INTEGRATING SOCIAL, POLITICAL, AND ECONOMIC FACTORS INTO

SPATIAL MODELS OF GRIZZLY BEAR CONFLICT AND CONNECTIVITY

by

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DEDICATION

I would like to dedicate this work to the people in my life who have constantly encouraged me to pursue what I am passionate about, and who have never doubted that I could achieve what I set my mind to. To my parents, Royal and Belinda, thank you for raising me with encouragement, discipline, and showing me that dreams don't have to stay intangible. To my grandparents, Ingrid, Mike, and Marion, thank you for teaching me what true perseverance looks like and the value of hard work. To my fiancé, Mackenzie, thank you for encouraging me to cultivate my passion for conservation and always reminding me of the steadfast love that I have through the Lord. To all of my incredible friends, in each of the many places that I have pursued my education, thank you for your constant joyful support and encouragement.

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ABSTRACT

The rapid expansion of the global human footprint is forcing humans and wildlife to share more space. There is rising concern over human wildlife conflict and its effects on human and animal wellbeing. Investigation into the biophysical and social landscape features that shape conflict or how spatial patterns in conflict ultimately affect species' movement or survival is limited. Characterizing landscape connectivity and identifying potential movement corridors is a key conservation strategy, but is challenged by the fact that many wildlife species navigate a mosaic of infrastructure, available habitat, land uses, and political boundaries. In this thesis, I investigated the social and biophysical factors that contribute to conflict with grizzly bears (*Ursus arctos*) and how this conflict may impact connectivity for bears across southern British Columbia and northern Washington. I selected this system due to its rich cultural history with grizzly bear biological and social complexity. The region has current grizzly bear populations, extirpated areas, state/provincial and international boundaries, diverse land uses, and a variety of social values towards wildlife. I used two resource selection approaches to first determine the probability of conflict reporting across all wildlife species, and then to determine the probability of bear conflict specifically. First, I used presence and background sampling in combination with Bayesian logistic regression to identify important predictors of conflict across species using 5,606 reported instances of conflict and 8,703 background points. Then, I fit a second regression treating 2,062 bear conflict

occurrences as presence points and 3,544 instances of other conflict as absences to characterize how bear conflict might differ from wildlife conflict in general.

I found that predictors of conflict differed between species and that the probability of general wildlife conflict was substantially different than the probability of bear conflict across the study system. The strongest predictors of conflict for all species were human population density and both livestock and row-crop operation density. The strongest predictors of bear conflict were public opinion of bears, proximity to existing grizzly bear populations, and suitable bear habitat. Generating spatial predictions on these models indicates that the urban centers of the Okanagan (e.g., Kelowna, Vernon) are hotspots for general wildlife conflict while the semi-urban and rural agriculture landscapes (e.g., outside Penticton and along the US and Canada border) are hotspots for bear conflict (Chapter 1). I then incorporated spatial predictions of the probability of bear conflict into the resistance surface for a connectivity model across the traditional territory of the Sylix people to investigate how spatial patterns of conflict may impact bear movement and the ability to recolonize the traditional Sylix territory. I used Omniscape to model connectivity as a function of biophysical variables to identify the most likely available movement pathways and compared this to model outputs that incorporated the probability of conflict into the resistance surface to determine the effects of conflict on grizzly bear connectivity. My research highlights the role that social and institutional variables play in conflict and how these effects may differ between species. Further, my results illustrate the potential for conflict to constrain wildlife movement and highlight the need to treat connectivity conservation as a socio-ecological issue rather than just an ecological one.

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LIST OF ABBREVIATIONS

SOI	Southern Interior Ecoprovince
WARP	Wildlife Alert Reporting Program
CCS	Consolidated Census Subdivision
ONA	Okanagan Nation Alliance

CHAPTER ONE: INTEGRATING SOCIAL, POLITICAL, AND ECONOMIC FACTORS INTO SPATIAL MODELS OF GRIZZLY BEAR (URSUS ARCTOS) CONFLICT IN THE SOUTHERN INTERIOR OF BRITISH COLUMBIA

Abstract

Public concerns about human-wildlife conflicts are often a barrier to large carnivore conservation. The effects of the spatial juxtaposition of ecological (e.g., suitable habitat or movement corridors) and social (e.g., land use or human attitudes) features on the potential for conflict or how recurrent conflicts ultimately affect conservation outcomes are not well understood. I investigated the factors that contribute to conflict with grizzly bears, a wide-ranging and culturally significant species that often inhabit areas of high human activity. I conducted two linked resource selection analyses using Bayesian logistic regression to distinguish the predictors of general human-wildlife conflict from those specific to human-bear conflict. For the first, I used 5,606 reported instances of conflict as presence points and 8,703 background points to identify important predictors of conflict for wildlife in general. I then fit a second regression treating 2,062 bear conflict reports as presence points and 3,544 instances of other wildlife conflict as absences to determine how predictors of bear conflict might differ from all other wildlife. I used distance to protected areas, bear habitat suitability, distance to extant grizzly populations, and predicted connectivity for bears as biophysical predictors. I included the probability of general wildlife conflict, distance to metropolitan areas, density of row-crop operations, density of livestock operations, population density, and public opinion

towards grizzly bears as characteristics of the social landscape. Predictors of bear conflict differed from those of wildlife conflict in general, giving rise to different spatial patterns in the probability of conflict. Human population density and agricultural land use were positively associated with both forms of conflict, though their effects were larger for general conflict. In addition, the probability of bear conflict was highest at intermediate levels of general wildlife conflict and in areas where there was general support for bear population increases. My results illustrate how the combination of socio-political factors and bear habitat requirements increase the probability of human-bear conflict and highlight areas where conflict mitigation may be necessary to achieve conservation objectives.

Introduction

Continued expansion of human communities into wildlife habitats has increased the frequency, intensity, and importance of human wildlife conflict (Fehlmann et al., 2021; Theobald et al., 2020; Allan et al., 2019; Newbold, 2015; Crooks et al., 2011). Human-wildlife conflict is known to impact both social and ecological systems, though the effects of conflict are often context dependent and vary between wildlife species, location, and who is involved (Fehlmann et al., 2021; König et al., 2020; Bhatia et al., 2020; Dickman, 2010). For example, conflict surrounding elephant crop raiding in rural Africa involves different socio-political dynamics than conflict with large carnivores navigating suburban and urban cityscapes in the American West (Pozo et al., 2021; Buchholtz et al., 2020; Young et al., 2015). Contemporary studies of human-wildlife conflict have focused on conflict with individual species or limited geographies (Lute et al., 2018; Goswami & Vasudev, 2017) and the ecological outcomes of these conflicts

(Schell et al., 2021; van Bommel et al., 2020; Lamb et al., 2018). Less is known, however, of how persistent social structures (e.g., human values, land use, economics, jurisdictional boundaries) impact human-wildlife conflict in general or how those impacts vary between species. My research addresses this gap by investigating how social, institutional, and ecological factors predict the probability of human-wildlife conflict occurrence.

Interactions between people and wildlife occur along a spectrum ranging from neutral sightings (i.e., no impacts on humans or wildlife) to "conflicts," depending on the nature of the encounter and cultural context (i.e., how certain species are perceived or valued) (Bhatia et al., 2020). I use Gore's (2004) definition of conflict as those incidents which include both defensive and predatory interactions (i.e., common in parks and wildlands) and nuisance encounters (i.e., occurring in developed landscapes) which are often due to perceived threats to property or safety. "Conflict" can take many forms (e.g., vehicle collision, aggressive encounters, livestock depredation) and is known to alter animals' spatial and temporal use of a human-impacted landscape (Whittington et al., 2022; Rio-Major et al., 2019; Blackwell et al., 2016; Young et al., 2015). Human-wildlife conflict is often driven by both assessed and perceived risks to a person's existing lifestyle (Gaynor et al., 2019; Bruskotter et al., 2017; Gore, 2004). Despite the seeming prevalence of conflict, people and wildlife also coexist in shared landscapes without conflict (Brenner & Metcalf, 2020; Bruskotter et al., 2015). For example, many Indigenous peoples have coexisted with wildlife species without persistent conflicts (Pooley et al., 2021; Kideghesho, 2008).

Contemporary evaluations of human impacts on wildlife behavior (i.e., landscape of fear, human-wildlife coexistence studies) focus on individual impacts and behavioral outcomes (e.g., risk avoidance between individual animals and people). With a few exceptions (e.g., Lamb et al., 2020; Suraci et al., 2019), the population level impacts of conflict have not been explored. For example, conflict that is consistent through space and time can result in populations of animals avoiding historic movement corridors (Schell et al., 2021; Tucker et al., 2018). Wildlife hazing, variation in land tenure and jurisdiction, and differing land uses may create persistent, spatially consistent patterns of conflict which can create population sinks or inhibit wildlife connectivity (Lamb et al., 2020; Buchholtz et al., 2020; Woodroffe et al., 2005), especially for contentious species.

Human-carnivore conflicts can have significant consequences, resulting in injury or death to both human and carnivore. Encounters between individual landowners and organisms can also produce collective responses such as changes in policy, management actions, and the formation of institutions and interest groups tasked with altering the effects of conflict (König et al., 2020; Dickman, 2010). Severe conflicts can result in a collective push for reflexive management action (e.g., translocation, recreational closures), lethal management approaches, and a collective increase in hostility towards problem wildlife species (Lamb et al., 2020; Woodroffe et al., 2005). Even persistent patterns of non-violent encounters between people and carnivores can affect future interactions and behavioral avoidance (Bruskotter et al., 2017). Given that the occurrence of conflict and the severity of response varies due to a number of socio-political factors, characterizing the importance of those factors and mapping their effects on the landscape is vital for understanding how conflict might ultimately affect wildlife populations.

Spatial patterns of human encroachment into grizzly bear (*Ursus arctos*) habitat coupled with efforts to restore grizzly bears to their historic range provide an opportunity to evaluate these human-wildlife conflict relations (Sage et al., 2022; Lamb et al., 2020; Peck et al., 2017). Grizzlies have expansive home-ranges (an average of 804 km^2 for males and 222 km^2 for females, in dry interior mountains and plateaus) and are known to have relatively frequent encounters with people (Gyug et al., 2004; Ciarniello et al. 2001; McLellan 1981; Russell et al., 1979). The spatial juxtaposition of undeveloped protected areas, urban developed areas, and a variety of agricultural lands across BC creates many opportunities for interactions between grizzly bears and people (Wilson et al., 2006; Kellert, 1994; McLellan, 1988) making them a highly contentious species (Clark et al., 2021; Darimont et al., 2018). Shifts in economic drivers of resource extraction and amenity-based income have driven the continued fragmentation of grizzly bear habitat and movement corridors (Lamb et al., 2020; 2018).

I used a resource selection function approach to identify variables associated with human-wildlife conflict in general, and human-bear conflict in particular. Rather than modeling bear occurrence as a function of spatial habitat covariates as is typical in resource selection functions, I modeled the occurrence of conflict as a function of spatial predictors describing the social and ecological landscape (Williamson et al., 2018). Modeling conflict across the human-influenced landscape helps to elucidate the spatial anthropogenic pressures that can threaten critical species populations. My research reveals where spatially consistent patterns of socio-political trends may create predictable pressures that result in wildlife conflict with people.

Methods

<u>Study System</u>

I evaluated the spatial drivers of general wildlife conflict and bear-specific conflict throughout the Southern Interior Ecoprovince (SOI) of British Columbia. The SOI provides an interesting region of study due to its proximity to existing grizzly bear populations, the prevalence of suitable habitat in areas where grizzly bears are considered extirpated, and a diverse suite of land uses (including conserved areas, resource extraction, agriculture land, and urban interfaces) (Lamb et al., 2018; Demarchi, 2011; Gyug et al., 2004; Map 1.1. There are existing black bear populations within this region and multiple documented populations of grizzly bears which exist along the edges of this Ecoprovince, outside of the extirpation zone. Recent estimates of grizzly bear density in population units (GBPU) outside the extirpation zone range from 1-10 per 1000km^2 in the southwest interior to 11-20 per 1000 km^2 along the eastern side of the SOI (BC Gov, 2020; Mowat, 2018).

The SOI extends from the southern Canadian border up through the central interior region of British Columbia, including the most southern parts of the Interior Plateau system (Map 1.1). The SOI is defined under the Ecoregion Classification System as an Ecoprovince, an area having consistent climatic processes, relief, and regional landforms (Demarchi, 2011). The SOI falls within the broader ecodomain of semi-arid steppe highlands, lies in between the Columbia and Cascade Mountains, and includes multiple ecoregions (Demarchi, 2011). The SOI receives little precipitation and includes a diverse array of vegetation communities ranging from open grassland to dense coniferous forests and a variety of lakes.

Data

I identified conflict locations using the British Columbia Conservation Foundation's Wildlife Alert Reporting Program (WARP) (WildSafeBC, 2020). WARP is a database of voluntarily reported instances of conflict containing the approximate location and a description of each encounter provided by members of the general public. I used all conflict reports between March 24, 2020 through March 31, 2021 within the Southern Interior (SOI) (5,606 total observations) (WildSafeBC, 2020). I filtered all reports to BC, cropped them to those within a 10 km buffer of the study region, and separated out all bear conflict reports. There were 2,016 black bear and 46 grizzly bear reports out of a total of 5,606 reports within the study region during the year under consideration. I combined conflict reports for both grizzly and black bear due to concerns over the veracity of identification; however, comparison of the kernel density estimates of reports for both species suggest that spatial patterns of conflict reporting for black and grizzly bears are similar enough to support combining them (Figure A.1, A.2).

Modeling Conflict

I conducted a series of Bayesian hierarchical logistic regressions to identify the predictors of conflict. First, I combined all documented occurrences of conflict with 8,703background points within the study region to identify factors associated with conflict in general. I used the results of the general conflict model to generate spatial predictions of conflict that were subsequently incorporated into a second hierarchical logistic regression of bear conflict. For this model, I treated all bear conflict reports as presences and any other conflict reports as absences. I used the first model to account for the general spatial patterns in conflict that have more to do with where people are on the

landscape (e.g., location of urban centers, patterns of land-use), than the particular species in question (Fehlmann et al., 2021; Lamb et al., 2020; König et al., 2020). Incorporating the general probability of conflict allowed me to identify predictors of conflict that were bear-specific and understand how those may differ from predictors of conflict, in general. I generated spatial predictions based on each model by multiplying the median posterior estimate of each coefficient by its respective spatial surface to generate spatially explicit estimates of conflict.

