# Evaluating Field-Based Grazing Intensity Measurements for Adaptive Rangeland Monitoring

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Alexander C. E. Laurence-Traynor

Major Professor: Jason W. Karl, PhD.
Committee Members: Courtney Conway, PhD.; Jim Sprinkle, PhD.;
Karen Launchbaugh, PhD.
Department Administrator: Charles Goebel, PhD.

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# Authorization to Submit Thesis

This thesis of Alexander Laurence-Traynor, submitted for the degree of Master of Science with a Major in Natural Resources and titled "Evaluating Field-Based Grazing Intensity Measurements for Adaptive Rangeland Monitoring," has been reviewed in final form. Permission, as indicated by the signatures and dates below, is now granted to submit final copies to the College of Graduate Studies for approval.

Major Professor: ________________________________________ Date: ____________
Jason W. Karl, PhD.

Committee Members: ________________________________________ Date: ____________
Courtney Conway, Ph.D.

________________________________________ Date: ____________
Jim Sprinkle, Ph.D.

________________________________________ Date: ____________
Karen Launchbaugh, Ph.D.

Department
Administrator: ________________________________________ Date: ____________
Charles Goebel, Ph.D.

# Abstract

A diversity of field-based grazing intensity measurements are used for rangeland management. However, there is a lack of acknowledgement that the choice of method and their implementation may influence the precision, accuracy, and sensitivity of grazing intensity estimates. Improved understanding of the sources of variation and bias within grazing intensity estimates can improve planning of monitoring programs, increase use of more appropriate methods for a given situation, and improve the ability of data to inform management. I evaluated and compared several methods for measuring utilization and grazing intensity in two semi-arid grassland and shrubland ecosystems: The Pacific Northwest bunchgrass prairie and sagebrush steppe. Utilization methods were also compared to actual stocking rates and locations of livestock using GPS data. A multiple-regression approach used to attribute variation in grazing intensity estimates found a significant proportion of variation was related to observer's recent experience and training, particularly with visual estimation methods. Other sources of variation in utilization estimates included plant composition and cover. Calibration techniques which used in-field estimates of utilization from quantitative measurements were able to improve the relationship between visual estimation methods and livestock GPS-based grazing intensity estimates. Different methods produced significantly different estimates of mean utilization at both fine and broad scales however correlation between methods and actual stocking rates increased at broader scales. Results suggested improvements to the implementation and design of rangeland monitoring including consideration of observers' recent experience, increasing site-specific training, and using sample designs which represent the fine scale spatial variation in grazing intensity and vegetation cover. Improved understanding of the relative limitations of different rangeland monitoring methods creates capacity to leverage the growing trend in citizen science and provides an opportunity for increased flexibility and resilience in rangeland management.

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# CHAPTER 1: QUANTIFYING VARIANCE AND OBSERVER BIAS IN FOUR UTILIZATION MEASUREMENT TECHNIQUES

## 1. Introduction

Effective rangeland management depends upon reliable information about the short and long term effects of grazing animals (Eyre et al., 2011; Karl et al., 2017; Ortega-S and Lukefahr, 2013; West, 2003). Monitoring at broad spatial and temporal scales is often required to understand these effects due to scale-dependent processes and the strong influence of environmental variation on arid and semi-arid grazinglands (Moir and Block, 2001; Turner, 1989). Similarly, having a strong foundation of monitoring data can help determine early warning signals and thresholds for ecological change such as shifts from one community state to another (Bestelmeyer et al., 2013; Wang et al., 2012). Effective monitoring then allows land managers to detect changes in land health and vegetation patterns so that they may shift grazing management practices accordingly.

For measurements to be comparable at multiple scales, estimates of grazing effects must be both accurate and repeatable across time and between different landscapes. At the same time, however, monitoring programs must work for the people implementing them. There can be significant financial and opportunity costs associated with intensive monitoring over broad landscapes including the need for higher level technical or statistical knowledge (Caughlan and Oakley, 2001). Thus, successful monitoring data should be efficient to collect and analyze for routine management (Jasmer and Holechek, 1984; Symstad et al., 2008).

The balancing act between precision and efficiency has been a major goal of many monitoring methods commonly used today for rangeland management (Booth and Cox, 2011). Rapid visual assessments of percent use are often preferred over more time-consuming residual vegetation measurements because they are understandable to a wide audience and are simple to perform (Heady, 1949). However, quantitative residual measurements may be a better measure of actual grazing severity which relates more directly to rangeland health than percent use (Holechek and Galt, 2000). Additionally, accuracy and repeatability of visual estimation methods such as general reconnaissance or landscape appearance can depend on the *"…experience and judgement of the inspector."* (Heady, 1949; Laycock, 1998).

Expertise and local knowledge are clearly an important part of sustainable and innovative grazing management (Biró et al., 2019; Ghorbani et al., 2013; Müller et al., 2007). Levels of expertise are also often variable within and between monitoring programs and differences in experience may affect the ability to accurately detect grazing effects. It is possible that higher levels of technical expertise (including knowledge of plant growth forms, phenology, grazing behavior, and monitoring methods) could lead to increased perception of signs of grazing which may be overlooked by less experienced observers. It is possible, that the reverse may also be true as more experience creates biased estimates from observers being more conscious of over-estimating utilization or recording what they expect to see (Marsh and Hanlon, 2007). Visual estimates of utilization, consumption or destruction of biomass by grazing animals (Bureau of Land Management, 1999), may be particularly vulnerable to these effects because they often require observers to both detect levels of grazing and estimate weight removed from visual assessments of plant heights.

Differences in observer experience are not the only factors which influence precision of grazing intensity estimates. Technique choice, training, and location of measurement within a study area can all significantly alter estimates of utilization. For example, Halstead et al., (2000) found that utilization from paired grazed and ungrazed plots was higher (~20%) than estimates based on grass height and weight relationships. Systematic underestimation of utilization over time could lead to overstocking in subsequent years. Thus, understanding how different techniques relate to each other and how closely they can track grazing intensity in a specific grazing system can give land managers better context for interpreting monitoring data and developing monitoring programs.

There are a variety of studies which have addressed variability among techniques and observers in bird surveys (Link et al. 1994, Sauer et al. 1994, Kendall et al. 1996, Thomas, 1996, Link & Sauer 1997), plant community estimates (Abadie et al., 2008; Symstad et al., 2008) and aquatic monitoring (Coles-Ritchie et al., 2003; Kaufmann et al., 2014). However, studies which consider sources of variability among techniques and observers in rangeland management are lacking. A recent review of utilization and residual measurements gives an overview of the challenges facing the field (SRM Rangeland Assessment and Monitoring Committee, 2018). Challenges include the scarce reporting of specified levels of precision in utilization estimates as well as a lack of recognition that training, technique choice, and technique implementation often affect method accuracy. Thus, an in-depth exploration of the biases and factors that influence variability of commonly used utilization techniques would benefit rangeland management.

The objective of this study was to evaluate the repeatability of utilization metrics in the context of a broad-scale experimental study investigating the effects of cattle grazing on greater sage-grouse (*Centrocercus urophasianus*). I tested the following two hypotheses: 1) estimates of utilization vary among observers; 2) observer variation differed among four different utilization techniques including visual estimates and quantitative residual measurements. In particular, I describe the variance in utilization estimates attributed to the technical expertise of observers and their recent vegetation monitoring experience.

# 2. Methods

The Idaho Grouse and Grazing Project began in 2014 as a collaborative research project of the Idaho Cooperative Fish and Wildlife Research Unit, the University of Idaho, the Bureau of Land Management, Idaho Department of Fish and Game, several private ranchers, and several other partners (https://idahogrousegrazing.wordpress.com). The overall goal of the study was to identify effects of cattle grazing on demographic traits of greater sage-grouse and sage-grouse habitat characteristics across southern Idaho. The study involved experimental manipulation of stocking rate and timing of grazing on five southern Idaho study areas (Figure 1.1). At ~100 plots in each study area, cover of shrubs and herbaceous plants, grass height and utilization were measured each year for the duration of the study. Livestock use across experimental pastures was assessed by four methods including plant-based (ocular estimates of utilization, height-weight relationships), plot-based methods (comparison of grazed/ungrazed plots), and pasture-scale pattern mapping (landscape appearance).

## 2.1 Study Areas

Study sites were located in southern Idaho within sage-grouse management zone IV: The Snake River Plain (Knick 2011, Figure 1.1). Each study site was selected based on the following characteristics: more than 15% foliar cover of sagebrush species, including Wyoming big sagebrush (*Artemisia tridentata ssp. wyomingensis)*, dominance of native grasses and forbs in the understory, and occurrence of at least one sage-grouse lek of >25 males. The study implemented a staggered entry design such that data collection began on the Browns Bench and Jim Sage sites in 2014, Big Butte and Sheep Creek sites in 2015, and the Pahsimeroi site was added in 2017. Study sites varied in size between 2,500-ha (Jim Sage) and 11,000-ha (Pahsimeroi).

Study sites showed physiographic features which are common among arid and semi-arid rangelands throughout the west. The Big Butte site consisted of an undulating landscape dominated by lava plains and remnant volcanoes with an average elevation of 1,561 m. Average annual precipitation during the study period was 220 mm. Soils were made up of loams and clay loams with a large proportion of rock outcroppings. Three-tip sagebrush (*Artemisia tripartita* Rydb.) and basin big sagebrush (*Artemisia tridentata ssp. tridentata* Nutt.) were the dominant shrub species. Brown's Bench was situated between the Salmon River reservoir and the Monument Springs Mountains. The landscape was made up of hillslopes, alluvial fans, and terraces with shallow to deep gravelly clay and clay loam soils interspersed with several ephemeral streams. Average elevation was 1,623-m and average annual precipitation was 270 mm. Plant communities were dominated by black sagebrush (*Artemisia nova* A. Nelson) and Wyoming big sagebrush. The Jim Sage site showed similar topography including hillslopes and remnant fans made up of loam and silt loam surface soils. Dominant shrubs included Wyoming big sagebrush, mountain big sagebrush (*Artemisia tridentata ssp. vaseyana* (Rydb.) Beetle), as well as low sagebrush (*Artemisia arbuscula* Nutt.) occurring in shallower soils. Average elevation at Jim Sage was 1,652-m and average annual precipitation was 246 mm. The Pahsimeroi valley site was located between Idaho's Lemhi and Big Lost River mountain ranges. This site had an average elevation of 2,000-m which varied between river floodplains at the valley floor to partially forested toe-slopes to the far east and west of the site. Average annual precipitation at the Pahsimeroi was 220 mm and vegetation cover was dominated by low sagebrush on the valley floor and Wyoming big sagebrush on the mountain slopes. The final site, Sheep Creek was a remote area characterized by lava plains, steep basalt canyons, mountain slopes and riparian areas situated at 1,640-m in elevation. Soils were mostly silt loams and silty clay loams, average annual precipitation was 330 mm and vegetation was characterized by Wyoming big and low sagebrush.

The most common understory grasses across all sites (ordered based on abundance) included Sandberg's bluegrass (*Poa secunda* J Presl), bottlebrush squirreltail (*Elymus elymoides* [Raf.] Swezey), bluebunch wheatgrass (*Pseudoroegneria spicata* [Pursh] A. Love), western wheatgrass (*Pascopyrum smithii* [Rydb.] A. Love), and needlegrass species (*Achnatherum* spp and *Hesperostipa* spp).

All five study sites included federally managed public lands often surrounded by or adjoining private pastures. Livestock grazing has been the primary land use in these areas since European-American settlement. Each site also provides important habitat for sagebrushobligate species and game species including bighorn sheep (*Ovis canadensis*) and pronghorn (*Antilocapra americana*).

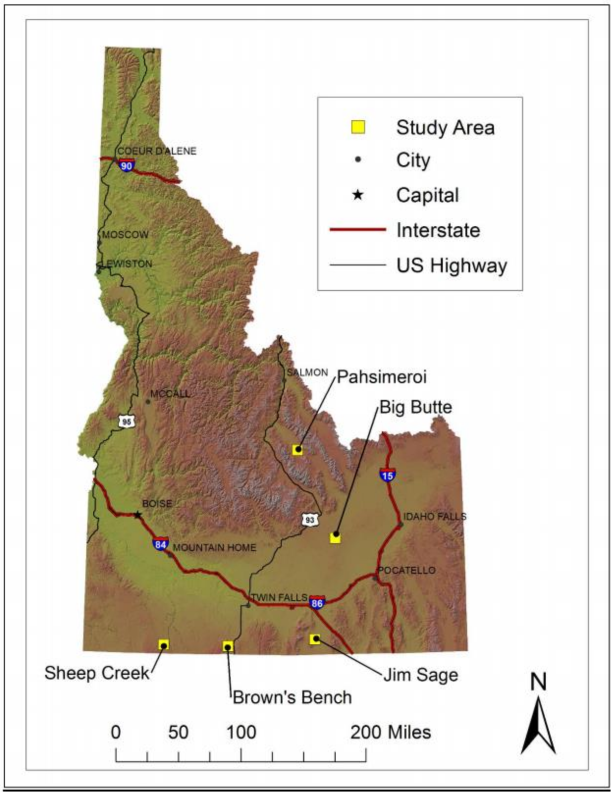


Figure 1.1 - Five study sites in southern Idaho where field work has been conducted for the Idaho Grouse and Grazing Project.

## 2.2 Design and Protocols

### Grazing Treatments

Each of the five study sites had four grazing treatments applied each year within separate pastures. Treatments included no grazing, spring grazing in even years (*i.e.*, 2016, 2018), spring grazing in odd years (*i.e.*, 2015, 2017), and annual alternation between spring and fall grazing. Spring grazing occurred between 1 March and 15 June and fall grazing between 1 September and 15 December. Measurement of utilization occurred in all pastures (both grazed and ungrazed) at the same time as the vegetation monitoring plots (described below). For this study only pastures which had been grazed in the spring were included in the data analysis.

### Sampling Design

Four methods were used to estimate the percent of above-ground perennial grass biomass removed by herbivores (% utilization) – ocular estimates, landscape appearance, the height-weight method, and paired grazing exclosure plots – and sampling design varied by method.

Ocular estimates of utilization were measured at 20 randomly selected sampling sites (referred to hereafter as vegetation plots) within each study pasture. Randomly-selected plots consisted of two perpendicular 30-m line intercept transects centered on a potential sage-grouse nest shrub (Conway et al., 2018). Vegetation plots were sampled at the end of the growing season, between July 19th and September 1st, following cattle removal.

Landscape appearance estimates and height-weight measurements were collected along randomly placed north-south transects 300-m apart (Figure 1.2). At 200-m intervals along each transect, observers estimated utilization according to the landscape appearance technique within a 15-m radius half-circle in front of them. Heights of grazed and ungrazed grasses were measured every 600-m along each north-south transects. See Conway et al. (2019) for more detailed description of methods. This resulted in between 50 and 500 landscape appearance observations per pasture depending on the pasture size and half as many for height-weight.

In 2018, paired grazed and ungrazed plots were established at 12 randomly chosen vegetation plots within each grazed pasture for a total of 60 paired plots across all five study sites. All other utilization measurements were taken throughout the duration of the study since 2014.

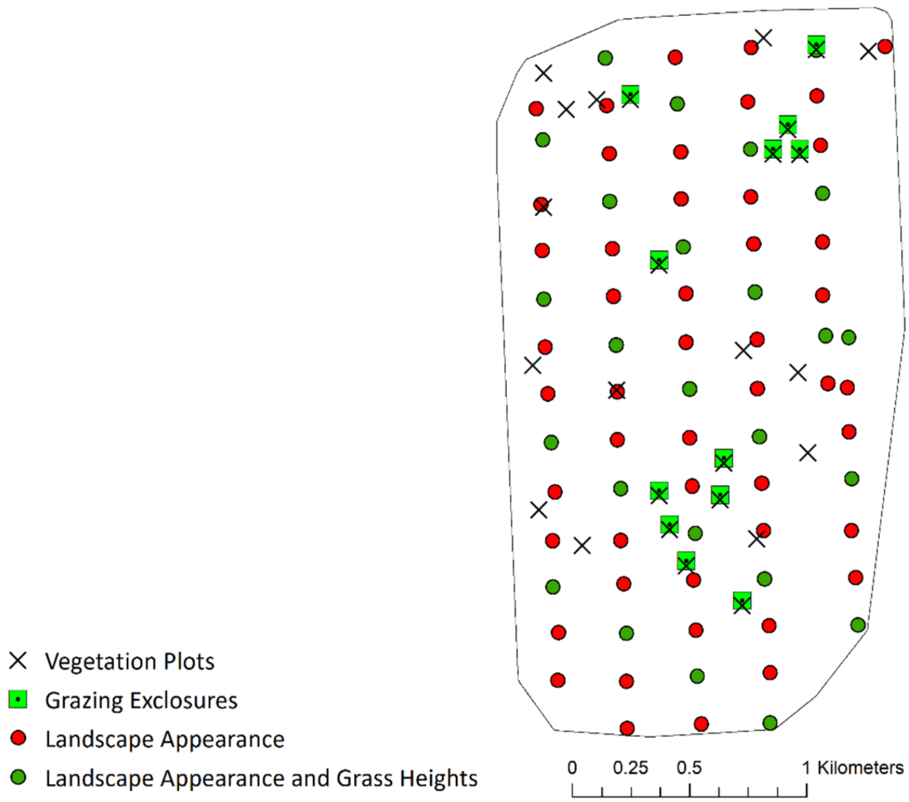


Figure 1.2 – An example of the sample design for one grazed pasture from the Grouse and Grazing Project. Vegetation plots were randomly located and a subset of 12 of these contained paired plots with grazing exclosures. Landscape appearance plots were located every 200-m on parallel transects spaced 300-m apart. Heights of grazed and ungrazed grasses were also collected every third point along these transects (every 600 m).

## Utilization Techniques

Ocular Estimates:

Ocular estimates of utilization (by grass species) were recorded at each vegetation plot every 2-m along the line transects for a total of 29 observations (subplots) per vegetation plot (estimating the center point only once). At each subplot location, up to three perennial grass species were measured within 1-m of the respective meter mark on the transect and plants were selected based on proximity to the meter mark. This resulted in a ~1.5-$m^2$ subplot area at each meter mark. For each individual perennial grass measured, field technicians made an ocular estimate of percent of the above-ground biomass consumed or destroyed by herbivores (Bureau of Land Management, 1999). Field technicians were trained on how to visually estimate percent biomass removed prior to sampling with the use of species-specific photographs. Each year this sampling was conducted at a minimum of 15 random vegetation plots in each pasture.

Ocular estimates of utilization were summarized in two ways: 1) average estimated weight removed across vegetation plot, and 2) frequency of grazed plants. Frequency was calculated by simplifying ocular subplots into grazed and ungrazed and then calculating a proportion of grazed subplots per vegetation plot.

Landscape Appearance:

The landscape appearance method (Bureau of Land Management, 1999) was used to estimate utilization in all experimental pastures using the classes shown in Table 1.1. This technique relied upon observing the extent and intensity of grazing based on knowledge of grazing behavior, forage preference, grass growth forms and phenology. For example, classifications were made using observations of the relative use of low and high value forage species, the presence of current year's culms, and the extent or patchiness of grazed areas.

Table 1.1 – Seven classes of utilization used in the landscape appearance method including descriptive guide (Bureau of Land Management, 1999).

| Utilization Class | Description |
|---|---|
| 0-5% | The rangeland shows no evidence of grazing or negligible use. |
| 6-20% | The rangeland has the appearance of very light grazing. The herbaceous forage plants may be topped or slightly used. Current seed stalks and young plants are little disturbed. |
| 21-40% | The rangeland may be topped, skimmed, or grazed in patches. The low value herbaceous plants are ungrazed and 60 to 80 percent of the number of current seedstalks of herbaceous plants remain intact. Most young plants are undamaged. |
| 41-60% | The rangeland appears entirely covered[a] as uniformly as natural features and facilities will allow. Fifteen to 25 percent of the number of current seed stalks of herbaceous species remain intact. No more than 10 percent of the number of low-value herbaceous forage plants are utilized. (Moderate use does not imply proper use.) |
| 61-80% | The rangeland has the appearance of complete search[b]. Herbaceous species are almost completely utilized, with less than 10 percent of the current seed stalks remaining. Shoots of rhizomatous grasses are missing. More than 10 percent of the number of low-value herbaceous forage plants have been utilized. |
| 81-94% | The rangeland has a mown appearance and there are indications of repeated coverage. There is no evidence of reproduction or current seed stalks of herbaceous species. Herbaceous forage species are completely utilized. The remaining stubble of preferred grasses is grazed to the soil surface. |
| 95-100% | The rangeland appears to have been completely utilized. More than 50 percent of the low-value herbaceous plants have been utilized. |

[a] "covered" means that foraging ungulates have passed through the area

[b] "complete search" means that foraging cattle have spent considerable time foraging in the area and were not just passing through

Height-Weight:

Heights were measured for up to four different species of grasses at four separate subplots along the north-south landscape appearance transects for a total of up to 16 individual plant measurements at each sampling location. Subplots were placed ~3-m apart as determined by pacing. The nearest four grass species within 1-m of the subplot location were measured. For each plant measured within each subplot, observers recorded if the grass plant had been grazed, the droop height, and the average height of all grazed stems (if there was evidence of grazing). Estimated height removed from grazed plants was calculated using the average ungrazed height specific to each study site, year and species (Bureau of Land Management, 1999). Utilization (weight removed by grazing) was then calculated using site- and species-specific height-weight relationships developed in 2017 (Julson, 2017) according to the protocol outlined by Sprinkle and Arispe (2017).

Paired plots:

Ungrazed subplots were contained within a 2.5-m by 2.5-m metal-fenced grazing exclosure (Figure 1.3). Exclosures were 1.5-m tall with ~20-cm by 20-cm wire mesh to prevent large herbivore grazing. The actual ungrazed subplot area was placed within the caged area with a ~45-cm buffer zone between the cage and the plot to mitigate any alterations in microclimate or effects due to livestock or wildlife attraction caused by the frame. The plot area was split into four 75-cm by 75-cm subplots for ease of clipping and collection. This resulted in a total clipped area of 2.25-$m^2$.

For each ungrazed subplot, a corresponding grazed plot was located nearby. Grazed plots were located >30-m from caged plots to prevent bias from cattle attraction to the grazing exclosure. Care was taken to place grazed plots in areas with the same soils, species composition and cover as within the caged plot. These plots were also made up of four 75-cm by 75-cm subplots (Figure 1.3).

After the grazing period when forage species had reached their growth potential (mid-July to mid-August) all herbaceous foliar cover in each caged and uncaged plot was clipped to within 2.5-cm of the soil surface and weighed in the field following the interagency technical reference on utilization studies (Bureau of Land Management, 1999). Clipped material was weighed by species for grasses. Because forbs typically made up a small portion of total subplot biomass, all forb species were grouped into one category and weighed together. Approximately 50 g of each grass species and group of forbs was retained in order to lab-dry and obtain a wet to dry weight conversion factor. Utilization estimates from paired plots were summarized by key forage species (*i.e.*, grass species which were preferred or desirable forage species for cattle).

