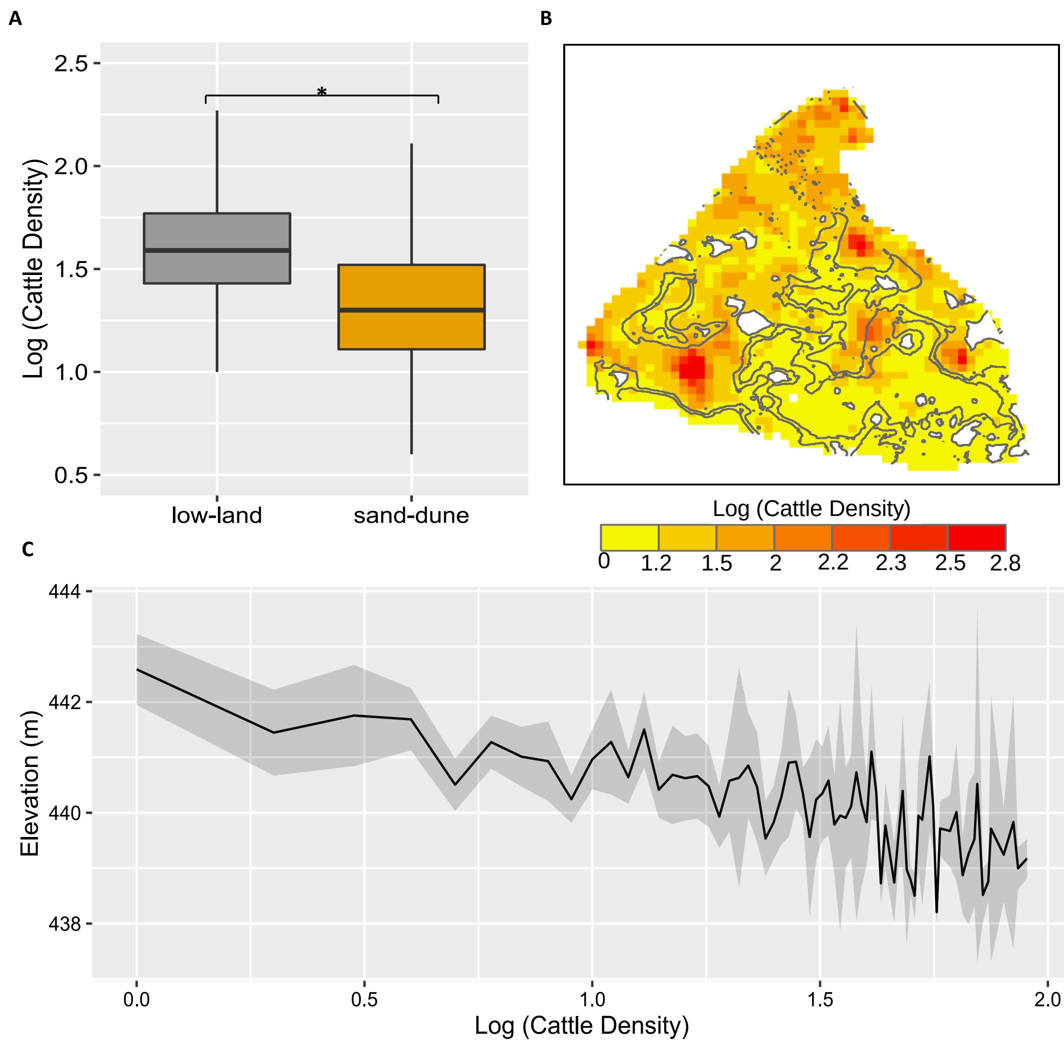


Figure 3. 2 (A) Seasonal summed cattle foraging density (log-transformed) in low-land and sand- dune areas (*P < 0.05), (B) the foraging density summed across the entire grazing season in each grid of the ranch, and (C) the relationship between cattle density and elevation (shading indicates the standard error of foraging density of grids at the same elevation; number of grid-cells = 1200). In the box plots, bounds of the box spans from 25 to 75% percentile, center line represents mean, and whiskers visualize 5 and 95% of the data points.

The spatial distributions of grazing density in July, August, and September are presented in Figure 3. During the grazing season, the proportion of time spent foraging across the entire ranch increased from 63% to 67% to 68% in July, August, and September, respectively, with a corresponding decrease in time spent not foraging. Likewise, the proportion of time spent foraging increased from 41% to 43% to 44% in the low-land areas and from 21% to 23% to 24% in the sand-dune areas in the July, August, and September grazing periods, respectively (Figure 3.3A).

The log-transformed foraging density significantly increased from 0.61 in July to 0.66 in August to 0.88 in September in low-land areas ($P < 0.05$), whereas no differences were observed in sand-dune areas (0.44, 0.44, and 0.66, respectively; Figure 3.3B). The detailed distribution of foraging behavior showed that higher foraging density (1.2–2.5) was mainly confined to the low-land area around the cattle shed in July (see Figure 3.1C for this location), but cattle spread to other areas of the ranch in August and September (Figure 3.3E). The proportion of area foraged by cattle increased in both low-land and sand-dune areas. Of the entire low-land area on the ranch, 31%, 35%, and 36% was used for foraging in July, August, and September, respectively; similarly, the relative area of sand dunes used increased in those months (45%, 47%, and 51%, respectively; Figure 3.3C). Low- and high-density foraging decreased whereas medium-density foraging increased from July to September in both low-land and sand-dune areas (Figure 3.3D).

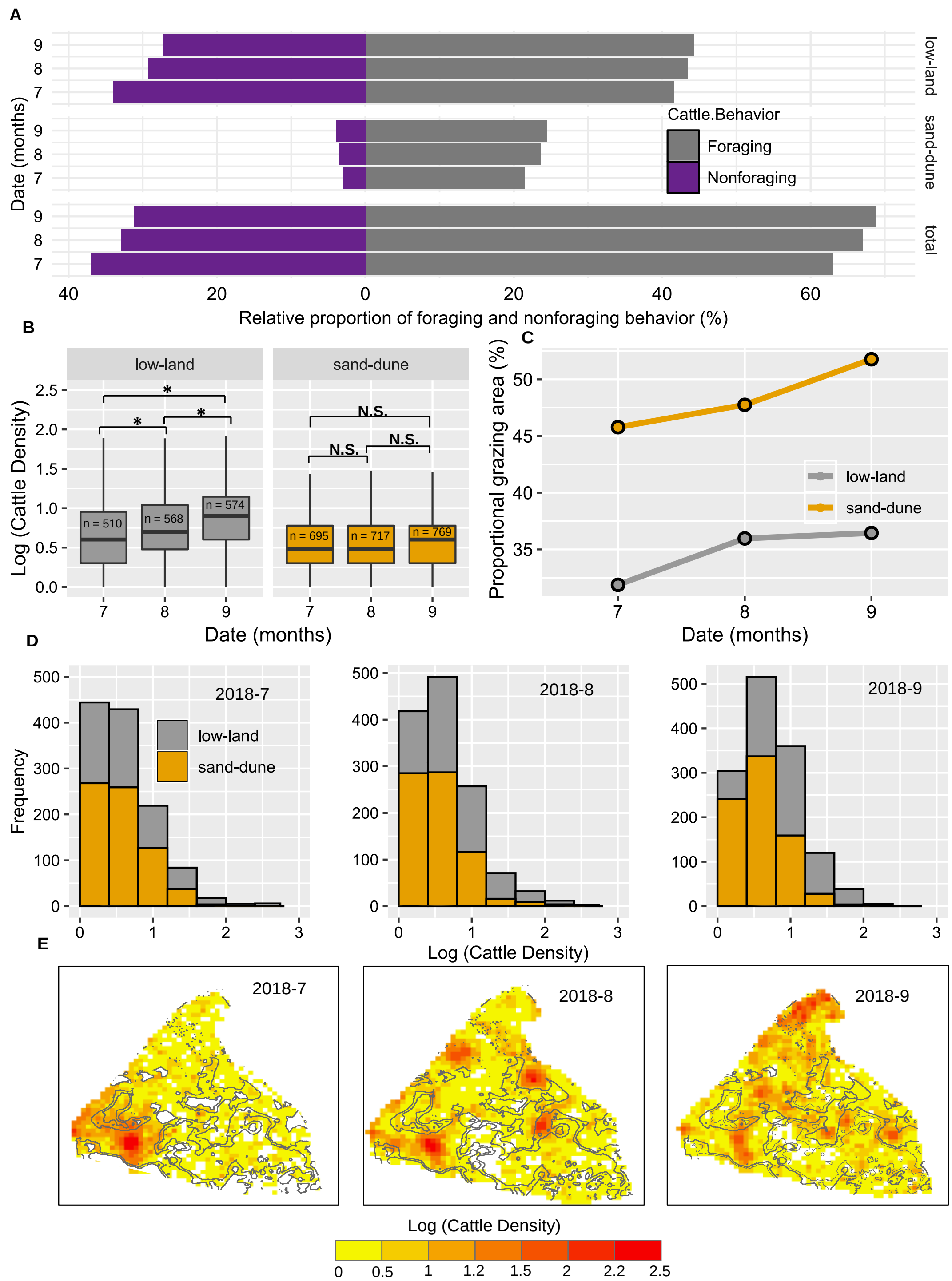


Figure 3.3 Seasonal dynamics of cattle behavior. (A) Relative proportions of foraging and non-foraging behaviors in the low-land and sand-dune areas and in the whole ranch area, (B) spatial averages of monthly foraging density (log-transformed) in low-land and sand-dune areas (*P <

0.05), In the box plots, bounds of the box spans from 25 to 75% percentile, center line represents mean, and whiskers visualize 5 and 95% of the data points, (C) proportion of total low-land and sand-dune areas used for foraging, (D) foraging density frequency in low-land and sand-dune areas in each month, and (E) spatial distributions of foraging density (log-transformed) in each grid in July, August, and September.

3.3.2 Temporal changes in forage quantity and quality

The average biomass of the 21 low-land quadrats was 144, 87, and 44 g m^{-2} in July, August, and September, respectively; these values are higher than those in the nine sand dune quadrats in those months (66, 50, and 30 g m^{-2}, respectively; Figure 3.4A). The decreasing trend of biomass in both low-land and sand-dune areas was significant ($P < 0.05$; Figure 3.4A). Species diversity was also higher in low-land than in sand-dune areas and declined from July to September in both (Figure 3.4B). The value of NDVI decreased significantly from July (0.41) to August (0.38) and September (0.23) in low-land areas. The same trend was observed in sand-dune areas (0.37 in July, 0.28 in August, and 0.22 in September). A significant difference of NDVI between low-land and sand-dune was observed in July and August, but not in September (Figure S3.4).

The CP and TDN significantly declined from July to September in both the low-land and sand-dune areas (Figure 3.4C, E). The ADF did not differ significantly between July and August in low-land areas, but it increased significantly from August to September; the same trend was observed in sand-dune areas (Figure 3.4D). The biomass, species diversity, and TDN in low-land was significantly higher than those in sand-dunes (Figure 3.4A, B, E). More detailed information is given in Tables S3.1 and S3.2.

