

Modeling the Habitat Suitability of Mule Deer (*Odocoileus hemionus*) in British Columbia  
Using Species Distribution Modeling (SDM)

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## ABSTRACT

This study models the distribution of mule deer (*Odocoileus hemionus*) in British Columbia using a Maxnet species distribution model (SDM). Verified occurrence records were analyzed with three predictors: elevation, minimum winter temperature, and distance to urban areas. The model performed well (AUC = 0.85), showing high suitability in southern and coastal regions where milder winters and lower elevations prevail. Minimum winter temperature was the strongest driver, while elevation and urban distance showed weaker effects. These results align with mule deer ecology and highlight the value of adding vegetation, and water layers to improve model accuracy.

## INTRODUCTION

Mule deer are among the most abundant ungulates in British Columbia and are highly valued as a game species (Ministry of Environment, Lands and Parks, n.d.). Their ranges widely across western North America, from the Alaska–Yukon border south to central Mexico and from the Great Plains westward to the Pacific Coast and the crest of the Cascade and Coast mountain ranges (Heffelfinger & Latch, 2023). In British Columbia, there are two other subspecies: the Columbian black-tailed deer (*O. h. columbianus*) in the southern coastal and island regions, and the Sitka black-tailed deer (*O. h. sitkensis*) along the northern coast into Southeast Alaska, whose ranges overlap and produce hybrid forms (Horn et al., 2009).

Mule deer movements are driven by the need to secure seasonal resources, resulting in defined migration routes linking distinct home ranges. Typically, deer occupy higher-elevation forests during the summer and move downslope to valley bottoms or south-facing slopes in winter as a response to changes in snowpack and forage availability (Anton et al., 2025; Monteith et al., 2011). Modern telemetry data reveal these migrations can span considerable distances, often tens to over 150 km, with the specific route length varying based on the landscape and annual conditions (Sawyer et al., 2016). A defining feature of this behavior is strong site fidelity: most individuals exhibit high consistency by returning to the exact same seasonal ranges and migration paths year after year (DeCesare et al., 2021). While consistent, the precise timing and staging of these movements can differ between individuals based on sex and reproductive status (e.g., females may stage longer on spring ranges before moving to fawning sites), with all movements primarily tracking environmental cues like forage phenology and weather (Ortega et al., 2023).

In British Columbia's snow-dominated mountain ecosystems, mule deer survival and distribution are directly governed by seasonal migration (D'Eon & Serrouya, 2005). Consequently, broad-scale ecological studies confirm that the primary determinants of habitat use and winter survival are terrain–climate constraints, notably winter temperature and snow-depth, where colder ambient temperatures drive deeper or more persistent snow-cover, increasing energetic costs and reducing forage access (Anton et al., 2022). This ecological context validates the choice of Digital Elevation Model (DEM) and minimum winter temperature as appropriate abiotic predictors for modeling the main constraints on the species' distribution. Furthermore, while habitat selection is primarily environmental, proximity to towns modifies resource use and risk, for example, higher *Toxoplasma gondii* exposure in urban vs. non-urban deer (Mathieu et al., 2018), making the distance-to-urban gradient a relevant ecological modifier. Given that mule deer range shifts and patch connectivity are strongly influenced by landscape fragmentation, predicting suitable habitat in British Columbia is ecologically relevant. This analysis can support targeted conservation planning under future climate and land-use change scenarios.

## METHODS

### 1.1 Study area and Data collection

We modeled mule deer distribution within British Columbia, Canada. Occurrence records were downloaded from GBIF (2025) and combined across 45 contributing datasets (museums and community science). Records were filtered to presence-only observations with non-missing coordinates, positive individual counts, and coordinate uncertainty  $\leq 1,000$  m.

### 1.2 Data cleaning

Cleaned WGS84 points were converted to vectors and re-projected to BC Albers (EPSG:3005). We intersected points with BC Natural Resource District boundaries to retain occurrences inside BC; a district-level tally verified a sufficient sample ( $>30$  occurrences) for modeling.

### 2.1 Data preparation

We prepared three predictors at 5-km resolution: (i) elevation (DEM; GeoBC, 2014), (ii) minimum winter temperature (PCIC climatology, 1981–2010), and (iii) Euclidean distance to urban areas derived from provincial land cover. Predictors were stacked and named dem, tmin\_winter, and dist\_urban.

### 2.2 Background definition

We drew 500 random background points across the study region, extracted predictor values at presences and background, and added a binary response (pb: 1 = presence, 0 = background).

