5-2022

Estimating Cattle Density Using Wildlife Cameras

Emily Bonebrake

ESTIMATING CATTLE DENSITY USING WILDLIFE CAMERAS

by

Emily Bonebrake

Capstone submitted in partial fulfillment of the requirements for graduation with

University Honors

with a major in
Wildlife Ecology and Management

in the Department of Wildland Resources

Approved:

Capstone Mentor
Dr. Tal Avgar

Departmental Honors Advisor
Dr. Kari Veblen

University Honors Program Executive Director
Dr. Kristine Miller

UTAH STATE UNIVERSITY
Logan, UT

Spring 2022

Abstract

Quantifying the abundance and distribution of animal populations is critical for effective wildlife research and management. Due to their cost-effectiveness, wildlife cameras have become an increasingly popular tool for estimating population densities. Previously, this technique relied on ‘capture-recapture’ models that utilized re-sightings of individually marked animals, but in recent years methods have been developed to estimate the population densities of unmarked animals. One such method is the random encounter and staying time (REST) technique, which does this by assuming that the cumulative time animals stay within the view of the camera scales linearly with the number of individuals. This allows for a density estimate without the need to determine individual identity. To evaluate the accuracy and precision of the REST method, I compared cattle (*Bos taurus*) density estimates based on trail-camera photos to the actual number of cattle stocked on a U.S. Forest Service (USFS) grazing allotment. Photos were collected across 96 motion-activated cameras distributed across a single grazing allotment in Spanish Fork, Utah. Based on the USFS grazing plan, the allotment operated under a rest-rotation grazing system, and therefore was divided into three pastures, only one of which held cattle at any given time in the year. Based on this plan cattle numbers also varied throughout the year according to a set schedule. For each stocking period and pasture, we generated REST-based abundance estimates, including empirical confidence bounds derived using either spatial or temporal averaging. Our results indicate very poor agreement between REST-based estimates and USFS stocking rates, where, at the allotment level, the former are typically 50-350% higher than the latter. Whether this indicates REST-based estimates are biased or inaccurate is hard to say; there is no doubt our cameras had detected cows (sometimes a lot of cows) in places and times that no cows should have been in based on USFS records. We thus have little confidence in

the reliability of these records. As for precision, coefficient of variation values for our estimates ranged between 0.1 and 0.5 (depending on the number of active camera days used to calculate the estimate, and on whether densities were averaged across space or across time). This indicates that REST-based estimates are at least precise enough to be reasonably consistent across time (and to a lesser degree, space), and may hence be a valuable tool at the hand of wildlife managers.

Acknowledgements

Throughout the writing of my Honors Capstone project, I have received a great deal of support and assistance. I would first like to thank Utah State University's Office of Research for supporting my research through the Undergraduate Research and Creative Opportunities Grant; Quinney College of Natural Resources for supporting my research through the Undergraduate Research Grant; and Utah State University's Honors Program for supporting my research through the Honors Research Grant. I next want to thank my research advisor, Dr. Tal Avgar, whose expertise was invaluable in formulating the research questions and methodology, and the writing process. Your insightful guidance pushed me to sharpen my thinking and brought my work to a higher level. I would also like to thank my departmental honors advisor, Dr. Kari Veblen, for supervision and critical review. I would like to acknowledge and thank my Wildlife Space-Use Ecology lab mate, Courtney Check. With your long hours helping me work on my code and your generosity of Aggie ice cream and coffee, I have been able to submit my Capstone, thank you. I also thank my other Wildlife Space-Use Ecology lab mates for supporting my research. Next, I want to thank all the volunteers and technicians who helped classify wildlife photos. In addition, I would like to thank my parents and sister for their wise advice and sympathetic ear. You are always there for me. Finally, I could not have completed this manuscipt without the support of my friends and the women of Alpha Chi Omega, who celebrated my accomplishments along the way and provided happy distractions to rest my mind outside of my research.

Table of Contents

List of Tables

List of Figures

Figure

Introduction

Estimating animal population size is an essential element for successful animal management (Xue et al.). The main issue with estimating animal abundance is that animals move; some animals may be hidden out of view during a survey, or some may be double counted if they move in and out of the view of the researcher. If the researcher cannot identify individuals or ensure that animal observations are independent from each other, there are very limited methods available to estimating animal populations. When dealing with cryptic, endangered, and elusive species, detecting animals my moreover be challenging, and the sample size may not be large enough to reliably estimate population size (Schlacher et al.).

There are several commonly used methods to estimate animal population size. One of the most common methods is capture-mark-recapture (CMR). CMR involves two or more sampling periods. In the first sampling period, all captured animals are marked and released. In the subsequent sampling period(s) more animals are captured. Of the captured animals, it is important to note how many were recaptured and how many were captured for the first time. CMR is a popular tool in estimating animal population size because there are many variations to its calculations, such as models that assume a close population versus those that assume an open population (Pollock et al.). Another benefit to using CMR is the wide variety of animals that the method can be used for [for birds (Pollo et al.), amphibians or reptiles (Šukalo et al.), aquatic species (Balázs et al.), and mammals (Jung et al.)]. Some negative aspects of using CMR are that it can become very time-consuming and expensive depending on the study species, it can be disruptive to the natural living conditions of animals so results may not adequately represent the real world, and it also assumes that detection probability is equal among individuals. This means that there cannot be any individuals who enjoy being trapped, or any who likely will not be recaptured.

Another method commonly used to obtain animal population estimates is distance sampling. Distance sampling is commonly used to measure abundance of animals along a line transect, where an observer moves along a transect and measures the distance to each detected animal. Distance sampling assumes that transect location is random in respect to animal distribution; detection probability on the transect is 100%; animals are detected at initial location; distances are measured accurately; and observations are independent. This method is good for slow moving animals that can be detected before they move, scat or other animal signs, and groups of animals. Distance sampling is a poor sampling method for fast moving animals, and for animals that flush in groups (Crum et al.).

Another method used to obtain animal population estimates is camera trapping, which is a relatively new and effective tool in the science of wildlife ecology and management. A camera trap works by capturing images and/or videos when an animal moves within the focal view. These data can then be used to estimate occupancy (the fraction of the landscape inhabited by a focal species), and at times even density, which is the number of individuals per unit area (Burton et al.). Camera trapping has proven to be a useful method for estimating density of individually identifiable animals as they can record high temporal resolution data for long of periods of time without human supervision (Parsons et al.).

There are several methods of obtaining animal population estimates using camera trapping data. One such method is spatially-explicit capture recapture (SECR) models, which are similar to CMR models – both rely on identifying individuals (Karanth). A major downfall of SECR models is that data collectors must be able to identify individuals in the population, but this requirement severely limits the number of species for which identifying individual identity from a photo is not possible. Lately, a growing attention is given to the use of camera traps in estimating densities of unmarked animals (Moeller et al.). The random encounter model (REM) is one method that makes estimating density possible without recognizing individuals (Rowcliffe et al.). REM works by treating individuals like ideal gas particles to estimate density within the camera's focal view (Gilbert et al.). A drawback to REM is that it requires measurement of animal movement speed, which can be hard to measure.

One way to obtain density estimates of unmarked individuals based on camera trapping without animal movement data is the random encounter and staying time (REST) model. The REST model relies on the connection among population density, mean number of camera trap detections during a sample period, and staying time of an individual in the camera's visual field (Nakashima et al.). The model assumes the time that animal species stay within the view of the camera scales linearly with the number of individuals (Garland et al.; Becker et al.). This allows for a density estimate without the need to determine individual identity, or animal movement data.

The REST model has previously been tested by comparing results to SECR-based inference or to a known human density, but has never been compared to known population densities of free-ranging animals (Nakashima et al.; Garland et al.). By obtaining known counts of cattle (*Bos taurus*) from land managers who oversee free-range cattle in a select study area, it is possible to validate the REST model without simulation or comparing to SECR estimates. Moreover, the ecological similarity between domestic cattle and several wild ungulate species (e.g. elk and deer) makes cattle an ideal study species to use for validation of wildlife monitoring techniques. Animal densities are typically quantified through labor intensive direct observation or use of GPS collars, which is expensive and only provides a small sample size (Millward et al.; Bailey et al.). Utilizing camera trapping provides a hassle-free, inexpensive, and representative sample size that traditional methods cannot provide. To evaluate the accuracy of the REST model, we compared cattle density estimates based on trail camera photos to the actual number of cattle stocking on a USFS grazing allotment.

