EVALUATION OF ANIMAL SENSORS AND TECHNOLOGY IN GRAZING ENVIRONMENTS

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EVALUATION OF ANIMAL SENOSORS AND

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Abstract: The object of the first experiments were to determine the effects of virtual fencing on cortisol concentrations and behavior of beef cattle. Mixed breed beef heifers and cows (*n* = 55 and 59, respectively; initial BW = 315 ± 30 kg and 484 ± 84 kg, respectively) were randomly assigned to a physically fenced (PF) or virtually fenced (VF) pasture. Animals were rotated within respective treatments for 28 or 56 d, respectively. No significant differences were observed in animal behaviors, cortisol concentrations in hair or feces, nor lactate and non-esterified fatty acid concentrations. Virtual fencing was not more stressful to animals when compared to electric fencing. The objective of the second experiment was to validate the classification of the activities, and resource, terrace position, and burn unit usage of grazing cattle made by remote monitoring collars. Angus steers (n = 12; BW = 227 ± 45.0 kg) were fitted with an electronic GPS receiver and activity collar (Herd MOOnitor Ltd). Animal activities (collected every 4 s) were determined by a real time microcontroller and an algorithm for analyzing accelerometer data, and GPS locations (collected every 5 min) were collected and classified by the collar. Animal activities included grazing, walking, and resting. GPS locations included position on terraces, burn patch, and resource utilized. Data from the collars were matched to human observation data measuring the same activity and location parameters. Data from walking and resting activities, and resource and burn patch usage were accurately matched. However, grazing activity classification (≥ 30%) and terrace position accuracies (≥ 39%) were less than the reported NIR (≥ 39% and ≥ 42%, respectively), leading researchers to conclude that grazing activities could not be accurately classified.

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REVIEW OF LITERATURE

Introduction

Livestock management practices have changed greatly over time, while still keeping fundamental principles intact. The end goal of livestock management continues to be to produce the most efficient animals in the most cost-effective manner. Livestock management has evolved to include new technologies, such as virtual fencing (VF) and motion sensor integrated global positioning systems (GPS) collars with the ability to remotely monitor animal behavior and health. Both technologies offer great advancements in the field of livestock management, as virtual fencing may provide the ability to fully utilize the diverse resources allotted to cattle on pasture (Umstatter et al., 2015); and integrative GPS collars may allow researchers to accurately measure animal distribution and behaviors while grazing (Ungar et al., 2005).

The implementation of these livestock management technologies offers a unique opportunity to utilize seemingly “un-fencable” terrain, execute various stocking and grazing management practices with limited labor costs, and even remotely monitor individual animal health status. However, the use of these technologies has been reported to produce adverse effects on animals. Animal discomfort has been linked to electrical shock, from either electrified wire fencing or through the use of VF collars (Lee et al., 2009; Teixeira et al., 2017). Any introduction of discomfort to livestock, by means of transportation, handling, or the implementation of grazing technologies may result in stress responses. An animal's response to stress results in the release of stress hormones such as catecholamines and cortisol (Brockman and Laarveld, 1986). The secretion of these stress-induced hormones have been reported to affect reproductive, metabolic, and immune functions within the animal (Sapolsky et al., 2000; Chrousos, 2009). Cattle response to stressors has also been linked to an increase of other blood metabolites, such as plasma lactate and non-esterified fatty acids (NEFA; Petherick et al., 2009). An increase of these metabolites may result in a decrease in animal performance, as both metabolites have been linked to a change in animal metabolism (increases or decreases in body condition score; BCS) due to prolonged exposure to stressors (Matteri et al., 2000; Bernabucci et al., 2005). Additionally, the integration of livestock management technologies such as motion sensor integrated GPS collars may not yet be without flaw. For example, to the author's knowledge, validation of motion sensor integrated GPS collars has not been completed, and issues with accuracy of both GPS location and animal behavior have not been fully nullified (Ungar et al., 2005).

There are many factors that influence the efficacy of grazing technologies. While the implementation of these technologies into livestock management practices holds many opportunities to increase the profitability of the livestock industry; many variables remain unknown in the validation of remote health monitoring collars, and the overall effect of technology use on livestock. Considerable research has been conducted regarding the aforementioned variables, and though great progress has been made towards the applicable use of these technologies, the ethical and economical aspects of such technology must be thoroughly examined.

History of Grazing Technology

According to Ensminger and Perry (1997), a good fence promotes good relationships with neighbors, makes livestock production possible, and increases land values. However, the art and science of managing livestock has undergone a long-term evolution in management practices over the centuries. Livestock management began with herding and shepherding practices, following the fluid movements of nomadic cultures (Reuter 2021, personal communication). As humans began to make settlements in various areas, some cultures chose to implement semi-sedentary livestock management, establishing residences and 'home pastures' to inhabit at certain times of the year. As societies became more established, permanent residences became more prevalent and transhumant management systems became more common (Reuter 2021, personal communication). This was and is still typical in mountainous areas, in which livestock herds were moved seasonally. Though all of these livestock management practices are still used today, the United States and other first world countries typically implement sedentary livestock management. Sedentary livestock management systems consist of permanent dwellings where livestock management is conducted using fenced pastures in close proximity to said dwellings. The original purposes of fences were to restrain cattle, to not only prevent loss of livestock but prevent destruction of croplands by livestock grazing (Pickard, 1999). Although in the United States, the rise of fences may have been implemented as a measure of ownership and status more so than livestock containment (Hayter, 1939). The evolution of livestock management towards fencing may also be credited to the Tragedy of the Commons, during which competition for resources such as land and water exceeded the productivity of such resources. As populations of both humans and livestock grew, implementation of more traditional methods of livestock management were necessary for vegetative and livestock productivity (Fafchamps, 1998). Some cultures first implemented “live fences” of hedges and utilized ditches to subdivide or contain various agricultural pursuits (dated to the early 1800’s; National Gallery of Art, 2021). As livestock management progressed, stone walls and wooden fences were implemented in early colonial America (Smithsonian, 2008). As settlers moved West across the United States, resources and lack therof led to the invention of smooth wire fences in the 1830’s to replace wood fences (Oklahoma Historical Society, 2021). However, these fences did little to fully contain livestock as the fences were easily uprooted or disrupted. Barbed wire fences were invented with aims to prevent animals from rubbing against and damaging fence lines (Mayberry, 1939). Although, barbed wire is the predominant fencing method across much of the livestock industry, there were initial hesitations in its implementation as many viewed barbed wire as cruel and compromising to animal welfare; and in some countries (i.e., Switzerland) barbed wire is still considered inhumane (Umstatter, 2011). Electric fences were originally derived as another form of protection for wire fences, implemented to keep cattle or horses from trampling fences enclosing pastures or crops. Electric fences utilize electrically insulated wires that are connected to a power supply (Vollmer, 2016). Each of these fencing methods evolved from one or more fence types before it, improving from not only a management perspective but economic perspective as well. From electric fences, the concept of VF has become of great interest within livestock management.

As the prevalence of livestock management increased, herding practices previously carried out across open ranges were implemented with the use of conventional fencing. Rotation of animals from paddock to paddock and separation of animals during various physiological stages could easily be achieved. Though the evolution of conventional fencing greatly improved the efficiency of pastures and rangeland through herding and animal husbandry tactics, the costs of both the fencing itself and labor-intensive management remain high. The implementation of grazing and livestock management technologies, such as VF, provide livestock managers new avenues to achieve the underlying goals of livestock production. Virtual fences provide an alternative for livestock managers to contain their cattle in new and more efficient ways. Virtual fencing technologies also provide the ability to create fences in otherwise un-fencable terrain, remotely gather or relocate animals, and remotely monitor animals.

Electric Fencing

Physical fencing systems that implement electric shock as a deterrent have become widely adopted across various livestock industries, and are even used with pets and wildlife. The purpose of such fencing systems is to cut down on costs, labor, and materials compared to conventional barbed wire fencing. However, costs may vary on the voltage of the energizer used to produce electric currents. As previously stated, electric fencing systems utilize electrically insulated wires. These wires are used to deliver a limited amount of energy through a current, and a small electric shock is administered when an animal comes in contact with the wire, closing the circuit (Vollmer, 2016). In order for electric fences to be useful, 3 major parameters must be fulfilled. Electric fences must have adequate electrical strength to deter animals from the fence line, the ability to withstand livestock pressures, such as rubbing or pushing the fences, and the ability to withstand naturally occurring pressures. First, the shock supplied by the fence must be sufficient to repel livestock, which relies heavily on proper wire insulation (Weston, 1963). Weston (1963) stated that controller units of electric fencing may produce voltages ranging from 300-2000V, with pulse rates of 70-80 per min. However, more recent research states that voltage delivered by electric fencing ranges from 2000-10,000V, dependent on the application (Vollmer, 2016). These voltages are much higher than can be humanely used in other fencing technologies, such as virtual fencing (Umstatter, 2011). According to Ohm's Law, an assumption can be made that electric shock will increase with the increase of electric voltage, heightening the effectiveness of electrical fences (Honda, 2021). However, as reported by Honda (2021), the effectiveness of electric fences in terms of voltage applied varies among species. Researchers have reported that larger animal species may be easily deterred with the use of lower voltages (1500V), while smaller species are more likely to require higher voltages (4000V). Animal disposition may act as the underlying cause for differences in the amount of voltage required to effectively deter animals from a fence line. Research has reported that foxes and raccoon dogs, while similar in size and weight, require differing voltages to deter the respective animals from an electric fence. Honda (2021) reported that raccoon dogs required a higher voltage to be deterred while foxes were deterred with a lower voltage. Researchers speculate this increased abhorrence to electric fences is due to the natural shyness and vigilance common among the fox species, suggesting foxes are less likely to test an electric fence compared to more curious raccoon dogs. The construction of electric fences may also be reflective of the ability to properly contain or exclude animals. Electric fences utilized in livestock management often have lengths that span ½ a mile or greater; in these cases the resistance of the wire may vary by length. Thus, long stretches of electric fence are prone to drops in voltage (Vollmer, 2016) and therefore, the efficacy of the electric shock delivered.

Secondly, the construction of the electric fencing must withstand livestock rubbing or pushing against non-electrified portions of the fence (Weston, 1963). A solution to this issue may lie in the wire used during the construction of an electric fence. Since the 1980's, the wire of choice for the construction of electric fences is often high-tensile wire, with tensile strength between 170,000 and 200,000 pounds per square inch (McCutchan, 1980). Karhu and Anderson (2006) reported that high tensile electric fencing was successful in separating cows from bulls, as well as cows from calves during weaning. Results from this study demonstrated a 100% containment of bulls utilizing 2-wire and 3-wire electric fences, and 99% and 100% respectively, for cow/calf separation.

Additionally, electric fence lines, similar to barbed wire fences must be erected in such a manner that the fence can withstand naturally occurring pressures (Weston, 1963). Terrestrial obstacles are a major factor in the construction of all static fences. Thick brush cover has been reported to reduce the effectiveness and power emitted from electric fencing, as heavily branched plants or thick brush may inadvertently ground the electric current (Weston, 1963). Slope and rugged terrain are also obstacles for static fences. Fencing in inaccessible locations may increase labor costs, either through the loss of fencing sections or through the costs of manually clearing the fence path (likely through mechanical means). Soil resistance may also affect the flow of the electrical current. Since the electric current must flow through soil to a ground stake, the large variation of resistance and moisture content between soil types can disrupt the distribution of the electric current (Vollmer, 2016). Cold temperatures may cause faults in the line that may become difficult to pinpoint and galvanized steel wire may become brittle in frigid temperatures (Weston, 1963). The impact of cold temperatures and seasonal changes on the soil again play a role in the efficiency of electric fencing. Increased moisture or dryness alter the conductivity of topsoil, and frozen soil is a poor electrical conductor (Vollmer, 2016).

Virtual Fencing

The concept of VF was actualized by Richard Peck in 1971 with his description of a mechanism and method for controlling animals (Peck, 1973). Commercially denoted the “Invisible Fence”, the system consisted of a collar worn by the animal and a signal-emitting wire placed as a perimeter fence with the aim to control cats and dogs. While physical fencing has been time-tested and utilized worldwide, physical fencing fails to offer the management flexibility that accompanies VF. Virtual fencing has evolved from static containment in a defined area to mobile fence lines (Umstatter, 2011). The implementation of VF could lead to improved utilization of seasonal forage growth or re-establishment of pasture biodiversity through the use of exclusion areas (Umstatter et al., 2015). Many of the aspects of herding or specialty stocking methods (i.e., limit, strip, creep, or swath grazing) can also be incorporated into livestock management practices through the use VF, as this technology has the ability to alter animal position within a landscape in near real-time (Anderson, 2007). Virtual fencing becomes effective by creating a boundary based upon geographical coordinates and applying a stimulus when an animal nears or crosses the boundary. This dynamic stimulus action allows for ‘virtual’ herding or mustering (Butler et al., 2006). Many studies have been conducted comparing the efficacy of VF to conventional fencing methods. Campbell et al. (2019)

reports that both electrical tape fencing and VF were successful in keeping cattle contained in prescribed areas, with VF animals spending less than 3% of time in areas excluded from the prescribed grazing zone. Similarly, 2 extensive grazing studies were conducted with cattle wearing VF ear tags set to provide a single audio warning prior to an electrical stimulus. Researchers reported that cattle remained in designated grazing zones within the pastures 93% and 100% of the time compared with cattle allowed to graze the pastures normally (52% and 44% of the time; Tiedemann et al., 1999).

Some disadvantages to utilizing VF are that animals must wear the device and the device may require adjustment as an animal grows (Umstatter, 2011); the VF device worn by animals must also have adequate power supply with a small size and mass, and be able to withstand impact and the elements (Tiedemann et al., 1999). Along with these issues, proper signal strength, communication, and energy supply of the device worn by the animals is crucial. The efficacy of VF relies heavily on the alteration of animal behavior. Thus, to minimize the physiological effects of electrical cues on grazing animals, Anderson (2007) states that virtual fencing technology must contain on-board fail-safes to prevent excessive stimulation, which could result in long-term physiological stress.

Effects of Electrical Impulses on Animals

In order for VF to be effective and also be ethically acceptable, cattle must be able to adapt to VF through the use of associative learning, with the goal to identify audible and electric shock stimuli associated with VF to avoid excessive or unnecessary stress. Cattle respond to stimuli that vary from audible to tactile, and the response produced by different stimuli can be trained (Laca, 2009). Allowing cattle to learn associations between stimuli and VF ensures that the technology remains ethically suitable for animal welfare and reduces stress on the animals (Umstatter, 2011). Conventional electric fencing is a prime example of associative learning by cattle, as cattle recognize the visual barrier of electric fencing and learn to avoid the electric shock that follows contact with the fence (Lee et al., 2009). The ability of cattle to learn and adapt to the association between both audible and electrical stimuli and virtual fence-lines was reported by Lee et al. (2009) in which cattle were contained by a VF line that changed weekly, with the number of audio cues and electric stimulus administered to the cattle decreasing over time. Similarly, Tiedemann et al. (1999) reported that heifers were able to learn the location of an exclusion zone after receiving as few as one audio-electrical stimulus. Lee et al. (2009) also reported that animals receiving only electrical stimulus received significantly more electrical shocks than cattle who experienced audio cues first.

Animal behavior can be a strong indicator of animal well-being and health status. The behavior response of one animal can also influence other animals; when 2 steers were grazing in close proximity and 1 received an audio-electrical stimulus, the other steer moved in tandem with the stimulated steer (Quigley et al., 1990). This data helps to solidify the practice that, in terms of VF, an audio cue and electric stimulus should be applied in response to an animal’s behavior rather than location alone (Lee et al., 2008). Quigley et al. (1990) also observed that cattle receiving both an audio and electric stimulation resumed grazing activity in less than 1 min and, at times, as soon as 10 sec with no perceivable agitation. Individual animal temperament may also play a role in each animal’s ability to adapt to a VF boundary. Anderson (2007) reports over multiple studies, some animals required a longer period to learn the association of stimuli and VF or even required more intense stimulation, while other animals learned quickly with little to no need for stimulation cues. The inability of some animals to properly learn the associations between stimuli and VF may be due to increased flight responses toVF reported in select animals (Lee et al., 2009). The presence of electrical stimuli may also affect cattle behavior patterns, primarily consisting of grazing, resting, and ruminating. Teixeira et al. (2017) reports that cattle exposed to electric fencing spent nearly 15% less time grazing compared to cattle exposed to non-electrified wire fencing. Researchers suggested that cattle grazing without the presence of an electrical stimuli spent more time grazing near the fence line, and the possibility exists that cattle can sense the presence or absence of the electric field itself. While Campbell et al. (2019), found no distinct differences in movement patterns or pasture utilization between cattle enclosed by VF or electric tape fencing, lying time was reduced by an average of less than 20 min per day and the number of electrical stimuli received by cattle decreased over time (Campbell et al., 2019). Markus et al. (2014) reports that cattle subjected to electrical stimulation displayed behaviors that included head shaking and changes in speed, direction, or body position; although others have reported no distinct changes in vocalizations, tail swishes, movement forward or back, or head movements in Santa Gertrudis steers subjected to a low energy shock (Lee et al., 2008*a*).

Due to the negatives associated with electrical stimuli, research has been conducted using positive or negative reinforcements, such as vibration, light, or reward with feed (Umstatter, 2011) to promote associative learning with VF. However, data indicate that electrical shock is the most effective form of reinforcement for the VF boundary (Umstatter et al., 2015). That being said, imprecise stimuli in duration or spatial terms lead to confusion for the animals and are not conducive towards proper associative learning by livestock (Umstatter, 2011); so, efforts to avoid technological malfunctions and implementing training periods to ensure proper associative learning are possible solutions. To exemplify the importance of the proper stimulus, Markus et al. (2014) reported that heifers quickly learned where electrical stimulus would be implemented, but it took little to no time for cattle to use the previously excluded areas once stimulus was removed. When appropriate levels of electrical stimuli are utilized, electric fencing and VF collars have been reported to produce similar stress responses in cattle (Markus et al., 2014; Campbell et al., 2019).

Measuring Stress in Grazing Animals

A stress event has been defined as a time when the body's basal homeostasis is perceived to be or is actually threatened. In response to a stress event, adaptive behavioral and physiological responses are implemented to re-establish homeostasis (Chrousos, 2009). Stressors may be categorized as acute or chronic, and any number of environmental or physiological factors may act as a stressor, including transport, nutrition, weather, physiological status and even routine handling of livestock. The sympathetic nervous system and the hypothalamic-pituitary-adrenocortical (HPA) axis act as the body's major neuroendocrine stress responses (Lu et al., 2018). Initial activation of the sympathetic nervous system and HPA axis often occur when the animal is subjected to an acute stressor, during which catecholamines and cortisol are secreted (Sapolsky et al., 2000; Chrousos, 2009). Cortisol is a pleiotropic hormone, affecting all major bodily systems associated with the preservation of homeostasis (Chrousos, 2009;

Papadimitriou and Priftis, 2009). A study by Cafe et al. (2011) reported a positive correlation between plasma cortisol, plasma lactate, and NEFA concentrations; suggesting the activation of a sympatho-adrenal-medullary axis interaction with cortisol and epinephrine/norepinephrine in response to a stressor (Sapolsky et al., 2000). As a ruminant animal undergoes a stress event, the regulation of glucose and the rate of gluconeogenesis are both affected. Thus, the release of hormones in response to stressors mobilizes stores of energy with the aim to metabolically adapt to a stressor (Brockman and Laarveld, 1986); and metabolic priority is placed on bodily systems directly associated with the 'fight or flight' reaction, such as the brain and skeletal muscle (Chrousos, 2009). Therefore, secretion of stress-induced hormones, such as catecholamines and cortisol, are known to affect the reproductive, metabolic, and immune functions within the animal (Sapolsky et al., 2000; Chrousos, 2009). Animals experiencing chronic stress have been shown to have lower average daily gain (ADG) due to increased metabolic maintenance requirements, resulting from a shift in the body's metabolic priority from a state of homeostasis to adaption to the stressor. This decrease in an animal's ability to gain weight may also be due to the inhibition of energy storage via insulin resistance caused by increased metabolic stress (Sapolsky et al., 2000). Cattle with calm temperaments have been both genetically and phenotypically associated with increased growth rates as reported by Nkrumah et al. (2007). Turner et al. (2011) stated that the relationship between ADG and temperament is likely the result of an animal's long-term susceptibility to stressors combined with subsequent behaviors associated with a prolonged stress response. In contrast with an animal's singular immediate reaction to stress, Boles et al. (2015) suggested that cattle responses to stress may differ in *Bos* *taurus* animals when compared with *Bos indicus*. Evidenced by a study conducted by Blecha et al. (1984), which found that cortisol concentrations of Angus cattle were lower for both control and transported steers than cortisol concentrations for both control and transported Brahman X Angus steers.

Cortisol

The activation of the HPA axis through either environmental or physiological stressors releases cortisol into the blood (Foury et al., 2011). This release of cortisol along with catecholamines activates gluconeogenesis and glycogenolysis, creating a metabolic shift and freeing more energy for the body to utilize (Brockman and Laarveld, 1986). Cortisol concentrations can be utilized to determine an animal's stress response to a wide range of stressors such as transport, handling, and experimental physiological manipulations (Hart, 2012). Cortisol is most commonly measured in plasma, saliva, feces, and hair. Cortisol assays aim to measure the biologically active, free portion of cortisol (Mormède et al., 2007) as the free portion has been found to be correlated with total plasma cortisol (Greenwood and Shutt, 1992). Cortisol concentrations within the body at any given time fluctuate greatly between individual animals, suggesting varied levels of HPA axis activity (Comin et al., 2013), as it is secreted in an ultradian cycle (short periods of active hormone release; Windle et al., 1998) over a 24-h period (Hart, 2012). Due to this secretion cycle, plasma cortisol is not an ideal measure for chronic stressors as they are known to have a down regulation effect on the HPA axis (Bornstein et al., 2008). However, research has shown that cortisol concentrations found in hair and fecal cortisol metabolites may serve as more long-term measures for cortisol (Schmidt et al., 2010).

In terms of cortisol measurements, hair seems to be the only matrix with the ability to evaluate long term chronic stress, due to the fact that as hair grows hormones are accumulated along the hair shaft (Tallo-Para et al., 2015; Comin et al., 2013). A drawback of using hair to measure cortisol is that initial samples may be an accumulation of previous stressfull situations unrelated to the present experiment (Tallo-Para et al., 2015). However; in terms of health status, hair cortisol remains an excellent biomarker for chronic health conditions, as short-term changes that may affect plasma cortisol concentrations are removed, such as the specific start and end of a disease or the intensity of the HPA reaction (Burnett et al., 2015; Comin et al., 2013). Cattle observations indicate that hair growth and texture are different when found in different regions on the body, likely effecting the total cortisol accumulated per region (Moya et al., 2013). Schwertl et al. (2003) reported that hair growth on the tail switch of dairy cattle ranges from 0.6-1.0 mm/d, suggesting that a 2-4 cm hair sample would be sufficient to measure changes in hormone levels (Comin et al., 2013). In a study comparing hair cortisol concentrations from various body locations of cattle, Moya et al. (2013) reported hair cortisol concentrations to range from 0.30 to 5.31 pg/mg for Angus cross bulls. These concentrations differed from hair cortisol concentrations reported by González de la Vara et al. (2011) recorded in 2-yr-old cows (12.15 ± 1.85 pg/mg). This variation could be due in part to physiological differences between age and sex. Other factors such as hair color, photoperiod, season of year and nutrition also play a role in hormone deposition within the hair shaft. Darker hair colors are known to have greater levels of melanin which may act as a buffer for UV radiation leaching of cortisol concentrations, supported by the research of Heimbürge et al. (2020); however, some researchers have reported lighter colored hair to contain greater cortisol concentrations (González de la Vara et al., 2011). It has also been reported that hair cortisol concentrations of cattle are greater in the winter months compared to summer (Heimbürge et al., 2020), possibly due to the decreased sunlight and UV radiation during the winter months. Moya et al. (2013) reported that hair collected through a clipping method showed greater cortisol concentrations in comparison to hair collected by a plucking method (2.35 ± 0.176 pg/mg and 1.75 ± 0.176 pg/mg, respectively), suggesting that the hair follicle contains lower cortisol concentrations than the hair shaft. This is likely due to the fact that as the hair emerges from the epidermis it is coated in hormone secretions from sebaceous and apocrine glands. Moya et al. (2013) also indicated that clipped hair may be a better measure of the accumulation of adrenocortical activity, as plucked hair only expresses cortisol accumulation days prior to extraction (likely due to a dilution of cortisol concentrations by follicle inclusion) while clipped hair has been shown to express cortisol accumulation from weeks to months prior to collection. This data agrees with results from Heimbürge et al. (2020), indicating that higher cortisol concentrations were expressed as hair was segmented proximally to distally from the hair follicle with distal hair showing 2.5 times greater cortisol concentrations. Hair clipped from the tail has also been shown to express higher concentrations of cortisol, compared with the head, neck, and hip (Moya et al., 2013) as this hair may be the most susceptible to the incorporation of external fluid containing cortisol, such as sweat, urine, and sebum. This suggests that the body location from which the hair is collected may be more important than coloring when measuring cortisol concentrations. It has also been reported that hair from the tail has a faster growth/rest cycle compared to body hair in cattle (Fisher et al., 1985), likely making tail hair the most suitable matrix to measure long-term hair cortisol concentrations. In a study conducted by Heimbürge et al. (2020) hair growth rates for cattle ranged from 3.5 to 17.0 mm/month, with hair growing from the tail at the fastest rate.

Hair cortisol concentrations have been reported at various concentrations within the literature. Comin et al. (2013) reported that cortisol concentrations of dairy cows range from 0.76 to 28.95 pg/mg in a study comparing healthy cattle to those suffering a disease or stressful event (i.e., calving). During the study, a threshold was established stating that hair cortisol concentrations below 4.17 pg/mg are indicative of healthy cattle (Comin et al., 2013). Burnett et al. (2015) also reported that hair cortisol concentrations remained greater in cows that were clinically diseased compared to healthy cows. The authors reported that increased cortisol concentrations for ‘unhealthy’ cattle in multiple studies is likely due to repeated HPA axis activation, ultimately leaving the animals more susceptible to disease and homeostatic disruption (Comin et al., 2013). In a study examining long-term effects of an automated milking system, Jerram et al. (2020) found average hair cortisol concentrations to be 1.99 ± 0.77 pg/mg. Throughout the literature other varying concentrations of hair cortisol have been reported:

Hair Cortisol, pg/mg	Citation	Animal type
0.69	Braun et al., 2017	Dairy cows
0.73	Braun et al., 2017	Dairy cows
2.35	Moya et al., 2013	Angus cross bulls
5.7	Burnett et al., 2014	Dairy cows
12.15	González-de-la-Vara et al., 2011	Dairy heifers

Range of hair cortisol concentrations reported in the literature.

which may be due to a variety of assays used to measure hair cortisol, breed type, hair collection location and even hair color (Braun et al., 2017).

Corticosterone

Cortisol is indirectly measured in feces through various metabolites (Möstl et al., 1999) or hormones co-released with cortisol such as corticosterone. Animals that are chronically stressed have been shown to release increased levels of corticosterone when challenged with adrenocorticotropic hormone (ACTH), a hormone that stimulates the production and secretion of glucocorticoids (Bornstein et al., 2008). In a study conducted to determine the cortisol/corticosterone ratio between 13 species of animals, results presented high plasma cortisol levels to be associated with high corticosterone levels, and vice versa, across 9 of the species (Koren et al., 2012). Though others in the literature have also reported that cortisol and corticosterone are correlated, the expression of each metabolite may vary depending on the stress response, meaning that the use of both metabolites may produce the most accurate results (Koren et al., 2012). The ratio of plasma cortisol to corticosterone in several breeds of dairy cattle has been reported as 4:0 in Holsteins, 1:5 in Guernseys, and 2:8 in Jerseys (Venkataseshu and Estergreen, 1970). Palme et al. (2000) reported basal and peak cortisol metabolite concentrations in cattle fecal samples following transportation to from 39 – 2301 nmol/kg (13.5 - 797.3 ng/g). Although cortisol metabolite concentrations may be influenced by changes in diet or intestinal, and bacterial activity, Möstl et al. (2002) stated that the concentration of fecal cortisol metabolites is a direct reflection of cortisol production that occurred approximately 12 h prior. However, elevated fecal cortisol levels can be excreted up to 5 d after a stressful transportation event (Möstl et al.,2002).

Lactate

Lactate is produced in muscle tissue through anaerobic glycolysis as a result of the conversion of pyruvate to lactic acid by way of lactate dehydrogenase (Burfeindand and Heuwieser, 2012). Neuroendocrine responses to stress activate the HPA axis, leading to increased rates of glycolysis within the body (Matteri et al., 2000). As physiological and environmental stressors activate the sympathetic nervous system, catecholamines are released from the adrenal medulla, intensifying the breakdown of glycogen in the liver and increasing lactate concentrations in the blood (Warriss, 2010). Diesch et al. (2004) reported that Friesian and Angus calves undergoing a stressful birthing process expressed increased plasma lactate concentrations (6.3 mmol/L and 9.1 mmol/L; respectively), in comparison with calves birthed without assistance (4.7 mmol/L and 6.5 mmol/L; respectively). Boles et al. (2015) reported a range of blood lactate concentrations from below 0.8 mmol/L to 11.3 mmol/L in Simmental X Angus steers with varying temperaments, with and average lactate concentrations reported to be between 2.5 mmol/L and 3.0 mmol/L.

Exercise can also be viewed as a stressor as exercise produces an anaerobic environment within the body. Davidson and Beede (2009) reported that exercise in the form of an acute stressor increases plasma lactate concentrations, suggesting an increase in metabolic acidosis caused by an anaerobic metabolism within the muscle. Holmes et al. (1972) reported, in a comparison of “double muscled” and normal Hereford heifers, initial lactate concentrations for normal and “double muscled” heifers were 2.8 mg/L and 4.2 mg/L, respectively; it was also reported that exercise increased the average blood lactate of the normal beef heifers to 3.14 mmol/L. A study conducted to determine blood lactate concentrations of horses undergoing various types of exercise found that lactate production is correlated with the level of intensity of the anaerobic process that results from exercise, leading to the conclusion that plasma lactate is more strongly related to the intensity of a stressor (i.e. exercise) than plasma cortisol (Desmecht et al., 1966). The addition of a strong base or loss of a bicarbonate may result in metabolic acidosis (Davidson and Beede, 2009), and acute stressors may affect the body's ability to compensate for such changes through respiration and buffering, resulting in an influx of anaerobic processes. Cattle exhibiting increased concentrations of blood lactate have also expressed a correlation with decreased fat thickness (Boles et al. 2015), possibly due to an increased chronic stress response and adaption of metabolism (Matteri et al., 2000). Research has previously reported that plasma lactate concentrations are influenced by the temperament of cattle; Coombes et al. (2014) reported that as flight speed in cattle increased from 1 to 5 m/s, and plasma lactate concentrations increased approximately 50%.

Non-esterified Fatty Acids

The production of glucose in the ruminant animal occurs mainly through the use of volatile fatty acids (VFA) resulting from the fermentation of carbohydrates within the rumen. Cattle rely on the conversion of VFA through gluconeogenesis for energy (Sanchez et al., 2013). Non-esterified fatty acids are released from adipose tissue in response to hormonal cues such as corticosteroids and catecholamines. The release of NEFA from adipose tissue provides increased energy to tissues throughout the body, though increased concentrations of NEFA have been reported to be problematic (Adewuyi et al., 2005; and Shi et al., 2015). Drackley (2000) reported normal NEFA concentrations to be no greater than 0.2 mM in cows with a positive energy balance. Non-esterified fatty acids may act as a marker for a negative energy balance (Adewuyi et al., 2005) and may be an inducing factor for inflammatory responses such as acidosis or ketosis. Shi et al. (2015) reported an increase in the release and expression of pro-inflammatory factors tumor necrosis factor alpha (TNF-α), interleukin six (IL-6) and interleukin 1 beta (IL-1β) when calf hepatocytes were treated with high NEFA concentrations; concluding that increased NEFA concentrations directly induces an inflammatory response in cattle. Several studies have reported that increased levels of plasma NEFA induced oxidative stress in cattle through decreasing the activity of several antioxidant enzymes (Shi et al., 2015; Bernabucci et al., 2005; and Contreras et al., 2012). There is also evidence that increased NEFA concentrations lead to a decrease in fat deposition, possibly reducing beef cattle performance. Bernabucci et al. (2005) also stated that animals exhibiting increased rates of fat mobilization had an increased affinity for a sensitivity to oxidative stress. Non-esterified fatty acid concentrations may also be related to animal behaviors. Sanchez et al. (2013) reported that animals classified as temperamental had greater circulating concentrations of NEFA compared to animals classified as calm prior to an immune challenge. These results correlate with a study conducted by Nkrumah et al. (2007) which reported a negative correlation between flight speed and carcass fat, concluding that flighty cattle had a decreased fat deposition in comparison with calmer cattle.

Behaviors

The effects of internal and external stressors on cattle impact a broad range of bodily functions including, behavior, productivity, and carcass quality. Behavioral activity of cattle is often used as an indication of overall animal comfort and well-being (Cooke et al., 2005). Temperament, defined as the variation of behavioral responses to stressful events (Cafe et al., 2011), has been correlated with the intensity of a stress response. It has been reported that cattle deemed to be more excitable have a higher basal concentration of catecholamines and cortisol in comparison with calmer cattle. Brahman bulls labeled as temperamental had higher stress metabolite levels before and after transportation than calm cattle, while only the calm cattle expressed an increase in cortisol as a direct response to the transportation event (Burdick et al., 2010). Literature also reports that cattle deemed 'flighty' or 'excitable' are more active (Grandin, 1993). This increase in muscle activity is likely due to increased glycogen mobilization, resulting in an increase of plasma lactate (Coombes et al., 2014). Cafe et al. (2011) reported steers deemed to be more temperamental exhibited greater concentrations of plasma cortisol, which were associated with increased plasma lactate and NEFA concentrations, leading to the conclusion that flightier or more temperamental cattle have a more intense stress response. Previous research has reported that cattle exhibiting an increased cortisol response fed more often per day and were associated with lower live carcass weights, lower ADG, and decreased rib fat thickness. These results suggest that cattle experiencing stress may increase net feed intake but exhibit a reduced feed efficiency (Cafe et al., 2011), likely caused by the metabolic shift previously explained. Changes in diet composition can also affect animal behavior. Miguel-Pacheco et al. (2019) stated that heifers fed a low crude protein (CP) diet during the preconception period affected both dam and calf behavior. Researchers reported that standing time was 12.6 minutes longer for heifers fed a low protein diet (10% CP) compared to heifers fed a high protein diet (18% CP). In addition, calves of low protein dams had an increased latency for initial standing and suckling compared to calves of high protein dams (Miguel-Pacheco et al., 2019). Cattle expressing increased cortisol levels have been reported to spend less time ruminating (Lindström et al., 2001; Bristow and Holmes, 2007); these cattle have also been reported to vocalize and stand more often, while remaining in close proximity with others in comparison with cattle exhibiting lower cortisol concentrations (Bristow and Holmes, 2007). During repeated transportation events, Falkenberg et al. (2013) reported a 6% decrease in body weight (BW) during the initial transportation event in heifers that were transported for 4 h, compared to only a 2.5% loss in BW for heifers that were not transported. As transportation and relocation are known stressors for livestock, even a small shift from metabolic homeostasis can alter an animal's wellbeing. The release of cortisol, even in small quantities can result in immunosuppression, leaving the animals more susceptible to disease and mortality (Blecha et al., 1984). On the other end of the spectrum, short-lived increases in cortisol may be indicative of a healthy animal's homeostatic compensation to a stressful event and the animal's ability to mobilize resources within the body to take preventative actions (Falkenberg et al., 2013).

