

OIL SANDS MONITORING SYNTHESIS:

**THE STATE OF KNOWLEDGE OF MAMMALIAN
RESPONSES TO OIL AND GAS FEATURES IN ALBERTA**

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INTRODUCTION

The Oil Sands Monitoring (OSM) conceptual framework is built around stressor-response pathways. We seek to (1) identify a potential stressor, such as seismic lines; (2) test whether there is a wildlife response to this stressor, such as changes to caribou population size; and (3) weigh evidence for the pathway or mechanism between stressor and response, such as increased caribou predation by wolves travelling faster on seismic lines. The OSM Synthesis seeks to synthesize existing data and information about the effects of oil sands activity on terrestrial biodiversity. For a wide range of mammals, we seek to answer three central questions:

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- (1) Is there a response by mammal species to oil sands features and activity?
 - (2) What specific features or activities are causing the response?
 - (3) What ecological mechanisms generate these responses, and how can we likely fix the problems?
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Wildlife responses to oil and gas stressors can manifest in three key processes, or **levels: behaviour, distribution, and population**. A change in behaviour, such as avoiding a well pad, may be ecologically trivial or it may alter that species' distribution in the landscape. Likewise, a change in distribution may just be a re-shuffling of space-use, or it could result in population changes, including declines which threatened persistence. Throughout this synthesis, we weigh evidence for mammalian species' response to OS at these three levels, recognizing that the importance of responses to species persistence increases from behaviour through population change. Using this paradigm, we aim to clearly reveal knowledge gaps, and provide recommendations for OSM monitoring to bridge these gaps.

Similarly, wildlife responses to oil and gas stressors can manifest at different **spatial scales: local, landscape, and regional**. **Local effects** can be interpreted as the effects at the scale of an energy lease, or similar sized feature: these represent individuals' responses to OS features, and hence are typically reflected in behaviour. **Landscape effects** can be construed as a collection of interacting landforms, including multiple leases, exploration areas, and surrounding forests, lakes, and other natural

habitat. Within a landscape, the assumption is that anthropogenic disturbances and natural features interact to create a habitat mosaic that supports (or fails to support) a species. Landscape effects are typically manifested through changes to distribution or to populations. **Regional effects** result from the interactions of multiple landscapes. Some landscapes (such as Christina Lake) may be heavily developed for oil and gas, whereas others (such as Richardson) may be relatively free of disturbance. The sum effects of these differing landscape-scale responses to stressors ultimately manifest at the regional scale, and are typically expressed as changes to metapopulation sizes (a collection of populations).

Each scale represents a different degree of risk. Local-scale effects are likely not critical to species persistence unless the stressor is very widespread and the response is strong and highly consistent, at which point it manifests as changes to distribution or population at landscape scales. Distribution responses may not be critical to species persistence unless the stressors occur across multiple landscapes with a region, and the response is strong and highly consistent, at which point it manifests as changes to metapopulations, and threatens species persistence. Although risk is most obvious at the regional scale, resolution of the stressor-response pathways is the coarsest. The region sums multiple OS features, landforms, habitats, and their associated pathways, into a small number of measures. Conversely, risk is most difficult to assess at the local scale, but here the stressor-response pathway can be examined at its highest resolution: a single species, at a single stressor, under a small set of conditions. Hence, effective oil sands monitoring **must** monitor at all three scales to simultaneously investigate stressor-response pathways and gauge the level of risk they present.

We approached this synthesis and exploration along three main lines. First, we reviewed published literature on mammalian responses to oil and gas features at these three spatial scales, and for the three ecological levels: behaviour, distribution, and population. We synthesize where the science is ample and where it is scant, or completely missing. Second, we examined evidence for regional-scale stressor-responses using available camera-trap data collected by ABMI across the whole OSR. We apply a new class of species distribution models and illustrate what regional-scale modelling as currently conducted can, and currently cannot, tell us about effects of OS features on the whole mammal community. Third, we explored the response of white-tailed deer to oil and gas features, including behaviour, distribution, and populations, across all three spatial scales. We synthesized and explored how deer behavioural response to oil and gas features translates into landscape-scale distribution and population changes, and what current regional-scale monitoring tells us about deer expansion across the entire Oil Sands Region.

CHAPTER 1: KNOWLEDGE ASSESSMENT OF MAMMALIAN WILDLIFE RESPONSES IN ALBERTA'S OIL SANDS REGION

SYNTHESIS

- (1) There is a **distribution** response by every mammal species examined – from red squirrels to moose – attributable to oil and gas features in the OSR. Uncertainty exists in how widespread these effects are, species responses (except for caribou, moose, and wolves) are recorded only from the Christina Lake region. There is also much less certainty about **behavioral** and **population** responses.
- (2) Both linear features and polygonal (block) features contribute to mammalian distribution responses. The feature(s) associated with the responses differ for every mammal species, so no one feature is the cause.
- (3) The ecological mechanisms generating responses remain unclear, with the exception of predator-prey interactions mediated by linear features. Much more research is needed to elucidate the stressor-response pathways for most mammal species in Alberta's oil sands region.

SUMMARY

We reviewed available technical and peer-reviewed reports on mammalian wildlife responses to industrial disturbances in Alberta's Oil Sands Region (OSR). The purpose of this synthesis is to assess the current state of knowledge regarding terrestrial wildlife responses to development in the region and identify knowledge gaps to guide future research efforts.

We targeted peer-reviewed and grey literature testing ecological responses of mammalian wildlife to disturbances from the energy sector. We sorted relevant findings across studies based on species and species' interactions, synthesizing observed responses across studies. Wolf, caribou, and white-tailed deer – and their interactions – have been the main research focus for the region. Moose and black bear responses have also been evaluated across landscapes, with significantly less research on lynx, coyote, fox and other mid-sized predators.

Wolf and caribou responses are well-established in the literature, with wolves benefitting from the intrusion of linear features across landscapes to the detriment of caribou populations. Extensive evidence indicates positive responses of white-tailed deer to block industrial features that replace mature stands with early seral vegetation. However, inconsistent responses to linear feature development in wolf primary-prey

indicates a need for further research into the interactions between deer, wolves, and linear features. Additional information is also needed to understand how black bear and coyote, and their interactions with caribou and the rest of the ecological community, are impacted by industrial activities in the OSR. Of particular importance will be monitoring mesopredator and prey species' responses to ongoing wolf management actions in the region. The complex and interacting processes of landscape change, wolf control, and resultant shifts to species' interactions demand a focus on community-level monitoring. We recommend a shift from monitoring individual species' responses to community-level monitoring to better disentangle community responses and species interactions. Such information will greatly help identify and manage the proximate and underlying mechanisms driving biodiversity loss and process change in this region.

METHODS

Data Sources

We included all peer-reviewed and grey literature available online, including published technical reports with a DOI, M.Sc. Theses, and Ph.D. Dissertations, which evaluated mammalian wildlife responses to human activity and landscape development within the Oil Sands Region of Alberta (OSR). Information may additionally be held by industry and their consultants, but we did not include these at this stage. We reasoned that any substantial and pertinent information – beyond simple local-scale descriptions of species occurrences – would already have been made widely available. This triaged approach was necessary given time and resources constraints. Studies focusing on wildlife responses to oil and gas development features outside the OSR were also selectively included to provide insights into processes potentially occurring within the OSR. We did not synthesize data analyses available from ABMI, as they regularly produce synthesis reports available online; as their work is well documented we did not repeat it here. We limited our synthesis to mid- and large-sized terrestrial mammals, including only studies published since 2000.

Study Area

Overlaying the Boreal Forest Natural Region, the Alberta Oil Sands Region (OSR) is the aggregate of three independently managed oil sands areas (ABMI 2014). Totalling an area of 140,000 km², the OSR is characterized by a mosaic of upland and lowland forests, wetlands, and human footprint features associated with natural resource extraction. Energy development, forestry, and agriculture are the main industries in the region, with a combined human footprint comprising 15.5% of total area (ABMI 2014).

This region supports a high diversity of boreal mammals, including wolf (*Canis lupus*), woodland caribou (*Rangifer tarandus caribou*), moose (*Alces alces*), black bear

(*Ursus americanus*), white-tailed deer (*Odocoileus virginianus*), lynx (*Lynx canadensis*), coyote (*Canis latrans*), red fox (*Vulpes vulpes*), fisher (*Pekania pennanti*), and marten (*Martes americana*).

WILDLIFE RESPONSES TO DEVELOPMENT IN ALBERTA'S OIL SANDS REGION

1. SPECIES

Wolves, *Canis lupus*

Extensive research has evaluated wolf **local-scale behavioural** responses to industrial developments in Alberta's Oil Sands Region (OSR). With a few exceptions, wolves select for almost all types of anthropogenic linear features, though strength of selection may vary seasonally and by line type (Dickie et al. 2017a, DeCesare 2012, Latham et al. 2011a, Neufeld 2006). Wolf selection for anthropogenic linear features – pipelines, roads, and seismic lines – in this region is well studied. Wolf selection for linear features is stronger during the snow-free season (Dickie et al. 2017a, Latham et al. 2011a). Wide straight features (conventional seismic lines) and those consistently cleared of obstruction (railways, transmission lines) are selected more strongly than winding or narrow features (trails, low-impact 3D seismic lines) (Dickie et al. 2017a). Wolves travel up to three times faster on linear features compared to adjacent forest, hence covering greater distances when traveling along them (Dickie et al. 2017a). While roads facilitate wolf movement (Dickie et al. 2017a), observed wolf responses to roads may be confounded by risks associated with human persecution. Latham et al. (2011a) observed wolf spatiotemporal avoidance of roads in relation to human activity. Coincident with these population changes, wolf territories have also extended further into peatland habitat with a resultant spatial overlap increase with woodland caribou (Latham et al. 2011b).

Fewer studies have examined how selection scales up into **landscape-scale distribution**, as most research has been conducted at small scales using telemetry on individuals. In the heavily impacted Christina Lake landscape, wolf relative abundance (as measured *via* camera traps) decreases with increasing road density (Fisher and Burton 2018). However, wolf relative abundance increased with anthropogenic block features (industrial sites) and trails (Fisher and Burton 2018), resulting in an overall net positive response to development. However, it is unclear whether these relationships are due to selection of these anthropogenic features, or the prey opportunities they provide; Darlington (2018) shows white-tailed deer occurrence plays a substantial role in explaining wolf occurrence in the region. How distribution varies among landscapes remains to be seen, and currently work is underway in the Algar and Richardson areas, as well as through ABMI and the Caribou monitoring Unit, to ask these questions.

Similarly, little knowledge exists about wolves' **regional-scale responses in distribution or population size**. The positive association with both linear and block industrial developments, as well as an increasing prey base including white-tailed deer, has putatively translated into an increasing wolf population in the OSR. Latham et al. (2011b) produced an *ad hoc* estimate for West Side Athabasca caribou range (WSAR) wolves (1.15/100 km²) and suggested an almost doubling of wolf population size in northeastern Alberta since the 1970s, following major industrial expansion in the region. However, due to limitations of technologies at the time, the *ad hoc* estimate was based on wolf pack range size and pack size, and lacks measures of accuracy or precision. Moreover, comparison between 1970s and 2000s is confounded by a reduction in predator persecution as well as OS activity. In the first statistically estimated wolf population survey in the oil sands (based on camera traps and spatial capture-recapture models), Burgar *et al.* (2018) estimated 0.77 wolves / 100 km² in the Christina Lake region, an area of known high wolf density. Wolf population dynamics using repeatable and reliable statistical methods remain largely unknown but should be a central focus for OSM; wolf population increases, altered habitat use, and territory extension into caribou habitat have consequently contributed to altered interactions with ungulate prey in the OSR, including caribou, white-tailed deer, and moose (see section 3.5).

Caribou, *Rangifer tarandus*

Extensive research has documented caribou responses to oil and gas features and activity. Much of this is treated elsewhere and we present only highlights here, as a thorough accounting is beyond our scope.

Caribou exhibit **local-scale behavioural responses** to oil and gas activity. Caribou avoid areas at least 500-m from industrial developments (Environment Canada 2011, 2012, Hebblewhite 2017), with human activity associated with stronger levels of avoidance from these features (Wasser et al. 2011, Dyer et al. 2001). Caribou select against areas with high cut-block densities at broad spatial scales and high linear feature density areas at smaller spatial scales (DeCesare 2012b). Avoidance of linear features such as roads (Wasser et al. 2011, Dyer et al. 2001) and seismic lines (Latham et al. 2011a, Neufeld 2006, Dyer et al. 2001) contribute to functional loss of caribou habitat that is greater than the human footprint of these features themselves, with up to 48% of otherwise suitable habitat expected to receive reduced use by caribou when avoidance distances are extrapolated across areas (Dyer et al. 2001). Functional habitat loss may be further exacerbated by barrier effects from linear features on the landscape, with roads acting as a semipermeable barrier to caribou movement (Dyer et al. 2002). Based on simulated cumulative effects models, Weclaw and Hudson (2004)

identify avoidance of good quality habitat in proximity to industrial features as the most detrimental factor on caribou population dynamics. Simulation studies by Muhly et al. (2015) indicate that industrial developments restricting caribou movement are expected to impact caribou home-range sizes and fine-scale movements, with potential demographic consequences. In addition to habitat loss and barrier effects from industrial developments, caribou physiological health is also negatively impacted by the degree of human activity on the landscape, with poor nutrition and increased stress observed with increasing proximity to industrial features (Wasser et al. 2011).

Caribou **landscape-scale distribution** has been researched using telemetry of individuals; range maps are derived from these data. Likewise, **regional-scale caribou population** growth rates have been extensively studied across Alberta's boreal forest, suggesting marked declines (Hervieux et al. 2013). Caribou monitoring is conducted by Alberta Environment and Parks (AEP) and ABMI's Caribou Monitoring Unit, and ongoing research identifies industrial developments from forestry and energy extraction as the ultimate causes driving rapid caribou declines across Alberta. The components of this relationship have been well reviewed elsewhere (Hebblewhite 2017, Boutin et al. 2012). Human-mediated landscape change is also implicated with altering wolf-caribou spatial overlap and interactions, as well as apparent competition with increasing populations of white-tailed deer benefiting from early-seral vegetation growth following human disturbances in the OSR (See section 3.5).