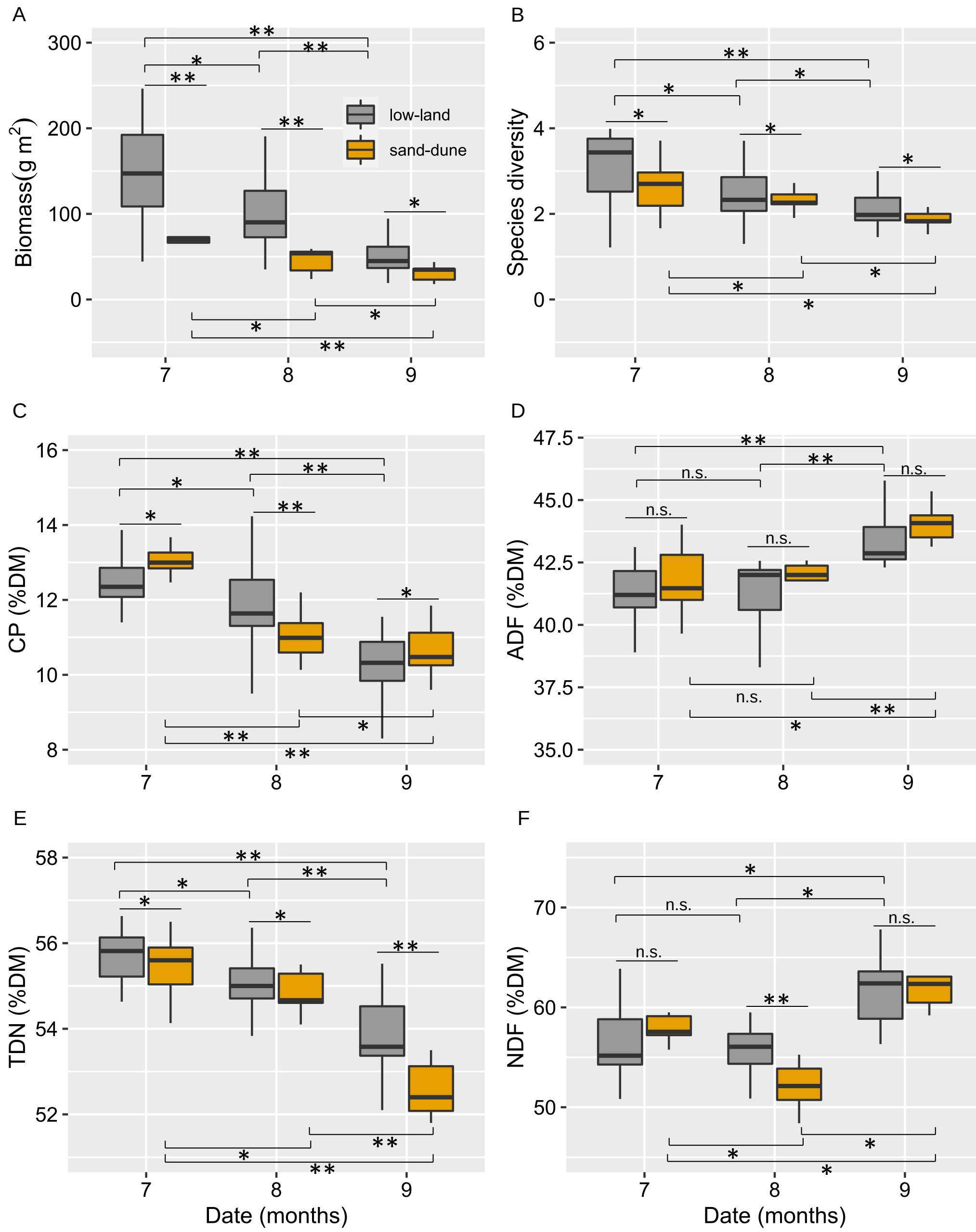


Figure 3.4. Comparison of herbage quantity and quality in different grazing periods between low-land and sand-dune. The box plots show the values of (A) pasture aboveground biomass, (B) species diversity, (C) crude protein (CP), (D) acid detergent fiber (ADF), (E) total digestible nutrients (TDN), (F) neutral detergent fiber (NDF). In the box plots, bounds of the box spans from 25 to 75% percentile, center line represents mean, and whiskers visualize 5 and 95% of the data points. (*$P < 0.01$, **$P < 0.001$).

Table 3.1 Multiple linear regression results for whole ranch, low-land and sand-dune areas.

Variable	Total ranch		low-land		sand-dune	
	Regression coefficient	P value	Regression coefficient	P value	Regression coefficient	P value
Biomass (g m^{-2})	-0.064	0.091	-0.157	0.053	-0.133	0.877
CP (% DM)	-0.7	0.078	-2.377	0.055	-0.641	0.771
ADF (% DM)	0.15	0.071	3.093	0.025*	1.026	0.795
NDF (% DM)	0.07	0.102	1.42	0.102	0.184	0.815
TDN (% DM)	-0.41	0.06	-5.731	0.017*	-2.512	0.811
August (dummy)	-0.508	0.143	-0.612	0.143	-3.81	0.653
September (dummy)	-0.806	0.147	-0.736	0.147	-1.541	0.915
Low-land (dummy)	1.328	0.05*				
R Square	0.45		0.75		0.379	
Adjusted R Square	0.34		0.624		-3.966	
F-statistic	2.86		5.74		0.087	
P value	0.064		0.034*		0.988	

*Notes: The variables used in the regression of cattle density was the dependent variable, and biomass, crude protein (CP), acid detergent fiber (ADF), neutral detergent fiber (NDF), and total detergent nutrient (TDN) were independent variables for the fixed effects in the model. August, September and low-land are the dummy variables for fixed effects of seasonal grazing periods, the variable of July and sand-dune were reference group in the model. In analysis, each dummy variable is compared with the reference group. *Indicates a significant relationship (P < 0.05).*

The adjusted R^2 of the multiple regression for the whole ranch was 0.34 (P = 0.06). The results showed that landform, rather than forage quality and quantity, significantly affected the foraging density: cattle foraging significantly increased (P = 0.05) in low-land but decreased in sand-dune areas. The adjusted R2 of the multiple linear regression for the low-land was 0.62 (P = 0.034). In the low-land, biomass (P = 0.053), CP (P = 0.055), and TDN (P = 0.017) were negatively related and ADF (P = 0.025) was positively related with foraging density (Table 3.1). No significant relationships were observed between foraging density and herbage nutrient contents in sand-dune areas.

3.4. Discussion

3.4.1 Cattle distribution pattern in low-land and sand-dune areas

Generally, livestock prefer gentle terrain and adjust their grazing strategies to avoid higher elevations (Roath and Krueger, 1982). The greater proportion of foraging behaviors in the low-land areas than in sand-dune areas (Figure 3.3A) supports the grazing habits of livestock in an undulating landscape, which led to higher foraging densities in the low-land areas (Figure 3.2A, B). Our study also demonstrated a negative relation between foraging density and elevation (Figure 3.2C). High energy costs are associated with cattle moving about a rugged terrain. A previous study reported that the cost of lifting one kilogram one vertical meter is 5.9 kcal for wild and domestic ungulates, regardless of body weight or species (Parker et al., 1984), and the oxygen consumption rate increases when they walk on steep slopes (Yousef et al., 1972).

Moreover, herbage quality and quantity are also associated with the different cattle distribution patterns between low-land and sand-dune areas (Sanaei et al., 2019). With respect to pasture quantity, our results showed greater biomass and species diversity in low-land areas than in sand-dune areas throughout the grazing period from July to September. These results are consistent with a previous works that reported livestock tend to lengthen their foraging time in plant communities that offer abundant quantities of preferred forages (Provenza, 1995; Launchbaugh and Howery, 2005). With regard to herbage quality, although the nutrient contents of forage species did not differ between low-land and sand-dune areas throughout the grazing period (Fig. 4), the livestock probably could gain more nutrients from forage species in low-land areas because the they were more abundant (higher biomass) (Sebata and Ndlovu, 2012). Cattle prefer to forage in plant communities with higher species diversity because a mixture of forage species can supply more nutrients and energy (Rosiere et al., 1975). Thus, the higher species diversity in low-land areas (Fig. 4) might be one possible reason for the higher foraging density there (Rosiere et al., 1975).

3.4.2 Variation of cattle behavioral activity and foraging density

Previous studies revealed a trade-off between livestock grazing time and intake rate per bite, which is determined by the pasture condition (Gordon and Lascano, 1993). The intake rate per bite declines with a reduction in forage availability, which results in at least partially compensatory changes in foraging time (Davies and Southey, 2001; Lachica and Aguilera, 2003). Cattle can meet their necessary energy requirement in a shorter foraging time with a high intake rate per bite (Prache et al., 1998). In our study, at the beginning of the grazing season in July, less foraging time and lower foraging density were observed both in low-land and sand- dune areas (Figure 3.3A, B). During this period, the biomass and nutrients of herbage were higher (Figure 3.4), consistent with there being a higher intake mass per bite and a higher nutrient intake per bite in a relatively small area (Figure 3.3C). Moreover, the relatively small foraging areas of cattle in both low-land and sand-dune areas supports the idea that livestock can gain the necessary energy in a relatively short period without moving to other areas for foraging.

Foraging time increased from July to September (Figure 3.3A), while the foraging density increased in August and September by cattle in the low-land areas (Figure 3.3B). The probable reason is that herbage quantity and quality both gradually decreased from July to September (Figure 3.4; Figure S3.4), as the herbage was consumed by cattle (Butt, 2010) and reached maturity

(Schönbach et al., 2009). Cattle density was negatively related with herbage quantity and quality in low-land areas (Table 3.1). The maturation process of herbage can lead to a decline in CP and an increase in ADF because the proportion of stems and leaves increases (Benvenutti et al., 2008). Therefore, the maturation of plants increases their tensile strength and causes the cattle to spend more time chewing and alters their biting position as they select more nutritious parts of the herbage (Tjardes et al., 2002). When forage availability is low and herbage quality is poor, cattle can improve their intake by taking smaller bites (Lyons and Machen, 2000), but they need a longer grazing time to compensate for the decline of intake mass and nutrients per bite (Baumont et al., 2007). The relative increase of foraging time from August to September was greater than that from July to August in both the low-land and sand-dune areas; this result can be explained by the decline of herbage quality, which caused the cattle to spend more time ruminating to absorb the nutrients from the herbage. The foraging density also increased as the proportion of low-land areas foraged increased. This finding implies that as the grazing season progresses, cattle spend more time foraging on herbage in a given area and they acquire more cumulative nutrients by foraging on different herbage communities by increasing the proportion of low-land areas foraged.

The variation of foraging behaviors on the ranch supports previous findings that cattle have the ability to alter their behaviors to cope with the balance between nutrient demand and energy consumption by using various spatiotemporal distribution patterns (Fierro and Bryant, 1990; Butt, 2010). In our study, there was no change of foraging density in sand-dune areas (Figure 3.3B) even though the proportion of sand-dune area foraged sharply increased from July to September given the elevated foraging time during this period. While the cattle foraged in sand-dune areas, they consumed more energy to maintain a standing posture and to walk on the soft sandy soils of the dunes (Relton, 2015). We also observed no relationship between cattle density and herbage nutrient content in sand-dune areas (Table 3.1), possibly because sand-dunes offer relatively lower cumulative herbage nutrients throughout the grazing period and because a larger grazing area is required to gain sufficient nutrients from sand-dune herbage communities.

In addition to the different distribution of cattle foraging between low-land and sand-dune areas, a heterogeneous distribution was observed in the low-land areas (Figure 3.3E). Generally, cattle can readily travel across gentle terrain while grazing (Bailey, 2005), but in rugged topography, the movement of cattle from one feeding site to another is restricted (Bailey, 1995). Livestock always show a concentrated distribution early in the grazing season and a more dispersed distribution as the season progresses (Evans et al., 2004). We observed a high density near the cattle shed at the beginning of the grazing season, but subsequently cattle spread to other areas; the decline in both high and low foraging density and the increase in medium foraging density (Figure 3.3D) indicated widely dispersed and evenly distributed foraging late in the grazing season (Figure 3.3E). The exploration of new grazing areas forces the cattle to pass through rugged terrain. Thus, the movement route for foraging might cross dunes on the ranch, thus increasing the foraging area in sand dunes later in the season.

3.4.3 Limitations of the study

Our study has several limitations, including insufficient data for the experiment design, and the results were affected by biotic and abiotic factors involved in the cattle behavior and distribution pattern. First, the cattle behaviors and distribution pattern varied under different climate conditions, such as extreme air temperature, which could increase the cattle's core body temperature and respiration rate and reduce activity, feed intake, and milk yield (Hahn, 1999, Ominski et al., 2002, West, 2003). Daily air temperature and precipitation were monitored at a meteorological station 20 km away from the study site. Few and similar precipitation events occurred during the recording periods of cattle behaviors in our study, and the difference in temperature among the grazing periods hardly affected the cattle behaviors and distribution during the experimental periods (Figure S3.1 and S3.2). Therefore, the results of our study may not be generalized to ranches affected by extreme climate conditions that would influence the cattle's normal behaviors and distribution pattern. In future studies, it will be critical to include longer grazing times under different climate conditions to broaden the scope of our findings.

