Systematic Conservation Prioritization Centered on Sage-grouse (*Centrocercus urophasianus*), in a Region of Competing Land Uses

by

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A thesis
presented to the University of Waterloo
in fulfillment of the
thesis requirement for the degree of
Master of Environmental Studies
in
Social and Ecological Sustainability

Waterloo, Ontario, Canada, 2021

AUTHOR'S DECLARATION

I hereby declare that I am the sole author of this thesis. This is a true copy of the thesis, including any required final revisions, as accepted by my examiners.

I understand that my thesis may be made electronically available to the public.

Abstract

The once expansive sagebrush habitat in the western United States has suffered substantial losses largely due to the encroachment of development for extractive and renewable resource-based industries. Sage-grouse (Centrocercus urophasianus; hereafter "sage-grouse") persistence is tied to protecting the remaining sagebrush, in recognition of this conservation actions like the creation of priority areas for conservation (PACs) have been forwarded, but further action is needed to address ongoing sage-grouse declines. Questions remain regarding how conservation actions should be prioritized, suggesting Systematic Conservation Planning (SCP) efforts are needed. We provide a case study for an SCP process for the Rock Springs Field Office (RSFO) located in southwestern Wyoming. Field offices are nested within the Bureau of Land Management (BLM) structure presenting a relevant spatial scale for sage-grouse management. Our case study was informed by broader investigation of how alterations to the prioritizations influence solution quality measured with metrics including irreplaceability and ROI. We focused on recommending sites for seasonal, annual, and multiple species benefitting plans with the goals of identifying priority areas and areas suitable for improving the PACs, entering conservation easement agreements, and restoration. We considered how selections of priority areas changed with the application of different objective types, feature weights, cost features, and the inclusion of connectivity. We found seasonal differences in the vulnerability of priority sage-grouse habitat, as expected, nesting habitat was the best represented by the PACs whereas brood and winter habitat could benefit from greater PAC coverage. Incorporating other species (elk and mule deer) into our prioritizations was beneficial to our process because we were able to identify common pathways between the three species involved. Assessing the trade-offs between various ways to quantify conservation objectives into specific parameters for a prioritization is expected to be unique to each SCP process and should be relevant to the species or species' and ecological, political, and social systems of focus. Future conservation planning projects at the landscape scale where multiple land uses need to be balanced, lacking land cost values but with fine scale ecological data could benefit from a similar set up for their prioritizations. Structuring our case study with a maximum utility (MUP) objective type, a cost feature to bring threatened areas into the prioritizations, feature weights created with local expert input, and incorporating connectivity with genetic informed data and spatial constraints led to improvements in solution quality.

Acknowledgements

This thesis could not have been completed without the support of my supervisor, Dr. Brad Fedy, who is an expert in ecological and statistical methods, critical thinking, and mentoring students to success. His passion for conservation, robust science and reading is incredibly contagious and he is a force to be reckoned with. My committee member Dr. Chris Kirol was a positive light throughout the process and gave me valuable guidance and encouragement. I appreciate all the hours he put in to help move me along, enhance my work, and support my success. I am obliged to Dr. Stephen Murphy who originally brought me into the SERS department and helped me through a smooth defence. Patrick Lionberger of the Bureau of Land Management was a key actor in this study and improved my work in many aspects, his ongoing involvement was instrumental to integrating management perspectives into this thesis.

I am very lucky to have worked with the Fedy Wildlife and Molecular Ecology lab. All members of the lab were conductive to many thoughtful discussions, and I appreciate my lab mates for their continued comradery. I'd like to acknowledge Dr. Todd Cross for his humor and expansive knowledge on sage-grouse and genetic approaches. Past and present PhD candidates Matt Dyson and Kelly McLean provided invaluable feedback and collaborations. I would also like to thank Ryan Johnstone for paving the way as a successful masters student who helped induct me through the process and Galen Pierce for being willing to pick up the slack as I got close to defending.

Multiple data contributors were instrumental to this work, past members of Fedy Lab who provided their insights and data include Dr. Kris Winiarski, Dr. Jeffery Row, and Dr. Jason Tack. I would also like to acknowledge researchers Dr. Holly Copeland, Dr. Matt Kauffman, Dr. Ben Hoen, Dr. Steven Garaman, Dr. Adrian Monroe, and Dr. Joseph Smith whose work was integrated into this process.

For supporting me behind the scenes, I would like to thank MES colleague Maggie Lui, her warmth and dedication to the injustices of others inspires me. I would also like to acknowledge the Racioppa family, David, Leanne, Jill, Julie, Jack, and Joseph for helping me grow, supporting me in all parts of life, being there for me during the onset of COVID-19, and ultimately believing in my ability to accomplish this and continue in my journey in education, wildlife ecology, and conservation.

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Chapter 1

Introduction

Existing protected areas have largely underperformed in capturing threatened species worldwide and future selections need to be strategically cognizant of weaknesses in the protected area network (Coad et al., 2015; Venter et al., 2014). Conservation planning addresses this issue with standardized procedures to inform what management actions should be taken, in what order, and where, including the designation of protected areas, policy change, and restoration (Pressey et al., 1993). Yet global targets have remained unmet, for example, the Aichi Target 11 endorsed by the United Nations, aimed for signatory nations to collectively designate 17% of ecologically representative terrestrial habitat for protection by 2020, a goal that is no longer achievable without restoration due to the declines of multiple unique ecoregions (Mappin et al., 2019). Meeting these targets challenges local conservation decision makers with navigating the trade-offs between implementation of various management actions and funding allocations while balancing competing land interests (Margules & Presey, 2000). More recently, the Global Deal for Nature (GDN) aims to conserve 30% of the Earth's surface by 2030, and unlike the Aichi Target 11, which was based on political and social factors, GDNs 30% goal comes from scientific estimates for global needs to maintain viable populations and ecosystem services (Baillie & Zhang, 2018; Dinerstein et al., 2019). Moving forward to achieve this goal requires utilizing rich data on species and habitat requirements and the best approaches for decision making and consulting with experts.

Systematic conservation planning (SCP) is a framework used to improve conservation planning efforts by guiding practitioners, outlining each stage of the planning process, and specifying where engagement with stakeholders is necessary to ensure data collection, objectives, prioritization parameters, and suggestions are unbiased and appropriate (Margules & Pressey, 2000; McIntosh, Pressey, Lloyd, Smith, & Grenyer, 2017). This chapter reviews the key concepts associated with SCP and spatial prioritizations, a step within the SCP process and the trade-offs between software tools used to determine *solutions,* spatial selections of *planning units* for reserve designs or designating management actions. In this chapter I consider software Marxan, Zonation, and the recently developed package for R software, *prioritizr*. The chosen study system and species are introduced for their suitability as an application of SCP with *prioritizr*, leading into the objectives and research questions of this thesis.

1.1 Systematic Conservation Planning

The act of setting aside natural areas for preservation is ancient in human history and many previous societies conserved areas they held sacred (Chandrashekara & Sankar, 1998; Margules & Pressey, 2000). Some of these places continue to be protected today for their cultural and environmental significance but most of the protected areas that exist today were established in an ad hoc fashion in the 20th century (Frascaroli et al., 2016; Joppa & Pfaff, 2009; Shen et al., 2012).

Designating new areas for conservation occurred in response to largescale habitat loss and land use changes, competing with agriculture, resource extraction, and urban development (Margules & Usher, 1981). Criteria used to select areas generally include capturing diversity, rare species, uniqueness, and particularly target vulnerable areas. In practice, remote areas undesirable for other land uses are often selected for protection (Joppa & Pfaff, 2009; Margules & Usher, 1981; Pressey, Humphries, Margules, Vane-Wright, & Williams, 1993).

The development of the SCP framework by Margules & Pressey, (2000) improved how researchers determine priority areas, integrate expert opinion, develop implementation strategies, and collaborate with stakeholders by increasing transparency throughout the planning process (Knight et al., 2006). The following section describes key components for consideration when engaging with SCP, including connectivity, irreplaceability and vulnerability, and uncertainty (Kukkala & Moilanen, 2013).

1.1.1 Connectivity

Connectivity is an important habitat feature to consider for the preservation of a target species because of its impacts on ecological processes like gene flow, migration, meta-population dynamics, range expansions, disease transfer, invasive species, and biodiversity (Crooks & Sanjayan, 2010; Mcrae et al., 2008; Moilanen et al., 2005). Ensuring that species can transverse the landscape and among habitat patches is increasingly important as range shifts and relocations are driven by climactic and land use changes (Doerr et al., 2011).

Conservation planning considers two types of connectivity: structural and functional. Structural connectivity is the spatial arrangement of different types of habitat across a landscape and functional connectivity is the ability for movement across the landscape by a species, individual, or ecological process (Crooks & Sanjayan, 2010). A myriad of approaches have been used to estimate connectivity, with ongoing misconceptions between the separation of resource use and movement and conflation of decisions relevant to habitat selection with movement decisions (Zeller et al., 2012). Resistance is the opposite of connectivity and describes areas that limit movement. There are a variety of methods available to model the connectivity of a landscape for a species of interest. Circuit theory, applied to a wide range of disciplines from electrical science, uses the concept of random walkers on a circuit board to determine pathways of least resistance (Mcrae et al., 2008). In ecological contexts, researchers have successfully used circuit theory to predict gene flow and movement (Mcrae et al., 2008; Rayfield et al., 2016).

Previous research has shown that prioritizations that consider genetic connectivity are more likely to enhance the ecological processes necessary for species survival and that incorporating different dimensions of connectivity is important as fragmentation influences species at multiple scales (Hanson et al., 2019; Prugh et al., 2008; Rayfield et al., 2016; Reino et al., 2013). Despite this, genetic connectivity is underrepresented in conservation planning (Howes et al., 2009; Keller et al., 2015). There are also risks associated with increasing connectivity across protected areas such as facilitating the movement of non-target and potentially invasive species (Drake et al., 2017).

1.1.2 Irreplaceability and Vulnerability

Irreplaceability is defined to represent the areas that are obligatory to meeting conservation objectives and can be used to relatively assess the importance of selected habitat (Kukkala & Moilanen, 2013). Determining irreplaceability of sites is useful for negotiations in conservation planning. For example, if some selected sites are unavailable, they could be replaced in the selection by another of similar importance (Sarkar et al., 2006). There are multiple approaches to calculating measures of irreplaceability which are appropriate for different sample sizes. This thesis applied two approaches to calculating irreplaceability implemented by *prioritizr*; replacement cost, based on Cabeza & Moilanen, 2006, and rarity weighted richness (Albuquerque & Beier, 2015). Rarity weighted richness ranks areas based on how many conservation features are represented by a planning unit while considering feature weights. This approach leads areas with overlapping conservation features being ranked highly. In contrast, the replacement cost approach is more robust than rarity weighted richness because it also considers the cost feature thereby more accurately assessing the relative utility of each planning unit and its value in terms of cost-efficiency. The drawback to replacement cost is that it is more computationally expensive and unfeasible to calculate for high resolution data spanning large areas.

Vulnerability refers to the potential for loss, this could be in reference to a species or a habitat, and is determined by assessing threats like development, climate change, and management issues (Noss et al., 2002; Wilson et al., 2005). The most important areas for targeted conservation can be determined as the most vulnerable and irreplaceable because these areas are at a relatively higher risk of being lost (Noss et al., 2002; R. L. Pressey et al., 1993; R. L. Pressey & Taffs, 2001). Vulnerability has three dimensions for assessment in conservation planning: exposure, intensity, and impact (Wilson et al., 2005). One can estimate vulnerability by considering current and projected land uses, environmental variables linked to vulnerability, and expert opinion (Wilson et al., 2005). There are several challenges when incorporating vulnerability into conservation planning, such as accurately mapping vulnerability across a landscape, combining the impacts of various threats, and considering vulnerability at different stages of the conservation planning process (Sarkar et al., 2006; Wilson et al., 2005).

1.1.3 Uncertainty

Identifying the sources of uncertainty in each component and assumptions made in conservation planning is crucial to understanding the trade-offs of management strategies and alternatives (Burgman et al., 2005). Habitat selection models for one or multiple species is the main quantification of ecological information influencing the selection of focal areas of habitat made through prioritization. These models are limited by the accuracy and resolution of the data collected and uncertainties in model creation (Burgman et al., 2005; Hermoso & Kennard, 2012; Meir et al., 2004).

The implementation of conservation action is impacted by shifts in economy, political contexts, climatic conditions, and social priorities and there is inherent uncertainty in any attempt to predict future conditions or proceed with the assumption that current conditions will continue through time (Burgman et al., 2005; Carvalho et al., 2011; Meir et al., 2004; Noss et al., 2002; Troupin & Carmel, 2018). Conservation planning efforts need to be aware of the assumptions being made in the creation of reserve designs which could impact outcomes and interpretations of the plan. For example, the assumption that habitat outside of protected areas will perish whereas habitat within will persist fails considering the uncertainty of future conditions and realities of habitat usage by a species. Therefore, it is important that conditions needed to maintain biodiversity are well understood, survey efforts are unbiased, threatened species denote vulnerable areas, and patterns and extents of past threats are used to predict future trends (Meir et al., 2004; Wilson et al., 2005).

There are numerous ways researchers can address uncertainty in conservation planning outcomes. Previous research has shown that keeping the objectives to conservation planning simple outperforms ad hoc and random approaches, as well as overly comprehensive approaches, which could bring in too many sources of uncertainty (Mccarthy et al., 2011; Meir et al., 2004). Integrating new data to update focal areas and management strategies is more important in situations of greater uncertainty and estimates of irreplaceability and vulnerability can also be reconsidered over time (Mccarthy et al., 2011; Noss et al., 2002). Conservation planning processes can be more robust to uncertainty through the transparent methods and assumptions and the consideration of multiple solutions and scenario parameters with clear explanations of the socio-economic and biological trade-offs (Carwardine et al., 2008; Sierra-Altamiranda et al., 2020; Troupin & Carmel, 2018).

1.2 Spatial Prioritization

Spatially explicit ecological data are the foundation for spatial prioritizations. By explicitly linking a species to various predictors in its environment, researchers can create models to predict occupancy or habitat use (Burgman et al., 2005). These data are broken into planning units, typically a uniform grid spanning the study area, or dictated by specific boundaries like management borders, watersheds, or landownerships (Beyer et al., 2016). Each planning unit is assigned a value, containing spatially explicit information such as the occupancy of a species or the area of coverage by habitat. A resource selection function (RSF) is a model defined as any function that is proportional to the probability of use by an organism (Manly et al., 1993). Similarly, habitat suitability models (HSM) express the same concept with a different method of generation. Although the collection of accurate data to create and test these models is typically intended for usage in prioritization, there is limited follow-through, due a lack of engagement between modelers and decision makers (Guisan et al., 2013).

1.2.1 Marxan

Marxan is a spatial optimization software that uses simulated annealing, a metaheuristic algorithm, to solve target-based, minimum-set problems, minimizing economic and social costs, boundaries, and unfulfilled targets, with iterative improvements (Kirkpatrick, 1983; Linke et al., 2011; Watts et al., 2009). Purely heuristic approaches are also available in Marxan to generate quick solutions but are less sophisticated (Possingham et al., 2000).

These methods can be used to determine a range of potential solutions and researchers typically produce a portfolio of spatial configurations to determine which areas are consistently selected within and across portfolios (Troupin & Carmel, 2018). This calculation is known as the selection frequency and can be determined for each planning unit. Although the concept of selection frequency is related to irreplaceability, irreplaceability scores, as defined by Ferrier et al., (2000), differ in how they rank planning units that are essential to meeting an objective or contain a unique feature (Ardron et al., 2010). Constraints can be implemented in Marxan to increase the connectivity of selected areas through boundary penalties and extensions of Marxan to handle uncertainty (Carvalho et al., 2011) and land-use zoning (Watts et al., 2009).

Marxan was notably implemented in the highly successful rezoning of The Great Barrier Reef (Fernandes et al., 2005) and applied on a continental scale to prioritize multiple conservation features and management actions, land acquisition and stewardship, across Australia (Klein et al., 2009). Limitations of Marxan and minimum-set problems in general include the lack of representation for important connecting habitat and do not incorporate the current configuration of reserve networks (Cabeza & Moilanen, 2003). Marxan also does not have a function to determine the representativeness of different features and can only support one cost feature (Ardron et al., 2010).

1.2.2 Zonation

Zonation is a successor of Marxan and can solve both minimum-set and maximum coverage problems by creating a hierarchal ranking of all planning units and iteratively removing them based on the loss of conservation value (Moilanen, 2007; Moilanen et al., 2005). A range of ecological features such as biodiversity, connectivity, and habitat quality, as well as cost features like administrative information and alternative land uses, can be weighted and incorporated into a Zonation prioritization (Lehtomäki & Moilanen, 2013; Moilanen, Anderson, et al., 2011; Moilanen, Leathwick, et al., 2011). Since anthropogenic information regarding costs and threats are implemented in Zonation as features, it is important to appropriately balance the representation of each spatial layer and only threats that can be mitigated with specific actions are prioritized (Santangeli et al., 2019). Prioritizations implicitly assume layers are static despite the dynamic nature of ecological processes. However, by including forecasted layers with increased uncertainty and decreased weighting, such as predicted range shifts under climate change scenarios, Zonation can address the uncertainty of future conditions (Carroll et al., 2010; Kujala et al., 2013; Lehtomäki & Moilanen, 2013).

Marxan and Zonation are both typically applied to binary conservation problems because a planning unit cannot be partially selected. Marxan and Zonation take similar approaches to determining solutions and generally produce similar solutions (Carwardine et al., 2007). Researchers have reported differences resulting from Marxan being solely target-based and using a minimizing algorithm, whereas Zonation can optimize non-targeted problems with a maximizing algorithm (Delavenne et al., 2012). For this reason, Zonation performs better than Marxan in situations considering multiple species when large-scale and high-resolution data are available (Lehtomäki & Moilanen, 2013). Zonation also has the capability to produce a set of performance curves that show the fraction of the conservation features remaining at any stage of the priority ranking for better comparison across outputs (Moilanen, Anderson, et al., 2011; Rayfield et al., 2016). In an application of Zonation across the United States and Canada, researchers found a disproportionate representation of mountainous areas already captured in protected area networks and a lack of protection for other biomes, the most threatened being Great Plains and Hudson Plains (Stralberg et al., 2020).

1.2.3 ***prioritizr***

prioritizr is a package for R software and uses integer linear programming (ILP), a mathematical optimization technique, to build and solve target-based conservation planning problems (Hanson, Schuster, et al., 2020). ILP has been previously applied to conservation problems but due to the complexity of utilizing this method, determining solutions was an NP-hard problem (unable to solve in a feasible amount of time) leading to the preference for heuristic approaches despite decreased performance (Possingham et al., 2000; Pressey et al., 1997).

The designation of protected areas can be heavily influenced by social and political rather than environmental factors (Campbell et al., 2014). For the designation of new marine protected areas in a data-limited, small-island context in the Caribbean, *prioritizr* was able to inform stakeholders by quantifying a vague objective, conserving biodiversity, with specific targets and presenting the trade-offs between potential selections (Flower et al., 2020). Compared to the heuristic approaches taken by Marxan and Zonation, an ILP approach allows for transparency with less likelihood of being misinterpreted or applied inappropriately because objectives and weights assigned to species and sites must be explicitly quantified in the problem formulation (Rodrigues et al., 2008).

Some researchers have critiqued target-based planning as leading to incorrect assumptions about unprotected areas, inadequate selections, and unachievable goals (Agardy et al., 2003; Woinarski et al., 2007) but similar assumptions are also made regarding non-targeted approaches and with expert opinion and rules of thumb, researchers can determine ecologically meaningful targets (Josie

Carwardine et al., 2009). *prioritizr* is flexible and supports different algorithms used in conservation that can be minimizing or maximizing, parameterized with targets, budgets, and/or feature weights. Incorporating connectivity is an important function for a prioritization software, in *prioritizr*, multiple functions are available to set constraints limiting the fragmentation of a solution. There are also numerous functions for analyzing solutions including determining the irreplaceability with various methods and calculating feature representation.

The most notable advantage to *prioritizr* is the capacity to find cheaper solutions in a shorter period of time than when using either Marxan or Zonation (Ball et al., 2009; Beyer et al., 2016; Hanson, Schuster, et al., 2020; Schuster et al., 2020). Although feature weights in *prioritizr* are based on concepts developed for use in Zonation, there are key differences in their application, such as, Zonation allows for negative weights and can support weights chosen from a range of 1 - 5 (Leathwick et al., 2008; Moilanen, Anderson, et al., 2011). Weights in *prioritizr* must be positive, non-zero, and limits are imposed by the solver (i.e., with the powerful commercial solver, gurobi, feature weights should be within 1e-6 and 1e6). ILP approaches also facilitate quantification of trade-off curves and sensitivity analysis similarly to Zonation (Beyer et al., 2016).

1.3 Greater Sage-Grouse

Greater Sage-grouse (*Centrocercus urophasianus*) (hereby referred to as sage-grouse) is an iconic and widespread species distributed in the sagebrush steppe habitat of Western USA, Southeastern Alberta, and Southwestern Saskatchewan. Sage-grouse occupy approximately half of their historical range, and populations are increasingly isolated as a result of habitat fragmentation and loss from agricultural, energy, and urban development (Knick et al., 2003; Schroeder et al., 2004). Prioritization is an appropriate progression for research and conservation pertaining to sage-grouse because of the availability of data and ecological information on the species, the obligate relationship between sage-grouse and sagebrush, and the sensitivity of sage-grouse to development (Aldridge et al., 2008). Wyoming is a known stronghold for sage-grouse, representing approximately 40% of remaining birds and a large producer for multiple industries (Connelly et al., 2004; Knick, Connelly, Naugle, et al., 2012). Our study system is within southwestern Wyoming, a critical area for sage-grouse persistence as it contains source populations and facilitates gene flow (Cross et al., 2018). This section details the history of management for sage-grouse broadly and within our study region, then discusses spatial ecology relevant to sage-grouse conservation.

1.3.1 Management History

Decisions taken over 100 years ago structuring land ownerships, uses, and policies continue influence our ability to manage the sagebrush ecosystem today (Knick, 2012). For example, across multiple states of the Western United States, the union pacific railroad land grants enacted in 1862 and 1864 led to the transfer of land to public and private entities in a checkerboard pattern that has remarkably persisted in current land use patterns (Kunce et al., 2002).

The Bureau of Land Management (BLM) manages public surface and subsurface resources and is an important steward for sage-grouse conservation, capturing 51% of sagebrush habitat in the United States and 40% of sagebrush habitat in Wyoming (Knick, 2012). In 2006, seven management zones for conservation were created based sage-grouse populations and subpopulations, considering the environmental similarities and differences in sagebrush steppe landscapes (Knick, Connelly, Miller, et al., 2012; Stiver et al., 2006). Each state in the US containing sage-grouse habitat determined core areas for sage-grouse based on (Doherty, Tack, Evans, & Naugle, 2010), using abundance data collected over 10 years at sage-grouse breeding grounds known as leks. These core areas were combined in a single map capturing breeding sage-grouse densities ranging from 25 – 100% to create priority areas for conservation (PACs) (Stiver, Rinkes, & Naugle, 2015). Because PACs were originally determined solely on abundances at leks, other important habitat like migration corridors, non-breeding, and winter habitat, that could have population level implications on gene flow and mortality, risk being overlooked (Fedy et al., 2014; Fretwell, 1972; Knick et al., 2003; Smith et al., 2016).

In 2010, the greater sage-grouse was flagged as a species of conservation concern and became a candidate for the designation of endangered species under the Endangered Species Act. In 2013 and in 2015 the federal government ruled that the species did not meet the criteria for endangered status and tasked each relevant state with the management of the species, creation of a federally approved conservation plan, and the mapping of critical habitat (U.S. Forest Service, 2015). In Wyoming, this led to a core area strategy enforced through executive orders which limit known impacts to sage-grouse regardless of land ownership within the core areas yet some land uses remained unrestricted in the core areas like residential development (Copeland et al., 2013). Since the 2015 decision, multiple amendments and revisions have been made to the conservation strategies specific to each state. The Habitat Assessment Framework (HAF) developed through a collaborative effort between the BLM, resource managers, and specialists, directed sage-grouse conservation efforts by standardizing the approaches, indicators, and scales for assessing sage-grouse habitat and linking populations to seasonal use areas (Stiver et al., 2015). Wyoming published a mandated environmental impact statement in 2020, highlighting the need to maintain alignment between federal goals, state laws, and local plans (United States Department of the Interior, 2020).

In the United States, funding for conservation action for the 10 year period of 1992-2001 totaled $32 billion and annual spending increased by 20% over the decade (Lerner et al., 2007). Annual spending targets of $5.4 billion - $7.7 billion were previously identified as necessary to create a connected protected area network spanning the nation, but these spending goals were not met (Lerner et al., 2007; Shaffer et al., 2002). The BLM in consultation with local sage-grouse working groups and conservation organizations, like the Sage Grouse Initiative (SGI), started by the U.S National Resources Conservation Service (NRCS) in 2010, worked to prioritize and implement management actions. The SGI conservation easement campaign had a $250 million budget and worked to protect key habitat by creating agreements with private landowners (Kunce et al., 2002). Wyoming has received sizeable portions of this funding, in 2011, SGI initiatives in Wyoming received over $52 million of funding and in 2018, another $128 million was committed to Wyoming for conservation actions (Natural Resources Conservation Service, 2015). According to SGI reports, a total investment of $760 million from various partners was projected to finance the conservation of 8 million acres across 11 states by 2018 (Natural Resources Conservation Service, 2015). On private lands, NRCS have invested more than $100 million to facilitate voluntary conservation easements which permanently restrict development in exchange for direct payments and/or tax incentives, an additional $250 million in targeted easements could avert 9% to 11% of potential sage-grouse declines (Copeland et al., 2013; Natural Resources Conservation Service, 2014).

The future of sage-grouse management is reviewed by the federal government every 5 years, currently the U.S. Fish and Wildlife service is facing criticism due to the increased resource extraction leases from 2015-2020, suggesting a failure to appropriately mitigate threats, engage with emerging science, and monitor and review the effectiveness of past and ongoing management actions (Gardner et al., 2019). The state of Wyoming, which captures the some of the most important contiguous areas sage-grouse habitat, has seen the greatest increases in leasing for extractive energy, the majority of this proposed development occurring on BLM managed lands (Doherty et al., 2012; Gardner et al., 2019).

Other designations used in conservation have been applied to sage-grouse including the concept of umbrella species which uses the conservation of a target species to forward the conservation of other species that have similar needs (Wilcox, 1984). Sage-grouse has been proposed as an indicator species for the sagebrush habitat due its sensitivity to habitat degradation, and as an umbrella species for its widespread range and usage of various community types overlapping with the habitat requirements of multiple species including sagebrush obligate songbirds, pygmy rabbits, reptiles, and migratory ungulates (Copeland et al., 2014; Fedy, Kirol, Sutphin, & Maechtle, 2015; Pilliod, Jeffries, Arkle, & Olson, 2020; Ricca & Coates, 2020; Rowland, Wisdom, Suring, & Meinke, 2006). The benefits of sage-grouse as an umbrella species are dependent on scale, in landscape contexts the concept is more appropriate but can still disproportionately confer protection for species that are similar, like other avian species, that are widespread, and also highly associated with sagebrush communities (Carlisle et al., 2018; Carlisle & Chalfoun, 2020; Knick, Connelly, Hanser, et al., 2012).

1.3.2 Spatial Ecology

Sage-grouse habitat selection is complex, impacted by landscape composition at multiple scales and varying through seasons (Doherty et al., 2010, 2016; Fedy et al., 2014). Sage-grouse populations are highly clustered and expected to be found within only 25-34% of their occupied ranges (Connelly et al., 2004; Doherty et al., 2016). Therefore, accurate modeling of regional sage-grouse habitat selection poses an important opportunity to use targeted conservation and protection against threats, with expected high biological returns (Doherty et al., 2016).

Sage-grouse is a good species to use for this study because of their strong association with sagebrush habitat, and distinction between seasonal habitats, leading to overlapping layers suitable for a prioritization effort. The species shows substantial individual and population-level variation in migratory strategies and movement within habitats, ranging from non-migratory populations to birds travelling over 50 km between life stages (Dahlgren et al., 2016; Fedy et al., 2012; Leonard et al., 2000). These movements are typically not cross-country making the species more manageable considering data collection and conservation perspectives but sage-grouse movements can be long distance reaching reported lengths of 194 km within one lekking season (Cross et al., 2017). Sage-grouse are a highly studied species, leading to a good understanding of their life cycle, habitat requirements, threats, and linkages to other conservation opportunities.

