Working Paper:

Valuing forecast-informed decision-making in range livestock production: Regular use of seasonal forage outlooks can increase ranch income[1]

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[1] **This project has been supported by the National Drought Mitigation Center (NDMC) University of Nebraska-Lincoln, the USDA Northern Plains Climate Hub, and the Western Water Assessment (a NOAA RISA project).**

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People engaged in a wide variety of natural resource, business, infrastructure and other systems must make decisions under great uncertainty, including market swings, policy changes, and environmental variability. Weather and climate variability are key factors in many cases, introducing both production and consumption uncertainty, and risks of loss. And while it is widely recognized that weather, climate, water and ocean observations and forecasts are relied on by decision-makers in all sectors, and that this use results in significant economic value to the U.S. economy (https://www.performance.noaa.gov/economics/societal-impacts/ ; see also NOAA Social Science Committee, 2016), quantifying both use and value-added remains a challenge.

Recent improvements in forecast skill may be underutilized in exposed sectors. A few key studies, including survey and macro-econometric approaches, show potential large value and strong demand for information (Lazo et al., 2009; Lazo et al., 2020). Yet, Morrs et al. (2008) concluded that "despite years of discussion and dispersed effort, research on socioeconomic aspects of weather forecasts has not reached the critical mass required to meet the needs of the weather enterprise." (p. 336). White et al. (2017) argued that many sectors that could benefit from improvements in mid- to long-term forecasts have not been analyzed. They call for a more concerted effort to evaluate economic impacts and benefits, assess the asymmetry of costs and benefits of decision-making under weather and climate uncertainty, and clarify how different forms of information influence decision-making and yield economic benefits (paraphrased from p. 322).

Several trends in the weather, water, climate and ocean enterprise challenge us to better understand the use and economic value of atmospheric, hydrologic, and oceanic information. First is the marked improvement over recent years, not fully recognized by all potential users, in accuracy and skill of weather-scale forecasts, extending up to two weeks (Baurer et al. 2015; Alley et al. 2019). The forecast enterprise is also broadening under the banner of "earth system

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prediction," ESP (Ruit et al. 2020; National Academies, 2020), which reaches beyond traditional weather and climate variables—e.g., to net primary production in the work presented here. The ESP realm is of particular note because it offers large potential for translating the suite of observed and predicted variables into new factors relevant to essential activities like transportation and food production. For example, radiation, land cover, and key meteorological variables are now combined to determine the time and rate at which snow and ice will form on roadways (Rutz and Gibson, 2013), providing critical information to a range of users who in the past had to estimate likely road icing based on snowfall and temperature forecasts, plus their own knowledge of recent conditions. A second important trend is the growing effort to fill the gap between sub-seasonal and seasonal forecasts (S2S; e.g., White et. al. 2017; Merryfield et al. 2020). This will especially serve decision-makers involved in recursive planning/response cycles that evolve over weeks and months. Third is programmatic effort to channel public and private elements of the weather and water enterprise into creating a "weather-ready" nation (Uccellini & Ten Hoeve 2019) and to deriving maximum socio-economic benefit from information through efforts like impact-based decision-support (Lazo et al., 2020) and improved weather and climate services (Brooks 2013). Undergirding these efforts are integrated prediction testbed and support platforms (e.g., the Earth Prediction Innovation Center), producing increasingly rich and complex information.

Complexity also marks the decision environments of information users. Exemplar weather decision models developed in the 1970s and 1980s (reviewed below), some still part of the decision and risk curriculum today (Clemen and Reilly, 2014; pp. 225-226), developed ways to assess forecast value rooted in decision science (Katz, Murphy, & Winkler 1982), but they also tended toward single decision points, and yes/no choices. Users though might be making recursive choices along a time-line, and up-dating both information acquired (including up-dated forecasts) and their decision parameters as they go along; they may also be choosing along a sliding scale of responses. This is what Morrs et al. (2017) called the "interconnected dynamic system complexities" of forecast and warning application. Fortunately, new tools for decision analysis can inculcate such complexities, including through robust treatment of uncertainty, Bayesian up-dating, and options analysis. More attention to the user decision setting is now common in value valuation studies and information design (e.g., for the new winter weather index; Curtis et al., 2019), and this encourages the application of decision analysis to capture realistically-complex decision structures.

In this study we emphasized those decision structures, seeking to reveal and test the efficacy of decision flexibilities and constraints in realizing economic benefits from better information. Our focus is on ranchers in the American West, especially as they make decisions in the face of drought. We first review the field of forecast value studies, and develop and apply a decision-analytic model to a new earth system prediction aimed to informing ranchers about seasonal forage availability.

Evaluating a new earth system forecast for the western range livestock industry

Decision challenges in the western range cattle production system vis-à-vis weather and climate were made starkly evident in the extensive mid-continental drought during 2012-2013 that caused a large reduction in forage, high feed prices, and depressed market prices (Hegeman 2012), all leading to the largest cattle herd reduction in the data (going back to 1950, Fig. 1) and record financial losses among ranchers. This event made concrete the need for tracking and predicting conditions important to livestock grazing, including of course precipitation and temperature, but it also increased interest in a new product that combined weather, climate and grassland ecology to project rangeland production.

The extensive grasslands of the U.S. Great Plains are utilized for domestic livestock grazing, providing meat and other resources and livelihoods for ranchers (Drummond et al., 2012). Cattle ranching is the most widespread land use in the Great Plains; nearly 50% of U.S. beef cattle are raised in the region (Dagel, 2011). Key uncertainties faced by ranchers stem from weather and climate conditions that affect forage availability and thus cattle weight gain. Market conditions also affect ranchers' ultimate income, and prices vary for a variety of reasons, some of which are in response to weather and climate conditions. Consequently, the focus of this research involves weather and climate variability, as well as interactions between weather-induced uncertainties and market responses.

Ranchers rely on relatively natural, less managed range conditions for livestock production (Shrum et al, 2018). Forage availability is highly correlated with precipitation, which is a key input to net primary production on grasslands (Parton et al., 1987; Kanpp et al., 1993), and thus grazing conditions vary widely year-to-year and within seasons (Reeves et al., 2015, Chen at al., 2019). This is especially true in the face of severe conditions, such as the 2012-2013 drought, but even more routine variability requires management adjustments to lessen impacts on profits. In many respects ranchers are more flexible than other agriculturalists, especially crop farmers, since they are able to adjust herd size, grazing strategies, and business operations on short-term timeframes as the grazing season progresses (Derner and Augustine, 2016; Shrum et al. 2018). Still, routine and more extreme fluctuations bedevil the industry, and, in the face of uncertainty about forage availability ranchers tend toward conservative stocking in order to reduce the risk of over-grazing and range degradation in the dry years. They thus forego some potential income during normal to good seasons (Ritten et al. 2010). An important dimension of this and other weather- and climate-related decisions is the potential for realizing additional economic value by relaxing this risk-averse strategy based on skillful, additional information (Yang et al. 2020; https://cw3e.ucsd.edu/firo/).

The theoretical value of skillful forecasts and other information may be large, but value is also tied to the decision maker's ability to ingest, process, and act on information in a timely manner. Researchers analyzing decision-making based on weather and climate information find that even relatively simple decisions (e.g., should I have some additional feed on hand?) are complex on closer inspection, involving risk tradeoffs, timing challenges, and conditional choices. Additionally, sequential decision-making results in carry-over effects that can either lower or enhance possibilities to improve subsequent decisions and outcomes as new information arrives.

We develop a decision-analytic approach to valuing forecasts in the range livestock sector, with a focus on drought conditions. We apply this decision analysis to ranches in

Colorado, and then explore ways to scale this analysis up to obtain aggregate value of weather and climate information.

Economic Value of Forecasts in the Range Livestock Industry

We applied risk and decision analysis to calculate the economic value of forage forecasts, while also retaining a descriptive approach that captures ranchers' decision setting. We have previously synthesized the literature to lay out the decision structure of typical western ranches facing drought conditions (Shrum et al., 2018), and derived a parsimonious set of propositions to focus the analysis:

1. Cattle ranches generally seek to increase profits by minimizing costs rather than by maximizing production (the cow-calf system runs near steady-state over multi-year periods).
2. Decisions are more critical during stressful conditions.
3. Ranchers inevitably have access to and consult non-forecast information and indicators, and methods are needed to bring these into the decision analysis.
4. Information is more useful and valuable when the decision-maker can access adaptation options logically triggered by the forecast conditions; that is, an operational nexus must exist between the information and decision options. This may seem obvious, but it is tempting in decision analysis to pursue optimal choices that might not be practical.