### 2.3 Data split

Data were split into training/test sets with a fixed seed for reproducibility. Using presence records against background (pseudoabsence) is standard for presence-only SDMs (Elith & Leathwick, 2009).

### 3.1 Model fitting

We fitted a presence-background model using the maxnet package (Phillips et al., 2006) with predictors dem, tmin\_winter, and dist\_urban. The fitted model was projected across the stacked rasters to generate a continuous suitability surface on the cloglog scale.

### 3.2 Evaluation

Predictive performance was assessed with AUC using held-out presences versus an equal-sized random subset of raster background values (fixed seed). To assess the relative influence of predictors, Pearson correlations were calculated between the predicted suitability surface and each environmental layer, identifying the strongest positive and negative associations.

## RESULT

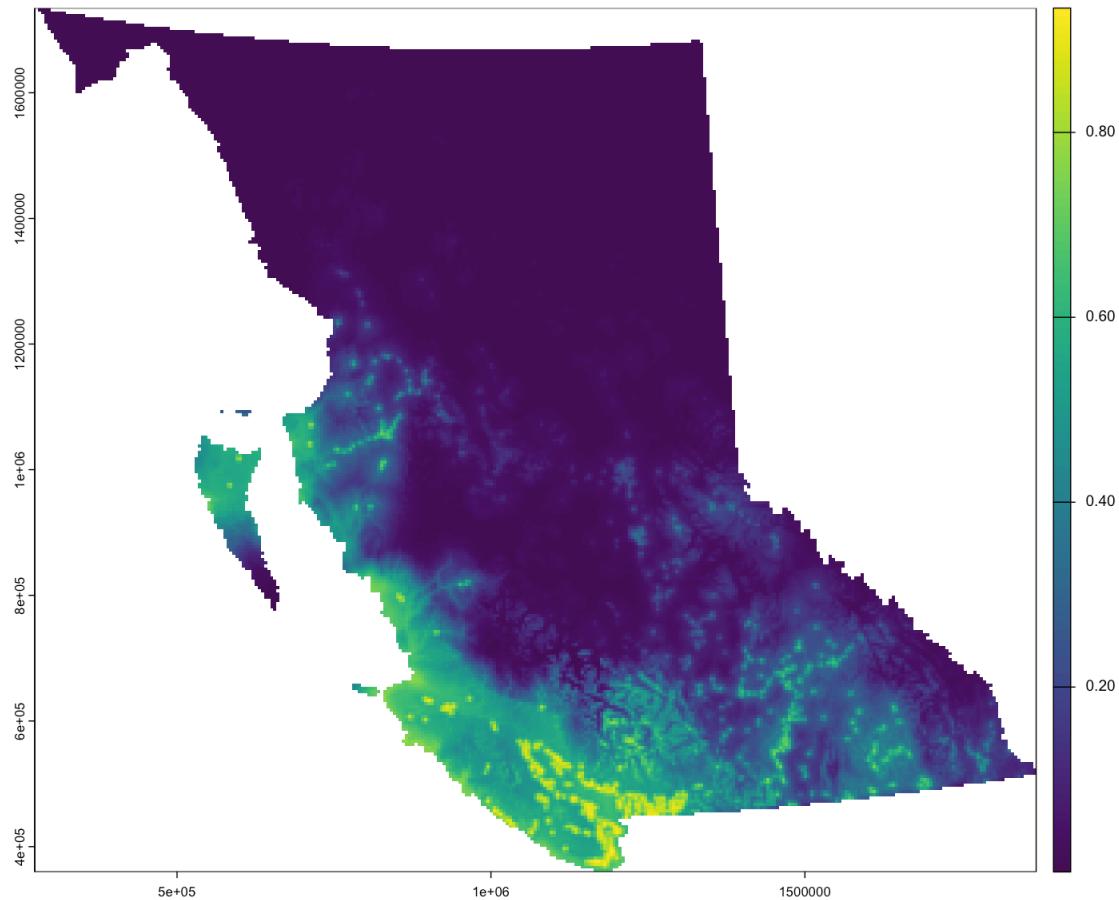
After filtering GBIF records and intersecting with BC district boundaries, we retained 98 unique occurrences for modelling. Predicted suitability concentrated in southern/coastal valleys and interior lowlands (Figure 1), and minimum winter temperature exhibited the strongest positive association with the prediction surface, consistent with higher suitability in milder regions (Figure 2). The held-out test set comprised 15 presence points paired with 72 randomly sampled background cells, and the Maxnet model using elevation (DEM), minimum winter temperature, and distance to urban areas as predictors showed a discrimination with an AUC of 0.85 on the test data (Figure 3).