Moose, *Alces alces*

Moose are the subject of an extensive companion report (Becker *et al.* 2019) and so we provide only highlights here.

Moose behaviourally **respond** to anthropogenic development features in the OSR, but strength and direction of responses are dependent upon disturbance types, and likely landscape context, in ways that are not currently clear. Wasser et al. (2011) observed moose avoidance of areas close to roads and other linear features, with stronger selection against features associated with human activity. However, moose exhibited improved nutrition in areas with high densities of linear features (Wasser et al. 2011). The Regional Industrial Caribou Collaboration (RICC) group has conducted research on moose behavioural response to oil and gas features in the Christina lake region, but those results are not yet released.

At the **landscape scale, distribution** of moose increases in relation to cut-blocks, block anthropogenic features, and 3D seismic lines, but decreases in response to cumulative anthropogenic features including pipelines, trails, well-sites, and conventional seismic lines (Fisher and Burton 2018). Similar to deer observed responses,

moose relationship with linear features may be complicated by trade-offs from increased predation risk from both humans and wolves in relation to linear features, despite a higher abundance of browse associated with these features. At the **regional (provincial) scale**, moose relative abundance is positively associated with forest harvest cut blocks between 10 – 40 years old (Toews et al. 2018), but their response to oil and gas features is still emerging.

Government of Alberta conducts aerial ungulate surveys for moose and **population responses** by moose are examined by Becker *et al.* (2019). Burgar et al. (2018) used camera traps and spatial mark-recapture models to estimate moose density in the heavily developed Christian lake region and estimated 0.77 moose per 100 km², but with low precision.

Black Bear, *Ursus americanus*

At **local scales**, Latham et al. (2011c) report black bear selection for anthropogenic habitat (including oil and gas camps) well-sites, and intermediate densities of linear features, with a high probability of habitat selection near seismic lines and pipelines. Tigner et al. (2014) observe increased black bear use of individual seismic lines over undisturbed forest interior, with the exception of lines less than 2m wide. Neufeld (2006) likewise reports a disproportionately high frequency of black bear scat on seismic lines compared to natural and other anthropogenic landscape features.

At **landscape scales**, black bear **distribution** responses to anthropogenic features in the OSR show mixed and sometimes conflicting results. Fisher and Burton (2018) observe a net negative association across anthropogenic landscape features, with decreased black bear relative abundance in relation to 3D seismic lines, industrial block features, and roads. However, at this scale, other studies did not observe black bear distribution to be influenced by seismic line density on the landscape (Tigner et al. 2014). Burgar *et al.* (2018) estimated 3.3 bears per 100 km² in the area. Beyond ABMI's mammal models, very little information exists for black bears at **regional scales**. *In summary, the response by black bears to oil sands features remains very variable, and in need of additional research and monitoring to elucidate relationships.*

Furbearers

Coyote (*Canis latrans*), lynx (*Lynx canadensis*), fisher (*Pekania pennanti*), red fox (*Vulpes vulpes*), snowshoe hare (*Lepus americanus*), and red squirrel (*Tamiasciurus hudsonicus*) **behavioural responses to local-scale OS features** have not been researched and remain a significant data gap.

At **landscape scales, distribution** and demographic responses to development in the OSR have been evaluated by only a handful of studies, despite those species being

widespread in the boreal region. Coyote generally benefit from anthropogenic features in the OSR. Coyote relative abundance increases in relation to net anthropogenic footprint, showing a positive association with roads, seismic lines, 3D seismic lines but negative in relation to pipelines and block anthropogenic features (Fisher et al. 2018). Latham et al. (2012) observe coyote selection for areas close to human settlements, roads, and pipelines, while Toews et al. (2018) report increased relative abundance with an increasing human footprint from agriculture, roads, and well sites. Coyote are also observed to select for caribou habitat during the caribou calving season on human-development impacted landscapes in the OSR (Latham et al. 2012), highlighting important considerations for future coyote-caribou interactions with ongoing landscape change. Similar to coyote, lynx relative abundance also increases with net anthropogenic footprint, with a positive response to trails, 3D seismic lines, and cut blocks (Fisher and Burton 2018). Well-sites, pipelines, and agriculture are associated with decreased relative abundance, with mixed results observed for road density effects between studies and landscapes (Fisher and Burton 2018, Toews et al. 2018). Smaller mesopredators, including fisher and red fox, exhibit decreased relative abundances in relation to net anthropogenic development (Fisher and Burton 2018). Fisher are negatively impacted by trails, 3D seismic lines, and pipelines. Red fox relative abundance decreases with well sites, seismic lines, and 3D seismic (Fisher and Burton 2018).

For other mammalian species whose current ranges extend close to or overlap the OSR - including grizzly bear (*Ursus arctos*), wolverine (*Gulo gulo*), and marten - little to no research has been done in the region although their responses to energy and forestry features have been evaluated in other areas of the province. In the northwest corner of AB, energy development is a primary but uncommon human land-use. While outside of the OSR, several studies have evaluated species' responses to industrial developments in this area. Grizzly responses to oil and gas infrastructure show highly conflicting results, with selection for and against well-sites observed between studies (McKay et al. 2014, Labaree et al. 2014). Wolverine in this area exhibit selection for seismic lines (Scrafford et al. 2017) while marten avoid seismic lines greater than 3m wide but no selection for or against narrow lines (<2m wide) or those with at least partial recovery of woody vegetation (Tigner et al. 2015). *Overall, however, the landscape-scale response to rarer species occurring in the OSR remains a considerable data gap.*

Population responses are similarly limited. Burgar et al. (2018) estimated 2.64 coyotes / 100 km² in the Christina Lake region, and noted that these densities are higher than for wolves. Given coyotes' expansion across the continent and their high population growth rates in the absence of wolves, coyotes may a significant role in prey population in the future, and should be subject to monitoring. *In summary, the*

responses of furbearers to oil and gas stressors at landscape scales across the OSR remain a considerable data gap.

2. PATHWAYS

Predator-Prey and Competitive Interactions in Relation to Anthropogenic Disturbance

In addition to the direct impacts on individual species, industrial developments in the OSR have altered predator-prey and competitive interactions between boreal species. Linear features enhance wolf hunting efficiency and access into caribou habitat, shifting wolf-caribou dynamics in favour of wolves and hence increasing predation rates (Dickie et al. 2017a). Meanwhile, apparent competition with white-tailed deer is identified as a contributory proximate mechanism for caribou declines in the OSR (Latham et al. 2011b, Festa-Bianchet et al. 2011), with industrial disturbance strongly implicated in supporting expanding deer populations in the region.

Earlier observations of caribou and wolf habitat selection indicate caribou use of fen/bog complexes as spatial refugia from wolves (James et al. 2004). Following industrialization of the region, increasing wolf observations in caribou range indicate considerable spatial overlap between the two species and a concurrent 10-fold increase of caribou in wolf diet (Latham et al. 2011b). Empirical and simulation studies provide strong evidence that linear features enhance wolf movement rate and hunting efficiency (Dickie et al. 2017a, DeCesare 2012a), while caribou mortality risk from wolf predation increases in proximity to linear features (Boutin et al. 2012, James and Stuart-Smith 2000). However, how linear feature density translates into predation rates on caribou is only inferred from declining caribou populations.

Anthropogenic landscape change in the OSR is implicated in indirectly increasing predation pressure on caribou by subsidizing wolf primary prey populations. Proliferation of early seral habitats in the region has supported an expanding population of white-tailed deer (Fisher et al. 2020, Dawe et al. 2014, Latham et al. 2011b), which in turn supports a higher wolf density. Wolf diet indicates a shift away from moose and increase in deer consumption (Latham et al. 2011b). White-tailed deer are now identified as the primary prey of wolf (Latham et al. 2011b), with wolves strongly selecting habitats representing deer distribution (Wasser et al. 2011, Darlington 2018). Despite heavily targeting white-tailed deer, high wolf densities continue to exert substantial predation pressures on caribou, with deer population control identified as a necessary management action to stabilize caribou populations in Alberta (See section 3.8).

Wolf-moose dynamics in response to oil and gas activities are less well understood. Fisher and Burton (2018) suggest enhanced wolf activity on linear features

render these features less suitable for moose due to increased predation risk, despite the associated abundance of browse. Industrial features associated with oil sands mining are also implicated in enhancing moose predation by wolves (Neilson and Boutin 2017). Altered space-use by wolf along the boundaries of mining developments (Neilson and Boutin 2017) increases relative predation rates on moose, and indicates that wolf select for prey access over avoidance of human disturbance.

Wildlife Responses to Landscape Restoration and Predator Management

Numerous studies have also examined ecological responses across wildlife communities in relation to landscape and predator mitigation actions throughout the OSR. Strong evidence linking linear features with increased wolf-caribou predation has established linear feature restoration as an important element of caribou conservation throughout Alberta's boreal (Environment Canada 2012). Structural restoration of linear features focuses on promoting and/or facilitating the natural succession of woody vegetation (Pyper et al. 2014), and is shown to reduce predator movement and selection for these features on the landscape. Dickie et al. (2017b) observed a significant reduction in wolf travel speeds on seismic lines with a minimum of 0.5 m vegetation height. Seismic lines with a least 30% area of vegetation over 4 m in height reduce wolf movement to observed travel speeds in undisturbed forest (Dickie et al. 2017b). Finnegan et al. (2018) report wolf selection against seismic lines with a minimum height of 0.7 m. While grizzly bear movement does not change in relation to vegetation height, Finnegan et al. (2018) observe grizzly selection for seismic lines with lower vegetation heights during springtime. Black bear use of seismic lines also differs across different states of vegetation recovery (Tigner et al. 2014). While bear use of seismic lines decreases with increasing recovery of woody vegetation, odds of observation for black bear along conventional seismic lines with considerable regrowth is still twice that of forest interior (Tigner et al. 2014). While structural restoration is shown to influence predator movement along linear features in the OSR, little evidence supports functional restoration practices such as tree felling for reducing predator movement and hunting efficiencies along linear features (Neufeld 2006).

In addition to habitat restoration practices, AEP has also applied predator reduction programs to reduce wolf abundance and predation on woodland caribou throughout their ranges. Hervieux et al. (2014) compared caribou population growth rates before and after wolf population control in west-central Alberta. While wolf population control did not stabilize the declining caribou herd population, they observed an increase in mean population growth of 4.6% following wolf removal in comparison to an observed 4.7% decline in an adjacent caribou herd where no predator

management actions were applied (Hervieux et al. 2014). However, simulation studies indicate that long-term recovery of caribou is best achieved via habitat restoration and preservation, with concurrent management of predator populations and habitat-mediated apparent competition with other ungulate species (Smith et al. 2008).

Wildlife Toxicology in Response to Oil and Gas Activities

Although oil refineries have been shown to release contaminants into waterways used by wildlife, few studies have directly tested for mammalian bioaccumulation of toxic substances associated with oil and gas activities within the OSR. Rodriguez et al. (2016) observe signs of local contamination and associated biological costs in native mammals in relation to reclaimed bitumen mine sites, with higher metal and reduced body condition in deer mice on reclaimed sites in comparison to reference sites. Lundin et al. (2015) observe increased toxic substance presence from *in situ* oil production in wolf scat in areas associated with high intensity of oil exploration and extraction. While not directly produced by activities from the energy sector, rodenticides used near human infrastructure in the OSR have been detected in fisher and marten through secondary poisoning (Thomas et al. 2017). In this study, oil sands mines and wells are included as the strongest predictors of the frequency of secondary poisoning in fisher (Thomas et al. 2017).

Currently, there is little to no indication that mammalian wildlife **populations** are being adversely impacted by contamination or bioaccumulation from toxins released via oil extraction and refinement in the region. However, monitoring for these responses in sensitive areas remains an important area of research to help mitigate against population-level responses in areas with higher outputs of toxic wastes.

RECOMMENDATIONS AND KNOWLEDGE GAPS

Mammalian monitoring in the OSR has been heavily concentrated on species of concern (woodland caribou, moose) and consequently the response of other species to OS stressors still remains relatively unknown.

Behavioural responses at local scales have been examined for very few species, typically using telemetry, which is expensive, yields small sample sizes, and is highly geographically constrained. *Opportunities exist to examine local-scale behavioural responses using new camera-trap technology over larger areas, longer timeframes, and repeated across multiple leases and forms of disturbance.*

Distribution and population responses at landscape scales have been examined for several species, but at a highly restricted number of landscapes (Christina Lake). Beyond caribou and moose, we have little idea about species numbers, or how these

change in relation to stressors. We also have very scant information about how species distribution changes in relation to accumulated stressors in the landscape. *Opportunities exist to examine landscape-scale responses using new camera-trap technology, and noninvasive genetic tagging technology (fecal sampling and hair trapping) over large areas, long timeframes, and repeated across multiple landscapes.*

Distribution responses at regional scales has been conducted by ABMI via snowtracking, and their resulting mammal models are available online. Additional analysis by Toews et al. (2018) show that response to stressor vary by species and across regions. However, the ability of those data to parse apart the effects of different OS features is challenged by collinearity among features, a natural limitation of a systematic design. Consequently, considerable uncertainty remains in these species-landscape disturbance relationships, and further research is required to better inform management and land-use practices in the region (see Chapter 2).

Stressor-response pathways also remain very poorly defined for most species, given the lack of data available to elucidate these relationships. Below, we identify key knowledge gaps on species' complex responses across disturbance types and management actions, with a focus on linear feature effects and predator control programs. Given the potential for indirect and cascading responses throughout the mammalian community, we strongly recommend research efforts to shift towards community-level monitoring to better understand the interacting effects of both landscape change and predator control in the region.

Wolf and Ungulate Responses to Linear Feature Development

Substantial evidence supports linear feature development as impacting species-landscape relationships and predator-prey interactions in the region. However, observed wolf and ungulate responses to linear features may be confounded by perceived risks of human persecution and natural predators associated with these features. While extensive research recognizes wolf use of seismic lines as travel corridors (Finnegan et al. 2018, Dickie et al. 2017a, James and Stuart-Smith 2000), wolf responses to road infrastructure indicate conflicting results with both selection for and against these features observed across studies (Dickie et al. 2017a; Latham et al. 2011a). As roads and railways are generally permanent features on the landscape, habitat restoration in areas with extensive road infrastructure may not provide benefits to caribou conservation if wolves use these features for enhanced hunting efficiency (Dickie et al. 2017b). Future seismic line restoration efforts in the region may therefore be better guided by a fine-scale and clearer understanding of wolf responses to road infrastructure and other permanent linear features on the landscape.