Steps in the analysis include (Fig. 2):

1. Develop a decision structure specific to range livestock ranching,
2. Adopt and adapt an enterprise model that allows realistic calculation of costs and income;
3. Build decision trees to simulate decisions under a range of forecasts and other information sources; and
4. Calculate value by some index (added value per head) that can be extrapolated to the larger sector.

The resulting forecast decision testbed (Fig. 2) has three main components in the first tier: (1) the forecast elements that are relevant to the weather- and climate-sensitive enterprise; (2) the decision-structure, which establishes how enhanced weather and climate information could make a difference in decisions, and (3) enterprise models to calculate added value, chiefly in efficiencies gained (e.g., costs reduced) or profits increased.

To specify this testbed for cow/calf ranches on the U.S. Great Plains we adopted and modified a spreadsheet model developed by Jeffrey Trannel, Rod Sharp and John Deering at Colorado State University (Tranel, Sharp, & Deering, 2011)---"*Strategies for Beef Cattle Herds During Times of Drought*"---specifically built to help ranchers make choices during drought. The original model was a good starting point because it focused on responding to drought by adjusting feed, marketing, and other decisions. We gave the model a five-year simulation window, up-dated costs and prices, added a drought calculator linking precipitation (actual or simulated) to forage availability (modified from USDA Agricultural Research Service drought calculators, see Dunn et al. 2013), and correlated feed prices with drought severity based on the U.S. Drought Monitor (USDM) drought levels. We also added a module that simulates the

USDA's Pasture, Forage and Range (PRF) insurance program (we did not run insurance simulations for this forecast study; see Williams and Travis, 2020).

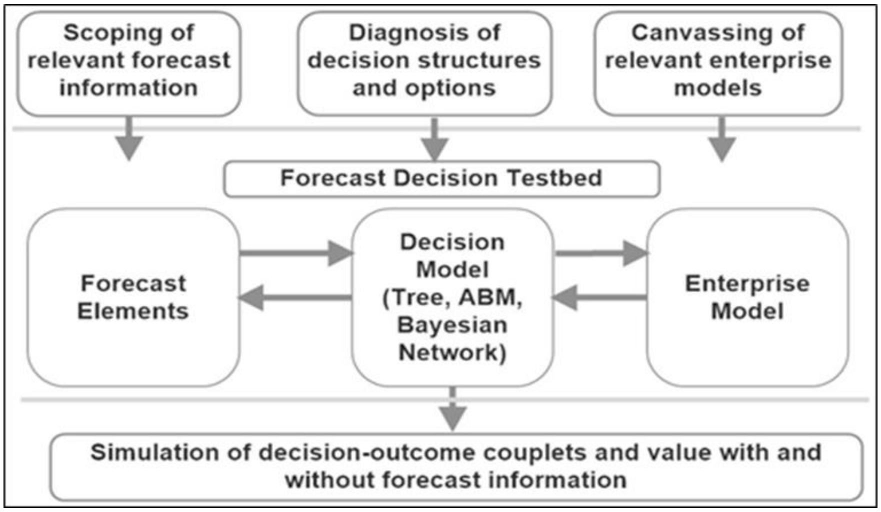

Figure 2: Structure of the testbed for array of steps and models for assessing the economic value of forecast information in weather- and climate-sensitive decision-making.

Grass-Cast: Forecasting how the grass grows

Grass-Cast provides projections of growing season vegetation productivity in the US Great Plains and Southwest by incorporating historical weather data and satellite derived normalized vegetation difference index (NDVI) with ecosystem modeling and seasonal precipitation forecasts (Peck, 2019; Hartman et al., 2020). It can reduce uncertainty about forage availability, helping ranchers make strategic decisions that can improve profit and conserve the ecology of rangelands by, for example, altering stocking rates to avoid overuse. It was piloted in 2017, and routine distribution of grassland productivity forecasts started in 2018. Grass-Cast is updated every two weeks with newly observed data and every four weeks with the National Weather Service Climate Prediction Center's monthly and seasonal precipitation outlook.

Grass-Cast is expressed in three maps according to expected above-, near- or below-normal precipitation for the region of interest. Each map predicts the percent change in the growing season's aboveground net primary productivity (ANPP) compared to the historical average ANPP of the particular area. Consequently, Grass-Cast provides several types of information and can be utilized in different ways. The approach recommended by the forecasters is for the rancher to first consult the National Weather Service Climate Prediction Center's seasonal precipitation outlooks and then choose the tercile map they think is most appropriate to the evolving season. On the chosen map, then, the percent change in grassland productivity also ranges between -30% and +30% compared to the historical mean ANPP at their location. Consequently, based on the precipitation outlooks, ranchers may expect below-normal grassland productivities, which mean less than average grass available for feeding the cattle, even though precipitation forecasts predict above-normal conditions at their areas. This phenomenon relates to Grass-Cast's ability to signal how sensitive grassland productivity is to precipitation, or to suggest that the already realized conditions help determine the trajectory of the growing season expected ANPP values (Hartman et al., 2020). The producers of Grass-Cast encourage users to incorporate their knowledge of local soils, plant communities, topography, experiences, and other conditions as part of their decision-making process instead of solely relying on the forecast (Durham, 2018; Peck, 2019).

Both observed and forecasted weather influence the grassland productivity forecast during the season from 1st of April to 31st of July. In general, the further into the growing season, the more observed data is incorporated into the forecasts, *so the accuracy improves with time as the growing season unfolds, and as a consequence, the three maps converge to the same values in the final map in August*. Hartman et al. (2020) evaluated Grass-Cast forecast outputs from 2017 and 2018 against independent, satellite-derived NDVI observations. They computed the percent difference of the ANPP from the normal precipitation forecast to the mean ANPP values. Yearly MODIS NDVI observations were compared to the mean MODIS values to calculate the difference. The percent differences for both Grass-Cast ANPP and MODIS NDVI were grouped into three categories; 8% above the mean, -8 and +8% near the mean, and 8% below the mean. Based on these categories Grass-Cast and MODIS NDVI values could differ by two categories, one category, or were in the same category.

The two-category-difference might be the most alarming for ranchers. Such a case either implies a scenario where the forecast signaled below normal values, but in reality, there was above normal annual productivity or vice versa. One category difference could be a result of below-normal forecast prediction when the realized condition is normal, and in this case a rancher who acts according to the forecast might end up spending on unnecessary protection/adaptation. Contrary, if the forecast predicted normal conditions but the growing season resulted in below normal productivity values then ranchers could lose part of their profits because they were not prepared for drought conditions. Furthermore, the missed normal and above-normal productivity values also result in one category difference but such forecast discrepancies only influence the economic output of the ranching enterprise if the operations are dynamically scaled according to expected forage (e.g., dynamic stocking for better-than-realized conditions). Hartman et al. (2020) found that the number of counties that differed by two categories at the beginning of the forecast period declined from 7% to 1% by the final output, while in 2018 the two categories difference was >10% until the middle of June but dropped to 0% by July 31 (2020).

Heidke Skill Scores (HSS) can be applied to express Grass-Cast ANPP accuracy compared to cumulative June-July MODIS NDVI observations. HSS range from -50 to 100, and the higher the value the more forecast categories correctly match observation categories besides the number of correct hits expected by chance alone. Between 2000-2018, the HSS scores of Grass-Cast varied between 33-84 with a mean value of 53.4, yielding higher values during drought years. As a result, HSS scores and R2 correlation between Grass-Cast ANPP and MODIS NDVI suggest that the forecast is more skillful during drought years by successfully recognizing below-normal ANPP conditions (Hartman et al., 2020). Consequently, the accuracy of Grass-Cast is conditioned on whether predictions are made for a dry or wet year since the expected forecast skill for a dry season is higher.

Weather and Climate Risk Management in Ranching

Ranchers in our study area track forage availability, develop expectations of future conditions, and make various interim adjustments in herd and grazing strategies to achieve a desired, or at least acceptable, economic outcome. Their decisions are concerned about allocating scarce resources each season based on their expectations about, for example, rainfall, forage, prices, and other uncertain variables, like access to rangelands and government policies (Ritten et al. 2010; Marshall & Smajgl, 2013). Adaptations to changing conditions might include: reducing or increasing herd size (e.g., by retaining some calves for a second grazing season), purchasing additional feed, or strategically selling livestock on short notice, due to range conditions, feed prices, and market swings (Shrum, et al. 2018). How and when to set stocking rates, provide supplemental feed, rent pasture, transport cattle, and wean calves, and sell animals are just a few decisions that influence the outcomes and economic profit of each season (Shrum et al., 2018).