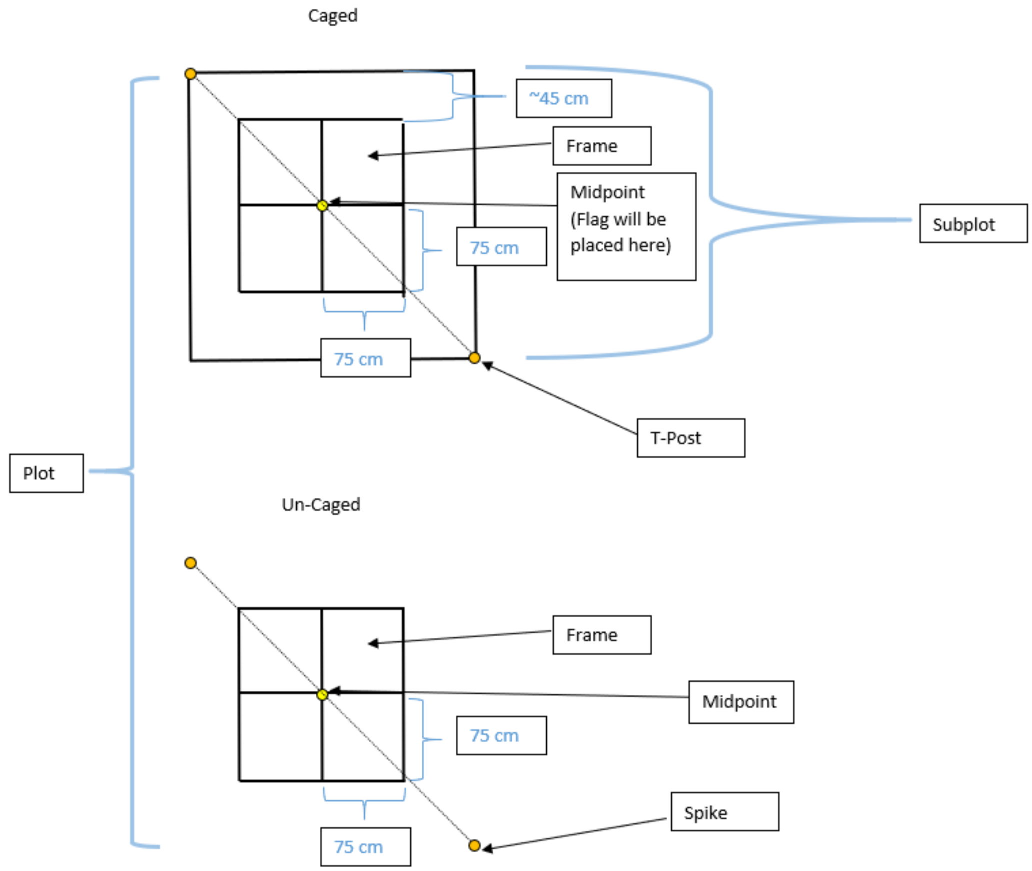


Figure 1.3 – Paired plots at the Idaho Grouse and Grazing Project. These consisted of two subpots: caged and uncaged, located at least 30-m apart. Subplots were placed such that they were similar in terms of species composition, cover, and soil type.

## 2.3 Data analysis

This study defined technical expertise as the broad differences in an observer's background and long-term experience. This included the observer's major field of study (*e.g.,* range, wildlife, or botany) and their official role within the research project. We defined monitoring experience as shorter-term differences between observers such as who they were working with, which plant communities they had most recently worked in, and levels of grazing they had recently perceived. Collectively, these metrics were referred to as observer effects.

A variance decomposition approach (Lawler and Edwards, 2006; Whittaker, 1984) was used to describe the amount of error caused by the observer effects within each measurement technique across all years and study sites of the grouse and grazing study. This approach used multiple linear regression to attribute and describe variance in the utilization estimates within and between observers. All data analysis and model creation was performed using R version 3.5.3 (R Core Team, 2013).

In evaluating sources of variability in utilization measurements, we defined precision as the amount of variation from each method caused by observer effects and other variables unrelated to the effects of grazing. More precise methods were those that did not vary because of differences between observers. A related concept, bias, was defined as a systematic or directional level of imprecision. Accuracy was defined as the degree to which the utilization estimates reflected the “true” grazing intensity in the study areas. Accuracy was harder to define in the context of this study because we had no independent measures of grazing intensity at plot scales. As a proxy, we evaluated accuracy of utilization measurements via the correlation of field estimates to pasture-level stocking rates (*i.e.*, the amount of livestock per unit of time and area), measured in Animal Unit Months per hectare (AUM $ha^{-1}$).

Four types of regression models were created for each utilization technique, all containing the utilization estimate as the dependent variable: 1. A simple model containing only the utilization estimate and study site and year of study as independent variables; 2. An observer effects model selected by stepwise selection using AIC (Akaike’s Information Criterion) containing site, year and any observer effects variables (described below) selected based on minimizing AIC as independent variables; 3. The ‘best’ model including any of the independent variables mentioned above as well as any site covariates described below which were selected by stepwise selection using AIC; 4. Technique comparison models with one utilization technique as a dependent variable and another technique’s estimate as the independent variable. Nested models were compared to assess which variables helped to explain the most amount of variation within the data.

The observer and best models were constructed using estimates of utilization from each of the different field techniques as the dependent variable and observer characteristics and in the case of the best models, study site covariates as independent variables. All models included study site and year of study as independent variables. Starting with the simplest model (Equation 1.1) which included only the utilization estimate, study site and year, independent variables were added using a forward and backward stepwise approach using AIC using the “stepAIC” function in the MASS package in R (Venables and Ripley, 2002). This function starts with the simplest model and adds or removes variables at each step when doing so would decrease model AIC. The amount of variance explained by adding additional variables was equated to the relative change in adjusted $R^2$ values.

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots \beta_p X_p + \epsilon_1 \quad \text{Equation 1.1}$$

Equation 1.1 – The multiple regression model structure used to analyze variance within utilization estimates. $Y$ is the utilization estimate, $\beta_0$ is the intercept, $\beta_1 \dots \beta_p$ represent independent variable parameters, and $\epsilon_1$ is the error. All models contained study site and year as explanatory variables. Additional variables describing differences between observers were added based on their ability to explain model error.

Particular attention was made to examine observer characteristics including: technical position which was related to an observer's technical experience and day to day workload (*e.g.*, wildlife biologist, range technician, or general volunteer); days of experience working on the grouse and grazing project; time spent at a sampling location; an observer performance rating; and the observer's original study site assignment and if they had moved between sites. Performance of each observer was rated by the project lead at the end of each year by three categories (Excellent, Average, Poor) based on work ethic and technical aptitude. Site covariates included the dominant plant functional groups, cover of plant species, and average grass and shrub heights.

Technique comparison models were constructed at two scales: individual plot locations and plots aggregated to the pasture. At the plot scale, this involved modeling paired plots against ocular estimates, then landscape appearance estimates were compared against height-weight estimates separately. All four techniques were compared against each other at the pasture scale. Since there were two separate sample designs used to locate utilization plots, landscape appearance and height weight could not be compared to either the paired plots or ocular estimates at the plot scale. Similarly, there was only one year of paired plot estimates and so comparisons were limited to five pastures in 2018. Correlation to paired plot estimates were used as a measure of precision since paired plots showed the least amount of observer variability and are regarded as a precise method for measuring utilization (Halstead et al., 2000, but see Chapter 2). To assess accuracy of each method, results were also compared to actual stocking rates measured in Animal Units Months (AUMs) per hectare. Closeness of fit between pairs of techniques was assessed using Pearson correlation coefficient (r) for continuous estimates and Spearman rank for the landscape appearance estimates. As above, observer characteristics, study site and year were added stepwise to these models to help explain differences between the utilization estimates.

Landscape appearance data was analyzed as both a categorical variable using the seven utilization classes and as a continuous variable using the midpoint values from each of the classes shown in Table 1.1. When considering class values, differences in landscape appearance estimates between sites and observers were compared using Chi-squared tests.

# 3. Results

## 3.1 Influence of Monitoring Experience

### Paired Plots

Across all forage species, Brown's Bench showed significantly higher levels of utilization in 2018 compared to all other study sites (61% ± 8% with 90% confidence, Figure 1.4). The Pahsimeroi site showed the lowest level of overall utilization when looking at the paired plots (18% ± 12%).

Estimates of utilization from paired plots showed slight observer bias due to the amount of time spent at each plot (observer model explained 5% more variation than simple model, model adjusted $R^2$ = 0.338 compared to 0.283 in simplest model, Table 1.2). Stepwise selection using AIC including site covariates explained another 5% of variation and included differences between individual observers and average grass heights at each plot.

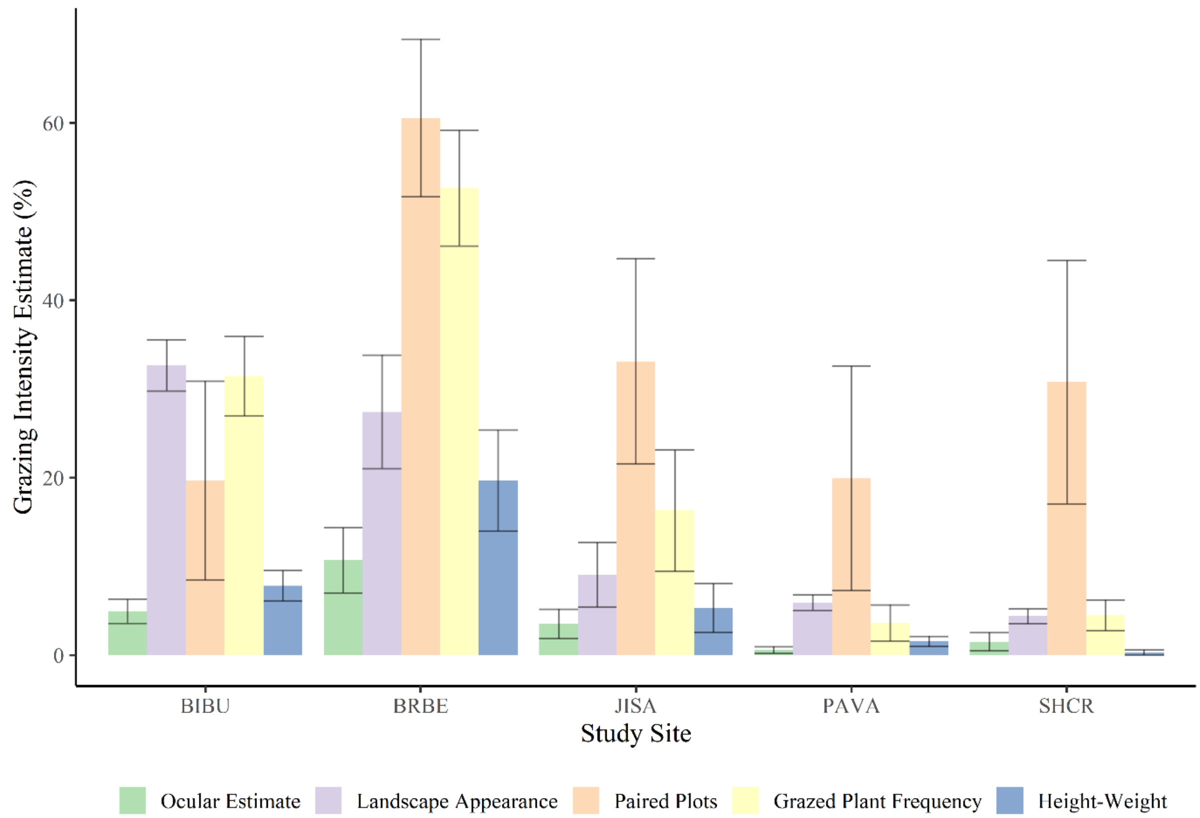


Figure 1.4 – Percent weight of key species removed determined by five techniques for measuring utilization across all five study sites of the grouse and grazing project in 2018. Error bars represent 90% confidence intervals and bar heights are mean utilization across all paired plots within grazed pastures. Utilization measured from different field techniques often produced significantly different estimates.

## Landscape Appearance

Landscape appearance data showed a high degree of sensitivity to changes in observer experience. The observer effects model included individual differences among observers as well as variation explained by observers who had moved between sites or not. These two variables accounted for roughly 13% of the variance in the landscape appearance data (model adjusted $R^2 = 0.268$ compared to $R^2 = 0.138$ in the simplest model, p-value < 0.005). The best model from stepwise selection using AIC included these same observer effects as well as several plant functional group covariates including, dominant perennial grass and shrub species. These covariates explained an additional 4% of the variation ($R^2 = 0.309$, p-value < 0.005).

Observers who had moved between sites and had a range of monitoring experience across different plant communities and grazing management schemes consistently recorded higher levels of utilization (mean utilization estimate = 17%) than observers who had a narrower range of recent monitoring experience across all study sites and years (10% utilization).

Table 1.2 – Comparison of simple models of utilization estimates (containing only study site and year as dependent variables), models containing only observer variables, and best models created with stepwise selection using AIC. The difference in Adjusted $R^2$ illustrates the amount of variation in utilization estimates explained by adding additional observer effect variables and plant composition variables into the models. All models were significant with $p < 0.005$.

| Method (Indicator) | Adjusted $R^2$ | | | Additional Variables in Best Model | Additional Variables in Observer Model |
|---|---|---|---|---|---|
| | Simple Model | Observer Model | Best Model | | |
| **Landscape Appearance** | 0.138 | 0.268 | 0.309 | Observer's identity, movement between sites | Observer's identity, movement between sites, dominant perennial grass, dominant shrub |
| **Ocular Estimates (% Use)** | 0.061 | 0.200 | 0.252 | Observer's identity, movement between sites | Grass heights, observer's identity, movement between sites |
| **Ocular Estimates (Frequency)** | 0.124 | 0.407 | 0.571 | Observer's identity | Observer's identity, grass height, shrub height |
| **Height-Weight** | 0.035 | 0.105 | 0.300 | Observer's identity, movement between sites | Dominant grass and shrub, cheatgrass cover, observer identity, movement between sites |
| **Paired plots** | 0.283 | 0.338 | 0.381 | Time spent at plot | Observer's identity, grass height |

The Pahsimeroi study site exemplified this effect strongly since each year it is visited by many different field observers. Crews from other study sites will help with data collection at the Pahsimeroi towards the end of field season since it is the largest study area and the final site to finish collecting utilization data. The original site assignment of these ‘help’ crews has a significant effect on the data collected at the Pahsimeroi study site (Figure 1.5). In general, field observers who spent the majority of their season collecting data at other study sites (Brown’s Bench, Jim Sage, Big Butte and Sheep Creek) gave significantly higher estimates of utilization at the Pahsimeroi compared to crews which had spent all year there.

From within these ‘help’ crews, observers who had worked at multiple sites per season (‘All Sites’ in Figure 1.5) showed the closest fit to Pahsimeroi crews but still recorded more observations in all four of the highest utilization classes. Observers which spent most of the season at the highest use site, Brown’s Bench, then went on to record the lowest estimates of utilization from the 'help' crews with more than 90% of sample sites recorded in the lowest two utilization categories (Figure 1.5). Conversely, observers from Sheep Creek and Big Butte, which had comparable levels of utilization to Pahsimeroi but different dominant plant species, recorded the highest levels of utilization compared to Pahsimeroi crews - Sheep Creek and Big Butte crews recorded 30% and 60% of their sampling locations, respectively within the 'Light' (21-40% utilization) and 'Moderate' (41-60%) classes.

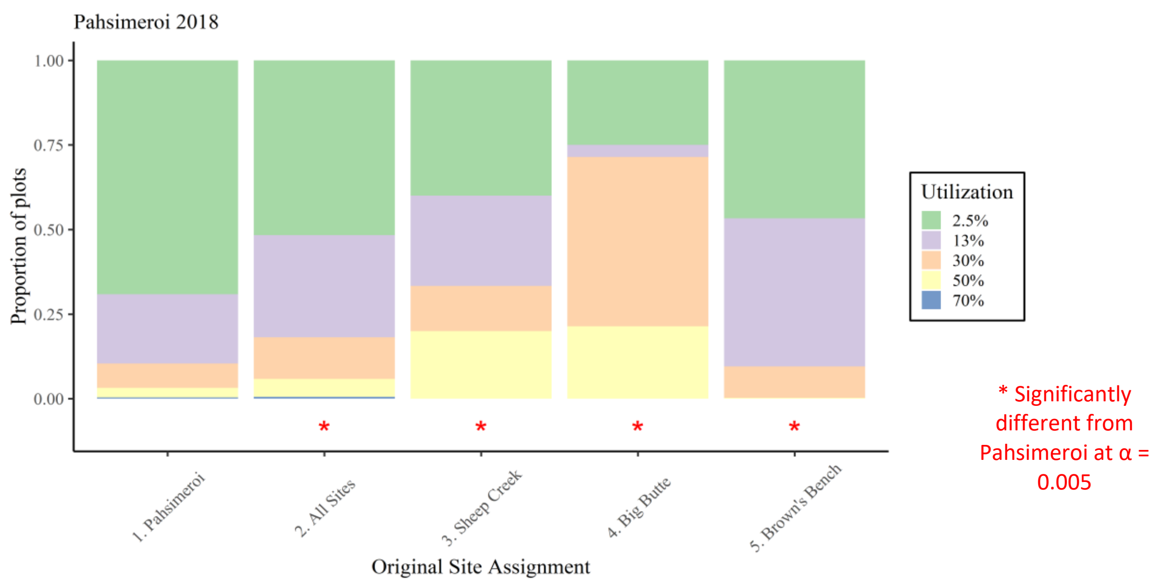


Figure 1.5 – Proportion of landscape apperance plots from the Pahsimeroi study site falling into each of the different utilization classes grouped by where the observers spent the majority of their field season. The legend and y axis describe utilization classes according to their midpoint value.

## Ocular estimates

The simplest model including ocular estimates of utilization, study site and year accounted for ~ 6% of the variation in the data (adjusted $R^2 = 0.061$, $p < 0.005$). The observer model produced by stepwise selection using AIC included study site, study year, the identity of both the observer and recorder (second observer) at the sample site, and whether the observer had moved between several study sites. Including these observer characteristics as explanatory variables explained an additional 14% of the variance (adjusted $R^2 = 0.200$, $p < 0.005$, Table 1.2). Observers who moved between different sites tended to give slightly higher estimates of utilization (4.3% versus 2.7%, difference between means was significant with $p = 0.03$). Addition of average grass heights as an independent variable on the best model explained an additional 5% of the variation on ocular estimates.

Ocular estimates were also influenced by the different daily experiences of different position types. For example, at the Jim Sage study site in 2015, graduate students, project coordinators and general technicians had significantly different ocular estimates compared to field crews which worked at the Jim Sage study site all season (Figure 1.6). These three groups with the most divergent estimates represented people who often worked by themselves, worked across multiple different study sites each season, and worked on multiple aspects of the project (wildlife, range, insect sampling). On the other hand, there do not seem to be any consistent patterns relating to the observer's technical expertise. Observers with wildlife backgrounds (crew leaders, IDFG technicians and wildlife technicians) had very similar estimates and amount of variability as range technicians. Similarly, the project coordinator position, which had the highest level of technical expertise, had similar estimates and variance as the generic technicians which included undergraduate students and volunteers with a relatively low level of expertise.

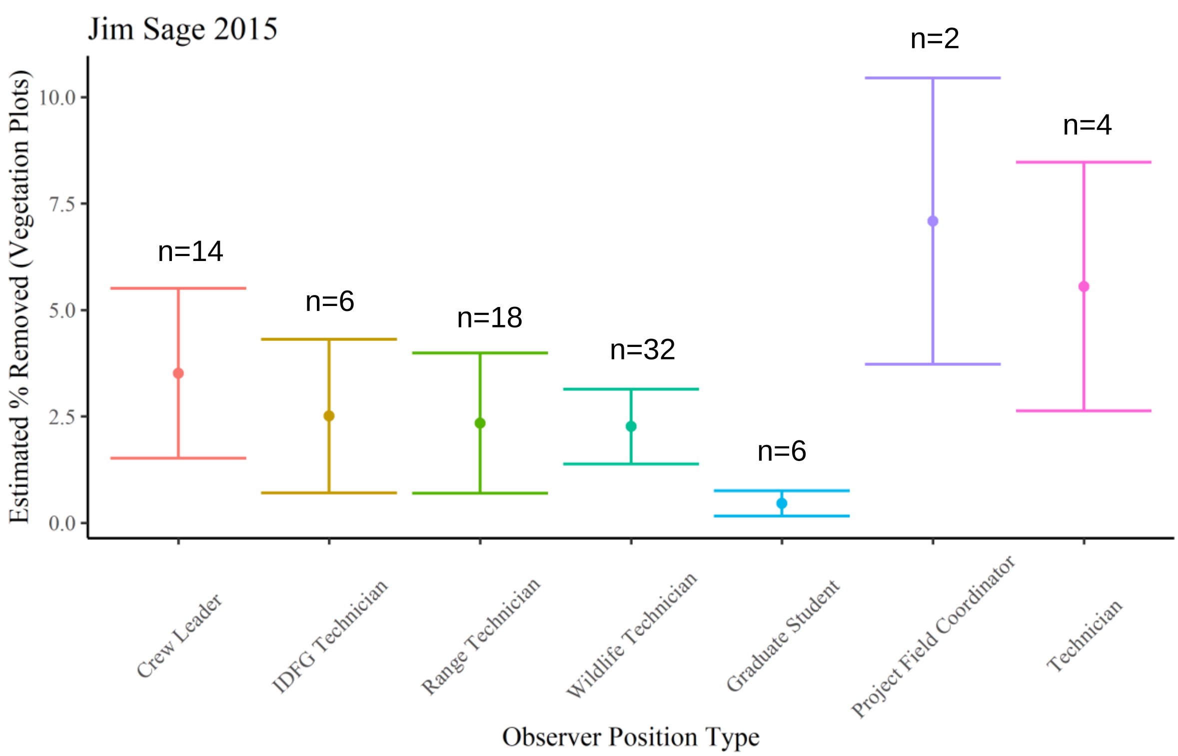


Figure 1.6 – Ocular estimates of percent herbaceous biomass removed by herbivores at the Jim Sage study site in 2015 split out by observer position. Points are mean utilization and error bars represent 90% confidence intervals. Sample size (n) represents the number of individuals within each position type.

### Frequency of Grazed Plants

A large degree of variation in the grazed frequency data was explained by differences between observers – adding observer characteristics to the grazed frequency model increased adjusted $R^2$ from 0.124 in the simplest model to 0.407 in the observer model chosen by stepwise selection with AIC. As well as the independent variables found in the simplest model (study site and study year), the best model also included observer effects from both observers (measurer and recorder) who collected data together at the plot and whether or not the observer had moved between study sites (Table 1.2). Frequency was also sensitive to vegetative site covariates including grass and shrub heights which explained ~17% more variation compared to the observer effects model (Adjusted $R^2$ = 0.571, Table 1.2).

