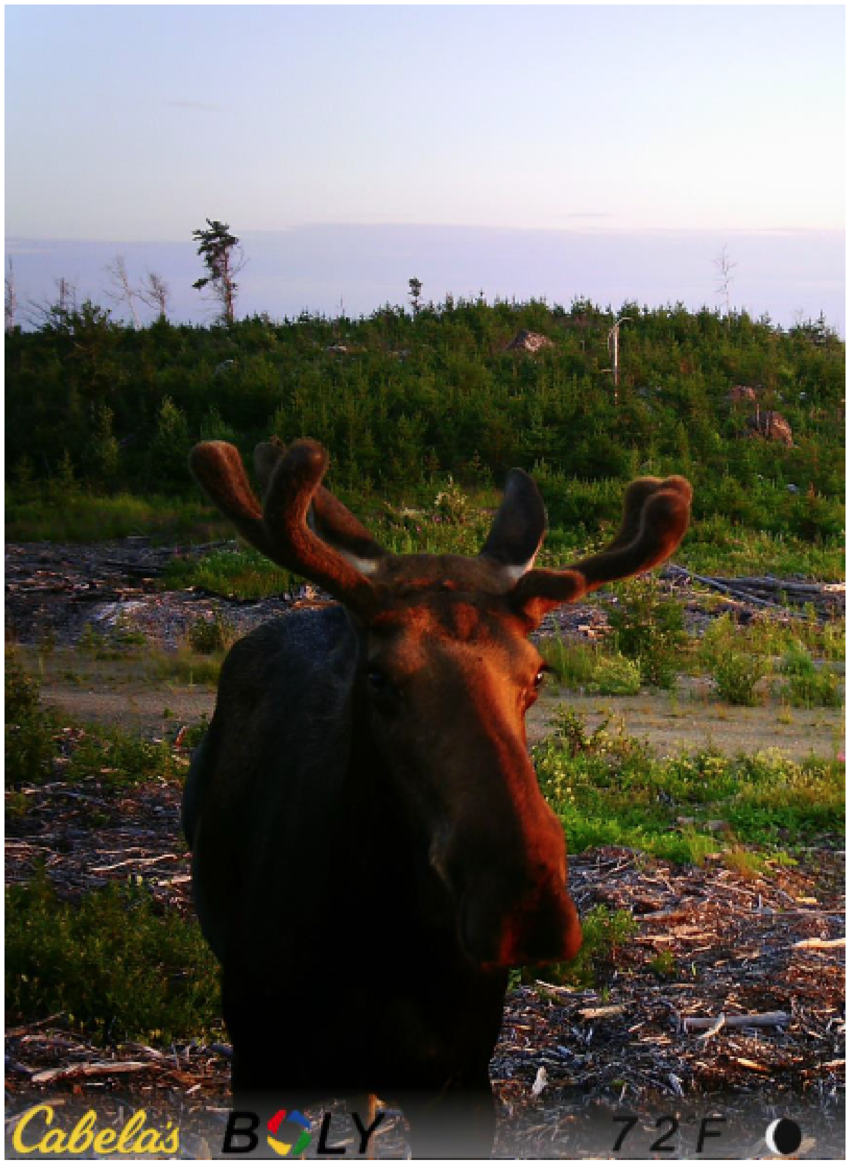
USING TRAIL CAMERA IMAGERY TO DEVELOP A HABITAT SUITABILITY INDEX (HSI) FOR MOOSE (*ALCES ALCES*) IN THE ENGLISH RIVER FOREST, ON



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USING TRAIL CAMERA IMAGERY TO DEVELOP A HABITAT SUITABILITY INDEX (HSI) FOR MOOSE (*ALCES ALCES*) IN THE ENGLISH RIVER FOREST, ON

by

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Thesis Suervisor

Second Reader

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ABSTRACT

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Keywords: moose, habitat, suitability, forage, wetland, mature forest, maximum entropy modelling, open-source, camera traps

Moose are a valuable economic and ecological resource in Ontario. Understanding their spatial distribution throughout the forest is essential for managing populations and preserving habitat. One method of identifying the spatial distribution of species is through the development of habitat suitability indices. Suitability models use presence points and environmental variables to predict the likely distribution of a species across a given landscape. This thesis examined the feasibility of using trail camera imagery to create a habitat suitability index for moose *Alces alces* in the English River Forest, ON. This was accomplished by using recreational trail camera purchased from Cabela's Canada, and an open-source maximum entropy modeling software called MaxEnt. Three runs through the modeling software were completed in order to produce the most accurate model possible. Results showed varying performance with the three models. The binary model had the highest AUC at 0.808. However, it was determined that suitabile habitat was highly correlated to the unclassified layer, which represents roads. The non-binary run rectified the issues with the binary model, but only produced an AUC of 0.661. Interestingly the pre-sapling – sapling layer was found to include information which was highly correlated to other variables. This resulted in the layer being relatively unimportant to the model, and it was subsequently removed. The non-binary run with omitted layers was determined to be the best spatial distribution fit with an AUC value of 0.771 and a standard deviation of 0.161. Overall, results concluded that it was possible to use trail camera imagery to develop a habitat suitability index for moose in the English River Forest.

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ACKNOWLEDGEMENTS

I would like to formally acknowledge several people for their involvement in the data collection, scoping and development of this thesis. I first would like to state that this thesis would not have been possible without the help from my advisor Dr. Ashley Thomson. Ashley took time to help scope out the direction of my thesis, and introduce me to industry standard modeling software used to create habitat suitability indices. Secondly, I would like to thank my second reader, Mr. Alex Bilyk. Without Alex's help throughout the data analysis portion of my thesis, my results would not have been remotely as comprehensive. Alex taught me to focus on what is truly important, and that the best thesis is the one you finish. I want to thank Mr. Tomislav Sapic for helping me figure out my layer projections in ArcGIS and Mrs. Jennifer Manion for giving me a shoulder to cry on after many sleepless nights. Finally, I would like to give an extended thanks to Mr. Ryan Wilkie, who collected all of the moose presence locals for this study during his Master's thesis. Ryan is a great friend and a true professional. This thesis would not have been possible without all of his hard work and invaluable guidance throughout the process.

INTRODUCTION

Moose (*Alces alces*) are a valuable economic and ecological resource in Ontario. These animals are a popular recreational game species in the province, with revenue from resident and non-resident hunters generating more than $500 million annually (Telfer 1997). Moose in Ontario are managed to ensure the provision of their ecological, cultural, economic and social importance to citizens of the province (OMNR 2009). While providing opportunities for economic growth and recreational ventures in the province, moose also have an intrinsic value in the boreal ecosystem (OMNR 2018). One of Ontario's main strategies for maintaining healthy populations is through the development of dynamic forest landscapes. These landscapes are established through the implementation of a selective harvesting system, which provides a variety of cover and forage stands within the moose's home range. Thus, promoting species persistence, facilitating movement and providing idealistic forage during sensitive times of the year.

Moose, as previously stated, hold an essential trophic position within the boreal ecosystem. These animals occupy a circumpolar distribution bounded by lack of habitat to the north, and temperatures exceeding 27°C to the south (Timmerman & McNicol 1988). Moose are able to tolerate cold temperatures quite well; however, during summer months they can suffer from heat stress (Telfer 1997). To mitigate this stress, moose will submerge themselves in cool lakes to regulate their internal body temperature. Therefore distance to water plays a significant factor in their spatial distribution during summer months. Main forage during summer months consists of small quantities of upland woody browse, with the majority of their diet consisting of macrophytes when available. As a result, moose tend to prefer early successional habitats in the summer where woody browse is abundant, and low-lying riparian zones with access to water.

Recently it has been discovered that populations of moose are in a state of decline from a number of factors such as the expansion of tick ranges, overharvesting and the influx of parasites and disease (ECO 2015). Across Canada numbers are down close to 20%, falling from 115 000 in the early 2000s to 92 000 in just over ten years. In fact, moose populations are declining on a global scale, leading to the assumption that common issues may be attributed to their regression.

Habitat suitability indices (HSI) have been used in many moose management studies to determine critical areas of habitat in a specific geographic region (Allen 1987). These indices can help to inform wildlife managers on the likely spatial distribution of species throughout a geographic location. This can help to pinpoint key areas where cover patches should be left untouched, and help to design harvest plans that maintain cover while providing ample forage opportunities. Previously conducted studies like the one by Dussalt *et al.* (2006), focus on moose selection in a regional context. Presence data is typically collected through either telemetry or radio-collaring, and forest-specific information is gained through provincial resource inventories. While results from these studies are highly accurate and represent a basis for moose management in the province, they are costly and time consuming to conduct.

To make HSIs more economically efficient for the average researcher or student, other methods of presence data collection must be examined. One relatively inexpensive and simplistic approach would be to use wildlife game cameras, also known as trail cameras, to collect point specific locations. High-quality cameras range in price from $300 to $600 USD, with options for both active and passive image collection (Swann *et* *al.* 2004). Trail cameras do not require the same amount of extensive fieldwork associated with other methods, while still producing highly accurate results.

Since moose are such an important ecological, cultural, social and economic resource in the province, understanding their spatial responses to climate change and dynamic harvesting landscapes in Northwestern Ontario is essential to implementing effective management strategies (Rempel 2011). The objective of this thesis is to define an HSI for moose in Northwestern Ontario's English River Forest (ERF) through the use of trail camera imagery. The study location for this project was located within the southeast portion of the English River Forest in the Sustainable Forest License (SFL) area held by Resolute Forest Products Ltd (Wilkie 2018). This study intends to determine if it is possible to create a moderately to highly accurate habitat suitability indices for Moose with the use of localized presence data. It is the hope that the HSI produced from this study will possess the ability to quantify localized habitat trends.

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LITERATURE REVIEW

MOOSE ECOLOGY

In Northwestern Ontario, moose are considered an essential part of the ecological biodiversity of the boreal forest. It is crucial to understand this species ecology and interactions with habitat, to effectively manage populations. Moose tend to occupy stands in young boreal forests, with highest densities found in mixedwood stands, or areas that have been affected by natural disturbance (Courtois *et al.* 2002). In the study of Poley *et al.* (2014), it was determined that Moose in Ontario's far north select for mixedwood stands with high terrain ruggedness. Moose occupancy was also high in areas with disturbed habitat.

As seasons change, moose will shift their diet to reflect seasonally available flora, and thus will select for different forest types. Optimal habitat is dominated by mature conifer stands in the summer and early winter, whereas young conifer stands are preferred in the late winter (Courtois *et al.* 2002). Clear cuts are avoided almost exclusively except for a short period in early winter. Subsequently, Herfindal *et al.* (2009) determined that moose selected for different habitats at the home range and landscape scales. At the landscape scale, it was discovered that moose prefer areas with good foraging opportunities and an abundance of cover. This differs significantly between age classes and sexes. Adult bull moose were found to have home ranges that were more than 24 km2, whereas females were closer to 12 km2. At the home range scale, moose selected for areas with an increase in cover and minimal human impacts. It was determined throughout the study that larger home ranges were associated with increased areas of unsuitable habitat, and at the home range scale, habitat type selection decreased with its availability. And thus, habitat selection at the home range scale was attributed to fluctuations in forest type and human influence. In turn, in areas with decreased resource availability moose tend to have lower reproductive and survival rates.

The OMNRF currently manage moose in Ontario on a fragmentation-based model to ensure idealistic habitats are available throughout the boreal forest region. In the OMNR's (1988) *Timber Management Guidelines for the Provision of Moose Habitat* that clear cuts should be 80 – 130 ha in size, with the optimal average cut size around 100 ha. Additionally, suitable shelter should be no further than 200 m away throughout the clear-cut. In areas where cuts exceed 100 ha, shelter patches must be left to promote movement through the stand. These are to be comprised of immature to mature conifer and be at least 3 – 5 ha in size. Shelter patches are to be placed 300 – 400 m apart. These patches help to facilitate movement throughout the stand and provide adequate protection from predators. Clear-cut areas can provide good forage opportunities when regeneration begins to occur. This process of leaving patches of fragmented habitat helps to facilitate movement throughout the forest stand while still providing adequate opportunities to access winter and summer forage.

FOREST MANAGEMENT FOR LARGE MAMMALS

Forest Management is a critical factor in terms of cervid habitat suitability. It influences forage availability, movement patterns, the introduction of predators, and can fragment populations. In Snaith & Beazley (2004), the effects of forest management practices on moose populations were examined. In general clear cuts tended to promote good moose habitat after 10-40 years after browse species had time to regenerate. Moose tend not to stray more than 80 – 200 m from cover and therefore are not found in large, newly – cut areas where forage may be available. Usually, moose avoid these areas until 10-15 years post-cut. Large-scale harvesting can lead to spatial fragmentation of populations, whereas selective or partial cutting can enhance moose habitat by creating new foraging sites while leaving residual cover. Habitat should ideally maintain 55-75% mature forest cover in patches no smaller than 8ha, and ensure that cover is no more than 200m away at any point.

Forestry developments such as roads are also shown to have adverse effects on moose density. Roads, both active and decommissioned, provide access to predators and competing cervid species, increase hunting-pressures, fragment habitat and disturb wildlife. Roads are essentially open-foraging corridors. However, Snaith & Beazley (2004) claim that moose do not frequently take advantage of these areas. In a Nova Scotia study site, fecal pellet analysis determined that moose selected for areas with few to no roads, making the decommissioning of roads essential to maintaining moose populations. In Beyer *et al.* (2013), the study determined that moose displayed a non-linear functional response to road-crossings. The most significant response was exhibited when road density exceeded thresholds of 0.2-0.4 km2, with crossing rates increasing during summer months. These seasonal differences in crossing rates were directly correlated to seasonal movement patterns and home ranges. Although there is a non-linear trend to road-crossings, the study found that moose crossroads less frequently in areas with higher road densities. Therefore, high traffic areas are at less of a risk for moose crossings than lower density areas.

In Ontario, timber harvests are planned to avoid specific areas of concern for moose in forest regions. OMNR (1988) establishes guidelines for both access road development and resource extraction. In terms of access, roads are not to be built in areas with identified aquatic feeding areas, mineral licks, and calving sites. Additionally, road placement should not facilitate the movement of hunters throughout the forest. Roads should be signed during operations and removed following harvest completion. Harvesting should follow a selection model, with shelter patches left throughout harvest blocks. These patches are not to be cut until surrounding vegetation has reached a minimum height of 2 m. In turn, renewal and tending operations should be conducted in a matter that promotes regeneration within the context of the quantity and quality of moose habitat.

REMOTE SENSING IN MOOSE MANAGEMENT

Remote sensing can be a useful tool in a variety of wildlife management settings. It can help to determine habitat selection responses of species based on large-scale distribution patterns and different temporal scales. In Michaud *et al.* (2014), remote sensing techniques were used to determine moose species-habitat relationships to estimate moose occurrence and abundance within the study site. Habitat suitability was determined by developing a Dynamic Habitat Index (DHI) with parameters set for land cover, topography, snow cover, and natural/anthropogenic disturbances. Moose occurrence/abundance data was collected through aerial surveys. The results were able to determine moose occurrence with moderate confidence, as they selected for areas with high quantities of protective cover. This is likely a response to predator avoidance. Abundance was not adequately determined in this study as the results were spatially variable. The model run was over-estimating abundance in areas of Northwestern Ontario, while under-estimating abundance in the northeast.

Camera traps are used in wildlife management to collect presence data in various settings. Meyer *et al.* (2015) used camera traps to determine if large-bodied mammal populations were intact following forest disturbance in Central Panama. The study was conducted between 2005-2014 across 15 national parks and forest fragments, with two sites in an undisturbed national park serving as a reference. It was determined based on the results that the disturbed forests had little to no apex predators or large mammals and lower species richness. The presence data collected serves as a baseline for the effectiveness of conservation efforts. In Tape and Gustine (2014) camera traps were used to determine migration phenology of terrestrial wildlife species. They placed 14 cameras were set along a 104km transect to record spring caribou migrations. Results showed evident northward migrations, with migration speed increasing with latitude. The findings of this study can be useful in determining how migration timing and speed could be affected by seasonal changes in habitat and snow depth.

Merlin et al. (2016) looked at Airborne Laser Scanning (ALS) data to look at forest structure and its role in moose habitat selection. They GPS-tagged 18 moose in Finland and collated it with ALS data from moose locations. ALS data was collected during the National Land Survey (NLS) of Finland using a Leica ALS50 laser scanning system. Results determined that females were selecting for forests with low levels of understory vegetation during calving periods (May-June). Following this period, females and calves relocated to areas where dense woody vegetation dominates the understory. From June to October moose were found in mature conifer dominant forests with dense canopies. Subsequently, moose moved back into areas with dense understory vegetation during winter months. This study shows how ALS scanning data can be applied to aid in the interpretation of wildlife ecology.

HABITAT MODELLING

Habitat Suitability Indices (HSI's) are a valuable tool in wildlife management as they allow researchers to assume areas where species are most likely to occur. (Dussault 2006). The U.S. Fish and Wildlife Service first introduced HSI's to wildlife management in 1981. They were designed to provide methods for evaluating habitat preferences of species and the present habitats ability to support these preferences. (Hepinstall *et al.* 1996). HSI's for a target species are scored on a scale of 0 to 1. A score of 1 indicates habitat that meets all of the suitability parameters and therefore is optimal for species persistence (Dussault 2006). Models can be used in moose management to identify areas with optimal habitat and subsequent regions where habitat quality can be improved (Allen *et al.* 1987). Preliminary HSI's for moose in the Lake Superior region; developed by the US Fish and Wildlife Service, prioritize abundance of growing forage site and canopy cover, in addition to forest cover type composition (Allen *et al.* 1987) However, the lake superior region HSl does not consider hunting, predation, or pathogens as a part of the index. Habitat suitability is based primarily on aquatic forage, woody browse, and cover (Hepinstall *et al.* 1996). This leaves the effects of forestry practices on predator, hunting and pathogen access on moose habitat selection relatively unknown.

In Rempel *et al.* (1997), vegetation maps along with the Lake Superior Model II HSI for moose were used to determine HSI inputs for ideal forage, cover, winter cover and landscape treatment. The HSI was found to be highest in the modified clear-cut stand, which had a high density of forestry roads connecting various cut blocks. Osko *et al.* (2004) applied an HSI to two separate populations of moose in Alberta with the overall goal of proving that wildlife habitat preferences are not fixed. For both these populations, the same habitat classes were available but varied in relative abundance.

Results showed fluctuation in habitat class selection between the two populations indicating that population preferences are not fixed, but highly variable. This paper provides useful insight into the need for localized habitat suitability indices rather than large-scale fixed ones. In Dussault (2006), a habitat suitability index for moose was created for Canada's Boreal Forest. The main components of this index were: a suitability index for forage (SIfood) and another for the transition zones between cover and food (SIedge). These components were applied at various spatial scales including 500, 100 and 10 ha. Results determined that SIedge had a more significant impact at larger plots (500ha) whereas; SIfood was more influential in smaller plots. The methods used in this index are transferable to a variety of other studies as it is based on biological requirements.

Maximum entropy modeling (MEM) is a mathematical process in which a probability distribution predicts the suitability of conditions for each grid cell on a rasterized image. Phillips *et al.* (2006) used MEM to identify the geographic distributions of species with presence-only data. The study was conducted on a species of sloth and a small montane rodent. Predictions were made based on ten subset occurrence records for both species. Results showed that the MaxEnt software conducting the MEM analysis provided significantly better distribution modeling for both species than what is available in field guides. MaxEnt was also able to produce an accurate delineation of suitable versus unsuitable habitat. This depicts the usefulness of MaxEnt in modeling a presence only data set

MATERIALS AND METHODS

STUDY AREA

The study area for this project is located at the southeastern edge of the English River Forest (ERF). The ERF is situated in the western portion of the province's ecoregion 3W (Fig. 1). The forest falls under the jurisdiction of the OMNRF's Wildlife Management Unit (WMU) 15A and cervid ecological zone B. The study site itself is situated between the Moberly lake/Brightsand River conservation areas to the east, tri-lake area to the west, Baltic lake to the north, and the Wagner Private forest to the south (Wilkie 2018). Lawson (2009) deemed the area to be a vital moose aquatic feeding habitat. Bedrock in this zone is primarily Precambrian Shield, which is overlain by a thin collection of glacial and post-glacial deposits (Hupf *et al.* 2019). The majority of soils in the region are thin layers of gravel and sand, with areas of exposed bedrock intermittently placed. Low-lying areas in the zone are comprised of small lakes and wetlands, which provide essential summer feeding habitat for moose (Lawson 2009). Resolute Forest Products is the current SFL license holder for the English River Forest, which is approximately 10 000 km2 in total area. The study site for this project is 87 km2 of the total 10 000 km2 ERF, located in the southeast corner of the forest (Wilkie 2018). The area is currently undergoing decommissioning and reclamation efforts and hosts no active harvesting blocks. Roads in the area are at varying degrees of reclamation spanning from active to fully vegetated.

Source: OMNRF, 2018

Figure 1. Location of the English River Forest within Ontario.

PRESENCE DATA AQUISITION

Presence-absence data for Moose was collected from 18 Cabela's Outfitter 14MP Black Infrared HD trail cameras between May 15th, 2017 and October 3rd, 2017 (Wilkie 2018) (Appendix A). These cameras use Passive Infrared motion sensors, which do not emit a detectable flash when the sensor is triggered. The maximum detection area is 30° on either side of the unit for 25 m, with a narrower 100 m detection range (Wilkie 2018). Cameras were affixed to suitable trees along targeted paths and locked in place to deter theft. Placement varied from 0.5 meters to 1.5 meters above ground level; this was to ensure all cameras were at least 30 cm above ground vegetation. The average distance between cameras was 3.2km, with the closest cameras placed 61.2 m apart (Fig. 2). Presence photos were produced at a resolution of 14 MP, and trigger speed was set to 1 second with a 3-image burst and 10-second videos with a one-minute delay. No baits or wildlife attractants were used (Wilkie 2018). This was to ensure unbiased results and monitor the natural behaviors of the animals. Post-capture, photos were sorted by camera location and date of capture, animals observed were then identified, and moose observations were pulled from the broader data set. All presence points were compiled in Microsoft Excel in UTM coordinates and exported in a Comma-separated value (.csv) file for use in MaxEnt.

Source: Wilke, 2018

Figure 2. Location of Trail Cameras Within the Plot

HABITAT DATA ACQUISITION

Forest Resource Inventory

To determine landscape classes present in the ERF, remotely derived data was extracted from the Ontario Forest Resources Inventory (FRI). The FRI is an open-source data set produced by the MNRF that provides spatial information on tree species forest composition, condition, and regeneration (OMNR 2016). Data acquisition in the FRI is a combination of leaf-on black and white aerial imagery collected at 20 cm resolution and color infrared imagery collected at 40 cm resolution. Field sampling is used as a means to ground-truth aerial imagery to ensure image interpretation is highly accurate. The FRI for the ERF was downloaded from the Land Information Ontario metadata tool.

<u>Ontario Landscape Tool</u>

In order to use landscape class to identify key areas of moose habitat, the base FRI needed to be plugged into a program called the Ontario Landscape Tool (OLT). This open-source program enables users to import FRIs from anywhere within the province and export shapefiles produced from landscape simulations, including landscape classes present within a specific forest (Fig. 3). For this study, the FRI for the English River Forest was imported into an OLT scenario, and the model was run. Shapefiles derived from the finished scenario included landscape classes for the ERF, moose aquatic feeding areas, growing season cover for moose and growing season forage for moose. The primary file used to determine habitat suitability was landscape class, with the latter three serving as reference files.

Source: Elkie *et al.* 2018

Figure 3. Landscape classes present in the Northwest Region of Ontario as defined by the Ontario Landscape Tool (OLT).

GIS Modeling

Once the landscape class file was exported from OLT, it was plugged into ArcGIS 10.6, which is a spatial mapping software developed by Esri. The attribute table for the FRI was altered to include additional feature classes for each landscape class identified by OLT. Polygons identified as each landscape class were given a value of 100 and all other polygons were given a value of zero. This was repeated 15 times to cover each landscape class. Following this, each of the newly created feature classes in the landscape class shapefile were rasterized at a pixel resolution of 10 m by 10 m independently, producing a series of overlapping raster files with pixel values of either 100 or 0 based on individual landscape classes.

In addition to the 15 landscape class rasters, an additional two layers were created based on moose habitat preference. These layers were distance to cover and distance to water (Table 1). Based on literature reviewed it was determined that these factors would play a significant factor in habitat preference within the ERF. The Euclidean Distance tool in ArcGIS was used to rasterize the selected feature classes for water and cover at the extent of the FRI in 10 m by 10 m pixels, then to describe each cell within the rasters spatial relationship to the source feature class. All raster layers created were then converted into American Standard Code for Information Interchange (ASCII) files and compiled in a base environmental layers folder.