Predictors of General Conflict:

For the general conflict model, I generated the maximum number of background points possible to avoid complete saturation of the study region and total separation in the modeling of presences and absences. My predictors for this general conflict model were distance to nearest protected area (in km), distance to nearest metropolitan area (in km), density of livestock operations calculated by consolidated census subdivision (# of operations/km^2), density of row crop operations calculated by consolidated census subdivision (# of operations/km^2), and human population density by square kilometer (Table A.1). Distance to the nearest protected area is closely related to critical habitat landscapes for a variety of species (Madden, 2004). Distance to the nearest metropolitan area, density of livestock and row crop operations, and population density are considered to be potentially indicative of human land use and infrastructures which can alter conflict patterns on a landscape (Fehlmann et al., 2021; Manfredo et al., 2021; Schell et al., 2021; Lamb et al., 2020).

I projected all variables to NAD83 / BC Albers to fit data to a regionally accurate projection of the study region. I resampled the data to a 1km^2 resolution to

match the scale of the bear habitat suitability data. I scaled all variables by subtracting the

mean and dividing by one standard deviation. I included a varying intercept for the

consolidated census subdivisions (CCS, n=38) to account for the likelihood that conflict

within each CCS may vary due to reasons not captured by my predictors. I estimated

values for probability of general conflict reporting for location i in consolidated census

subdivision j as the outcome of a Bernoulli trial where $p_{i,j} = 1$ with probability $\pi_{i,j}$ and 0

otherwise according to

$$p_{i,j} \sim Bernoulli(\pi_{i,j})$$

$$logit(\pi_{i,j}) = \beta_0 + \varphi_j + x'_i\beta$$

where β_0 is the intercept of conflict reporting probability, $x'_{i,j}$ is a vector of spatially

varying predictors, β is a vector of coefficients relating the predictor variables to

probability of conflict reporting, and $\varphi_{i,j}$ is the varying intercept for CCS region. It is

worth noting that the intercept, β_0, is biologically uninterpretable due to my use of

background points (Fieberg et al., 2021).

<u>Predictors of Bear Conflict</u>

     I included the estimate of general conflict probability as a predictor in a second

hierarchical logistic regression of human-bear conflict, to characterize the relations

between predictors and bear-specific conflict. I used the agriculture density and distance

to protected area predictors from the general conflict model to compare how density of

agriculture operations and proximity to protected areas could differ between general and

bear conflict patterns. Additionally, I included public support for increasing grizzly bear

populations, distance to extant grizzly populations, current estimated grizzly bear density

representing bear habitat suitability (Lamb et al., *in progress*), and biophysical

connectivity of bears based on topographic ruggedness and global human modification

(gHM) (Theobald et al., 2020; Appendix A). I included the quadratic form of general

conflict probability as a predictor to reflect the potential for bear conflict to occur at

intermediate levels of general conflict. I did so because the highest probabilities of

conflict were in areas where human population density made bear encounters less likely. I

used public opinion towards grizzlies to indicate specific regions which were more

hostile towards bears and bear management (Sage et al., 2022; Manfredo et al., 2021;

Lamb et al., 2020; Lute et al., 2018; Young et al., 2015). I used cumulative current

density resulting from a connectivity model based on topographic ruggedness, human

modification, and bear habitat suitability to reflects the probability of a bear moving

through a given location on the landscape and distinguishes areas of high habitat quality

from areas with high movement potential. I used grizzly bear density, distance to extant

grizzly populations, and topographic ruggedness to estimate movement patterns and

potential critical habitat of grizzly bears (Lamb et al., 2018; Proctor et al., 2018;

Singleton et al., 2004). I used global human modification (gHM) as an indicator of

human land use and infrastructures which impact how bears navigate and coexist on a

shared landscape (Theobald et al., 2020; CIESIN, 2018; Wilson et al., 2005; Wilson et

al., 2003).

I prepared all predictors following the same approach for the general conflict

model. I estimated the probability of bear conflict reporting for report location i in

consolidated census subdivision j as the outcome of a Bernoulli trial where $b_{i,j} = 1$ with

probability $u_{i,j}$ and 0 otherwise according to

$$b_{i,j} \sim Bernoulli(u_{i,j})$$

$$logit(u_{i,j}) = \beta_0 + \varphi_j + x_i'\boldsymbol{\beta}$$

where $\boldsymbol{\beta}_0$ is the intercept and reflects the overall average of bear conflict reporting, $x'_{i,j}$ is a vector of spatially variable predictors that represent characteristic of bear conflict reporting including the probability of general conflict reporting calculated in the first model, $\boldsymbol{\beta}$ is a vector of coefficients relating the predictor variables to probability of bear conflict reporting, and $\varphi_{i,j}$ represents a varying intercept for CCS region.

Model Specifications

I conducted all analyses in R v.4.1.2 (RStudio Team, 2020) using rstanarm (Goodrich et al., 2022) a wrapper to Stan, a Bayesian estimation software. I used weakly informative (student's t with mean=0, degrees of freedom = 7, and scale = 2) priors for regression coefficients to account for the likelihood of coefficients remaining close to zero, but having some chance of being large (Gelman & Hill, 2007). I assessed goodness-of-fit for each model by evaluating the area under the receiver-operating curve (AUC). An AUC > 0.75 is regarded as a good model fit and an AUC ~ 1 is a near perfect fit to the data (Robin et al., 2011). I used leave-one-out information criteria (LOOIC) to summarize model quality between the analysis models and the corresponding "null" models that contained only intercepts. I computed LOOIC using pareto smoothed importance sampling (Vehtari et al., 2017). LOOIC is considered convenient for assessing Bayesian model quality and is a more robust version of Watanabe-Akaike Information Criterion (Hingee et al., 2022; Gelman et al., 2014).

Results

There was a total of 5,606 wildlife conflict reports occurring between March 2020 to March of 2021, including 2,062 combined bear conflict reports. The general conflict

model had 14,309 total observations (5,606 reports and 8,703 background points) and included reports for large carnivores (e.g., cougars, wolves), mesocarnivores (e.g., bobcat, coyote, lynx), and ungulates (e.g., deer, moose, elk). The encounter types (i.e., characteristics and outcome of each encounter) of these general species reports ranged from food conditioned and damage to property to aggressive, injured/distressed animals, and dead wildlife (WildSafeBC, 2020). The general conflict model included predictors for distance to protected and metropolitan areas, density of livestock and row crop operations, population density, and a varying intercept for the CCS regions. This model fit the data well (AUC > 0.95 for the posterior estimates of p) and outperformed the varying-intercept (ΔLOOIC = 2039, Figure 1.9).

The bear conflict model had 5,606 observations (2,062 bear reports and 3,544 other species reports) including encounter types ranging from food conditioned, property damage, and residential interactions to aggressive, distressed, dead wildlife and human injury or death (WildSafeBC, 2020). The full bear conflict model included distance to protected areas and extant grizzly populations, bear habitat suitability, public opinion of bears, biophysical connectivity, density of livestock and row crop operations, the probability of general species conflict, and a quadratic term for general species conflict. I compared this to a model without a quadratic term for general conflict that performed worse than the model including both general conflict predictors (ΔLOOIC = 9.4). A partial model completely excluding general conflict also preformed worse than the full model with both predictors for general conflict (ΔLOOIC = 10.3). The full model fit the data had reasonable predictive accuracy (AUC > 0.71 for the posterior estimates of p) and

outperformed the varying-intercept only model (ΔLOOIC = 86.6) suggesting a plausible fit to the data (Figure 1.10).

Predictors of General Conflict

The coefficients of the general conflict model indicated that wildlife conflict was more likely to occur in regions of high population density across the SOI of British Columbia (Figure 1.9). General species conflict was highest in consolidated census subdivision (CCS) regions with high density of livestock operations, medium density of row crop operations, and closer proximity to protected areas (Figure 1.5). Within the upper 10th percentile of population density, there was 100% predicted probability of conflict regardless of the values of other predictors. At the mean and lower 10th percentiles of population density, however, the effects of other predictors become more evident. Distance to metropolitan areas was negatively associated, indicating that the probability of general wildlife conflict was highest within or near metropolitan areas (Figure 1.5).

Predictors of Bear Conflict

Population density, public perceptions of grizzly bears, probability of general wildlife conflict, and density of agriculture operations had substantial influence on the probability of bear conflict. The quadratic term for general conflict indicated that bear conflict is highest at intermediate levels of general species conflict (Figure 1.10). Bear conflict probability was highest in CCS regions with medium population density, general support for grizzly bears increasing, and in the regions nearest or within extant grizzly populations (Figure 1.6; 1.7). There was some similarity in agriculture density for predicting probability of conflict between the two models; with density of row crop

operations being a slightly stronger predictor of bear conflict. Distance to extant grizzly bear populations had a negative effect on the probability of bear conflict, indicating that the majority of conflict events occurred close to existing populations. Bear habitat suitability had a slight positive effect on probability of bear conflict and biophysical connectivity had a slight negative effect (Figure 1.6). The results of the bear conflict model indicated that the social predictors had a greater influence on the probability of bear conflict than the biophysical predictors. The probability of bear conflict was strongly associated with social support for grizzly bears increasing throughout the region (Figure 1.7). As the proportion of people that supported grizzly bears increasing grew from 40-50%, the probability of bear conflict approximately doubled (increasing from about 40% to 80%) in the lower 10th percentile of probability of general conflict.

Spatial Variation in Predicted Conflict

Differences in the predictors of general conflict and the predictors of bear conflict resulted in different spatial patterns. Visual comparison of these patterns suggests that the most concentrated areas of general wildlife conflict occurred throughout the Okanagan region, surrounding Kamloops, north of Vernon, and continuing down near Penticton. The highest probability of conflict (between 0.7 and 1.0) was predicted to occur around each major city, with larger hotspots just north of Vernon and on the outskirts of Kelowna. Overall, the general conflict map showed a high probability of conflict occurring in the central eastern region of the Southern Interior. This was similar for parts of the probability of bear conflict map, but I observed a much wider range of probability of bear conflict across the entire region. In the bear conflict map, the most concentrated areas of predicted conflict still occurred within the Okanagan valley, but there was also

some increased conflict probability along the edge of the South Chilcotin Mountains northwest of Merritt and the northmost tip of the SOI. The highest probability of bear conflict (between 0.8 and 1.0) was predicted to occur north of Vernon, surrounding Penticton, and along the U.S. and Canadian border by highway BC 97. Overall, the probability of bear conflict map showed a substantial increase in conflict probability from the general wildlife conflict estimates (the majority of predicted bear conflict probability was > 0.5 across the SOI) (Figure 1.8).

Discussion

This research reveals where social and biophysical variables create predictable spatial patterns in human-wildlife conflict. Conflict has been defined as the events which include both defensive and predatory interactions (i.e., common in parks and wildlands) and nuisance encounters (i.e., occurring in developed landscapes) which are often due to perceived threats towards human property or safety (Gore, 2004). These results indicate that general wildlife conflict is influenced strongly by human population density and land use variation. They reveal that at the highest levels of population density, general wildlife conflict likelihood is close to 100%. At intermediate and lower levels of population density, however, land use variation becomes important in determining conflict probability. These results also reveal that the variables driving conflict probability may be species specific, particularly with more contentious species such as large carnivores. Additionally, this analysis suggests that high public support for grizzly bear population increase and density of agriculture operations are more substantial indicators of bear conflict reporting than proximity to protected areas or biophysical landscape features. In comparison to the probability of wildlife conflict in

general, the probability of bear conflict is much higher on average across all of the SOI

landscape (Figure 1.8).

This analysis is consistent with existing literature that identifies population

density, land use, and density of agricultural operations as predictors of conflict (Lamb et

al., 2017; Blackwell et al., 2016; Wilson et al., 2006; Treves & Naughton-Treves, 2005).

These findings are consistent with previous studies of human-bear interaction and the

estimated attractants that drive bear activity in protected areas and row crop operations

(including fruit, tree nut, & field crops) (Lamb et al., 2020; Proctor et al., 2018; Lamb et

al., 2017). The regions of high conflict probability throughout the Okanagan largely

coincide with the presence of row crop production, protected areas, and high population

density surrounding Kelowna and Penticton (Lamb et al., 2020; Wilson et al., 2006,

2005, 2003; Kellert, 1994). There appears to be high consistency of bear reporting across

mean human population densities in residential and agricultural land use areas within

current grizzly home ranges.

This research reveals that positive attitudes of people towards contentious wildlife

may not actually reduce the likelihood of conflict occurrence. My results indicate that the

probability of conflict with bears is actually highest in census districts that support bear

population increases. The fact that conflict reports are high in regions where people are

generally supportive of bears is an important insight. These findings differ from the

commonly held idea that wildlife friendly attitudes will correspond with less problem

interactions with wildlife (Ditmer et al., 2022). Although some literature indicates that

social values can impact bear movement and interactions with people (Sage at al., 2022;

Dallimer & Strange, 2015), this research provides new insight into how these social

values manifest across physical space to drive conflict likelihood. This research suggests that even in regions where social attitudes allow for successful reintroduction of carnivores (e.g., wolf reintroductions in Colorado), managers should still be prepared for increased incidences of conflict, possibly even in places where reintroduction was very popular (Ditmer et al., 2022; Manfredo et al., 2021; Dietsch et al., 2016). This could be particularly prevalent in regions where growing recreational activity in wilderness areas and increased traffic on highways result in increases in recreationist-bear encounters or vehicle collisions (Lamb et al., 2018; Blackwell et al., 2016; Peine, 2001).

<u>Potential for Further Research</u>

This research has some important limitations. The data for this study was based largely off of public reporting of wildlife conflict, which can introduce issues with report accuracy and consistency. For the purposes of this analysis, I ensured that the impact of misidentification between bear species was minimized by pooling the reports of grizzly and black bears, but the ability to model verified grizzly conflicts would substantially improve this model (Appendix A). The study region for this research likely includes unique biological and socio-political contexts that may drive patterns of conflict reporting at different rates than the surrounding regions. Grizzly bears are potentially re-colonizing parts of their historic territories that occur around the SOI, which could also be driving social bias surrounding bears (Sylix Okanagan Nation, 2022; Proctor et al., 2018; Kasworm et al., 2017).