### Height-Weight

Compared to the ocular estimates, utilization as estimated from grass heights showed a much smaller amount of variation derived from observer differences. Observer effects explained roughly 7% of the variation found in the height-weight estimates. Adjusted $R^2$ of the simplest model was 0.035 compared to 0.105 in the model containing observer effects chosen with stepwise selection. A larger portion of variation in the best model chosen by stepwise selection using AIC was driven by site covariates including cheatgrass (*Bromus tectorum* L.) cover, as well as dominant shrub and perennial grass species. These covariates explained an additional 20% of the variation (best model $R^2$ = 0.300s, $p < 0.005$). The best model also included differences between observers who had worked at multiple study sites during the same season and had worked for multiple years on the project. Observers who had worked at multiple different study sites tended to estimate higher levels of utilization compared to observers who collected data at a single site all season (p-value from t test comparing the two groups < 0.005). However, the difference in average utilization between these two groups was small (4% utilization compared to 5%).

Utilization estimates from grass height measurements were consistently lower than visual estimates using the landscape appearance method collected at the same sampling locations (Figure 1.7). Height-derived utilization estimates had the largest range at locations classified in the moderate utilization classes (between 20-60% use). For example, plots classified in the 41-60% use category based on landscape appearance had between 0 to 80% utilization based on the height-weight method at that same sampling location by the same observer.

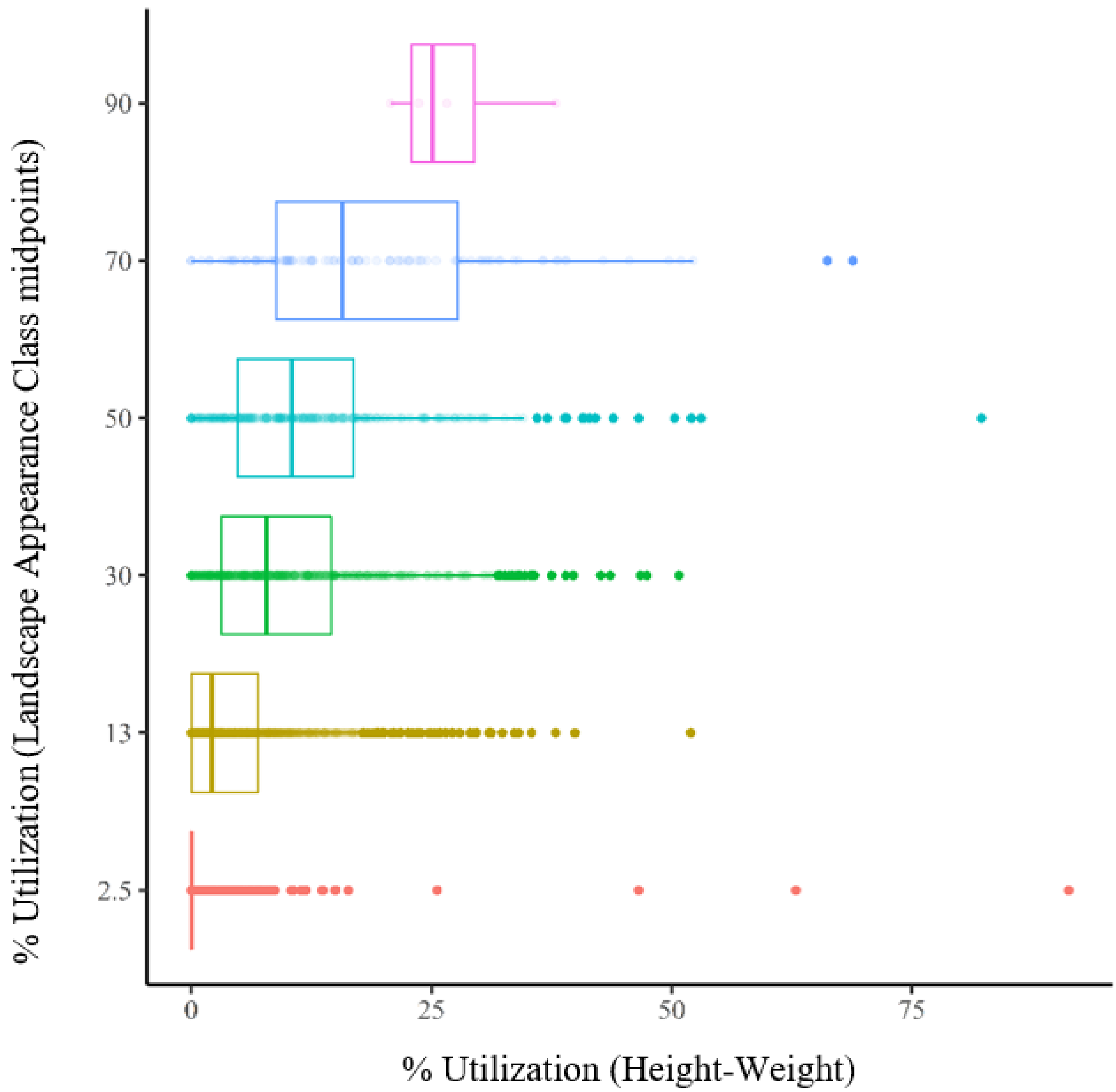


Figure 1.7 – Relationship between utilization estimated from grass heights and visual estimates using landscape appearance collected at the same sampling locations. Utilization estimates from grass height measurements were much lower than those based on landscape appearance classes.

### 3.2 Influence of Technical Expertise

Ocular estimates of individual plant use at sampling sites were compared to paired plots at the same sampling locations (Figure 1.8). In general, the ocular estimates underestimated utilization and showed no linear relationship with estimates from paired plots. More than 70% of the sampling locations had ocular utilization estimates of 5% weight removed, despite this representing between 0 and 80% utilization from paired plots at the same locations.

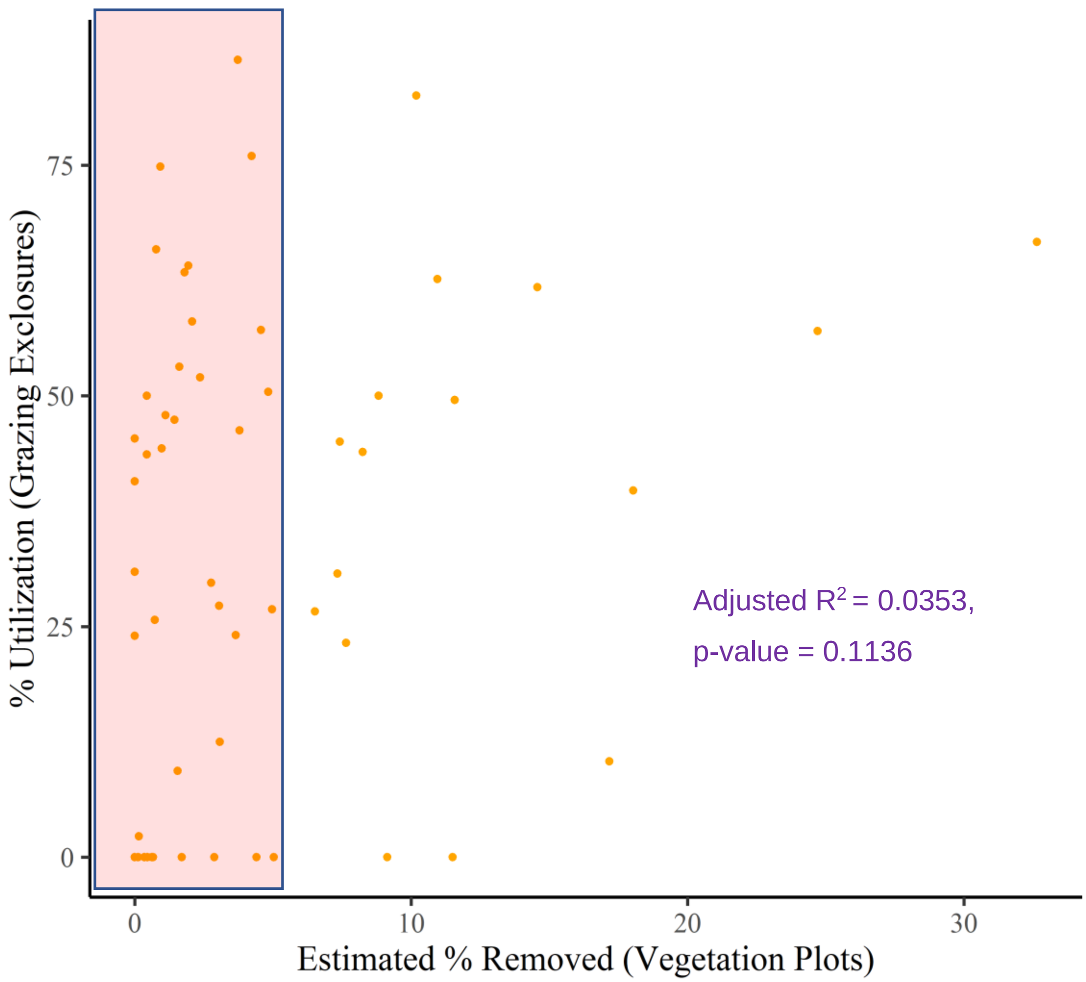


Figure 1.8 – Relationship between ocular estimates of percent herbaceous biomass removed and co-located paired exclosure plots. The two techniques show very little resemblance to each other – ocular estimates underestimated use with the majority of data points below 5% utilization. These represented anywhere between 0 and 80% utilization based on estimates from paired exclosures plots.

Converting the ocular estimates of utilization into frequency of grazed plants improved the fit of the linear relationship with the paired plots (*i.e.*, Pearson's correlation coefficient increased from 0.239 to 0.398). The strongest relationships between paired plots and grazed frequency came from the Brown's Bench study site (Figure 1.9). In comparison to the other four sites, Brown's Bench had the highest utilization overall in 2018 (61% ± 8% estimated from paired plots) and data was consistently collected by the same two observers both of whom were range technicians (technicians hired specifically to sample vegetation based on their botanical expertise). Other study sites which lacked observers with as much botanical expertise showed more variance in estimates when compared to paired plots.

Height-weight, landscape appearance, and paired plot estimates did not appear to be influenced by technical expertise or position title.

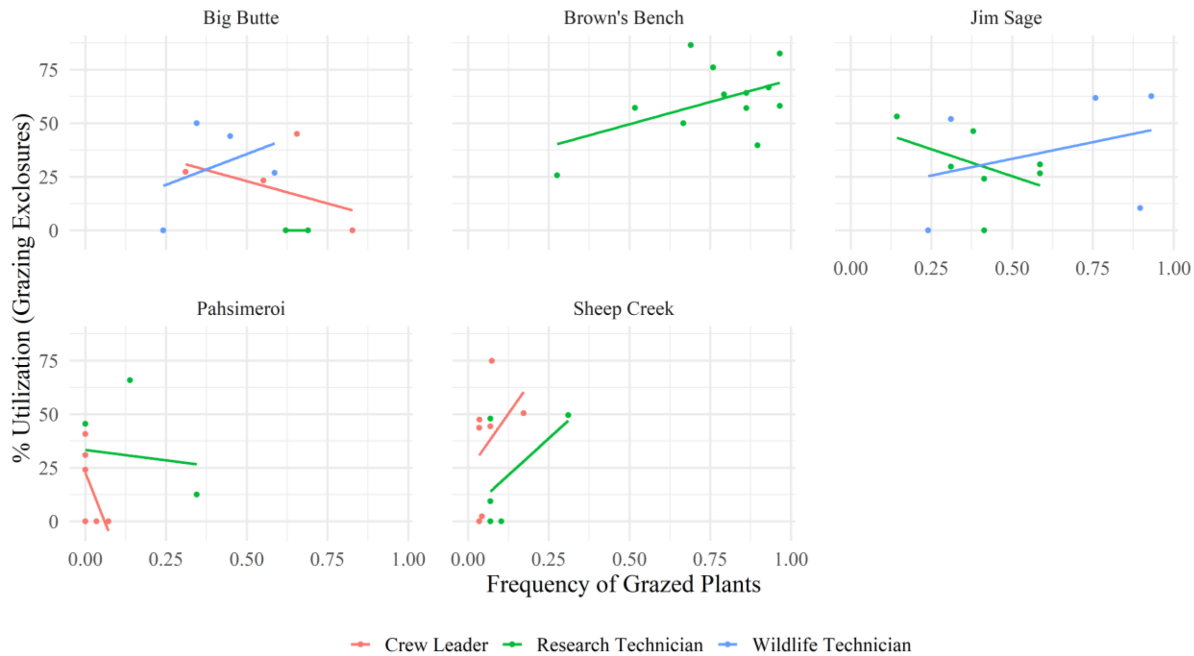


Figure 1.9 – Multiple regression of frequency of grazed plants (derived from plant-based ocular estimates of utilization), utilization from paired plots at the same locations in 2018, and observer job title grouped by study site. Overall, including observer title as a covariate helped to explain variation in the frequency data (adjusted $R^2$ increased by 6%).

### 3.3 Comparing to Stocking Rates

Relationships between different field techniques improved at broader scales. At the pasture scale, paired plots had the strongest correlation to actual stocking rates (r = 0.786), followed by height weight (r = 0.506) and frequency of grazed plants (r = 0.462, Figure 1.10). Height-weight estimates also showed consistently high precision when compared to other techniques (r = 0.759, 0.791, 0.767, 0.848 with ocular estimates, frequency, landscape appearance and paired plots, respectively).

Separating estimates from observers who had remained at one study site versus observers who had moved between sites in a single season influenced the accuracy of the landscape appearance and grazed frequency techniques. Estimates from observers who worked at a single study showed higher correlations to stocking rates – r increased from 0.26 to 0.50 for landscape appearance and from 0.43 to 0.61 in frequency. Both these changes were significant at α = 0.05. Moving between sites did not change the precision of these techniques (*i.e.*, correlation with other techniques remained relatively constant).

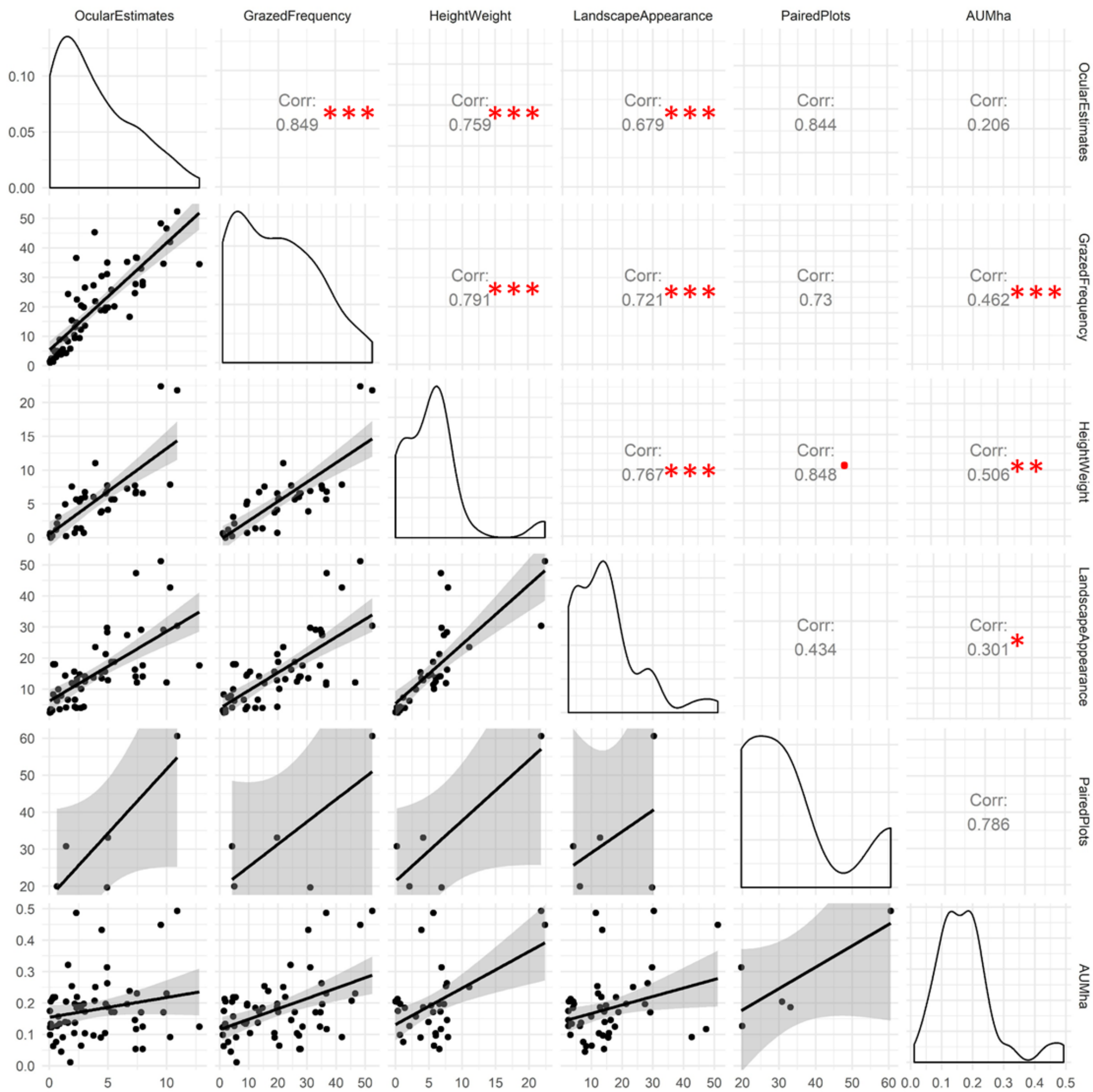


Figure 1.10 – Pearson's correlation, frequency distributions, and regression lines between utilization estimates from five different field techniques and stocking rates when summarized to the pasture scale. AUMha = Animal Unit Months per hectare. Stars represent significance level of the correlation: *** ($p < 0.0001$), ** ($p < 0.001$), * ($p < 0.01$), **.** ($p < 0.05$). Shaded areas represent 95% confidence intervals around the regression lines.

# 4. Discussion

## 4.1 Observer Experience

Across all utilization techniques other than paired grazing exclosures, a significant amount of variation was explained by where observers had worked during the year: Observers who moved between multiple study sites gave consistently higher estimates of utilization compared to observers who worked at a single site. One potential reason for this effect was observer familiarity with plant communities and grazing levels at a site where they spent the most time. The Idaho Grouse and Grazing project study sites had a variety of dominant plant species and levels of grazing intensity. It is possible that recent experiences observing specific patterns of grazing in a study area can lead to more precise measurements. This was illustrated when comparing techniques at the pasture scale: correlations between stocking rates and both landscape appearance and frequency estimates were higher with observers who had spent all their time at a single site.

Not surprisingly, the effect of past observer experience was most strongly seen with visual estimation techniques more so than with metrics based on height measurements or biomass clippings from exclosures. The efficacy of these methods depends largely on the observer’s knowledge of plant growth forms, forage preference and phenological cycles of forage species. For the landscape appearance method, bias was a result of switching from one study area to another with different levels of cattle use. Observers familiar with higher grazing intensity tended to record higher estimates when at lower use sites. This suggests some level of confirmation bias with estimation techniques (*i.e.*, observers are recording what they expect to see).

For height-weight and paired plots there was a small amount of variation related to observer experience and these differences tended to be small (1-2% utilization). Conversely, differences in utilization estimates between landscape appearance observers tended to be larger and thus more consequential to potential management decisions. This also suggests landscape appearance may be less repeatable over time and poorer at detecting long-term changes in grazing effects. Given that utilization techniques are generally intended to be used to evaluate short-term grazing management goals (SRM Rangeland Assessment and Monitoring Committee, 2018), observer bias may be offset by also collecting long term monitoring data such as cover and composition of plants, bare ground amount, or soil aggregate stability to provide more context on rangeland health and trend.

## 4.2 Technical Expertise and Ocular Estimates

Ocular estimates of utilization on individual plants showed the highest amount of variability compared to other field techniques. A large portion of this variance was explained by differences among observers (*i.e.*, observer bias). Observers with more experience monitoring utilization, including field technicians and project coordinators who had worked in their positions for several consecutive seasons, tended to record higher ocular estimates of utilization than technicians with less experience. The ocular estimate method generally underestimated utilization compared to other methods (*i.e.*, most estimates recorded as less than 5%, despite paired plot estimates in the same locations giving estimates of up to 80%). These results highlight difficulties involved in visually estimating plant material that has been removed, and then converting this estimate to a weight-based measure.

Slightly amending the ocular estimation method by converting to frequency of grazed plants helped to reduce some of the observer bias. Observers tended to be better at differentiating between grazed and ungrazed plants as opposed to determining a specific amount of grazing when it had occurred. While frequency of grazed plants does not directly measure utilization, it appears to improve the clarity of observation, improve detection of differences in grazing intensity, and improve consistency between observers. The frequency method also improved correlation with actual stocking rates, providing evidence for higher accuracy.

For ocular estimates – technical experience did not appear to affect the overall estimate of utilization (which was more closely related to day to day experience), but it did influence the correlation between paired plots. Since paired plots were the measurement with the least amount of susceptibility to observer imprecision, it was assumed that higher correlation to paired plot estimates related to greater precision. This suggests that for ocular estimates, accuracy (closeness to population value) was more closely influenced by technical expertise while precision (variability around sample estimate) was driven by day to day monitoring experience.

## 4.3 Comparisons between Techniques

The height-weight method showed the least amount of variability explained by differences between observers. Variation in this technique was influenced more highly by differences in plant functional groups and cover estimates. Despite this, height-weight estimates showed consistently high precision and accuracy at the pasture scale evidenced by high correlations with all other techniques and the second highest correlation with stocking rates (following paired plots).

Both height-weight and ocular utilization estimates did, however, produce consistently lower estimates of utilization than all other techniques (particular landscape appearance and paired plots), suggesting a systematic bias associated with the technique (McKinney, 1997). This supports results from Halstead et al. (2000) who compared the height-weight to paired plots at the plot and pasture scale. This result is significant to rangeland managers since consistently underestimating utilization could have effects on short- and long-term management decisions – for example, failing to move cattle out of an overused area or overstocking a pasture the following year.

## 1.3 Challenges in Rangeland Monitoring

While plant or plot-based approaches may accurately reflect conditions at small spatial scales, these approaches alone may be insufficient to reflect grazing intensity at ranch or landscape scales due to high variability between sampling areas. This may be particularly true in moderately grazed areas in which even seemingly homogenous ‘key areas’ can have a large amount of variability (SRM Rangeland Assessment and Monitoring Committee, 2018). In practice, assessments of forage biomass and utilization are often rough estimates made from quick observations by the rancher or manager, and high sample sizes are often impractical for annual rangeland monitoring (SRM Rangeland Assessment and Monitoring Committee, 2018). The inability to accurately assess biomass and livestock impacts (as a function of grazing intensity and duration), in both the short and long term, can result in overstocking for the coming year (Ortega-S and Lukefahr, 2013). Thus, improvements are needed in the ability to accurately measure forage production, utilization, and residual biomass in the field and to aggregate those measurements up to the scale at which management decisions are made.