Table 1. Landscape class layers used to create preference layers of distance to cover (m) and distance to water (m) for moose in the English River Forest, ON.

Preference Layers	Landscape Class Layers
Distance to Cover (m)	Mature - Late Upland Conifer & Mixed
	Immature Conifer
Distance to Water (m)	Water

The focal statistics tool in ArcGIS was used to quantify distance to features. This tool uses neighborhood analysis to create an output raster in which each output cell is given a value that is a function of proximity to input cells (ESRI 2019). Focal statistics were run on the base rasters derived from the landscape class shapefile, including each of the landscape classes and the two additional preference files. These rasters were then converted into ASCII files and uploaded into a separate environmental layers folder for the focal sweep run.

A bias file for the moose presence points was created to manipulate the data set to select background data with the same bias as presence data collected from the trail cameras. The minimum bounding geometry tool in ArcGIS was used to create a minimum convex polygon around the presence locations. The buffer tool was then applied to this shapefile to create a 1 km buffer around the data points. The buffered shapefile was then rasterized at the same 10 m by 10 m pixel resolution.

MaxEnt

Moose habitat suitability in the ERF was determined and modeled by an open-source maximum entropy modeling software package called MaxEnt. The MaxEnt software package uses presence points, and environmental landscape layers to extract background information and cross-examine it with the given presence locations (Merow et al. 2013). Using this information, the program outputs a series of graphs and suitability maps that illustrate the prospective species distribution across the given landscape. MaxEnt settings (Table 2) and the bias file were kept the same in both runs to minimize variability. The output formats were set to logistic, the output file type was set to ASCII, and output grids were removed from both runs to reduce disk space and increase speed.

MaxEnt Models

Models produced through the implementation of the MaxEnt software included proposed spatial distribution maps, Area Under the Receiver Operating Characteristic graphs, permutation models and analyses of variable contributions. Output models were available through MaxEnt for each moose presence local and the collective group of locations. Three different runs were utilized to ensure the best habitat suitability index possible is produced from the given environmental variables. These three runs were a binary run without a focal sweep, a non-binary run with a focal sweep, and a non-binary run with non-contributing layers omitted. Habitat suitability was quantified for each of the three runs as minimum suitability, maximum suitability, median suitability and average suitability (Appendix B). Output results that were examined for the context of this thesis focused on the graphs and maps produced from the collection of variables. Focus was placed on the average suitability maps for each run, which provided the context for the likely spatial distribution of moose, as identified by the environmental variables.

Table 2. MaxEnt settings used for both binary and non-binary runs.

Settings Menu	Test Data Parameters	Values
Basic	Random Test Percentage	25
	Regularization Multiplier	1
	Max. # of Background Points	10000
	Replicates	15
	Replicated Run Type	Subsample
Advanced	Maximum Iterations	5000
	Convergence Threshold	0.00001
	Adjust Sample Radius	0
	Log File	maxent.log
	Default Prevalence	0.5

Jackknife Predictions

Jackknife predictions were used to evaluate the correlation of each environmental variable in the model. Jackknife predictions are a method of cross-validating results to determine the bias of an estimator (Abdi & Williams 2010). Each parameter in the model is estimated from the whole sample, then individual elements are removed from the model, and it is rerun. This enables the parameter of interest to be calculated from a smaller sample size. Jackknife predictions for this study were computed using AUC on test data

Receiver Operating Characteristic

Values for Area Under the Receiver Operating Characteristic (AUC) were used to evaluate the overall suitability of the model. AUC values can range anywhere from 0 to 1.0. If the AUC values are less than 0.5 the environmental layers are worse indicators of average fit than random predictions. If AUC values are closer to 1.0, it indicates better model performance.

RESULTS

CAMERA TRAPS

A total of 108 images of moose were collected during the 142-day capture period. Moose were captured on 14 of the 18 cameras deployed. Images were obtained throughout the day, with no direct temporal-specific preference. Most images were identifiable to sex, with the majority of the captures identified as males at 57 images, whereas females only accounted for 27 images. The remaining 24 images were not identifiable to sex.

MAXENT MODELS

Binary Input Run

The binary run produced a pointwise mean distribution model with spatial distribution encompassing a range of values from high probable occupancy indicated in red with a value of 1.0 to areas of no probably occupancy indicated in blue with a value of 0 (Fig. 4). Habitat distribution for this model was widespread throughout the forest without a significant range of suitability, however most habitat occupied a value range of around 0.46 to 0.15. Red areas identified in this model are indicative of high probability of occupancy. Interestingly, the areas identified as having the highest probable occupancy fell along identified road corridors. This is likely a result of the rasterization process in ArcGIS. Environmental layers with the highest relative contributions to the model include mature – late upland conifer and mixed, pre-sapling – sapling, and mature – late lowland conifer and mixed (Appendix C). These habitat types were identified earlier in the study as potential indicators of moose growing season cover and growing season forage respectively.

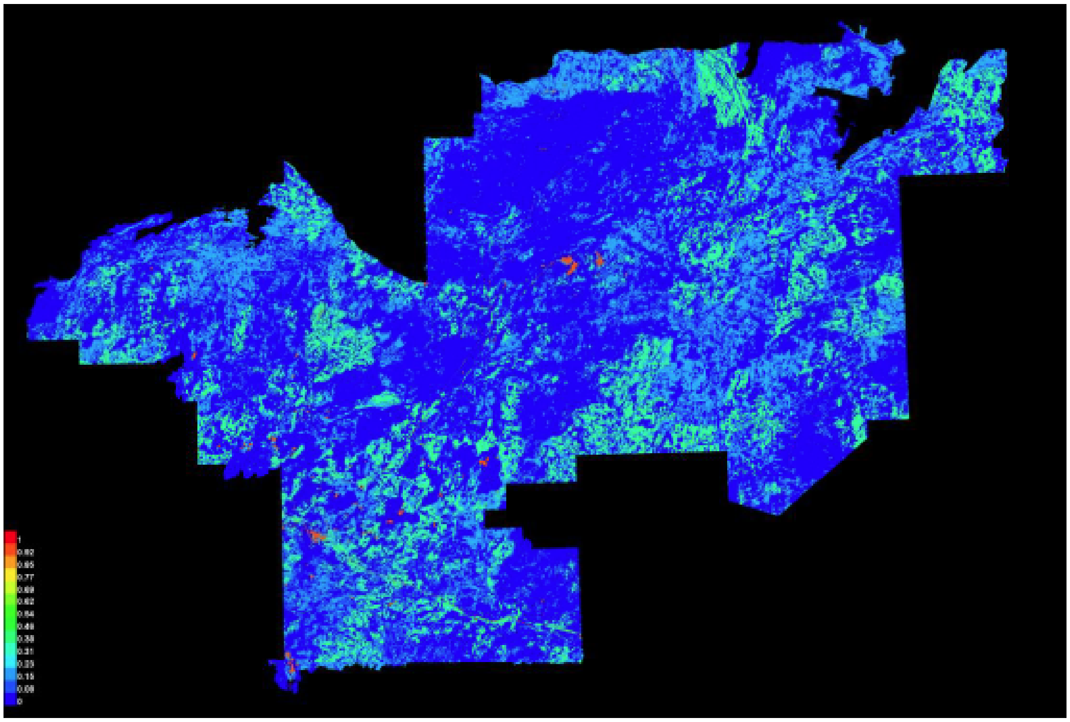

Figure 4. Mean spatial distribution of moose in the ERF based on binary values for environmental layers.

The receiver operating characteristic (ROC) graph for this model (Fig. 5) shows that the average test AUC for the model is 0.808 and the standard deviation is 0.191, suggesting a relatively high predictive power of the model.

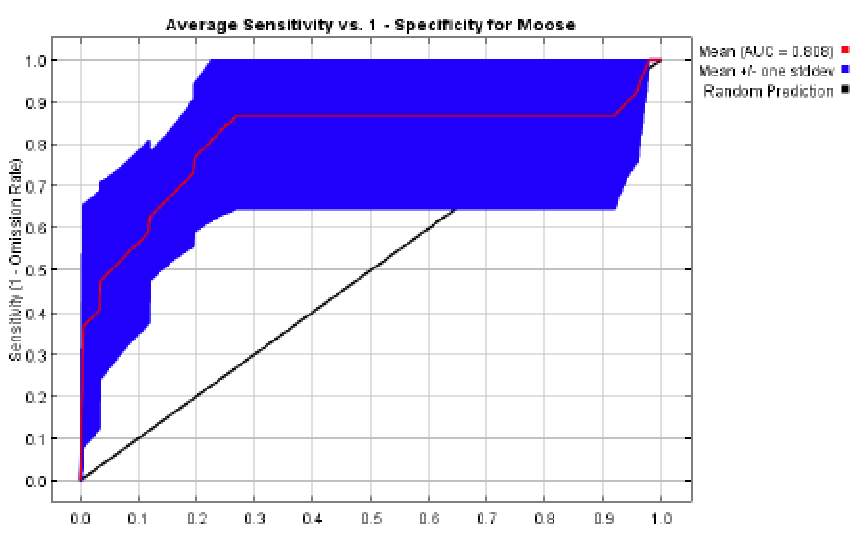

Figure 5. Receiver operating characteristic (ROC) curve for binary data averaging over replicate runs.

Jackknifing tests for the binary model (Fig. 6) showed that the layers with the highest variable importance in the binary model were mature – late upland conifer and mixed, water and mature – late lowland conifer and mixed (Appendix E). The layer with the lowest variable importance in the model were distance to cover, distance to water, grass and rock. Training gain values dropped the most with the removal of the mature – late lowland conifer and mixed, and mature – late upland conifer and mixed layers. This indicates that these layers were key predictors of moose occurrence in the English River study area.

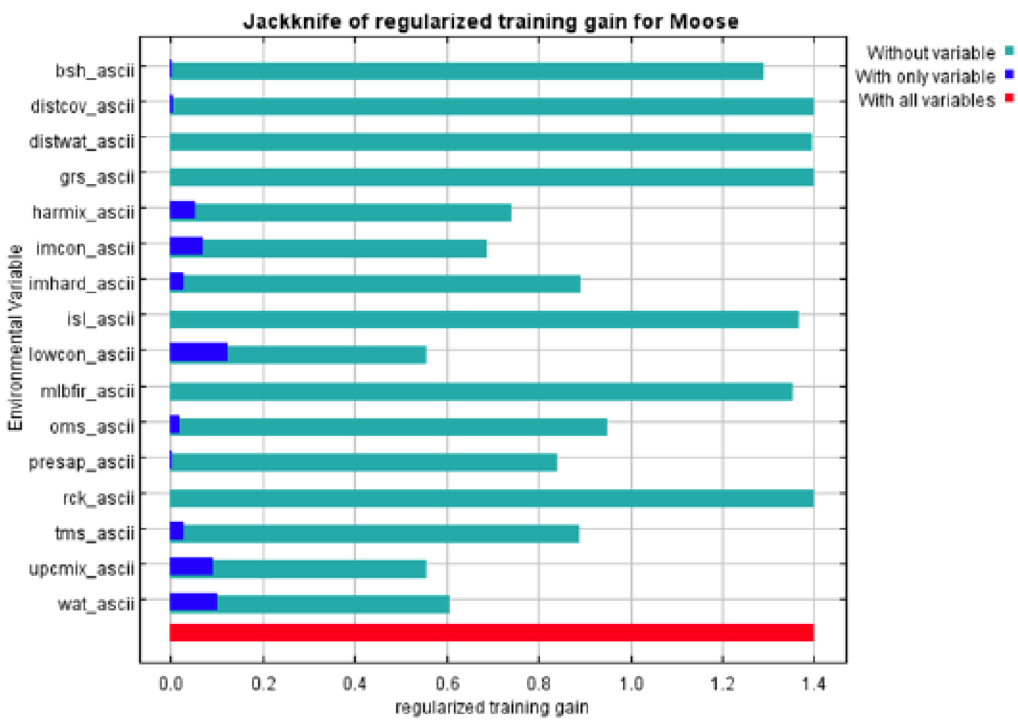

Figure 6. Jackknife predictions of Regularized Training Gain for moose for individual environmental variables (binary).

<u>Non-Binary Input Run (With Focal Sweep)</u>

The non-binary (focal sweep) run produced a pointwise mean distribution model with spatial distribution encompassing a range of values from moderate distribution indicated in yellow, to areas of no distribution indicated in blue (Fig. 7). Habitat suitability in this model encompasses a wider range of values with the highest probability focused in areas of lowland conifer, immature conifer and mixed-wood, and stands adjacent to these variables with values spanning from 0.77 to 0.23. Environmental layers with the highest relative contributions to this model include mature – late lowland conifer and mixed, pre-sapling – sapling, and immature conifer (Appendix C). Interestingly, pre-sapling sapling had the second highest percent contribution to the model. However, it had zero permutation importance. This indicates that there may be other highly correlated variables associated with this particular layer, skewing the results.

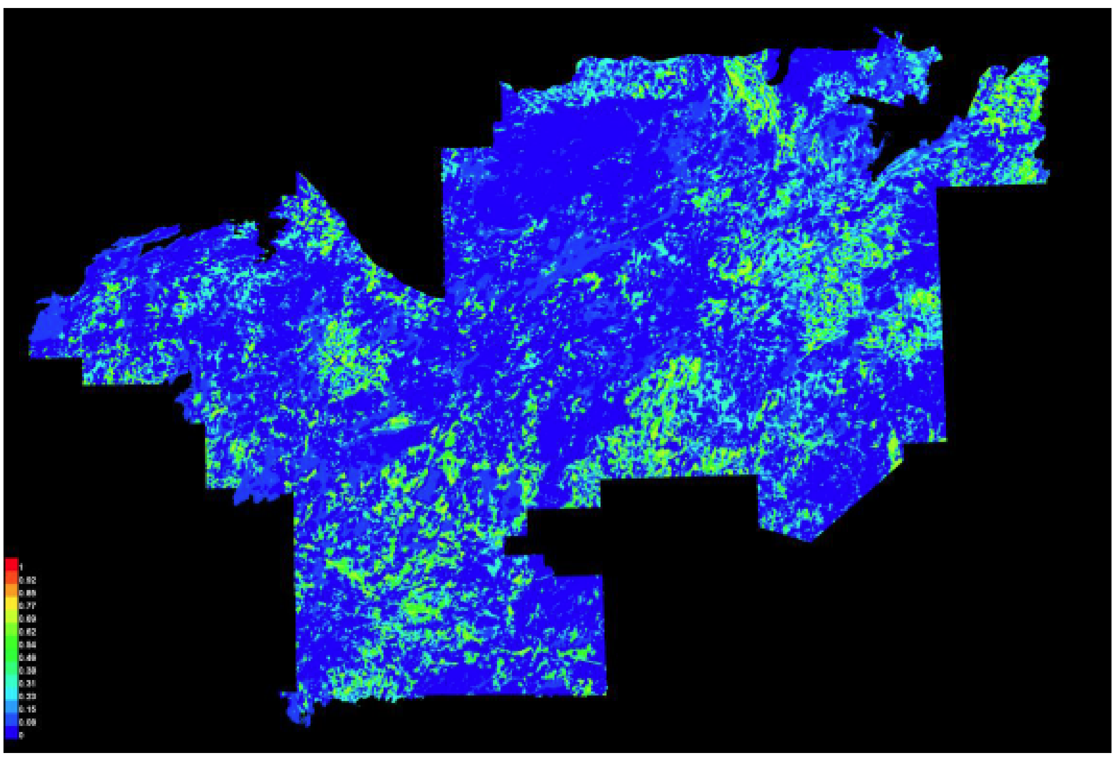

Figure 7. Mean spatial distribution of moose in the ERF based on non-binary (focal sweep) values for environmental layers.

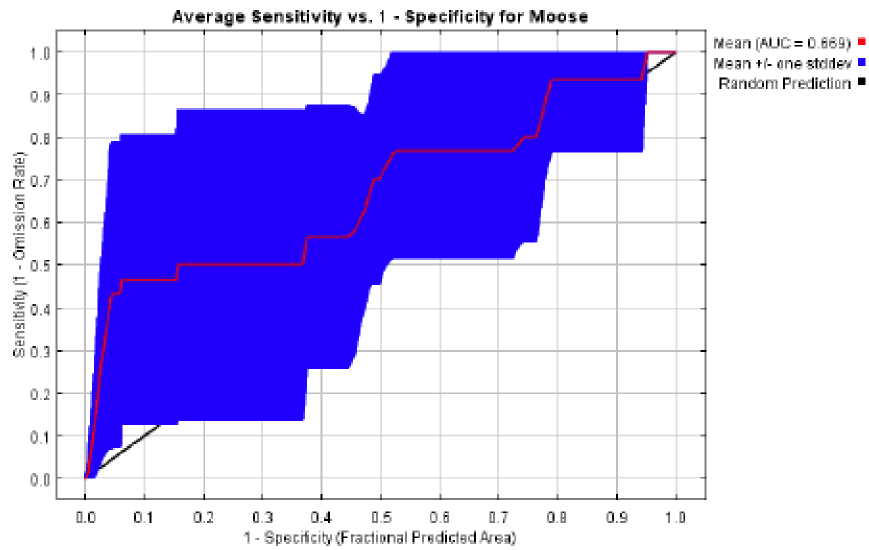

Figure 8. Receiver operating characteristic (ROC) curve for non – binary (focal sweep) data averaging over replicate runs.

The receiver operating characteristic (ROC) graph for the non-binary (focal sweep) model (Fig. 8) indicates that the average test AUC for the model is 0.669 and the standard deviation is 0.188. Although the AUC values for this model are less than the previous binary run, the model is no longer classifying the road corridors as habitat and is likely a better predictor of moose distribution.

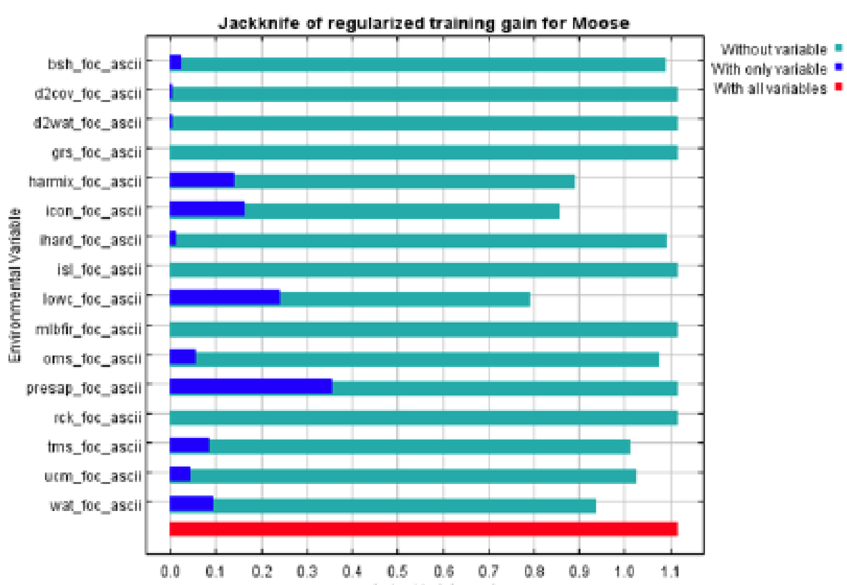

Figure 9. Jackknife predictions of Regularized Training Gain for moose for individual environmental variables (non-binary).

Jacknife tests also indicted that layers with the highest contribution to the model were mature – late upland conifer and mixed, and mature – late lowland conifer and mixed (Fig. 9). The layers with the lowest variable importance in the model were immature hardwood and open muskeg (Appendix E). Regularized training gain values for pre-sapling – sapling were significantly higher when running with only that layer as opposed to the run that did not include the variable. Without the variable there is no changed in the training gain giving the indication that this model does not contribute any additional information and should be subsequently removed from the run to ensure a better overall fit.

Non-Binary Run With Omitted Layers

The binary run produced a pointwise mean distribution model with spatial distribution encompassing a range of values from moderate distribution indicated in yellow to areas of no distribution indicated in blue (Fig. 10). Habitat distribution in this model mirrored that of the non-binary run, but increased the focus on areas of upland conifer & mixed and lowland conifer with most values spanning the range of 0.77 to 0.23. Environmental layers with the highest relative contributions to the model include mature – late upland conifer and mixed, and mature – late lowland conifer and mixed (Appendix C). Notable layers omitted from this model include rock, islands, grass, mature – late balsam fir and mixed and pre-sapling – sapling. All layers except pre-sapling – sapling were removed after consulting the original non-binary run, as they were determined to be insignificant in predicting moose distribution throughout the ERF.

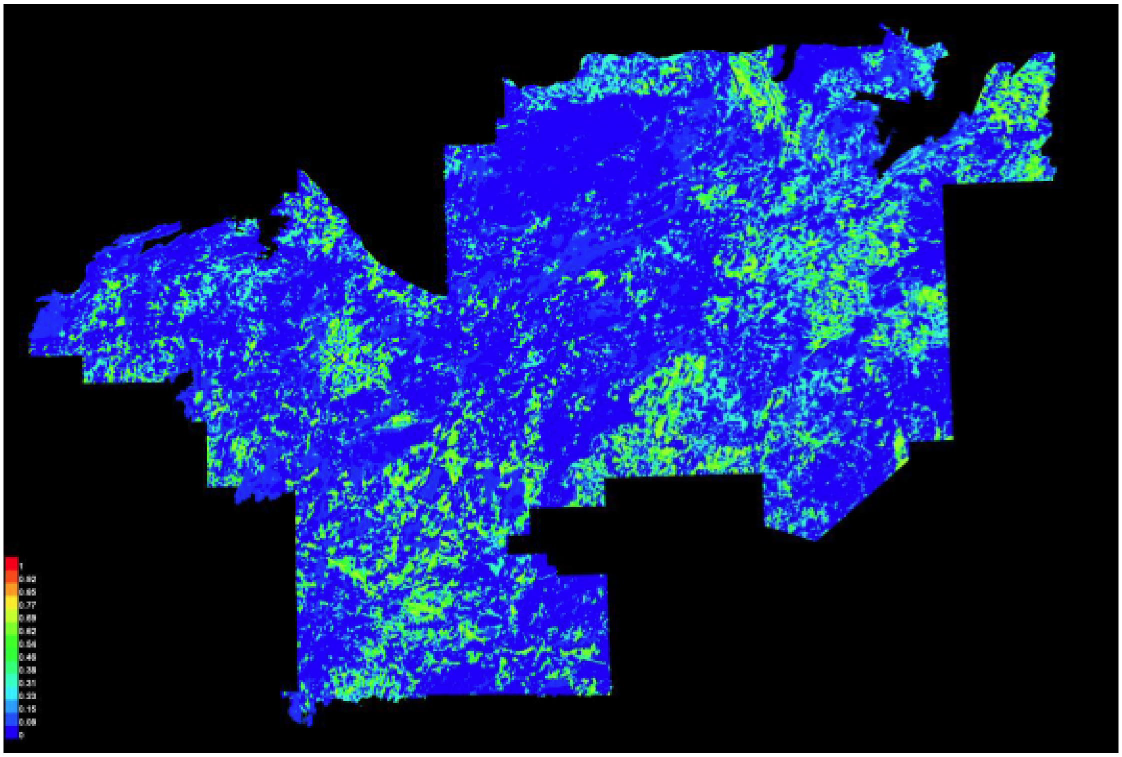

Figure 10. Mean spatial distribution of moose in the ERF based on non- binary values for select environmental layers.

The receiver operating characteristic (ROC) graph for the non-binary run with omitted layers (Fig. 11) indicates that the average test AUC for the model is 0.771 and the standard deviation is 0.161. This is again an improvement on the previous model.

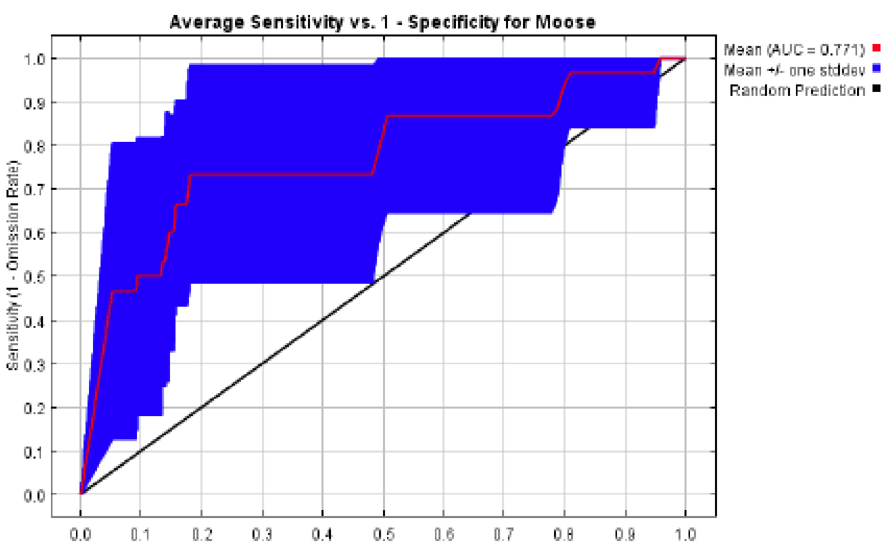

Figure 11. Receiver operating characteristic (ROC) curve for non – binary run with omitted layers data averaging over replicate runs.