1.4 Research Questions and Objectives

This thesis uses the most current available tool for spatial prioritization, *prioritizr*, to delineate areas expected to have the greatest importance for conservation, referred to as 'priority areas', within the Rocksprings Field Office (RSFO). We considered objectives relevant to BLM needs highlighted in management plans like the Habitat Assessment Framework (HAF), to develop the following questions:

1. Where are the seasonal and annual priority areas of habitat for sage-grouse located within the RSFO and,
2. Where are areas suitable for conservation actions such as expanding the PACs, conservation easements, and habitat restoration?

Chapter 3 investigates the options available within *prioritizr* for structuring conservation problems to best fit management goals. There are advantages and drawbacks to building complexity by incorporating more conservation features, cost features, and feature weights as these changes fundamentally alter how solutions are determined. Chapter 3 addresses the research questions:

1. How can objective types and feature weights be used in a prioritization process to most effectively determine priority habitat when considering various environmental and anthropogenic data together?
2. What are the impacts of posing costs as 'development potential' or as 'threats'?
3. How are solutions impacted by data variability?
4. How does connectivity alter solutions?

Chapter 2

Greater Sage-Grouse in the Rock Springs Field Office: A Case Study in Systematic Conservation Planning

2.1 Introduction

Conservation biology is uniquely mission-oriented, with the overarching goal to prevent species loss and benefits from multidisciplinary collaboration from fields like wildlife and restoration ecology, ornithology, and social sciences (Soulé, 1985). Preventing species loss is a complex goal, requiring the balancing of diverse wants and needs for land use, and conservation biologists face challenges including severe uncertainty and risks, and limited reproducibility (Haddaway & Verhoeven, 2015; Regan et al., 2005). Historically, conservation spaces have been defined by land that is unproductive and undesirable for development, lacking extractable resources, or being remote and inaccessible (Brooks, 2014; Joppa & Pfaff, 2009; R L Pressey & Tully, 1994; Venter et al., 2018). Using spatial ecological data to guide the selection of priority areas for conservation management is a crucial task to ensuring the continuation of biodiversity in the face of rapid expansions in multiple industries (Watson et al., 2014). Unfortunately, the implementation of conservation plans in management spaces is underwhelming relative to the availability of information (Coad et al., 2015; Sinclair et al., 2018). This is in part due to a lack of accurate data pertaining to land values or cost, that is necessary to consider the feasibility of conserving sites and for decision-makers to assess potential opportunities and constraints for management (Cook et al., 2017; Knight & Cowling, 2007).

Systematic Conservation Planning (SCP) is a framework developed to combat the prevalence of ad hoc and ineffective reserve designs by setting guidelines standardizing the best practices for data processing, stakeholder consultation, and identifying priority areas under uncertainty (Margules & Pressey, 2000). Modern SCP approaches typically use decision-making software which process data relevant to a singular or multiple priority species to assess the value of potential conservation areas and help frame regional conservation plans. Within the Western United States, public land management is largely under the responsibility of the Bureau of Land Management (BLM) which is guided by a multiple-use mandate. Therefore, the BLM is tasked with balancing a variety of land uses, such as energy development, livestock grazing and recreation, with conservation of all species while also considering the long-term health of the land.

Greater sage-grouse (*Centrocercus urophasianus;* hereafter sage-grouse) is a gallinaceous species found in the sagebrush habitat which is dominated by multiple species of sagebrush (*Artemisia* spp.) and characteristic to the intermountain landscapes of the Western United States. Currently, sage-grouse populations occupy less than 50% of their historic range, loss of sagebrush has been identified as a key driver of sage-grouse declines and research has predicted 7–19% range-wide population declines from future energy development in sagebrush habitats (Copeland et al., 2009; Knick et al., 2003). Extensive habitat fragmentation isolating sage-grouse populations has made the species increasingly vulnerable to stochastic events (Aldridge et al., 2008). The management of sage-grouse presents a perfect opportunity to test new methods and bridge gaps between research outcomes and management to identify areas of high risk and importance.

Sage-grouse are a highly researched species and there is a wide availability of datasets pertaining to the species including as historic lek counts dating to the 1940s (Connelly & Schroeder, 2007; Crist et al., 2015). Sage-grouse have been designated as an obligate species, depending on sagebrush for survival, and an umbrella species, whose habitat conservation is expected to confer protection to other co-occurring species like other avian groups, reptiles, and mule deer (Barlow et al., 2020; Copeland et al., 2014; Donnelly et al., 2017; Knick, Connelly, Hanser, et al., 2012; Pilliod et al., 2020; Rowland et al., 2006; Runge et al., 2019). Priority areas for conservation (PACs) boundaries were determined by each state capturing sage-grouse populations, based on lek locations, breeding bird densities, known sage-grouse distributions derived from observations or telemetry data, and in some cases pre-existing development and Federal lands approved for or in the process of being developed (Crist et al., 2015; Doherty et al., 2010). PACs were used to spatially delineate key sage-grouse population areas (Doherty et al., 2010). Surface disturbance caps are the primary regulatory mechanism used to limit development in PACs (Kirol et al., 2020). Nesting habitat for sage-grouse, compared to the brood and winter seasons, is the best understood season and better represented in the PACs because priority areas were first based on lek locations and females nest in close proximity to leks; although some PACs have been updated to better represent other seasonal areas (U.S. Fish and Wildlife Service, 2013; Wisdom et al., 2005). Despite this, key areas for sage-grouse persistence are expected to remain outside of the PACs (Gamo & Beck, 2017; Smith et al., 2016; Stiver et al., 2015). For example, marginal habitat that may be important for connectivity between PACs should be considered for conservation focus. Functional connectivity refers to the movement of individuals across a landscape considering landscape features and the behavioral response of organisms to their landscape and can be quantified with genetic approaches. This differs from structural connectivity which predicts the ability for movement based solely on physical factors such as connected habitat, topography (natural barriers), and structures limiting movement like roads and urban expansion. The functional connectivity is more descriptive of movement for a species living in fragmented habitats and has greater utility when applied at landscape scales as it indicates the reproductive success of individuals (Mühlner et al., 2010). This is useful for conservation as the identification of key movement corridors maintaining gene flow between populations or subpopulations is important for maintaining resiliency, the species ability to respond to further fragmentation and changing future conditions, the loss of which could eventually contribute to the decline of the species (Fahrig & Merriam, 1985; Howes et al., 2009; Schultz & Crone, 2005).

To guide future management actions, the Habitat Assessment Framework (HAF) started development in the early 2000s and was published in 2010 to standardize indictors used for monitoring sagebrush habitat for sage-grouse usage at various scales and tasked land managers to develop future visions of the landscape (Stiver et al., 2015). MZ II, the Wyoming Basin, overlaps with the central and western portions of Wyoming and contains the highest density of sage-grouse, harboring 40% of their remaining population (Doherty et al., 2010; Knick et al., 2003). Although Wyoming is an important stronghold for sage-grouse with sagebrush dominating 70% of landscape, sage-grouse populations in Wyoming have shown declines (Fedy et al., 2014; Fedy & Aldridge, 2011). The most severely declining populations were in northeast, central, and southwestern Wyoming (Monroe et al., 2016). In these populations, energy development for industries including oil, gas, and wind, have constrained habitat availability due to habitat loss and the avoidance of disturbed habitat shown by females, resulting in lek abandonment, declines in nest survival, and reduced breeding populations (Green et al., 2017; Kirol et al., 2020).

Within Wyoming, the Bureau of Land Management (BLM) is divided across 3 districts encompassing 11 field offices. Sage-grouse habitat is primarily on public lands and highly vulnerable to development, this is because key predictors of sage-grouse habitat like ruggedness are also important factors in development suitability leading to competition for similar areas (Doherty et al., 2012). Local nuance is important to addressing these issues because accurate data of seasonal sage-grouse habitat and land ownership at the field office level can uncover weaknesses in the protected area network and conservation opportunities. Southwestern Wyoming has been highlighted as a genetically important area, which is increasingly important with continued isolation of sage-grouse populations (Cross et al., 2018). Addressing gaps in seasonal habitat representation and connectivity are objectives outlined by the HAF for managers to focus on and move forward with conservation efforts, and therefore these were guiding principles for this prioritization effort (Stiver et al., 2015).

This study focused on the identification of priority areas for sage-grouse in the Rock Springs Field Office (RSFO), a management area of Southwestern Wyoming, and an area that has experienced high levels of energy development (Connelly et al., 2004; Knick, Connelly, Doherty, et al., 2012). The research questions guiding this study included:

1. Where are the seasonal and annual focal areas of habitat for sage-grouse located within the RSFO and how does this selection change when also considering connectivity, land tenure, and oil and gas development potential?
2. What is the distribution of sage-grouse seasonal and annual focal areas of habitat in relation to the PACs?

These questions led to the following objectives for meeting management goals in the RSFO:

1. Identify regions in the RSFO currently underrepresented in the protected areas that connect seasonal sage-grouse habitats and are vulnerable to loss.
2. Identify potential locations in the RSFO for conservation easements.
3. Identify locations in the RSFO that could be suitable for restoration.

2.2 Methods

2.2.1 Study Site

Our study was located in Southwestern Wyoming, an area characterized by shrub steppe habitat, predominantly Wyoming big sagebrush (*Artemisia tridentata wyomingensis*) and Basin big sagebrush (*A. t. tridentata*) (K. Davies et al., 2006). We defined our study site based on relevant management boundaries for implementation of conservation actions. The U.S. Bureau of Land Management is responsible for 98% of land in Wyoming (61.3 million acres) and divides the state into 3 district offices and 11 field offices. Our study focused on the Rock Springs field Office (RSFO) which oversees the management of approximately 3.6 million acres of public land (Figure 1).

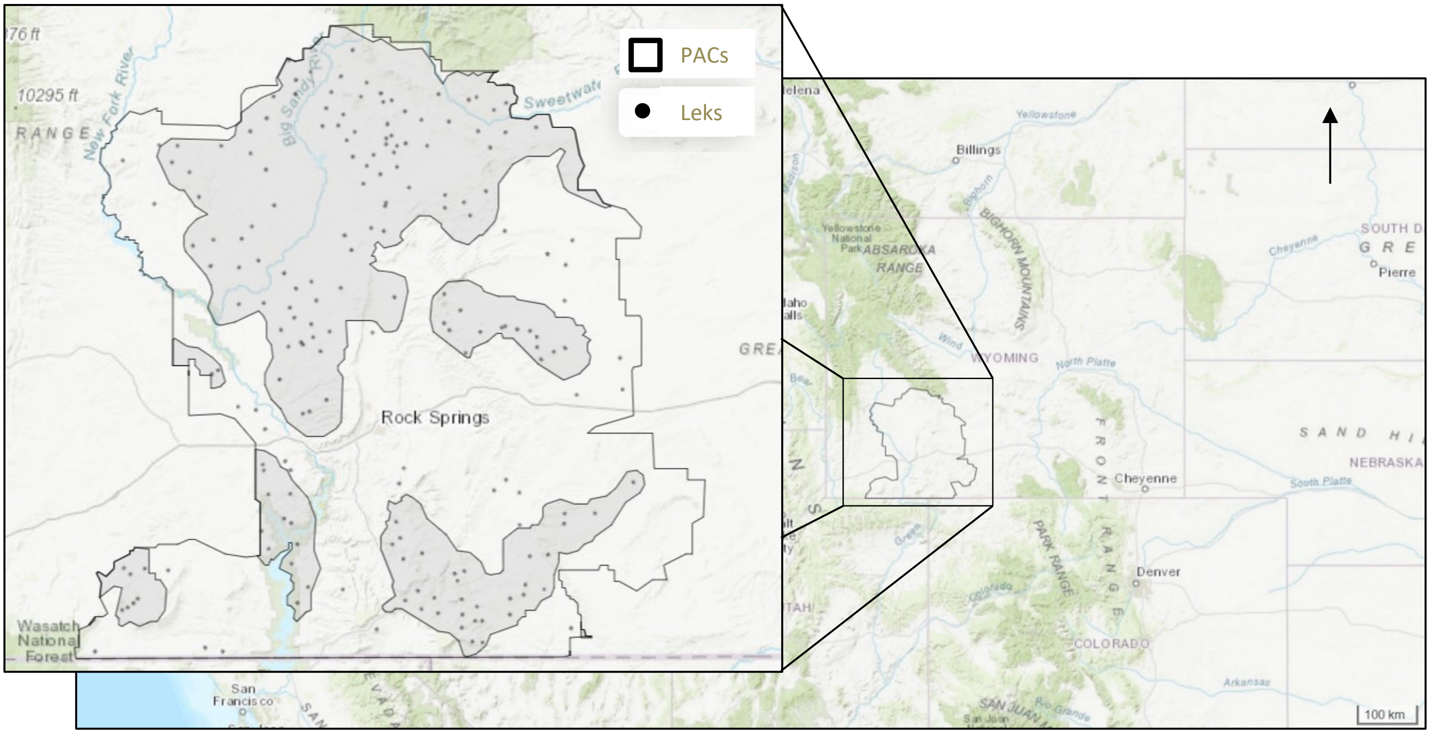


Figure 1. Map of the study extent, the RSFO, located in Southwestern Wyoming, the priority areas for sage-grouse conservation (PACs), and locations of sage-grouse leks.

Southwestern Wyoming is an important area of sage-grouse habitat both within Wyoming and range wide due to its importance in maintaining viable sage-grouse populations and population connectivity (Cross et al., 2018; Doherty et al., 2016; Fedy et al., 2017; Row et al., 2018). The RSFO is within sage-grouse Management Zone II (MZ II), the Wyoming Basin. Compared to the other 6 management zones, the Wyoming Basin, contains the most connected landscape with the highest proportion of remaining sagebrush habitat (45%) but is at a high risk of development, representing an important opportunity for sage-grouse conservation (Knick & Connelly, 2011; Knick, Connelly, Doherty, et al., 2012; Row et al., 2018).

Land ownership in the RSFO was predominantly public including BLM federal land (67.3%), Bureau of Reclamation (USBR) (3.3%), and United States Forest Service (USFS) (1.8%). Private land ownership comprised 22.9% of the landscape. The remaining < 5% of ownership belonged to state and local agencies. The RSFO supported a mosaic of land uses, including surface and subsurface resource extraction, crop cultivation, livestock grazing, urban and suburban developments, and wind farms. PACs cover 45% of land in the RSFO, on these lands, new surface energy and mineral extraction leases are limited to an average of one pad or mining operation per 640 acres and surface disturbance is capped at 5% (USDA Forest Service, 2015).

2.2.2 Spatial Layers

Spatial layers were used in the prioritization process as either a *conservation feature*, such as species distributions, or a *cost feature*, delineating a price for acquiring any planning unit (Figure **2**). For the prioritization process spatial layers need to be in the same format, projection, resolution, and extent, therefore, all surfaces were pre-processed in ArcMap version 10.7.1 to ensure these consistencies (ESRI, 2019). A complete list of surfaces and their data sources is included in Table 1.

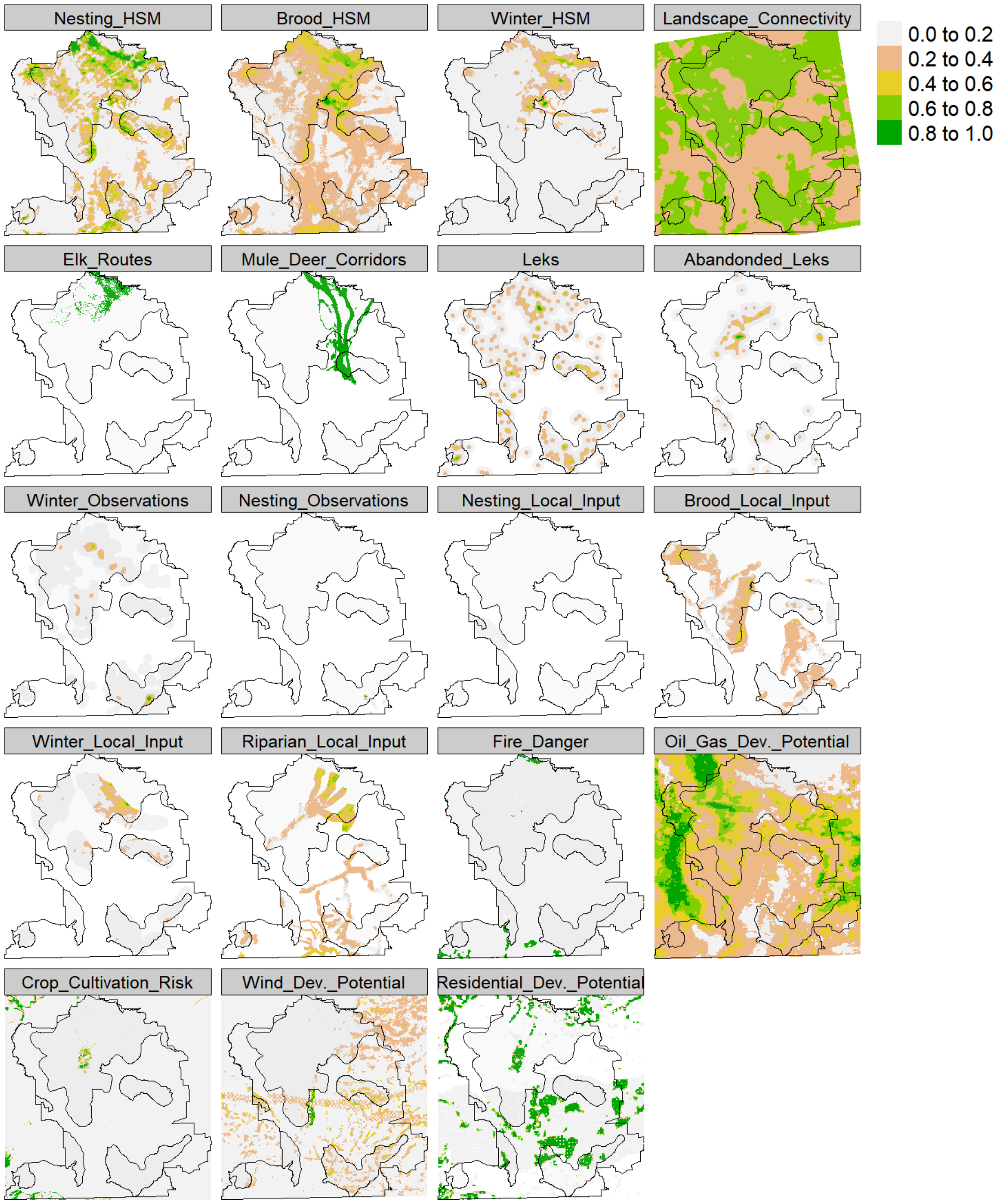


Figure 2. Surfaces used as conservation features and to generate cost features including (A) nesting, (B) brood, and (C) winter habitat suitability models, (D) landscape connectivity, (E) elk migratory routes, (F) mule deer migratory corridors, (G) leks, (H) abandoned leks, (I) winter observations, (J) nesting observations, (K) nesting expert input, (L) brood expert input, (M) winter expert input, (N) riparian expert input, (O) fire danger, (P) oil and gas development probability, (Q) crop cultivation risk, (R) wind development probability, and (S) residential development probability.

Table 1. Spatial surfaces and their sources used for this prioritization.

Surface	*Source*
Seasonal HSMs (nesting, brood, and winter)	Winiarski et al., In Review
Landscape connectivity	Row et al., 2018
Elk and mule deer migratory corridors	Kauffman et al., 2020
Leks	Wyoming Game & Fish Department (WYGFD)
Winter point observations	RSFO
Development potential (oil and gas, wind, residential)	Copeland et al., 2013
Crop cultivation risk	Smith et al., 2016
NLCD	https://www.mrlc.gov/
Wyoming roads	https://pubs.usgs.gov/ds/821/
Well pad scars	Garman & McBeth, 2015
Land ownership	USGS Gap Analysis Project, 2018
PACs	WGFD
Wind turbines	Hoen, et al., 2018
DDCT	https://onesteppe.wygisc.org/
Nesting point observations	RSFO
Sagebrush recovery time	Monroe et al., 2020
Fire danger	https://firedanger.cr.usgs.gov/viewer/index.html

Sage-grouse habitat requirements vary throughout the annual cycle. These are generally categorized into nesting, brood, and winter habitats and each season can influence population performance and connectivity (Fedy et al., 2012). We included habitat selection models developed for each season in our prioritization efforts. Details on model development and validation can be found in Winiarski et al. in review.

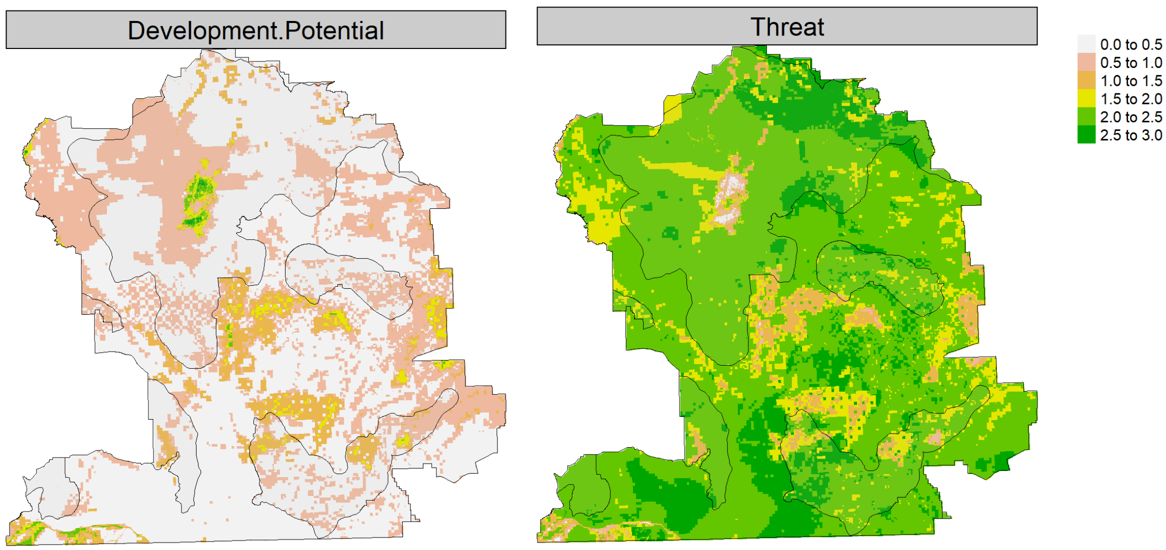
Although the importance of incorporating genetic data into prioritizations has been demonstrated, most prioritizations are based on solely on habitat and species distributions (Hanson, Marques, et al., 2020; Nielsen et al., 2017). Functional connectivity of sage-grouse populations was previously determined in a landscape genetics context by Row et al., 2018. A resistance surface was developed using circuit theory to estimate omnidirectional movement pathways based on genetic samples and landscape features in circuitscape (Mcrae et al., 2008; Rayfield et al., 2016). For convenience this was re-expressed as landscape connectivity (the reciprocal values of the resistance layer), therefore areas with high values were more likely to facilitate movement and gene flow (Hanson et al., 2019). The landscape connectivity surface was clipped and rescaled to the RSFO study area and included in the prioritization as a conservation feature.

Incorporating numerous species distributions into a prioritization process comes with trade-offs; increasing complexity and number of objectives may reduce the representation of key conservation features, on the other hand, their inclusion can lead to the identification of multiple conservation objectives that can be simultaneously realized (Nielsen et al., 2017). To engage with more information and increase the potential utility and benefits derived from this prioritization, migratory routes and corridors for ungulate species elk (*Cervus canadensis*) and mule deer (*Odocoileus hemionus*) obtained from Kauffman et al., 2020 were also incorporated as conservation features.

Restorative management for sage-grouse is typically aimed at conifer expansion, reclamation from resource extraction projects, and wildfire mitigation and response (Chambers et al., 2017; Coates et al., 2016; Reinhardt et al., 2017; Rottler et al., 2018). To determine locations in the RSFO that could be suitable for restoration we followed guidelines outlined by Knick & Connelly, 2011, which state: look for previously developed areas like abandoned wells, abandoned leks, previously shrub dominated areas that have become grass or conifer forest dominated, areas vulnerable to fire and climate change, and habitat edges that have a low risk of development and contain few sage-grouse currently. We used surfaces including existing development, abandoned leks, USGS Fire Danger Forecast (Preisler et al., 2015), and modified our seasonal HSMs to isolate edge habitat.

The usage of cost features and proxies, a model or substitute for land values to represent cost in prioritizations, can produce unintended results and introduce greater uncertainty into the prioritizations especially if costs are highly variable (Armsworth et al., 2017; Arponen et al., 2010; Carwardine et al., 2010). Transparently and critically reporting how costs were determined and assumptions, and producing prioritizations for comparative purposes or a sensitivity analysis are strategies to avoid unreliable or shortsighted incorporations of costs (Armsworth, 2014). Due to the unavailability of land value data, multiple surfaces were generated for usage as the cost feature for the prioritizations in this study. A *uniform* cost feature was generated to assign each planning unit with a cost of 1. Proxies were developed with the underlying assumption that land values are related to the predictors of land suitability that inform certain high impact industries. The probability of development for multiple land uses including oil and gas, residential housing, wind development, and cropland conversion have been investigated by previous researchers, leading to predictive spatial layers spanning the range of sage-grouse (Copeland et al., 2013; Smith et al., 2016). These layers were clipped to the study extent and summed together to create the *development potential* layer. With this surface as the cost, opportunistic areas that are valuable for conservation but unsuitable for development and thereby theoretically inexpensive could be targeted for selection in the prioritizations. Since areas targeted for development, especially areas with competition for use by multiple industries, are expected to be vulnerable to loss, the development potential layer was inverted to create a *threat* cost feature (Figure 3). With usage of the threat surface, planning units with a high likelihood of being developed corresponded with a lower cost to attain, similar to approaches taken in previous studies prioritizing sage-grouse habitats in development contexts (Smith et al., 2016; Tack et al., 2019). By pursuing prioritizations with these variations, using development probability to inform costs, tradeoffs were able to be readily identified between planning units of similar conservation value but varying economic, political, and social importance. For our restoration aimed problems we used the predicted time to recovery for sagebrush as the cost feature, incorporating a predictor of restorative success and areas with some suitability to sagebrush (Duchardt et al., 2021; Monroe et al., 2020).

Figure 3. Cost features for priority conservation problems generated by summing the development probability of oil and gas, residential housing, wind development, and cropland conversion by Copeland et al., 2009, 2013, and Smith et al., 2016, and inverting this cumulative surface to develop a threat cost feature.



The Density Disturbance Calculation Tool (DDCT) was created to measure and manage total disturbance and disruption occurring in sage-grouse habitat in Wyoming. Disturbance refers to direct alteration of surface or vegetation whereas disruption describes the indirect impacts of proximal anthropogenic activities. Surface disturbance in PACs is limited to 5% disturbance and disruption to an average of 1 per 640 acres within DDCT area (USDA Forest Service, 2015). The DDCT was included in the prioritization by modifying the seasonal habitat suitability surfaces so reclaimed areas with burn and agricultural histories had a reduced value, therefore favoring previously unmanaged areas which are expected to be more resilient. Areas with agricultural disruption were lowered in suitability by 10% and areas with a burn history were lowered by 20%.

2.2.3 **Prioritizations**

A systematic conservation planning (SCP) approach was used to structure the prioritization process (Figure 4). The structuring of the prioritization scheme was framed to investigate multiple goals: identifying priority areas on public lands, areas on private land which could be suitable for conservation easements and areas that could be suitable for restoration. For each of these goals, constraints were used to limit prioritization solutions to high-quality seasonal sage-grouse habitat outside of PACs. These objectives were investigated using different combinations of conservation features to create seasonal, annual, and multi-species scenarios.