Methods

Study Area

This work was conducted on the Diamond Fork grazing allotment in the Spanish Fork Canyon of central Utah. We placed 96 camera trap sites across all three pastures (Diamond Fork, Hollows, Waters) of the allotment and along and elevational gradient (5000-8500 ft.) (Fig. 1). Cameras were also positioned approximately one meter off the ground and facing an open area to maximize detection of animals. All camera sites were all established at least 250 meters apart from each other. Cameras were deployed in March of 2019 and have been continuously maintained for the last two years. To delineate a set area that could be used for our density calculations, three pieces of steel conduit were placed nine meters away from each camera and two meters away from each adjacent conduit pole, creating a 21.2 m^2 triangular area (Fig. 2). Test photos

Figure 2: Site 11 in Summer 2019 photo example. Note the three pieces of conduit visible in the frame, and the date and time visible at the base of the photo.

were taken at each site to ensure all three poles were visible in the field of view and the direction the camera was facing was recorded.

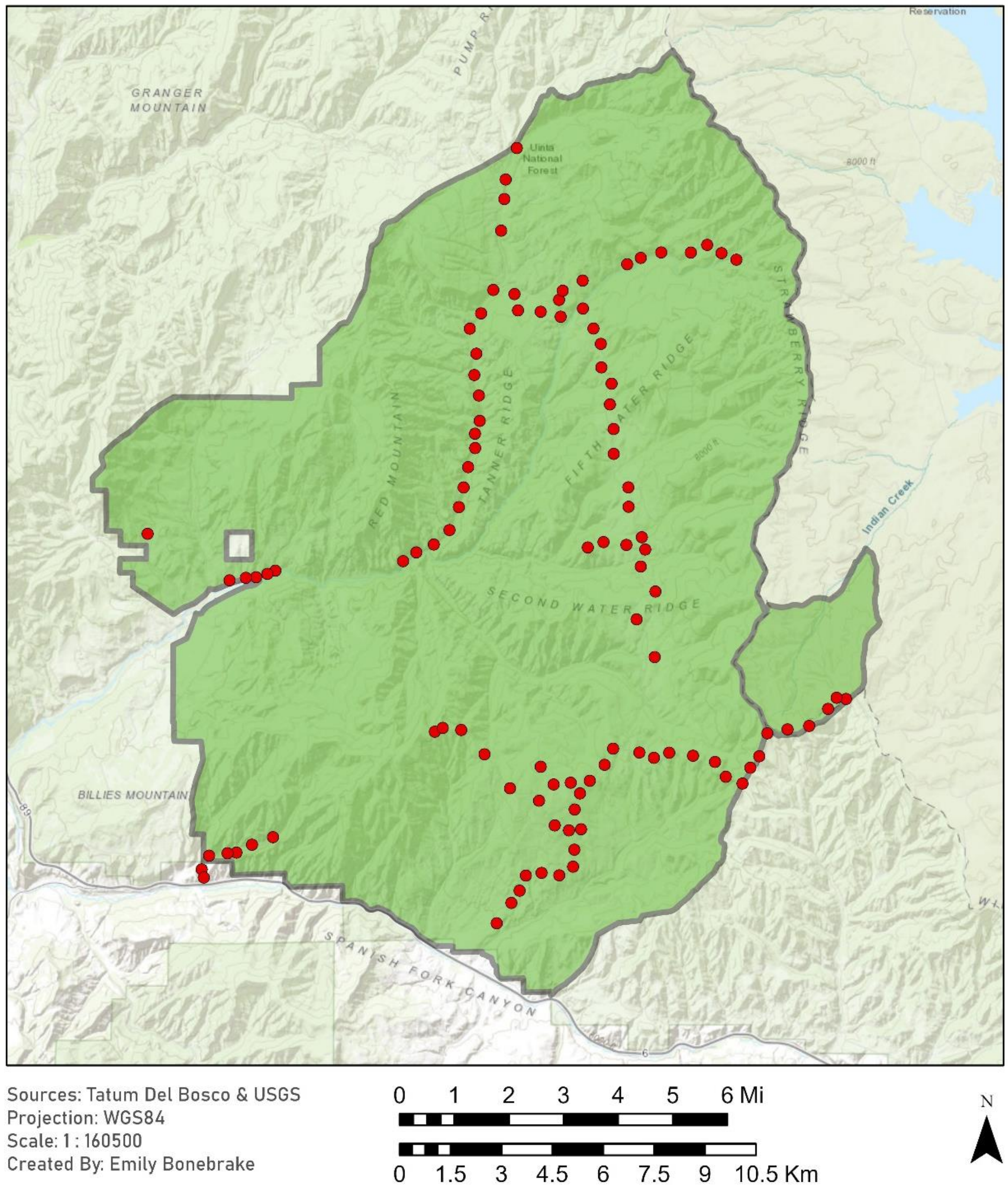

Figure 1: Map of research area in Spanish Fork Canyon showing the 106 camera trap sites along cattle foraging sites. Camera traps were placed across an elevation gradient of approximately 1,000 meters. The two divisions in green represent the grazing allotments that the study sites are located in. The bigger allotment on the left is Diamond Fork and the smaller allotment on the right is Streeper Creek South.

Density Calculations

Cattle were present on the allotment from June-October 2019, so only photos from this time period were examined for our analysis. To calculate density at a given camera site, used the REST model (see calculation below). More than 50% of a cow's body (i.e. its center of mass)

$$Density\ of\ Camera\ Site\ on\ Given\ Day = \frac{\#\ cows * 2\ seconds}{21.2\ m^2 * (24\ hours *\ 60\ minutes *\ 60\ seconds)}$$

needed to fall within the 21.2 m^2 area for it to be included in our density calculations. Cows that did that meet this criteria, or that fell outside of the sampling area were excluded from our analysis.

Comparing Observed and Actual Cattle Densities

To estimate density over the entire allotment in a given stocking period, we first calculated a mean density for each site and for day in the stocking period. For both of these groups of means (site and day) we then used bootstrapping to calculate an overall mean for the allotment over 1000 trials. Hence, for a stocking period of D days and a unit that had S sites (with at least one site active within each of these D days), we obtain D daily density averages, regardless on the value of S. Next, we randomly sampled (with replacement) and averaged D of these values, resulting in a single random value of mean density for a given spatial unit in a given stocking period. We then repeated this process (sample D days with replacement and average) 1000 times, resulting in an empirical distribution of 1000 mean densities for a given spatial unit in a given stocking period.

To obtain temporally averaged bootstrapped densities within a given spatial unit and stocking period, we first calculated the average density for each site across all days within the unit and period. Hence, for a stocking period of D days and a unit that had S sites, we obtain S site-level density averages, regardless on the value of D. Next, we randomly sampled (with replacement) and averaged S of these values, resulting in a single random value of mean density for a given spatial unit in a given stocking period. We then repeated this process (sample S sites with replacement and average) 1000 times, resulting in an empirical distribution of 1000 mean densities for a given spatial unit in a given stocking period. We used the 0.5, 0.25, and 0.75 quantiles of these empirical distributions to represent the median and upper and lower 95% confidence bounds, respectively. To sum, for each spatial unit in each stocking period, we obtain both spatially and temporally averaged densities, each with its own empirical distribution of values. Densities were then converted into absolute numbers (abundance) by multiplying by the spatial unit's area, and rounding up to the nearest integer.

Results

Bootstrapping By Space

Stocking period #1 lasted for 30 days, from June 11 – July 10 (see Figure 3 for a graphical representation of the data, and Table 1 for tabulated data). The supposedly 'unstocked' pastures during stocking period #1, Diamond Fork and Waters, had estimated abundances of 3 (95% CI: 0-6) and 3299 (95% CI: 2438-4129) cows, respectively. The supposedly 'stocked' pasture, Hollows, which was supposed to have 2041 cows during period #1, had no cow detections and hence an estimated abundance of 0 cows. At the allotment level in period #1, there were supposed to be 2041 cows based on Forest Service records, while we estimated 4413 (95% CI: 1845-7419) cows (see Figure 4 for a graphical representation of the data, and Table 2 for tabulated data).

