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Forage Inventory and Modeling in Uintah and Ouray Reservation Rangelands

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FORAGE INVENTORY AND MODELING IN UINTAH AND OURAY

RESERVATION RANGELANDS

by

Scott N. Zimmer

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ABSTRACT

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Department: Wildland Resources

The more than one million acres comprising the Uintah and Ouray Reservation in northeastern Utah have not been widely studied, and access to non-tribal members is highly restricted. We sampled vegetation to summarize condition in 300,000 acres of unsurveyed Reservation lands in 2017-2018, combining these data with data collected by the Bureau of Indian Affairs from 2010-2015 to complete an initial rangeland vegetation inventory of the Reservation. This survey was designed to inform management of the area by determining initial cattle stocking rates and overall ecological condition across the Reservation. The density of forage available to cattle is highly variable throughout this area, with some management units containing approximately 46 times denser forage than others. Initial stocking rates within units vary widely, from 11 to 5,000 animal unit months.

We also used the vegetation inventory data to construct a random forest model to further complement this initial inventory. By associating forage availability with environmental and climatic covariates, the model predicts annual forage availability on a

pixel by pixel basis from 1984-2018, explicitly considering spatiotemporal variability in forage availability. The model shows that forage availability within management units is highly variable from year to year. On average, forage availability in units can decline up to 32% below median availability, and can increase up to 33% above median availability.

Such variability indicates that typical forage availability, the measure used to determine stocking rates in the initial inventory, does not fully address forage availability dynamics. The model results therefore lend a fuller picture of appropriate stocking rates than the initial inventory. They may further improve grazing management and help prevent the negative effects of forage overutilization by revealing the degree to which available forage declines in unfavorable years such as drought. The forage availability model can continue to be used in the future to monitor trends in vegetation over time, and the modeling method may be applicable to other similar study systems.

(102 pages)

PUBLIC ABSTRACT

Forage Inventory and Modeling in Uintah and Ouray Reservation Rangelands

Scott N. Zimmer

The Uintah and Ouray Reservation in northeastern Utah has not been widely studied, and access to non-tribal members is highly restricted. We sampled vegetation to summarize condition in 300,000 acres of unsurveyed Reservation lands in 2017-2018, combining these data with data collected by the Bureau of Indian Affairs from 2010-2015 to complete an initial rangeland vegetation inventory of the Reservation. This survey was designed to inform management of the area by determining cattle stocking rates and overall ecological condition across the Reservation. Both the density of forage available to cattle and appropriate cattle stocking rates vary greatly throughout management units in the Reservation.

We also used the vegetation inventory data to run a model which estimates forage availability in every year from 1984-2018 throughout the Reservation. Whereas the initial inventory only considers the typical forage availability in management units, this method allows us to estimate how forage varies through space and time. The results show that forage availability varies significantly through time, declining and increasing by approximately one-third from median forage availability.

Such variability indicates that typical forage availability, the measure used to determine stocking rates in the initial inventory, does not fully address forage availability dynamics. Since actual forage availability can be far lesser or greater than typical forage availability, stocking rates based on typical availability will often be an under or over

estimation. The model results therefore lend a fuller picture of appropriate stocking rates. This may improve grazing management by revealing how much forage declines in unfavorable years such as during drought, and improving grazing planning during these years. The forage availability model can continue to be used in the future to monitor trends in vegetation over time, and the modeling method may be applicable to other similar study systems.

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All the other QCNR graduate students were amazing resources, and were a great community of people to be around. Thank you so much to Sofia Koutzoukis for making my time in Logan great, and always being an amazing support. Lastly, thank you to my family for everything and tolerating me always living thousands of miles from home.

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CHAPTER 1

INTRODUCTION

Introduction

Rangelands are complex ecosystems, encompassing grasslands, savannas, shrublands, steppe, and other similar systems. They cover vast spatial extents, typically estimated at around 45% of the Earth's ice-free surface (Reid et al. 2008). Rangelands provide numerous ecosystem services, such as providing forage for domestic livestock and wildlife, establishing suitable wildlife habitat, carbon sequestration, and many more (Havstad et al. 2007). Often occurring in remote locations with harsh climates and without ample water resources, rangelands largely exist today because they were not conducive to extensive urbanization or agriculture (Sayre 2017). They therefore persist as essentially undeveloped "natural" ecosystems, and continue to serve important ecological functions.

Rangelands also provide many important functions for human land uses. Grazing is perhaps the most widespread and influential land use on rangelands, occurring on 25% of the Earth's land surface and supporting ranchers and pastoralists worldwide (Asner et al. 2004). This ubiquitous land use, though, can threaten ecological health through improper management such as overgrazing and overutilization, which can cause extensive biotic and abiotic degradation (Fuls 1992; Menke and Bradford 1992). Therefore, effectively measuring ecological condition in rangelands and managing uses such as grazing accordingly is crucial to their continued functioning.

This thesis details an initial rangeland vegetation inventory of the Uintah and Ouray Reservation in northeastern Utah. This Reservation includes more than one million

acres of undeveloped rangelands which are a vital resource for the Ute Tribe, but had not been formally studied previously.

In 2010, the Bureau of Indian Affairs (BIA) began an initial inventory of vegetation in the Reservation, aiming to determine the amount of forage available for grazing cattle so that appropriate stocking rates could be determined. The study stalled when the BIA's rangeland management specialist retired in 2015, but Utah State University (USU) was contracted in 2017 to complete the study. The goals were for USU to continue sampling vegetation in the remaining unsampled areas in a way consistent with how the BIA had previously collected data, determine appropriate stocking rates for the Reservation, and prepare a final report detailing the overall findings of the study.

Chapter 2 details the methodology of that vegetation inventory, how the data were analyzed to summarize stocking rates and other measures for the Reservation range units (management areas from approximately 200 to 50,000 acres in size), and the overall management implications of these findings. This study aimed to determine the typical forage availability in range units, and set appropriate initial stocking rates according to these. Though forage availability can vary from year to year, an initial inventory such as this aims to summarize representative conditions. In addition to stocking rates, we also determined indicators of vegetation health such as total canopy cover, bare ground cover, and cover of cheatgrass, an invasive species.

Chapter 3 describes an additional application of the vegetation data collected in the Reservation. By associating the vegetation data, particularly the total amount of forage available for grazing cattle, with environmental and climatic covariates at sampling locations, we built a model to predict annual forage availability throughout the

Reservation and surroundings. This chapter details the modeling methods and results, and the ways in which this information complements the findings of Chapter 2. By determining forage availability on a pixel-by-pixel basis and predicting forage availability annually from 1984-2018, the model provides much more information than the range unit stocking rates based on typical forage availability shown in Chapter 2. Most importantly, this model allows us to estimate the minimum, maximum, and median forage availability in range units. In Chapter 2, we estimate typical forage availability for range units and determine stocking rates from this, but the results in Chapter 3 lend a fuller view of the range of possible forage availability in a given year.

In summary, this thesis encompasses a highly applied overall inventory of vegetation in the Uintah and Ouray Reservation, and a more generalized application of the vegetation inventory data. The inventory will improve management in the area by documenting overall ecological condition and determining typical cattle stocking rates for Reservation range units. The results in Chapter 3 provide more context to these stocking rate findings, and can further improve management by revealing ranges of possible forage availability.

The modeling method in Chapter 3 incorporates only freely-available data which can be accessed remotely (in conjunction with the vegetation data collected in the field). Frequently resampling vegetation in the field is costly, and may typically make monitoring vegetation condition over time prohibitive. However, the model we use can provide similar monitoring without resampling vegetation in the field, by incorporating annual climatic data and satellite imagery. Therefore, this model method is particularly useful for monitoring large, remote areas that cannot be sampled easily, and therefore

may be useful in other similar study systems such as other Reservations and large Bureau of Land Management or Forest Service units.

References

Asner, G.P., Elmore, A.J., Olander, L.P., Martin, R.E., Harris, A.T., 2004. Grazing Systems, Ecosystem Responses, and Global Change. Annual Review of Environment and Resources 29, 261–299. https://doi.org/10.1146/annurev.energy.29.062403.102142

Fuls, E.R., 1992. Ecosystem modification created by patch-overgrazing in semi-arid grassland. Journal of Arid Environments 23, 59–69. https://doi.org/10.1016/S0140-1963(18)30541-X

Havstad, K.M., Peters, D.P.C., Skaggs, R., Brown, J., Bestelmeyer, B., Fredrickson, E., Herrick, J., Wright, J., 2007. Ecological services to and from rangelands of the United States. Ecological Economics 64, 261–268. https://doi.org/10.1016/j.ecolecon.2007.08.005

Menke, J., Bradford, G.E., 1992. Rangelands. Agriculture, Ecosystems & Environment 42, 141–163. https://doi.org/10.1016/0167-8809(92)90024-6

Reid, R.S., Galvin, K.A., Kruska, R.S., 2008. Global Significance of Extensive Grazing Lands and Pastoral Societies: An Introduction, in: Galvin, K.A., Reid, R.S., Jr, R.H.B., Hobbs, N.T. (Eds.), Fragmentation in Semi-Arid and Arid Landscapes: Consequences for Human and Natural Systems. Springer Netherlands, Dordrecht, pp. 1–24. https://doi.org/10.1007/978-1-4020-4906-4_1

Sayre, N.F., 2017. The Politics of Scale: A History of Rangeland Science. University of Chicago Press.

CHAPTER 2

INITIAL RANGELAND VEGETATION INVENTORY OF THE UINTAH AND OURAY RESERVATION

Abstract

In 2017, Utah State University was contracted to complete rangeland vegetation surveys of the Uintah and Ouray Reservation. We conducted field surveys in 2017 and 2018, with methods matching those used in prior surveys of the Reservation. We used the collected data to calculate livestock stocking rates for all range units in the Reservation, and model important vegetation cover measures and cheatgrass abundance.

We found available forage is greatest in the far northwest of the Reservation, in the Dry Mountain area, and in the far southeastern Tavaputs Plateau. These areas can support the highest stocking rates and are likely the most areas appropriate for extensive livestock grazing. However, the Tavaputs Plateau in particular has considerable populations of ungulates such as horses and bison. These ungulates will reduce forage availability and may complicate livestock grazing in the Tavaputs Plateau. The Dry Mountain area has had little grazing activity and ungulate populations are not as great a concern there.

Though cheatgrass is present in much of the Reservation, we found only the eastern Uinta Basin and southeastern Uinta Mountains had abundant cheatgrass production. Disturbance in these areas has likely promoted cheatgrass. Our vegetation cover analysis shows that lower elevations of the Uinta Basin and Tavaputs Plateau have high bare ground cover and low canopy, litter, and tree cover. Conversely, bare ground cover is much lower and canopy, litter, and tree cover are higher in higher elevations of

the Uinta Mountains and southern Tavaputs Plateau. This indicates the Uinta Basin is generally at a higher risk of disturbance and erosion than the Uinta Mountains and southern Tavaputs Plateau, and management of these areas should consider this.

Introduction

The Uintah and Ouray Reservation covers a diverse area in northeastern Utah. Range units established for grazing livestock in the Reservation comprise more than 1.2 million acres, and range in elevation from approximately 1,300 meters above sea level to 3,350 meters above sea level. These lands encompass the foothills of the Uinta Mountains to the north, the Tavaputs Plateau to the south, and the Uinta Basin in between. There are major climatic variations throughout the area. Low elevation areas have an arid climate with cold winters and warm summers, such as 6 inches (150 mm) mean annual precipitation (MAP) and 47°F (8°C) mean annual temperature (MAT) in Fort Duchesne (1540 m, Ft. Duchesne Station ID:USC00422996, Utah Climate Center 2019). The mid-elevation transition zone from the Uinta Basin to the foothills of the Uinta Mountains have a semiarid climate with cold winters and warm summers, such as 13 inches (333 mm) MAP and 43°F (6°C) MAT at Hanna (2054 m, Hanna Station ID:USC00423624, Utah Climate Center 2019). Higher elevation areas in the Uinta Mountains have a subhumid climate with cold winters and short, cool summers, such as 35 inches (885 mm) MAP and 34°F (1°C) MAT (3231 m elevation, Brown Duck Station ID:USS0010J30S, Utah Climate Center 2019).

Vegetation, in turn, varies greatly throughout the Reservation. Greasewood, saltbush and galleta grass dominate the lowest elevations (Fig. 2-1), while middle elevations include Wyoming big sagebrush, pinyon-juniper and bunchgrasses (Fig. 2-2).

The highest elevations include a variety of shrubs such as mountain big sagebrush, serviceberry and antelope bitterbrush, as well as bunchgrasses and trees including aspen and lodgepole pine (Fig. 2-3). Total productivity, forage quality, cover, and other characteristics vary greatly across these diverse habitats, creating a variety of rangeland management concerns and opportunities for uses such as grazing or wildlife habitat.

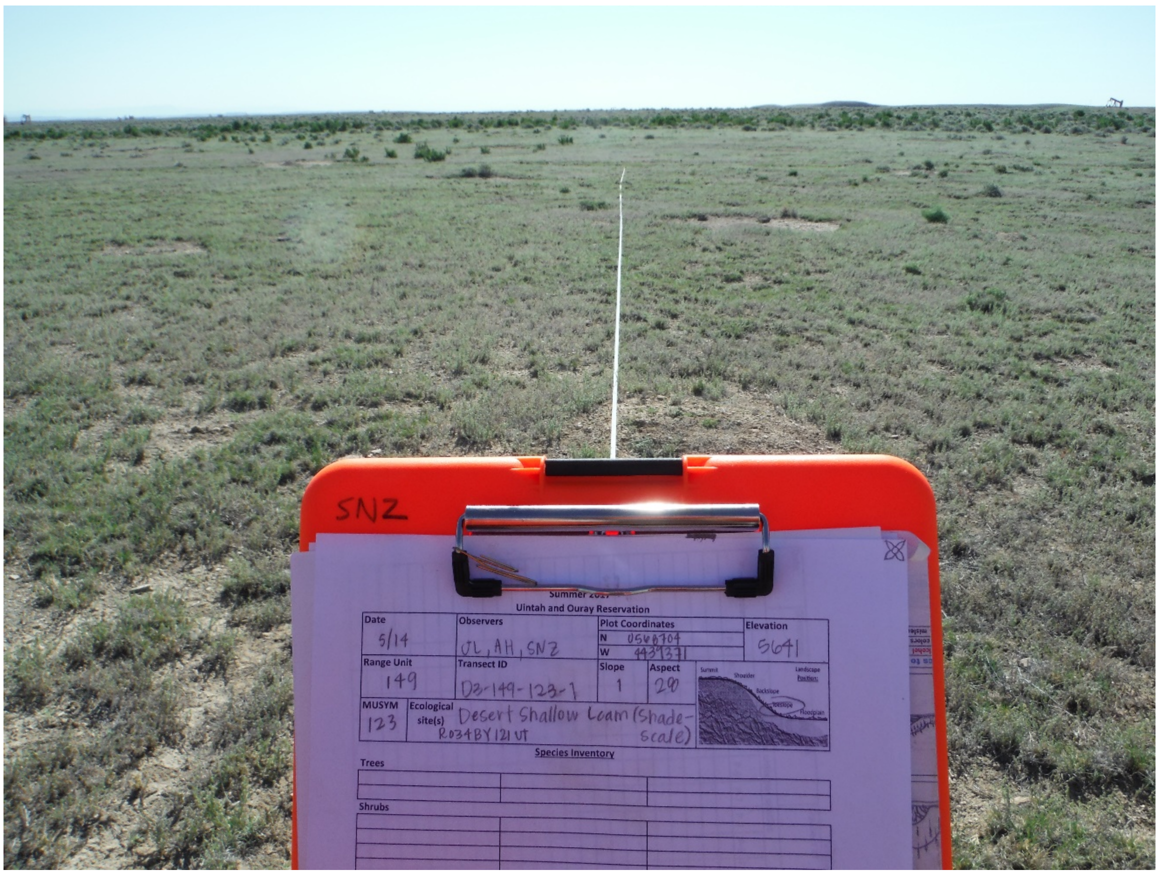

Figure 2-1. Low elevation saltbush and galleta grass site.

Figure 2-2. Mid elevation site featuring Wyoming big sagebrush, bunchgrasses and pinyon-juniper.

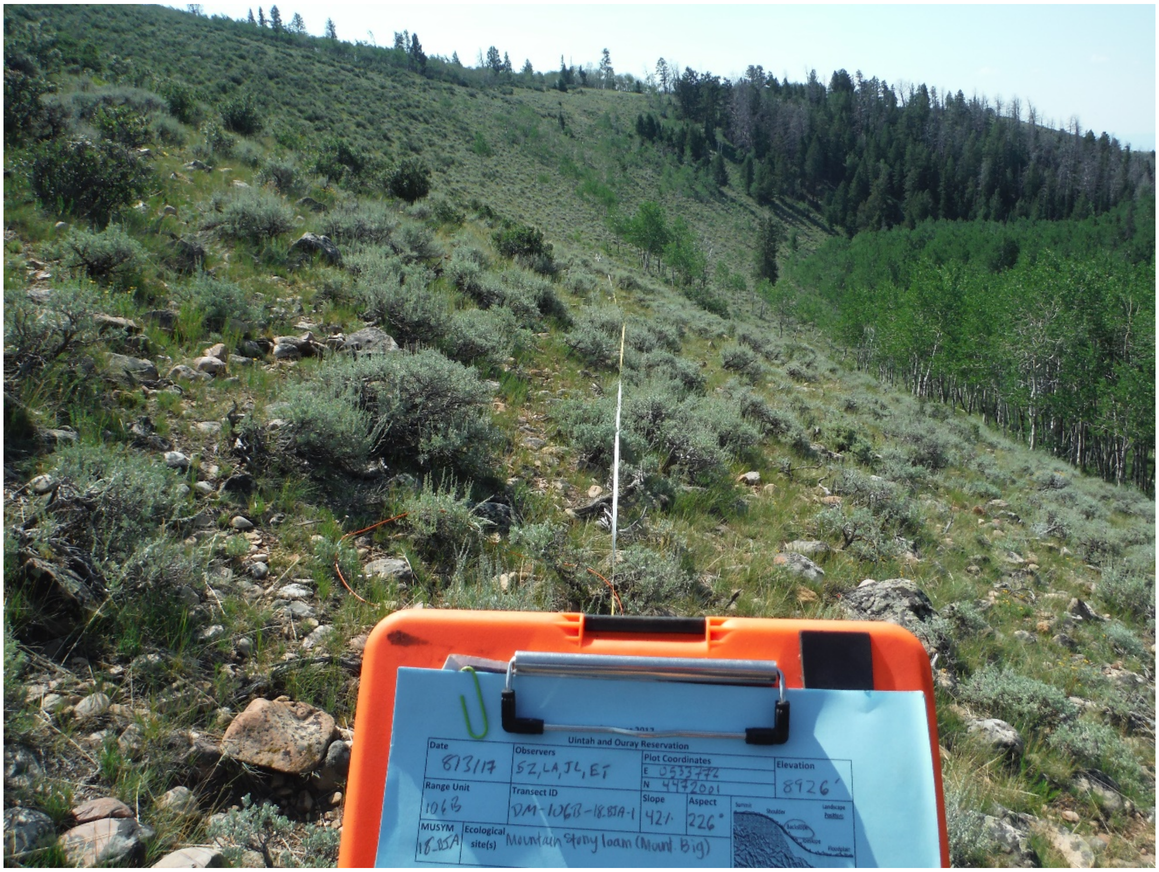

Figure 2-3. High elevation site featuring mountain big sagebrush and bunchgrasses, adjacent to aspen and lodgepole pine.

Rangeland management requires measuring key indicators of rangeland condition like vegetation composition, bare ground, and canopy cover (Pellant et al. 2005). Stocking rate, which estimates the level of grazing a location can tolerate while maintaining habitat quality (Holechek 1988), is another essential measure where rangelands are managed for grazing. Appropriate stocking rates prevent overgrazing and overutilization, which can lead to extensive biotic and abiotic degradation (Fuls 1992; Menke and Bradford 1992). Therefore, accurately determining forage availability and stocking rates is key to proper rangeland management.

The Bureau of Indian Affairs (BIA) began surveying transects to establish stocking rates throughout the Uintah and Ouray Reservation in 2010. These transects sampled the productivity of vegetation to determine forage availability and appropriate stocking rates. By 2015, the BIA had completed 761 transects and determined stocking rates on approximately 900,00 acres of the Reservation. However, 300,000 acres remained unsampled and did not have calculated stocking rates when Paul Starkey, the former BIA rangeland management specialist, retired.

In 2017, Utah State University (USU) was contracted to complete surveys of the unsampled areas of the Reservation in order to determine stocking rates and assess overall rangeland condition. We conducted field surveys during the summers of 2017 and 2018, and calculated stocking rates for all remaining range units of the Reservation. See Fig. 2-4 for a map of range unit borders and completed transects.