Layers with the highest variable importance in the non –binary with omitted layers Jackknife prediction model were mature – late upland conifer and mixed, and mature – late lowland conifer and mixed (Fig. 12). The layers with the lowest variable importance in the model were immature hardwood and open muskeg (Appendix E). These values are similar to the non-binary (focal sweep) run and therefore indicate that the omission of selected layers had little to no adverse impact on the predictions results. The removal of the pre-sapling – sapling layer improved the model's predictability and removed potential bias associated with the overfitting of that layer.

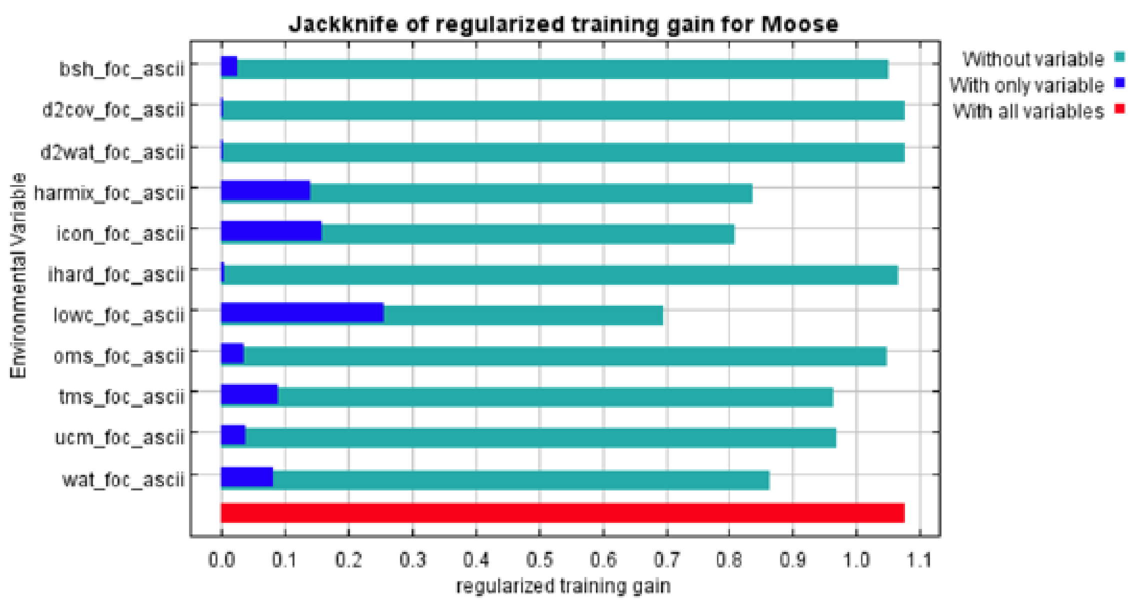

Figure 12. Jackknife predictions of AUC for moose for individual environmental variables (non-binary with omissions).

DISCUSSION

This study aimed to develop a rudimentary habitat suitability index (HSI) for moose (*Alces alces*) in the English River Forest, ON with presence data collected from trail camera imagery. While this method produced several models with reasonably accurate performance, improvements can be made to both the presence and habitat data acquisition phases to better understand the actual spatial distribution of the species within the forest. The first area examined was the method used to acquire presence locals through camera traps. The main issue with the method employed was the limited number of data points acquired, which will be examined in the following section. Additionally, errors within the GIS modeling process limited the contributions of certain environmental layers within the models, this was due to operator bias and not a result of software limitations. In terms of the three models developed, each model varies in their overall suitability with the binary model being the worst overall fit with an inherent bias towards roads and the non-binary model with non-contributing layers omitted having the best overall fit out of three. HSIs are not a new concept in wildlife management. They are widespread throughout many biogeographical flora and fauna studies. However, this study attempted to create an accurate model using localized presence points, essentially making the model more accessible in terms of cost efficiency. The results of this study will be discussed in detail below in terms of their fit, limitations, and biases, which enable recommendations to be made to ensure future studies can improve on these shortfalls.

CAMERA TRAPS

Source: Wilke, 2018

Figure 13. Cabela's Outfitter 14 MP Black Infrared HD trail camera being affixed to tree.

Presence points for this study were gathered from camera traps placed along road corridors in a southeastern block of the ERF. There were two main reasons why camera traps were employed in this study. The first was to reduce observer bias in the data collection (Randler & Kalb 2018). Images captured require observers to go into the field a minimum of two times to set and collect the image memory cards. Captured photos may then be examined in a lab by a variety of observers to ensure accurate species identification. The second reason as to why camera traps were employed in this study was to ensure that the data collection process was cost efficient and repeatable. Tracking systems that utilize global positioning systems (GPS) can range in price from $7000 to $9000 USD per individual unit, for a one-year study. These numbers however do not factor in battery replacements or technician fieldwork wages (Thomas *et al.* 2011).

Whereas, the average cost for a high-quality trail camera is around \$300 to \$600 USD (Swann *et al.* 2004). This might seem like quite a high number when buying cameras in bulk. However, these devices have relatively no maintenance costs, unlike GPS devices. Trail cameras again only require the placement and collection of the unit at the start and end of the study period, and the resulting images can be examined in a variety of contexts other than for presence locals. With both of these benefits considered, trail cameras were identified as an idealistic tracking method for this study. Cameras used in this study fell into the more affordable category of around \$99 USD (Cabelas Canada 2018).

The use of camera traps provided accurate and reliable presence data for use in the MaxEnt suitability index. However, this method was not immune to shortfalls. The way in which the image locals were collected for this study incorporated potential bias into the model. There are three main areas where potential bias was incorporated through the use of trail cameras. The first potential bias contributor would be the location of camera traps. Trail cameras used in this study were placed as part of a Masters of Science in Forestry thesis on road reclamation efforts. Therefore, all presence points were collected on road corridors, as the original intended use of the data was to monitor wildlife on roads following various decommissioning methods. A second contributor of potential bias was the number of cameras included in the study. While the use of an 18-camera suite was sufficient to produce an HSI, the results could have been more comprehensive and representative if additional cameras were included. The final area where bias could have been introduced is through the delineation of the study area. The study area was around 87 km^2, located in the southeastern portion of the ERF. The surrounding forest type in this area is primarily mature – late lowland conifer and pre-sapling - sapling. This caused the models to consider moose habitat as a product of mainly lowland conifer and sapling stands. As a result, two out of the three models were highly correlated to these variables.

Future studies that intend to incorporate camera traps to quantify ungulate presence throughout a forest should consider implementing some of the following recommendations. The first recommendation would be to ensure that enough cameras are placed throughout the study area to amass more than 20 presence points during the collection period. Guisan *et al.* (2017) suggest that an idealistic number of observations should fall somewhere within the range of 20 to 50. While increasing the number of cameras in the suite is beneficial in a quantifiable context, it is redundant in terms of qualitative results if cameras locations are biased. Future studies should place cameras in a multitude of different forest compositions to ensure unbiased results. A final recommendation for future studies would be to ensure that cameras are not set directly on road corridors to ensure that these areas are not being unfairly considered as habitat throughout the modeling process.

HABITAT SUITABILITY MODELS

The habitat suitability models produced during this study used a standard method called maximum entropy modeling (MEM). The process of MEM enables habitat suitability to be quantified as a combination of environmental input variables and species presence localities (Phillips *et al.* 2004). The MEM software used in this study was MaxEnt. This program uses the distribution of maximum entropy, subject to the constraint of each input variable, to determine a species target distribution. This software has been used in many spatial distribution models in the past, including Phillips *et al.*'s (2006) inquisition into the spatial distribution of *Bradypus variegatus*, a small species of sloth. One of the benefits of the open-source MaxEnt software is its user-friendliness. The program utilizes a simple graphical interface that requires minimal inputs (Venette 2015). With a base knowledge of GIS modeling software and file conversions, the program runs seamlessly.

Three models were produced through the use of MaxEnt to quantify the spatial distribution of moose in the ERF. The first model was a binary run where all environmental layers were given a raster cell value of either 100 or 0 based on the corresponding variable. The second model was a non-binary run where a focal sweep was employed to attribute range values to raster cells based on their distance from the corresponding variable. The third run was a non-binary run where layers that were found to be non-contributing or overfit to the original non-binary run were removed. These various models were selected for this study to illustrate the differences between binary and non-binary methods fully, and how distance to select environmental variables can play a significant factor in the spatial distribution of moose. Comparisons of the three habitat suitability models produced in this study can help to identify which model was the most accurate in terms of probable distribution and identify deficiencies accumulated throughout the modeling.

The first model produced was from the binary input run. This run utilized binary input layers as the environmental variables for the model. The binary run produced a habitat suitability index with the highest AUC value of all three models at 0.808. However, even with a high AUC score the accuracy of this model was determined to be quite low as a result of manual rasterization biases. The FRI is acquired from the Land Information Ontario metadata tool as a vector package and must be rasterized in a GIS modeling software to utilize it within MaxEnt. During this process, each variable was given a value of 100, and all subsequent variables in the attribute table were assigned a value of 0. This process was complete for each landscape class. The main issue with this process is that in ArcGIS values of 0 are not considered null. When the environmental variables were plugged into MaxEnt the unclassified layer which houses all the roads information was left unchecked and not included in the model. This was done under the assumption that if left unchecked, the results would not be inaccurately skewed towards identifying roads as habitat. However, since raster cells labeled unclassified in each of the other models were given a value of 0, the model still identified these areas as having high potential suitability. This issue could have been mitigated if, during the rasterization process, cells labeled as unclassified are given a null value instead of 0.

The second model that was produced came from the non-binary (focal sweep) run. For this run, binary raster's generated from the previous model had focal statistics run on them in ArcGIS. This enabled cells previously labeled as 0 to acquire new values based on their distance from each identified environmental variable. The focal sweep also solved the issue with the unclassified cells in the binary run as these areas were provided values based on the surrounding landscape classes. The AUC value for this run was 0.669, a significant drop from the value of the binary run. Although the test AUC was lower for this run compared to the previous, it is no longer identifying roads a prime moose habitat, which would warrant a reduction in the suitability matrix. While an improvement on the previous model, the non-binary run was not immune to its shortfalls. Based on the jackknife predictions for the AUC, the model is significantly overfitting to the pre-sapling – sapling layer, so much so that the AUC value would improve to nearly 0.9 if the model were rerun with this variable alone. Essentially, areas classified as pre-sapling – sapling are being selected at a significantly higher rate than other variables.

To mitigate the issues prevalent in the previous two models, a third model was run. This model utilized the environmental variables from the non-binary run, and omitted layers that were found to be non-contributing, or overfit to the model. Layers that were omitted include rock, islands, grass, mature – late balsam fir and mixed and pre-sapling – sapling. The AUC value for this run was 0.771, which is higher than the binary model but still less than the non-binary. Although the AUC falls in the middle of the pack, this model was determined to be the best overall fit for the spatial distribution of moose in the ERF. All layers in the model were found to have a percent contribution and permutation importance to the model except for distance to cover and distance to water, which was found to have no significant effect on the model. It is unknown as to why these variables did not have a considerable contribution within the context of this model. However, it is likely a result of some sort of error throughout the rasterization process.

Based on the findings of each of the three models outlined in this study, recommendations can be made on how to improve this process for future studies. The first recommendation would be to ensure that there are no issues present in the rasterization process before executing the model. This was a significant source of error in two out of the three runs, and could not be rectified due to time constraints. The second recommendation would be to ensure environmental variables selected are of recognized ecological value to moose. Some of the variables included in this study were not necessarily influential predictors of moose occurrence, such as grass, rock and pre-sapling-sapling. Their subsequent removal ended up improving the model. Additionally, if layers such as distance to cover and distance to water were removed, it may also improve the model's overall fit. Environmental variables that may be of interest to include in future studies to introduce new information to the model include terrain elevation, burn areas and distance to roads.

CONCLUSIONS

This study demonstrated how trail camera imagery can be a useful tool in developing a habitat suitability index for moose. Camera units are inherently affordable when compared to telemetry or GPS methods. Additionally their portability, and ease of use are unmatched by other presence point, acquisition methods, which require extensive fieldwork and multiple crews to deploy and maintain tracking devices. This makes them an excellent option for research projects where the budget is a constraint. Camera traps were used throughout this study in conjunction with a maximum entropy modelling software called MaxEnt. This software proved its worth as a potential option to use in conjunction with camera traps. MaxEnt is both open-source and relatively user-friendly, which makes it an ideal match with trail cameras if affordability and accuracy are the ultimate goal. Together, these methods make the production of a habitat suitability index more accessible to researchers. The models generated from this study however were not immune to shortfalls. Bias introduced in the GIS modelling process and the high correlation of certain environmental variables included in the study, resulted in two out of the three models lacking accuracy. The best model was clearly the non-binary run with non-contributing layers omitted, however distance to cover and distance to water should have been removed to enhance accuracy, but they were left in to illustrate their relative unimportance to the overall fit all three models. It is recommended that future studies look into removing these last two layers, rectifying issue present in the GIS modelling process and introducing additional variables such as elevation or burn areas.

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APPENDICIES

APPENDIX A – INVENTORY OF MOOSE IMAGES AND LOCATIONS

Camera Location	Camera Number	Serial Number	Coordinates (N)	Coordinates (W)	File Type	Common Name	Genus	Species	Sex	Date Captured	Time	Date Collected From Field
Corner of road	Camera 20	1612080109	49°32'52.20"	90°40'28.80"	Image	Moose	Alces	alces	Male	17-05-23	11:45 AM	17-05-25
Corner of road	Camera 20	1612080109	49°32'52.20"	90°40'28.80"	Video	Moose	Alces	alces	Male	17-05-23	22:52 PM	17-05-25
Hill-corner	Camera 6	1612080108	49°32'52.20"	90°40'28.80"	Image	Moose	Alces	alces	Female	17-05-23	23:06 PM	17-05-25
Hill-corner	Camera 6	1612080108	49°32'52.20"	90°40'28.80"	Video	Moose	Alces	alces	Female	17-05-23	22:57 PM	17-05-25
South Access	Camera 11	1612080102	49°32'44.90"	90°40'40.77"	Video	Moose	Alces	alces	NA	17-05-20	13:59 PM	17-05-25
Bridge Pull	Camera 8	1612080156	49°33'25.98"	90°38'54.07"	Image	Moose	Alces	alces	Male	17-06-07	10:53 AM	17-06-22
Chip Pile	Camera 5	1612080187	49°34'40.43"	90°39'00.71"	Image	Moose	Alces	alces	NA	17-05-27	8:17AM	17-06-22
Chip Pile	Camera 5	1612080187	49°34'40.43"	90°39'00.71"	Video	Moose	Alces	alces	NA	17-05-27	8:18 AM	17-06-22
Chip Pile	Camera 5	1612080187	49°34'40.43"	90°39'00.71"	Image	Moose	Alces	alces	Male	17-06-04	9:40 AM	17-06-22
Chip Pile	Camera 5	1612080187	49°34'40.43"	90°39'00.71"	Video	Moose	Alces	alces	Male	17-06-04	9:42 AM	17-06-22
Chip Pile	Camera 5	1612080187	49°34'40.43"	90°39'00.71"	Video	Moose	Alces	alces	NA	17-06-11	7:43 AM	17-06-22
North access	Camera 18	1612080117	49°34'56.38"	90°38'31.27"	Image	Moose	Alces	alces	Male	17-06-04	14:13 PM	17-06-22
North access	Camera 18	1612080117	49°34'56.38"	90°38'31.27"	Video	Moose	Alces	alces	Male	17-06-04	21:59 PM	17-06-22
North culvert pull	Camera 19	1612080156	49°34'54.60"	90°37'32.10"	Image	Moose	Alces	alces	Female	17-05-25	21:17 PM	17-06-22
North culvert pull	Camera 19	1612080156	49°34'54.60"	90°37'32.10"	Image	Moose	Alces	alces	Female	17-05-25	13:53 PM	17-06-22
North culvert pull	Camera 19	1612080156	49°34'54.60"	90°37'32.10"	Video	Moose	Alces	alces	Female	17-05-25	8:03 AM	17-06-22
North culvert pull	Camera 19	1612080156	49°34'54.60"	90°37'32.10"	Image	Moose	Alces	alces	Female	17-05-25	21:58 PM	17-06-22
North culvert pull	Camera 19	1612080156	49°34'54.60"	90°37'32.10"	Video	Moose	Alces	alces	Female	17-05-25	12:09 AM	17-06-22
North culvert pull	Camera 19	1612080156	49°34'54.60"	90°37'32.10"	Image	Moose	Alces	alces	Female	17-05-25	8:30 AM	17-06-22
North culvert pull	Camera 19	1612080156	49°34'54.60"	90°37'32.10"	Video	Moose	Alces	alces	Female	17-05-25	21:42 PM	17-06-22
North culvert pull	Camera 19	1612080156	49°34'54.60"	90°37'32.10"	Image	Moose	Alces	alces	Female	17-05-25	9:33 AM	17-06-22
North culvert pull	Camera 19	1612080156	49°34'54.60"	90°37'32.10"	Video	Moose	Alces	alces	Female	17-05-25	23:15 PM	17-06-22
North culvert pull	Camera 19	1612080156	49°34'54.60"	90°37'32.10"	Image	Moose	Alces	alces	Male	17-05-25	23:10 PM	17-06-22

Appendix A. cont'd.

Camera Location	Camera Number	Serial Number	Coordinates (N)	Coordinates (W)	File Type	Common Name	Genus	Species	Sex	Date Captured	Time	Date Collected From Field
North culvert pull	Camera 19	1612080156	49°34'54.60"	90°37'32.10"	Video	Moose	Alces	alces	Male	17-05-25	1:05 AM	17-06-22
North culvert pull	Camera 19	1612080156	49°34'54.60"	90°37'32.10"	Image	Moose	Alces	alces	Male	17-05-25	7:18 AM	17-06-22
North culvert pull	Camera 19	1612080156	49°34'54.60"	90°37'32.10"	Video	Moose	Alces	alces	Male	17-05-25	8:26 AM	17-06-22
North culvert pull	Camera 19	1612080156	49°34'54.60"	90°37'32.10"	Image	Moose	Alces	alces	Male	17-05-25	13:07 PM	17-06-22
North culvert pull	Camera 19	1612080156	49°34'54.60"	90°37'32.10"	Video	Moose	Alces	alces	Male	17-05-25	13:08 PM	17-06-22
North culvert pull	Camera 19	1612080156	49°34'54.60"	90°37'32.10"	Image	Moose	Alces	alces	Male	17-05-25	9:07 AM	17-06-22
North culvert pull	Camera 19	1612080156	49°34'54.60"	90°37'32.10"	Image	Moose	Alces	alces	Male	17-05-26	9:41 AM	17-06-22
North culvert pull	Camera 19	1612080156	49°34'54.60"	90°37'32.10"	Video	Moose	Alces	alces	Male	17-05-26	16:57 PM	17-06-22
North culvert pull	Camera 19	1612080156	49°34'54.60"	90°37'32.10"	Image	Moose	Alces	alces	Male	17-05-26	5:20 AM	17-06-22
North culvert pull	Camera 19	1612080156	49°34'54.60"	90°37'32.10"	Video	Moose	Alces	alces	Male	17-05-26	11:22 AM	17-06-22
North culvert pull	Camera 19	1612080156	49°34'54.60"	90°37'32.10"	Image	Moose	Alces	alces	Male	17-05-26	21:06 PM	17-06-22
North culvert pull	Camera 19	1612080156	49°34'54.60"	90°37'32.10"	Video	Moose	Alces	alces	Male	17-05-26	6:46 AM	17-06-22
North culvert pull	Camera 19	1612080156	49°34'54.60"	90°37'32.10"	Image	Moose	Alces	alces	NA	17-06-06	11:54 AM	17-06-22
North culvert pull	Camera 19	1612080156	49°34'54.60"	90°37'32.10"	Video	Moose	Alces	alces	NA	17-06-06	21:27 PM	17-06-22
North culvert pull	Camera 19	1612080156	49°34'54.60"	90°37'32.10"	Image	Moose	Alces	alces	Male	17-06-11	21:28 PM	17-06-22
North culvert pull	Camera 19	1612080156	49°34'54.60"	90°37'32.10"	Video	Moose	Alces	alces	Male	17-06-11	8:21 AM	17-06-22
South Access	Camera 11	1612080102	49°32'44.90"	90°40'40.77"	Image	Moose	Alces	alces	NA	17-06-21	14:04 PM	17-06-22
Chip Pile	Camera 5	1612080187	49°34'40.43"	90°39'00.71"	Image	Moose	Alces	alces	Male	17-06-28	2:38 AM	17-07-26
Chip Pile	Camera 5	1612080187	49°34'40.43"	90°39'00.71"	Video	Moose	Alces	alces	Male	17-06-28	12:14 AM	17-07-26
Chip Pile	Camera 5	1612080187	49°34'40.43"	90°39'00.71"	Image	Moose	Alces	alces	Female	17-07-04	20:38 PM	17-07-26
Chip Pile	Camera 5	1612080187	49°34'40.43"	90°39'00.71"	Image	Moose	Alces	alces	Female	17-07-12	20:01 PM	17-07-26

Appendix A. cont'd.

Camera Location	Camera Number	Serial Number	Coordinates (N)	Coordinates (W)	File Type	Common Name	Genus	Species	Sex	Date Captured	Time	Date Collected From Field
Chip Pile	Camera 5	1612080187	49°34'40.43"	90°39'00.71"	Video	Moose	Alces	alces	Female	17-07-12	7:10 AM	17-07-26
Chip Pile	Camera 5	1612080187	49°34'40.43"	90°39'00.71"	Image	Moose	Alces	alces	Female	17-07-16	22:30 PM	17-07-26
Chip Pile	Camera 5	1612080187	49°34'40.43"	90°39'00.71"	Video	Moose	Alces	alces	Female	17-07-16	21:44 PM	17-07-26
Corner of road	Camera 6	1612080109	49°32'52.20"	90°40'28.80"	Image	Moose	Alces	alces	Male	17-07-13	11:01 AM	17-07-26
Corner of road	Camera 6	1612080109	49°32'52.20"	90°40'28.80"	Video	Moose	Alces	alces	Male	17-07-13	6:41 AM	17-07-26
South Access	Camera 11	1612080102	49°32'44.90"	90°40'40.77"	Image	Moose	Alces	alces	Female	17-06-28	12:34 PM	17-07-26
South Access	Camera 11	1612080102	49°32'44.90"	90°40'40.77"	Video	Moose	Alces	alces	Female	17-06-28	18:32 PM	17-07-26
South Access	Camera 11	1612080102	49°32'44.90"	90°40'40.77"	Image	Moose	Alces	alces	Female	17-07-12	13:32 PM	17-07-26
North access	Camera 18	1612080117	49°34'56.38"	90°38'31.27"	Image	Moose	Alces	alces	Male	17-06-28	9:45 AM	17-07-26
North access	Camera 18	1612080117	49°34'56.38"	90°38'31.27"	Video	Moose	Alces	alces	Male	17-06-28	9:46 AM	17-07-26
North access	Camera 18	1612080117	49°34'56.38"	90°38'31.27"	Video	Moose	Alces	alces	NA	17-07-09	14:34 PM	17-07-26
North access	Camera 18	1612080117	49°34'56.38"	90°38'31.27"	Image	Moose	Alces	alces	Male	17-07-09	11:20 AM	17-07-26
North access	Camera 18	1612080117	49°34'56.38"	90°38'31.27"	Video	Moose	Alces	alces	NA	17-07-09	12:41 PM	17-07-26
North access	Camera 18	1612080117	49°34'56.38"	90°38'31.27"	Video	Moose	Alces	alces	NA	17-07-09	13:12 PM	17-07-26
North access	Camera 18	1612080117	49°34'56.38"	90°38'31.27"	Video	Moose	Alces	alces	NA	17-07-09	13:38 PM	17-07-26
North access	Camera 18	1612080117	49°34'56.38"	90°38'31.27"	Image	Moose	Alces	alces	NA	17-07-09	11:26 AM	17-07-26
North access	Camera 18	1612080117	49°34'56.38"	90°38'31.27"	Video	Moose	Alces	alces	NA	17-07-09	21:25 PM	17-07-26
North access	Camera 18	1612080117	49°34'56.38"	90°38'31.27"	Video	Moose	Alces	alces	NA	17-07-09	21:29 PM	17-07-26
North access	Camera 18	1612080117	49°34'56.38"	90°38'31.27"	Image	Moose	Alces	alces	Male	17-07-14	10:40 AM	17-07-26
North access	Camera 18	1612080117	49°34'56.38"	90°38'31.27"	Video	Moose	Alces	alces	Male	17-07-14	19:46 PM	17-07-26
North access	Camera 18	1612080117	49°34'56.38"	90°38'31.27"	Video	Moose	Alces	alces	Male	17-07-18	23:02 PM	17-07-26
Middle of road	Camera 20	1612080109	49°32'49.79"	90°40'30.58"	Image	Moose	Alces	alces	NA	17-06-28	15:09 PM	17-07-26
Middle of road	Camera 20	1612080109	49°32'49.79"	90°40'30.58"	Video	Moose	Alces	alces	NA	17-06-28	15:28 PM	17-07-26
Middle of road	Camera 20	1612080109	49°32'49.79"	90°40'30.58"	Image	Moose	Alces	alces	Male	17-07-13	5:53 AM	17-07-26
Middle of road	Camera 20	1612080109	49°32'49.79"	90°40'30.58"	Video	Moose	Alces	alces	Male	17-07-13	10:19 AM	17-07-26
Chip Pile	Camera 5	1612080187	49°34'40.43"	90°39'00.71"	Image	Moose	Alces	alces	Male	17-08-02	15:58 PM	17-08-02

Appendix A. cont'd.