The environment of an animal can also alter its behavior. In a study comparing the effects of rearing calves on river stone or sawdust, Sutherland et al. (2013) reported that calves reared on river stones spent more time standing and less time lying, playing, and had lower skin temperatures, which may indicate a decreased ease of movement and comfort. Factors such as handling style have also been reported to affect livestock physically and physiologically. In a comparison of different handling styles in both a backgrounding and feedlot setting, Petherick et al. (2009) reported that both flight score and animal movement around a test arena were correlated with cortisol, NEFA, and lactate concentrations. It was reported that all of the aforementioned metabolites were greatest in calves that were subjected to poor handling practices, poorly handled calves also had the lowest BW and BCS, likely due to a stress-mediated change in metabolism (Petherick et al., 2009).

Monitoring Grazing Behavior

Traditional methods of livestock management are limited to the use of time-tested tools such as adjusting stocking rates, rotational grazing, and adjusting supplementation at a herd level to improve the productivity of a grazing herd. However, the use of technology to aid in herd management provides the flexibility to focus on individual animals while implementing proper rangeland management practices (Andriamandroso et al., 2016); as the interaction between plants and animals can be observed and remotely managed by combining feeding behavior and animal position data (Laca, 2009). When monitoring is aimed at managing individual animal grazing behaviors, it is important to note that grazing, ruminating, and resting take up 90 - 95% of the daily activity of cattle (Andriamandroso et al., 2016). The basis for recording individual grazing animals lies in 3 parameters: animal location, animal posture, and animal movement (Andriamandroso et al., 2016).

There are three primary methods of monitoring cattle behavior that utilize various technologies: accelerometers measuring physical behavior, radio frequency sensors measuring feeding and watering behaviors, and spatial measurements utilizing GPS

(Richeson et al., 2018). Remote monitoring of beef cattle can provide useful information regarding animal use and proximity to food and water, changes in activity and social behaviors, as well as detection of changes in health status (Richeson et al., 2018). A variety of other technologies have been developed to monitor grazing animal behaviors. Mercury switches have been developed to measure head movements along with steps and lying behaviors (Laca, 2009). Acoustic monitors aim to classify behaviors while estimating feed intake rates, while other sensors specifically measure acceleration of the head or legs, heart rate, core temperature, chewing motions, or chewing/biting sounds (Laca, 2009). Researchers have even developed remote devices to measure cattle BW passively as animals move across a weighing platform to access food or water (Charmley et al., 2006).

Evaluation of Accuracy of Sensors

The utilization of remote health monitoring technologies is centered on a reduction of labor costs and an increase in animal performance while decreasing events of mortality (Richeson et al., 2018). Because the act of grazing is a combination of periods when an animal is actually eating and periods of activity associated with eating (i.e., searching for forage or moving from one patch to another; Gibb, 1996), the accuracy of remote behavior sensors becomes a key element in estimating actual animal behaviors.

Global positioning technology utilizes the triangulation of radio signals and geo-orbiting satellites to determine coordinates of latitude, longitude, and elevation. Global positioning technology derived positions have been proven to be geographically accurate (79 and 71%) after ex-post differential correction (Schlecht et al., 2004). Data received from GPS units provide information regarding location changes in time, and from this the speed of change in position and distances traveled by animals can be computed, allowing for a more complete representation of habitual and spatial distribution of ruminant animals (Laca, 2009). In early GPS research, Schlecht et al. (2004) reported that reliable estimates (error rates < 0.5) of daily activity and hourly activity patterns of grazing cattle could be computed using GPS technology; later research shows that GPS fixes as short as 1-s intervals are successful in characterizing foraging, walking, and stationary behaviors (Anderson et al., 2012). Schlecht et al. (2004) also stated that behaviors of cattle wearing GPS equipment did not differ from control cattle within herd, as no excessive resting behaviors, grazing disturbances, nor skin irritations from wearing GPS equipment were reported. Similarly, in a study utilizing GPS collars worn by sheep, Hulbert et al. (1998) reported that animals wearing GPS collars equivalent to 2.2% of BW exhibited similar grazing and circadian behaviors compared to uncollared sheep.

While GPS technology has been reported to be effective in classifying animal behaviors, there are inefficiencies in the technology itself. Though Anderson et al. (2012) was able to use GPS fixes to determine animal behaviors, abnormalities were reported. Even if there was no directional movement for animals undergoing stationary behaviors, GPS technology always reported some movement. Performance of the electronic equipment was also faulty, complete failure of hardware and software occurred during periods of observation, and issues were also reported with the durability and consistency of placement of the GPS units. Due to these issues, it was determined that speed thresholds, one identifying transitions from stationary to foraging and another identifying transitions form foraging to walking behaviors, used to optimize the total of correctly identified behaviors was a better model compared to discriminately utilizing observational data (Anderson et al., 2012). Issues have also been reported in GPS collars utilizing the Global System for Mobile communications, as transmission functions properly in areas with adequate cellular service, however, in remote areas where the use of GPS units to monitor grazing behavior may be most beneficial, there is frequently inadequate signal for unit communications (Umstatter, 2011).

Accelerometers are electronic sensors that transform physical acceleration from motion and gravity into a voltage signal output (Andriamandroso et al., 2016). Accelerometers are utilized to measure step rates, as the acceleration per step can be measured and converted to a square pulse that can be counted (Frost et al., 1997). This technology is also capable of measuring the amount of time an animal spends conducting an activity, such as lying or walking (Robert et al., 2009), by classifying animal activity through specific algorithms. Though accelerometers have the ability to remotely monitor livestock health, the validity of such abilities has yet to be validated. In order to fully monitor animal behaviors with the option to monitor health status, an integration of multiple categories of sensors may provide the most accurate information to remotely manage and detect early health and welfare issues within a livestock herd.

Remote Monitoring Collars

Remote monitoring of the health status and grazing behaviors of beef cattle has been attempted by researchers with the use of spatial temporal information provided by GPS collars integrated with motion sensors. The use of GPS tracking collars is common practice for the observation and management of many species of wildlife, as the information provided by GPS collars coupled with geographic information systems (GIS) allow researchers to evaluate animal movement and distribution among landscapes (Ungar et al., 2005). This methodology has been implemented into cattle grazing practices as a way to evaluate resources utilized by grazing animals. Ungar et al. (2005) found in 2 studies utilizing GPS collars integrated with motion sensors, that the addition of a motion sensor improved the ability of the collars to classify grazing behaviors and distance traveled. This study also showed that distance data alone was not sufficient in predicting animal activities such as grazing or resting. Similar results were reported by Turner et al. (2000) in which a high accuracy rate was reported for the classification of cattle behaviors. Additionally, González et al. (2015) reported success in utilizing a higher frequency rate of data collection to most accurately classify behaviors that closely resemble each other (i.e., rumination from resting or foraging from traveling).

Though results have been reported in the classification of grazing cattle behaviors with the use of integrative GPS collars, some issues remain to be addressed. An accurate account of cattle behavior cannot yet be derived from remote monitors, as the monitors cannot yet fully distinguish between small movements of the animal's head and neck and transitions within larger movements of resting, walking, grazing, etc. For example, a resting animal may still move its head to groom or deter insects, and walking while grazing may not be easily distinguished from walking while traveling to a new location. In addition to these flaws, Ungar et al. (2005) stated several other reasons why complete accuracy is not easily obtainable using these GPS collars; i.e. all animals may not exhibit similar motion behaviors while grazing, GPS motion fixes are not always represented on the exact same time scale, and one collar may differ from another in how it senses motion, affecting how different motions are translated into activity records (Turner et al., 2000). Most methodologies utilized for behavioral classification data also have the disadvantage of requiring large power sources and computing powers, along with the need for subjective human observation to establish classification thresholds, leaving much room for error.

SUMMARY OF LITERATURE

Livestock management practices have evolved greatly over time. With this evolution comes the responsibility to not only choose the grazing technology most suited for producer and animal needs, but to ensure that the technology implemented is morally and ethically sound in application. Grazing technologies provide a wide range of implications for producers to attempt to meet management needs. Fences ranging from traditional permanent wire fences to semi-permanent electrified wire fences, to essentially mobile VF systems allow for a great range of grazing methods and landscapes to be utilized in the livestock industry. Remote behavior and health monitoring technologies provide another resource for livestock managers to increase the profitability of their herds. The addition of motion sensors to GPS location monitors may provide livestock producers with vital data to improve the health and well-being of livestock herds.

While these technologies are innovative and present a path of progress for the livestock industry, the introduction of these novel management practices may cause unnecessary physical and physiological stress. In terms of an animal's response to stress, it is important to understand that responses will differ among type of stressor, breed of animal (Boles et al. 2015), physiological state or sex (Diesch et al. 2004; Boles et al. 2015), and even between individual animals (Anderson, 2007; Lee et al. 2009; Quigley et al., 1990). Much of the literature suggests that the use of technologies such as VF or remote monitoring collars, as compared to electric fencing or the absence of collars, produce little to no difference in the stress response of animals. However, more research implementing various livestock management technologies is required to fully assess the effectiveness of remote livestock management, along with both short- and long-term effects on livestock.

CHAPTER II

Effects of virtual fencing on cortisol concentrations and behavior of beef cattle

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ABSTRACT

Objective: Two experiments were conducted to evaluate the effects of virtual fencing (**VF**) on stress in beef cattle.

Materials and Methods: Cattle were contained by physical, 2-strand electric fencing (**PF**) or by use of proprietary, GPS-based VF collars, with no physical interior fencing. Tail switch hair and fecal samples were analyzed for cortisol concentrations to measure accumulated stress experienced by the cattle. A subset of cattle were fitted with pedometers to evaluate behavior.

In Study 1, 55 heifers were rotated in 1 PF or 1 VF pasture over 28 d. In Study 2, 59 mature cows and heifers were rotated in 1 of 2 PF or 1 of 2 VF pastures (n = 4) over 56 d.

In the second experiment, blood samples were also collected to quantify NEFA and lactate in serum.

Results and Discussion: In Study 1, in both PF and VF, hair cortisol (0.39 ± 0.3 and 0.37 ± 0.1 pg/mg, respectively) and fecal corticosterone (140 ± 79.6 and 128 ± 56.7 ng/g) were within published normal ranges. Step counts and motion index appeared elevated in the adaptation phase for VF. Study 2 was analyzed using analysis of variance as a completely randomized design with pasture as the experimental unit. No effect of fence type was observed for standing time or lying bouts ($P > 0.16$). However, VF cattle moved more than PF ($P \leq 0.002$; likely due to the VF training period) in the first few days, but not later in the experiment. No differences were observed in cortisol metabolites, lactate, or NEFA ($P \geq 0.14$) due to fence type.

Implications and Applications: These data indicate that VF is not more stressful to cattle than PF. These results warrant further research and development of virtual fencing technology.

Key Words: Fence, Stress, Livestock management

INTRODUCTION

Technology continues to allow new and innovative ways to manage livestock; one such technology is virtual fencing (**VF**). Virtual fencing could improve utilization of seasonal forage growth, or re-establishment of pasture biodiversity through the use of exclusion areas (Anderson, 2007; Umstatter et al., 2015), while also allowing for “virtual” herding or mustering of animals (Butler et al., 2006). Virtual fencing technology has been reported to effectively contain cattle without substantially affecting animal behavior and welfare (Campbell et al., 2019), with efficacy rates reported at ≥ 90 % for containing cattle with VF technology (Tiedemann et al., 1999).

Electrical shock, either in the form of electrified wire fencing or VF collars, has been reported to cause some animal discomfort (Lee et al., 2009; Teixeira et al., 2017). Stressors in cattle cause an increase in stress hormones (i.e. cortisol) and blood metabolites such as plasma lactate and non-esterified fatty acids. These metabolites may result in decreased animal performance, as they elicit a change in animal metabolism, especially when due to prolonged exposure to stressors (Matteri et al., 2000; Bernabucci et al., 2005). Stress caused by electrical shock has also been reported to adversely affect animal behaviors by interrupting normal grazing activities and increasing agitation following electrical shock (Markus et al., 2014; Campbell et al., 2019).

Therefore, the objective of these studies was to evaluate the effects of VF on stress and behaviorial responses in beef cattle when compared to physical electric wire fencing in a rotational grazing management system.

MATERIALS AND METHODS

All procedures were approved by the Institutional Animal Care and Use Committee at Oklahoma State University (Animal Care and Use Protocol number: IACUC-19-63-STW)

Pastures

The pastures utilized in these studies consisted of warm-season perennial grasses, primarily Bermuda grass (*Cynodon dactylon*) or yellow bluestem (*Bothriochloa* *ischaemum*). This research was conducted at the Bluestem Research Range at Oklahoma State University, 14.5 km SW of Stillwater, OK.

Study 1. This pilot study was conducted over the course of 28 d, beginning in August 2020. Two pastures, each approximately 24 ha in size, were selected for this study. One pasture was assigned to VF and one to physical fencing (**PF**). In PF, the pasture was divided into 2 approximately equally sized paddocks with a double-stranded, electrified, high-tensile wire fence. The fence controller (Gallagher B600 Solar; Gallagher, Riverside, MO) maintained a voltage of 7kV throughout the study. In the VF pasture, each pasture was divided similarly to PF, using only the VF system for animal rotation (described below in greater detail). The VF pasture did not contain any physical interior fencing. Weekly, 10 forage samples were hand-clipped to ground level using a 0.09-m^2 quadrat, in the area that cattle had access to. Clippings were composited by pasture. Concurently with pasture sampling, forage mass was estimated by collecting 30 readings per pasture using a calibrated rising plate meter (Model EC-20; Jenquip, Feilding, New Zealand; Moffet et al., 2012; Reuter et al., 2012).

Study 2. This study was conducted over the course of 56 d, beginning in October 2020. Four pastures ranging in size from 9.4 ha to 16.5 ha were selected for this study. Each pasture was randomly assigned 1 of 2 fencing types: VF or PF. In PF pastures, each pasture was divided into 4 approximately equally-sized paddocks with a double-stranded, electrified high-tensile wire fence. The fence controller maintained a voltage of 7kV throughout the study. In VF pastures, each pasture was divided similarly to PF, but using only the VF system for animal rotation (described below in detail). The VF pasture did not contain any physical interior fence. Forage sampling and plate meter readings were conducted similarly to the method described in Study 1.

Animals in both studies were rotated to the next pasture at approximately 0800 h on Mondays. Physically-fenced animals were manually rotated by a herdsman in a utility terrain vehicle (UTV; Gator XUV835M, John Deere, Moline, IL). Virtually-fenced animals were rotated solely through the use of the VF system. A one-way gate action was used on the day of rotation, where the VF that was preventing animals from entering the next rotation paddock was disabled. Once animals crossed into the next assigned paddock, the VF re-enabled. If animals attempted to return to the previous rotation, sound and shock patterns were initiated by the VF collar (described below in greater detail). Each pasture contained one water tank to provide ad libitum water in either the SE, SW, or NE corner of each pasture, sourced from the rural water district in Payne County. Ponds were present in 3 of the 4 pastures. To establish a similar environment in each pasture, animals were excluded from accessing these ponds by either a single electrified, high-tensile, wire or through the use of the VF system.

Animals

Study 1. Fifty-five Angus heifers (BW= 315 ± 30 kg) were utilized for this study. Animals were randomly allocated into a PF (*n* = 24) or VF (*n* = 31) pasture. All animals utilized for this study had no prior exposure to the VF system and were not accustomed to the pastures, however, animals did have prior experience to PF, the herdsman and UTV. Virtually-fenced animals wore version 1 VF collars (Figure 2.1).

Study 2. Fifty-nine Angus, Beefmaster, and Angus-Hereford cross mature cows and heifers (BW = 484 ± 84 kg) were utilized for this study. These cows had previously been managed in the pastures utilized in this experiment or similar pastures and were familiar with the fencing, water tanks, herdsman and UTV etc. of the Bluestem Research Range. All animals had also undergone at least 2 wk of exposure to the VF collars and VF system. Calves were weaned from the cows 4 d prior to the start of the study. Cows were stratified by previous calf status (calf weaned vs. no calf) and breed type (Angus/Angus-Hereford cross, n = 38 or Beefmaster, n = 21). Within these stratifications, cows were randomly assigned to one of two PF (n = 15 and 15) or 1 of 2 VF (n = 14 and 15) pastures. All animals wore a version 2 VF collar (Figure 2.2 and 2.3). Animals in the PF treatment wore collars set only to track global positioning system (GPS) location, while collars in VF pastures tracked GPS location in addition to actively fencing the animals.

Virtual Fencing System

The VF system (Vence.io; Vence, Inc., San Diego, CA) consisted of collars utilizing GPS technology, remotely deployed radio telemetry masts, a cloud server, and an end user software interface. Virtual fence boundaries were defined through the Vence computer software and the outlined parameters and instructions were communicated to each collar through the server network. Global positioning system location functions of the program allowed for visualization and analysis of animal movements and VF efficiency via the Vence computer software.

The VF system was set to alter animal behavior through the use of sensory cues administered as animals attempted to penetrate a virtual boundary. The width of the boundary for which sensory cues were administered was determined in the Vence computer software as a stimulus zone (50m) from the VF fenceline and an additional sound zone (5m) for a total of 55m of VF boundary (Figure 2.4). An auditory tone (4kHz; experienced by the animal at 75 dB for 0.5 sec) was administered by the collar as an animal approached the VF boundary (the sound zone). If the animal responded to the auditory cue and turned away from the VF boundary, no other stimulus was applied. However, if an animal continued toward the VF boundary after receiving the auditory cue, a short electrical pulse was applied to the animal's neck through the collar (at 800V for 0.5 sec). If the animal remained in the VF boundary after receiving both an audio and electrical stimulus, a pattern of 0.5 sec of sound, 1.5 sec of no stimulus, 0.5 sec of electrical stimulus, then 2.5 sec of no stimulus would continue for 100 sec. After 100 sec there was a 180 sec-period of no stimulus. This pattern would continue for approximately 20 min; at that time, built-in fail-safes would disable any further stimuli until the collar was manually reset by the manager.

On d 0 of each study, animals entered the assigned pastures. Virtual fencing animals were immediately placed into a 48-h training period (Figure 2.4) in which no interior VF lines were activated. During the first 24 h, animals were subjected to a 10-m stimulus zone along the perimeter fence line. Animals were also excluded from any ponds within the pasture using the VF system. The following 24 h included the previous exclusions, with the addition of a 5-m sound zone added to the interior portion of the stimulus zone. This caused animals to first pass through a sound zone, then stimulus zone, prior to reaching the physical fence line surrounding each pasture. After the 48-h training period, exclusions from the perimeter of the VF pastures were removed and the VF lines of the rotation paddocks were implemented. Therefore, during the first 48 h, VF animals had access to a much larger pasture (24 or 58 ha) compared to animals in the PF paired pastures. After the first 48 h, all animals had access to pastures of approximately the same size (Figure 2.5).

Sample Collection

Study 1. A subset of animals was randomly selected (n = 18; n = 9 per treatment) to wear an additional, custom-built global positioning system (GPS) collar (i-gotU GT-120; Mobile Action Technology Inc., New Taipei City, Taiwan; Bailey et al., 2018), and an IceQube pedometer (IceRobotics Ltd.; Edinburgh, Scotland; Borchers et al., 2016). The pedometers were placed on the rear right leg of the selected animals on d 0. Data from the i-gotU GPS collars is not presented here.

Feces were collected from all animals via rectal palpation on d 0 and d 28 to measure corticosterone levels (Moya et al., 2013; Foote et al., 2016). Fecal samples were stored in airtight sample bags at -20℃ until corticosterone analysis was completed. Additionally, once per wk, fecal samples from animals in the subset group were collected from the pasture while the herd was grazing. Fecal samples were obtained by observing animals then collecting a sample from a fresh pat produced by each animal. Also at this time, a weekly fecal composite was created for each of the 2 treatments by combining samples of 20 fresh pats from each pasture. To measure cortisol levels, hair was shaved from the tip of the tail switch with clippers equipped with a surgical blade; hair was shaved as close to the skin as possible (Moya et al., 2013; Tallo-Parra et al., 2015). Hair was shaved on d 0 to remove existing hair and was not collected, on d 28 hair grown over the study period was shaved and collected for analysis. Hair was stored in airtight sample bags at -20°C until cortisol analysis was completed.

Study 2. A subset of animals (*n* = 16; *n* = 4 per pasture) were randomly selected and fitted with an IceQube pedometer as described above.

Feces were collected from all animals via rectal palpation on d 0 and d 56 to measure corticosterone levels. Fecal samples were stored as described above. Additionally, once per wk, fecal samples from the subset of animals wearing pedometers were collected from the pasture while the herd was naturally grazing. This fecal collection was conducted in the same fashion as described above. Also at this time, a weekly fecal composite from each of the 4 pastures was taken from samples of 20 fresh pats. Hair was shaved from each animal while in the chute on d 0 and d 56 in order to isolate cortisol levels. Hair was shaved and stored as described above. Blood was collected from each animal via coccygeal venipuncture on d 0 and d 56 into vacutainer tubes (BD Vacutainer; Franklin Lakes, NJ). Samples were placed on ice after collection and transported to the laboratory in Stillwater, OK. A wooden stir stick was used to release the blood clot before centrifuging samples (Foote 2020, personal communication). Blood tubes were centrifuged at 3,000 × *g* for 25 min at 4°C (Sorvall RC6; Thermo Scientific, Waltham, MA). All d-0 samples required re-centrifuging at 5,000 × *g*. Serum was collected and stored at -20°C until lactate and NEFA analysis.

Laboratory Analysis

All forage samples were dried to a constant weight at 50°C in a forced air oven for 24 h and ground to pass through a 1-mm screen in a cutting mill (Pulverisette 19; Fritsch Milling and Sizing, Inc. Pittsboro, NC), samples were composited by fence type and collection date. Samples were then stored at room temperature in airtight sample bags.

Serum samples were thawed at room temperature immediately before lactate and NEFA analysis. Serum L-lactate was analyzed using an immobilized enzyme system (YSI Model 2950 D; YSI Inc., Yellow Springs, OH). Non-esterified fatty acid concentrations were quantified utilizing a commercial kit (HR Series NEFA HR2; Wako Pure Chemical Industries, Osaka, Japan) following manufacturer instructions.

Hair cortisol analysis was performed using methods described by Koren et al. (2002) modified by Moya et al. (2013); during which, samples were saturated with methanol, incubated and the supernatant was evaporated to dryness. Cortisol was then isolated with the use of a commercial RIA kit (MP Biomedicals; Irvine, California). Fecal corticosterone analysis was performed utilizing the method described by Foote et al. (2016). Fecal glucocorticoid metabolites were extracted and analyzed for corticosterone concentrations in duplicate using a commercial RIA kit (MP Biomedicals; Irvine, California). Intra- and interassay CV were 3.16% and 5.13%.

Statistical Analysis

All data were analyzed in R (R Core Team; 2020). Descriptive statistics were summarized for Study 1. Study 2 was analyzed as a completely randomized design using ANOVA with pasture as the experimental unit. Dependent variables were cortisol, corticosterone, NEFA, lactate, and behavior variables provided from pedometers (step count, standing time, lying bouts, and motion index). Independent variables were fence type, wk or d, and the interaction between these variables. Week was modeled as a continuous variable such that quadratic effects of wk were considered.

RESULTS AND DISCUSSION

Behavior Variables

Study 1 was a pilot study and only descriptive statistics were reported (Table 2.1). Values were numerically similar in each treatment and compared to published values (discussed below). Step count and motion index of VF animals were numerically increased compared to PF during the training stage of the study (Figure 2.6).

In Study 2, daily step count was affected by an interaction between fence type and the quadratic effect of day ($P < 0.001$; Figure 2.7). These results indicate that fence type impacted the step count response of animals differently across the duration of the study, with step count generally decreasing in VF over the study period. Standing time in Study 2 was not different between treatments ($P = 0.59$; Figure 2.8). Mean standing time for PF was 761 min/d and VF was 751 min/d. However, standing time for both treatments decreased over the study period ($P = 0.005$). The spike in standing time was due to an ice storm that affected the Stillwater, OK area on d 11 of the study (October 26th, 2020; OK Mesonet, 2020 data). On this day, animals were unable to graze the standing forage and had to be fed hay. Lying bouts did not differ among treatments ($P = 0.68$). Average lying bouts per day for PF was 8.07 and VF was 7.63 (Figure 2.9). Similar to step count, motion index (Figure 2.10) was affected by an interaction between fence type and the quadratic effect of day (P = 0.002). Motion index is defined as a measure of an animals' activity relative to acceleration and energy expenditure (IceRobotics Ltd. 2021). Motion index is affected by the duration of activity and the extent of leg movement, making motion index indicative of overall activity (Gladden et al., 2020). These results from Study 2 indicate that fence type affected the overall activity response of animals differently across the study, in that VF animals moved more early in the trial, but standing and lying times did not differ due to fence type.

The behavioral activity of cattle is often indicative of animal comfort and well-being (Cooke et al., 2005). Grazing cattle spend the majority of the time resting, ruminating, and grazing (normally 90-95% of daily activity; Andriamandroso et al., 2016). Behavioral activities of the cattle monitored in Study 1 and Study 2 are not indicative of animals that are stressed or experiencing discomfort based upon results reported in the literature. Large increases or decreases in animal motion are direct stress responses. Grandin (1993) reported that cattle are more active when excited or stressed, and others have reported that cattle placed in stressful situations spend less time ruminating and lying and more time standing (Bristow and Holmes, 2007; Sutherland et al., 2013). Animals in Study 1 and 2 did not exhibit large deviations from normal activities of grazing cattle, as no large increases in standing time, step count, and motion index were observed. Animals in the current studies also exhibited no decrease in number of lying bouts. These results indicate that VF was not more stressful than PF.

Cortisol & Corticosterone

Hair cortisol concentrations at the end of Study 1 were 0.40 ± 0.32 pg/mg for PF and 0.37 ± 0.15 pg/mg for VF (Table 2.1; Figure 2.11).

Hair cortisol concentrations reported in Study 2 did not differ due to fence type on d 0 ($P = 0.16$) nor d 56 ($P = 0.34$; Table 2.2, Figure 2.12). Hair cortisol concentrations decreased over the study period, but no differences were found in the magnitude of change from d 0 and d 56 due to fence type ($P = 0.14$). The numerical decrease in cortisol concentrations over the study period could be attributed to residual cortisol concentrations reported in the d 0 samples, as previous management unrelated to the current study may have resulted in cortisol deposition in the d 0 samples.

Hair cortisol concentrations from both Study 1 and Study 2 are within reported reference ranges, (0.76 to 28.95 pg/mg in multiparous cows; Comin et al., 2013). Other researchers have reported hair cortisol concentration ranges as low as 0.30 to 5.31 pg/mg in Angus cross bulls (Moya et al., 2013). The large range in concentrations reported in the literature may be due to the breed, sex, physiological state of study animals, and lab-to-lab analysis variation (González de la Vara et al., 2011; Moya et al., 2013; and Braun et al., 2017). The hair cortisol concentrations reported for Study 1 and 2 may be indicative of an animal's healthy, homeostatic response to acute stress events, rather than a prolonged or chronic stress response. Falkenberg et al. (2013) reported that short-lived increases in cortisol are representative of an animal's ability to beneficially mobilize resources within the body and take preventive actions against other stressors.

Fecal corticosterone concentrations reported for Study 1 were 140 ± 79.6 ng/g for VF and 128 ± 56.7 ng/g for PF at final collection (d 28; Figure 2.13). Corticosterone concentrations did increase numerically on d 28 when compared to d 0. However, no consistent pattern of increase in fecal corticosterone can be reported over the study period (Table 2.1; Figure 2.14 and 2.15).

Fecal corticosterone concentrations reported in Study 2 (Table 2.2) did not differ due to fence type on d 0 (P = 0.46) nor d 56 (P = 0.51; Figure 2.16). Fecal corticosterone concentrations reported in Study 2 numerically increased over the study period, though there was not a difference between concentrations from d 0 and d 56 (P = 0.66; Table 2.2). No difference in fence type was observed for weekly fecal corticosterone concentrations (P = 0.79; Figure 2.17) nor for weekly corticosterone composite concentrations (P = 0.16; Figure 2.18).

Fecal corticosterone concentrations from both Study 1 and Study 2 were within concentration ranges reported for normal cattle in the literature. Fecal corticosterone reported in Study 1, with the exception of d 28, were similar to basal fecal cortisol metabolite concentrations reported by Palme et al. (2000), where lactating cows were subjected to transportation, loading and unloading, or no handling. The authors reported basal fecal cortisol metabolite concentrations ranging from 13.5 to 97.7 ng/g. Concentrations from d 28 were slightly greater than basal cortisol metabolite levels reported in Palme et al. (2000), but are similar to the range reported for peak concentrations, 75.2 to 797.3 ng/g. Corticosterone concentrations from Study 2 were just above the basal or just below the peak fecal cortisol metabolite concentrations reported by Palme et al. (1999), where cattle were challenged with adrenocorticotropic hormone (ACTH). The basal cortisol metabolite concentration range by the authors was 11.8 to 154.2 ng/g and peak cortisol metabolite range was 258.1 to 677.1 ng/g. Although d 56 corticosterone concentrations were numerically increased compared to d 0 in Study 2, the effect of fence type was not significant ($P \geq 0.16$) in d 0, d 56, weekly samples, or weekly composites, leading us to the conclusion that VF was not more stressful than PF.

Serum Metabolites

Serum lactate concentrations analyzed in Study 2 (Table 2.3) did not differ due to fence type on d 0 ($P = 0.85$) nor d 56 ($P = 0.91$; Figure 2.19). Average lactate concentrations in beef cattle have been reported to range between 9 and 115 mg/dL (Sako et al., 2007; Burfeind and Heuwiese, 2012). Mitchell et al. (1988) reported elevated serum lactate concentrations in cattle post transportation of 42 mg/dL, which are similar to d 56 concentrations from Study 2, with serum lactate concentrations of 42.3 ± 4.8 mg/dL (VF) and 40.9 ± 4.9 mg/dL (PF; Table 2.3). Although d 56 lactate concentrations were increased compared to the literature, the change in concentration between d 0 and d 56 was not significant due to fence type ($P = 0.86$; Table 2.3).

Lactate is produced in the muscle through anaerobic glycolysis as a result of the conversion of pyruvate to lactic acid via lactate dehydrogenase (Burfeindand and Heuwieser, 2012). Increases in lactate concentrations have been reported in animals undergoing a stress event (Diesch et al., 2004; Petherick et al., 2009) and are strongly related to the intensity of a stressor (Desmecht et al., 1996). Therefore, serum lactate concentrations reflect that animals in Study 2 were undergoing some form of a stress response, however lactate concentrations were only slightly elevated in comparison to the literature, and fence type did not affect the magnitude of change between d 0 and d 56.

Non-esterified fatty acid concentrations were different between fence types on d 0 (*P* = 0.04), but not on d 56 (*P* = 0.65; Table 2.3; Figure 2.20). Eleveated NEFA on d 0 may be caused by the weaning event shortly before d 0, or the different physiological stages of the animals utilized for Study 2, as both bred and open cows and heifers were utilized (Garverick et al., 2012). However, as cattle were randomly assigned to treatment, within physiological stage, on d 0, we cannot explain why there was a difference in NEFA. Fence type did not affect the change in NEFA between d 0 and d 56 (*P* = 0.35). Non-esterified fatty acids are released from adipose tissue in response to the presence of corticosteroids and catecholamines. Increased NEFA concentrations have been reported to induce inflammatory responses in cattle (Shi et al., 2015), and concentrations ≥ 700 meq/L have been linked to an increased risk for disease (Ospina et al., 2010). Non-esterified fatty acid concentrations reported in Study 2 were slightly increased compared to the published range of normal NEFA concentrations, which was reported to be no greater than 200 meq/L (Drackley, 2000; Adewuyi et al., 2005). The increase in NEFA concentrations reported in this study may not be due to a stress response, but to the physiological state of the animals used in Study 2. It is presumed that as cattle progress through gestation, adipose tissues mobilize, thereby increasing serum NEFA concentrations (Beever, 2006).

Correlations

Previous research indicates that movement of cattle is strongly associated with a stress response. While limited correlations between the specific behavior variables measured in these studies and cortisol metabolites were reported in the literature, it has been reported that cattle deemed to be excited or stressed have a higher basal concentration of catecholamines and cortisol (Burdick et al., 2010). Literature also reports that cattle deemed ‘flighty’ or ‘excitable’ are more active (Grandin, 1993), and cattle expressing increased cortisol levels have been reported to spend less time ruminating and more time standing (Lindström et al., 2001; Bristow and Holmes, 2007). Therefore, positive associations between some behaviors, cortisol metabolites, and blood metabolites would be expected during the current studies if the animals were experiencing chronic stressors.

Most of the behavior variables measured in these studies were not correlated with the cortisol metabolites in either study. We did, however, observe that in Study 1 (n = 4), d 0 fecal corticosterone and standing time were correlated (R = 0.97; Figure 2.21), while hair cortisol was correlated with step count (R = 0.70) and standing time (R = 0.99). However, in Study 2, there were no positive correlations between the behavior variables most strongly associated with a stress response (step count and motion index; $P > 0.49$) and the cortisol metabolites measured on d 0 and d 56 (Figure 2.22).

Cattle behavior has also been associated with the blood metabolites measured in Study 2. Lactate is associated with the stress response in cattle, as stressors increase the rate of anaerobic glycolysis (Matteri et al., 2000) resulting in an increase in lactate production in the muscle (Burfeind and and Heuwieser, 2012). However, lactate is most commonly reported in the literature (Coombes et al., 2014; Holmes et al., 1972) to be correlated with acts of motion. Similar results were reported by Petherick et al. (2009), in a comparison of different handling styles of cattle in both backgrounding and feedlot settings. Both flight speed (the speed at which cattle exit confinement) and animal movement around a test arena were correlated with cortisol, NEFA, and lactate concentrations.

Based upon the existing literature, we expected that lactate concentrations and standing time would be negatively correlated. However, standing time in Study 2 was weakly correlated with d 56 lactate concentrations (*P* = 0.24; R = 0.41). That result, in combination with the fact that no other behavior variables measured in Study 2 produced a positive correlation with the physiological variable measured, we conclude that the correlation between standing time and d-56 lactate concentrations is insignificant. Similar to standing time, lying bouts were correlated to d 56 NEFA concentrations (*P* = 0.10; R = 0.54; Figure 2.22). This correlation could be due to the increased standing time caused by the ice storm that occurred during a portion of Study 2; although NEFA concentrations were not elevated during this time, animals may have relied on circulating NEFA for energy (Sanchez et al., 2013) when the animals were experiencing cold stress.