Stocking period #2 lasted for 29 days from July 11 – August 7. The supposedly 'unstocked' pastures during stocking period #2, Diamond Fork and Waters, had estimated abundances of 9 (95% CI: 2-21) and 3382 (95% CI: 1466-3600) cows, respectively. The supposedly 'stocked' pasture, Hollows, which was supposed to have 2141 cows during period #2, had an estimated abundance of 551 (95% CI: 232-1240) cows. At the allotment level in period #2, there were supposed to be 2141 cows based on Forest service records, while we estimated 5066 (95% CI: 2239-9465) cows.

Stocking period #3 lasted for 59 days from August 8 – October 4. The supposedly 'unstocked' pastures during stocking period #3, Hollows and Waters, had estimated abundances of 1268 (95% CI: 1150-2050) and 928 (95% CI: 696-1367) cows, respectively. The supposedly 'stocked' pasture, Diamond Fork, which was supposed to have 2141 cows during period #3, had an estimated abundance of 1845 (95% CI: 992-3302) cows. At the allotment level in period #3, there were supposed to be 2141 cows based on Forest Service records, while we estimated 3728 (95% CI: 2416-5363) cows.

Stocking period #4 lasted seven days from October 5 – 11. The supposedly 'unstocked' pastures during stocking period #4, Hollows and Waters, had estimated abundances of 290 (95% CI: 69-593) and 811 (95% CI: 363-1533) cows, respectively. The stocked pasture, Diamond Fork, which was supposed to have 1600 cows during period #4, had an estimated abundance of 6131 (95% CI: 1191-13919) cows. At the allotment level in period #4, there were supposed to be 1600 cows based on Forest Service records, while we estimated 6298 (95% CI: 1854- 12403) cows.

Stocking period #5 lasted eight days from October 12 – 19. The supposedly 'unstocked' pastures during stocking period #5, Hollows and Waters, had estimated abundances of 832 (95%

CI: 254-1580) and 413 (95% CI: 81-457) cows, respectively. The supposedly ‘stocked’ pasture, Diamond Fork, which was supposed to have 1060 cows during period #5, had an estimated abundance of 787 (95% CI: 68-1853) cows. At the allotment level in period #5, there wre supposed to be 1060 cows based on Forest Service records, while we estimated 1986 (95% CI: 763-3472) cows.

Stocking period #6 lasted seven days from October 20 – 26. The supposedly ‘unstocked’ pastures during stocking period #6, Hollows and Waters, had estimated abundances of 285 (95% CI: 140-447) and 123 (95% CI: 31-236) cows, respectively. The supposedly ‘stocked’ pasture, Diamond Fork, which was supposed to have 520 cows during period #6, had an abundance estimate of 417 (95% CI: 155-1107) cows. At the allotment level in period #6, there were supposed to be 520 cows based on Forest Service records, while we estimated 840 (95% CI: 400-1409) cows.

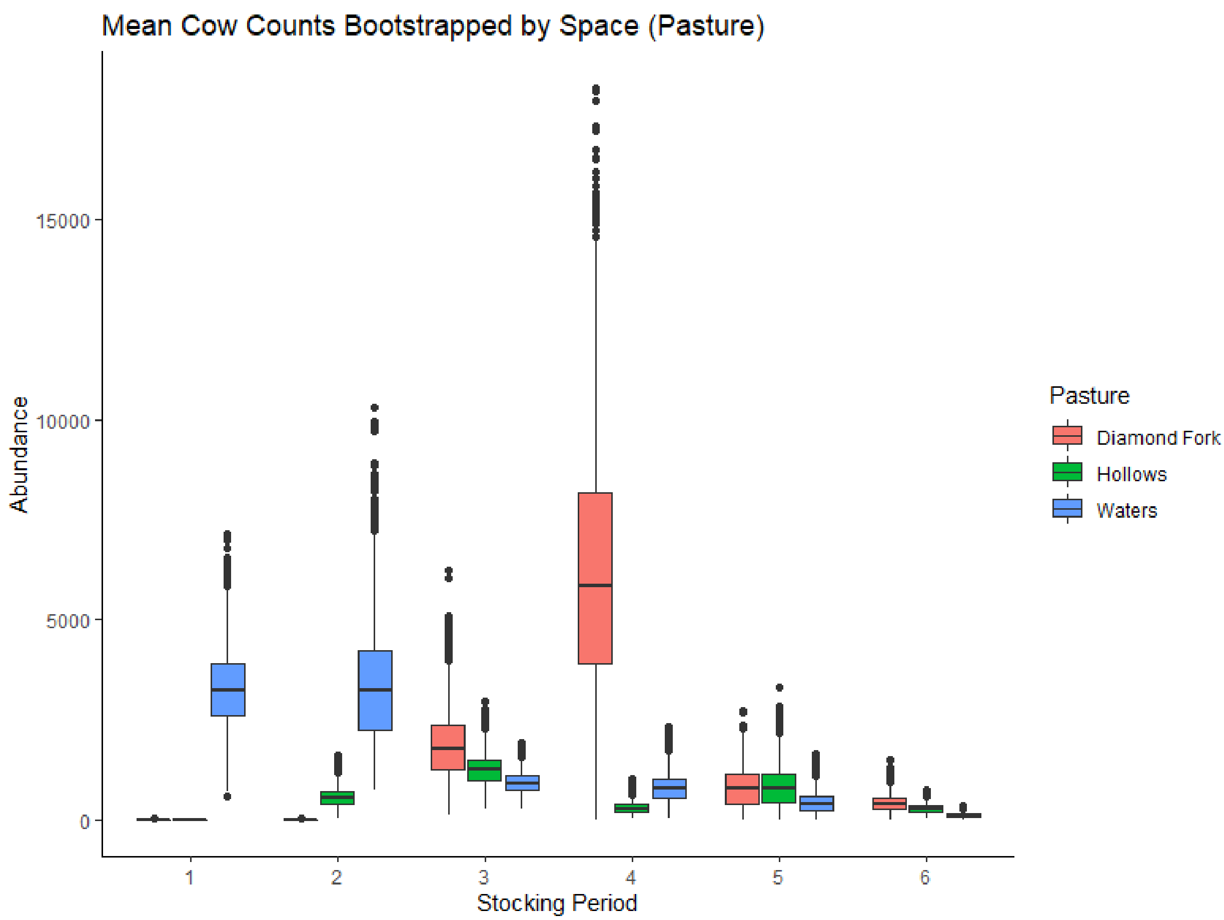

Figure 3: Boxplots of cattle abundance estimates bootstrapped by space over pasture for the six stocking periods. Mean values are provided in Table 1, column 6.

Table 1. Bootstrapping by space across pastures.

Stocking Period	Number of Days in Stocking Period	Pasture	USFS Cattle Stocking Rate	Cattle Abundance Estimate	95% Lower CI	Median	95% Upper CI
1	30	Diamond Fork	0	3	0	2	6
		Hollows	2041	0	0	0	0
		Waters	0	3299	2438	3227	4129
2	29	Diamond Fork	0	9	2	10	21
		Hollows	2141	551	232	613	1240
		Waters	0	3382	1466	2335	3600
3	59	Diamond Fork	2141	1845	992	1948	3302
		Hollows	0	1268	1150	1575	2050
		Waters	0	928	696	984	1367
4	7	Diamond Fork	1600	6131	1191	5912	13919
		Hollows	0	290	69	277	593
		Waters	0	811	363	828	1533

5	8	Diamond Fork	1060	787	68	803	1853
		Hollows	0	823	254	807	1580
		Waters	0	413	81	247	457
6	7	Diamond Fork	520	417	155	539	1107
		Hollows	0	285	140	277	447
		Waters	0	123	31	118	236