Similarly, assessments of grazing effects should be appropriate for the specific management objectives and incorporate current ecological knowledge of disturbance and ecosystem processes. Utilization measures tend to focus on the amount and condition of residual biomass from which a measure of utilization or forage consumed can be calculated. While percent utilization can provide useful insights into managing cattle, it tells only part of the story. Because plant growth and resilience is dependent on environmental conditions including precipitation, similar levels of utilization from year to year may have varying effects on plant communities (Biondini et al., 1998). Thus, management decisions should be made based on a combination of utilization measures, environmental conditions, past management history and trend (Agricultural Experiment Station Oregon State University, 1998; Holechek et al., 2001). Past management actions and disturbance regimes can have considerable influence on plant species distributions and persistence and in some cases may be more influential than precipitation levels (Chýlová and Münzbergová, 2008; Vandewalle et al., 2014). Moreover, past disturbances which alter plant community structure can have far reaching influences on ecosystem responses to future disturbance (Foster et al., 2003). These feedbacks, as described in the state and transition model concept, provide strong evidence for monitoring trend in grazing intensity over broad temporal scales as well as documenting plant community transitions (Bestelmeyer et al., 2003; Briske et al., 2005; Stringham et al., 2003). Thus, grazing field measurements should both be able to consider current years conditions and be consistent enough to provide reliable estimates of trend over time.

## 4.4 Management Implications

Most of the monitoring techniques evaluated here showed imprecision based on an observer's experience at different study sites and whether they moved between sites. Understanding the source of this variation is extremely beneficial since it is easy to detect and thus mitigate. One solution could be increasing training time at a site – learning the differences between grazing systems and plant communities. This may involve 'calibrating' or learning from other observers with in-depth knowledge of that site.

The height-weight technique showed the least amount of variability due to observer effects, but it also gave consistently lower utilization estimates. This illustrates that variability (*i.e.*, precision) only tells one part of the story and substituting high precision for lower accuracy in a monitoring technique can create equally negative consequences for rangeland management. This may be particularly true in public rangeland management in the Western U.S. where utilization estimates are often used in combination with long-term land health monitoring to inform causal factors of land degradation (Bureau of Land Management, 2001).

One major source of variability in utilization estimates not addressed here is the spatial heterogeneity of grazing intensity inherent in moderately grazed systems. This study assumed that correlation between utilization estimates and stocking rate at the pasture level was equivalent to accuracy in grazing intensity. These correlations were useful because they directly related to a specific management action that could be altered. However, this approach fails to recognize the spatial variation in the cattle use throughout the pasture. Comparing utilization estimates to actual cattle locations could help to further improve our understanding of the accuracy of these techniques are multiple scales.

A key strength of this study design that should not be overlooked is that observers were collecting multiple types of utilization estimates which could be used in tandem for their most appropriate applications. Routine collection of multiple monitoring techniques for measuring utilization allows rangeland managers to get a better sense of actual livestock use. This approach adds resilience to the monitoring program and allows for the potential use of a combination of indicators or methods based on shifting management questions and needs.

In recent years there has been a shift across multiple disciplines towards a higher amount of 'citizen science' style monitoring in which data is collected by volunteers or student observers with minimal training (Eglington et al., 2010; Foster-Smith and Evans, 2003; Mitchell, 2000). In the field of rangeland management, this would encompass collaborative monitoring data collection by ranchers as well as land managers. This trend has great potential to improve scientific inquiry and resource management (Hochachka et al., 2012; Kosmala et al., 2016). In order to leverage this growing trend in citizen science, rangeland managers and practitioners should have a thorough knowledge of which monitoring techniques are more or less susceptible to variability in experience. This will facilitate informed choices when designing monitoring programs and improve interpretation and analysis of monitoring results. Similarly, further knowledge of the sources of these biases can reduce or mitigate them and improve the quality of monitoring data and thus the decisions dependent on them.

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# CHAPTER 2: EVALUATING ACCURACY AND PRECISION OF UTILIZATION MEASUREMENT USING CATTLE GPS LOCATIONS AND TECHNIQUE CALIBRATION

## 1. Introduction

### 1.1 Overview

Livestock grazing occurs on approximately 30% of the Earth's ice-free land globally, by far the most extensive land use in the Anthropocene (Ellis et al., 2010). The outcomes of this land use have extensive implications for wildlife management (Beck and Mitchell, 2000; Vavra, 2005), ecosystem function (Augustine, 2003; DiTomaso, 2000; Fleischner, 1994; Fuhlendorf and Engle, 2004), food security (O'Mara, 2012), and socio-economic development (Aryal et al., 2014; Wilmer et al., 2018). This is particularly true in the arid grasslands and shrublands of the western United States where energy development, recreation and residential expansion continue to change the way these rangelands are perceived and managed (Brunson and Gilbert, 2003; Ellis et al., 2010; Gamo and Beck, 2017). Monitoring the direct effects of grazing animals and understanding how they modify the environment for other resource uses is fundamental to successful management of grazing lands. Isolating these effects is challenging due to climatic variability as well as heterogeneity in vegetation and grazing severity. Similarly, changes in disturbance regimes such as wildfire and invasive species add an additional layer of complexity and enhance our need for precise grazing management and measurement (Berg et al., 2016; Manier et al., 2014).

Improving the certainty and clarity of grazing measurements may also have wider implications for public land management policy as a whole (Haynes et al., 2001). Rangeland ecology and management in the United States stands at the intersection between scientific research and public land policy. Public land management decisions and policies regarding these landscapes are often controversial since there are many stakeholders and objectives involved (Clark and Meidinger, 1998). Thus, it is especially important to recognize the limitations of the data and measurement techniques used to make these decisions. Similarly, techniques should be selected based on specific objectives and with end users in mind (Elzinga et al., 2001; Krebs, 1989). Reducing bias and improving confidence in the monitoring of management outcomes such as grazing is the first step in understanding which management actions work best and why, which is fundamental to both adaptive management and policy.

## 1.2 Field Techniques for Measuring Grazing Effects

Quantifying the impacts of grazing within constantly changing natural systems necessitates accurate and unbiased measurements which are representative of the grazed area over time. The cumulative effects of grazing animals depend on the intensity, timing, and distribution of grazing (Holechek and Galt, 2000). Historically, measurements of the effect of grazing animals have focused on grazing intensity as this is seen as the most influential of these three factors. The key indicators of grazing intensity are forage production, utilization, residual biomass and cover (Holechek et al., 2001). This study focuses on measurement of two indictors of grazing intensity: utilization and residual cover. Utilization is defined as the percent weight of current years forage removed or destroyed by grazing animals, and residual indicators are the cover and condition of forage plants following the grazing period (Society for Range Management, 1998). Accurate utilization and residual measurements can improve decision making for: when and where to move livestock (Clary and Leininger, 2000), setting sustainable stocking rates (Ash et al., 2011), assessing rangeland health (Veblen et al., 2014), and describing the effects of livestock on fuels managements (Davies et al., 2016) and wildlife species (Kolada et al., 2009).

In general, grazing intensity monitoring techniques fall into two categories: 1) visual estimates of the amount of plant material removed by grazing either at the individual plant or plot scale, and 2) measurements of individual plants.

### *Visual Estimation Techniques*

Visual estimation techniques rely on ocular evaluation of grazing signs such as amount of plant material removed, distribution of grazing events, reproductive capability of plants, and relative consumption of highly preferred versus low preference forage plants (Bureau of Land Management, 1999). These techniques include plot- or transect-based methods such as landscape appearance or general reconnaissance as well as visual estimates of individual plants, tend to be rapid, and are thus preferred when monitoring large areas. Implementing visual estimates over large pastures can be a fast method for obtaining spatial pattern maps of grazing intensity (Bureau of Land Management, 1999). Visual estimation methods also have a high degree of flexibility for use over large areas such that well trained observers can estimate use of a variety of forage and browse species (Smith et al., 2007). However, accuracy and precision of these methods can depend significantly on the experience and training of the observer (Agricultural Experiment Station Oregon State University, 1998; Jasmer and Holechek, 1984). These techniques require knowledge of local species growth forms, spatial differences in plant growth potential and phenology, animal forage preference as well as skill in detecting signs of grazing which may be variable between observers.

*Measurement Techniques*

Measurement-based techniques for grazing intensity include measuring vegetation heights, clipping and weighing biomass from paired plots (grazing exclosures), stem counts, and frequency of grazed plants (Bureau of Land Management, 1999). These methods tend to be more intensive and time-consuming compared with visual estimation. Measurement-based techniques may require less specialized experience to implement and can be more easily replicated over time and between observers. The additional complexity and time required by measurement-based techniques often mean fewer data can be collected per grazed area and thus spatial patterns of grazing intensity at broad scales may be difficult to obtain.

However, this may be offset by increased accuracy and reduced variation between observers. Due to the complementary nature of the two approaches, efforts have been made to combine the speed and ease of visual estimates with the accuracy of measurement-based techniques (Holechek and Galt, 2000). This type of double sampling or visual estimation calibration has been adopted for use in biomass sampling (Parrott et al., 2012) and annual production (Herrick et al., 2009), but is not widely used for grazing intensity measurements. Calibration techniques for improving consistency between observers are used in vegetation monitoring programs and have shown to be an effective quality assurance measure, for example Duniway et al. (2012) achieved agreement and consistency between observers using an image interpretation tool classified by experts. Improving utilization in this way could be a time-effective method of improving accuracy and precision.

While there have been several studies documenting the various benefits and limitations of visual estimation versus measurement methods for grazing intensity related to accuracy, simplicity, and potential for observer bias (Agricultural Experiment Station Oregon State University, 1998; Jasmer and Holechek, 1984), there is a lack of research evaluating these methods within the context of contemporary land management objectives. For example, many descriptions of the relative merits of individual techniques relate only to grazing management instead of a multiple use viewpoint reflected by more broad management objectives such as wildlife habitat management and ecological resilience. Similarly, comparisons between measurement techniques are most often qualitative descriptions instead of direct quantitative evaluations of different methods within the same study area. Grazing intensity techniques could benefit from a ‘variance decomposition’ style approach which aims to isolate specific sources of error (Lawler and Edwards, 2006; Whittaker, 1984).

## 1.3 Spatial and Temporal Patterns in Rangelands

There have been many significant advancements in the field of rangeland ecology since the establishment of grazing intensity methodologies - most notably, the development of the field of landscape ecology (Wiens, 2009, 1999) and the advancement of remote sensing technology (Hunt et al., 2003). Advances in landscape ecology have illustrated the importance of spatial and temporal patterns as well as the varying effects of scale on ecological processes (Dunning et al., 1992; Turner, 1989). All the methods above provide estimates of grazing intensity which are often only looking at a single temporal or spatial scale. However, the spatial extent and distribution of grazing events can have a significant influence on the landscape, independent from grazing intensity. For example, the degree of spatial heterogeneity in grazing events can influence plant community dynamics, pattern, diversity, and interactions with disturbance, such as wildfire (Adler et al., 2001; Collins and Smith, 2006; Weber et al., 1998). Since the pattern and spatial heterogeneity of grazing varies with scale, it is important to match the resolution and extent of observational techniques to these relevant scales as well as use techniques and sampling designs which can be useful at multiple scales (Atkinson, 1997; Toevs et al., 2011).

While field-based measurements of grazing intensity may help to infer the distribution of grazing, direct measurements of the exact locations and movement of livestock is rarely collected. This lack of information can also have consequences to the productivity or sustainability of livestock operations. For example, management decisions are often made based on general principles of livestock distribution, but actual use patterns may vary by individual animal, be pasture specific and related to other factors such as historic use or predators (Stephenson and Bailey, 2017). Moreover, indirect measurements of use patterns typically assign all herbivory to cattle and can be misleading if other herbivores are removing a substantial amount of herbaceous biomass and/or their use patterns differ from cattle. Direct measurements of livestock movements within pastures could provide ranchers with knowledge and options for making better use of forage resources. Global Positioning System (GPS) collars provide a means for gathering this type of information. Modern GPS collars can record the location of individual animals to within a few meters every 5 to 10 minutes (Bailey et al., 2018). Many studies have demonstrated the value of GPS location data for understanding grazing behavior (Turner et al., 2000), describing livestock use of rangelands (Liao et al., 2017), and quantifying livestock/wildlife interactions (Clark et al., 2017).

By integrating field estimates of grazing intensity and GPS movement and distribution, a more rigorous and accurate understanding of grazing at management scales can be achieved. Stocking rate, density, and to some extent spatial and temporal distribution of cattle on a landscape are factors which can be altered by land managers. Increasing our knowledge of how different techniques relate to these factors and how they affect other resources on the landscape will improve our ability to adapt our management practices based on monitoring results.

This study used small experimental grazing paddocks to characterize the relationship between four methods for estimating grazing intensity under a range of known stocking rates. This involved comparing estimates from the different methods and examining sources of error and variation within them using a variance decomposition approach. Secondly, we looked at the influence of several different ‘calibration’ techniques for improving accuracy of grazing intensity estimates using the landscape appearance method. Lastly, we tested the accuracy of each technique by comparing plot-based estimates to spatial patterns and intensity of grazing based on actual cattle locations at several spatial scales by comparing field measurements of grazing intensity to those estimated from low-cost GPS collars.

# 2. Methods

## 2.1. Zumwalt Prairie Study Site

Data collection for evaluating calibration techniques and GPS collars was conducted in 2019 at the Zumwalt Prairie Preserve in Wallowa County, Oregon (Figure 2.1). The 13,000-ha preserve is owned and managed by The Nature Conservancy. The prairie is dominated by cool season bunchgrasses including Idaho fescue (*Festuca idahoensis* Elmer), bluebunch wheatgrass (*Psuedoroegneria spicata [Pursh] Á. Löve*), Sandberg’s bluegrass (*Poa secunda J. Presl*) and prairie junegrass (*Koeleria macrantha [Ledeb.] Schult*). Mean annual precipitation as recorded by the Zumwalt weather station for the last 13 years (2006-2018) was 358mm, most of which falls in the spring months. Annual mean temperature for this same period was 5.9° C (42.6° F) with July and December as the hottest and coldest months of the year, respectively (The Nature Conservancy, 2018). The year of this study had above average precipitation in the spring (March-May was 55mm more than 30-year average) and drier than average summer (June-August was 65mm less than 30 year average) (Oregon State University, 2017).

Due to the short growing season and shallow soils, the Zumwalt prairie was not historically used for intensive agriculture. Since the early 1700's these grasslands were grazed by horses and subsequently by cattle following Euro-american settlement in the late 1800's (Kennedy et al. 2009). Cattle grazing for beef production has been the primary land use for the last century.

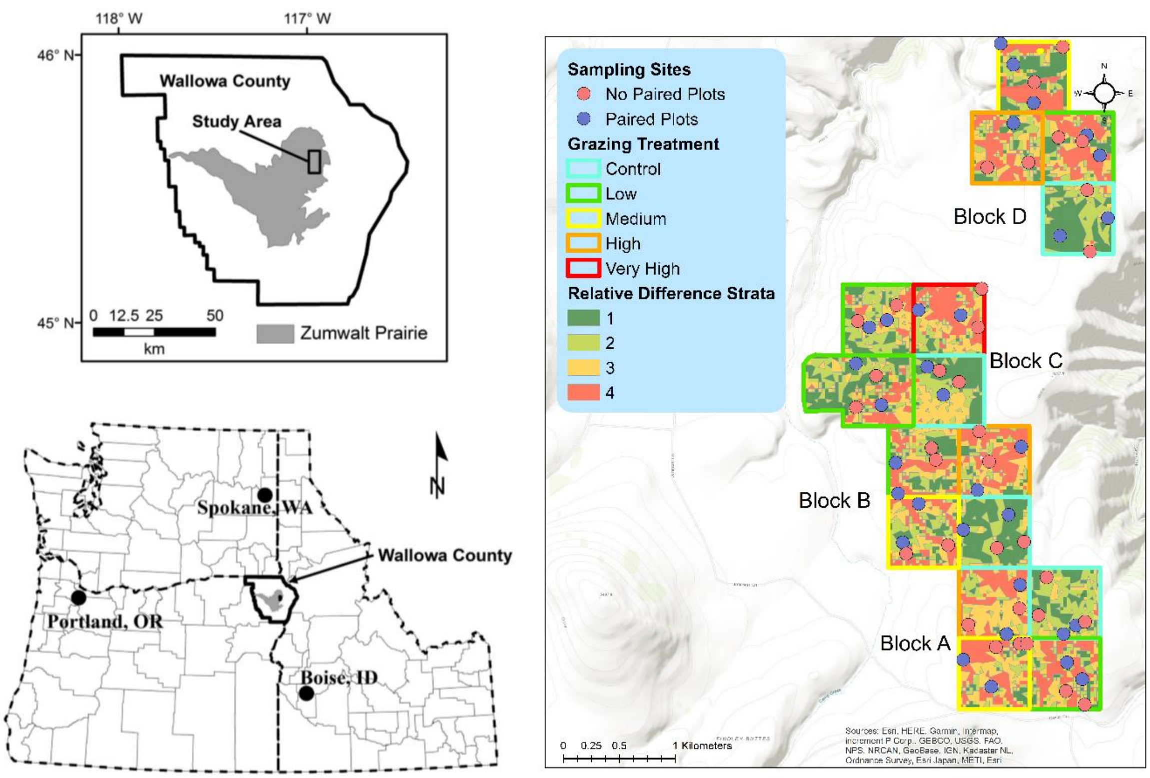


Figure 2.1 - Sample design and plot locations for the Zumwalt prairie grazing intensity study. Plots were located using a spatially balanced random sample design stratified by grazing intensity levels from 2018, as modelled using the Landsat- biomass models from Jansen et al. (2016). A subset of two plots per paddock also had grazing exclosure cages. Map of the Zumwalt Prairie, Oregon (adapted from Jansen et al. 2016).

## 2.2 Study Design

The research was conducted using an existing experimental design from Johnson et al., (2011) using a randomized complete block design of 4 blocks of 4 paddocks, totaling 16 paddocks, with each paddock equaling roughly 40 hectares in area (Figure 2.1). Within each block, 4 different grazing treatments (three grazing levels plus a no-grazing control) were randomly assigned. One block (C) did not follow this assignment due to a lack of water during the study period. This resulted in one paddock in a fifth treatment level – "Very High" and two "Low" treatment paddocks within that block (Figure 2.1). Stocking rate was manipulated by maintaining the number of cattle and varying the length of time in each paddock. Very high was 5 days, high was 4 days, medium was 3 days and low was 2 days of grazing. We also had a no grazing paddock. Based on the number of cattle present, this was equivalent to 50, 40, 30, 20 and 0 Animal Unit Months (AUMs) or 1.25, 1, 0.75, 0.5, and 0 AUM*ha$^{-1}$, respectively. Within each block, paddocks were grazed sequentially from south to north.

Across the experimental paddocks, a total of 64 grazing intensity/vegetation sampling sites (4 per paddock) were located using a spatially-balanced random stratified design (Stevens and Olsen, 2004). Strata were defined using the relative difference of pre- and post-grazing modelled biomass during the summer of 2018 as measured by Landsat 8 ETM+ biomass models described by (Jansen et al., 2016). Relative difference was calculated using the change in modelled biomass prior to and immediately following removal of cows from the pasture. Relative difference was summarized to 30-m pixels and was categorized into equal-sized quantiles representing high, medium-high, medium-low and low grazing intensity.

## 2.3 Field Data Collection

At each sampling site, grazing intensity was measured using three methods: frequency of grazed plants, heights of grazed and ungrazed grasses (*i.e.*, height-weight method) and landscape appearance. Measurements were taken 14 to 28 days following the removal of cattle. When collecting field data in each paddock field observers did not have knowledge of which grazing treatment level was used. At each sampling location, measurements were taken along three 25-m transects placed parallel to each other running towards a randomly selected azimuth. Transects were spaced 10-meters apart (Figure 2.2) with a small buffer area for a total sampling area of ~ 30 by 30 meters.

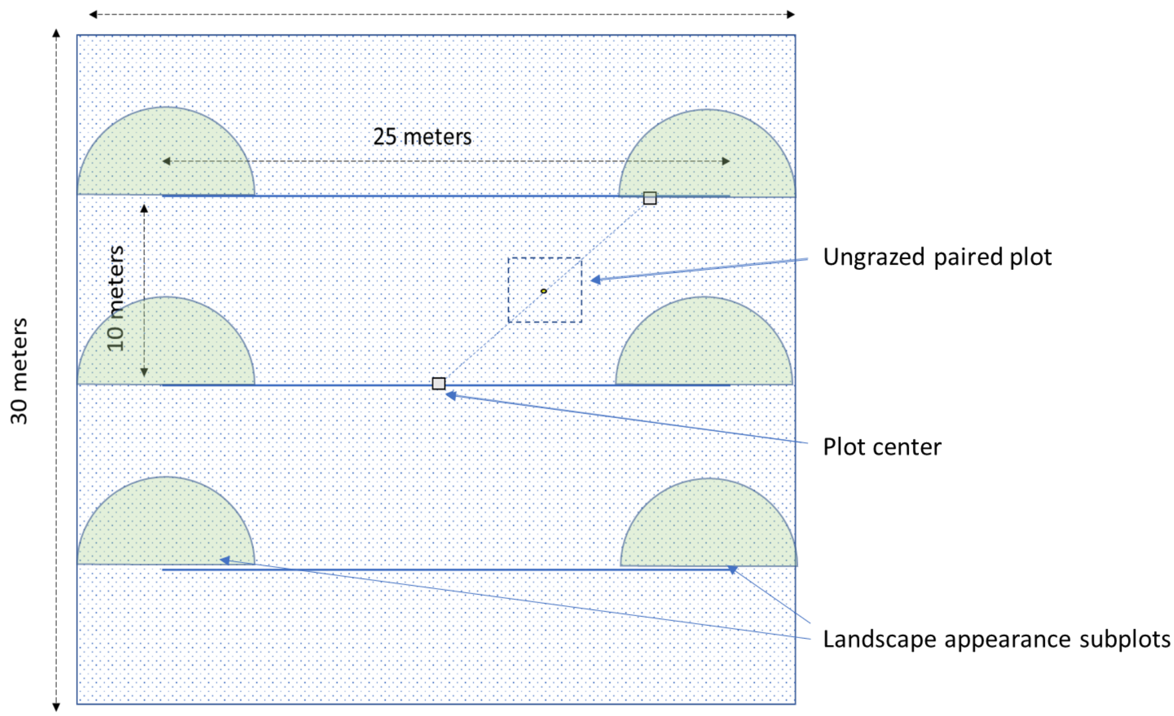


Figure 2.2 – Sampling site and transect lay-out. Line-point intercept and height-weight measurements were collected along three parallel transects spaced 10-meters apart. Landscape appearance was collected at six subplots at the start and end of each transect and clipped paired plots were located in between the first and second transects.