Camera Location	Camera Number	Serial Number	Coordinates (N)	Coordinates (W)	File Type	Common Name	Genus	Species	Sex	Date Captured	Time	Date Collected From Field
Chip Pile	Camera 5	1612080187	49°34'40.43"	90°39'00.71"	Image	Moose	Alces	alces	Male	17-08-02	2:46 AM	17-08-02
Chip Pile	Camera 5	1612080187	49°34'40.43"	90°39'00.71"	Image	Moose	Alces	alces	Male	17-08-02	13:51 PM	17-08-02
Corner of road	Camera 6	1612080109	49°32'52.20"	90°40'28.80"	Video	Moose	Alces	alces	Male	17-08-01	20:48 PM	17-08-02
Bridge Pull	Camera 8	1612080156	49°33'25.98"	90°38'54.07"	Video	Moose	Alces	alces	Female	17-06-29	21:02 PM	17-08-02
Bridge Pull	Camera 8	1612080156	49°33'25.98"	90°38'54.07"	Image	Moose	Alces	alces	Female	17-07-05	21:05 PM	17-08-02
Bridge Pull	Camera 8	1612080156	49°33'25.98"	90°38'54.07"	Image	Moose	Alces	alces	NA	17-07-05	16:23 PM	17-08-02
Bridge Pull	Camera 8	1612080156	49°33'25.98"	90°38'54.07"	Video	Moose	Alces	alces	Female	17-07-16	11:41 AM	17-08-02
Bridge Pull	Camera 8	1612080156	49°33'25.98"	90°38'54.07"	Image	Moose	Alces	alces	Male	17-07-20	12:22 PM	17-08-02
Bridge Pull	Camera 8	1612080156	49°33'25.98"	90°38'54.07"	Image	Moose	Alces	alces	Male	17-07-21	19:23 PM	17-08-02
Bridge Pull	Camera 8	1612080156	49°33'25.98"	90°38'54.07"	Video	Moose	Alces	alces	Male	17-07-21	8:58 AM	17-08-02
Bridge Pull	Camera 8	1612080156	49°33'25.98"	90°38'54.07"	Video	Moose	Alces	alces	Male	17-07-21	13:28 PM	17-08-02
South Access	Camera 11	1612080102	49°32'44.90"	90°40'40.77"	Image	Moose	Alces	alces	Male	17-08-01	12:00 PM	17-08-02
South Access	Camera 11	1612080102	49°32'44.90"	90°40'40.77"	Video	Moose	Alces	alces	Male	17-08-01	23:07 PM	17-08-02
North Landing	Camera 12	1612080115	49°34'56.88"	90°39'2.86"	Image	Moose	Alces	alces	Male	17-07-26	13:58 PM	17-08-02
North Landing	Camera 12	1612080115	49°34'56.88"	90°39'2.86"	Video	Moose	Alces	alces	Male	17-07-26	2:54 AM	17-08-02
North Landing	Camera 12	1612080115	49°34'56.88"	90°39'2.86"	Image	Moose	Alces	alces	Male	17-07-26	15:10 PM	17-08-02
North Landing	Camera 12	1612080115	49°34'56.88"	90°39'2.86"	Video	Moose	Alces	alces	Male	17-07-26	15:30 PM	17-08-02
North Landing	Camera 12	1612080115	49°34'56.88"	90°39'2.86"	Image	Moose	Alces	alces	Male	17-07-26	2:44 AM	17-08-02
North Landing	Camera 12	1612080115	49°34'56.88"	90°39'2.86"	Video	Moose	Alces	alces	Male	17-07-26	15:49 PM	17-08-02
North Landing	Camera 12	1612080115	49°34'56.88"	90°39'2.86"	Image	Moose	Alces	alces	Male	17-07-26	6:51 AM	17-08-02
North Landing	Camera 12	1612080115	49°34'56.88"	90°39'2.86"	Video	Moose	Alces	alces	Male	17-07-26	22:33 PM	17-08-02
North Landing	Camera 12	1612080115	49°34'56.88"	90°39'2.86"	Image	Moose	Alces	alces	Male	17-07-26	16:12 PM	17-08-02
North Landing	Camera 12	1612080115	49°34'56.88"	90°39'2.86"	Video	Moose	Alces	alces	Male	17-07-26	16:46 PM	17-08-02
North Landing	Camera 12	1612080115	49°34'56.88"	90°39'2.86"	Image	Moose	Alces	alces	Male	17-07-27	11:25AM	17-08-02
North Landing	Camera 12	1612080115	49°34'56.88"	90°39'2.86"	Video	Moose	Alces	alces	Male	17-07-27	21:19 PM	17-08-02
North Landing	Camera 12	1612080115	49°34'56.88"	90°39'2.86"	Image	Moose	Alces	alces	Female	17-07-30	16:11 PM	17-08-02

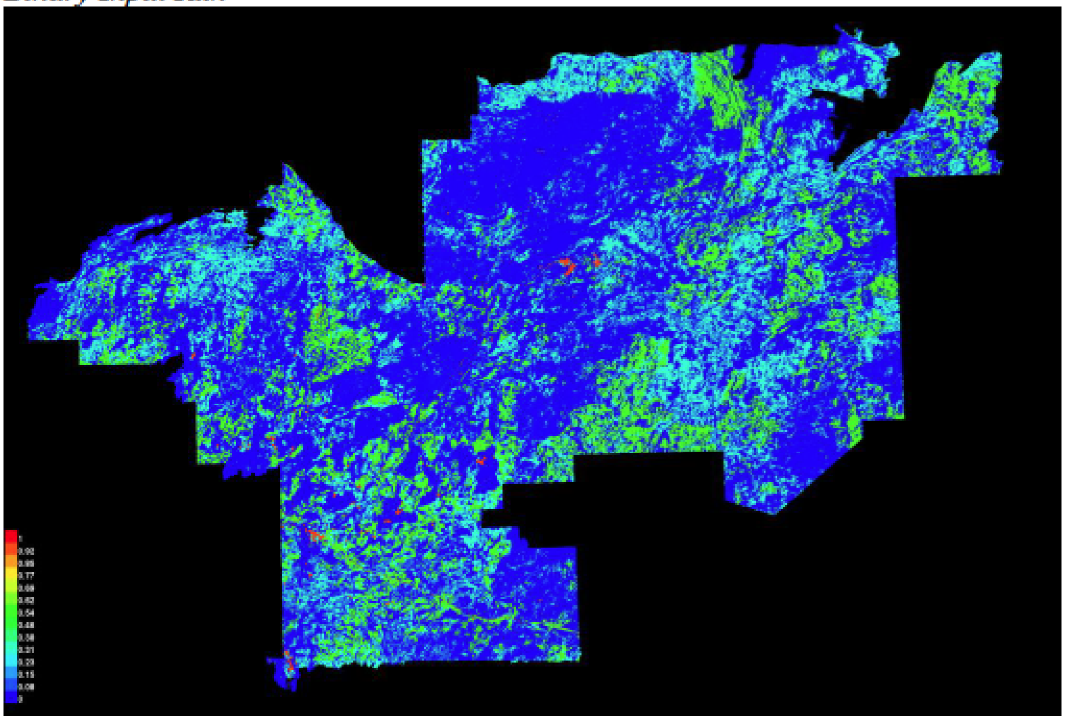
Appendix A. cont'd.

Camera Location	Camera Number	Serial Number	Coordinates (N)	Coordinates (W)	File Type	Common Name	Genus	Species	Sex	Date Captured	Time	Date Collected From Field
North Landing	Camera 12	1612080115	49°34'56.88"	90°39'2.86"	Video	Moose	Alces	alces	Female	17-07-30	19:30 PM	17-08-02
SW Corner	Camera 17	1612080106	49°32'50.82"	90°41'31.23"	Image	Moose	Alces	alces	Male	17-07-29	15:23 PM	17-08-02
NE Corner	Camera 19	1612080156	49°34'55.46"	90°36'34.41"	Image	Moose	Alces	alces	NA	17-07-02	2:29 PM	17-08-02
NE Corner	Camera 19	1612080156	49°34'55.46"	90°36'34.41"	Video	Moose	Alces	alces	NA	17-07-02	12:43 PM	17-08-02
NE Corner	Camera 19	1612080156	49°34'55.46"	90°36'34.41"	Video	Moose	Alces	alces	NA	17-07-14	12:37 PM	17-08-02
Middle of road	Camera 20	1612080109	49°32'49.79"	90°40'30.58"	Video	Moose	Alces	alces	NA	17-07-31	20:03 PM	17-08-02
Middle of road	Camera 20	1612080109	49°32'49.79"	90°40'30.58"	Image	Moose	Alces	alces	NA	17-07-31	12:08 AM	17-08-02
Middle of road	Camera 20	1612080109	49°32'49.79"	90°40'30.58"	Video	Moose	Alces	alces	NA	17-07-31	22:06 PM	17-08-02
Chip Pile	Camera 5	1612080187	49°34'40.43"	90°39'00.71"	Image	Moose	Alces	alces	Female	17-08-12	15:04 PM	17-08-26
Chip Pile	Camera 5	1612080187	49°34'40.43"	90°39'00.71"	Image	Moose	Alces	alces	Female	17-08-12	18:23 PM	17-08-26
Chip Pile	Camera 5	1612080187	49°34'40.43"	90°39'00.71"	Image	Moose	Alces	alces	Female	17-08-12	10:41 AM	17-08-26

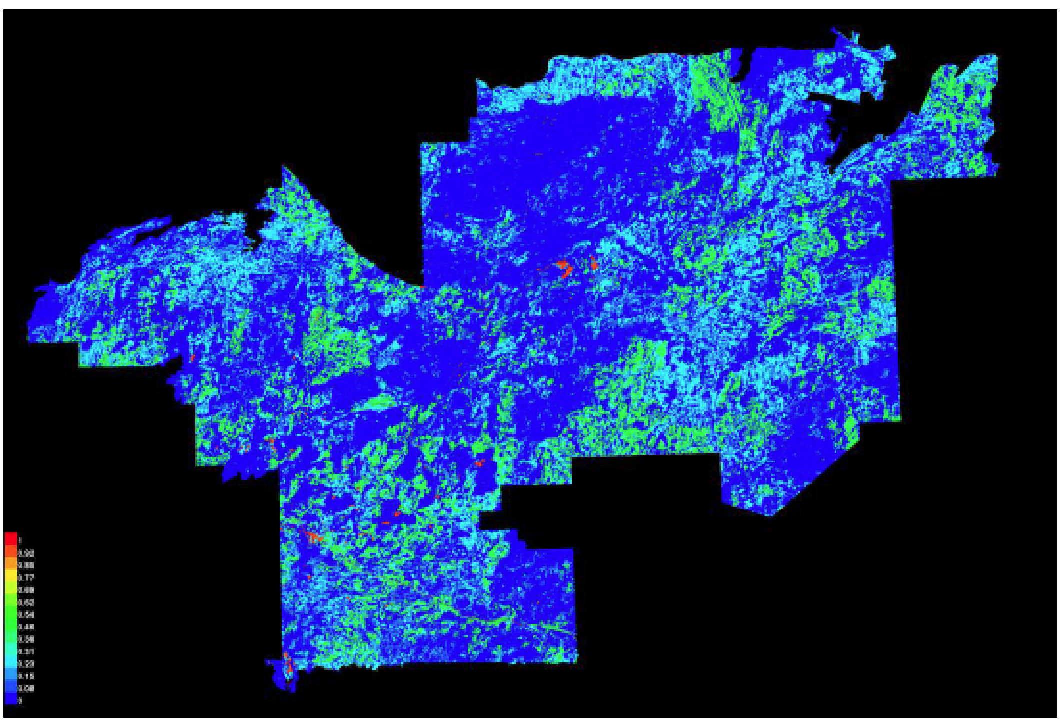
Source: Wilke, 2018

APPENDIX B – HABITAT SUITABILITY INDICIES FOR EACH MODEL

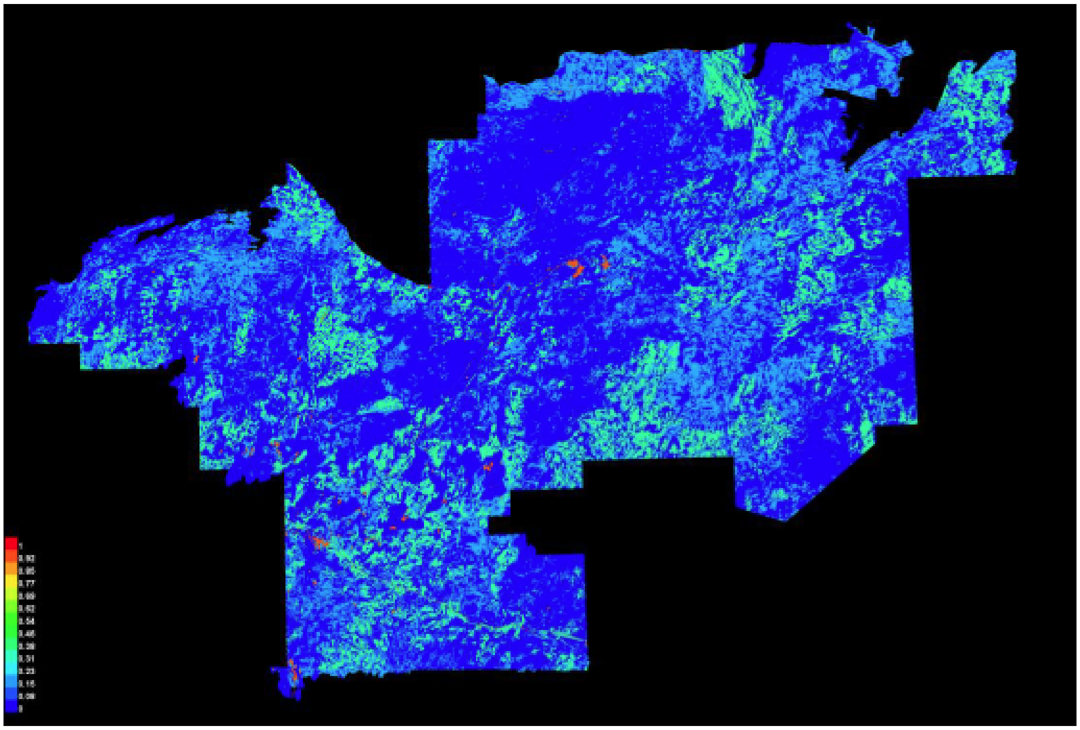
Binary Input Run



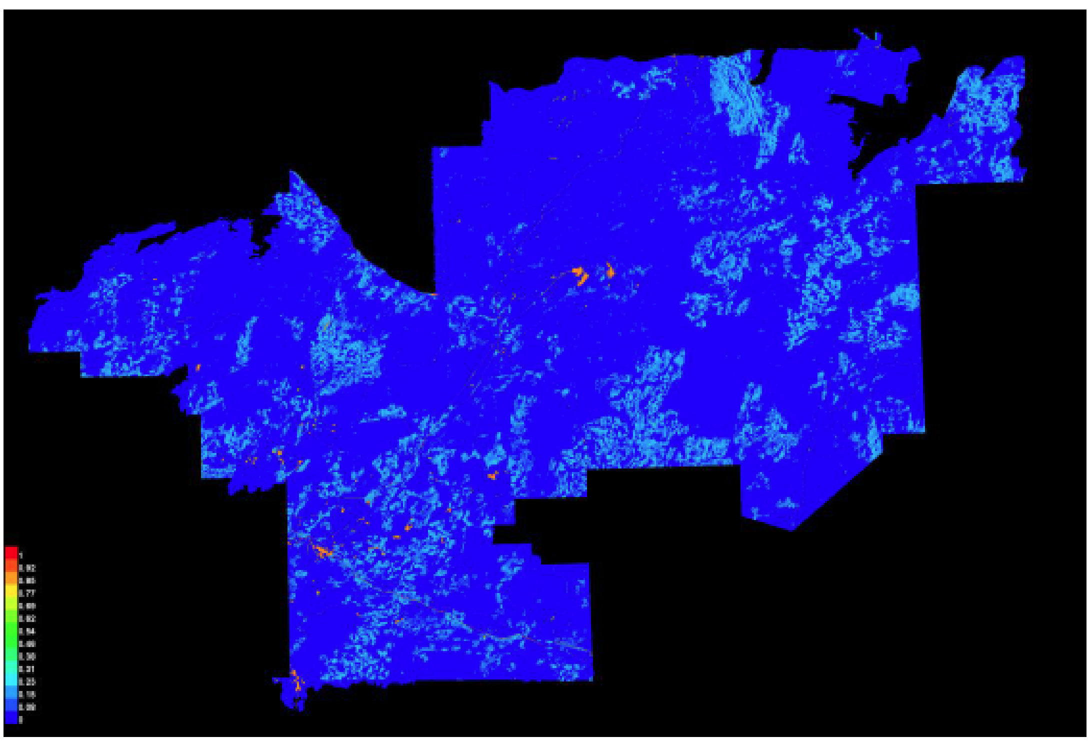
Appendix B-1. Maximum habitat suitability for moose in the ERF based on the binary input run.



Appendix B-2. Median habitat suitability for moose in the ERF based on the binary input run.

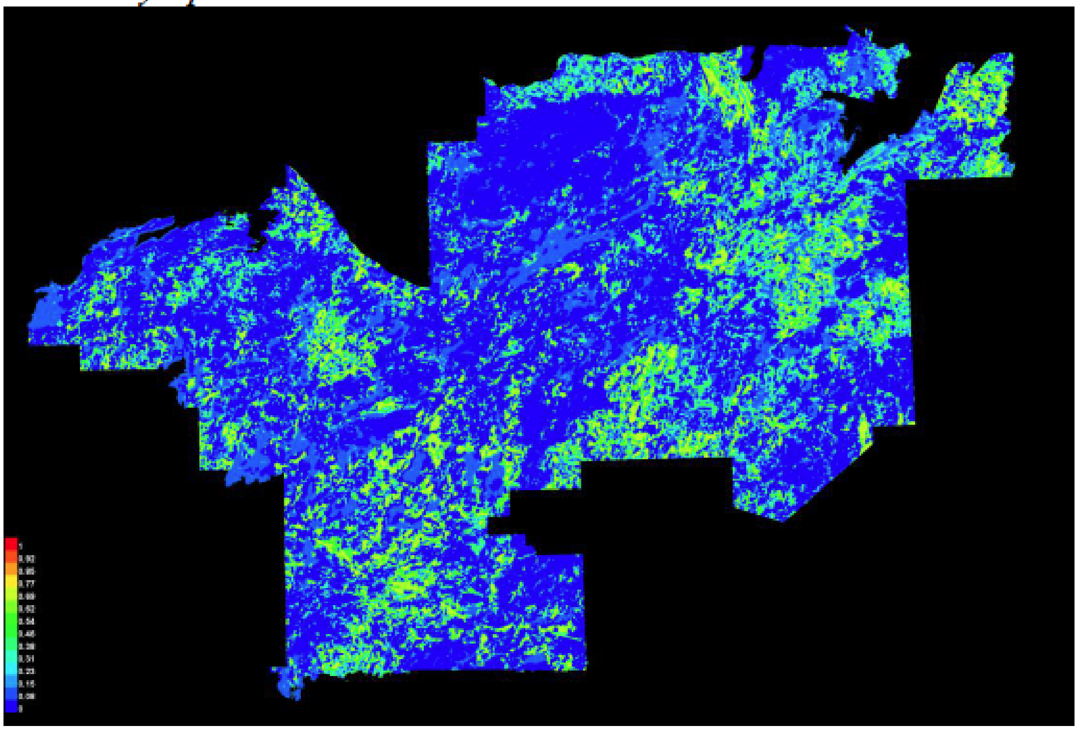


Appendix B-3. Average habitat suitability for moose in the ERF based on the binary input run.

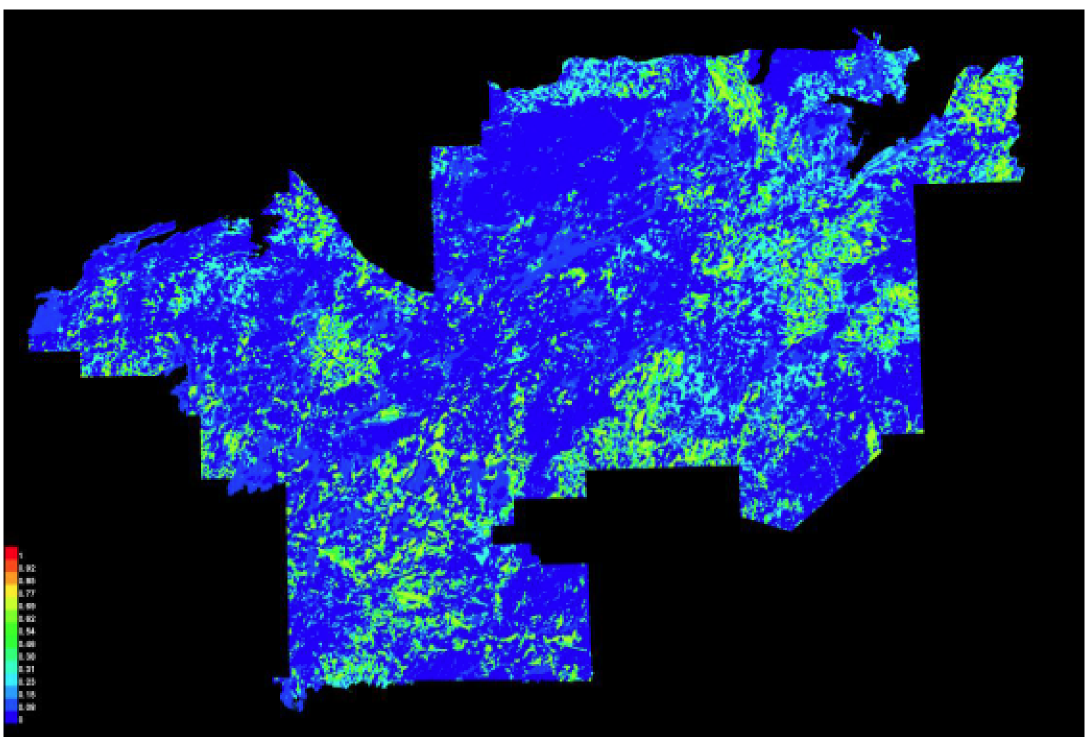


Appendix B-4. Minimum habitat suitability for moose in the ERF based on the binary input run.