Correlations between hair cortisol and fecal corticosterone reported in the literature do not follow a consistent pattern. Moya et al. (2013) reported correlations between hair cortisol and glucocorticoid concentrations, but the correlations were not strong or homogenous across the study. Similarly, Tallo-Parra et al. (2015) reported a significant correlation between fecal cortisol metabolites and white hair collected from dairy cattle. Conversely, these researchers reported no such correlation between fecal cortisol metabolites and black hair collected from the same animals. In the current experiments, Study 1 hair cortisol concentrations were not correlated with fecal corticosterone concentrations. Further, fecal corticosterone measured across weeks for Study 1 did not display a consistent pattern when measured in individuals vs. the composite sample (Figure 2.23). In Study 2, no correlations were observed between d 0 hair cortisol concentrations and any other cortisol metabolite collection dates (Figure 2.24). However, hair cortisol concentrations on d 56 were correlated with fecal corticosterone concentrations from only wk 2 and 6 (P = 0.02, R = 0.63 and P = 0.42, R = 0.24, respectively). Similar to Study 1, fecal corticosterone measured across weeks in Study 2 were inconsistent when comparing individuals to the composite sample.

Correlations between blood metabolite and cortisol metabolite concentrations were inconsistent across Study 2. No correlation was reported between either measure of hair cortisol and NEFA concentrations. Conversely, the literature reports positive correlations between blood cortisol and NEFA concentrations (Sanchez et al., 2013). Final lactate concentrations were negatively correlated with both measures of fecal corticosterone, similar to results reported by Chen et al. (2017) in which the expression of lactate in rat cells was inhibited by exposure to corticosterone. Positive correlations between NEFA and corticosterone concentrations have been previously reported in the literature (Gross et al., 2021). However, a negative correlation was reported between fecal corticosterone and NEFA concentrations in Study 2 (Figure 2.25).

Animals experiencing an electrical shock are likely to exhibit more movement and move away from the stimulus. Markus et al. (2014), reported that cattle subjected to electrical stimulation displayed behaviors that included head shaking and a change in speed, direction, or body position. The literature also reports that grazing cattle not experiencing a stress response spend the majority of the time grazing or ruminating, up to 90-95% of daily activity (Andriamandroso et al., 2016). Due to this, it was expected that animals exhibiting a stress response would display movement and behaviors different than those of animals not subjected to a stress event.

The total shock count for animals in the VF treatment were recorded and a correlation analysis was performed between shock count, behavior variables, and cortisol metabolites (Figure 2.21; Table 2.4). In Study 1, the total shock count received by VF animals was positively correlated with standing time (R = 0.83), but there was no correlation between shock count and any other behavior measured. As expected, shock count for Study 1 was also positively correlated with fecal corticosterone on d 0 (R = 0.91; Figure 2.22), and hair cortisol concentration on d 28 (R = 0.79). In Study 2, shock count was positively correlated with step count, standing time, and motion index (Figure 2.26). Given the results from Study 1, it was expected that shock count would have been positively correlated with the cortisol metabolites measured in Study 2. However, the correlation between shock count and physiological stress measures collected on d 56 of Study 2 produced interesting results in that, only negative correlations were reported between total shock count and final concentrations (d 56) of hair cortisol, fecal corticosterone, NEFA, and lactate (Figure 2.25). These negative correlations would indicate that the shocks received by animals in the VF treatment did not result in a measurable stress response.

APPLICATIONS

Physiological metabolites were not affected by fence type, and the expected correlations were either absent or inconsistent in both studies. We conclude that using a VF system to contain and rotate cattle was not more stressful to the livestock than the industry standard, double-strand electrified wire fencing. Further research, development and use of VF is warrented.

CHAPTER III

VALIDATION OF REMOTE BEHAVIOR MONITORING COLLARS IN GRAZING BEEF CATTLE

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ABSTRACT

The objective of this study was to validate the classification of activity, and resource usage of grazing cattle made by remote monitoring collars. Angus steers (*n* = 12; BW = 227 ± 45.0 kg) were fitted with an electronic global positioning system (GPS) receiver and activity collar (Herd MOOnitor Ltd; Ra'anna, Israel). Animal activities (collected every 4 s) were determined by a real time microcontroller and an algorithm for classifying the accelerometer data, and GPS locations (collected every 5 min) were collected by the collar. Animal activities were classed as grazing, walking, and resting. Global positioning system locations were intersected with maps in a geographic information system (GIS) to the location from 3 layers: landscape position, burn patch,

and resource (forage, water, or shade) utilized. Data from the collars were matched to simultaneous human observation of the same activity and location in resource areas. Accuracy rates for location classification in the resource usage (≥ 67%) and burn patch (≥ 75%) layers suggest that MOOnitor collars can classify GPS locations of grazing animals in large, wide features. However, grazing activity classifications (≥ 30%) and terrace position accuracies (≥ 39%) were less than the reported Non-inclusion rates (≥ 39% and ≥ 42%, respectively), leading researchers to conclude that human observed and collar predicted grazing activity classifications did not agree well.

INTRODUCTION

Traditional methods of livestock management are limited to the use of time-tested tools such as adjusting stocking rates, rotational grazing, and adjusting supplementation at a herd level to improve the productivity of a grazing herd. However, the implementation of grazing technologies to aid in livestock management provide producers the ability to focus on individual animals while implementing proper rangeland management practices (Andriamandroso et al., 2016). Researchers have reported that utilizing grazing technologies allow the interaction between plants and animals to be observed and remotely managed by combining feeding behavior, animal position (Laca, 2009), and animal behavior data (Richeson et al., 2018).

Activity-monitoring collars provide an opportunity to remotely manage cattle herd health status and behavior. Global positioning system (GPS)-based collars are commonly used in studying wildlife species, and motion sensors have allowed researchers to monitor behavior and resource utilization by grazing cattle (Ungar et al., 2005). While promising, the accuracy of these sensor systems has not been well described in peer reviewed literature, especially for use on growing steers. Understanding accuracy is critical for interpretation of the data these sensors provide. Therefore, the objective of this study was to characterize the accuracies of activity classification and geographic position for grazing cattle made by remote monitoring collars.

MATERIALS AND METHODS

All procedures were approved by the Institutional Animal Care and Use Committee at USDA-ARS-SPRRS (Animal Care and Use Protocol number: AUP-025)

Pastures

All pastures utilized in this study were located at the USDA-ARS, Southern Plains Range Research Station in Woodward, OK. This study was conducted over approximately 60 d, beginning in June 2021. A total of 6 pastures (8 to 16 ha) were utilized for the current study. Terraces were present in 4 of the 6 pastures. Pastures utilized in the current study were part of a long-term burn treatment study, in which 3 of the pastures were in a broadcast burn rotation (Laveled “-0” after the pasture id in Figure 3.1) and 3 pastures were in a 4-patch, burn rotation rotation. The patches in the rotations were likewise labeled: -A, -B, -C, or -D after the pasture id (Figure 3.1). The locations of terraces (Figure 3.2), along with the water, salt block, and shade locations (Figure 3.3) within each pasture were defined in GIS (QGIS; Open-Source Geospatial Foundation) software and matched to the GPS locations provided by the collars.

Animals

Animals were sourced from Wanger Farms, Ft. Supply, OK. A subset of 12 Angus steers (BW = 227 ± 45.0 kg) were utilized for this study. A total of 34 steers were grazed in the 6 separate pastures to consume approximately 14% of expected annual forage production in a 90-d grazing period.

MOOnitor Collars

At the initiation of the study, 12 pre-allocated steers were fitted with an electronic GPS receiver and activity collar (Herd MOOnitor Ltd; Figure 3.4). The collars were equipped with satellite communication, 3-axis accelerometers, a GPS receiver, and solar panels for power supply. Collars were configured to record the steer's location every 5 min and the steer's activity every 4 s for the duration of the grazing period. Steers activities were classed into grazing, walking (walking without grazing), and resting (standing and lying combined) by a real-time microcontroller and an algorithm for classifying the accelerometer data approximately every 4 s. The collars also collected GPS data, which was used to determine animal locations relative to 3 map layers defining available resources (shade, forage, water/salt), terrace positions (terrace top, bottom, and in between terraces), and burn patches (burn patch A, B, C, D, or no patch). Data from the collars was downloaded utilizing a short-range radio via a PC user interface. Two streams of data were derived from the collars (an algorithm file and an activity file) The activity file is data that was stored on board the collar and was downloaded approximately weekly. The algorithm file contained the same classification data as the activity fiel with the addition of an activity index measured by the collar. These two sources of data were also attributed with times from different sources that were often available at different times of data download. Due to this variability, suspected to be due to the inability of the microcontroller of the collar to simultaneously write data while streaming data to the PC, observational classifications were compared to the activity file data. Each collar weighed <1% of steer BW (2.2 kg).

Data Collection

For the current study, the collared animals were observed in the pasture and 12 animals were selected, on the basis of collar data output strength and visually distinguishable characteristics on the cattle, in order to make observations from a distance and avoid disturbing the animals while making observations. In order to validate the classification of activities and locations by the MOOnitor collar, cattle were periodically observed. A single human observer recorded steers activities to include walking, resting (a combination of standing and lying), and grazing; the resource being utilized during the observation period (shade, forage, or water/salt); where steers were positioned relative to the terrace features top (the ground that has been pushed higher than natural ground along the contour), bottom (ground up slope of the terrace top but lower than the natural ground that occasionally become ponded), or between two terraces (the ground between terraces that is sloped as the natural ground); and the burn patch the animal was utilizing (A, B, C, D, or No patch). A single animal was observed for a minimum of 20 min per observation period, during which, a distance was maintained between cattle and the observer to avoid human interference in animal behaviors. During an observation period, the aforementioned activities and locations of the observed steer were manually recorded to the nearest sec as reported on a handheld GPS unit. Observations were not recorded on days animals were handled for weighing. Observations were not conducted on days with adverse weather or overcast skies as experience had taught us that powering the radio continuously for 20 min to communicate the data without good light to keep the betteries charged was often difficult and would result in incomplete observations. A total of 382 five-min periods were recorded during this study. Approximately 30 five-min observation periods were conducted per steer, with approximately 24 to 30 five-min observation periods recorded per day.

Statistical Analysis

Data were stored in a geopackage (GPKG) using the ‘sf’ package (Pebesma, 2018) and analyzed in R (R Core Team, 2020) to format geospatial information. Data reporting GPS locations outside the assigned pasture area were removed. Activity data were summarized into a confusion matrix, with reference parameters set as 0, 0.25, 0.5, 0.75, 0.99, or 1 such that, if a behavior was observed (by either MOOnitor or human observation) at any time during a 5 min observation period, the activity was assigned a 1, denoting a true positive. The ‘caret’ package (Kuhn, 2008) in R was utilized to assess the multiple-category prediction model and a cross tabulation of actual and predicted activities (confusion matrix) was created. Within the confusion matrix, the factor of the predicted classes (MOOnitor activity classification) was used as the first argument and the factor of classes to be used as the true results (Observation classification) was the second argument. This determination of predictor and true results were utilized for all activity and location parameters measured in this study. The accuracy percentage, *P*-value, no-information rate (NIR), and the Kappa coefficient were reported. For the purposes of this study, NIR is defined as the largest proportion of the observed classes, or a naive classifier that must be exceeded to prove the model to be significant (Machine Learning, 2018), and the *P*-value is a computed hypothesis test to determine if the overall accuracy rate is greater than the rate of the largest class (NIR; Dahiru, 2008). Accuracy is defined (Machine Learning, 2020) as the proportion of correctly classified activities within the 382, five-min observation periods, and Kappa measures the agreement between 2 raters (i.e. classification or observation; Cohen, 1960).

RESULTS AND DISCUSSION

The results for the activities, terrace location, resource locations, and burn patch location observations were matched against classifications made by the MOOnitor collar. The classifications made by the MOOnitor were also matched against the classifications made by the algorithm. Accuracy, NIR, Kappa, and a P – value were reported.

Activities

Statistical variables for activities are presented in Table 3.1. The linear regression of the fraction of a 5-min observation period observed vs. the fraction of a 5-min observation period classified by the MOOnitor show that the data follow a linear model for resting ($P < 0.001$; Figure 3.5) and walking ($P < 0.001$; Figure 3.7), though it was not a strong linear relationship. The same can be reported for the linear regression of observation vs. algorithm classification for resting ($P = 0.15$; Figure 3.5) and walking ($P = 0.07$; Figure 3.7). Observation vs. classification accuracies for resting activities (≤ 43%; Table 3.1) and for walking (≤ 58%; Table 3.1) led us to the conclude that the MOOnitor collars accurately predicted and classified resting and walking behaviors (accuracies > NIR). However, this was not the case for both linear relationships reported for grazing behaviors (Figure 3.6). The overall observation vs. classification accuracies are reported as ≤ 31 % (accuracies < NIR; Table 3.1). Based upon these results, the MOOnitor collars did not accurately predict and classify grazing behaviors, however walking and resting were accurately classified.

The inaccuracies reported by the MOOnitor collar in classifying activities of grazing cattle may be due to movement of the head and neck of the animals while they were conducting resting activities. In the current study, the observer took note that even during resting activites (i.e. lying or standing) animals often moved the head and neck to perform grooming or to repel pests. The motion of these activities was also registered and recorded by the MOOnitor collars. Similarly, Ungar et al. (2005) speculated that similar movements while resting may have been a cause for their reported misclassification rate. This may be further supported by the high accuracy rate reported by Robert et al. (2009), in which head and neck movements were not measured, as 3-dimensional accelerometers were placed on the rear legs of calves. Researchers reported that these accelerometers exhibited 99.2% and 98.0% accuracy rates for the classification of lying and standing activities.

Locations

Results for the use of resources, water/salt, forage, and shade are presented in Table 3.3. The linear regression for the fraction of a 5-min observation period observed as in the water/salt location and the fraction of a 5-min observation period classified as in the water/salt location by the MOOnitor followed a linear model (*P* = 0.002; Figure 3.8). However, the linear regressions performed for forage and shade did not follow a linear model (Figure 3.8). The dominant resource utilized by the animals was determined to be forage (Table 3.4) and reported to be accurately classified by the MOOnitor collar (77.5

%; Table 3.3). Resource utilization accuracies for all resources measured were ≥ 67% (accuracies > NIR; Table 3.3), leading researchers to conclude that the MOOnitor collars can accurately determine resource usage via GPS location.

The results for the terrace positions utilized are presented in Table 3.5. The linear regressions for the fraction of a 5-min observation period observed as in terrace top, bottom, and in between terrace and the fraction of a 5-min observation period classified as in terrace top, bottom, and in between terrace by the MOOnitor did not follow a linear model (P = 0.99, 0.95, and 0.88, respectively; Figure 3.9). Terrace position utilization accuracies were reported as ≥ 39% (accuracies < NIR; Table 3.5). Based upon these results, the MOOnitor collars cannot accurately determine terrace position via GPS location.

Results for the burn patch utilized are presented in Table 3.7. The linear regressions for the fraction of a 5-min observation period observed as in burn patch A (P < 0.001), B (P = 0.17), C (P = 0.04), and D (P < 0.001; Figure 3.10), and the fraction of a 5-min observation period classified as in the aforementioned burn patches followed a linear model, though not all linear relationships were strong. However, the linear regression for the fraction of a 5-min period observed as in No burn patch did not follow a linear model (P = 0.99). Burn patch utilization accuracies were reported as ≥ 75 % (accuracies > NIR; Table 3.7). Results indicate that MOOnitor collars can accurately determine burn patch utilization via GPS location.

No research could be found in the literature relating to the prediction of the specific resources, terrace positions, or burn patches utilized via GPS location as measured in the current study. However previous research reports that the basis for recording individual grazing animals lies in animal location, animal posture, and animal movements (Andriamandroso et al., 2016), and the interaction between plants and animals has been previously observed and utilized to remotely manage livestock by combining feeding behavior and animal position data (Laca, 2009). Hulbert and French (2001) reported that continuous and accurate spatial location data is required to accurately model resource selection by animals. The selection of heterogeneously-distributed resources has been reported to be affected by the scale of heterogeneity (Nams, 2005). Research utilizing high fix rate (4 Hz) GPS data to predict animal resource (forage) selection within a 1-ha patch has been reported to be approximately 30% accurate (the probability of accurately predicting resource selection; Swain et al., 2008) however, prediction errors (calculated using speed variables derived from velocity) were 90% for sample frequencies greater than half an hr. These researchers also reported that accurate resource selection predictions for small patches (< 25 m^2), are possible at a GPS fix interval of at least 10 s. Although data presented in the current study suggest that MOOnitor collars can accurately predict resource usage through GPS location, better accuracy rates may have been possible at GPS fix intervals smaller than every 5-min.

Prescribed fire in often applied to rangelands to enhance habitats and manage resource selection of grazing animals (Butz, 2009). Although observations in the current study are not comperable, the burn unit usage data presented in the current study is in agreement with reports in the literature, in that the dominant burn unit used by animals (A; Table 3.8) was the unit most recently burned. Similarly, over a 5-yr study, researchers report that cattle selected light and moderately burned forages during all 5-yrs post burning (Clark et al., 2014).

The use of motion integrative GPS collars and the accuracy of activity classification has been previously reported in the literature. In a study utilizing Lotek GPS collars set to collect GPS locations every 5 min and activity samples every 4 sec, observations were conducted in a similar manner to those in the current study and activity classes were classified as grazing, traveling, and resting (a combination of lying and standing). Researchers stated a misclassification rate of 12-14%, with the main source of misclassification due to collars incorrectly classifying resting activities as grazing (Ungar et al., 2005). Other researchers, deploying Lotek GPS collars at the same operational schedule as Ungar et al. (2005), reported an overall accuracy rate of 91.7% for the classification of grazing and resting activities of cattle (Turner et al., 2000). Success in accurately classifying cattle behaviors using motion integrative GPS collars has also been reported when utilizing high frequency data collection. In 2 trials conducted by Gonzalez et al. (2015), GPS collars were reported to correctly classify animal behaviors at 85.5% and 90.5% utilizing GPS and accelerometer data collection frequencies of 4Hz (345,000 data points/d) and 10Hz (862,500 data points/d), respectively.

The complete and accurate estimation of activities through the use of motion integrated GPS collars has proved difficult to achieve. Reasons for this difficulty reported in the literature include: resting activities are not always associated with no or very low motion, walking is integrated into both grazing and traveling, movement patterns of animals may differ within herd (Ungar et al., 2005), and GPS collars themselves may differ in the sensitivity to motion (Turner et al., 2000).

CONCLUSION

Difficulties in the accuracy of grazing behavior classification reported in this study are likely caused be one or more of the aforementioned issues. We can also speculate that the frequency at which data is summarized by the collars may not have been high enough to accurately distinguish different cattle activities, evidenced by Gonzalez et al. (2015). The frequency of data summarization in the current study was low (288 data points for GPS and 21,600 data points for accelerometer data collection, per day) in comparison to the studies performed by Gonzalez et al. (2015). Therefore, data presented in this study leads researchers to conclude that MOOnitor collars could only accurately monitor and predict resting and walking behavior of beef cattle. More research and adjustments to the inner workings of the collars are necessary to achieve an accurate validation of the ability of remote monitoring collars to classify grazing cattle behaviors.

Table 2.1 Effects of virtual fencing on behavior and physiology of beef cattle: Study 1

	Treatments[1]									
	VF					PF				
	Mean	SD	CV	Min	Max	Mean	SD	CV	Min	Max
Steps[2,3], per d	4656	1345	0.29	1911	11522	4440	985	0.22	2085	8334
Lying bouts[4,3], per d	13.8	3.75	0.27	6.0	31	11.3	2.77	0.25	5.0	20
Standing time[5,3], min per d	740	83.5	0.11	532.9	1084.4	744	79.4	0.11	515.9	1062.8
Motion index[3,6], per d	19848	6129	0.31	7613	52722	18494	4867	0.26	7287	41155
Hair cortisol[7], pg/mg										
d 28	0.37	0.15	0.39	0.13	0.59	0.40	0.32	0.80	0.01	0.86
Fecal corticosterone, ng/g										
d 0[7]	77.9	46.8	0.60	11.5	158	73.8	34.1	0.46	14.4	113
d 7[3]	96.5	65.6	0.68	22.8	177	67.4	37.8	0.56	31.1	131
d 14[3]	59.5	33.4	0.56	23.9	96.9	39.6	32	0.81	13.3	92.1
d 21[3]	86	33.5	0.39	46.4	133	75.2	28.6	0.38	28.3	99.5
d 28[7]	140	79.6	0.57	50.5	296	128	56.7	0.44	21.9	180

[1]Treatments included a virtually fenced pasture (**VF**) or a physically fenced pasture (**PF**)
[2]Number of steps taken per d
[3]n = 8 animals total; 4 animals per treatment

[4]Average number of lying bouts per d
[5]Time spent standing, in minutes per d
[6]Motion index per d; activity relative to acceleration and energy
[7]n = 55; animals per treatment = 31 and 24, respectively

Table 2.2 Effects of virtual fencing on cortisol metabolite concentrations of beef cattle: Study 2

	VF[1]	PF	SE	*P*-value
Hair cortisol, pg/mg				
d 0	0.52	0.29	0.072	0.16
d 56	0.09	0.17	0.046	0.34
Delta, d 56-d 0	0.43	0.13	0.090	0.14
Fecal corticosterone, ng/g				
d 0	168	224	43.7	0.46
d 56	223	265	37.5	0.51
Delta, d 56-d 0	-56.8	-4.4	74.0	0.66

[1]Treatments included 2 virtually fenced pastures (**VF**) or 2 physically fenced pastures (**PF**)
[2]*n* = 59; animals per treatment = 29 and 30, respectively

Table 2.3 Effects of virtual fencing on blood metabolite concentrations of beef cattle: Study 2

	VF[1]	PF	SE	*P*-value
Lactate, mg/dL				
d 0	36.1	37.6	4.9	0.85
d 56	42.3	40.9	7.8	0.91
Delta (d 56-d 0)	-6.2	-4.2	7.6	0.86
NEFA[3], meq/L				
d 0	452.8	346.4	16.8	0.04
d 56	367.1	428.4	84.2	0.65
Delta (d 56-d 0)	85.7	-71.9	91.7	0.35

[1]Treatments included 2 virtually fenced (**VF**) or 2 physically fenced pastures (**PF**)
[2]*n* = 59; animals per treatment = 29 and 30, respectively
[3]Non-esterified fatty acid concentration, meq/L

Table 2.4 Summary of shocks recieved[1]

	Study 1	**Study 2**
Max	452	1385
Min	0	115
Mean	164	418
SD	137	353

[1]Shocks were received by virtually fenced **(VF)** animals

Table 3.1 Confusion matrix for activity class variables[1]

	Accuracy, %	NIR[2], %	*P*-value	Kappa[3]
Resting				
Obs vs. Moon[4]	42.9	28.9	<0.001	0.32
Obs vs. Alg[5]	36.7	34.0	0.15	0.25
Alg vs. Moon[6]	84.8	36.8	<0.001	0.81
Grazing				
Obs vs. Moon[4]	30.7	39.4	0.99	0.19
Obs vs. Alg[5]	25.5	44.2	1.0	0.14
Alg vs. Moon[6]	76.6	24.9	<0.001	0.71
Walking				
Obs vs. Moon[4]	57.9	46.9	<0.001	0.30
Obs vs. Alg[5]	54.5	50.5	0.07	0.22
Alg vs. Moon[6]	78.1	45.9	<0.001	0.64
Dominant Activity[7]	82.6	50.1	<0.001	0.67

[1]*n* = 12 animals and 382 observation periods

[2]No-inclusion rate

[3]Measure agreement between classification and true values

[4]Fraction of 5-min observation period observed as an activity and fraction of 5-min observation period classified as an activity by MOOnitor collar

[5]Fraction of 5-min observation period observed as an activity and fraction of 5-min observation period classified as an activity by Algorithm

[6]Fraction of 5-min observation period classified as an activity by Algorithm and fraction of 5-min observation period classified as an activity by MOOnitor collar

[7]Activity performed the most during 5-min observation periods

Table 3.2 Confusion matrix of the dominant activity in an observation period[1]

	Observed[3]		
Predicted[2]	Grazing	Resting	Walking
Grazing	151	44	2
Resting	2	123	0
Walking	9	1	3

[1]n = 12 animals and 382 observation periods

[2]Activiy predicted by MOOnitor collar

[3]Activity recorded by human observer

Table 3.3 Confusion matrix for resource variables[1]

	Accuracy, %	NIR[2], %	*P*-value	Kappa[3]
Forage				
Obs vs. Loc[4]	67.3	53.3	<0.001	0.46
Shade				
Obs vs. Loc[4]	79.9	71.3	<0.001	0.52
Water/Salt				
Obs vs. Loc[4]	87.7	82.2	0.002	0.57
Dominant Resource[5]	77.5	57.9	<0.001	0.57

[1]n = 12 animals and 382 observation periods

[2]No-inclusion rate

[3]Measure agreement between classification and true values

[4]Fraction of 5-min observation period observed as in a resource location and fraction of 5-min observation period classified as in a resource location by MOOnitor location

[5]Resource utilized the most during 5-min observation periods

Table 3.4 Confusion matrix of the dominant resource utilized in an observation period[1]

	Observed[3]		
Predicted[2]	Forage	Shade	Water
Forage	207	49	22
Shade	10	46	0
Water	5	0	44

[1]*n* = 12 animals and 382 observation periods

[2]Resource predicted by MOOnitor collar location

[3]Resource recored by human observer

Table 3.5 Confusion matrix for terrace position variables[1]

	Accuracy, %	NIR[2], %	*P*-value	Kappa[3]
Terrace top				
Obs vs. Loc[4]	72.5	79.8	0.99	0.25
Terrace bottom				
Obs vs. Loc[4]	72.1	76.4	0.95	0.33
In between terrace				
Obs vs. Loc[4]	39.3	42.8	0.88	0.13
Dominant Terrace Location[5]	56.9	58.9	0.76	0.04

[1]n = 6 animals and 191 observation periods

[2]No-inclusion rate

[3]Measure agreement between classification and true values

[4]Fraction of 5-min observation period observed as on terrace position and fraction of 5-min observation period classified as on terrace position by MOOnitor location

[5]Terrace position utilized the most during 5-min observation periods

Table 3.6 Confusion matrix of the dominant terrace position utilized in an observation period[1]

	Observed[3]		
Predicted[2]	Terrace bottom	In between terrace	Terrace top
Terrace bottom	2	4	4
In between terrace	22	136	69
Terrace top	0	12	9

[1]*n* = 6 animals and 191 observation periods

[2]Terrace position predicted by MOOnitor collar location

[3]Terrace position recorded by human observer

Table 3.7 Confusion matrix for burn patch position variables[1]

	Accuracy, %	NIR[2], %	*P*-value	Kappa[3]
Patch A				
Obs vs. Loc[4]	87.3	54.4	<0.001	0.76
Patch B				
Obs vs. Loc[4]	94.6	92.6	0.17	0.61
Patch C				
Obs vs. Loc[4]	95.1	91.7	0.04	0.64
Patch D				
Obs vs. Loc[4]	87.8	71.6	<0.001	0.68
Not in Patch				
Obs vs. Loc[4]	75.7	85.2	0.99	0.39
Dominant Patch Location[5]	82.8	44.6	<0.001	0.75

[1]n = 6 animals and 191 observation periods

[2]No-inclusion rate

[3]Measure agreement between classification and true values

[4]Fraction of 5-min observation period observed as in burn patch and fraction of 5-min observation period classified as in burn patch by MOOnitor location

[5]Burn patch utilized the most during 5-min observation periods

Table 3.8 Confusion matrix of the dominant burn patch utilized in an observation period[1]

	Observed[3]				
Predicted[2]	Not in Patch	Patch A	Patch B	Patch C	Patch D
Not in Patch	24	3	2	5	13
Patch A	4	86	2	0	4
Patch B	0	2	9	0	0
Patch C	0	0	0	11	0
Patch D	0	0	0	0	39

[1]n = 6 animals and 191 observation periods

[2]Burn patch position predicted by MOOnitor collar location

[3]Burn patch position recorded by human observer

Figure 2.1: Virtual fencing collar version 1.

Figure 2.2: Virtual fencing collar version 2.

Figure 2.3: Virtual fencing collar version 2, on animal.

Figure 2.4: Two phase training period for VF treatment implemented during the first 48 h of trial

A: 50 m shock zone (red) active along the perimeter of the VF pasture, including exclusion from 2 ponds, was active for the first 24 h of the training period.

B: A with the addition of a 5 m sound zone (white), was active for the second 24 h of the training period.

Figure 2.5: Representation of the VF boundary on d 0. The dashed line represented the VF boundary separating the weekly rotation pastures.

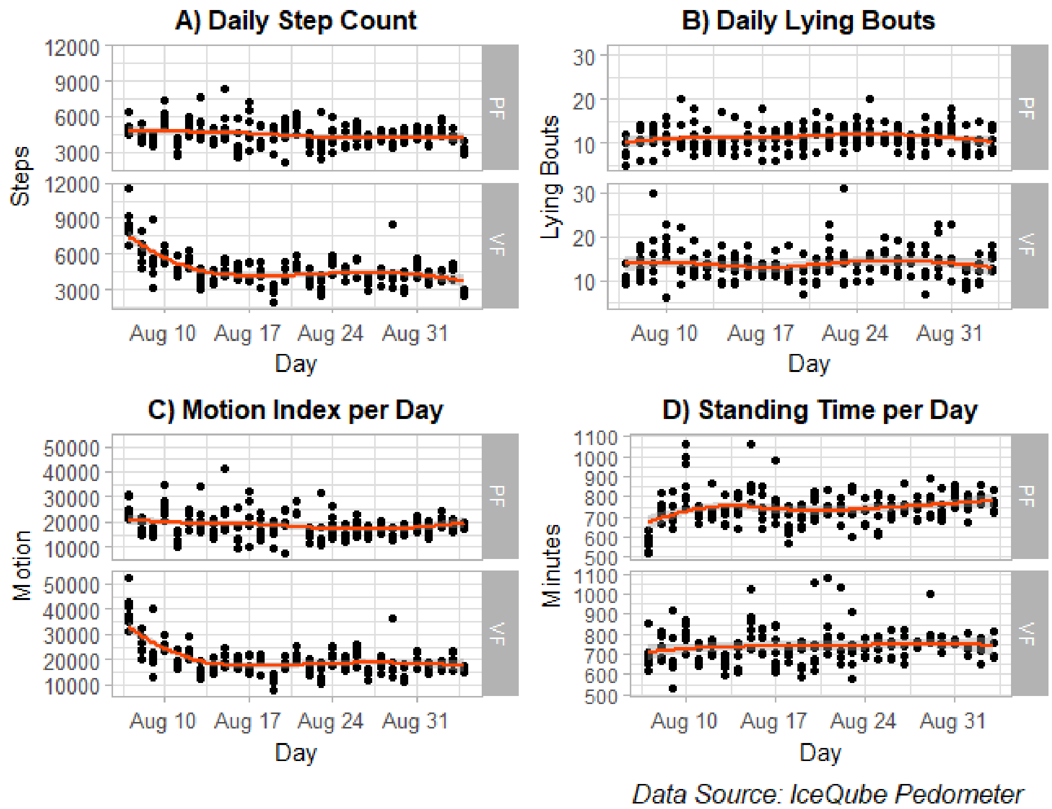

Figure 2.6: Effects of virtual fencing on behavior of beef cattle - Study 1. Treatments included a virtually fenced pasture (**VF**) or a physically fenced pasture (**PF**) (n = 18; animals per treatment = 9). Motion index is activity relative to acceleration and energy expenditure.

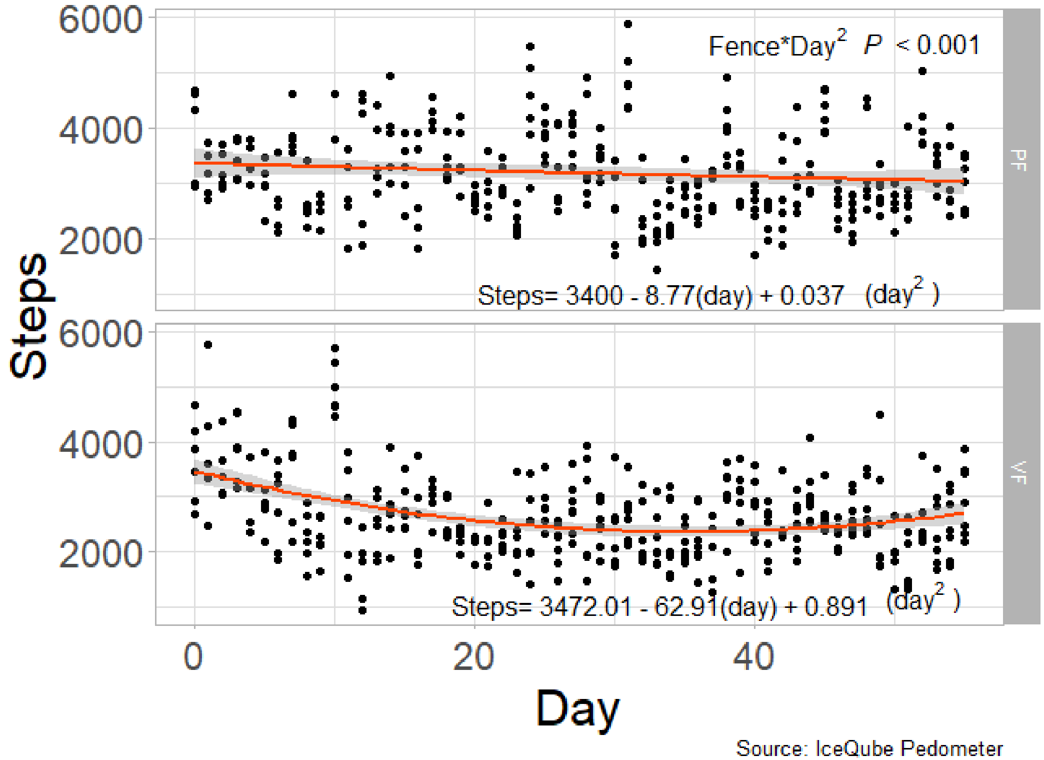

Figure 2.7: Effects of virtual fencing on daily step count of beef cattle – Study 2, a linear regression model (red line) with standard error bands (grey shading). Treatments included 2 virtually fenced pastures (**VF**) or 2 physically fenced pastures (**PF**) (n = 16; animals per treatment = 8).