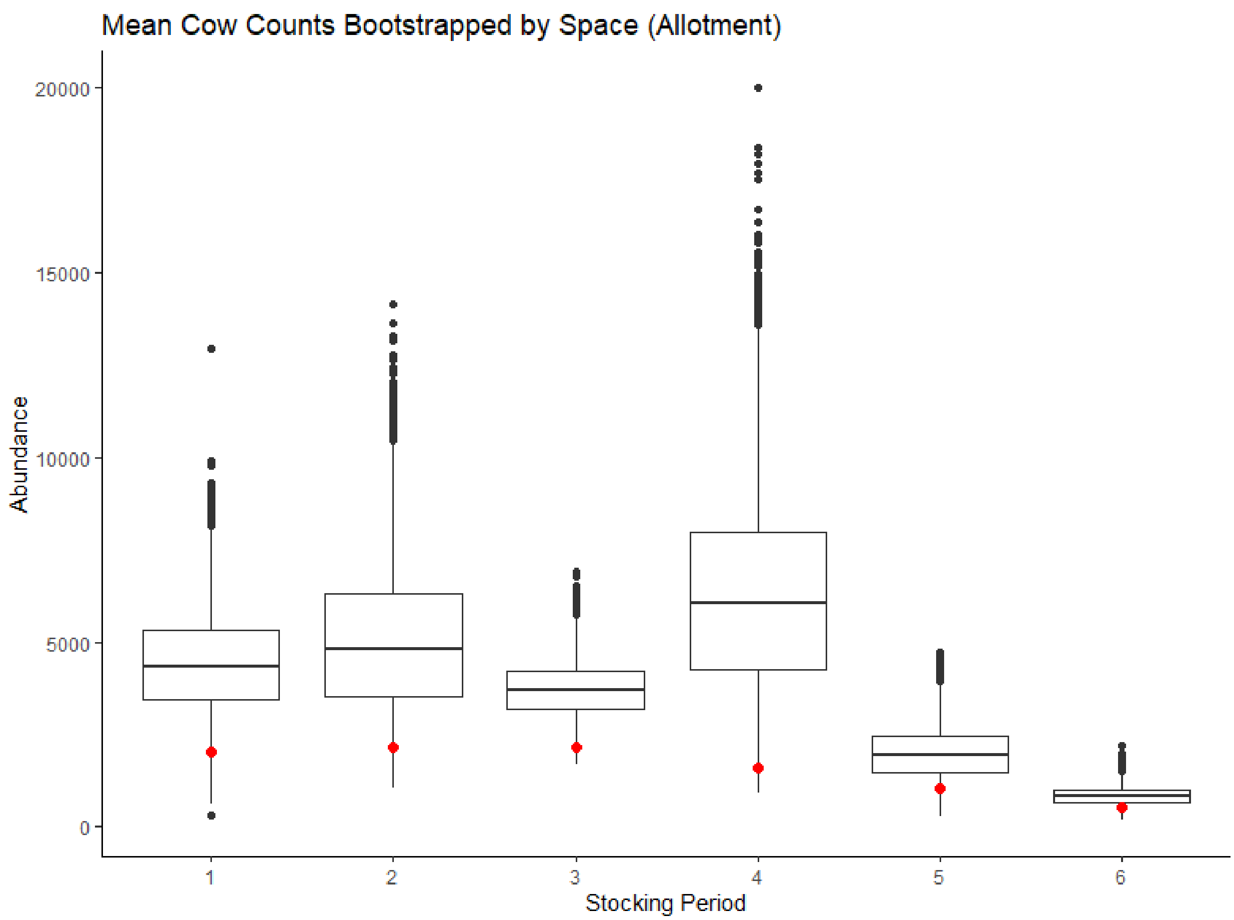

Figure 4: Boxplots of cattle abundance estimates bootstrapped by space over pasture for the six stocking periods. The red dots represent the USFS stocking rate. Mean abundance values values are provided in Table 3, column 6.

Table 2. Bootstrapping by space over allotment.

Stocking Period	**Number of Days in Stocking Period**	**Total USFS Cattle Stocking Rate**	**Cattle Abundance Estimate**	**95% Lower CI**	**Median**	**95% Upper CI**
1	30	2041	4413	1844	4321	7419
2	29	2141	5066	2239	4825	9465

3	59	2141	3728	2416	3685	5363
4	7	1600	6298	1854	6045	12403
5	8	1060	1986	763	1943	3472
6	7	520	840	400	814	1409

Bootstrapping By Time

Stocking period #1 lasted for 30 days from June 11 – July 10 (see Figure 5 for a graphical representation of the data, and Table 3 for tabulated data). The supposedly 'unstocked' pastures during stocking period #1, Diamond Fork and Waters, had estimated abundances of 2 (95% CI: 2-6) and 3241 (95% CI: 2438-4129) cows, respectively. The supposedly 'stocked' pasture, Hollows, which was supposed to have 2041 cows during period #1, had no cow detections, and hence an estimated abundance of 0 cows. At the allotment level in period #1, there were supposed to be 2041 cows based on Forest Service records, while we estimated 3412 (95% CI: 2141-4807) cows (see Figure 5 for a graphical representation of the data, and Table 3 for tabulated data).

Stocking period #2 lasted for 29 days from July 11 – August 7. The supposedly 'unstocked' pastures during stocking period #2, Diamond Fork and Waters, had estimated abundances of 11 (95% CI: 2-21) and 2382 (95% CI: 1466-3600) cows, respectively. The supposedly 'stocked' pasture, Hollows, which was supposed to have 2141 cows during period #2, had an estimated abundance of 645 (95% CI: 232-1240) cows. At the allotment level in period #2, there were supposed to be 2141 cows based on Forest Service records, while we estimated 3148 (95% CI: 1890-4752) cows.

Stocking period #3 lasted for 59 days from August 8 – October 4. The supposedly 'unstocked' pastures during stocking period #3, Hollows and Waters, had estimated abundances of 1581 (95% CI: 1150-2050) and 995 (95% CI: 696-1367) cows, respectively. The supposedly ‘stocked’ pasture, Diamond Fork, which was supposed to have 2141 cows during period #3, had an estimated abundance of 2001 (95% CI: 992-3302) cows. At the allotment level in period #3, there were supposed to be 2141 cows based on Forest Service records, while we estimated 4537 (95% CI: 3370-5917) cows.

Stocking period #4 lasted seven days from October 5 – 11. The supposedly ‘unstocked’ pastures during stocking period #4, Hollows and Waters, had estimated abundances of 289 (95% CI: 69-593) and 856 (95% CI: 363-153) cows, respectively. The supposedly ‘stocked’ pasture, Diamond Fork, which was supposed to have 1600 cows during period #4, had an estimated abundance of 6236 (95% CI: 1191-13919) cows. At the allotment level in period #4, there were supposed to be 1600 cows based on Forest Service records, while we estimated 7338 (95% CI: 1917-16205) cows.

Stocking period #5 lasted eight days from October 12 – 19. The supposedly ‘unstocked’ pastures during stocking period #5, Hollows and Waters, had estimated abundances of 836 (95% CI: 254-1580) and 249 (95% CI: 81-457) cows, respectively. The supposedly ‘stocked’ pasture, Diamond Fork, which was supposed to have 1060 cows during period #5, had an estimated abundance of 859 (95% CI: 68-1853) cows. At the allotment level in period #5, there were supposed to be 1060 cows based on Forest Service records, while we estimated 1898 (95% CI: 818-3201) cows.

Stocking period #6 lasted seven days from October 20 – 26. The unstocked pastures during stocking period #6, Hollows and Waters, had estimated abundances of 282 (95% CI: 140-447) and 129 (95% CI: 30-244) cows, respectively. The stocked pasture, Diamond Fork, which was supposed to have 520 cows during period #6, had an abundance estimate of 560 (95% CI:

155-1107) cows. At the allotment level in period #6, there were supposed to be 520 cows based on Forest Service records, while we estimated 965 (95% CI: 495-1620) cows.