### *Line-point Intercept:*

Foliar cover and proportion of grazed plants were measured using the line-point intercept (LPI) method as defined by Herrick et al. (2017). LPI observations occurred every 0.5 meters along each transect for a total of 150 points per plot, and plant intercepts were determined using a gimbaled laser pointer. LPI intercepts (*i.e.*, 'hits') were counted when the laser intercepted any rooted plant material and all plant species intercepting the laser were recorded at each observation. In addition, individual plants were categorized as grazed or ungrazed based on visual signs of grazing of the plant part intercepting the laser. Presence of plant litter and the type of ground cover (bare soil, rock fragments, plant bases or non-vascular plants/biological crust) were also recorded at each observation. Two grazing intensity indicators were calculated from LPI: proportion of key species grazed and cover of grazed plants. Cover of grazed plants was calculated as the proportion of LPI intercepts which included a grazed plant. Proportion of key species grazed was calculated as the cover of grazed plants divided by the cover of key forage species within the same sampling site.

### *Height-Weight:*

Heights of key forage grasses were measured at 75 subplots along the 3 transects (*i.e.*, every meter along each transect). At each subplot, the closest key forage species was measured to the nearest cm and classified as grazed or ungrazed, according to the interagency technical reference on utilization studies (Bureau of Land Management, 1999). Key forage species were Idaho fescue (Festuca idahoensis), bluebunch wheatgrass (Pseudoroegneria spicata), Sandberg's bluegrass (*Poa secunda*) and prairie junegrass *(Koeleria spicata*). Average ungrazed key forage species heights were calculated for each plot and used in variance decomposition models (described below).

Utilization of key forage species was calculated using height to weight relationships determined by species for the study area by collecting and weighing key forage grasses according to interagency technical reference on utilization studies (Bureau of Land Management, 1999) and Sprinkle et al. (personal communication). Logarithmic models were fit to these data to predict percent weight removed from percent height removed. Height removed from grazed plants was calculated using mean ungrazed heights grouped by species and growth form (with and without culms). Ungrazed average heights were calculated using at least 20 ungrazed plants found within the same sampling site or within the same paddock and ecological site. In the rare situation when grazed height was taller than the mean ungrazed height, utilization was recorded as zero.

Height-weight relationships were determined for Block A and Block D separately in order to account for any differences in environmental conditions and phenology. However, there were an insufficient number of mature plants to create separate curves for Sandberg's bluegrass and prairie junegrass and so a single curve was created for all blocks. While separate observations were made for culmed and un-culmed plants for each species, height-weight relationships were similar between the two growth forms and so all observations were grouped into a single model, except in the case of bluebunch wheatgrass which showed a distinctly different height-weight curve in culmed plants in Block D and so separate curves were created.

*Landscape Appearance:*

Landscape appearance classes were determined for six subplots located across the sampling site according to interagency technical reference on utilization studies (Bureau of Land Management, 1999). This technique relies upon observing the extent and intensity of grazing based on knowledge of grazing behavior, forage preference, grass growth forms and phenology. Classifications are made using observations of the relative use of low and high value forage species, the presence of current year's culms, and the extent or patchiness of grazed areas (Table 2.1). Landscape appearance subplots were a 5-m radius semicircle centered at the beginning and end of each transect (Figure 2.2).

Table 2.1 - Seven classes of utilization used in the landscape appearance method including descriptive guide (Bureau of Land Management, 1999).

| Class | % Utilization | Description |
|---|---|---|
| None | 0-5% | The rangeland shows no evidence of grazing use or negligible use. |
| Slight | 6-20% | The rangeland has the appearance of very light grazing. The herbaceous forage plants may be topped or slightly used. Current seedstalks and young plants are little disturbed. |
| Light | 21-40% | The rangeland may be topped, skimmed, or grazed in patches. The low value herbaceous plants are ungrazed and 60 to 80 percent of the number of current seedstalks of herbaceous plants remain intact. Most young plants are undamaged. |
| Moderate | 41-60% | The rangeland appears entirely covered as uniformly as natural features and facilities will allow. Fifteen to 25 percent of the number of current seedstalks of herbaceous species remain intact. No more than 10 percent of the number of low-value herbaceous forage plants are utilized. (Moderate use does not imply proper use.) |
| Heavy | 61-80% | The rangeland has the appearance of complete search. Herbaceous species are almost completely utilized, with less than 10 percent of the current seedstalks remaining. Shoots of rhizomatous grasses are missing. More than 10 percent of the number of low-value herbaceous forage plants have been utilized. |
| Severe | 81-94 % | The rangeland has a mown appearance and there are indications of repeated coverage. There is no evidence of reproduction or current seedstalks of herbaceous species. Herbaceous forage species are completely utilized. The remaining stubble of preferred grasses is grazed to the soil surface. |
| Total | 95-100 % | The rangeland appears to have been completely utilized. More than 50 percent of the low-value herbaceous plants have been utilized. |

### *Grazing Exclosure Paired plots:*

Within each paddock, two randomly selected sampling sites contained paired plots with grazing exclosures for a total of 32 paired plots. Paired plots included two 75 by 75-cm subplots one of which was excluded from grazing with a metal framed cage (Figure 2.3). Actual sampling location was buffered inside the frames by 50-cm to prevent confounding factors due to alterations in microclimate and/or wildlife influences (Figure 2.3). Due to potential influences from wildlife or cattle, the caged ungrazed subplot was located ~30-meters from its paired grazing sampling site where other field data was collected. The uncaged subplot was located within the sample site area (Figure 2.2). Plant material within each subplot was identified to species and then clipped and weighed in the field. A portion of clipped material from each species per paddock was collected for oven drying to determine appropriate wet-to-dry weight conversions. Careful consideration was made to locate paired grazed and ungrazed subplots in similar soils, microclimates, plant communities and topography to reduce confounding effects of differential plant growth between them.

*Technique Training:*

Data were collected by five dedicated technicians with three additional observers who assisted occasionally. In general, observers had a low level of experience conducting grazing intensity and vegetation monitoring (<1 year) prior to the study except for the crew lead and several of the occasional observers (between 5-10 years of experience each). As well as a week-long period of learning each of the field techniques prior to data collection, all observers (with exceptions noted below) conducted training exercises together on each of the field methods once every 2 weeks (3 instances in total). For line point intercept, grass heights and landscape appearance, training involved measuring the same subplots or transect until all observers were consistent with each other. Discrepancies between observers were discussed in order to clarify protocols and plots were repeated if observers recorded indicator estimates which differed by 5% from the crew average. Two observers were not able to attend all these training exercises, and this was noted during the data analysis.

## 2.3 Landscape Appearance Calibration

Within each paddock, sample sites were randomly assigned one of four calibration methods for implementing the landscape appearance protocol such that each treatment level within each block had a mixture of all four calibration methods. The calibration methods are based around calculating a quantitative estimate of utilization prior to assessing the landscape appearance. The calibration methods were:

For plots with caged and uncaged paired plots:

1. *Visual calibration* – Landscape appearance was collected following LPI but prior to height-weight data collection and clipping the paired plots. Landscape appearance was collected by a different observer to height-weight measurement without discussion of utilization estimates. An estimate of the proportion of grazed plants was calculated in the field in order to inform the landscape appearance assessment.

2. *Paired plot calibration* – The plot was clipped, weighed and a wet-weight utilization measurement was calculated using the difference between both paired plots prior to estimating landscape appearance.

For plots without cages:

3. *Height-weight calibration* – Landscape appearance was collected following height measurements and prior to LPI. An estimate of utilization using the height-weight method and height-weight curves was calculated prior to estimating landscape appearance.
4. *No calibration* – Landscape appearance was conducted prior to all other methods.

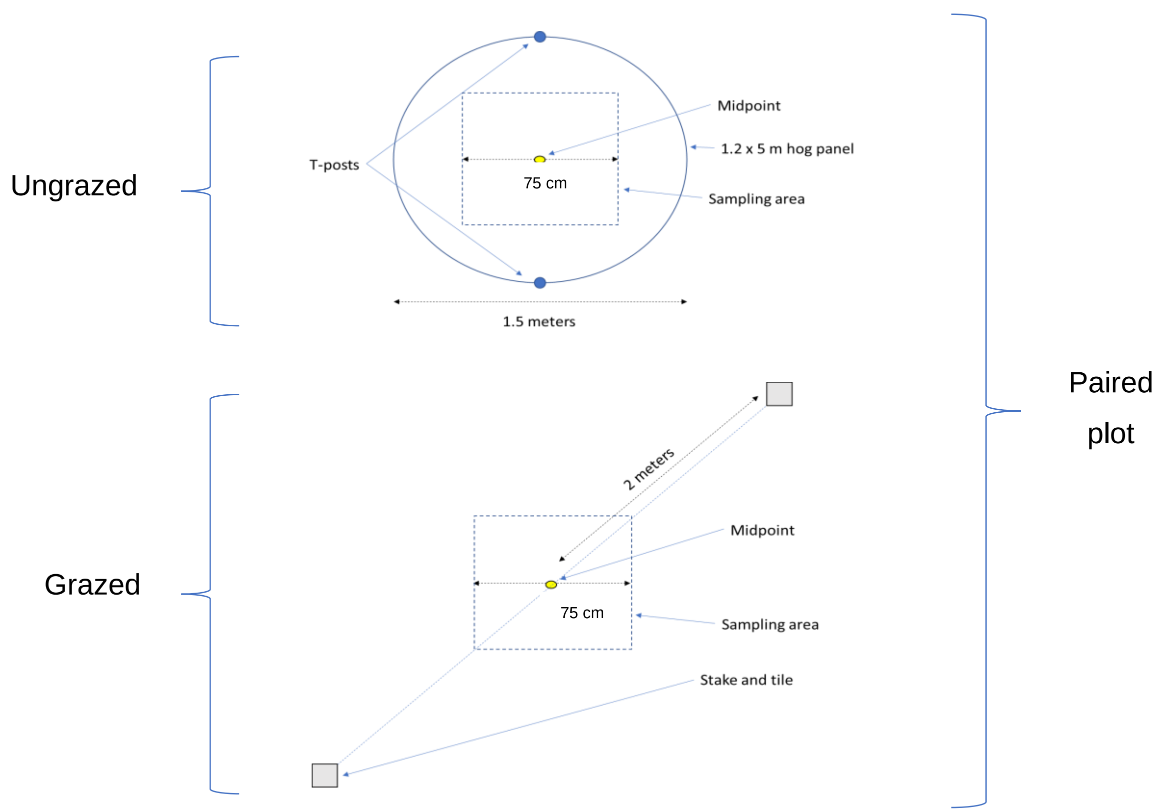


Figure 2.3 – Subplot design for paired plot method. Ungrazed subplots were prohibited from grazing with 1.5-m tall metal hog panels secured with t-posts.

## 2.4 GPS Collar Deployment

GPS collars were deployed prior to grazing the study paddocks on June 14, 2019 and recorded location at 10-minute intervals for the duration of the 8-week study. Cattle herd size was 299 head made up of yearling heifers intermixed with cow-calf pairs. A total of 52 low-cost GPS collars (Karl and Sprinkle 2019) were spread throughout the herd. Twenty-six collars were placed on yearling heifers and 26 collars on cow-calf pairs, assuming the two groups may exhibit different distribution patterns.

*GPS Data Screening:*

Erroneous GPS location values were filtered to eliminate points outside the experimental pasture boundaries similar to methods described by Knight et al. (2018). These erroneous data points accounted for less than 5% of the total GPS locations collected. Point locations were resampled to 10-minute interval tracks with a resampling tolerance of 2-minutes to account for lags in GPS location measurement. Tracks were then converted into steps for each individual cow using the “adehabitatLT” package in R (Calenge et al., 2019) where steps describe the change in direction and the velocity between subsequent locations every 10 minutes (Figure 2.4). Points were further refined by removing steps that showed cows moving faster than 1.2 m/s to reduce error caused by inaccurate GPS location measurement and remove instances where cows are running: Cattle moving faster than 1.2 m/s (based on mean walking speed of *Bos taurus*, Chapinal et al. 2011) were assumed to be travelling and therefore not grazing. Lastly, data were filtered to account for variable battery life of collars. For example, locations in block A were filtered to contain only data from collars which survived the entire grazing time throughout block A. This maximized the number of locations for data analysis while preventing bias between different treatment levels due to failing batteries.

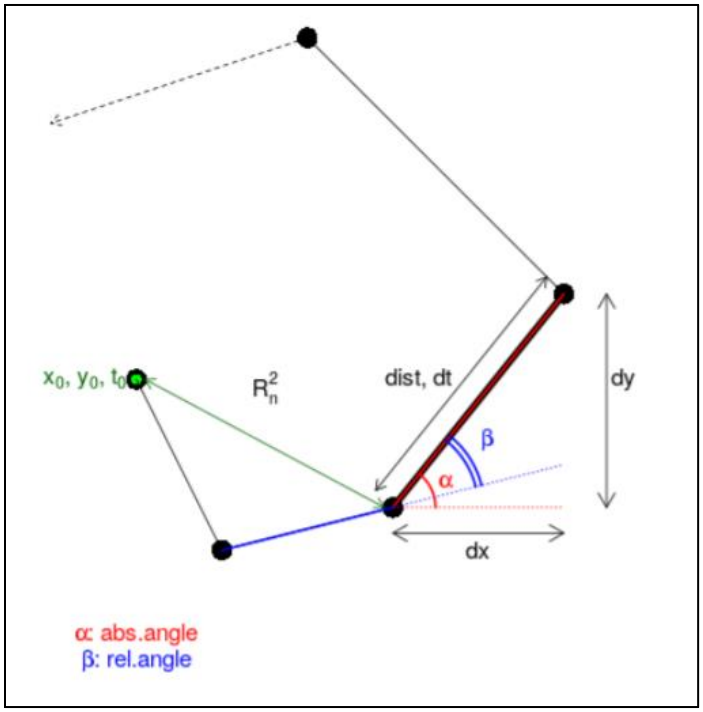


Figure 2.4 - At each step, the distance (dt) and turning angles (α and β) between two GPS locations (collected 10 minutes apart) were calculated using the adehabitatLT package on cran (Calenge et al. 2019). Cattle travel velocity can then be calculated to filter erroneous GPS records.

*Grazing Intensity Rasters:*

Once erroneous values were removed, GPS points were rasterized at a resolution of 30-m (0.09 ha). This resolution was chosen in order to maintain consistency with the Landsat 8 grid used for the sampling design. Each pixel in the raster image was assigned the count of how many GPS points it contained. Rasters were then standardized to reflect the number of collars operational at that time compared to the total number of cattle present to account for collar battery failure, similar to methods used by Kawamura et al., (2005). For example, GPS points from within a paddock with 10 collars and 100 animals were weighted twice as much as points from a paddock with 20 collars and 100 animals. Thus, sample sites could be compared to collar data across the entire study area without bias due to failed collars.

For the filtered raster, GPS points were filtered further to remove points where cattle were not likely to be actively grazing. Firstly, points were removed in which cattle were stationary for 10 minutes or more. Cattle were classified as stationary when properly functioning collars recorded at least 2 GPS locations within 10 minutes that were less than 1-m apart. In these instances, the cattle were assumed to be drinking or resting. Similarly, points between dusk and dawn were removed (11pm and 4am) because cattle tend to show far less grazing behavior during these hours (Kilgour, 2012).

To examine how fine-scale variation in grazing intensity contributed to variation in grazing measurements, GPS collar data were also summarized to 5-m resolution (0.0025 ha) rasters. Variation in grazing intensity within each plot (sampling site) area was quantified using the standard deviation of these fine-scale rasters and added as an independent variable in the best subset regression models.

Each of the different rasters was compared to sample site measurements to assess how well each form of GPS filtering compared to field-based methods for estimating utilization using simple linear and quantile regression. This was done by extracting the raster values found in each sampling area (Figure 2.2) and calculating an average raster value within this area. Each measurement method was compared to the grazing intensity rasters at the plot, paddock, and study area scales. Comparisons involved simple linear regression and calculation of Spearman's rank correlation.

## 2.5 Data Analysis

*Evaluation of Field Techniques:*

Several statistical methods were employed to assess the sensitivity, precision, and accuracy of the four different techniques for measuring grazing intensity as well as determine the dominant sources of error within estimates. We defined sensitivity as the ability to detect differences in grazing intensity, we defined precision as the amount of spread (*i.e.*, variance) of estimates at specific scales, and we defined accuracy as the correlation to actual cattle use measured both spatially and temporally using GPS data.

Data were analyzed with the study's randomized block design to examine the power of each field technique to detect differences between grazing treatments. Blocks were used to control for any differential effects from the grazing timing/sequence and plant phenology. Analysis of variance (ANOVA) models were used to evaluate the numerical measurements: frequency of grazed plants, height-weight method, and paired plot method. The two paddocks which diverged from the randomized grazing treatment levels and had a “Very High” treatment level and an additional “Low” treatment were removed from the ANOVA models to maintain consistency in treatment levels. Because the landscape appearance data was semi-ordinal, a model was constructed using non-parametric methods. Landscape appearance values were also converted to median utilization values for their class (Table 2.1) and modelled with an ANOVA. All models were evaluated in their ability to detect different levels of grazing by reporting model coefficients and p-values for a global F test to detect difference between grazing treatments. Post hoc tests including Tukey's HSD and protected Fisher's exact tests were conducted to test pairwise differences between each grazing treatment.

*Variance Decomposition of Field Techniques:*

Multiple regression and model selection methods were used to evaluate the relative importance of various covariates for explaining variation in each of the field-based methods, following approaches from Hudak et al. (2006) and Jansen et al (2016). This included using stepwise selection using Akaike Information Criterion (AIC) and best subset regression using bootstrapping with replacement. Linear models initially contained all relevant covariates including sampling site level variables: cover of different plant functional groups, litter amount, and total foliar cover from line-point intercept, mean ungrazed grass heights, observer identity, and calibration method. Broader level variables were also included such as observer experience - calculated in days since learning the techniques, grazing treatment level, and block. Finally, two sampling site metrics derived from the GPS locations were included. These were the mean GPS location count from the filtered raster (described below) at 30-m resolution and the standard deviation of location counts within the sampling site area at 5-m resolution. These two metrics represent both the total grazing intensity as well as the fine-scale variation of grazing intensity at each sampling site. In order to reduce multicollinearity, models with any covariates with Generalized Variance Inflation Factors (GVIF) greater than 10 were removed (Friendly and Kwan, 2009).

For each grazing intensity field method, a 'full' model containing all covariates and an intercept was created using the 'lm' function in R. Stepwise selection using the full model was then used to find the optimum number of explanatory variables using the 'stepAIC' function in the 'MASS' package in R. Starting with the simplest possible model both forward and backward stepwise selection using corrected AIC (AICc) was then used to assess which covariates helped to explain variation in utilization estimates. AICc was used for selection due to its ability to penalize more complex models with small to medium sized datasets ($N/p < 40$) (Hurvich and Tasi, 1989).

Following this, best-subset regression from the 'leaps' package in R was performed using the optimum variable number from stepwise selection as a limit (Hudak et al., 2006). Best-subset models were created using bootstrapping with replacement to assess model stability and variation in covariate inclusion rates. The number of covariates in the best model was chosen based on Mallows' cp and the covariate choice was based on the highest inclusion rates from 500 bootstrap simulations.

*Evaluating Calibration Methods:*

ANOVA models and Friedman's tests using the randomized block design were used to test differences in landscape appearance grazing estimates between the different calibration methods. Similarly, Spearman's rank correlation coefficients were calculated between landscape appearance estimates, estimates from other field techniques and the GPS-based grazing intensity for each of the separate calibration methods. Significance in Spearman's rank correlation differences and 90% confidence intervals were approximated by calculating z-scores (Myers and Sirois, 2006).

# 3. Results

## 3.1 Evaluation of Field Techniques

*Detecting treatment effects*

Utilization as estimated from the height-weight, LPI, and landscape appearance methods produced a significant ANOVA result when comparing different grazing treatments and blocks (global F-tests from the randomized block ANOVA were significant with $p < 0.005$). Post-hoc comparisons (Tukey's HSD and Fisher's exact tests) showed significant differences between all grazed and ungrazed paddocks for all methods except paired plots ($p < 0.005$).

Differences between the three levels of grazing were more difficult to detect. No differences were detected between treatments with the height-weight method or the proportion of key species grazed from LPI. Filtering height-weight data by individual key species did not improve the power to detect treatment differences. A post-hoc Tukey's HSD test revealed a slight sensitivity to differentiating between the low and high treatments with the cover of grazed plants from the LPI method ($p = 0.092$).

The landscape appearance data were first analyzed as categorical data comparing counts of each of the landscape appearance classes between all four grazing treatments. A global chi-squared test showed a significant difference in utilization estimates across all four treatment levels ($p < 0.001$). Fisher's exact tests between individual treatment combinations were all significantly different: between control and low ($p<0.005$), low and medium ($p < 0.005$) and medium and high ($p < 0.048$).

Using the landscape appearance utilization class midpoints, the ANOVA to detect the difference between treatments using the block design was significant ($p < 0.001$). Post hoc Tukey's HSD test showed similar patterns as with the categorical data, however, there were no differences between medium and low treatments ($p = 0.670$). There were significant differences between the high grazing treatment and low treatment ($p = 0.002$) as well as between the high and medium treatments ($p = 0.003$).

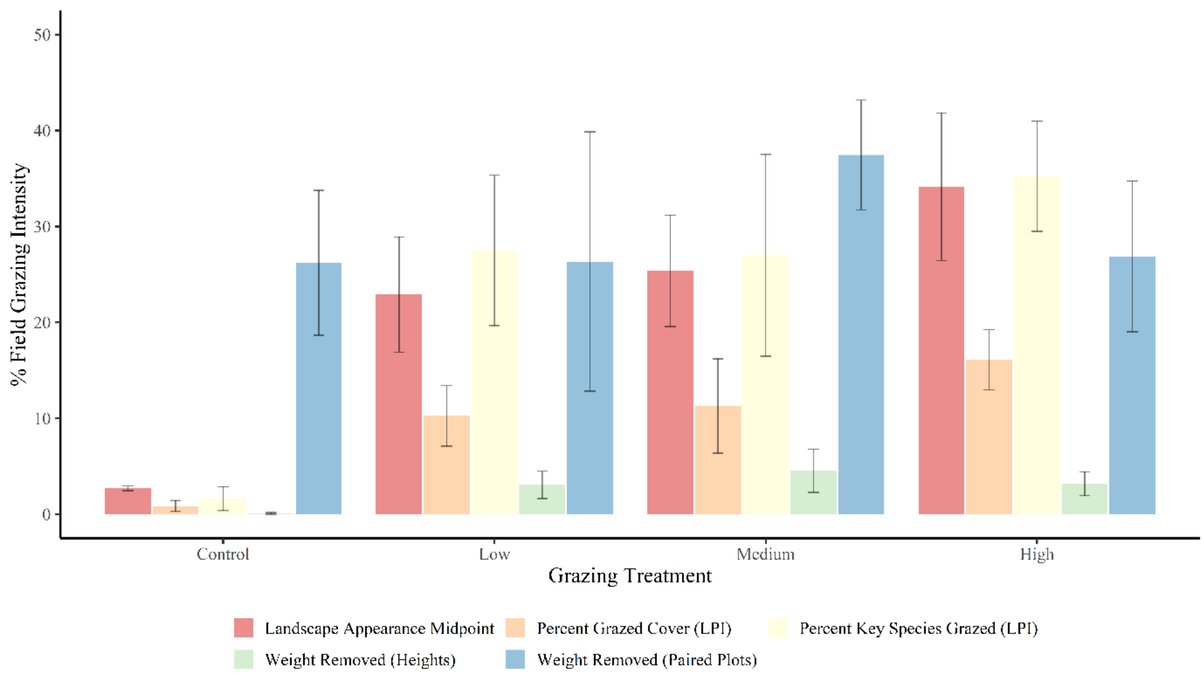


Figure 2.5 - Mean utilization and 90% confidence intervals across all sample sites for five different measurement techniques. All techniques except for the paired plots could differentiate between grazed and ungrazed pastures. Estimates from height-weight measurements were not able to differentiate between the three different levels of grazing intensity. Cover of grazed plants from LPI and landscape appearance both showed significant differences between the low and the high treatments.