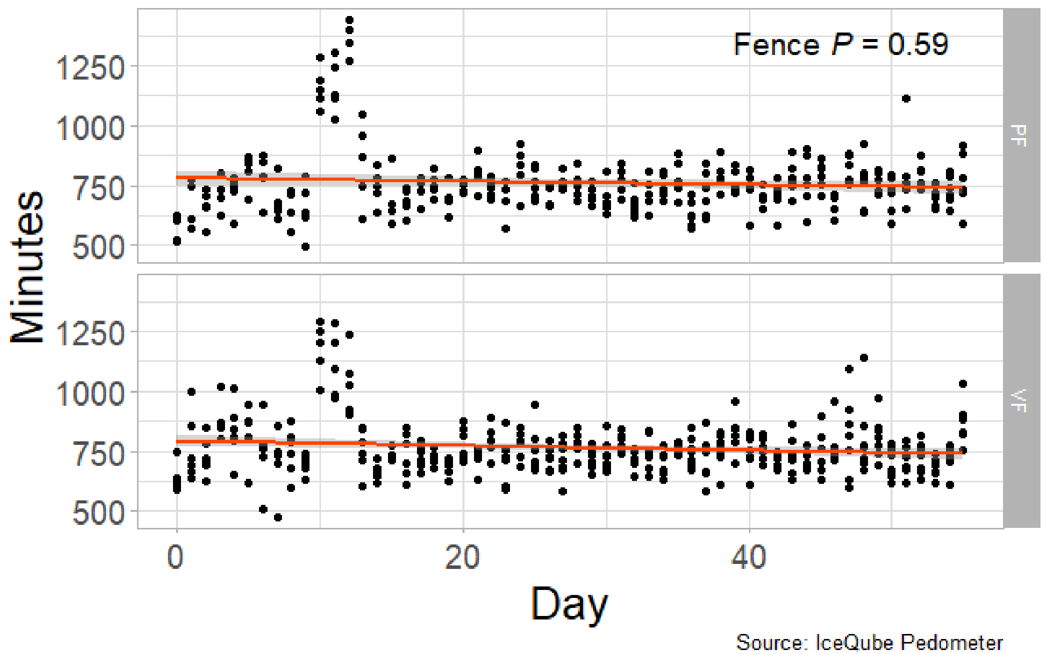

Figure 2.8: Effects of virtual fencing on standing time (min/d) of beef cattle – Study 2, a linear regression model (red line) with standard error bands (grey shading). Treatments included 2 virtually fenced pastures (**VF**) or 2 physically fenced pastures (**PF**) (n = 16; animals per treatment = 8).

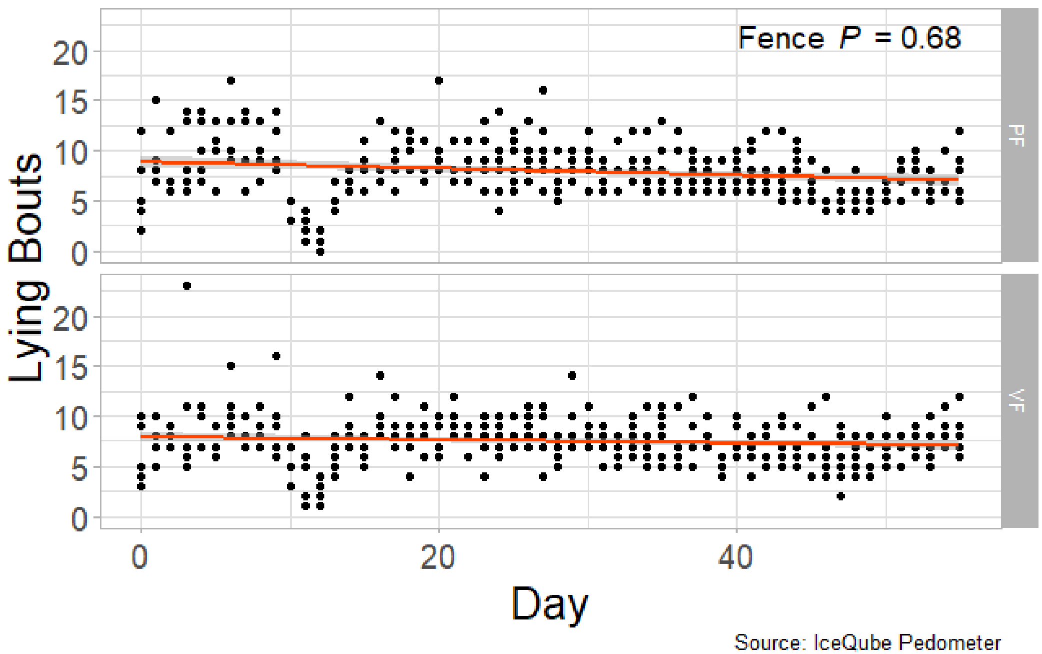

Figure 2.9: Effects of virtual fencing on number of daily lying bouts of beef cattle – Study 2, a linear regression model (red line) with standard error bands (grey shading). Treatments included 2 virtually fenced pastures (VF) or 2 physically fenced pastures (PF) (n = 16; animals per treatment = 8).

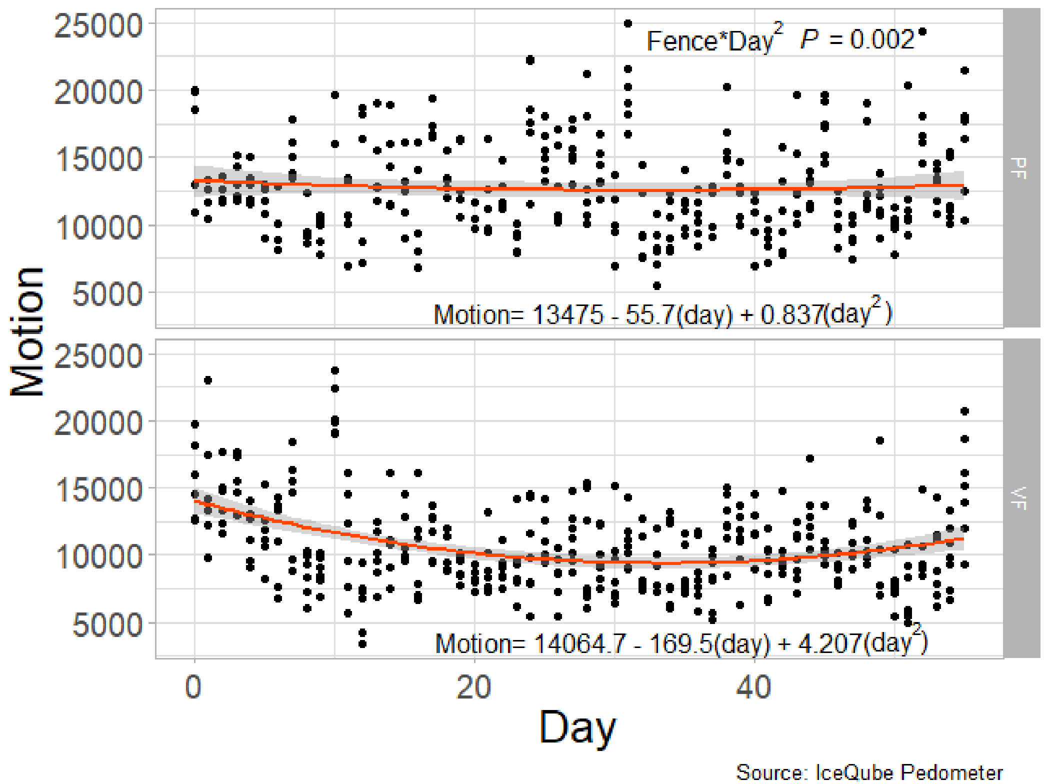

Figure 2.10: Effects of virtual fencing on daily motion index of beef cattle – Study 2, a linear regression model (red line) with standard error bands (grey shading). Treatments included 2 virtually fenced pastures (**VF**) or 2 physically fenced pastures (**PF**) (n = 16; animals per treatment = 8).

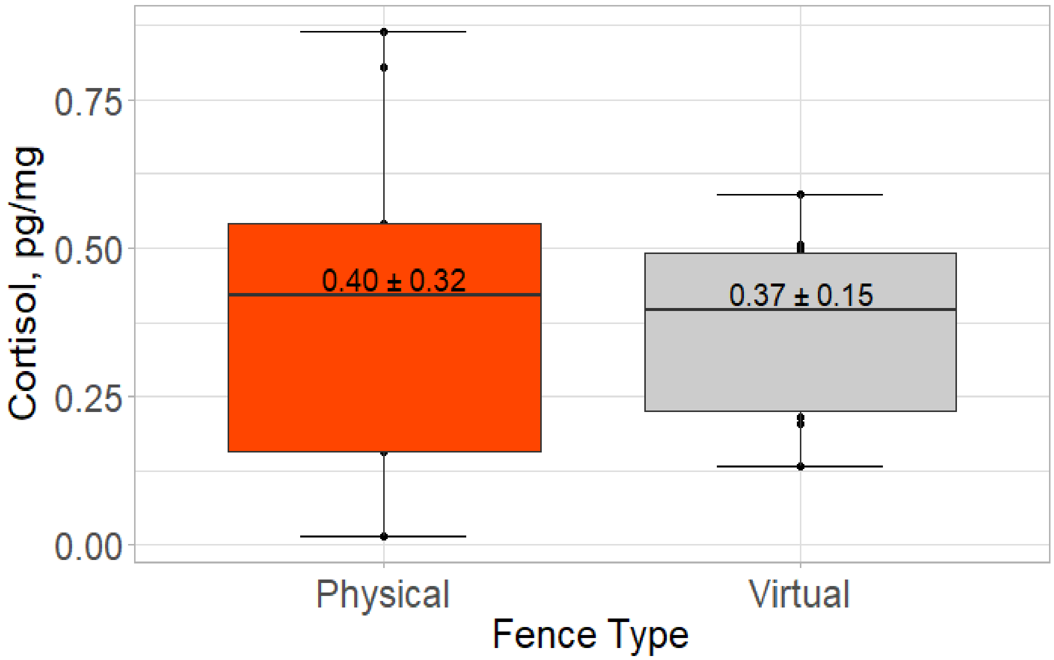

Figure 2.11: Effects of virtual fencing on hair cortisol concentrations of beef cattle, d28 – Study 1. Treatments included a virtually fenced pasture (**VF**) or a physically fenced pasture (**PF**) (*n* = 55; animals per treatment = 31 and 24, respectively).

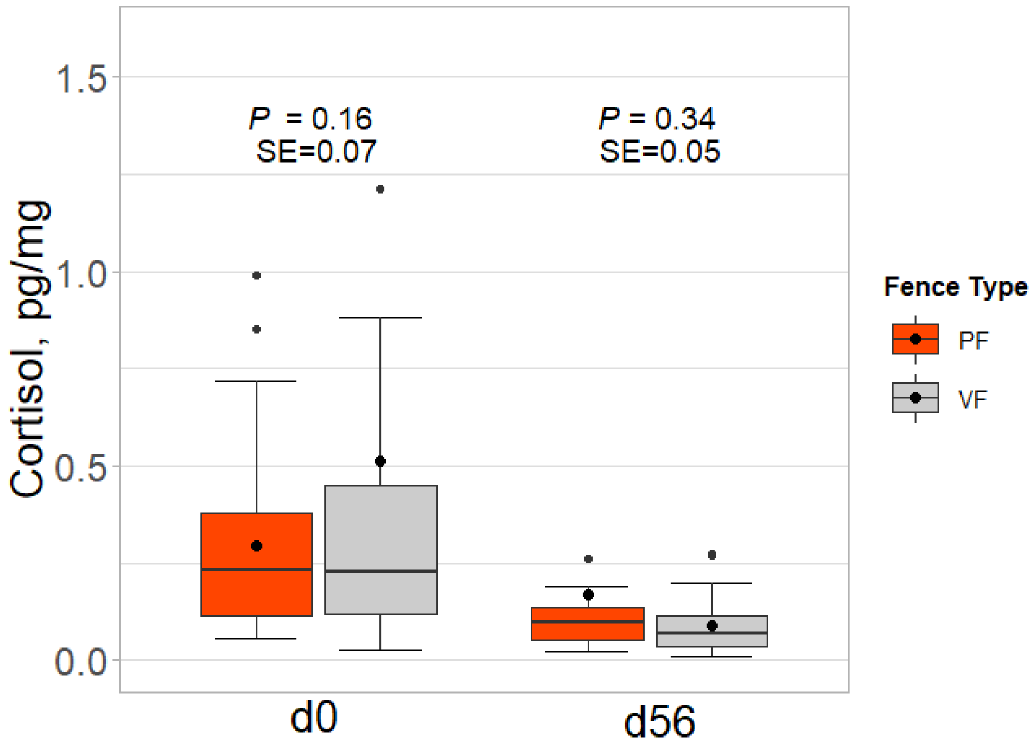

Figure 2.12: Effects of virtual fencing on hair cortisol concentrations of beef cattle - Study 2. Treatments included 2 virtually fenced pastures (**VF**) or 2 physically fenced pastures (**PF**) (n = 59; animals per treatment = 30 and 29, respectively). D 56-d 0: P = 0.14.

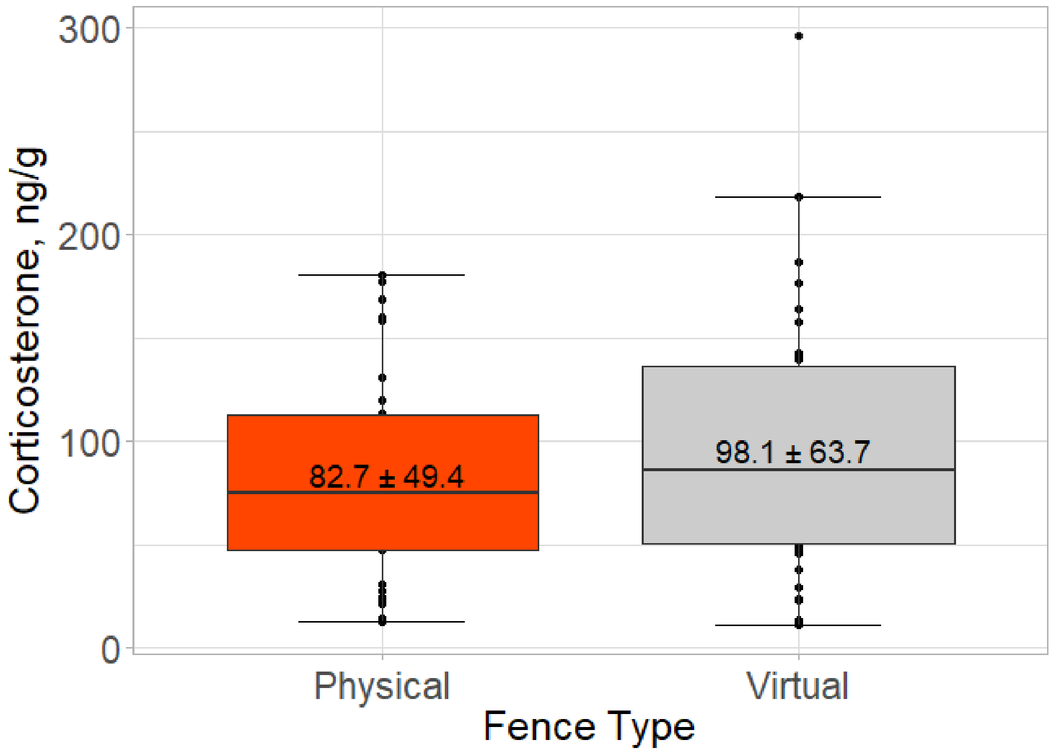

Figure 2.13: Effects of virtual fencing on fecal corticosterone concentrations of beef cattle – Study 1. Treatments included a virtually fenced pasture (**VF**) or a physically fenced pasture (**PF**) (n = 55; animals per treatment = 31 and 24, respectively).

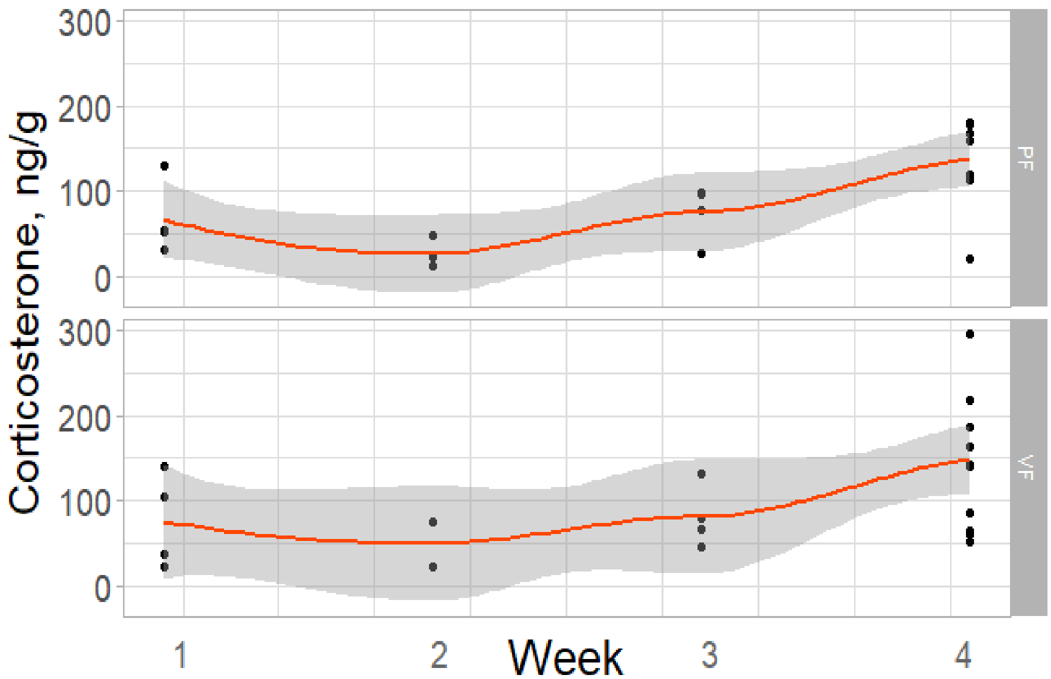

Figure 2.14: Effects of virtual fencing on weekly fecal corticosterone concentrations – Study 1, a loess regression model (red line) with standard error bands (grey shading). Treatments included a virtually fenced pasture (**VF**) or a physically fenced pasture (**PF**) (*n* = 18; animals per treatment = 9).

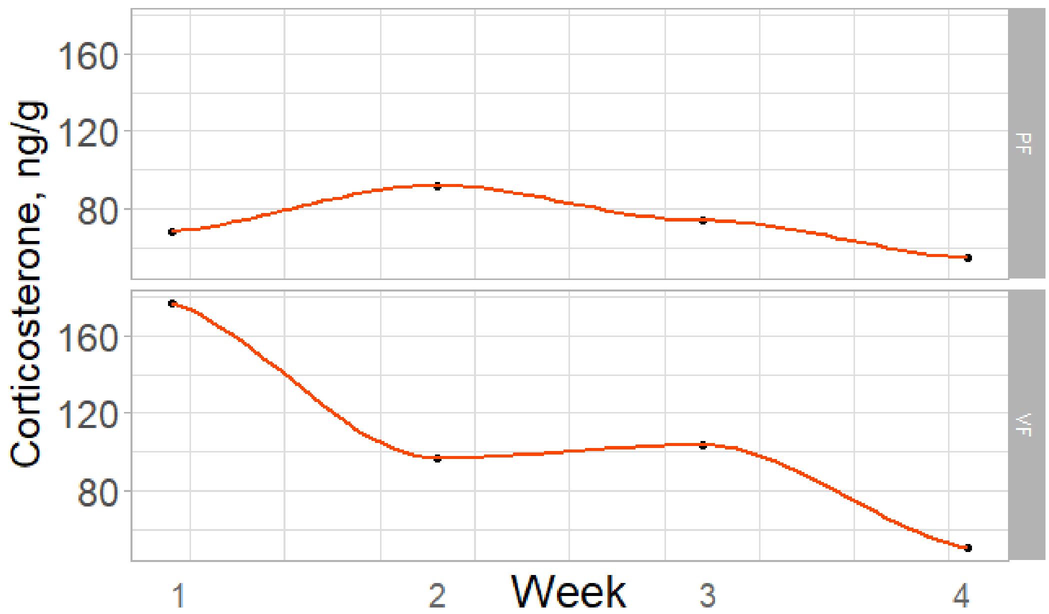

Figure 2.15: Effects of virtual fencing on weekly fecal corticosterone composites – Study 1. Treatments included a virtually fenced pasture (**VF**) or a physically fenced pasture (**PF**), a loess regression model is represented by the red line (*n* = 18; animals per treatment = 9).

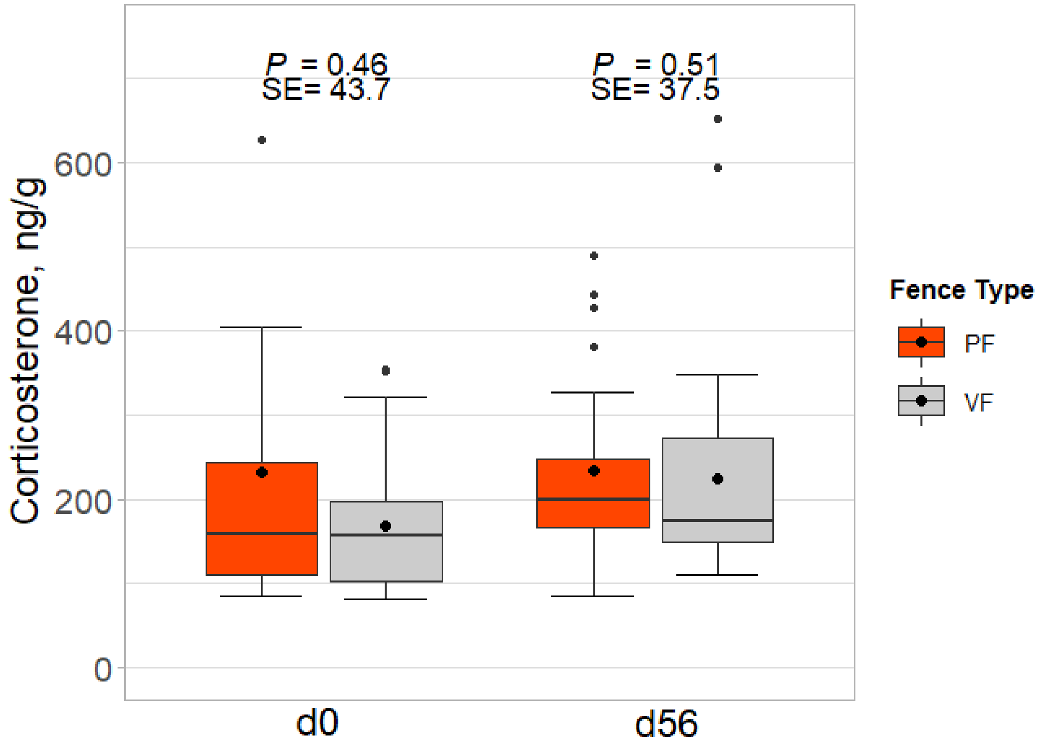

Figure 2.16: Effects of virtual fencing on fecal corticosterone concentrations in beef cattle – Study 2. Treatments included 2 virtually fenced pastures (**VF**) or 2 physically fenced pastures (**PF**) (n = 59; animals per treatment = 30 and 29, respectively). D 56-d 0: P = 0.66.

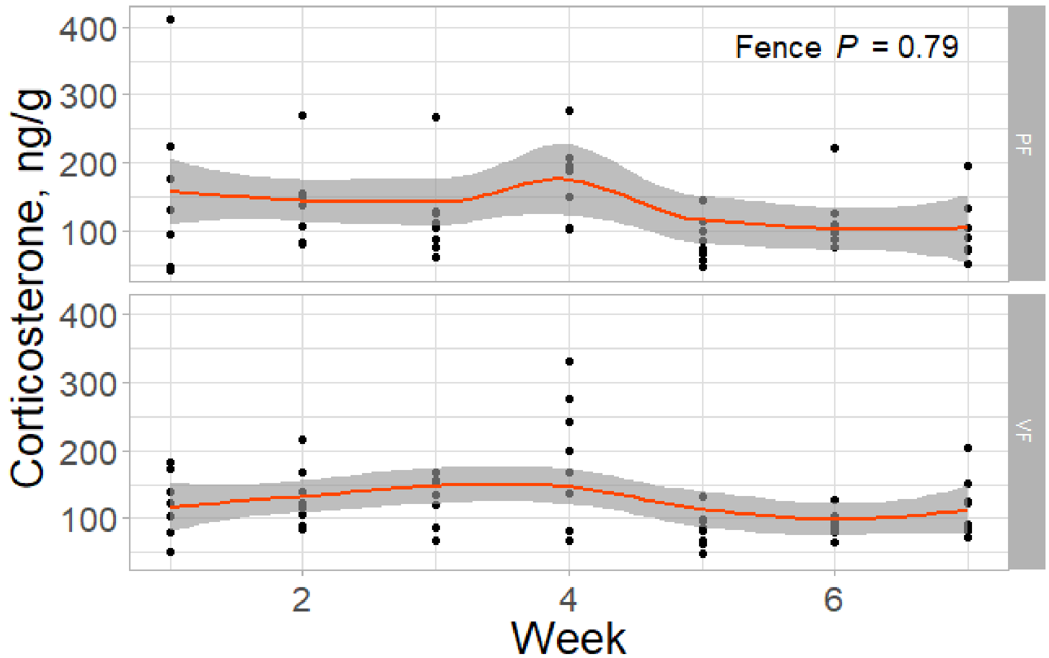

Figure 2.17: Effects of virtual fencing on weekly fecal corticosterone concentrations of beef cattle- Study 2, a loess regression model (red line) with standard error bands (grey shading). Treatments included 2 virtually fenced pastures (**VF**) or 2 physically fenced pastures (**PF**) (n = 16; animals per treatment = 8)

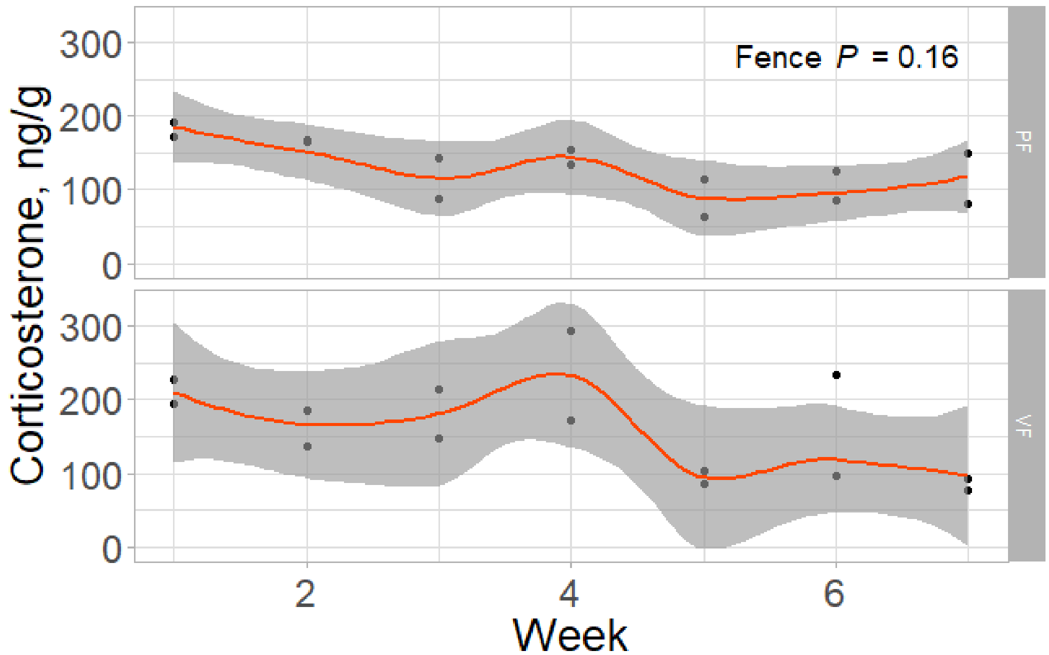

Figure 2.18: Effects of virtual fencing on weekly corticosterone concentrations in weekly fecal composites of beef cattle – Study 2, a loess regression model (red line) with standard error bands (grey shading). Treatments included 2 virtually fenced pastures (**VF**) or 2 physically fenced pastures (**PF**) (*n* = 2 per treatment; 20 pats composited per pasture).

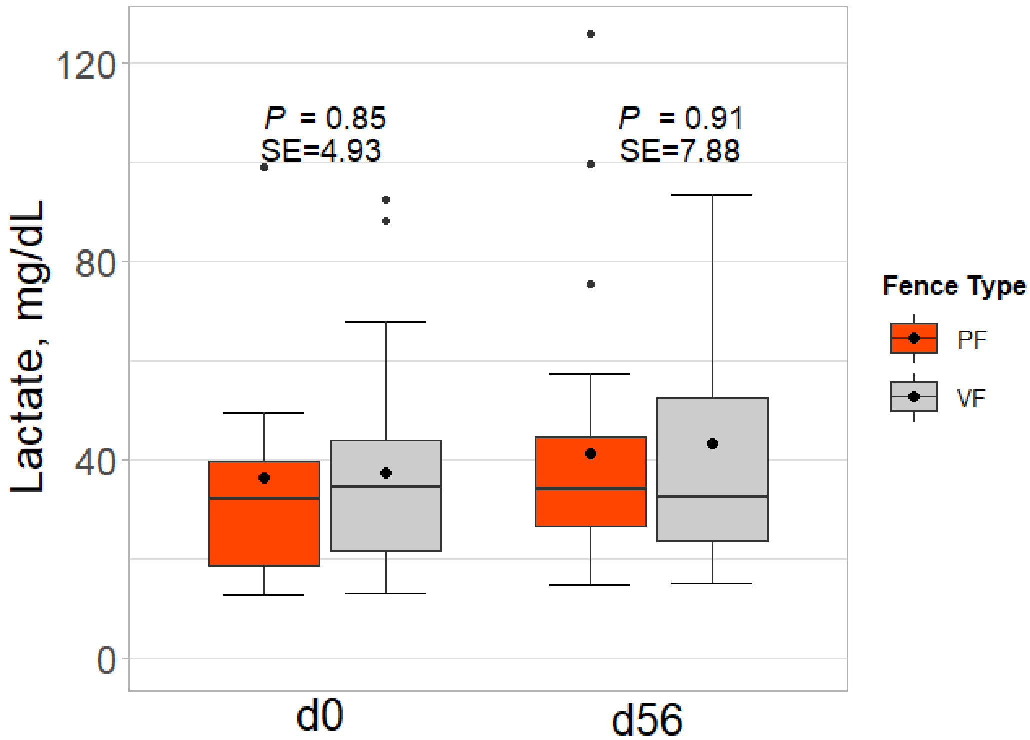

Figure 2.19: Effects of virtual fencing on serum lactate concentrations of beef cattle – Study 2. Treatments included 2 virtually fenced pastures (**VF**) or 2 physically fenced pastures (**PF**) (*n* = 59; animals per treatment = 30 and 29, respectively). D 56-d 0: *P* = 0.87.

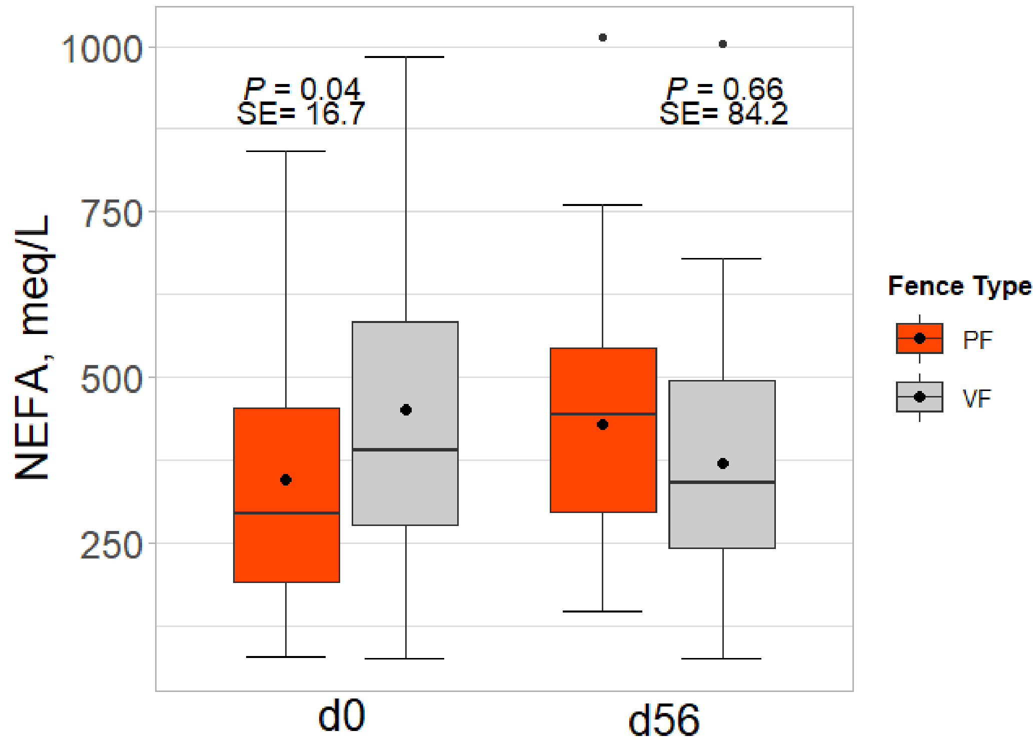

Figure 2.20: Effects of virtual fencing on serum NEFA concentrations of beef cattle – Study 2. Treatments included 2 virtually fenced pastures (**VF**) or 2 physically fenced pastures (**PF**) (*n* = 59; animals per treatment = 30 and 29, respectively). D 56-d 0: *P* = 0.35.

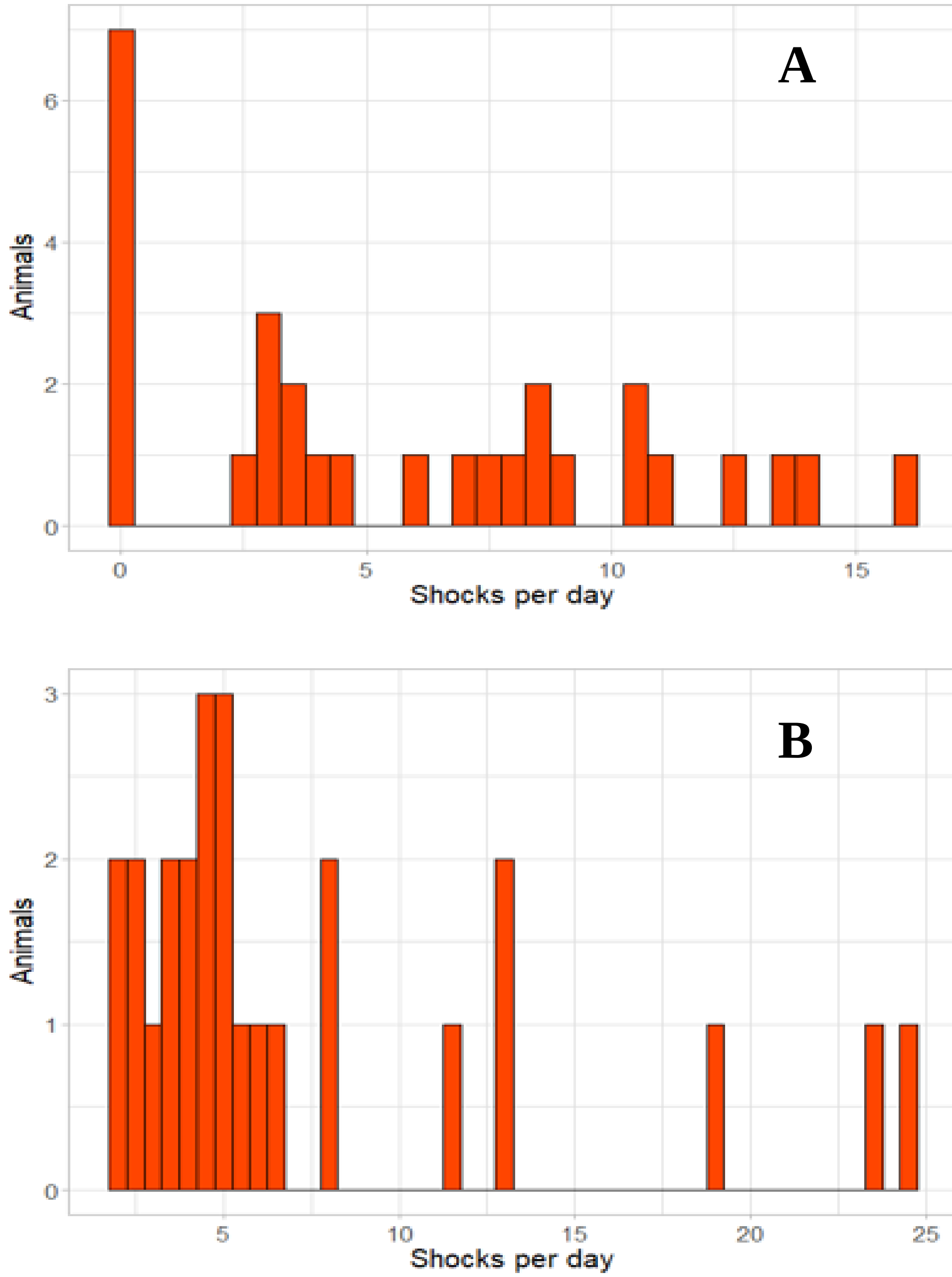

Figure 2.21: Distribution of shocks received by virtually fenced (**VF**) animals from Study 1 (A) and Study 2 (B).