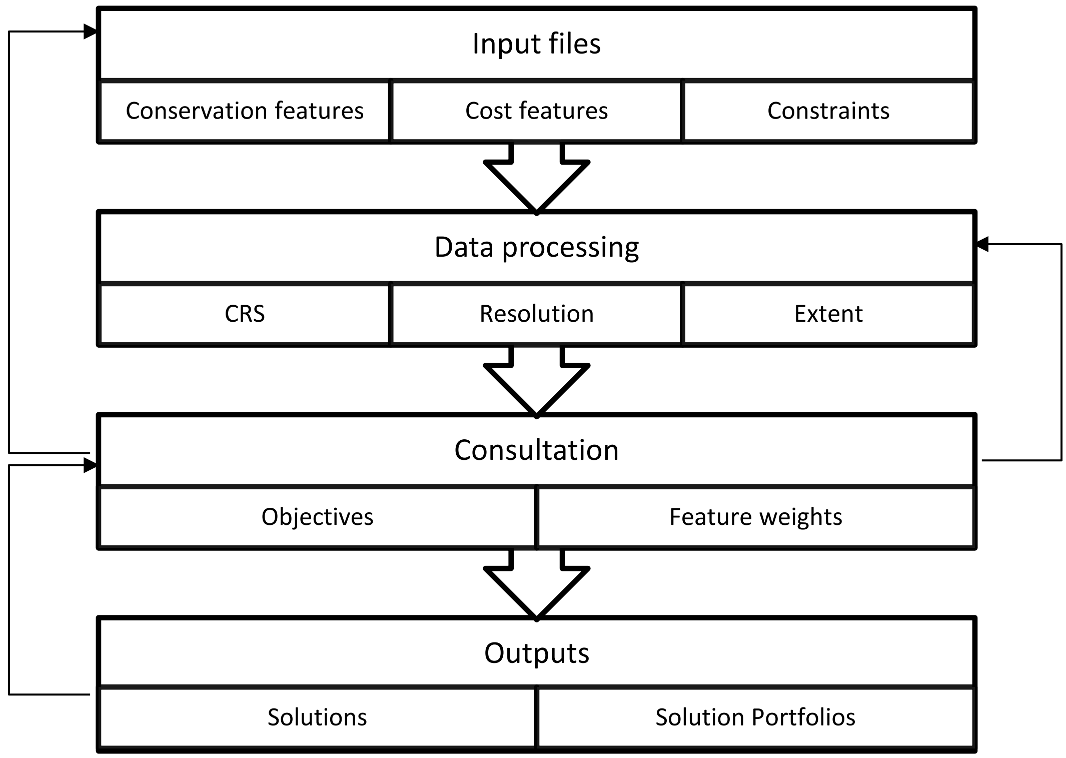


Figure 4. Workflow of the approach taken to engage in a prioritization process starting from the collection of input files, processing data for spatial consistency including Coordinate Reference Systems (CRS), iteratively engaging with consultation, and ending with the delivery of outputs, solutions and solution portfolios highlighting the best options for conservation action. Conservation features were optimized under different constraints and costs, to create a suite of comparable alternatives that have different complexities, trade-offs, and degrees of uncertainty. Consultation with land managers at the RSFO was used to identify relevant data, incorporate expert opinion, align the project goals with plans for the greater landscape, and determine feature weights.

Although SCP is typically used in the creation of protected areas and reserve designs, it is also applicable for determining areas that are suitable for expanding protected area networks, restoration, or other management actions. Restoration for sage-grouse can be highly costly and challenging, therefore most of our prioritizations focused on the mitigation of surface disturbance and identification of key areas outside of the PACs that support the movement of sage-grouse between habitat (Reinhardt et al., 2017; Rottler et al., 2018).

The prioritizations were carried out using *prioritizr*, a package available for use with R software, which applies an integer linear programming (ILP) to pose conservation problems that are optimized by third party solvers (Hanson, Schuster, et al., 2020; R Development Core Team, 2011). Recent advancements have expanded the capabilities of ILP making it possible to find deterministically optimal solutions for larger datasets, more complex problems, and in faster timeframes (Schuster et al., 2020). The seasonal sage-grouse HSMs contain more than 1,500,000 planning units at a fine-scale resolution of 120m x 120m, therefore *prioritizr* poses the best and most efficient approach for this application of SCP.

Decisions taken to structure the prioritizations can impact the usefulness of the resulting solutions, and researchers in ongoing consultation with stakeholders must scope prioritizations by software, data, objective type, targets, and budgets. Prioritizations typically use maximizing approaches with feature weights or target-based minimizing problems. Maximizing approaches determine the most ecologically beneficial configuration within a budget, although this may be less cost efficient than a minimizing approach, it addresses omission errors associated with targets (Davis et al., 2006; Kreitler et al., 2014). Maximizing approaches can be tailored to emphasize overall coverage, representation, diversity, or spatial overlap of conservation features, reflecting certain goals and data specific considerations. A maximum utility objective is a modification of the typical maximizing coverage approach which prioritizes for areas with the greatest overlap between features to determine where conservation actions could be most beneficial for multiple species. This objective type was chosen to structure the problem formulation for this study, due to its suitability for supporting decisions regarding the trade-offs between planning units which can inform negotiation among competing interest groups (Davis et al., 2006).

Conservation problems were limited by a budget informed by previous funding allocations for sage-grouse, the spatial needs of sage-grouse, and identified vulnerabilities. Seasonal sage-grouse habitat is highly clustered (Doherty et al., 2016; Walker et al., 2016), The PACs did not fully capture areas with ≥0.50 suitability for the nesting, brood, and winter seasons, leaving 13% of habitat unrepresented, half of which had a cumulative development probability = 1. Assuming management costs for a planning unit is $1,000, a budget of at least $195 million would be required to represent all 13%. Previous budget reports by the Sage-grouse Initiative (SGI) show that yearly investments of ~$50 million have been committed to sage-grouse conservation, while research has suggested that ~$250 million in targeted easements is needed to avert 9% to 11% of potential sage-grouse declines (Copeland et al., 2013). We applied a budget corresponding to an 8% or ~121,000 ha to address vulnerable habitat outside of PACs and restoration. Since we also determined priority areas across the landscape, including the PACs, we used a larger budget of 15% (~ 325,000 ha) to align with long-term funding plans.

Feature weights were used in the problem formulation to influence the representation of different conservation features and ensure that habitat which was underrepresented in the PACs could be targeted for selection. Feature weights were only applied to the annual and multi-species scenarios. Four weighting scenarios were used to influence the selection to favor 1) brood habitat, 2) winter and brood habitat, 3) landscape connectivity and 4) expert opinion. Winter and brood habitat were weighted higher in some scenarios as previous methods used lek counts to delineate priority areas which are more spatially related to nesting habitat and due to the higher degree of overlap between nesting and brood use areas, there is a higher representation of nesting (and multi season nesting and brood) habitat in the current protected area network (Smith, Beck, & Pratt, 2016). Sage-grouse populations show highly variable dispersal and interseasonal movement patterns (Fedy et al., 2012), in Wyoming, there is some overlap between seasonal habitat, especially nesting and brood, while winter habitat is more distinct and isolated (Berry & Eng, 1985; Fedy et al., 2014). Increasing the connectivity between patches of high-quality habitat has been identified as an important goal for future sage-grouse management (Connelly et al., 2012; Crist, Knick, & Hanser, 2017; Row, Oyler-Mccance, & Fedy, 2016). Therefore, to quantify and incorporate this feature, we also considered scenarios where landscape connectivity was weighted relatively higher than the other incorporated conservation features. We used consultation to solicit expert opinions from local state and federal biologists at the RSFO BLM office (See appendix for feature weight consultation form). To generate priority rankings for each conservation feature involved in the prioritization we used an analytical hierarchy approach and instructed experts to consider each conservation feature in pairs then summed the relative rankings for each feature to determine their weight (Mu & Pereyra-Rojas, 2018; Saaty & Vargas, 2012).

Study area boundaries and scale are important data features of the study design that can fundamentally influence the outcome of the prioritization process (Wiersma et al., 2019). Therefore, in addition to establishing what areas and data are appropriate to include in the analysis, it is also critical to consider where exclusions from consideration in the spatial prioritization process should be made. We addressed this issue in several different ways in our analyses, firstly, unsuitable areas including land that was already conserved, forested areas, open water, topographically unsuitable lands, major roads, pipelines, wind turbine sites, and urbanized areas were constrained from the solution. We also needed to consider trade-offs between pursuing prioritizations at different scales. For better application into management, multiple scales were presented in the final products of this study including an aggregated solution created with a factor of 13.41, resulting in a resolution of 1609 m x 1609 m, to reflect the management scale of 640 acres (USDA Forest Service, 2015). We ultimately pursued solutions using both scales, aggregating the data to increase computational capabilities, and then we reaggregated solutions to a resolution of 120 m x 120 m to incorporate land ownership used to mask out unsuitable areas at the finest scale. A nearest neighbor constraint was also used to incorporate greater connectivity in all scenarios as each selected planning unit had to have two bordering planning units also held in the solution.

It is unlikely that any single solution will be perfect given the highly complex nature of ecological management. Additionally, comparing multiple potential solutions can reveal the relative impact of the different user-defined parameters and help in the assessment of variance in solution outcomes. Portfolios can benefit a prioritization process by identifying more potential areas that could be useful for conservation providing greater flexibility to land managers. Therefore, we generated portfolios of 10 unique solutions for our priority area problems for each conservation feature scenario and summed the results to determine the selection frequencies of the planning units. Each of the 10 solutions had to be within 10% of the conservation value of the optimal selection and created with the same problem formulation, to allow for a greater degree of flexibility in the final product. Some of the prioritization scenarios in this study were formulated to determine vulnerable areas, but conflicting economic, political, and social needs for land in the RSFO were not explicitly addressed in these scenarios and therefore some of the lands selected may be in contradiction with other management goals. Providing land managers with multiple options and potential trade-offs is expected to lead to a higher probability of appropriately applying the plans and achieving conservation goals (Rodrigues et al., 2008; Sierra-Altamiranda et al., 2020).

2.2.4 **Analysis**

We assessed the relative performance of different solutions by quantifying the representation of key features in the solutions, the degree of fragmentation of the solutions, ROI, and capture of irreplaceable sites. Irreplaceability refers to the relative importance (range 0 - 1) of each planning unit in the selection, values of 1 being irreplaceable sites which are necessary to include in the prioritization meet conservation goals (Carwardine et al., 2007). Irreplaceability can be calculated in several ways, in this study irreplaceability was determined firstly with rarity weighted richness (RWR) which ranks each planning unit by its capture of species diversity based on Williams et al., 1996 which when translated into *prioritizr* refers to areas with the most overlapping features. A more robust measure of irreplaceability is the replacement cost based on Cabeza & Moilanen, 2006, which considers the value and costs specified for each planning unit to determine the loss in overall value (also termed as utility when using the maximum utility objective) incurred when a planning unit was locked out of the selection. This allows for the identification of planning units that could be suitable for trade-offs, for example, planning units with replacement cost values of 0 can reallocated to areas identified by expert opinion without impacting the solution quality. Calculating the replacement cost involves solving a unique problem for each planning unit in the study area, therefore it is highly computationally intensive for high resolution solutions and was only feasibly calculated for the aggregated solutions in this study.

Using irreplaceability as a measure of conservation value for each planning unit, return on investment (ROI) was calculated as sum of irreplaceability values in a solution divided by the cost of that solution (Cook et al., 2017; Murdoch et al., 2007). We assessed solutions in their structural connectivity with the landscapemetrics package for R. We calculated solutions at the landscape level, which provides a metric from 0-1 by identifying patches, to assess the size of each patch and the connectedness of planning units in the patches (Hesselbart et al., 2019). Annual and seasonal solutions were compared to determine if the annual solutions were able to capture the same highly irreplaceable areas identified by seasonal solutions and to determine if feature weights could appropriately address underrepresentation concerns. We generated solutions from multi-species scenarios to investigate how the added complexity altered site selection in terms of solution quality and the potential to reveal locations for synergistically beneficial conservation or policy action.

Prioritizations and analyses were implemented using R version 1.2.1335, *Prioritizr* version 5.0.2, and solved with Gurobi Optimizer version 9.1 (Gurobi Optimizer LLC, 2020; Hanson et al., 2020; R Development Core Team, 2011).

2.3 Results

2.3.1 **Site Characteristics**

Development has fragmented some of the RSFO landscape, development types included agricultural fields (0.6%), residential urbanization (0.02%), oil and gas extraction (7.2%) and wind farms (0.22%). Agriculture and wind development probability surfaces were more restricted spatially than oil and gas and residential development probability. Oil and gas development was the most expansive industry across the RSFO and 37% of areas in the RSFO had at least a 50% probability of being developed. Planning units with development probabilities ≥ 50% for residential, wind, and agriculture covered 13%, 1%, and 2% of the RSFO, respectively. We calculated the cumulative development probability for each planning unit by summing each development surface and 9.8% of the land in the RSFO had a cumulative development probability ≥ 1. Half of these sites were on private lands which, on average, had a 18% higher probability than BLM lands to undergo future development. Most (66%) of this vulnerable land (i.e., cumulative development probability ≥ 1) was outside of the PACs.

PACs in the RSFO overlapped with substantial proportions of important sage-grouse habitat, capturing 91%, 42%, and 37% of the top ranked (≥ 0.75) nesting, brood, and winter habitat. Including more marginal habitat (≥0.50), the PACs captured 80%, 79%, and 85% of nesting, brood, and winter habitat. The distribution of values in each habitat model were left skewed with mean values of 0.20, 0.25, and 0.11 for nesting, brood, and winter habitat. Suitability in the HSMs had a maximum value of 1, which made up 1% of the distribution in the winter HSM compared to 11% and 5% for nesting and brood HSMs. The upper quantile (75%) values for each season were 0.29 for nesting and brood and 0.12 for winter. Using the upper quartile to threshold the HSMs to the best 25% of habitat for each season, PACs captured 69%, 65%, and 73% of nesting, brood, and winter habitat and 7% of the nesting and brood seasons and 2% of the winter habitat model overlapped with vulnerable areas. A gap in coverage within the PACs for the best habitat in the brood and winter seasons and overlap between important habitat and areas predicted to be developed on poses potential vulnerabilities to sage-grouse throughout their lifecycle. Sage-grouse habitat also demonstrated variable vulnerability to the considered industries. For example, well pad scars had the most overlap with winter habitat at the upper quartile distribution whereas wind turbines overlapped more with nesting habitat. These vulnerabilities were addressed here using multiple information sources and consultation for a more comprehensive prioritization process.

Elk migratory routes and mule deer corridors were almost completely encompassed by PACs, capturing 88% and 70% of their respective distributions. Suitable habitat (≥0.5) for each season had varying overlap with other species data. Nesting habitat was present on 29% and 33% of the elk and mule deer migratory paths, whereas the brood and winter seasons spatially converged with 16% of the elk routes and 32% and 36% for brood and winter with the mule deer corridors. When considering habitat in the top 25% quantile, we found there was potential for the prioritization of sage-grouse to also benefit other species as the HSMs overlapped with 10% – 12% of the elk and 20% – 21% of the mule deer data. Elk and mule deer data also showed spatial consistencies with the landscape connectivity surface as 74% and 73% fell onto connected areas (landscape connectivity ≥ 0.75).

2.3.2 **Priority Areas**

We identified the most critical areas for sage-grouse as areas selected using the threat cost feature and limited to public lands, for the nesting, brood (Figure 5), and winter seasons, across the seasons or annually (Figure 6), and considering multiple species (Figure 7). Refer to Appendix A for priority area solutions not limited by land ownership (Supplementary Material; Figure 1 - 5). Of the seasonal solutions, 98%, 88%, and 99% of the selection were within the PACs. Additionally, 97% and 98% of the annual and multi-species solutions were also in the PACs.

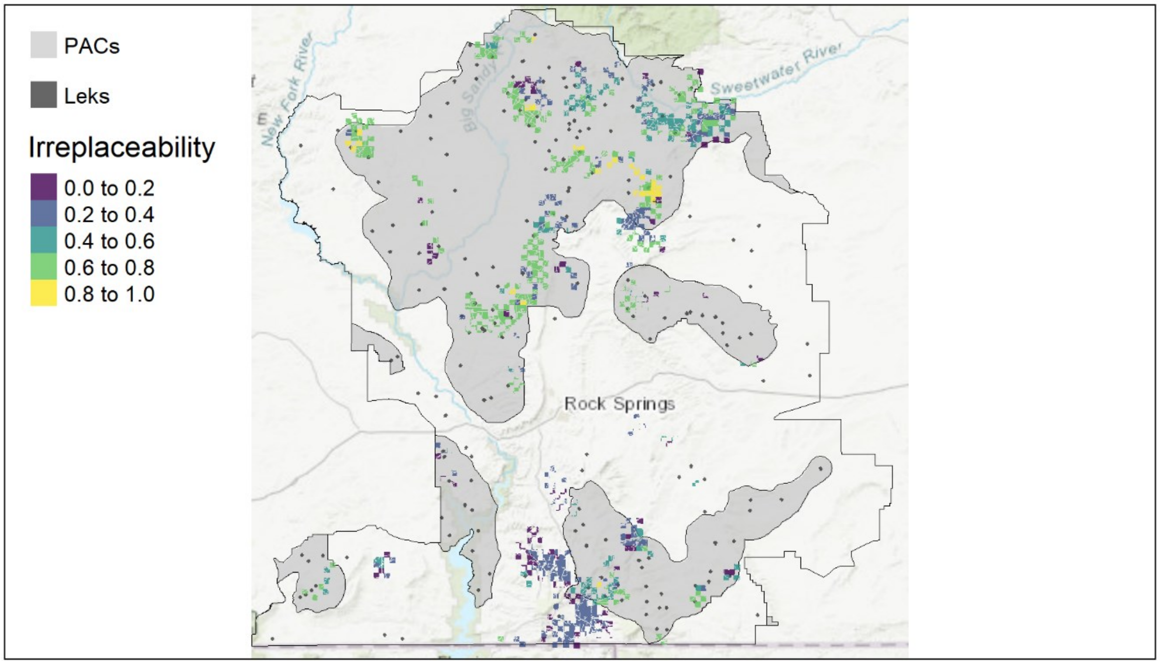


Figure 5. Priority brood habitat determined as areas on public lands with modelled high-quality brood habitat, areas important for connectivity, specific areas highlighted by consultation with experts, and areas with high predicted development probability, ranked by irreplaceability, the relative value of each selected area.

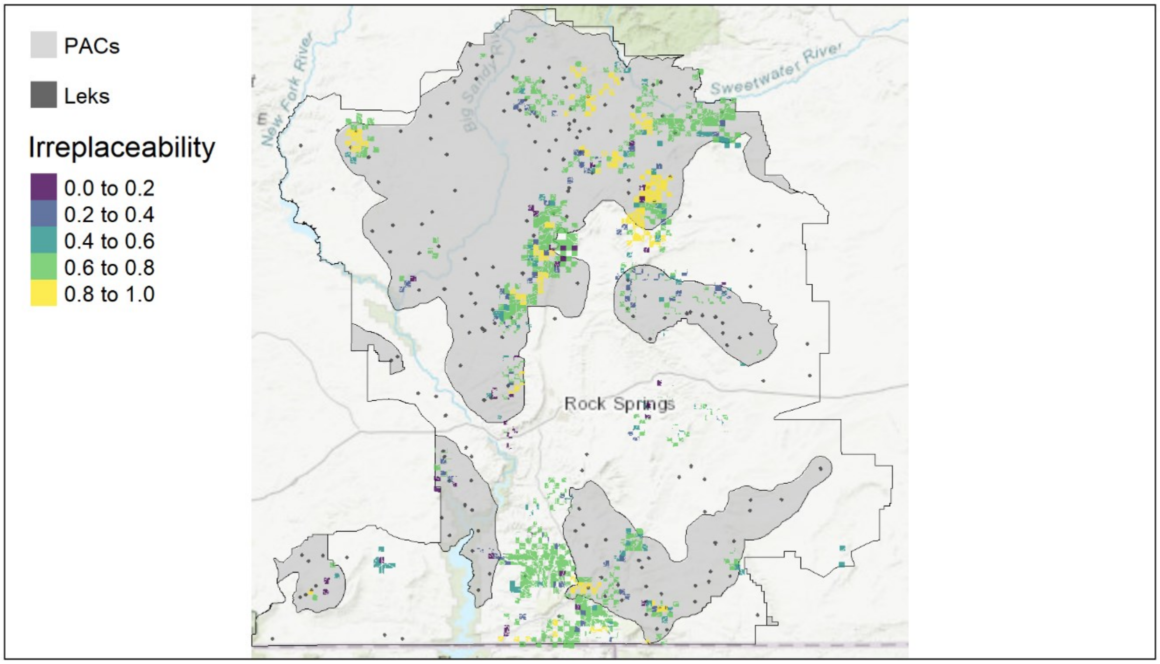


Figure 6. Annual priority habitat determined as areas on public lands with modelled high-quality habitat for each of the nesting, brood, and winter seasons, areas important for connectivity, with observed sage-grouse usage, specific areas highlighted by consultation with experts, and areas with high predicted development probability, ranked by irreplaceability, the relative value of each selected area.

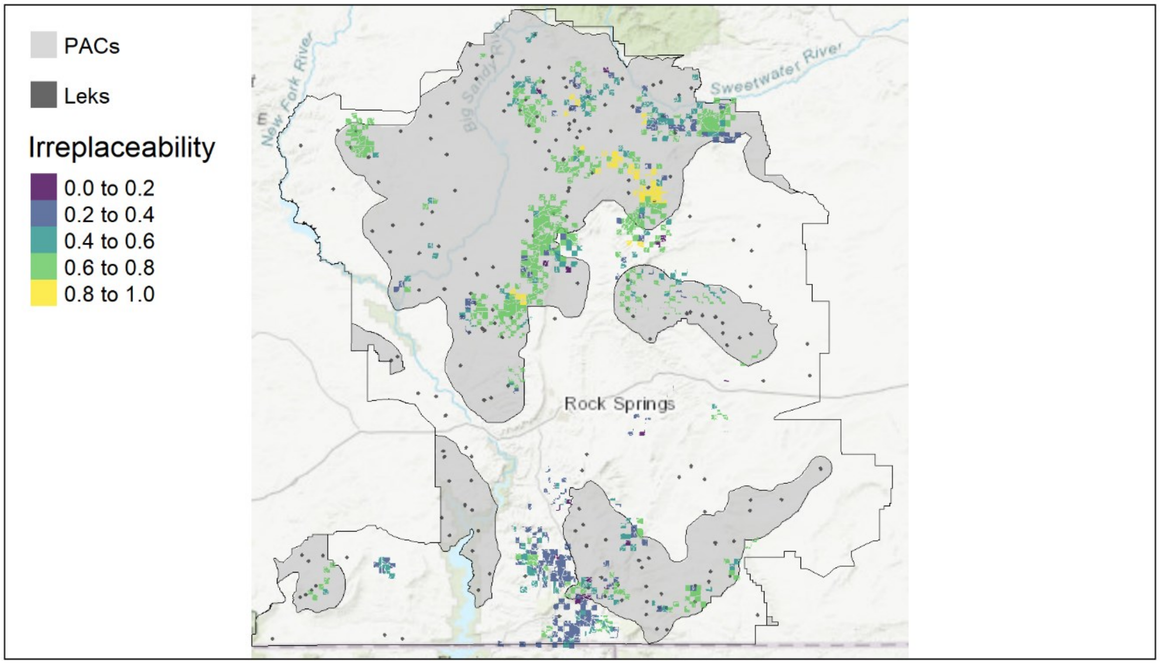


Figure 7. Multi-species priority habitat determined as areas with high conservation value on public lands with high predicted development probability. Surfaces included in this prioritization were habitat suitability models for each of the nesting, brood, and winter seasons, landscape connectivity, sage-grouse point observations, migratory corridors for ungulates mule deer and elk, and specific areas highlighted by consultation with experts, ranked by irreplaceability, the relative value of each selected area.

These solutions were assessed and compared to those similarly generated with the uniform and development potential cost features and modified with feature weights. We used metrics including representation of certain features, irreplaceability, ROI, and contiguity to evaluate the solutions. We determined the representation, the percentage of a surface's distribution retained in the solution, for key conservation features involved in our prioritizations including our foundational surfaces, the seasonal HSMs, and landscape connectivity. The maximum representation achieved for each seasonal habitat suitability model in our suite of prioritizations was 8.07%, 5.79%, and 9.58% for nesting, brood, and winter habitat. We addressed connectivity by explicitly incorporating the landscape connectivity surface and applying feature weights and contiguity constraints. The distribution of our landscape connectivity surface was generally bimodal with peaks at 0.25 and 0.75. Across the RSFO, 69% of the land was important for maintaining connectivity (landscape connectivity ≥0.75), although much of this landscape was within PACs, a sizeable portion (55%) of connecting landscape remains outside of PACs. Landscape connectivity was represented at a maximum of 4.04% of its distribution in priority areas solutions. In terms of irreplaceability, the proportion of selected sites ranked as irreplaceable (irreplaceability = 1) was ≤ 1% (mean = 0.63, SD = 0.21) for each priority solution. The sum of irreplaceability values ranged from approximately 13,000 – 16,000, with the annual and multi-species solutions demonstrating the largest irreplaceability overall and the winter seasonal solution being the lowest. Irreplaceability was impacted by the application of feature weights, although the winter and brood weighted solutions had comparable capture of irreplaceable sites, the total irreplaceability values were highest with landscape connectivity weights for the annual solutions and brood weights for the multi-species solutions and lowest for winter and brood weighted solutions (Table 2).

Table 2. Comparison of irreplaceability metrics for weighted solutions

Conservation features:	**Annual**				**Multi-species**			
Feature weight scenario:	Equal	Brood	Winter and brood	Landscape connectivity	Equal	Brood	Winter and brood	Landscape connectivity
% Sites irreplaceable	0.465	0.892	0.808	0.655	0.740	0.508	0.982	0.714
Sum of irreplaceability values	16566	16599	15724	19379	16611	25410	14563	11352
Irreplaceability per 1.44 Ha planning unit	0.260	0.258	0.205	0.308	0.252	0.345	0.208	0.187

ROI values ranged from 0.09 – 0.18 (mean = 0.15, SD = 0.029) with winter seasonal solutions demonstrating the lowest ROI and the highest achieved with the nesting seasonal solution. ROI was improved with weighting scenarios, for annual solutions, ROI ranged from 0.129 – 0.214 (mean = 0.167, SD = 0.035), and with equal weights the ROI was 0.164 which was increased by 0.05 when weights were set to target landscape connectivity. For multi-species solutions, ROI ranged from 0.127

– 0.217 (mean = 0.158, SD = 0.042), the equal weight scenario corresponded with an ROI of 0.159 and the greatest increase from that ROI was by 0.058 when the brood weighting scenario was applied. For both annual and multi-species solutions using a winter and brood weighting scenario returned the lowest ROI values.

Contiguity was similar across solutions although there were slight differences dependent on the features included in the prioritization and the application of feature weights. Considering only the solutions determined with equal feature weights, brood seasonal solutions were the least connected and annual seasonal solutions were the most connected (range: 0.93 – 0.94) (Figure 8. Contiguity, an index of spatial connectedness ranging from 0-1 determined for solutions identifying priority areas across seasonal, annual, and multiple species (multisp) which refer to scenarios signifying which conservation features were included in the prioritization.).

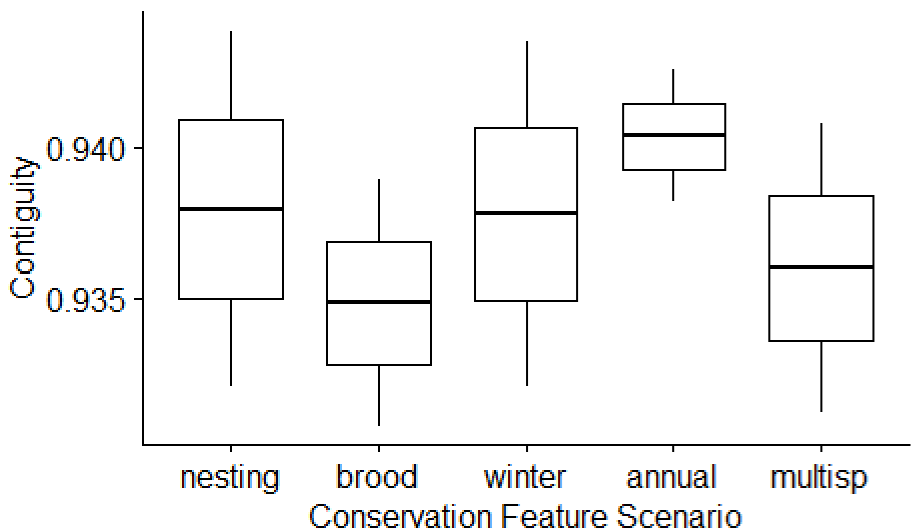


Figure 8. Contiguity, an index of spatial connectedness ranging from 0-1 determined for solutions identifying priority areas across seasonal, annual, and multiple species (multisp) which refer to scenarios signifying which conservation features were included in the prioritization.

Surprisingly, the application of landscape connectivity led to slightly decreased contiguity, whereas the winter and brood specific weights led to a the most contiguous solutions (Figure 9. Contiguity, an index from 0 – 1, compared across feature weight scenarios applied to the annual and multi-species solutions, more contiguity indicating better connected solutions (N=16).). The lack of variation in contiguity was likely due to the usage of a contiguity constraint which successfully offset the drawbacks of assigning priority weights to disparate features.