Several studies suggest that traditional stocking practices could be made more efficient with dynamic adjustments. Ritten, Frasier, Bastian, and Gray (2010) argue that the optimization of stocking decisions is complicated by highly variable forage production caused largely by stochastic variations in precipitation (Vetter 2005). Additionally, some decisions such as herd size, stocking rate, and even supplemental feed purchases or pasture rental, must be made before growing season precipitation and forage production is fully revealed (Fang et al., 2014). As a result, ranchers lean toward conservative, fixed stocking rates that protect against loss and over-grazing when drought does occur, but also forego some efficiencies and profit that could be had given a more dynamic grazing management (Peck et al., 2019). Fixed seasonal grazing plans are unable to respond to stochastic weather events, therefore dynamic modeling with adaptive stocking strategies provides more options to ranchers. Ritten et al.'s comparison of a dynamic model maximizing return to land over stochastic weather, and a static model with fixed stocking rates, shows how forecasts can enhance the decisions of ranchers and lead to higher economic profits as well as sustainable rangeland management (Ritten, Frasier, Bastian, & Gray, 2010).

The DRIR Model of Drought Decisions

To capture these decision structure we built the "Drought, Ranching and Insurance Response" (DRIR) model, which calculates income based on herd size, market weight, prices, and costs. An embedded drought calculator adjusts forage proportionate to monthly moisture conditions in each annual step. Modifying this forage factor is one way to incorporate forecast, rather than observed, grazing conditions into the model. The model can be parameterized for different ranch sizes and strategies (Table 1); values for a simulated ranch located at the USDA's Central Plains Experimental Range (CPER; see: https://ltar.ars.usda.gov/sites/cper/). DRIR allows for three main types of response to drought: altering herd size, purchasing extra feed, renting pasture elsewhere, and includes a "no adaptation" choice, which in drought conditions reduces cattle weight gain and thus gross and net income. The five-year outcomes compare "no adaption" to various levels of stock reduction, and supplemental feed.

We treat the model not as an optimizing tool, but rather a simulation for testing outcomes of different information, drought conditions, market and adaptation combinations. It can be customized somewhat to a particular ranching structure, mainly according to herd size, and simple off-sets to range productivity and rates of cattle weight gain. It is applied here for a typical "cow-calf" production system, which maintains a steady-state herd of mother cows and sells the spring calf crop each fall.

DRIR applies *monte carlo* simulation to provide distributions of stochastic variables, like cattle weight gain and market prices, so that outcomes are a range of values instead of a single number. This reflects the reality of uncertainty but also allows inclusion of variable risk aversion. A correlation matrix in the models allows costs such as feed to correlate with USDM drought intensity, thus simulating an effect that every rancher faces. The model can also carry over range status from one year to the next, so that if full grazing (without supplemental feeding) is conducted in a drought year, a proportionate reduction in the next year forage is implemented---thus, as in the real world, the range recovers or degrades over time with drought and rancher responses to drought (Holechek et al. 1999). This allows the model to capture cumulative, sequential cost/loss outcomes.

Table 1. Ranch spreadsheet for livestock operations: Set to a cow/calf ranch in northeastern Colorado

Budget item (annual)	**Base values (2010-2020 simulations ($)**	**Notes**
Value of cows	850	
Cow costs	500	All variable costs (vet services, etc.)
Price of feed (hay or equivalent ratio)	110-140	Hay in tons delivered or on ranch. [Varies a lot, correlated with local and regional drought conditions; only if needed, times duration and herd count]
Pasture rent (AUM) per day, adjusted for calf weight	18	Not including transportation [Varies a bit; only if needed, times duration and herd count]
Prices received (per pound) at weaning	1.40	Prorated if early sale
Additional Operational Parameters		
Herd size	650	Mother cows
Average cow weight (pounds)	1,200	

Cows culled (normal year)	2%	Attempt to achieve steady-state cow/calf operation
Average weaning percentage	94%	Attempt to achieve steady-state cow/calf operation
Average percent calves sold	75%	Attempt to achieve steady-state cow/calf operation
Current calf weight (pounds)	300	Calving weight plus about two months of early-season weight gain (e.g., about June 1).
Expected weight at weaning (pounds)	650	By sale about October 1. Affected by forage availability or supplemental feed

The Forecast Decision Model

DRIR is integrated with a Forecast Decision Model (FDM), which deploys decision trees (Clemen and Riley 2014) to structure both adaptation choices and the information on which they can be based. It is through these decision trees that Grass-Cast, 30- and 90-day outlooks, the USDM, and other information, can be incorporated into adaptation choices, and outcomes calculated. The decision trees can be parameterized for a variety of information use and decision pathways, one of which is illustrated in Fig. 3.

Forecast Decision Model (FDM)

The Forecast decision Model (FDM), built from scratch for this research, uses decision trees to simulate ranchers' responses to forecast and associated information. It includes a requisite decision tree with Grass Cast information and seasonal forage for the CPER location. The FDM simulates different ranchers' responses to the forecast. Furthermore, as a result of qualitatively analyzing ranchers' decision settings and quantitatively modeling a simulated rancher's decision process, FDM allows running various scenarios. Such scenarios are based on, for example, forecast skills, different risk attitudes, forage availability, rancher's skills to help us assessing forecast value and identifying underlying trends.

The FDM was written in commercial decision analysis software (*Palisade Decision Suite*) which includes simulation, pay-off matrices, and decision trees as *Excel* adds-on (Clemen and Riley 2014). The FDM results from integrating DRIR with Grass-Cast and other relevant decision elements of ranchers' decision environments. The decision trees can be parameterized for a variety of information use and decision pathways, one of which is illustrated in Figure X.

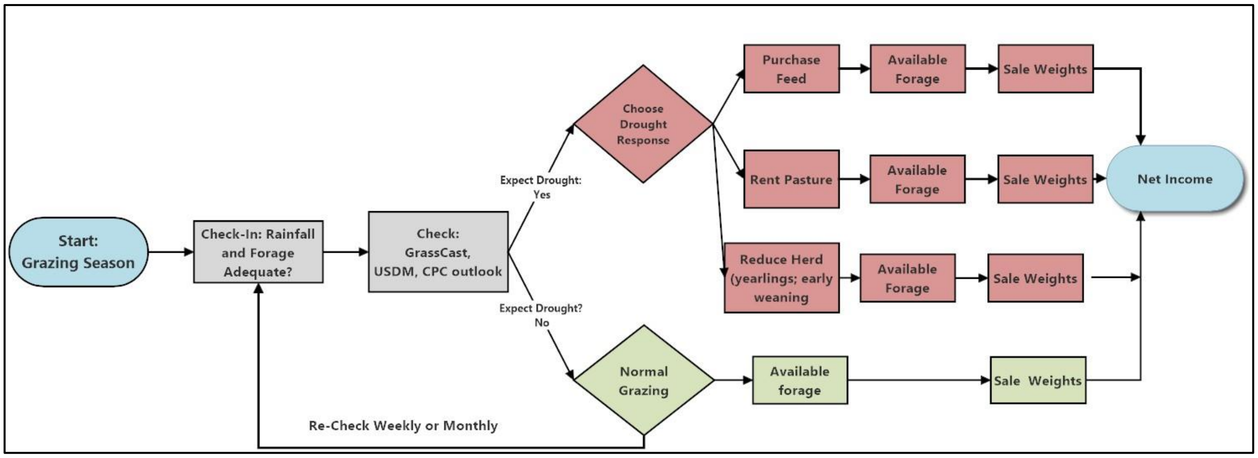

Figure 3. A decision scenario for a ranch operator concerned about drought and forage shortages and thus checking current and prediction information, then deciding whether to respond by purchasing supplemental feed. This is the "protect/don't protect" choice first outlined in the cost-loss framework by Thompson (1962). The model allows for a one-loop check-and-decide or sequential and iterative check-and-decide process.