Another limitation was that we obtained GPS data for only two cattle and used them to represent the behaviors and distribution pattern of the entire cattle population. The size of a herd will vary with resource conditions on a ranch (Howery et al., 1998). When resources are relatively abundant, cattle in a herd usually feed and rest together, and dominant animals displace subordinates less frequently. A previous study showed that as cattle herds extend their home ranges, they divide into several small groups in winter and spring but form a large group and concentrate near water and feed at other times (Lazo, 1994). Our study period was from July through September. Because the forage resource of this period was relatively abundant, the cattle congregated in a large group. Our field observations during the period also provide evidence of group behaviors where cattle foraged together in the same low-land area and sand-dune area. Therefore, the behavior of two cattle might actually be representative of the population. However, in our study, the recorded grazing density might be higher than the actual density because we used the grazing density of just two cattle to represent the whole population in September. The home range of the cattle herd in September might be larger because of the low quality and quantity of herbage (Venter et al., 2019). Therefore, location data obtained from more cattle over a longer period are needed to clarify cattle behaviors and distribution patterns.

3.4.4 Implications for land management

The spatial and temporal variation of livestock foraging density can affect ecosystem functions (Venter et al., 2019). Our results indicate that higher foraging density occurred in low-land areas than in sand-dune areas (Figure 3.2A), especially when the herbage quantity and quality were low (Figure 3.3B). In the grazing periods with poor herbage conditions, foraging in low-land areas tended to occur at high density because of the reduction in forage quality and availability. Thus, ranchers should initiate interventions such as a rotational grazing system, in which a ranch is delineated into two grazing areas, such as low-land and sand-dune areas.

The essential role of rotational grazing is to decrease the grazing time in the area with higher grazing density (Heitschmidt and Taylor, 1991). Continuous grazing may lead to ranch degradation over the long term (Venter et al., 2019). For policymakers, when recommending the management practice of rotational grazing to herdsman, low-land and sand-dune areas should be recognized as two grazing camps. The management of grazing duration at each camp is determined by the herbage conditions; for example, cattle might be moved to the sand-dune camp once the herbage condition at the low-land camp fell as a result of poor herbage weather conditions.

3.5. Conclusion

The cattle preferred to forage in low-land areas compared to sand-dune areas, probably reflecting the greater energy consumption required and poorer herbage conditions in the high-elevation areas. The temporal dynamics of foraging pressure showed different patterns in low-land and sand-dune areas from July to September. The foraging pressure and proportional area used by cattle both increased from July to September in low-land areas, whereas only the proportional area foraged increased in the sand-dune areas. As the grazing season progressed, the foraging time increased in both low-land and sand-dune areas. The foraging density increased as herbage quality and quantity declined in low-land areas.

Our results indicate that microtopographic variation facilitates uneven and patchy foraging distributions on the ranch, and that high foraging density is likely to occur in low-land areas of an undulating landscape. When making grazing policies in this region, the microtopography of a ranch and seasonal dynamics of the spatial distribution of foraging density should be considered to manage grazing density. Ranch owners should consider using a rotational grazing system in which cattle are shifted from a low-land grazing camp to a higher elevation camp during periods of herbage decline.

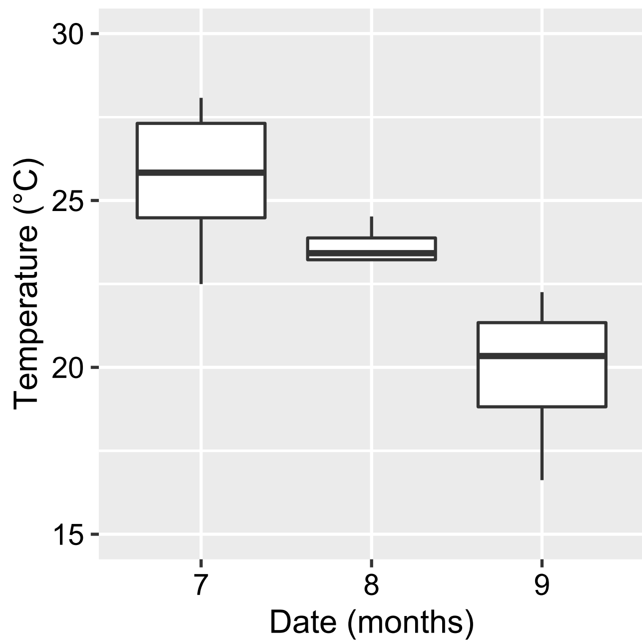


Figure S3.1 Mean air temperature in the three grazing periods (11–15 July; 11–15 August; 11–15 September). In the box plots, the lower and upper bounds of the box span the interval from the 25th to the 75th percentile, the center line represents the mean, and the whiskers represent the 5th and 95th percentiles.

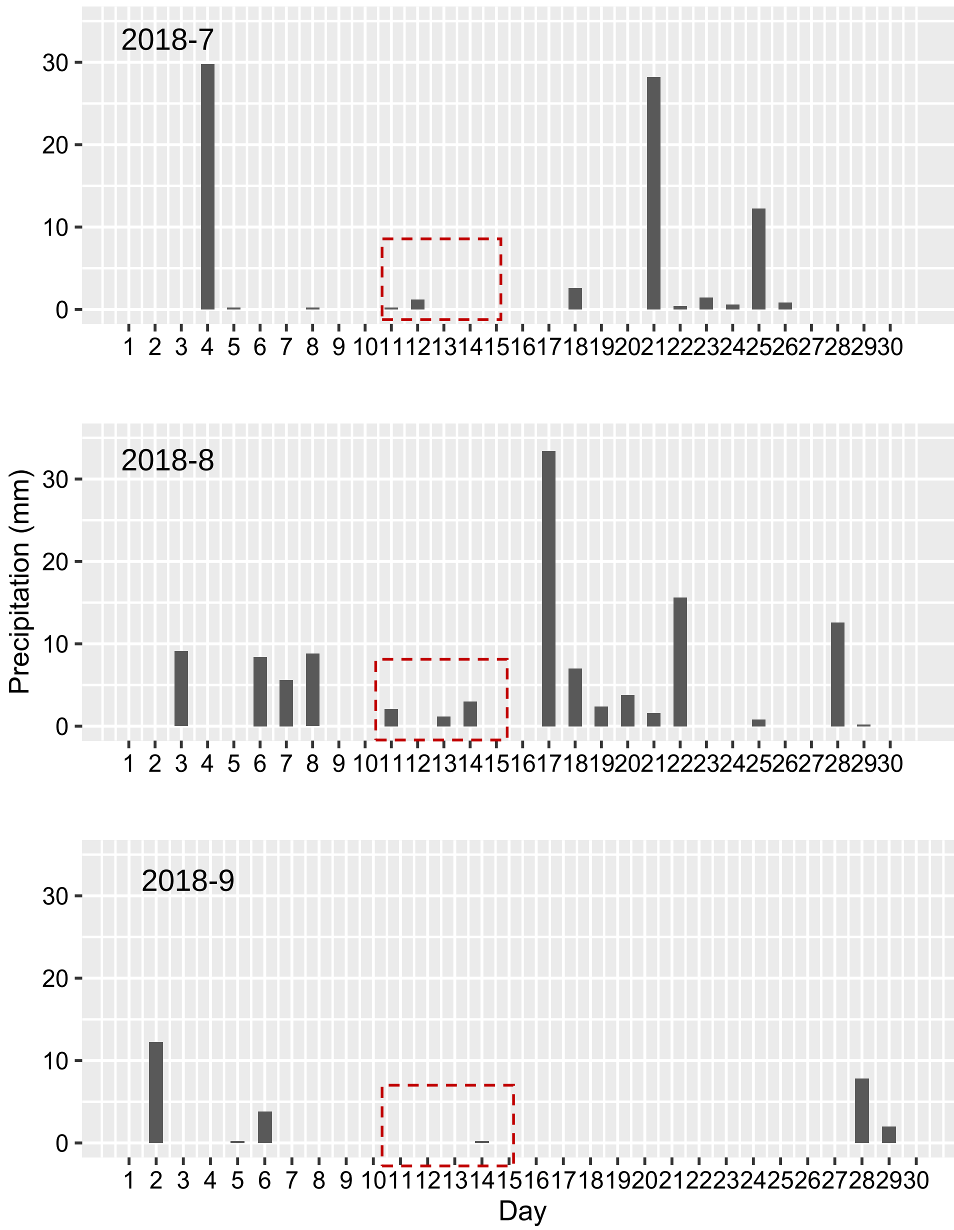


Figure S3. 2 Daily precipitation in the study area in July, August, and September. The red dotted square represents the period when cattle data were recorded in each month.

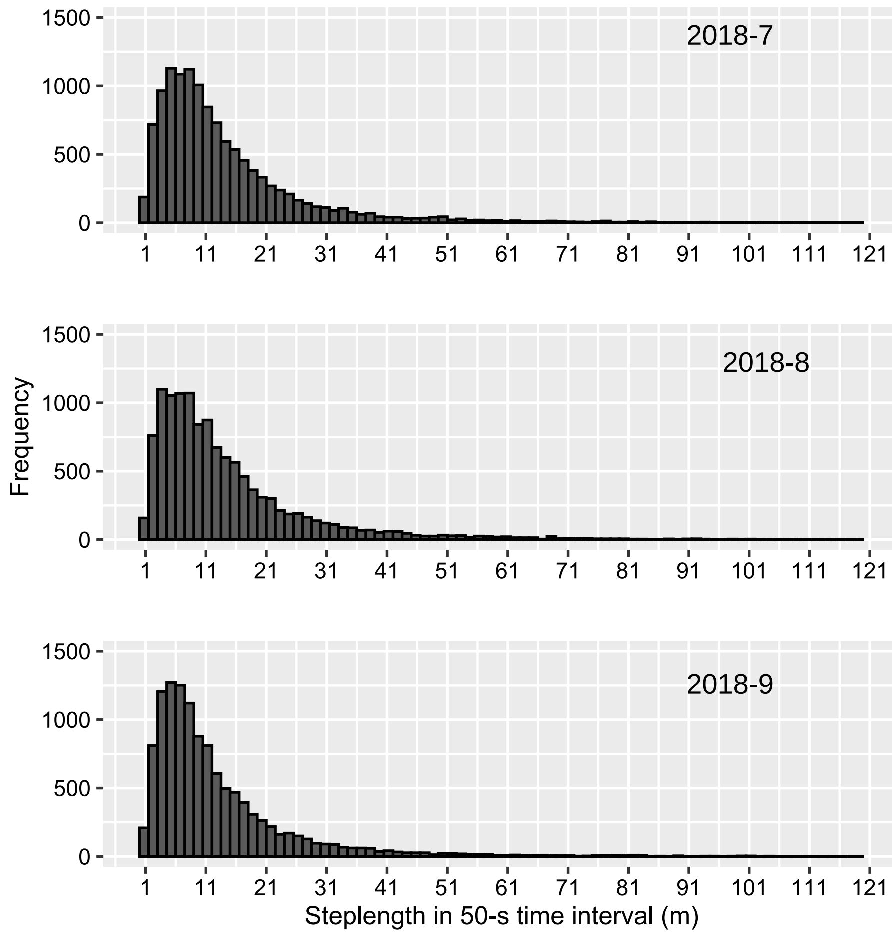


Figure S3.3 Frequency of step-length walked by livestock in a 50-s time interval during three grazing periods (11–15 July; 11–15 August; 11–15 September) in 2018.

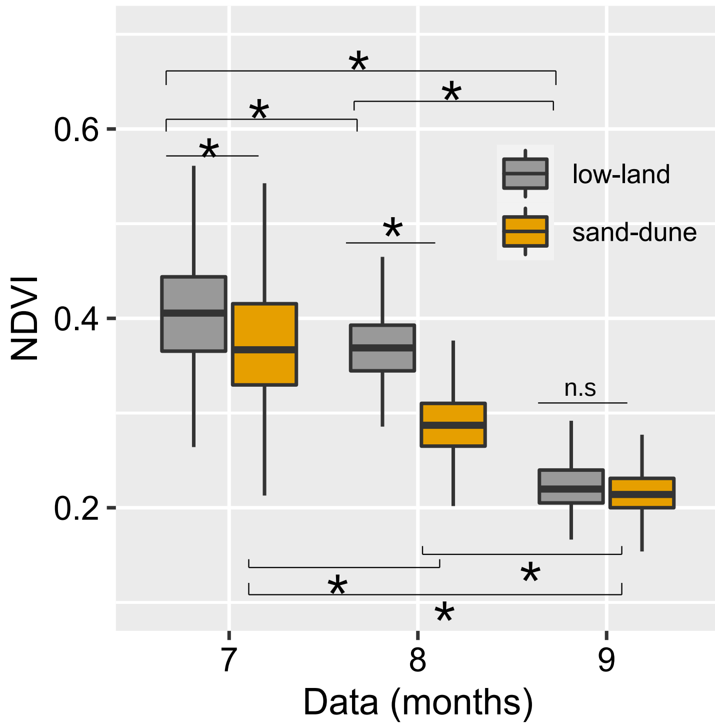


Figure S3. 4 Comparison of the box plots of pasture NDVI values compared between lowland and sand dune areas and among the different grazing periods. In the box plots, the lower and upper bounds of the box span the interval from the 25th to the 75th percentile, the center line represents the mean, and whiskers represent the 5th and 95th percentiles. Significance was assessed by a Kolmogorov–Smirnov test; * denotes statistical significance at $P < 0.05$.