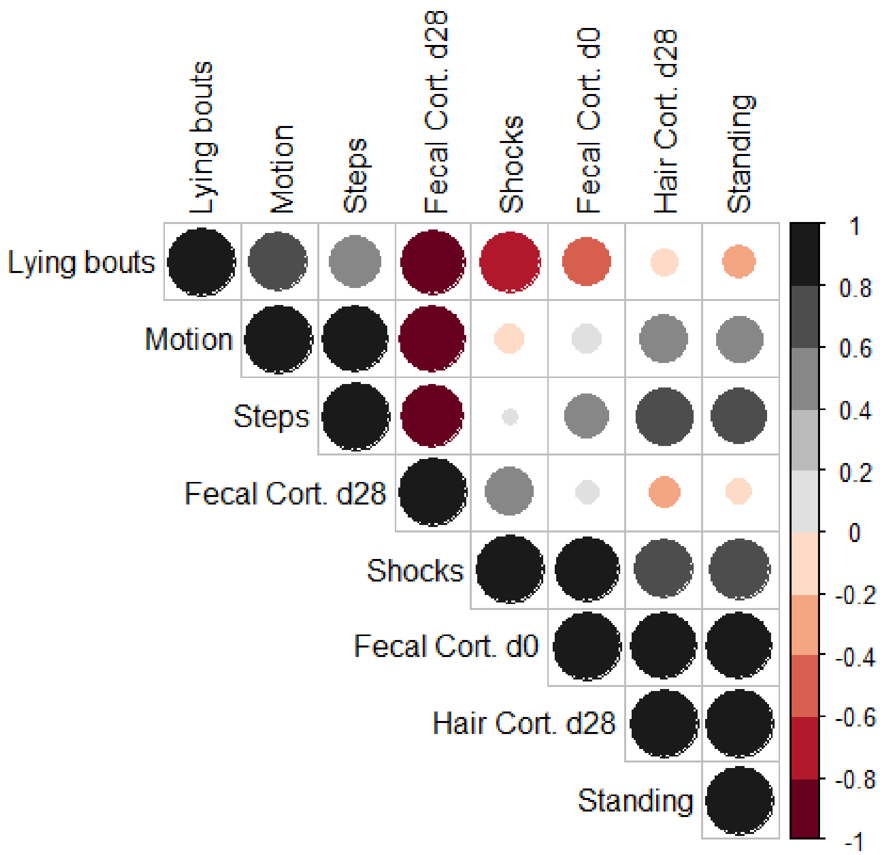

Figure 2.22: Correlations between behavior variables, cortisol metabolites, and shock count - Study 1. Treatments included a virtually fenced pasture (**VF**) (*n* = 4). Lying bouts are the average number of lying bouts per day. Motion is the average of motion index per day. Motion index is activity relative to acceleration. Steps is the average step count per day. Fecal cort. d28 is the fecal corticosterone concentrations collected on d 28. Shocks is the average of electrical stimulus experienced by the VF treatment during Study 1. Fecal cort. d0 is the fecal corticosterone concentrations collected on d 0. Hair cort. d28 is the hair cortisol concentrations collected on d 28**.** Standing is average standing time per day.

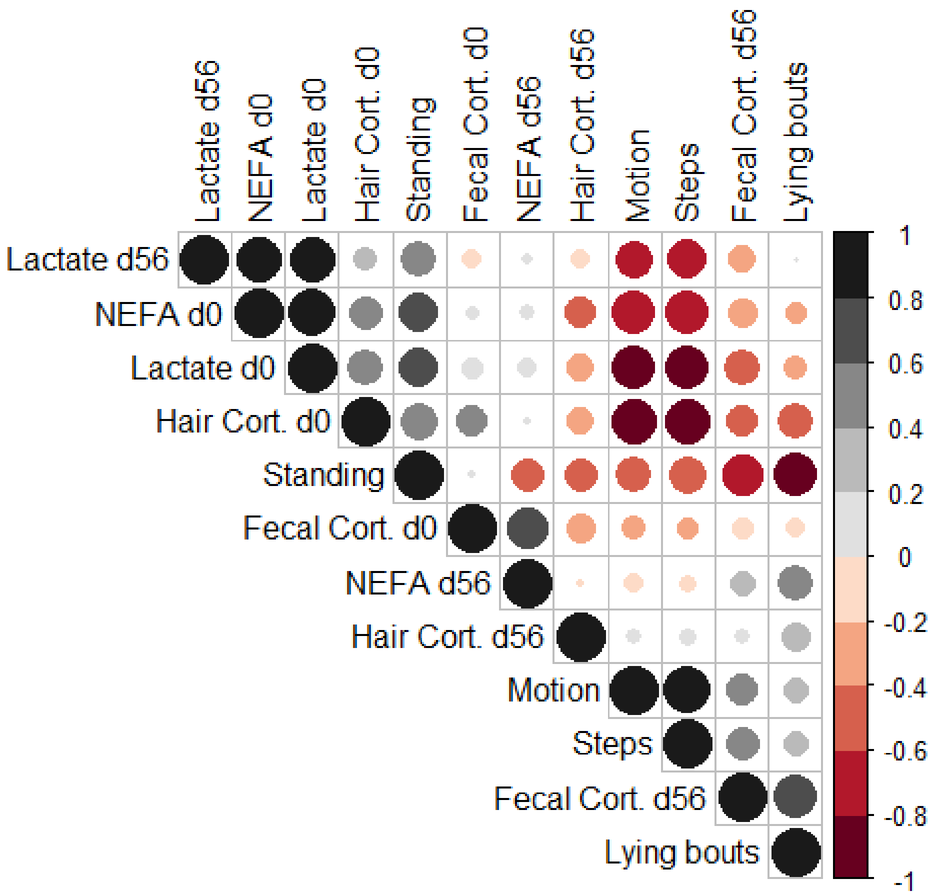

Figure 2.23: Correlations between behavior variables, cortisol metabolites, and blood metabolites – Study 2. Treatments included 2 virtually fenced pastures (**VF**) or 2 physically fenced pastures (**PF**) (*n* = 10). Lying bouts is the average number of lying bouts per day. Motion is the average of the motion index per day. Motion index is the activity relative to acceleration. Steps is the average step count per day. Fecal cort. d28 is the fecal corticosterone concentrations collected on d 28. Hair cort. d0 is the hair cortisol concentrations collected on d 0. Fecal cort. d0 is the fecal corticosterone concentrations collected on d 0. Hair cort. d28 is the hair cortisol concentrations collected on d 28. Standing is the average standing time per day. Lactate d0 is serum lactate concentrations collected on d 0. Lactate d56 is serum lactate concentrations collected on d 56. NEFA is non-esterified fatty acid. NEFA d0 is serum non-esterified fatty acid concentrations collected on d 0. NEFA d56 is serum non-esterified fatty acid concentrations collected on d 56.

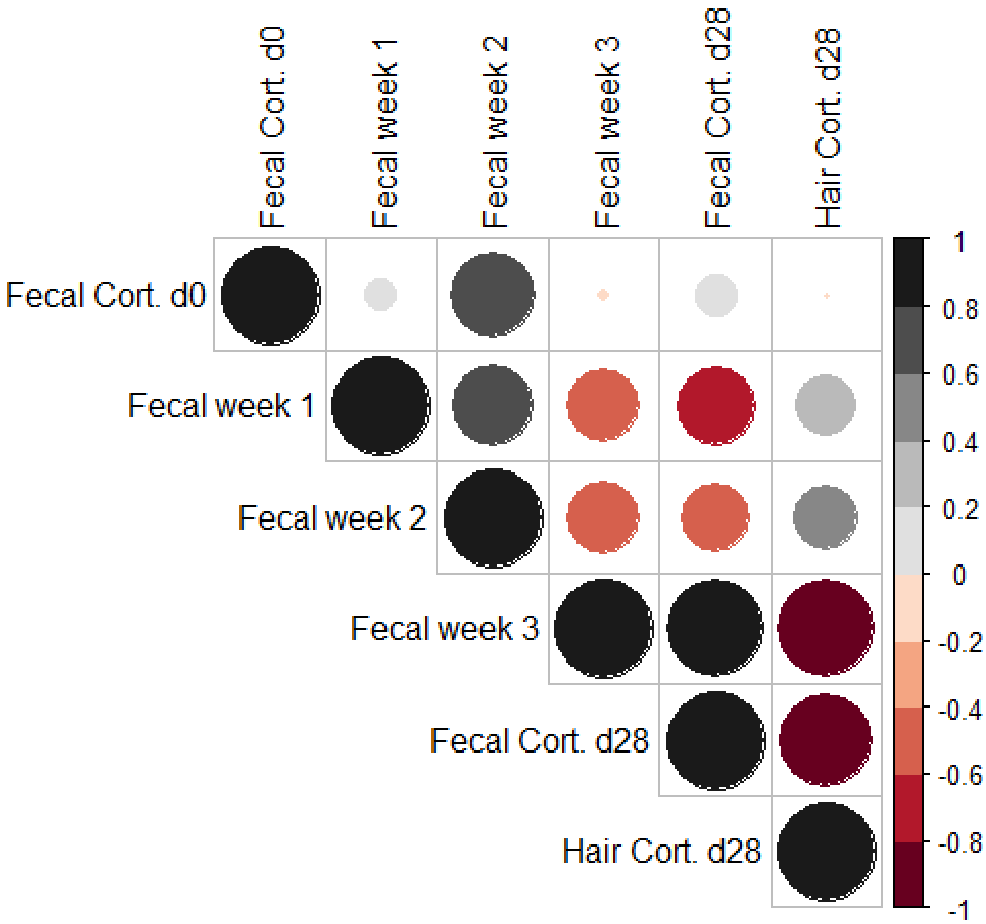

Figure 2.24: Correlations between fecal corticosterone and hair cortisol concentrations – Study 1. Treatments included a virtually fenced pasture (**VF**) or a physically fenced pasture (**PF**) (*n* = 18; animals per treatment = 9). Fecal cort. d0 is the fecal corticosterone concentrations collected on d 0. Fecal week 1 is the fecal corticosterone concentrations collected on week 1. Fecal week 2 is the fecal corticosterone concentrations collected on week 2. Fecal week 2 is the fecal corticosterone concentrations collected on week 2. Fecal cort. d28 is the fecal corticosterone concentrations collected on d 28. Hair cort. d28 is the hair cortisol concentrations collected on d 28.

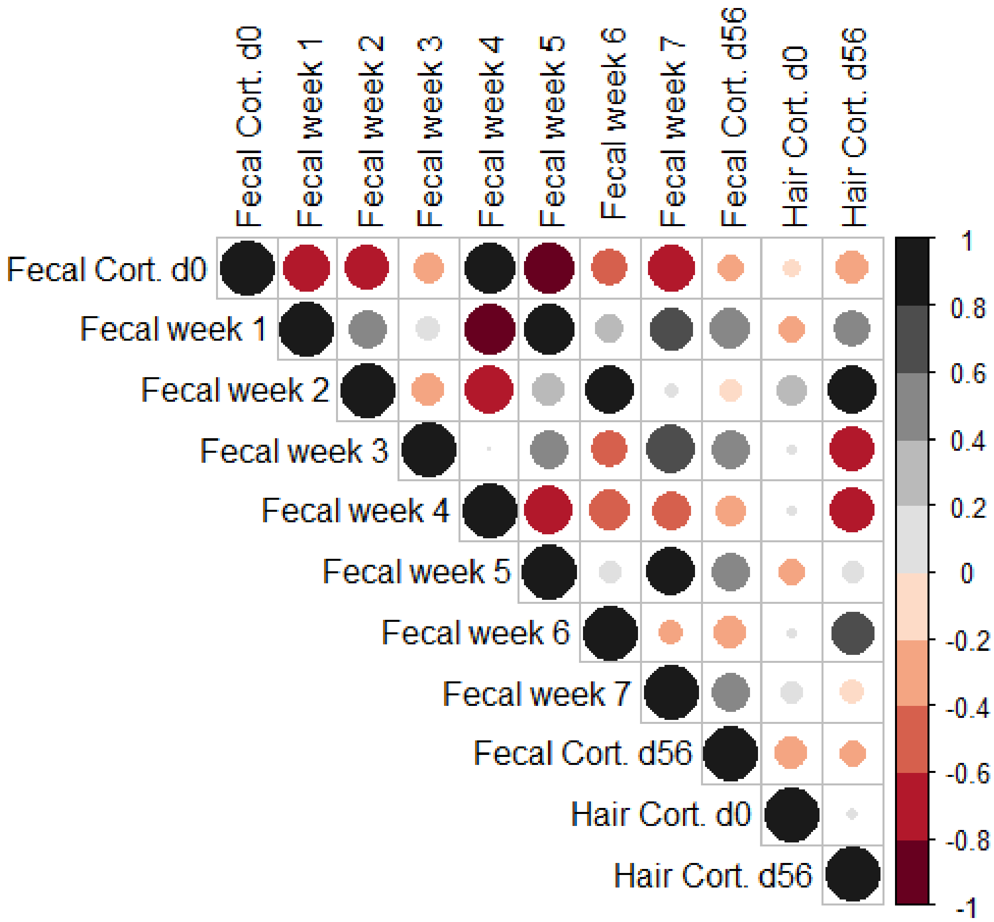

Figure 2.25: Correlations between hair cortisol and fecal corticosterone concentrations – Study 2. Treatments included 2 virtually fenced pastures (**VF**) or 2 physically fenced pastures (**PF**) (*n* = 13). Fecal Cort. d 0 is the fecal corticosterone concentrations collected on d 0. Fecal week 1 is the fecal corticosterone concentrations collected on week 1. Fecal week 2 is the fecal corticosterone concentrations collected on week 2. Fecal week 3 is the fecal corticosterone concentrations collected on week 3. Fecal week 4 is the fecal corticosterone concentrations collected on week 4. Fecal week 5 is the fecal corticosterone concentrations collected on week 5. Fecal week 6 is the fecal corticosterone concentrations collected on week 6. Fecal week 7 is the fecal corticosterone concentrations collected on week 7. Fecal Cort. d 56 is the fecal corticosterone concentrations collected on d 56. Hair cort. d 0 is the hair cortisol concentrations collected on d 0. Hair Cort. d 56 is the hair cortisol concentrations collected on d 56.

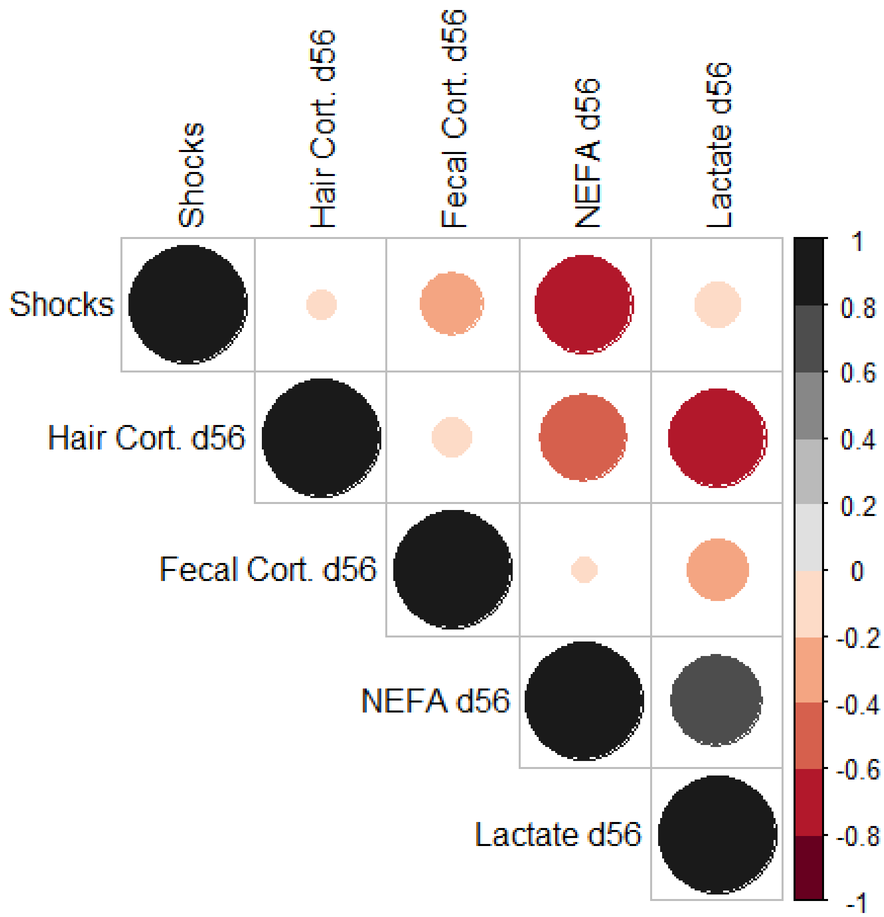

Figure 2.26: Correlations between cortisol metabolites, blood metabolites, and shock – Study 2. Treatments included 2 virtually fenced pastures (**VF**) (*n* = 13 animals). Shocks is the average of electrical stimulus experienced by the **VF** treatment during Study 1. Fecal Cort. d 56 is the fecal corticosterone concentrations collected on d 56. Hair Cort. d 56 is the hair cortisol concentrations collected on d 56. Lactate d 56 is the serum lactate concentrations collected on d 56. NEFA is non-esterified fatty acid concentrations. NEFA d 56 is the serum non-esterified fatty acid concentrations collected on d 56.

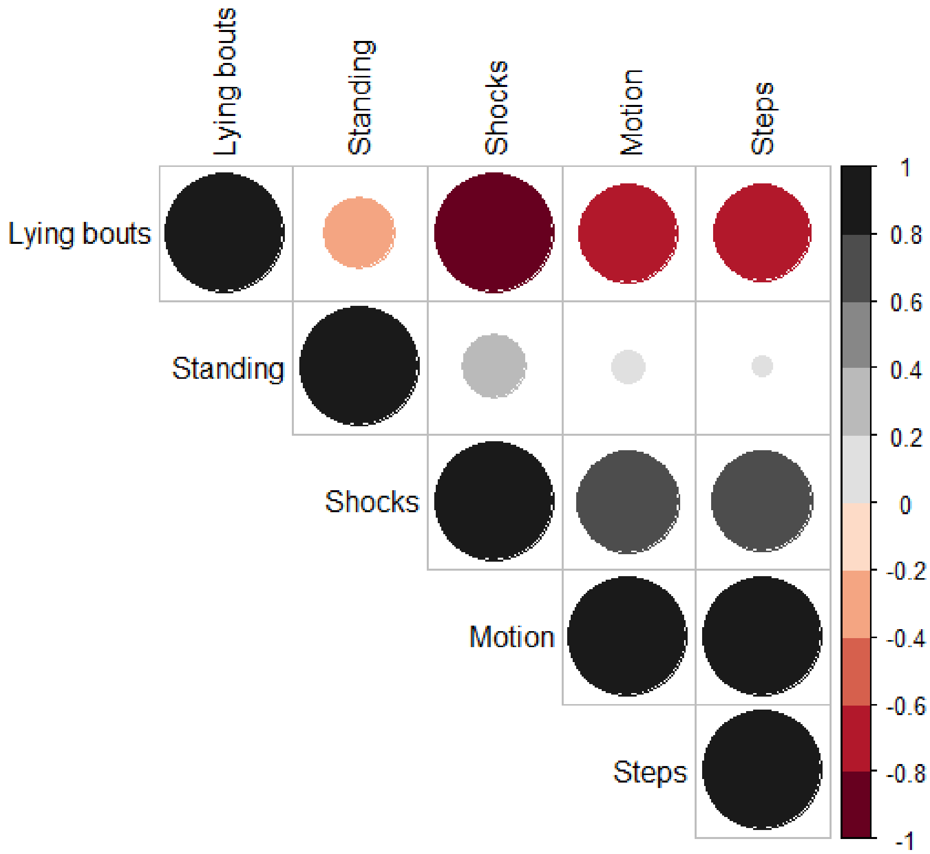

Figure 2.27: Correlations between behavior variables and shock counts – Study 2. Treatments included 2 virtually fenced pastures (**VF**) (*n* = 6). Lying bouts is the average number of lying bouts per day. Motion is the average motion index per day. Motion index is activity relative to acceleration. Steps is the average step count per day. Shocks is the average of electrical stimulus experienced by the **VF** treatment during Study 2. Standing is the average standing time per day.

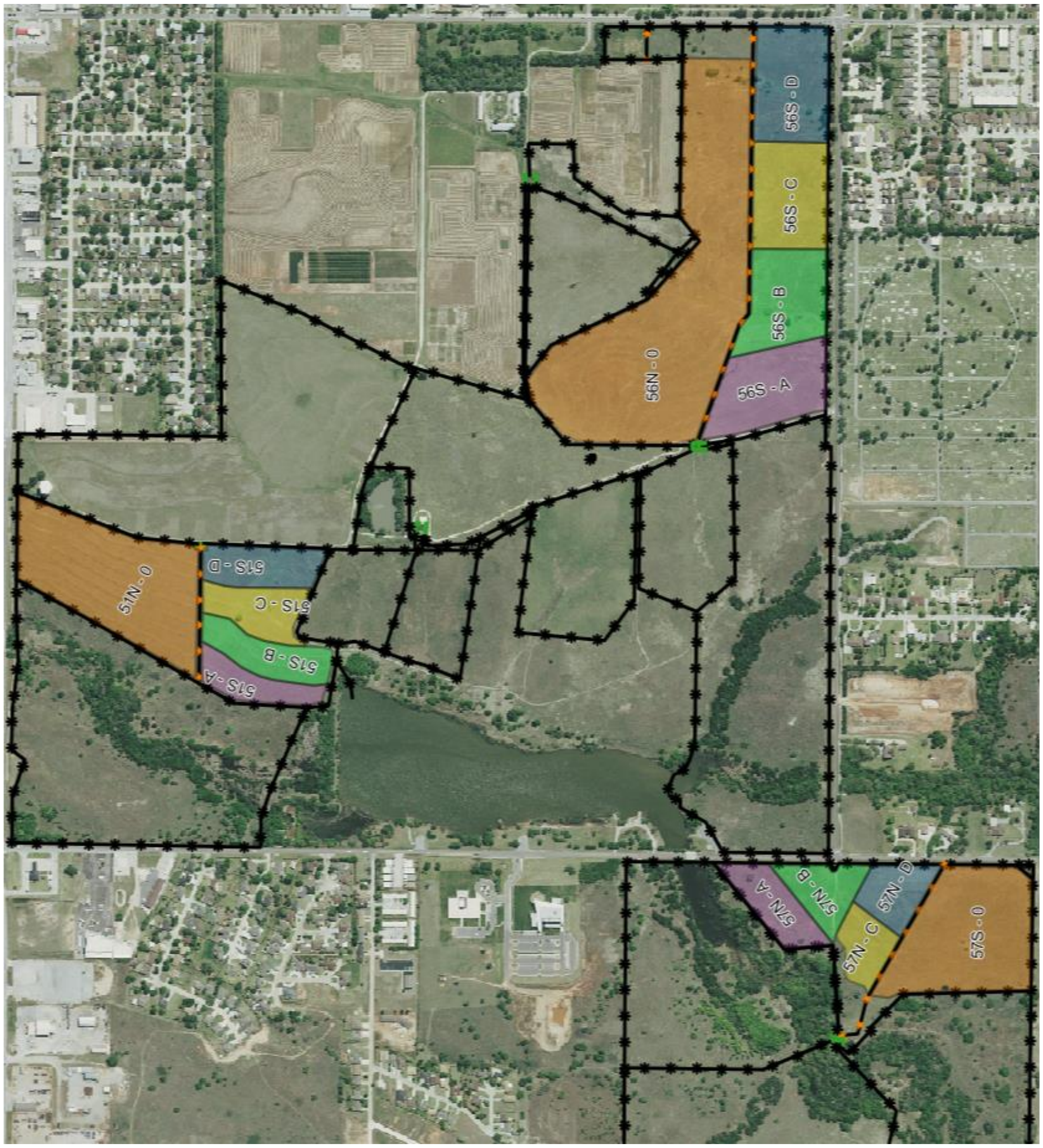

Figure 3.1: Pasture map - orange areas denote pastures without burn patches. Purple, green, yellow and blue denote burn patches.

Figure 3.2: Terrace position within pastures. Orange denotes terrace bottom, purple denotes terrace top.

Figure 3.3: Locations of water/salt and shade within pasture. Shade denoted as pink polygons and water/salt location denoted as orange circles.

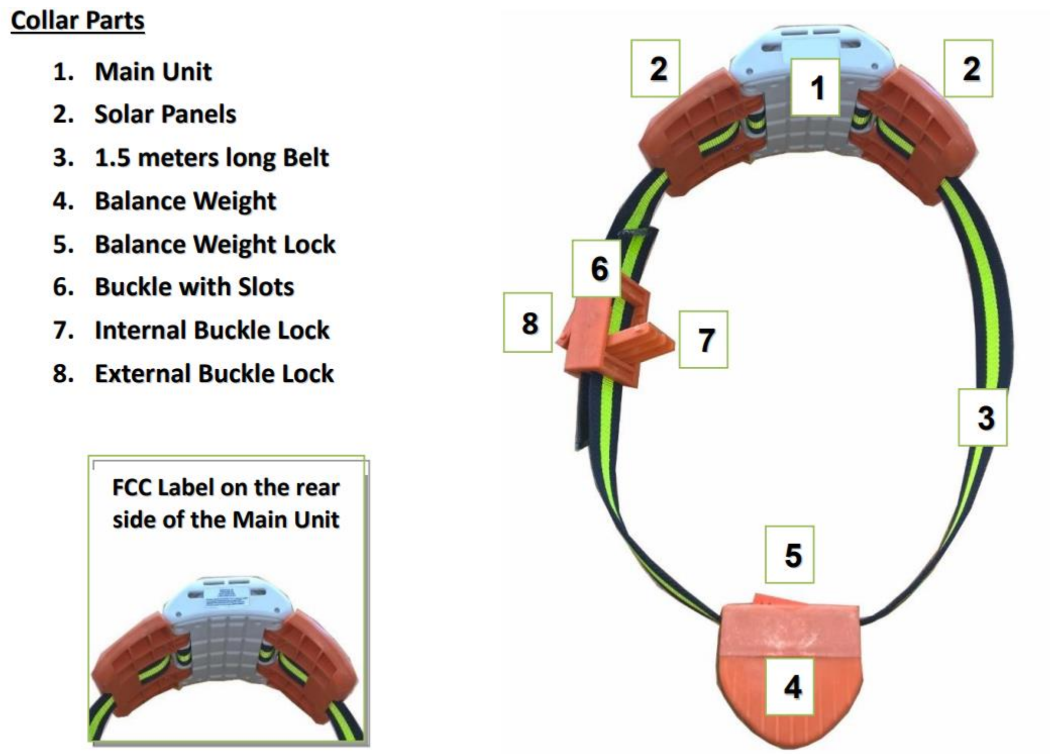

Figure 3.4: MOOnitor collar

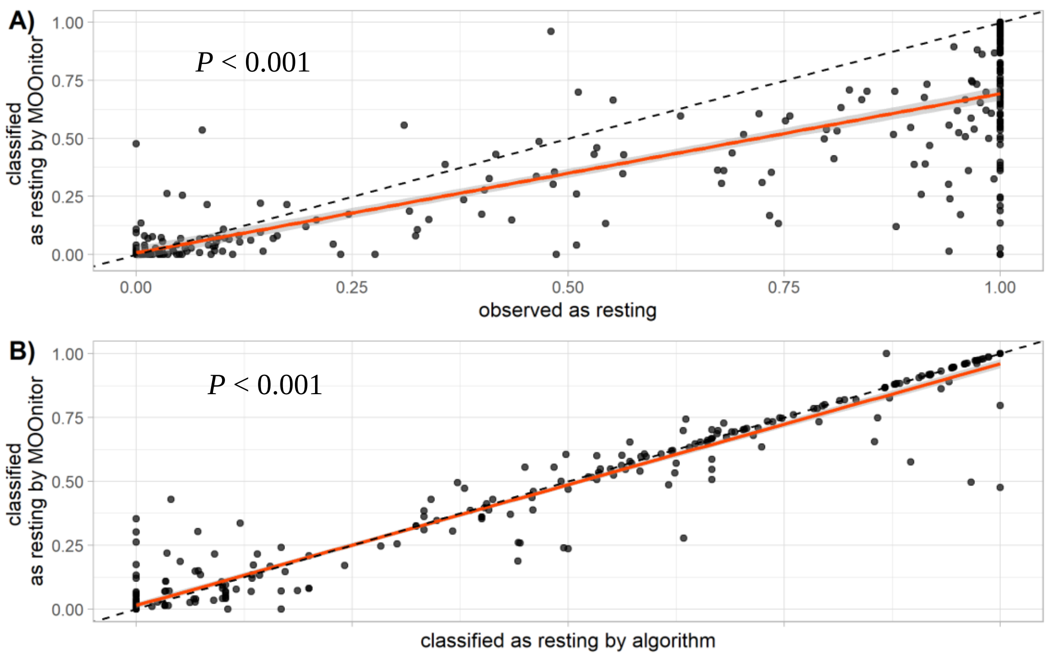

Figure 3.5: Fraction of 5-min observation periods matched to MOOnitor collar classification for resting (n = 12 animals, and 382 observation periods). A is the fraction of 5-min period classified as resting by MOOnitor collar vs. fraction of 5-min observed as resting. B is the fraction of 5-min period classified as resting by algorithm vs. fraction of 5-min period observed as resting. C is the fraction of 5-min period classified as resting by MOOnitor collar vs. fraction of 5-min period classified as resting by algorithm.

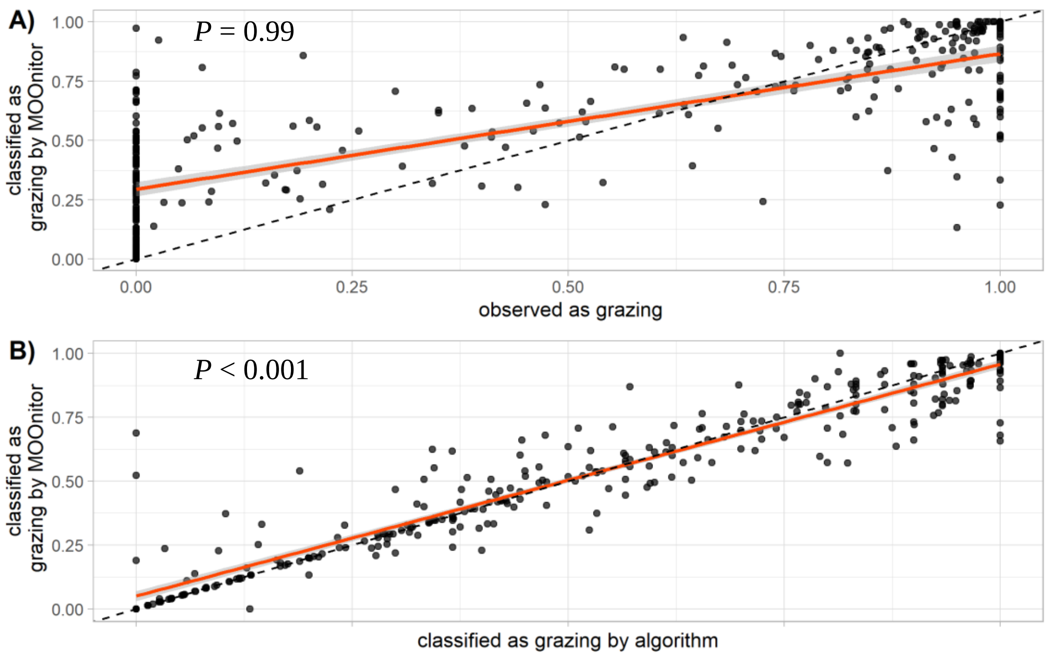

Figure 3.6: Fraction of 5-min observation periods matched to MOOnitor collar classification for grazing (*n* = 12 animals, and 382 observation periods). A is thefraction of 5-min period classified as grazing by MOOnitor collar vs. fraction of 5-min observed as grazing. B is the fraction of 5-min period classified as grazing by algorithm vs. fraction of 5-min period observed as grazing. C is the fraction of 5-min period classified as grazing by MOOnitor collar vs. fraction of 5-min period classified as grazing by algorithm.

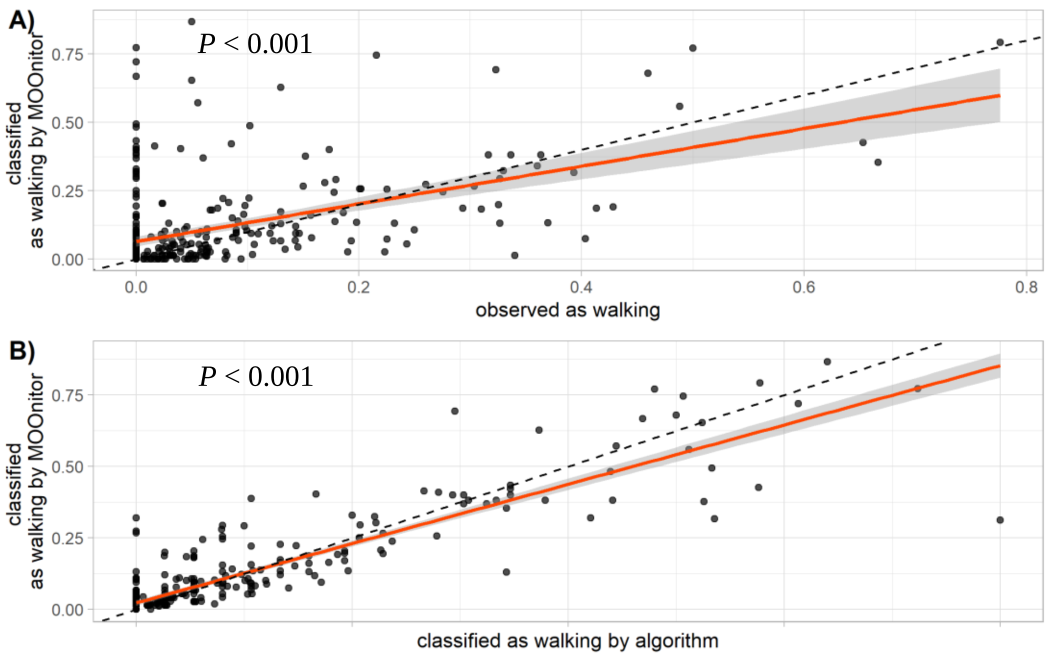

Figure 3.7: Fraction of 5-min observation periods matched to MOOnitor collar classification for walking (*n* = 12 animals, and 382 observation periods). A is the fraction of 5-min period classified as walking by MOOnitor collar vs. fraction of 5-min period observed as walking. B is the fraction of 5-min period classified as walking by algorithm vs. fraction of 5-min period observed as walking. C is the fraction of 5-min period classified as walking by MOOnitor collar vs. fraction of 5-min period classified as walking by algorithm.