We simulate three main information use and adaptation scenarios (or decision structures):

1. An early season check-in that can result in a one-time adaptation choice for the remainder of the grazing season;
2. A sequential check-and-decide process that allows decision up-dating over the season as new information becomes available, and provides multiple potential adaptation pathways; subsequent decisions are affected by previous choices and by the passage of time whereby some choices are foreclosed and some adaptations becomes less effective and/or incur different (typically increased) costs; and
3. A multiple-input decision, using the seasonal forecast and Grass-Cast, but also checking the USDM to assess the extent and severity of local and regional drought.

Following the logic of the Tranel et al. spreadsheet model on which DRIR was based, we include two main types of adaptations, either as one-time or sequential decisions:

1. Purchasing supplemental feed to make-up for drought-induced deficit (typical hay or some cattle feed ration; or arranging to lease additional pasturage, often involving transport of some or all of a herd to a distant grazing location less affected by drought);
2. Altering the herd size, which changes the stocking rate to match current or expected forage (this function is not yet working as of this paper in October, 2021).

Each of these adaptations involve a range of complex choices and trade-offs, and present the rancher with tough choices, such as marketing more cattle than planned and abrogating carefully-planned herd and genetic strategies.

Our goal was to create what decision analysts refer to as a "requisite" decision tree, capturing only the essential, decision-relevant steps in a ranch operation. Decision trees generally consist of various elements like decision nodes, chance nodes, logical conditions, and values associated with potential losses or gains. These elements help to calculate the final expected value of each branch (or subtree), as well as the expected value of the overall model.

The FDM decision tree first bifurcates on whether the decision-maker uses any additional information. In this case, additional information is the forage forecast from Grass-Cast. As discussed earlier, Gress-Cast consists of three maps depending on the Climate Prediction Center (CPC) 90-day precipitation forecast outlooks. The producers of Grass-Cast suggest consulting the CPC forecast outlooks before choosing the appropriate Grass-Cast map based on below-, near-, or above-normal precipitation scenarios. For our analysis, we considered the possibility of modeling this initial choice between the three output maps. However, since we used the forecast skill, which corresponds to the final map's skill, modeling the map choice did not seem feasible and adds complexity that makes the economic outcomes less specific (e.g., was the resulting value based more on chocie of map or on skill of the forecast?).

Instead, we created the FDM with focusing on the forecast skill given any of the three maps and assessed the value of information with the assumption that regardless of below, near, or above-normal precipitation scenarios, the forecast would still have 70% skill. This approach allows us to look at the expected value given this static forecast skill but also enables us to run sensitivity analyses for the forecast skill and provide feedback to Grass-Cast producers about the relationship between forecast value and forecast skill.

Figure 4 is a subtree from the FDM and shows the scenario when decision-makers (ranchers) choose to incorporate additional information into their decision-making process. The first chance node corresponds to the potential Grass-Cast outputs that indicate how likely ANPP values will be below-, near-, or above-normal compared to the area's 38 years of average forage availability. Furthermore, once ranchers see such values, they act according to the forecast information and adapt in case of below-normal predictions. In comparison, ranchers conduct normal operations during near- or above-normal predictions.

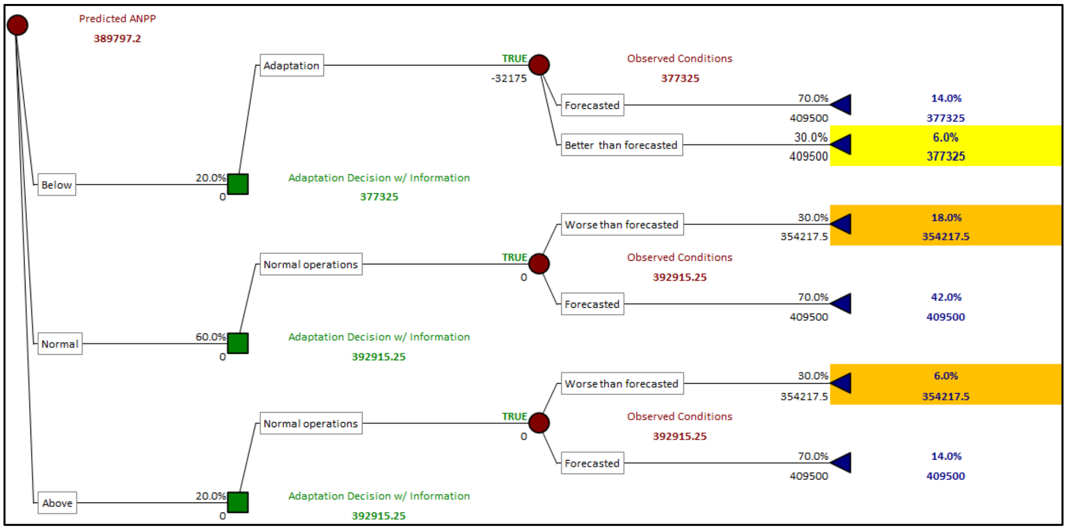

Figure 4 Forecast Decision Model showing the subtree with added information.

It is important to note that the current FDM models scenarios where ranchers adapt by buying additional feed or renting pasture elsewhere during drought conditions, but ranchers do not respond with dynamic stocking if conditions signal above-normal forage availability. Additionally, since DRIR was designed to help cow-calf producers compare the financial consequences of alternative management strategies during times of limited grazing forage, we also concentrate on scenarios with limited grazing conditions. The FDM's last chance nodes are connected to the forecast skill. This final branch captures the probability, which reflects whether forecast predictions are realized/observed. So, for example, 70% skill would align with the findings of Melannie et al. (2020), which measured that, on average, 70% of predicted conditions fell into the same category as observed conditions at the end of the analyzed growing seasons.

Figure 5 is the other subtree of FDM, which captures the rancher's decision-making process who does not use additional forecast information.

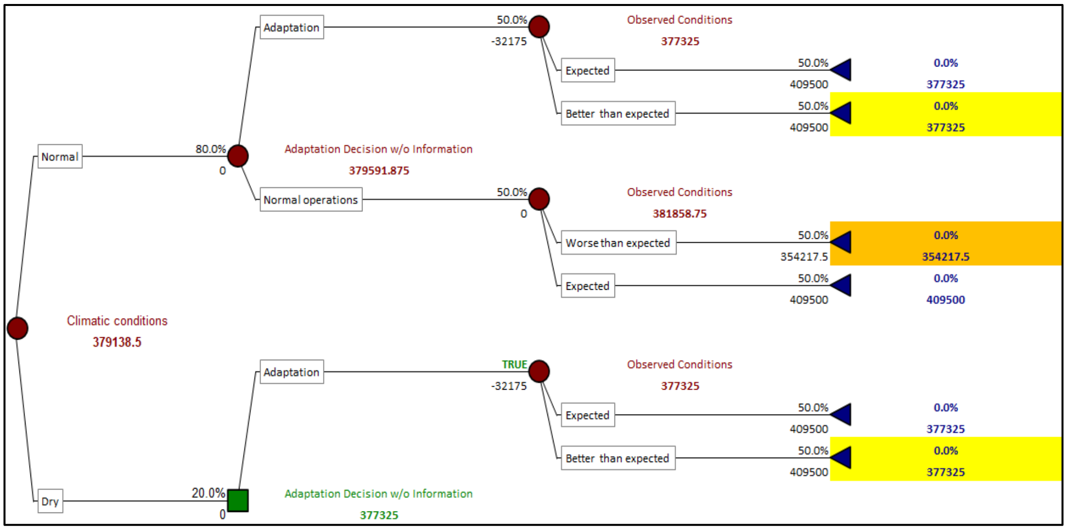

Figure 5 – Forecast Decision Model showing the subtree without added information.

This subtree is similar in structure to the above-mentioned decision flow where ranchers use Grass-Cast; however, it also has some unique additions like the adaptation likelihood chance node. The first chance node indicates the possibility of normal or dry climatic conditions. Contrary to the three potential options from Figure 3 (below-, near-, above-normal ANPP), this section of the FDM only models normal and dry conditions. As mentioned above, the current configuration of FDM does not allow for dynamic stocking if below-normal conditions are realized. Instead, we focus on adaptation scenarios with risk aversion where ranchers strive to mitigate lacking forage.

In case of expected dry climatic conditions, ranchers act according to such expectations and adapt. On the other hand, if chances are higher for normal conditions, we implemented a chance node that allocates probabilities between normal operations and safety adaptation scenarios depending on the risk aversion that a rancher might have. This safety adaptation can be equal to a minimal 5-10% forage shortage value (adaptation cost) but given a highly risk-averse decision-maker, the value of additional safety buffer might be even higher. Furthermore, it is worth recognizing that this locked-in resource (financial spending on extra forage) might be beyond the already underutilizing resource use, which is another form of risk aversion that ranchers can exhibit.