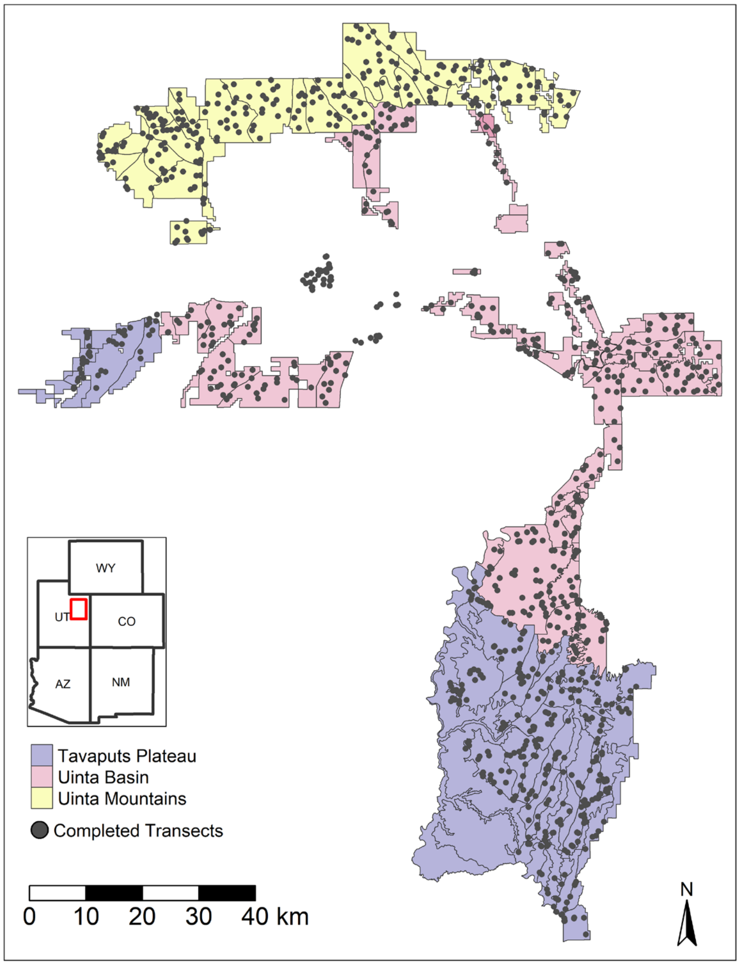

Figure 2-4. Map of study area showing range unit borders. The three broad regions of the Reservation are colored, and the locations of completed transects are shown.

Methods

Field Methods

To ensure data collected by USU were comparable to prior data collected by BIA, we emulated the original field methods employed by BIA as much as possible. We surveyed at least one transect per 1,000 acres of each soil map unit in the unsurveyed range units. We used the most up-to-date Natural Resources Conservation Service (NRCS) Soil Survey available to determine the areal extent and location of soil map

units. Transect locations were randomly generated before going into the field, stratified by soil map unit and located within 2 miles from existing roads. Once in the field, we navigated to each generated transect location and ensured it did not occur in an atypical patch of soil map units. If the transect occurred in an atypical area, we shifted the transect location in order to collect data in a representative area.

Once an appropriate location was selected, we dug a small pit to observe the soil and ensure that it matched the soil map unit we intended to sample. Ecological sites were determined based on soil type and vegetation, as many soil map units are composed of multiple soil types with different associated ecological sites.

At each transect we laid out a 30.5 meter (100-foot) transect tape in a random orientation and recorded site data including geographic coordinates, elevation, slope, aspect, landscape position, soil series, and ecological site. We then inventoried the plant species present by scanning the entire transect area over a ten-minute period and noting all species encountered. Four photos were taken at each transect: down the transect line and turned 90˚, 180˚, and 270˚ from the transect.

The primary data necessary to calculate total available forage and stocking rates were obtained by sampling the aboveground biomass of plant species. After laying out the transect tape, aboveground biomass of grasses and forbs was sampled in ten locations by laying out a 0.89 meter^2 hoop every 3.05 meters along the transect. If vegetation in the hoop was sparse, all aboveground biomass of vegetation within each hoop was clipped and weighed (referred to as “total harvest”). Alternatively, when vegetation was abundant and dense, a representative unit of biomass of each species was weighed and used to estimate the number of units of that species in each hoop. The total weight of each

species biomass was calculated by multiplying the weight of the representative biomass unit by the number of units estimated in the plot. When using the representative unit biomass approach, we then clipped all of the vegetation in two hoops to evaluate the accuracy of estimates and adjusted estimations as necessary (this process is referred to as "double sampling"). For example, if 100 grams of biomass of a species was estimated among two hoops, but clipping and weighing the biomass in those hoops yielded only 50 grams of that species, it was assumed that all estimates of that species along that transect were twice as high as they should be, and all estimates were divided by two to correct this bias.

Shrub productivity was sampled through a similar but separate method, by tracing a circle with an outstretched 3.6-meter rope at two locations along the transect, starting from the 3-meter and 27-meter locations of the transect. Then, the amount of every shrub species occurring within the circles was estimated by collecting a reference unit of biomass of each shrub species (such as one large branch) and estimating how many of these reference units were found within each shrub circle. The reference unit of shrub biomass was later weighed, stripped of foliage, and weighed again to determine the foliage weight of the unit, and therefore an estimate of the total foliage weight within the shrub circles.

We then determined the "growth curve completed" and "amount ungrazed" of all species present at each transect. These characteristics help determine how much plant productivity we were unable to measure when sampling the transect. The "growth curve complete" addresses situations where a species is only beginning to flower at the time of surveying, and will continue to accumulate biomass later in the season that we cannot

measure at the time of sampling. To estimate the total annual production of these species, we must increase our biomass measurements accordingly. For example, if we measured 100 grams of a species which is finishing flowering at the time of sampling, we would assume that only 75% of the species' total annual production had been achieved, and we would estimate that 133.33 grams (100 grams / 0.75) of that species will be produced through the whole growing season.

Similarly, the "amount ungrazed" allows us to account for potential productivity lost to grazing by wildlife or livestock prior to sampling. If we estimated that 10% of a species' productivity had been grazed by wildlife or livestock before sampling, we noted this and assumed that the species' actual productivity was 10% greater than we measured at the time of sampling.

A small sample of every species was collected to be dried later. This is necessary because stocking calculations are based on dried biomass, not green biomass. We dried biomass samples in an oven, calculated the proportion of mass lost by drying samples, and used this ratio to calculate the amount of dry biomass of species at each transect.

At each transect we also used the line point intercept method to determine bare ground cover, canopy cover, litter cover, and other characteristics such as cover of individual species or functional groups. We also determined total biomass of trees present using the tree zig-zag sampling method. However, tree biomass is not used in calculating stocking rates since tree biomass is not considered as forage.

Determining Typical Productivity

Biomass collected in any single year may be atypical, if collected during unusually dry or wet years with less or more vegetative productivity than usual. Since

initial stocking rates should reflect typical conditions, we adjusted all biomass to achieve an estimated typical productivity. This was accomplished by referencing the Vegetation Drought Response Index (VegDRI) (Brown et al. 2008), which estimates vegetation drought stress on a weekly basis. At each transect we referenced the VegDRI data closest to the sampling date, and adjusted all measurements based on vegetation condition at that time. For example, a transect which VegDRI determined was in "pre-drought" conditions at the time of sampling was assumed to have produced only 90% of its typical productivity at that time, so measurements were multiplied by 1.11 to achieve estimated typical productivity.

Calculating Available Forage

To determine total available forage at every transect, we calculated what proportion of total species biomass should be considered forage based on the relative palatability of species. These species palatability factors had already been established for the Reservation by the BIA. Most grasses have a palatability factor of 100%, meaning they are extremely palatable to cattle, while the palatability of shrubs and forbs varies from 0% to 100%.

Additionally, to prevent overutilization and preserve ecological integrity, not all palatable forage should be allotted for grazing—stocking rates on the Reservation have aimed to maintain a maximum of 50% forage utilization. This is in keeping with the "take half, leave half" rule of thumb of forage utilization. Therefore, only half of palatable forage is considered available for grazing.

Together, species palatability and desired forage utilization determine the "proper use factor" of each species, used to calculate forage availability from total sampled

biomass. Because desired forage utilization had been determined as 50% throughout the Reservation, the proper use factors in the Reservation are the species palatability factors divided by two.

After multiplying the total dry biomass production of each species by its proper use factor, we obtained the total available forage of each species at each transect. Finally, we added together the total available forage of each species to obtain the total available forage at each transect.

We used total forage availability at each transects to determine mean forage availability in each soil map unit we sampled in each year. We then multiplied mean forage availability of each soil map unit by the total area of each soil map unit in a range unit to determine total forage amounts in each unit. For example, if a range unit contained 1,000 acres of a soil map unit with a mean forage availability of 100 pounds per acre, we calculated that this range unit contained a total of 100,000 pounds of forage within this soil map unit. By completing this same calculation for every soil map unit present in a unit, we calculated the total amount of available forage in each range unit.

Total forage amounts were used to calculate animal unit months (AUMs), which represent the forage required to support a cow weighing from approximately 900 to 1,100 pounds (Manske 1997). We assumed 790 pounds of dry forage as the equivalent of 1 AUM because our forage measurements represent oven-dried biomass (Thorne and Stevenson 2007). Therefore, 100,000 pounds of forage represents approximately 128 AUMs. A range unit with 128 AUMs can support grazing by 128 animal units for 1 month, 64 animal units for 2 months, and so on.

Before we could make final AUM calculations for each range unit, we had to

determine what areas of the Reservation are actually accessible for grazing. Areas too far from water sources or occurring on extremely steep slopes will not be readily grazed by cattle, so they do not contribute to available forage. For every soil map unit in each range unit, we calculated how much area was actually accessible for grazing.

We followed prior BIA determinations of how distance from water and slope gradients affect grazing utilization. These determinations assume areas within 2 miles of water sources will be fully accessible for grazing, areas 2 to 3 miles from water sources will only be 50% utilized, and areas farther than 3 miles will not be utilized at all. Similarly, it is assumed that cattle will fully utilize slopes from 0 to 30%, only utilize half of forage on slopes from 30% to 50%, and will not graze at all where slopes are steeper than 50%.

We used GIS layers to determine the area of soil map units falling into each of these grazing accessibility categories, and adjusted available forage in each soil map unit areas in each range unit accordingly. For example, if a range unit contains 500 acres of a particular soil map unit, but 100 acres are within 2 to 3 miles from a water source, we assumed those 100 acres will only be 50% utilized by cattle. Therefore, we would calculate total available forage for that soil map unit based on 400 acres being fully utilized, and 100 acres being utilized only 50% (meaning we assume only half of potential forage in those 100 acres contribute to available forage).

Lastly, BIA precedent dictated that 15% of total available AUMs should be reserved for wildlife, and removed from stocking considerations. We followed this precedent, reducing calculated AUMs by 15%. Effectively, this reduces desired forage utilization rate from 50% to 42.5% (50 * (1 - 0.15) = 42.5).

Modeling Cheatgrass Production and Vegetation Cover

We modeled cheatgrass production (*Bromus tectorum*, abbreviated as BRTE) and vegetation cover (bare ground cover, tree canopy cover, total canopy cover, and litter cover) throughout the Reservation. These models were built from cheatgrass biomass, and cover collected from line point intercept at transects. We modeled these data using two methods—random forest (RF) and inverse distance weighted interpolation (IDW).

RF associates a variable of interest with biophysical covariates like slope and soil characteristics occurring at transects. The relationship between variables is then used to predict the variable of interest throughout the Reservation. IDW, on the other hand, simply predicts a variable's value at pixels based on measurements from nearby transects.

RF generally works well to predict plant species biomass and cover. However, IDW may have an advantage over RF when predicting cheatgrass biomass, for example, because cheatgrass is strongly associated with local disturbance. Disturbance was not factored into the RF model, so RF may predict cheatgrass to occur in habitats that appear suitable, but have had little disturbance. IDW, on the other hand, will show similar cheatgrass predictions strongly grouped together.

We used the models to predict cheatgrass production, the proportion of total production in the form of cheatgrass, and four cover measures (bare ground cover, tree canopy cover, total canopy cover, and litter cover). RF allowed us to make predictions everywhere we had soil data, which covered the entire Reservation. IDW only allowed us to make predictions close to transect locations. Since only cover data collected by USU was available for this analysis, we could not make IDW predictions of cover for much of the Reservation, so we present only RF predictions of cover here.

Results

AUMs and Stocking Rates

Available animal unit months (AUMs) of forage in all range units of the Reservation, after adjusting for distance to water and slope gradients, are shown in Fig. 2-5. AUMs are the main determinant of grazing practices, determining how many livestock can graze an area and for how long. Available AUMs in range units vary significantly, from 11 to over 5,000 AUMs. The median 50% of range units have between 159 to 636 available AUMs.

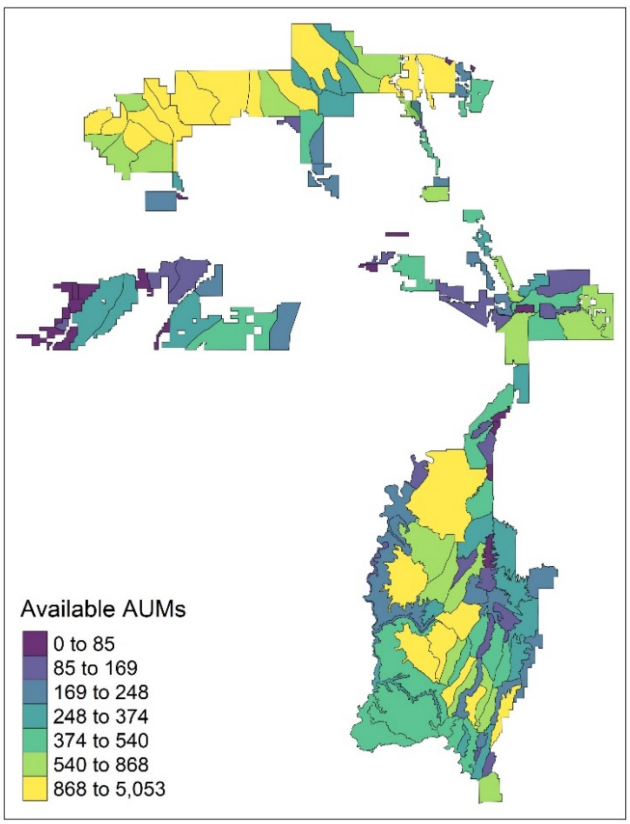

Figure 2-5. Available animal unit months (AUMs) of forage in all range units.

Stocking rates of range units, defined as accessible acres per available AUMs in each range unit, are shown in Fig. 2-6. A lower number indicates fewer acres are required

to constitute an AUM. Stocking rates vary significantly, from 81.84 acres / AUM (indicating the lowest stocking rate and least dense forage) to 2.17 acres / AUM (indicating the highest stocking rate and most dense forage). Stocking rates in the median 50% of range units range from 6.86 to 21.86 acres / AUM.

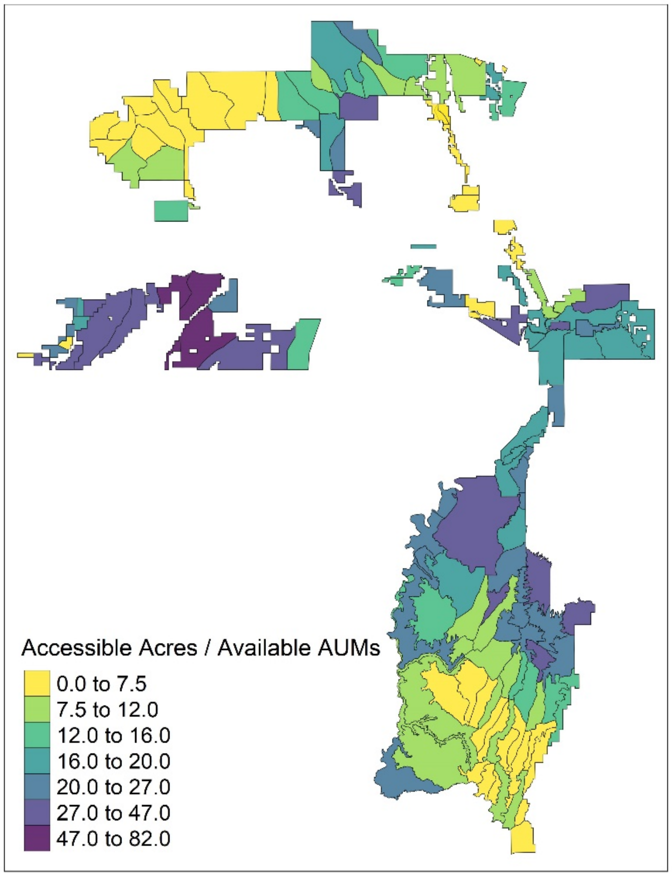

Figure 2-6. Accessible acres per available animal unit months (AUMs) of forage in all range units.

Cheatgrass (BRTE)

Random forest (RF) and inverse distance weighted interpolation (IDW) predictions both show that cheatgrass (BRTE) comprised the greatest proportion of total production in the Uinta Basin and southeastern Uinta Mountains regions (Fig. 2-7). However, whereas IDW predicted nearly zero cheatgrass in many areas (Fig. 2-7b), RF

predicted low but nonzero cheatgrass proportions in many areas (Fig. 2-7a). IDW also predicted extremely high BRTE proportions in some areas (up to 0.68), whereas RF predictions did not exceed 0.35. Since RF predictions were based on covariates such as soil, for which we had data beyond the Reservation, RF model predictions extend beyond the Reservation into surrounding BLM and private lands.

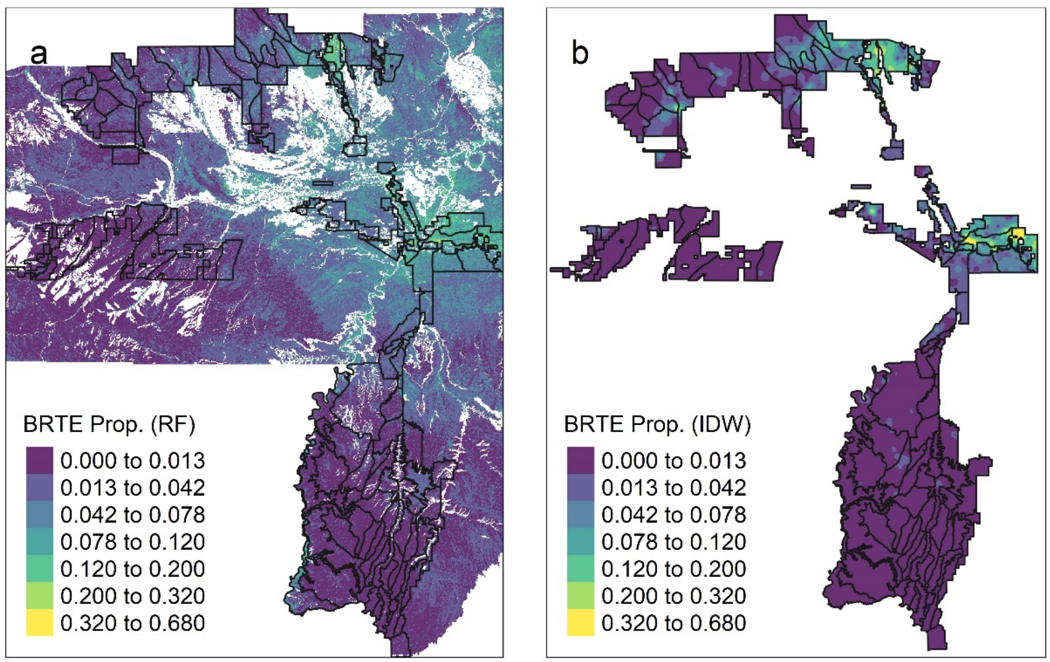

Figure 2-7. Cheatgrass (BRTE) proportion of total plant production, as predicted by RF (a) and IDW (b).

These results are made somewhat clearer by calculating the mean cheatgrass proportion of total production in each range unit (Fig. 2-8), rather than plotting the cheatgrass proportions on a pixel by pixel basis. This allows data throughout a range unit to be summarized.

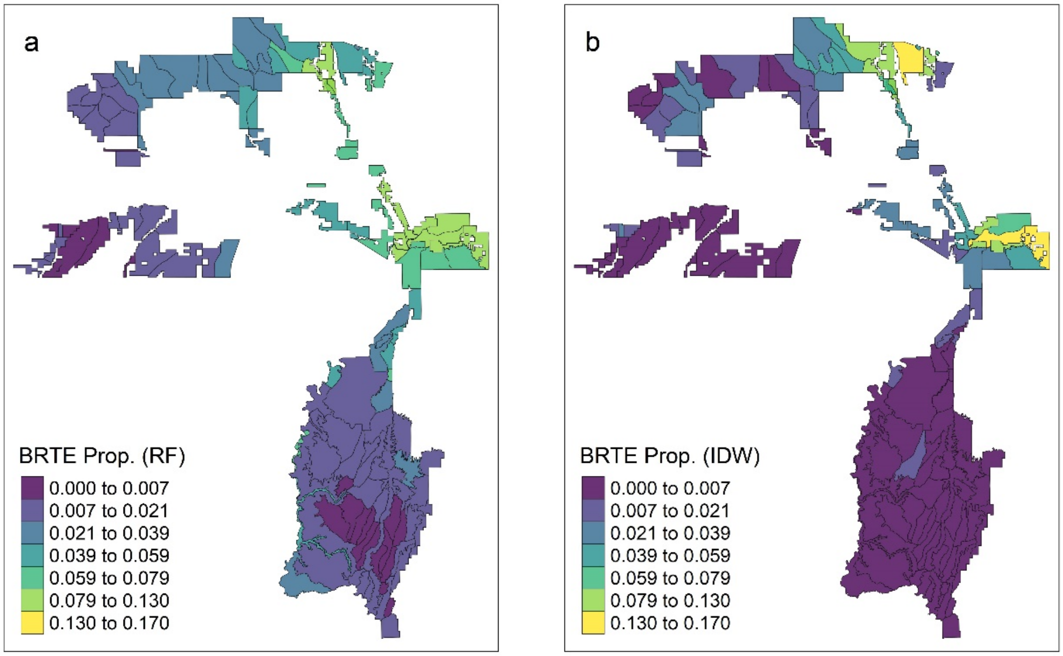

Figure 2-8. Mean BRTE proportion of total plant production in each range unit, as predicted by RF (a) and IDW (b).