Similarly to wolves, ungulate selection for linear features appears to be complicated by trade-offs between forage availability and increased predation risk. Studies observe differences between behavioural and distributional responses to seismic line density (Fisher and Burton 2018, Darlington 2018, Fisher et al. 2020). Likewise, moose responses to linear features are observed to differ across linear feature disturbance types (Fisher and Burton 2018, Wasser et al. 2011). With disturbance-mediated apparent competition identified as a leading hypothesis for caribou declines (Festa-Bianchet et al. 2011), understanding the underlying mechanisms driving wolf primary-prey species' responses across human footprint features and spatial scales is particularly important. Expanding this knowledge base may also help shed further light on the drivers of white-tailed deer expansion into the north, and help inform habitat restoration and deer control practices aimed at reducing wolf primary-prey populations in caribou range.

Black Bear & Mesopredator Responses to Landscape Change & Wolf Control

In response to declining caribou populations across Alberta, a large component of wildlife research in the OSR has focused on wolf responses to ongoing human landscape change. However, very little research has tested how land-use practices and concurrent wolf control affect other predator species' habitat-use and caribou-interactions. Both ongoing processes are likely to influence the distribution, abundance, and behaviour of the broader predator community, with important implications for biodiversity and caribou conservation in the region.

Select studies have evaluated black bear and mesopredator responses to human footprint features at the landscape scale, highlighting important hypotheses on caribou-predator interactions and cascading responses throughout the community that remain to be tested. Tigner et al.'s (2014) study on black bear use of seismic lines identifies the need to directly test whether linear features increase interactions between caribou and black bear. Mesopredator interactions with caribou are also an important research to direct future monitoring efforts, with a special focus on coyote. Coyote are observed to benefit from human activities in the OSR (Fisher and Burton 2018, Toews et al. 2018, Latham et al. 2012). Furthermore, expanding white-tailed deer populations in the OSR are hypothesized to support higher densities of coyote (Latham et al. 2012).

Coyote are also observed to select for caribou habitat during the caribou calving season (Latham et al. 2012), and expanding coyote populations may therefore increase predation pressures on caribou. Increased density and distribution of coyote on the landscape would be expected to not only potentially impact caribou, but also smaller prey species and mesopredator competitors (e.g. lynx, fisher). Cascading responses

within prey and predator guilds to coyote expansion may have significant implications on community structure and biodiversity in the region. We therefore recommend demanding close monitoring of coyote response to land-use and other management actions yielding benefits to this dominant mesopredators, including wolf control.

Removal of apex predator populations across the OSR through government sponsored wolf culls may be expected to impact the rest of the predator community. However, despite the removal of hundreds of wolves in caribou ranges (Hebblewhite 2017), we are aware of no studies that have directly evaluated predator species' responses to the removal of apex predators from the system. The potential for secondary and cascading responses following release from top-down control by wolves throughout the rest of the predator guild and broader ecological community is very high. The absence of community-level monitoring in conjunction with wolf control actions represents a critical knowledge gap with the potential for significant responses. Future research should focus on understanding these complex and secondary responses following ongoing and interacting landscape changes in the region.

Community-level monitoring

Given the interacting processes of landscape change, predator control, and resultant shifts to species' interactions in the OSR, evaluating wildlife responses at the species-level will likely be insufficient to explain patterns of process change. Increasing evidence indicates wildlife responses to landscape development differ across species and disturbance types (Fisher and Burton 2018), and disturbance-mediated shifts to the distribution, abundance, and behaviour of one species are likely to impact competitor and prey species. The potential for cascading responses throughout the community is therefore high, with secondary and indirect effects driving species and community-level responses on impacted landscapes.

The complex and indirect effects of habitat conversion and intrusion of linear features on the landscape from oil and gas activities across the OSR produce similarly complex responses in the species they impact. Species responses to the interacting effects of resource subsidization and linearization of the landscape indicate additive, synergistic, and antagonistic processes may be at play, likely involving interactions with competitor and predator species. Understanding and predicting community-level responses and resultant ecological process change on this landscape in response to landscape development and predator control is challenging. We recommend future research in this region focuses on careful formulation and testing of hypotheses evaluating altered species interactions and community-level responses. Such a community-level approach may help disentangle the proximate and underlying

mechanisms driving broader patterns of ecological change across the region, providing important insights to help guide better wildlife management and land-use practices.

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CHAPTER 2: REGIONAL-SCALE RESPONSES IN WILDLIFE DISTRIBUTION RELATIVE TO OIL AND GAS STRESSORS: A NEW APPROACH TO ANALYSIS

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SYNTHESIS

- (1) Evidence from **landscape** and **regional scales** suggest multiple mammal species show a **distribution** response to oil and gas footprint. Our ability to parse apart regional-scale stressor-response relationships varies among species, and is limited by detection rates.
- (2) In general, data suggest both linear features and polygonal (block) features contribute to mammalian distribution responses. The feature(s) associated with the responses differ for every mammal species, so no one feature is the cause.
- (3) The ecological mechanisms generating responses remain to be well understood. We can infer that early seral vegetation (by cutting mature stands) seems to benefit herbivores, providing a resource subsidy. Linear features benefit carnivores, providing a movement subsidy. Currently the weight of evidence suggests *both linear feature restoration and block feature restoration – as well as a marked reduction in forest clearing – is needed to mitigate these distribution responses*. Moreover, evidence suggests isolating the effects of single oil and gas features, while useful for identifying problems to fix, fails to capture the ecological mechanisms generating the stressor-response relationship. *Interactions between natural and anthropogenic features are common, meaning that mitigation of oil and gas features will necessarily be different in different landscape contexts*.
- (4) **Regional-scale monitoring** from ABMI data collected as of 2018 provides substantial analytical challenges due to low frequency of detections on camera traps for many species. However, it does provide substantial spatial extent, covering across many landscapes with differing environmental conditions and degrees of disturbance – which is very useful, as we know responses vary from landscape to landscape. **Nested sampling that combines regional and landscape monitoring** will provide a more complex and informative analysis of stressor-response relationships. Modelling nested data remains analytically challenging, but can be made more successful with

applications of new classes of hierarchical models that can accommodate samples from what are effectively different sampling populations.

INTRODUCTION

Regional-scale mammal monitoring has been a core component of oil sands monitoring (OSM) in Alberta's boreal forest, conducted by Alberta Biodiversity Monitoring Institute (ABMI). For a decade, snowtracking was the standard mode of surveying mammal occurrence, and the results of that surveying has been extensively analyzed by ABMI (abmi.ca) and others (Toews *et al.* 2017). Since 2015 ABMI has begun using infra remote cameras (camera traps) to survey mammals across Alberta.

Here, we use **camera data from ABMI regional-scale monitoring** to conduct two analyses. First, use regional-scale data to explore stressor-response relationships to infer the pathways responsible for those relationships. We sought to provide an exploration of what regional-scale sampling can tell us, and to provide guidance on its opportunities and limitations.

METHODS

Camera trap data

The Alberta Biodiversity Monitoring Institute (ABMI) deployed camera traps across the Lower Athabasca Regional Planning area (LARP) using the methods described at abmi.ca. Following their disclosure protocol the following data were used in this analysis: *Terrestrial T29B Camera Trap -- Species Raw Data Metadata, Requested 02 October 2018*.

Mammal occurrence data covered 161 camera trap sites within the ABMI network, located across northeastern Alberta (Figure 1), and came from three years of collection (2015, 2016, and 2017). This dataset included 5 predator species: black bear (*Ursus americanus*), grey wolf (*Canis lupus*), coyote (*Canis latrans*), fisher (*Pekania pennanti*), lynx (*Lynx canadensis*), and two prey species: white-tailed deer (*Odocoileus virginianus*), and moose (*Alces alces*).

Figure 1: Map showing the publicly-available approximate locations for ABMI camera trap sites in northeastern Alberta (n=161).

Some of the ABMI site data had noted irregularities, mostly around deployment dates and image dates not lining up. That is, several sites had 2017 deployments with 2016 images, and *vice versa*. Where it was possible to do the forensics to determine the error, we fixed the data, otherwise the site was deleted; several sites were deleted due to errors. We also assumed that all cameras were fully functioning during the deployment period as there were no data to the contrary – *this is a critical assumption*. Continuous data was then binned into discrete week-long periods starting at the deployment date and ending with the retrieval date.

Each site consisted of four cameras: two lured cameras and two non-lured cameras (four at the corners of a 36-ha square around each central site, which are deployed 20-km apart along the NTS grid). The detection rates at the unlured ABMI sites were exceedingly low; for example, fishers were detected only at 2 sites, and coyotes only at 6. In order to build more robust models based on higher detection rates, we used one lured camera at each ABMI site for this analysis.

Landscape cover analysis

Landscape variables were provided by Alberta Environment and Parks (AEP) and included both natural and anthropogenic features from a “flat” GIS map, wherein the sum of the proportion all features surrounding each camera site summed to 100%. Initially, these data were available for multiple scales of coverage around each camera site, but fully exploring these multiple scales was untenable for this analysis across multiple species and multiple candidate models (see “Statistical analysis”). We therefore worked with landcover data that reflected a 2500m radius of coverage around the camera trap sites. To make comparison among landscape features possible, we scaled all landscape variables to mean = 0 and SD = 1.

To aid in comparison with past work and because of the relatively low number of observations in this dataset (161 camera trap sites), we have maintained the variable set developed in a previous study of the Christina Lakes region (Fisher, 2019). In addition, to work efficiently across candidate models and multiple species to reveal initial patterns, we created additional combined variables based around specific hypotheses. The resulting variable set is listed and described in Table 1.

Statistical analysis

Earlier work with ABMI camera trap data suggested that across species most regular binomial generalized linear models (GLMs) were overdispersed ($\sigma > 3$) (Fisher, 2019). Overdispersion is undesirable, because it suggests that the model is failing to account for the true variation in the data. This makes models more likely to overestimate significance and suggest inaccurately strong relationships between variables of interest. Overdispersion is a common problem with highly variable ecological data, and in this case is likely exacerbated by the high number of zeros and occasional extreme values present (Zuur et al, 2012).

To address this issue, we used a betabinomial model structure. Betabinomial models are similar in structure to binomial GLMs, but have an additional component (a beta distribution) that allows the model to better account for variance (Kim and Lee, 2017).

During exploratory modeling, key variables of interest (fire, cutline, pipeline, soft_linear), were seen to cause high variance inflation ($VIF > 3$, Zuur et al. 2007, Zuur et al., 2010) in an initial global model containing all variables. As a result, instead of beginning with a global model and using a stepwise approach to select the most predictive model, a hypothesis-testing approach was used. 26 Candidate models were constructed based on current ecological knowledge as well as a desire to investigate the most salient landscape features for management decisions, balanced against the degree of collinearity – as highly collinear variables cannot be included in the same model.

Table 1: Variable set used in candidate models and corresponding descriptions. From AEP landscape cover data.

	Variable name	Description
Natural	fire	all ages and all deciduous and coniferous fire merged together
	water	original AEP landcover variable
	upland_deciduous	original AEP landcover variable
	lowland_spruce	original AEP landcover variable
	upland_mixedwood	original AEP landcover variable
	all_forest	all species of forest cover merged together (balsam_fir, tamarack, pine, upland_deciduous, upland_mixedwood, upland_spruce, lowland_mixedwood, lowland_spruce)
	shrub	lowland_shrub and upland_shrub merged together
Anthropogenic	cutline	original AEP landcover variable
	pipeline	original AEP landcover variable
	soft_linear	trails and all unpaved roads merged together
	hard_linear	rail and all paved roads merged together
	3D_seismic	original AEP landcover variable
	well	original AEP landcover variable
	industrial	abandoned_industrial and active_industrial merged together
	cutblock decid	all ages of deciduous cutblocks merged together
	cutblock conif	all ages of coniferous cutblocks merged together
	soft_access	cutline, pipeline, and soft_linear merged together
	cutblocks	deciduous and coniferous cutblocks merged together
	well_indust	well and industrial merged together
	anthforage	well, industrial, and all cutblocks merged together

The ultimate goal of this work is answering our three central questions about the effect of oil sands features on mammalian **distribution**. This would require us to isolate, and test, the relationship between each feature and each species independently. This is certainly possible, but not expedient. It also hampers our ability to infer the **pathways for these stressor-response relationships**, which theory and data dictate should stem from multiple interacting factors – both anthropogenic and natural (Turner, 2005; Reinhardt et al., 2010; Zarnetske et al., 2017).

Therefore, the first set of candidate models focused on natural features, the second on anthropogenic features, and the third on interactions among features. Models that include **interaction terms** allow the models to test whether a species' relationship with a particular variable changes across values of another variable. This is what is often happening in ecosystems (Turner, 2005; Reinhardt et al., 2010; Zarnetske et al., 2017), but can be more complex to test statistically and is often left out of analyses for this reason. Despite the statistical challenges, we wanted to take an initial coarse look at potential interactions, because this is frequently the true picture on the landscape.

Models were constructed using the `glmmTMB()` function in statistical analysis software package R (R version 3.5.3, R Core Team, 2019) and took the general form:

```
betabinmodel <- glmmTMB(cbind(species.1,species.0)~  
                        landcovervariables,  
                        family = betabinomial(link="logit"),  
                        data = ABMI2500m)
```

Candidate models were then compared using the `AICtab()` function which calculates a delta AIC value and AIC weight value. The higher the delta AIC value and the higher the AIC weight, the more a given model explains compared to the rest of the set of candidate models. For model validation, betabinomial models were considered well-fit when the overdispersion parameter sigma was <2 and DHARMA residual plots showed relatively even spread across residuals.