## DISCUSSION

### 1. Model Performance and Key Drivers

The Maxnet model demonstrated good discriminatory power (AUC = 0.854), indicating that a randomly selected mule deer presence was assigned a higher predicted suitability than a random background point approximately 85% of the time. Model diagnostics show this performance was

overwhelmingly driven by minimum winter temperature, which had a strong positive correlation and a steep response curve. Elevation exerted a moderate negative influence, with colder, higher-terrain areas showing lower suitability. A weak negative relationship with distance to urban areas was also observed, though this likely reflects observation bias near towns and roads rather than true habitat selection.

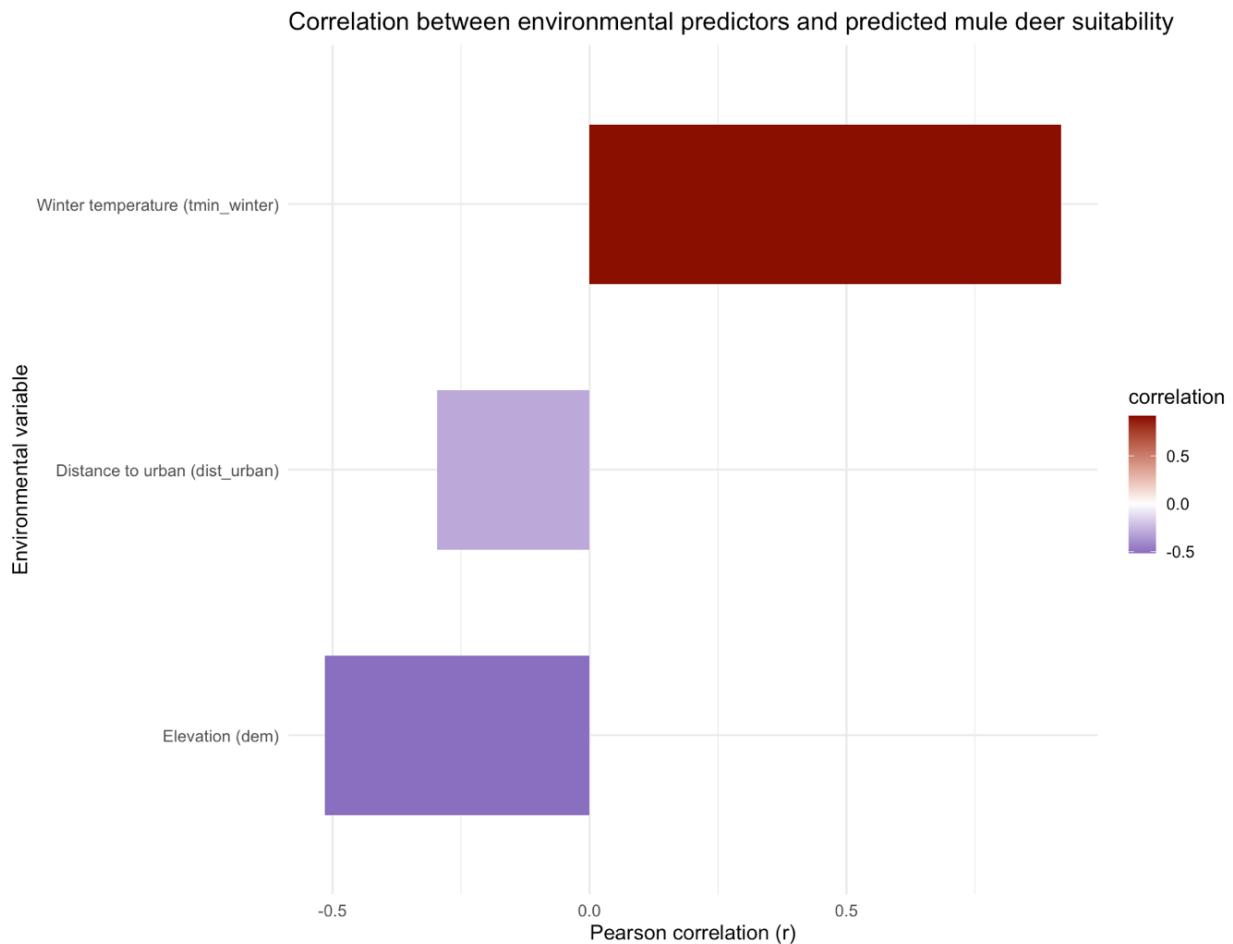


**Figure 1. Predicted mule deer habitat suitability in British Columbia.** Raster shows Maxnet model predictions on the cloglog scale (0–1). Higher values concentrate in southern/coastal valleys, consistent with milder winter temperatures and lower elevations. Predictions are based on three predictors: elevation (DEM), minimum winter temperature, and distance to urban areas.