BRTE total production results (in pounds of dry matter per acre) were similar to BRTE proportion results (Figs. 2-9 and 2-10). Again, IDW predictions were more extreme than RF predictions, and were higher in high areas and lower in low areas, but both methods agreed that BRTE production was highest in the Uinta Basin and southeastern Uinta Mountains.

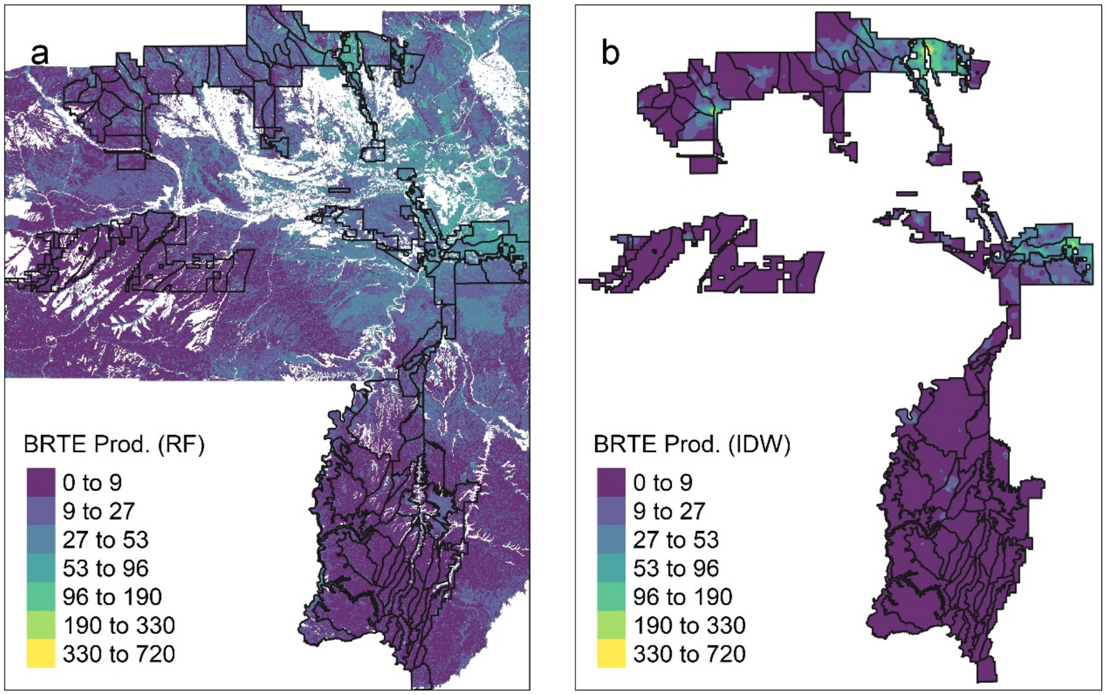

Figure 2-9. BRTE production (in pounds of dry matter per acre), as predicted by RF (a) and IDW (b).

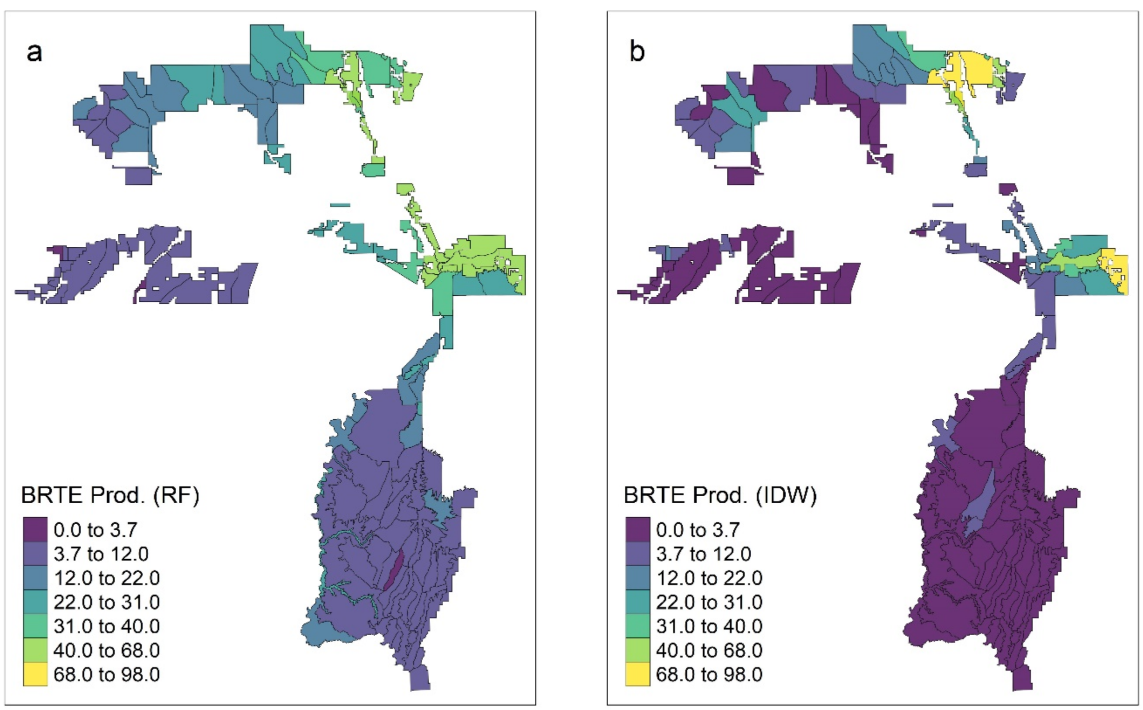

Figure 2-10. Mean BRTE production (in pounds of dry matter per acre) in each range unit, as predicted by RF (a) and IDW (b).

Cover

Bare ground cover proportion was predicted to be highest in the low elevation, drier areas of the Uinta Basin (Fig. 2-11), averaging around 0.40 throughout much of the area. Conversely, bare ground cover was less than 0.18 through much of the Uinta Mountains and southeast Tavaputs Plateau. Bare ground cover was predicted to range from 0 to 0.57 throughout the study area, and range unit means vary from 0.05 to 0.46.

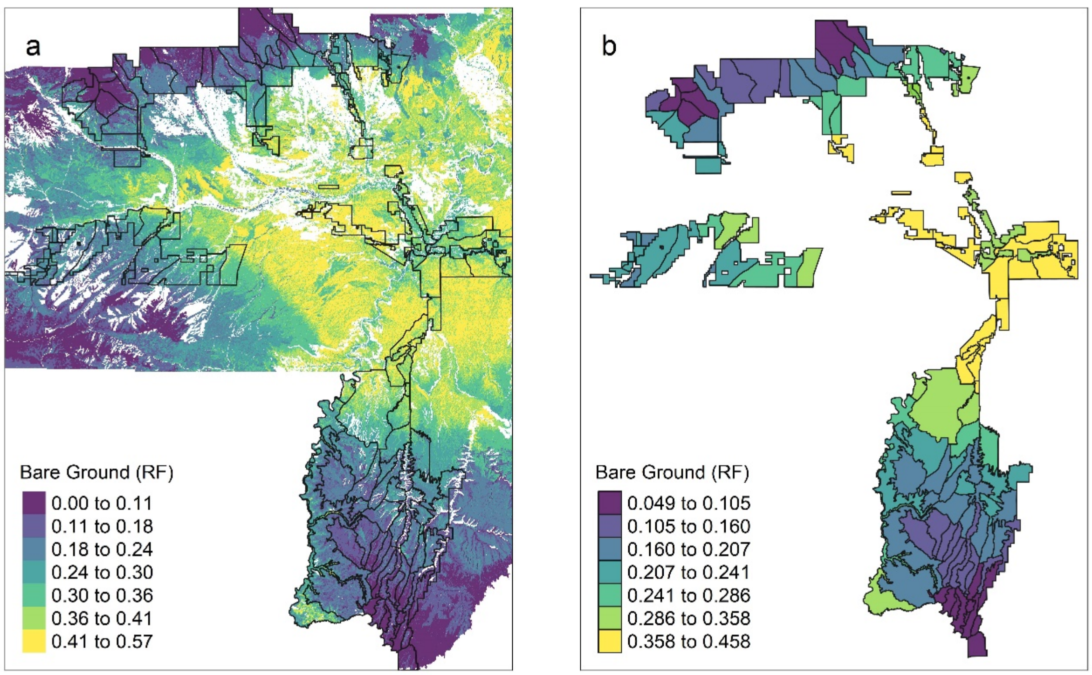

Figure 2-11. Bare ground cover proportion (a), and mean bare ground cover proportion in each range unit (b), as predicted by RF.

Total canopy cover proportion was predicted to be lowest in the Uinta Basin and highest through the Uinta Mountains and southeast Tavaputs Plateau (Fig. 2-12). Total canopy cover predictions ranged from nearly 0 to 0.98, with range unit means varying from 0.24 to 0.86.

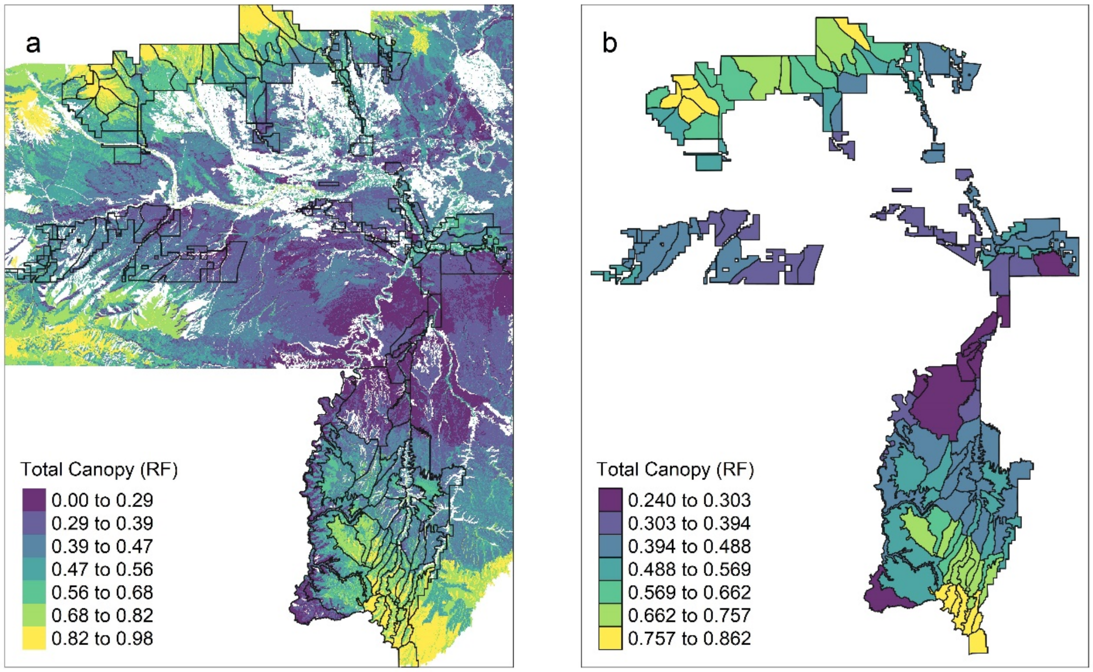

Figure 2-12. Total canopy cover proportion (a), and mean total canopy cover proportion in each range unit (b), as predicted by RF.

Litter cover proportions (Fig. 2-13) closely match total canopy cover proportions, and were lowest in the Uinta Basin and highest in the Uinta Mountains and Tavaputs Plateau. Litter cover ranged from nearly 0 to 0.96, with range unit means from 0.20 to 0.85.

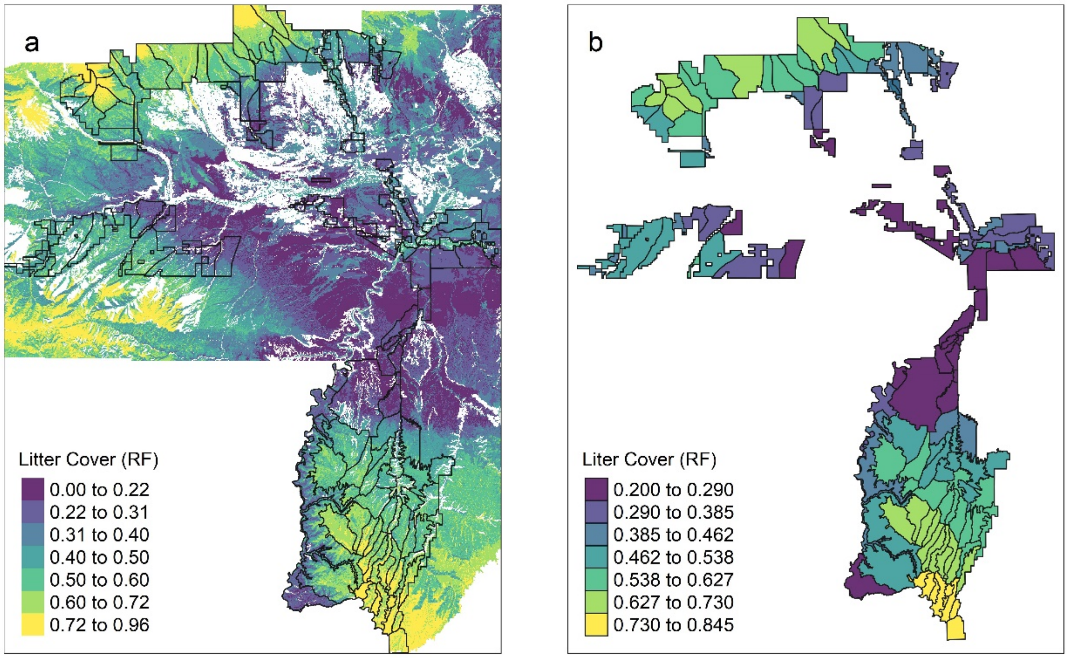

Figure 2-13. Litter cover proportion (a), and mean litter cover proportion in each range unit (b), as predicted by RF.

Tree canopy cover proportions were predicted to be nearly zero throughout most of the Uinta Basin, and higher in high elevations of the Uinta Mountains and Tavaputs Plateau (Fig. 2-14). Tree canopy cover was generally below 0.40 throughout much of the Uinta Mountains and Tavaputs Plateau regions, but was very high in small patches of these regions. Tree canopy cover ranged from 0 to 0.87 throughout the study area, with range unit means ranging from 0.01 to 0.54.

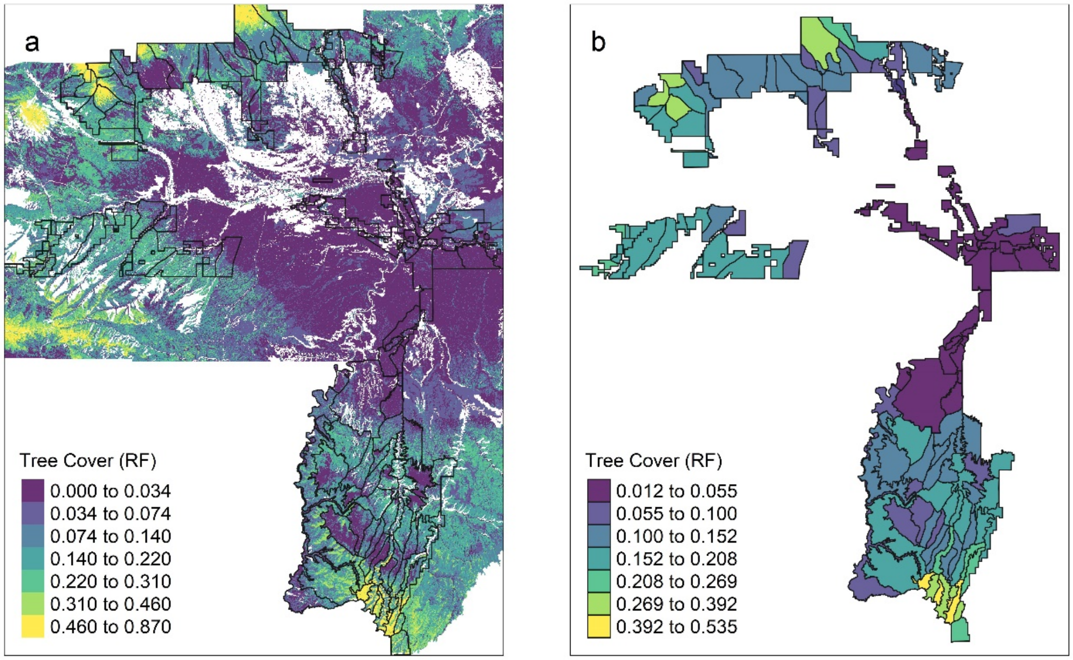

Figure 2-14. Tree canopy cover proportion (a), and mean tree canopy cover proportion in each range unit (b), as predicted by RF.

Discussion

AUMs and Stocking Rates

Available AUMs vary greatly among range units (Fig. 2-5). Northern range units of the Reservation in the foothills of the Uinta Mountains consistently have large numbers of AUMs. Many units in this area have more than 1,000 available AUMs, representing significant grazing opportunities. In particular, the Dry Mountain area to the far northwest of the Reservation represents a prime location for grazing, with nearly 13,000 AUMs in the range units throughout this area. Nonetheless, livestock use here has been minimal to date. There are also some range units with a large number of AUMs in the southeastern Tavaputs Plateau. However, there are not as many range units concentrated together with significant AUMs in this area.

Stocking rates (summarized in accessible acres / available AUMs) further reveal possible grazing opportunities, as areas with higher stocking rates can support more dense livestock grazing. Range units in the far northwest and southeast of the Reservation have the highest stocking rates (Fig. 2-6).

Range units in the far southeast of the Tavaputs Plateau do not have very large numbers of AUMs (Fig. 2-5), but do have high stocking rates (Fig. 2-6). Each unit has relatively few AUMs because these units cover small areas, but they are likely suitable grazing locations given their high stocking rates. However, this area currently has large populations of wild horses, bison and other wildlife. These ungulates may complicate livestock grazing in the area, and actual available AUMs are likely lower than calculated in these units because these ungulates are currently utilizing the available forage.

Most range units within the Uinta Basin and northern Tavaputs Plateau have relatively low stocking rates and low numbers of available AUMs. Collectively, they still contain a large number of AUMs and may be valuable for grazing, but available forage is generally sparser than units in the southeastern Tavaputs Plateau and most of the Uinta Mountains area and may not be as suitable for grazing overall.

Grazing management will necessarily impact wildlife management. Increasing cattle stocking in the Uinta Mountains, for example, will remove forage that wildlife could otherwise utilize, and could negatively impact wildlife or cause them to move elsewhere. Therefore, grazing objectives should be weighed against wildlife management objectives, such as increasing populations to permit additional hunting. Maps of AUMs similar to Fig. 2-5 could be calculated in reference to elk and deer rather than cattle, but

would require altering species palatability factors to consider potential utilization by these wildlife rather than cattle.

Grazing Seasonality

Given the different climatic regimes and vegetation phenology through the Reservation, it is important to consider the seasonality of livestock grazing. Generally, range units in the Uinta Basin are likely most appropriate for grazing from fall to spring. Due to the low elevations in this region, the summer climate here is the most harsh, but climate from fall to spring is not as harsh as it is at higher elevations. Forage production begins earliest in the Uinta Basin (though it may not peak until late in the season due to the presence of warm-season grasses). At higher elevations in the Uinta Mountains and Tavaputs Plateau, forage production beings later in the year, winter climate is more prohibitive, and summer climate is less prohibitive. Therefore, grazing in these regions is likely most appropriate in late spring through early fall.

Cheatgrass (BRTE)

Cheatgrass is an annual invasive grass that can establish in disturbed areas and degrade ecological condition, outcompeting native species and reducing available forage, especially late in the season and in drier years (Knapp 1996). To assess cheatgrass invasion in the Reservation, we modeled total cheatgrass production and the proportion of total production in the form of cheatgrass throughout the Reservation. Cheatgrass proportion likely gives a more consistent measure of relative cheatgrass dominance across the area, since total production varies throughout the Reservation.

Though cheatgrass was present in many sampled transects, it did not constitute a large proportion of total plant production in most areas (Figs. 2-7 and 2-8). The highest proportion of cheatgrass was found in the eastern Uinta Basin. Cheatgrass is also somewhat prominent throughout the Uinta Basin near these range units, and in the eastern Uinta Mountains region. Range units in the northwestern Uinta Mountains and the majority of the Tavaputs Plateau do not appear to have significant amounts of cheatgrass. Total cheatgrass production results (Figs. 2-9 and 2-10) are similar to cheatgrass proportion results.