The paired-plot method showed no ability to detect grazing differences. A global F-test based on the randomized block ANOVA showed no significant treatment effect ($p = 0.241$). Paired plot estimates showed very large variation within the same treatment areas even within control paddocks (Figure 2.5).

Across almost all field techniques (except for paired plots) there were increases in the mean estimates between the low, medium, and high grazing treatments, but the confidence intervals were too wide to conclude these differences were significant.

*Investigating Precision with Variance Decomposition*

Differences among observers were the main drivers of variation among plots for the landscape appearance, proportion of key species grazed, and height-weight methods but not for the paired-plot and percent of grazed plants from LPI methods (Table 2.2). In particular, landscape appearance had one observer with consistently lower estimates compared to the crew lead. Similarly, two observers consistently estimated higher and lower proportion of grazed key species from LPI when compared with the crew lead. These two observers were also the only two LPI observers who did not complete the training exercises with the crew for the LPI method at the start of the sampling period (observer 2 and 5 from Table 2.2).

Calibration type did not help to explain variation except in the height-weight model which showed slightly lower estimates of weight removed when using visual, height-weight and paired plot methods as calibration. In other words, when no calibration was used (*i.e.*, when landscape appearance was estimated first), grazing intensity estimates from height-weight method were higher. However, these differences were small (differences of 1.5-3% use).

Grazing treatment helped improve model fit for landscape appearance and LPI estimates with significant differences between grazed treatments and ungrazed control sites (Table 2.2). Grazing treatment did not help improve model fit for the height-weight and paired plot methods.

All models were sensitive to changes in site plant community characteristics such as total foliar cover, annual grass cover, and herbaceous litter (*i.e.*, detached plant material) amount. Landscape appearance, height-weight and paired plot estimates were all negatively correlated with total foliar cover, estimates from LPI were positively correlated to annual grass cover, and height-weight had a negative relationship with litter and a positive relationship with perennial forb cover. The paired-plot method illustrated this effect most strongly. For example, paired plots showed a decrease in utilization of 2.3% with each 1% in total foliar cover (all other variables remaining equal).

Estimates of grazing intensity from landscape appearance and grass heights varied between experimental blocks. Landscape appearance showed consistently higher estimates of grazing intensity in the final three blocks compared to the first block. On the other hand, estimates from height-weight became progressively higher from Block A to Block D (*i.e.*, utilization estimates increased over time).

The strength of relationships between field techniques differed between differed levels of grazing. Correlations between utilization estimates tended to be highest within the high grazing treatment, and there was more variability in the medium and low treatments (Figure 2.6).

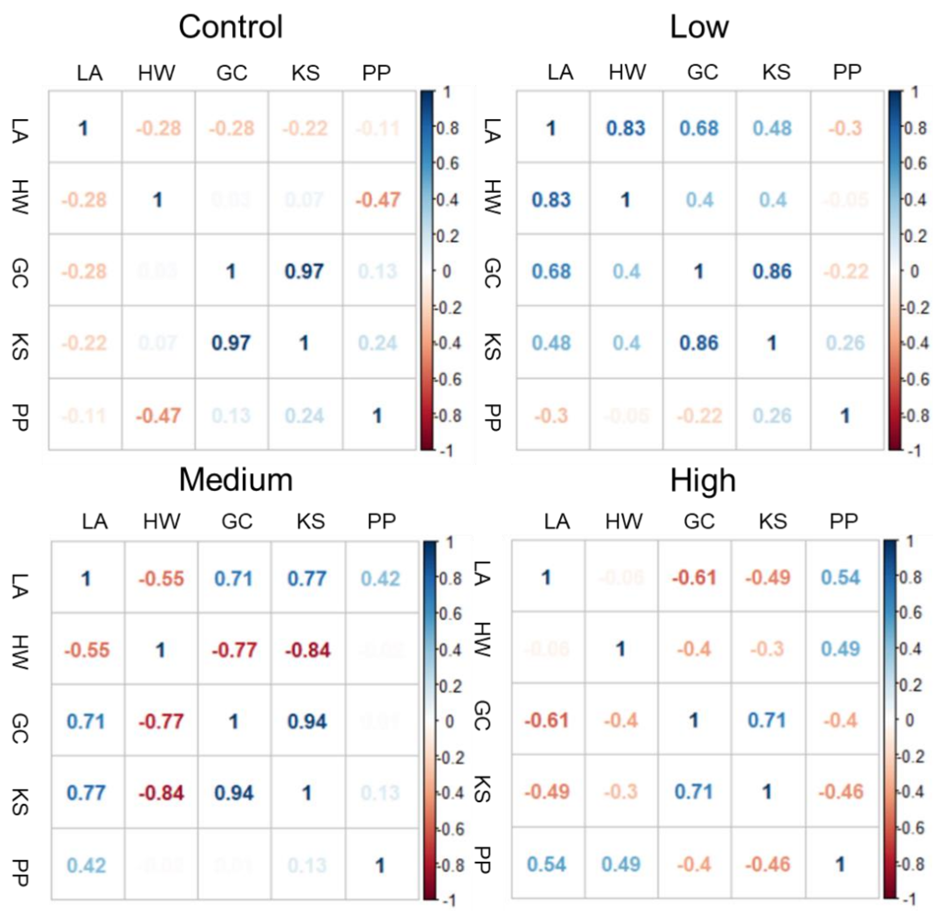


Figure 2.6 – Pairwise correlation coefficients between different grazing intensity techniques at four different stocking rates when summarized to the 30 by 30-m sampling site level. LA = landscape appearance, HW – height weight, GC = cover of grazed plants, KS = proportion of key species grazed, PP = paired grazed and ungrazed plots. Techniques showed the strongest correlations with each other at the lowest grazing treatment.

Table 2.2 – Model statistics and coefficient estimates for best subset regression models explaining variation within each of the field-based techniques. Only variables with significant ($p < 0.1$) effect sizes are shown. All variables in the final models had generalized variance inflation factors (GVIF) <10

| | Landscape Appearance | Grazed Cover | Key Species Grazed | Height Weight | Paired Plots |
|---|---|---|---|---|---|
| **Number of Variables** | 9 | 11 | 6 | 10 | 8 |
| **Adjusted $R^2$** | 0.76 | 0.61 | 0.64 | 0.73 | 0.52 |
| **AICc** | 476.64 | 434.21 | 529.97 | 278.20 | 278.96 |
| **Model P-value** | 1.93E-10 | 2.05E-07 | 1.81E-10 | 2.56E-10 | 0.02147 |
| **Observer LA 1** | -11.34*** | -4.01. | - | -1.34. | NS |
| **Observer LA 2** | NS | NS | - | -1.42. | NS |
| **Observer LA 3** | NS | NS | - | -1.99* | NS |
| **Observer HW 1** | NS | - | - | -2.36** | - |
| **Observer LPI 2** | NS | NS | 15.06** | - | NS |
| **Observer LPI 3** | NS | NS | NS | - | NS |
| **Observer LPI 4** | 18.26** | NS | NS | - | NS |
| **Observer LPI 5** | NS | NS | -14.39** | - | - |
| **Calibration Visual** | - | - | - | -2.89*** | - |
| **Calibration Height** | - | - | - | -2.09** | - |
| **Calibration Paired plot** | - | - | - | -1.53* | - |
| **Annual Grass** | - | 0.17** | 0.29** | - | - |
| **Litter** | - | - | NS | -0.12* | - |
| **Perennial Forb** | - | - | - | 0.054** | - |
| **Perennial Grass** | - | 0.24** | - | - | NS |
| **Rock** | - | - | - | - | -3.49. |
| **Total Foliar Cover** | -0.28* | - | - | -0.11** | -2.31** |
| **Block B** | 11.50*** | NS | - | 2.01* | NS |
| **Block C** | 9.08** | NS | - | 3.02*** | -17.32. |
| **Block D** | 8.39* | NS | - | 6.58*** | NS |
| **High Grazing** | 19.32*** | 15.11*** | 34.63*** | - | - |
| **Medium Grazing** | 11.97** | 14.30*** | 29.99*** | - | - |
| **Low Grazing** | 10.66** | 9.04** | 18.50** | - | - |
| **Ungrazed Grass Heights** | - | - | - | -0.16* | - |
| **Raster Std Dev** | NS | - | - | - | - |
| **Grazing Intensity Raster** | NS | 0.0071* | 0.01. | 0.0021** | -0.027. |

"NS" – variable present in model but non-significant, "***" – $p < 0.001$, "**" – $p < 0.01$, "*" – $p < 0.05$, "." – $p < 0.1$, "-" – variable not present in model

## 3.2 Calibrating Landscape Appearance with other Techniques

At the sampling site scale, the mean midpoints calculated from landscape appearance were positively correlated with the utilization estimates from LPI and height-weight measurements and poorly related to estimates from paired plots.

The relationships between landscape appearance and the other techniques were strengthened when using their respective calibration methods and were weakest when using calibration from a different method (Table 2.3). For example, sample sites using LPI as a calibration method showed a high correlation with landscape appearance for both cover of grazed plants and proportion of key species grazed (ρ = 0.79 and 0.87, respectively) but poor correlation with estimates from the height-weight method (ρ = 0.19). This was also true for height-weight calibration where the correlation between landscape appearance and height-weight estimates (ρ = 0.85) was significantly higher than when calibrating with LPI or without calibration.

Table 2.3 – Spearman's rank correlation between landscape appearance midpoints, the four other field-based techniques and remotely sensed grazing intensity. Correlation was compared across sample sites with different calibration methods. The GPS-based grazing intensity estimates are from unfiltered GPS locations summarized to 30-m resolution. Matching pairs of superscript letters indicate a significant difference with α = 0.1

| **Spearman's rank correlation between landscape appearance midpoints** | | | | | |
|---|---|---|---|---|---|
| **Calibration Method** | **Grazed cover** | **Key species grazed** | **Height-weight** | **Paired plots** | **Grazing Intensity from GPS** |
| 1. Line-point intercept | 0.79 | 0.87 | 0.19[ab] | -0.33 | 0.62 |
| 2. Paired plots | 0.77 | 0.73 | 0.72[a] | 0.22 | 0.80 |
| 3. Height-weight | 0.58 | 0.76 | 0.85[b] | NA | 0.86[f] |
| 4. None | 0.73 | 0.78 | 0.64 | NA | 0.61[f] |

## 3.3 Comparing Field Techniques to GPS Collar Data

From the three grazing-intensity rasters (Figure 2.9) created from the cattle locations, the filtered raster had the strongest relationship in field-based estimates of grazing intensity for all methods except height-weight, although the basic raster performed similarly (Table 2.4).

Table 2.4 – Pearson correlation coefficient values for the three grazing intensity rasters and each field technique at the plot scale. The basic and filtered rasters (both at 30-m resolution) showed similar relationships to the field estimates. In general, the fine raster (5-m resolution) had significantly different correlation than the other two rasters except for % cover of grazed plants.

| Field Techniques | Grazing Intensity Rasters | | |
|---|---|---|---|
| | Basic | Filtered | Fine |
| Landscape Appearance | 0.64885 | 0.65422 | 0.56745 |
| Height-weight | 0.35071 | 0.31623 | 0.14142 |
| Paired Plots | 0.12247 | 0.13038 | 0.17321 |
| % Cover of Grazed Plants | 0.45277 | 0.46583 | 0.44159 |
| % Cover of Grazed Key Species | 0.39623 | 0.41952 | 0.34641 |

Field techniques showed significant positive relationships to GPS-derived grazing intensity (with α = 0.1), except for estimates from paired plots which showed no relationship. Landscape appearance class midpoints showed the closest fit to the GPS-derived grazing intensity (ρ = 0.65 for the filtered raster) and this was true across all three raster types. The correlation of landscape appearance to the raster data also varied significantly between different calibration methods. Landscape appearance estimates which used the height-weight calibration had the highest correlation between GPS-derived estimates (ρ = 0.86, Table 2.3). This was significantly higher than estimates collected without calibration.

Table 2.5 – Quantile regression of field estimates and the filtered raster showing slope coefficients and p-values for the 10th, 50th and 90th percentiles for field-based utilization estimates. Landscape appearance was the only method which had estimates with significant positive relationships at all three percentiles.

| Field Techniques | 10th percentile | | 50th percentile | | 90th percentile | |
|---|---|---|---|---|---|---|
| | Slope | p-value | Slope | p-value | Slope | p-value |
| Landscape Appearance | 0.378 | 0.000 | 1.088 | 0.000 | 1.069 | 0.043 |
| Height-weight | 0.037 | 0.000 | 0.112 | 0.002 | 0.310 | 0.164 |
| Paired Plots | 0.000 | 1.000 | -0.419 | 0.351 | -0.824 | 0.507 |
| % Cover of Grazed Plants | 0.167 | 0.000 | 0.473 | 0.000 | 0.406 | 0.454 |
| % Cover of Grazed Key Species | 0.380 | 0.001 | 0.974 | 0.000 | 0.874 | 0.378 |

Quantile regression showed the relationship between field-based estimates and actual cattle locations was variable across different levels of grazing intensity (Table 2.5, Figure 2.7). This was the case with proportion of both LPI indicators and height-weight estimates, which had consistently lower estimates than shown with the raster data. On the other hand, landscape appearance estimates had a relatively consistent relationship with the grazing intensity rasters at all recorded levels of utilization.

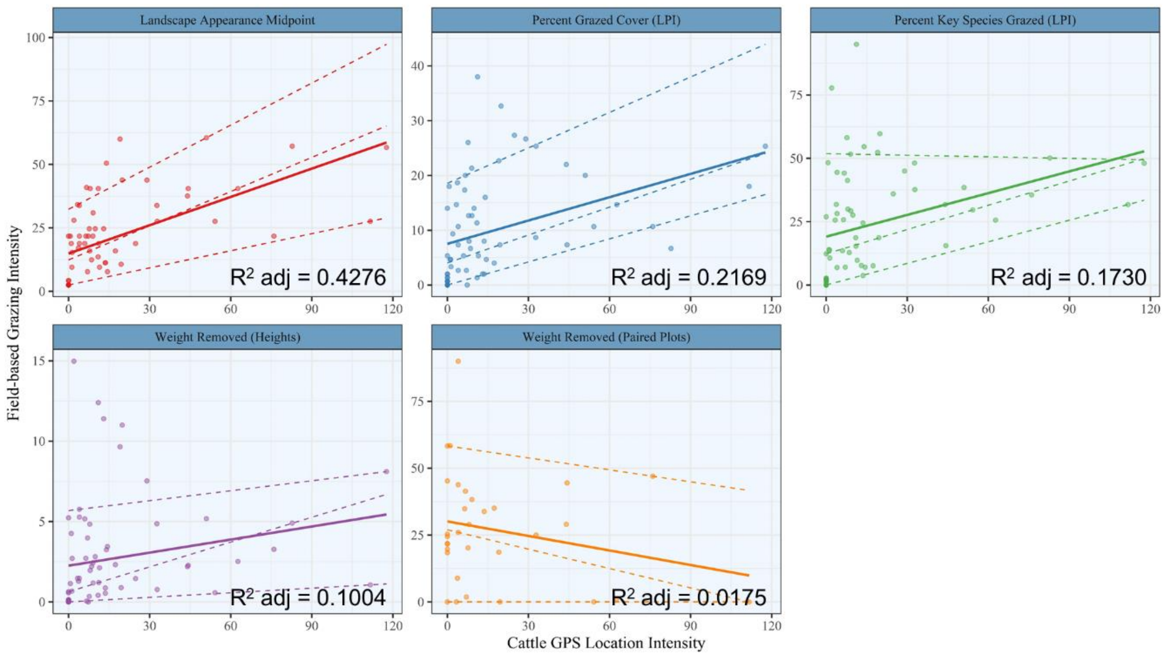


Figure 2.7 – Comparing five different field-based estimates of utilization with GPS-derived grazing intensity based on actual cattle locations at the sampling site scale. The GPS grazing intensity represents the number of cattle locations (once filtered for stationary cattle and daytime GPS points) found within the 30-m pixel surrounding each sampling site. All variables were fit with a simple linear model (solid line) and quantile regression (dash lines) at the 10th, 50th and 90th quantiles. Adjusted $R^2$ values are reported from the simple linear regression models. Average mid-point values from the landscape appearance method showed the strongest relationship with GPS-based grazing intensity (adjusted $R^2$ = 0.4276). The 90th percentile regression lines from height-weight and proportion of key species grazed showed very poor relationships with raster data.

Field-based metrics were also compared to the GPS-derived grazing intensity at the paddock level (Figure 2.8). Mean utilization for each method was calculated from all sample sites within each paddock and then compared to the sum of the GPS-derived grazing intensity within that paddock. This was limited to looking at the filtered raster only since this fit the field-based methods best at the sampling site scale. At the paddock scale, landscape appearance showed the strongest correlation to GPS-grazing intensity (adjusted $R^2$=0.755) followed by LPI estimates (adjusted $R^2$ = 0.584 and 0.551) and then grass heights (adjusted $R^2$=0.250). Paired plots showed no relationship (adjusted $R^2$=-0.124, p = 0.860).

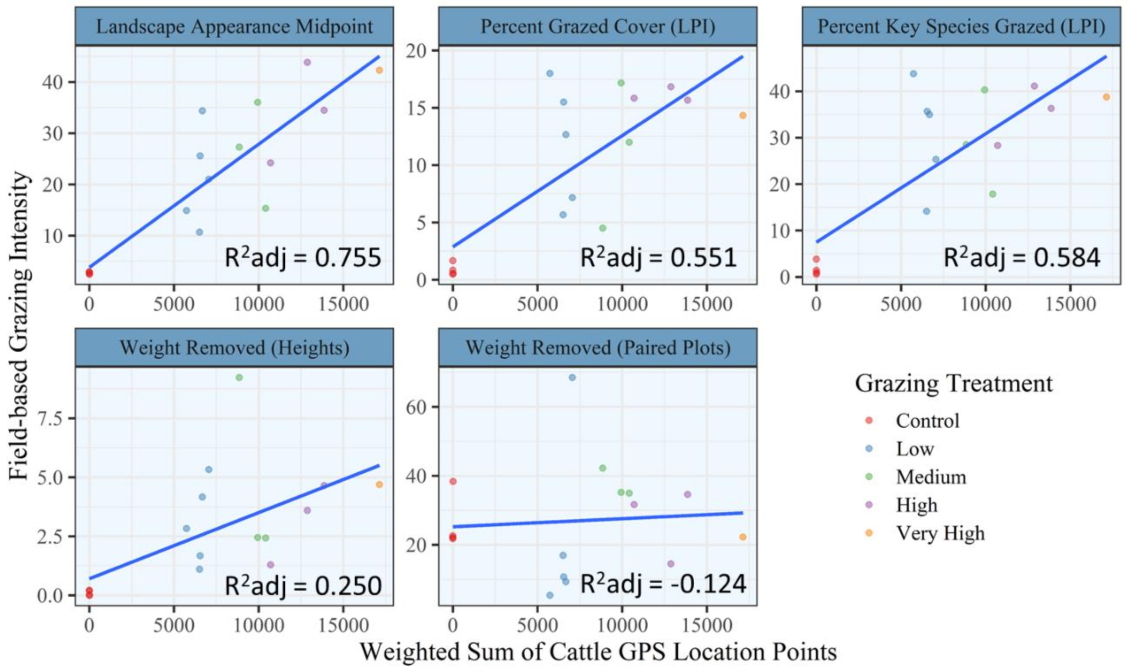


Figure 2.8 - Comparing field-based estimates to GPS-derived grazing intensity at the paddock level. Points represent mean values summarized to each 40-ha paddock. The x axis is the sum of all GPS locations recorded in each paddock weighted to reflect the number of GPS collars used. Simple linear regression models were fit for each technique (blue line).

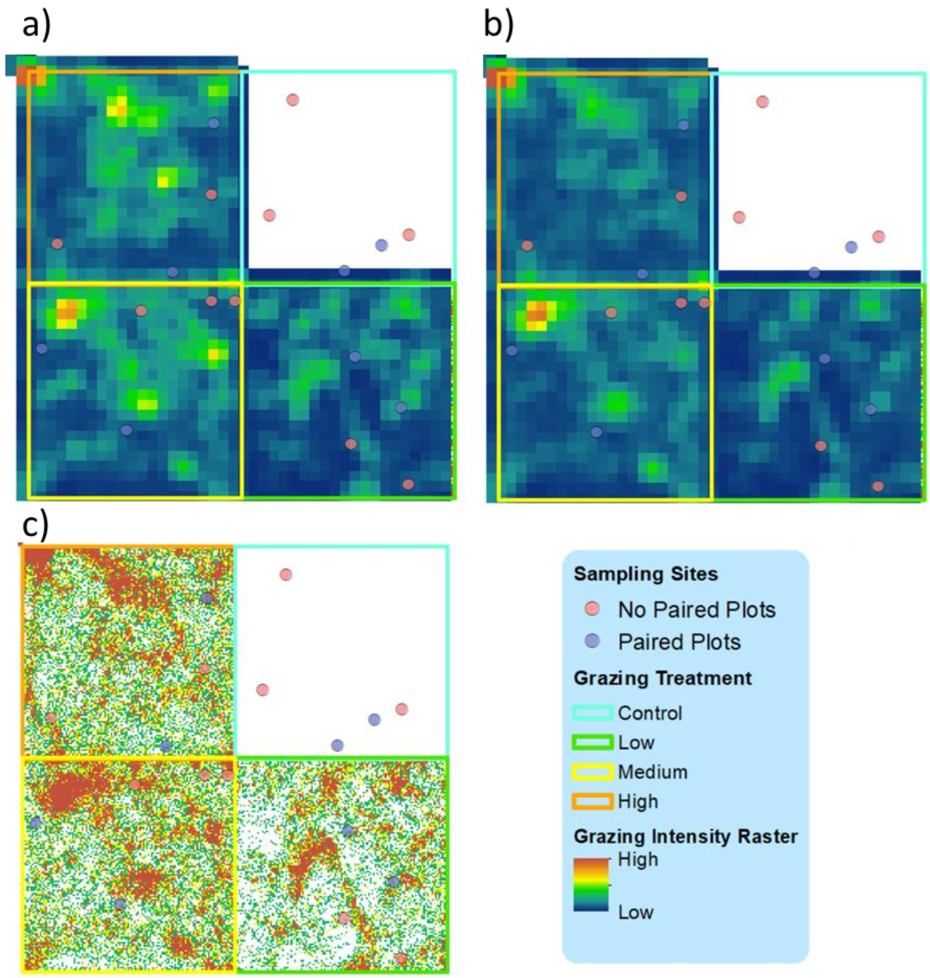


Figure 2.9 – Three grazing intensity rasters from cattle locations recorded by GPS collars every 10 minutes from block A of the Zumwalt study area: a) The basic raster created using all GPS points at 30-m resolution; b) The filtered raster with only daytime points (between 4am -11pm) and stationary cattle removed at 30-m resolution; and c) The 5-m raster created using the filtered GPS points to look at fine-scale variation. Pixel values represent the count of cattle GPS locations recorded once GPS data were filtered for errors and standardized to reflect GPS battery failure.