Table S3. 1 The two-way ANOVA table for the herbage indicators in the study

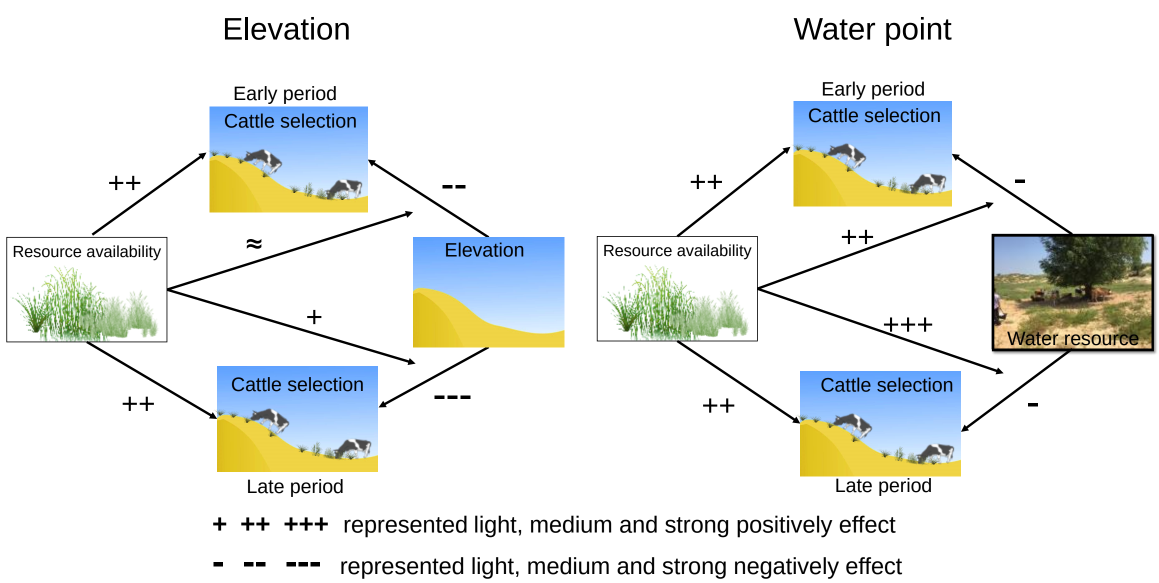
Variables	Effect	Df	F-value	P value
Biomass (g m^{-2})	Time	1	39.898	< 0.001
	Landform	1	24.471	< 0.001
	T×L	2	4.747	<0.01
Species diversity	Time	2	19.575	< 0.001
	Landform	1	5.034	<0.01
	T×L	2	1.03	0.36
Crude protein (DM %)	Time	1	80.613	< 0.001
	Landform	1	0.058	0.07
	T×L	1	0.52	0.47
Total digestion (DM %)	Time	1	88.40	< 0.001
	Landform	1	4.62	< 0.01
	T×L	1	1.22	0.27
Acid detergent fiber (DM %)	Time	1	9.353	< 0.001
	Landform	1	0.448	0.51
	T×L	1	0.19	0.66
Neutral Detergent Fiber (DM %)	Time	1	17.089	< 0.001
	Landform	1	0.132	0.71
	T×L	1	0.148	0.7

Table S3.2 Number of samples, Means and SD for the herbage indicators in the study

Variables	low-land			sand-dune		
	Number	**Mean**	**Std. deviation**	**Number**	**Mean**	**Std. deviation**
Biomass (g m^{-2})						
June	21	147.5	1.8	9	69.1	6.1
August	21	112.7	5.6	9	51.7	1.7
September	21	51.9	1.5	9	30.7	5.1
Species diversity						
June	21	3.2	0.75	9	2.65	0.63
August	21	2.39	0.78	9	2.36	0.3
September	21	2.06	0.49	9	1.83	0.25
Crude protein (%DM)						
June	21	12.5	0.63	9	13.1	0.38
August	21	11.8	1.2	9	11.2	1.01
September	21	10.	1.09	9	10.7	0.67
Total digestion (%DM)						
June	21	55.9	1.16	9	55.5	0.73
August	21	55.1	0.67	9	55	0.99
September	21	53.6	1.38	9	52.6	0.62
Neutral Detergent Fiber (DM %)						
June	21	55.9	4.04	9	58.6	2.9
August	21	55.4	3.67	9	52.1	4.7
September	21	62.1	4.29	9	62.8	3.22
Acid detergent fiber (DM %)						
June	21	41.4	1.84	9	41.9	1.36
August	21	42.2	4.04	9	41.7	1.04
September	21	43	1.34	9	44	0.71

Chapter 4

Impacts of landform and distance to water resource on the spatial use of forage by cattle change with the resource availability



Chapter 4. Impacts of landform and distance to water resource on the spatial use of forage by cattle change with the resource availability

4.1 Introduction

Livestock grazing is the most widespread land-use practice and significantly benefits the society in terms of food, income, nutrients and others (Fuhlendorf and Engle, 2001; Gibson, 2012). In the provision of these benefits, the total number of livestock will increase by two times by 2050 owing to the increased population density and corresponding demand (Rosegrant et al., 2009). The overgrazing can alter ecosystem function and reduce vegetation nutrient and yield, especially in the arid and semi-arid land globally (Ayantunde et al., 1999; Gutman et al., 1999).

Negative livestock grazing impacts on rangelands are often the result of uneven distribution when the rangeland is over-stocked. The fence has been widely used to reduce overgrazing by breaking a whole ranch into several sub-areas to promote uniformity of the foraging pressure over the ranch (Smith and Owensby, 1978; Charles et al., 1985). Grassland managers in China implemented the fences in the name of ‘Grazing exclusion’ and ‘Livestock-forage balance management’ since the 1970s to prevent grassland degradation from continuously increasing the number of livestock units in the household ranch (Conte & Tilt, 2014). Relevant studies showed the application of fencing could enhance plant community recovery, soil physicochemical and biological properties of the degraded grassland (Wang et al., 2018). Yet the positive effect of fencing will decrease over time (Yao et al., 2019). For instance, the implement of rotational grazing with fencing showed few efforts for the selection of proportional grazing of available plants (Launchbaugh and Howery, 2005; Bailey and Brown, 2011), because animals choose to eat plants based on nutritional status and digestibility regardless of how tightly they are concentrated (Bailey and Brown, 2011).

Understanding livestock distribution is crucial to sustainable management in the ranch (Vallentine 2001). The critical driving factors related to the abiotic such as the settlement of watering points and topography, biotic factors such as pasture quality and quantity determine the selective distribution pattern (Jouven et al., 2010). However, these factors are often ignored to consider in the practical management of livestock grazing, which is critical for preventing degradation and restoration of degraded grassland (Briske et al., 2008; Hao et al., 2018). The rugged terrain strongly facilitates the uneven grazing distribution while the livestock concentrated and spent more time on gentle terrain (Bailey et al. 2015; Ganskopp and Vavra 1987; Mueggler 1965). The concentration of grazing in areas preferred by livestock can result in adverse impacts on forage production, water quality, wildlife habitat, and other ecosystem goods and services (Pinchak et al. 1991). For example, cattle often prefer riparian areas and spend a disproportionate amount of time in these areas as compared to uplands (Smith et al. 1992). Concentrated grazing, especially in riparian zones, may reduce vegetative cover and stream bank stability as well as increase soil erosion (Kauffman et al. 1983; Blackburn 1984). If cattle spend more time grazing upland slopes farther from water, condition and function of riparian areas can be improved effectively. The problem is determining trade-offs between energy expenditure and cost of livestock selecting forage, and the efficient and cost-effective method to modify grazing patterns and prevent animals from overusing preferred areas pastures (Bailey 2004).

The Horqin Sandy Land in northern China has suffered from serious desertification (Chen and Su, 2008). In the past two decades, the fences were established to restore the decertified grassland. But, the desertification in this region grassland is still ongoing (Miao et al., 2015). The landforms characterized by the rugged micro-topography result in the complex interaction between livestock distribution and landforms and relative herbage conditions. Before the use of fences, the ratio of dune areas decreased because they were fattened to cropland for the economic benefits, which shift landscape and vegetation community (Zuo et al., 2009). Previous studies used the number of unit livestock per unit area as a surrogate of grazing density on plant communities and soil properties (Zhang et al., 2005; Li et al., 2012; Tang et al., 2016). Results from these studies can provide some insight into the relationship between livestock grazing and the ecological processes of the grassland, however, it neglects the spatiotemporal dynamics of actual foraging pressure. Our previous study showed that cattle spent more time foraging on lowland areas than dunes areas with the seasonal decline of herbage conditions (Gou et al., 2020). Knowledge of fine scale-space use and seasonal foraging strategies of cattle in the rangelands of Horqin Sandy Land would be a critical component of developing optimized grazing strategies to reduce overgrazing.

A comprehensive analysis of the mechanisms governing livestock distribution can provide guidelines for local farmers to minimize overgrazing. With the emergency of the high-resolution sensors with drone extracted the image such as landform characteristic, which could support detailed and fine information about biophysical and biochemical parameters of vegetation remotely and overbroad spatial extents (Lu, 2017). An RSF is defined by characteristics measured on resource units such that its value for a unit is proportional to the probability of that unit being used by an organism (McLoughlin et al., 2010).

We hypothesized that cattle will utilize productive vegetation in the lowland areas, located closer to waster point and avoid high land areas during both early and late grazing period. The difference is that the strength of preventing high elevation areas become stronger while the decline of available vegetation resource during the late grazing period due as to minimalize energy losses. Therefore, the study is to develop models to predict cattle behaviors distribution on contrasting landforms. To predict and map the probability of cattle use habitat and inform ranch management efforts, 1) to determine the important factors affecting resource selection by cattle grazing between early and late grazing period, 2) to quantify the impact of the interaction between landforms and available vegetation resource to the cattle selection distribution, 3) to assess the accuracy of RSF model by comparing RSF value in each grid and actual counting number of each grid.

4.2 Materials and methods

4.2.1 Study area

The study area was located in Horqin Sandy Land (42°00′N, 119°39′E) of northern China. The landforms mainly include low-land areas, fixed and semi-fixed dunes, with the dunes was the dominate landforms in the area account for 70% the total area (Zhang et al., 2012) with averaged 5–8m in height, 400–600 m in length and 20–40 m in width (Zhang et al., 2005).

Precipitation occurs mainly between June and August with per cent of 70-80 % and the annual mean temperature was 7.3 °C from 1980 to 2014. The period of windy days with windstorms occur mainly between March and May with speed ranged from 3.2 to 4.5 m s^{-1} (Zhang et al., 2012).

The practical management of livestock grazing in Horqin Sandy Land include ‘Grazing exclusion’ and ‘Livestock-forage balance management’, and the breed is sheep, goats, and cattle have been grazed in this region in recent decades. With the decline of grazing capacity of the pasture from 1.81 to 0.19 sheep unit (Jiang et al., 2003; Li et al., 2012), the study area (42°51′24.59″N, 120°55′50.34″E) implemented the ‘Livestock-forage balance management’ allowed grazing periods from 1st July to 30th September to reduce the number of livestock in the region (Jiang et al., 2003; Li et al., 2012).

The study ranch represented the typical household ranch with typical landforms included both fixed dunes and low-land areas in the Horqin Sandy Land (total area is 20.1 ha, with 8.04 ha of lowland and 12.06 ha of sand dunes). The history of land use was to grow corn and millet on the low land areas in the past decade. The vegetation is typical of a temperate desert steppe; the dominant species are *Pennisetum centrasiaticum, Cleistogenes squarrosa*, and some dwarf shrubs (*Artemisia oxycephala and Artemisia halodendron*). The low-land area characterized by Kastanozems, and sand-dune by Ustic Sandic Entisols (FAO, 2006). The Ustic Sandic Entisols are with a loose structure, and they are particularly susceptible to wind erosion (Li et al., 2009). Soils in the low-land areas have more nutrients and higher soil moisture level, as compared with soil property in dunes (Li et al., 2009).