Conclusion

As the human-dominated landscape continues to expand, so does the need for considering the foundational drivers of human-wildlife conflict. Anthropogenic presence

has been found to cause significant disruptions to wildlife utilization of a landscape,

particularly for bears in contentious areas due to human activity (Lamb et al., 2020;

Northrup et al., 2012). Mapping landscapes of conflict can play a critical role in

determining key social and ecological processes for both large carnivores and a variety of

other species (Whittington et al., 2022; Lamb et al., 2020; Rio Major et al., 2019; Gaynor

et al., 2019). Furthermore, predicting the variables which drive highly contentious

attitudes and actions towards wildlife may improve our ability to prevent damaging

conflict in the future. Advancing insight into dynamics such as these is fundamental to

approaching management and conservation across this rapidly changing global landscape.

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Chapter Figures
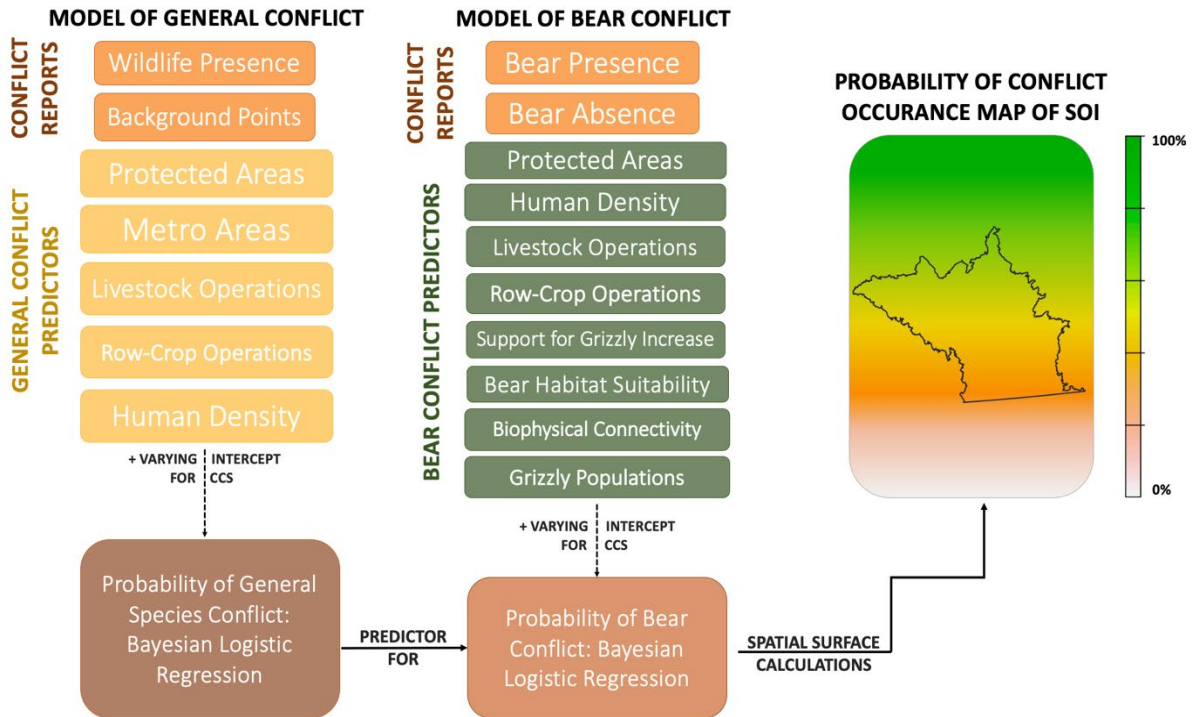
Figure 1.1. **Conceptual diagram of the two resource selection analyses used to characterize the predictors of general wildlife conflict and bear-specific conflict.**
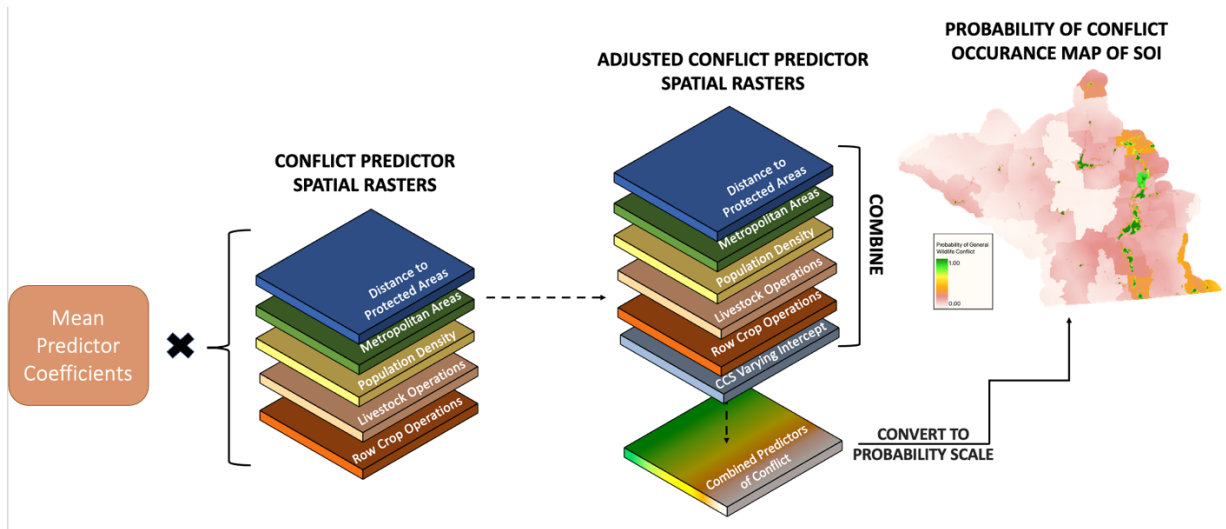
Figure 1.2. **Conceptual model of the spatial calculations used to produce the probabilistic maps of conflict occurrence.**
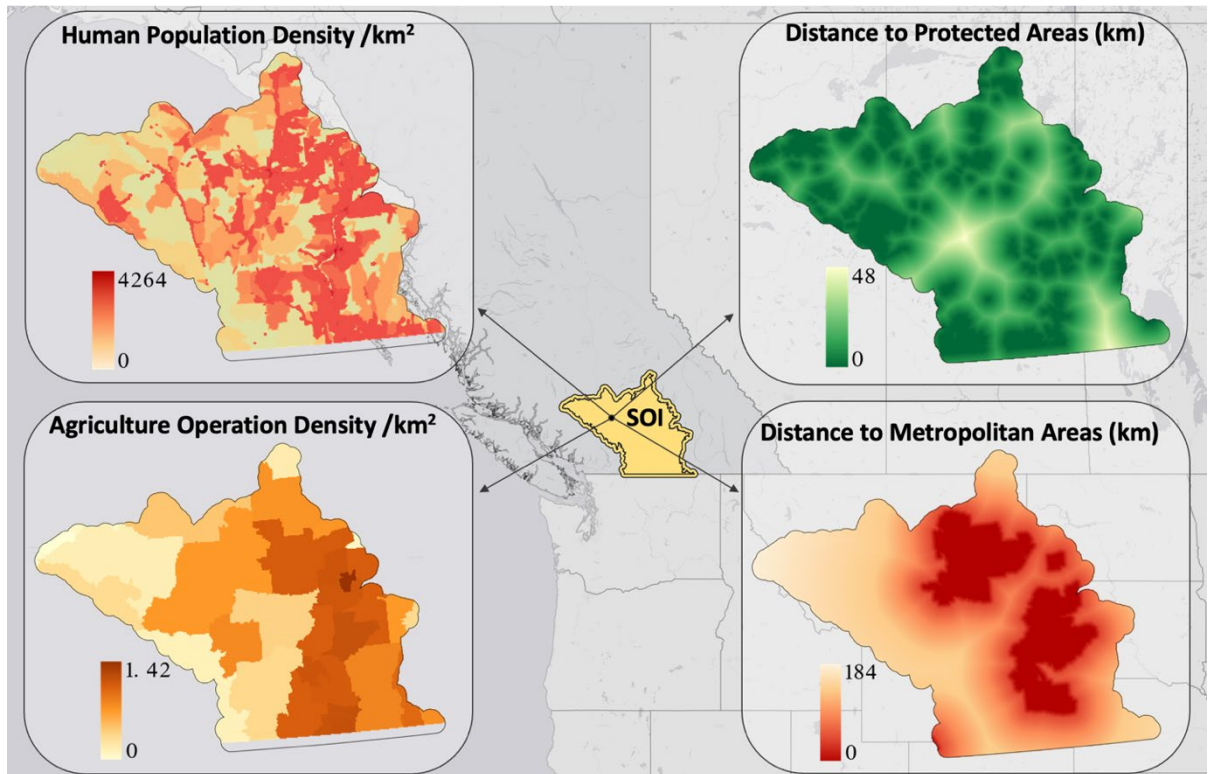
Figure 1.3. **Spatial surfaces of the strong predictors for all wildlife conflict including human population density (number of people per km^2), distance to the nearest protected area larger than 100ha (km), combined livestock and row crop operation density per km^2, and distance to the nearest metropolitan area (km).**
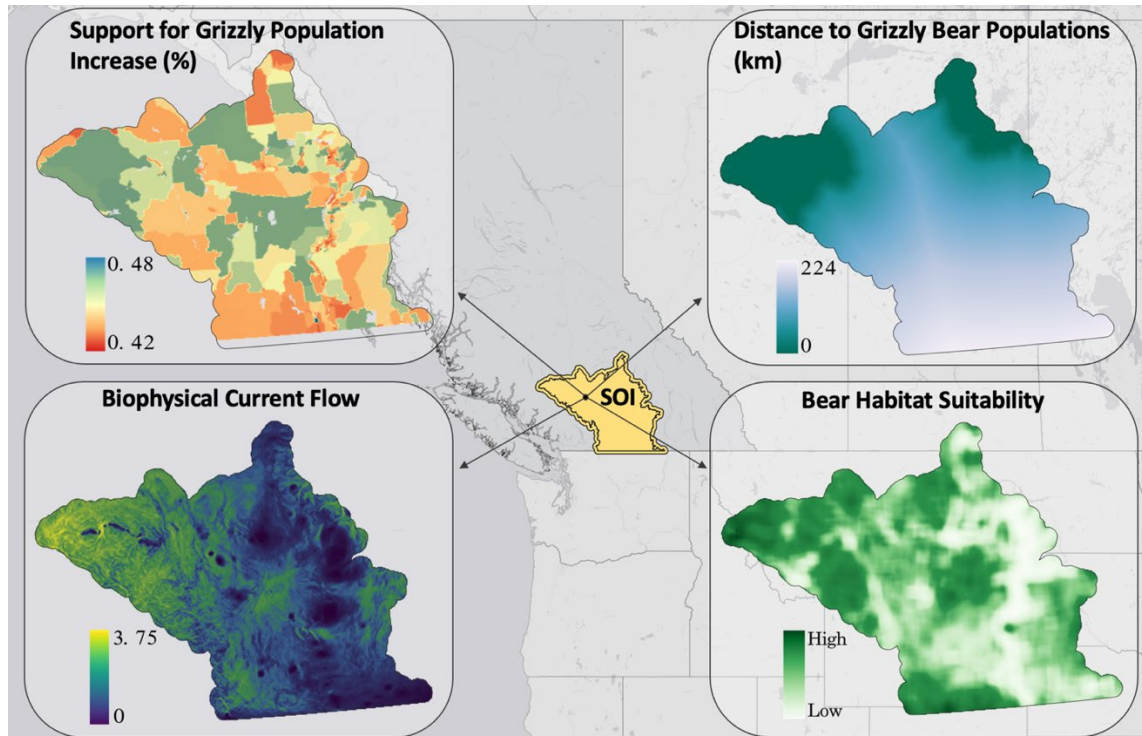
Figure 1.4. **Spatial surfaces of the strong predictors for bear conflict including proportion of census regions in support for grizzly bear populations increasing (percent of people per census district), distance to the nearest grizzly bear population (km), biophysical cumulative current flow (connectivity; representing available bear movement pathways), and estimated bear habitat suitability.**
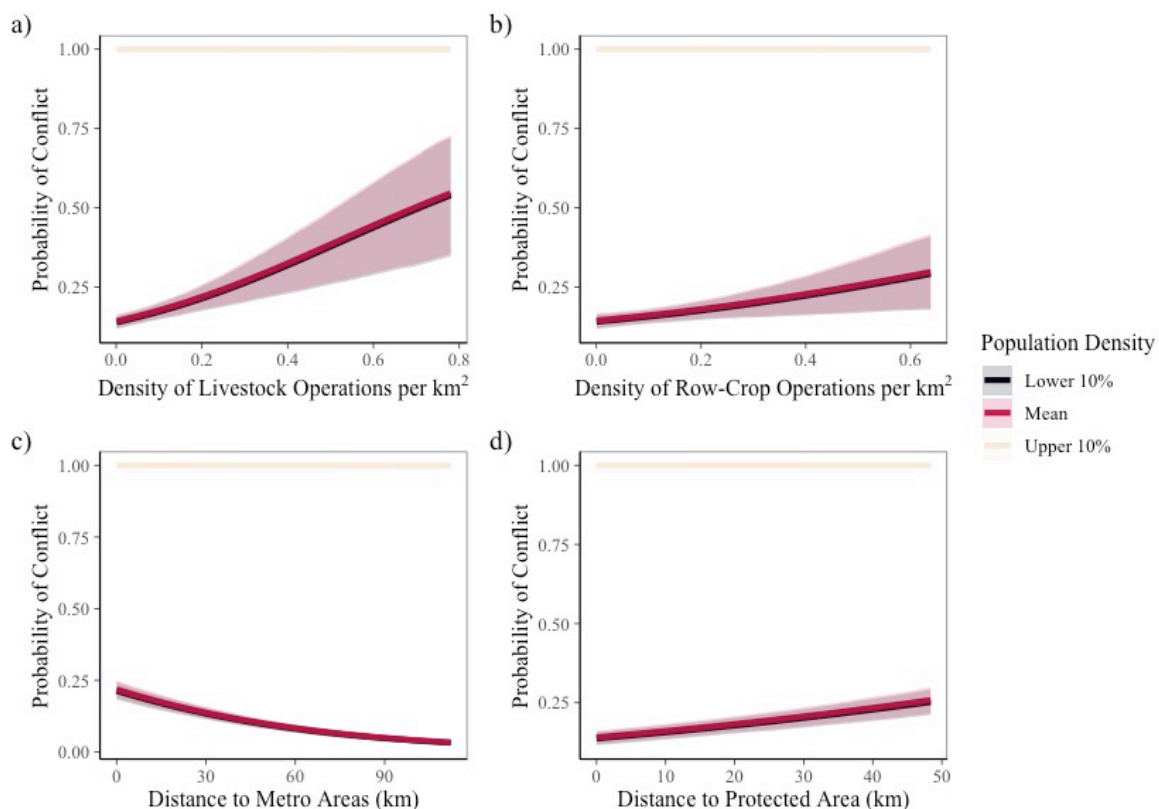
Figure 1.5. **Marginal effects of the density of livestock operations (a), density of row-crop operations (b), distance from metropolitan areas (c), and distance to protected areas (d) on the probability of conflict with any species across three levels of population density (lowest 10th percentile, mean, and upper 10th percentile) based on logistic regression of all conflict points and background points. Shaded regions depict the 80% posterior predictive interval.**
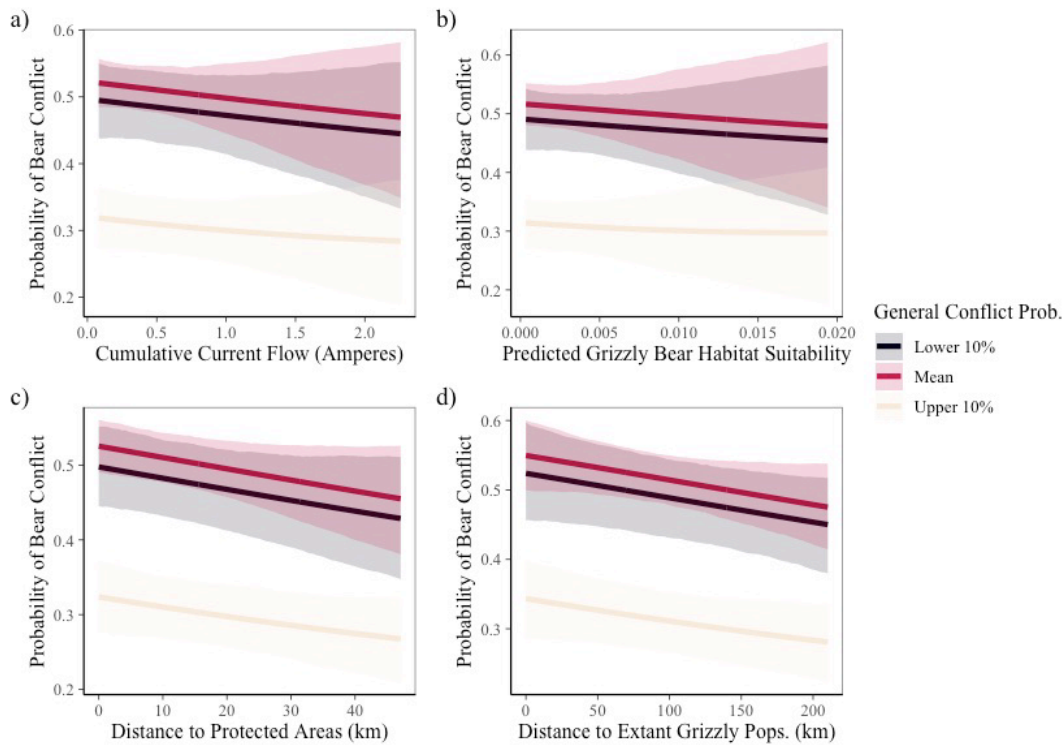