## 2. Spatial Patterns and Ecological Interpretation

These environmental drivers generate a suitability map with strong spatial gradients. The highest predicted suitability is concentrated in southern valleys and coastal lowlands, while central and northern British Columbia show markedly lower suitability. This pattern reflects known climatic

and topographic constraints, where milder winters and heterogeneous vegetation support year-round forage and shelter.

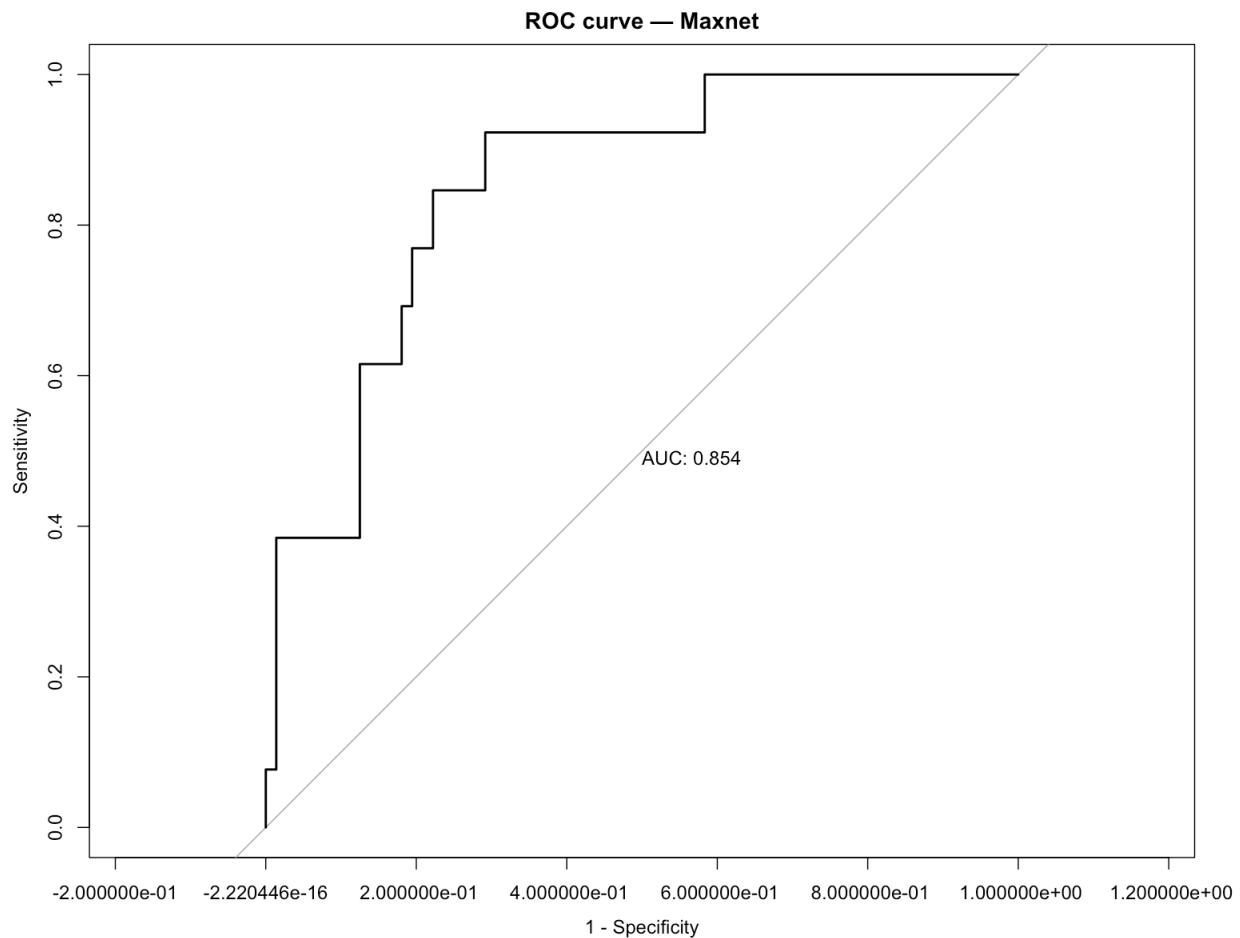


**Figure 2. Correlation between environmental predictors and predicted mule deer habitat suitability from the Maxnet model.**  
Minimum winter temperature shows a strong positive correlation with predicted suitability, indicating that warmer winter conditions increase habitat suitability, whereas elevation and distance to urban areas show weak to moderate negative relationships.