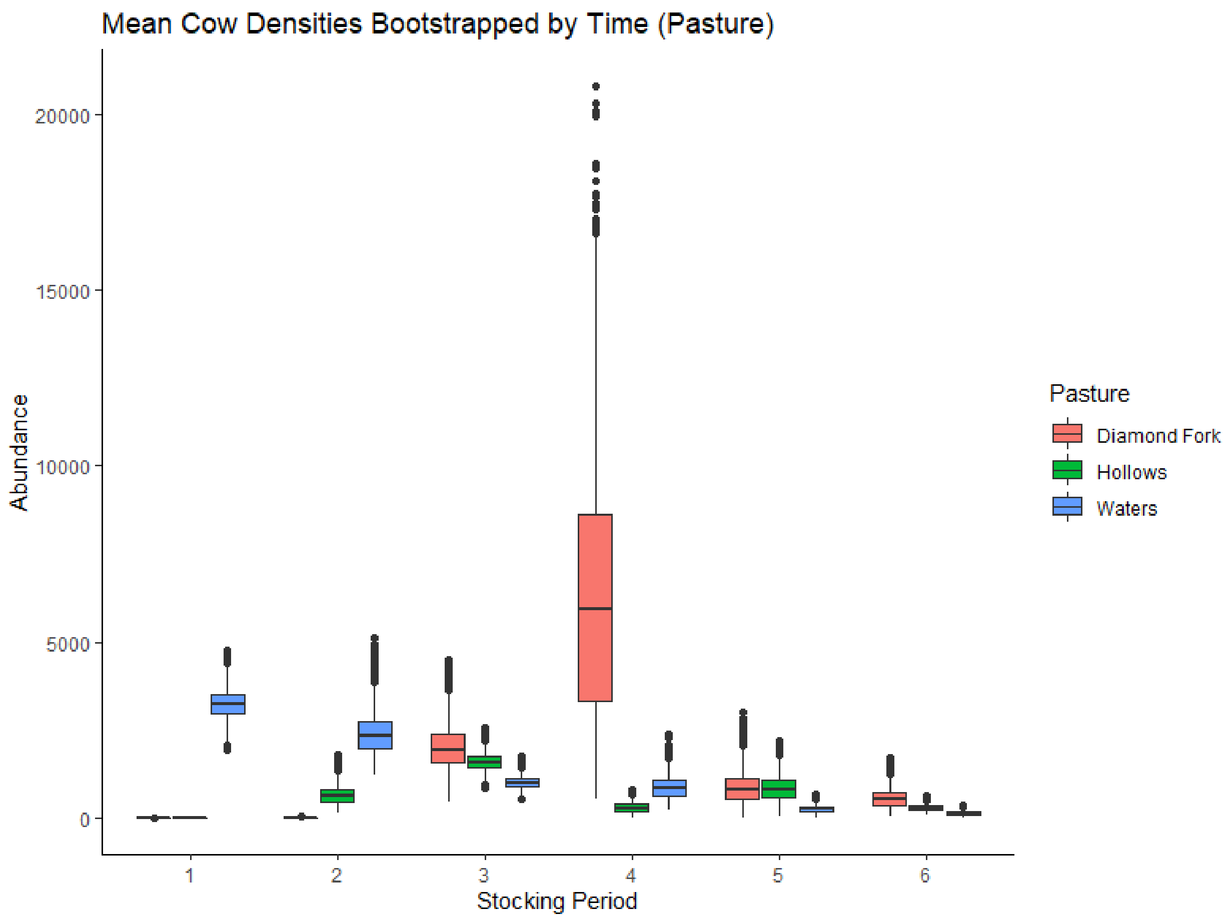

Figure 5: Boxplots of cattle abundance estimates bootstrapped by space over pasture for the six stocking periods. Mean values are provided in Table 2, column 6.

Table 3. Bootstrapping by time across pastures.

Stocking Period	Number of Days in Stocking Period	Pasture	USFS Cattle Stocking Rate	Cattle Abundance Estimate	95% Lower CI	Median	95% Upper CI
1	30	Diamond Fork	0	2	0	2	6
		Hollows	2041	0	0	0	0
		Waters	0	3241	2438	3227	4129
2	29	Diamond Fork	0	11	2	10	21
		Hollows	2141	645	232	613	1240
		Waters	0	2382	1466	2335	3600
3	59	Diamond Fork	2141	2001	992	1948	3302
		Hollows	0	1581	1150	1575	2050

		Waters	0	995	696	984	1367
4	7	Diamond Fork	1600	6236	1191	5912	13919
		Hollows	0	289	69	277	593
		Waters	0	856	363	828	1533
5	8	Diamond Fork	1060	849	68	803	1853
		Hollows	0	836	254	807	1580
		Waters	0	249	81	247	457
6	7	Diamond Fork	520	560	155	539	1107
		Hollows	0	282	140	277	447
		Waters	0	129	30	127	244

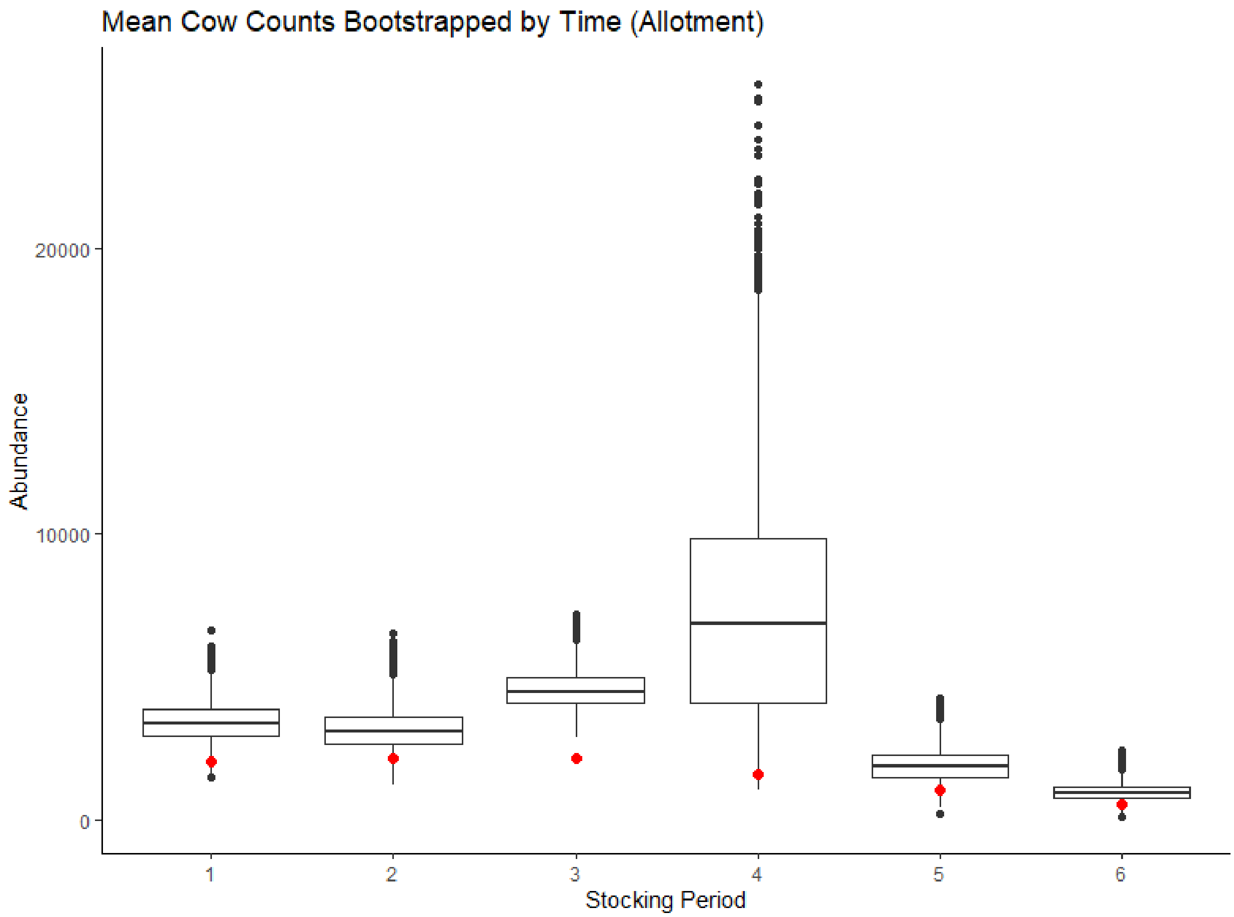

Figure 6: Boxplots of cattle abundance estimates bootstrapped by space over pasture for the six stocking periods. The red dots represent the USFS stocking rate. Mean abundance values are provided in Table 4, column 6.