# 4. Discussion

A good monitoring method for the effects of livestock grazing should be able to detect differences in the effects of grazing over time and space, accurately reflect stocking rates as well as spatial distribution of use, and be objective (*i.e.,* easily repeatable and not influenced by differences in an observer's experience or training).

We compared the utility of five grazing intensity monitoring methods according to the following descending order of importance: 1) sensitivity, 2) accuracy, and 3) precision. Sensitivity was evaluated by describing the ability of each utilization method to detect differences between four different stocking rates. Accuracy was evaluated as the ability of field methods to reflect the distribution, variation, and amount of actual cattle resource use across the landscape using GPS locations. We also looked at ways to improve this accuracy using calibration methods. Precision was assessed by quantifying the amount of variation within methods caused by ‘nuisance’ variables such as observer traits, and differences in plant communities. Precision was also assessed by looking at correspondence to other methods. Using this framework can increase understanding of the relative strengths and weaknesses of each method to better choose the most appropriate method for each situation.

## 4.1 Sensitivity to Different Grazing Levels

Estimates of grazing intensity from height-weight, LPI, and landscape appearance methods were able to detect the difference between grazed and ungrazed sampling sites. However, this was not the case with the paired-plot measurements which showed little difference between all four stocking rates when summarized at the treatment level. This was also reflected in the linear model between paired plot estimates and GPS-derived grazing intensity which showed no significant relationship with paired-plot estimates at the site or paddock scale.

While paired plots can be an objective way to isolate the effects of grazing in homogenously grazed areas, relying on such small sampling areas in heterogeneous areas makes utilization estimates vulnerable to sampling error. In our case, it is unlikely that a single uncaged clipped plot was able to fully represent the grazing intensity for each 0.09-ha sampling site. One potential explanation for this is the large amount of spatial variation in both grazing intensity and plant community composition and cover within plots and paddocks in the study area. This spatial variation in grazing intensity was present even at the highest stocking rate treatment as seen in the grazing intensity raster images (Figure 2.9).

Several improvements could be made to the design of the paired-plot method that could address these issues. First, larger sample sizes could better reflect the heterogeneity within the paddocks. This could include using multiple uncaged plots for each caged plot to better capture the patchy nature of grazing events and provide a quantitative estimate of variation at each sampling site (see Bureau of Land Management, 1999). Increasing the size of clipped areas could represent spatial variation in both plant communities and grazing. However, it is also important to consider the practical implications involved with increased sampling: the time and cost of establishing, clipping, and weighing additional plots could be prohibitive.

Another consideration for improving the performance of the paired plot method could be using a higher-resolution sampling design that better reflects the fine-scale heterogeneity in grazing intensity and plant community composition. The 30-m resolution used for the stratified random sample design may be appropriate for the higher sample sizes of the landscape appearance, LPI, and height-weight methods but may have been too coarse to accurately place the small 50 x 50-cm paired plots. In a study within the same Zumwalt prairie study area, Jansen et al., (2019) provided evidence that resolutions of 1- to 8-m may be more suitable for detecting changes in grazing effects. Therefore, using a probabilistic sample design that incorporates higher resolution satellite imagery (*i.e.*, <10-m) or lidar data may help capture variation with field-based methods without compromising sampling efficiency.

Paired plots also showed the highest estimates of utilization from the control paddocks (22±18% weight removed). The relatively high mean and wide confidence intervals from paired plot estimates in the control paddocks point to issues unrelated to grazing. While there was grazing by elk (*Cervus canadensis*) within the control paddocks (based on anecdotal observations), all other field techniques showed almost negligible amounts of utilization in the control paddocks (<5%). Therefore, differences between caged and uncaged subplots in control paddocks likely stemmed from differences in plant species composition and cover. While care was taken to visually match paired subplots, this was difficult in early spring when plants were senescent or dormant. Matching plots may be improved by establishing paired plot locations during the preceding growing season or with the assistance of site-specific vegetation maps or remotely sensed data (*e.g.,* ground-based lidar or drone imagery).

Landscape appearance was the only technique that was able to detect differences among the three different stocking rates (at $\alpha = 0.05$); although, cover of grazed plants from LPI was able to detect a difference between the high and low grazing treatments at $\alpha = 0.1$. Summarizing the landscape appearance data as a categorical variable was more sensitive to changes in grazing compared to averaging grazing class midpoint values. While landscape appearance estimates were similar to the proportion of key forage species grazed, the latter method was less sensitive to changes in grazing intensity. This similarity was likely due to the phrasing of the landscape appearance class descriptions which focus largely on the “percent of current year’s seed stalks utilized” which made it essentially a visual estimate of the proportion of forage species grazed.

A key consideration when interpreting these results is the use of the quantitative calibration techniques. Three quarters of the landscape appearance sampling areas used a second technique to guide or calibrate the visual estimation, and it is possible that these combinations of techniques helped to improve the sensitivity of the landscape appearance method to detect differences in grazing. In comparison, all other techniques relied solely on a single source for their measurements (*i.e.,* they did not employ an explicit pre-measurement calibration technique). At the least, using the other methods as calibration techniques for the landscape appearance method allowed observers to spend more time at each sampling site and become more familiar with the plant community and grazing patterns present which may have improved detection of visual signs of grazing.

Another consideration for the landscape appearance method was our implementation of plot-based landscape appearance using a stratified random spatially-balanced sampling design which differed from typical uses of the method which are designed around systematically walking long transects across entire pastures and stopping periodically to estimate utilization (Bureau of Land Management, 1999). From our results though, there may be specific benefits of using the landscape appearance method within a probabilistic plot-based design. Focusing on discrete sampling locations that fall within relatively homogenous areas of grazing (*i.e.,* stratum) could increase reliability of the data. Observers can gain better familiarity with each sample area and are not basing observations on relative difference to adjacent sites along systematically placed transects.

Except for landscape appearance and proportion of key species grazed, there were significant differences between estimates of grazing intensity at the paddock scale depending on the technique used. For example, within the high-grazing treatment (40 AUMs) across all blocks, landscape appearance (36.2% use) closely reflected proportion of key species grazed (36.1% grazed), whereas cover of grazed plants was 15.7%, and height-weight estimates were 2.9%. Based on annual production estimates from this study area by Damiran et al., (2007) these differences equated to a range of 817 – 1224 kg/ha of annual production remaining following grazing. Such a wide range of estimates suggests technique choice can be a vital factor when considering field-based utilization estimates, particularly when used in the context of changing grazing management or attempting to understand the effects of cattle on ecological processes.

## 4.2 Comparing Field Estimates with GPS-Derived Grazing Intensity

At both the sampling site scale (*i.e.* individual 0.09-ha sampling sites) and the paddock scale (*i.e.,* four to five sampling sites within 40-ha), landscape appearance had the strongest relationship with GPS-derived grazing intensity compared to the four other field-based indicators of grazing intensity. The strength and slope of this relationship was consistent across low, moderate, and high levels of utilization suggesting that the landscape appearance method was not dependent on a particular minimum or maximum level of grazing to provide reliable estimates. Landscape appearance also showed the closest relationship to the fine-scale raster suggesting it did well at representing fine-scale spatial patterns in grazing.

Conversely, the more quantitative field techniques showed threshold effects in which the highest 10% of field-estimated values (*i.e.,* 90$^{th}$ percentile) fit poorly with actual cattle locations. In the case of the LPI-derived indicators this suggested that high cover of grazed plants did not equate to high utilization. In other words, cattle can lightly forage on a large proportion of forage plants while still maintaining a large amount of biomass in the base of the plant. Thus, when evidence of grazing was common (greater than 20% cover of grazed plants or 50% of key forage species) the LPI-based techniques became saturated and could no longer detect changes in grazing intensity leading them to overestimate grazing intensity. Because forage availability has been shown to influence cattle behavior, such as bite rate and grazing time (Scarnecchia et al., 1985; Werner et al., 2019), these thresholds may be specific to areas similar to the Zumwalt prairie which have high cover and production of forage plants.

Height-weight estimates also showed underestimation of use levels compared to other methods. This supports statements from Halstead et al., (2000) and McKinney, (1997) describing the tendency of ungulates to selectively graze only parts of a single plant. This may lead to issues in visually estimating the proportion of the plant (by weight) which has been removed which can lead to underestimation due the difficulty in estimating exponential height-weight relationships.

Across all techniques other than paired plots, accuracy increased as estimates were aggregated at the broader paddock scale (increases of adjusted $R^2$ with grazing intensity rasters or between 15-41%). This reflects the benefits of scaling estimates to larger areas in combination with the stratified spatially balanced random sampling design. This sampling methodology using biomass models from Jansen et al., (2016) was able to capture the large amount of spatial variation in grazing intensity shown in the GPS data. This increase in accuracy is particularly pertinent because these are the scales at which management decisions are often made: including changes to the rate and timing of stocking. Having higher confidence in grazing intensity measurements at this scale then, can help improve sustainable livestock management.

### Calibration Techniques

Calibration by performing the height-weight method and calculating an in-field estimate of utilization prior to the landscape appearance technique resulted in a significant improvement in the relationship between landscape appearance utilization estimates and grazing intensity from actual cattle spatial use. This effect was seen across all sampling sites irrespective of observer experience or other factors. The higher correlation to GPS-based grazing intensity (*i.e.,* accuracy) was seen in comparison to both no-calibration (*i.e.,* landscape appearance was performed first) and calibration with line-point intercept. When using a calibration method, the observers spent more time at the sampling site before completing the landscape appearance method and became more familiar with the plant species and grazing patterns. This increased time at the site may have improved the observers' ability to detect signs of grazing and thus more accurately estimate utilization classes with the landscape appearance method.

However, sampling time may not have been the only influencing factor since there were large differences between LPI and height-weight methods as calibration. These two techniques take approximately the same amount of time to implement and require similar actions (*i.e.,* inspection and measurement of plants throughout the sampling site). Thus, the increased accuracy of landscape appearance estimates was likely caused using in-field calculations of utilization from height-weight data. Despite its relatively poor relationship with the GPS grazing-intensity rasters individually, the landscape appearance estimates calibrated with the height-weight method produced the closest fit to the grazing rasters with a Spearman's rank correlation of 0.86. This suggests that the landscape appearance method alone may be overestimating grazing intensity, but when calibrated with the height-weight method (which gave consistently lower utilization estimates), landscape appearance produced estimates that better reflected the actual cattle use of the landscape. This effect also held true in reverse. When landscape appearance was conducted prior to height-weight measurements, height-weight measurements were higher (*i.e.,* more similar to landscape appearance).

Despite the different calibration methods having a significant effect on the relationship between landscape appearance and GPS grazing intensity, they were not selected as variables in the landscape appearance best-subset regression models. The fairly strict rules enforced for model selection, which aimed to limit overfitting and multicollinearity, were executed before calibration effects could be included. This model selection process indicated that other variables such as observer effects, grazing treatment, and plant community attributes explained more of the variation in landscape appearance data, but this result does not preclude a significant calibration method effect.

## 4.3 Precision and Bias of Field Techniques

Across the techniques, variation in utilization estimates was largely explained by differences among observers, levels of utilization, and, to a lesser degree, differences in vegetation characteristics. Landscape appearance and proportion of key species from LPI showed the largest differences between observers, and these effect sizes tended to be large (Table 2.2). With respect to the LPI-based measurements, the two observers who had the largest differences from each other and the crew lead had either not taken part in the bi-weekly crew training exercise at the start of the sampling period or had never conducted the exercise with the entire crew. These training exercises involved all crew members observing the same LPI transect, discussing discrepancies and repeating observations if a single observer recorded an indicator value which differed more than 5% above or below the crew average. This process was intended to help crew members learn and practice the LPI technique and resolve any misunderstandings. Crew members missing out on this process could create a higher number of technique misinterpretations and thus differing estimates of grazing intensity.

Another significant source of variation came from differences between blocks despite the blocks sharing the same grazing treatment levels and having similar plant communities and landforms. Timing of both grazing and sampling as well as the experience of the observers (*i.e.* their familiarity with the techniques and sampling area) could explain this variation. Both the landscape appearance and height-weight estimates showed an increase in utilization over time despite GPS-based grazing intensity showing similar levels of grazing between blocks. This could be a factor of increased awareness of observers to detect signs of grazing as they improve over time.

Phenology and vigor of forage species may also have influenced utilization estimates over time particularly due to the below-average rainfall during the later weeks of the study period. Cattle have a proportionately greater effect on drought-affected plants (Souther et al., 2019) thus, differences in the resilience and vigor of forage plants may account for the observed increases in estimates of utilization over the duration of the study as vegetation dried out through the summer. This highlights the fact that the GPS-based grazing intensity estimates can only detect intensity of grazing (effectively fine scale, spatially explicit stocking rates) and do not necessarily reflect grazing severity – which is dependent on the health and vigor of forage species and site potential.

Cover of grazed species from LPI was the least susceptible to observer-derived variation. Best subset regression models for this measurement technique did not show significant effects from differences in observers suggesting a high level of precision and repeatability. This technique only relied on detecting signs of grazing on individual plants and differed from the other LPI-based metric because it did not require any knowledge of plant species. Methods such as this which require less training or experience with grazing systems can be useful especially when considering the growing trend of citizen science in ecological data collection (Hochachka et al., 2012; Kosmala et al., 2016).

*Grazing Treatments*

Grazing treatment levels were a large source of variability within the best subset models which was expected if the utilization techniques were effectively measuring changes in grazing intensity. However, differences in grazing treatment also affected variability in pairwise comparisons of techniques (Figure 2.6). Thus, the amount to which different techniques agreed or disagreed on their grazing intensity estimates changed based on the actual stocking rate. Surprisingly, the highest correlation between estimates was found in the low treatment paddocks (20 AUMs). This may be related to the limitations in the LPI and height-weight methods at high utilization rates discussed above.

This study aimed to assess how well each field technique could capture the differences in grazing intensity under four different stocking rates. While these treatment levels did differ in stocking rate – 0, 0.5, 0.75, and 1 (1.25 in one paddock) AUMha$^{-1}$, they all represented relatively low stocking rates and did not cover a wide range of grazing intensity. For comparison, a recent study on the effects of ‘moderate’ grazing used a stocking rate of 2 AUMha$^{-1}$ (Milligan et al., 2019). This becomes more evident when the carrying capacity of the Zumwalt Prairie study area is considered. This area has higher cover and annual production (1261 ± 51 kg/ha during 2006) in comparison to many rangeland grazing systems in the western United States (Damiran et al., 2007). Thus, difficulties in detecting differences between these relatively low levels of grazing intensity is particularly challenging when using field techniques designed to be used in less productive systems.

Comparing these methods at higher stocking rates may further elucidate the threshold limitations of the LPI and height-weight methods discussed above. If the LPI methods do indeed become saturated above a certain level of grazing, we would expect accuracy of these methods to decrease at very high stocking rates. On the other hand, accuracy of the height-weight method may improve at higher stocking rates: as individual plants become more uniformly grazed, measurement of the residual plant material becomes simpler and less subjective.

## 4.4 Management Implications

The first step for establishing a successful rangeland monitoring program should be developing specific, concise and quantifiable management goals and objectives (Karl et al., 2017; Vos et al., 2000). The most appropriate method for a given situation first depends on their ability to effectively inform these objectives in terms of sensitivity, accuracy, and precision. Secondly, method selection should reflect how a monitoring program is implemented and designed including consideration of observer experience and training. There is no silver bullet when it comes to field-based utilization monitoring methods. Accordingly, the use of multiple methods and indicators may be the best option to create resilience for effective rangeland management.

In general, the plot-based landscape appearance method combined with quantitative calibration was the most sensitive to changes in grazing and most accurately reflected actual cattle use locations. However, landscape appearance was also the method most susceptible to imprecision related to differences in observers. This vulnerability could make it less suitable to applications involving lower-skilled observers especially in the absence of quantitative calibration. However, the malleability in the landscape appearance method may also mean estimates can be positively influenced by the recent experience of observers. Accuracy and precision of estimates may have high potential to benefit from increased training and quantitative calibration techniques. Landscape appearance estimates also showed consistent relationships with GPS-based grazing intensity estimates across multiple levels of grazing intensity. This suggests it may be an effective method to implement in systems that have a wide range of stocking rates.

Alternatively, LPI-based methods showed less variance related to differences in observers and may be more appropriate for less skilled observers or for multi-scale projects conducted by observers with varying levels of training and expertise. This is particularly true of the grazed cover indicator which required only minimal training and botanical expertise. However, LPI indicators had weaker relationships with GPS-based grazing intensity and had only moderate levels of sensitivity to stocking rates employed in this study. There was also evidence that this method was less applicable to higher stocking rates, however this remains to be tested thoroughly. Nevertheless, the LPI methods is advantageous because it is easy to learn, quantifiable, and repeatable.

The paired plot method was not the most appropriate for monitoring spatially variable sites with low stocking rates in this study area. However, effective implementation of the paired plot method could be improved with probabilistic sample designs which accurately reflect spatial heterogeneity in both grazing intensity and plant community patterns. Since this method is time and labor intensive, maximizing the efficacy of the sample design could prevent the need for prohibitively large sample sizes.

Regular implementation of crew training exercises was an effective method for creating confidence with method protocols and increasing utilization estimate consistency between observers. A key recommendation from this study would be increased training and practice of utilization methods which are specific to the levels and spatial patterns of grazing as well as the vegetation composition and plant phenological states present in the study area.

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# APPENDIX A: GPS Collar Pilot Study

The goal of the pilot study was to test the accuracy and durability of the first version of the low-cost GPS devices as described by Karl & Sprinkle (personal communication).

*Study Area*:

The GPS collars were deployed at one pasture within the Jim Sage study site of the Grouse and Grazing project in southern Idaho. The pasture was grazed in the spring of 2018 between May 5$^{th}$ and June 1$^{st}$. The pasture is roughly 5km$^2$ and is comprised of a big sagebrush steppe and grassland with pinyon-juniper woodland at higher elevations. Cows were able to freely roam over the entirety of the pasture which was bounded by fence-line on the east, north and south and a natural boundary characterized by steep slopes (>50%) on the west side.

*Data screening:*

Location and GPS signal quality were recorded at 5-minute intervals for the duration of the livestock grazing in the pastures. The GPS collars are designed to record observations to a micro SD card so that data persists in the event of collar malfunction or battery depletion. Following collar retrieval, the location data from each collar were screened to remove low-quality GPS readings and then composited to a master distribution file for the study area. This included removing points with fixes on fewer than 3 satellites, data that were located outside of the study pasture, and data from collars which had faulty batteries (only lasted several days). This resulted in collar data from 21 individual cows with a total of 38,703 GPS locations.

*Data Analysis and Results:*

Due to their hierarchical nature the GPS location data was analyzed within a mixed modelling framework to assess cattle spatial distribution relative to environmental variables derived from satellite imagery including slope, Normalized Difference Vegetation Index (NDVI) and distance to water. A generalized linear model with a binomial response and logit link function was created in order to analyze spatial patterns of cattle use within the study pasture. NDVI, slope and distance to water all were significant predictors of cattle presence. Resampling of the location data from 5-minute time intervals to 10 and 15 minutes did not reduce the strength of the model significantly.

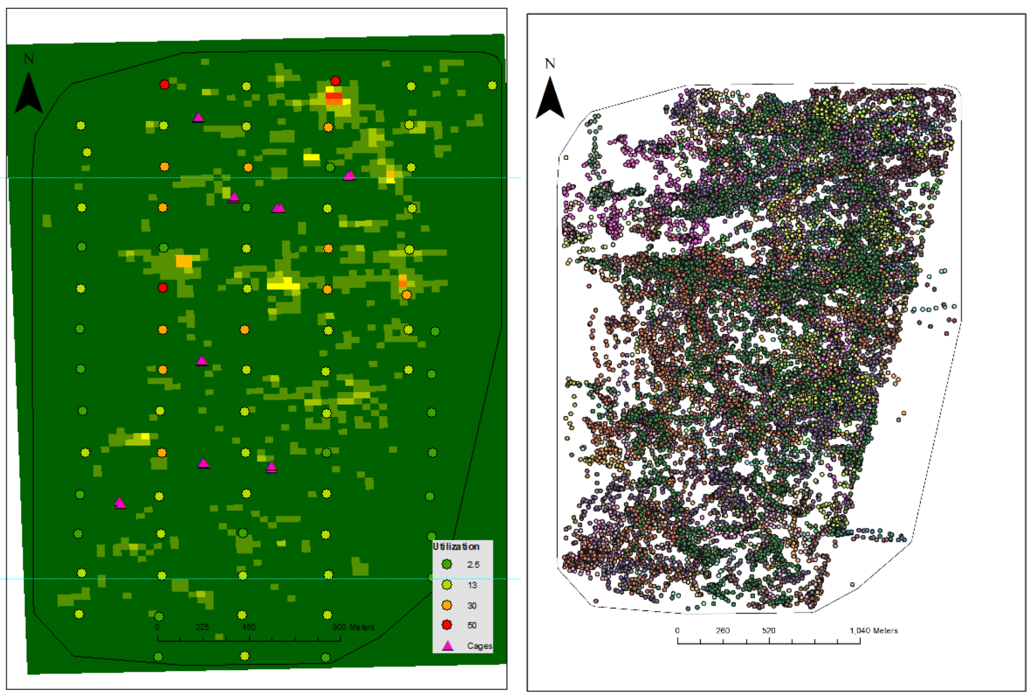
Marginal and condition $R^2$ values were calculated according to Nakagawa and Schielzeth, (2013). This test compares the amount of variation described by the fixed effect alone – the marginal $R^2$ relative to the amount of variation caused by the random effect (individual cows)

– the conditional $R^2$. The marginal $R^2$ was significantly lower than the conditional $R^2$ suggesting there was a large amount of variation between individual cows.