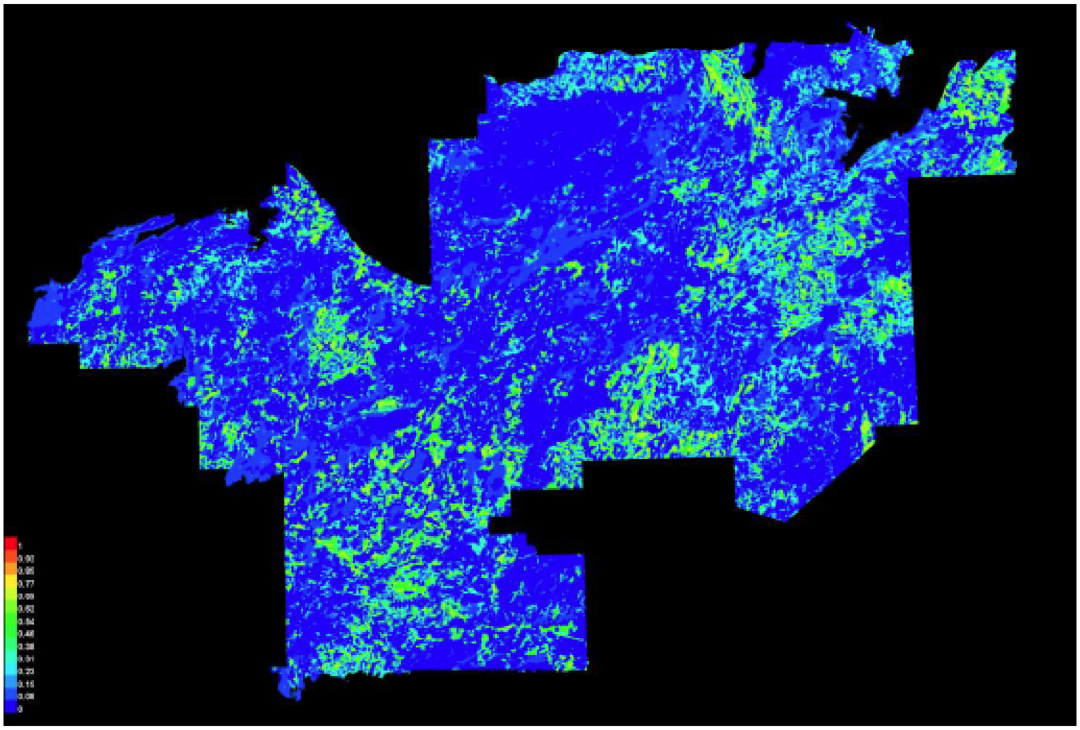
Non-Binary Input Run



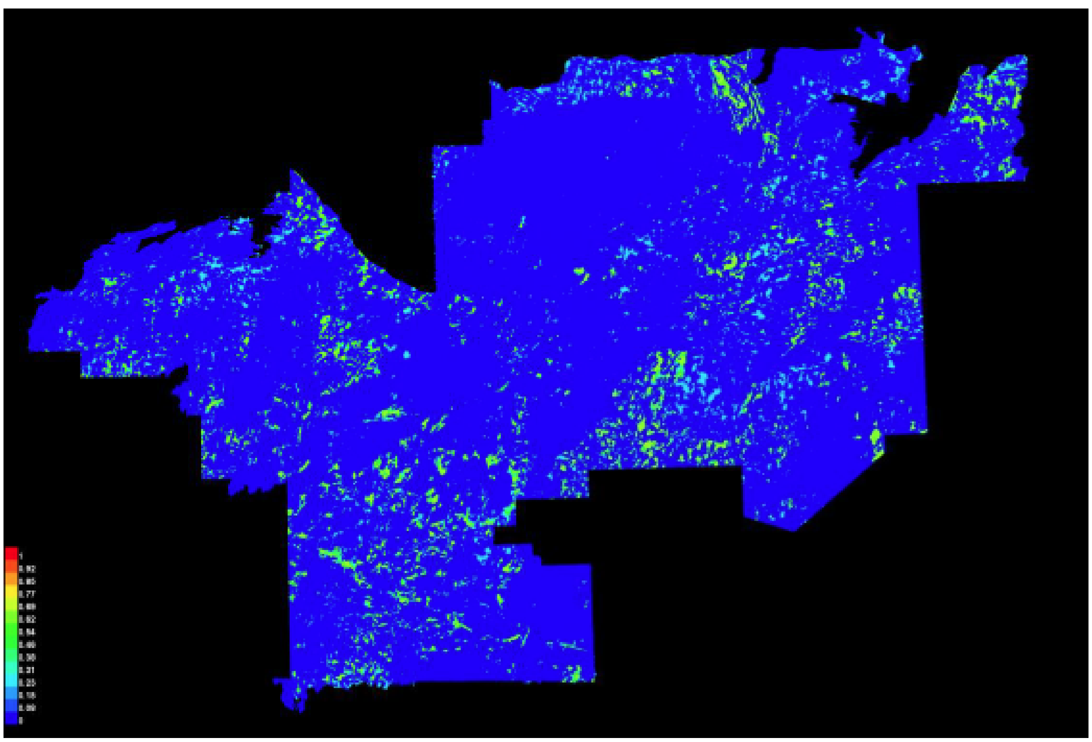
Appendix B-5. Maximum habitat suitability for moose in the ERF based on the non-binary input run.



Appendix B-6. Median habitat suitability for moose in the ERF based on the non-binary input run.

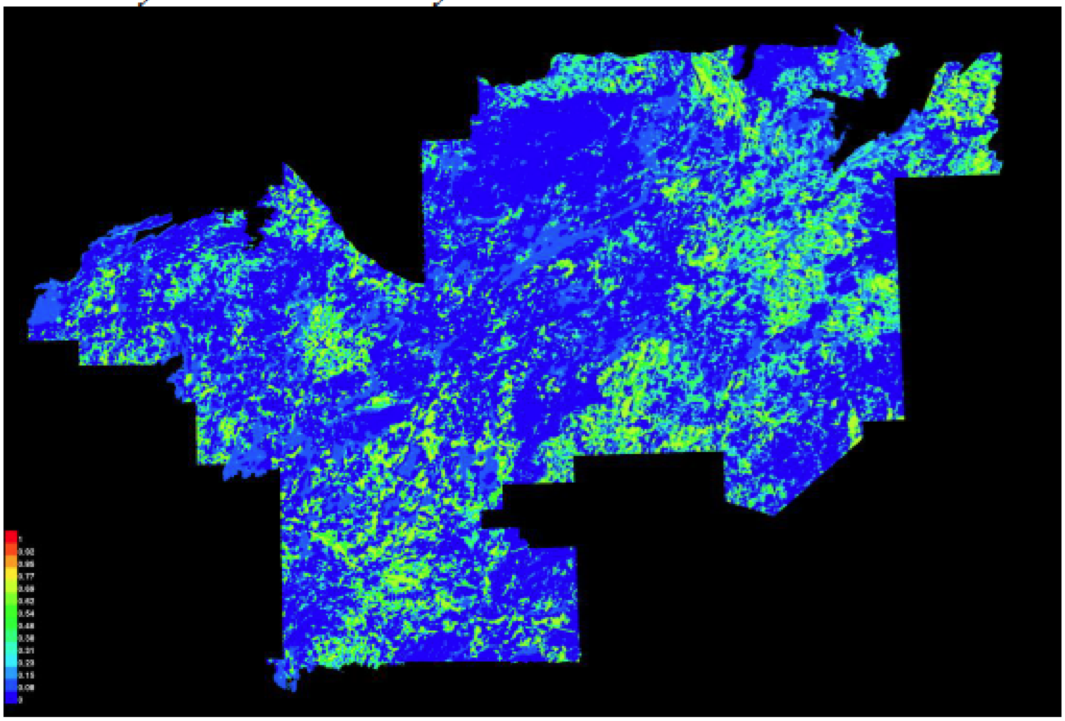


Appendix B-7. Average habitat suitability for moose in the ERF based on the non-binary input run.

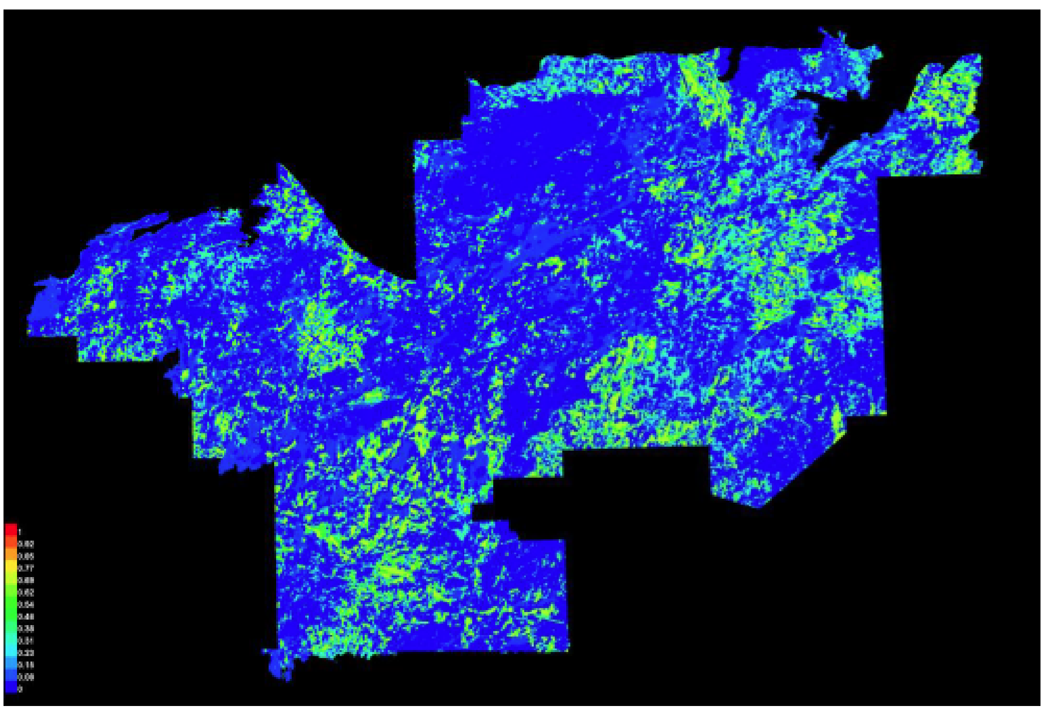


Appendix B-8. Minimum habitat suitability for moose in the ERF based on the non-binary input run.

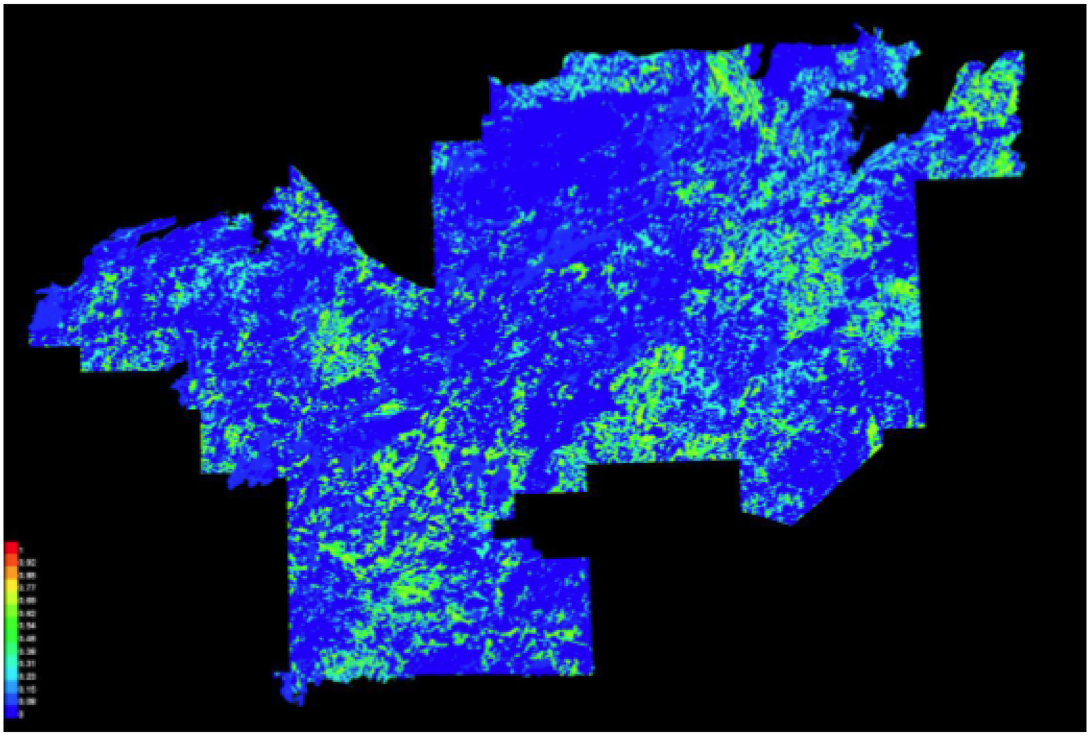
Non-Binary Run With Omitted Layers



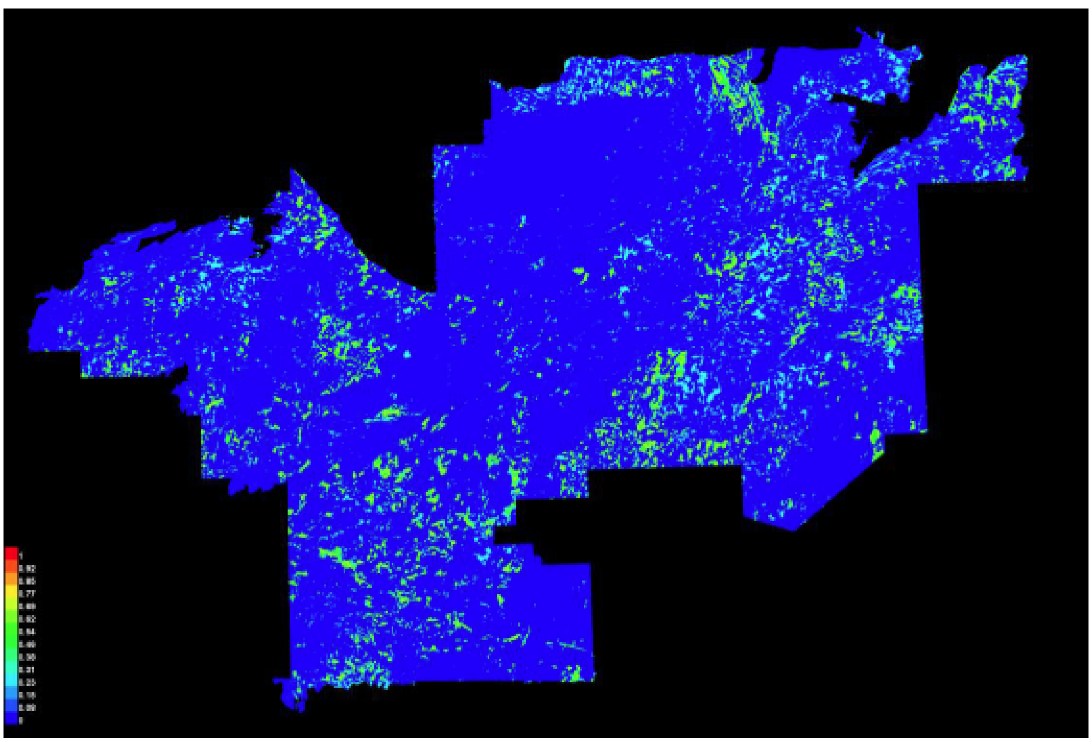
Appendix B-9. Maximum habitat suitability for moose in the ERF based on the non-binary run with omitted layers.



Appendix B-10. Median habitat suitability for moose in the ERF based on the non-binary run with omitted layers.



Appendix B-11. Average habitat suitability for moose in the ERF based on the non-binary run with omitted layers.



Appendix B-12. Minimum habitat suitability for moose in the ERF based on the non-binary run with omitted layers.

APPENDIX C – CONTRIBUTION OF VARIABLES TO EACH MODEL RUN

The tables below provide estimates of the percent contributions and permutation importance of each variable used in the corresponding model. Percent contribution is measured as factor of the regularized gain in relation to the contribution of the corresponding variable. Permutation importance is measured as a randomized permutation of the background data in combination with the training value for each corresponding variable. The model is then re-run on the permuted data and the resulting drop in AUC levels are then presented in the Permutation Importance section as a normalized percentage.

Binary Input Run

Variable	Percent contribution	Permutation importance
upcmix_ascii	15.9	28.7
lowcon_ascii	15	7.3
presap_ascii	14.5	3.9
wat_ascii	13.1	16.7
imcon_ascii	10.6	14.3
harmix_ascii	8.6	11.9
tms_ascii	5.7	12.4
imhard_ascii	5.3	2.1
oms_ascii	5.3	1.7
bsh_ascii	2.5	0.2
mlbfir_ascii	2.1	0.1
isl_ascii	1.5	0
distwat_ascii	0.1	0.8
distcov_ascii	0	0
rck_ascii	0	0
grs_ascii	0	0

Non-Binary Input Run

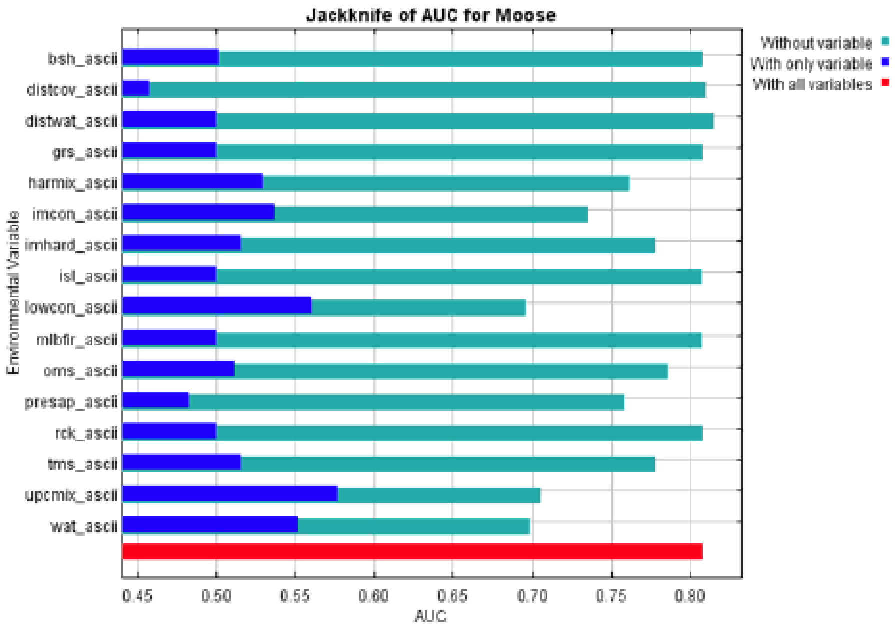
Variable	Percent contribution	Permutation importance
lowc_foc_ascii	21.8	14.5
presap_foc_ascii	21.3	0
icon_foc_ascii	16.7	14.3
harmix_foc_ascii	12.9	22.6
wat_foc_ascii	8.8	11.8
tms_foc_ascii	7.4	7.5
oms_foc_ascii	3.8	0
ucm_foc_ascii	3.4	10.7
bsh_foc_ascii	2.7	14.1
ihard_foc_ascii	1.2	4.5
d2cov_foc_ascii	0	0
grs_foc_ascii	0	0
d2wat_foc_ascii	0	0
mlbfir_foc_ascii	0	0
rck_foc_ascii	0	0
isl_foc_ascii	0	0

Non-Binary Input Run with Omitted Layers

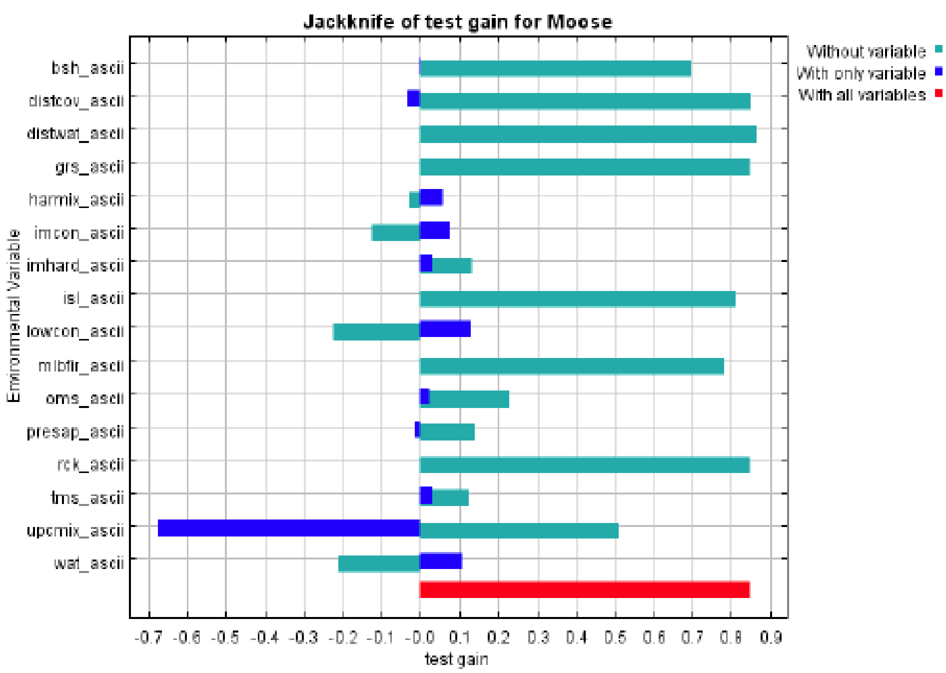
Variable	Percent contribution	Permutation importance
lowc_foc_ascii	28.2	16.5
icon_foc_ascii	19.2	24.9
harmix_foc_ascii	16.8	14.8
wat_foc_ascii	12.9	2.1
tms_foc_ascii	9	23.5
ucm_foc_ascii	8.1	7.8
bsh_foc_ascii	2.6	8.1
oms_foc_ascii	2.5	2.2
ihard_foc_ascii	0.6	0.1
d2cov_foc_ascii	0	0
d2wat_foc_ascii	0	0

APPENDIX D – JACKKNIFE T-TEST AND AUC PREDICTIONS

Binary Input Run

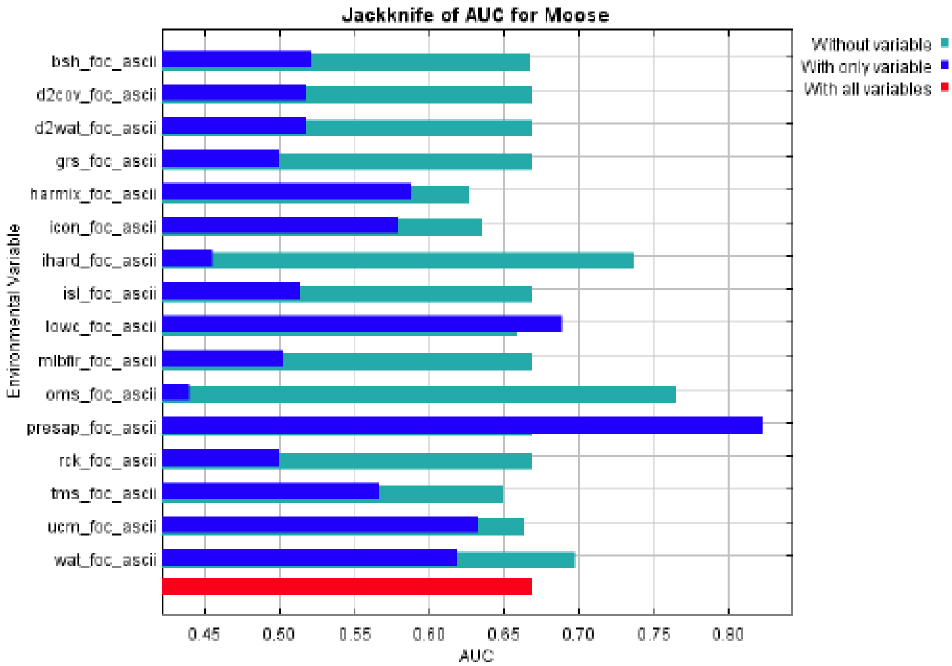


Appendix D-1. Jackknife predictions of AUC for moose for individual environmental variables (binary).