Drought Decision Scenarios

Simulations under different assumptions were run for the model CPR ranch, a cow-calf operation. The CPER provides a long-term precipitation record, a fixed grid-cell for calculating Pasture, Forage and Range (PRF) Insurance, and some ground-truth data on forage production. The ranch parameters are shown in Table 1.

The list of scenarios applied to this ranch (table 2) starts with basic runs which improve as we add more complexity. While we kept our goal to build a requisite model, the scenarios allow experiments with variables like forecast and rancher skill, cost of adaptation, and risk aversion (adaptation likelihood). The variations in the input values capture the decision environment's complexity and test the value of information in context. This approach also results in a range of expected forecast values instead of a single outcome value.

Each of these scenarios might be thought of as a unique storyline of the realizations that ranchers can face. The value of information is highly context-dependent, but the sensitivity analyses and different dynamic configurations of the FDM allow us to assess the forecast value under a range of specific circumstances. Table 2 lists essential scenarios which provide insights to measure the viability and value of forecast information. The *FDM Base* captures the simplest case where all the values are static, and the expected value is a single estimator. The following four runs (*FDM Grass-Cast, FDM Rancher Skill, FDM Risk Aversion, FDM Forage Factor*) each has a single varying variable, while the final two runs (*FDM Forecast – Rancher skill, FDM Grass-Cast – Forage Factor*) are the results of two-way sensitivity analyses, in which two parameters are varied jointly.

Table 2. The list of scenarios possible with sensitivity analyses and dynamic configuration of FDM. The static values are chosen according to expert opinion/literature review, while the varying variables (set of variables) are derived from two-way sensitivity analyses.

Scenarios Runs	Forecast Skill	Rancher Skill	Adaptation Likelihood	Forage Factor	Drought Conditions
FDM Base	0.7	0.5	0.5	0.8	0.2
FDM Grass-Cast	Varies	0.5	0.5	0.8	0.2
FDM Rancher Skill	0.7	Varies	0.5	0.8	0.2
FDM Risk Aversion	0.7	0.5	Varies	0.8	0.2
FDM Forage Factor	0.7	0.5	0.5	Varies	0.2
FDM Forecast – Rancher skill	Varies	Varies	0.5	0.8	0.2
FDM Grass-Cast – Forage Factor	Varies	0.5	0.5	Varies	0.2

The scenarios with only one varying factor help us to analyze the expected value of the entire model as we recognize the uncertainty of single, static values for all variables. On the other hand, two-way sensitivity analyses are more complex and powerful ways to investigate the co-variance of paired variables. These scenario runs either relate to the present environment's uncertainty, or future conditions' uncertainty. For example, the scenario of varying forage factor along with forecast skill can be a step towards gaining insight about forecast value given a changing climate.

We recognize that our current list of simulations is not exhaustive but for our research, we aim to follow an experimental approach and ask what we can learn from the proposed simulations? Our runs consist of realistic variables like feed cost, comparable configurations of cow-calf operations, and location-specific climatic conditions to tell reasonable stories under realistic circumstances. The range of expected values provides upper and lower bounds to the forecast value and gives feedback for the producers of Grass-Cast.

Results

DRIR Base Simulations

Base runs are simulations on actual precipitation for 5-10 year periods using the DRIR model tuned to the "CPER Ranch" with selected operational parameters (Table 1). These simulations test adaptation (acquire extra feed that makes up the forage deficit, if any), no adaptation (forage deficit, if any, translates into lower weight gain and market returns), and a "normal" year marked by 100% forage. Each outcome is expressed as the ranch annual net income (Fig. 6). Since the forage availability is set by the ranch precipitation translated into growing season forage percent through the embedded USDA-ARS Drought Calculator (set for northeastern Colorado), the uncertainty expressed in the outcome distributions derives from two sources: the price of acquiring supplemental feed and relatively small variations in weight gain for a given forage availability.

In a "normal" year (e.g., forage factor at about 100% and prices typical during the simulation time period in the central Plains; Table 1) this cow/calf enterprise nets about $85,000 from cattle production alone (ranches often derive income from other operations and sources). The 2011-2020 simulations shown in Fig. 6 included four notably dry years (2012, 2016, 2018, and 2020) with forage below normal (57%---the worst since 2002, 78%, 72% and 66%, respectively).

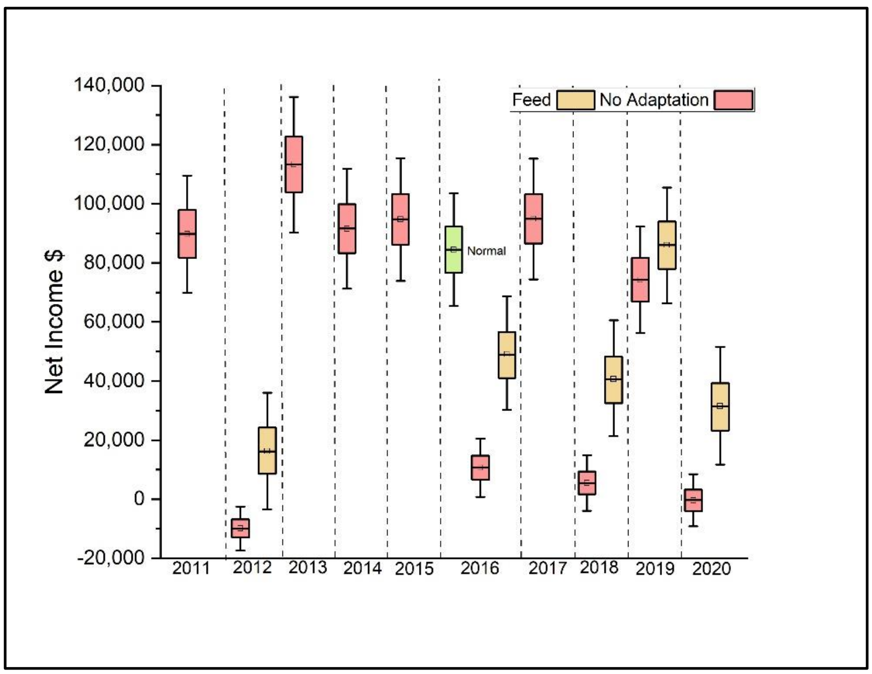

Figure 6: DRIR model results for actual conditions for a simulated 650-head cow/calf ranch located at the Central Plains Experimental Range (CPER) near Nunn, Colorado.

Forecast Value Simulations

The Forecast Decision Model (FDM) has two main decision branches: one with and one without Grass-Cast information (Figures 4 and 5). Results are typically presented as net income (profit) for the simulated ranch or as additional net income associated with forecast use. The *FDM Base* is the most static scenario and relies on the automated forage factor-adaptation cost calculator in DRIR. This calculator uses DRIR equations to translate the *forage factor* into *additional days of feeding*. Once the forage factor triggers a drought response (initially triggered by a *forage factor* below 0.95; this threshold can be varied by the modeler as desired), the cost of additional feed is linearly correlated with the lack of forage. Thus, as configured, the simulations show linear outcomes, but more complex relationships (e.g., between forage and weight gain) are possible and in some cases, more realistic.

Forecast skill is an essential part of the analysis; the *FDM Forecast Skill* runs analyze Grass-Cast's skill and its impacts on forecast-informed decision-making. A rancher who makes decisions based on Grass-Cast information can only maximize expected profits if Grass-Cast correctly predicts the end-of-season forage availability. Since Grass-Cast skill improves with time, an exact forecast skill always involves uncertainty, especially as the change in forecast skill interacts with the decision-making timeline of ranchers. Sensitivity analysis is a powerful way to analyze the expected value of the information given variations in the skill. "One-way" sensitivity analysis keeps all but the variable of interest constant and gives insights about the chosen variable's influence on the model (Clemen and Riley 2014). As the first result from the *FDM Forecast Skill* runs, Figure 9 depicts enterprise profits (expected value) given forecast skill variation.