RESULTS

Species detection rates

Within the ABMI camera trap data set, species detection rates were very low (Table 2). For all species, the majority of camera trap sites saw no detections throughout the study time period. Bear had the highest number of sites that saw at least one detection (50 sites out of 161), while coyote had the lowest (8 out of 161). Histograms for each species show the count of sites with the corresponding number of weeks with positive detections (Figure 2).

Table 2: Species detection rates across 161 ABMI camera trap sites.

Species	# sites with non-zero detection rates	% non-zeroes
<i>Bear</i>	50	31%
<i>Lynx</i>	25	16%
<i>Moose</i>	24	15%
<i>Deer</i>	14	9%
<i>Fisher</i>	14	9%
<i>Wolf</i>	14	9%
<i>Coyote</i>	8	5%

Candidate Models

In selecting candidate models (Table 3), we focused our emphasis on looking for effects of anthropogenic disturbance and interactions between anthropogenic disturbances and natural features. For this reason there are four natural features models that provide a natural feature “baseline”: a combined forest cover variable, lowland and upland shrub cover, water, fire.

The next model set included anthropogenic features as univariate (models 5-11) and multivariate (linear) models (models 12-16). Univariate models were included to isolate the effects of particular features, while combined models suggested mechanisms of additive effects for certain potentially similar features (*e.g.* combining cutlines with pipelines and soft_linear features such as unpaved roads and trails.).

Finally, a set of interaction models were included that focused on a combined variable (soft_access) and various natural and anthropogenic features. This was based on the hypothesis that access to areas may interact with use of areas (*e.g.* presence of forage or water). Soft access routes may be important corridors for some species (*e.g.* wolf) while other species may avoid these corridors due to predator risk (*e.g.* deer) (Fisher and Burton, 2018). The core hypothesis in constructing the last model set was that the effects of linear features may influence, and be influenced by, species’ relationships to other landscape variables such as forage habitat.

Figure 2: Histograms for each species showing number of sites with their respective number of weeks with at least one positive detection.

Model Results

Betabinomial models performed better than more common approaches, such as binomial or poisson regression models. All 26 candidate models across species were below the overdispersion threshold of $\sigma < 2$, and top models were validated based on DHARMA residual plots as well. Across most species, the top candidate model had an AIC weight of 40% or less, which suggests that top models failed to account for more than 50% of the variance explained compared with other models in the running. This is very likely due to the low number of non-zero observations across species and sites, which even betabinomial models could not fully account for.

Running a consistent candidate model set across 7 different mammal species, some of which are predators, some of which are prey, has the potential to miss important species-specific relationships. A full exploration of these relationships was outside the scope of this report. However, in cases where combined variables were used and/or model patterns strongly suggested a relationship that was not being tested by the candidate model set, *post hoc* models were constructed and tested against the initial candidate set. The full summaries of these post hoc models are also shown in the species-specific sections below.

Table 3: Candidate model sets with corresponding variables and descriptions of models where needed.

Model set	Model Name	Variables	Description
Landcover	Natmod1	all_forest	All forest cover merged into univariate model
	Natmod2	lowland_shrub and upland_shrub	
	Natmod3	water	
	Natmod4	fire	
Human Disturbance	Antmod5	cutline	Trails, Gravel Roads Rails, Paved Roads Active and Abandoned Industrial sites Deciduous and Coniferous Cutblocks All cutblocks Cutline, soft_linear, and pipeline merged for univariate model Roads, trails, rails
	Antmod6	pipeline	
	Antmod7	soft_linear	
	Antmod8	hard_linear	
	Antmod9	X3d_seismic_line	
	Antmod10	well	
	Antmod11	industrial	
	Antmod12	cutblock_decid+cutblock_conif	
	Antmod13	cutblocks	
	Antmod14	cutline+soft_linear+pipeline	
	Antmod15	soft_access	
	Antmod16	hard_linear+soft_linear	
Interaction Models	Intmod17	soft_access*shrub	Interaction between access and natural shrub
	Intmod18	soft_access*well_indust	Interaction between access and potential forage from well and industrial sites
	Intmod19	soft_access*cutblocks	Interaction between access and potential forage from cutblocks
	Intmod20	soft_access*anthforage	Interaction between access and potential forage from cutblocks, well sites, and industrial sites
	Intmod21	soft_access*shrub+soft_access*anthforage	Interaction between access and all potential forage separated by natural and anthropogenic sources
	Intmod22	soft_access*water	Interaction between access and water
	Intmod23	soft_access*upland_deciduous	Interaction between access and upland deciduous
	Intmod24	soft_access*lowland_spruce	Interaction between access and lowland spruce
	Intmod25	soft_access*upland_mixedwood+soft_access*lowland_mixedwood	Interaction between access and mixedwood sites
	Intmod26	soft_access*fire	Interaction between access and fire

Table 4: Post hoc models. Rationale for construction provided in species-specific sections of text.

Post Hoc Models	Species	Variables	Description
IntmodPH_bear	Bear	cutline*water	Interaction between cutline and water
IntmodPH_moose	Moose	pipeline*water	Interaction between pipeline and water
IntmodPH_lynx	Lynx	cutline*shrub	Interaction between cutline and combined shrub
IntmodPH_fisher	Fisher	well+industrial+soft_linear	Additive model with three anthropogenic features

Species-specific Results: Bear

Bear relative abundance was best explained by lowland shrub and upland shrub landcover, followed by the interaction model containing water and soft_access (Table 5). The best model showed that bear relative abundance was strongly negatively correlated with lowland_shrub (Table 6).

Table 5: AIC table for bear models. Only showing models with weight >0.01.

Model	dAIC	df	weight
Natmod2_bear	0	4	0.315
IntmodPH_bear	0.3	5	0.268
Intmod22_bear	1.3	5	0.168
Intmod17_bear	2.5	5	0.092
Intmod21_bear	2.7	7	0.08
Natmod3_bear	2.9	3	0.074

To probe further into whether the soft_access components may have been having contradictory effects, we checked whether an interaction model of water and each soft_access component could show an improvement (based on AIC weight) over the original soft_access*water model. Isolating *cutline* proved to be an improvement, leading to the construction of a tentative *post hoc* model containing the interaction of cutline and water. This model suggested that both cutline and water may be factors influencing bear abundance, with cutlines having a negative correlation with bear abundance and water having a positive correlation.

Table 6: Summaries of top bear models.

Natmod2_bear	Estimate	Std.Error	z value	Pr(> z)	
(Intercept)	-3.5912	0.2302	-15.601	<2.00E-16	***
lowland_shrub	-1.0005	0.2991	-3.345	0.000824	***
upland_shrub	-0.9199	0.5252	-1.752	0.079847	.

Natmod22_bear	Estimate	Std.Error	z value	Pr(> z)	
(Intercept)	-3.4972	0.1811	-19.306	<2.00E-16	***
soft_access	-0.3103	0.1745	-1.778	0.0754	.
water	0.2849	0.1813	1.572	0.116	
soft_access:water	-0.2741	0.2013	-1.361	0.1734	

IntmodPH_bear	Estimate	Std.Error	z value	Pr(> z)	
(Intercept)	-3.48297	0.18166	-19.173	<2.00E-16	***
cutline	-0.35871	0.16504	-2.174	0.02974	*
water	0.40534	0.14275	2.839	0.00452	**
cutline:water	-0.08288	0.132	-0.628	0.5301	

Species-specific Results: Deer

None of the models clearly outperformed others in explaining deer relative abundance (Table 7). The highest AIC weighted model only carried 16% of the explanatory weight compared to the rest of the candidate models. This means the top model is to be interpreted with caution and *does not signify a highly influential or well-defined relationship*. The top model for deer contained cutline, soft_linear, and pipeline (Table 8). Cutline showed a negative correlation with deer abundance, while soft_linear showed a positive correlation. Pipeline did not show a clear relationship with deer abundance.

Table 7: AIC table for deer models. Only showing models with weight >0.01.

Model	dAIC	df	weight
Antmod14_deer	0	5	0.1635
Antmod5_deer	0.2	3	0.1464
Natmod1_deer	1.8	3	0.0673
Natmod4_deer	2.1	3	0.0581
Antmod13_deer	2.2	3	0.0545
Antmod10_deer	2.4	3	0.0498
Antmod7_deer	2.4	3	0.0484
Natmod3_deer	2.5	3	0.0465
Intmod20_deer	2.7	5	0.0426
Intmod18_deer	3.3	5	0.032

Table 8: Summary of the top deer model.

Antmod14_deer	Estimate	Std.Error	z value	Pr(> z)	
			-		
(Intercept)	-4.8397	0.4167	11.616	<2e-16	***
cutline	-0.9384	0.433	-2.167	0.0302	*
soft_linear	0.5085	0.2548	1.996	0.046	*
pipeline	0.1714	0.2866	0.598	0.5498	

Species-specific Results: Moose

Moose relative abundance was best explained by candidate model 22 (Table 9), which contained soft_access and water. Intmod22 suggested that soft_access was correlated negatively with moose abundance while water had a positive correlation (Table 10). In addition, there was a positive interaction between soft_access and water, suggesting that the relationship moose have with water depends on soft_access and vice versa. This can be seen more clearly in Figure 4, which shows that moose relative abundance in areas with less water has a negative correlation with soft_access, whereas in areas with more water the correlation with soft_access is positive.

Table 9: AIC table for moose models. Only showing models with weight >0.01.

Model	dAIC	df	weight
IntmodPH_moose	0	5	0.919
Intmod22_moose	5	5	0.075
Intmod3_moose	10.4	3	0.005

To probe further into whether the *soft_access* components may have been having contradictory effects, we again checked whether an interaction model of water and each *soft_access* component could show an improvement (based on AIC weight) over the winning model. For moose, the model *pipeline*water* improved AIC weight over the original winning model. In this *post hoc* model the same relationships appeared, in that pipeline showed a significant positive interaction with water (Table 10). Again, this suggests that moose relative abundance switches from being negatively correlated with pipelines at low water cover to positively correlated with pipelines at higher water cover.

Table 10: Summaries of top moose models.

Intmod22_moose	Estimate	Std.Error	z value	Pr(> z)	
(Intercept)	-4.9868	0.3527	-14.139	<2.00E-16	***
soft_access	-0.861	0.4023	-2.14	0.0323	*
water	0.8404	0.1823	4.611	4.01E-06	***
soft_access:water	0.4752	0.2096	2.267	0.0234	*

IntmodPH_moose	Estimate	Std.Error	z value	Pr(> z)	
(Intercept)	-5.2781	0.4187	-12.605	<2.00E-16	***
pipeline	-1.5897	0.6377	-2.493	0.01268	*
water	0.9811	0.2061	4.76	1.93E-06	***
pipeline:water	0.9243	0.3149	2.935	0.00333	**

Figure 3: Trend lines showing interaction between moose relative abundance and soft_access at different proportions of water cover. Units shown are based on standardized variables, with negative values representing low proportions of landscape cover. Plot made using default settings with allEffects() from effects package in R.

Species-specific Results: Lynx

Among candidate models, lynx abundance was best explained by *lowland_shrub* and *upland_shrub*, with a negative correlation with both (Table 11, Table 12). However, the clear second-best model was the univariate *cutline* model, and we again constructed a *post hoc* model of cutline interacting with the combined shrub variable. This post hoc model was a substantial improvement (dAIC of 5.6 and weight of 0.81, see Table 11) and suggested that there may be an interaction between lynx relative abundance and cutline features (Table 12). A lower percentage of cover by cutlines corresponds to a negative correlation between shrub cover and lynx abundance, while a higher percentage of cutline cover corresponds to a positive correlation between shrub cover and lynx abundance (Figure 4).

Table 11: AIC table for lynx models. Only showing models with weight >0.01.

Model	dAIC	df	weight
IntmodPH_lynx	0	5	0.8181
Natmod2_lynx	5.6	4	0.0491
Antmod5_lynx	6	3	0.0413
Natmod1_lynx	6.4	3	0.0326
Intmod17_lynx	7.1	5	0.0237
Antmod14_lynx	8.1	5	0.0141

Table 12: Summaries of the top lynx models.

Natmod2_lynx	Estimate	Std.Error	z value	Pr(> z)	
(Intercept)	-4.6748	0.3638	-12.851	<2e-16	***
lowland_shrub	-1.3618	0.539	-2.526	0.0115	*
upland_shrub	-0.6093	0.5559	-1.096	0.2731	

IntmodPH_lynx	Estimate	Std.Error	z value	Pr(> z)	
(Intercept)	-4.9716	0.4305	-11.549	<2e-16	***
shrub	-1.2976	0.6275	-2.068	0.0387	*
cutline	-0.1308	0.3807	-0.344	0.731	
shrub:cutline	0.7153	0.3457	2.069	0.0385	*

Figure 4: Trend lines showing interaction between lynx relative abundance and shrubby landcover at different proportions of cutline cover. Units shown are based on standardized variables, with negative values representing low proportions of landscape cover. Plot made using default settings with allEffects() from *effects* package in R.

Species-specific Results: Coyote

The coyote model that had the highest AIC weight was the natural features model containing fire (Table 13). However, within the model fire was not significant, and the coefficient estimate is so high as to likely be spurious (Table 14). Given these model were constructed around 8 non-zero observations out of 161 sites, it was challenging to uncover well-validated relationships.

Table 13: AIC table for coyote models. Only showing models with weight >0.01.

Model	dAIC	df	weight
Natmod4_coyote	0	3	0.6131
Natmod3_coyote	4.7	3	0.0597
Natmod1_coyote	5.8	3	0.0337
Antmod11_coyote	6.1	3	0.0293
Intmod22_coyote	6.1	5	0.0288
Antmod6_coyote	6.4	3	0.0248
Antmod7_coyote	6.4	3	0.0245
Antmod13_coyote	6.5	3	0.024
Antmod8_coyote	6.7	3	0.022
Antmod9_coyote	6.8	3	0.0205

Table 14: Summary of top coyote model.

Natmod4_coyote	Estimate	Std.Error	z value	Pr(> z)
(Intercept)	-19.3	26.43	-0.73	0.465
fire	-26.27	48.25	-0.544	0.586

Species-specific Results: Fisher

Among the candidate models, the top model was the interaction model with *soft_access* by a combined variable of well and industrial sites (Table 15). However, this interaction model showed no significant variables within the model, and was a very weak top model initially (data not shown; before adding the post hoc model to the AIC table, Intbmod18 only carried 11% of the AIC weight and had a dAIC above the next model of only 0.4).