Figure 1.6. **Marginal effects of the biophysical cumulative current flow (a), predicted bear habitat suitability (b), distance from protected areas (c), and distance to extant grizzly bear populations (d) on the probability of bear conflict across three levels of general conflict probability (lowest 10th percentile, mean, and upper 10th percentile) based on logistic regression of bear conflict points and all other species points. Shaded regions depict the 80% posterior predictive interval.**
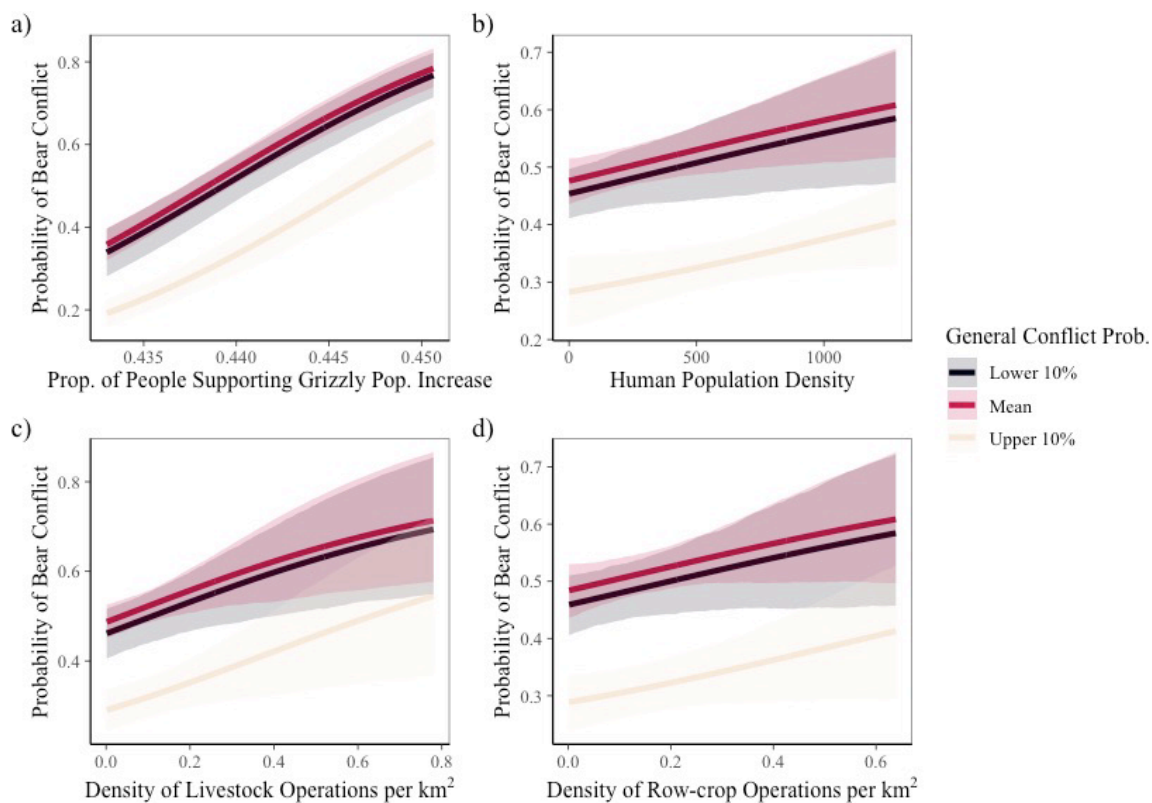
Figure 1.7. **Marginal effects of the proportion of people supporting grizzly bears increasing (a), human population density (b), density of livestock operations per km^2 (c), and density of row-crop operations per km^2 (d) on the probability of bear conflict across three levels of general conflict probability (lowest 10th percentile, mean, and upper 10th percentile) based on logistic regression of bear conflict points and all other species points. Shaded regions depict the 80% posterior predictive interval.**
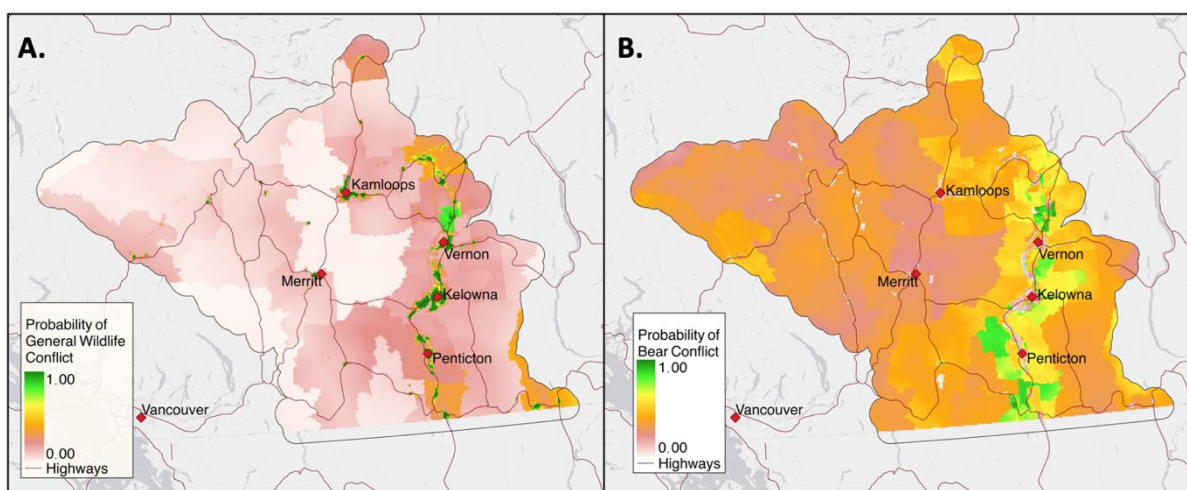
Figure 1.8. **Probability of conflict occurring across the Southern Interior Ecoprovince (SOI) for general wildlife conflict (A) and bear conflict (B).**
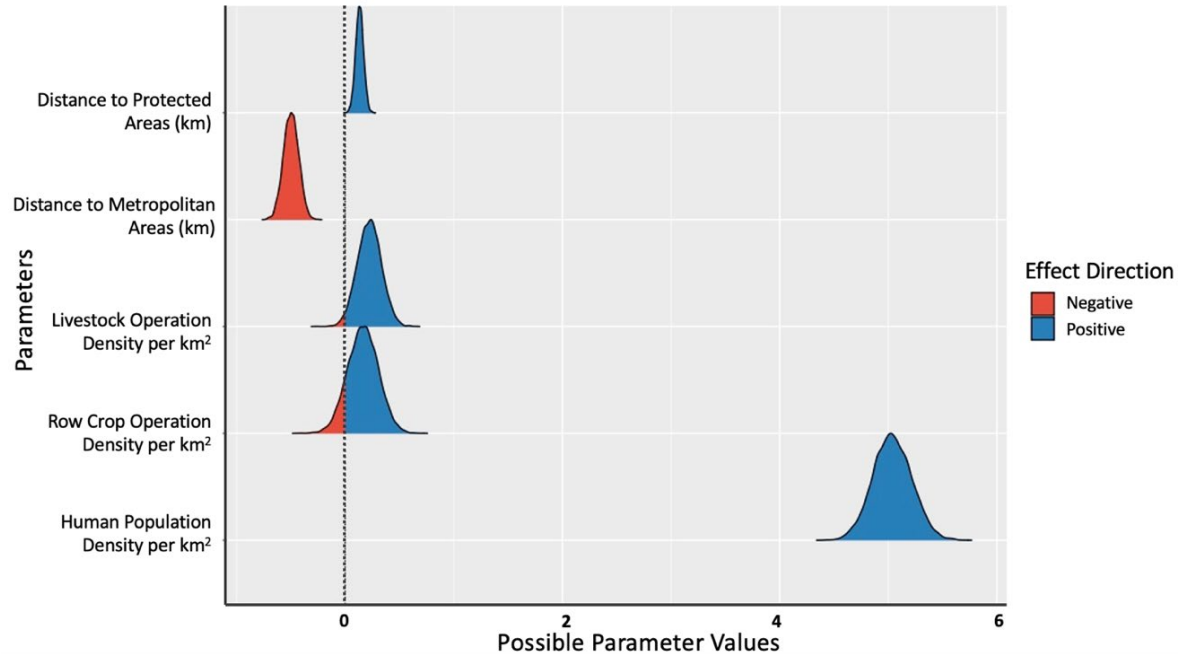
Figure 1.9. **Posterior distributions for predictors in the logistic regression for all wildlife conflict. The full model outperformed a model including only the varying intercepts for each Consolidated Census Subdivision (Δ2039 LOOIC). Predictors are distance to the nearest protected area larger than 100ha (km), distance to metropolitan areas (km), density of livestock operations (number of livestock-based agricultural operations per km[2]), density of row-crop operations (number of row-crop agricultural operations per km[2]), and population density (number of people per km[2]). Each curve depicts a parameter posterior distribution and the probability that a parameter has a positive (blue) or negative (red) effect on all wildlife conflict. The full model has a correct classification rate of 0.89 and an area under the receiver operating curve of 94.6.**
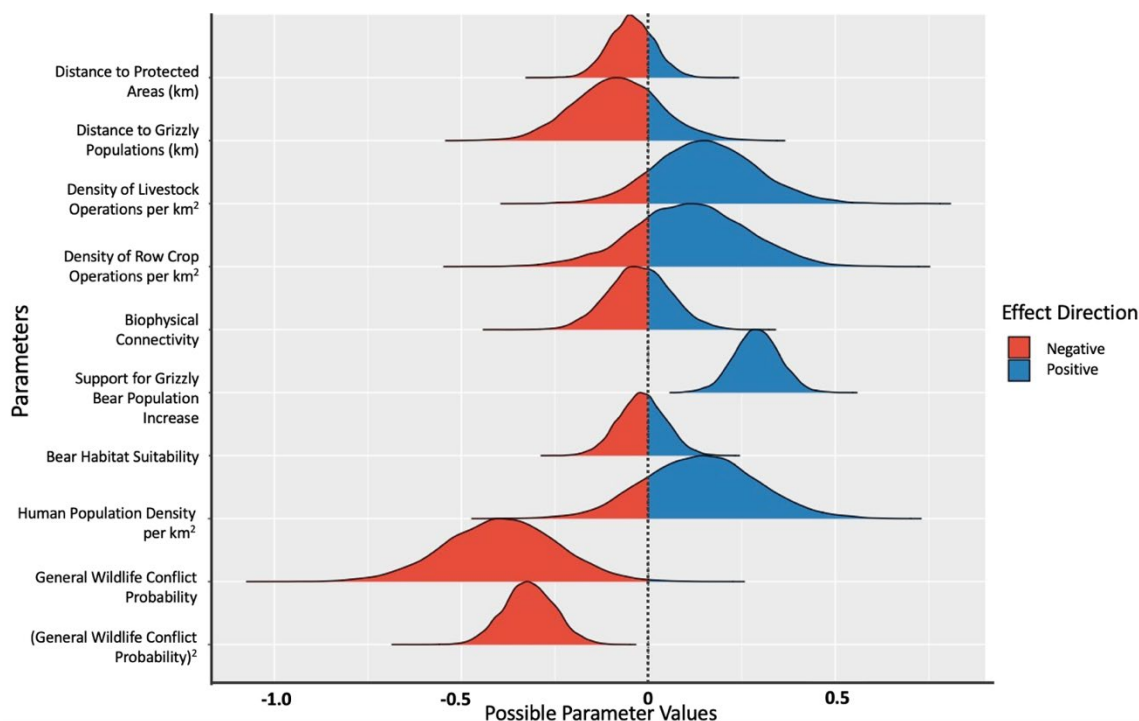
Figure 1.10.   Posterior distributions for predictors in the logistic regression for bear conflict. The full model outperformed a model including only the varying intercepts for each Consolidated Census Subdivision (Δ86.6 LOOIC). Predictors are distance to the nearest protected area larger than 100ha (km), distance to extant grizzly bear populations (km), density of livestock operations (number of livestock-based agricultural operations per km^2), density of row-crop operations (number of row-crop agricultural operations per km^2), biophysical connectivity, public support of grizzly bears, grizzly bear habitat suitability, population density (number of people per km^2), probability of wildlife conflict, and a quadratic term for probability of wildlife conflict. Each curve depicts a parameter posterior distribution and the probability that a parameter has a positive (blue) or negative (red) effect on bear conflict. The full model has a correct classification rate of 0.68 and an area under the receiver operating curve of 70.