Cover

Bare ground is an important indicator of overall site stability (Pellant et al. 2005). Locations with higher bare ground cover are generally more susceptible to disturbance and erosion than those with low bare ground cover. Unsurprisingly, bare ground cover was highest in the low elevation Uinta Basin, and lower in higher elevation areas in the Uinta Mountains and Tavaputs Plateau (Fig. 2-11). This indicates areas in the Uinta Basin are more susceptible to soil disturbance and erosion, whereas units at higher elevations are likely more resilient.

Total canopy cover, representing the total proportion of land covered by vegetation, is also an important indicator of site stability. Vegetation helps protect soils from soil disturbance and erosion, and is generally indicative of healthier sites. As expected from the bare ground cover, we found canopy cover to be lowest in the Uinta Basin and highest through the Uinta Mountains units and southeast Tavaputs Plateau (Fig. 2-12).

Litter cover represents the proportion of ground covered by dead and decaying plant material. Like vegetation cover, litter cover helps protect soils from disturbance and erosion, and helps replenish organic matter in the soil. Litter cover (Fig. 2-13) closely matches vegetation cover, meaning litter cover is lowest in the Uinta Basin and highest through the Uinta Mountains units and southeast Tavaputs Plateau.

Tree cover represents the cover only of tree species. In the context of grazing, high tree cover may reduce cover of quality forage species like grasses. However, tree cover can have benefits for livestock and wildlife by providing a refuge from the sun on hot days (Mitlohner et al. 2001). Tree cover is extremely high in small patches of the Dry Mountain region and southern Tavaputs Plateau (Fig. 2-14), but is moderate throughout most of these regions, averaging cover between 0.20 to 0.40. This suggests large areas may have sufficient cover to shade livestock without having excessive tree cover that dramatically reduces forage. In much of the Uinta Basin and lower elevations of the Uinta Mountains and Tavaputs Plateau, tree cover is nearly zero. This lack of shade may additionally stress livestock in these areas.

The various cover measures collectively show largely predictable relationships. In the Uinta Basin, bare ground cover is highest, tree cover is almost nonexistent, and total canopy and litter cover are fairly low. In higher elevations in the Tavaputs Plateau and Uinta Mountains, total canopy cover and litter cover are significantly higher and bare ground cover is significantly lower. Tree cover is somewhat patchier, and is very high in more isolated areas within the Uinta Mountains Tavaputs Plateau, but not throughout the entire area.

Overall, these measures show that lower elevations in the Uinta Basin are less stable and at a greater risk of erosion and disturbance than higher elevations in the Uinta Mountains and Tavaputs Plateau. This indicates that generally, management of the Uinta Basin should be more conservative, to prevent potential disturbance and degradation.

Conclusion

We completed an inventory of vegetation in the Uintah and Ouray Reservation to determine forage availability, appropriate stocking rates, and measures of ecological health throughout the area. We found significant numbers of AUMs, particularly in higher elevation range units of the Reservation in the Uinta Mountains and Tavaputs Plateau. Greater AUMs allow more livestock to sustainably graze in a unit for longer time periods.

Stocking rates are very high in the northwest Uinta Mountains and southeastern Tavaputs Plateau, in comparison to notably lower stocking rates throughout the Uinta Basin and northern Tavaputs Plateau. Where high stocking rates are matched with high AUMs, as in the northwestern Uinta Mountains, grazing suitability is maximized.

Our analysis of cheatgrass shows that while cheatgrass is present throughout the Reservation, few areas are dominated by it. Only small patches of the Uinta Basin and eastern Uinta Mountains have significant cheatgrass production. Increased disturbance and the generally low plant cover in these drier areas have likely promoted cheatgrass, whereas many other areas have experienced less disturbance and have less significant cheatgrass invasion, and may also be more resilient to invasion.

Analysis of cover shows the Uinta Basin has more bare ground and less canopy and litter cover than other regions of the Reservation, and generally indicates that the

Uinta Basin may be less resilient to disturbance than other regions, or may have historically experienced greater disturbance. Conversely, litter and canopy cover are extremely high, while bare ground is very low, throughout the Uinta Mountains and southeastern Tavaputs Plateau, indicating these regions have experienced less disturbance or are more resilient to disturbance.

Together, the high total canopy cover, high litter cover, high stocking rates, and large numbers of AUMs makes range units in the Uinta Mountains ideal grazing locations. Units in the Dry Mountain region alone, in the far northwest of the region, contain more than 13,000 AUMs, a significant number to support grazing operations. If grazed for four months (for example, from June to September), these units could support approximately 3,250 head of cattle. The high canopy cover and littler cover predicted here generally indicate a resilience to disturbance and possibly a historic lack of disturbance in the area.

The southeastern Tavaputs Plateau is also a high-quality area for grazing, with high stocking rates and high canopy and litter cover. However, range units are smaller in this area, so units do not have large numbers of AUMs. More significantly, this area also has large populations of bison, horses and other wildlife. These ungulates are utilizing forage in the area, so actual AUMs available for livestock in present conditions will be lower than we determined. If data on the size of the ungulate populations were available, their level of grazing could be estimated, and available AUMs could be adjusted accordingly. The ungulates in this area may also disturb or overutilize forage in the area if their populations grow too high, which could potentially reduce available forage, decrease canopy cover, and promote cheatgrass invasion. Given these concerns, this area

should be closely monitored, particularly if livestock grazing is increased.

The Uinta Basin and northern Tavaputs Plateau generally have low stocking rates and fewer AUMs than units in the Uinta Mountains or Tavaputs Plateau. There are still a large number of AUMs throughout the entire area, though, as these range units collectively cover a very large area. However, this area is likely less resilient to disturbance than the Uinta Mountains and southeast Tavaputs Plateau, given its lower canopy and litter cover, and higher bare ground cover. The high cheatgrass abundance in the area indicates it likely has already been disturbed and degraded, and further livestock grazing could exacerbate these issues. Therefore, grazing in the area should be undertaken carefully.

References

Brown, J.F., Wardlow, B.D., Tadesse, T., Hayes, M.J., Reed, B.C., 2008. The Vegetation Drought Response Index (VegDRI): A New Integrated Approach for Monitoring Drought Stress in Vegetation. GIScience & Remote Sensing 45, 16–46. https://doi.org/10.2747/1548-1603.45.1.16

Fuls, E.R., 1992. Ecosystem modification created by patch-overgrazing in semi-arid grassland. Journal of Arid Environments 23, 59–69. https://doi.org/10.1016/S0140-1963(18)30541-X

Holechek, J.L., 1988. An Approach for Setting the Stocking Rate. Rangelands 10, 10–14.

Knapp, P.A., 1996. Cheatgrass (Bromus tectorum L) dominance in the Great Basin Desert: History, persistence, and influences to human activities. Global Environmental Change 6, 37–52. https://doi.org/10.1016/0959-3780(95)00112-3

Manske, L.L., 1997. Animal Unit Equivalent for Beef Cattle Based on Metabolic Weight 3.

Menke, J., Bradford, G.E., 1992. Rangelands. Agriculture, Ecosystems & Environment 42, 141–163. https://doi.org/10.1016/0167-8809(92)90024-6

Mitlohner, F.M., Morrow, J.L., Dailey, J.W., Wilson, S.C., Galyean, M.L., Miller, M.F., McGlone, J.J., 2001. Shade and water misting effects on behavior, physiology, performance, and carcass traits of heat-stressed feedlot cattle. J Anim Sci 79, 2327–2335. https://doi.org/10.2527/2001.7992327x

Pellant, M., Shaver, P., Pyke, D., Herrick, J.E., 2005. Interpreting Indicators of Rangeland Health: Version 4. Technical Reference 1734-6. USDI, BLM, NSTC, Division of Science Integration, Branch of Publishing Services, Denver, Colorado.

Thorne, M.S., Stevenson, M.H., 2007. Stocking Rate: The Most Important Tool in the Toolbox 10.

CHAPTER 3

CONSIDERING SPATIOTEMPORAL VARIABILITY IN AVAILABLE FORAGE TO IMPROVE RANGELAND INVENTORY AND MONITORING

Abstract

Rangelands are depended upon to provide numerous ecosystem services, particularly livestock grazing. Grazing management requires measuring attributes such as forage availability, which influences the level of grazing a location can sustain without degrading ecological condition. However, spatiotemporal variability makes such determinations of forage availability difficult. We sampled vegetation throughout the Uintah and Ouray Reservation and constructed a random forest model to predict annual forage availability in the Reservation and surroundings. By associating forage availability with environmental and climatic covariates which vary annually, the model predicts annual forage availability on a pixel by pixel basis from 1984-2018, explicitly considering spatiotemporal variability.

The model shows that forage availability is highly variable throughout the area. On average, forage availability in Reservation range units can decline up to 32% below median availability in some years, and can increase up to 33% above median availability in others. Recognizing such variability can improve grazing management by providing a fuller picture of the range of possible forage availability in range units, and can help avoid forage utilization during unfavorable years such as drought. The model can continue to be used into the future to monitor vegetation tends, and the modeling method may be applicable to other similar study systems.

Introduction

Rangelands, including grasslands, savannas, shrublands, and steppe, cover large swaths of the western United States and provide numerous ecological and social benefits (Havstad et al. 2007; Reid et al. 2008). Healthy rangelands are integral for providing forage for domestic livestock and wildlife, the establishment of suitable wildlife habitat, and a multitude of other ecosystem services (Havstad et al. 2007). Therefore, effective management of rangelands is vital economically and ecologically.

Informed rangeland management requires measuring key indicators such as vegetation composition, bare ground, and annual production (Pellant et al. 2005). Though general methods to assess rangeland characteristics are well-established (Galt et al. 2000), accurate and economical inventory and monitoring of rangelands still poses challenges (Booth and Tueller 2003). In many regions, including the western U.S., the vast spatial extent, remoteness, and spatiotemporal variability of rangeland environments makes adequately sampling and summarizing ecological condition difficult, especially across large areas and through time.

Annual production and subsequent forage availability are among the most widely studied rangeland attributes, given their inherent link to herbivory by wildlife and domestic livestock and their influence on sustainable stocking rates (Holechek 1988). Appropriate stocking rates are essential to rangeland management, helping prevent overgrazing and overutilization and the extensive biotic and abiotic degradation they can cause (Fuls 1992; Menke and Bradford 1992).

However, spatiotemporal variability in vegetation production makes determining forage availability and stocking rates difficult across large areas. Given this variability,

any single stocking rate is a simplification (Stoddart 1960), but a "typical" stocking rate or grazing capacity is useful for management (Galt et al. 2000; Holechek 1988; Holechek and Pieper 1992).

Spatial variability can be partially addressed when determining stocking rates by stratifying field sampling locations by characteristics such as soil map units or ecological sites, and assuming measurements from each unit represent units as a whole (Karl and Herrick 2010). However, vegetation can vary within these units depending on microclimate and topography throughout units. Temporal variability in productivity is difficult to determine in the field without sampling vegetation for many years, which is typically impractical prior to setting stocking rates. Inevitably, field vegetation sampling may occur in unusually wet or dry years, so a presumed typical production can be estimated from field data collected in wet or dry years (Holechek 1988). If done improperly, though, this could lead to spurious assumptions about typical conditions or trends through time.

Remote sensing is an attractive tool to address rangeland vegetation sampling challenges given its widespread availability throughout space and time, allowing spatiotemporal variability to be addressed. Remote sensing has been used for decades to determine indicators such as ground cover (Booth and Tueller 2003; Boswell et al. 2017; Ford et al. 2019), land degradation (Allbed and Kumar 2013), and total vegetation production (Del Grosso et al. 2008; Hunt, Jr. et al. 2003; Running et al. 2004). However, a gap still exists in utilizing remote sensing to determine forage availability in rangelands.

Most commonly, spectral indices like normalized difference vegetation index (NDVI) are assumed to represent available forage, given its association with total

aboveground annual net primary productivity (ANPP) (Borowik et al. 2013; Mitchell 2010; Paruelo et al. 2000). However, the proportion of vegetation that is palatable and available to livestock as forage varies widely between vegetation communities (Miller and Krueger 1976; Mueggler and Stewart 1981), so ANPP may not be an appropriate proxy for forage across environments dominated by multiple vegetation types or complex vegetation mixes. Therefore, directly determining forage availability is preferable to treating ANPP as a proxy. Furthermore, NDVI alone is an imperfect predictor of vegetation biomass, and its accuracy varies by soil, topography and habitat type (Garroutte et al. 2016).

Here, we detail a method to predict annual forage availability throughout more than 5 million acres of the Uintah and Ouray Reservation and surroundings in northeastern Utah, fitting climatic, topographic, and edaphic covariates to plant production data collected in the field. This location is an ideal study area for this analysis given its large elevation range (from 1300-3350 meters above sea level), diversity of dominant vegetation types, high interannual variability in production, and the availability of a large plant production dataset collected in the field.

Our method predicts forage availability annually over a 35-year time span, explicitly addressing spatiotemporal variability and yielding time-series of high-resolution gridded layers of forage availability and ANPP. In comparison to determining a single, supposed typical forage availability for locations, these time series can greatly enhance rangeland inventory and monitoring by quantifying how forage availability varies. As the method incorporates only freely-available remotely-sensed data, it can greatly reduce the expenditure of money, time, and effort typically devoted to resampling

vegetation in the field, while providing high quality, high resolution predictions of forage availability.

Reservation lands such as the Uintah and Ouray Reservation cover large areas and are often understudied, and Tribes may lack both the funds required to frequently sample vegetation in the field and the scientific information needed to make the most informed land management decisions. Therefore, this method may be particularly valuable on Reservation lands, or other vast, remote lands managed by the Bureau of Land Management or Forest Service.

Methods

Study Area

Our study region is centered on the Uintah and Ouray Reservation and surroundings in northeastern Utah (Fig. 3-1), including three broad areas: the Uinta Mountains foothills in the north, the Tavaputs Plateau in the south, and the low elevation Uinta Basin between the two. This region covers an elevation range of over 2000 meters, from 1300 to 3350 meters above sea level. Climate varies greatly throughout this area, with the lowest elevations typified by an arid climate with cold winters and warm summers, while higher elevations have a subhumid climate with cold winters and short, cool summers. The lowest elevations in the Uinta Basin receive approximately 150 mm mean annual precipitation (MAP) and 8°C mean annual temperature (MAT) (1540 m, Ft. Duchesne Station ID:USC00422996, Utah Climate Center 2019). The highest elevations receive approximately 885 mm MAP and 1°C MAT (3231 m elevation, Brown Duck Station ID:USS0010J30S, Utah Climate Center 2019).

Geologically, the Uinta Basin is dominated by the Duchesne River and Uinta Formations, the Tavaputs Plateau is composed mainly of the Green River Formation, and the Uinta Mountains foothills include the Mancos Shale and older Jurassic to Triassic Formations (Hintze et al. 2000). Soils include Aridisols in much of the Uinta Basin, Entisols in middle elevations of the Tavaputs Plateau and Uinta Basin, and Mollisols in higher elevation, more moist sites in the Tavaputs Plateau and Uinta Mountains (Boettinger 2009).

Many distinct vegetation communities occur throughout this region. Generally, the lowest elevations are dominated by saltbush (*Atriplex* spp.) and galleta grass (*Hilaria jamesii*), middle elevations include pinyon-juniper (*Pinus edulis* and *Juniperus osterosperma*), Wyoming big sagebrush (*Artemisia tridentata* var. *wyomingensis*) and bunchgrasses (*Leymus* spp., *Achnaterum* spp. and others), and the highest elevations feature mountain big sagebrush (*Artemisia tridentata* ssp. *vaseyana*) and other shrubs, lodgepole pine (*Pinus contorta*), aspen (*Populus tremuloides*), and grasses.

The Reservation has experienced little livestock grazing in recent history. A bison herd introduced in 1986 has increased to several hundred individuals (Bates and Hersey 2016) and wild horses, elk and other ungulates are common in some areas, but domestic grazing by cattle and other livestock has been limited (A. Pingree, personal communication, June 21, 2019).

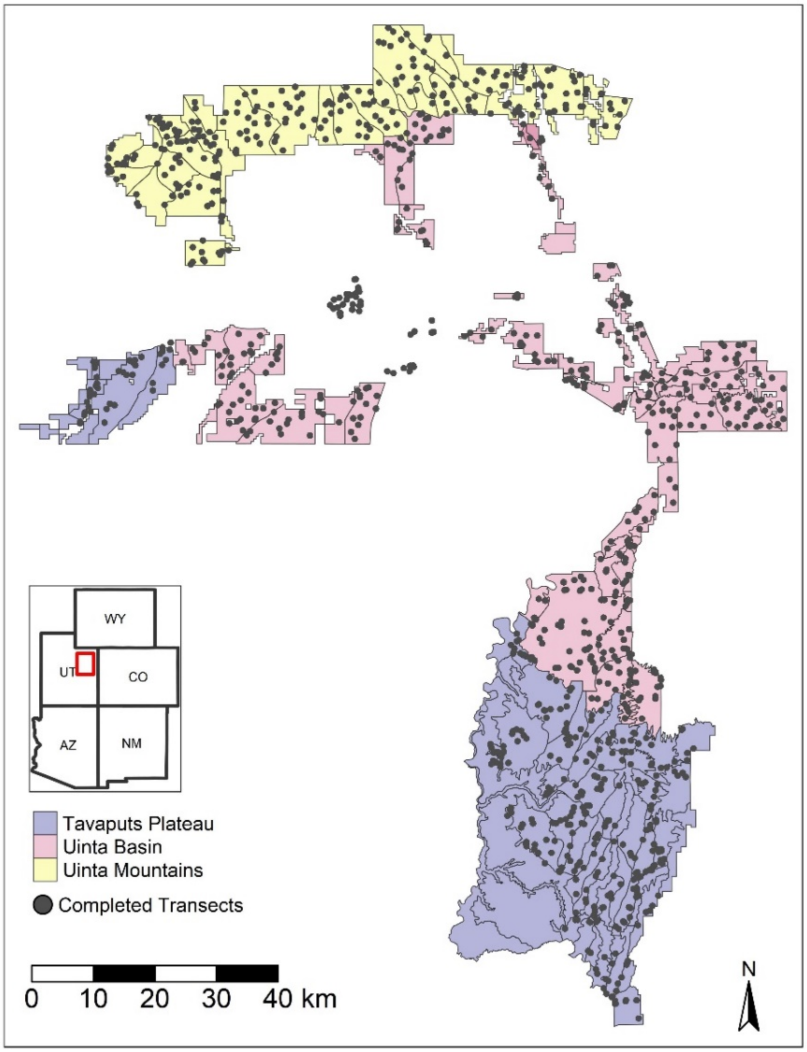

Figure 3-1. Map of study area, showing range unit borders of the Reservation and transect sampling locations. Range units are colored by the three main regions within the Reservation.

Assembling the Database

We compiled annual plant production data from 872 transects surveyed across the Uintah and Ouray Reservation between 2010 and 2017 (Fig. 3-1). In these data, plant production represents annual aboveground net primary production (ANPP) among grasses, forbs, and shrubs. Available forage at each transect was calculated by multiplying the total production of each species by an appropriate palatability factor for

that species, representing the proportion of the species' total production cattle will readily graze. Palatability factors had previously been established to quantify forage utilization by cattle in the region (see Table S-1). ANPP and forage values used in this analysis represent oven-dried biomass and are reported in kilograms per hectare.

Lower elevation transects were sampled earlier in the season and higher elevation transects were sampled later to capture as much of each year's plant production as possible. However, the stage of development for each species at each transect was also noted to estimate total annual production from the observed production. For example, a forb flowering at the time of sampling would be assumed to have produced only approximately 75% of its total annual production, and its observed biomass measurements would be multiplied by 1.33 to calculate its estimated total annual production. When wildlife grazing was evident, we also estimated what proportion of a species' total biomass had been grazed, and increased observed measurements by that proportion to estimate the total biomass produced by the species before grazing. Full methods for collecting species biomass are available in Supplementary Information.

We associated forage availability and ANPP at each transect with numerous covariates as predictors. Covariates and their derivations are shown in Table 3-1.

Table 3-1. Covariates included as predictors of ANPP and forage availability at transects, and the source and processing of those covariates.