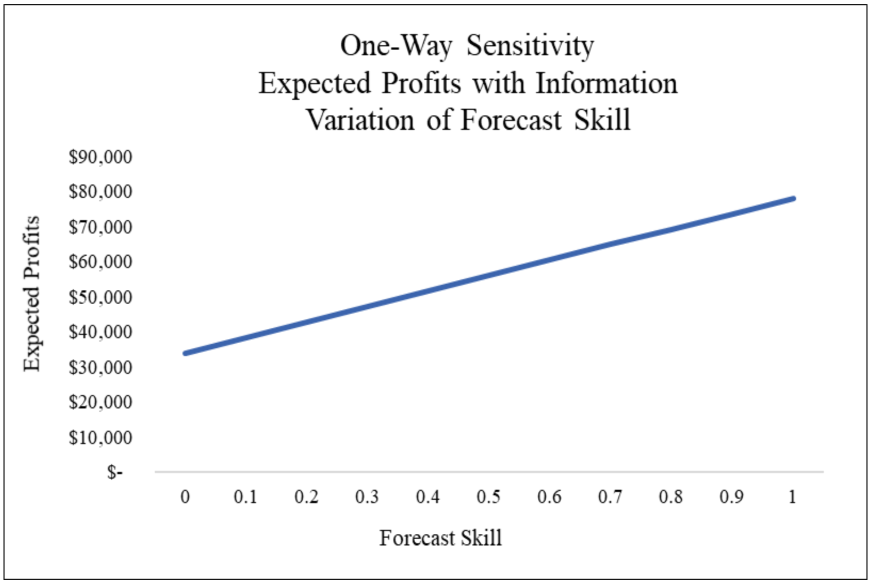

Figure 9 – FDM Forecast Skill scenario one-way sensitivity run results have a positive relationship between forecast skill and expected profits. The sensitivity run was targeted for the with information subtree to assess the change in expected profits as the forecast skill improves.

This one-away sensitivity analysis resulted in a linear relationship between forecast skill and expected profits. As the forecast skill increases, expected profits also increase (if, of course, the rancher uses the forecast correctly; the FDM forces that correct use). Since forecast skill is a way to translate uncertainty, these results make logical sense and align with general trends from the literature of forecast valuation. The higher skill involves less uncertainty, consequently, a more realistic description of the future. If decision-makers have a clearer idea about the future, they can make decisions that yield more value. Empirically, the skill of Grass-Cast varies between 55.3% and 100% (the latter value is reached at the end of the season when Grass-Cast is more of a cumulative observed value than it is a forecast). Figure 9 shows that given the variation in forecast skill, expected profits range approximately from $50,000 to $80,000 in a given year. Furthermore, it is important to note that the expected values represented in Figure 9 correspond to the 'with added information subtree' (Figure 7). Therefore, these values are realized by a rancher who uses forecast information.

Figure 10, similarly to Figure 9, shows expected profits but combines results from the FDM Forecast Skill and FDM Rancher Skill scenarios compare to ranchers' expected profits with and without added information.

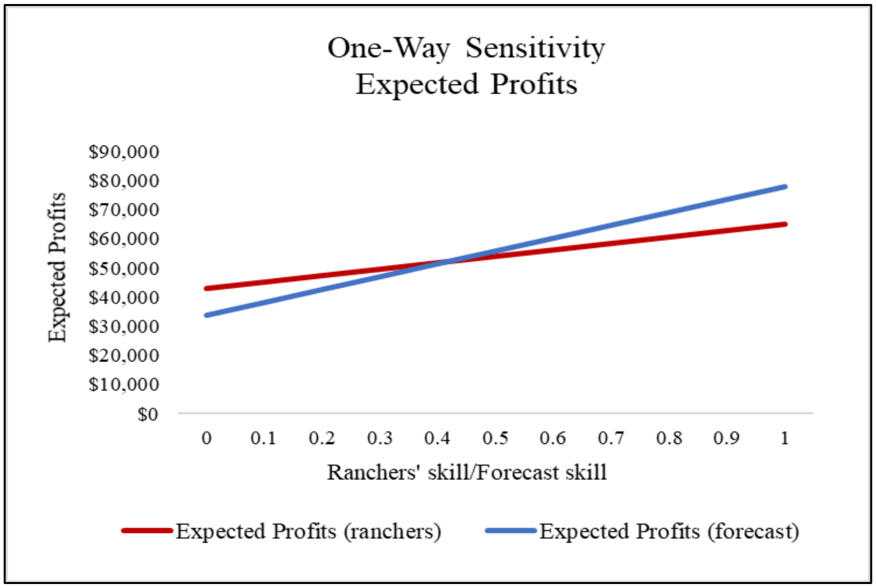

Figure 10 – Expected profits of FDM based on one-way sensitivity analyses.

The red line corresponds to a rancher's expected profits who do not use additional forecast information besides their own skills. While the blue line captures the potential outcomes of forecast informed decision making. Based on Figure 10, the variation in forecast skill results in a broader range of expected profits than the variation of rancher skill. Furthermore, Figure 10 shows that, for example, a 50% forecast skill yields slightly higher expected profits compared to 50% rancher skill. Additionally, since the current configuration of FDM involves the adaptation likelihood variable (set at 0.5), the difference between perfect forecast skill and rancher skill is driven by the risk-averse attitude of the decision-maker.

Expected profits are meaningful measures to assess ranching enterprise outcomes. However, to analyze the viability and value of forecast informed decision-making, we also calculated the added value of forecast information for the scenarios. As previously described, this research defines the value of information (VOI) as the difference between expected profits with and without information. Figure 11 expresses the expected VOI given the variation in forecast skill.

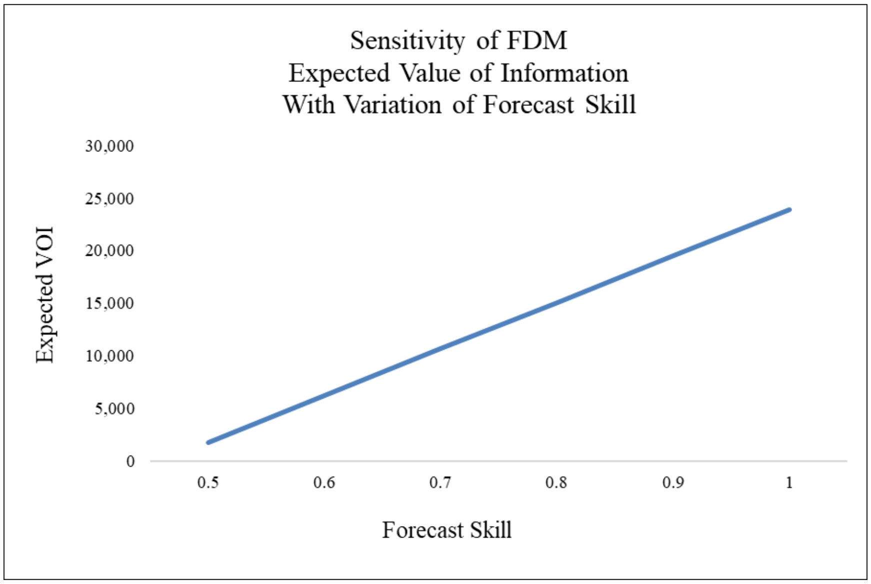

Figure 11 – *FDM Grass-Cast* scenario's results indicate a positive relationship between the forecast skill and expected value of information.

This graph only shows the expected VOI for the range of 50% to 100% forecasts skill because according to Hartman et al. (2020), the lowest analyzed Grass-Cast skill has been 55.3% from 2000 to 2018. Similarly to the trends of expected profits (Figures 9 and 10), increasing forecast skill also corresponds to higher expected VOI. This pattern is no surprise; however, the producers of Grass-Cast might find the new insight useful to improve their forecast product after gaining insight about how increased forecast skill yields higher VOI.

According to Figure 11, a 55% forecast skill is equivalent to about \$5,000 VOI, a 70% forecast skill yields approximately \$10,000 VOI, while a 90% skill is around \$20,000 VOI for the simulated ranch described in Table 1. The trend in Figure 11 is positive and linear; however, if the diminishing returns of increasing forecast skill are relevant and captured, then the additional increase in forecast skill would yield a smaller marginal increase in the additional value of information after a threshold skill level is reached.

Figure 12 is connected to the FDM Rancher Skill results. Contrary to Figure 11, the relationship between increasing rancher skill and expected VOI is negative.