Chapter Maps
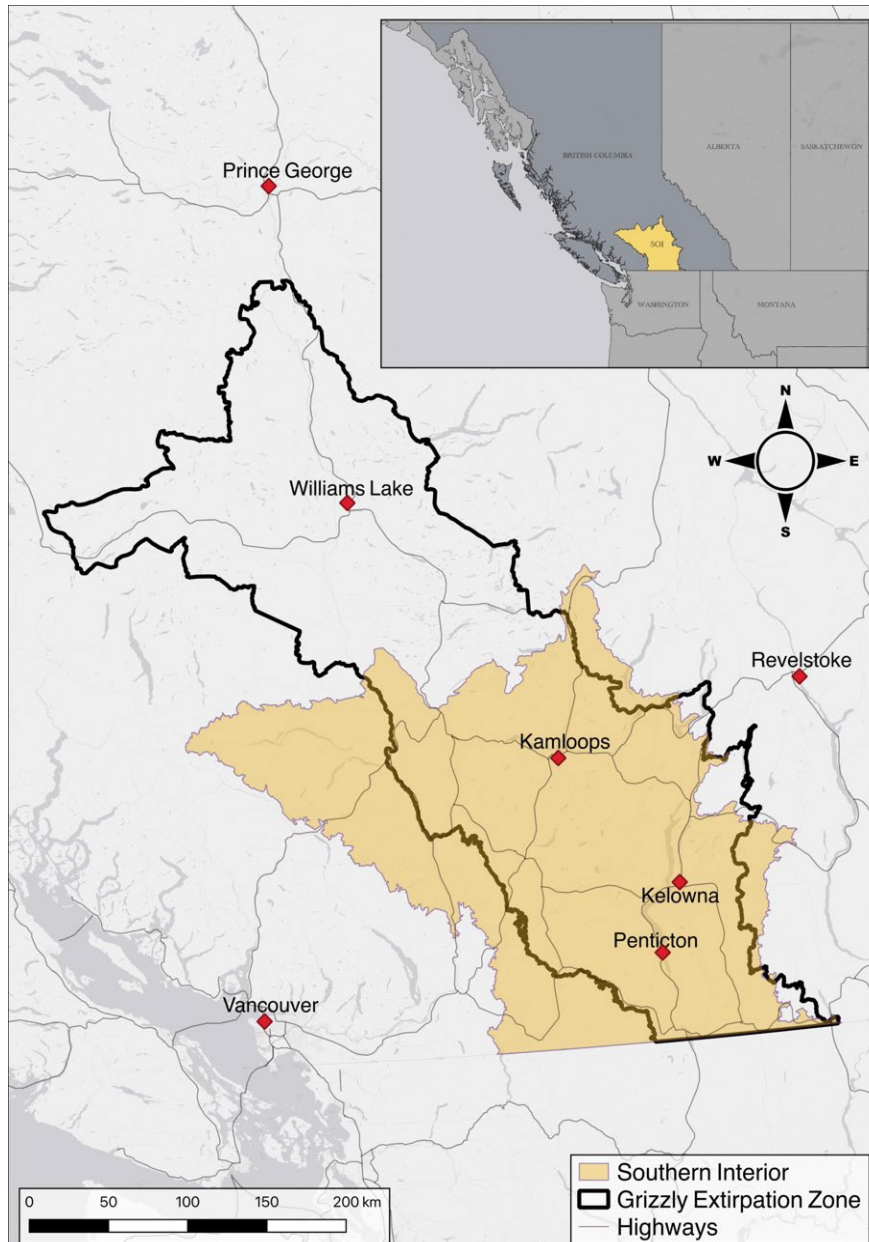
Map 1.1.   **The study area in British Columbia is comprised of the Southern Interior Ecoprovince (SOI) which stretches across the interior plateau, between the Coastal, Cascade, and Selkirk Mountain ranges.**

CHAPTER TWO: USING HUMAN-BEAR CONFLICT PREDICTIONS TO MAP

CONNECTIVITY ALONG THE US AND CANADIAN BORDER

Abstract

Human populations continue to expand into intact habitats around the world. At the same time, conservation efforts have focused on restoring species to formerly occupied habitats or facilitating recolonization of those habitats. This increases the likelihood of human-wildlife conflict especially for large carnivores, yet little is known about how conflict might ultimately affect long-term connectivity for these species. In this analysis, I examined how the potential for conflict affects connectivity for grizzly bears, a wide-ranging species that is recolonizing formerly occupied habitats and the subject of several different reintroduction debates in southern British Columbia and northern Washington. I compared the results of omnidirectional analyses of connectivity based solely on biophysical factors to those produced when the probability of human-wildlife conflict is included. My results highlight the potential for conflict to alter or inhibit bear movement across the biophysical landscape. My results provide insight into the effects of human-wildlife conflict on habitat connectivity that can help target conflict mitigation strategies associated with grizzly bear conservation and restoration in the region.

Introduction

The expansion of human dominated landscapes continues to pose a substantial challenge to the conservation and management of threatened wildlife (O'Bryan et al.,

2020; Theobald et al., 2020; Crooks et al., 2011). This growth of human infrastructure has produced large-scale habitat fragmentation, isolation, and degradation, sending cascading effects throughout ecological systems (Crooks et al., 2011; Wilcove et al., 1998). Many wildlife species, particularly those with large home ranges, require connectivity between habitat patches to ensure the ability to access food, find mates, and maintain gene flow (Whittington et al., 2022; Fletcher et al., 2019). Anthropogenic impacts of development and habitat fragmentation ultimately reduce connectivity and pose significant threats to species gene flow and survival (Ghoddousi et al., 2021; Gaynor et al., 2019; Heller and Zavaleta 2009). Habitat fragmentation can cause significant damage to ecosystems, threatening genetic diversity and fitness of wildlife populations (Ghoddousi et al., 2021; De Montis et al., 2018; Schlaepfer et al., 2018; Tilman et al., 2017). Direct threats to wildlife can include escalated mortality due to vehicle collision, increased predation, or severe outcomes of conflict (Goswami & Vasudev, 2017; Fehlmann et al., 2021; Schell et al., 2021; Northrup et al., 2012). Contemporary conservation approaches to maintain habitat connectivity have included prioritizing the conservation of critical habitat patches and preserving movement corridors. Although the potential for conflict has been recognized as important in determining the success of these strategies (Ghoddousi et al. 2021; Buchholtz et al., 2020; König et al., 2020), incorporating the complex interplay between human values, economics, and politics directly into connectivity conservation strategies remains rare (Williamson et al., 2021 *in review*; Tucker et al., 2018). This research addresses the gap in understanding of how spatial patterns in the socio-ecological factors associated with conflict may alter long-term habitat connectivity.

Occurrence of human-wildlife conflict is known to alter the behavior of wildlife (both spatially and temporally) and their ability to utilize habitats (Buchholtz et al., 2020; Laundré et al., 2010; Suraci et al., 2019; Blackwell et al., 2016; Gaynor et al., 2019). Conflict, however, is variable and ranges from passive interactions or those deemed a nuisance, to those that cause threats to safety, injury, and death of one or both parties (Bhatia et al., 2020; Gore, 2004; Schell et al., 2021). The response of people and communities to conflict varies widely with encounter severity and the variety of socio-political values (Blackwell et al., 2016; Treves & Naughton-Treves, 2005; Young et al., 2015). Conflict has become especially pertinent for large carnivores (e.g., grizzly bears, cougars, wolves) that occupy expansive ranges and must frequently navigate the mosaic of habitat and human infrastructure (Sage et al., 2022; Rio-Maior et al., 2019; Peck et al., 2017; Crooks et al., 2011). As a result, large carnivores experience habitat fragmentation as infrastructure and development change both the biophysical and social landscape (Whittington et al., 2022; Lamb et al., 2020; Crooks et al., 2011). Incorporating the implications of spatial patterns of potential human-wildlife conflict into connectivity conservation is necessary for anticipating the role that conflict plays in the success of connectivity conservation.

Mapping landscape connectivity is a valuable strategy for overcoming the effects of fragmentation due to human infrastructure and development. Connectivity models often incorporate characteristics of the biophysical landscape (e.g., topography, vegetation, habitat patches) to reflect the costs (i.e., energetic or mortality threat) of navigating natural landscape features (Whittington et al., 2022; Fletcher et al., 2019; Dickson et al., 2019; Correa Ayram et al., 2016). Human-wildlife conflict is a common

source of mortality for large carnivores across shared landscapes (Lamb et al., 2020; Rio Maior et al., 2019; Lute et al., 2018). Therefore, incorporating the likelihood of conflict occurrence into connectivity models is valuable for designing connectivity conservation strategies in landscapes that are socially and ecologically fragmented.

The grizzly bear (*Ursus arctos*) is a wide-ranging and politically controversial species (Clark et al., 2021; Darimont et al., 2018; Proctor et al., 2018). The grizzly bear is also culturally significant for a number of Canadian First Nations and American Indian Tribes (Rine et al., 2020; Housty, 2014; Kellert et al., 1996; Kellert, 1994). For example, the grizzly bear (Kelowna) plays an important role in the laws, cultural tradition, and creation stories of the Sylix peoples in south-central British Columbia and northern Washington (Sylix Okanagan Nation, 2022). As such, grizzly bear recovery is a stated priority for Indigenous conservation efforts within large portions of the Sylix people's traditional territory (Sylix Okanagan Nation, 2022). Although grizzly bears are considered extirpated by the British Columbia government, there is evidence of these animals moving into and persisting around portions of the Okanagan region. In addition, the US Fish and Wildlife Service and National Park Service have been engaged in grizzly bear reintroduction planning in North Cascades National Park since 2014 (Schultz & Froschauer, 2019; Kasworm et al., 2017). Despite large regions of suitable habitat, efforts to restore grizzly bears on both sides of the border are complicated by the variety of socio-political values, governance structures, and land uses within the region. For this reason, this region is an ideal case study for considering how the potential for conflict may ultimately affect grizzly connectivity and the success of reintroduction and conservation efforts.

In this research, I demonstrate the importance of incorporating the potential for conflict into connectivity models using grizzly bears in southern British Columbia and northern Washington as a case study. I compare the results of a connectivity model based on the purely biophysical aspects of the landscape with those of a model that includes a spatially explicit depiction of the probability of conflict based on a database of over 5,600 conflict reports. I evaluate the effects of incorporating conflict probability into movement potential under both models and characterize the differences in spatial locations of common targets for connectivity conservation interventions (e.g., barriers and pinch points). Finally, I consider how the potential for wildlife conflict might shape grizzly bear conservation strategies across southern British Columbia and northern Washington, especially in the context of efforts by the Sylix First Nation to restore grizzly bears to their ancestral territory.

Methods

Study System

The traditional territory of the Sylix people encompasses a diverse landscape including both extant populations of grizzly bears and large areas where bears are currently considered extirpated (Map 2.1). This semi-arid landscape has an elevation range from 300m to 3,000m with Interior Douglas Fir (IDF) and Ponderosa Pine as the dominant vegetation type in lower elevations and Western Larch, Western Red Cedar and Lodgepole Pine in higher elevations (Kelowna Topographic Map, 2020; Living Landscapes, 1996). Grizzly bears generally occupy partially forested areas and closed forests near quality foraging sites, although their large territories include a range of elevations and vegetation types (Hamilton & Austin, 2004). This landscape also includes

a range of urban developments, agricultural land uses, protected and conserved areas, and Indigenous and privately owned lands resulting in encounters between bears and people (Gyug, 2004; Ciarnello et al., 2003; McLellan & Shackleton, 1988).

Developing Resistance Surfaces

I created two resistance surfaces. The first of which included only human modification and slope (i.e., biophysical only) and a second that included biophysical factors and the probability of bear conflict (estimated in Chapter 1). I used Omniscape (Landau et al., 2021; McRae et al., 2016) to estimate cumulative current flow based on each resistance surface (i.e., two separate analyses) using grizzly bear habitat suitability (Lamb et al., *in progress*) as the source strength. Because habitat quality in the northern WA portion of the study area was not available, I set areas within the North Cascades recovery unit to have habitat quality equal to the upper 75th percentile of Canadian habitat quality and all other areas outside the recovery unit to the median habitat quality value in Canada. I projected all data to NAD83/BC Albers and resampled resistance surfaces to a 1 km^2 resolution to match the habitat suitability raster.