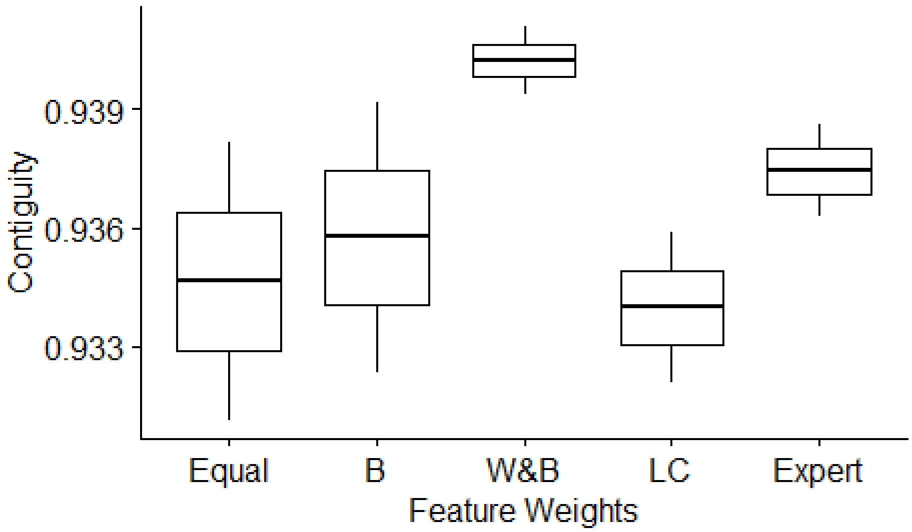


Figure 9. Contiguity, an index from 0 – 1, compared across feature weight scenarios applied to the annual and multi-species solutions, more contiguity indicating better connected solutions (N=16).

Next, we pursued solutions constrained to areas outside of the PACs to determine if focal areas were being overlooked by existing protections and to target areas that could be suitable for expanding the PACs (Figure 10).

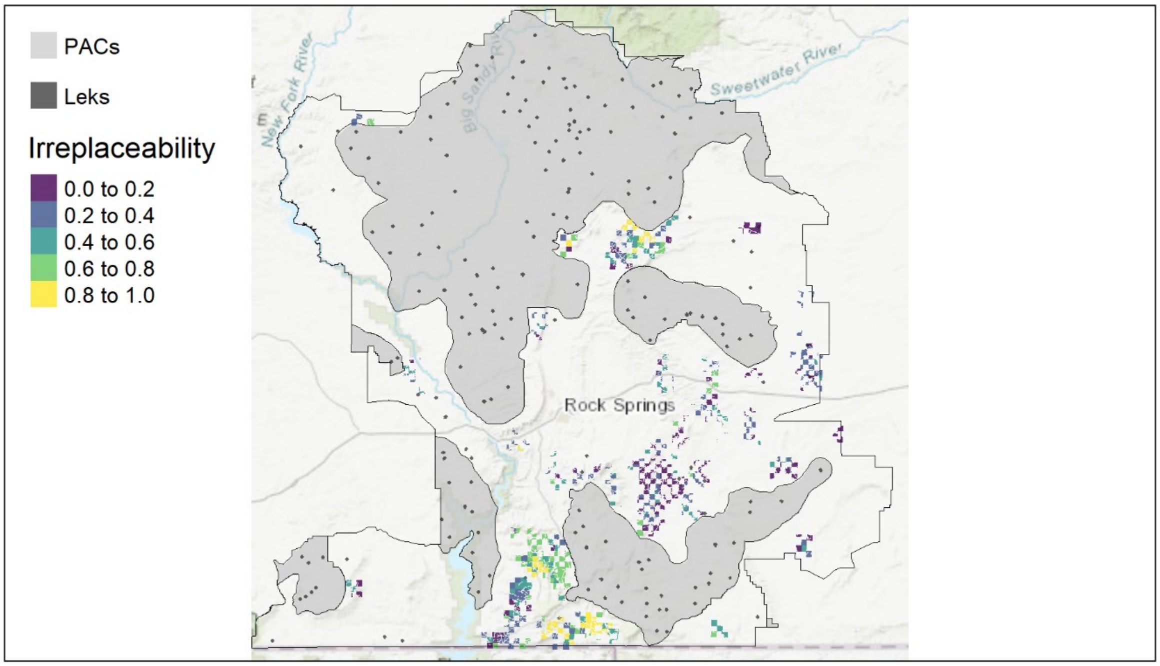


Figure 10. Priority habitat that could benefit from disturbance limits or the expansion of policies relevant to the priority areas for conservation (PACs). This was determined as areas outside of the PACs on public lands with modelled high-quality habitat for each of the nesting, brood, and winter seasons, important for connectivity, with observed sage-grouse usage, specific areas highlighted by consultation with experts, and areas with high predicted development probability, ranked by irreplaceability, the relative value of each selected area. A complete list of the surfaces involved in generating this solution is provided at Table 1. Spatial surfaces and their sources used for this prioritization.

Table 3. Comparison of how applying the priority areas for conservation (PACs) as a constraint alters the representation of key conservation features including the three seasonal habitat suitability models (nesting, brood, and winter) and landscape connectivity.

	PACs included				PACs excluded			
Conservation features:	**Nesting**	**Brood**	**Winter**	**Landscape Connectivity**	**Nesting**	**Brood**	**Winter**	**Landscape Connectivity**
% feature representation (max)	8.07	5.79	9.58	4.04	8.44	6.54	4.69	4.01
% feature representation (mean)	6.86	4.99	6.93	2.95	3.44	3.53	2.54	2.20
% feature representation (SD)	0.92	0.70	1.47	0.44	1.74	1.09	1.03	0.79

Irreplaceability had the highest sum for the nesting seasonal solutions (28,563, mean = 21,658.83, sd = 7332.95), the lowest was determined for multi-species (13,890) and winter seasonal solutions (13,509). These values differed from when PACs were included in the solutions and excluding PACs led to an increase in irreplaceability values for each scenario except for the multi-species solutions (.

Table **4**).

Table 4. Irreplaceability sums for priority solutions with priority areas for conservation (PACs) included for selection and excluded as a constraint.

Conservation feature scenarios:	**Sum of irreplaceability values**		
	PACs included	PACs excluded	Difference (PACs excluded – PACs included)
Nesting	16006	28563	12557
Brood	15248	26176	10928
Winter	13222	13509	287
Annual	16566	26157	9591
Multi-species	16611	13890	-2721

ROI values for PAC constrained solutions ranged from 0.4 – 1.23 (mean = 0.81 standard deviation = 0.27), the lowest ROI value was determined for a winter seasonal solution and the highest was for a brood seasonal solution. Interestingly, comparing solutions that included or excluded PACs, the brood seasonal and the annual solutions had higher ROI values when PACs were excluded suggesting valuable and cost effective areas important for the brood habitat are outside of PACs. In comparision, all other solutions had higher ROI values when PACs were included in the solution presumuably because the PACs represented the best habitat in the landscape. In contrast to solutions with the PACs included, solutions outside of PACs were most connected when pursuing multi-species scenarios and without the usage of features weights.

2.3.3 **Conservation Easements**

We applied constraints based on landownership to tailor our prioritizations to objectives that aimed to identify areas suitable for specific management actions including conservation easements and restoration. BLM and USBR lands (referred to as public lands) covered 71% of the RSFO and comprised a large portion of the upper quantile values for each seasonal HSM, capturing 78%, 79%, and 80% for nesting, brood, and winter. Private lands made up 23% of land ownership in the RSFO and represented 18% of the top nesting habitat and 16% for brood and winter. The remaining lands are largely state-owned and US Fish and Wildlife conservation areas. Existing development occurs at similar rates on private and public lands, covering 21% and 23% of their respective distributions.

We used landowner constraints to find private land areas that could be suitable for conservation easements benefiting multiple species using our threat and development potential cost surfaces (Figure 11 and Figure 12).

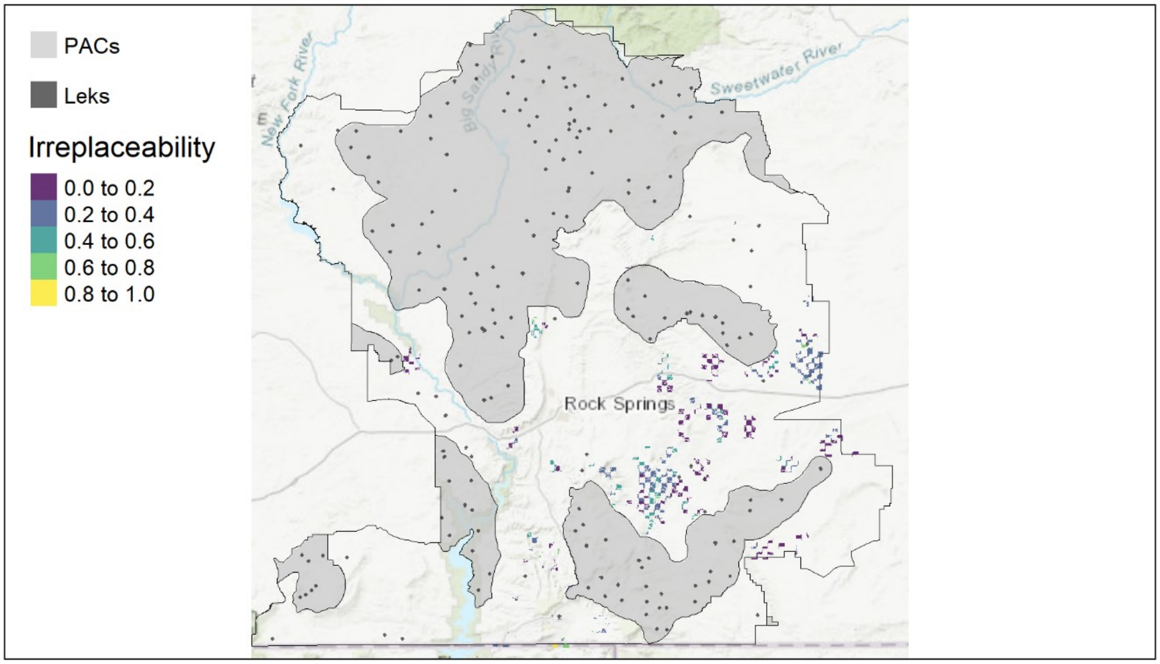


Figure 11. Priority habitat that could benefit from conservation easements were determined as areas outside of the PACs on private lands with high predicted development probability. Features included the seasonal habitat suitability models, landscape connectivity, sage-grouse point observations, elk and mule deer migratory data, and expert opinion surfaces, Selected planning units are ranked by irreplaceability, the relative value of each selected area.

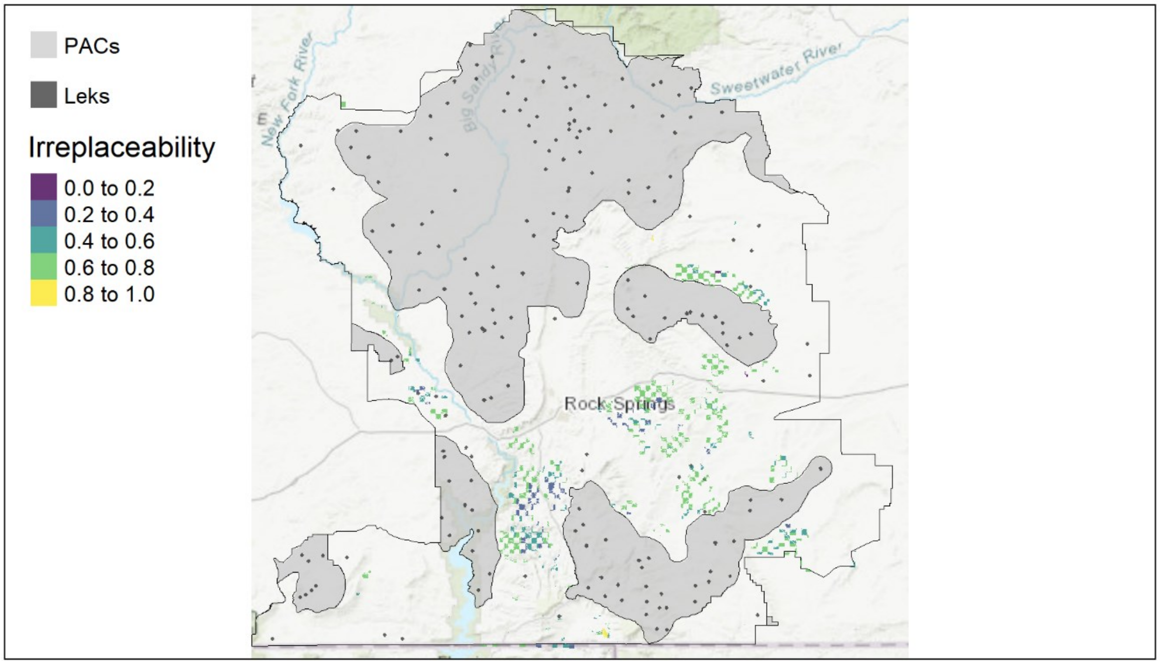


Figure 12. Priority habitat that could benefit from conservation easements and with low development potential determined as areas outside of the PACs on private lands. Surfaces included in this prioritization were the seasonal habitat suitability models, landscape connectivity, sage-grouse point observations, elk and mule deer migratory data, and expert opinion surfaces. The selected planning units were ranked by irreplaceability, the relative value of each selected area.

Easement solutions compared to the priority area solutions had reduced representation of each HSM and of landscape connectivity. The highest representation for each feature was achieved by pursuing a nesting seasonal solution which captured nesting, brood, winter, and landscape connectivity across 3.14%, 2.39%, 1.83% and 1.86% of their respective distributions. The sum of irreplaceability values was impacted by the solution size, since there is less private land available in the RSFO, easement solutions had lower sums, however, considering irreplaceability per planning unit, easement scenarios had similar gains in irreplaceability per planning unit. When investigating solutions for priority areas including and excluding the PACs, when PACs were included the nesting seasonal solution had the highest irreplaceability per planning unit, in contrast, conservation easements solutions achieved the highest irreplaceability per planning unit for annual and brood seasonal solutions regardless of the inclusion of PACs. Similar to priority area solutions, the ROI values for easement solutions were highest with the brood seasonal solutions and annual and multi-species solutions were improved with the landscape connectivity weighting scenario. Finally, easement solutions demonstrated the lowest contiguity compared to priority area solutions. Feature weights did not significantly improve the contiguity of these solutions but the inclusion of more conservation features in the multi-species solutions achieved the highest contiguity.

2.3.4 Restoration

We determined areas suitable for restoration using different conservation features from our other solutions and our development potential cost feature (Figure 13). We only calculated representation for the landscape connectivity surface for these selections because we targeted marginal habitat to avoid suggesting intensive management on areas that are maintaining resiliency, and relatively untouched by development. The representation of landscape connectivity in restoration solutions was low at capturing ~ 1% of its distribution. Constraining restoration solutions outside of PACs had a noticeable impact on the calculation of irreplaceability and each planning unit was much more important when PACs were not included. For restoration solutions excluding PACs each planning unit had an average irreplaceability of 0.52, when PACs were included the average irreplaceability of a planning unit was 0.16. Restoration solutions including the PACs achieved better ROI values than solutions excluding PACs, due to a reduced solution cost. Contrastingly, there were less clumps but more boundary planning units for restoration solutions in PACs compared to solutions outside of PACs.

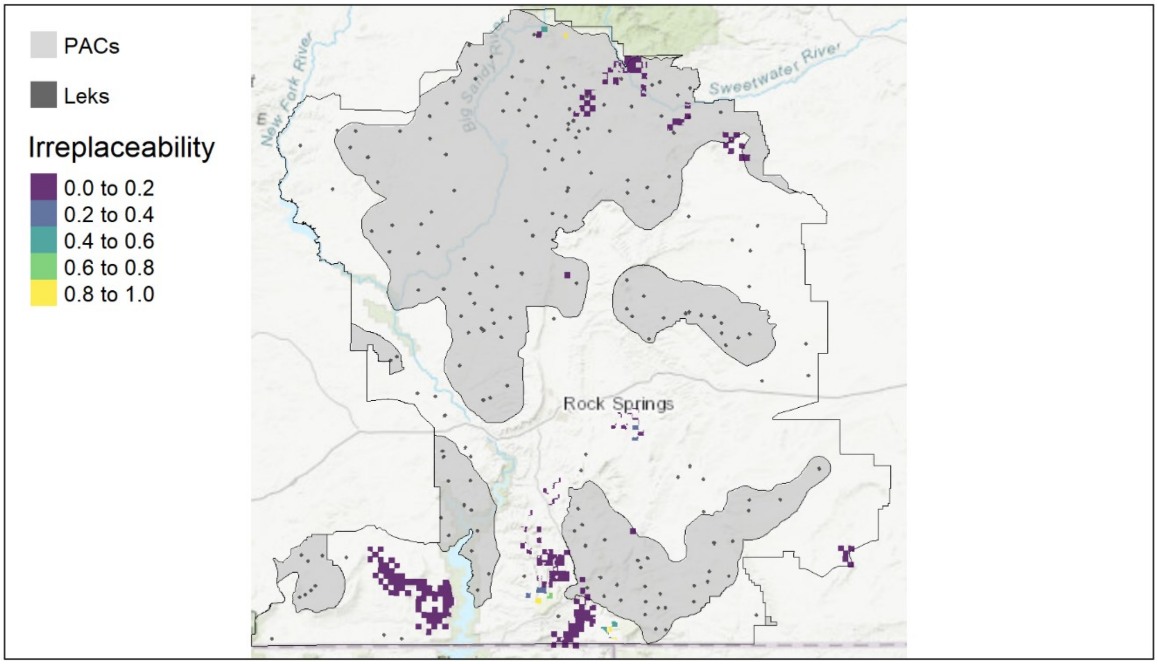


Figure 13. Areas suitable for restorative management that could benefit sage-grouse for any season, these locations were determined as edge habitat, connecting areas, with increased fire danger, proximal to existing development, and to abandoned leks.

2.3.5 **Features**

Incorporating cost as development potential or threat, impacted the representation of the seasonal HSMs and landscape connectivity in the solutions. Regardless of the inclusion of PACs or landowner constraints, using the development potential cost feature achieved higher representation for each HSM and landscape connectivity (Table 5). In other metrics development potential solutions out-performed threat solutions such as higher ROI and irreplaceability values as a sum or per planning unit. In terms of contiguity, solutions generated with the threat cost feature were more connected.

Table 5. Comparison of representation of the nesting habitat suitability model for solutions generated with either the development potential or threat cost feature (N=88).

Cost feature	N	Mean nesting habitat representation (%)	SD
Development Potential	44	4.25	2.48
Threat	44	3.10	2.08

The conservation features included in the prioritizations largely shaped most of the selection of priority areas. Some key areas for conservation were selected regardless of the cost feature but remaining conservation funds were allocated differently, revealing patterns of threatened landscape closer to existing development and on disproportionately occurring on private land (Figure 14).

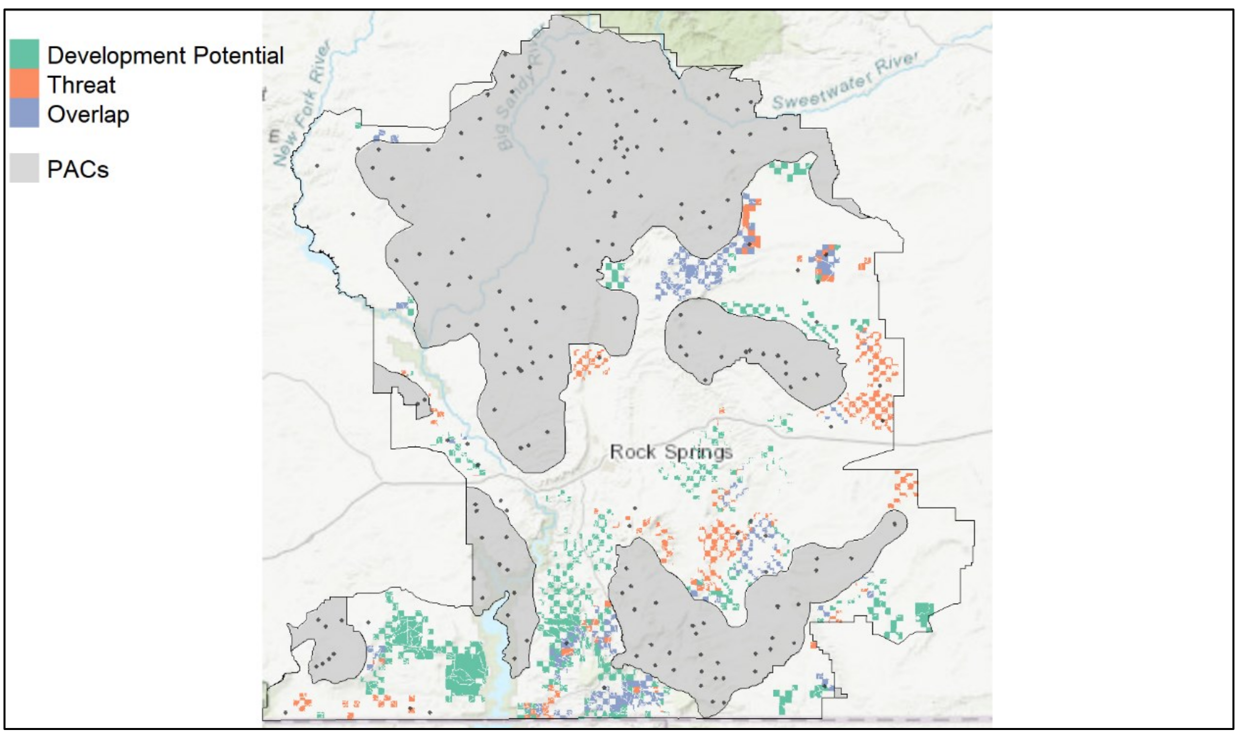


Figure 14. Overlay of two solutions generated with differing cost features, development potential and threat cost otherwise parameterized with the same objective: to target multiple species on public lands outside of the priority areas for conservation (PACs).

We expected to observe a trade-off with the inclusion of more features in the prioritizations, with an expected decrease in the representation of each seasonal habitat feature as the algorithms solved for a balanced representation with each additional feature. However, including more conservation features in the prioritizations led to reductions in the representation of the seasonal HSMs as representation was balanced across additional features. Comparing seasonal and annual solutions, representation of the seasonal HSMs was reduced by < 1% except for the nesting HSM which was reduced by 1.3%. Multiple species solutions which also included the elk and mule deer migratory surfaces came with a greater trade-off as both the nesting and winter representation was decreased by > 1%. A benefit to including more conservation features is the potential to identify more areas with overlapping benefits while minimizing undesirable aspects of the solution like fragmentation by virtue of more viable options available for selection that increase utility of the solution. Delineating groups of conservation features by seasonal, annual, and multi-species prioritizations allowed us to assess the potential benefits and drawbacks of applying concepts like umbrella species in this species-specific prioritization effort.

2.3.6 **Feature Weights and Expert Opinion**

Using feature weights to increase the representation of target conservation features, had variable success depending on the features targeted and the problem parameters. The mean representation of landscape connectivity, and brood and winter HSMs were higher with the use of feature weights but effects were minor and feature weights were less effective in directing representation when solutions were limited to private lands and when development potential was used as the cost feature (Figure 15 - 17).

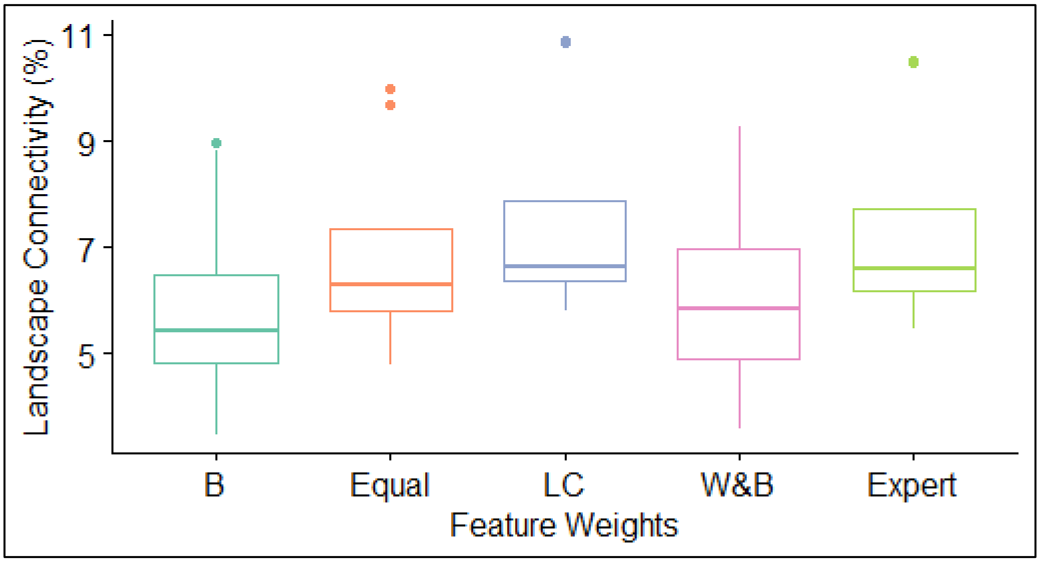


Figure 15. Representation of the landscape connectivity surface with feature weight scenarios brood (B), Equal, landscape connectivity (LC), winter and brood (W&B), and expert.

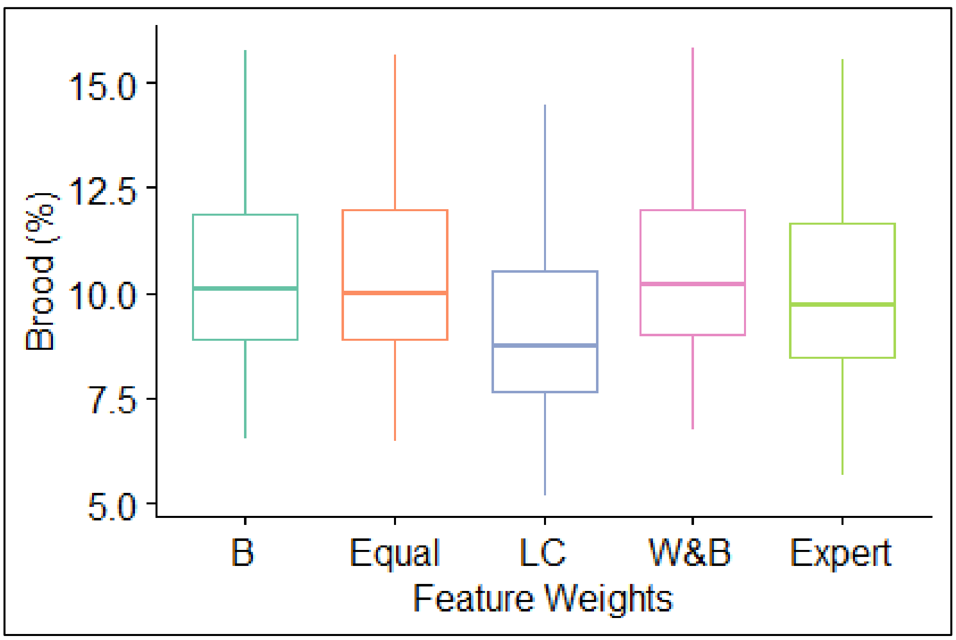


Figure 16. Representation of the brood habitat suitability model with feature weight scenarios brood (B), Equal, landscape connectivity (LC), winter and brood (W&B), and expert.

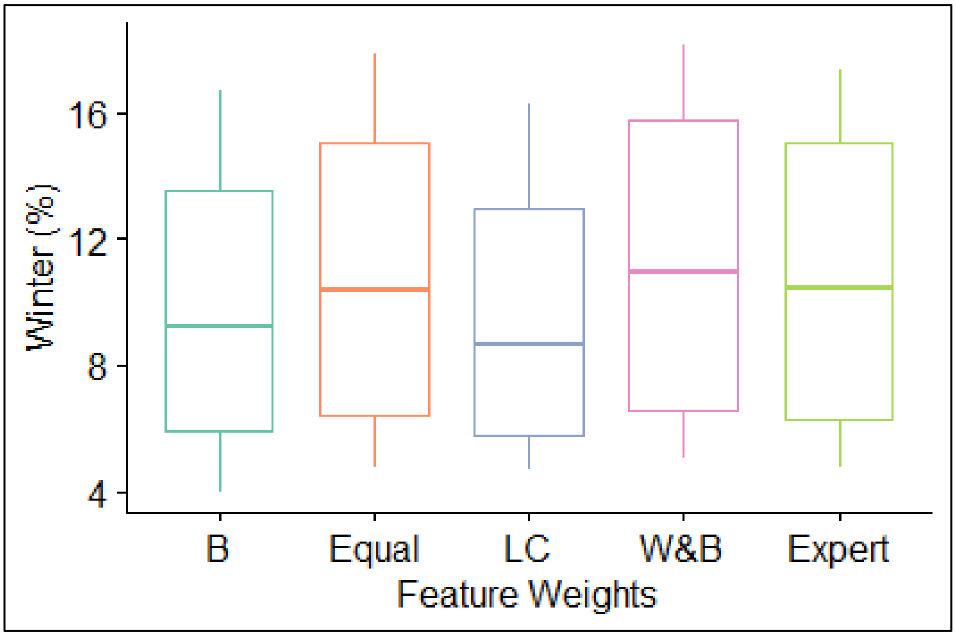


Figure 17**.** Representation of the winter habitat suitability model with feature weight scenarios brood (B), Equal, landscape connectivity (LC), winter and brood (W&B), and expert.