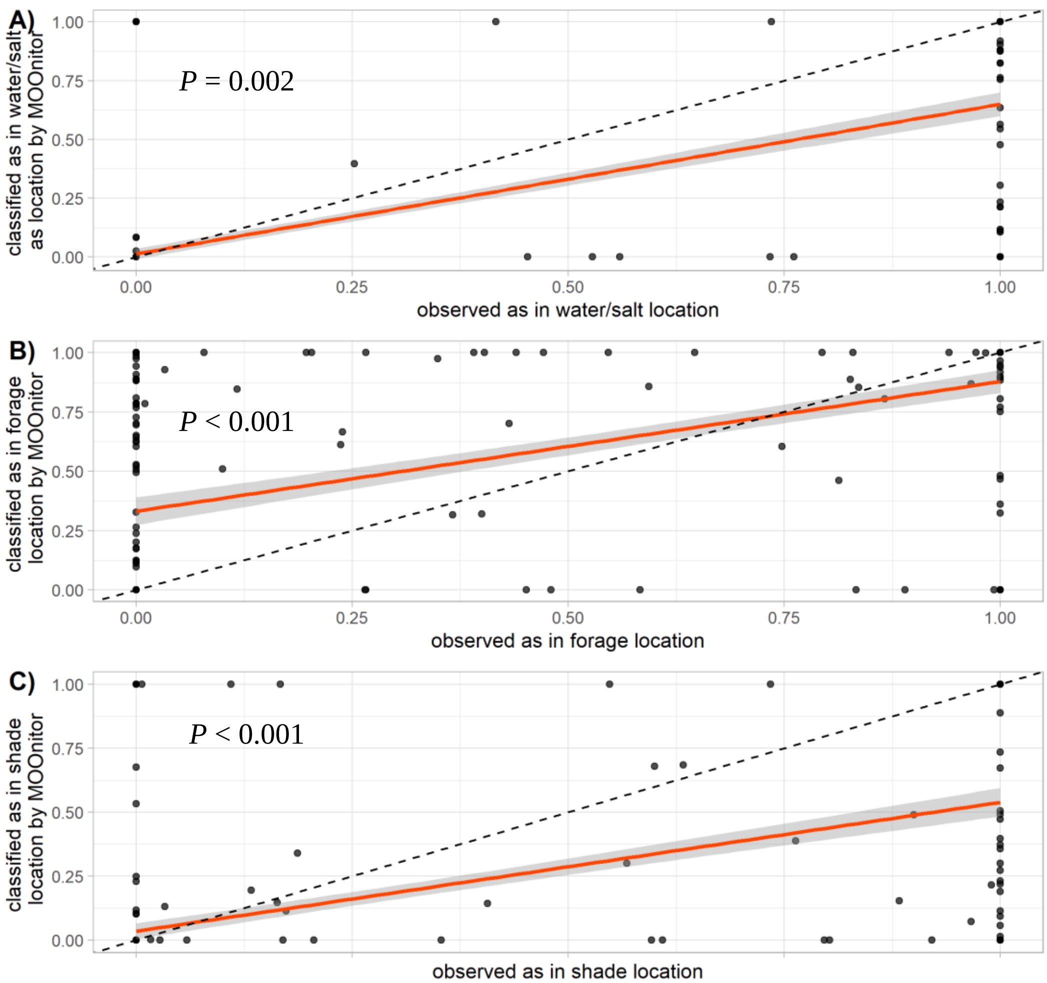

Figure 3.8: Fraction of 5-min observation periods matched to MOOnitor collar classification of resource usage (*n* = 12 animals, and 382 observation periods). A is the fraction of 5-min period classified as in water/salt location by MOOnitor collar vs. fraction of 5-min period observed as in water/salt location. B is the fraction of 5-min period classified as in forage location by MOOnitor collar vs. fraction of 5-min period observed as in forage location. C is the fraction of 5-min period classified in shade location by MOOnitor collar vs. fraction of 5-min period observed as in shade location.

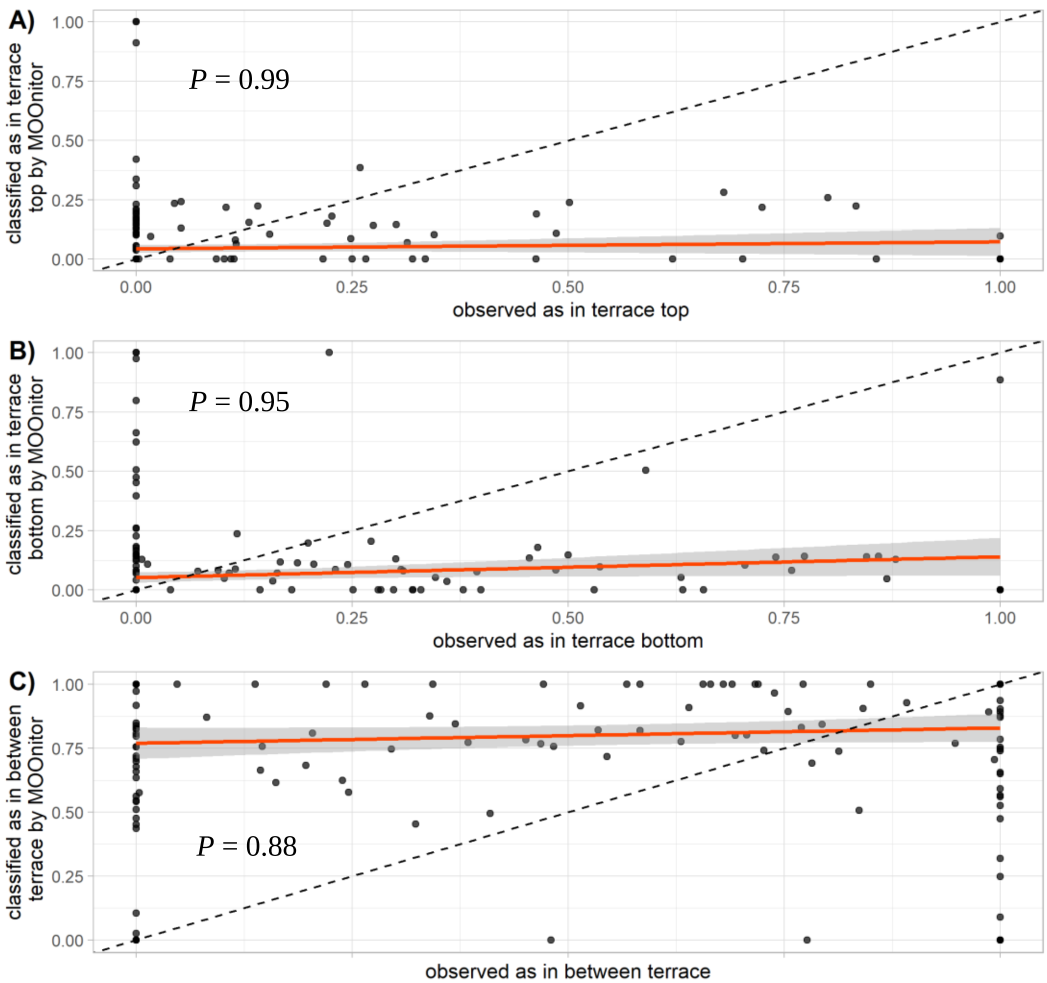

Figure 3.9: Fraction of 5-min observation periods matched to MOOnitor collar classification of terrace location usage (*n* = 12 animals, and 382 observation periods). A is the fraction of 5-min period classified as in terrace top by MOOnitor collar vs. fraction of 5-min period observed as in terrace top. B is the fraction of 5-min period classified as in terrace bottom by MOOnitor collar vs. fraction of 5-min period observed as in terrace bottom. C is the fraction of 5-min period classified in between terrace by MOOnitor collar vs. fraction of 5-min period observed as in between terrace.

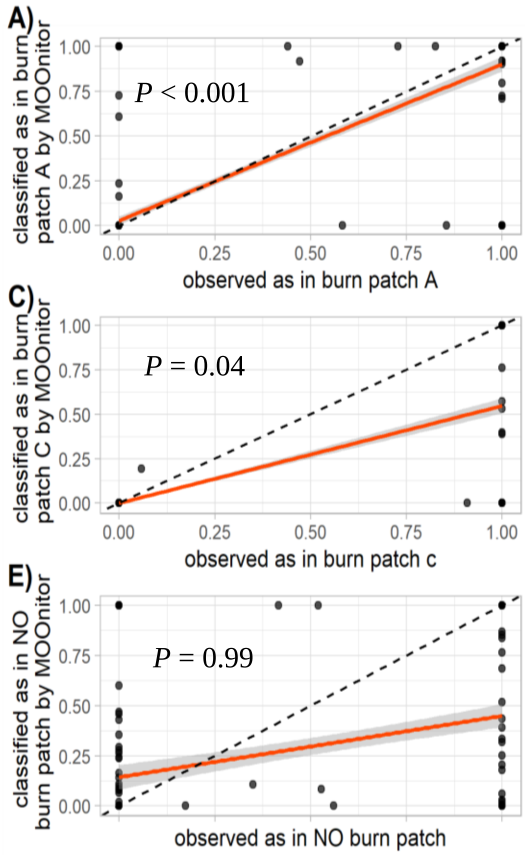

Figure 3.10: Fraction of 5-min observation periods matched to MOOnitor collar classification of burn patch usage (n = 6 animals). A is the fraction of 5-min period classified as in burn patch A by MOOnitor collar vs. fraction of 5-min period observed as in burn patch A. B is the fraction of 5-min period classified as in burn patch B by MOOnitor collar vs. fraction of 5-min period observed as in burn patch B. C is the fraction of 5-min period classified in burn patch C by MOOnitor collar vs. fraction of 5-min period observed as in burn patch C. D is the fraction of 5-min period classified in burn patch D by MOOnitor collar vs. fraction of 5-min period observed as in burn patch D. E is the fraction of 5-min period classified as in no burn patch by MOOnitor collar vs. fraction of 5-min period observed as in no burn patch.