Covariate	**Derivation**
Elevation	USGS 30-meter digital elevation model (DEM) (U.S. Geological Survey 2017)
Slope	Calculated from DEM
Aspect	Calculated from DEM, transformed to eastness and northness

Solar radiation	Calculated in ArcGIS from DEM from Julian day 91-243 (April 1-August 31), spanning the main growing season in the region
Compound topographic index (CTI)	Calculated from DEM, this is a measure of the water-gathering potential of locations (Gessler et al. 1995)
Edaphic characteristics (Available water capacity, cation exchange capacity, depth to any restrictive layer, organic material percent by weight, pH, sodium adsorption ratio, sand proportion, silt proportion, clay proportion, estimated rangeland production in a typical year)	SSURGO soil data for the area (currently not publicly available) were summarized in NRCS Soil Data Viewer (Natural Resources Conservation Service 2019). Characteristics were calculated from soil surface to a depth of 20cm, because many soils in the region are no deeper than 20cm. Characteristics were calculated as a weighted average of characteristics from all soil components greater than 5% abundance within a soil map unit. Edaphic data were rasterized at 30-meter resolution from the original vector data output
Estimated tree cover	Determined from Landfire existing vegetation cover at 30-meter resolution (LANDFIRE 2008). We recoded data from 0 (indicating less than 10% tree cover) to 9 (indicating 90-100% cover)
Annual climatic variables (precipitation, vapor pressure deficit, maximum temperatures, minimum temperatures)	Determined from Daymet (Thornton et al. 2018). Calculated over multiple temporal windows. Vapor pressure deficit was calculated by subtracting actual vapor pressure from saturation vapor pressure (Zotarelli et al. 2010). Originally in 1000-meter resolution, resampled by nearest neighbor to 30-meter resolution
Normalized difference vegetation index (NDVI)	Determined from Landsat imagery at 30-meter resolution

Processing Landsat Imagery

Landsat imagery available from 1984 to 2018 were accessed from Google Earth Engine (Gorelick et al. 2017). We accessed Thematic Mapper (Landsat 5) from 1984 to

2013, Enhanced Thematic Mapper (Landsat 7) from 1999-2018, and Operational Land Imager (Landsat 8) from 2013 through 2018.

Landsat data were used to calculate Normalized Difference Vegetation Index (NDVI), formulated as:

$$\mathrm{NDVI} = (\mathrm{NIR} - \mathrm{Red}) / (\mathrm{NIR} + \mathrm{Red}) \quad (1)$$

where Red and NIR represent spectral reflectance in the red and near-infrared regions, respectively.

Only Tier 1 data, representing the highest quality images, were selected for analysis. Images were processed to terrain-corrected surface reflectance, then further screened for clouds, snow, and shadows using the CFMask algorithm (Zhu et al. 2012). This process is often used to produce consistent time-series data such as Landsat Analysis Ready Data (Dwyer et al. 2018). After this imagery selection and processing, we determined the maximum NDVI value attained in each pixel in each year from 1984 to 2018. NDVI values obtained from the three sensors differ slightly, but by less than 5% (Li et al. 2014; Roy et al. 2016; Teillet et al. 2001).

Modeling Forage Availability and ANPP

We used a random forest model to predict forage availability and ANPP from environmental and climatic covariates. Random forest fits a series of classification trees to random samples of input data (in-bag observations) and evaluates tree prediction accuracy by predicting values of out-of-bag observations not included in a given tree (Breiman 2001; Cutler et al. 2007). Each tree utilizes only a random subset of predictor variables ("split variables") per node, making trees more variable and reducing correlations between trees (Cutler et al. 2007).

Random forest is appropriate for modeling moderate size datasets with many nonlinear, interacting variables (Cutler et al. 2007). We used the randomForest package in R to perform modeling (Liaw and Wiener 2002; R Core Team 2018), building 800 trees with 5 split variables per node.

We utilized only two thirds of the input data as training points included in modeling, and reserved one third of data as validation points for model evaluation. The validation points are therefore never incorporated in model construction, and are not to be confused with out-of-bag observations, which vary from tree to tree within the random forest. Model performance was evaluated by calculating the mean absolute error (MAE) and root mean square error (RMSE) of the model's predictions of the validation points not included in modeling. MAE evaluates the average absolute value of errors by the following equation, where $\widehat{y_t}$ represents the predicted value, y_t represents the observed value, and T represents the total number of points:

$$\mathrm{MAE} = \frac{\sum_t^T |\widehat{y_t} - y_t|}{T} \tag{2}$$

RMSE calculates the square of all errors, determines the average squared error, then evaluates the square root of the average squared error:

$$\mathrm{RMSE} = \sqrt{\frac{\sum_t^T (\ \widehat{y_t} - y_t)^2}{T}} \tag{3}$$

Low MAE and RMSE indicate close fit between predicted and observed values of points. All errors are weighted equally in MAE, whereas RMSE allows large errors to be identified by giving greater weight to larger errors. We prioritized the minimization of RMSE over MAE in model selection to reduce the occurrence of large errors.

There is some debate as to how variables should be selected or excluded from random forest models (Behnamian et al. 2017; Degenhardt et al. 2019; Fox et al. 2017). Fox et al. (2017) found, using a dataset similar to ours, that iteratively eliminating variables after attempting to identify unimportant variables did not significantly affect model performance. Therefore, we eliminated only two predictors that random forest variable importance measures strongly suggested were unimportant (solar radiation and eastness). We included all climatic covariates, but selected only the temporal window that variable importance suggested was most influential.

The final variables included in modeling forage and ANPP were: all edaphic characteristics (available water capacity, cation exchange capacity, depth to restrictive layer, organic matter, pH, sodium adsorption ratio, sand proportion, silt proportion, clay proportion, NRCS estimated rangeland production for a given soil map unit), elevation, slope, northness, compound topographic index, estimated tree cover, maximum annual NDVI, January-June precipitation sum, May-June mean vapor pressure deficit, May-June mean maximum temperature, and May-June mean minimum temperature.

Bias Correction

Random forest predictions often have a systematic bias, where predictions are too high at very low and too low at very high observed values (Xu 2013; Zhang and Lu 2012). Therefore, prediction errors (observed values minus predicted values) tend to be negative at low predicted values and positive at high predicted values.

We corrected this bias by employing a method from Xu (2013) and Zhang (2012), which applies a second random forest to the results of the first random forest, modeling the prediction error of the first forest as a function of the prediction. This modeled

prediction bias is then subtracted from the first random forest to calculate a bias-corrected prediction.

Predicted Forage Availability Rasters

Rasters of modeled annual forage availability and ANPP were calculated in R by associating the random forest model with rasters corresponding to the variables included in the model, and calculating pixel-by-pixel predictions annually. This required raster layers corresponding to every covariate in our database. All rasters were projected to the WGS84 coordinate system (EPSG:4326) and were resampled to 30-meter resolution (when necessary) through nearest neighbor resampling.

Modeled rasters of forage availability and ANPP were calculated annually from 1984-2018. To correct for bias, bias prediction rasters were also calculated, then subtracted from the modeled rasters to calculate bias-corrected results. Resulting rasters were masked where the underlying landscape corresponded to urban areas, agricultural land, or water.

Mean Raster Values of Range Units

The Reservation is divided into 148 grazing allotments, referred to as range units. To summarize forage availability and ANPP in each unit, we calculated the mean forage availability and ANPP in each range unit in each year. This is accomplished by masking the rasters to include only pixels falling within a single range unit, then calculating a mean value and standard deviation of pixel values for each year. Processing data in this way allowed us to summarize results at a scale relevant to land management, and analyze

mean forage availability and variations in forage availability in individual units of the Reservation.

Results

Modeled Forage and Forage Variability

We calculated rasters of modeled forage availability annually from 1984-2018 at 30-meter resolution (Fig. 3-2a). Forage availability is highly variable spatially throughout the area, ranging from under 100 kg/ha to over 800 kg/ha. Generally, available forage increases at higher elevations throughout the area, with higher predictions in the Uinta Mountains and Tavaputs Plateau than in the Uinta Basin.

We used annual forage availability rasters to calculate time series results of forage availability in range units. Time series for two highly contrasting range units are shown in Figs. 3-2b and 3-2c. These units are Steer Ridge, ranging from 2500 to 2800 meters above sea level in the higher elevation, more moist Tavaputs Plateau region, and Alger Draw, from 1600 to 1800 meters above sea level in the lower elevation, drier Uinta Basin. Vegetation composition varies greatly between these units. Steer Ridge is characterized by mountain big sagebrush, aspen, Gambel oak, and sedges. Alger Draw is dominated by alkali sites with greasewood, saltbush species, snakeweed, halogeton, and basin big sagebrush. These range units are outlined in Fig. 3-2a.

In Steer Ridge, median forage availability was 485 kg/ha, and most years fell within 10% of the median, between 436-506 kg/ha (Fig. 3-2b). However, forage declined dramatically in a few years (2002, 2007, 2014), as low as 314 kg/ha, 35% below the median. In contrast to the drastic forage declines in some years, large increases in forage

above the median are not evident. These results are typical of units within the higher elevation, cooler, moister Uinta Mountains and Tavaputs Plateau regions.

Forage varies differently within Alger Draw, in the Uinta Basin region (Fig. 3-2c). Here, forage availability was centered around a median of 162 kg/ha. Most years fell within 17% of the median, but forage increased dramatically in some years, up to 43% above the median, to 232 kg/ha. In contrast to these pronounced forage increases, large forage declines below median conditions were not evident. These results are typical for units in the lower elevation, warmer, drier Uinta Basin region.

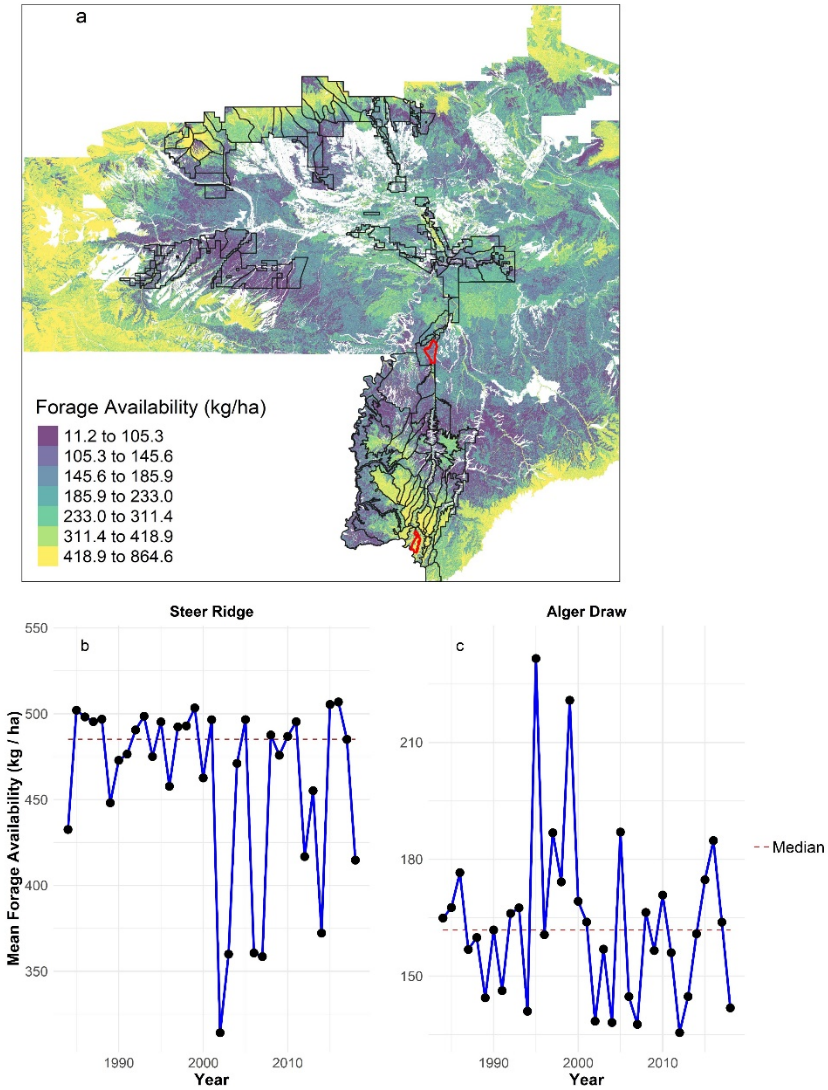

Figure 3-2. Example raster of forage availability in 1984 (a). Time series results of mean forage availability in the Steer Ridge (b) and Alger Draw (c) range units. Borders of the Reservation range units are shown in (a), with Steer Ridge and Alger Draw outlined in red in the southeast and east, respectively.

We assessed the overall interannual variability of available forage in range units by calculating the coefficient of variation (CV) of forage, the ratio of standard deviation of forage to mean forage, multiplied by 100 to put in terms of percent. Forage CV ranged from 6% to 28% among all range units, with a mean of 16%. Forage CV was negatively correlated with median forage availability, indicating that greater median forage

availability is associated with lesser interannual variability in forage. This relationship was weak, but statistically significant (Pearson's correlation $r^2 = 0.1968$; $p<0.001$) (Fig. 3-3).

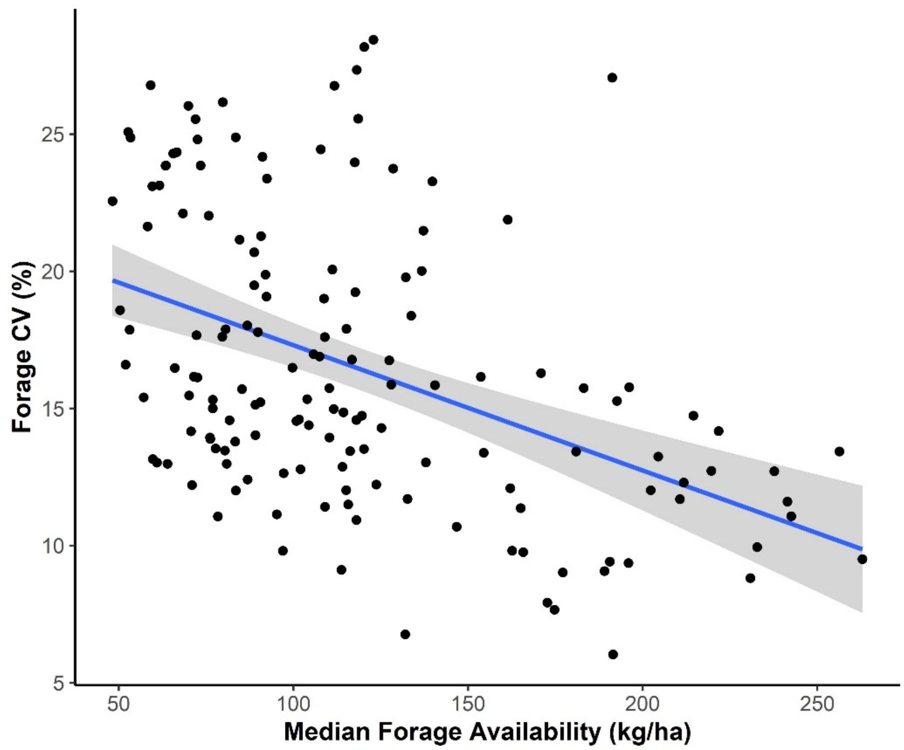

Figure 3-3. Coefficient of variation (CV) of forage availability in range units against median forage availability of range units (Pearson's correlation $r^2 = 0.1968$; $p<0.001$).

Perhaps more than overall variability, the degree of deviation from median forage availability in years with minimum or maximum forage availability is of particular importance. We assessed this by calculating the percent deviation from median forage in the years with minimum and maximum forage availability in each unit. These represent the maximum decrease below median forage, and the maximum increase above median forage for each unit.

Fig. 3-4 shows histograms of these deviations colored by region. Range units in the Uinta Basin tend to have large forage increases above median, and small decreases below median. Conversely, units in the Uinta Mountains and Tavaputs Plateau tend to have small forage increases above medium, and large forage decreases below median. This matches the relationship shown in the Fig. 3-2 time series results.

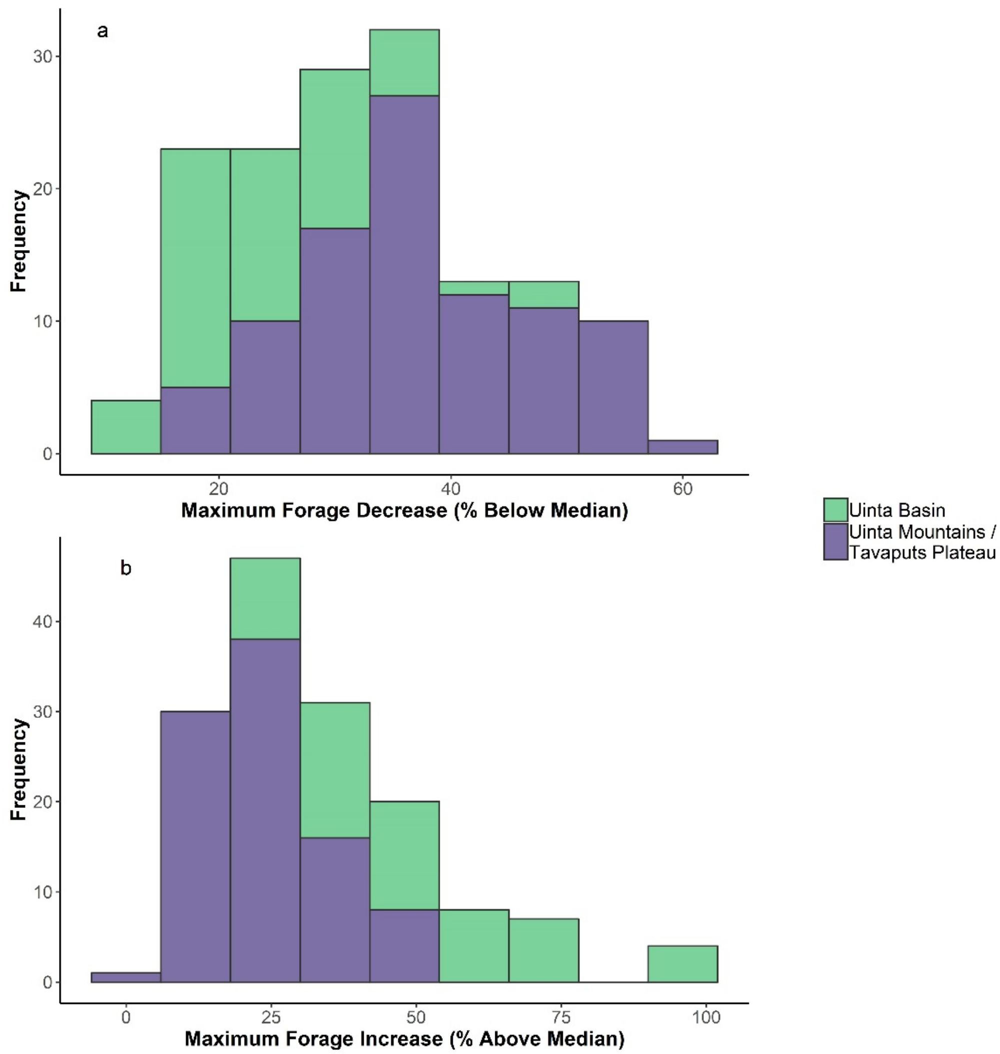

Figure 3-4. Histogram of maximum forage decrease below median forage in range units (a), and maximum forage increase above median forage (b), colored by region.

Relationship Between Forage and ANPP

Using the plant production data collected in the field, we examined the relationship between forage availability and ANPP at transects. They are clearly associated, but vary considerably (Fig. 3-5a). This indicates that ANPP is not a perfect predictor of forage availability throughout the study area, and therefore directly modeling forage is preferable to treating ANPP as a proxy.

Using the modeled forage availability and modeled ANPP results, we also examined the relationship between median forage availability and ANPP within range units (Fig. 3-5b). There is a closer relationship between forage and ANPP aggregated to range units than at individual transects. However, there is some variability in their relationship, indicating forage quality among range units varies somewhat.

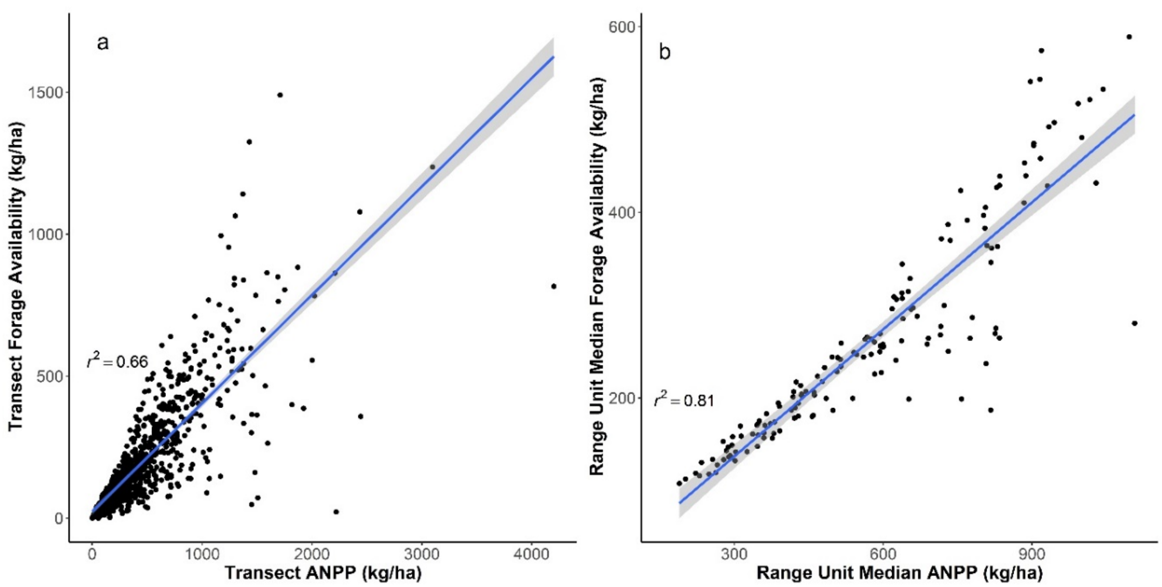

Figure 3-5. Forage availability versus ANPP as measured at individual transects (a), and median forage availability versus median ANPP as calculated from modeled results in each range unit (b).