4.2.2 Data selection

We generated cattle locations from 2 of the adult Simmental cattle attached to the GPS device with 50-s recording time intervals (precision ±3 m; catalog no. GT-600, i-gotU, Mobile Action Technology, Taipei, Taiwan) during the grazing season 2018 (1 July to 30 September). As the damage of GPS devices through the water damage and loss, the available GPS data was only for 5 consecutive days (11 to 15 September) two cattle. The available data of cattle location in July was selected following the same time length from 11 to 15 July. During the grazing season, we observed cattle activities for around 15 days (09:00 to 17:00 UTC + 8) per month and found that the 13 animals moved together around the ranch. Therefore, we selected 5 consecutive days in early and late grazing period, and the GPS data of two cattle were used for the following analysis.

As the objective of this study is to understand the cattle behavior distribution pattern, we only focus on foraging behaviors. The predicted metrics of distance (linear distance, cumulative distance) and turning angle were calculated by using the focal locations from 100- to 800-s time intervals. We applied the random forest algorithm to classify livestock behaviors by using predicted metrics and field-observed behavioral data. To evaluate the performance of the random forest model, we used 10-fold (i.e., performed 5 times) cross-validation to separate the data into smaller training data sets and testing sets. The overall accuracy of the random forest model was 87% (95% CI = 85 - 90%). Then, imported cattle positions into the constructed algorithm to classify foraging and non-foraging behaviors (Gou et al.,2019).

4.2.3 Resource selection

We developed separate cattle resource selection function (RSF) models for foraging behavior and season (early and late grazing period). The RSF was conducted by using the logistic regression model by compared used locations and randomly generated available locations from GPS (Gillies et al., 2006). Cattle locations generated within fenced lines of study ranch approximated to the home range.

To obtain unbiased estimator of β with the adequate number of random locations, we followed the method of Northup et al. (2013) and Roever et al. (2015) and fit logistic regression models to incrementally increasing samples of random locations (100, 1000, 5000, 10000, 30000) from the larger availability samples within the home range (ranch size, 100,000 grid cells). We repeated this process 1000 times and monitored the β coefficients of 4 representative covariates to identity the density at which coefficient values begin to converge. Convergence occurred at a minimum of 10000 random locations in both early and late RSF model (Figure S4.1).

To explore the cattle resource selection preferences, we considered several environment variables including seasonal vegetation types, slope, elevation, aspect and distance to water and Normalized Difference Vegetation Index (NDVI). NDVI as high-resolution image, as all variables converted to 2 meters as the following analysis.

The methods to generate the ranch true color map and DSM map have shown in Gou et al (2020) in 2 m × 2 m resolution. the vegetation classification map was generalized into 5 habitat categories (bare land, grassland, forest land and brushland). The maximum likelihood classification to calculates the probability that a given pixel belongs to a specific class. Each of the classes selected 200 samples randomly through inside the ranch, and 80% of the data set was developed model and remained data was used to test the data. Elevation, aspect and slope (degrees, north–south–facing slopes) were derived from the DSM map with 2-m resolution.

4.2.4 Statistical analyses

We used R software and package MuMin to compare all possible variable combinations and Akaike Information Criterion to assess model fit (AICc; Grueber et al., 2011; Zuur et al., 2009). We considered that models with DAICc < 2 with respect to the best model had similar empirical support (Burnham and Anderson, 2002). To obtain the final coefficients we averaged the models using Akaike weights within the given AICc threshold.

To assess how well predictive maps fit the test data, we classified pixels of the predictive map into 20 equal-interval RSF intervals that corresponded to the relative probability of use (i.e. 0–5%, 5–10%, 10–15%, etc.; Durner et al. 2009). We plotted data corresponding to the appropriate time period on the predictive map and calculated the frequency distributions of observed elk locations within RSF intervals.

Conditional indirect effects of the NDVI moderating the effects of landforms characteristics on RSF value were examined by decomposing the significant interactions between NDVI and landforms characteristics using bootstrapping analysis. To identify the extent of the conditional indirect effects, the Johnson–Neyman (JN) technique was used to estimate the region of significant standard deviation values of the moderator (NDVI). A bootstrapping procedure was used and obtained 95% bias corrected confidence intervals based on 50 000 replicates for the lowest (or highest negative) significant standard deviation (SD) values of the moderator from the JN technique rounded to the nearest 0.05 SD. If the moderator value was not significant (P > 0.05), it was lowered by 0.05 SD. This process was repeated until a moderator SD value was significant. When this happened, the previous value tested was retained.

4.3 Results

The most supported model of cattle resource selection in early grazing periods (ΔAICc=0; Table 4.1), considered that models with ΔAICc < 2 with respect to the best model had similar empirical support (Burnham and Anderson, 2002).

Table 4.1 Model selection results for the examination of habitat use by cattle in July. The 5 highest-ranking models are presented.

Model	Covariate composition	DF	AICc	ΔAICc	Weight
1	vegetation + slope + elevation + aspect + dist to water + NDVI	9	22813.2	48.9	<0.001
2	vegetation + elevation + slope + dist to water + NDVI	8	22764.3	0.0	0.975
3	vegetation + elevation + dist to water + NDVI	8	22771.6	7.3	0.025
4	vegetation + slope+ dist to water + NDVI	7	Inf	Inf	<0.001
5	vegetation + slope + elevation + aspect + NDVI	8	22822.9	58.6	<0.001

During the period of early grazing, habitat use selected vegetation classes dominated by trees and bush over grass, prefer to higher NDVI and areas closer to water, avoiding areas at higher elevation and distance to settlement (Table 4.2).

Table 4. 2 Coefficients (β) of standardized effects from best performance regression model explaining variations in habitat use by cattle in July. The coefficients of land cover classes are calculated in related to class "bare land".

Predictor	**β**	**SE**	**P value**
Intercept	-0.67	0.04	< .01 **
Forestland	0.33	0.06	< .01 **
Grassland	0.02	0.05	0.64
Bushland	0.13	0.05	0.21
Elevation	-0.20	0.01	< .01 **
Distance to water	-0.14	0.03	< .01 **
Slope	-0.06	0.01	0.01458 *
NDVI	0.22	0.02	< .01 **
NDVI × Elevation	0.02	0.01	n.s
NDVI × Slope	0.04	0.01	n.s
NDVI × DTW	0.49	0.03	< .01 **

Additionally, the interaction effects were no significant between NDVI and slope and elevation but was positive significant with distance to water, which significantly reduced the negative effects of DTW under 0.4 of NDVI and increased positive effects over 0.43 in early grazing period (Figure 4.1)

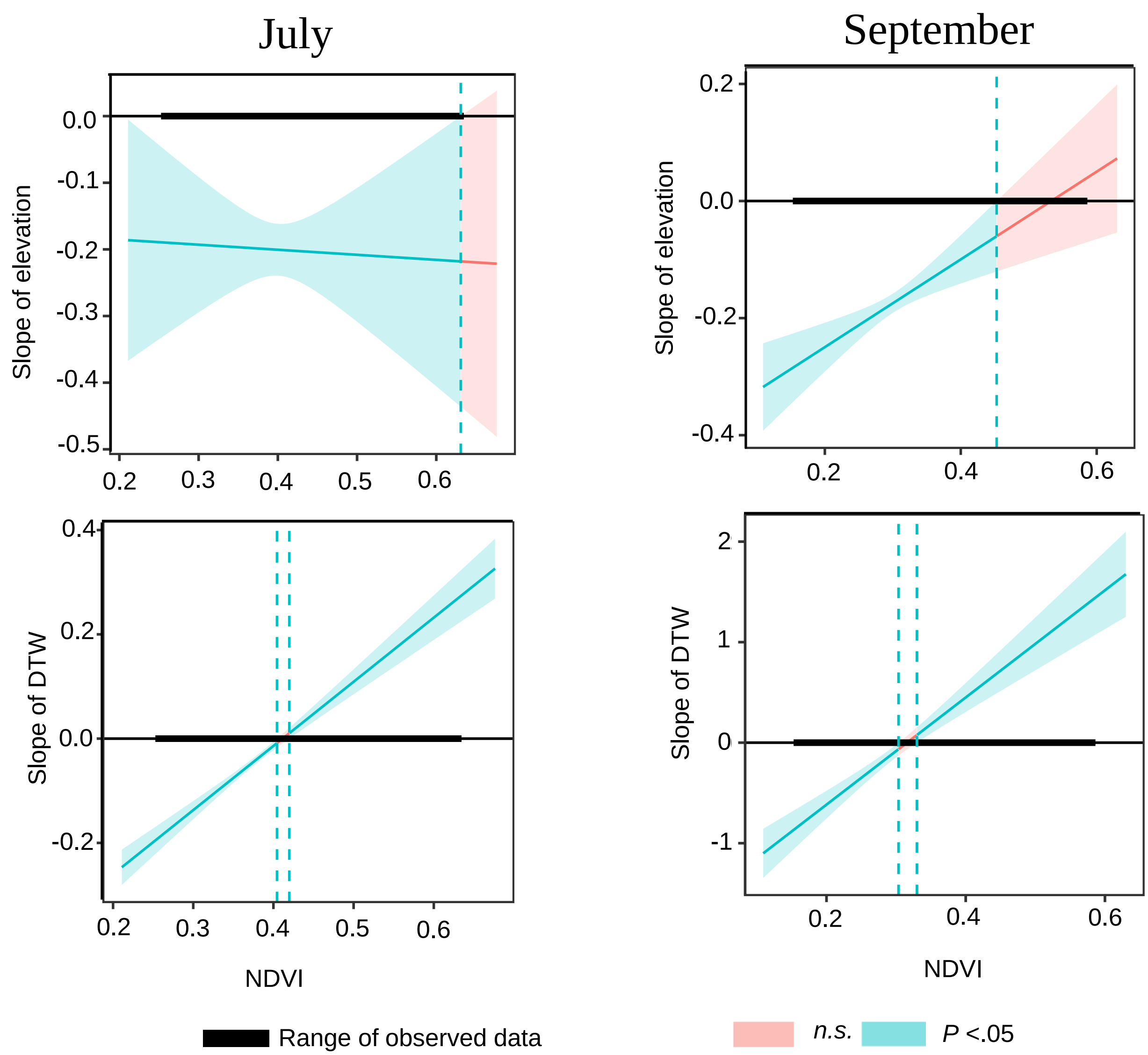


Figure 4.1 The conditional indirect effects of Normalized Difference Vegetation Index (NDVI) with 95% confidence intervals on elevation (m) and distance to water point (DTW) as a function of RSF value corresponding Johnson-Neyman plot in early and late grazing period.

The best model explaining cattle resource selection during the late grazing period was the same as the period of the early period include all variables expect aspect (ΔAICc=0; Table 4.3).

Table 4.3 Model selection results for the examination of habitat use by cattle in September. The 5 highest-ranking models are presented.

Model	Covariate composition	DF	AICc	ΔAICc	Weight
1	vegetation + slope + elevation + aspect + dist to water + NDVI	9	53697.2	53.1	<0.001
2	vegetation + slope + elevation + dist to water + NDVI	8	53644.1	0.0	1
3	vegetation + elevation + dist to water + NDVI	8	53660.7	16.6	<0.001
4	vegetation + slope + dist to water + NDVI	7	Inf	Inf	<0.001
5	vegetation + slope + elevation + aspect + NDVI	8	53680.8	36.7	<0.001

During the period of late grazing cattle prefer to forest land over both bush and grassland, lower elevation, higher NDVI, even slope and areas closer to water (Table 4.4).

Table 4. 4 Coefficients (β) of standardized effects from best performance regression model explaining variations in habitat use by cattle in September. The coefficients of land cover classes are calculated in related to class "bare land".