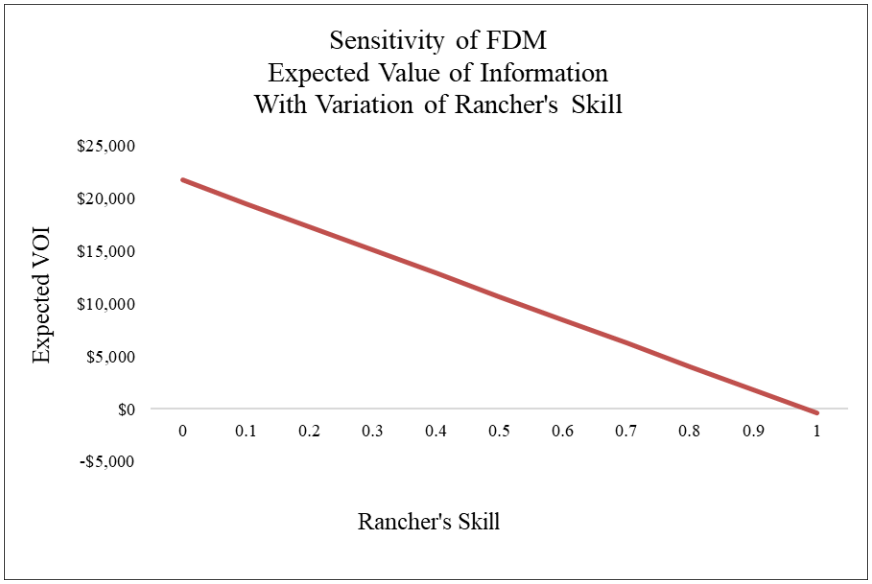

Figure 12 – *FDM Rancher's Skill* scenario results in an inverse relationship between rancher's skill and expected value of information.

As rancher skill increases, the forecast informed decisions become less valuable. This trend is intuitive because if ranchers are knowledgeable and face decreasing uncertainty, they are less reliant on additional information sources, like forecast information. Figure 12 shows that, for example, a rancher who has 50% skill could make an additional $10,000 each year by using forecast information. Similarly, a rancher with 70% skill could gain approximately $5000 in case of forecast-informed decision-making.

Figures 13 shows the relationship between adaptation likelihood and expected VOI based on the FDM Risk Aversion scenario.

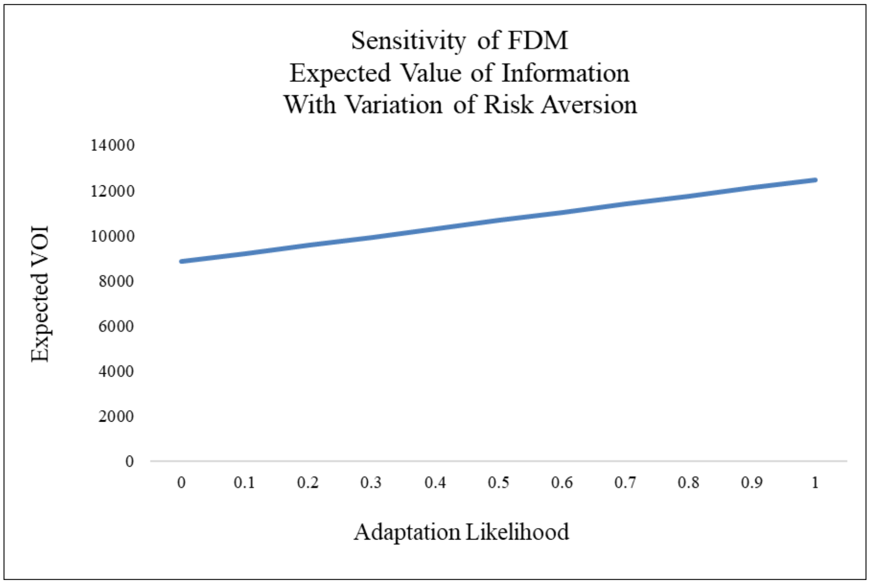

Figure 13 – *FDM Risk Aversion* scenario results in slight positive relationship of adaptation likelihood and expected value of information. Adaptation likelihood indicating the additional adaptation ranchers are willing to spend to avoid risk.

The slightly positive relationship between increasing adaptation likelihood and forecast value indicates the opportunity which is present for risk-averse ranchers who spend on unnecessary adaptation to secure supplemental forage even in normal years. Since the adaptation likelihood variable was defined as an indicator of risk aversion, the more risk-averse that ranchers are, the more expected VOI can be gained by applying forecast-informed decision-making. For example, risk-averse ranchers can gain about $10,000 on average, while highly risk-averse decision-makers can make up to $12,472 with added forecast information.

The *FDM Forage Factor* scenario's results are illustrated in Figure 14.

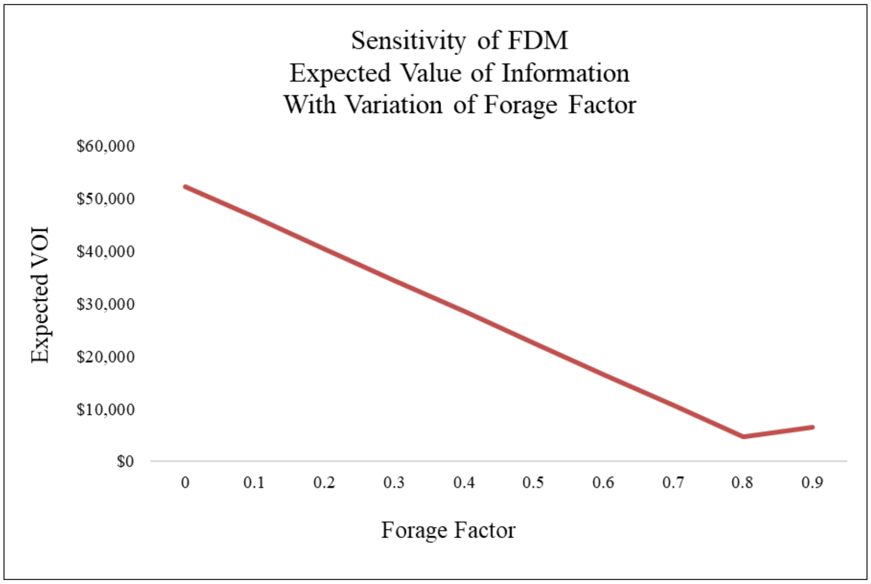

Figure 14 - *FDM Forage Factor* scenario's results show an inverse relationship between the forage factor and the expected value of information. Note that the DRIR model's drought response factor is 0.95, so the expected VOI starts to increase when risk averse ranchers spend on adaptation during normal conditions.

Forage factor is a variable adapted from DRIR to express the deviation of forage availability from normal conditions. Consequently, the lower forage factor values correlate with drier conditions, while values close to 1 (100%) correspond to near-normal forage conditions. Figure 14 shows a mainly negative relationship between the forage factor and expected VOI; the higher the forage factor, the lower the additional value derived from forecast information. Thus forecast information is more useful in drier, lower forage conditions. The graph increases around 95% forage factor. This change is connected to the 95% 'drought response factor' in the DRIR model. The 'drought response factor' is a threshold value below which the DRIR model's algorithms start to account for additional days of adaptation because of below-normal forage conditions. According to Figure 14, the increase in VOI at nearly 100% forage factor relates to the FDM configuration when the DRIR model does not calculate any additional cost for adaptation (forage factor is above the drought response factor), but risk-averse ranchers still spend on adaptation contrary to the near-normal expected forage. Consequently, the expected VOI starts to increase if risk-averse ranchers spend on adaptation during normal conditions (the value is driven by the unnecessary adaptation when the forage factor is above 95%).