Table 15: AIC table for fisher models. Only showing models with weight >0.01.

Model	dAIC	df	weight
IntmodPH_fisher	0	5	0.8367
Intmod18_fisher	7.7	5	0.018
Antmod10_fisher	8.1	3	0.0146
Antmod7_fisher	8.1	3	0.0144
Antmod11_fisher	8.4	3	0.0124

In probing this further we first investigated whether well sites and industrial sites might be having opposite effects on fisher abundance. It appeared that industrial sites potentially had a positive correlation with fisher abundance while well sites had a negative correlation. Similarly, *soft_linear* was unique among *soft_access* components as having a significant positive correlation with fisher abundance in Antmod14, which contains cutline, pipeline, and *soft_linear* as separate variables. Based on these explorations we created a *post hoc* model containing well sites, industrial sites, and *soft_linear* as separate variables, and this model clearly outperformed all candidate models (see Table 16).

This *post hoc* model should especially be treated with caution, as the separation and recombination of variables across models does not reliably reflect overall explanatory weight within the dataset. The broad scale suggestion from this *post hoc* model, however, is that multiple different anthropogenic features may be more important to fisher than natural features or interactions between anthropogenic and natural features.

Table 16: Summaries of top fisher models.

Intmod18_fisher	Estimate	Std.Error	z value	Pr(> z)	
(Intercept)	-5.8254	0.5947	-9.796		***
soft_access	-0.4171	0.6201	-0.673	0.501	
well_indust	-4.6716	3.3185	-1.408	0.159	
soft_access:well_indust	-6.0045	4.0436	-1.485	0.138	

IntmodPH_fisher	Estimate	Std.Error	z value	Pr(> z)	
(Intercept)	-5.8218	0.4585	-12.697	<2e-16	***
well	-2.4501	1.1356	-2.157	0.031	*
industrial	0.2783	0.1206	2.307	0.021	*
soft_linear	0.8707	0.2217	3.927	8.61E-05	***

Species-specific Results: Wolf

The wolf model with the highest AIC weight was the anthropogenic features model, containing the combined cutblocks variable (Table 17). The second highest was the model containing the cutblocks separated into deciduous and coniferous cover. However, neither of these two models showed significance in the individual factors (only the top model shown in Table 18).

Table 17: AIC table for wolf models. Only showing models with weight >0.01.

Model	dAIC	df	weight
Antmod13_wolf	0	3	0.3036
Antmod12_wolf	1.2	4	0.1669
Intmodex_wolf	1.2	4	0.1669
Intmod20_wolf	2	5	0.1096
Intmod19_wolf	2.2	5	0.1007
Intmod21_wolf	3.1	7	0.0658
Antmod9_wolf	6	3	0.0153
Antmod10_wolf	6.1	3	0.0145

Table 18: Summary of top wolf model.

Antmod13_wolf	Estimate	Std.Error	z value	Pr(> z)	
(Intercept)	-6.474	1.289	-5.022	5.11E-07	***
cutblocks	-3.61	2.295	-1.573	0.116	

Goodness of fit of models

The relatively high number of zeros (non-detections on camera traps) as well as occasional extreme non-zero values (sporadic high detection rates) meant that a model specification more sophisticated than a binomial glm was necessary to meet model assumptions. Based on betabinomial models' flexibility, error probability distribution, and assumptions that conform to overdispersed data (where variance is greater than the mean), this is a promising and useful tool for analyzing regional-scale mammal monitoring data. However, a consequence of using more nuanced models is that some of the basic tools for diagnosis are not yet available in R. We have so far been able to visually assess the betabinomial models to test whether the models seem fundamentally sound (not overdispersed, residual plots looking as expected). However, we are still working towards

implementing a reliable method for assessing how much variation a given model is explaining from the data (e.g. a R-squared or deviance explained value).

Given that, Table 19 shows the deviance explained and adjusted R squared for regular binomial GLMs containing the same variables as their betabinomial counterparts. These values are to be taken with great caution, as betabinomial models contain more parameters than regular binomial GLMs, and the deviance explained of the corresponding regular binomial GLM may not apply to the equivalent betabinomial model. It is more likely, although not guaranteed, that the deviance explained by a betabinomial model would be lower than the values shown here. With these caveats in mind, we tentatively suggest that *the models thus far described are explaining a relatively small proportion of the variation present in these systems.*

Table 19: Goodness-of-fit of regular binomial GLMs with similar model specifications to corresponding betabinomial models. To be interpreted with caution, see text for additional explanation.

Model	Sigma	Deviance	
		Explained (%)	Adjusted R ²
Natmod2_bear	3.3	17.3	0.08
Intmod22_bear	2.9	25.8	0.40
IntmodPH_bear	3.1	25.6	0.39
Intmod22_moose	2.2	21.0	0.13
IntmodPH_moose	1.6	27.7	0.15
Natmod2_lynx	2.8	8.3	0.03
Antmod5_lynx	2.8	5.2	0.02
IntmodPH_lynx	2.9	12.9	0.05
Antmod14_deer	3.7	7.2	0.01
Natmod4_coyote	2.4	11.6	0.01
Intmod18_fisher	1.6	9.0	0.02
IntmodPH_fisher	1.3	21.9	0.14
Antbmod13_wolf	1.9	12.8	0.03

DISCUSSION and RECOMMENDATIONS

ABMI camera data detection rates were much lower than in Fisher and Burton (2018)'s landscape-scale analysis from Christina Lake. This likely owes to (1) a dissimilar method of choosing camera locations; and (2) a dissimilar sampling design, which resulted in more low-density areas being sampled by ABMI than by Fisher and Burton (2018). Low detection rates yielded an abundance of zeroes, which led to a greater degree of model overdispersion in these models. The causes and effects of overdispersion are not widely understood, save that they are known to entrain both imprecision and bias in parameter estimates. In this case overdispersion

yielded unreliable parameter estimates, such as the deer and coyote models. However, if the zeros represent missed detections (failing to detect a species when it is in fact present), then a zero inflated model – which models true (ecological) zeros and sampling (failed detection) zeros – might have been a better specification. This is worth further investigation as the ABMI data provide a wealth of information, spanning the province as they do.

The drawback of targeted landscape-scale monitoring like Fisher and Burton (2018) is that a single landscape is not necessarily representative of the entire OSR region. It is heavily impacted and without large areas of intact forest, as exists in many areas of the OSR. Our recommendation for future modelling is adopt a nested sampling design that includes both landscape-scale monitoring, distributed across multiple landscapes, as well as regional-scale surveillance monitoring. Integrating data from these two scales will be analytically challenging, but could be accomplished with new classes of hierarchical models.

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CHAPTER 3: WHITE-TAILED DEER (*ODOCOILEUS VIRGINIANUS*) BEHAVIOUR, DISTRIBUTION, AND POPULATION RESPONSES TO OIL AND GAS STRESSORS IN ALBERTA

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SYNTHESIS

- (1) White-tailed deer show a distinct **local-scale behavioral response** to oil and gas features. Deer select polygonal features with early seral vegetation and avoid linear features where they can. Where they do not avoid linear features – because these also provide sources of early-seral forage – deer behavior is characteristic of a predation risk response, moving rapidly through high-quality habitat rather than staying long to exploit it fully.
- (2) White-tailed deer show a distinct **landscape-scale distribution response** to oil and gas features. They have higher relative abundance at sites with high proportions of early seral vegetation (such as well sites and industrial block features) and lower relative abundances at sites with high proportion of linear features, such as trails and roads.
- (3) White-tailed deer show a variable, vague **regional-scale population response** to oil and gas landscapes, as indicated by aerial survey data. This is due to imprecision inherent in AUS estimates using traditional techniques, which prevent a clear pattern in population through time, or across space. The development of methods to precisely estimate white-tailed deer populations through different aerial survey techniques (such a newly-implemented distance sampling) and camera traps with spatial-capture recapture is vital to understanding deer population responses to oil and gas activity.
- (4) White-tailed deer **regional-scale habitat-use** indicates that deer distribution is predicted by both natural and anthropogenic landcover features. Deer show a stronger association to features associated with energy extraction and exploration than agriculture and forestry, with deer habitat-use decreasing by 50% at distances greater than 500m from seismic lines. Regenerating forest and riparian habitat are strongly associated with deer-use across the OSR, while deer avoid coniferous forest and wetland.

INTRODUCTION

White-tailed deer (*Odocoileus virginianus*) expansion into Alberta's boreal is linked to both climate change and human landscape disturbance. While climate has been identified as the most influential driver of white-tailed deer (WTD) expansion into the north at a **provincial scale** (Dawe et al. 2014; Dawe et al. 2016), human footprint features strongly influence both WTD distribution and relative abundances **at landscape and local scales** (Fisher and Burton 2018; Darlington 2018; Fisher et al. 2020). Data at the **regional scale** is sparse, as traditional snow-tracking surveys cannot isolate white-tailed deer from mule deer, and camera data at this scale have generate very low detections, a challenge to modelling. However, aerial ungulate surveys (AUS) have been conducted somewhat regularly throughout the OSR, and offer a potentially useful source of information.

Our objective here is to concisely and informatively summarize what is known about white-tailed deer response to oil and gas features in the OSR, and to offer a new analytical approach for aerial survey data to understand the relationship between deer and ongoing anthropogenic landscape development. Throughout, we examine the response by deer from the perspective of individual **behaviour**, landscape-scale **distributions**, and **populations**.

LOCAL-SCALE BEHAVIOUR RESPONSES

Although white-tailed deer play an extremely important role in woodland caribou declines, until recently little information existed about deer **local-scale behavioural response** to OS stressors. In the Christina Lake region, 40 satellite-collared female white-tailed deer were tracked for up to three years to model individual habitat selection in relation to anthropogenic features (Darlington 2018). Deer strongly selected areas closer to forest harvest cutblocks, roads, seismic lines, trails, and well sites. Deer strongly avoided 3D seismic lines and pipelines. Behavioural responses were consistent among seasons, with some features being more strongly selected or avoided in summer and winter. Notably, behavioural responses and habitat selection to linear features may be complicated by trade-offs between predation risk and availability of quality forage (Darlington 2018), as predation risk was consistently an important feature in white-tailed deer habitat selection). Predators make extensive use of roads, trails, and seismic lines in this region, and though deer are attracted to these areas, they move through them very quickly, indicating fear of predation risk.

LANDSCAPE-SCALE DISTRIBUTION AND POPULATION RESPONSES

Very little publicly available data exist on white-tailed deer landscape-scale distribution across the OSR. The best-studied landscape is Christina Lake, where Fisher et al. (2020) use three years of camera trapping data across 4,000 km² to model deer relative abundance across

a gradient of natural and anthropogenic features. Across all three years, industrial block features, well sites, and forest harvest cutblocks had large positive effects on deer persistence (Table 1). Deer persistence was negatively associated with off-highway vehicle trails. The same relationships were observed in a winter-only analysis: deer persistence in winter months was positively related to industrial block features, cutblocks, and well sites, and negatively related to trails. Deer's negative response to trails (β estimate) was twice as great in winter as for annual persistence.

Anthropogenic features from forestry and energy extraction have augmented availability of early seral vegetation providing abundant forage for ungulate browsers, including deer. This subsidization from industrial disturbance is strongly implicated in facilitating the expansion of white-tailed deer in Alberta's boreal forest (Fisher et al. 2020; Fisher and Burton 2018), where deer populations have increased *ca.* 17.5-fold since the industrialization of the region (Latham et al. 2011b).

REGIONAL-SCALE DISTRIBUTION AND POPULATION RESPONSES

At the scale of the entire province, climate change has been identified as the strongest factor influencing white-tailed deer expansions, with some contribution from landscape change (Dawe and Boutin 2016, Dawe et al. 2014). **There are few regional-scale data on white-tailed deer distribution responses to oil and gas features** beyond ABMI models, which have not performed well due to low detection rates (Chapter 2).

However, abundant aerial ungulate survey data (AUS) have been collected across the OSR over the last three decades. Using these data, we evaluated regional-scale WTD distribution and abundances in relation to natural habitat and industrial disturbance features. We tested for temporal trends in WTD population abundance across the region. We also evaluated WTD population density and distribution in relation to landcover features including human footprint. We hypothesized that WTD populations have increased over time, following industrialization of the OSR. We hypothesized that oil and gas features, more so than agriculture or natural features, would explain variability in deer occurrence in the OSR. Alternatively, if natural features (likely facilitated by climate change) were enabling deer invasion, then those characterized by young deciduous stands and potential movement corridors— notably, riverine and lacustrine riparian zones – would be most associated with deer occurrence. We used an information-theoretic model selection approach (Burnham & Anderson 2002) to test the hypothesis: deer spatial distribution is positively related to oil and gas extraction features creating early seral vegetation subsidies, even after accounting for natural heterogeneity. Understanding these spatial and temporal responses WTD populations provides important insights into the anthropogenic activities facilitating expansion of this species into the boreal region of Alberta. By testing these responses at the regional level, we provide direct

insights into WTD population responses at the most relevant scale informing land-use practices in the OSR.

METHODS

Study Area

The Alberta Oil Sands Region (OSR) is comprised of four oil sand deposits and managed as three administrative units (ABMI 2014). With a total area of over 140,000 km², this region represents over 20% of Alberta's total land area. Classified as Boreal Forest Natural Region, the OSR is characterized by an extensive human footprint of over 15% primarily made up of agriculture, energy, forestry developments (ABMI 2014). Overlaying the OSR are a total of 27 Wildlife Management Units (WMUs; Figure 1). Wildlife, including WTD, are managed within each WMU by Alberta's Ministry of Environment and Parks (AEP).