Development of the Biophysical Resistance Surface

In order to represent biophysical costs of movement across the study area, I developed biophysical resistance on topography and human modification. Topography (i.e., slope and elevation) impacts the energetic costs a bear incurs when moving across the landscape (Lamb et al., 2020, 2018; Wilson et al., 2005). The human modification index characterizes the human footprint on the landscape and is frequently used to identify available corridors or quantify the impact of development on habitats (Dickson et al., 2017; Theobald et al., 2012). I downloaded elevation data from SRTM 90 m Digital

Elevation Database using the getData raster package in R (Hijmans, 2015) and then

terrain roughness according to the equation

$$x_{roughness} = (x - x_{min})/(x_{max} - x_{min})$$

where $x_{roughness}$ is the difference between the maximum and the minimum value of

a cell and its 8 surrounding cells (Burrough & McDonnell, 1998; Appendix 2). I

downloaded global human modification (gHM) data and rescaled it according to

Theobald et al. (2020) (Appendix 2). Values close to 1 indicate highly modified

landscapes while values close to 0 represent more natural landscapes. To combine the

topographic roughness with gHM into a single resistance surface, I used a "fuzzy sum"

algebraic approach following Theobald (2013)

$$B_{sum} = 1.0 - \prod_{j=1}^{k} (1 - b_i)$$

where the value (B_{sum}) at each cell, i, is based on the resistance value (b_i) for $j= 1...k$ data

layers with values ranging from 0.0 (no cost) to 1.0 (high cost). The two layers included

in this fuzzy sum calculation were the scaled human modification and normalized

topographic ruggedness. The fuzzy sum method ensures that values for the biophysical

surface were at least as high as the largest contributing cell, without exceeding one

(Theobald, 2013). I then translated this into a resistance surface representing the

biophysical landscape with the equation following Dickson et al. (2017)

$$R_{biophysical} = (B_{sum} + 1)^{10}$$

where B_{sum} is the fuzzy sum biophysical layers.

Development of the Probability of Conflict Resistance Surface

I derived a spatial surface depicting the probability of bear conflict based on the

regression coefficients from the bear conflict model in the previous chapter. Because

conflict can result in mortality, including spatial variation in the probability of conflict allows estimation of the potential impacts of the social landscape on grizzly bear connectivity (Schell et al., 2021; Lamb et al., 2020; Fletcher et al., 2019). The variables contributing to the probability of conflict predictions included human population density, distance to protected areas, distance to extant grizzly bear populations, animal product farm density, ground crop farm density, estimated grizzly bear density (representing habitat suitability), biophysical connectivity for bears, support for grizzly population increase, probability of general wildlife conflict, a quadratic term for probability of general wildlife conflict, and varying intercepts for each census region (Appendix B). Support for grizzly increase was based on survey responses by census tract (US) or dissemination area (Canada) across the study region that included moderate or substantial support of grizzly populations increasing to represent estimates of social values towards grizzly bears (Sweet et al., *in progress*). I created the biophysical + probability of conflict layer by adding the probability of conflict to terrain ruggedness and gHM datasets using the fuzzy sum approach and estimating the resistance following the equation above.

<u>Modeling Connectivity in Omniscape</u>

I estimated the current flow resulting from each resistance surface using Omniscape (Landau et al., 2021; McRae et al., 2016) implemented in Julia 1.7 (Bezanson et al., 2017). Omniscape simulates omnidirectional current flow (representing animal movement or dispersal) between all pixels based on the source strength (i.e., habitat quality) and the resistance (based on either the biophysical or biophysical + conflict surfaces). Omniscape injects each pixel with current strength based on the source input, and determines the "traversal cost" (i.e., ability of current to move from one pixel to

another) based on the resistance value for each corresponding pixel (Tessier et al., 2020; McRae et al., 2016). Omniscape uses a moving window approach (with user specified radius) to estimate current flow based on the assumption that an organism is aware of its immediate surroundings, but has little knowledge of the entire landscape. I buffered the study area extent by 25 km to reduce any possible edge effects. I used a moving window radius of 140 km, based on the home range of male grizzly bears (roughly 137km^2) which accounts for dispersal distance and a block size of 13, approximately 1/10 of the search radius size (Phillips et al., 2021; McClure et al., 2016; Gyug, 2004; Proctor et al., 2004). I estimated the cumulative and normalized current flow for each of the resistance surfaces. Cumulative current flow depicts the probability of movement based on both the source strength and resistance surface. Normalized current flow outputs are created by dividing current flow by regional flow potential, or how much flow would be expected in the absence of resistance and help to distinguish between natural areas with diffuse current and those areas where flow is being blocked by barriers or channeled through pinch points (McRae et al., 2016). Normalized current values greater than one have highly concentrated current flow (i.e., channelized or pinch-points), values around one indicate places with diffuse current, and values below one indicate areas where current flow is impeded by resistance (McRae et al., 2016). I compared the cumulative and normalized current outputs for biophysical and biophysical + probability of conflict to visualize how conflict changes the way that current flows across the landscape.

Results

Comparing Cumulative Current Flow

The biophysical cumulative current output revealed where bears are more likely to move based on habitat suitability, topography, and human modification. This had a maximum current flow value of 7.21 and the highest levels of current flow occurred in the northern and southwestern parts of the territory. About 75% of current flow was moderate to low, ranging from 0.03 to 2.90, and the rest of the current flow was dispersed (i.e., some current flow throughout the majority of the landscape) (Figure 2.2 A). The biophysical + probability of conflict cumulative current flows illustrate how conflict alters bear movement. Current flows for the biophysical + probability of conflict surface had a maximum current flow value of 8.71 and the highest levels of current flow were also in the northeast and southwest. Approximately 75% of current flow was moderate to low, ranging from 0.13 to 3.56, concentrating in few regions with moderate current flow values (Figure 2.2 B).

Comparing Normalized Current Flow

There were several potential pinch-points where normalized current values were intensified (i.e., values > 1), and many areas where values were diffuse (i.e., values = 1) as current fanned out across a wider range of pathways (Figure 2.3 A). Areas where movement was impeded (i.e., values < 1) were present in the central parts of the study area surrounding urban sprawl. The space where current values were lowest (i.e., values = 0) indicated parts of the landscape that did not facilitate any potential movement. The most concentrated flow regions on the normalized biophysical landscape were on the outskirts of Kelowna and Vernon, south of Merritt and near Penticton, and east of

Wenatchee. There appeared to be more concentrated current flow east of Kelowna near Graystokes and Granby Provincial Parks, along the eastern Cascade Mountains south of Merritt, and through the valley between Gifford Pinchot National Forest and Umatilla National Forest in Washington. The majority of the areas with channeled flow were in regions where the terrain transitions from higher elevation to lower elevation and into increasing levels of human development. The normalized biophysical + probability of conflict output revealed that highly concentrated current pathways and potential pinch points of grizzly bear movement were produced when factoring in human-bear conflict attributes onto the landscape. I observed a significant increase in channeled current flow (values between 2 and 3.5) and an overall reduction in visible corridors, indicating prominent bottlenecks and overall decrease in connectivity between habitat patches (Figure 2.3 B). The most prominent flow channels were along the Monashee mountains south of Revelstoke, south of Kamloops along the Thompson's Plateau, along the edge of the Cascade mountains west of Merritt, and below the U.S. Canada border between Wenatchee and Spokane. There was an increase in parts of the landscape representing outright barriers to movement of any kind (values between 0.04 and 0.85), coinciding with regions of higher predictions of human-bear conflict.

Discussion

Integrating Probability of Conflict into Connectivity

My analysis of the effects of human-bear conflict on grizzly connectivity highlights the important role that conflict plays in creating barriers to wildlife movement. My results illustrate that conflict reduces overall connectivity and results in pinch-points and barriers that are not really apparent when considering only biophysical factors.

Although my study focused on bears, a number of other North American species (e.g., wolves (*Canis lupus*), bison (*Bison bison*), mountain lion (*Puma concolor*)) are also subject to intense conflict (Teixeira et al., 2021; Pejchar et al., 2021; König et al., 2020; Lute et al., 2016). As human settlements continue to expand, these conflicts are likely to intensify making the incorporation of conflict into connectivity modeling a key component for successful connectivity conservation.

Results from the biological models are consistent with Fehlmann et al. (2021), Ghoddousi et al. (2021), and Lamb et al. (2020). In my study, this is evident in the with high levels of human modification and agriculture producing substantial barriers to wildlife connectivity. Similarly, conflict with humans is known to change wildlife behavior (Sage et al., 2022; van Bommel et al., 2020); however, there have been few efforts to evaluate how those changes ultimately affect connectivity across large landscapes. By integrating conflict directly into resistance surfaces underlying connectivity models, I was able to expand this research to illustrate that the effects of conflict extend beyond the fate of individual animals and may ultimately affect gene flow across the region. Further, my approach helps conservation practitioners avoid investment in areas that are biologically important but socio-politically infeasible.

Implications for Bears

My results highlight several important issues for bear connectivity conservation in the Sylix traditional territory. One of the most concentrated flow channels when including probability of conflict to the biophysical landscape began along Upper Arrow Lake outside Castlegar and intensified along the Monashee Mountains in Monashee Provincial Park. This is a region that connects several vital mountain habitats, but due to

its proximity to high human density in the Okanagan, likely faces social and political barriers that force current flow into a narrower corridor. South of the US and Canadian border, there is another prominent current concentration that falls between two large national forests indicating a prominent pinch point with bottleneck potential as terrain transitions from mountain wilderness to dense agriculture production and different governance boundaries (Figure 2.3; USDA 2021; BC Topographic Maps, 2013). This region indicates highly channeled flow that funnels down from the North Cascade Mountains to Gifford Pinchot National Forest near Yakima and concentrates along Umatilla National Forest east of Spokane (Figure 2.3 B). The resulting bottlenecks could be due to many variables interacting, such as changes in governance due to the crossing of international borders, decreased social support for grizzlies in the United States, reduced habitat suitability, major roadways, and concentrated human development (Whittington et al., 2022; Sage et al., 2022; Ghoddousi et al., 2021; Lamb et al., 2020; Parrott et al., 2019; Rio-Maior et al., 2019). In addition, considering the probability of conflict reveals that current pathways are more spread out south of the U.S. and Canadian border. While social support for grizzly bears is comparatively high in British Columbia (the majority of census subdivisions at 48% support), this changes when crossing into the United States. The major pinch-point and more spread-out current flow areas surrounding this in northern Washington coincide with where there is less support (the majority of counties at 42% support) for grizzly bear populations increasing (Figure B.1).

In the traditional Sylix territory, cultural values, rich habitat, and dialogues of bears returning to historic corridors highlight the importance of further understanding connectivity dynamics. The Sylix people have been stewards of this land for generations,

tending to the land and its resources, considering the "continued presence of grizzly bears to be a strong indicator of healthy land" (Okanagan Nation Alliance, Mowat, 2017). Despite the federal delineation of extirpation across much of Okanagan Nation's historic territory, discussions of bears moving throughout and persisting near the Okanagan are ongoing (Ministry of Forests and Lands, 2022). My research contributes to continued conversations between Okanagan Nation Alliance and other communities in this region regarding grizzly bear population recovery reintroduction options, community engagement and education, and management implementation (Sylix Okanagan Nation, 2022). Connectivity models are often used to evaluate different scenarios for corridor protection and land use intervention (Sage et al., 2022; Dickson et al., 2019; Correa Ayram et al., 2016). My research demonstrates the importance of incorporating wildlife conflict into connectivity modeling to understand how variation in social landscapes may inhibit conservation efforts and could be extended to evaluate the potential efficacy of interventions designed to reduce conflict.

Areas for Additional Research

Caveats for this research are that data on bear habitat was not available for the US and conflict data was based on combined black and grizzly bear reports over a snapshot of time. Fine scale telemetry data or long-term genetic studies could help to verify whether conflict is truly affecting connectivity. Future research could be done to evaluate how persistent conflict must be in order to impact connectivity, how social and economic changes alter the social landscape, and how the use of corridors by bears may change conflict.

Conclusion

My research provides new knowledge on the role that conflict plays in creating barriers to grizzly bear movements across a mosaic of habitat quality, Indigenous territories, governance borders, and land use. The ability to visualize potential pinch points of bear movement based on relatively unseen landscape variables (i.e., probability of conflict occurrence) can contribute to collaborative conservation efforts in and around this region. As the use of connectivity mapping becomes more prevalent in assessing the impacts of conservation, management decisions, and human infrastructure on regions of interest, so will the need for integration of socio-political variables into these analyses. By investigating how spatial variation in human-wildlife conflict impacts coexistence on a landscape, we can identify barriers that people may be imposing on habitat connectivity that are less obvious than habitat changes (Sage et al., 2022; Ghoddousi et al., 2021; Manfredo et al., 2021).