Expert opinion influenced this prioritization effort by helping to identify data that could be included in the prioritizations, aligning objectives with management goals, identifying unsuitable locations, and pointing out special areas of interest. Through the application of feature weights guided by expert knowledge we were able to better tailor our prioritizations to the specific needs of the RSFO. For example, considering a conservation problem that aimed to conserve multiple species on public land with each of the feature weight scenarios: equal, brood, winter and brood, landscape connectivity, and expert, 81.2% of selected planning units were identified in at least two of the feature weight scenarios (Figure 18). Of the planning units that were unique to a feature weight scenario, the majority (38.2%) were identified with winter and brood feature weights, in contrast the applying the expert opinion feature weights made up 9.53% of the unique planning units. Solutions generated with landscape connectivity and expert opinion weights performed best in terms of ROI values (Figure 19).

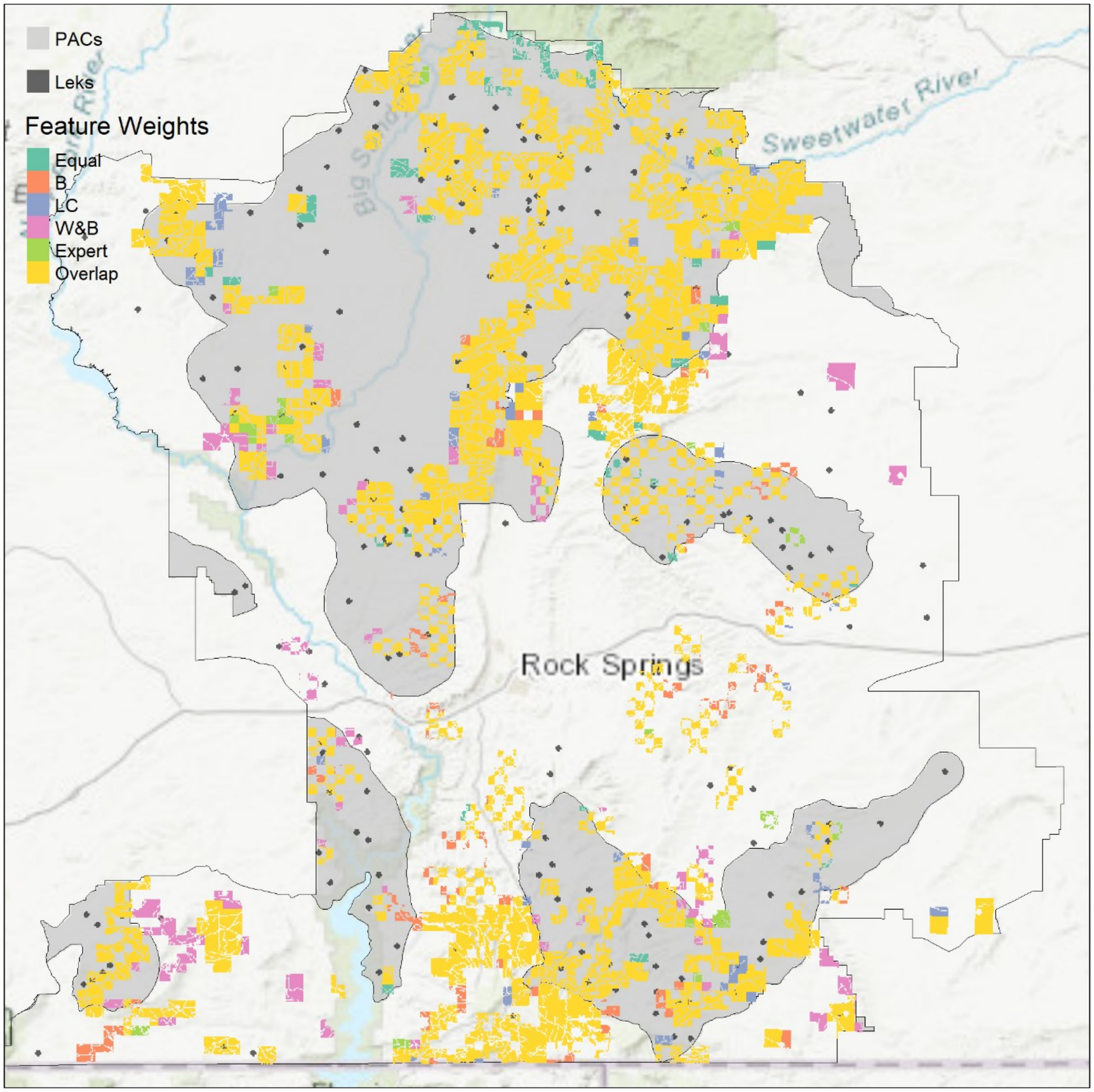


Figure 18. Selected areas for multiple species on public land across the landscape by the five feature weight scenarios: equal, brood (B), winter and brood (W&B), landscape connectivity (LC), and expert, overlap being areas selected by any two solutions.

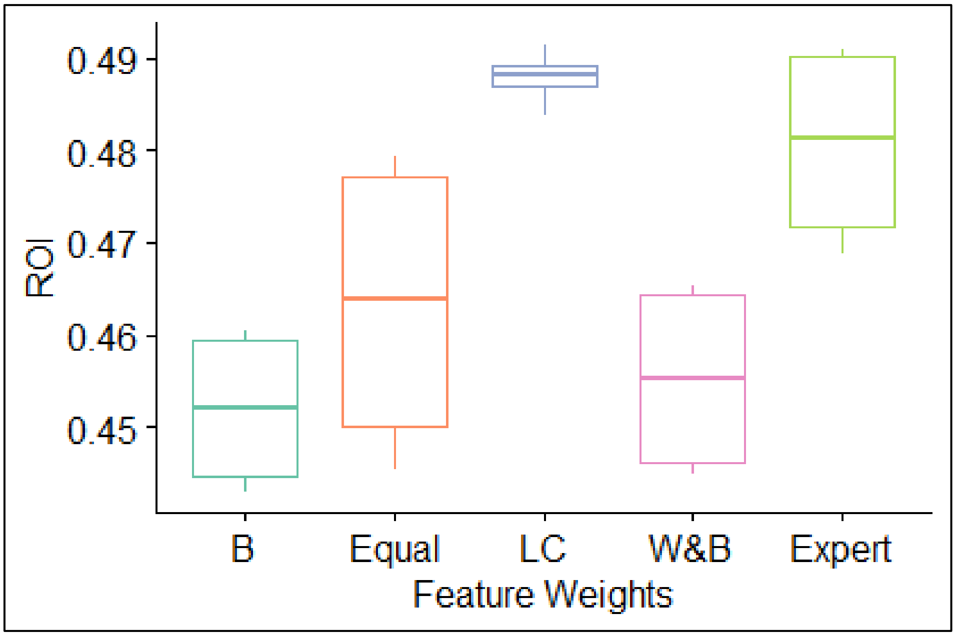


Figure 19. Return on investment (ROI) for the five feature weight scenarios: brood (B), equal, landscape connectivity (LC), winter and brood (W&B), and expert.

Developing fine-scale solutions can be time intensive due to the computational speed and power required, aggregated data was useful to investigate a greater variety of scenarios and access more robust calculations (rarity weighted richness vs. replacement cost). Data pertaining to landowner constraints could not be aggregated to a coarse scale without losing relevant accuracy therefore we incorporated landownership after the solutions had been generated causing an omission of certain areas that were unsuitable. Constraining our solutions to private lands led to the loss of more planning units and had a greater impact on solution quality than constraining solutions to public land. It is important to note that our solutions do not represent minimums for persistence but a starting point for suggesting suitable areas and need to be considered together to form a connected protected area network. Portfolios were left unconstrained by landowner data to provide a broader picture of where conservation priority areas are and what offsets would be suitable if certain areas are unavailable or infeasible for a proposed conservation action. The portfolios in Figure 20 show priority areas outside of PACs with the highest selection frequencies in yellow, areas consistently selected are represented in green, and blue and purple show areas that are not necessary to meet conservation goals and would be suitable for reallocating funds with consideration of onsite realities and to negotiate different reserve designs.

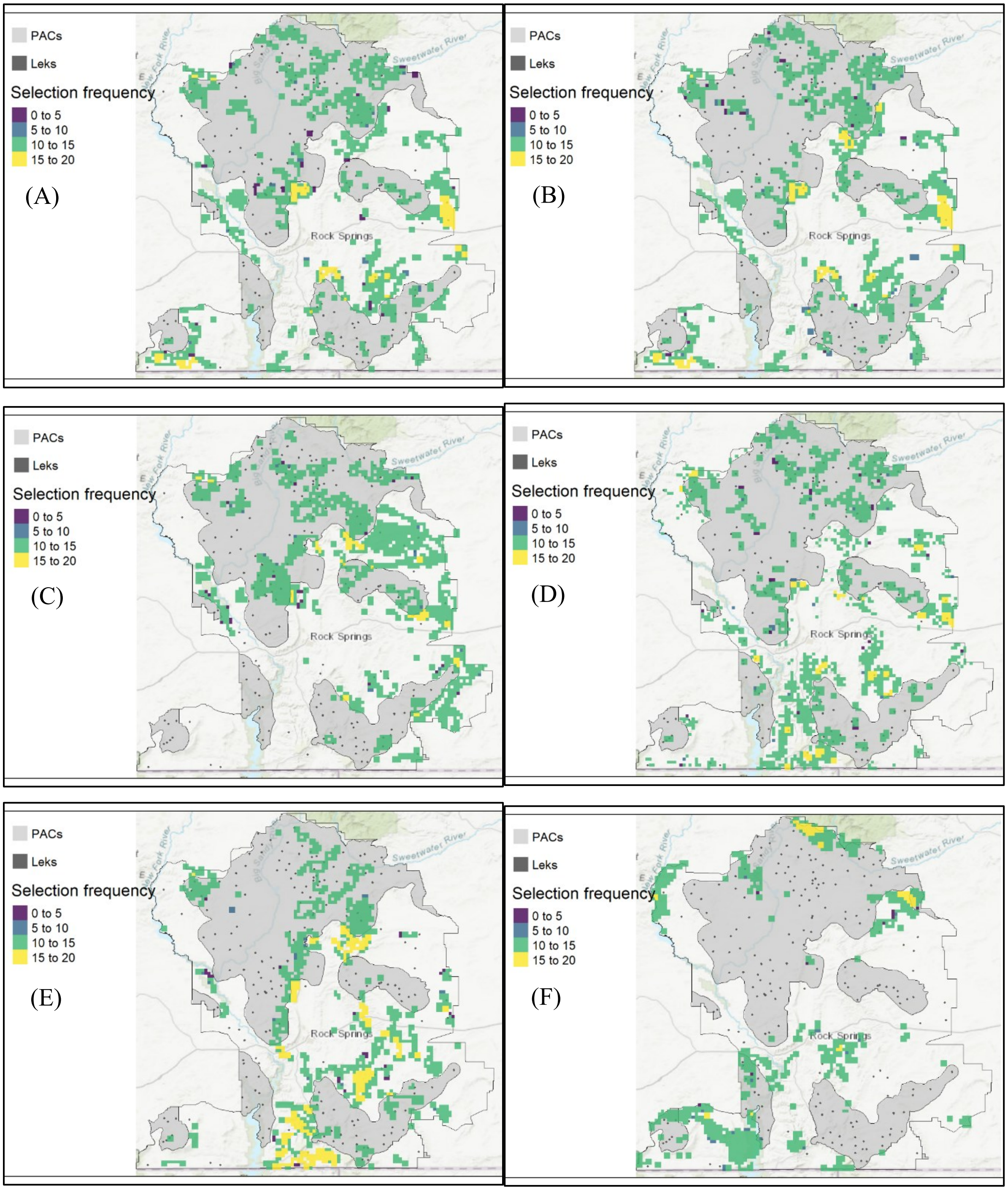


Figure 20. Selection frequencies with an emphasis for areas consistently selected outside of the PACs, even when PACs were included in the prioritizations. We determined these by generating portfolios of 10 unique solutions within 10% of optimality for two options, including and excluding the PACs,

leading to 20 solutions for the A) nesting, B) brood, C) winter, D) annual, E) multiple-species, and F) restoration scenarios.

2.4 Discussion

2.4.1 Conservation Priorities

We successfully identified areas across the RSFO that are the most important for sage-grouse persistence, the best habitat being largely in the northern areas of the RSFO and captured in the PACs. Engaging with habitat management outside of the PACs is expected to be important for the long-term survival of sage-grouse which rely on connectivity between PACs for genetic and habitat linkages, population expansion, and uncaptured seasonal use areas (Fedy et al., 2012). Habitat outside of PACs could also be key for managers to maintain flexibility in changing climactic conditions. An emerging objective in the RSFO is to address the threats to sage-grouse conservation in by identifying vulnerable areas outside of PACs on private and public lands, suitable for management actions (Doherty et al., 2012). Therefore, we focused our selections to identify priority habitat that borders and connects the PACs to find areas suitable for PAC expansion. We determined that there is an unprotected corridor linking the PACs in the northeastern portion of the study site that is predicted to be used by sage-grouse in the brood and winter seasons, facilitates sage-grouse gene flow indicated by the landscape connectivity surface, and is also important for elk and mule deer migration (Figure 10).

Pursuing prioritizations for each stage of the sage-grouse lifecycle was important to this prioritization process because it allowed for the consideration of management actions specific to a season and addressed concerns with uncertainty in the data brought up through consultation. We also found varying degrees of vulnerability to loss across the seasons indicated by underrepresentation by the PACs and a high proportion of irreplaceable sites especially when PACs were used as a constraint. Previous research has suggested that the designation of irreplaceable sites should be limited to 20% of the selection (Levin et al., 2015). Of our selections <1% of the planning units were irreplaceable corresponding to an area of 257.5 ha on average. Comparing solutions using PACs as a constraint and those including PACs, we found there were similar proportions of irreplaceable sites, but the winter and multiple species solutions had more irreplaceable sites outside of PACs. This result demonstrates the vulnerability of sage-grouse winter habitat and the vulnerability of elk and mule deer routes due to lacking coverage of the PACs.

Seasonal sage-grouse habitat is highly clustered (Doherty et al., 2016; Walker et al., 2016) and the protection of core population areas has been the focus of the management actions and the development of the PACs. As a result, areas with marginal suitability values which are likely also important for population connectivity, require greater attention in future conservation plans. As expected, nesting habitat was the best represented season by the PACs, and we determined that brood habitat was the most underrepresented season in terms of selected areas outside of PACs. However, winter habitat had the most irreplaceable areas outside of PACs. Using PACs as a constraint in our solutions benefitted our prioritizations because solutions limited to areas outside of the PACs had higher ROI and irreplaceability values and similar contiguity to when habitat inside of the PACs could be selected.

We were able to identify areas surrounding the PACs that would benefit from being assessed for expanding the PAC policies. The benefits of PAC designation can extend to other species including the migratory corridors of elk and mule deer in the region. Maintaining greater connectivity across the PACs could also benefit multiple species, in fact, terrestrial migrants rely on intact connectivity throughout their entire route more than avian species and our study is further evidence for the compatibility of considering ungulate movement pathways alongside sage-grouse conservation (Copeland et al., 2014; Gamo & Beck, 2017; Tack et al., 2019). Previous research found that extractive energy leases in Wyoming are increasing outside of PACs when compared to within PACs (Gamo & Beck, 2017). An important caveat of enforcing surface disturbance caps within the PACs is that areas outside PACs may be developed more intensively (Tack et al., 2019). Pervasive to conservation planning efforts is the assumption that populations within protected areas will persist and populations outside of protections will decline or be lost. Therefore, the long-term viability of sage-grouse populations may require not only supporting priority areas but also considering expanding the PACs to underrepresented seasonal and connecting habitats and engaging in active restoration.

Conservation easements are an important route for conservation; they have demonstrated previous successes in contributing to large conservation plans for sage-grouse (Copeland et al., 2013; Pocewicz et al., 2011) and engaging with private landowners will be necessary to manage sage-grouse with cohesive conservation plans that target vulnerable habitat (Smith et al., 2016).

Engaging in restoration to increase sagebrush coverage at strategically selected areas can help sage-grouse populations by mitigating interacting stressors including the spread of invasive grasses, increasing in intensity of wildfires, and conifer expansion (Balch et al., 2013; Chambers et al., 2017; Coates et al., 2016; Pilliod et al., 2017). Habitat requirements for sage-grouse persistence are closely related to contiguous stretches of sagebrush but sage-grouse can also be found on areas with low sagebrush coverage. The Wyoming Basin is particularly well connected and this management zone has a relatively low minimum of ~ 35% sagebrush coverage associated with a high probability (>65%) of sage-grouse occurrence (Doherty et al., 2016). This makes the area opportune for restoration because marginal habitat areas support movement across core areas of sage-grouse habitat, this is important for maintaining sink populations and the opportunity for adaptation to changing conditions (Connelly et al., 2012). Passive restoration, allowing a habitat to restore itself, can be an effective approach to restoration, but for the sagebrush system, due the multifaceted threats and ongoing declines, active restoration, like planting seed mixes, is necessary (Finch et al., 2016). Sagebrush recovery has been estimated to take from 15 – 100 years, dependent on the species, climate and conditions of the site prior to restoration (Baker, 2006; Davies & Bates, 2017; Nelson et al., 2014). Sagebrush restoration faces many challenges including low success rates especially at previously burned sites and sagebrush seeds are viable for only two years leading to restricted seed banks (Pyke et al., 2020). Using the results presented in this study to select areas for restoration must be met with caution and reserved for areas that have also been thoroughly assessed for suitability for passive or active restoration using previously developed approaches and frameworks (e.g., Pyke et al., 2017; Ricca & Coates, 2020). Planning restoration in this ecosystem requires a long view of future outcomes because sagebrush is slow growing (Davies & Bates, 2017). Land managers can use our products to develop a schedule for management by prioritizing areas that need immediate action denoted with high irreplaceability values.

2.4.2 Study Limitations

The certainty of the prioritization results was impacted by the accuracy and precision of the underlying data pieces. Compared to the resulting nesting and brood HSMs, the winter HSM is expected to have the most uncertainty due to the importance of microhabitat features and variability of snow cover impacting how sage-grouse choose winter habitat each season (Connelly et al., 2000; Crawford et al., 2004; Doherty et al., 2008). Annual and multiple species solutions were useful in mitigating the drawbacks between individual seasonal solutions. For example, winter seasonal solutions had relatively low ROI and irreplaceability values, nesting seasonal solutions had the lowest contiguity and the highest solution cost, annual solutions performed the best in terms of ROI and irreplaceability whereas multiple species solutions were the most contiguous and the cheapest. Incorporating multiple conservation features, in particular features generated through consultation (expert opinion surfaces) and utilizing priority rankings, were effective in offsetting uncertainty in some surfaces because the emphasis of certain areas that were misaligned with on-site realities were restricted. For example, although sage-grouse have been shown to use agricultural fields (e.g., Shirk et al., 2017), these areas are not expected to be suitable for conservation and therefore HSM values were manually reduced to decrease the representation of these areas. Similarly, we adjusted how burned areas would be included in our prioritization, excluding them as priority areas and instead considering these areas for restoration. We also constrained developed areas from multiple industries from being retained in our solutions but did not consider that some areas, like well pad scars, may be inactive or reclaimed.

Although we did not address how targets compare to feature weights in this study, we expect that feature weights led to higher quality solutions. Determining ecologically relevant and feasible targets is challenging, especially in the context of multiple and overlapping conservation features (Arponen et al., 2005; Svancara et al., 2005). Instead, policy objectives have formed the basis of many commonly used targets despite criticism that policy-based targets are typically set too low to adequately cover ecological needs, and targets that are set too high can lead to underrepresentation as infeasible targets are abandoned (Laitila & Moilanen, 2012). In this study, feature weights were developed through consultation and influenced the representation of expert opinions in the solutions. Utilizing an analytical hierarchical approach (Mu & Pereyra-Rojas, 2018; Saaty & Vargas, 2012) was effective in developing priority rankings and ensuring stakeholders objectives were understood and represented. Future studies should consider how the use of targets compare to feature weights and assess the trade-offs between the two approaches or combining them.

An important limitation to our products is the assumption that data like landownership and development probabilities are static or fixed in time which could be unrepresentative of the realities at the site considering lease changes, land sales and transfers, emerging technologies, and changing social and economic factors that impact resource industries. Therefore, usage of spatial tools developed for this area need to be met with local knowledge that can better inform threats and highlight or exclude certain sites. The contiguity of solutions aimed at identifying areas suitable for conservation easements were limited by the pattern of landownership, checkerboarding, a remnant of railroad land allocations in the Western United States. Conservation plans that are multi-ownership are necessary to confer contiguity across this landscape. We also limited our applications of *prioritizr* to one budget instead of pursuing a variety of situations. Sage-grouse conservation can be volatile based on the political and economic context. For instance, the 2015 decision not to list sage-grouse as an endangered species is being re-visited in 2021 and this decision could influence how sage-grouse management is conducted in the future. Working across field offices will likely also be important for sage-grouse conservation as some of our selections of priority areas border the RSFO.

2.4.3 **Management Implications**

Although using development potential cost feature outperformed solutions generated with the threat cost feature, we expect threat to be a more realistic interpretation of the development potential data because areas with low development probabilities may not be cheaper to obtain or more suitable for management. Furthermore, areas with high development potential may not be appropriate for selection as there is uncertainty in the ability for conservation to overcome competition for the area, its availability, costs for acquisition or management actions, and regulations tied to the land (Kiesecker et al., 2009).

Within the RSFO there are 2 subpopulations of sage-grouse, one a source in the North and the other a sink population in the South (Row et al., 2016). Maintaining links between sage-grouse populations and managing sink populations for recovery are important steps for maintaining viable populations in this area. Our prioritizations align well with previous research in the area clearly showing priority areas in the north RSFO and identifying at risk areas suitable for restoration across the landscape and in the southern areas of the RSFO. In future management decisions, vulnerable and irreplaceable priority areas linking PACs in the north and to the east of the Green River should take conservation priority (Figure 10).

Cognizant of the need to address on site realities and improve these selections with updated information, the findings from our research can serve as a basis for where and in what order areas in the RSFO should be assessed for conservation and management actions.

Chapter 3

Maximizing Target-less Prioritizations in a Data Limited Context with *prioritizr*

3.1 Introduction

Since the 1960s, the loss of biodiversity across the world has been of serious concern leading to the development of protected areas or reserves, conservation entities, policies, and planning (R. L. Pressey et al., 1993). Yet, the designation of protected areas historically occurred in an ad hoc fashion, favouring areas that are undesirable for development due to inaccessibility or remoteness (Joppa & Pfaff, 2009; R L Pressey & Tully, 1994; Venter et al., 2018). As methods for estimating species abundance and ranges have improved, so has conservation planning advanced into systematic conservation planning (SCP). SCP is a comprehensive guideline for creating informed conservation plans, dictating that future conservation plans are informed by ecological and anthropogenic data (Margules & Pressey, 2000). SCP can be more effective when data are incorporated for multiple species and disciplines because landscape management is complex, involves many stakeholders, and impacts multiple systems (Kukkala & Moilanen, 2013). The Bureau of Land Management (BLM) manages public lands in the United States, in sagebrush ecosystems, roughly 50% of remaining sage-grouse habitat is on public lands and therefore the BLM is an essential driver of conservation actions for this system (Christiansen & Belton, 2017; Knick, 2012). The BLM works to balance multiple conflicting land uses including wildlife, revenue driven industries like extractive and renewable energy, and recreational use, for long-term health and sustainability (Federal Land Ownership: Overview and Data, 2020). The BLM structure is hierarchical with a head office to serve each state, broken into district, and field offices. Conservation plans are developed at the field office level and require data relevant to that landscape, but funding and data availability can differ between offices.

Greater Sage-grouse (*Centrocercus urophasianus*; hereafter sage-grouse) are an iconic species and have been proposed as an indicator species of the health of the sagebrush ecosystem due to their widespread range and obligate relationship with sagebrush (Barlow et al., 2020; Copeland et al., 2014; Pilliod et al., 2020; Rowland et al., 2006). In the Western United States, the priority areas for conservation (PACs) were created to support the long-term viability of sage-grouse populations (U.S. Fish and Wildlife Service, 2013). Addressing vulnerabilities in the representation of seasonal habitat by the PACs to inform management decisions is a priority for field offices and conservation groups across Wyoming, outlined by the state mandated Wyoming Core Population Area Strategy enacted in 2007 (The Southwest Wyoming Local Sage-grouse Working Group, 2013). The habitat assessment framework (HAF) has also tasked field offices with generating habitat prioritizations for the conservation of sage-grouse (Stiver et al., 2015). Southwestern Wyoming is an area of particular importance for the persistence of sage-grouse because the region supports high connectivity and gene flow (Cross et al., 2018; Knick et al., 2013). Radio-telemetry data have served as the basis of multiple sage-grouse habitat prioritizations (e.g., Fedy et al., 2014; Rice et al., 2017; Tack et al., 2019), but there is no evidence that the type of data used impacts implementation (Keeley et al., 2019). The Rock Springs Field Office (RSFO) located in southwestern Wyoming has limited telemetry data for sage-grouse but with novel modelling methods and the collaboration across studies in Wyoming, habitat suitability models (HSMs) were generated for nesting, brood, and winter sage-grouse habitat in the area (Winiarski, In Review).

Spatial prioritizations are one step in the SCP process that involve engaging with a decision support tool to generate a spatial configuration of areas for conservation action. Prioritizations generate *solutions,* via the optimization of desirable features like species distributions, referred to as *conservation features*, while minimizing a *cost feature*. Utilizing optimization tools facilitates researchers in providing robust evidence-based recommendations for management and can increase the likelihood of implementing a plan by maximizing cost efficiency (Rodewald et al., 2019). Most of the spatial prioritizations in SCP projects have been developed with Marxan and Zonation (Moilanen, 2007; Watts et al., 2009). These software use heuristic approaches to approximate suitable areas for conservation. However, heuristic approaches can lead to suboptimal reserve designs because planning units are randomly added to the solution, requiring many iterations to generate certainty and optimal solutions may still not be found (Rodrigues et al., 2008). A more robust method for prioritizations, integer linear programming (ILP), can deterministically find the best solutions, by simultaneously assessing the relative value of each planning unit, a method that has been conceptualized for decades, but only recently have advancements in computational capabilities led to its availability for general applications (Williams et al., 1990). ILP is the approach employed by *prioritizr*, a package developed for R computational software (Hanson, Schuster, et al., 2020; R Development Core Team, 2011). ILP outperforms both Marxan and Zonation in terms of solution quality and speed of computation (Schuster et al., 2020). The ILP approach has been applied to comparatively few conservation planning projects.

Marxan and Zonation represent two options for how a conservation problem can be solved, Marxan aims to minimize costs while meeting minimum targets for conservation whereas Zonation maximizes conservation at a specified cost. These approaches typically select similar priority areas but come with trade-offs in terms of efficiency, connectivity, and suitability to the available data and goals of the prioritization (e.g. Allnutt et al., 2012; Delavenne et al., 2012). In *prioritizr* these different approaches are referred to as *objective types* and there are multiple variations that specify the algorithm used to solve a prioritization problem. Failing to choose an objective type that aligns with stakeholder objectives could reduce the likelihood of implementation of a conservation plan. Developing a better understanding of how *prioritizr* can be applied to create and solve conservation problems is expected to benefit interested researchers and stakeholders by clarifying how certain decisions in the SCP process impact solution quality.