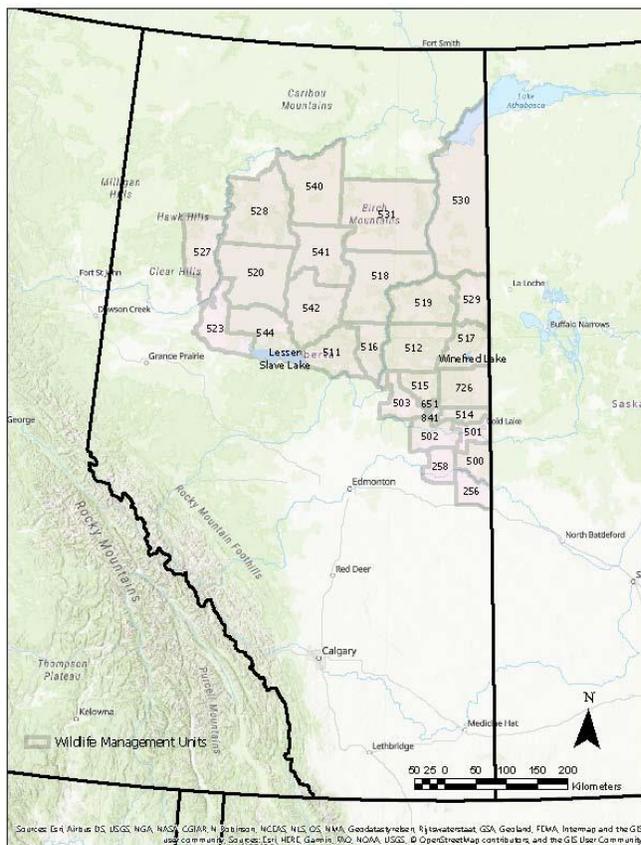


Figure 1. Wildlife Management Units within Alberta's Oil Sands Region.

Aerial Ungulate Survey Data

Alberta's Ministry of Environment and Parks assesses the abundance and distribution of ungulate species to guide conservation and management practices. Aerial ungulate surveys (AUS) are conducted across Alberta collect information on population size, trends, distribution, trends, and herd composition for a number of ungulate species. Aerial ungulate surveys employ statistically rigorous survey approaches, including distance sampling techniques (Buckland et al. 2001; 2010) and random block surveys ('Gasaway Method'; Gasaway et al. 1986). Distance sampling offers a cost-effective and efficient alternative to Gasaway Methods, and is the primary survey method currently being used for AUS in Alberta.

Distance sampling transects are spatially established across WMUs and randomly selected to collect data on ungulate observations. Surveys are conducted during the winter months (December-March) when animal sightability is at a maximum. All ungulates observed on transect lines are counted and classified, with location data also accurately recorded. Ungulate count and location data are then extrapolated to determine population densities within WMUs for ungulate species, including WTD. Full details on survey methodology are provided in the Aerial Ungulate Survey Protocol Manual (AERSD 2010).

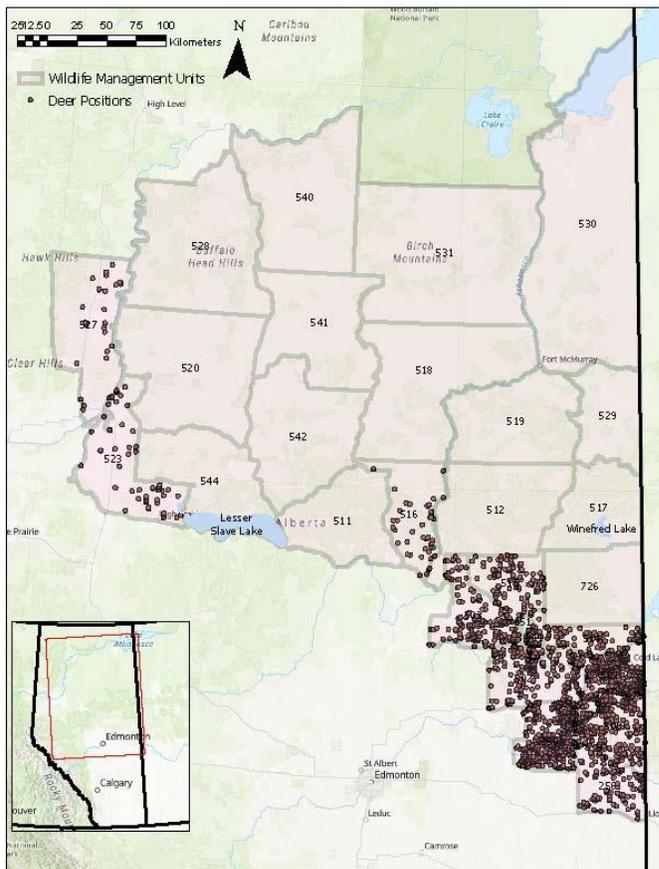


Figure 2. White-tailed deer observations across surveyed Wildlife Management Units within Alberta's Oil Sands Region.

Data Analysis

We selected available WTD abundance, population density, and location data from multi-year aerial surveys to test for WTD population trends and associations with natural and anthropogenic landscape features.

Human footprint was measured as proportion area within each WMU using Alberta Environment and Parks 2016 Provincial Human Footprint layers in ArcGIS v10.3 (ESRI, Redlands, CA, USA) Geographic Information Systems. Human footprint covariates included both linear (e.g. roads, pipelines, seismic lines) and block features (e.g. industrial sites, cut-blocks, well-sites; Appendix A, Table A.3). Primary natural landcover features were quantified using Landsat digital map inventories from the Alberta Biodiversity Monitoring Institute (Landsat Map 2014).

Temporal trends in WTD abundance within WMUs

We selected available WTD population abundance data from multi-year surveys across WMUs overlapping Alberta's OSR to test for temporal trends in the region. Population size estimates were available for 13 WMUs, for which one to four surveys were conducted between 1995 and 2019 (See Appendix A, Table A.1). Multi-year survey data were available for evaluation of temporal trends in WTD abundance size were available for ten WMUs.

WTD population density in relation to human footprint

We modelled available WMU deer population densities (deer/km²) against spatial and temporal covariates hypothesized to influence deer abundance in the region. When multi-year survey data were available, we selected the most recent available population density corresponding most closely with the observed human footprint for 2016.

We included various candidate models specifying anthropogenic landscape features, WMU latitude, and survey year (Table 1). Due to a relatively low number of WMU deer population density estimates (n=13; Appendix A, Table A.2), we limited the number of covariates tested within each candidate model to two. We therefore combined densities of all individual human landscape features into two categories: block versus linear features (See Appendix A, Table A.3). Block features included the sum of all polygonal human footprint within each WMU, represented as the proportional area of the WMU. Linear features included the sum of all types of roads, railways, seismic lines, pipelines, and transmission lines in the WMU, represented as a proportional density of km/km². As selected WMUs were irregular shapes and clustered into two geographic locations in the OSR (see Figure 1), we categorized WMUs as high or low latitude based on whether they fell primarily above or below a latitude of 55.2100° N (Figure 1; Appendix A Table A.2). This grouping yielded two natural aggregations of WMUs, clustered above and below Lesser Slave and Winefred lakes (See Figure 1). Lastly, as survey year varied from 2013 to 2019, we included year as a candidate model to account for the influence of temporal changes to WTD populations.

We hypothesized WTD population densities to increase with increasing proportion of human footprint across WMUs, with a stronger response to block development features given their association with increased early seral vegetation availability. We expected WMUs at higher latitudes to support a lower density of WTD due to increased winter die-off from high severity winters.

Table 1. List and description of human landscape disturbance, survey year, and latitude variables hypothesized to explain white-tailed deer density across wildlife management units in Alberta’s Oil Sands Region.

Model Set	Model Variables	Hypothesis: White-tailed deer density is predicted by:
<i>Human Landscape Disturbance</i>	Linear	Density of all linear anthropogenic features
	Block	Density of all block anthropogenic features
	Linear + Block	Density of both linear and block anthropogenic features
<i>Survey Year</i>	Year	Year of aerial ungulate survey
<i>Latitude</i>	Latitude	WMU latitude
<i>Latitude and Human Landscape Disturbance</i>	Latitude + Linear	WMU latitude and density linear anthropogenic features
	Latitude + Block	WMU latitude and linear anthropogenic features

We ranked models corresponding to each hypothesis using an information-theoretic approach (AIC; Burnham and Anderson 2002). This approach uses maximum likelihood estimation and the principle of parsimony to test the relative support for alternative

hypotheses. Lower AIC scores indicate improved fit and parsimony relative to other candidate models tested. Candidate models are ranked based on AIC weight: models with the highest AIC weights are interpreted as the best-supported models describing WTD population density, and support for their corresponding hypotheses.

WTD habitat-use in the OSR

We applied resource selection functions (RSFs) with a used-available design to evaluate the spatial relationship between deer and landscape variables in the boreal (Manly *et al.* 2007). White-tailed deer use and avoidance of landscape features are indicated by the probability of use of each variable, as determined by RSF output values. We used logistic regression in a General Linear Model (GLM; binomial errors, logit link) with used locations (1) and randomly selected available but unused points (0) regressed against natural and anthropogenic landscape covariates.

We defined “used” locations as observed deer locations from AUS transects, for a total of 2251 used locations. “Available” locations were randomly generated within available but unused habitat bounded by a distance threshold around each AUS transect flight path (Figure 3). To reduce spatial-autocorrelation between “used” versus “available” habitat buffers, we excluded available deer locations within 500m of any observed deer occurrences. Transects are spaced 1-1.2 km apart, and observers generally do not count ungulates sighted beyond 600-m from the aircraft. We therefore bounded available habitat as 600-m on either side of the flight transect path. We randomly generated five available points for each used point, which generated stable parameter estimates relative to availability ratios (Northrup *et al.* 2013; Gerber & Northrup 2020). Following exclusion of off-transect deer observations, this yielded a total of 11,012 available points.



Figure 3. Visualization of the aerial ungulate distance survey transects, featuring deer observations (“used”; blue dots) and randomly selected “available” locations (red dots) within a 1.2km buffer zone around the flight transect (outlined in yellow). We summarized landscape features within a 500m radius buffer around each used and available location (outlined in light blue) to determine white-tailed deer habitat selection in the Oil Sands Region using resource-selection functions

We used model selection to rank 8 candidate sets of RSF models (Burnham and Anderson 2002). Our null hypothesis predicted deer resource-use to be best explained by natural land cover features, with no influence of anthropogenic disturbance features (Model 2, Table 2). Specifically, we predicted a positive association between deer-habitat use and riverine, lacustrine, and other deciduous habitats. Remaining models tested deer resource

selection against a combination of anthropogenic (Models 3-5) or anthropogenic and natural land cover features (Models 1, 6-8). Anthropogenic features on the landscape include polygonal “block” features, largely associated with agriculture (i.e. cultivation areas) and forestry (e.g. harvest cut-blocks) (Appendix B, Table B.1). Energy exploration and extraction activities generally manifest as linear features on the landscape, such as seismic lines, 3D seismic grids, and pipelines. We predicted deer to select for anthropogenic block features converting mature forest to early seral-stage vegetation (e.g. harvest cut-blocks) as well as linear features providing both movement corridors and foraging opportunities (e.g. seismic lines, transmission lines, roads). We tested the impact of anthropogenic block and linear features in isolation, and combined with natural land cover features. We ranked candidate models using AIC scores and AIC weights normalized 0-1, which are analogous to the probability that the model is the best-supported model (Burnham & Anderson, 2002), with the highest weight of evidence. We examined variable coefficients retained in the best-supported multivariate models to identify individual natural and land cover features best predicting deer habitat-use and avoidance. Best-supported models were validated using spatially-blocked k-fold cross validation and deviance explained (Supplementary Information, Appendix C). We plotted beta coefficients for models to examine effect size and calculated deviance explained.

Table 2. Natural and anthropogenic land cover variables predicted to influence deer habitat-use in the boreal forest. Number of variables included in each variable class are shown in parentheses for our global model.

Model Set	Model Number	Model Variable Classes (number of included variables)	Hypothesis: Deer habitat-use best predicted by:
Global	1	Natural_LandCover(9) + DistanceRiparian(2) + DistanceLinear(6) + Cultivation(1) + Cutblocks(3)	All natural and anthropogenic features
Natural Land Features (Null Hypotheses)	2	Natural_LandCover + DistanceRiparian	All natural land cover features, including distance to riparian habitat
	3	Cultivation + Cutblocks	Area of block anthropogenic features providing forage opportunities
Anthropogenic Features	4	DistanceLinear	Proximity to anthropogenic linear features providing forage and travel opportunities

	5	Cultivation + Cutblocks + DistanceLinear	Block and linear anthropogenic features providing forage opportunities
Natural + Anthropogenic Features	6	Natural Land Cover + DistanceRiparian + Cultivation + Cutblocks	Natural land cover, distance to riparian, and anthropogenic block features providing forage opportunities
	7	Natural Land Cover + DistanceRiparian + DistanceLinear	Natural land cover, distance to riparian, and anthropogenic linear features providing forage and travel opportunities
	8	DistanceLinear + DistanceRiparian	Distance to riparian areas and anthropogenic linear features associated with forage and travel opportunities

RESULTS

Temporal trends in WTD abundance in the OSR

We did not detect for any directional trends in WTD abundance within WMUs over time (Figure 3). Directional trends in deer abundances within WMUs across survey years may have been confounded by wide confidence intervals around population size estimates, limiting our ability to draw reliable conclusions on WTD population trends. Variable aerial survey methods used to collect ungulate data (e.g. Distance sampling versus Modified Gassaway) may have also confounded trends in population densities over time. These results indicate that while AUS provide important insights into WTD abundance among WMUs, these surveys may not yield sufficient precision to monitor population fluctuations within WMUs over time. Therefore, while we expected to see population size increases over time, we are unable to draw any definitive conclusions on WTD temporal trends in this region.