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Chapter Figures
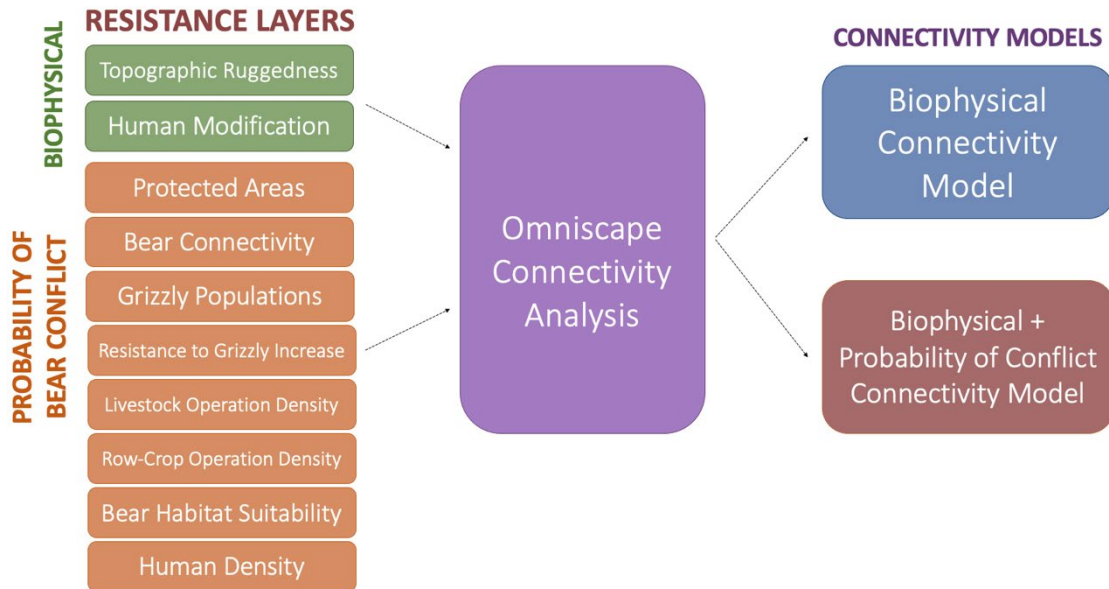
Figure 2.1.   Inputs for the biophysical and biophysical + probability of conflict resistance surfaces used to estimate connectivity with Omniscape in Julia to map grizzly bear connectivity.
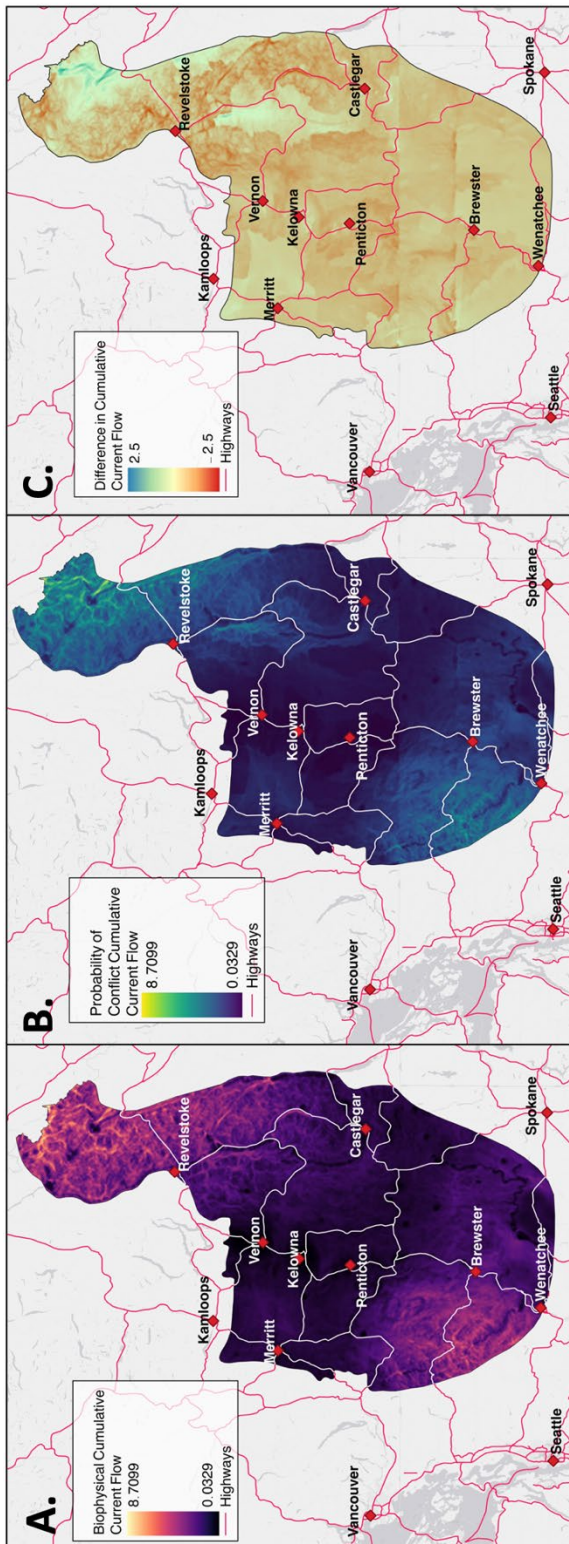
Figure 2.2.   Cumulative current flow outputs for biophysical (A), biophysical + probability of conflict (B), and (C) the difference between the two cumulative current flow outputs (B – A). Cumulative current flow outputs reveal the most likely movement pathways available based on habitat suitability and resistance.
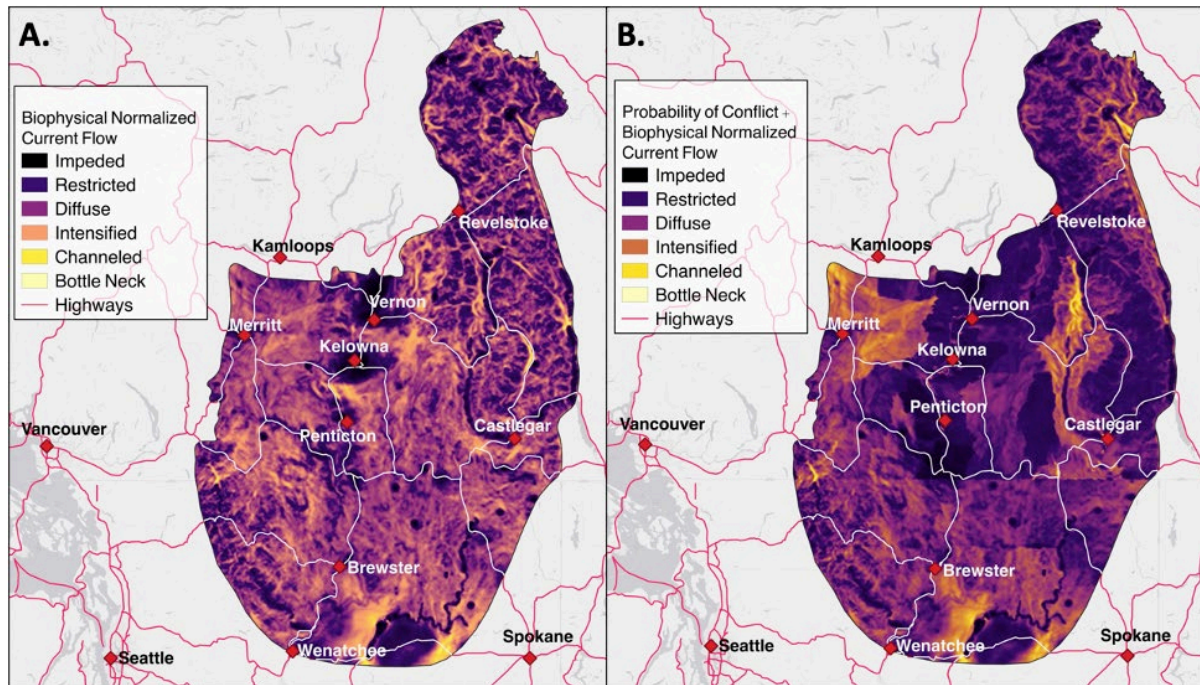
Figure 2.3. **Normalized current outputs for the biophysical (A) and the biophysical + probability of conflict (B). Normalized current flow outputs are made by dividing current flow by flow potential (i.e., the amount of flow expected without barriers) to visualize how surrounding barriers produce resistance that greatly concentrates flow into pinch points, creates diffuse movement pathways, or entirely impedes movement potential.**

Chapter Maps
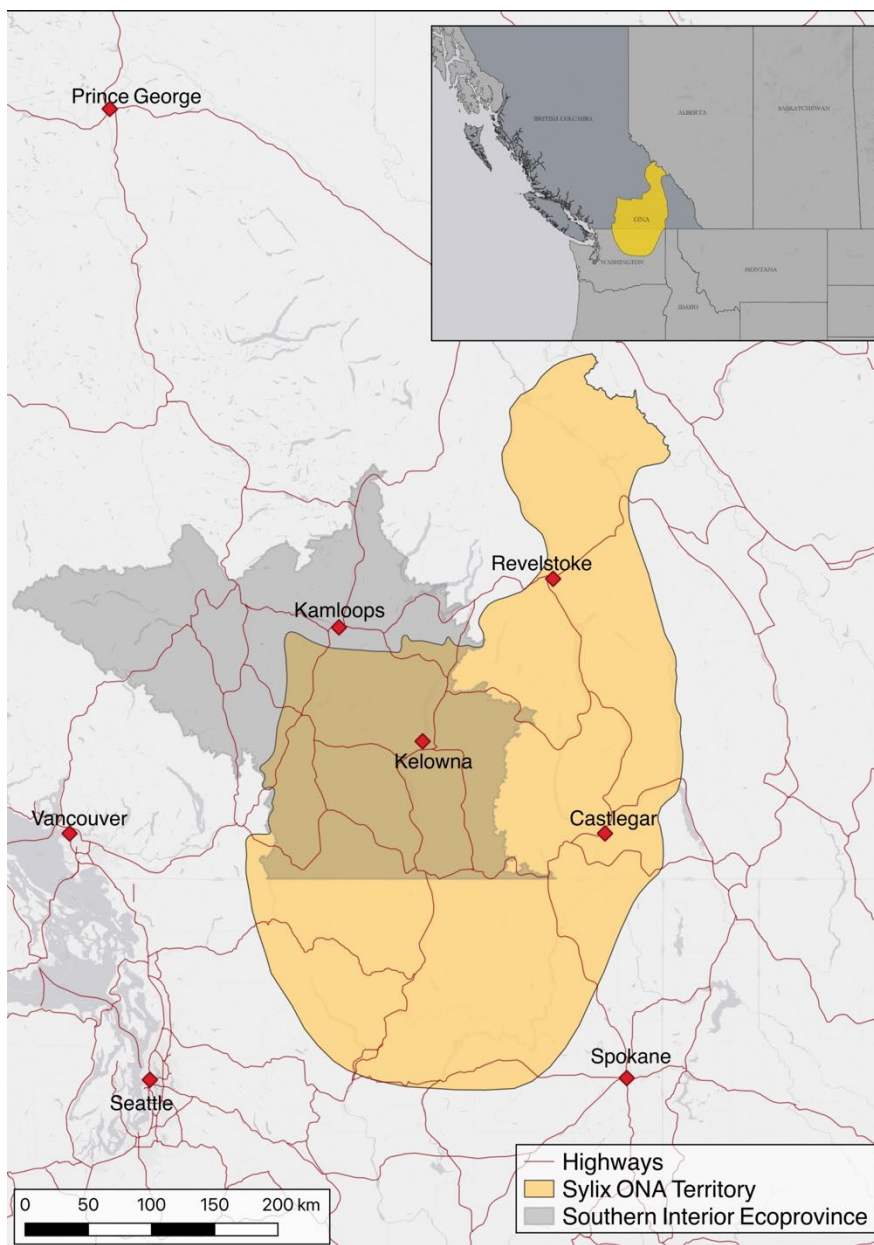
Map 2.1.   The study area in British Columbia, CAN and Northern Washington, USA is the traditional Sylix territory for the Okanagan Nation which spans from the edge of Alberta north of Revelstoke down to the Cascade Mountains near Seattle.

APPENDIX A

Chapter 1 Supplementary Figures & Tables

Table A.1. The predictors that were used in the two-step Bayesian logistic regression, and the specific model that each predictor was utilized in.

Relating Model	Predictor	Predictor Description	Dataset(s)	Data Description
	Conflict Reports	Individual wildlife encounter/conflict reports including attractants, nature of encounter, locality, outcome.	*Wildlife Alert Reporting Program (WARP)*	Reports of human-wildlife encounters collected via web and phone by WildSafeBC's public reporting program. Locations of reports are approximate, within a few miles of the exact encounter location (WildSafeBC, 2020).
	Distance to Protected Area	Minimum distance to the nearest protected area. Provides an estimate of proximity to viable bear habitat patches and/or human recreation locations (Lamb et al., 2018; Gibeau et al., 2002).	*Canada Protected and Conserved Areas*	A conglomeration of the provincial, federal and state protected areas across British Columbia at a 1 meter resolution provided by Clayton Lamb. Sourced from a variety of federal and provincial datasets, including the Canada Protected and Conserved Areas Database (Statistics Canada, 2019).
Probability of General Conflict	**Distance to Metropolitan Area**	Minimum distance to the nearest metropolitan census area. Provides an estimate of proximity to metropolitan or residential areas (Schell et al., 2021; Lamb et al., 2018).	*Current Census Metropolitan Areas*	A conglomeration of the census metropolitan areas across British Columbia at a 1 meter resolution provided by the 2016 Census from BC Data Catalogue (BC Stats, 2016).

Relating Model	Predictor	Predictor Description	Dataset(s)	Data Description
Probability of General Conflict	**Density of Livestock Operations**	Total number of livestock operations in the CCS region area. Provides an indication of potential livestock attractants or land use barriers to bear movement (Northrup et al., 2012; Wilson et al., 2006, 2005).	*Agricultural Census Land Classification*	Classifications of agriculture production on a 1 meter resolution of Agriculture Region and Consolidated Census Subdivisions by Statistics Canada 2016 Agriculture Census (Statistics Canada, 2016).
	Density of Row Crop Operations	Total number of row crop operations out of the CCS region area. Provides an indication of potential row crop attractants or land use barriers to bear movement (Northrup et al., 2012; Wilson et al., 2006, 2005).	*Agricultural Census Land Classification*	Classifications of agriculture production on a 1 meter resolution of Agriculture Region and Consolidated Census Subdivisions by Statistics Canada 2016 Agriculture Census (Statistics Canada, 2016).
	Human Population Density	Human population density (km^2) across British Columbia. Provides an idea of how conflict patterns may fluctuate across different levels of population density (Lamb et al., 2020).	*NASA Gridded Population of the World (GPW), v4*	The UN WPP-Adjusted Population Density distribution of human population counts and densities on a continuous raster at an approximately 1 kilometer resolution by NASA Socioeconomic Data and Applications Center (SEDAC) (CIESIN, 2018).

Relating Model	Predictor	Predictor Description	Dataset(s)	Data Description
	Public Opinion of Grizzly Bears & Management *Public support for grizzly increase*	Relating patterns of public opinion of grizzlies, wildlife conservation management, and political affiliation with the distribution of conflict reports. Serves as a proxy for wildlife attitudes and a way to measure spatial variation in support for grizzly bear populations (Sage et al., 2022; Lute et al., 2020; Wilkinson et al., 2018).	*North American Public Opinion Surveys of Wildlife & Management*	A collection of public opinion and experience survey responses ranging from 0-100% proportion of census region in support of grizzly bear populations expanding. Survey includes responses from landowners and residents across Canada, the United States, and Mexico at a 270 meter resolution and zip code identification level, conducted by Dr. Matt Williamson.
	Bear Habitat Suitability	Estimate of grizzly bear density across British Columbia. Serves as a proxy for habitat suitability to determine the most ideal habitat locations for grizzly bears (Lamb et al., 2018; Proctor et al., 2018).	*Grizzly Bear Density*	The estimated existing and potential density of grizzly bears throughout British Columbia at a 500 meter resolution (Clayton Lamb, unpublished).
Probability of Bear Conflict	**Distance to Extant Grizzly Bear Populations**	Minimum distance to the nearest viable extant population of grizzly bears. Provides an estimate of existing grizzly bear home ranges and activity (Proctor et al., 2018; Lamb et al., 2018).	*Grizzly Bear Population Units*	The boundaries identifying similar behavioral ecotypes and sub-populations of Grizzly bears (GBPU) based on population estimated from 2020 (BC Gov, 2020; Mowat, 2018).