Predictor	**β**	**SE**	**P value**
Intercept	-1.73	0.03	< .01 **
Forestland	0.30	0.04	< .01 **
Grassland	0.06	0.03	0.150
Bushland	0.03	0.03	0.982
Elevation	-0.42	0.01	< .01 **
Distance to water	-0.17	0.02	< .01 **
Slope	-0.06	0.02	< .01 **
NDVI	0.20	0.01	< .01 **
NDVI × Elevation	0.10	0.02	< .01 **
NDVI × Slope	0.03	0.01	n.s
NDVI × DTW	0.31	0.03	< .05 *

The interaction effects between NDVI and elevation and distance to water were positive significant, the conditional indirect effect of NDVI significantly reduced the negative effects of elevation while the value of NDVI less than 0.44 and significantly decreased the negative effects of DTW under 0.3 of NDVI and increased positive effects over 0.33 of NDVI in late grazing period (Figure 4.1). The average NDVI decreased with increasing elevation in the early grazing period, and the average NDVI slightly increased with increasing elevation in the late grazing period (Figure 4.2).

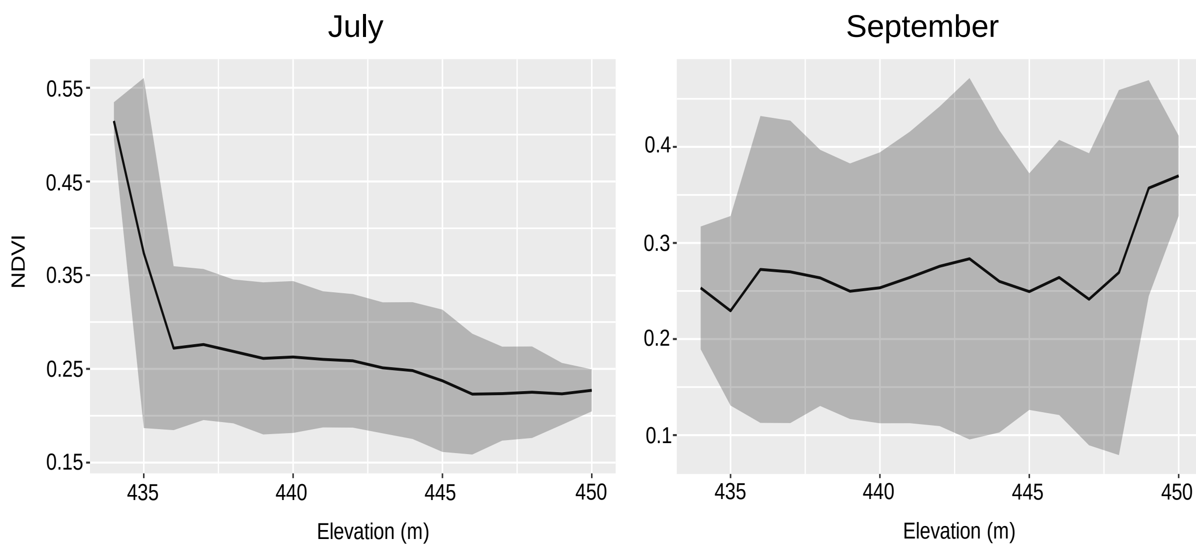


Figure 4.2 The relationship between elevation and NDVI in July grazing period (A) and in September grazing period (B). Shading indicates the standard error of NDVI at the same elevation.

Maps in Figure 4.3 present cattle seasonal space utilization in the study area, after extrapolating the resource selection function to the whole study area in both early and late grazing period. Cattle high utilization is concentrated near cattle settlement in the early grazing period, in contrast, cattle are spread to the areas far from cattle settlement along the fences of the ranch.

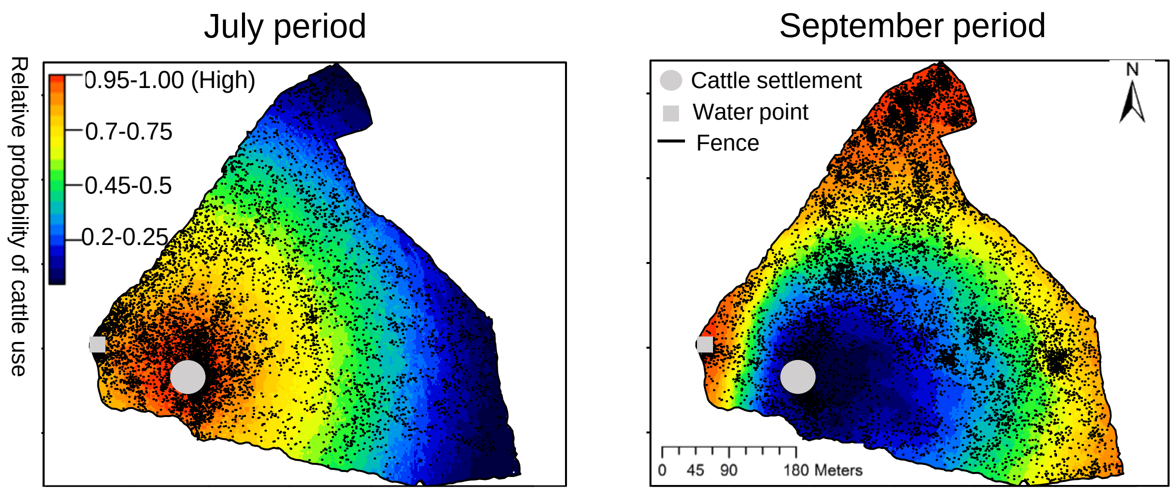


Figure 4. 3 The predicted relative probability of cattle use during the July period and September period. Areas of the highest relative probability of use are shown in red and areas of the lowest relative probability of use are shown in dark blue.

The predictive accuracy of early grazing period was higher than that late grazing period. Of the accuracy during the early period, 72 % of locations occurred in > 75% RSF interval and 85 % of locations occurred in > 50% RSF interval. Forty-eight per cent of September period locations occurred in > 75% RSF interval and 70 % of locations occurred in > 50 % RSF interval. Thirty per cent of August period locations occurred in > 75% RSF interval and 60 % of locations occurred in > 50 % RSF interval (Table S4.1).

4.4 Discussion

4.4.1 Comparisons of early and late grazing distribution

Yet few studies have quantified the cattle selective foraging for fine-scale ranches and examined how strength selection of contrasting landform varies across a seasonal variation of available vegetation resource. Our study provides a framework for modelling and predicting the occurrence of cattle foraging selectivity in the Horqin Sandy Land, separately in the early and late grazing period. In support of our hypothesis, cattle showed the preference of high resource availability and avoid high elevation areas of sand dunes in both early and late grazing periods. Cattle distribution pattern varied between early and late of grazing periods with the landform characteristics of dunes responding to changes in resource availability across the seasonal cattle grazing periods (Table 4.2 and Table 4.4).

During the early grazing periods, cattle locations concentrated around the cattle settlement which was consistent with the previous study showed cattle start from the central place for foraging in the semi-free ranging system (Table 4.2; Figure 4.3). Cattle appear to maximize the efficiency of nutrient intake during the period with high quality and quantity in the early grazing time, were foraging on the lowlands near the water resource and avoid dunes and related vegetation resource on dunes. During the late grazing period with a decline of vegetation conditions, after grazing these areas in the grazing early period within the ranch, cattle used vegetation resource on steeper areas and grazed farther from water in the late period, which is the likely explanation of the general increase in the uniformity of grazing. and, where to strength the weight of avoiding dunes but higher areas of dunes while the more productive availability resource occurred (Table 4.4; Figure 4.3).

The water resource is also a critical factor to affect cattle selection for vegetation resource (Moyo et al., 2013; Zengeya et al., 2014). The results of the study showed cattle prefer to stay around the cattle resource in both early and late grazing period (Figure 4.3). The interpretation of the resource selection function is a trade-off between cattle moving long-distance against water point, which is the most limiting resource, but also maximizing access to high-quality forage.

In the early period, cattle did not select for higher quality or quantity forage, behaving more like a bulk feeder, as food is generally more abundant in herbage quality and quantity than in the late season. Therefore, in the early grazing period cattle can easily fulfil their energetic and nutritious needs with medium or even lower quality fodder. On the contrary, cattle exhibited preference towards quality forage even in the late period, and especially when using areas further from the water and higher elevation (Kaszta et al., 2016b).

In both seasons, cattle exhibited preference towards areas covered by trees. This preference, however, was significant only in the wet period, which is also the hottest season, when trees provide shade. Furthermore, below-canopy grasses are usually richer in nutrients than grasses that grow in the open, differentially attracting grazers (Treydte et al., 2010). As pointed out by several authors (Vavra and Ganskopp 1987; Pinchak et al. 1991), cattle prefer grazing areas on gentler landforms and closer to water, with higher forage quality and more preferred species, as these areas allow them to maximize the average energy intake rate through optimal foraging (MacArthur and Pianka 1966).

4.4.2 Interaction between NDVI and landforms

The utility of these predicted metrics is not limited to the original products and can be used to derive additional landform properties that reflect specific spatial processes of interest of livestock. The metrics of NDVI and elevation can be used to identify the timing of migration in ungulates and seasonal resource use. We were also interested in fine-scale processes that influenced the energetics of movement and accessibility of forage. We suspect that to minimize energy losses in the late season when forage condition is low animals may limit the distance for foraging. However, the results showed cattle move longer from water point near the boundary fences for foraging more resource availability. The explanation was the indirect effect of NDVI decreased the negative effects of distance to water on space use of cattle foraging (Table 4.2; Table 4.4). These are conflicting goals, as overgrazing near water sources results in low forage availability. Such grazing patterns can lead to overgrazing of the rangelands directly surrounding villages, especially those close to rivers and other water sources. Cattle kept close to water resource in season will minimize energy expenditures, but as the cost of limiting energy and nutritional intake. Therefore, the cattle move further areas to forage more productive availability resources in both early and late of grazing periods. Considering cattle preferences for specific resources, fine-scale resource selection function modelling revealed patterns that can be explained as an adaptation to reduced availability of water and high-quality fodder during the dry season.

Thus, the energetic costs of moving through dunes are likely to affect the way animals navigate landscapes (Lundmark and Ball 2008, Avgar et al. 2013). As we predicted, cattle selected for areas with rugged landforms, corresponding to wind-blown ridges at moderate-to-high elevations. Such selection patterns may help offset energy deficits by minimizing the effort required to forage ground herbage on sand dunes (Nichols and Bunnell 1999). Contrary to expectations, however, cattle selected for higher elevation while higher NDVI of herbage distributed on the dunes. Cattle should avoid higher elevation of dunes unless sufficient available herbage exists to support an individual's foot loadings because the costs of travelling through dunes increase exponentially with a density below some threshold of support (Parker et al. 1984). These results imply a link between behavioral state and selection for specific landforms conditions.

4.4.3 Implement of livestock grazing management

It is crucial to sustainable range livestock production that managers manipulate livestock distribution to meet production and conservation goals. Thus, removing livestock that concentrates in overused areas and selecting livestock that travels farther from water and up steeper slopes has the potential to improve livestock grazing distribution (Bailey et al., 2006). Attracting livestock away from critical areas and into underused areas of pastures requires innovative management and an understanding of livestock grazing behavior.

While fences and water developments strongly influence livestock distribution, they are not the only tools available to the manager. The results of these studies demonstrate that strategic placement of supplement can be an effective tool for altering livestock distribution during the dry season. Assessment of the effects of conservation practices used on grazing lands is ongoing but does not include nutrient supplement placement (Kannan et al. 2005; Maderik et al. 2006). Previous studies (McDougald et al. 1989; Bailey and Welling 1999) suggest that supplement placement is an effective practice for attracting livestock into areas where grazing is desired and keeping livestock away from environmentally critical areas such as riparian zones. When green forage is adequate, the supplement sites are less attractive. When the supplement is placed in rangeland pastures or allotments, cattle not only congregate at the supplement site, but they graze and rest in adjacent areas within 600 m of the supplement site. While supplement placement has a strong influence on beef cow distribution, it must be integrated with fencing, water development, and other practices to accomplish grazing management goals.

Further work should be carried out to extend the predictive mapping of cattle occurrence to the more ranches and involving more types of rangeland management systems. Local authorities need tools to understand cattle spatial behavior and predict patterns of utilization to prevent overgrazing. Our modelling approach based on fine-scale environmental data and detailed information on cattle movement allowed new insights and mapped predictions that can guide management actions to minimize the rangelands overutilization. Adaptive management of rangelands should take into account seasonal differences in cattle spatial behavior, mainly related to the diversity of landforms and changes in the availability of forage quality and quantity. We advise that the local authorities consider seasonal ranging patterns of herders in efforts to avoid rangeland overgrazing in the areas of high seasonal cattle home range overlap. Creating grazing regimes in which early and late season grazing areas (or at least core areas) do not extensively overlap would allow vegetation to more effectively regenerate.