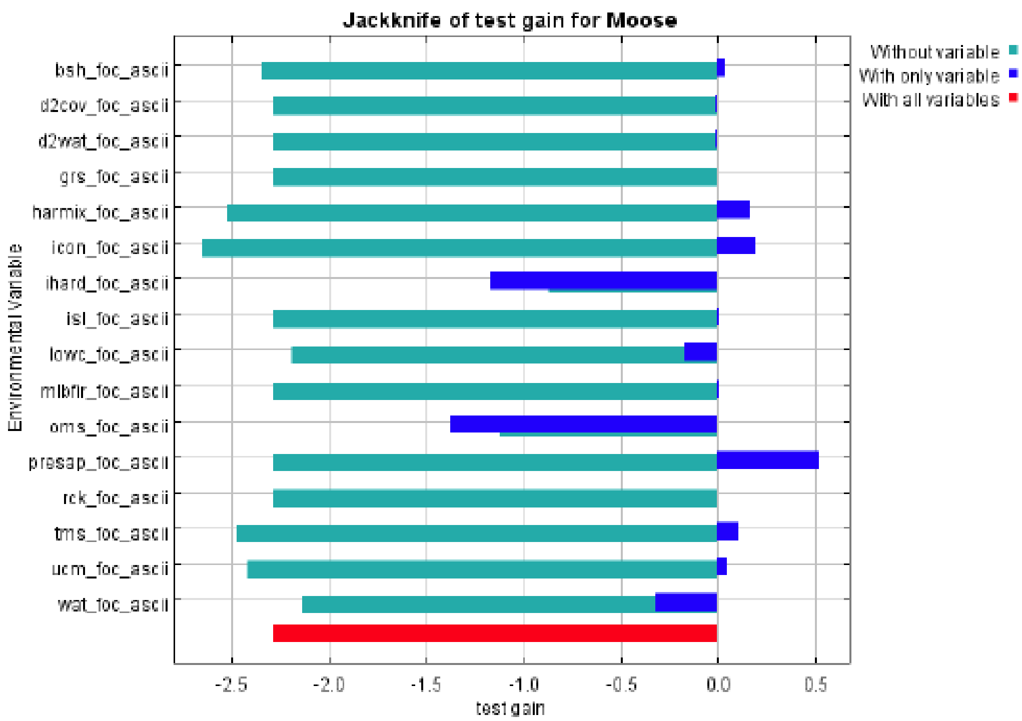


Appendix D-2. Jackknife predictions of Test Gain for moose for individual environmental variables (binary).

Non-Binary Input Run

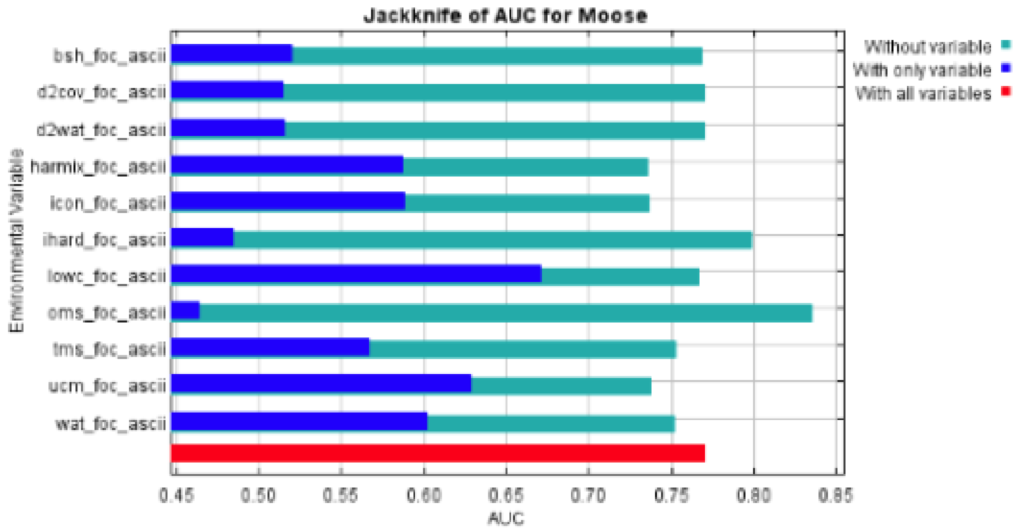


Appendix D-3. Jackknife predictions of AUC for moose for individual environmental variables (non-binary).

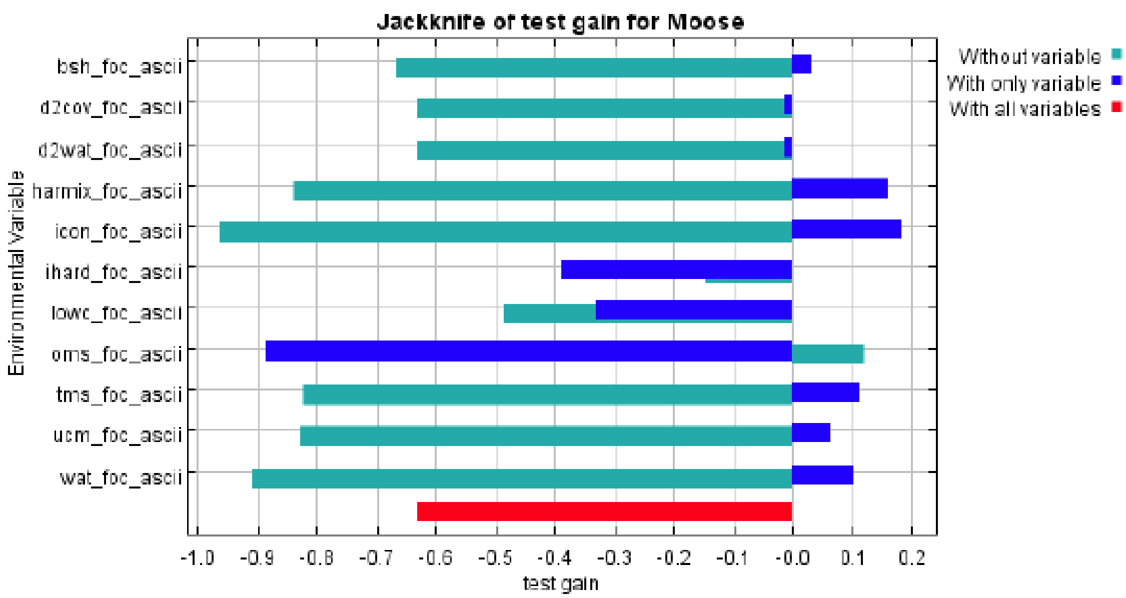


Appendix D-4. Jackknife predictions of Test Gain for moose for individual environmental variables (non-binary).

Non-Binary Input Run with Omitted Layers



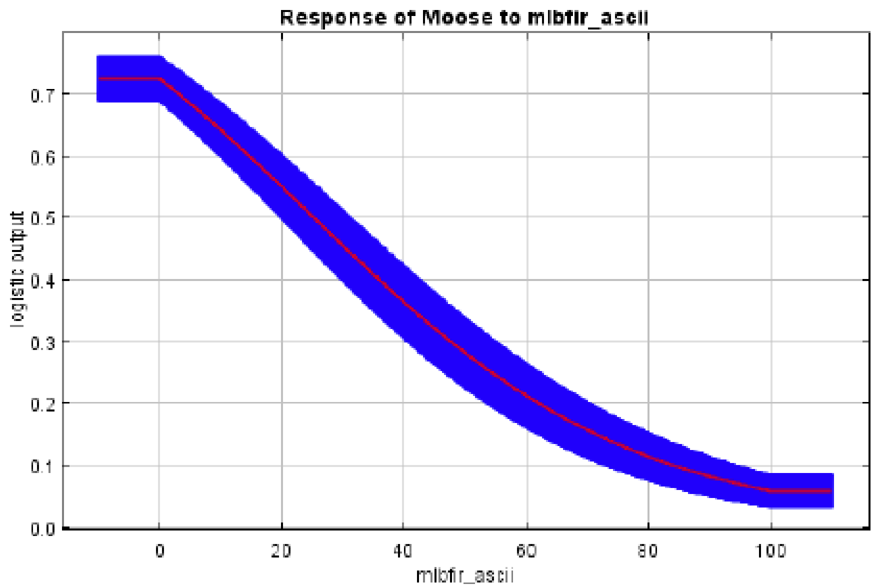
Appendix D-5. Jackknife predictions of AUC for moose for individual environmental variables (non-binary with omitted layers).



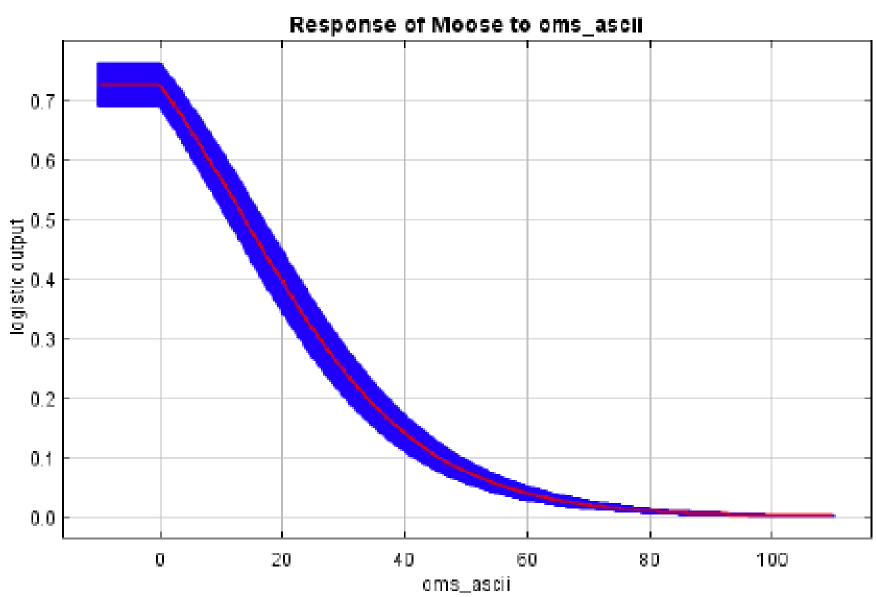
Appendix D-6. Jackknife predictions of Test Gain for moose for individual environmental variables (non-binary with omitted layers).

APPENDIX E – ENVIRONMENTAL LAYER RESPONSE CURVES

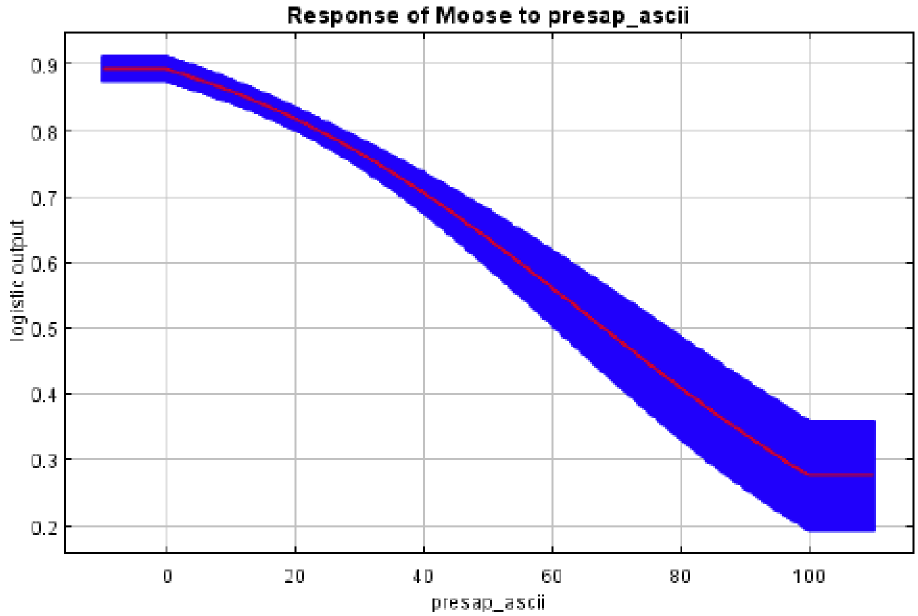
Binary Input Run



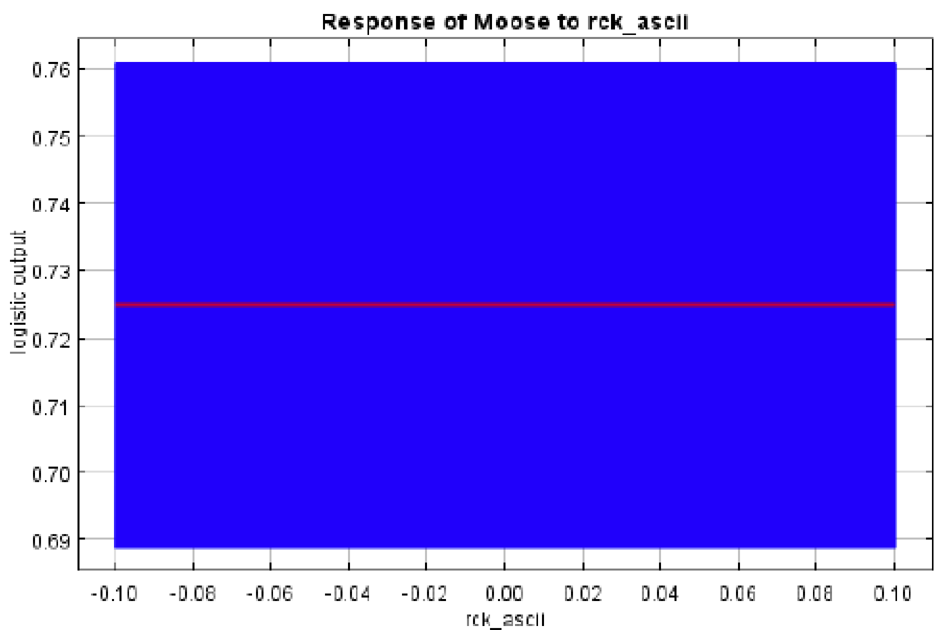
Appendix E-1. Response curve depicting the relative contribution of Mature to Late Balsam Fir to the binary model.



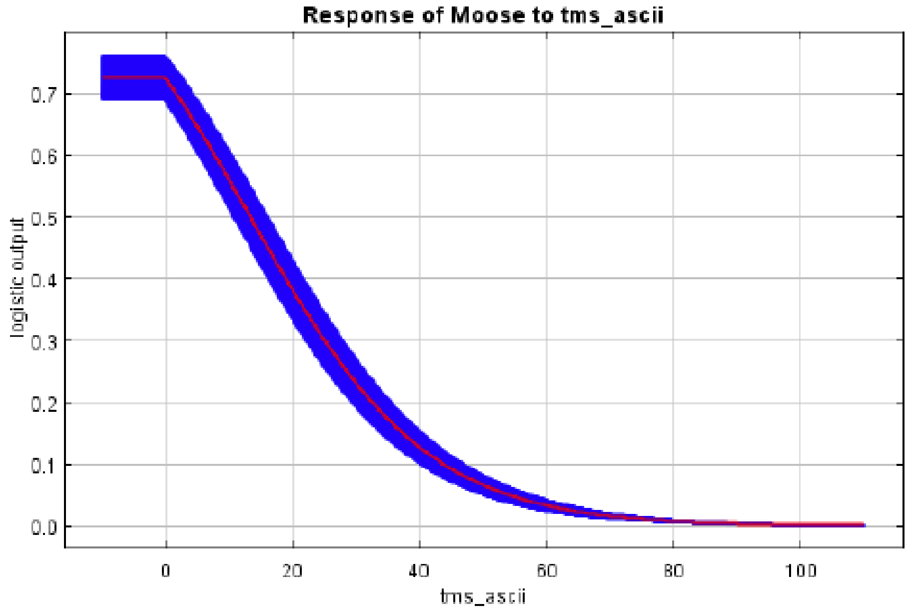
Appendix E-2. Response curve depicting the relative contribution of Open Muskeg to the binary model.



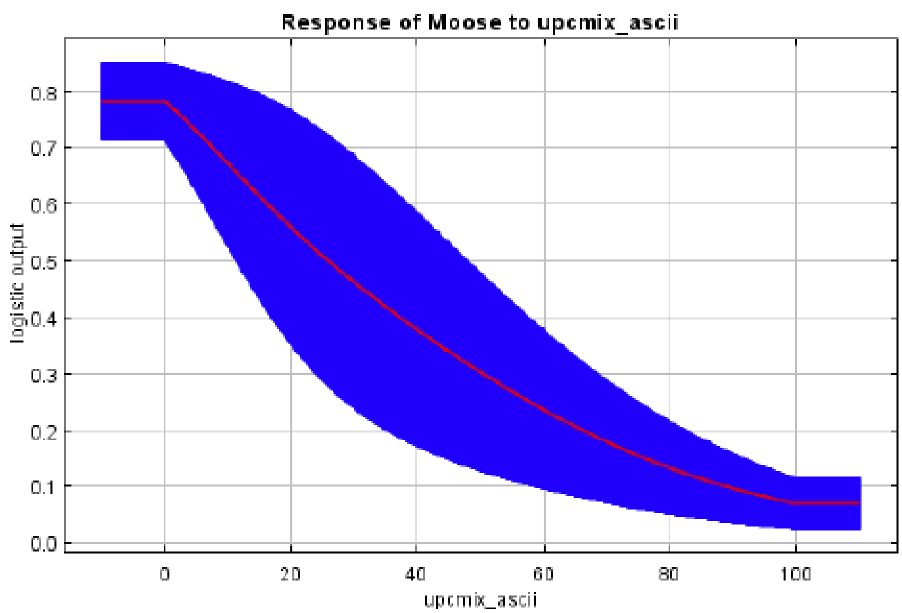
Appendix E-3. Response curve depicting the relative contribution of Pre-sapling – Sapling to the binary model.



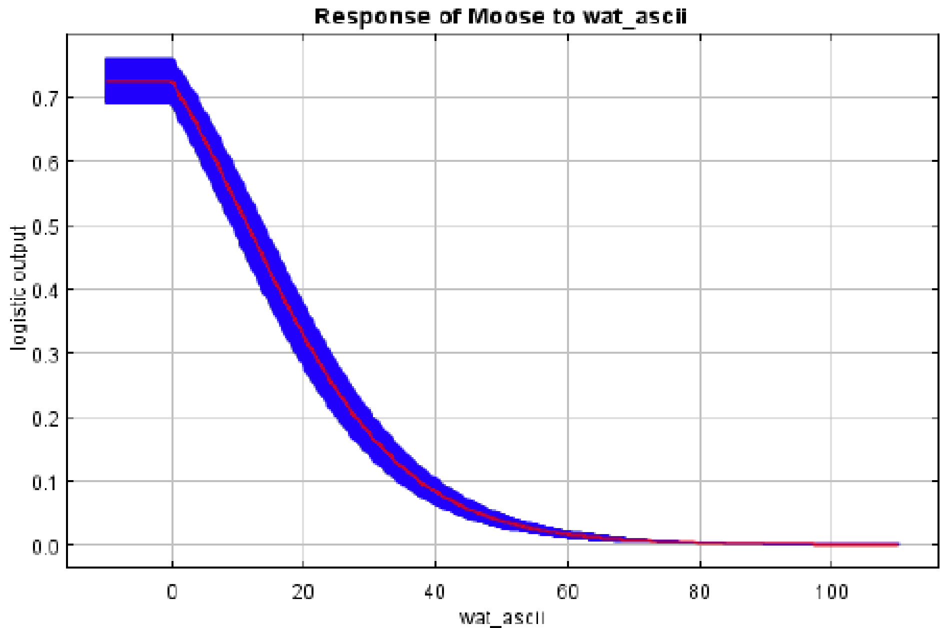
Appendix E-4. Response curve depicting the relative contribution of Rock to the binary model.



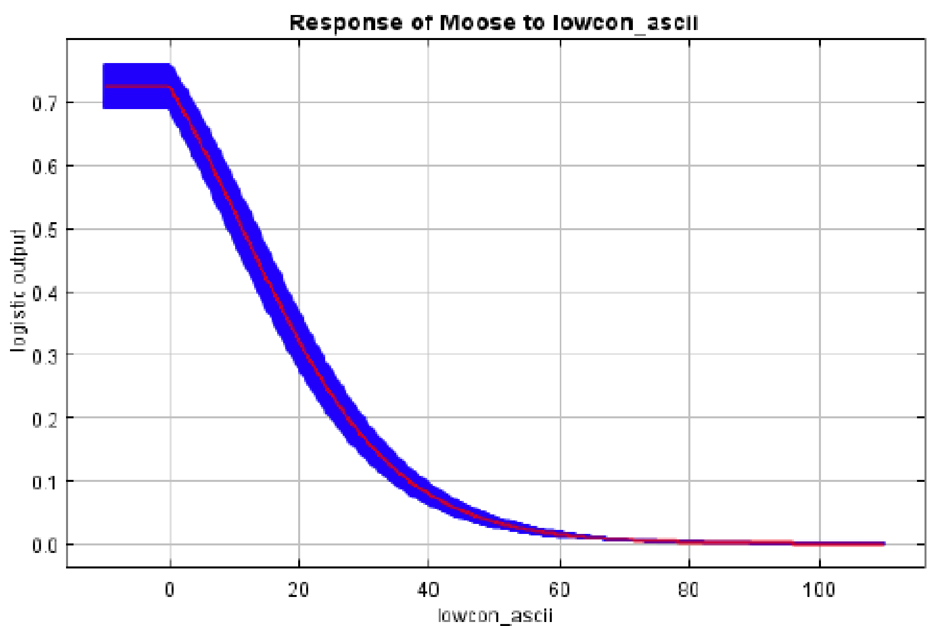
Appendix E-5. Response curve depicting the relative contribution of Treed Muskeg to the binary model.



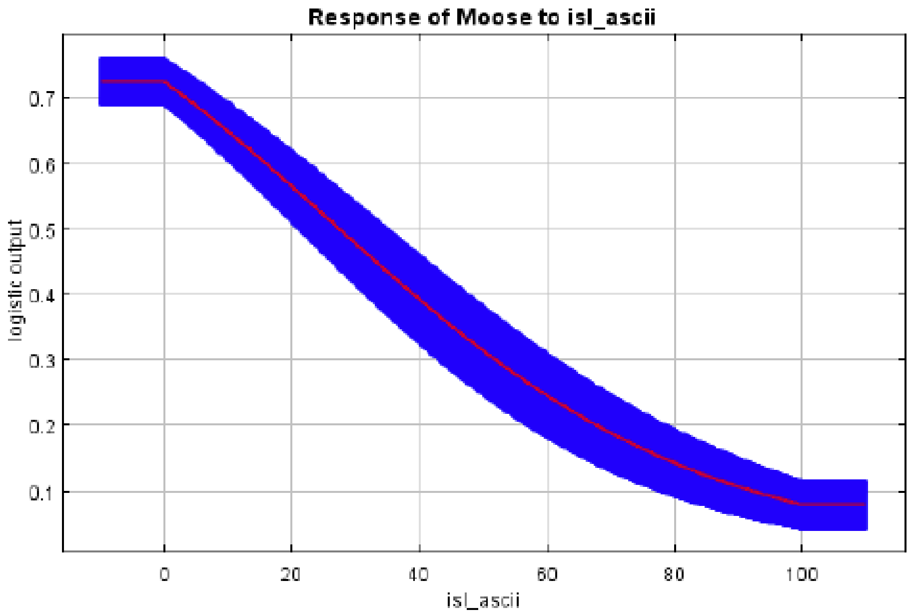
Appendix E-6. Response curve depicting the relative contribution of Mature to Late Upland Conifer & Mixed to the binary model.



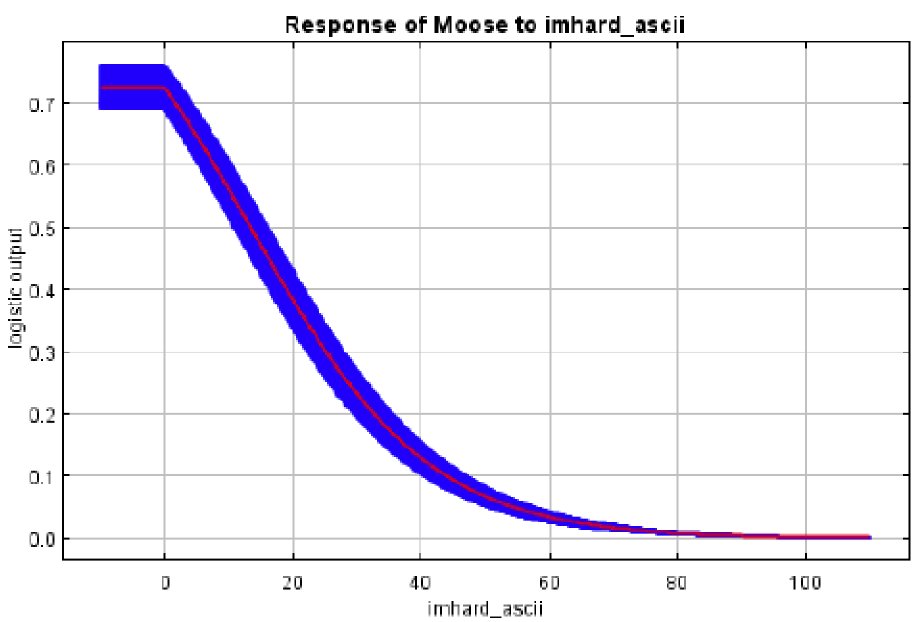
Appendix E-7. Response curve depicting the relative contribution of Water to the binary model.