Relating Model	Predictor	Predictor Description	Dataset(s)	Data Description
Probability of Bear Conflict	**Biophysical Landscape Connectivity Surface** *gHM* + *topographic ruggedness*	Human population density, human land use and infrastructure modification (built-up areas, nighttime lights, agriculture, human intrusion, pollution), and human utilization (mining, roads, railroads, powerlines) (Theobald et al., 2020). Provides a spatial distribution of areas with little to no movement potential for bears (Lamb et al., 2020).	*Global Human Modification (gHM)*	Dataset of the global human land use modification of terrestrial land at a 300m resolution with 14 stressors, updated to the year 2017. Produced by Theobald et al., 2020. The original data from Theobald et al., (2020) had been scaled 0-1 (1 representing full human modification) and then multiplied by 65536 to reduce file size, so I divided the data by 65536 to revert it back to a 0-1 scale.
		Slope and elevation data across the study region used as a proxy for topographic ruggedness. Serves as a representation of the natural biophysical landscape barriers to bear movement (Singleton et al., 2004; Gyug et al., 2004).	*Topographic Ruggedness*	Terrain Ruggedness Index (TRI) and Topographic Position Index (TPI) by meter derived from the Terrain characteristics from the raster package in R (Burrough et al., 1998, Fleming & Hoffer, 1979).
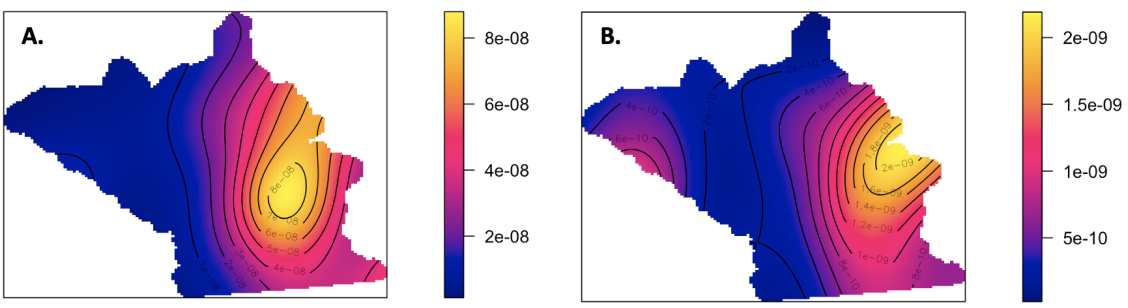
Figure A.1. **The Kernel Density Estimate (KDE) calculation of bear density for black bears and grizzly bears. A Displays the KDE results for black bear conflict reports across the 10km buffered SOI. B shows the KDE results for grizzly bear conflict reports across the 10km buffered SOI.**

Figure A.2. **The distribution of black bear and grizzly bear reports, indicating level of correlation between the two in green (100% correlated).**

APPENDIX B

Chapter 2 Supplementary Figures & Tables

Table B.1. **The raster layers used for resistance surfaces in the analysis and the data sources for compiling them.**

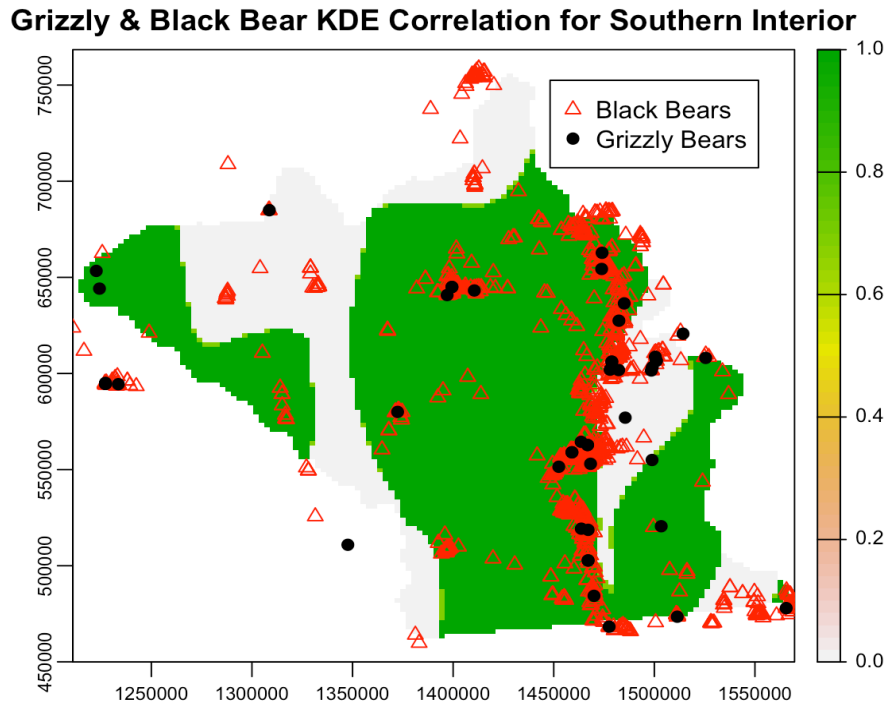| Layers	Layer Description	Data Description	Dataset(s)	Dataset Sources
Biophysical	**Biophysical Landscape Resistance Surface** (*gHM*) + *topographic ruggedness*	Human population density, human land use and infrastructure modification (built-up areas, nighttime lights, agriculture, human intrusion, pollution), and human utilization (mining, roads, railroads, powerlines) (Theobald et al., 2020).	***Global Human Modification (gHM)***	Dataset of the global human land use modification of terrestrial land at a 300m resolution with 14 stressors, updated to the year 2017. Produced by Theobald et al., 2020. The original data from Theobald et al., (2020) had been scaled 0-1 (1 representing full human modification) and then multiplied by 65536 to reduce file size, so I divided the data by 65536 to revert it back to a 0-1 scale.
	Distance to Protected Area	Characterizing elevation into levels of terrain ruggedness to produce a natural topographic landscape description.	***Topographic Ruggedness***	Elevation, Terrain Ruggedness Index (TRI) and Topographic Position Index (TPI) by meter derived from the Terrain characteristics from the raster package in R (Burrough & McDonnell, 1998, Fleming & Hoffer, 1979).

Layers	Layer Description	Data Description	Dataset(s)	Dataset Source
Probability of Bear Conflict	**Probability of Bear Conflict Resistance Surface** *Distance to Protected Areas* + *Distance to Extant Grizzly Population* + *Support for Grizzly Increase* + *Biophysical Connectivity* + *Density of Animal Farms* + *Density of Ground Crop Farms* + *Bear Habitat Suitability*	Extrapolating probability of bear conflict regression predictions to a series of predictor rasters, producing a resistance surface corresponding to predicted likelihood of human-bear conflict.	***Probability of Bear Conflict Regression***	The Bayesian probability of bear conflict regression results applied to corresponding predictor rasters expanded to the ONA territory. Produced by Spragg in Chapter 1 (2022).
		Distance to Protected Areas: Raster representing the minimum distance to the nearest protected area.	***Canada Protected and Conserved Areas***	A conglomeration of the provincial, federal and state protected areas across British Columbia at a 1 meter resolution provided by Clayton Lamb. Sourced from a variety of federal and provincial datasets, including the Canada Protected and Conserved Areas Database (Statistics Canada, 2019).
		Distance to Extant Grizzly Bear Populations: Raster representing the minimum distance to the nearest viable extant population of grizzly bears within and around the ONA territory.	***Grizzly Bear Population Units***	The boundaries identifying similar behavioral ecotypes and sub-populations of Grizzly bears (GBPU) based on British Columbia population estimated from 2020 (BC Gov, 2020; Mowat, 2018). Recovery zones for grizzly bears in the U.S. were included to account for grizzly populations in the southern part of the territory (USGS, 2020).
		Public Opinion of Grizzly Bears: Raster representing the proportion of survey respondents by census district in support of grizzly bear populations increasing or increasing substantially over the next several years.	***North American Public Opinion Surveys of Wildlife & Management***	A collection of public opinion and experience survey responses from landowners and residents across Canada, the United States, and Mexico at a 270 meter resolution and zip code identification level, conducted by Dr. Matt Williamson.

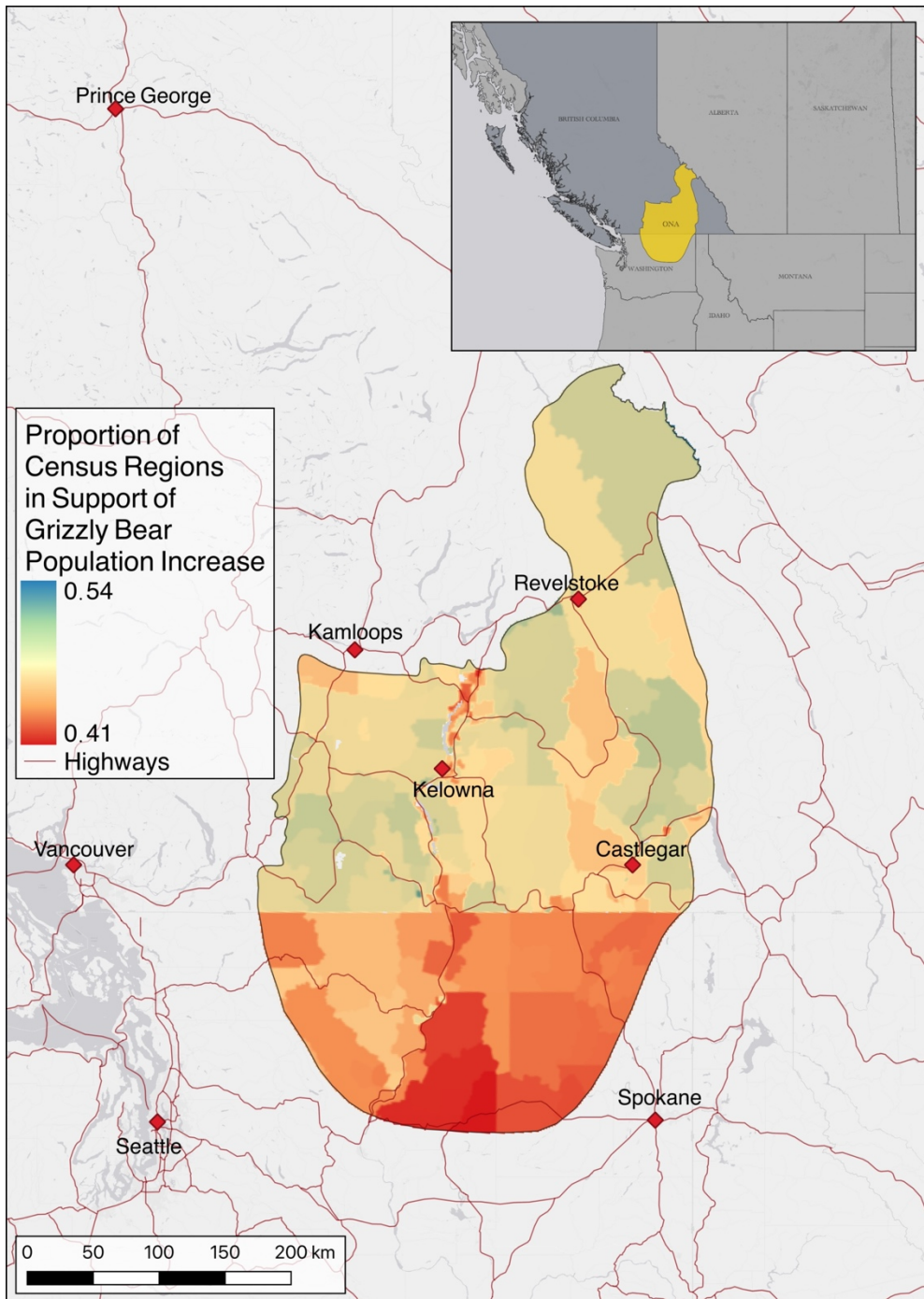| Layers	Layer Description	Data Description	Dataset(s)	Dataset Source
Probability of Bear Conflict	**Probability of Bear Conflict Resistance Surface** *Distance to Protected Areas* + *Distance to Extant Grizzly Population* + *Support for Grizzly Increase* + *Biophysical Connectivity* + *Density of Animal Farms* + *Density of Ground Crop Farms* + *Bear Habitat Suitability*	**Biophysical Landscape Connectivity Surface:** Raster representing the biophysical connectivity for bear movement. The resulting circuitscape output of a resistance surface made from ghM + topographic ruggedness,	***Human Influence Index*** ***&*** ***Topographic Ruggedness***	Dataset of the global human land use modification of terrestrial land at a 300m resolution with 14 stressors, updated to the year 2017. Produced by Theobald et al., 2020. The original data from Theobald et al., (2020) had been scaled 0-1 (1 representing full human modification) and then multiplied by 65536 to reduce file size, so I divided the data by 65536 to revert it back to a 0-1 scale. Elevation data by meter derived from the Terrain characteristics from the raster package in R (Burrough et al., 1998, Fleming & Hoffer, 1979).
		Density of Animal & Meat Farming: Raster representing the density of animal meat and product farms by census region (CCS for Canada, Census Tract for US).	***Agricultural Census Land Classification***	Classifications of agriculture production on a 1 meter resolution of Agriculture Region and Consolidated Census Subdivisions for British Columbia and Alberta by Statistics Canada 2016 Agriculture Census (Statistics Canada, 2016). Additional classifications of agricultural production on a 1 meter resolution of county region for Washington and Idaho by USDA National Agricultural Statistics Service (USDA, 2021).
		Density of Ground Crop & Produce Farming: Raster representing the density of ground crop producing farms by census region (CCS for Canada, Census Tract for US).	***Agricultural Census Land Classification***	Classifications of agriculture production on a 1 meter resolution of Agriculture Region and Consolidated Census Subdivisions for British Columbia and Alberta by Statistics Canada 2016 Agriculture Census (Statistics Canada, 2016). Additional classifications of agricultural production on a 1 meter resolution of county region for Washington and Idaho by USDA National Agricultural Statistics Service (USDA, 2021).
Grizzly Source	**Bear Habitat Suitability**	Using the estimated existing and potential density of grizzly bears in British Columbia as an estimate for bear habitat suitability.	***Grizzly Bear Density***	The estimated existing and potential density of grizzly bears throughout British Columbia at a 500 meter resolution (Lamb et al., *in progress*). This data was expanded to include Washington by assigning the North Cascades Recovery Zone to the 80th percentile of habitat suitability and extrapolating the mean value for habitat suitability to all other areas outside of the 50km buffer of British Columbia.

Figure B.1. **The proportion of people per census region that responded in support of grizzly bears increasing or increasing substantially over the next 5-10 years.**

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