Table 4. Bootstrapping by time over allotment.

Stocking Period	Number of Days in Stocking Period	Total USFS Cattle Stocking Rate	Cattle Abundance Estimate	95% Lower CI	Median	95% Upper CI
1	30	2041	3412	2141	3379	4807
2	29	2141	3148	1890	3087	4752
3	59	2141	4537	3370	4501	5917
4	7	1600	7338	1917	6866	16205
5	8	1060	1898	818	1859	3201
6	7	520	965	495	937	1620

Discussion

With bootstrapping across both space and time over each pasture, we observed that all three pastures during their rest periods always had an estimated abundance greater than zero, whereas USFS stocking rates indicated that there were not supposed to be any cows on these pastures during their rest periods. We have photographic evidence of cattle present (inside or outside of the conduits) on unstocked pastures during all six stocking periods; evidence of cattle present on pastures before stocking began on June 11, 2019; and evidence of cattle present on pastures after all stocking ends on October 27, 2019. In total there are 339,668 photos that show cattle present on pastures that were not supposed to be stocked, according to USFS. There are also 430 photos that show cattle present on pastures before stocking begins. These early cows were on the landscape beginning on June 8, 2019, so they were only on the landscape three days prior to stocking starting. Additionally, there are 1,108 photos that show cattle present on pastures after stocking ends in October through December 30, 2019. We have strong reason to believe that the numbers provided to us by USFS were not accurate on the pasture level. Due to the inaccuracy, we cannot compare our cattle abundance estimates to USFS on the pasture level, therefore, we focus on allotment-level estimates, assuming that the total USFS stocking rate is accurate across the entire Diamond Fork grazing allotment.

The mean cattle abundance estimates across the allotment for both bootstrapping methods were always biased high. Figures 7 and 8 show how our mean cattle abundance estimates and their 95% confidence intervals compare to USFS stocking rates when we bootstrapped by space and time, respectively. With bootstrapping over space, stocking periods one, five, and six had 95% confidence intervals which captured the USFS stocking rate. With bootstrapping over time, stocking periods two, five, and six had 95% confidence intervals which captured the USFS stocking rate.

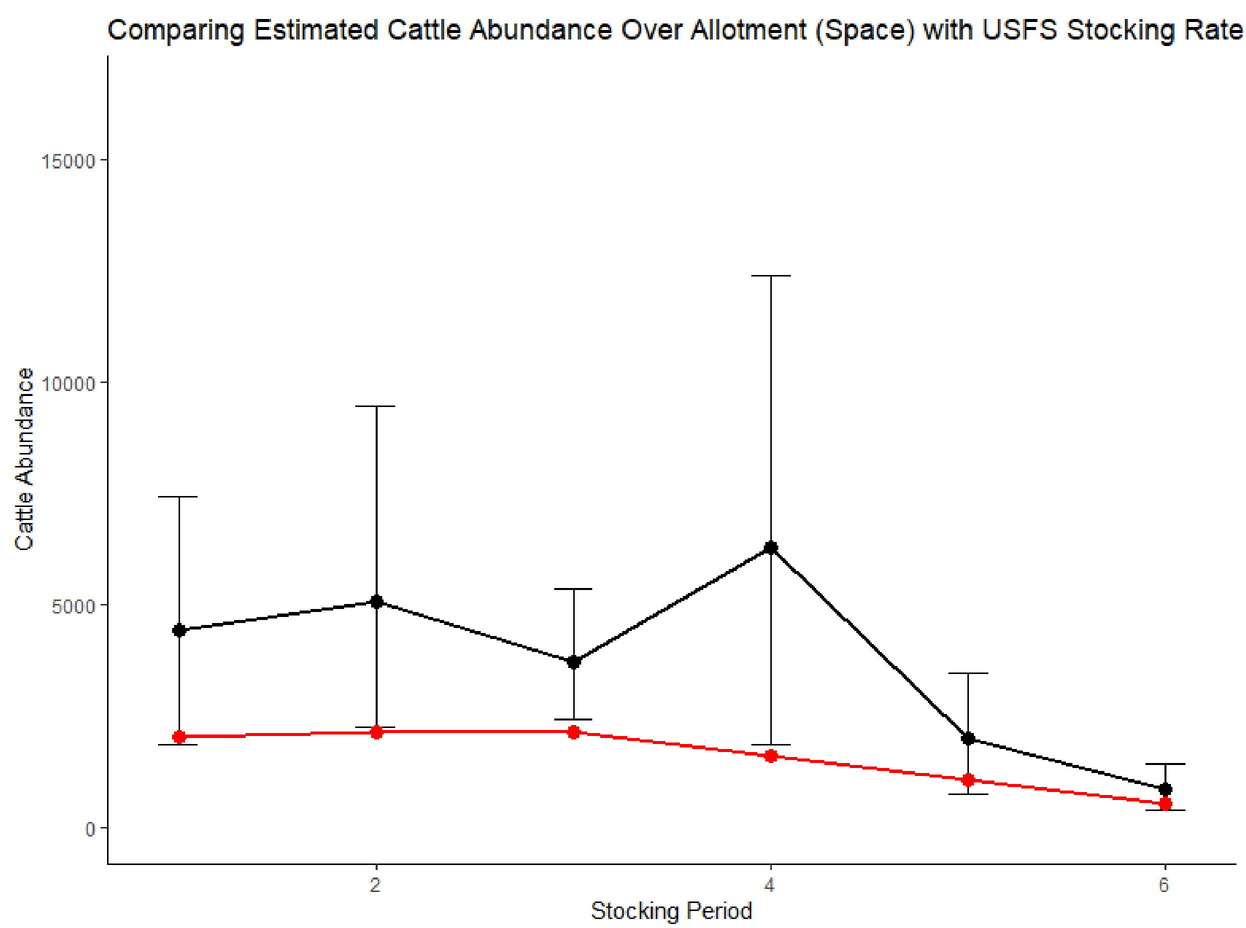

Figure 7: Estimated mean cattle abundances from bootstrapping over space are plotted with error bars showing the 95% confidence interval. The red dots represent the USFS stocking rate. The 95% confidence intervals for stocking periods one, five, and six capture the USFS stocking rate.