This would help to minimize the negative consequences of overgrazing, such as soil degradation, erosion, declines in grassland productivity and/or bush encroachment. Our models can be used to map and predict trends in overgrazing areas based on current environmental factors. Doing so will help managers to identify areas of high suitability during vegetation-covered periods, and to anticipate how these high-value areas will shift as the snowpack evolves through time (Hoefs 1984, Post and Stenseth 1999, Mysterud and Saether 2011). Understanding the spatial requirements and resource needs of livestock, while accommodating dynamic landscapes, will be critical in predicting how livestock will respond to increasingly variable and severe environmental conditions change.

4.5 Conclusion

Local farmers in the ranch of Horqin Sandy Land need tools to understand cattle spatial behaviors and the patterns of utilization to prevent overgrazing. Our modelling approach based on fine-scale environmental data and detailed information on cattle movement allowed new insights and mapped predictions that can guide management actions to minimize the risk of rangelands overutilization. Adaptive management of rangelands should consider seasonal differences in cattle spatial behavior, mainly related to changes in the availability of forage resource availability, and the interaction with the elevation of sand dunes.

We advise that the local farmers consider seasonal management of grazing cattle in efforts to avoid ranch overgrazing. Creating grazing regimes in the early grazing period where the core areas of cattle foraging concentrated near the water point separate ranch into several groups to reduce foraging pressure to allow vegetation to more effectively regenerate. Furthermore, the practice of forage supplement should be conducted near the water point and lower areas of sand dunes to prevent cattle walking longer on lowland and moving upper on sand dunes for saving energy and keep animals' body weight.

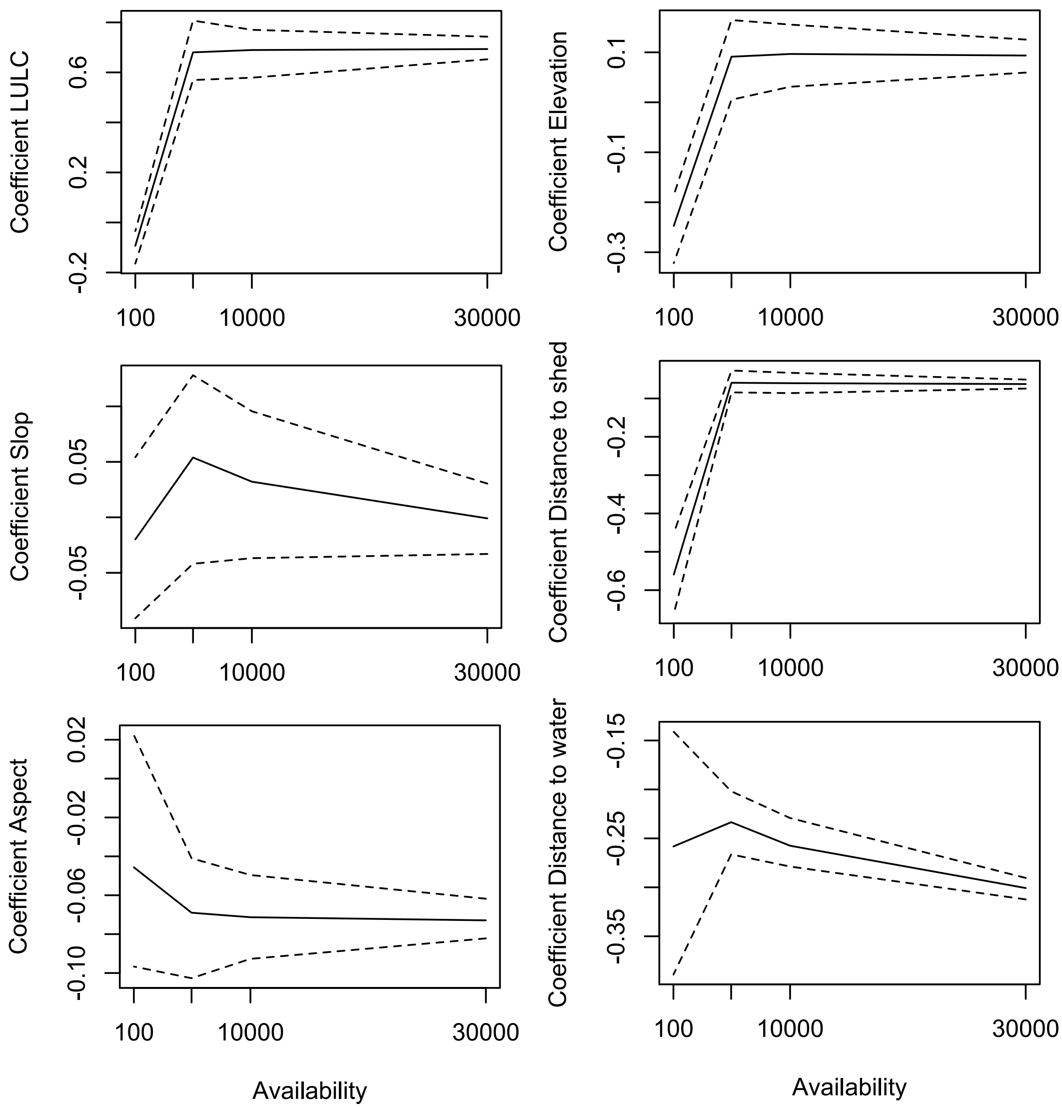


Figure S4.1 Coefficient estimator and 95% simulation envelopes (solid lines) from 500 RSF model iterations fit to data simulated from variables.

Table S4.1 Frequency distributions and percentage of cattle locations within equal-area RSF intervals during the periods of early and late grazing

RSF interval	Early grazing time		Late grazing tome	
	Number of locations	Percentage locations	Number of locations	Percentage locations
0-5%	100	0.953%	251	2.41%
5-10%	169	1.611%	392	3.76%
10-15%	176	1.678%	302	2.90%
15-20%	157	1.497%	384	3.69%
20-25%	115	1.096%	302	2.90%
25-30%	167	1.592%	328	3.15%
30-35%	185	1.764%	390	3.74%
35-40%	199	1.897%	451	4.33%
40-45%	221	2.107%	384	3.69%
45-50%	247	2.355%	333	3.20%
50-55%	240	2.288%	301	2.89%
55-60%	193	1.840%	315	3.02%
60-65%	303	2.889%	311	2.99%
65-70%	285	2.717%	549	5.27%
70-75%	261	2.489%	463	4.45%
75-80%	344	3.280%	691	6.64%
80-85%	797	7.599%	794	7.62%
85-90%	777	7.408%	774	7.43%
90-95%	1039	9.907%	894	8.58%
95-100%	4513	43.030%	1805	17.33%
Total	10488		10414	

Chapter 5

General conclusions

Chapter 5: General conclusions

This thesis generated the seasonal variation of cattle foraging behaviors and spatial distribution on the contrasting landforms of fenced ranch in northern China.

We found that the GPS model is sufficient for livestock behaviors classification and provides information regarding an animal's location; this feature is associated with the interaction between livestock activities and the rangeland ecosystem. The classification model with the different time intervals of GPS location data, the tri-accelerometers, and the combination of the two kinds of the dataset were tested. The overall accuracy of GPS models was 85% to 90% when the time interval was greater than 300–800 s, which was approximated to the tri-axis model (96%) and GPS-tri models (96%). In the GPS model, the linear backward or forward distance were the most important determinants of behavior classification, and nonforaging behavior was less than 30% when livestock traveled more than 30–50 m over a 5-min interval. For the tri-axis accelerometer model, the anteroposterior acceleration (–3 m s-2) of neck movement was the most accurate determinant of livestock behavior classification. The instantaneous acceleration of livestock body movement more precisely classified livestock behaviors than did GPS location-based distance metrics. When a tri-axis model is unavailable, GPS models will yield sufficiently reliable classification accuracy when an appropriate time interval is defined. These findings may improve our understanding of how the selection of the time interval influences the process of distinguishing livestock activities in a GPS model and provide insight into selecting an optimal time interval when using GPS data only to classify livestock behaviors.

Then, we found that cattle preferred to forage in low-land areas compared to sand dune areas, probably reflecting the greater energy consumption required and poorer herbage conditions in the high-elevation areas. The temporal dynamics of foraging pressure showed different patterns in low-land and sand-dune areas from July to September. The foraging pressure and proportional area used by cattle both increased from July to September in low-land areas, whereas only the proportional area foraged increased in the sand-dune areas. As the grazing season progressed, the foraging time increased in both low-land and sand dune areas. The foraging density increased as herbage quality and quantity declined in low-land areas. Our results indicate that topographic features should be considered when managing livestock, especially during periods with adverse conditions of herbage quality and quantity.

The predicting map based on RSF model showed the process that the affecting factors derived foraging distribution from early to late grazing. The mechanism behind this change is that seasonal variation of resource availability moderates the responding pattern of cattle foraging selectivity to the sand dunes and water resource. The seasonal increasing of foraging areas expanded from water point to the further places where the higher abundant vegetation distributed on lowland areas, and move to higher areas of sand dunes for the rich resources on sand dunes. the probability of everywhere to be foraged by cattle was modeled by the resource function selection and the affecting factors of the probability were examined. The high probability to be used areas by cattle was the forest land, and areas with high NDVI and closer to the watering point, the low probability areas was the area with high elevation. The high probability areas moved from near the water point to the far areas from the early to the late grazing period. During the early grazing season, the probability to be forage is negatively related to the elevation and positively related to the NDVI. During the late grazing period, the NDVI and elevation influence on the probability to be foraged decreased, and the interaction between NDVI and elevation influence the probability.

These conclusions for the implications for ranch management strategies to prevent overgrazing depend on the requirements and fine scale to be achieved. If just considering the rugged landform derived from distribution of sand dunes across the ranch, ranch owners should use a rotational grazing system in which cattle are shifted from a low-land grazing camp to a higher elevation camp during periods of herbage decline. Moreover, the implication of more fine management, the owner should consider the conditions of seasonal resource availability and interaction effects with landform characteristics and waster point. In the early grazing time, creating camp to separate the core grazing areas into several groups to reduce the overgrazing, and in the late grazing time, the forage supplement should conduct near the water point and lower areas of dunes to reduce animal's energy cost by walking longer and climbing upper places.

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SUMMARY

Overgrazing can alter ecosystem function and reduce the nutrient content and yield of vegetation, especially in arid and semi-arid regions. Overgrazing of rangelands often results from uneven distribution of grazing pressure due to either under- or overstocking. Fencing has widely been used to manage grazing pressure, by breaking large tracts into several smaller areas, thus preventing patchy degradation of grasslands and maintaining the productivity of vegetation and livestock.

To prevent grassland degradation, the spatial distribution of livestock grazing must be understood. Previous grazing experiments have used the number of livestock per unit area to investigate the effects of grazing on herbage production, soil properties, plant communities, and other factors. However, this approach cannot provide detailed information regarding how livestock graze, especially in terms of seasonal changes in the spatial distribution of grazing pressure on grassland. In addition, an underlying assumption of these previous studies is the even distribution of grazing pressure, which is not characteristic of actual livestock grazing behavior.

The trade-off between the energy expended in searching for and reaching the forage source and the potential energy gain provided by the herbage determines the movement of livestock during their grazing activities and consequently the spatial distribution of livestock grazing pressure. Therefore abiotic factors, such as topography and access to drinking water, as well as biotic factors, such as pasture quality and quantity, are critical factors that influence the spatial variation of herbage and the energy expended during livestock's acquisition of sufficient forage. These elements in turn influence the spatial distribution of grazing pressure and its seasonal dynamic.

The grassland in the arid and semi-arid regions of northern China has degraded severely since the 1970s. This degradation has contributed to several environmental problems, one of the most

striking of which is dust storms. In particular, the Horqin Sandy Land, in the central eastern region of China's Inner Mongolia province, suffers from desertification and is a material source for the dust storms that have ravaged Beijing and other, distant areas. The landform of the Horquin Sandy Land is characterized by sand dunes interwoven with interdune lowlands; this intricate topography complicates understanding of the relationship between livestock grazing and land degradation in this region.