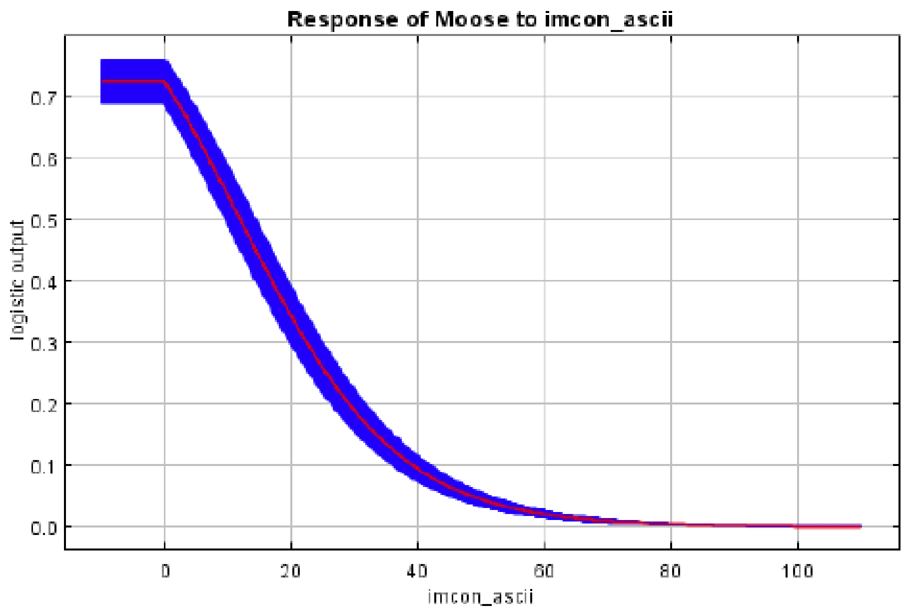
Appendix E-8. Response curve depicting the relative contribution of Mature to Late Lowland Conifer to the binary model.



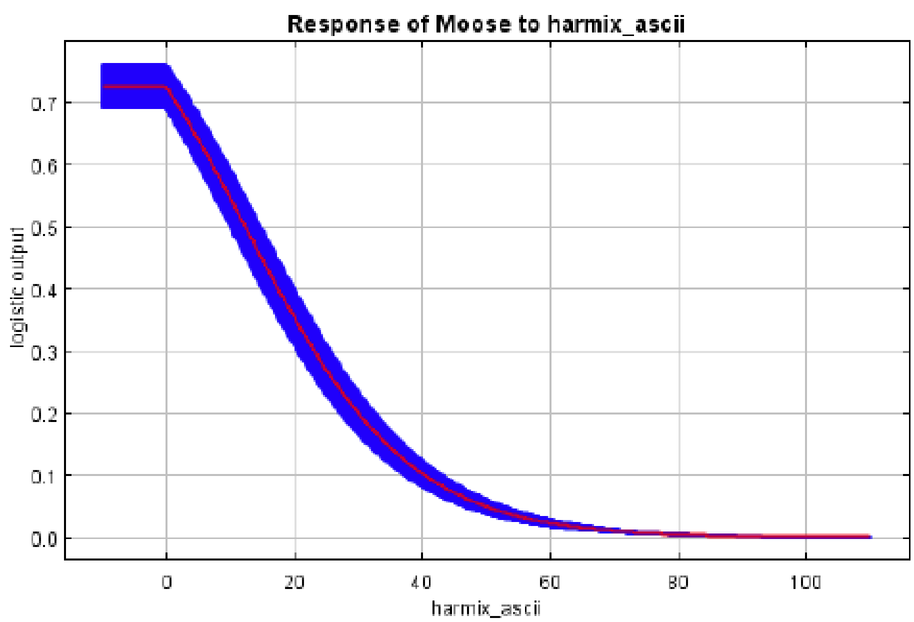
Appendix E-9. Response curve depicting the relative contribution of Islands to the binary model.



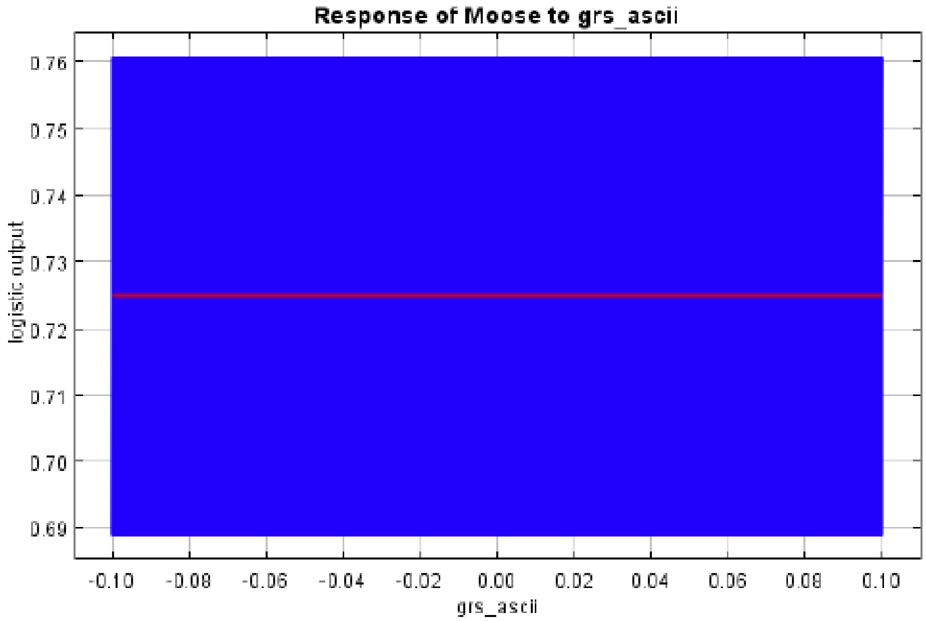
Appendix E-10. Response curve depicting the relative contribution of Immature Hardwood to the binary model.



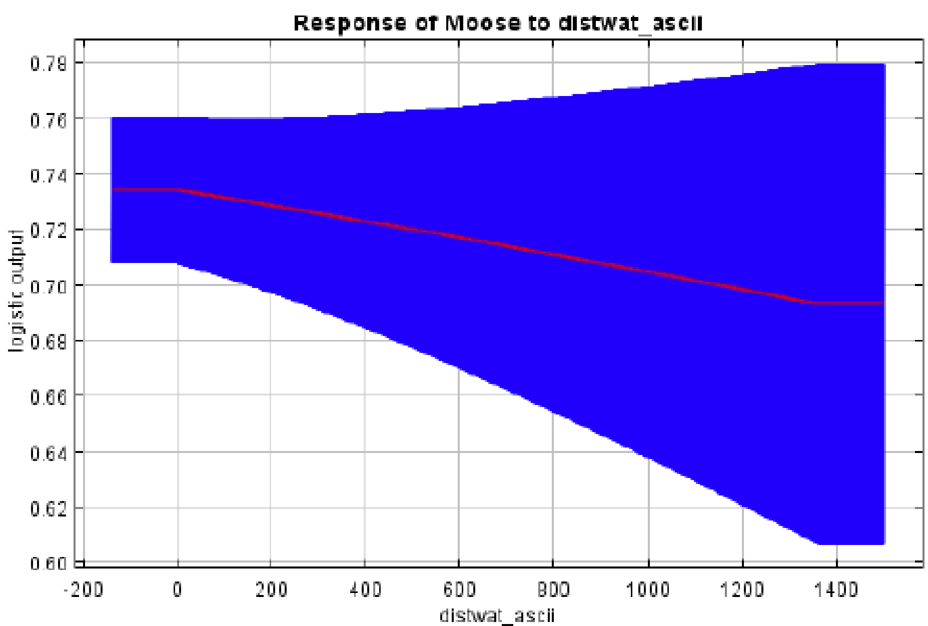
Appendix E-11. Response curve depicting the relative contribution of Immature Conifer to the binary model.



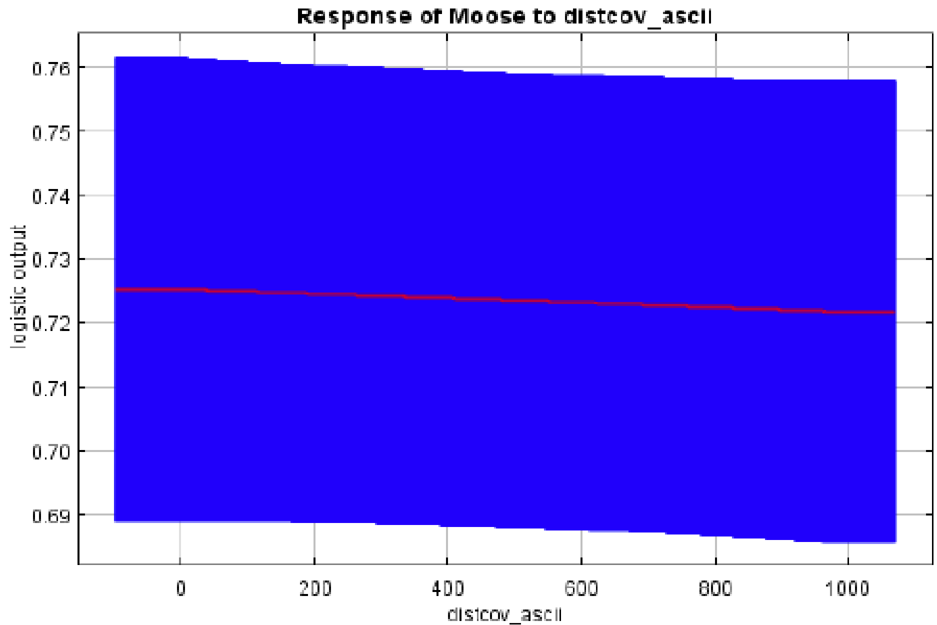
Appendix E-12. Response curve depicting the relative contribution of Mature to Late Hardwood and Mixed to the binary model.



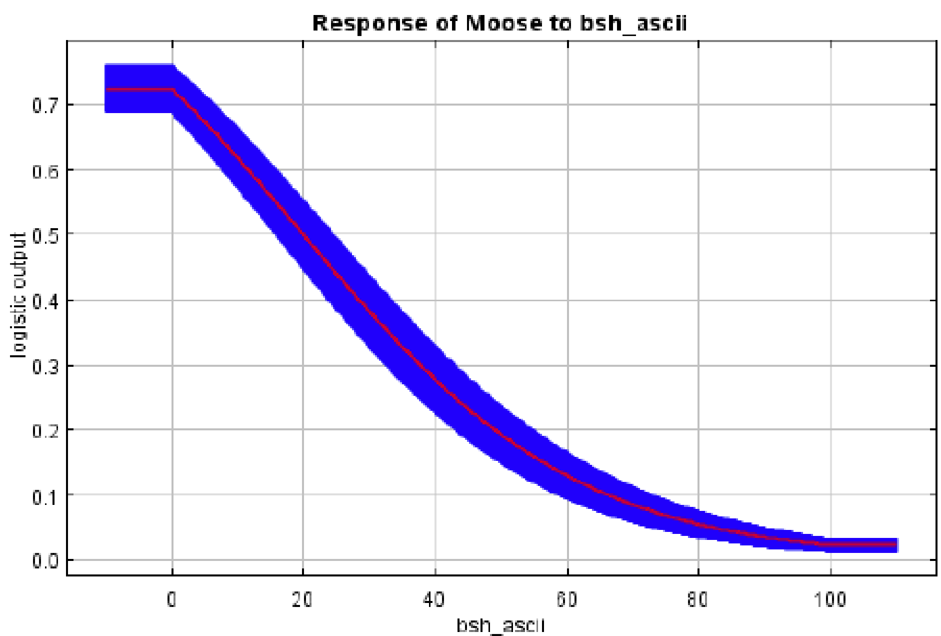
Appendix E-13. Response curve depicting the relative contribution of Grass to the binary model.



Appendix E-14. Response curve depicting the relative contribution of Distance to Water (m) to the binary model.

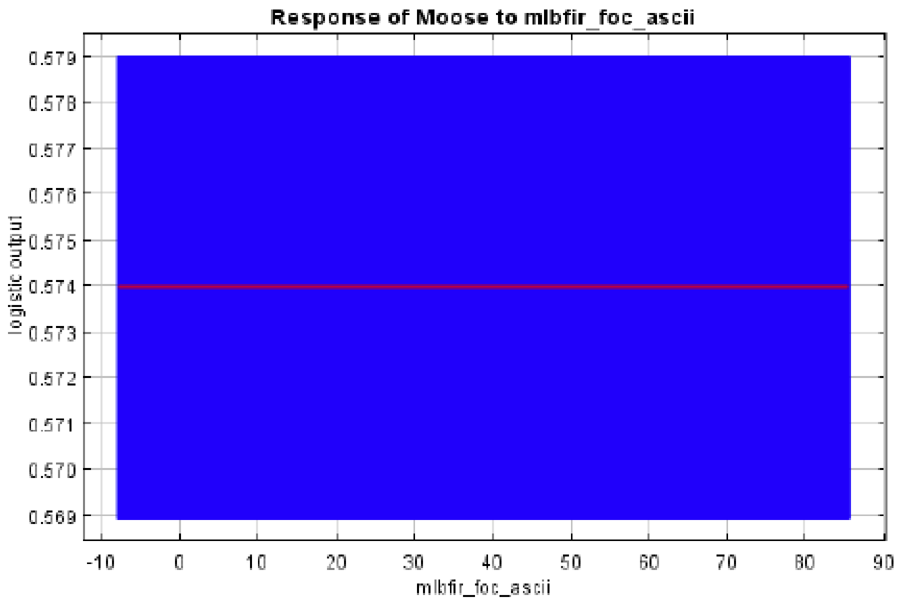


Appendix E-15. Response curve depicting the relative contribution of Distance to Cover (m) to the binary model.

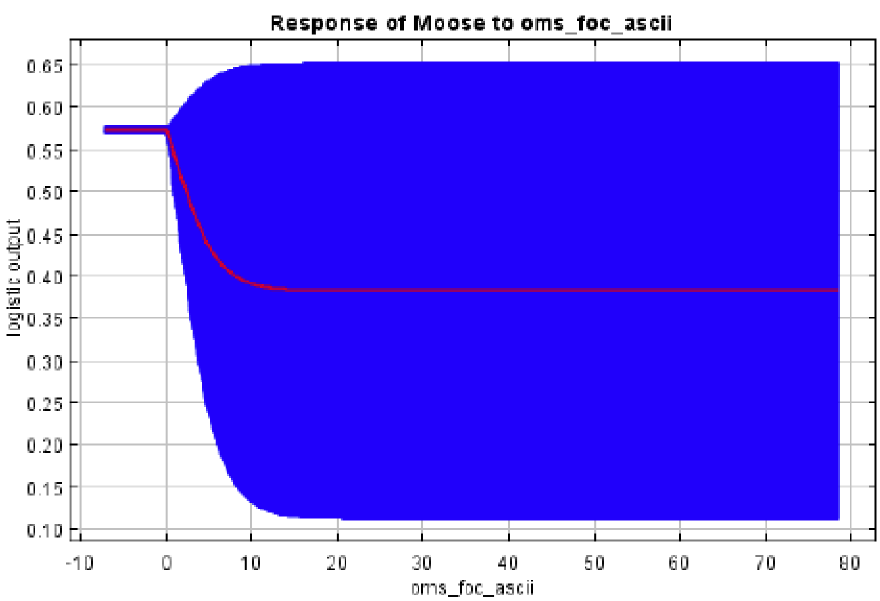


Appendix E-16. Response curve depicting the relative contribution of Brush to the binary model.

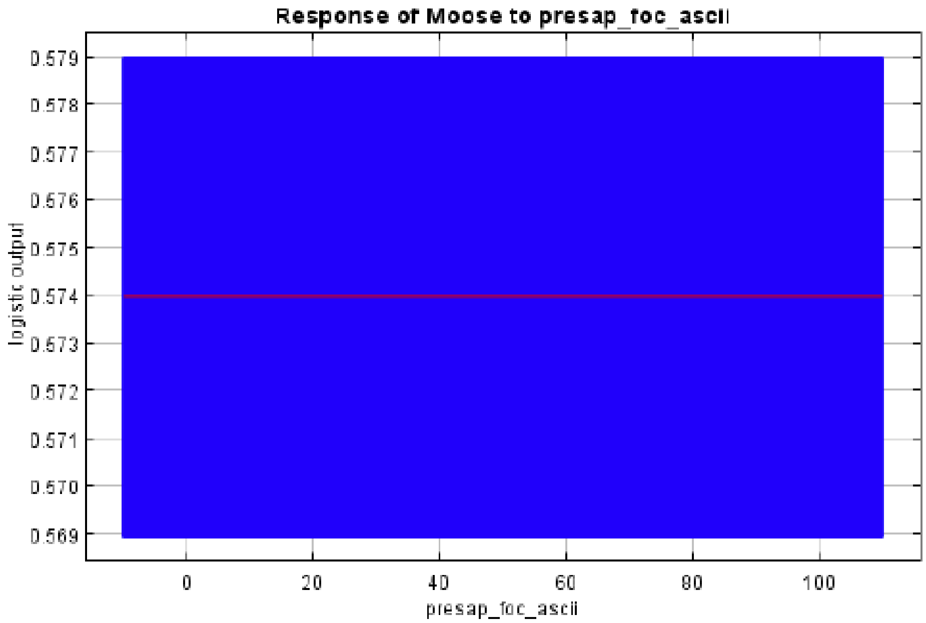
Non-Binary Input Run



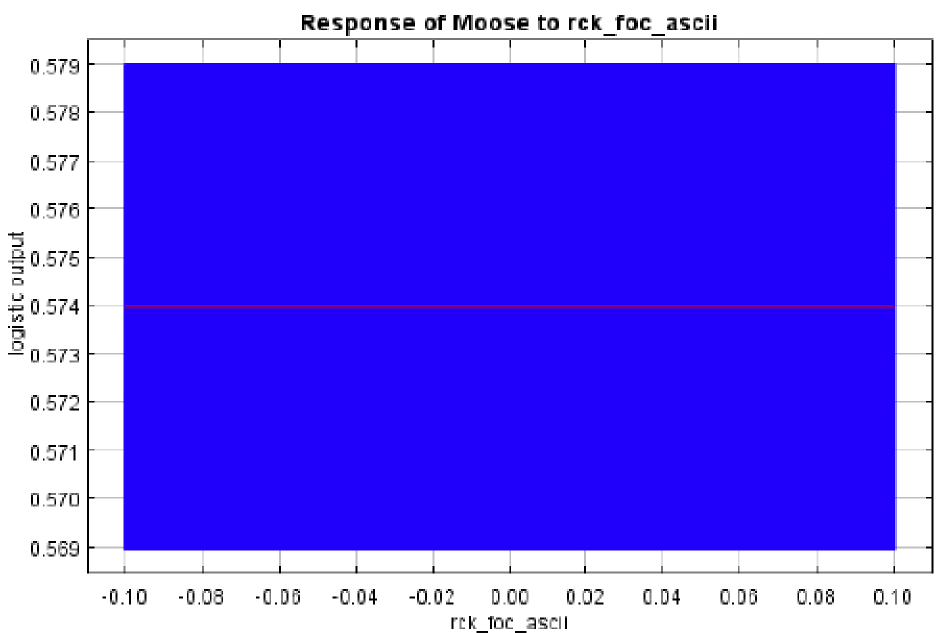
Appendix E-17. Response curve depicting the relative contribution of Mature to Late Balsam Fir to the non-binary model.



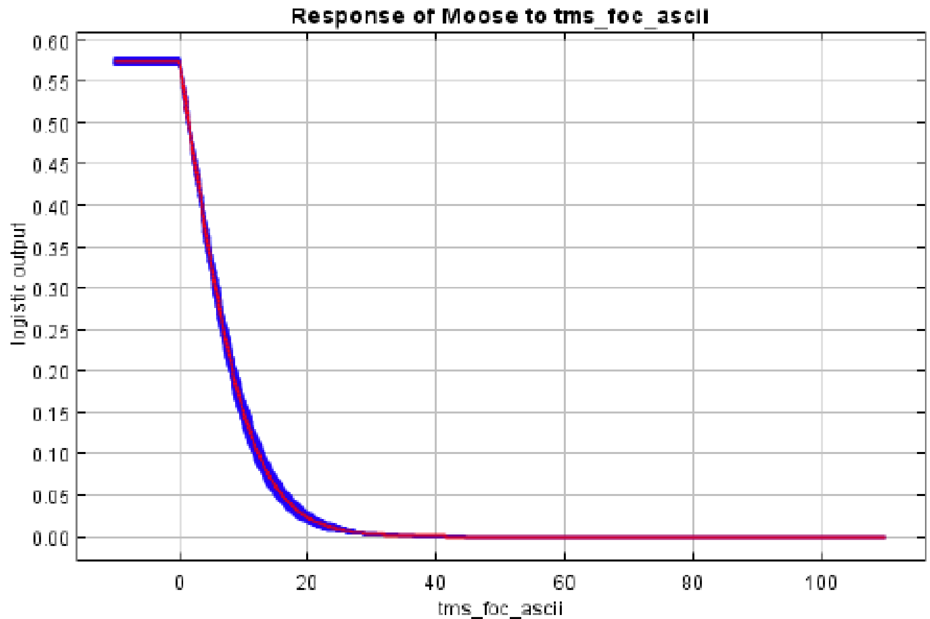
Appendix E-18. Response curve depicting the relative contribution of Open Muskeg to the non-binary model.



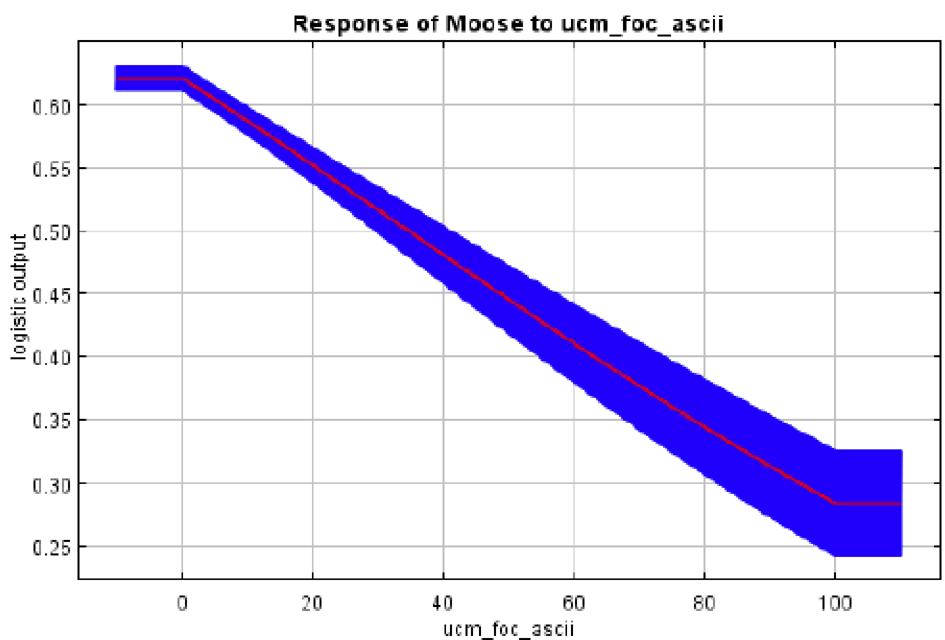
Appendix E-19. Response curve depicting the relative contribution of Pre-sapling – Sapling to the non-binary model.