Prioritizations use thresholds to set goals or limit the area implicated for consideration. Some objective types require the researcher to identify targets that specify representation goals for each conservation feature whereas others use budgets and feature weights. Prioritizations are most frequently quantified using policy goals leading to representation targets of 10% - 12% (Svancara et al., 2005). Features weights reflect varying economic, social or environmental values attributed to conservation features and can be established using approaches like scaling the feature weights to the relative rarity of each conservation feature, iteratively updating feature weights based on the representation of each feature in the solution, or using expert opinion to generate priority rankings (Moilanen, Anderson, et al., 2011). Feature weights are on a continuous scale and might range from values such as 1 – 5, or 0 – 1 depending on the relative importance of each feature (Moilanen & Arponen, 2011a). Using expert opinion is a subjective process typically involving consultation with local specialists to influence the solution towards a higher representation of certain features (Lehtomäki & Moilanen, 2013). Inherent advantages and drawbacks lie in both targets and feature weights. Although target-based planning has been the most common approach for SCP, ongoing discourse over setting targets have identified issues like the prevalence of unjustified or explained targets, the rigidity targets impose on a prioritization effort, and that targeted conservation problems can lead to fragmented solutions (Di Minin & Moilanen, 2012; Laitila & Moilanen, 2012; Moilanen & Arponen, 2011b). However, targets can be more straightforward and effective in linking policy goals and ecological data together when a budget is known and when cost efficiency is an important aspect of the prioritization (Svancara et al., 2005). Feature weights can be applied less strictly and are more suited to conservation problems with uncertain funding because they allow for more flexibility

(Arponen et al., 2005). The majority of previous research using *prioritizr* have focused on minimizing objective types using targets for their prioritizations (e.g. Lin et al., 2020; Schuster et al., 2019). Elucidating how solution quality can be impacted when the conservation and cost features, objective type, and feature weights, are adjusted and applied in *prioritizr* is an important next step for effectively applying SCP approaches to conservation objectives. Using the previously developed seasonal HSMs (Winiarski, In Review), as the basis of a prioritization we investigated how spatial prioritizations could be improved using *prioritizr*.

Specifically, this study aims to answer the following research questions:

1. How can objective types and feature weights be used in a prioritization process to most effectively determine priority habitat when considering various environmental and anthropogenic data together?
2. What are the impacts of posing costs as 'development potential' or as 'threats'?
3. How are solutions impacted by data variability?
4. How does connectivity alter solutions?

To answer the first two questions, we developed 9 *deterministic* and 6 bootstrapped conservation problems assigning various objective types, cost features, and feature weights. Unweighted solutions are referred to as deterministic because they had an optimal solution and were solved once. We then used a sensitivity analysis to address the second two questions. The sensitivity analysis consisted of starting with one conservation feature and iteratively adding conservation features (of 13 features) to the conservation problem, termed as sensitivity scenarios. Our bootstrapping approach sampled random feature weights from a low and high range of values for 100 iterations, therefore, we generated and solved 600 conservation problems. By investigating potential approaches for prioritization in a situation characteristic to modern conservation planning efforts (i.e., prioritizing spatially overlapping features with unknown costs for land acquisitions) we aimed to help future researchers make informed decisions on how they translate stakeholder needs into a conservation problem. With the outcomes of this study, we were able to reconsider and improve our SCP process and products highlighted in Chapter 2.

Table 1. Analysis approach including 9 deterministic and 13 sensitivity scenarios run once, and 12 bootstrapped scenarios based on 6 of the deterministic scenarios with randomly sampled feature weights from 2 ranges sampled for 10 runs performed over 100 iterations (Lentini et al., 2013; Schuster et al., 2020).

Analysis:	***Deterministic***	***Bootstrap***	***Sensitivity***
Conservation features	Seasonal HSMs (3), landscape connectivity	Seasonal HSMs (3), landscape connectivity	Seasonal HSMs (3), landscape connectivity, leks, winter observations, nesting observations, elk and mule deer migratory routes, expert opinion surfaces (4)
Cost features	Uniform, development potential, threat	Uniform, development potential, threat	Threat
Feature weights	None	Range 1: 1 – 2 and Range 2: 1 – 10	None

3.2 Methods

3.2.1 Objective Types

Decision support tools are used to compile relevant data, incorporate constraints, and sort prioritization options to pose a subset of relevant prioritization scenarios. Prioritizations are typically solved under the paradigm of two objective types: *minimum-set coverage* (MSC) and *maximum coverage problems* (MCP) which lead to subtle differences in solution quality (Moilanen & Arponen, 2011b). For example, MSC are expected to achieve the best cost efficiency which can be suitable to situations where conservation resources are severely limited. But, MSC has been critiqued as leading to highly fragmented plans that lack biological relevance (Arponen et al., 2005; Williams et al., 2004). In contrast, MCP assumes that some areas identified by the prioritization may not be available for protection and addresses that issue by maximizing representation of conservation features within a budget constraint (Arponen et al., 2005). *Maximum utility problems* (MUP) is a variation of the maximizing objective type available in *prioritizr* that was explicitly created to use threats as a proxy for cost and suitable for management scenarios interested in the conservation of multiple overlapping features (Davis et al., 2006). Due to this difference, MCP can be more effective in maintaining complementarity (i.e., balanced representation of features) especially when spatial features are isolated, whereas MUP can result in more efficient solutions (maximum diversity at minimum cost) when features overlap (Kreitler et al., 2014). Since accurate data regarding the economic realities for conservation in terms of acquiring land, implementing management actions, and setting feasible budgets, is often lacking, (Carwardine et al., 2010; Knight et al., 2011; Rodewald et al., 2019) the MUP objective type addresses a key issue regarding how to consider cost in data limited situations. Thus far, there have been limited applications of MUP with an ILP approach (Kreitler et al., 2014), and only one usage with *prioritizr* which focused on investigating the impact of incorporating connectivity in prioritizations (Williams et al., 2019).

We considered how solution quality was affected by the three objective types MSC, MCP, and MUP with the unweighted deterministic scenarios. Since minimizing objective types are unsuited for the application of feature weights, only the MCP and MUP objective types were compared in the bootstrapped scenarios. The 13 scenarios for the sensitivity analysis were generated with an MUP objective type.

3.2.2 Conservation Features

Our study site was in southwestern Wyoming and corresponded with the boundaries of the Rock Springs Field Office (RSFO). The RSFO was well suited as an application for testing functions within *prioritizr* because of the availability of multiple datasets pertaining to biological, environmental, and anthropogenic data (**Table 2**), the extent and resolution of which were within the capabilities of the software.

Table 2. List of surfaces used in this study and their respective sources.

Surface name	*Source*
Seasonal HSMs (nesting, brood, and winter) and expert opinion features (nesting_expert, brood_expert, riparian, and winter_expert)	Winiarski et al., In Review; RSFO experts
Landscape connectivity (LC)	Row et al., 2018
Elk and mule deer (MD) migratory corridors	Kauffman et al., 2020
Leks	WGFD
PACs	WGFD
Land ownership	USGS Gap Analysis Project, 2018
Winter point observations (Winter_obs)	RSFO
Nesting point observations (Nest_obs)	RSFO
NLCD	https://www.mrlc.gov/
Wyoming roads	https://pubs.usgs.gov/ds/821/
Well pad scars	Garmon et al., 2012
Wind turbines	Hoen, et al., 2018
Development potential (oil & gas, wind, residential)	Copeland et al., 2009; Copeland et al., 2013
Crop cultivation risk	Smith et al., 2016
DDCT	https://onesteppe.wygisc.org/
Sagebrush recovery time	Monroe et al., 2020
Fire danger	https://firedanger.cr.usgs.gov/viewer/index.html

The RSFO manages approximately 3.6 million acres of public land, dominated by an increasingly fragmented landscape of sagebrush steppe habitat. The RSFO contain important habitat for a variety of species including notably, the sage-grouse, and ungulates like mule deer (*Odocoileus hemionus*) and elk (*Cervus canadensis*), which are reliant on distinct seasonal use areas and the migratory routes that connect those areas. We consulted with experts at the RSFO to determine where sage-grouse are locally known to use habitat that might be lacking representation in the HSMs or the PACs. The results were hand drawn maps identifying areas to emphasize in the prioritization based on expert opinion.

Recently developed migratory routes and corridors for ungulate species mule deer and elk from Kauffman et al., 2020, were also included in the prioritization. Previous SCP processes have identified the benefits to incorporating numerous species distributions to help realize multiple conservation objectives simultaneously (Nielsen et al., 2017).

Landscape resistance refers to the degree at which an area impedes a movement or gene flow for a species (Shirk et al., 2015). Functional landscape resistance for the range of sage-grouse was previously modelled and spatially predicted (Row et al., 2018). We cropped the resistance layer developed by Row et al. 2018 (Figure 4. in Row et al. 2018) to our site, inverted the surface values to represent landscape connectivity, and incorporated the layer as a conservation feature.

The local state wildlife management agency, Wyoming Game and Fish Department, developed an approach to quantifying surface disturbance within potential development areas termed the Density and Disturbance Calculation Tool (DDCT). Disturbance refers to direct habitat modification of the surface and vegetation such as roads, well pads, mining operations, cropland, buildings, wind turbine pads, pipelines, and some vegetation treatments. We used the DDCT layer to modify the seasonal HSMs by lowering the suitability of agricultural fields and burned areas by 10% and 20%, respectively. This helped remove unsuitable areas with disturbance histories from our prioritizations.

We also incorporated point data into our prioritizations to better represent management goals and the realities of sage-grouse presence. Lek locations, winter observations, and nesting observations, were provided by various data sources. Leks are ideal for population monitoring because they are consistently in the same locations and have been monitored over decades to estimate population sizes (Johnson & Rowland, 2007; Walsh et al., 2004). We created contour surfaces with kernel density estimators setting bandwidths at 6400 for leks and winter observations (Doherty et al., 2010) and a bandwidth of 2500 for nesting observations. Since the nesting observations covered a small area (11.7 km^2) compared to the study extent (~ 5 million acres or 20234.3 km^2) their inclusion into fine scale solutions heavily skewed the rarity weighted richness calculation for irreplaceability. Therefore, we only incorporated nesting observations into the coarse solutions because the replacement cost calculation is better equipped to handle unequal distributions.

3.2.3 **Cost Features**

Costs features specify a value for each planning unit that is representative of the economic cost of protecting each site or implementing a management action. Historically, cost data was not explicitly included in prioritization efforts (Carwardine et al., 2007; Kirkpatrick, 1983; Linke, Pressey, Bailey,

& Norris, 2007) but has become more common with the growing use of SCP standards (Naidoo et al., 2006). The incorporation of cost data can improve prioritization efforts by engaging with the onsite realities of conservation to make conservation plans more feasible and thus more likely to be carried out (Carwardine et al., 2010; Naidoo et al., 2006).

Many studies have demonstrated the negative impacts of anthropogenic development on sage-grouse (e.g., Conover & Roberts, 2016; Hess & Beck, 2012; Lebeau et al., 2017; Naugle et al., 2011) and southwestern Wyoming has been described as an area experiencing rapid development in multiple sectors (Knick et al., 2012). Therefore, it is important to consider costs when addressing vulnerability in the protected area network for an area that is key to the overall persistence of the species. Three cost features were explored in this study. To incorporate the threats to sage-grouse into the prioritization, predicted development potential layers pertaining to oil and gas, wind, residential expansion (Copeland et al., 2013), and a predicted risk of crop cultivation layer (Smith et al., 2016), were used to develop the cost features for this study. We assumed an additive impact of each of these industries and summed the development probabilities together to create our *development potential* feature and then inverted those summed probabilities to create a *threat* cost feature. We also assessed each planning unit with a uniform cost of one (*sensu* Domisch et al., 2019; Williams et al., 2019) to investigate how incorporating land cost and threat proxies impacted the prioritization results.

Land costs are rarely homogeneous and typically positively correlated with conservation threat (Ando, 1998), therefore, we used the development potential feature to model land acquisition costs on the assumption that areas likely to be developed are more expensive to acquire. The inversion of this layer was used to consider cost as threats posed by development and thereby identify vulnerable areas to bring into the solution (Tack et al., 2019).

3.2.4 **Problem Parameters**

Feature weights are used to adjust the relative importance of each conservation feature in the prioritization process. By raising the feature weight of any conservation feature, its representation will be increased in the solution, at the expense of lowering the representation for other features. Feature weights can be used to allocate conservation features differently across sub-sets within a landscape. For example, feature weights can be applied differentially to administrative, policy, environmental, or physical features, to improve the connectivity of the solution and to align local conservation plans with broader national and global priorities (Moilanen & Arponen, 2011a).

In *prioritizr* feature weights are required to be positive numbers or equal to zero, must be greater than 0.01 to drive the algorithm more than the cost feature, and within 1e+6 (Hanson, Schuster, et al., 2020). Further limitations are imposed by the solver used to carry out the prioritization, Gurobi Optimizer recommends that variables and constraints should be scaled to be within the order of magnitude of 1e+5 or less (Gurobi Optimizer Reference Manual, 2020). We used bootstrapping to randomly select feature weights from two ranges, the first being 0 – 1.9 sequentially increasing by 0.1, and the second high and more variable range of 0 – 10, sequentially increasing by 1.

Constraints were used to simplify the conservation problem by excluding unsuitable areas from consideration. Unsuitable areas were constrained for the selection. Unsuitable areas included forested areas, and large water bodies, well and wind turbine pads. The PACs were also used as a constraint in some solutions to target areas outside of the PACs. Furthermore, we used contiguity constraints to force solutions into more connected configurations by using the nearest neighbor rule which limits selected planning unit with the rule that at least two (or 4, or 8) bordering planning units were also included in the selection.

Budget limited prioritizations are applied with the assumption that not everything across the landscape can be protected and therefore are suitable for situations when the conservation needs are long term and conservation will occur in stages (Arponen et al., 2005). Setting a budget is an important step to the prioritization process because it acts as a threshold limiting how many planning units will be retained in the solution. In SCP, using a realistic budget is recommended because it is beneficial for straightforward collaboration with stakeholders and ensuring the utility of the product (Dale et al., 2019). Determining adequate budgets for this prioritization was dependent on the conservation features included in the prioritization, for example capturing 10% of each seasonal sage-grouse habitat suitability model requires a budget of 60,000 planning units or $6 million, the inclusion of landscape connectivity substantially raised the budget because of its wide coverage across the study area. To put our planning units sized 1.44 ha into perspective, 1 ha of pasture, crop, and farmland were respectively valued at $4,100, $3,160, and $1,400 in 2019 (USDA, 2019). Planning units for our study were ranked in development potential from 1 to 3.74, since land values are approximately three orders of magnitude larger than the costs used in our prioritizations, we multiplied by 1e+3 to express our budgets in US dollars. A maximum of 200,000 planning units (out of 1,505,915 total planning units) was set as the budget for problems involving a uniform cost. This value was multiplied by the average cost of a planning unit for the development potential and threat cost features leading to budgets of approximately 150,000 and 300,000 planning units, respectively and therefore, our selections were limited to a budget of $200 million. A budget of $200 million is expected to be high compared to the realities of funding at the RSFO, but by selecting more planning units than what is needed to meet management goals, we were able to maintain flexibility in the solutions.

3.2.5 **Analysis**

Solutions were assessed using performance measures including the return on investment (ROI), degree of fragmentation, contiguity, and capture of irreplaceable sites. ROI was calculated as the number of highly irreplaceable sites in a solution divided by the cost of that solution (Cook, Pullin, Sutherland, Stewart, & Carrasco, 2017; Murdoch et al., 2007). Rarity weighted richness was used to calculate irreplaceability, the relative importance from 0 - 1 of each planning unit in the selection (Williams et al., 1996). Our calculation of irreplaceability, therefore, was complementary-based where the value of a planning unit varied depended on the relationship between that site, all other selected sites, and the representation of each conservation feature (Perhans et al., 2008).

We compared unweighted or deterministic solutions and bootstrapped solutions to determine the potential to alter solutions using feature weights. We statistically assessed each performance measure with nonparametric Kruskal-Wallis rank sum tests, grouping solutions by the cost feature or feature weight range used in the problem creation (Cameron et al., 2008). We determined the spatial agreement between conservation features and solutions using the Jaccard Index and the zonator package (Lehtomaki, 2018). This allowed us to quantify how changes in problem design altered the solutions. We then investigated significant Kruskal-Wallis relationships with Wilcox ranked summed tests for unpaired comparisons across two groups.

Next, we used the bootstrapped simulations to assess our H_1 hypothesis (

Table **3.** Hypotheses regarding how the cost and conservation features impact the spatial agreement between solutions.). We expected that applying the development potential and threat cost features would drive the solution towards cost effective areas with a loss of conservation value, whereas the uniform cost feature would be exclusively influenced by conservation value. Based on previous studies, highly variable cost features can unexpectedly drive solutions and the relative variability between cost and conservation features is expected to mediate their influence on the resulting selection (Boyd et al., 2015; Rodewald et al., 2019). Therefore, we calculated this ratio for each problem in the sensitivity analysis to address our H_2 hypothesis. As stated by the second hypothesis,

H_2, we expected that as overlap between conservation features increased by the sequential inclusion of each conservation feature, the influence of the cost feature to select budget areas was diminished (Williams et al., 2019). We determined budget and expensive areas relevant to our cost feature by assessing if a planning unit is greater or less than the mean cost of a planning unit, 2.2. We also assessed the sensitivity of each solution with the inclusion of a contiguity constraint in the problem design.

All prioritizations and analyses were implemented using R version 1.2.1335, *Prioritizr* version 5.0.2, and solved with Gurobi Optimizer version 9.1 (Gurobi Optimizer LLC, 2020; Hanson et al., 2020; R Development Core Team, 2011).

3.3 Results

3.3.1 Objective Types and Feature Weights

We compared MSC, MCP, and MUP objective types using our deterministic solutions and found multiple differences in solution quality (

Table 4). MSC generated the cheapest solutions when compared to solutions with the same cost feature using MCP or MUP. For the uniform and development potential solutions, MSC presented an intermediate between MCP and MUP, outperforming MCP in terms of ROI, and feature representation of the HSMs but not MUP. Conversely, contiguity was the highest for MCP solutions and lowest for MUP solutions, with one exception being MSC having the lowest contiguity with the uniform cost feature. The deterministic solutions showed consistency in the number of irreplaceable sites regardless of objective type, with ~ 9% of the selection being irreplaceable (number of irreplaceable sites = 169) for 66.7% of the prioritizations.

Table 3. Hypotheses regarding how the cost and conservation features impact the spatial agreement between solutions.

Hypothesis	Simulation Results	*p*-value
H_1: Variation in the cost feature limits the influence of feature weights and conservation features in the solution	**Unsupported**	Landscape connectivity and winter were similarly represented with threat and uniform cost features (Chi-square < 2, $p > 0.05$, df = 1), brood and nesting representation showed significant differences but with higher variation (Chi-square > 10, $p < 0.05$, df = 1).
H_2: Overlap between conservation features increases the influence of conservation features over cost features in the solution	**Supported**	Used linear regression to understand the relationship between the overlap of conservation features (log transformed) and the identification of areas below the median cost (budget areas) finding that as overlap increased the selection of budget areas decreased (r = 0.31, p = 0.027)

Table 4. Solution quality metrics for deterministic solutions presented as Mean ± SD averaged across the three objective types: maximum cover problems (MCP), minimum-set coverage (MSC), and maximum utility problems (MUP). Three solutions were developed for each objective type, corresponding to one solution for each of the cost features: uniform, threat, and development potential. Six of the nine solutions served as the foundation of the bootstrap analysis which added randomly assigned feature weights to the MCP and MUP problems, MSC problems were not used further because minimizing objective types are only suitable for targets and not feature weights.

Objective type	*Contiguity*	*Solution cost*	*Sum of irreplaceability values*	*Number of irreplaceable sites*	*ROI*
MCP	0.43 ± 0.12	1504 ± 264	19495 ± 10734	173 ± 7.51	0.67 ± 0.097
MSC	0.44 ± 0.072	1461 ± 278	13831 ± 6494	225 ± 97.6	0.71 ± 0.11
MUP	0.48 ± 0.039	1533 ± 262	74344 ± 21384	177 ± 14.4	0.83 ± 0.13
Objective type	*Nesting (%)*	*Brood (%)*	*Winter (%)*	*Landscape Connectivity (%)*	
MCP	28.5 ± 0.011	23.0 ± 0.01	27.3 ± 0.14	20.0 ± 0.0	
MSC	30.1 ± 0.023	23.4 ± 0.015	28.5 ± 0.029	20.0 ± 0.0	
MUP	40.5 ± 0.004	29.0 ± 0.006	35.5 ± 0.004	19.8 ± 0.004	

Since only maximizing objective types can be assigned feature weights, we compared the impact of feature weights on MCP and MUP solutions only. Applying feature weights from the high range led to more variable solutions in terms of feature representation but this effect was mediated by the objective type and cost feature. We found that the MUP objective type was more sensitive to the application of feature weights than MCP because regardless of the range feature weights were sampled from and feature representation remained unchanged with MCP. Feature weights did impact how MCP solutions were assessed by irreplaceability. Feature weights from the high range led to higher irreplaceability values and more irreplaceable sites this change was significant with a Wilcoxon rank sum test with continuity correction ($W = 49462$, $p < 0.05$). With the MUP objective type, the application of feature weights led to minor changes in the representation of conservation features.

3.3.2 **Cost Features and Conservation Features**

Comparing our cost features, the uniform cost had a mean value of 1.0 ± 0.00081 and the threat and development potential cost features had mean values of 2.22 ± 0.35 and 0.52 ± 0.35, respectively. This was more variable than any of our 13 conservation features, some of which were binary, like the elk and mule deer data. The most variable conservation feature was landscape connectivity, with a mean of 0.54 ± 0.24 (mean standard deviation: 0.096, range: 0 – 0.24). Using a more variable cost feature did not alter the effect of feature weights. Using the development and potential and threat cost features led to more contiguous, cheaper, highly irreplaceable, and cost effective (ROI) solutions, compared to the uniform cost feature (Table 5; significance tests are reported in Appendix A. Table 1.).

High quality nesting, brood, and winter seasonal habitat ($\geq 0.75^{th}$ quartile) overlapped with high costs ($\geq 0.75^{th}$ quartile) on the development potential surface 11%, 21%, and 3% more than the threat surface. This means that high quality habitat was more available on threatened areas which could be opportunistically selected with the threat cost feature. Despite this, the development potential cost feature led to the highest representation of the HSMs and the landscape connectivity surface, achieved the best ROI, contiguity, and irreplaceability values. Irrespective of the cost feature, certain areas were prioritized because of their ecological importance, or the influence of the conservation features, and key differences were found in how remaining conservation funds were allocated. This suggests that the RSFO holds marginal sage-grouse habitat that is not likely to be developed on and may be opportune for conservation.

Planning units selected using the development potential solutions had lower agreement with other solutions meaning these areas were not selected in alternate problem set-ups. In comparison, the threat cost feature could be applied with less uncertainty of its impacts because solutions demonstrated higher overlap with similar solutions generated with a uniform cost feature and improved them by identifying sites with greater irreplaceability values (Table 5Figure).

Table 5. Solution metrics presented as Mean ± SD for the deterministic solutions grouped by the three cost features development potential (Dev), threat, and uniform.

Cost Feature	*Contiguity*	*Solution cost*	*Sum of irreplaceability values*	*Number of irreplaceable sites*	*ROI*
Dev	0.501 ± 0.033	1370 ± 58.7	48818 ± 43695	177 ± 14.4	0.81 ± 0.084
Threat	0.439 ± 0.12	1320 ± 26.1	33213 ± 24552	169 ± 0	0.79 ± 0.11
Uniform	0.412 ± 0.042	1807 ± 25.5	25639 ± 32168	230 ± 94.0	0.61 ± 0.063

Cost Feature	*Nesting (%)*	*Brood (%)*	*Winter (%)*	*Landscape Connectivity (%)*
Dev	33.8 ± 0.062	26.0 ± 2.46	31.4 ± 4.05	20.1 ± 0.15
Threat	31.6 ± 0.073	24.0 ± 2.18	28.7 ± 5.65	19.9 ± 0.23
Uniform	33.7 ± 0.061	25.4 ± 2.39	31.3 ± 3.78	19.8 ± 0.29

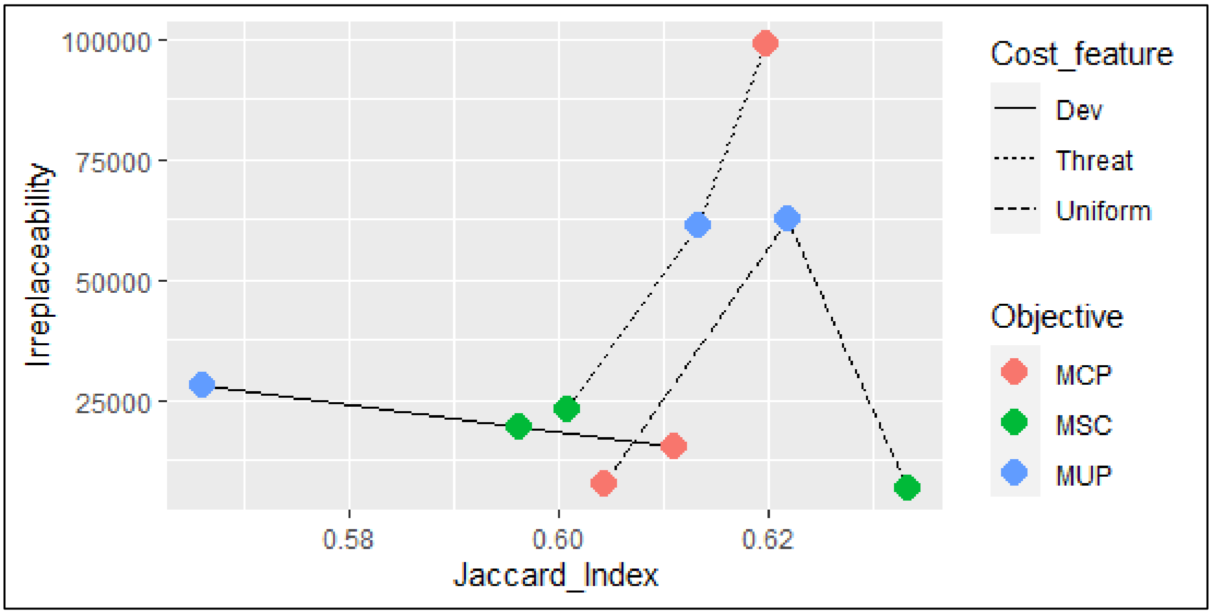


Figure 1. Irreplaceability of each deterministic solution plotted against solution agreement separated by the three cost features, development potential (Dev), threat, and uniform with three solutions for each cost feature, one for each objective type: maximum cover problems (MCP), minimum-set coverage (MSC), and maximum utility problems (MUP). Solution agreement is indicated by the Jaccard Index which ranges from 0-1, higher values denoting greater similarity between solutions, irreplaceability was measured as replacement cost. The Jaccard Indices presented here are averages of the indices calculated for each paired combination of solutions because the index is calculated as the area of intersection between two rasters divided by the total area covered by both rasters.

When investigating relationships between our cost features and the representation of target conservation features, seasonal HSM and landscape connectivity we found that incorporating cost features had minimal impacts on representation of top habitat ($\geq$0.75th quartile) for the nesting, brood, and winter HSMs. Most notably the threat cost feature led to a loss of 1% of representation for each HSM on average (Figure 2). Using a cost feature led to solutions with a lower solution cost, higher irreplaceability values on average, and higher ROI but lower contiguity (Figure 3).

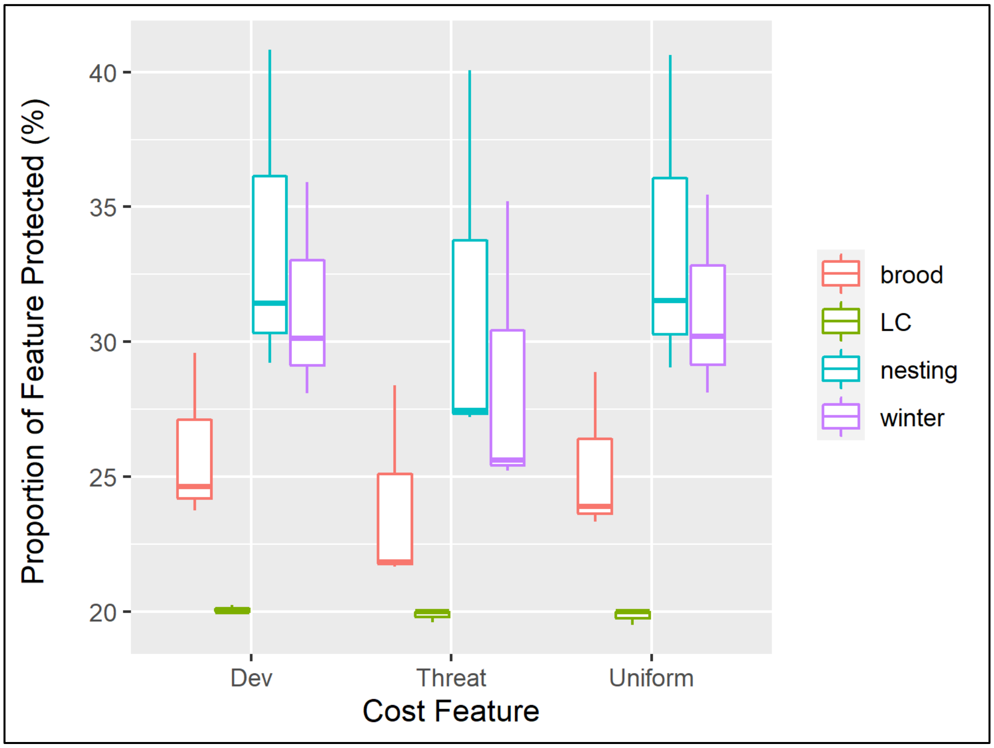


Figure 2. Percentage of the representation of each seasonal HSM and landscape connectivity (LC) captured by bootstrapped scenarios (N = 600) and grouped by the three cost features: development potential (Dev), threat and uniform.