The relationship between forage availability and ANPP varies spatially (Fig. 3-6). Generally, lower elevation areas in the Uinta Basin have lower forage to ANPP ratios, whereas higher elevations in the Uinta Mountains and Tavaputs Plateau have higher forage to ANPP ratios. This means available forage constitutes a greater proportion of total ANPP in these higher elevation areas. Forage to ANPP ratios range from 0.23 to 0.63 among all range units.

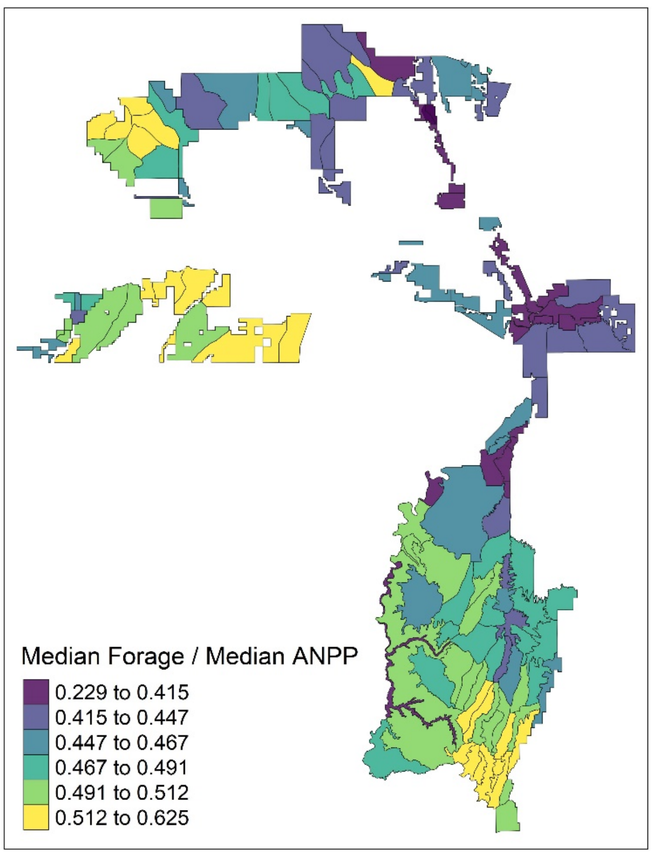

Figure 3-6. Forage availability to ANPP ratio of range units, from median modeled results in each range unit.

Trends

We tested for potential trends in forage availability with the Mann-Kendall test, a common method to assess non-parametric trends (Kendall 1948; Mann 1945). We found

no range units with statistically significant ($p < 0.05$) trends in forage availability from 1984-2018, though some approached significant declines. In 21 range units, primarily in the southern Tavaputs Plateau, we found declines approaching significance (p values from 0.08-0.25). Fig. 3-7 shows the time series of annual forage availability in Flat Rock, the range unit where forage availability decline was most significant ($p = 0.08$).

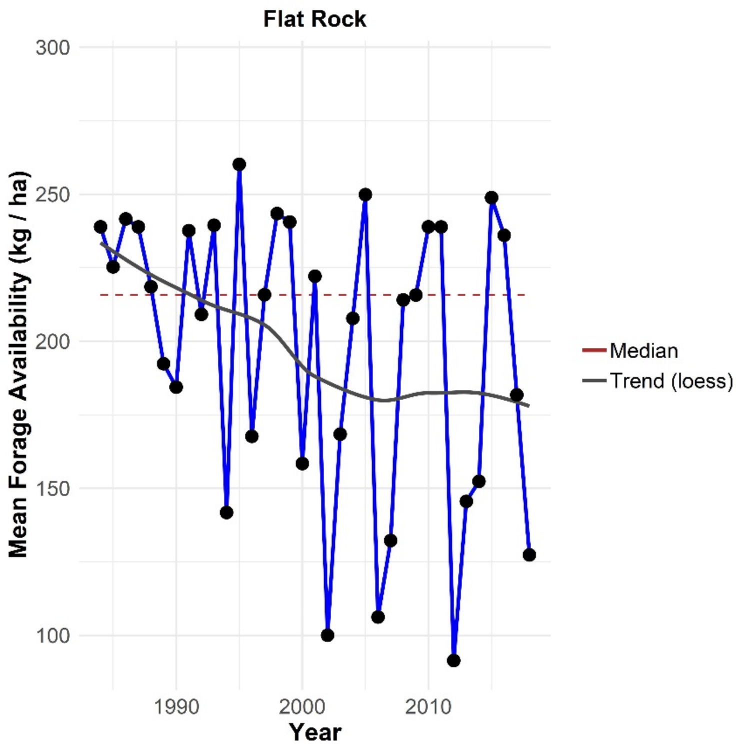

Figure 3-7. Time series of mean annual forage availability in the Flat Rock range unit, with forage trend line (from loess fit). The Mann-Kendall test determines a nonsignificant forage trend ($p = 0.08$) in this unit.

We also tested for trends in climatic variables included in modeling. We found significant increases in maximum and minimum temperature in approximately one-third of range units, but found no units with significant changes in precipitation and only three with significant increases in vapor pressure deficit.

Drivers of Forage Availability

Individual covariates were only weakly correlated with forage at transects, meaning each covariate only partially explained the variance in forage availability. The highest correlations were found for annual maximum NDVI ($r^2 = 0.138$), NRCS estimated rangeland production of soil map units ($r^2 = 0.116$), and May-June vapor pressure deficit ($r^2 = 0.104$). Lesser forage availability was associated with typical drought conditions—higher vapor pressure deficit, lower precipitation, and higher temperatures (Table S-2). Therefore, warmer, drier years are associated with lesser forage availability than cooler, moister years.

Random Forest Model Fit and Bias Correction

Though individual covariates were weakly correlated with forage, the variance explained by the random forest model was strong. After bias correction, $r^2 = 0.72$, RMSE = 99.11 and MAE = 64.54 among validation points not included in model training. Fit for the entire dataset including validation and training points is higher ($r^2 = 0.86$, RMSE = 73.37, MAE = 44.07 after bias correction) (Fig. 3-8).

Model predictions showed a slight bias before bias correction, with prediction errors slightly skewed negative at low modeled values and positive at high modeled values. Correction reduced this systematic bias and improved model performance, reducing RMSE by 27% and MAE by 33% among validation points.

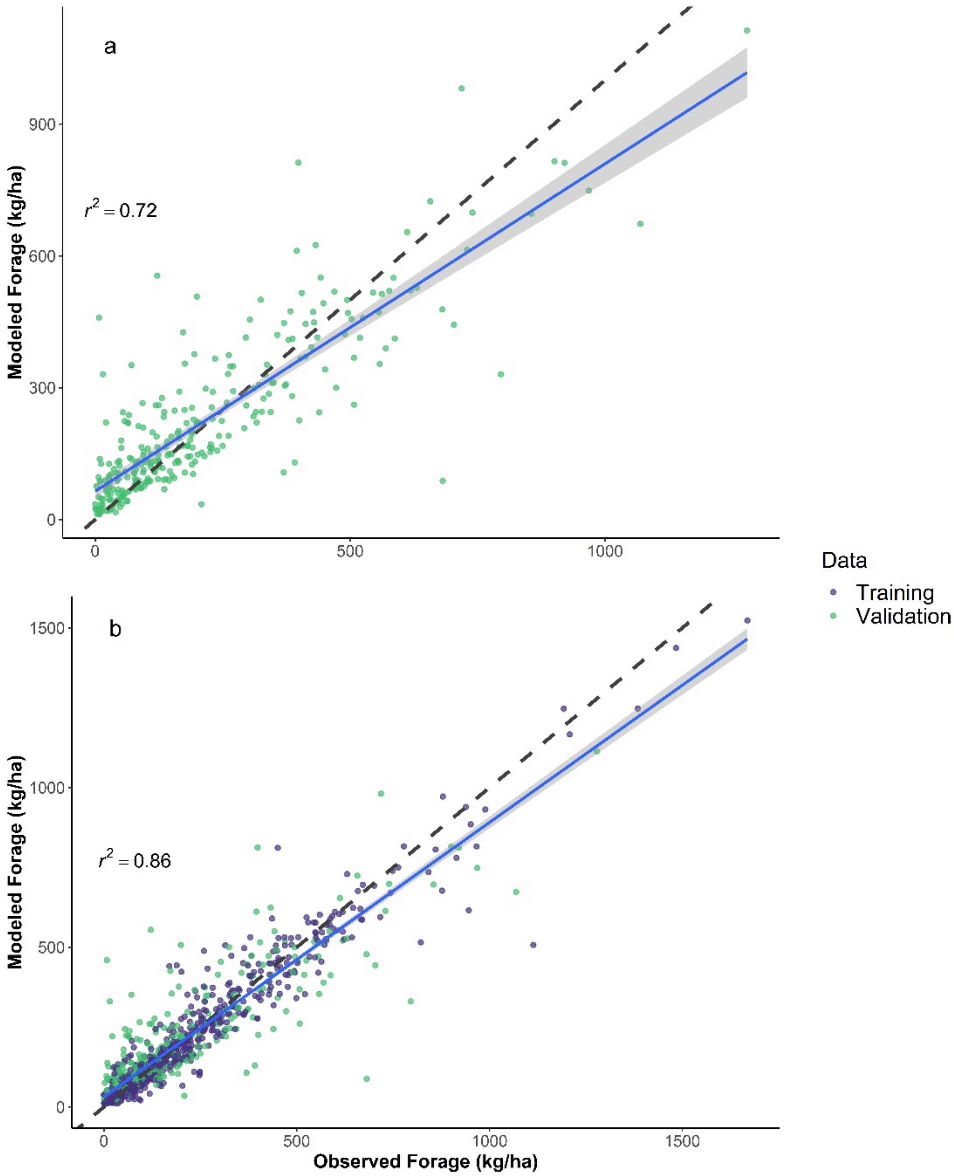

Figure 3-8. Post-correction modeled forage versus observed forage among validation points (a); and validation and training points (b). 1:1 relationship lines shown in black.

The random forest model calculates a variable importance plot to assess the relative explanatory power of variables included in modeling (Fig. 3-9). In this plot, higher %IncMSE indicates a greater increase in mean squared errors among random forest trees which do not include a given variable. This metric suggests tree cover, maximum NDVI, elevation, and precipitation are the most important variables

influencing forage, as model trees which did not include these variables had the greatest increase in mean squared error.

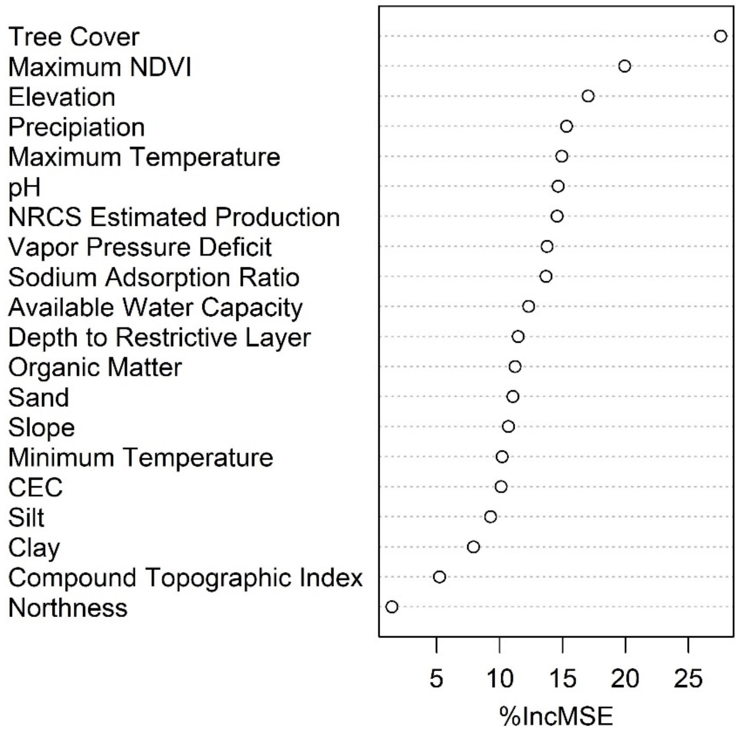

Figure 3-9. Random forest model variable importance plot. %IncMSE refers to the percent increase in mean squared error among trees which did not include a given variable.

Discussion

Modeled Forage and Forage Variability

We found considerable interannual variability in forage availability. In particular, we found large deviations between median forage availability and extremes in years with minimum or maximum forage availability (Figs. 3-2, 3-4). On average across range units, minimum forage is 32% below median forage, and can be as low as 58% below median

in some units. Conversely, maximum forage is on average 33% above median forage, and can be as high as 100% above.

These results are similar to those from a recent study which found that across publicly owned western U.S. rangelands, ANPP from 1993-2017 varied from 23% below to 28% above mean ANPP (Robinson et al. 2019). Variability throughout our predominantly shrubland study area is considerably less than what others have found in grassland environments though (Swemmer et al. 2007; Wehlage et al. 2016). Whereas we found the mean CV of forage in range units was 16%, CV of ANPP in grasslands may typically be closer to 30% (Knapp and Smith 2001), and even 50% in some shortgrass steppe regions (Reeves et al. in press).

Our results showed that higher elevation areas in the Uinta Mountains and Tavaputs Plateau tend to experience large forage declines below median conditions in some years, but do not experience dramatic increases above median (Fig. 3-2b, 3-4). Conversely, lower elevation units in the Uinta Basin tend to experience large spikes above in some years, but lesser declines below median conditions (Fig. 3-2c, 3-4). Since lesser forage availability was associated with typical drought conditions (Table S-2), forage declines likely occur in years with warmer, drier conditions (drought conditions), while forage increases occur in years with cooler, moister conditions.

Notably, many dominant plants in the Uinta Basin perform C4 photosynthesis, and these species are nearly absent in the Uinta Mountains and Tavaputs Plateau. These C4 species include *Aristida purpurea*, *Atriplex* spp., *Bouteloua gracilis*, *Halogeton glomeratus, Hilaria jamesii*, *Kochia* spp., *Salsola kali*, *Sporobolus cryptandrus*, and *Suaeda moqunii* (Alen and Allen 1990; Elmore and Paul 1983; Fisher et al. 1997; Glenn

et al. 1992; Hoover et al. 2015; Kadereit and Freitag 2011; Strong, et al. 2013; Warner and Edwards 1989).

C4 species typically exhibit greater water use efficiency than species performing C3 photosynthesis, making them more productive in warm and dry conditions (Knapp and Medina 1999). Therefore, they are likely able to tolerate drought better than C3 species (Ward et al. 1999), and may also grow more rapidly under more favorable conditions (Nippert et al. 2007).

This dynamic closely matches the variability dynamics we observed in the Uinta Basin, where we found lesser declines in drought years and greater increases in cooler, moister years than the Uinta Mountains and Tavaputs Plateau. Therefore, the dominance of C4 species in the Uinta Basin may be an ecological explanation for this relationship. Relative dominance of perennial versus annual vegetation (Schmidt and Karnieli 2000), or differing plant communities generally (Weiss et al. 2004), are other possible explanations for the differing forage availability responses we found.

Relationship Between Forage and ANPP

Across the Reservation, there was considerable variation in the relationship between forage availability and ANPP at transects (Fig. 3-5a). Since ANPP does not fully explain forage availability in the study area, directly modeling forage is clearly preferable to considering ANPP as a proxy, as is sometimes done (Mitchell 2010; Paruelo et al. 2000). We were able to directly model forage availability because our field data identified vegetation to the species level, and the palatability of species to cattle were previously determined for the area (Table S-1).

Forage and ANPP differences were less pronounced when modeled ANPP and forage availability results were aggregated across range units (Fig. 3-5b). However, the ratio between the two varied somewhat, with higher elevation units in the Uinta Mountains and Tavaputs Plateau having a higher forage to ANPP ratio (Fig. 3-6). This indicates that palatable species comprise a greater proportion of total ANPP in these units, meaning forage quality is generally higher. Vegetation communities differ significantly throughout the area, but higher elevations likely have higher production of grasses and palatable shrubs than lower elevation areas.

Trends

We found no statistically significant ($p < 0.05$) trends in forage availability from 1984-2018, though we found trends approaching significance in some range units ($p = 0.08$). Others have not found clear NPP trends across western U.S. rangelands (Robinson et al. 2019), and shrublands, particularly those in the U.S. southwest, may have experienced particularly little NPP change in recent history (Hicke et al. 2002).

The absence of significant forage trends in the study area are likely explained by the lack of major changes in climate or land management relevant to forage production in the study period. Maximum and minimum temperature increased significantly over the study period in approximately one-third of range units, but we found no units with significant trends in precipitation and only three with significant increases in vapor pressure deficit. Random forest variable importance metrics determined precipitation was the most important climatic covariate, followed by maximum temperature and vapor pressure deficit (Fig. 3-9), and variable correlations showed temperatures were less associated with forage than vapor pressure deficit or precipitation (Table S-2).

Grazing and wildlife management can also influence forage availability, but livestock grazing has been limited throughout the study period (A. Pingree, personal communication, June 21, 2019). Bison populations have recently grown in the southern Tavaputs Plateau (Bates and Hersey 2016), where we have also observed many wild horses and associated grazing. Grazing by these ungulates could cause forage declines, and many range units in this area show forage declines beginning to approach significance ($p < 0.25$). However, it is difficult to precisely link ungulates to forage trends without more precise data on the location and size of populations. Regardless, forage trends can continue to be monitored in the future using the model, particularly as climate, grazing use, or wildlife management may change over time.

Random Forest Model Fit and Bias Correction

Fit achieved by the random forest model was generally high, achieving $r^2 = 0.72$ for validation points after bias correction, with RMSE = 99.11 and MAE = 64.54. Bias correction improved model fit, so we recommend others follow random forest bias correction methods (Xu 2013; Zhang and Lu 2012) when appropriate.

Individual covariates were only weakly associated with forage measured at transects, with the strongest association found for annual maximum NDVI ($r^2 = 0.138$). The random forest model including edaphic, topographic, and climatic covariates had vastly higher fit, achieving $r^2 = 0.72$ for validation points and $r^2 = 0.86$ for training and validation points (Fig. 3-8).

Predicting forage from annual maximum NDVI is clearly not appropriate across our study area. Others have found stronger correlations between NPP and NDVI (Paruelo et al. 2000; Schloss et al. 1999), but NDVI is likely a weaker predictor of forage,

especially across multiple habitat and soil types (Garroutte et al. 2016). However, our results show that NDVI, in conjunction with edaphic, topographic, and climatic covariates in a model such as random forest, can predict forage with acceptable accuracy.

Implications

We found large interannual variability in forage, indicating median forage values are limited in their utility to address forage availability, and therefore stocking rates. Planning for median forage and not considering declines in drought years could promote overgrazing in some units (Menke and Bradford 1992), as potentially less than half of median forage is available for livestock in these years. Planning for forage declines during drought may also promote more conservative grazing practices, which reduce economic risk to ranchers (Holechek 1996; Quaas et al. 2007). On the other hand, forage will not be fully utilized in years with forage increases unless stocking rates are increased, so recognizing potential increases above median conditions is also useful. Forage varies differently in range units in the lower elevation Uinta Basin and those in the higher elevation Uinta Mountains and Tavaputs Plateau, possibly due to the high relative dominance of C4 vegetation at lower elevations. This spatial variation suggests that management should reflect forage availability dynamics unit-by-unit, allowing for stocking rates to be appropriately reduced in drought years (or potentially increased if spring or early summer conditions are highly favorable) based on local, site-specific conditions.

The relationship between forage and ANPP varied significantly throughout the Reservation, so explicitly modeling forage is clearly preferable to treating ANPP as a proxy. However, few others have directly modeled forage availability rather than ANPP

(see Smolko et al. 2018; Wam and Hjeljord 2010). Doing so would likely improve forage predictions and stocking rate determinations by addressing differences in forage quality throughout a study area. The modeling method we employed here is simple, and could easily be implemented by others with similar datasets of plant production collected in the field. Since our method incorporates only freely-available data in conjunction with field observations, it would be easy to replicate at low cost wherever training data is available, and could greatly reduce the expenditure of time and money required for monitoring because change can be monitored remotely with free data. That makes this method especially useful for groups unable to frequently resample vegetation in the field. Here, we applied the model on Reservation lands, which are underfunded, understudied, and cover large areas in the U.S. West. Large Bureau of Land Management or Forest Service units, particularly in remote areas difficult to sample, could similarly benefit from a model like ours to improve inventory and monitoring. High quality SSURGO data like we employed in this study may not be available in some remote areas. However, soil characteristics were not strongly important covariates in our model, and some soil characteristics could be determined remotely where SSURGO data are not available.

Conclusion

Effective, economical inventory and monitoring is a basic challenge in rangeland environments. Due to high spatiotemporal variability and vast spatial scales, it is difficult to adequately sample and summarize indicators essential for informed management, such as forage availability, across rangelands. Here, we used a random forest model to predict annual forage availability across the Uintah and Ouray Reservation and surroundings, trained on field-collected plant production data and freely-available climatic and

environmental data. Producing results from 1984-2018, this model greatly enhances standard rangeland vegetation inventory in the region by explicitly addressing variability in forage availability. Rather than assessing a presumed typical forage availability for locations, the model allows us to identify minimum, maximum, and median forage availability over time. Understanding how forage varies through time may help improve rangeland management in the region by informing how to adjust stocking rates in atypical years, and how to graze more conservatively and avoid exposing ranchers to risk of overgrazing or insufficient forage availability in drought years. We found forage varies differently among range units in the lower elevation Uinta Basin and those in the higher elevation Uinta Mountains and Tavaputs Plateau, indicating these areas require different management. Our model can be used into the future to continue monitoring potential trends in forage availability in the study region.