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APPENDICES

Appendix 1. MOOnitor Collar R Code

```
> library(sf)
Linking to GEOS 3.9.0, GDAL 3.2.1, PROJ 7.2.1
> library(tidyverse)
-- Attaching packages ---------------------------------------------------------------------
tidyverse 1.3.1 --
v ggplot2 3.3.5     v purrr   0.3.4
v tibble  3.1.4     v dplyr   1.0.7
v tidyr   1.1.3     v stringr 1.4.0
v readr   2.0.1     v forcats 0.5.1
-- Conflicts ----------------------------------------------------------------------------
tidyverse_conflicts() --
x dplyr::filter() masks stats::filter()
x dplyr::lag()    masks stats::lag()
> library(grid)
> library(ggpubr)
> GEOPKG    <-
+   "./Data/Processed/CollarValidation_moonitor-val_5-min-lines.gpkg"
> VALID_BUF <- 10
> features.5min.val <- st_read(GEOPKG,
+           layer = "features_act_loc_5min_val")
Reading layer `features_act_loc_5min_val' from data source
  `G:\.shortcut-targets-by-
id\1lEXMbRSSDgi0BDt1u631O6PxqzCMbcfg\Jeffus_Moffet\Data\Processed\CollarVali
dation_moonitor-val_5-min-lines.gpkg'
  using driver `GPKG'
Simple feature collection with 383 features and 62 fields
Geometry type: GEOMETRY
Dimension:     XY
Bounding box:  xmin: 461588 ymin: 4030131 xmax: 463472.9 ymax: 4031875
Projected CRS: WGS 84 / UTM zone 14N
> ##### ACTIVITY  ####
> ##### Resting ####
> activity.summary.mult <- as.data.frame(features.5min.val) %>%
+   select(aniID, obs.a.Ra.f, obs.a.G.f, obs.a.W.f,
+         moon.a.R.f, moon.a.G.f, moon.a.W.f,
```

```
+         alg.a.R.f, alg.a.G.f, alg.a.W.f,) %>%
+   arrange(aniID) %>%
+   mutate(obs.a.Ra.mult = NA,
+         moon.a.R.mult = NA,
+         alg.a.R.mult = NA) %>%
+   mutate(obs.a.Ra.mult = ifelse(obs.a.Ra.f == 0, 0, obs.a.Ra.mult),
+         obs.a.Ra.mult = ifelse(obs.a.Ra.f > 0.00 & obs.a.Ra.f <= 0.25, 0.25,
obs.a.Ra.mult),
+         obs.a.Ra.mult = ifelse(obs.a.Ra.f > 0.25 & obs.a.Ra.f <= 0.50, 0.50,
obs.a.Ra.mult),
+         obs.a.Ra.mult = ifelse(obs.a.Ra.f > 0.50 & obs.a.Ra.f <= 0.75, 0.75,
obs.a.Ra.mult),
+         obs.a.Ra.mult = ifelse(obs.a.Ra.f > 0.75 & obs.a.Ra.f < 1, 0.99, obs.a.Ra.mult),
+         obs.a.Ra.mult = ifelse(obs.a.Ra.f == 1, 1, obs.a.Ra.mult),
+         moon.a.R.mult = ifelse(moon.a.R.f == 0, 0, moon.a.R.mult),
+         moon.a.R.mult = ifelse(moon.a.R.f > 0.00 & moon.a.R.f <= 0.25, 0.25,
moon.a.R.mult),
+         moon.a.R.mult = ifelse(moon.a.R.f > 0.25 & moon.a.R.f <= 0.50, 0.50,
moon.a.R.mult),
+         moon.a.R.mult = ifelse(moon.a.R.f > 0.50 & moon.a.R.f <= 0.75, 0.75,
moon.a.R.mult),
+         moon.a.R.mult = ifelse(moon.a.R.f > 0.75 & moon.a.R.f < 1, 0.99,
moon.a.R.mult),
+         moon.a.R.mult = ifelse(moon.a.R.f == 1, 1, moon.a.R.mult),
+         alg.a.R.mult = ifelse(alg.a.R.f == 0, 0, alg.a.R.mult),
+         alg.a.R.mult = ifelse(alg.a.R.f > 0.00 & alg.a.R.f <= 0.25, 0.25, alg.a.R.mult),
+         alg.a.R.mult = ifelse(alg.a.R.f > 0.25 & alg.a.R.f <= 0.50, 0.50, alg.a.R.mult),
+         alg.a.R.mult = ifelse(alg.a.R.f > 0.50 & alg.a.R.f <= 0.75, 0.75, alg.a.R.mult),
+         alg.a.R.mult = ifelse(alg.a.R.f > 0.75 & alg.a.R.f < 1, 0.99, alg.a.R.mult),
+         alg.a.R.mult = ifelse(alg.a.R.f == 1, 1, alg.a.R.mult),
+               ) %>%
+   select(!(obs.a.Ra.f:alg.a.W.f))  %>%
+   mutate(obs.a.Ra.mult = as.factor(obs.a.Ra.mult),
+         moon.a.R.mult = as.factor(moon.a.R.mult),
+         alg.a.R.mult = as.factor(alg.a.R.mult))
> caret::confusionMatrix(activity.summary.mult$moon.a.R.mult,
activity.summary.mult$obs.a.Ra.mult)
Confusion Matrix and Statistics

          Reference
Prediction  0 0.25 0.5 0.75 0.99  1
      0    71   22   2    0    0  2
      0.25  9   48   7    4    4  6
      0.5   1    2   8   11   10  6
      0.75  0    1   1    5   27 30
      0.99  0    0   1    0    4 45
```

```
     1     0    0   0    0    0  8

Overall Statistics
    Accuracy : 0.4299
    95% CI : (0.3762, 0.4848)
    No Information Rate : 0.2896
    P-Value [Acc > NIR] : 3.243e-08
     Kappa : 0.3167

 Mcnemar's Test P-Value : NA
Statistics by Class:

                     Class: 0 Class: 0.25 Class: 0.5 Class: 0.75 Class: 0.99 Class: 1
Sensitivity            0.8765      0.6575    0.42105     0.25000     0.08889  0.08247
Specificity            0.8976      0.8855    0.90506     0.81270     0.84138  1.00000
Pos Pred Value         0.7320      0.6154    0.21053     0.07812     0.08000  1.00000
Neg Pred Value         0.9580      0.9027    0.96296     0.94465     0.85614  0.72783
Prevalence             0.2418      0.2179    0.05672     0.05970     0.13433  0.28955
Detection Rate         0.2119      0.1433    0.02388     0.01493     0.01194  0.02388
Detection Prevalence   0.2896      0.2328    0.11343     0.19104     0.14925  0.02388
Balanced Accuracy      0.8871      0.7715    0.66306     0.53135     0.46513  0.54124
> caret::confusionMatrix(activity.summary.mult$alg.a.R.mult,
activity.summary.mult$obs.a.Ra.mult)
Confusion Matrix and Statistics

          Reference
Prediction  0 0.25 0.5 0.75 0.99  1
     0    76   41   3    1    1  3
     0.25  6   33   8    4    3  3
     0.5   0    1   5   13   12  8
     0.75  0    0   2    4   23 29
     0.99  0    0   1    0   10 75
     1     1    0   0    0    0 10

Overall Statistics
Accuracy : 0.367
    95% CI : (0.3182, 0.418)
    No Information Rate : 0.3404
    P-Value [Acc > NIR] : 0.1507
    Kappa : 0.2485

 Mcnemar's Test P-Value : <2e-16
Statistics by Class:

                     Class: 0 Class: 0.25 Class: 0.5 Class: 0.75 Class: 0.99 Class: 1
Sensitivity            0.9157     0.44000    0.26316     0.18182      0.2041  0.07812
```

```
Specificity          0.8328    0.92027   0.90476    0.84746     0.7676  0.99597
Pos Pred Value       0.6080    0.57895   0.12821    0.06897     0.1163  0.90909
Neg Pred Value       0.9721    0.86834   0.95846    0.94340     0.8655  0.67671
Prevalence           0.2207    0.19947   0.05053    0.05851     0.1303  0.34043
Detection Rate       0.2021    0.08777   0.01330    0.01064     0.0266  0.02660
Detection Prevalence 0.3324    0.15160   0.10372    0.15426     0.2287  0.02926
Balanced Accuracy    0.8742    0.68013   0.58396    0.51464     0.4858  0.53705
> caret::confusionMatrix(activity.summary.mult$moon.a.R.mult,
activity.summary.mult$alg.a.R.mult)
Confusion Matrix and Statistics

          Reference
Prediction  0 0.25 0.5 0.75 0.99  1
      0    93    2   0    0    0  0
      0.25 25   48   4    0    0  0
      0.5   3    3  28    2    1  1
      0.75  0    0   3   54    4  0
      0.99  0    0   0    0   49  1
      1     0    0   0    0    1  7

Overall Statistics
   Accuracy : 0.848
    95% CI : (0.8046, 0.885)
   No Information Rate : 0.3678
   P-Value [Acc > NIR] : < 2.2e-16
   Kappa : 0.8067

 Mcnemar's Test P-Value : NA
Statistics by Class:

                     Class: 0 Class: 0.25 Class: 0.5 Class: 0.75 Class: 0.99 Class: 1
Sensitivity          0.7686      0.9057    0.80000      0.9643      0.8909  0.77778
Specificity          0.9904      0.8949    0.96599      0.9744      0.9964  0.99687
Pos Pred Value       0.9789      0.6234    0.73684      0.8852      0.9800  0.87500
Neg Pred Value       0.8803      0.9802    0.97595      0.9925      0.9785  0.99377
Prevalence           0.3678      0.1611    0.10638      0.1702      0.1672  0.02736
Detection Rate       0.2827      0.1459    0.08511      0.1641      0.1489  0.02128
Detection Prevalence 0.2888      0.2340    0.11550      0.1854      0.1520  0.02432
Balanced Accuracy    0.8795      0.9003    0.88299      0.9693      0.9436  0.88733
> ROM <- ggplot(features.5min.val, aes(x=obs.a.Ra.f, y=moon.a.R.f)) +
geom_point(alpha = 0.7) +
+   stat_smooth(method = "lm", #formula = y ~ x + I(x^2),
+               size = 1, colour= "orangered1") +
+   geom_abline(slope = 1, intercept = 0, linetype = "dashed") +
+   theme_set(theme_light()) +
+   labs(y= "classified \nas resting by MOOnitor",
```

```
+       x="observed as resting")
> ROM
`geom_smooth()` using formula 'y ~ x'
Warning messages:
1: Removed 48 rows containing non-finite values (stat_smooth).
2: Removed 48 rows containing missing values (geom_point).
> ROA <- ggplot(features.5min.val, aes(x=obs.a.Ra.f, y=alg.a.R.f)) + geom_point(alpha
= 0.7) +
+   stat_smooth(method = "lm", #formula = y ~ x + I(x^2),
+               size = 1, colour= "orangered1") +
+   geom_abline(slope = 1, intercept = 0, linetype = "dashed") +
+   theme_set(theme_light()) +
+   labs(y= "classified \nas resting by algorithm",
+       x="observed as resting")
> ROA
`geom_smooth()` using formula 'y ~ x'
Warning messages:
1: Removed 7 rows containing non-finite values (stat_smooth).
2: Removed 7 rows containing missing values (geom_point).
> RAM <- ggplot(features.5min.val, aes(x=alg.a.R.f, y=moon.a.R.f)) + geom_point(alpha
= 0.7) +
+   stat_smooth(method = "lm", #formula = y ~ x + I(x^2),
+               size = 1, colour= "orangered1") +
+   geom_abline(slope = 1, intercept = 0, linetype = "dashed") +
+   theme_set(theme_light()) +
+   labs(y= "classified \nas resting by MOOnitor",
+       x="classified as resting by algorithm")
> RAM
>ggarrange(ROM, ROA, RAM + rremove("x.text"),
       labels = c("A)", "B)", "C)"),
       ncol = 1, nrow = 3)
>ggsave("Plots/resting_combined.png", height = 7.5, width = 8)
> ##### Grazing ####
> activity.summary.mult <- as.data.frame(features.5min.val) %>%
+   select(aniID, obs.a.Ra.f, obs.a.G.f, obs.a.W.f,
+          moon.a.R.f, moon.a.G.f, moon.a.W.f,
+          alg.a.R.f, alg.a.G.f, alg.a.W.f,) %>%
+   arrange(aniID) %>%
+   mutate(obs.a.G.mult = NA,
+          moon.a.G.mult = NA,
+          alg.a.G.mult = NA) %>%
+   mutate(obs.a.G.mult = ifelse(obs.a.G.f == 0, 0, obs.a.G.mult),
+          obs.a.G.mult = ifelse(obs.a.G.f > 0.00 & obs.a.G.f <= 0.25, 0.25, obs.a.G.mult),
+          obs.a.G.mult = ifelse(obs.a.G.f > 0.25 & obs.a.G.f <= 0.50, 0.50, obs.a.G.mult),
+          obs.a.G.mult = ifelse(obs.a.G.f > 0.50 & obs.a.G.f <= 0.75, 0.75, obs.a.G.mult),
+          obs.a.G.mult = ifelse(obs.a.G.f > 0.75 & obs.a.G.f < 1, 0.99, obs.a.G.mult),
```

```
+         obs.a.G.mult = ifelse(obs.a.G.f == 1, 1, obs.a.G.mult),
+         moon.a.G.mult = ifelse(moon.a.G.f == 0, 0, moon.a.G.mult),
+         moon.a.G.mult = ifelse(moon.a.G.f > 0.00 & moon.a.G.f <= 0.25, 0.25,
moon.a.G.mult),
+         moon.a.G.mult = ifelse(moon.a.G.f > 0.25 & moon.a.G.f <= 0.50, 0.50,
moon.a.G.mult),
+         moon.a.G.mult = ifelse(moon.a.G.f > 0.50 & moon.a.G.f <= 0.75, 0.75,
moon.a.G.mult),
+         moon.a.G.mult = ifelse(moon.a.G.f > 0.75 & moon.a.G.f < 1, 0.99,
moon.a.G.mult),
+         moon.a.G.mult = ifelse(moon.a.G.f == 1, 1, moon.a.G.mult),
+         alg.a.G.mult = ifelse(alg.a.G.f == 0, 0, alg.a.G.mult),
+         alg.a.G.mult = ifelse(alg.a.G.f > 0.00 & alg.a.G.f <= 0.25, 0.25, alg.a.G.mult),
+         alg.a.G.mult = ifelse(alg.a.G.f > 0.25 & alg.a.G.f <= 0.50, 0.50, alg.a.G.mult),
+         alg.a.G.mult = ifelse(alg.a.G.f > 0.50 & alg.a.G.f <= 0.75, 0.75, alg.a.G.mult),
+         alg.a.G.mult = ifelse(alg.a.G.f > 0.75 & alg.a.G.f < 1, 0.99, alg.a.G.mult),
+         alg.a.G.mult = ifelse(alg.a.G.f == 1, 1, alg.a.G.mult),
+   ) %>%
+   mutate(obs.a.G.mult = as.factor(obs.a.G.mult),
+         moon.a.G.mult = as.factor(moon.a.G.mult),
+         alg.a.G.mult = as.factor(alg.a.G.mult))
> caret::confusionMatrix(activity.summary.mult$moon.a.G.mult,
activity.summary.mult$obs.a.G.mult)
Confusion Matrix and Statistics

          Reference
Prediction  0 0.25 0.5 0.75 0.99  1
      0    10    0   0    0    0  0
      0.25 55    5   1    1    1  1
      0.5  47   12   6    2    4  1
      0.75 17    9  12   12   15 13
      0.99  3    3   0   11   64 15
      1     0    0   0    0    9  6

Overall Statistics:
    Accuracy : 0.3075
    95% CI : (0.2585, 0.3599)
    No Information Rate : 0.394
    P-Value [Acc > NIR] : 0.9996
    Kappa : 0.192

 Mcnemar's Test P-Value : NA
Statistics by Class:

                     Class: 0 Class: 0.25 Class: 0.5 Class: 0.75 Class: 0.99 Class: 1
Sensitivity           0.07576     0.17241    0.31579     0.46154      0.6882  0.16667
```

```
Specificity          1.00000     0.80719    0.79114     0.78641      0.8678  0.96990
Pos Pred Value       1.00000     0.07813    0.08333     0.15385      0.6667  0.40000
Neg Pred Value       0.62462     0.91144    0.95057     0.94553      0.8787  0.90625
Prevalence           0.39403     0.08657    0.05672     0.07761      0.2776  0.10746
Detection Rate       0.02985     0.01493    0.01791     0.03582      0.1910  0.01791
Detection Prevalence 0.02985     0.19104    0.21493     0.23284      0.2866  0.04478
Balanced Accuracy    0.53788     0.48980    0.55346     0.62397      0.7780  0.56828
> caret::confusionMatrix(activity.summary.mult$alg.a.G.mult,
activity.summary.mult$obs.a.G.mult)
Confusion Matrix and Statistics

          Reference
Prediction  0 0.25 0.5 0.75 0.99  1
      0    12    0   0    0    0  2
      0.25 86    5   1    0    1  1
      0.5  49   13   6    6    3  4
      0.75 16    9   7    8   13  8
      0.99  3    3   4   10   55 14
      1     0    1   1    3   23  9

Overall Statistics
    Accuracy : 0.2527
    95% CI : (0.2095, 0.2998)
    No Information Rate : 0.4415
    P-Value [Acc > NIR] : 1
    Kappa : 0.1416

 Mcnemar's Test P-Value : <2e-16
Statistics by Class:

                     Class: 0 Class: 0.25 Class: 0.5 Class: 0.75 Class: 0.99 Class: 1
Sensitivity          0.07229     0.16129    0.31579     0.29630      0.5789  0.23684
Specificity          0.99048     0.74203    0.78992     0.84814      0.8790  0.91716
Pos Pred Value       0.85714     0.05319    0.07407     0.13115      0.6180  0.24324
Neg Pred Value       0.57459     0.90780    0.95593     0.93968      0.8606  0.91445
Prevalence           0.44149     0.08245    0.05053     0.07181      0.2527  0.10106
Detection Rate       0.03191     0.01330    0.01596     0.02128      0.1463  0.02394
Detection Prevalence 0.03723     0.25000    0.21543     0.16223      0.2367  0.09840
Balanced Accuracy    0.53138     0.45166    0.55285     0.57222      0.7290  0.57700
> caret::confusionMatrix(activity.summary.mult$moon.a.G.mult,
activity.summary.mult$alg.a.G.mult)
Confusion Matrix and Statistics

          Reference
Prediction  0 0.25 0.5 0.75 0.99  1
      0     9    1   0    0    0  0
```

```
    0.25  1   56   6    0    0  0
    0.5   0    5  57    8    0  0
    0.75  2    1  15   45   10  3
    0.99  0    0   0    4   71 20
    1     0    0   0    0    1 14
```

```
Overall Statistics
   Accuracy : 0.766
   95% CI : (0.7164, 0.8107)
   No Information Rate : 0.2492
   P-Value [Acc > NIR] : < 2.2e-16
   Kappa : 0.7055

 Mcnemar's Test P-Value : NA
Statistics by Class:

                     Class: 0 Class: 0.25 Class: 0.5 Class: 0.75 Class: 0.99 Class: 1
Sensitivity          0.75000      0.8889     0.7308      0.7895      0.8659  0.37838
Specificity          0.99685      0.9737     0.9482      0.8860      0.9028  0.99658
Pos Pred Value       0.90000      0.8889     0.8143      0.5921      0.7474  0.93333
Neg Pred Value       0.99060      0.9737     0.9189      0.9526      0.9530  0.92675
Prevalence           0.03647      0.1915     0.2371      0.1733      0.2492  0.11246
Detection Rate       0.02736      0.1702     0.1733      0.1368      0.2158  0.04255
Detection Prevalence 0.03040      0.1915     0.2128      0.2310      0.2888  0.04559
Balanced Accuracy    0.87342      0.9313     0.8395      0.8378      0.8843  0.68748
## plot

GOM <- ggplot(features.5min.val, aes(x=obs.a.G.f, y=moon.a.G.f)) + geom_point(alpha
= 0.7) +
  stat_smooth(method = "lm", #formula = y ~ x + I(x^2),
              size = 1, colour= "orangered1") +
  geom_abline(slope = 1, intercept = 0, linetype = "dashed") +
  theme_set(theme_light()) +
  labs(y= "classified \nas grazing by MOOnitor",
       x="observed as grazing")
GOM
ggsave("Plots/obs_moon_grazing_PVALUE.png", height = 4, width = 5)

GOA <- ggplot(features.5min.val, aes(x=obs.a.G.f, y=alg.a.G.f)) + geom_point(alpha =
0.7) +
  stat_smooth(method = "lm", #formula = y ~ x + I(x^2),
              size = 1, colour= "orangered1") +
  geom_abline(slope = 1, intercept = 0, linetype = "dashed") +
  theme_set(theme_light()) +
  labs(y= "classified \nas grazing by algorithm",
       x="observed as grazing")
```

```
GOA
ggsave("Plots/obs_alg_grazing_PVALUE.png", height = 4, width = 5)

GAM <- ggplot(features.5min.val, aes(x=alg.a.G.f, y=moon.a.G.f)) + geom_point(alpha
= 0.7) +
  stat_smooth(method = "lm", #formula = y ~ x + I(x^2),
              size = 1, colour= "orangered1") +
  geom_abline(slope = 1, intercept = 0, linetype = "dashed") +
  theme_set(theme_light()) +
  labs(y= "classified \nas grazing by algorithm",
       x = "classified as grazing by MOOnitor")
GAM
ggsave("Plots/alg_moon_grazing_PVALUE.png", height = 4, width = 5)
#### combine plots ####
ggarrange(GOM, GOA, GAM + rremove("x.text"),
          labels = c("A)", "B)", "C)"),
          ncol = 1, nrow = 3,
          align = "v")
ggsave("Plots/grazing_combined.png", height = 7.5, width = 8)
> activity.summary.mult <- as.data.frame(features.5min.val) %>%
+   select(aniID, obs.a.Ra.f, obs.a.W.f, obs.a.W.f,
+          moon.a.R.f, moon.a.W.f, moon.a.W.f,
+          alg.a.R.f, alg.a.W.f, alg.a.W.f,) %>%
+   arrange(aniID) %>%
+   mutate(obs.a.W.mult = NA,
+          moon.a.W.mult = NA,
+          alg.a.W.mult = NA) %>%
+   mutate(obs.a.W.mult = ifelse(obs.a.W.f == 0, 0, obs.a.W.mult),
+          obs.a.W.mult = ifelse(obs.a.W.f > 0.00 & obs.a.W.f <= 0.25, 0.25, obs.a.W.mult),
+          obs.a.W.mult = ifelse(obs.a.W.f > 0.25 & obs.a.W.f <= 0.50, 0.50, obs.a.W.mult),
+          obs.a.W.mult = ifelse(obs.a.W.f > 0.50 & obs.a.W.f <= 0.75, 0.75, obs.a.W.mult),
+          obs.a.W.mult = ifelse(obs.a.W.f > 0.75 & obs.a.W.f < 1, 0.99, obs.a.W.mult),
+          obs.a.W.mult = ifelse(obs.a.W.f == 1, 1, obs.a.W.mult),
+          moon.a.W.mult = ifelse(moon.a.W.f == 0, 0, moon.a.W.mult),
+          moon.a.W.mult = ifelse(moon.a.W.f > 0.00 & moon.a.W.f <= 0.25, 0.25,
moon.a.W.mult),
+          moon.a.W.mult = ifelse(moon.a.W.f > 0.25 & moon.a.W.f <= 0.50, 0.50,
moon.a.W.mult),
+          moon.a.W.mult = ifelse(moon.a.W.f > 0.50 & moon.a.W.f <= 0.75, 0.75,
moon.a.W.mult),
+          moon.a.W.mult = ifelse(moon.a.W.f > 0.75 & moon.a.W.f < 1, 0.99,
moon.a.W.mult),
+          moon.a.W.mult = ifelse(moon.a.W.f == 1, 1, moon.a.W.mult),
+          alg.a.W.mult = ifelse(alg.a.W.f == 0, 0, alg.a.W.mult),
+          alg.a.W.mult = ifelse(alg.a.W.f > 0.00 & alg.a.W.f <= 0.25, 0.25, alg.a.W.mult),
+          alg.a.W.mult = ifelse(alg.a.W.f > 0.25 & alg.a.W.f <= 0.50, 0.50, alg.a.W.mult),
```

```
+         alg.a.W.mult = ifelse(alg.a.W.f > 0.50 & alg.a.W.f <= 0.75, 0.75, alg.a.W.mult),
+         alg.a.W.mult = ifelse(alg.a.W.f > 0.75 & alg.a.W.f < 1, 0.99, alg.a.W.mult),
+         alg.a.W.mult = ifelse(alg.a.W.f == 1, 1, alg.a.W.mult),
+   ) %>%
+   mutate(obs.a.W.mult = as.factor(obs.a.W.mult),
+         moon.a.W.mult = as.factor(moon.a.W.mult),
+         alg.a.W.mult = as.factor(alg.a.W.mult))
> caret::confusionMatrix(activity.summary.mult$moon.a.W.mult,
activity.summary.mult$obs.a.W.mult)
Confusion Matrix and Statistics

          Reference
Prediction   0 0.25 0.5 0.75 0.99
     0     70   20   0    0    0
     0.25  69  114  10    0    0
     0.5   15   13   9    2    0
     0.75   2    4   3    0    0
     0.99   1    1   1    0    1

Overall Statistics

    Accuracy : 0.5791
     95% CI : (0.5242, 0.6326)
    No Information Rate : 0.4687
    P-Value [Acc > NIR] : 3.248e-05
    Kappa : 0.3037

 Mcnemar's Test P-Value : NA
Statistics by Class:

                     Class: 0 Class: 0.25 Class: 0.5 Class: 0.75 Class: 0.99
Sensitivity           0.4459      0.7500    0.39130     0.00000    1.000000
Specificity           0.8876      0.5683    0.90385     0.97297    0.991018
Pos Pred Value        0.7778      0.5907    0.23077     0.00000    0.250000
Neg Pred Value        0.6449      0.7324    0.95270     0.99387    1.000000
Prevalence            0.4687      0.4537    0.06866     0.00597    0.002985
Detection Rate        0.2090      0.3403    0.02687     0.00000    0.002985
Detection Prevalence  0.2687      0.5761    0.11642     0.02687    0.011940
Balanced Accuracy     0.6668      0.6592    0.64758     0.48649    0.995509
> caret::confusionMatrix(activity.summary.mult$alg.a.W.mult,
activity.summary.mult$obs.a.W.mult)
Error in confusionMatrix.default(activity.summary.mult$alg.a.W.mult,
activity.summary.mult$obs.a.W.mult) :
  the data cannot have more levels than the reference
> caret::confusionMatrix(activity.summary.mult$moon.a.W.mult,
activity.summary.mult$alg.a.W.mult)
```

```
Confusion Matrix and Statistics

          Reference
Prediction   0 0.25 0.5 0.75 0.99   1
      0     88    1   0    0    0   0
      0.25  43  143   5    0    0   0
      0.5    3    7  18    7    0   1
      0.75   0    0   2    6    1   0
      0.99   0    0   0    2    2   0
      1      0    0   0    0    0   0

Overall Statistics
    Accuracy : 0.7812
    95% CI : (0.7325, 0.8246)
    No Information Rate : 0.459
    P-Value [Acc > NIR] : < 2.2e-16
    Kappa : 0.6434

 Mcnemar's Test P-Value : NA
Statistics by Class:

                     Class: 0 Class: 0.25 Class: 0.5 Class: 0.75 Class: 0.99 Class: 1
Sensitivity            0.6567      0.9470    0.72000     0.40000    0.666667  0.00000
Specificity            0.9949      0.7303    0.94079     0.99045    0.993865  1.00000
Pos Pred Value         0.9888      0.7487    0.50000     0.66667    0.500000      NaN
Neg Pred Value         0.8083      0.9420    0.97611     0.97188    0.996923  0.99696
Prevalence             0.4073      0.4590    0.07599     0.04559    0.009119  0.00304
Detection Rate         0.2675      0.4347    0.05471     0.01824    0.006079  0.00000
Detection Prevalence   0.2705      0.5805    0.10942     0.02736    0.012158  0.00000
Balanced Accuracy      0.8258      0.8387    0.83039     0.69522    0.830266  0.50000
## plot

WOM <- ggplot(features.5min.val, aes(x=obs.a.W.f, y=moon.a.W.f)) +
geom_point(alpha = 0.7) +
  stat_smooth(method = "lm", #formula = y ~ x + I(x^2),
              size = 1, colour= "orangered1") +
  geom_abline(slope = 1, intercept = 0, linetype = "dashed") +
  theme_set(theme_light()) +
  labs(y= "classified \nas walking by MOOnitor",
       x="observed as walking")
WOM
ggsave("Plots/obs_moon_walking_PVALUE.png", height = 4, width = 5)

WOA <- ggplot(features.5min.val, aes(x=obs.a.W.f, y=alg.a.W.f)) + geom_point(alpha =
0.7) +
  stat_smooth(method = "lm", #formula = y ~ x + I(x^2),
```

```
            size = 1, colour= "orangered1") +
  geom_abline(slope = 1, intercept = 0, linetype = "dashed") +
  theme_set(theme_light()) +
  labs(y= "classified \nas walking by algorithm",
       x="observed as walking")
WOA
  ggsave("Plots/obs_alg_walking.png", height = 4, width = 5)

WAM <- ggplot(features.5min.val, aes(x=alg.a.W.f, y=moon.a.W.f)) + geom_point(alpha
= 0.7) +
  stat_smooth(method = "lm", #formula = y ~ x + I(x^2),
            size = 1, colour= "orangered1") +
  geom_abline(slope = 1, intercept = 0, linetype = "dashed") +
  theme_set(theme_light()) +
  labs(y= "classified \nas walking by MOOnitor",
       x="classified as walking by algorithm")
WAM
ggsave("Plots/alg_moon_walking_PVALUE.png", height = 4, width = 5)
#### combine plots ####
ggarrange(WOM, WOA, WAM + rremove("x.text"),
          labels = c("A)", "B)", "C)"),
          ncol = 1, nrow = 3,
          align = "v")
ggsave("Plots/walking_combined.png", height = 7.5, width = 8)
>   activity.summary.mult <- as.data.frame(features.5min.val) %>%
+     select(aniID, assignPasture,
+            obs.a.Ra.f:obs.a.W.f,
+            moon.a.R.f:moon.a.W.f,
+            alg.a.R.f:alg.a.W.f
+            ) %>%
+     arrange(aniID) %>%
+     mutate(obs.dominant.act = NA,
+            moon.dominant.act = NA) %>%
+     mutate(obs.dominant.act.max = pmax(obs.a.Ra.f, obs.a.G.f, obs.a.W.f)) %>%
+     mutate(obs.dominant.act = ifelse(obs.dominant.act.max == obs.a.Ra.f, "R",
obs.dominant.act),
+            obs.dominant.act = ifelse(obs.dominant.act.max == obs.a.G.f, "G",
obs.dominant.act),
+            obs.dominant.act = ifelse(obs.dominant.act.max == obs.a.W.f, "W",
obs.dominant.act),
+     ) %>%
+     mutate(moon.dominant.act.max = pmax(moon.a.R.f, moon.a.G.f, moon.a.W.f))
%>%
+     mutate(moon.dominant.act = ifelse(moon.dominant.act.max == moon.a.R.f, "R",
moon.dominant.act),
```

```
+           moon.dominant.act = ifelse(moon.dominant.act.max == moon.a.G.f, "G",
moon.dominant.act),
+           moon.dominant.act = ifelse(moon.dominant.act.max == moon.a.W.f, "W",
moon.dominant.act),
+     ) %>%
+     mutate(obs.dominant.act = as.factor(obs.dominant.act),
+           moon.dominant.act = as.factor(moon.dominant.act))
>   caret::confusionMatrix(activity.summary.mult$moon.dominant.act,
activity.summary.mult$obs.dominant.act)
Confusion Matrix and Statistics

          Reference
Prediction   G   R   W
         G 151  44   2
         R   2 123   0
         W   9   1   3

Overall Statistics
    Accuracy : 0.8269
    95% CI : (0.782, 0.8658)
    No Information Rate : 0.5015
    P-Value [Acc > NIR] : < 2.2e-16
    Kappa : 0.672
 Mcnemar's Test P-Value : 1.662e-09
Statistics by Class:
                     Class: G Class: R Class: W
Sensitivity            0.9321   0.7321 0.600000
Specificity            0.7341   0.9880 0.969697
Pos Pred Value         0.7665   0.9840 0.230769
Neg Pred Value         0.9203   0.7857 0.993789
Prevalence             0.4836   0.5015 0.014925
Detection Rate         0.4507   0.3672 0.008955
Detection Prevalence   0.5881   0.3731 0.038806
Balanced Accuracy      0.8331   0.8601 0.784848
> ##### RESOURCE ####
> #### water/salt ####
> resource.summary.mult <- as.data.frame(features.5min.val) %>%
+   select(aniID,
+          rec,
+          obs.r.ws.f, obs.r.sh.f, obs.r.fg.f,
+          loc.r.ws.f, loc.r.sh.f, loc.r.fg.f) %>%
+   arrange(aniID) %>%
+   mutate(obs.r.ws.mult = NA,
+          loc.r.ws.mult = NA) %>%
+   mutate(obs.r.ws.mult = ifelse(obs.r.ws.f == 0, 0, obs.r.ws.mult),
```

```
+         obs.r.ws.mult = ifelse(obs.r.ws.f > 0.00 & obs.r.ws.f <= 0.25, 0.25,
obs.r.ws.mult),
+         obs.r.ws.mult = ifelse(obs.r.ws.f > 0.25 & obs.r.ws.f <= 0.50, 0.50,
obs.r.ws.mult),
+         obs.r.ws.mult = ifelse(obs.r.ws.f > 0.50 & obs.r.ws.f <= 0.75, 0.75,
obs.r.ws.mult),
+         obs.r.ws.mult = ifelse(obs.r.ws.f > 0.75 & obs.r.ws.f < 1, 0.99, obs.r.ws.mult),
+         obs.r.ws.mult = ifelse(obs.r.ws.f == 1, 1, obs.r.ws.mult),
+         loc.r.ws.mult = ifelse(loc.r.ws.f == 0, 0, loc.r.ws.mult),
+         loc.r.ws.mult = ifelse(loc.r.ws.f > 0.00 & loc.r.ws.f <= 0.25, 0.25, loc.r.ws.mult),
+         loc.r.ws.mult = ifelse(loc.r.ws.f > 0.25 & loc.r.ws.f <= 0.50, 0.50, loc.r.ws.mult),
+         loc.r.ws.mult = ifelse(loc.r.ws.f > 0.50 & loc.r.ws.f <= 0.75, 0.75, loc.r.ws.mult),
+         loc.r.ws.mult = ifelse(loc.r.ws.f > 0.75 & loc.r.ws.f < 1, 0.99, loc.r.ws.mult),
+         loc.r.ws.mult = ifelse(loc.r.ws.f == 1, 1, loc.r.ws.mult),
+   ) %>%
+   mutate(obs.r.ws.mult = factor(obs.r.ws.mult, levels = c(0, 0.25, 0.5, 0.75, 0.99, 1)),
+         loc.r.ws.mult = factor(loc.r.ws.mult, levels = c(0, 0.25, 0.5, 0.75, 0.99, 1)))
> caret::confusionMatrix(resource.summary.mult$loc.r.ws.mult,
resource.summary.mult$obs.r.ws.mult)
Confusion Matrix and Statistics

          Reference
Prediction   0 0.25 0.5 0.75 0.99   1
      0    307    0   1    3    1  12
      0.25   3    0   0    0    0   6
      0.5    0    0   1    0    0   2
      0.75   0    0   0    0    0   3
      0.99   0    0   0    0    0  10
      1      4    0   1    1    0  27

Overall Statistics
    Accuracy : 0.877
    95% CI : (0.8398, 0.9082)
    No Information Rate : 0.822
    P-Value [Acc > NIR] : 0.002169
    Kappa : 0.5743

 Mcnemar's Test P-Value : NA
Statistics by Class:

                     Class: 0 Class: 0.25 Class: 0.5 Class: 0.75 Class: 0.99 Class: 1
Sensitivity            0.9777          NA   0.333333    0.000000    0.000000  0.45000
Specificity            0.7500     0.97644   0.994723    0.992063    0.973753  0.98137
Pos Pred Value         0.9475          NA   0.333333    0.000000    0.000000  0.81818
Neg Pred Value         0.8793          NA   0.994723    0.989446    0.997312  0.90544
Prevalence             0.8220     0.00000   0.007853    0.010471    0.002618  0.15707
```

```
Detection Rate         0.8037     0.00000   0.002618    0.000000    0.000000  0.07068
Detection Prevalence   0.8482     0.02356   0.007853    0.007853    0.026178  0.08639
Balanced Accuracy      0.8639          NA   0.664028    0.496032    0.486877  0.71568
## plot
WS <-ggplot(features.5min.val, aes(x=obs.r.ws.f, y=loc.r.ws.f)) + geom_point(alpha =
0.7) +
  stat_smooth(method = "lm", #formula = y ~ x + I(x^2),
              size = 1, colour= "orangered1") +
  geom_abline(slope = 1, intercept = 0, linetype = "dashed") +
  theme_set(theme_light()) +
  labs(y= "classified as in water/salt \nas location by MOOnitor",
       x="observed as in water/salt location")
WS
ggsave("Plots/obs_loc_watersalt_PVALUE.png", height = 4, width = 5)
> #### forage ####
> resource.summary.mult <- as.data.frame(features.5min.val) %>%
+   select(aniID, obs.r.fg.f, obs.pos.t.f, obs.r.fg.f,
+          loc.r.fg.f, loc.pos.t.f, loc.r.fg.f,
+          length.m) %>%
+   arrange(aniID) %>%
+   #  filter(length.m == 0) %>%
+   mutate(obs.r.fg.mult = NA,
+          loc.r.fg.mult = NA) %>%
+   mutate(obs.r.fg.mult = ifelse(obs.r.fg.f == 0, 0, obs.r.fg.mult),
+          obs.r.fg.mult = ifelse(obs.r.fg.f > 0.00 & obs.r.fg.f <= 0.25, 0.25, obs.r.fg.mult),
+          obs.r.fg.mult = ifelse(obs.r.fg.f > 0.25 & obs.r.fg.f <= 0.50, 0.50, obs.r.fg.mult),
+          obs.r.fg.mult = ifelse(obs.r.fg.f > 0.50 & obs.r.fg.f <= 0.75, 0.75, obs.r.fg.mult),
+          obs.r.fg.mult = ifelse(obs.r.fg.f > 0.75 & obs.r.fg.f < 1, 0.99, obs.r.fg.mult),
+          obs.r.fg.mult = ifelse(obs.r.fg.f == 1, 1, obs.r.fg.mult),
+          loc.r.fg.mult = ifelse(loc.r.fg.f == 0, 0, loc.r.fg.mult),
+          loc.r.fg.mult = ifelse(loc.r.fg.f > 0.00 & loc.r.fg.f <= 0.25, 0.25, loc.r.fg.mult),
+          loc.r.fg.mult = ifelse(loc.r.fg.f > 0.25 & loc.r.fg.f <= 0.50, 0.50, loc.r.fg.mult),
+          loc.r.fg.mult = ifelse(loc.r.fg.f > 0.50 & loc.r.fg.f <= 0.75, 0.75, loc.r.fg.mult),
+          loc.r.fg.mult = ifelse(loc.r.fg.f > 0.75 & loc.r.fg.f < 1, 0.99, loc.r.fg.mult),
+          loc.r.fg.mult = ifelse(loc.r.fg.f == 1, 1, loc.r.fg.mult),
+   ) %>%
+   mutate(obs.r.fg.mult = as.factor(obs.r.fg.mult),
+          loc.r.fg.mult = as.factor(loc.r.fg.mult))
> caret::confusionMatrix(resource.summary.mult$loc.r.fg.mult,
resource.summary.mult$obs.r.fg.mult)
Confusion Matrix and Statistics

          Reference
Prediction   0 0.25 0.5 0.75 0.99   1
      0     79    0   4    1    3  20
      0.25   9    0   0    0    0   0
```

```
     0.5    3    0   2    0    1   4
     0.75  11    3   1    1    0   0
     0.99  13    3   1    1    5  10
     1     22    3   5    2    4 168

Overall Statistics
    Accuracy : 0.6728
     95% CI : (0.6231, 0.7199)
    No Information Rate : 0.533
    P-Value [Acc > NIR] : 2.205e-08
    Kappa : 0.4602

 Mcnemar's Test P-Value : NA
Statistics by Class:

                     Class: 0 Class: 0.25 Class: 0.5 Class: 0.75 Class: 0.99 Class: 1
Sensitivity            0.5766     0.00000   0.153846    0.200000     0.38462   0.8317
Specificity            0.8843     0.97568   0.978142    0.959893     0.92350   0.7966
Pos Pred Value         0.7383     0.00000   0.200000    0.062500     0.15152   0.8235
Neg Pred Value         0.7868     0.97568   0.970190    0.988981     0.97688   0.8057
Prevalence             0.3615     0.02375   0.034301    0.013193     0.03430   0.5330
Detection Rate         0.2084     0.00000   0.005277    0.002639     0.01319   0.4433
Detection Prevalence   0.2823     0.02375   0.026385    0.042216     0.08707   0.5383
Balanced Accuracy      0.7305     0.48784   0.565994    0.579947     0.65406   0.8141
## plot

FG <- ggplot(features.5min.val, aes(x=obs.r.fg.f, y=loc.r.fg.f)) + geom_point(alpha =
0.7) +
  stat_smooth(method = "lm", #formula = y ~ x + I(x^2),
              size = 1, colour= "orangered1") +
  geom_abline(slope = 1, intercept = 0, linetype = "dashed") +
  theme_set(theme_light()) +
  labs(y= "classified as in forage \n location by MOOnitor",
       x="observed as in forage location")
FG
ggsave("Plots/obs_loc_forage_PVALUE.png", height = 4, width = 5)
> #### shade ####
> resource.summary.mult <- as.data.frame(features.5min.val) %>%
+   select(aniID, obs.r.sh.f, obs.r.sh.f, obs.r.sh.f,
+          loc.r.sh.f, loc.r.sh.f, loc.r.sh.f) %>%
+   arrange(aniID) %>%
+   mutate(obs.r.sh.mult = NA,
+          loc.r.sh.mult = NA) %>%
+   mutate(obs.r.sh.mult = ifelse(obs.r.sh.f == 0, 0, obs.r.sh.mult),
+          obs.r.sh.mult = ifelse(obs.r.sh.f > 0.00 & obs.r.sh.f <= 0.25, 0.25, obs.r.sh.mult),
+          obs.r.sh.mult = ifelse(obs.r.sh.f > 0.25 & obs.r.sh.f <= 0.50, 0.50, obs.r.sh.mult),
```

```
+         obs.r.sh.mult = ifelse(obs.r.sh.f > 0.50 & obs.r.sh.f <= 0.75, 0.75, obs.r.sh.mult),
+         obs.r.sh.mult = ifelse(obs.r.sh.f > 0.75 & obs.r.sh.f < 1, 0.99, obs.r.sh.mult),
+         obs.r.sh.mult = ifelse(obs.r.sh.f == 1, 1, obs.r.sh.mult),
+         loc.r.sh.mult = ifelse(loc.r.sh.f == 0, 0, loc.r.sh.mult),
+         loc.r.sh.mult = ifelse(loc.r.sh.f > 0.00 & loc.r.sh.f <= 0.25, 0.25, loc.r.sh.mult),
+         loc.r.sh.mult = ifelse(loc.r.sh.f > 0.25 & loc.r.sh.f <= 0.50, 0.50, loc.r.sh.mult),
+         loc.r.sh.mult = ifelse(loc.r.sh.f > 0.50 & loc.r.sh.f <= 0.75, 0.75, loc.r.sh.mult),
+         loc.r.sh.mult = ifelse(loc.r.sh.f > 0.75 & loc.r.sh.f < 1, 0.99, loc.r.sh.mult),
+         loc.r.sh.mult = ifelse(loc.r.sh.f == 1, 1, loc.r.sh.mult),
+   ) %>%
+   mutate(obs.r.sh.mult = as.factor(obs.r.sh.mult),
+         loc.r.sh.mult = as.factor(loc.r.sh.mult))
> caret::confusionMatrix(resource.summary.mult$loc.r.sh.mult,
resource.summary.mult$obs.r.sh.mult)
Confusion Matrix and Statistics

          Reference
Prediction   0 0.25 0.5 0.75 0.99   1
      0    261    4   1    2    3  24
      0.25   5    5   1    0    3   7
      0.5    0    1   0    1    2   7
      0.75   2    0   0    2    0   3
      0.99   0    0   0    0    0   1
      1      5    3   0    2    0  38

Overall Statistics
  Accuracy : 0.799
   95% CI : (0.7553, 0.838)
    No Information Rate : 0.7128
    P-Value [Acc > NIR] : 7.497e-05
    Kappa : 0.524

 Mcnemar's Test P-Value : NA
Statistics by Class:

                     Class: 0 Class: 0.25 Class: 0.5 Class: 0.75 Class: 0.99 Class: 1
Sensitivity            0.9560     0.38462   0.000000    0.285714    0.000000  0.47500
Specificity            0.6909     0.95676   0.971129    0.986702    0.997333  0.96700
Pos Pred Value         0.8847     0.23810   0.000000    0.285714    0.000000  0.79167
Neg Pred Value         0.8636     0.97790   0.994624    0.986702    0.979058  0.87463
Prevalence             0.7128     0.03394   0.005222    0.018277    0.020888  0.20888
Detection Rate         0.6815     0.01305   0.000000    0.005222    0.000000  0.09922
Detection Prevalence   0.7702     0.05483   0.028721    0.018277    0.002611  0.12533
Balanced Accuracy      0.8235     0.67069   0.485564    0.636208    0.498667  0.72100
## plot
```

```
SH <- ggplot(features.5min.val, aes(x=obs.r.sh.f, y=loc.r.sh.f)) + geom_point(alpha =
0.7) +
  stat_smooth(method = "lm", #formula = y ~ x + I(x^2),
              size = 1, colour= "orangered1") +
  geom_abline(slope = 1, intercept = 0, linetype = "dashed") +
  theme_set(theme_light()) +
  labs(y= "classified as in shade \n location by MOOnitor",
       x="observed as in shade location")
SH
ggsave("Plots/obs_loc_shade_PVALUE.png", height = 4, width = 5)
#### combine plots ####
ggarrange(WS, FG, SH + rremove("x.text"),
          labels = c("A)", "B)", "C)"),
          ncol = 1, nrow = 3,
          align = "v")
ggsave("Plots/resources_combined.png", height = 7.5, width = 8)
>   #### resource overall ####
>  resource.summary.mult <- as.data.frame(features.5min.val) %>%
+     select(aniID, assignPasture,
+            obs.r.ws.f:obs.r.fg.f,
+            loc.r.ws.f:loc.r.fg.f
+     ) %>%
+     arrange(aniID) %>%
+     mutate(obs.dominant.res = NA,
+            loc.dominant.res = NA) %>%