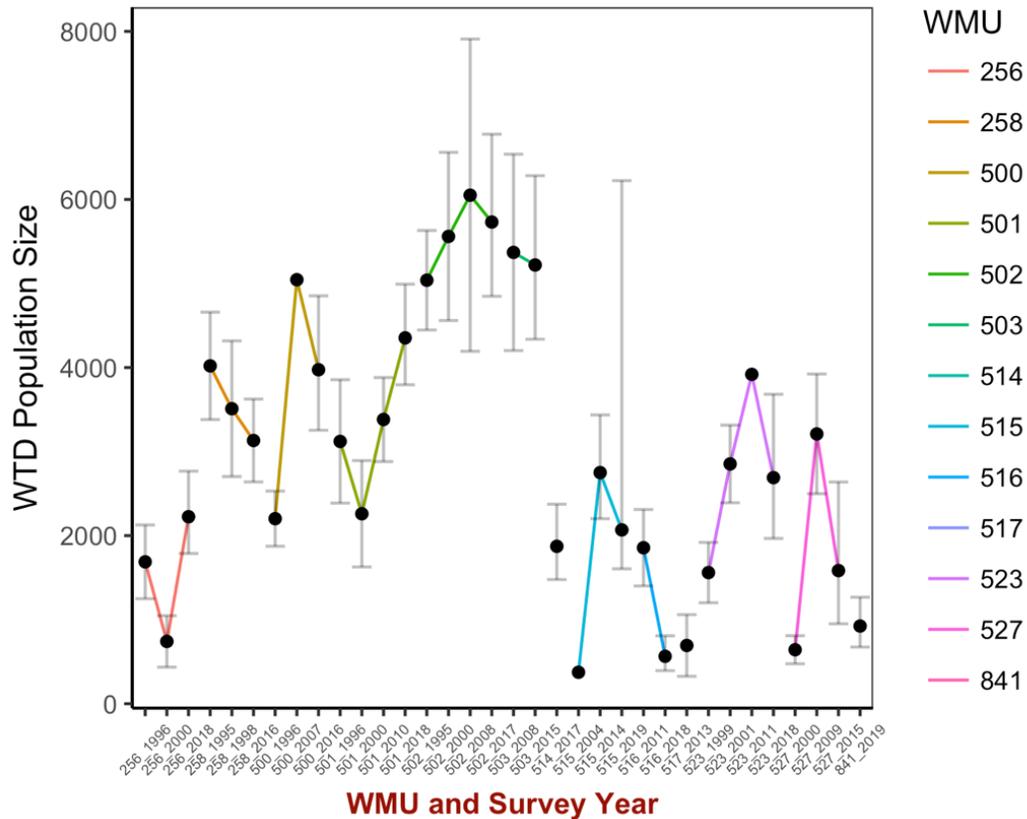


Figure 3. Temporal fluctuations in white-tailed deer (WTD) population size across wildlife management units (WMUs). WMUs arranged by colour and survey years arranged chronologically from left to right, representing population change over time. Error bars represent the upper and lower confidence limits of estimated WTD population size.

Spatial trends in WTD populations densities

White-tailed deer densities in the OSR are best predicted by latitude (see Model 5, Table 3), supporting our hypothesis that climate strongly impacts WTD regional abundance. We observed lower densities in northern WMUs expected to have more severe winters (Table 4). Candidate model testing indicates that inclusion of linear or block development features did not improve our ability to predict WTD population density.

Table 3. White-tailed deer population density in response to human footprint, latitude, and survey year. Model 5 is the best supported.

Model Set	Model No.	Model Variables	AICc score	Δ AICc	AICc weight
<i>Latitude</i>	5	Latitude	29.77	0	0.66
<i>Latitude + Human Disturbance</i>	6	Latitude + Linear	31.94	2.16	0.22
<i>Latitude + Human Disturbance</i>	7	Latitude + Block	33.54	3.76	0.10
<i>Year</i>	4	Year	37.74	7.96	0.01
<i>Human Disturbance</i>	1	Linear	39.38	9.61	0.01
<i>Human Disturbance</i>	2	Block	39.49	9.72	0.01
<i>Human Disturbance</i>	3	Linear + Block	43.71	13.94	0

Table 4. Parameter estimates of the top model predicting white-tailed deer density.

	Estimate	Standard Error	p-value
Intercept	2.74	5.55	<0.001
Latitude	-1.25	0.36	<0.01

White-tailed deer habitat selection in the OSR

White-tailed deer resource-selection is best explained by a combination of natural and anthropogenic features. Our global model (Model 1; Table 3) which included natural land cover vegetation, distance to riparian areas, anthropogenic block features, and distance to linear disturbance features as predictors for deer habitat-use, had the highest weight of evidence when compared against other models (AIC_w = 1.00, null deviance = 13,290, df = 14,631; residual deviance = 11, 970, df =14,619).

White-tailed deer avoid and select for different natural features of the boreal landscape, and deer habitat-use around anthropogenic features indicates avoidance of some block features but a strong affinity for most linear features. Of all natural habitat types, white-tailed deer strongly select for broadleaf forest habitat, with the strongest positive association observed for broadleaf regenerating forest (Figure 3). Deer increased habitat-use by over 50% with an increase in 0.8km² of broadleaf regenerating habitat (Figure 4a). Deer also selected strongly for riparian habitat (Figure 3), and deer resource-use sharply increased with increasing proximity to lakes (Figure 4b). In contrast, deer avoid coniferous forest and wetland areas (Figure 3), with considerable decreases in habitat-use with increasing low-density coniferous forest and wetland landcover (Figure 4c & d). Anthropogenic disturbance features, including both block and linear features, help further explain deer habitat-use. Deer avoid cultivated areas, with a considerable decrease in habitat-use with increasing proportion of cultivated area (Figure 4e). Deer showed a weaker response to old and young cut-blocks, with a weak selection for moderate-aged cut-blocks between 5 and 20 years old (Figure 3). White-tailed deer strongly select for areas close to anthropogenic linear features, but no displayed no selection or avoidance of well sites (Figure 3). Among anthropogenic linear features, deer exhibit the strongest affinity for seismic lines, with deer habitat-use decreasing by nearly 50% in areas more than 500-m from a seismic line (Figure 4f). Likewise, deer also exhibited a sharp decrease in habitat-use at increasing distances from 3D seismic grids (Figure 4g) and roads (4h).

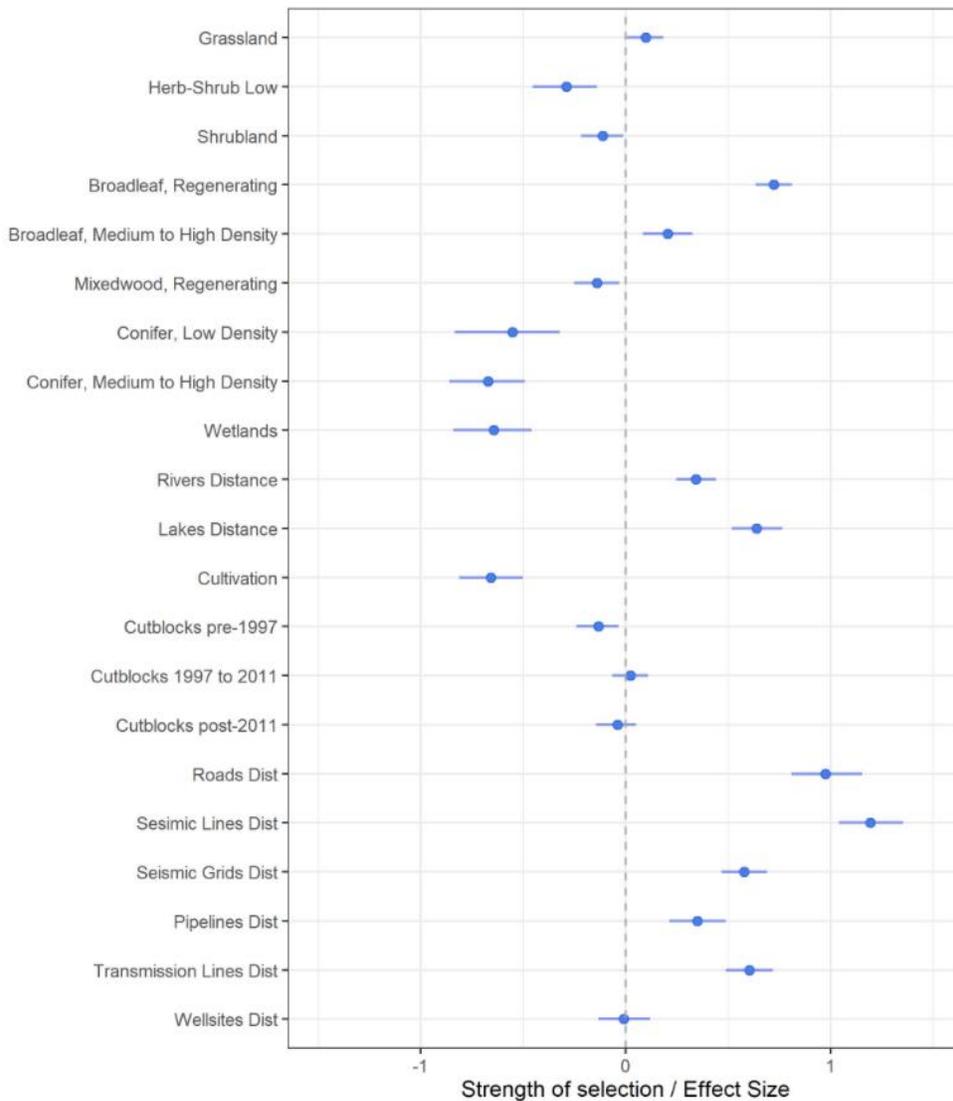


Figure 3. Standardized coefficient estimates for the best-supported model predicting white-tailed deer resource-use across the boreal forest of Alberta's Oil Sands Region. Positive values indicate selection for features, while negative values indicate avoidance. Note: distance to the nearest riparian habitat (lakes, rivers) and anthropogenic linear features (roads, seismic lines, seismic grids, pipelines, transmission lines, and well-sites) are shown as proximity measurements, with positive values indicating deer selection for areas close to these features.

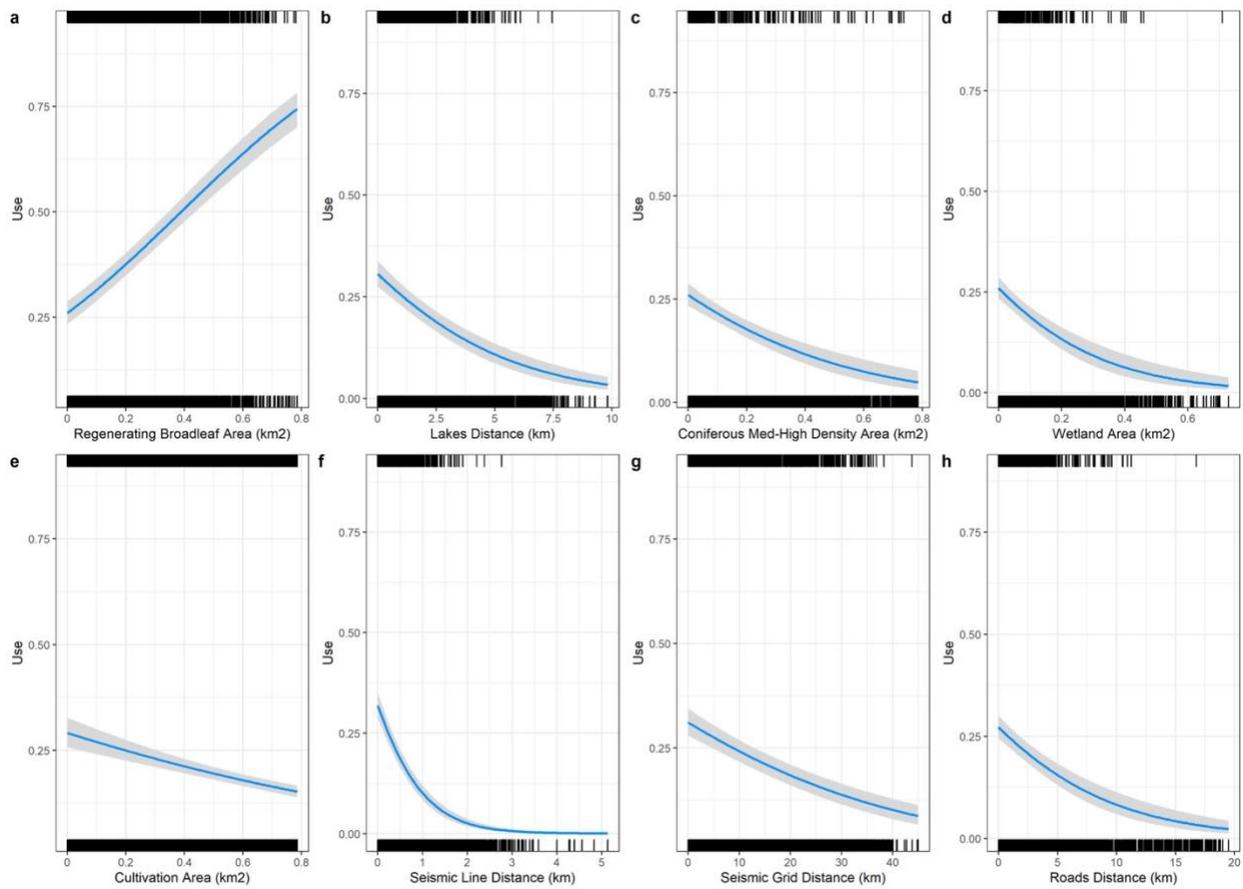


Figure 4. Generalized linear model plots showing relationship between white-tailed deer resource-selection (“Use”) and select natural land-cover and anthropogenic disturbance features. Note: a negative relationship with distance measurements indicate selection for areas in proximity to these features.

Table 3. Selection of best-fit deer resource-selection models across the boreal forest in the Oil Sands Region of Alberta. Models were ranked using AIC with the best-fit model set is indicated by $\Delta AIC = 0$ and AIC weight = 1.00.

Model Name	Model No.	K	AICc	ΔAIC	AIC weight	Residual Deviance
Global (Natural Land Cover + Distance to Linear Features + Anthropogenic Block Features)	1	22	11,154	0	1	11,010
Natural Land Cover + Distance to Linear Features	7	18	11,215	61	0	11,180
Natural Land Cover + Anthropogenic Block Features	6	16	11,973	818	0	11,840
Natural Land Cover	2	13	12,001	946	0	11,970
Distance to Linear Features + Distance to Riparian	8	9	12,131	977	0	12,110
Distance to Linear Features + Anthropogenic Block Features	5	11	12,214	1,059	0	12,050
Distance to Linear Features	4	7	12,273	1,119	0	12,260
Anthropogenic Block Features	3	5	13,220	2,067	0	13,060

Model Validation and Spatial Autocorrelation

Spatially blocked k-fold cross validation indicated a mean area under curve of 77.2% for our top selected model (<Supplementary Information, Figure C.1>)). Residual deviance for this model was 11,010 (d.f. = 14,619), with a dispersion parameter estimate of 0.82 indicating that this model provided a good fit to the data.