References

Alen, M.F., Allen, E.B., 1990. Carbon Source of Va Mycorrhizal Fungi Associated with Chenopodiaceae from a Semiarid Shrub-Steppe. Ecology 71, 2019–2021. https://doi.org/10.2307/1937610

Allbed, A., Kumar, L., 2013. Soil Salinity Mapping and Monitoring in Arid and Semi-Arid Regions Using Remote Sensing Technology: A Review. Advances in Remote Sensing 02, 373–385. https://doi.org/10.4236/ars.2013.24040

Bates, B., Hersey, K., 2016. Lessons Learned from Bison Restoration Efforts in Utah on Western Rangelands. Rangelands 38, 256–265.

Behnamian, A., Millard, K., Banks, S.N., White, L., Richardson, M., Pasher, J., 2017. A Systematic Approach for Variable Selection with Random Forests: Achieving Stable

Variable Importance Values. IEEE Geoscience and Remote Sensing Letters 14, 1988–1992. https://doi.org/10.1109/LGRS.2017.2745049

Boettinger, J., 2009. Soils of Utah, in: Rangeland Resources of Utah. Utah State University Cooperative Extension Service in Cooperation with the State of Utah Governor's Public Lands Policy Coordination Office, pp. 46–48.

Booth, D.T., Tueller, P.T., 2003. Rangeland Monitoring Using Remote Sensing. Arid Land Research and Management 17, 455–467. https://doi.org/10.1080/713936105

Borowik, T., Pettorelli, N., Sönnichsen, L., Jędrzejewska, B., 2013. Normalized difference vegetation index (NDVI) as a predictor of forage availability for ungulates in forest and field habitats. Eur J Wildl Res 59, 675–682. https://doi.org/10.1007/s10344-013-0720-0

Boswell, A., Petersen, S., Roundy, B., Jensen, R., Summers, D., Hulet, A., 2017. Rangeland monitoring using remote sensing: comparison of cover estimates from field measurements and image analysis. AIMS Environmental Science 4, 1–16. https://doi.org/10.3934/environsci.2017.1.1

Breiman, L., 2001. Random Forests. Machine Learning 45, 5–32. https://doi.org/10.1023/A:1010933404324

Cutler, D.R., Edwards, T.C., Beard, K.H., Cutler, A., Hess, K.T., Gibson, J., Lawler, J.J., 2007. Random forests for classification in ecology. Ecology 88, 2783–2792. https://doi.org/10.1890/07-0539.1

Degenhardt, F., Seifert, S., Szymczak, S., 2019. Evaluation of variable selection methods for random forests and omics data sets. Briefings in Bioinformatics 20, 492–503. https://doi.org/10.1093/bib/bbx124

Del Grosso, S., Parton, W., Stohlgren, T., Zheng, D., Bachelet, D., Prince, S., Hibbard, K., Olson, R., 2008. Global Potential Net Primary Production Predicted from Vegetation Class, Precipitation, and Temperature. Ecology 89, 2117–2126. https://doi.org/10.1890/07-0850.1

Dwyer, J., Roy, D., Sauer, B., Jenkerson, C., Zhang, H., Lymburner, L., 2018. Analysis Ready Data: Enabling Analysis of the Landsat Archive. https://doi.org/10.20944/preprints201808.0029.v1

Elmore, C.D., Paul, R.N., 1983. Composite List of C_4 Weeds. Weed Science 31, 686–692.

Fisher, D.D., Schenk, H.J., Thorsch, J.A., Ferren, W.R., 1997. Leaf anatomy and subgeneric affiliations of C_3 and C_4 species of *Suaeda* (Chenopodiaceae) in North America. American Journal of Botany 84, 1198–1210. https://doi.org/10.2307/2446043

Ford, P.L., Reeves, M.C., Frid, L., 2019. A Tool for Projecting Rangeland Vegetation Response to Management and Climate. Rangelands 41, 49–60. https://doi.org/10.1016/j.rala.2018.10.010

Fox, E.W., Hill, R.A., Leibowitz, S.G., Olsen, A.R., Thornbrugh, D.J., Weber, M.H., 2017. Assessing the accuracy and stability of variable selection methods for random forest modeling in ecology. Environmental Monitoring and Assessment 189. https://doi.org/10.1007/s10661-017-6025-0

Fuls, E.R., 1992. Ecosystem modification created by patch-overgrazing in semi-arid grassland. Journal of Arid Environments 23, 59–69. https://doi.org/10.1016/S0140-1963(18)30541-X

Galt, D., Molinar, F., Navarro, J., Joseph, J., Holechek, J., 2000. Grazing Capacity and Stocking Rate. Rangelands 22, 7–11.

Garroutte, E.L., Hansen, A.J., Lawrence, R.L., 2016. Using NDVI and EVI to Map Spatiotemporal Variation in the Biomass and Quality of Forage for Migratory Elk in the Greater Yellowstone Ecosystem. Remote Sensing 8, 404. https://doi.org/10.3390/rs8050404

Gessler, P.E., Moore, I.D., McKENZIE, N.J., Ryan, P.J., 1995. Soil-landscape modelling and spatial prediction of soil attributes. International journal of geographical information systems 9, 421–432. https://doi.org/10.1080/02693799508902047

Glenn, E.P., Watson, M.C., O'Leary, J.W., Axelson, R.D., 1992. Comparison of salt tolerance and osmotic adjustment of low-sodium and high-sodium subspecies of the C4 halophyte, Atriplex canescens. Plant, Cell & Environment 15, 711–718. https://doi.org/10.1111/j.1365-3040.1992.tb01013.x

Gorelick, N., Hancher, M., Dixon, M., Ilyushchenko, S., Thau, D., Moore, R., 2017. Google Earth Engine: Planetary-scale geospatial analysis for everyone. Remote Sensing of Environment. https://doi.org/10.1016/j.rse.2017.06.031

Havstad, K.M., Peters, D.P.C., Skaggs, R., Brown, J., Bestelmeyer, B., Fredrickson, E., Herrick, J., Wright, J., 2007. Ecological services to and from rangelands of the United States. Ecological Economics 64, 261–268. https://doi.org/10.1016/j.ecolecon.2007.08.005

Hicke, J.A., Asner, G.P., Randerson, J.T., Tucker, C., Los, S., Birdsey, R., Jenkins, J.C., Field, C., 2002. Trends in North American net primary productivity derived from

satellite observations, 1982–1998. Global Biogeochemical Cycles 16, 2-1-2–14. https://doi.org/10.1029/2001GB001550

Hintze, L., Willis, G., Laes, D., Sprinkel, D., Brown, K., 2000. Digital Geologic Map of Utah. Utah Geological Survey.

Holechek, J.L., 1996. Drought in New Mexico: Prospects and Management. Rangelands 18, 3.

Holechek, J.L., 1988. An Approach for Setting the Stocking Rate. Rangelands 10, 10–14.

Holechek, J.L., Pieper, R.D., 1992. Estimation of stocking rate on New Mexico rangelands. Journal of Soil and Water Conservation 47, 116–119.

Hoover, D.L., Duniway, M.C., Belnap, J., 2015. Pulse-drought atop press-drought: unexpected plant responses and implications for dryland ecosystems. Oecologia 179, 1211–1221. https://doi.org/10.1007/s00442-015-3414-3

Hunt, Jr., E.R., Everitt, J.H., Ritchie, J.C., Moran, M.S., Booth, D.T., Anderson, G.L., Clark, P.E., Seyfried, M.S., 2003. Applications and Research Using Remote Sensing for Rangeland Management. Photogrammetric Engineering & Remote Sensing 69, 675–693. https://doi.org/10.14358/PERS.69.6.675

Kadereit, G., Freitag, H., 2011. Molecular phylogeny of Camphorosmeae (Camphorosmoideae, Chenopodiaceae): Implications for biogeography, evolution of C_4 -photosynthesis and taxonomy. TAXON 60, 51–78. https://doi.org/10.1002/tax.601006

Karl, J., Herrick, J.E., 2010. Monitoring and Assessment Based on Ecological Sites. Rangelands 32, 60–64. https://doi.org/10.2111/RANGELANDS-D-10-00082.1

Kendall, M.G., 1948. Rank correlation methods., Rank correlation methods. Griffin, Oxford, England.

Knapp, A.K., Medina, E., 1999. Success of C4 photosynthesis in the field: lessons from communities dominated by C4 plants, in: Sage, R.F., Monson, R.K. (Eds.), C4 Plant Biology. Academic Press, New York.

Knapp, A.K., Smith, M.D., 2001. Variation Among Biomes in Temporal Dynamics of Aboveground Primary Production. Science 291, 481–484. https://doi.org/10.1126/science.291.5503.481

LANDFIRE, 2008. LANDFIRE Program: Data Products - Vegetation - Existing Vegetation Type [WWW Document]. URL https://www.landfire.gov/evt.php (accessed 8.1.19).

Li, P., Jiang, L., Feng, Z., 2014. Cross-Comparison of Vegetation Indices Derived from Landsat-7 Enhanced Thematic Mapper Plus (ETM+) and Landsat-8 Operational Land Imager (OLI) Sensors. Remote Sensing 6, 310–329. https://doi.org/10.3390/rs6010310

Liaw, A., Wiener, M., 2002. Classification and Regression by randomForest. R News 2, 18–22.

Mann, H.B., 1945. Nonparametric Tests Against Trend. Econometrica 13, 245–259. https://doi.org/10.2307/1907187

Menke, J., Bradford, G.E., 1992. Rangelands. Agriculture, Ecosystems & Environment 42, 141–163. https://doi.org/10.1016/0167-8809(92)90024-6

Miller, R.F., Krueger, W.C., 1976. Cattle Use on Summer Foothill Rangelands in Northeastern Oregon. Journal of Range Management 29, 367. https://doi.org/10.2307/3897141

Mitchell, J.E., 2010. Criteria and Indicators of Sustainable Rangeland Management. University of Wyoming Extension 242.

Mueggler, W., Stewart, W., 1981. Forage Production on Important Rangeland Habitat Types in Western Montana. Journal of Range Management 34, 347. https://doi.org/10.2307/3897900

Natural Resources Conservation Service, 2019. Soil Data Viewer | NRCS Soils [WWW Document]. URL https://www.nrcs.usda.gov/wps/portal/nrcs/detailfull/soils/survey/geo/?cid=nrcs142p2_053620 (accessed 9.11.19).

Nippert, J.B., Fay, P.A., Knapp, A.K., 2007. Photosynthetic traits in C3 and C4 grassland species in mesocosm and field environments. Environmental and Experimental Botany 60, 412–420. https://doi.org/10.1016/j.envexpbot.2006.12.012

Paruelo, J.M., Oesterheld, M., Di Bella, C.M., Arzadum, M., Lafontaine, J., Cahuepé, M., Rebella, C.M., 2000. Estimation of primary production of subhumid rangelands from remote sensing data. Applied Vegetation Science 3, 189–195. https://doi.org/10.2307/1478997

Pellant, M., Shaver, P., Pyke, D., Herrick, J.E., 2005. Interpreting Indicators of Rangeland Health: Version 4. Technical Reference 1734-6. USDI, BLM, NSTC, Division of Science Integration, Branch of Publishing Services, Denver, Colorado.

Quaas, M.F., Baumgärtner, S., Becker, C., Frank, K., Müller, B., 2007. Uncertainty and sustainability in the management of rangelands. Ecological Economics 62, 251–266. https://doi.org/10.1016/j.ecolecon.2006.03.028

R Core Team, 2018. R: A Language and Environment for Statistical Computing. R Foundation for Statistical Computing, Vienna, Austria.

Reeves, M.C., Hanberry, B., Wilmer, H., Kaplan, N., Lauenroth, W., in press. An Assessment of Production Trends on the Great Plains from 1984 to 2017. Rangeland Ecology and Management.

Reid, R.S., Galvin, K.A., Kruska, R.S., 2008. Global Significance of Extensive Grazing Lands and Pastoral Societies: An Introduction, in: Galvin, K.A., Reid, R.S., Jr, R.H.B., Hobbs, N.T. (Eds.), Fragmentation in Semi-Arid and Arid Landscapes: Consequences for Human and Natural Systems. Springer Netherlands, Dordrecht, pp. 1–24. https://doi.org/10.1007/978-1-4020-4906-4_1

Robinson, N.P., Allred, B.W., Naugle, D.E., Jones, M.O., 2019. Patterns of rangeland productivity and land ownership: Implications for conservation and management. Ecological Applications 29, e01862. https://doi.org/10.1002/eap.1862

Roy, D.P., Kovalskyy, V., Zhang, H.K., Vermote, E.F., Yan, L., Kumar, S.S., Egorov, A., 2016. Characterization of Landsat-7 to Landsat-8 reflective wavelength and normalized difference vegetation index continuity. Remote Sensing of Environment, Landsat 8 Science Results 185, 57–70. https://doi.org/10.1016/j.rse.2015.12.024

Running, S.W., Nemani, R.R., Heinsch, F.A., Zhao, M., Reeves, M., Hashimoto, H., 2004. A Continuous Satellite-Derived Measure of Global Terrestrial Primary

Production. BioScience 54, 547. https://doi.org/10.1641/0006-3568(2004)054[0547:ACSMOG]2.0.CO;2

Schloss, A.L., Kicklighter, D.W., Kaduk, J., Wittenberg, U., The Participants Of The Potsdam Intercomparison, 1999. Comparing global models of terrestrial net primary productivity (NPP): comparison of NPP to climate and the Normalized Difference Vegetation Index (NDVI). Global Change Biology 5, 25–34. https://doi.org/10.1046/j.1365-2486.1999.00004.x

Schmidt, H., Karnieli, A., 2000. Remote sensing of the seasonal variability of vegetation in a semi-arid environment. Journal of Arid Environments 45, 43–59. https://doi.org/10.1006/jare.1999.0607

Smolko, P., Veselovská, A., Kropil, R., 2018. Seasonal dynamics of forage for red deer in temperate forests: importance of the habitat properties, stand development stage and overstorey dynamics. wbio 2018. https://doi.org/10.2981/wlb.00366

Stoddart, L.A., 1960. Determining Correct Stocking Rate on Range Land. Journal of Range Management 13, 251. https://doi.org/10.2307/3895053

Strong, D.J., Ganguli, A.C., Vermeire, L.T., 2013. Fire Effects on Basal Area, Tiller Production, and Mortality of the C4 Bunchgrass, Purple Threeawn. Fire Ecology 9, 89–99. https://doi.org/10.4996/fireecology.0903089

Swemmer, A.M., Knapp, A.K., Snyman, H.A., 2007. Intra-seasonal precipitation patterns and above-ground productivity in three perennial grasslands. Journal of Ecology 95, 780–788. https://doi.org/10.1111/j.1365-2745.2007.01237.x

Teillet, P.M., Barker, J.L., Markham, B.L., Irish, R.R., Fedosejevs, G., Storey, J.C., 2001. Radiometric cross-calibration of the Landsat-7 ETM+ and Landsat-5 TM sensors

based on tandem data sets. Remote Sensing of Environment, Landsat 7 78, 39–54. https://doi.org/10.1016/S0034-4257(01)00248-6

Thornton, M.M., Thornton, P.E., Wei, Y., Mayer, B.W., Cook, R.B., Vose, R.S., 2018. Daymet: Monthly Climate Summaries on a 1-km Grid for North America, Version 3. ORNL Distributed Active Archive Center. https://doi.org/10.3334/ornldaac/1345

U.S. Geological Survey, 2017. 1 Arc-second Digital Elevation Models (DEMs) - USGS National Map 3DEP Downloadable Data Collection: U.S. Geological Survey [WWW Document].

Wam, H.K., Hjeljord, O., 2010. Moose summer and winter diets along a large scale gradient of forage availability in southern Norway. European Journal of Wildlife Research 56, 745–755. https://doi.org/10.1007/s10344-010-0370-4

Ward, J.K., Tissue, D.T., Thomas, R.B., Strain, B.R., 1999. Comparative responses of model C3 and C4 plants to drought in low and elevated CO2. Global Change Biology 5, 857–867. https://doi.org/10.1046/j.1365-2486.1999.00270.x

Warner, D.A., Edwards, G.E., 1989. Effects of Polyploidy on Photosynthetic Rates, Photosynthetic Enzymes, Contents of DNA, Chlorophyll, and Sizes and Numbers of Photosynthetic Cells in the C_4 Dicot *Atriplex confertifolia*. Plant Physiology 91, 1143–1151. https://doi.org/10.1104/pp.91.3.1143

Wehlage, D.C., Gamon, J.A., Thayer, D., Hildebrand, D.V., 2016. Interannual Variability in Dry Mixed-Grass Prairie Yield: A Comparison of MODIS, SPOT, and Field Measurements. Remote Sensing 8, 872. https://doi.org/10.3390/rs8100872

Weiss, J.L., Gutzler, D.S., Coonrod, J.E.A., Dahm, C.N., 2004. Long-term vegetation monitoring with NDVI in a diverse semi-arid setting, central New Mexico, USA.

Journal of Arid Environments 58, 249–272. https://doi.org/10.1016/j.jaridenv.2003.07.001

Xu, R., 2013. Improvements to random forest methodology (Dissertation). Iowa State University.

Zhang, G., Lu, Y., 2012. Bias-corrected random forests in regression. Journal of Applied Statistics 39, 151–160. https://doi.org/10.1080/02664763.2011.578621

Zhu, Z., Woodcock, C.E., Olofsson, P., 2012. Continuous monitoring of forest disturbance using all available Landsat imagery. Remote Sensing of Environment 122, 75–91. https://doi.org/10.1016/j.rse.2011.10.030

Zotarelli, L., Dukes, M.D., Romero, C.C., Migliaccio, K.W., 2010. Step by Step Calculation of the Penman-Monteith Evapotranspiration (FAO-56 Method). Institute of Food and Agricultural Sciences, University of Florida, Gainesville.

CHAPTER 4

CONCLUSION

This thesis includes a highly applied vegetation inventory of the Uintah and Ouray Reservation with immediate applications to inform land management in the area, and a more generalized application of that data, considering spatiotemporal variability to improve inventory and monitoring. Chapter 2 determines stocking rates by typical vegetation inventory methods, setting stocking rates at a level which is presumed to represent typical forage availability for Reservation range units. This chapter also details overall measures of ecosystem health, such as bare ground, canopy, and cheatgrass cover. In Chapter 3, the same vegetation inventory data are used to analyze forage availability on a pixel-by-pixel basis annually from 1984-2018, specifically considering both spatial and temporal variability in forage availability.

Spatial variability is addressed in this method because it allows forage to vary on a pixel-by-pixel basis within soil map units. In Chapter 2, available forage is presumed to be equal throughout an entire soil map unit. The methods in Chapter 3 allow forage availability to vary within soil map units based on local climate, NDVI, and topography throughout units.

The method address temporal variability by predicting available forage on an annual basis, by incorporating climatic data and NDVI which vary annually. This allows forage availability to vary, reflecting declines in years with unfavorable conditions (warmer and drier), and increases in years with favorable conditions (cooler and moister).

The results of Chapter 3 enhance those from Chapter 2, providing more context for how forage availability, and therefore appropriate stocking rates, vary annually within

range units. Most importantly, the results of Chapter 3 allow the degree of forage decline and increase in atypical years to be quantified for each range unit.

These results from Chapter 2 and 3 are similar, but differ somewhat. Fig. 4-1 shows maps of the "typical" available AUMs (animal unit months) as determined by the vegetation inventory in Chapter 2 (Fig. 4-1a), and the available AUMs as determined by the median of modeled results in Chapter 3 (Fig. 4-1b). Since the inventory aims to approximate typical forage availability, the most appropriate comparison to these results are the median forage availability results determined by the model.

Available AUMs appear to be similar in both methods, with many AUMs in the Uinta Mountains to the north and fewer in the Uinta Basin and parts of the Tavaputs Plateau. There are some discrepancies in the northeast and southwest, but the maps do not strongly reveal differences between the methods.