Similarly, an intraclass correlation was calculated according to Zuur et al., (2009) to test the correlation of distribution patterns between individual cows. This resulted in an intraclass correlation of 0.914, suggesting there was high similarity of habitat preference for individual cows.

*Conclusions:*

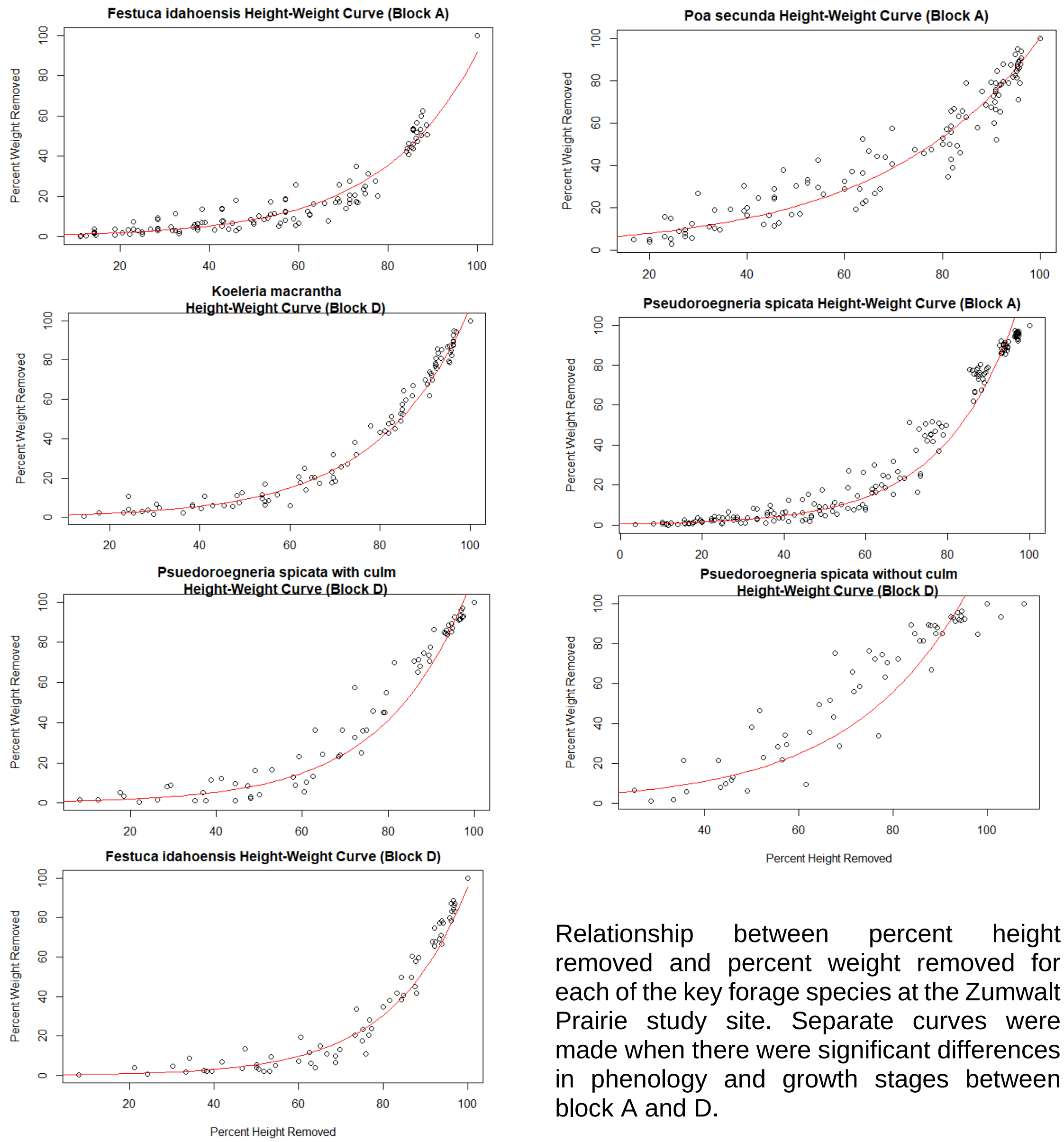
The results of the pilot study showed that the low-cost GPS collars could reliably collect GPS




GPS locations of cattle at the Jim Sage pilot study (right). Cattle locations can be screened for outliers and converted to a grazing intensity raster and compared to field-based data locations (left).

location data for analysis of cattle spatial distribution patterns with a certain amount of data filtering and quality control. There was considerable intra-class correlation *i.e.* locations from individual cattle are highly correlated with each other. This suggests that there is a high degree of redundancy in the amount of GPS locations collected per cow and that the study would benefit from a larger number of collars per herd. Similarly, it is likely that the 5-minute interval for GPS locations could be extended without losing any statistical inference. This could help preserve battery life and data storage space for future use if the collars.

# APPENDIX B: Height-Weight Curves



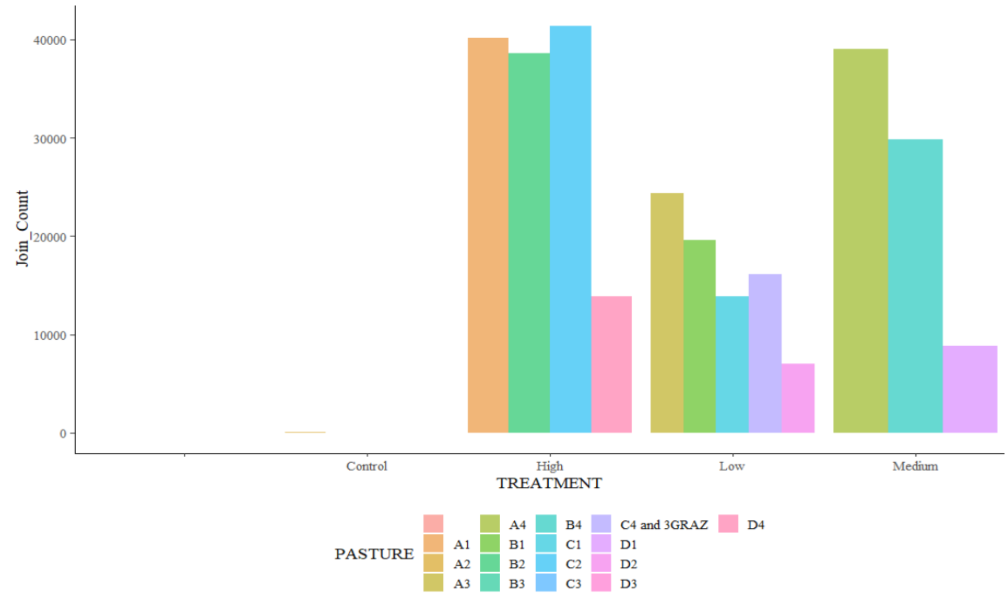

Relationship between percent height removed and percent weight removed for each of the key forage species at the Zumwalt Prairie study site. Separate curves were made when there were significant differences in phenology and growth stages between block A and D.

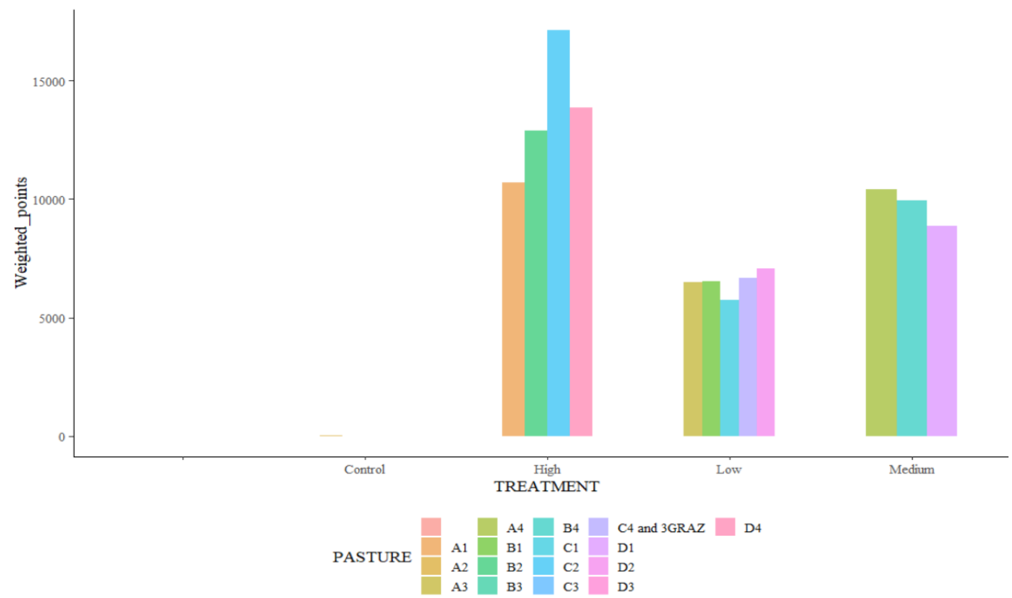
# APPENDIX C: Best-subset Regression - Bootstrap Inclusion Frequencies

| | **Best subset bootstrap inclusion percent - Landscape Appearance** | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Number of Variables in Model** | **1** | **2** | **3** | **4** | **5** | **6** | **7** | **8** | **9** | **10** | **11** | **12** | **13** | **14** | **15** | **16** |
| **GrazeType_High** | 0 | 26 | 53 | 70 | 79 | 80 | 83 | 84 | 85 | 83 | 84 | 83 | 82 | 80 | 79 | 80 |
| **Observer_LA_1** | 0 | 3 | 21 | 38 | 52 | 62 | 67 | 73 | 80 | 81 | 85 | 88 | 89 | 92 | 93 | 92 |
| **Block_B** | 0 | 0 | 1 | 4 | 15 | 29 | 39 | 53 | 56 | 57 | 60 | 59 | 64 | 65 | 66 | 69 |
| **% Foliar Cover** | 0 | 7 | 13 | 16 | 27 | 41 | 46 | 51 | 55 | 58 | 59 | 62 | 65 | 67 | 68 | 69 |
| **GrazeType_Medium** | 0 | 0 | 1 | 15 | 28 | 34 | 42 | 48 | 55 | 57 | 61 | 64 | 70 | 69 | 67 | 68 |
| **Observer_LPI_5** | 0 | 5 | 16 | 29 | 41 | 45 | 47 | 49 | 50 | 48 | 48 | 47 | 47 | 49 | 48 | 47 |
| **Fine scale grazing raster std dev** | 43 | 41 | 48 | 49 | 51 | 53 | 52 | 52 | 49 | 45 | 42 | 42 | 41 | 41 | 41 | 42 |
| **Observer_HW_3** | 0 | 0 | 0 | 2 | 5 | 11 | 26 | 37 | 48 | 58 | 65 | 68 | 73 | 74 | 76 | 76 |
| **Filtered grazing raster** | 45 | 51 | 50 | 48 | 46 | 45 | 46 | 45 | 46 | 49 | 50 | 53 | 56 | 57 | 57 | 59 |
| **Days of Experience** | 0 | 14 | 16 | 25 | 28 | 33 | 35 | 34 | 31 | 29 | 25 | 23 | 25 | 30 | 27 | 27 |
| **Calibration1_Visual** | 0 | 0 | 0 | 1 | 3 | 11 | 16 | 23 | 30 | 36 | 43 | 48 | 55 | 57 | 62 | 67 |
| **% Annual grass cover** | 0 | 4 | 5 | 6 | 12 | 18 | 20 | 24 | 30 | 34 | 40 | 45 | 51 | 55 | 59 | 64 |
| **GrazeType_Low** | 0 | 0 | 1 | 3 | 5 | 9 | 17 | 22 | 29 | 35 | 40 | 47 | 49 | 53 | 56 | 58 |
| **% Moss cover** | 0 | 0 | 5 | 7 | 9 | 13 | 17 | 20 | 26 | 33 | 38 | 44 | 47 | 51 | 54 | 59 |
| **% Cover of cattle feces** | 11 | 9 | 10 | 12 | 13 | 15 | 18 | 20 | 23 | 26 | 30 | 33 | 33 | 35 | 40 | 41 |
| **Observer_LA_2** | 0 | 0 | 0 | 0 | 2 | 4 | 8 | 12 | 20 | 31 | 37 | 45 | 54 | 58 | 64 | 67 |
| **Block_D** | 0 | 0 | 0 | 1 | 4 | 7 | 9 | 13 | 17 | 22 | 24 | 26 | 27 | 28 | 33 | 37 |
| **% Perennial grass cover** | 0 | 6 | 12 | 11 | 10 | 8 | 8 | 13 | 17 | 22 | 27 | 34 | 39 | 41 | 44 | 46 |
| **Observer_HW_1** | 0 | 0 | 1 | 4 | 7 | 10 | 13 | 16 | 16 | 19 | 19 | 21 | 20 | 23 | 27 | 29 |
| **Block_C** | 0 | 0 | 0 | 1 | 1 | 1 | 3 | 8 | 16 | 19 | 24 | 26 | 30 | 32 | 36 | 38 |
| **% Litter cover** | 0 | 0 | 1 | 2 | 5 | 7 | 10 | 12 | 15 | 18 | 22 | 29 | 32 | 37 | 41 | 44 |
| **% Perennial forb cover** | 0 | 9 | 21 | 28 | 27 | 22 | 20 | 17 | 14 | 15 | 19 | 23 | 23 | 26 | 29 | 34 |
| **Observer_LA_4** | 0 | 0 | 0 | 0 | 0 | 2 | 6 | 8 | 13 | 20 | 26 | 32 | 37 | 42 | 48 | 49 |
| **Observer_LPI_4** | 0 | 0 | 0 | 1 | 2 | 3 | 6 | 10 | 11 | 12 | 14 | 13 | 13 | 17 | 19 | 25 |
| **% Annual forb cover** | 0 | 0 | 0 | 1 | 2 | 5 | 7 | 9 | 11 | 12 | 16 | 15 | 16 | 19 | 22 | 24 |
| **Average ungrazed grass height** | 1 | 23 | 24 | 24 | 22 | 19 | 17 | 12 | 11 | 10 | 9 | 9 | 10 | 14 | 20 | 23 |
| **Calibration3_Height** | 0 | 0 | 0 | 0 | 1 | 3 | 6 | 9 | 10 | 14 | 15 | 18 | 19 | 21 | 24 | 30 |
| **Observer_LA_3** | 0 | 0 | 0 | 0 | 1 | 3 | 5 | 8 | 10 | 12 | 13 | 14 | 18 | 22 | 26 | 33 |
| **Observer_HW_2** | 0 | 0 | 0 | 0 | 0 | 1 | 2 | 5 | 5 | 5 | 9 | 11 | 14 | 16 | 19 | 23 |
| **Calibration_Paired plot** | 0 | 0 | 0 | 1 | 1 | 2 | 2 | 2 | 4 | 7 | 11 | 17 | 20 | 26 | 31 | 35 |
| **Observer_LPI_3** | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 1 | 4 | 6 | 8 | 11 | 14 | 15 | 19 | 23 |
| **Observer_LPI_1** | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 4 | 6 | 10 | 12 | 14 | 19 | 20 | 19 |
| **Observer_LPI_2** | 0 | 0 | 0 | 0 | 0 | 0 | 2 | 3 | 4 | 6 | 8 | 10 | 14 | 17 | 20 | 23 |
| **Observer_HW_4** | 0 | 0 | 0 | 0 | 1 | 1 | 3 | 3 | 3 | 6 | 8 | 12 | 15 | 21 | 24 | 28 |
| **% Rock cover** | 0 | 0 | 0 | 0 | 1 | 1 | 2 | 3 | 3 | 6 | 10 | 13 | 16 | 21 | 29 | 36 |
| **Observer_LA_6** | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 2 | 3 | 4 | 7 | 9 | 12 | 15 |

| | Best Subset Inclusion Percent - Proportion of Key Species Grazed | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Number of Variables** | **1** | **2** | **3** | **4** | **5** | **6** | **7** | **8** | **9** | **10** | **11** | **12** | **13** | **14** | **15** | **16** |
| **Graze Type Medium** | 0 | 2 | 27 | 77 | 86 | 90 | 92 | 92 | 95 | 95 | 95 | 95 | 95 | 95 | 95 | 95 |
| **Graze Type High** | 0 | 11 | 39 | 81 | 87 | 90 | 92 | 94 | 95 | 93 | 94 | 94 | 95 | 95 | 95 | 96 |
| **Observer LPI - 5** | 2 | 21 | 46 | 42 | 64 | 79 | 78 | 80 | 79 | 80 | 81 | 81 | 80 | 82 | 80 | 80 |
| **Annual Grass** | 1 | 42 | 35 | 10 | 18 | 27 | 42 | 55 | 70 | 77 | 78 | 82 | 84 | 86 | 90 | 92 |
| **Observer LPI - 3** | 0 | 1 | 6 | 51 | 68 | 70 | 64 | 59 | 61 | 59 | 59 | 58 | 62 | 61 | 60 | 59 |
| **Graze Type Low** | 0 | 0 | 9 | 65 | 74 | 72 | 64 | 59 | 58 | 59 | 61 | 62 | 65 | 64 | 69 | 71 |
| **Filtered GI Raster** | 20 | 35 | 26 | 10 | 12 | 17 | 26 | 38 | 46 | 49 | 55 | 63 | 64 | 66 | 67 | 69 |
| **Litter** | 0 | 0 | 1 | 2 | 6 | 10 | 15 | 27 | 40 | 46 | 52 | 57 | 60 | 64 | 71 | 74 |
| **Block C** | 0 | 1 | 3 | 3 | 11 | 26 | 28 | 32 | 34 | 38 | 45 | 44 | 50 | 53 | 57 | 58 |
| **Calibration 2.Paired.plot** | 0 | 0 | 1 | 1 | 3 | 11 | 22 | 29 | 32 | 38 | 43 | 48 | 51 | 54 | 58 | 59 |
| **Moss** | 0 | 0 | 4 | 2 | 5 | 7 | 13 | 20 | 28 | 32 | 36 | 36 | 40 | 41 | 44 | 48 |
| **Observer LA - 1** | 0 | 0 | 10 | 6 | 5 | 7 | 12 | 20 | 25 | 30 | 32 | 35 | 38 | 41 | 42 | 46 |
| **Observer HW - 5** | 0 | 1 | 0 | 0 | 0 | 3 | 7 | 15 | 21 | 31 | 34 | 39 | 41 | 45 | 49 | 53 |
| **Observer LA - 4** | 0 | 1 | 1 | 1 | 4 | 7 | 16 | 19 | 19 | 21 | 21 | 23 | 24 | 26 | 27 | 29 |
| **Observer LPI - 2** | 0 | 0 | 0 | 0 | 3 | 6 | 11 | 13 | 17 | 22 | 27 | 28 | 32 | 33 | 34 | 34 |
| **Rock** | 0 | 0 | 1 | 1 | 1 | 4 | 7 | 11 | 16 | 21 | 27 | 30 | 35 | 39 | 43 | 44 |
| **Cattle Feces** | 2 | 6 | 7 | 3 | 4 | 7 | 13 | 14 | 15 | 18 | 19 | 20 | 23 | 23 | 25 | 28 |
| **Observer LA - 3** | 0 | 0 | 1 | 1 | 1 | 3 | 6 | 10 | 13 | 20 | 22 | 26 | 30 | 31 | 34 | 38 |
| **Block D** | 0 | 0 | 0 | 1 | 1 | 1 | 3 | 8 | 13 | 16 | 18 | 23 | 24 | 29 | 32 | 33 |
| **St Dev GPS count** | 37 | 37 | 24 | 8 | 4 | 2 | 6 | 8 | 12 | 17 | 24 | 33 | 41 | 43 | 49 | 49 |
| **Block B** | 0 | 0 | 0 | 0 | 1 | 2 | 6 | 8 | 12 | 14 | 17 | 19 | 22 | 24 | 26 | 30 |
| **Total Foliar Cover** | 1 | 0 | 2 | 1 | 2 | 2 | 5 | 6 | 10 | 15 | 18 | 24 | 26 | 32 | 35 | 40 |
| **Calibration 3.Height** | 0 | 0 | 2 | 0 | 1 | 2 | 4 | 7 | 10 | 13 | 16 | 18 | 21 | 25 | 26 | 29 |
| **Observer LPI - 6** | 0 | 0 | 0 | 0 | 1 | 4 | 9 | 11 | 9 | 12 | 11 | 12 | 13 | 16 | 18 | 21 |
| **Observer HW - 4** | 0 | 3 | 12 | 9 | 5 | 5 | 6 | 6 | 8 | 9 | 12 | 15 | 15 | 18 | 22 | 25 |
| **Mean Ungrazed Grass Heights** | 34 | 24 | 28 | 15 | 18 | 25 | 19 | 14 | 8 | 7 | 9 | 10 | 15 | 21 | 24 | 30 |
| **Perennial Forb** | 0 | 4 | 4 | 4 | 5 | 7 | 9 | 10 | 8 | 10 | 12 | 16 | 21 | 24 | 32 | 39 |
| **Observer LPI - 4** | 0 | 0 | 0 | 0 | 0 | 1 | 3 | 4 | 7 | 9 | 10 | 14 | 16 | 20 | 27 | 31 |
| **Observer HW - 2** | 0 | 0 | 0 | 1 | 1 | 1 | 2 | 5 | 6 | 9 | 13 | 15 | 16 | 21 | 23 | 27 |
| **Perennial Grass** | 2 | 7 | 6 | 2 | 3 | 3 | 5 | 4 | 6 | 7 | 10 | 17 | 18 | 27 | 28 | 36 |
| **Annual Forb** | 0 | 0 | 0 | 0 | 2 | 4 | 8 | 7 | 6 | 7 | 10 | 11 | 14 | 17 | 20 | 20 |
| **Experience** | 0 | 4 | 2 | 1 | 2 | 1 | 2 | 2 | 5 | 6 | 9 | 12 | 18 | 20 | 23 | 26 |
| **Observer LA - 5** | 0 | 0 | 0 | 0 | 1 | 0 | 2 | 3 | 4 | 6 | 8 | 13 | 15 | 18 | 24 | 28 |
| **Observer HW - 3** | 0 | 0 | 1 | 1 | 1 | 1 | 1 | 4 | 4 | 5 | 8 | 10 | 14 | 16 | 18 | 21 |
| **Calibration 1.Visual** | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 2 | 3 | 6 | 9 | 11 | 15 | 20 | 24 | 28 |
| **Observer LA - 7** | 0 | 0 | 0 | 0 | 0 | 1 | 2 | 3 | 3 | 3 | 5 | 6 | 7 | 11 | 10 | 12 |

# APPENDIX D: GPS Collar Location Counts




Count of GPS collar points within each paddock for weighted and unweighted points. There were fewer points over time as cattle moved from block A to B to C to D due to collar battery failure. Thus, number of points per paddock were weighted based on the number of active collars at the time. Thus, one GPS point in block D (12 active collars) had ~3 times higher weight than a point in block A (45 active collars). Weighting the points helped to increase evenness of grazing intensity rasters within the same grazing treatment between different blocks.