DISCUSSION

Regional-scale population responses by white-tailed deer to oil and gas features in the OSR are not apparent. We did not detect any significant trends in WTD population density with increasing human footprint across WMUs, or across time with increasing development. However, we contend that this is due to low power in our analysis, incurred by relatively infrequent AUS and a small coverage of WMU's relative to the whole OSR. We highly recommend an increased spatial coverage, and increased rotation, within the OSR to monitor population changes through time. Our analysis of WTD population densities across Alberta's OSR does however highlight some spatial relationships between deer and the boreal landscape. While WTD population estimates derived from AUS data may not provide sufficient precision to reliably monitor temporal fluctuations, WTD distribution and abundance data provide important insights into the drivers of WTD expansion in the OSR.

In contrast, **regional-scale behavioural responses** by white-tailed deer to oil and gas features in the OSR are highly apparent. Seismic lines are 3D seismic grids are highly selected, as are roads. These responses augment the positive effects of riparian areas and regenerating broadleaf forests (a combination of recovering fires and recovering cutblocks) to facilitate white-tailed deer distribution within the OSR. These signals are very strong and very clear, suggesting these OS features should be targets for restoration and management. As theory suggests these behavioural responses should scale up to population responses, we again content that our failure to find population responses is due to lack of power and data, not due to absence of an ecological effect.

Landscape-scale behavioural responses WTD relative abundances increase have been observed to increase in response to total human footprint (Fisher and Burton 2018; Fisher et al. 2020), with small polygonal features such as well sites being a primary drover of deer occurrence. However, as WTD responses differ in strength and direction to individual development features at the landscape scale (e.g. seismic lines, cut-blocks; Fisher and Burton 2018), it is likely that our coarser analysis combining all anthropogenic features into two broad categories did not allow for disentangling existing trends at the regional scale. Detecting for feature-specific responses of WTD densities to human disturbance requires deer population density estimates across a greater number of WMUs encompassing a wider gradient of human footprint. While such data are available for moose in the OSR, future ungulate monitoring

should focus on collecting data on WTD densities across the region. The currently limited dataset of only 13 WMUs precludes any fine-scale analysis of deer population responses to development in this region, yielding only significant responses to the more obvious effects of climate across a latitudinal gradient of WMUs and masking subtler responses to landscape development features.

Our analysis of WTD resource selection in the boreal forest indicated that habitat-use is best predicted by a combination of natural and anthropogenic land-use features. Deer select for both natural and anthropogenic features providing early-seral stage vegetation and potentially movement corridors, including regenerating forests, riparian habitats, medium-young cut-blocks, and anthropogenic linear features. White-tailed deer select for areas with regenerating broadleaf forest and near riparian habitats, including river and lakes. These features are associated with a high availability of forage as well as potential movement corridors. Deer are observed to avoid habitat more closely associated with woodland caribou, including coniferous forests and wetlands.

We observed energy exploration and extraction features in the boreal forest influence WTD resource-use more strongly than agricultural or forestry activities. Deer exhibit the strongest selection for seismic lines, with habitat-use dropping by ~50% in areas more than 500m from a seismic line. Deer also select for seismic grids, pipelines, transmission lines, and roads, likely due to their association with early seral vegetation and facilitated movement corridors. To a lesser extent, WTD avoid cultivation areas. Deer also avoid young and old forestry cutblocks, but show only a weak association with medium-young cut-blocks that provide both foraging opportunities and escape cover. These results highlight linear features, especially those associated with energy extraction and exploration, as an important component of WTD resource-use, and potentially expansion, in the boreal forest of western Canada.

*In summary, there exists nearly no **population** signal of white-tailed deer responses to oil and gas features, but given the strength of evidence at **landscape** and **local** scales, we contend this may be due to a lack of power in current monitoring, and additional monitoring is much needed to investigate whether white-tailed deer are expanding in population size in the OSR due to the features resulting from exploration and extraction. White-tailed deer habitat-use is influenced by both natural and anthropogenic features on the landscape, and we observe a strong positive association between deer distribution and linear features associated with oil and gas activities.*

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APPENDIX A

Table A.1. White-tailed deer (WTD) population size across survey years within wildlife management units (WMUs).

WMU	Year	WTD Population Size	Population Size Upper Limit	Population Size Lower Limit	Survey Methods
256	1996	1688	1249	2127	Trend Block
256	2000	741	435	1047	Modified Gassaway / Random Stratified Block
256	2018	2225	1788	2767	Distance
258	1995	4020	3381	4659	Modified Gassaway / Random Stratified Block
258	1998	3510	2703	4317	Modified Gassaway / Random Stratified Block
258	2016	3132	2639	3625	Strip Transect
500	1996	2202	1874	2530	Modified Gassaway / Random Stratified Block
500	2007	5045	NA	NA	Modified Gassaway / Random Stratified Block
500	2016	3974	3254	4853	Distance
501	1996	3121	2387	3855	Modified Gassaway / Random Stratified Block
501	2000	2260	1627.2	2892.8	Modified Gassaway / Random Stratified Block
501	2010	3382	2881	3881	Modified Gassaway / Random Stratified Block
501	2018	4353	3795	4992	Distance
502	1995	5039	4447	5631	Modified Gassaway / Random Stratified Block
502	2000	5560	4559.2	6560.8	Modified Gassaway / Random Stratified Block
502	2008	6051	4193	7909	Modified Gassaway / Random Stratified Block
502	2017	5731	4848	6776	Distance
503	2008	5370	4202	6539	Modified Gassaway / Random Stratified Block
503	2015	5220	4337	6283	Distance
514	2017	1873	1477	2374	Distance
515	2004	374	NA	NA	Total Count
515	2014	2750	2201	3436	Modified Gassaway / Random Stratified Block

515	2019	2068	1605	6224	Distance
516	2011	1856	1401	2310	Modified Gassaway / Random Stratified Block Distance
516	2018	564	393	808	Distance
517	2013	693	326	1060	Modified Gassaway / Random Stratified Block
523	1999	1560	1201	1919	Modified Gassaway / Random Stratified Block
523	2001	2853	2391	3315	Modified Gassaway / Random Stratified Block
523	2011	3919	NA	NA	Modified Gassaway / Random Stratified Block
523	2018	2690	1966	3682	Distance
527	2000	642	475.08	808.92	Modified Gassaway / Random Stratified Block
527	2009	3210	2498	3923	Modified Gassaway / Random Stratified Block
527	2015	1584	951	2638	Distance
841	2019	924	674	1267	Distance

Table A.2. White-tailed deer (WTD) population density estimates and human footprint density across Wildlife Management Units (WMUs) in the OSR. Latitude category corresponds to whether the WMU was primarily south (1) or north (2) of 55.2100° N.

WMU	Survey Method	Survey Year	WTD Density (deer/km ²)	WTD Density Lower Limit (deer/km ²)	WTD Density Upper Limit (deer/km ²)	Latitude Category	Block Feature Density (km/km ²)	Linear Feature Density (km/km ²)
256	Distance	2018	0.82	0.66	1.03	1	2.72	76.67
258	Transect	2016	1.18	0.99	1.36	1	2.63	60.45
500	Distance	2016	1.34	1.1	1.64	1	4.35	22.57
501	Distance	2018	2.4	2.1	2.8	1	3.18	39.13
502	Distance	2017	1.59	1.35	1.89	1	3.60	43.35
503	Distance	2015	1.62	1.3	2	1	3.22	29.43
514	Distance	2017	0.98	0.77	1.24	1	3.32	8.31
515	Distance	2019	0.77	0.6	0.99	1	2.51	14.80
516	Distance	2018	0.14	0.09	0.2	2	2.29	6.34

517	Gassaway	2013	0.15	0.07	0.23	2	2.49	5.41
523	Distance	2018	0.47	0.35	0.65	2	2.87	57.00
527	Distance	2015	0.23	0.14	0.39	2	2.48	35.07
841	Distance	2019	2.75	2	3.77	1	0.76	1.41

Table A.3. List of human landscape development features included in candidate model hypothesis testing of white-tailed deer population densities in response to human footprint.

Human Footprint Category	Human Footprint Features
Linear	Seismic Line, Pipeline, Railways, Roads, Trail, Transmission Line
Block	Cut-block, Borrowpit, Industrial Site, Rural Residence, Urban Residence, Facility, Agricultural/Cultivation Areas, Sand Pit, Dugout, Mill, Mine, Gas Plant, Well Site

APPENDIX B

Table B.1. List and description of individual variables included in natural versus anthropogenic feature categories.

Class	Variables	Description
<i>Natural_Land Cover</i> (Percent Area)	conifer_low	Low density coniferous forest
	conifer_medhigh	Medium-high density coniferous forest
	broadleaf_medhigh	Medium-high density broadleaf forest
	broadleaf_regen	Regenerating broadleaf forest
	mixedwood_medhigh	Medium-high density mixedwood forest
	shrubland	Shrubland
	herb_shrub_low	Low density shrub and herbaceous land
	grassland	Grassland
	wetland	Wetland
Distance_Riparian (Distance to nearest feature)	Lakes	Lakes
	Rivers	Rivers
<i>Distance_Linear</i> (Distance to nearest features)	roads	All paved and gravel roads
	seismic_grids	3-D seismic grids
	seismic_lines	Conventional seismic lines
	pipelines	Pipelines
	transmission_lines	Transmission Lines
	wellsites	Well Sites
<i>Cultivation</i> (Percent Area)	cultivation	Low, medium, and high density biomass cultivation sites
<i>Cutblocks</i> (Percent Area)	pre_1997	Old forestry cutblock harvested pre-1997
	1997_to_2011	Medium young forestry cutblock harvested between 1997 – 2011
	post_2011	Young forestry cutblocks harvested post 2011

Appendix C

Spatially-blocked k-fold cross validation

The R package *blockCV* (source) was used with square blocks of 32924m per side and random allocation of spatial blocks to folds. Spatial blocks were randomly assigned to folds 250 times, and the distribution with the most even dispersal of used and available points between blocks was chosen as the fold system to follow. The mean Area-Under-Curve (AUC) for the top model was 77.15 percent, and AUCs for the 10 individual folds ranged from 66 percent to 82 percent.

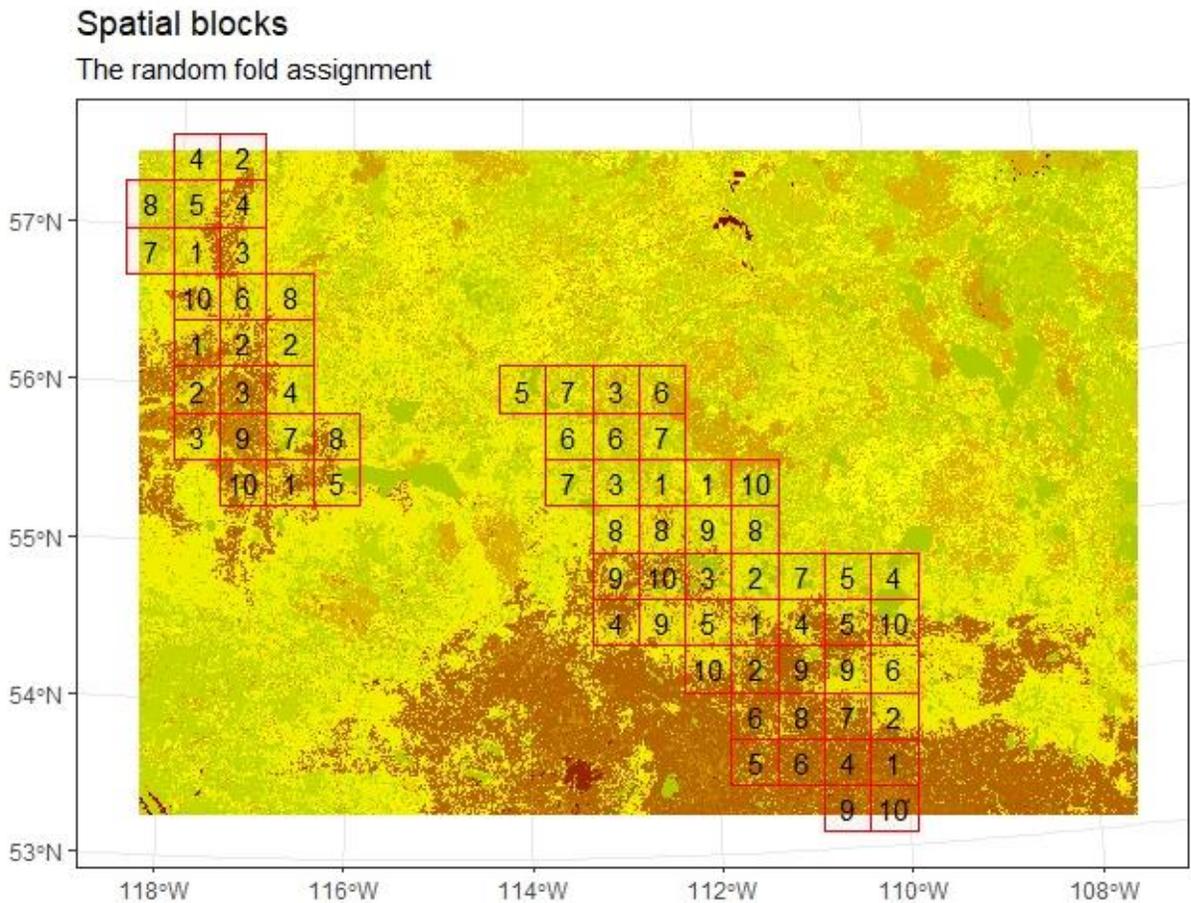


Figure C.1 Spatial blocks and random fold assignment for cross-validation