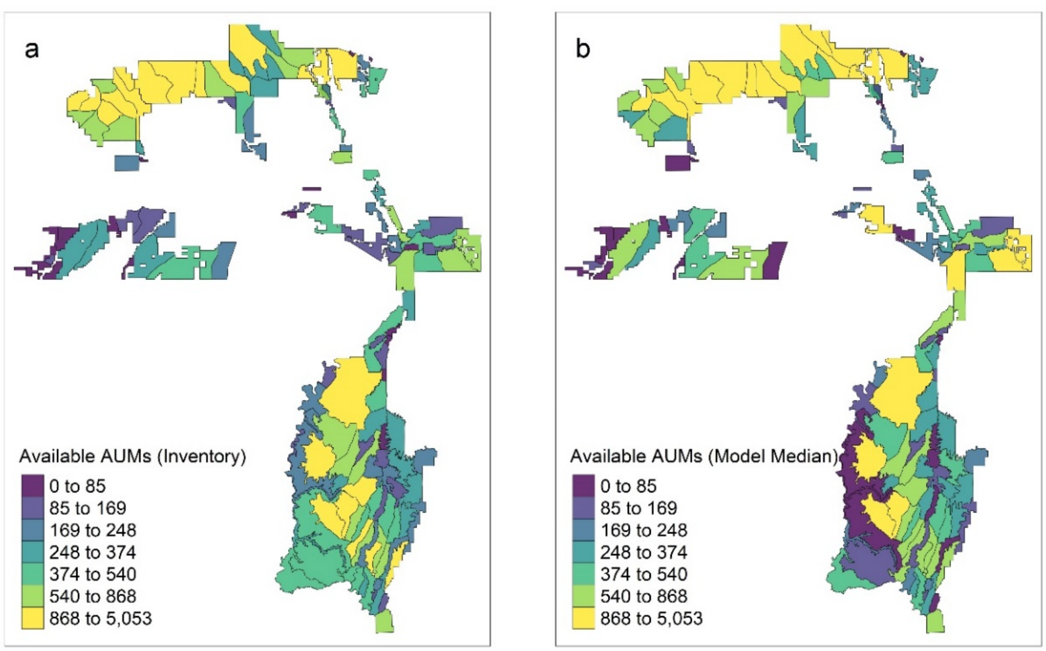

Figure 4-1. Available AUMs as determined by the inventory method (a), and available AUMs as determined by the median model results (b).

The differences between the methods are more easily observed in a scatterplot of the inventory results against the median model results, as shown in Fig. 4-2. Here, the correlation between them is not extremely strong ($r^2 = 0.71$). However, the line of best fit (in blue) is quite close to a 1:1 relationship (dashed line), indicating model results are not strongly biased to be greater or lesser than inventory results. There is simply a fairly wide scatter around the 1:1 relationship, especially among the units with very large numbers of AUMs.

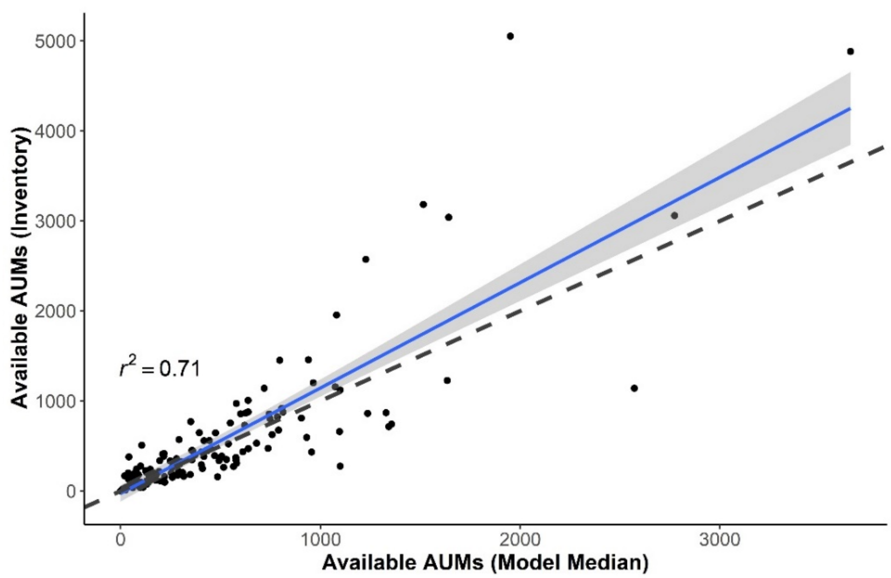

Figure 4-2. Scatterplot of available AUMs of range units as determined by inventory method, against available AUMs as determined by the median of model results. Dashed line indicates a 1:1 relationship, and blue line indicates the line of best fit.

The simplest way these results might differ is if "typical" forage availability was not adequately determined in the inventory method. If vegetation in a range unit was sampled in a very dry year, but we incorrectly believed that to be a typical year, then the inventory method would set stocking rates in that unit lower than they should be. The modeling method, however, would correctly identify the sampling year as atypically dry,

and median model results in that unit would therefore be higher than inventory results. This could be true of any points below the 1:1 line in Fig. 4-2. Alternatively, if vegetation were sampled in a wet year that was incorrectly believed to be typical, inventory results would be greater than model median results. This could be the case for points above the 1:1 line.

The model's ability to account for spatial variability in forage within soil map units likely contributes to differences between the inventory and model results as well. However, it is more difficult to determine exactly how this would affect the relationship between model and inventory results. The model may identify locations within a soil map unit with atypically high or atypically low forage availability, but it is unclear whether this would shift estimates to be greater or lesser overall within a range unit.

Overall, the model and inventory results are largely similar, but sufficiently different to indicate that the model addresses factors not addressed in the inventory method. Furthermore, these results address only the median of model results, which are comparable. The model also allows us to estimate minimum and maximum forage availability within range units, which is not addressed by the inventory method.

The results presented here can immediately improve land management in the Uintah and Ouray Reservation. Stocking rates had not been determined across the Reservation previously, so these data can now be used to determine appropriate cattle stocking rates and overall ecological health throughout the area. Either the stocking rates determined by the inventory method or the model method would improve management of the region, but the model results likely provide a more accurate view of typical forage availability than the inventory method, and can promote more informed management by

more fully addressing forage availability dynamics.

The model method we employed is fairly simple, and required only freely-available, remotely-sensed and soils data in addition to the vegetation inventory data. Therefore, a model similar to ours could be easily implemented in other regions, wherever sufficient vegetation training data and soils data are available. Because the model provides additional context for stocking rate determinations, and can continue to be used in the future to monitor trends in forage availability, we believe it could greatly enhance rangeland inventory and monitoring. Other Reservations or large Bureau of Land Management or Forest Service units could potentially benefit from a model like the one here. These large, remote areas, where frequently resampling vegetation may be difficult or prohibitively costly, would similarly benefit from methods to remotely monitor forage availability.

APPENDIX

CHAPTER 3 SUPPLEMENTAL INFORMATION

Table S-1. Species codes and palatability factors of vegetation (for cattle) in the study area. Palatability factor ranges from 0, meaning completely unpalatable and unavailable for cattle grazing, to 1, meaning completely palatable and fully available for cattle grazing. Species codes match USDA plant symbols.

Species Code	Palatability Factor	Species Code	Palatability Factor	Species Code	Palatability Factor
AAFF	0.2	CYPU2	0	MIAL5	0.2
AAGG	0.6	DAFR6	0.2	MUAS	0.4
ABFR2	0.2	DAGL	1	MUPU2	1
ACGL	0.2	DALEA	0.2	MURI	1
ACHY	1	DECA18	0.6	NABR	0
ACLE9	1	DELPH PF	0	OECA10	0.1
ACMI2	0.5	DENU2	0.2	OENOT PF	0
ACNE9	1	DEOC	0.2	OEPA	0.1
ACRE3	0.2	DEPI	0	OPFR	0
AGAU2	0.5	DESCU	0.2	OPPO	0
AGCR	1	DESO2	0	ORFA	0
AGGI2	1	DISP	0.5	ORLU	0.2
AGGL	0.4	ECCO5	0	OROBA AF	0
AGST2	0.5	ECHIN3	0	ORPA3	0.3
AGUR	0.4	ECTR	0	ORSE	0
ALBR	0.2	ELEL5	1	ORTO	0.1
ALDE	0	ELLA3	1	OSDE	0
ALLIU PF	0.2	ELTR7	1	PACA6	0.4
ALYSS AF	0	ELYMU AG	1	PAMU11	0
AMAL2	0.8	ELYMU PG	1	PAMY	0.2
AMBRO	0.2	ENNU	0	PASM	1
AMSIN	0.2	EPBR3	0	PECE	0
AMTE3	0.2	EPCA3	0	PEDIC	0
AMUT	0.8	EPHED SH	0.2	PEHU	0.2
ANDI2	0	EPTO	0.2	PENST PF	0.2
ANMI3	0	EPVI	0.2	PEPA6	0.2
ANPA4	0	EQAR	0	PEPU7	0.1
ANPR4	0	EQHY	0	PERA4	0.4
ANTEN PF	0	EQUIS	0	PESI	0
APIAC PF	0	ERAL4	0.2	PEWA	0.2
AQCA2	0	ERAR3	0.2	PHACE PF	0.2
ARABI2 PF	0.1	ERBA5	0.2	PHAR3	0.7

ARAC2	0.2	ERCA8	0.2	PHCO16	0.2
ARBI3	0.2	ERCE2	0.2	PHCRC	0
ARCAV2	0.4	ERCI6	0	PHGR16	0.2
ARCO5	0.2	ERCO14	0.2	PHHA	0.2
ARCO9	0.2	ERCO3	0.2	PHHO	0
ARCOC4	0.2	ERCO4	0.1	PHLO2	0.2
ARENA PF	0	ERCO6	0.1	PHLOX PF	0.2
ARFE3	0.2	EREP	0.2	PHMI4	0.4
ARFI2	0.2	ERGO	0.2	PHYSA PF	0
ARFR4	0.4	ERHE2	0.2	PHYSA2 PF	0.2
ARHO2	0.2	ERIGE2 PF	0.1	PIDE4	0.2
ARHO4	0.2	ERIN4	0.2	PLIN7	0
ARHOR	0.1	ERIOG PF	0.2	PLJA	1
ARLUI2	0.2	ERMI4	0.2	PLMA2	0
ARMI2	0	ERNA10	0	PLPA2	0
ARNIC PF	0.2	EROC	0.2	POA PG	1
ARNICA PF	0.3	EROV	0.2	POBU	1
ARNO4	0.6	ERPU2	0.1	POCO	1
ARNU	0	ERPU9	0	PODI2	0.6
ARPA6	0.2	ERRA3	0.2	POFE	1
ARPE	0.1	ERSH	0.2	POGR9	0.2
ARPU2	0.2	ERSP4	0.1	POPR	1
ARPU9	0.2	ERUM	0.2	POSE	1
ARTEM PF	0.2	EUBR	0	POTEN	0.2
ARTRB3	0.3	EUEN	0.3	POTR5	0.5
ARTRT	0.2	EUES	0	PPFF	0.2
ARTRV	0.4	EUPHO	0	PPGG	1
ARTRW8	0.2	FABAC PF	0.6	PRUNU SH	0.2
ASCH7	0.2	FEOV	1	PRVI	0.2
ASCO12	0.2	FESTU	0.2	PSJU3	1
ASFL	0	FETH	1	PSSP6	1
ASPU9	0	FRITI PF	0	PTAN2	0
ASRA2	0	FRSP	0.4	PUTR2	1
ASTE5	0.2	FRVI	0.2	QUGA	0.4
ASTER AF	0.1	GABO2	0.1	RAJO	0
ASTER PF	0.2	GALIU PF	0.1	RHAR4	0.2
ASTER SH	0.2	GERAN PF	0.3	RHTR	0.2
ASTRA PF	0	GERI	0.3	RIAU	0.2
ATCA2	0.6	GEVI2	0.3	RIBES SH	0
ATCO	0.6	GLLE3	0.1	RICE	0.2

ATCO4	0.6	GLSPM	0.2	RIIN2	0.2
ATCUC	0.6	GRSP	0.6	RIMO2	0
ATRIP	0.6	GRSQ	0	ROWO	0.2
BAAM4	1	GUSA2	0	RUHY	0.1
BAHO	0.4	HACKE PF	0	RUID	0.2
BAPR5	1	HAFL2	0	RUPA	0.1
BASA3	0.4	HAGL	0	SACO6	0.6
BASC5	0	HEAN3	0.2	SADR	0.1
BOGR2	1	HEBO	1	SAEX	0.1
BORAG AF	0	HECO26	1	SALIX SH	0.1
BORAG PF	0.1	HECY2	0	SALSO	0
BRAN	1	HEMU3	0	SALU2	0.4
BRASS2 AF	0	HENU	0.2	SANIC5	0.4
BRASS2 PF	0	HETER8	0.2	SARA2	0.4
BRCA5	1	HEVIV	0	SATR12	0
BRCI2	1	HOJU	1	SAVE4	0.4
BRIN2	1	HOUM	0	SAXIF PF	0
BRMA4	1	HYFI	0.2	SCLER10	0
BROB	0.2	HYLA7	0	SCLI	0
BROMU AG	0	IPAG	0.1	SEIN2	0
BROMU PG	1	IPPO2	0.1	SELA	0
BRTE	0	IPPU4	0	SENEC PF	0
CAAN7	0.2	IRIS PF	0.2	SESE2	0.2
CACR11	0.2	IRMI	0.1	SHCA	0.1
CAFL	0	IVAX	0.1	SIAL2	0
CAFL7	0.2	JUBAM	0.4	SILI5	0
CAGE2	0.2	JUCO6	0.1	SIOF	0
CALI4	0.2	JUNCU PG	0.4	SOLID	0
CALOC PF	0.2	KOAM	1	SOMI2	0.2
CANE2	0.2	KOMA	0.8	SONA	0
CANU3	0.2	KOPR80	1	SOVE6	0
CAPR5	0.2	KOSC	1	SPAI	0.6
CAREX	0.2	KRLA2	1	SPCO	0.6
CAREX PG	0.2	LACTU PF	0.1	SPCR	0.6
CARH4	0.2	LALA3	0.4	SPHAE PF	0.6
CARO5	0.2	LAOC3	0	SPPA2	0.6
CASTI2	0	LASE	0.1	STAC	0
CASTI2 PF	0.2	LECI4	1	STARA	0
CEANO SH	0.2	LEFR2	0.2	STELL PF	0
CELE3	0.4	LELA2	0	STEX	0

CEMO2	0.4	LEMO2	0.2	STMIM	0.2
CETE5	0	LEPE2	0.2	STPI6	0
CEVE	0.4	LEPID	0.2	SUCA2	0.2
CHAEN PF	0	LEPU	0.2	SUMO	0
CHAL7	0.3	LESA4	1	SYOR2	0.2
CHAME2	0	LESAS	1	TAOF	0.6
CHDE2	0	LIGL2	0	TARA	0
CHDO	0	LILE3	0	TARAX	0
CHENO AF	0	LILY AF	0.2	TEAX	0.2
CHER2	0.1	LILY PF	0	TECA2	0
CHFE3	0.1	LINAN2 PF	0	TEGL	0.2
CHGR6	0	LIPE2	0.6	TENU2	0
CHMA15	0	LIPU11	0	TESP2	0
CHRYS SH	0	LIRU4	0.1	THAR5	0
CHST	0	LITHO3	0.2	THCA11	0
CHTE2	0	LOCA4	0.6	THCL	0
CHVI8	0	LOCO6	0.4	THFE	0.1
CHVIL4	0	LOMAT PF	0.2	THLAS AF	0
CIAR4	0.1	LOTR2	0.2	THMO6	0
CINE	0.2	LUAR3	0	THSA2	0.2
CIRSI PF	0.1	LUPIN PF	0	TOIN	0
CIUN	0.1	LUPU	0	TORY	0
CIVU	0.1	LYJU	0	TOWNS PF	0.2
CLCO2	0	MAAF	0	TRCA13	0
CLLI2	0.2	MACA2	0.1	TRDU	0.2
CLLU2	0	MAGR2	0.1	TRIFO PF	1
COKI	0.2	MALE3	0.6	TRRE3	1
COLLO PF	0	MARA7	0.2	UKSH	0.2
COOR	0.2	MARE11	0	URDI	0
COPA3	0	MASO	0	VAED	0
CORET	0.2	MAST4	0.2	VETH	0.1
COUM	0.1	MATO2	0.2	VIAM	0.8
CRAC2	0.4	MEAL6	0	VUOC	0
CRBA6	0.2	MEAR4	0.4	YUCCA	0
CREPI PF	0.4	MEDI6	1	YUHA	0
CRFL6	0	MEDIC	0.6	YUHAS	0
CRYPT AF	0	MENTZ	0.2	ZIGAD	0
CRYPT PF	0	MEOF	0.6	ZUBRP	0.4
CYOF	0.2				

Table S-2. Pearson's correlations and significance of observed forage at transects to individual covariates included in modeling.

Covariate	***r***	r^2	***p* value**
Annual Maximum NDVI	0.372	0.138	$4.99*10^{-30}$
NRCS Estimated Rangeland Production	0.340	0.116	$5.14*10^{-25}$
May-June VPD	-0.323	0.104	$1.22*10^{-22}$
January-June Precipitation	0.288	0.083	$4.21*10^{-18}$
May-June Maximum Temperature	-0.262	0.069	$3.64*10^{-15}$
May-June Minimum Temperature	-0.260	0.068	$5.72*10^{-15}$
Depth to Restrictive Layer	0.243	0.059	$3.58*10^{-13}$
Available Water Capacity	0.227	0.052	$1.17*10^{-11}$
pH	-0.224	0.050	$2.39*10^{-11}$
Elevation	0.218	0.048	$8.41*10^{-11}$
Tree Cover	-0.150	0.023	$8.75*10^{-6}$
Silt	-0.137	0.019	$5.21*10^{-5}$
Sand	0.113	0.013	0.0009
Sodium Adsorption Ratio	-0.110	0.012	0.0011
Northness	-0.081	0.007	0.0170
Organic Matter	0.077	0.006	0.0222
Cation Exchange Capacity	0.063	0.004	0.0641
Clay	-0.043	0.002	0.2084
Compound Topographic Index	0.013	0.000	0.6907
Slope	0.013	0.000	0.7070

Supplemental Field Methods

To ensure data collected by USU were comparable to prior data collected by BIA, we emulated the original field methods employed by BIA as much as possible. We surveyed at least one transect per 1,000 acres of each soil map unit in the unsurveyed

range units. We used the most up-to-date Natural Resources Conservation Service (NRCS) Soil Survey available to determine the areal extent and location of soil map units. Transect locations were randomly generated before going into the field, stratified by soil map unit and located within 2 miles from existing roads. Once in the field, we navigated to each generated transect location and ensured it did not occur in an atypical patch of soil map units. If the transect occurred in an atypical area, we shifted the transect location in order to collect data in a representative area.

Once an appropriate location was selected, we dug a small pit to observe the soil and ensure that it matched the soil map unit we intended to sample. Ecological sites were determined based on soil type and vegetation, as many soil map units are composed of multiple soil types with different associated ecological sites.

At each transect we laid out a 30.5 meter (100-foot) transect tape in a random orientation and recorded site data including geographic coordinates, elevation, slope, aspect, landscape position, soil series, and ecological site. We then inventoried the plant species present by scanning the entire transect area over a ten-minute period and noting all species encountered. Four photos were taken at each transect: down the transect line and turned 90˚, 180˚, and 270˚ from the transect.

The primary data necessary to calculate total available forage and stocking rates were obtained by sampling the aboveground biomass of plant species. After laying out the transect tape, aboveground biomass of grasses and forbs was sampled in ten locations by laying out a 0.89 meter^2 hoop every 3.05 meters along the transect. If vegetation in the hoop was sparse, all aboveground biomass of vegetation within each hoop was clipped and weighed (referred to as “total harvest”). Alternatively, when vegetation was abundant

and dense, a representative unit of biomass of each species was weighed and used to estimate the number of units of that species in each hoop. The total weight of each species biomass was calculated by multiplying the weight of the representative biomass unit by the number of units estimated in the plot. When using the representative unit biomass approach, we then clipped all of the vegetation in two hoops to evaluate the accuracy of estimates and adjusted estimations as necessary (this process is referred to as "double sampling"). For example, if 100 grams of biomass of a species was estimated among two hoops, but clipping and weighing the biomass in those hoops yielded only 50 grams of that species, it was assumed that all estimates of that species along that transect were twice as high as they should be, and all estimates were divided by two to correct this bias.

Shrub productivity was sampled through a similar but separate method, by tracing a circle with an outstretched 3.6-meter rope at two locations along the transect, starting from the 3-meter and 27-meter locations of the transect. Then, the amount of every shrub species occurring within the circles was estimated by collecting a reference unit of biomass of each shrub species (such as one large branch) and estimating how many of these reference units were found within each shrub circle. The reference unit of shrub biomass was later weighed, stripped of foliage, and weighed again to determine the foliage weight of the unit, and therefore an estimate of the total foliage weight within the shrub circles.

We then determined the "growth curve completed" and "amount ungrazed" of all species present at each transect. These characteristics help determine how much plant productivity we were unable to measure when sampling the transect. The "growth curve

complete" addresses situations where a species is only beginning to flower at the time of surveying, and will continue to accumulate biomass later in the season that we cannot measure at the time of sampling. To estimate the total annual production of these species, we must increase our biomass measurements accordingly. For example, if we measured 100 grams of a species which is finishing flowering at the time of sampling, we would assume that only 75% of the species' total annual production had been achieved, and we would estimate that 133.33 grams (100 grams / 0.75) of that species will be produced through the whole growing season.

Similarly, the "amount ungrazed" allows us to account for potential productivity lost to grazing by wildlife or livestock prior to sampling. If we estimated that 10% of a species' productivity had been grazed by wildlife or livestock before sampling, we noted this and assumed that the species' actual productivity was 10% greater than we measured at the time of sampling.

A small sample of every species was collected to be dried later. This is necessary because stocking calculations are based on dried biomass, not green biomass. We dried biomass samples in an oven, calculated the proportion of mass lost by drying samples, and used this ratio to calculate the amount of dry biomass of species at each transect.