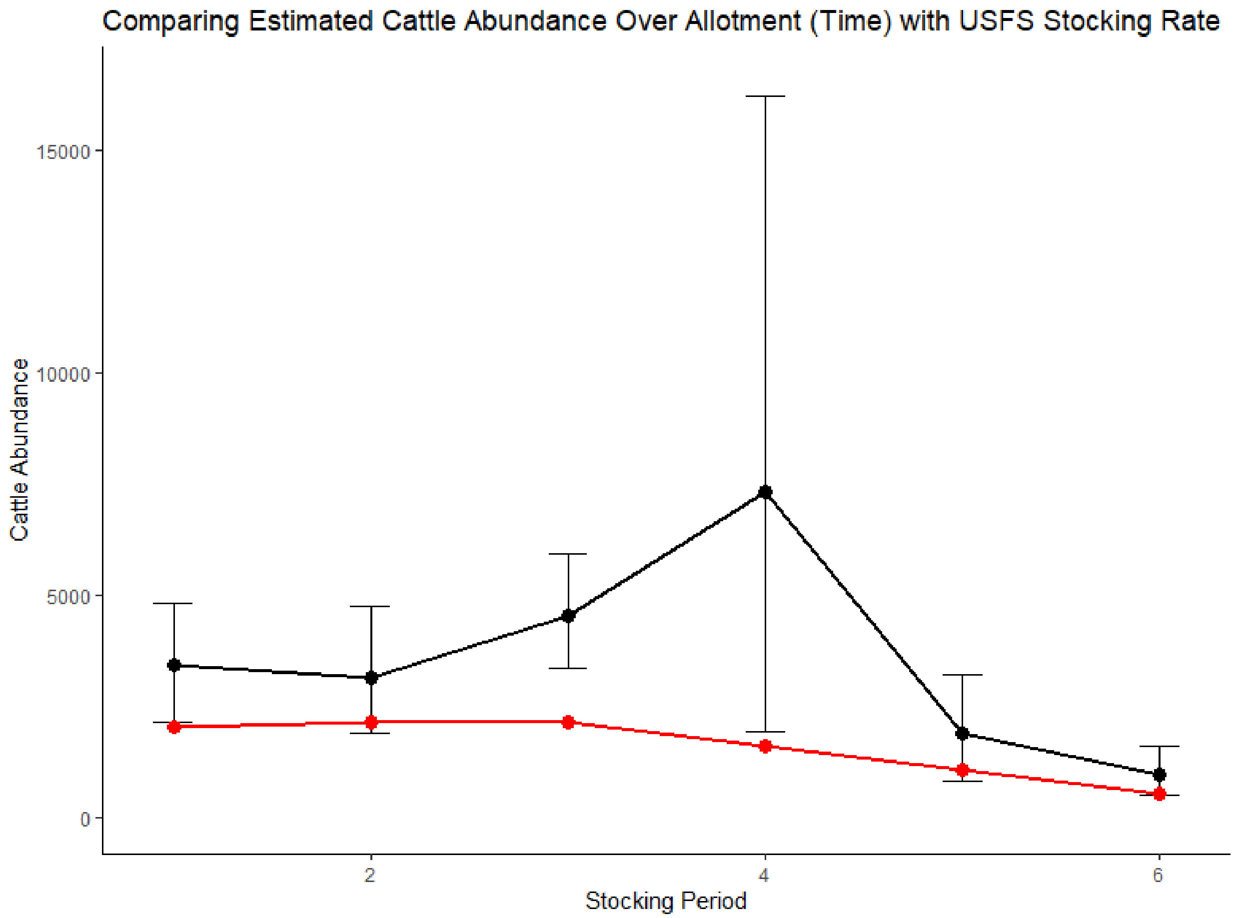

Figure 8: Estimated mean cattle abundances from bootstrapping over space are plotted with error bars showing the 95% confidence interval. The red dots represent the USFS stocking rate. The 95% confidence intervals for stocking periods two, five, and six capture the USFS stocking rate.

There are several reasons why our allotment cattle abundance estimates are biased high when compared to USFS stocking rates. One being the stocking rate fluctuations as cows were moved in and out of the allotment over the course of several days. This may explain the variation in some stocking periods, specifically stocking period four, which lasted only seven days, and had cattle reduced by 541 from the previous stocking period. As a result, our cattle abundance estimates were much higher than the true stocking rate because a large amount of cattle likely stayed on the landscape for longer than USFS indicated. Another reasoning is likely because our cameras were placed in locations that overrepresented cattle density. Most of our cameras were not placed in remote locations or locations that had a steep slope, which represent areas that cattle likely don't go. This means that our densities were calculated from areas where cattle are likely to aggregate, thus our estimates are higher than the true value. A third possible reason why our estimates were biased high was because we overestimated the time we assigned each 'cow in in front of the camera' event (2 seconds). We believe that this is the least likely reasoning for our estimates to be biased high, 2 seconds is by far a minimalist estimate of the camera's recovery time (the time from taking one photo until being able to take another if triggered).

In terms of precision, our results indicate REST estimates are reasonably precise, as can be seen in our bootstrapped confidence intervals (with the exception of stocking period #4). For bootstrapping across space, the coefficient of variation of our estimates ranged from 0.2 to 0.4. For bootstrapping across time, the coefficient of variation ranged from 0.1 to 0.5. Both ranges of coefficient of variation are comparable to other methods of estimating animal densities from camera trap data (Green et al.).

Our results indicate the REST-based abundance estimates are relatively precise, but are biased high. Practitioners should be careful about using this model to tell absolute abundance, More testing is needed with the REST model to compare density estimates to known wildlife populations such as we attempted to accomplish in this study. Without several trials of testing and comparing to known wildlife populations, the REST model cannot be truly validated. Another topic to explore in the future, would be what environmental factors drive cattle density. This area of study will greatly help land managers control their cattle herds by knowing what qualities cattle prefer when choosing grazing and resting locations. We are currently looking into this topic, and early results show that Normalized Difference Vegetation Index is most influential in cattle site selection.

Word Count: 4321

Reflective Writing

By conducting an Honors Capstone project, I have grown tremendously as a student. Throughout the course of my project, I have been able to incorporate topics I have learned in just about every course I have taken throughout my time at Utah State University. From the courses I took for my major and for my Geographic Information System certificate, I used just about every piece of information from those courses. From my Spanish courses, I utilized good writing skills. From my breath and depth creative arts classes, I have utilized my skills to make aesthetically pleasing visuals. From my physical education classes, I learned how to de-stress and have fun when I needed a break from conducting my research. To integrate these topics into my Honors Capstone project, I have had to think critically and conduct a literature review to fully understand concepts. I then built on these concepts during the process of my project, which has led me to master all the content I have learned thus far in my undergraduate career.

I have also learned new skills and concepts throughout the process of my Capstone project. The biggest change for me is that I'm used to studying wildlife in my courses, not domestic livestock. To adjust to this new kind of study species, I had to conduct lots of outside research and reach out to several professors who study livestock. I also had to think about concepts such as range management and a ranching career. Although I grew up in Illinois surrounded by cornfields and farmers, I knew next to nothing about how my study results may impact professionals in such careers. This also resulted in lots of research and a conference with a Utah State University Extension specialist for ranchers in Utah. Another experience that helped me connect with the local community was on my first trip to Spanish Fork, UT to change out camera batteries and SD cards. I accidentally stumbled upon a rancher "looking for rogue cows," and he thought that my field work partner and I were trying to access the hot springs located in

Spanish Fork canyon. We didn’t dare tell him that we were actually conducting research with his cows, but I learned that even though these ranchers might not be following the stocking rates, they actually care about their cows, and they might want to know where their cows like to spend time out on the range.

In relation to not knowing everything about my research topic ahead of time, there were other stumbles along the way. The main one being time. I learned that it is incredibly easy to be optimistic about your timeline and how fast you will complete certain tasks. I learned this the hard way because I originally planned to use wildlife camera data from both 2019 and 2020. Unfortunately, over summer 2021 not as much photo tagging was completed as I had anticipated, and the volunteers, technicians, and myself are *still* working to complete photo tagging for 2020. For the wildlife majors out there, who may end up working with wildlife camera data, you should start tagging photos as soon as possible and round up as many volunteers as possible to help you. Another struggle I encountered was data management. When I began analyzing my data, I quickly found out that those in charge of data management before me were not consistent with the way they analyzed photos and stored the photo tagging data. There were several seasons of data that had been tagged twice but saved under different files names. Had I not caught those mistakes, we would have double counted our cattle counts. I also had to deal with malfunctioning cameras that would randomly get off time so a photo taken in bright daylight would have a timestamp of midnight. Word of advice, if you ever work with wildlife cameras, make sure to be consistent with checking the technology and how photos are tagged and stored.

I have also been able to create important relationships with my mentors. When I first began the process of determining what my Honors Capstone project would be I visited my academic advisor, Shelly Kotynek, who then pointed me to Dr. Tal Avgar. When I first met with

Tal, I was so nervous and shy to talk to a professor about research, let alone starting my own research project. After testing my dedication to completing my own research project Tal welcomed me into his lab, and I have relied heavily on him throughout the process of my project. We met every week to discuss how the current task for my project was going, and what the next steps were. I asked so many questions during our meetings, and Tal would always be glad to answer them, and re-explain them when I still didn't understand. He also never let me lose sight of what the end goal of my project was. When I was stressed about meeting deadlines, or certain pieces of the project weren't going how they were supposed to, he always reassured me that it would work out in the end, even if that meant readjusting goals and timelines. By working with Tal, I have gained an incredible professional mentor. So, for all of you Honors students who are in the beginning stages of your Capstone project, pick a mentor who pushes you to succeed and will not let you lose sight of your goals.