Various grazing behaviors, such as foraging, resting, and walking, have different consequences on grassland. Using traditional methods to track and record these behaviors is laborious and rarely provides continuous and long-term data. However, the development of the Global Positioning System (GPS), accelerometers, and machine learning now make it possible to elucidate the relative effects of different grazing behaviors. Therefore, the current study used GPS and machine learning techniques to reveal the spatial distribution of foraging and non-foraging behaviors of cattle in the Horqin Sandy Land.

In this research, we first developed a method to classify cattle grazing into component foraging and nonforaging behaviors according to GPS location and tri-accelerometry data. We then investigated seasonal changes in the spatial distribution of grazing pressure and the relative contributions of the sand dune and interdune regions to this seasonality. Finally, we modeled the probability to be forage of everywhere in the ranch and analyzed the factors that influenced the likelihood of use.

First, we tested various models for classifying various behaviors as foraging or nonforaging behaviors; these models were based on GPS location data solely, tri-axis accelerometry data only, and the combination of these two datasets; in addition, we assessed various time intervals with each model. When the time interval was greater than 300–800 s, the overall accuracy of the GPS model was 85% to 90%, which approximated the accuracies of the tri-axis accelerometry model (96%) and the combined GPS-tri model (96%). In the GPS model, the linear backward or forward distance was the most important determinant of behavior classification, and nonforaging behavior accounted for less than 30% of all grazing behavior when livestock traveled more than 30–50 m over a 5-min interval. For the tri-axis accelerometry model, the anteroposterior acceleration (–3 m s^{-2}) of neck movement was the most accurate determinant of livestock behavior classification. The instantaneous acceleration of livestock body movement classified livestock behaviors more precisely than did GPS location-based distance metrics. However, when a tri-axis model is unavailable, a GPS model yields sufficiently reliable classification accuracy as long as an appropriate time interval is defined.

Second, we determined the foraging density and the area associated with foraging behavior for both the dune and lowland regions. Overall, the time that livestock spent foraging increased from 63% in July to 67% in August and 69% in September, and nonforaging behavior decreased in a compensatory manner in both dune and lowland regions. In lowland, the log-transformed average foraging density (i.e., total number of foraging behaviors in 5 days measured at 50-s intervals per 10 × 10 m grid) increased significantly from 0.61 in July to 0.66 in August and 0.88 in September; in contrast, on sand dunes, this parameter remained constant throughout this period. The relative area of lowland foraged by cattle was 31% in July, 35% in August, and 36% in September. In comparison, the proportion for sand dunes increased from 45% in July to 47% in August and 51% in September. In lowland, foraging density was negatively correlated with biomass ($P = 0.07$), total digestible nutrients ($P < 0.05$), and crude protein ($P = 0.06$) and positively correlated with acid detergent fiber ($P < 0.05$), whereas no such relationships occurred in sand dunes. Our results indicate that topographic features should be considered when managing livestock, especially during periods with low herbage quality and quantity.

Third, we used resource function selection to model the probability of a landform to be foraged by cattle and then examined the factors that influenced this probability. The factors associated with a high probability of being grazed by cattle were forest land, areas with high NDVI, and areas close to watering sites; conversely areas at high elevation had a low probability of being grazed. The high-probability areas moved further from watering sites as the grazing period progressed from early to late. During the early grazing season, the probability of being grazed was negatively related to elevation and positively related to NDVI. During the late grazing period, the individual influences of NDVI and elevation on the probability of being grazed decreased, and instead the interaction between NDVI and elevation influenced this probability.

The findings from this study show that the instantaneous acceleration of livestock body movement more precisely classified livestock behaviors than did GPS location-based distance metrics. When a tri-axis model is unavailable, a GPS model yields sufficiently reliable classification accuracy as long as an appropriate time interval is defined. The foraging duration was greater in lowland than dunes areas in both early and late grazing periods. On both sand dunes and lowland, foraging time increased as the grazing period progressed from early to late. In lowland areas, the increase in foraging time resulted from increases in both average foraging density and foraging area. However, increased foraging time on sand dunes was due solely to increases in foraging area. Resource selection function modeling can successfully predict the probability that cattle will graze a particular area; this probability is comparable to the observed duration of grazing.

In the Horqin Sandy Land, cattle spent more time foraging on interdune lowland than on sand dunes. However, foraging time increased over the grazing season as resource availability declined in both lowland and dune regions. This increase in foraging time over the grazing season reflects changes in the cattle's behavior patterns that is, extending foraging areas away from water sources in lowland areas and climbing sand dunes to obtain additional resources.

学位論文概要

過放牧は、特に乾燥および半乾燥地域で、生態系機能を変化させ、栄養と生産力を減少させる可能性がある。放牧地の過放牧は、多くの場合、不適正な放牧圧の不均一な分布に起因する。牧柵は、広い地域をいくつかの小さな領域に分割することで放牧圧を管理するために広く使用されており、草地のパッチ状の劣化を防ぎ、植生と家畜の生産性の維持に役立つ。

草地の劣化を防ぐためには、家畜の放牧の空間分布を理解する必要がある。以前の放牧実験では、単位面積あたりの家畜の数を使用して、放牧が草地生産、土壌特性、植物群落、およびその他の要因に及ぼす影響を調査している。しかし、このアプローチでは、特に草地の放牧圧の空間分布の季節変化に関して、家畜がどのように放牧するかに関する詳細な情報を提供することはできない。さらに、これらの以前の研究の根底には、実際の家畜の放牧行動の特徴ではない、放牧圧の均一な分布を仮定している。

飼料源を探して到達するために費やされるエネルギーと、牧草によって提供される潜在的なエネルギー獲得との間のトレードオフは、放牧活動中の家畜の動き、ひいては家畜の放牧圧力の空間分布を決定する。したがって、地形や飲料水へのアクセスなどの非生物的要因、および牧草の質や量などの生物的要因は、家畜が十分な飼料を取得する際に消費される草本の空間的変動とエネルギーに影響を与える重要な要因である。これらの要素は、さらに放牧圧の空間分布とその季節的動態に影響を与える。

中国北部の乾燥および半乾燥地域の草地は、1970 年代以降、深刻に劣化している。この劣化はいくつかの環境問題の一因となっており、その中で最も顕著なものの 1 つは砂嵐である。特に中国の内モンゴル自治区の中央東部にあるホルチン沙地は砂漠化に苦しんでおり、北京やその他の遠方の地域を襲った砂嵐の発生源である。ホルチン沙地の地形は、砂丘と砂丘間低地が織り交ぜられているのが特徴である。この複雑な地形は、この地域の家畜の放牧と土地の劣化との関係の理解を複雑にしている。

採食、休息、歩行などのさまざまな放牧行動は、草地にさまざまな影響を及ぼします。従来の方法を使用してこれらの動作を追跡および記録するのは多大な労力を要し、継続的かつ長期的なデータを提供することは困難であった。しかし全球測位システム（GPS）、加速度計、機械学習の開発により、さまざまな放牧行動の相対的な影響を解明できるようになった。したがって、本研究では、GPS と機械学習技術を使用して、ホルチン沙地における牛の採食行動と非採食行動の空間分布を明らかにした。

本研究では、最初に、GPS の位置と 3 つの加速度計のデータに従って、牛の放牧を採食行動と非採食行動に分類する方法を開発した。次に、放牧圧の空間分布の季節変化と、この季節性に対する砂丘と砂丘間地域の相対的な寄与を調査した。最後に、牧場のある点で採食される確率をモデル化し、採食の可能性に影響を与える要因を分析した。

第一にさまざまな行動を採食行動または非採食行動として分類するためのさまざまなモデルを検定した。これらのモデルは、GPS 位置データのみ、3 軸加速度計データのみ、

およびこれら2つのデータセットの組み合わせに基づいているた。さらに各モデルでさまざまな時間間隔を評価した。時間間隔が 300～800 秒を超える場合、GPS モデルの全体的な精度は85%～90%であり、これは3軸加速度計モデル（96%）とGPS-triモデルの組み合わせ（96%）の精度に近い。GPS モデルでは、線形の後方または前方距離が行動分類の最も重要な決定要因であり、家畜が5分間隔で30～50 m以上移動した場合、非採食行動はすべての放牧行動の30%未満を占めた。3軸加速度計モデルの場合、首の動きの前後加速度（$-3\ \mathrm{m\ s^{-2}}$）が、家畜の行動分類の最も正確な決定要因だった。家畜の体の動きの瞬間的な加速度によって、GPS 位置ベースの距離メトリックよりも正確に家畜の行動を分類することができた。ただし、3 軸モデルが利用できない場合、適切な時間間隔を定義すれば、GPS モデルは信頼できる分類精度で十分な結果を提供することが示された。

第二に砂丘と低地の両方の地域で、採食密度と採食行動に関連する面積を決定した。全体として、家畜が採食に費やした時間は、7月の63%から8月の67%、9月の69%に増加し、砂丘と低地の両方の地域で非採食行動が代償的に減少した。低地では、対数変換された平均採食密度（つまり、10×10 mグリッドあたり50秒間隔で測定された5日間の採食行動の総数）は、7月の0.61から8月の0.66、9月の0.88に大幅に増加した。対照的に、砂丘では、このパラメータはこの期間を通して一定のままだった。牛が採食する低地の相対面積は、7月に31%、8月に35%、9月に36%だった。それに比べて、砂丘の割合は7月の45%から8月の47%、9月の51%に増加した。低地では、採食密度はバイオマス（$P = 0.07$）、総可消化栄養素（$P < 0.05$）、粗タンパク質（$P = 0.06$）と負の相関があり、酸性デタージェント繊維（$P < 0.05$）と正の相関があったが、砂丘ではそのような関係はなかった。この結果は、家畜を管理する際、特に草本の質と量が少ない時期には、地形的特徴を考慮する必要があることを示している。

第三に、資源選択関数法を使用して、牛が採食する確率をモデル化し、この確率に影響を与える要因を調べた。牛が利用する可能性が高いことに関連する要因は、林地、NDVI が高い地域、および水飲み場に近い地域だった。逆に標高の高い地域では、放牧される可能性は低かった。放牧期間が早い時期から遅い時期に進むにつれ、確率の高い地域は給水場所から遠方に移動した。放牧期間前期には、放牧される確率は標高と負の関係があり、NDVI と正の関係があった。放牧期間後期には、NDVI と標高が放牧される確率に及ぼす個々の影響が減少し、代わりに NDVI と標高の相互作用がこの確率に影響を与えた。

本研究の結果は、家畜の体の動きがもたらす瞬間的な加速度が、GPS ロケーションベースの距離メトリックよりも正確に家畜の行動を分類したことを示している。3 軸モデルが利用できない場合、適切な時間間隔が定義されている限り、GPS モデルは十分に信頼できる分類精度を提供する。採食期間は、放牧の前期と後期の両方で、砂丘地域よりも低地で長かった。砂丘と低地の両方で、放牧期間が早いものから遅いものへと進むにつれて、採食時間が増加した。低地では、採食時間の増加は、平均採食密度と採食面積の両方の増加に起因していた。しかし、砂丘での採食時間の増加は、採食面積の増加の

みによるものだった。資源選択関数モデルは、牛が特定の地域を放牧する確率を的確に予測しており、この確率は、観察された放牧期間に符合する。

　ホルチン沙地では、牛は砂丘よりも砂丘間低地での採食に多くの時間を費やしていた。しかし、低地と砂丘の両方の地形で資源の利用可能性が低下したため、放牧期間中に採食時間が増加した。この放牧季節中の採食時間の増加は、牛の行動パターンの変化、すなわち低地の水飲み場周辺から採食エリアを拡張し、追加のリソースを取得するために砂丘に登っているという行動の変化を反映している。

LIST OF PUBLICATIONS

Gou, X., Tsunekawa, A., Peng, F., Zhao, X., Li, Y., & Lian, J. (2019). Method for Classifying Behavior of Livestock on Fenced Temperate Rangeland in Northern China. Sensors, 19(23), 5334. (DOI: 10.3390/s19235334) (Pressed, this article covers in **Chapter 2**)

Gou, X., Tsunekawa, A., Tsubo, M., Peng, F., Sun, J., Li, Y., Zhao, X. and Lian, J. (2020). Seasonal dynamics of cattle grazing behaviors on contrasting landforms of a fenced ranch in northern China. Science of The Total Environment, 749, 141613. (DOI: 10.1016/j.scitotenv.2020.141613) (Published online, this article covers in **Chapter 3**)