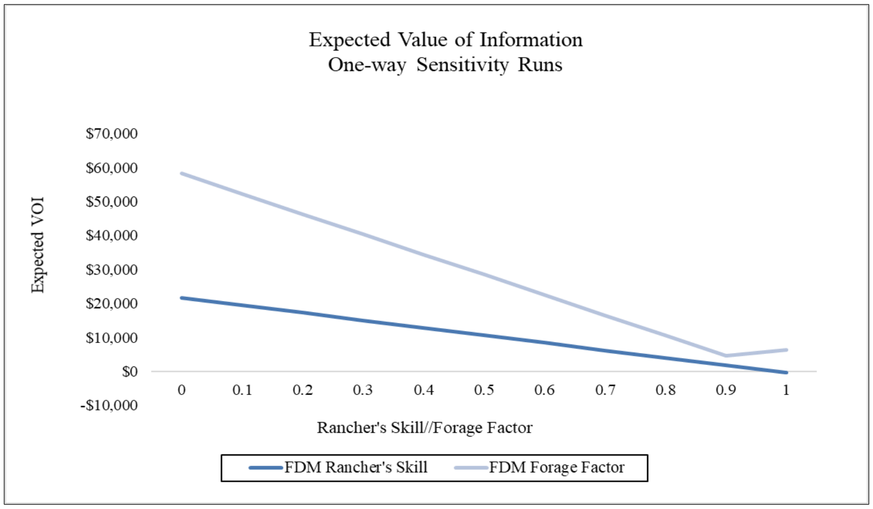

Figure 15 – Comparison of the *FDM Rancher's Skill* and *FDM Forage Factor* results. Rancher's skill has a wider range of potential values indicating greater influence on the overall model value.

Figure 15 compares the expected VOI from the *FDM Rancher's Skill*, and *FDM Forage Factor* runs. The darker blue line shows increasing rancher's skill (x-axis) while the expected value of the information decreases (y-axis). On the other hand, the lighter blue line (FDM Forage Factor) recapitulates the trend in Figure 14. The *FDM Forage Factor* simulation runs indicate a broader range of potential values compared to *FDM Rancher's Skill* results, thus the steeper negative slope. The gap between the two value outcomes decreases until the forage factor and drought response factor converge; however, the gap starts to increase again when risk aversion results in unnecessary adaptation.

The previously described graphs are all results of one-way sensitivity runs; therefore, they are limited to capture the variation in FDM expected outcomes given a single variable because such scenarios show the impact of one variable on the final expected profits and VOI, while the rest of the FDM parameters remain static. Beyond one-way sensitivities, two-way sensitivity analyses allow more dynamic configurations and show combined impacts of two variables. During two-way sensitivity runs, the variables of interest are given lower and upper bounds within which they vary to cover the possible combinations of interest (Clemen and Reilly 2014). Consequently, the *FDM Forecast - Rancher's Skill* and *FDM Forage Factor - Grass-Cast* scenarios calculate the value of forecast informed decision making according to variable pairs.

Decision analysts refer to the areas scribed by the intersecting values as "strategy regions", graphed to reveal the parameter space where one or another strategy yields a better payoff (Clemen and Reilly 2014). This visual approach shows the expected value of FDM as a result of the variables' combined impact. Furthermore, strategy regions provide a quick summary about the relative value of different subtrees in the FDM by expressing where with or without information decision-making is more valuable given the changes in the two critical variables.

Figures 16 and 17 are strategy regions indicating which variable pairs lead to more valuable decisions with and without additional forecast information. Figure 16 represents the scenario where forecast skill (x-axis) and forage factor (y-axis) are dynamic variables and shows where their combinations yield higher expected profits either with or without additional forecast information.

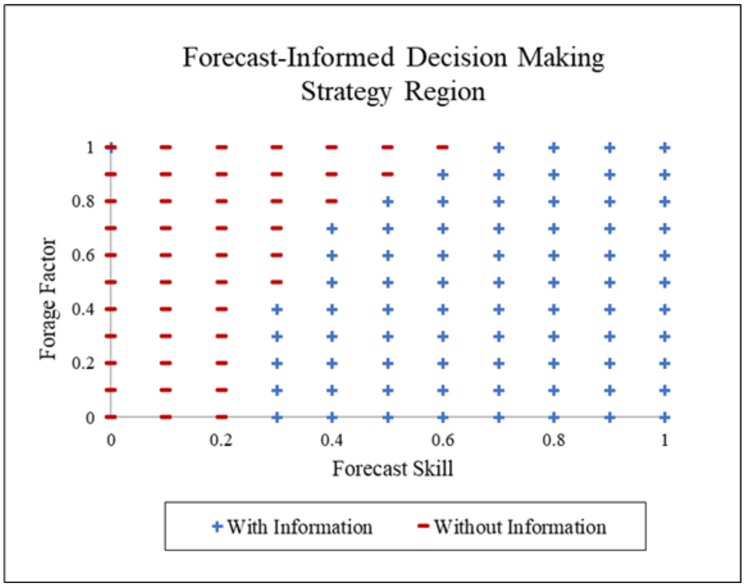

Figure 16 - FDM Grass-Cast – Forage Factor results. Two-way sensitivity analysis's strategy region with Grass-Cast (forecast skill) and forage factor combinations.

Red minus signs represent the area within the parameter space where the without forecast information subtree yields more value than the forecast-informed decision branches. While blue plus signs correspond to x-y combinations where the with forecast information subtree results in higher expected FDM values. If forecast skill is relatively low (around 30%), then the forecast-informed decision-making can still be more valuable given low (below 50%) forage factor values (Fig. 17). Furthermore, Figure 17 also shows that once forecast skill reaches 70%, decisions with forecast information yield higher expected profits regardless of the forage factor. This insight is helpful for Grass-Cast producers because the earlier the forecast skill exceeds 70%, the earlier forecast-based decision-making becomes the best alternative for ranchers.

Figure 18 shows the strategy region where FDM expected outcomes are analyzed with dynamic combinations of forecast and rancher's skills.

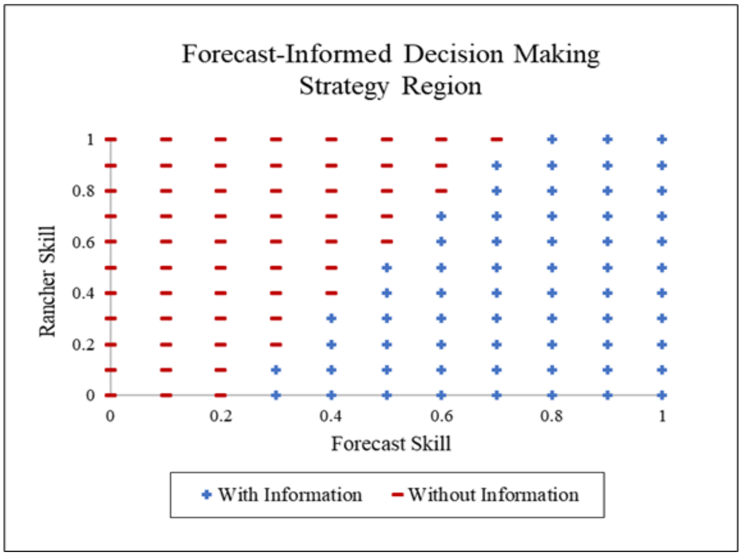

Figure17 - FDM Forecast – Rancher's Skill results. Two-way sensitivity analysis's strategy region with forecast skill and rancher's skill combinations.

Once forecast skill reaches 80%, decisions with forecast information are more valuable regardless of the rancher's skill. Additionally, if the forecast skill is 70%, only ranchers with perfect skills could make decisions that lead to higher expected outcomes without using Grass-Cast.

Conclusion and Discussion

The Grass-Cast basic decision model's initial run for the "CPER Ranch" indicates that the value of information is also significant if climatic conditions are within the normal range. The most simple decision tree model (Grass-Cast Basic Runs), which analyzes the value of Grass-Cast information and decision-making under normal precipitation conditions, suggests that the highest economic value corresponds to decision scenarios when Grass-Cast helps to avoid unnecessary adaptation. This might be surprising given that ranchers would not need to adapt in such circumstances. However, since ranchers tend to be conservative and underutilize resources, spending on unnecessary adaptation drives the value of information in such years. If forecast information can influence decision-making and ranchers become comfortable with reducing their "over-adaptation" (for example buying and holding on to feed because expecting worse than normal conditions) then the yearly profits are higher.

Conservative ranching strategies, and risk-averse attitudes, might lead to the underutilization of resources by preparing for worse forage availability than end-of-season conditions, therefore ranchers applying more conservative grazing plans can especially increase their net profits by using Grass-Cast. Consequently, a skillful forecast can enhance flexible and dynamic decision-making while it adds value to the enterprise operations.

Another important insight from the initial simulations is the point in the season when Grass-Cast information becomes more valuable. In general, the strategy region whether to get the forecast suggests higher expected outcomes with the forecast information once the forecast skill reaches at least 66%. Since Grass-Cast is updated biweekly with observed information, the further into the grazing season ranchers make choices, the more skillful the forecast is. Therefore, if ranchers can wait to make a decision, they can reduce uncertainty in their grazing operations.

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