Overall, the Honors Capstone experience has proved to be a great end cap to my experience at Utah State University and I will forever appreciate the memories, skills, and relationships that I have gained. As my reflection comes to an end, I would like to close with some words of advice to future Honors Capstone students. First off, it is never too soon to start your project. I started in October 2020, and I am submitting my Honors Capstone project in December 2020. Start looking now! Second, find a good mentor. I won't expand on this since I just raved about my mentor in the previous paragraph. Third, don't be afraid to ask questions when you don't know. If I didn't ask questions or understand why I was doing certain things for my project, you wouldn't be sitting here reading a completed Capstone project. Fourth, always look into the details of your data. If you're using data that was collected and/or compiled by someone else, always double check it to ensure the accuracy of the data. Fifth, incorporate extra time into your timeline. You never know when something may not go according to plan, and you still want to end up submitting your final project on time. Sixth, take time to reflect on your progress throughout the course of the project and not just at the end when you're writing the required reflective writing. Looking at myself from when I started in October 2020, I was not confident speaking with master's students, PhD students, or professors because I thought they were all so much smarter than me, but now I'm more confident and I'm not afraid to admit to them that I sometimes have no idea what they're talking about. And finally, seventh, have fun! This is your last experience in the Honors College at Utah State, and possibly the last time you'll ever conduct research, so make it a positive memory that you can reflect on.

Word Count: 1234

Literature Cited

Bailey, Derek W., et al. "Use of GPS Tracking Collars and Accelerometers for Rangeland Livestock Production Research." *Translational Animal Science*, vol. 2, no. 1, Oxford University Press, Feb. 2018, pp. 81–88, doi:10.1093/tas/txx006.

Balázs, G., et al. "Extreme Site Fidelity of the Olm (Proteus Anguinus) Revealed by a Long-Term Capture–Mark–Recapture Study." *Journal of Zoology*, vol. 311, no. 2, Blackwell Publishing Ltd, June 2020, pp. 99–105, doi:10.1111/JZO.12760.

Becker, Marcus, et al. *Applying and Testing a Novel Method to Estimate Animal Density from Motion-Triggered Cameras*. Aug. 2021, https://arxiv.org/abs/2108.13572v1.

Burton, A. Cole, et al. "Wildlife Camera Trapping: A Review and Recommendations for Linking Surveys to Ecological Processes." *Journal of Applied Ecology*, vol. 52, no. 3, Blackwell Publishing Ltd, 1 June 2015, pp. 675–85, doi:10.1111/1365-2664.12432.

Crum, Nathan J., et al. "Abundance Estimation for Line Transect Sampling: A Comparison of Distance Sampling and Spatial Capture-Recapture Models." *PLoS ONE*, vol. 16, no. 5 May, Public Library of Science, May 2021, doi:10.1371/JOURNAL.PONE.0252231.

Garland, Laura, et al. "Random Encounter and Staying Time Model Testing with Human Volunteers." *Journal of Wildlife Management*, vol. 84, no. 6, Wiley-Blackwell, Aug. 2020, pp. 1179–84, doi:10.1002/jwmg.21879.

Gilbert, Neil A., et al. "Abundance Estimation of Unmarked Animals Based on Camera-Trap Data." *Conservation Biology*, vol. 35, no. 1, Blackwell Publishing Inc., 1 Feb. 2021, pp. 88–100, doi:10.1111/cobi.13517.

Green, Austin M., et al. “Spatially Explicit Capture-Recapture Through Camera Trapping: A Review of Benchmark Analyses for Wildlife Density Estimation.” *Frontiers in Ecology and Evolution*, vol. 8, Frontiers Media S.A., Dec. 2020, p. 473, doi:10.3389/FEVO.2020.563477/BIBTEX.

Jung, Thomas S., et al. “Mark My Words: Experts’ Choice of Marking Methods Used in Capture-Mark-Recapture Studies of Small Mammals.” *Journal of Mammalogy*, vol. 101, no. 1, Oxford University Press, Feb. 2020, pp. 307–17, doi:10.1093/JMAMMAL/GYZ188.

Karanth, K. Ullas. “Estimating Tiger Panthera Tigris Populations from Camera-Trap Data Using Capture—Recapture Models.” *Biological Conservation*, vol. 71, no. 3, Elsevier, Jan. 1995, pp. 333–38, doi:10.1016/0006-3207(94)00057-W.

Millward, Michael F., et al. “A GPS-Based Evaluation of Factors Commonly Used to Adjust Cattle Stocking Rates on Both Extensive and Mountainous Rangelands.” *Rangelands*, vol. 42, no. 3, 2020, pp. 63–71, doi:10.1016/j.rala.2020.04.001.

Moeller, Anna K., et al. “Three Novel Methods to Estimate Abundance of Unmarked Animals Using Remote Cameras.” *Ecosphere*, vol. 9, no. 8, Wiley-Blackwell, Aug. 2018, doi:10.1002/ecs2.2331.

Nakashima, Yoshihiro, et al. “Estimating Animal Density without Individual Recognition Using Information Derivable Exclusively from Camera Traps.” *Journal of Applied Ecology*, vol. 55, no. 2, Blackwell Publishing Ltd, Mar. 2018, pp. 735–44, doi:10.1111/1365-2664.13059.

Parsons, Arielle Waldstein, et al. “Do Occupancy or Detection Rates from Camera Traps Reflect Deer Density?” *Journal of Mammalogy*, vol. 98, no. 6, 2017, pp. 1547–57, doi:10.1093/jmammal/gyx128.

Pollo, Roberto, et al. “Estimation of the Demographic Parameters of Common Reed Warbler Acrocephalu...: EBSCOhost.” *Avocetta*, vol. 42, 2018, pp. 21–30, https://web.s.ebscohost.com/ehost/pdfviewer/pdfviewer?vid=1&sid=5f532487-ec88-4560-9950-289d1529bc28%40redis.

Pollock, Kenneth H., et al. “Statistical Inference for Capture-Recapture Experiments.” *Wildlife Monographs*, no. 107, 1990, pp. 3–97, https://www.jstor.org/stable/3830560?seq=5#metadata_info_tab_contents.

Rowcliffe, J. Marcus, et al. “Estimating Animal Density Using Camera Traps without the Need for Individual Recognition.” *Journal of Applied Ecology*, vol. 45, no. 4, Aug. 2008, pp. 1228–36, doi:10.1111/j.1365-2664.2008.01473.x.

Schlacher, Thomas A., et al. “Estimating Animal Populations and Body Sizes from Burrows: Marine Ecologists Have Their Heads Buried in the Sand.” *Journal of Sea Research*, vol. 112, Elsevier, June 2016, pp. 55–64, doi:10.1016/J.SEARES.2016.04.001.

Šukalo, Goran, et al. “Novel, Non-Invasive Method for Distinguishing the Individuals of the Fire Ssalamander (Salamandra Salamandra) in Capture-Mark-Recapture Studies.” *Acta Herpetologica*, vol. 8, no. 1, 2013, pp. 41–45, https://web.p.ebscohost.com/ehost/detail/detail?vid=9&sid=ea47edff-d376-4550-a28e-98ccb36c3edd%40redis&bdata=JnNpdGU9ZWhvc3QtbGl2ZQ%3D%3D#db=asn&AN=90393038.

Xue, Yifei, et al. “Automatic Counting of Large Mammals from Very High Resolution Panchromatic Satellite Imagery.” *Remote Sensing*, vol. 9, no. 9, MDPI AG, Sept. 2017, doi:10.3390/RS9090878.

Author Biography

Emily Bonebrake grew up in Frankfort, IL and graduated from Lincoln-Way East High School in May 2018 with Magna Cum Laude honors. Emily will graduate in May 2022 from Utah State University with a B.S. in Wildlife Ecology and Management with a Geographic Information Systems certificate. During her undergraduate career, Emily served as an Undergraduate Teaching Fellow for the Wildland Plants and Ecosystem course. Emily also held many positions for The Wildlife Society and Alpha Chi Omega sorority. She is a part of Xi Sigma Pi, the national honors society for forestry and natural resources, and Order of Omega, the national honors society for members of fraternities and sororities. Emily has been employed with Utah State University Water Quality Extension as an environmental education intern and the programs coordinator; Quinney College of Natural Resources Wildlife Space-Use Ecology lab as a technician; and the Utah Division of Wildlife Resources as the northern regional intern. Emily enjoys spending time with friends and family, and hiking, hammocking, swimming, paddleboarding, and rock climbing. In the future, she plans to work as a wildlife technician and attend graduate school.