This finding aligns with existing research from western British Columbia, where mule deer preferentially use open deciduous stands and low-snow environments that provide greater forage availability and easier movement during winter (Serrouya & D'Eon, 2008). In contrast, northern plateaus and alpine zones present harsher climatic conditions, reducing resource availability and overwinter survival. This observation is consistent with classic population gradient theory, which emphasizes how environmental tolerance limits and resource heterogeneity structure species distributions across latitudinal and elevational gradients (With, 2019A).

### 3. Implications: Fragmentation and Model Limitations

Beyond these broad gradients, the map suggests potential habitat fragmentation between southern and interior populations. These discontinuities could correspond to ecological barriers (e.g., mountain ranges, rivers, or urban corridors) that restrict dispersal and genetic flow. As discussed in landscape ecology theory (With, 2019B), such fragmentation reduces functional connectivity and can lead to metapopulation-like dynamics, where local extinctions and recolonizations shape long-term persistence.



**Figure 3. ROC curve for the mule deer Maxnet model in British Columbia.** Evaluated on test presence points ( $n = 15$ ) versus random background ( $n = 72$ ). The curve sits above the grey “chance” diagonal, with  $AUC = 0.85$ . Axes show Sensitivity (true positive rate) versus  $1 - \text{Specificity}$  (false positive rate).

However, some predicted areas of high suitability extend over the ocean because the model evaluated all pixels within the provincial extent, and the predictors used retain plausible numeric values over marine surfaces. In the absence of a land–water mask, Maxnet treats ocean pixels as valid input data, resulting in the misclassification of nearshore or coastal cells as suitable habitat.

This artifact likely arises from mixed-pixel effects, where environmental gradients near coastlines resemble terrestrial covariate combinations (Elith et al., 2011; Merow et al., 2013). Moreover, the inclusion of extensive oceanic areas in the background sampling can influence thresholding and AUC computation, as the altered background distribution may slightly bias model discrimination (Lobo et al., 2008). In ecological terms, large water bodies act as barriers to movement and habitat connectivity, fragmenting otherwise continuous terrestrial landscapes and limiting migration pathways for mule deer.

## CONCLUSION

To improve the robustness and ecological realism of this species distribution model, several key refinements are recommended.

First, the model's structure must be improved by integrating missing environmental and landscape components. The most urgent refinement is the inclusion of hydrological layers to mask large water bodies. This would correct the current logical flaw of predicting suitability in open water and, more importantly, would explicitly model major barriers to movement, addressing the "Movement" (M) component of the species' distribution (as per the BAM diagram framework). Following this, incorporating ecologically relevant predictors such as vegetation cover and type is essential. These layers would introduce the critical "Biotic" (B) factors currently missing from the model, moving it beyond simple abiotic predictors to capture key niche conditions related to forage and shelter (Beumer et al., 2023). Studies show that using both static (e.g., vegetation type) and dynamic, remotely-sensed productivity indices significantly improve SDM performance by reflecting seasonal resource abundance, a key driver of habitat selection (Tiago et al., 2024).

Second, the occurrence dataset itself must be expanded to address significant sampling bias. The current records, being clustered near populated areas and roads, are a classic example of "unbiased species data collection" issues discussed in class (Gaul et al., 2020; Syfert et al., 2013). This biased sampling inflates apparent suitability around urban regions and means the model is trained on data that fails to represent the species' full environmental gradient. Consequently, the model describes only a fragmented portion of the realized niche, rather than a comprehensive approximation of it. Incorporating additional verified occurrences from systematic surveys or remote regions is necessary to balance the presence-background contrasts (Moudrý et al., 2024).

By integrating these critical biotic predictors and movement barriers, and by training the model on a dataset that more accurately reflects the species' true realized niche, future iterations will provide a far more robust and defensible tool for ecological inference and management.

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