+     mutate(obs.dominant.res.max = pmax(obs.r.ws.f, obs.r.sh.f, obs.r.fg.f)) %>%
+     mutate(obs.dominant.res = ifelse(obs.dominant.res.max == obs.r.ws.f, "W",
obs.dominant.res),
+            obs.dominant.res = ifelse(obs.dominant.res.max == obs.r.sh.f, "S",
obs.dominant.res),
+            obs.dominant.res = ifelse(obs.dominant.res.max == obs.r.fg.f, "F",
obs.dominant.res),
+     ) %>%
+     mutate(loc.dominant.res.max = pmax(loc.r.ws.f, loc.r.sh.f, loc.r.fg.f)) %>%
+     mutate(loc.dominant.res = ifelse(loc.dominant.res.max == loc.r.ws.f, "W",
loc.dominant.res),
+            loc.dominant.res = ifelse(loc.dominant.res.max == loc.r.sh.f, "S",
loc.dominant.res),
+            loc.dominant.res = ifelse(loc.dominant.res.max == loc.r.fg.f, "F",
loc.dominant.res),
+     ) %>%
+     mutate(obs.dominant.res = as.factor(obs.dominant.res),
+            loc.dominant.res = as.factor(loc.dominant.res))
>   caret::confusionMatrix(resource.summary.mult$loc.dominant.res,
resource.summary.mult$obs.dominant.res)
Confusion Matrix and Statistics
```

```
          Reference
Prediction   F   S   W
         F 207  49  22
         S  10  46   0
         W   5   0  44

Overall Statistics
  Accuracy : 0.7755
   95% CI : (0.7303, 0.8163)
    No Information Rate : 0.5796
    P-Value [Acc > NIR] : 6.087e-16
    Kappa : 0.569

 Mcnemar's Test P-Value : NA
Statistics by Class:

                     Class: F Class: S Class: W
Sensitivity           0.9324   0.4842   0.6667
Specificity           0.5590   0.9653   0.9842
Pos Pred Value        0.7446   0.8214   0.8980
Neg Pred Value        0.8571   0.8502   0.9341
Prevalence            0.5796   0.2480   0.1723
Detection Rate        0.5405   0.1201   0.1149
Detection Prevalence  0.7258   0.1462   0.1279
Balanced Accuracy     0.7457   0.7247   0.8254
> ##### POSITION ####
> #### terrace top ####
> position.summary.mult <- as.data.frame(features.5min.val) %>%
+   select(aniID, obs.pos.t.f, obs.pos.t.f, obs.pos.t.f,
+          loc.pos.t.f, loc.pos.t.f, loc.pos.t.f) %>%
+   arrange(aniID) %>%
+   mutate(obs.pos.t.mult = NA,
+          loc.pos.t.mult = NA) %>%
+   mutate(obs.pos.t.mult = ifelse(obs.pos.t.f == 0, 0, obs.pos.t.mult),
+          obs.pos.t.mult = ifelse(obs.pos.t.f > 0.00 & obs.pos.t.f <= 0.25, 0.25,
obs.pos.t.mult),
+          obs.pos.t.mult = ifelse(obs.pos.t.f > 0.25 & obs.pos.t.f <= 0.50, 0.50,
obs.pos.t.mult),
+          obs.pos.t.mult = ifelse(obs.pos.t.f > 0.50 & obs.pos.t.f <= 0.75, 0.75,
obs.pos.t.mult),
+          obs.pos.t.mult = ifelse(obs.pos.t.f > 0.75 & obs.pos.t.f < 1, 0.99, obs.pos.t.mult),
+          obs.pos.t.mult = ifelse(obs.pos.t.f == 1, 1, obs.pos.t.mult),
+          loc.pos.t.mult = ifelse(loc.pos.t.f == 0, 0, loc.pos.t.mult),
+          loc.pos.t.mult = ifelse(loc.pos.t.f > 0.00 & loc.pos.t.f <= 0.25, 0.25,
loc.pos.t.mult),
```

```
+         loc.pos.t.mult = ifelse(loc.pos.t.f > 0.25 & loc.pos.t.f <= 0.50, 0.50,
loc.pos.t.mult),
+         loc.pos.t.mult = ifelse(loc.pos.t.f > 0.50 & loc.pos.t.f <= 0.75, 0.75,
loc.pos.t.mult),
+         loc.pos.t.mult = ifelse(loc.pos.t.f > 0.75 & loc.pos.t.f < 1, 0.99, loc.pos.t.mult),
+         loc.pos.t.mult = ifelse(loc.pos.t.f == 1, 1, loc.pos.t.mult),
+   ) %>%
+   mutate(obs.pos.t.mult = as.factor(obs.pos.t.mult),
+         loc.pos.t.mult = as.factor(loc.pos.t.mult))
> caret::confusionMatrix(position.summary.mult$loc.pos.t.mult,
position.summary.mult$obs.pos.t.mult)
Confusion Matrix and Statistics

          Reference
Prediction   0 0.25 0.5 0.75 0.99   1
     0    173    8   4    2    1  11
     0.25  27   13   6    2    1   1
     0.5    3    0   1    1    1   0
     0.75   0    0   0    0    0   0
     0.99   1    0   0    0    0   0
     1      2    0   0    0    0   0

Overall Statistics
    Accuracy : 0.7248
     95% CI : (0.666, 0.7784)
    No Information Rate : 0.7984
    P-Value [Acc > NIR] : 0.9983
    Kappa : 0.2501

 Mcnemar's Test P-Value : NA
Statistics by Class:

                     Class: 0 Class: 0.25 Class: 0.5 Class: 0.75 Class: 0.99 Class: 1
Sensitivity            0.8398     0.61905   0.090909     0.00000    0.000000 0.000000
Specificity            0.5000     0.84388   0.979757     1.00000    0.996078 0.991870
Pos Pred Value         0.8693     0.26000   0.166667         NaN    0.000000 0.000000
Neg Pred Value         0.4407     0.96154   0.960317     0.98062    0.988327 0.953125
Prevalence             0.7984     0.08140   0.042636     0.01938    0.011628 0.046512
Detection Rate         0.6705     0.05039   0.003876     0.00000    0.000000 0.000000
Detection Prevalence   0.7713     0.19380   0.023256     0.00000    0.003876 0.007752
Balanced Accuracy      0.6699     0.73146   0.535333     0.50000    0.498039 0.495935
## plot

TT <- ggplot(features.5min.val, aes(x=obs.pos.t.f, y=loc.pos.t.f)) + geom_point(alpha =
0.7) +
  stat_smooth(method = "lm", #formula = y ~ x + I(x^2),
```

```
            size = 1, colour= "orangered1") +
  geom_abline(slope = 1, intercept = 0, linetype = "dashed") +
  theme_set(theme_light()) +
  labs(y= "classified as in terrace \n top by MOOnitor",
      x=" observed as in terrace top")
TT
ggsave("Plots/obs_loc_terrace_top_PVALUE.png", height = 4, width = 5)
> #### terrace bottom ####
> position.summary.mult <- as.data.frame(features.5min.val) %>%
+   select(aniID, obs.pos.b.f, obs.pos.b.f, obs.pos.b.f,
+          loc.pos.b.f, loc.pos.b.f, loc.pos.b.f) %>%
+   arrange(aniID) %>%
+   mutate(obs.pos.b.mult = NA,
+          loc.pos.b.mult = NA) %>%
+   mutate(obs.pos.b.mult = ifelse(obs.pos.b.f == 0, 0, obs.pos.b.mult),
+          obs.pos.b.mult = ifelse(obs.pos.b.f > 0.00 & obs.pos.b.f <= 0.25, 0.25,
obs.pos.b.mult),
+          obs.pos.b.mult = ifelse(obs.pos.b.f > 0.25 & obs.pos.b.f <= 0.50, 0.50,
obs.pos.b.mult),
+          obs.pos.b.mult = ifelse(obs.pos.b.f > 0.50 & obs.pos.b.f <= 0.75, 0.75,
obs.pos.b.mult),
+          obs.pos.b.mult = ifelse(obs.pos.b.f > 0.75 & obs.pos.b.f < 1, 0.99,
obs.pos.b.mult),
+          obs.pos.b.mult = ifelse(obs.pos.b.f == 1, 1, obs.pos.b.mult),
+          loc.pos.b.mult = ifelse(loc.pos.b.f == 0, 0, loc.pos.b.mult),
+          loc.pos.b.mult = ifelse(loc.pos.b.f > 0.00 & loc.pos.b.f <= 0.25, 0.25,
loc.pos.b.mult),
+          loc.pos.b.mult = ifelse(loc.pos.b.f > 0.25 & loc.pos.b.f <= 0.50, 0.50,
loc.pos.b.mult),
+          loc.pos.b.mult = ifelse(loc.pos.b.f > 0.50 & loc.pos.b.f <= 0.75, 0.75,
loc.pos.b.mult),
+          loc.pos.b.mult = ifelse(loc.pos.b.f > 0.75 & loc.pos.b.f < 1, 0.99, loc.pos.b.mult),
+          loc.pos.b.mult = ifelse(loc.pos.b.f == 1, 1, loc.pos.b.mult),
+   ) %>%
+   mutate(obs.pos.b.mult = as.factor(obs.pos.b.mult),
+          loc.pos.b.mult = as.factor(loc.pos.b.mult))
> caret::confusionMatrix(position.summary.mult$loc.pos.b.mult,
position.summary.mult$obs.pos.b.mult)
Confusion Matrix and Statistics

          Reference
Prediction   0 0.25 0.5 0.75 0.99   1
      0    169    3   9    3    0   6
      0.25  16   16  11    4    6   0
      0.5    5    0   0    0    0   0
      0.75   3    0   0    1    0   0
```

```
  0.99   2    0   0    0    0   1
  1      2    1   0    0    0   0

Overall Statistics
 Accuracy : 0.7209
   95% CI : (0.6619, 0.7748)
    No Information Rate : 0.7636
    P-Value [Acc > NIR] : 0.9519
    Kappa : 0.3343

 Mcnemar's Test P-Value : NA
Statistics by Class:

                     Class: 0 Class: 0.25 Class: 0.5 Class: 0.75 Class: 0.99 Class: 1
Sensitivity            0.8579     0.80000    0.00000    0.125000     0.00000  0.00000
Specificity            0.6557     0.84454    0.97899    0.988000     0.98810  0.98805
Pos Pred Value         0.8895     0.30189    0.00000    0.250000     0.00000  0.00000
Neg Pred Value         0.5882     0.98049    0.92095    0.972441     0.97647  0.97255
Prevalence             0.7636     0.07752    0.07752    0.031008     0.02326  0.02713
Detection Rate         0.6550     0.06202    0.00000    0.003876     0.00000  0.00000
Detection Prevalence   0.7364     0.20543    0.01938    0.015504     0.01163  0.01163
Balanced Accuracy      0.7568     0.82227    0.48950    0.556500     0.49405  0.49402

## plot

TB <-ggplot(features.5min.val, aes(x=obs.pos.b.f, y=loc.pos.b.f)) + geom_point(alpha = 
0.7) +
  stat_smooth(method = "lm", #formula = y ~ x + I(x^2),
              size = 1, colour= "orangered1") +
  geom_abline(slope = 1, intercept = 0, linetype = "dashed") +
  theme_set(theme_light()) +
  labs(y= "classified as in terrace \n bottom by MOOnitor",
       x="observed as in terrace bottom")
TB
ggsave("Plots/obs_loc_terrace_bottom_PVALUE.png", height = 4, width = 5)
> #### terrace middle ####
> position.summary.mult <- as.data.frame(features.5min.val) %>%
+   select(aniID, obs.pos.i.f, obs.pos.i.f, obs.pos.i.f,
+          loc.pos.i.f, loc.pos.i.f, loc.pos.i.f) %>%
+   arrange(aniID) %>%
+   mutate(obs.pos.i.mult = NA,
+          loc.pos.i.mult = NA) %>%
+   mutate(obs.pos.i.mult = ifelse(obs.pos.i.f == 0, 0, obs.pos.i.mult),
+          obs.pos.i.mult = ifelse(obs.pos.i.f > 0.00 & obs.pos.i.f <= 0.25, 0.25, 
obs.pos.i.mult),
```

```
+         obs.pos.i.mult = ifelse(obs.pos.i.f > 0.25 & obs.pos.i.f <= 0.50, 0.50,
obs.pos.i.mult),
+         obs.pos.i.mult = ifelse(obs.pos.i.f > 0.50 & obs.pos.i.f <= 0.75, 0.75,
obs.pos.i.mult),
+         obs.pos.i.mult = ifelse(obs.pos.i.f > 0.75 & obs.pos.i.f < 1, 0.99, obs.pos.i.mult),
+         obs.pos.i.mult = ifelse(obs.pos.i.f == 1, 1, obs.pos.i.mult),
+         loc.pos.i.mult = ifelse(loc.pos.i.f == 0, 0, loc.pos.i.mult),
+         loc.pos.i.mult = ifelse(loc.pos.i.f > 0.00 & loc.pos.i.f <= 0.25, 0.25,
loc.pos.i.mult),
+         loc.pos.i.mult = ifelse(loc.pos.i.f > 0.25 & loc.pos.i.f <= 0.50, 0.50,
loc.pos.i.mult),
+         loc.pos.i.mult = ifelse(loc.pos.i.f > 0.50 & loc.pos.i.f <= 0.75, 0.75,
loc.pos.i.mult),
+         loc.pos.i.mult = ifelse(loc.pos.i.f > 0.75 & loc.pos.i.f < 1, 0.99, loc.pos.i.mult),
+         loc.pos.i.mult = ifelse(loc.pos.i.f == 1, 1, loc.pos.i.mult),
+   ) %>%
+   mutate(obs.pos.i.mult = as.factor(obs.pos.i.mult),
+         loc.pos.i.mult = as.factor(loc.pos.i.mult))
> caret::confusionMatrix(position.summary.mult$loc.pos.i.mult,
position.summary.mult$obs.pos.i.mult)
Confusion Matrix and Statistics

          Reference
Prediction  0 0.25 0.5 0.75 0.99  1
      0    11    0   1    0    1 12
      0.25  3    0   0    0    0  2
      0.5   3    0   2    0    0  2
      0.75 10    6   1    2    4  8
      0.99 11    3   6    8    7  7
      1    52    3   3    8    2 79

Overall Statistics
Accuracy : 0.393
  95% CI : (0.3329, 0.4556)
    No Information Rate : 0.428
    P-Value [Acc > NIR] : 0.8848
Kappa : 0.1347

 Mcnemar's Test P-Value : NA
Statistics by Class:

                     Class: 0 Class: 0.25 Class: 0.5 Class: 0.75 Class: 0.99 Class: 1
Sensitivity           0.12222     0.00000   0.153846    0.111111     0.50000   0.7182
Specificity           0.91617     0.97959   0.979508    0.878661     0.85597   0.5374
Pos Pred Value        0.44000     0.00000   0.285714    0.064516     0.16667   0.5374
Neg Pred Value        0.65948     0.95238   0.956000    0.929204     0.96744   0.7182
```

```
Prevalence           0.35019    0.04669  0.050584   0.070039    0.05447  0.4280
Detection Rate       0.04280    0.00000  0.007782   0.007782    0.02724  0.3074
Detection Prevalence 0.09728    0.01946  0.027237   0.120623    0.16342  0.5720
Balanced Accuracy    0.51919    0.48980  0.566677   0.494886    0.67798  0.6278
## plot

IBT <- ggplot(features.5min.val, aes(x=obs.pos.i.f, y=loc.pos.i.f)) + geom_point(alpha = 0.7) +
  stat_smooth(method = "lm", #formula = y ~ x + I(x^2),
              size = 1, colour= "orangered1") +
  geom_abline(slope = 1, intercept = 0, linetype = "dashed") +
  theme_set(theme_light()) +
  labs(y= "classified as in between\n terrace by MOOnitor",
       x="observed as in between terrace")
IBT
ggsave("Plots/obs_loc_terrace_middle_PVALUE.png", height = 4, width = 5)
####combine plots ####
ggarrange(TT, TB, IBT + rremove("x.text"),
          labels = c("A)", "B)", "C)"),
          ncol = 1, nrow = 3,
          align = "v")
ggsave("Plots/terraces_combined.png", height = 7.5, width = 8)
> #### TERRACE OVERALL ####
> position.summary.mult <- as.data.frame(features.5min.val) %>%
+   select(aniID, assignPasture,
+          obs.pos.i.f, obs.pos.b.f, obs.pos.t.f,
+          loc.pos.i.f, loc.pos.b.f, loc.pos.t.f
+   ) %>%
+   arrange(aniID) %>%
+   mutate(obs.dominant.pos = NA,
+          loc.dominant.pos = NA) %>%
+   mutate(obs.dominant.pos.max = pmax(obs.pos.i.f, obs.pos.b.f, obs.pos.t.f)) %>%
+   mutate(obs.dominant.pos = ifelse(obs.dominant.pos.max == obs.pos.i.f, "I",
obs.dominant.pos),
+          obs.dominant.pos = ifelse(obs.dominant.pos.max == obs.pos.b.f, "B",
obs.dominant.pos),
+          obs.dominant.pos = ifelse(obs.dominant.pos.max == obs.pos.t.f, "T",
obs.dominant.pos),
+   ) %>%
+   mutate(loc.dominant.pos.max = pmax(loc.pos.i.f, loc.pos.b.f, loc.pos.t.f)) %>%
+   mutate(loc.dominant.pos = ifelse(loc.dominant.pos.max == loc.pos.i.f, "I",
loc.dominant.pos),
+          loc.dominant.pos = ifelse(loc.dominant.pos.max == loc.pos.b.f, "B",
loc.dominant.pos),
+          loc.dominant.pos = ifelse(loc.dominant.pos.max == loc.pos.t.f, "T",
loc.dominant.pos),
```

```
+    ) %>%
+    mutate(obs.dominant.pos = as.factor(obs.dominant.pos),
+           loc.dominant.pos = as.factor(loc.dominant.pos))
>   caret::confusionMatrix(position.summary.mult$loc.dominant.pos,
position.summary.mult$obs.dominant.pos)
Confusion Matrix and Statistics

          Reference
Prediction   B   I   T
         B   2   4   4
         I  22 136  69
         T   0  12   9

Overall Statistics
Accuracy : 0.5698
 95% CI : (0.5069, 0.631)
    No Information Rate : 0.5891
    P-Value [Acc > NIR] : 0.7574
Kappa : 0.0485
 Mcnemar's Test P-Value : 3.171e-12
Statistics by Class:
                     Class: B Class: I Class: T
Sensitivity          0.083333   0.8947  0.10976
Specificity          0.965812   0.1415  0.93182
Pos Pred Value       0.200000   0.5991  0.42857
Neg Pred Value       0.911290   0.4839  0.69198
Prevalence           0.093023   0.5891  0.31783
Detection Rate       0.007752   0.5271  0.03488
Detection Prevalence 0.038760   0.8798  0.08140
Balanced Accuracy    0.524573   0.5181  0.52079
> ##### PATCH  ####
> #### patch A ####
>   patch.summary.mult <- as.data.frame(features.5min.val) %>%
+    select(aniID, assignPasture,
+           obs.pat.A.f, obs.pat.A.f, obs.pat.A.f,
+           loc.pat.A.f, loc.pat.A.f, loc.pat.A.f) %>%
+    arrange(aniID) %>%
+    mutate(obs.pat.A.mult = NA,
+           loc.pat.A.mult = NA) %>%
+    filter(assignPasture %in% c("51S", "56S", "57N")) %>%
+    mutate(obs.pat.A.mult = ifelse(obs.pat.A.f == 0, 0, obs.pat.A.mult),
+           obs.pat.A.mult = ifelse(obs.pat.A.f > 0.00 & obs.pat.A.f <= 0.25, 0.25,
obs.pat.A.mult),
+           obs.pat.A.mult = ifelse(obs.pat.A.f > 0.25 & obs.pat.A.f <= 0.50, 0.50,
obs.pat.A.mult),
```

```
+           obs.pat.A.mult = ifelse(obs.pat.A.f > 0.50 & obs.pat.A.f <= 0.75, 0.75,
obs.pat.A.mult),
+           obs.pat.A.mult = ifelse(obs.pat.A.f > 0.75 & obs.pat.A.f < 1, 0.99,
obs.pat.A.mult),
+           obs.pat.A.mult = ifelse(obs.pat.A.f == 1, 1, obs.pat.A.mult),
+           loc.pat.A.mult = ifelse(loc.pat.A.f == 0, 0, loc.pat.A.mult),
+           loc.pat.A.mult = ifelse(loc.pat.A.f > 0.00 & loc.pat.A.f <= 0.25, 0.25,
loc.pat.A.mult),
+           loc.pat.A.mult = ifelse(loc.pat.A.f > 0.25 & loc.pat.A.f <= 0.50, 0.50,
loc.pat.A.mult),
+           loc.pat.A.mult = ifelse(loc.pat.A.f > 0.50 & loc.pat.A.f <= 0.75, 0.75,
loc.pat.A.mult),
+           loc.pat.A.mult = ifelse(loc.pat.A.f > 0.75 & loc.pat.A.f < 1, 0.99,
loc.pat.A.mult),
+           loc.pat.A.mult = ifelse(loc.pat.A.f == 1, 1, loc.pat.A.mult),
+    ) %>%
+    mutate(obs.pat.A.mult = factor(obs.pat.A.mult, levels = c(0, 0.25, 0.5, 0.75, 0.99,
1)),
+           loc.pat.A.mult = factor(loc.pat.A.mult, levels = c(0, 0.25, 0.5, 0.75, 0.99, 1)))
>   caret::confusionMatrix(patch.summary.mult$loc.pat.A.mult,
patch.summary.mult$obs.pat.A.mult)
Confusion Matrix and Statistics

          Reference
Prediction   0 0.25 0.5 0.75 0.99   1
      0    101    0   0    1    1   3
      0.25   2    0   0    0    0   0
      0.5    0    0   0    0    0   0
      0.75   2    0   0    0    0   2
      0.99   0    0   1    0    0   5
      1      6    0   1    1    1  77

Overall Statistics
Accuracy : 0.8725
95% CI : (0.8189, 0.915)
    No Information Rate : 0.5441
    P-Value [Acc > NIR] : < 2.2e-16
Kappa : 0.7627

 Mcnemar's Test P-Value : NA

Statistics by Class:

                     Class: 0 Class: 0.25 Class: 0.5 Class: 0.75 Class: 0.99 Class: 1
Sensitivity            0.9099          NA   0.000000    0.000000    0.000000   0.8851
Specificity            0.9462    0.990196   1.000000    0.980198    0.970297   0.9231
```

```
Pos Pred Value        0.9528         NA        NaN    0.000000    0.000000   0.8953
Neg Pred Value        0.8980         NA   0.990196    0.990000    0.989899   0.9153
Prevalence            0.5441    0.000000   0.009804    0.009804    0.009804   0.4265
Detection Rate        0.4951    0.000000   0.000000    0.000000    0.000000   0.3775
Detection Prevalence   0.5196    0.009804   0.000000    0.019608    0.029412   0.4216
Balanced Accuracy      0.9281         NA   0.500000    0.490099    0.485149   0.9041
## plot

PA <- ggplot(features.5min.val, aes(x=obs.pat.A.f, y=loc.pat.A.f)) + geom_point(alpha =
0.7) +
   stat_smooth(method = "lm", #formula = y ~ x + I(x^2),
              size = 1, colour= "orangered1") +
   geom_abline(slope = 1, intercept = 0, linetype = "dashed") +
   theme_set(theme_light()) +
   labs(y= "classified as in burn \n patch A by MOOnitor",
       x="observed as in burn patch A")
PA
ggsave("Plots/obs_loc_patch_A_PVALUE.png", height = 4, width = 5)
> #### patch B ####
>   patch.summary.mult <- as.data.frame(features.5min.val) %>%
+    select(aniID, assignPasture,
+           obs.pat.B.f, obs.pat.B.f, obs.pat.B.f,
+           loc.pat.B.f, loc.pat.B.f, loc.pat.B.f) %>%
+    arrange(aniID) %>%
+    mutate(obs.pat.B.mult = NA,
+           loc.pat.B.mult = NA) %>%
+    filter(assignPasture %in% c("51S", "56S", "57N")) %>%
+    mutate(obs.pat.B.mult = ifelse(obs.pat.B.f == 0, 0, obs.pat.B.mult),
+           obs.pat.B.mult = ifelse(obs.pat.B.f > 0.00 & obs.pat.B.f <= 0.25, 0.25,
obs.pat.B.mult),
+           obs.pat.B.mult = ifelse(obs.pat.B.f > 0.25 & obs.pat.B.f <= 0.50, 0.50,
obs.pat.B.mult),
+           obs.pat.B.mult = ifelse(obs.pat.B.f > 0.50 & obs.pat.B.f <= 0.75, 0.75,
obs.pat.B.mult),
+           obs.pat.B.mult = ifelse(obs.pat.B.f > 0.75 & obs.pat.B.f < 1, 0.99,
obs.pat.B.mult),
+           obs.pat.B.mult = ifelse(obs.pat.B.f == 1, 1, obs.pat.B.mult),
+           loc.pat.B.mult = ifelse(loc.pat.B.f == 0, 0, loc.pat.B.mult),
+           loc.pat.B.mult = ifelse(loc.pat.B.f > 0.00 & loc.pat.B.f <= 0.25, 0.25,
loc.pat.B.mult),
+           loc.pat.B.mult = ifelse(loc.pat.B.f > 0.25 & loc.pat.B.f <= 0.50, 0.50,
loc.pat.B.mult),
+           loc.pat.B.mult = ifelse(loc.pat.B.f > 0.50 & loc.pat.B.f <= 0.75, 0.75,
loc.pat.B.mult),
+           loc.pat.B.mult = ifelse(loc.pat.B.f > 0.75 & loc.pat.B.f < 1, 0.99, loc.pat.B.mult),
+           loc.pat.B.mult = ifelse(loc.pat.B.f == 1, 1, loc.pat.B.mult),
```

```
+    ) %>%
+    mutate(obs.pat.B.mult = factor(obs.pat.B.mult, levels = c(0, 0.25, 0.5, 0.75, 0.99, 1)),
+           loc.pat.B.mult = factor(loc.pat.B.mult, levels = c(0, 0.25, 0.5, 0.75, 0.99, 1)))
>   caret::confusionMatrix(patch.summary.mult$loc.pat.B.mult,
patch.summary.mult$obs.pat.B.mult)
Confusion Matrix and Statistics

          Reference
Prediction   0 0.25 0.5 0.75 0.99   1
     0    185    0   1    0    0   3
     0.25   2    0   0    0    0   0
     0.5    1    0   0    0    0   1
     0.75   0    0   0    0    1   0
     0.99   0    0   0    0    0   0
     1      1    1   0    0    0   8

Overall Statistics
Accuracy : 0.9461
95% CI : (0.9056, 0.9728)
   No Information Rate : 0.9265
   P-Value [Acc > NIR] : 0.1747
Kappa : 0.6112

 Mcnemar's Test P-Value : NA
Statistics by Class:

                     Class: 0 Class: 0.25 Class: 0.5 Class: 0.75 Class: 0.99 Class: 1
Sensitivity            0.9788    0.000000   0.000000          NA    0.000000  0.66667
Specificity            0.7333    0.990148   0.990148    0.995098    1.000000  0.98958
Pos Pred Value         0.9788    0.000000   0.000000          NA         NaN  0.80000
Neg Pred Value         0.7333    0.995050   0.995050          NA    0.995098  0.97938
Prevalence             0.9265    0.004902   0.004902    0.000000    0.004902  0.05882
Detection Rate         0.9069    0.000000   0.000000    0.000000    0.000000  0.03922
Detection Prevalence   0.9265    0.009804   0.009804    0.004902    0.000000  0.04902
Balanced Accuracy      0.8561    0.495074   0.495074          NA    0.500000  0.82812
## plot

B <-  ggplot(features.5min.val, aes(x=obs.pat.B.f, y=loc.pat.B.f)) + geom_point(alpha =
0.7) +
   stat_smooth(method = "lm", #formula = y ~ x + I(x^2),
            size = 1, colour= "orangered1") +
   geom_abline(slope = 1, intercept = 0, linetype = "dashed") +
   theme_set(theme_light()) +
   labs(y= "classified as in burn \n patch B by MOOnitor",
        x="observed as in burn patch B")
B
```

```
ggsave("Plots/obs_loc_patch_B_PVALUE.png", height = 4, width = 5)
> #### patch C ####
>   patch.summary.mult <- as.data.frame(features.5min.val) %>%
+     select(aniID, assignPasture,
+            obs.pat.C.f, obs.pat.C.f, obs.pat.C.f,
+            loc.pat.C.f, loc.pat.C.f, loc.pat.C.f) %>%
+     arrange(aniID) %>%
+     mutate(obs.pat.C.mult = NA,
+            loc.pat.C.mult = NA) %>%
+     filter(assignPasture %in% c("51S", "56S", "57N")) %>%
+     mutate(obs.pat.C.mult = ifelse(obs.pat.C.f == 0, 0, obs.pat.C.mult),
+            obs.pat.C.mult = ifelse(obs.pat.C.f > 0.00 & obs.pat.C.f <= 0.25, 0.25,
obs.pat.C.mult),
+            obs.pat.C.mult = ifelse(obs.pat.C.f > 0.25 & obs.pat.C.f <= 0.50, 0.50,
obs.pat.C.mult),
+            obs.pat.C.mult = ifelse(obs.pat.C.f > 0.50 & obs.pat.C.f <= 0.75, 0.75,
obs.pat.C.mult),
+            obs.pat.C.mult = ifelse(obs.pat.C.f > 0.75 & obs.pat.C.f < 1, 0.99,
obs.pat.C.mult),
+            obs.pat.C.mult = ifelse(obs.pat.C.f == 1, 1, obs.pat.C.mult),
+            loc.pat.C.mult = ifelse(loc.pat.C.f == 0, 0, loc.pat.C.mult),
+            loc.pat.C.mult = ifelse(loc.pat.C.f > 0.00 & loc.pat.C.f <= 0.25, 0.25,
loc.pat.C.mult),
+            loc.pat.C.mult = ifelse(loc.pat.C.f > 0.25 & loc.pat.C.f <= 0.50, 0.50,
loc.pat.C.mult),
+            loc.pat.C.mult = ifelse(loc.pat.C.f > 0.50 & loc.pat.C.f <= 0.75, 0.75,
loc.pat.C.mult),
+            loc.pat.C.mult = ifelse(loc.pat.C.f > 0.75 & loc.pat.C.f < 1, 0.99, loc.pat.C.mult),
+            loc.pat.C.mult = ifelse(loc.pat.C.f == 1, 1, loc.pat.C.mult),
+     ) %>%
+     mutate(obs.pat.C.mult = factor(obs.pat.C.mult, levels = c(0, 0.25, 0.5, 0.75, 0.99, 1)),
+            loc.pat.C.mult = factor(loc.pat.C.mult, levels = c(0, 0.25, 0.5, 0.75, 0.99, 1)))
>   caret::confusionMatrix(patch.summary.mult$loc.pat.C.mult,
patch.summary.mult$obs.pat.C.mult)
Confusion Matrix and Statistics

          Reference
Prediction   0 0.25 0.5 0.75 0.99   1
      0    187    0   0    0    1   4
      0.25   0    1   0    0    0   0
      0.5    0    0   0    0    0   2
      0.75   0    0   0    0    0   2
      0.99   0    0   0    0    0   1
      1      0    0   0    0    0   6

Overall Statistics
```

```
Accuracy : 0.951
95% CI : (0.9117, 0.9762)
    No Information Rate : 0.9167
    P-Value [Acc > NIR] : 0.04244
Kappa : 0.637

 Mcnemar's Test P-Value : NA
Statistics by Class:

                     Class: 0 Class: 0.25 Class: 0.5 Class: 0.75 Class: 0.99 Class: 1
Sensitivity            1.0000    1.000000        NA          NA    0.000000  0.40000
Specificity            0.7059    1.000000   0.990196    0.990196    0.995074  1.00000
Pos Pred Value         0.9740    1.000000        NA          NA    0.000000  1.00000
Neg Pred Value         1.0000    1.000000        NA          NA    0.995074  0.95455
Prevalence             0.9167    0.004902   0.000000    0.000000    0.004902  0.07353
Detection Rate         0.9167    0.004902   0.000000    0.000000    0.000000  0.02941
Detection Prevalence   0.9412    0.004902   0.009804    0.009804    0.004902  0.02941
Balanced Accuracy      0.8529    1.000000        NA          NA    0.497537  0.70000
  ## plot

C <-  ggplot(features.5min.val, aes(x=obs.pat.C.f, y=loc.pat.C.f)) + geom_point(alpha = 
0.7) +
    stat_smooth(method = "lm", #formula = y ~ x + I(x^2),
                size = 1, colour= "orangered1") +
    geom_abline(slope = 1, intercept = 0, linetype = "dashed") +
    theme_set(theme_light()) +
    labs(y= "classified as in burn \n patch C by MOOnitor",
         x="observed as in burn patch c")
C
ggsave("Plots/obs_loc_patch_c_PVALUE.png", height = 4, width = 5)
> #### patch D ####
>   patch.summary.mult <- as.data.frame(features.5min.val) %>%
+     select(aniID, assignPasture,
+            obs.pat.D.f, obs.pat.D.f, obs.pat.D.f,
+            loc.pat.D.f, loc.pat.D.f, loc.pat.D.f) %>%
+     arrange(aniID) %>%
+     mutate(obs.pat.D.mult = NA,
+            loc.pat.D.mult = NA) %>%
+     filter(assignPasture %in% c("51S", "56S", "57N")) %>%
+     mutate(obs.pat.D.mult = ifelse(obs.pat.D.f == 0, 0, obs.pat.D.mult),
+            obs.pat.D.mult = ifelse(obs.pat.D.f > 0.00 & obs.pat.D.f <= 0.25, 0.25, 
obs.pat.D.mult),
+            obs.pat.D.mult = ifelse(obs.pat.D.f > 0.25 & obs.pat.D.f <= 0.50, 0.50, 
obs.pat.D.mult),
+            obs.pat.D.mult = ifelse(obs.pat.D.f > 0.50 & obs.pat.D.f <= 0.75, 0.75, 
obs.pat.D.mult),
```

```
+           obs.pat.D.mult = ifelse(obs.pat.D.f > 0.75 & obs.pat.D.f < 1, 0.99,
obs.pat.D.mult),
+           obs.pat.D.mult = ifelse(obs.pat.D.f == 1, 1, obs.pat.D.mult),
+           loc.pat.D.mult = ifelse(loc.pat.D.f == 0, 0, loc.pat.D.mult),
+           loc.pat.D.mult = ifelse(loc.pat.D.f > 0.00 & loc.pat.D.f <= 0.25, 0.25,
loc.pat.D.mult),
+           loc.pat.D.mult = ifelse(loc.pat.D.f > 0.25 & loc.pat.D.f <= 0.50, 0.50,
loc.pat.D.mult),
+           loc.pat.D.mult = ifelse(loc.pat.D.f > 0.50 & loc.pat.D.f <= 0.75, 0.75,
loc.pat.D.mult),
+           loc.pat.D.mult = ifelse(loc.pat.D.f > 0.75 & loc.pat.D.f < 1, 0.99,
loc.pat.D.mult),
+           loc.pat.D.mult = ifelse(loc.pat.D.f == 1, 1, loc.pat.D.mult),
+    ) %>%
+    mutate(obs.pat.D.mult = factor(obs.pat.D.mult, levels = c(0, 0.25, 0.5, 0.75, 0.99,
1)),
+           loc.pat.D.mult = factor(loc.pat.D.mult, levels = c(0, 0.25, 0.5, 0.75, 0.99, 1)))
>   caret::confusionMatrix(patch.summary.mult$loc.pat.D.mult,
patch.summary.mult$obs.pat.D.mult)
Confusion Matrix and Statistics

          Reference
Prediction   0 0.25 0.5 0.75 0.99   1
      0    146    1   1    0    0  16
      0.25   0    0   0    0    0   0
      0.5    0    0   0    0    0   1
      0.75   0    0   0    0    0   2
      0.99   0    0   0    0    0   4
      1      0    0   0    0    0  33

Overall Statistics
Accuracy : 0.8775
  95% CI : (0.8244, 0.9191)
    No Information Rate : 0.7157
    P-Value [Acc > NIR] : 2.547e-08
Kappa : 0.6777

 Mcnemar's Test P-Value : NA
Statistics by Class:

                     Class: 0 Class: 0.25 Class: 0.5 Class: 0.75 Class: 0.99 Class: 1
Sensitivity            1.0000    0.000000   0.000000          NA          NA   0.5893
Specificity            0.6897    1.000000   0.995074    0.990196     0.98039   1.0000
Pos Pred Value         0.8902         NaN   0.000000          NA          NA   1.0000
Neg Pred Value         1.0000    0.995098   0.995074          NA          NA   0.8655
Prevalence             0.7157    0.004902   0.004902    0.000000     0.00000   0.2745
```

```
Detection Rate         0.7157    0.000000   0.000000    0.000000     0.00000   0.1618
Detection Prevalence   0.8039    0.000000   0.004902    0.009804     0.01961   0.1618
Balanced Accuracy      0.8448    0.500000   0.497537         NA          NA   0.7946
## plot

D <-  ggplot(features.5min.val, aes(x=obs.pat.D.f, y=loc.pat.D.f)) + geom_point(alpha =
0.7) +
   stat_smooth(method = "lm", #formula = y ~ x + I(x^2),
             size = 1, colour= "orangered1") +
   geom_abline(slope = 1, intercept = 0, linetype = "dashed") +
   theme_set(theme_light()) +
   labs(y= "classified as in burn \n patch D by MOOnitor",
       x="observed as in burn patch D")
D
  ggsave("Plots/obs_loc_patch_D_PVALUE.png", height = 4, width = 5)
> #### no patch ####
>   patch.summary.mult <- as.data.frame(features.5min.val) %>%
+    select(aniID, assignPasture,
+           obs.pat._.f, obs.pat._.f, obs.pat._.f,
+           loc.pat._.f, loc.pat._.f, loc.pat._.f) %>%
+    arrange(aniID) %>%
+    mutate(obs.pat._.mult = NA,
+           loc.pat._.mult = NA) %>%
+    filter(assignPasture %in% c("51S", "56S", "57N")) %>%
+    mutate(obs.pat._.mult = ifelse(obs.pat._.f == 0, 0, obs.pat._.mult),
+           obs.pat._.mult = ifelse(obs.pat._.f > 0.00 & obs.pat._.f <= 0.25, 0.25,
obs.pat._.mult),
+           obs.pat._.mult = ifelse(obs.pat._.f > 0.25 & obs.pat._.f <= 0.50, 0.50,
obs.pat._.mult),
+           obs.pat._.mult = ifelse(obs.pat._.f > 0.50 & obs.pat._.f <= 0.75, 0.75,
obs.pat._.mult),
+           obs.pat._.mult = ifelse(obs.pat._.f > 0.75 & obs.pat._.f < 1, 0.99, obs.pat._.mult),
+           obs.pat._.mult = ifelse(obs.pat._.f == 1, 1, obs.pat._.mult),
+           loc.pat._.mult = ifelse(loc.pat._.f == 0, 0, loc.pat._.mult),
+           loc.pat._.mult = ifelse(loc.pat._.f > 0.00 & loc.pat._.f <= 0.25, 0.25,
loc.pat._.mult),
+           loc.pat._.mult = ifelse(loc.pat._.f > 0.25 & loc.pat._.f <= 0.50, 0.50,
loc.pat._.mult),
+           loc.pat._.mult = ifelse(loc.pat._.f > 0.50 & loc.pat._.f <= 0.75, 0.75,
loc.pat._.mult),
+           loc.pat._.mult = ifelse(loc.pat._.f > 0.75 & loc.pat._.f < 1, 0.99, loc.pat._.mult),
+           loc.pat._.mult = ifelse(loc.pat._.f == 1, 1, loc.pat._.mult),
+    ) %>%
+    mutate(obs.pat._.mult = factor(obs.pat._.mult, levels = c(0, 0.25, 0.5, 0.75, 0.99, 1)),
+           loc.pat._.mult = factor(loc.pat._.mult, levels = c(0, 0.25, 0.5, 0.75, 0.99, 1)))
```

```
>   caret::confusionMatrix(patch.summary.mult$loc.pat._.mult,
patch.summary.mult$obs.pat._.mult)
Confusion Matrix and Statistics

          Reference
Prediction   0 0.25 0.5 0.75 0.99   1
      0    132    1   0    1    0   1
      0.25  11    0   0    1    0   0
      0.5    7    0   0    0    0   1
      0.75   1    0   0    0    0   0
      0.99   0    0   0    0    0   2
      1     21    0   1    1    0  21

Overall Statistics
Accuracy : 0.7574
95% CI : (0.6923, 0.8148)
    No Information Rate : 0.8515
    P-Value [Acc > NIR] : 0.9998
Kappa : 0.3987

 Mcnemar's Test P-Value : NA
Statistics by Class:

                     Class: 0 Class: 0.25 Class: 0.5 Class: 0.75 Class: 0.99 Class: 1
Sensitivity            0.7674     0.00000    0.00000     0.00000          NA   0.8400
Specificity            0.9000     0.94030    0.96020     0.99497    0.990099   0.8701
Pos Pred Value         0.9778     0.00000    0.00000     0.00000          NA   0.4773
Neg Pred Value         0.4030     0.99474    0.99485     0.98507          NA   0.9747
Prevalence             0.8515     0.00495    0.00495     0.01485    0.000000   0.1238
Detection Rate         0.6535     0.00000    0.00000     0.00000    0.000000   0.1040
Detection Prevalence   0.6683     0.05941    0.03960     0.00495    0.009901   0.2178
Balanced Accuracy      0.8337     0.47015    0.48010     0.49749          NA   0.8550
## plot

NO <-  ggplot(features.5min.val, aes(x=obs.pat._.f, y=loc.pat._.f)) + geom_point(alpha =
0.7) +
    stat_smooth(method = "lm", #formula = y ~ x + I(x^2),
                size = 1, colour= "orangered1") +
    geom_abline(slope = 1, intercept = 0, linetype = "dashed") +
    theme_set(theme_light()) +
    labs(y= "classified  as in NO \n burn patch by MOOnitor",
         x="observed as in NO burn patch")
NO
 ggsave("Plots/obs_loc_patch_NONE_PVALUE.png", height = 4, width = 5)
#### combine plots ####
ggarrange(PA, B, C, D, NO + rremove("x.text"),
```

```
          labels = c("A)", "B)", "C)", "D)", "E)"),
          vjust = 0.1,
          hjust = -0.2,
          ncol = 2, nrow = 4,
          align = "v") +
   theme(plot.margin = margin(0.8,0,0,0, "cm"))

 ggsave("Plots/patch_combined.png", height = 7.5, width = 8)
> ### patch overall ####
>   patch.summary.mult <- as.data.frame(features.5min.val) %>%
+     select(aniID, assignPasture,
+            obs.pat.A.f:obs.pat._.f,
+            loc.pat.0.f:loc.pat._.f) %>%
+     arrange(aniID) %>%
+     filter(assignPasture %in% c("51S", "56S", "57N")) %>%
+     mutate(obs.dominant.patch = NA,
+            loc.dominant.patch = NA) %>%
+     mutate(obs.dominant.patch.max = pmax(obs.pat.0.f, obs.pat.A.f, obs.pat.B.f,
obs.pat.C.f, obs.pat.D.f, obs.pat._.f)) %>%
+     mutate(obs.dominant.patch = ifelse(obs.dominant.patch.max == obs.pat.A.f, "A",
obs.dominant.patch),
+            obs.dominant.patch = ifelse(obs.dominant.patch.max == obs.pat.B.f, "B",
obs.dominant.patch),
+            obs.dominant.patch = ifelse(obs.dominant.patch.max == obs.pat.C.f, "C",
obs.dominant.patch),
+            obs.dominant.patch = ifelse(obs.dominant.patch.max == obs.pat.D.f, "D",
obs.dominant.patch),
+            obs.dominant.patch = ifelse(obs.dominant.patch.max == obs.pat.0.f, "0",
obs.dominant.patch),
+            obs.dominant.patch = ifelse(obs.dominant.patch.max == obs.pat._.f, "_",
obs.dominant.patch),
+     ) %>%
+   mutate(loc.dominant.patch.max = pmax(loc.pat.0.f, loc.pat.A.f, loc.pat.B.f,
loc.pat.C.f, loc.pat.D.f, loc.pat._.f)) %>%
+     mutate(loc.dominant.patch = ifelse(loc.dominant.patch.max == loc.pat.A.f, "A",
loc.dominant.patch),
+            loc.dominant.patch = ifelse(loc.dominant.patch.max == loc.pat.B.f, "B",
loc.dominant.patch),
+            loc.dominant.patch = ifelse(loc.dominant.patch.max == loc.pat.C.f, "C",
loc.dominant.patch),
+            loc.dominant.patch = ifelse(loc.dominant.patch.max == loc.pat.D.f, "D",
loc.dominant.patch),
+            loc.dominant.patch = ifelse(loc.dominant.patch.max == loc.pat.0.f, "0",
loc.dominant.patch),
+            loc.dominant.patch = ifelse(loc.dominant.patch.max == loc.pat._.f, "_",
loc.dominant.patch),
```

```
+     ) %>%
+   mutate(obs.dominant.patch = as.factor(obs.dominant.patch),
+          loc.dominant.patch = as.factor(loc.dominant.patch))
>   caret::confusionMatrix(patch.summary.mult$loc.dominant.patch,
patch.summary.mult$obs.dominant.patch)
Confusion Matrix and Statistics

          Reference
Prediction  _  A  B  C  D
         _ 24  3  2  5 13
         A  4 86  2  0  4
         B  0  2  9  0  0
         C  0  0  0 11  0
         D  0  0  0  0 39

Overall Statistics
Accuracy : 0.8284
95% CI : (0.7696, 0.8775)
    No Information Rate : 0.4461
    P-Value [Acc > NIR] : < 2.2e-16
Kappa : 0.7543

 Mcnemar's Test P-Value : NA
Statistics by Class:

                     Class: _ Class: A Class: B Class: C Class: D
Sensitivity            0.8571   0.9451  0.69231  0.68750   0.6964
Specificity            0.8693   0.9115  0.98953  1.00000   1.0000
Pos Pred Value         0.5106   0.8958  0.81818  1.00000   1.0000
Neg Pred Value         0.9745   0.9537  0.97927  0.97409   0.8970
Prevalence             0.1373   0.4461  0.06373  0.07843   0.2745
Detection Rate         0.1176   0.4216  0.04412  0.05392   0.1912
Detection Prevalence   0.2304   0.4706  0.05392  0.05392   0.1912
Balanced Accuracy      0.8632   0.9283  0.84092  0.84375   0.8482
```

VITA

Jancy L. Jeffus

Candidate for the Degree of

Master of Science

Thesis: EVALUATION OF ANIMAL SENSORS AND TECHNOLOGY IN GRAZING ENVIRONMENTS

Major Field: Animal Science

Biographical:

Education:

Completed the requirements for the Master of Science in Animal Science at Oklahoma State University, Stillwater, Oklahoma in May, 2022.

Completed the requirements for the Bachelor of Science in Animal Science at Cameron University, Lawton, Oklahoma in May, 2019.

Experience:

Graduate Research and Teaching Assistant Oklahoma State University (August 2019 – December 2021)

Oral presentation: National section – American Society of Animal Science (Louisville, KY, 2021)

Professional Memberships:

American Society of Animal Science, Southern Section of the American Society of Animal Science, Phi Eta Sigma Honors Society