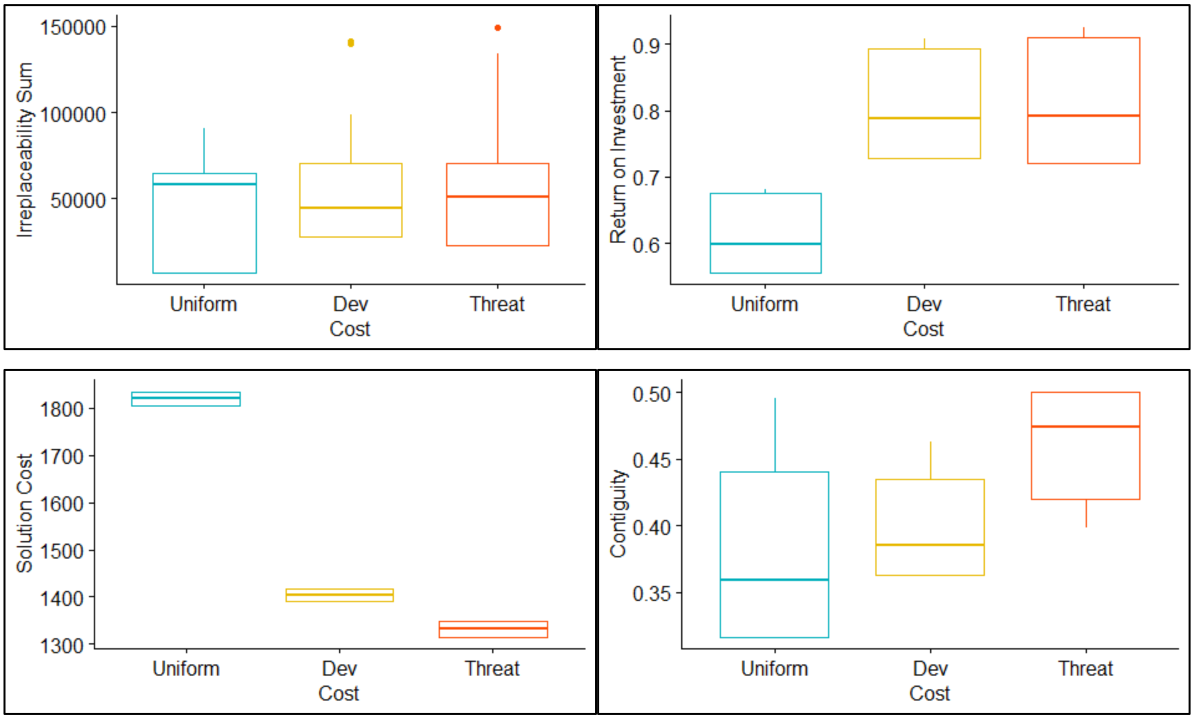
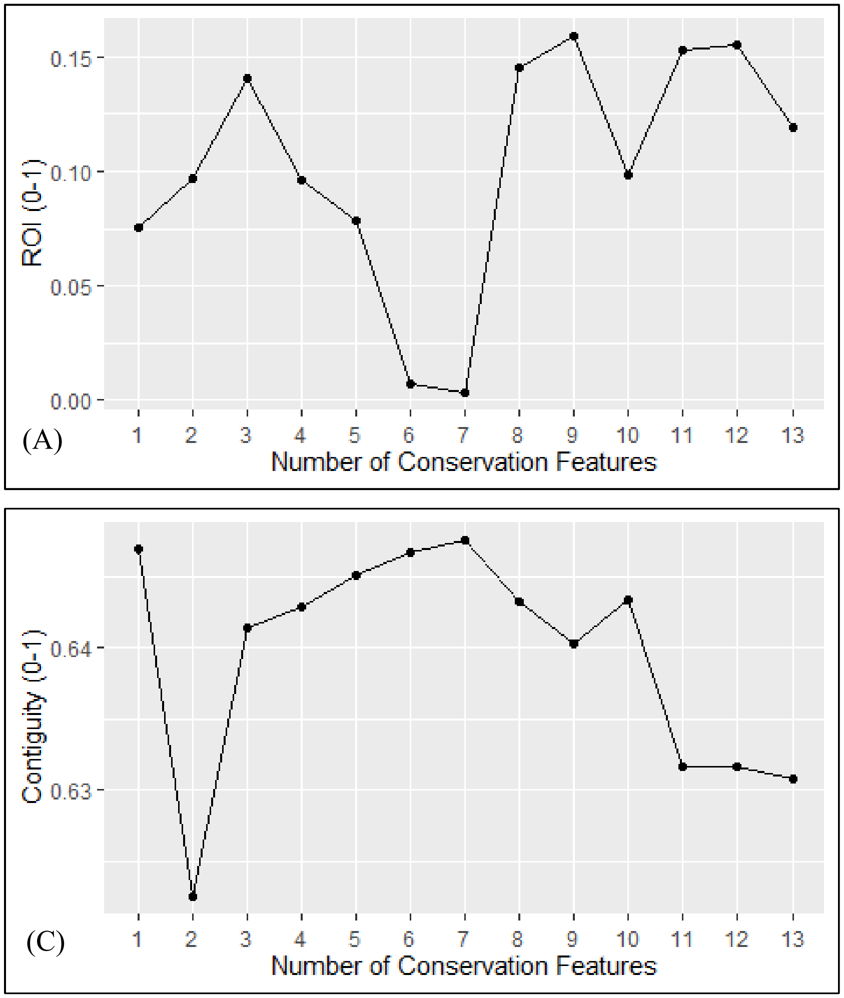


Figure 3. Comparison of the sum of irreplaceability values, return on investment (ROI), solution cost, and contiguity when prioritizing across each of the three cost features (N = 600).

Overlap between our conservation features ranged from highly overlapping to completely disparate features, the degree of overlap was influenced by the distribution and thresholds applied to the values in the surfaces. For example, the proportion of suitable habitat in the HSMs on connected areas identified the by the landscape connectivity surface (connected areas have values >0.25) suitable at a threshold of ≥0.5 led to overlap of 88.76%, 82.78% and 88.05% between the nesting, brood, and winter seasonal HSMs. In contrast, using the median values to threshold conservation features, led to 65.13%, 57.68%, and 64.97% of overlap between nesting, brood, and winter habitat and connected areas on the landscape connectivity surface. Using median values of each conservation feature as a threshold we determined that the average proportion of representation for the upper quantiles of each conservation feature by another conservation feature was 30.40%. We ordered our conservation features in the sensitivity analysis starting with the features with the greatest coverage of other features, landscape connectivity, and iteratively adding conservation features one at a time, ending with the most disparate features, (i.e., in the order presented in Table 6).

Table 6. Lower half of a matrix of Jaccard Indices, a measure of agreement between spatial data ranging from 0-1, determined for each pairwise combination of surfaces in the sensitivity analysis. Nesting and winter point observations are denoted with the season followed by _obs, similarly expert opinion surfaces are named with _expert.

	Landscape connectivity	Brood	Nesting	Winter	Leks	Winter_ obs	Winter_ expert	Riparian	Brood_ expert	Mule deer	Elk	Nesting _expert	Nest_obs
Landscape connectivity	1.00												
Brood	1.00	1.00											
Nesting	0.79	0.79	1.00										
Winter	0.76	0.76	0.69	1.00									
Leks	1.00	1.00	0.86	0.82	1.00								
Winter_obs	1.00	1.00	0.87	0.85	1.00	1.00							
Winter_ expert	0.88	0.88	0.85	1.00	0.88	0.89	1.00						
Riparian	1.00	1.00	0.78	0.68	1.00	1.00	0.80	1.00					
Brood_ expert	1.00	1.00	0.82	0.82	1.00	1.00	0.90	1.00	1.00				
Mule deer	0.05	0.05	0.06	0.05	0.07	0.06	0.07	0.09	0.00	1.00			
Elk	0.02	0.02	0.02	0.02	0.03	0.03	0.03	0.04	0.00	0.15	1.00		
Nesting_ expert	0.59	0.59	1.00	0.58	0.60	0.65	0.00	0.00	0.46	0.00	0.00	1.00	
Nest_obs	1.00	1.00	0.86	0.70	1.00	1.00	0.91	1.00	1.00	0.00	0.00	0.00	1.00



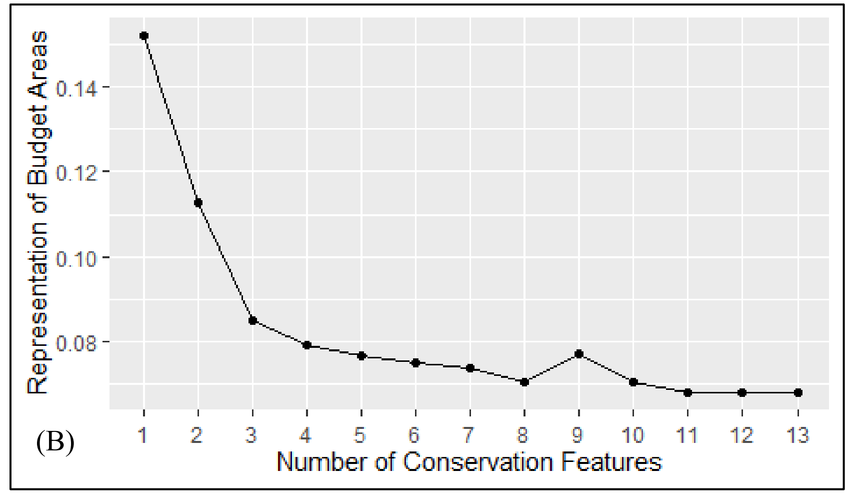


Figure 4. The influence of the scenario in the sensitivity analysis (N=13) termed in the X-axis by which conservation feature was added to the problems, on (A) ROI, (B) the representation of values below the median (budget areas) in the cost feature, and (C) contiguity. Contiguity was assessed using the landscapemetrics package for R, calculated at the landscape level, and ROI was calculated as the benefit (representation of the seasonal HSMs and landscape connectivity surfaces) accrued by each solution divided by the cost of the solution per hectare. Refer to Table 2 for a complete list of the 13 surfaces included in the study and their sources.

The number of conservation features in the x-axis of each chart in Figure 4 ranges from 1 – 13 and corresponds to a conservation feature being added to the conservation problem, listed in order in Table 6. We expected to see that as more conservation features were added to the conservation problem, the contiguity of the solutions would decrease and ROI would increase, instead we found these metrics were impacted by the specific feature included (Figure 4). When the 6^{th} and 7^{th} conservation features were incorporated, ROI reduced highlighting a disparity between key areas for the winter observations (winter_obs) and winter expert opinion surfaces and the other conservation features because a high ROI was dependent on selecting areas with overlapping features. Another potential explanation is that the winter observations and winter expert opinion surfaces had reduced ROI due to increased costs, this is unlikely because all solutions had similar costs dictated by the set budget and these surfaces had more of their distributions covered by budget areas than expensive areas (~ 2 – 6% more of these surfaces were on budget areas).

3.3.3 Connectivity

Comparing the representation of the each of the conservation features in the selection and selected outside of the PACs revealed key areas of improvement in the current protected area network for specific conservation features (Figure 6) like the brood and lek features which showed over 5% of the feature being represented outside of PACs. The PACs are clearly informed by ecological needs as the majority (78.2%) of priority areas identified by the sensitivity analysis fell into PACs. When PACs were constrained from the selection, representation of the conservation features reduced by a mean of 11.5% (range: 6.7 – 23.9, sd = 6.6). The elk and nesting observation (nest_obs) conservation features showed the greatest (> 20 %) reductions in representation and the elk conservation feature had a significantly reduced representation (p-value = 0.01). This is likely due to 88% of its distribution being within PACs, similarly, 51.7% the nesting observation surface was within the PACs, including the largest cluster of points on the surface.

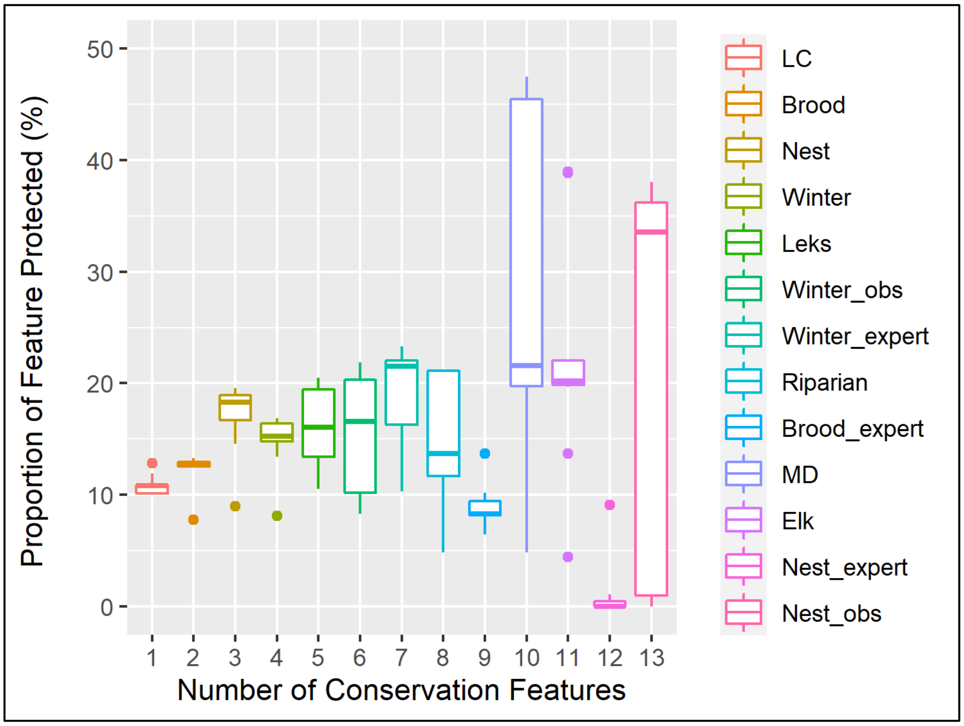


Figure 5. Proportion of conservation features represented in 13 solutions, consecutively adding a conservation feature to the conservation problem in the order listed on the legend. Conservation features are listed including landscape connectivity (LC), nesting and winter observations (nest_obs, winter_obs). Refer to Table 2 for a complete list of the 13 surfaces included in the study and their sources.

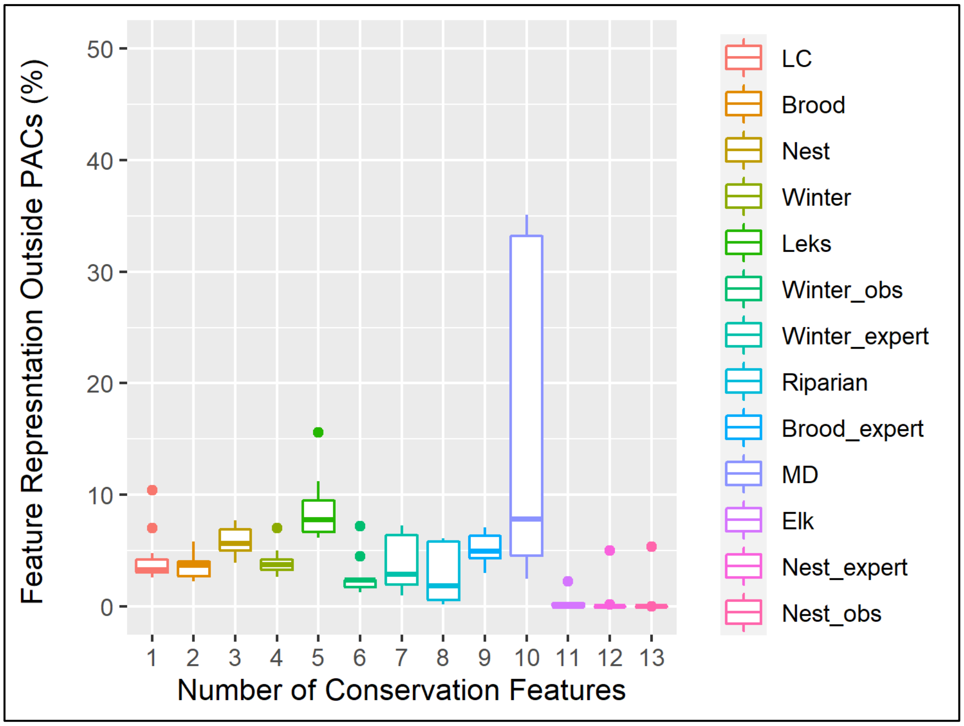


Figure 6. Representation of conservation features in 13 solutions restricted from selecting priority areas within the established priority areas for conservation (PACs). Conservation features are listed including landscape connectivity (LC), nesting and winter observations (nest_obs, winter_obs). Refer to Table 2 for a complete list of the 13 surfaces included in the study and their sources.

Incorporating the landscape connectivity feature increased the potential to find locations representing at least two conservation features by 10%. The landscape connectivity feature was represented by 1.4% more with its inclusion with a trade-off of reduced representation of the HSMs by 0.4% (Figure 7). In Figure 7. Multi-species priority habitat determined as areas with high conservation value on public lands with high predicted development probability. Surfaces included in this prioritization were habitat suitability models for each of the nesting, brood, and winter seasons, landscape connectivity, sage-grouse point observations, migratory corridors for ungulates mule deer and elk, and specific areas highlighted by consultation with experts, ranked by irreplaceability, the relative value of each selected area., representation of the nesting observations feature (nest_obs) is highly variable because of its small distribution (0.5% of the study area). Despite being the last conservation feature added to the sensitivity analysis, some solutions chose areas relevant to the nesting observation feature because of its high degree of overlap, Jaccard Indices of 1 for 50% of the other conservation features (mean = 0.71, sd = 0.43; Table 6). Contiguity constraints also led to minor

(< 1%) decreases in the representation of the nesting, brood, and winter seasonal habitat suitability in the solutions (0.97%, 0.35%, and 0.51% respectively) and a mean increase of 0.12 in contiguity. When both methods for incorporating connectivity were used, the representation of the nesting, brood, and winter habitat suitability models increased by 0.95%, 0.32%, and 0.46% respectively. Although the usage of contiguity constraints led to a higher representation of the landscape connectivity surface, it was not as effective when used without also incorporating the landscape connectivity surface which more adeptly captured areas that contributed to the representation of the HSMs.

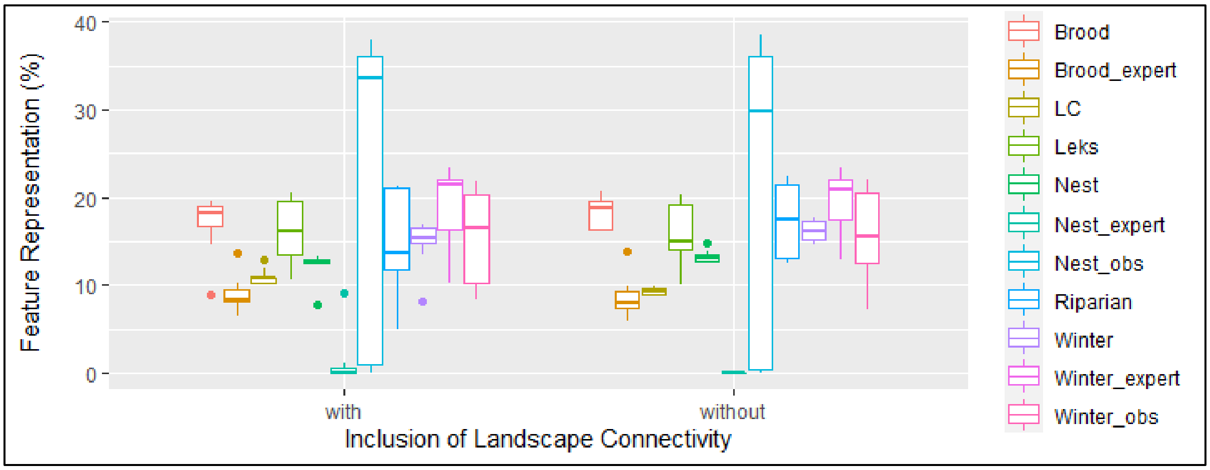


Figure 7. Feature representation for the 13 solutions in the sensitivity analysis run with and without the inclusion of the landscape connectivity surface. Conservation features are listed on the right including landscape connectivity (LC), expert opinion surfaces (_expert), and nesting and winter observations (nest_obs, winter_obs). Refer to Table 2 for a complete list of the 13 surfaces included in the study and their sources.

3.4 Discussion

Identifying priority areas for the conservation of sage-grouse was influenced, in terms of solution quality, by decisions regarding the problem formulation and understanding potential trade-offs is relevant to conservation planning processes in general. Clarity in how the usage of conservation and cost features, objective types, and feature weights, impact the representation of conservation features, identification of irreplaceable sites, efficiency measured by ROI, and contiguity effect solutions will help other researchers make informed decisions for effective conservation planning projects.

3.4.1 **Objective Types**

The minimum-set coverage (MSC) successfully produced lower cost conservation plans as expected (Laitila & Moilanen, 2012), and, in some cases, performed better than the maximum coverage problem (MCP) type in terms of representation of conservation features. The MUP objective type performed the best in terms of representation of conservation features and ROI but with the trade-off of large selection sizes and costs. MUP was the only objective type that was easily modified with feature weights whereas with the MCP objective type, feature representation was consistent regardless of the feature weights applied.

Deciding on which objective type is most suitable for future prioritizations depends on factors like if the budget is known and stakeholder involvement. MSC depends on targets alone which can be more readily deciphered from policies and mandates relating to conservation goals. In contrast, maximizing conservation problems require more decisions, a budget and feature weights and better suit the needs of conservation practitioners. This is because assumptions with maximizing problems are more realistic, they assume that not everything can be conserved but efforts within some budget will be put forward, perhaps over time. MSC assumes that a species is adequately protected if it is represented to some target despite targets often being unrelated to persistence (Alagador et al., 2020).

When cost efficiency is the forefront of the conservation planning goals, the MSC objective type is arguably be most suitable, and this would be especially true for small scale or local planning projects that have accurate cost data. Unfortunately, most conservation planning projects are based on data with high uncertainty and take a minimizing approach despite many researchers agreeing that maximizing objective types (MCP and maximum utility problems or MUP) are the future of SCP (Alagador & Cerdeira, 2017; Pressey et al., 2004; Underhill, 1994). Maximizing objective types are particularly beneficial because they contrast historic methods that have shaped today's conservation lands, typically avoiding public lands in competition with extractive industries and are more realistic to conservation contexts because of the underlying assumptions that funds are limited and not everything can be protected. When practitioners are considering a variety of conservation actions like policy change or restoration, the cost of carrying them out can vary by orders of magnitude, furthermore uncertainties with availability, and landowner willingness to engage or comply with conservation, can impact implementation (Murdoch et al., 2007). These issues can be addressed by assuming conservation will occur incrementally over time, which is more conductive with a budget-limited MUP objective type because it is more flexible and realistic than target-based approaches and can better deal with data limitations (Josie Carwardine et al., 2009).

3.4.2 **Feature Weights**

The use of feature weights directly opposes some of the assumptions and shortcomings associated with targets. For example, targets are often described as too prescriptive, inflexible, and unjustified, because they typically link to either minimum requirements for persistence or directly to policy goals and are abandoned if they cannot be fully met by a solution. In contrast, feature weights are on a continuous scale and can be informed by ecological importance as well as economic, social values and threat levels (Di Minin & Moilanen, 2012; Laitila & Moilanen, 2012). Unweighted solutions were outperformed by weighted solutions in terms of feature representation and ROI but with increased solution cost.

Prioritizations are expected to lead to selections of areas with highly overlapping distributions, but isolated, rare, and disparate features may be important for conservation. This becomes increasingly important as complexity is built into a conservation problem by including more conservation features leading to the over-representation of features that overlap. Feature weights can address redundancy by applying an iterative process in which conservation features not represented in the first prioritization are assigned higher weights for a more balanced representation of each feature (Kirkpatrick, 1983; Williams et al., 2004). Furthermore, highly variable feature weights can alter selections to focus on certain conservation features and outweigh the impacts of a variable cost feature. Therefore, setting and taking advantage of weights is an important part in the prioritization process to offset uncertainties in the data, ensure there is a balancing of ecological, economic, social, and political considerations, and integrate expert opinion (Velazco et al., 2020). Standardizing how feature weights are identified and adjusted based on specific aspects of the data like the distribution and overlap between conservation features is a potential avenue of future research.

3.4.3 **Cost Features and Conservation Features**

The inclusion of cost features can be beneficial by directing management to specific areas based on social-economic data but relies on the accuracy of the data used and relevance to the goals of the prioritization which may be overstated in conservation planning efforts. There is a heavy reliance on proxies, a model for cost, because datasets for the availability and cost of purchasing land for conservation is often non-existent leading to the use of aggregated surfaces with high uncertainty (Armsworth et al., 2017). Some of the most common ways to represent cost with proxies include using the area or size of the land parcel (Carwardine, Wilson, Watts, et al., 2008), agricultural land values (Naidoo & Iwamura, 2007; Sutton, Cho, & Armsworth, 2016), real estate costs (Fois et al., 2019; McDonald-Madden et al., 2008), land assessment values (Ando, 1998; Carwardine et al., 2008; Rodewald et al., 2019), the cost of implementing management actions (Boyd et al., 2015), and forgone revenue or opportunity costs (Klein et al., 2008; Smith, Eastwood, Ota, & Rogers, 2009; Stewart & Possingham, 2005). There are multiple potential pitfalls with basing prioritizations on proxies that may be uncertain or inaccurate. For example, landowner willingness to sell or cooperate with management impacts the realities of being able to carry out conservation plans at an expected cost (Guerrero et al., 2010; Knight et al., 2011). This issue can be addressed by maintaining flexibility and generating multiple conservation plans to meet conservation goals despite unexpected limitations. Overall, our results suggest that cost data is beneficial to include because it can increase the efficiency of the prioritization efforts by identifying plans that are able to garner ecological benefits at a lowered costs (Carwardine et al., 2010).

Transparency with the accuracy of cost data and the pursual of multiple scenarios are important themes in this research that could benefit future conservation planning efforts. We show that the inclusion of cost data can alter the resulting selection and therefore should be considered with caution and consultation with local managers and stakeholders. Priority areas selected for their ecological features were consistently chosen regardless of the cost feature and feature weights, but the allocation of remaining conservation funds was altered by the cost feature and feature weights. Identifying these marginally important areas is useful because local land managers may be able to clearly define the most important areas for conservation but have difficulty narrowing and ranking other beneficial habitat, or areas that provide a key service like connectivity, without being characteristically identifiable as high priority habitat.

As predicted by the H_2 hypothesis, as the number of features in the prioritization and the overlap between features increased, the representation of budget areas decreased and therefore the influence of the cost feature on the selection was diminished. Including additional conservation features to build complexity in a prioritization effort should be carefully considered in terms of how they will impact the solution and uncertainty. Prioritizations that consider local economies and align with social and political climates are more likely to be implemented but, implementation is difficult to measure because of the lack of monitoring or evaluation plans (McIntosh et al., 2017). Reducing the power of a robust cost feature by incorporating conservation features or feature weights should be approached with caution because of the link between costs, cost efficiency, and implementation.

3.4.4 **Connectivity**

Functional connectivity represents the movement of individuals and their genes, through a landscape, thus representing survival and reproductive success. Functional connectivity is an important measure for conservation because the ability for an animal to travel to different habitat patches can ultimately influence the viability of populations and the opportunity for individuals to respond to changing conditions (Tischendorf & Fahrig, 2000). The persistence of sage-grouse populations is dependent on the functional connectivity of the landscape shaping dispersal and inter-seasonal movements (Burkhalter et al., 2018; Cross et al., 2018; Row et al., 2016, 2018).

Connectivity was incorporated to our prioritizations in multiple ways, firstly with a contiguity constraint applied in the problem formulation and secondly by including the genetic connectivity layer (Row et al., 2018) as a conservation feature. Both approaches led to changes in the location of areas that were selected by the prioritization and impacted the representation of certain conservation features. Similar to previous studies that investigated the impacts of including connectivity into prioritization, we detected a minor decrease in representation of the HSMs with the incorporation of the landscape connectivity surface (Arponen et al., 2012; Williams et al., 2019). Since sage-grouse disperse seasonally and rely on corridors of contiguous habitat for movement, considering connectivity in the prioritizations addresses concerns highlighted for this species and its advantages for consideration as an umbrella species for migratory mammals such as elk and mule deer (Copeland et al., 2014) and passerine birds (Barlow et al., 2020). Future planning efforts should consider the connectivity across management borders including field office bounds, districts, states and internationally. When a surface predicting landscape connectivity at the relevant scale is unavailable using a contiguity constraint is a less valuable but viable way to reduce edge in conservation plans.

3.4.5 **Conclusion**

Generally, we found bootstrapping the data to perform a varied set of prioritizations was helpful in informing the prioritization process (Chapter 2) because it fostered a better understanding how different cost features and conservation features shape the solution, leading us towards more robust methods grounded in realistic principals that we recommended for further application. It also allowed us to attempt a large variety of feature weight combinations and take a broad view at how solutions can be fine-tuned to meet specific management objectives. It is important to note that true experimental replication could not be achieved because runs were performed on the same data and constrained to the same region, instead we increased the experimental rigor of this study by focusing on randomness by bootstrapping feature weights (Wiersma et al., 2019).

In conclusion, researchers should consider the relative importance of cost and conservation features to avoid giving undue importance to features applied with multiple assumptions and high uncertainty. Landscape connectivity or similar genetically informed, fine-scale, and widely spanning data are highly useful for prioritization processes because of the potential for benefit or utility to be accrued by a selection can be increased bringing in opportunity for flexibility and complementarity, which are important SCP concepts. Feature weights can be useful to better align conservation problems with expert opinion and management goals which is expected to positively impact the likelihood of implementation. While the details of the solutions presented are specific to the data and context of this study, the general benefits of incorporating cost features, landscape connectivity, and features weights can likely be successfully applied to other systems in which future conservation planning will occur.

Chapter 4

Conclusion

In southwestern Wyoming nesting and brood habitat are predicted to decline by 11.4% and 4% by 2050, assuming current trends persist under climate scenario IPCC A1B (Homer et al., 2015). Preventing the loss of sagebrush is expected to require multiscale efforts across landowners and stakeholder perspectives. Prioritizations are a logical next step for the progression of conservation in this ecosystem (Pratt et al., 2019). We identified priority areas across the RSFO considering seasonal priority habitat, annual priority habitat, and areas that could benefit multiple migratory species, using consultation to incorporate the needs of land managers. Vulnerable priority areas were identified outside of the PACs, and we used landownership to consider where management actions like conservation easements could potentially be effective. We also identified areas that could be suitable for restoration. Considering multiple objectives, we addressed the need to identify areas supporting high density population centers which has been the focus of management actions thus far like the PACs and highlighted areas with low suitability and potential for improvement (Crist et al., 2017). To increase the rigor of our prioritizations we considered a range of problem set-ups adjusting the objective types, feature weights, cost features, and the inclusion of connectivity. We found that applying a maximum utility objective type, threat-based cost feature, feature weights created with local expert input, and incorporating connectivity with genetic informed data and spatial constraints led to improvements in solution quality. Considering multiple species in this prioritization which centered on recommending key areas for a single species had some benefits as the inclusion of more conservation features in the problem that overlapped with conservation features of high priority mitigated the influence of conservation features that were more isolated and with high uncertainty and similarly reduced the influence of the cost feature. As similarly reported, we found that prioritization based on sage-grouse habitat can benefit other species, like mule deer, likely due to the preference for many species to travel on less rugged terrain (Copeland et al., 2014).

Landscape connectivity is an important consideration for conservation plans to support movement between local populations and meet species needs. Protected areas that are detached from a network, even large ones, can lead to the isolation of a population that will be unable to relocate or adapt to changing conditions if threats increase or the area becomes unhabitable. Sage-grouse make landscape-scale movements, use a mosaic of seasonal habitats, and often travel distances > 50 km between seasonal habitats (Beck et al., 2006; Fedy et al., 2012). Incorporating a landscape connectivity surface (Row et al., 2018) improved this prioritization effort because connecting areas are widely distributed across the landscape, bringing in flexibility to select a larger variety of areas that are beneficial for multiple seasons or species to meet conservation goals.

Vulnerability was used to help understand the priorities for conservation in the RSFO and threshold our selections. We found that sage-grouse habitat is represented differently across the seasons and addressing vulnerability will require targeting brood and winter seasons and connectivity between PACs. Nesting and brood habitat showed more similarities in priority areas whereas identifying priority winter habitat led to more unique solutions. High quality winter habitat is expected to be less predictable in models and for sage-grouse because snow cover can be highly variable and addressing the underrepresentation of limited and high-quality winter habitat is an important goal for conservation actions in the RSFO and across the sage-grouse range (Smith et al., 2014). Survival rates have been reported to be lower for the brood season than winter, still, winter is expected to be a limiting period to female sage-grouse survival because sagebrush covered in snow cannot be used as forage or shelter making these seasons particularly important for management (Anthony & Willis, 2009; Baxter et al., 2013; Beck et al., 2006; Moynahan et al., 2006; Schroeder & Baydack, 2001). How the conservation problem was constrained impacted irreplaceability values, for example, identifying priority areas outside of PACs led to higher irreplaceability values because there were fewer planning units to choose from to meet the set budget.

Small changes to the parameters of a conservation problem can shape the resulting solutions and impact solution quality unexpectedly. Comprehensively analyzing a repertoire of conservation problems improves the SCP process by uncovering uncertainty and providing methods to mitigate uncertainty like informed feature weights. Budgets can be set arbitrarily or tailored to the objective and cost feature of the prioritization by running through the problem with a minimum-set objective type to find the least amount of planning units that can accomplish the desired increase (Laitila & Moilanen, 2012). Incorporating too many data pieces and scenarios for the prioritization can bring more uncertainty into the process and lead researchers to misrepresent the conservation goals in their conservation problems. Utilizing large data assemblages to create conservation plans is more suited to situations where conservation action can be implemented in full and immediately, since our approach assumed that not everything could be protected at once and that conservation will likely occur in stages, it was more appropriate to consider sage-grouse individually and we only incorporated other species with overlapping distributions (Meir et al., 2004). Engaging with ongoing consultation to facilitate discussion around priorities and the relative importance of each surface can help researchers narrow into the data that should be driving the selection and address uncertainties in certain surfaces.

SCP processes will be unique to the ecosystem, data availability, management goals and actors involved. Still, we expect the results from this research can be broadly applied to future conservation planning efforts. Going forward conservation planners should focus on utilizing cost features that have reasonable assumptions instead of attempting to predict land costs with uncertainty (i.e., using a threat cost feature instead of modeling land acquisition with development potential or a uniform cost feature).

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Appendix A

Supplementary Material

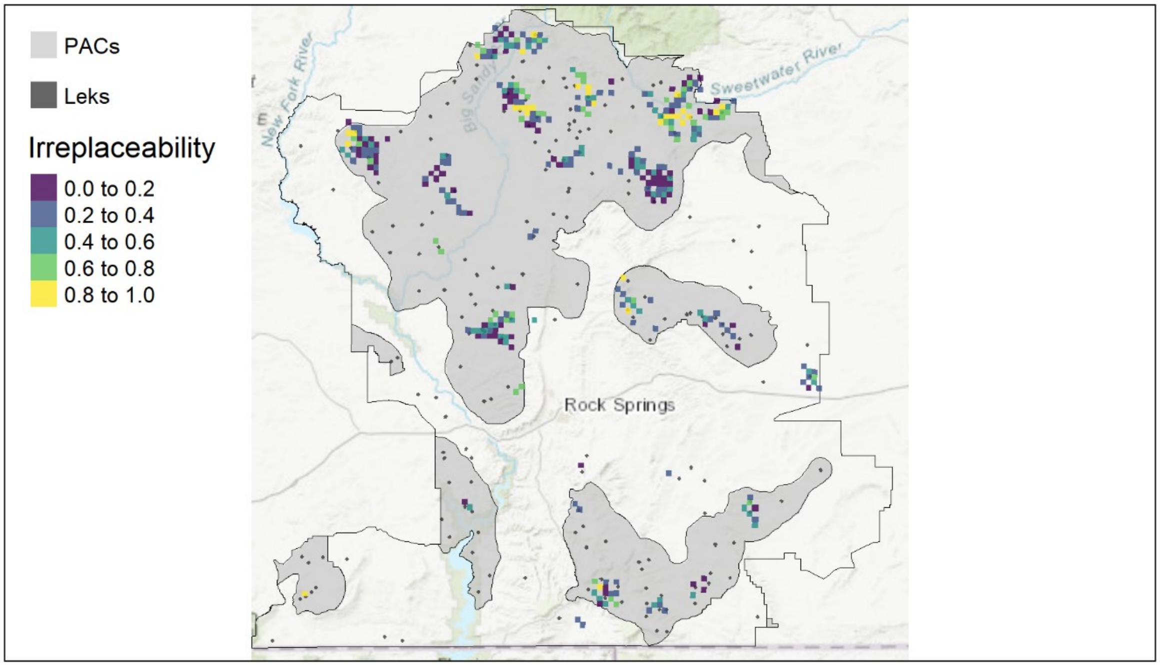

Figure 1. Nesting priority areas on unprotected and protected public and private lands using threat to inform costs.

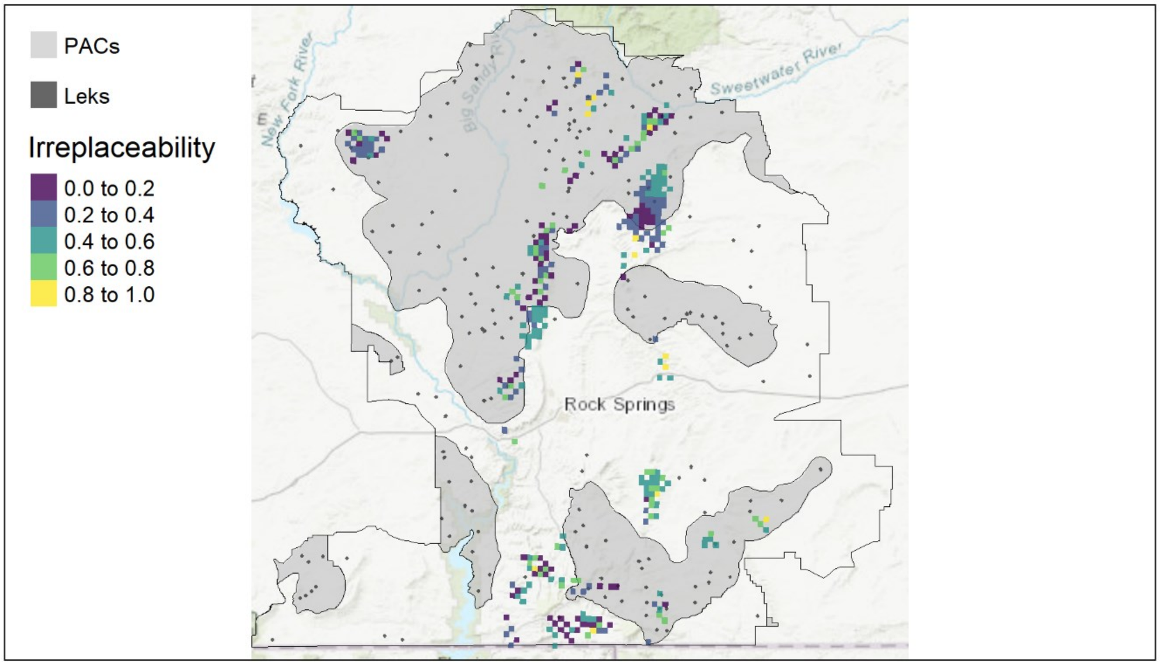

Figure 2. Brood priority areas on unprotected and protected public and private lands using threat to inform costs.

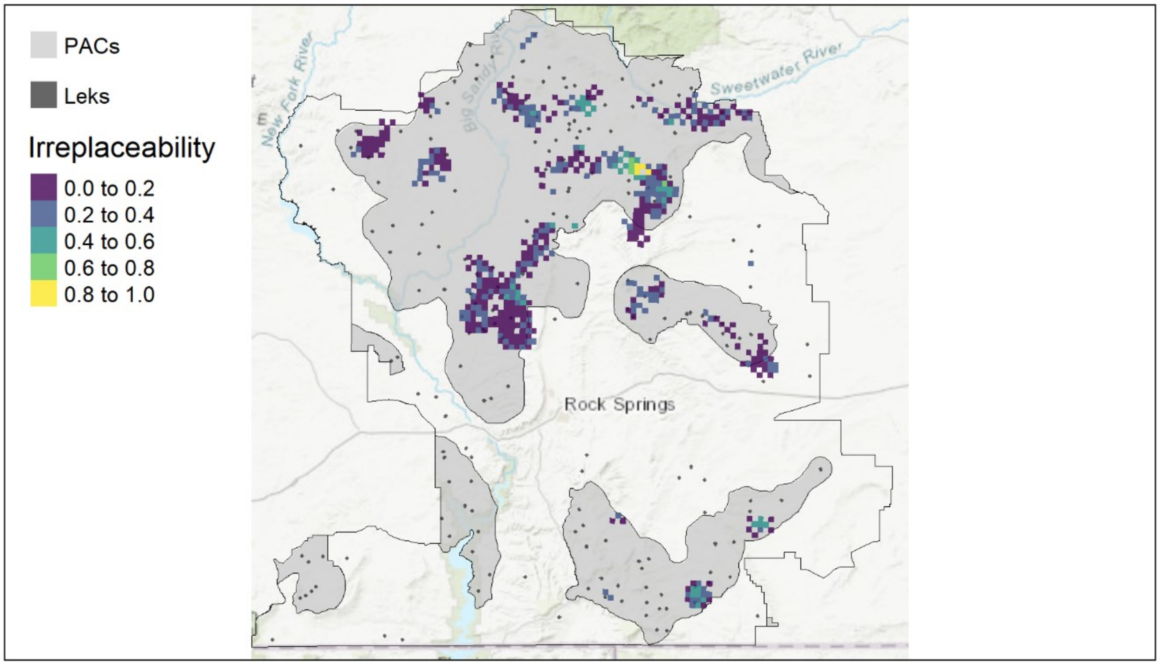

Figure 3. Winter priority areas on unprotected and protected public and private lands using threat to inform costs.

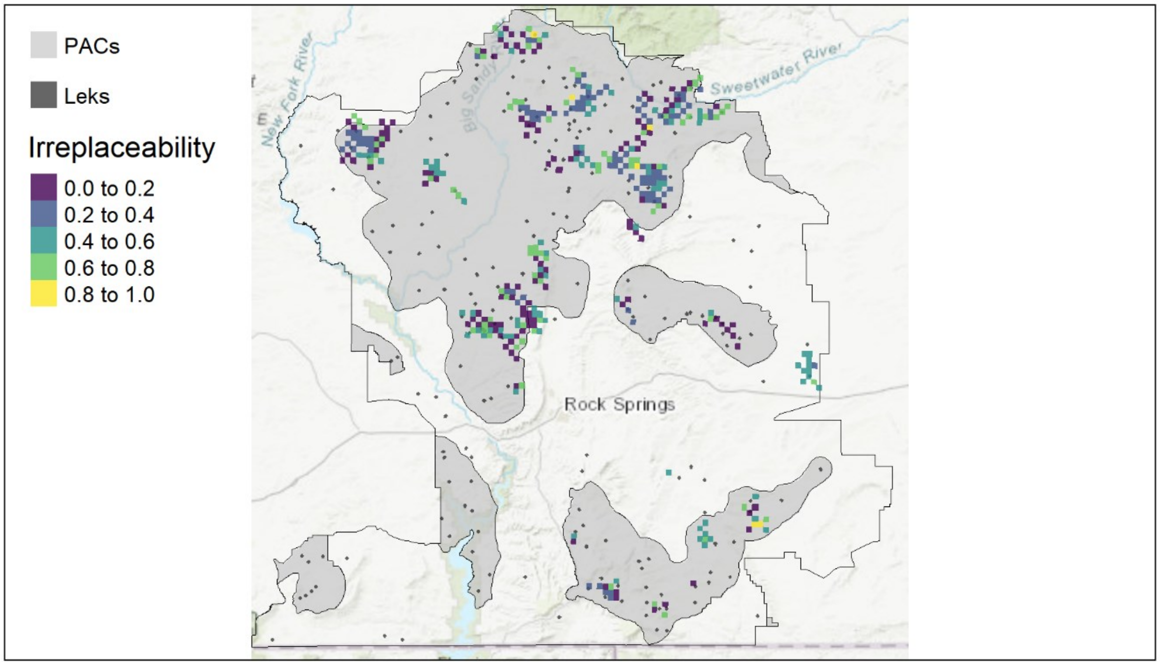

Figure 4. Annual priority areas on unprotected and protected public and private lands using threat to inform costs.

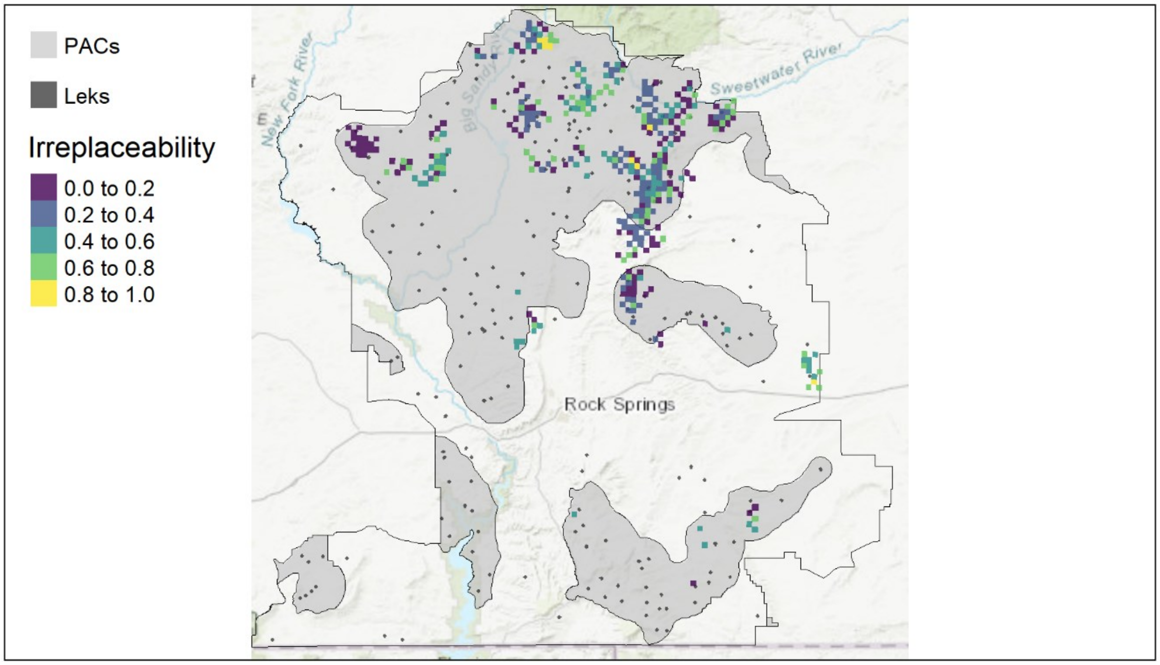

Figure 5. Multiple species priority areas on unprotected and protected public and private lands using threat to inform costs.

Table 1. Wilcox ranked sum test results for each performance metric calculated for the bootstrapped solutions (N=600) and reported as the W-values and *p*-values, significant relationships are shown in bold. The relationships tested included all combinations of the three cost features uniform, threat, and development potential, the two feature weight scenarios, and the two objective types.

Metrics	Uniform ~ threat cost features	Uniform ~ development potential cost features	Threat ~ development potential cost features	High ~ low feature weight ranges	MUP ~ MSC objective types
Irreplaceability	**W = 25533, p-value = 1.707e-06**	**W = 24759, p-value = 3.857e-05**	**W = 23014, p-value = 0.009147**	**W = 49462, p-value = 0.0356**	**W = 7869, p-value < 2.2e-16**
ROI	**W = 40000, p-value < 2.2e-16**	**W = 40000, p-value < 2.2e-16**	W = 20917, p-value = 0.4206	W = 43554, p-value = 0.4929	**W = 20000, p-value < 2.2e-16**
Contiguity	**W = 5104, p-value = 4.117e-11**	W = 3701, p-value = 0.08268	**W = 1053, p-value = 9.893e-14**	W = 7460, p-value = 0.627	**W = 4800, p-value = 7.016e-06**
HSM representation	**W = 13220, p-value = 2.558e-09**	**W = 27415, p-value = 7.233e-11**	**W = 28315, p-value = 2.739e-13**	W = 43516, p-value = 0.4817	**W = 0, p-value < 2.2e-16**
Solution cost	**W = 0, p-value < 2.2e-16**	**W = 0, p-value < 2.2e-16**	**W = 40000, p-value < 2.2e-16**	W = 20212, p-value = 0.8526	**W = 30000, p-value = 9.944e-13**

Prepared by:
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for the BLM RSFO on April 28th, 2021

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Feature Weights Consultation

Purpose

We are currently developing integrated habitat prioritization surfaces for the BLM Rock Springs Field Office. The approach we are using allows for the integration of multiple surfaces (or "features") in our optimization process. The weight of each feature can vary in relation to how much importance is placed on each conservation feature included in the prioritization. Varying feature weights can change the representation of conservation features and the calculation of the relative importance (i.e., irreplaceability) for each planning unit. Feature weights present an important opportunity to consult with local experts and better reflect management goals and local knowledge. We are using an analytic hierarchy process (AHP) to quantify priorities for decision making. We have included maps of potential input surfaces for reference and would like you, in your role as a local expert, to provide rankings for the importance of each surface in the table provided on the final page of this document. This should take less than 30 minutes to complete and will have important influence on the final products provided to the BLM. Additionally, to provide some idea of the consequences of varying the weight of the different features, we have included an example illustrating how feature weights could be set, such as targeting what is suspected to be underrepresented by conservation efforts thus far (e.g. winter and brood habitat) and landscape connectivity. When you have completed the rating, please return the document to Patrick Lionberger. Submissions will be accepted until May 30th, 2021.

For more information questions may be directed to:
Marie Racioppa, m2raciop@uwaterloo.ca or
Dr. Brad Fedy, bfedy@uwaterloo.ca

1

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Instructions to complete the evaluation in the empty ranking table at the end of the document:

Start with the feature in each row (e.g., nesting). Move across the columns and assign a value based on the pairwise comparison table below. Values should be assigned to all features that are of equal or less importance than the feature in the row name. In the example on page 4, for the nesting row the first value is 1, because it is compared to itself and therefore is of equal weight. The next column represents brood habitat suitability. If the expert believes that brood habitat is more important than nesting, then they will leave it blank. If the expert believes that nesting is more important than winter habitat (the next column) they will fill that cell with the number that corresponds to *how much more important* they think nesting is compared to winter. If moderately more important then perhaps they would assign it a 3. The next column is landscape connectivity. If this variable is of equal importance to nesting, then it too can receive a value of 1. Once the first row is complete, the expert should move to the next row and complete the process again assigning values to only those features that are less than or equal to the importance of the variable listed in that row.

Intensity of importance	*Definition*	*Explanation*
1	Equal importance	Two features contribute equally to the objective
2	Weak	
3	Moderate importance	Experience and judgement slightly favor one feature over another
4	Moderate plus	
5	Strong importance	Experience and judgement strongly favor one feature over another
6	Strong plus	
7	Very strong, demonstrated importance	One feature is very strongly favoured, it's importance is demonstrated in practice
8	Very, very strong	
9	Extreme importance	The evidence favoring one feature over another is of the highest possible order

2

Figure 6. Pages 1-2 of the analytic hierarchy process (AHP) approach to feature weight consultation introducing the aim of the document, instructions and the fundamental scale introduced in (Saaty & Vargas, 2012).

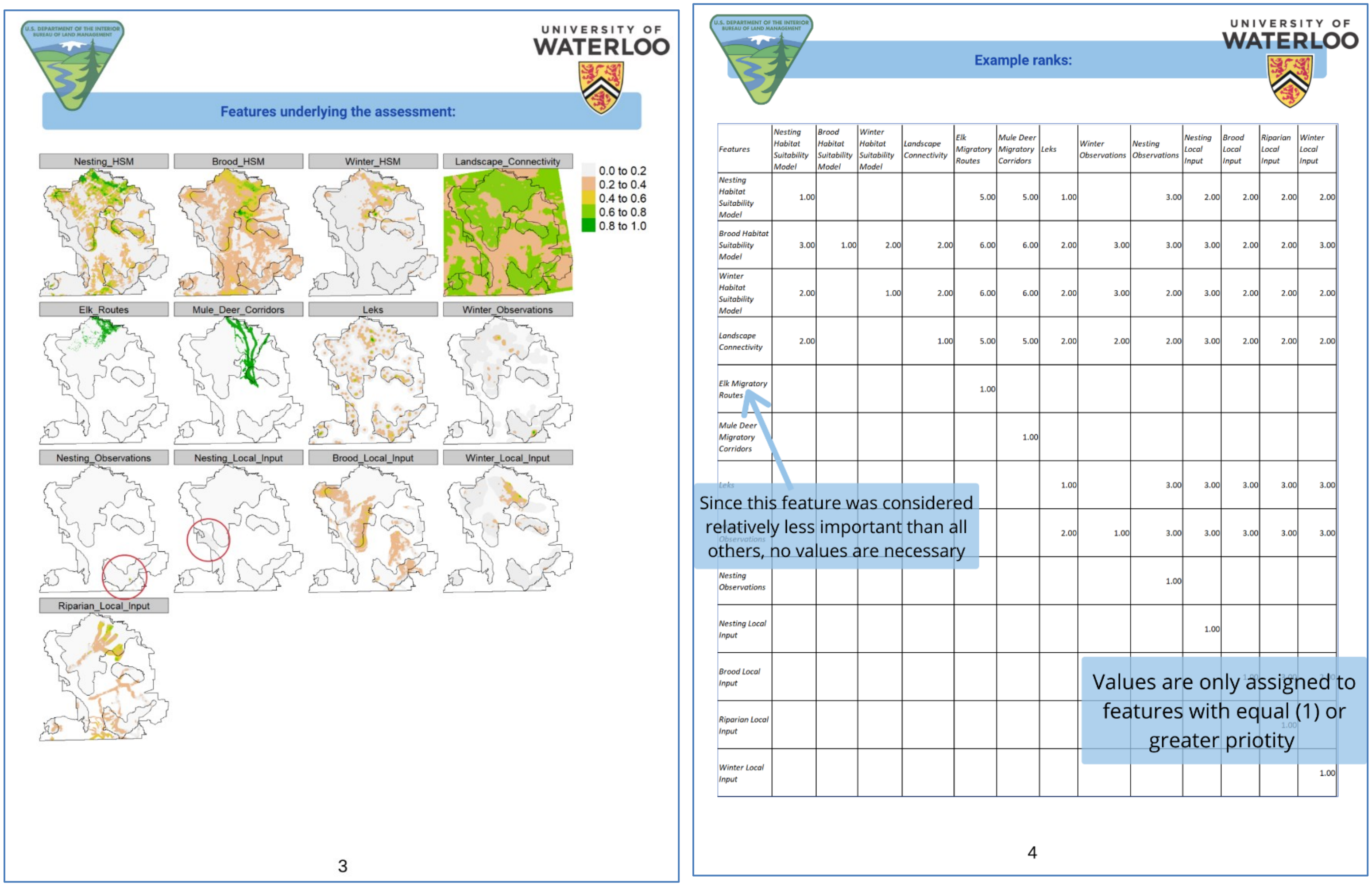

Figure 7. Pages 3-4 of the analytic hierarchy process (AHP) approach to feature weight consultation depicting the relevant conservation features and an example for how ranks are to be assigned to each feature using a pairwise comparison.

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Empty table, please fill following instructions:

Features	Nesting Habitat Suitability Model	Brood Habitat Suitability Model	Winter Habitat Suitability Model	Landscape Connectivity	Elk Migratory Routes	Mule Deer Migratory Corridors	Leks	Winter Observations	Nesting Observations	Nesting Local Input	Brood Local Input	Riparian Local Input	Winter Local Input
Nesting Habitat Suitability Model	1												
Brood Habitat Suitability Model		1											
Winter Habitat Suitability Model			1										
Landscape Connectivity				1									
Elk Migratory Routes					1								
Mule Deer Migratory Corridors						1							
Leks							1						
Winter Observations								1					
Nesting Observations									1				
Nesting Local Input										1			
Brood Local Input											1		
Riparian Local Input												1	
Winter Local Input													1

5

Figure 8. Page five of the analytic hierarchy process (AHP) approach to feature weight consultation containing a blank table for ranking each feature