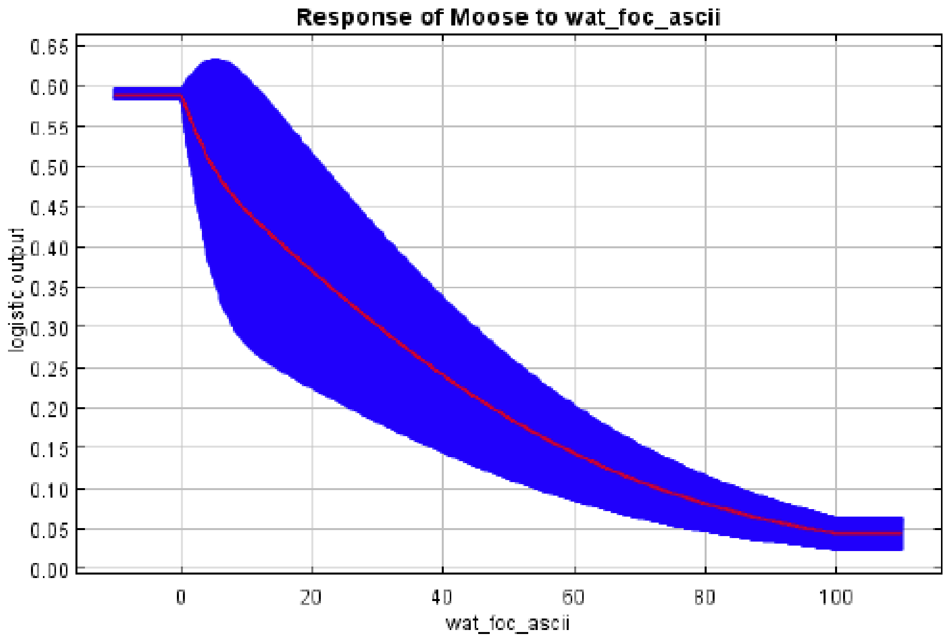
Appendix E-19. Response curve depicting the relative contribution of Rock to the non-binary model.



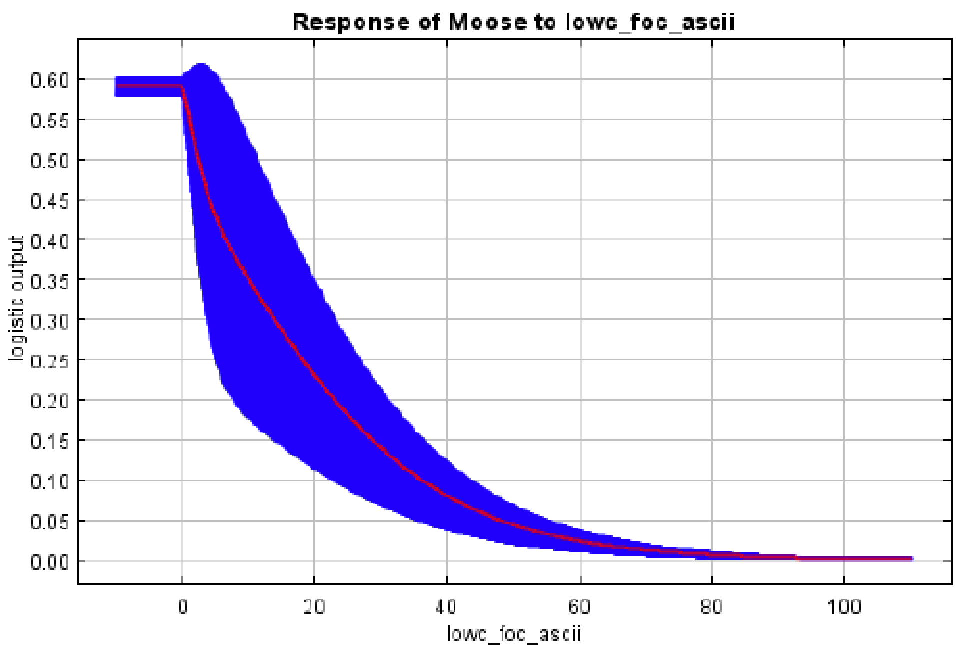
Appendix E-20. Response curve depicting the relative contribution of Treed Muskeg to the non-binary model.



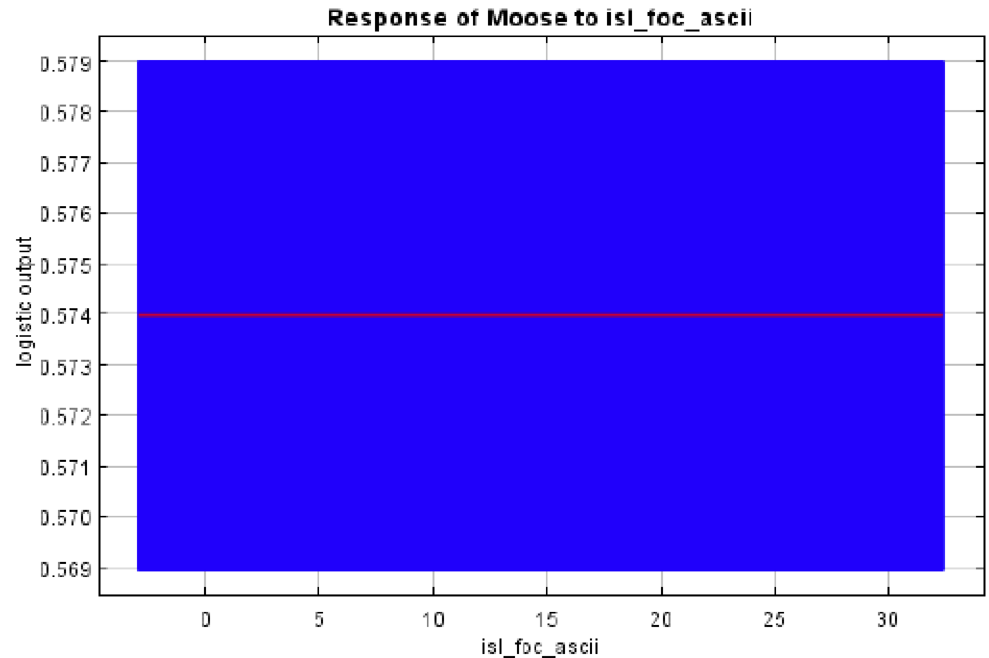
Appendix E-21. Response curve depicting the relative contribution of Mature to Late Upland Conifer & Mixed to the non-binary model.



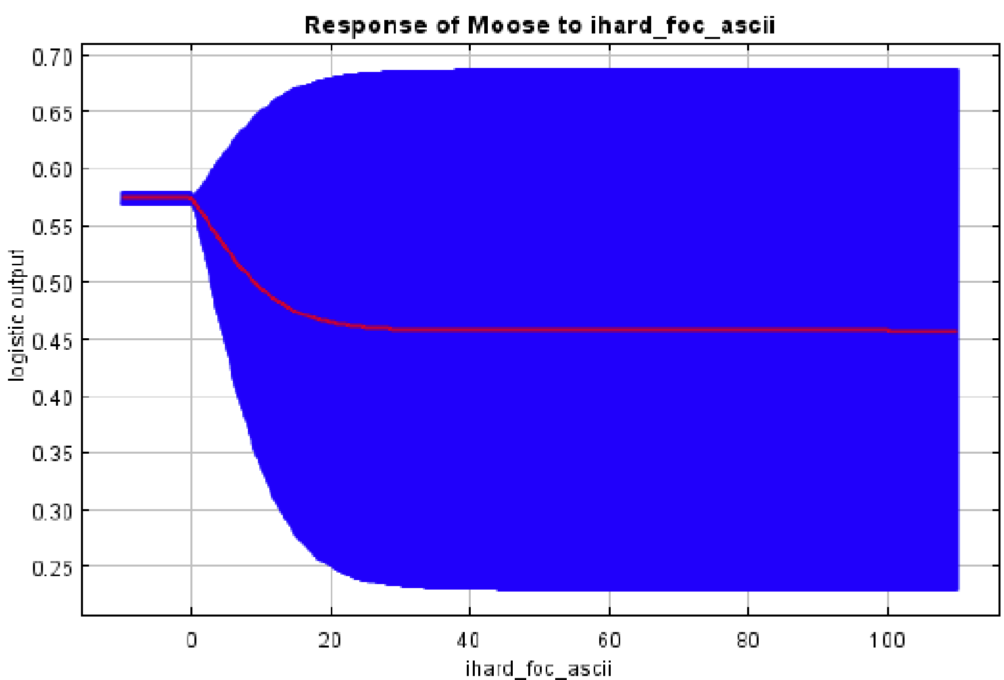
Appendix E-22. Response curve depicting the relative contribution of Water to the non-binary model.



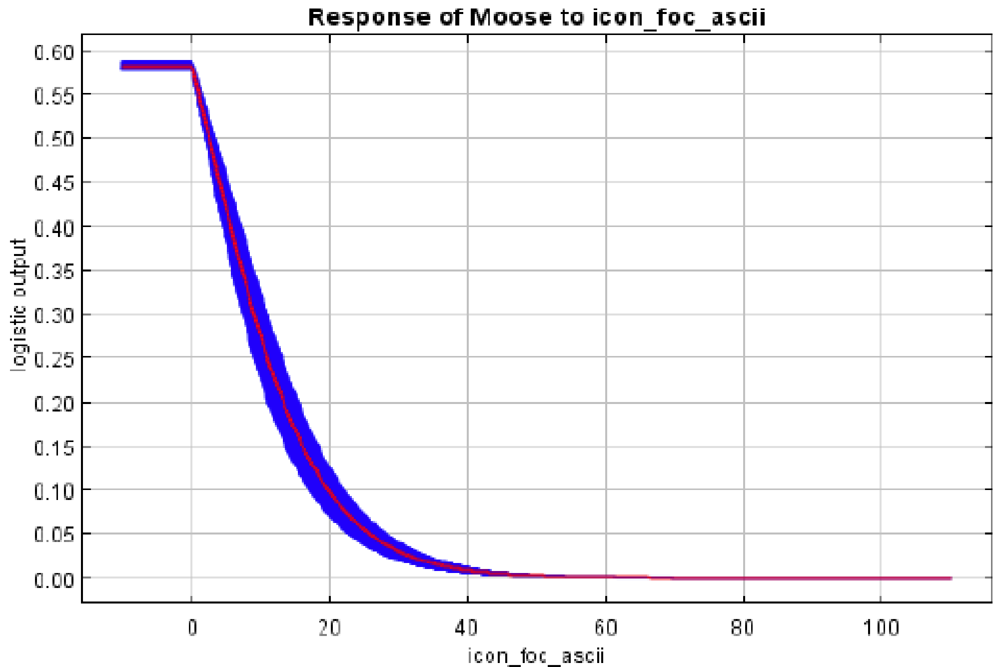
Appendix E-23. Response curve depicting the relative contribution of Mature to Late Lowland Conifer to the non-binary model.



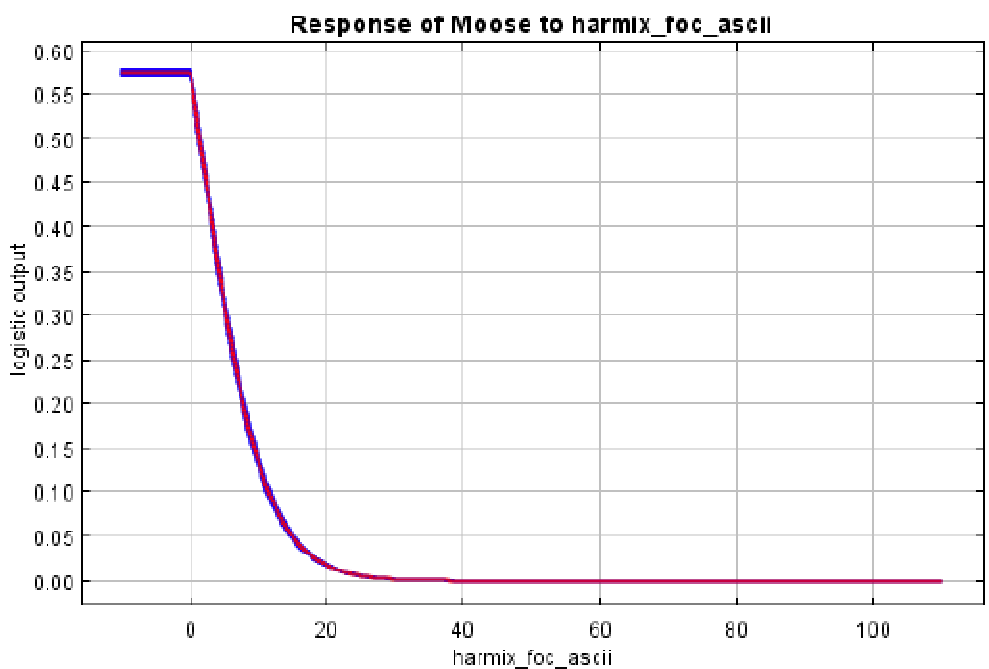
Appendix E-24. Response curve depicting the relative contribution of Islands to the non-binary model.



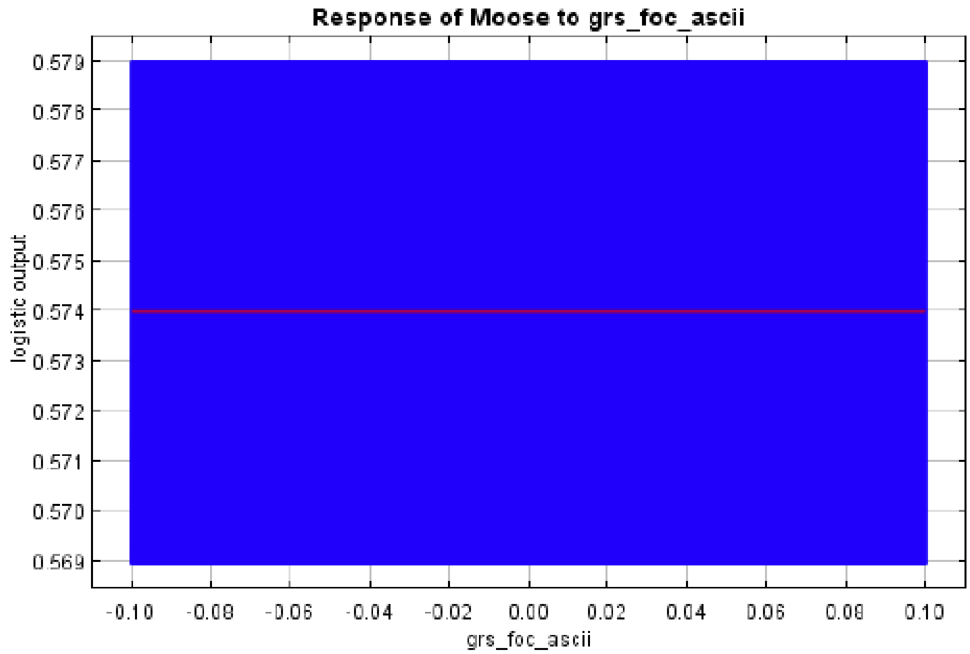
Appendix E-25. Response curve depicting the relative contribution of Immature Hardwood to the non-binary model.



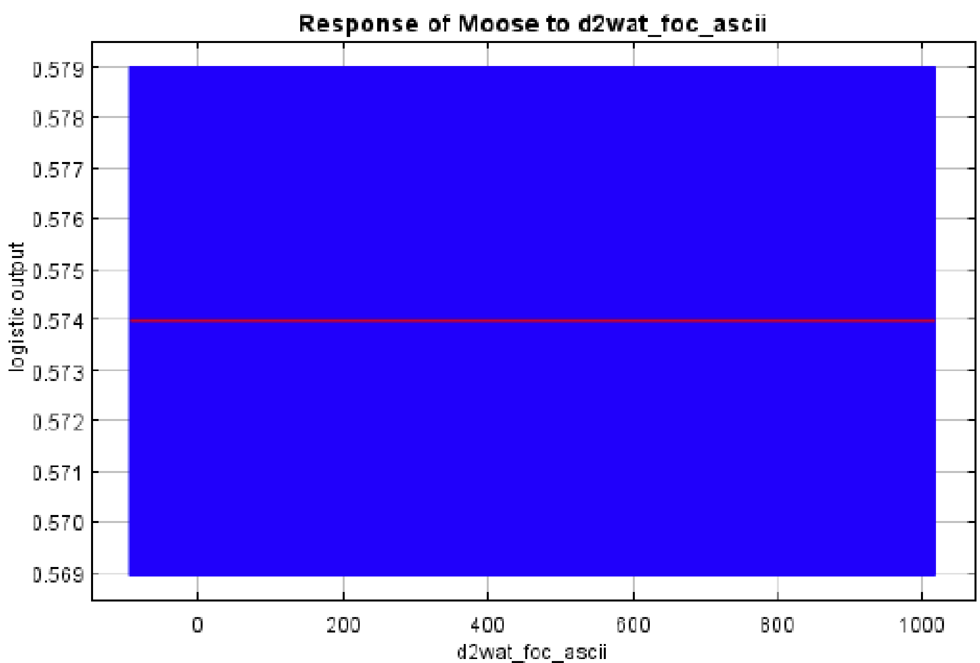
Appendix E-26. Response curve depicting the relative contribution of Immature Conifer to the non-binary model.



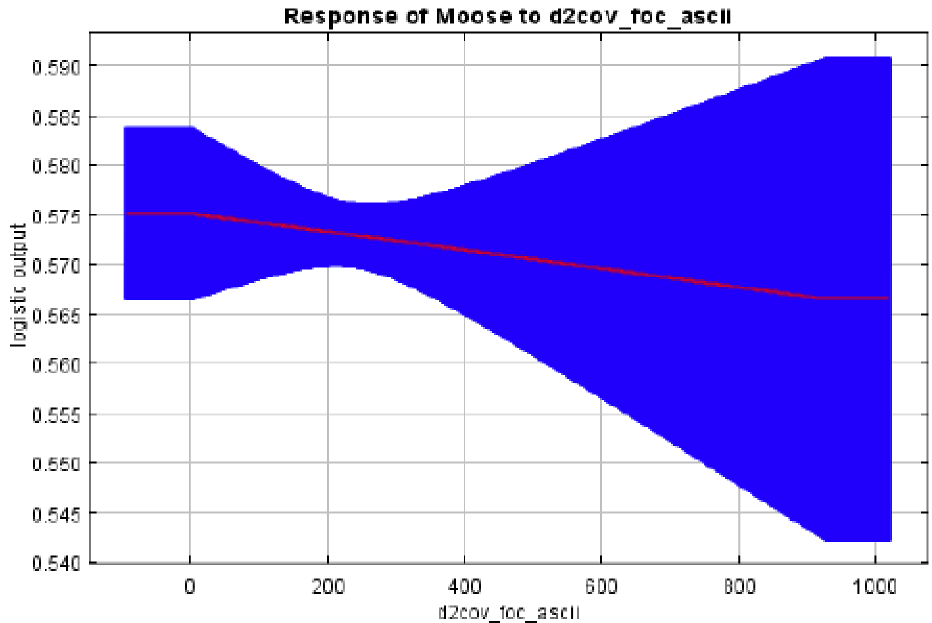
Appendix E-27. Response curve depicting the relative contribution of Mature to Late Hardwood and Mixed to the non-binary model.



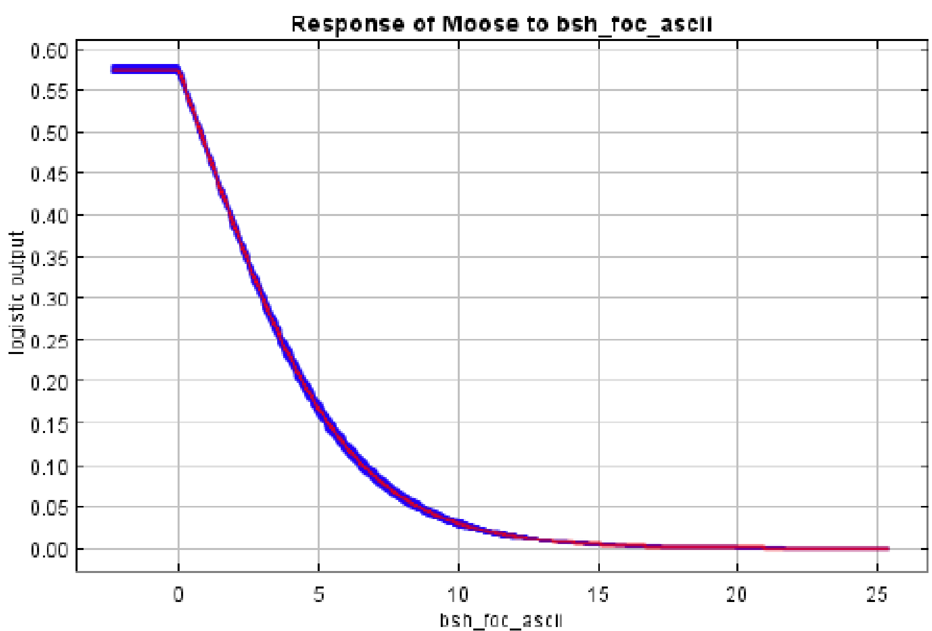
Appendix E-28. Response curve depicting the relative contribution of Grass to the non-binary model.



Appendix E-29. Response curve depicting the relative contribution of Distance to Water (m) to the non-binary model.

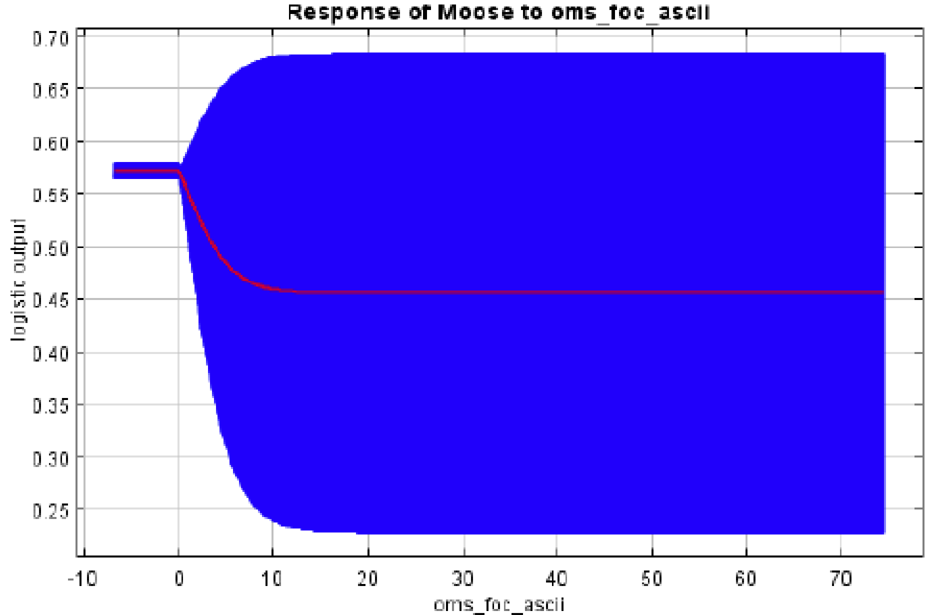


Appendix E-30. Response curve depicting the relative contribution of Distance to Cover (m) to the non-binary model.

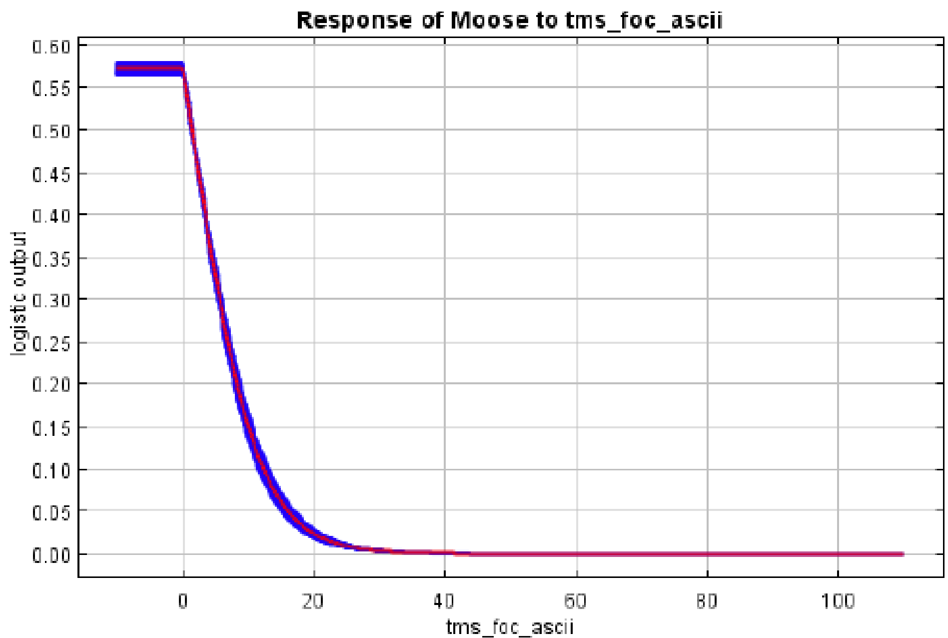


Appendix E-31. Response curve depicting the relative contribution of Brush to the non-binary model.

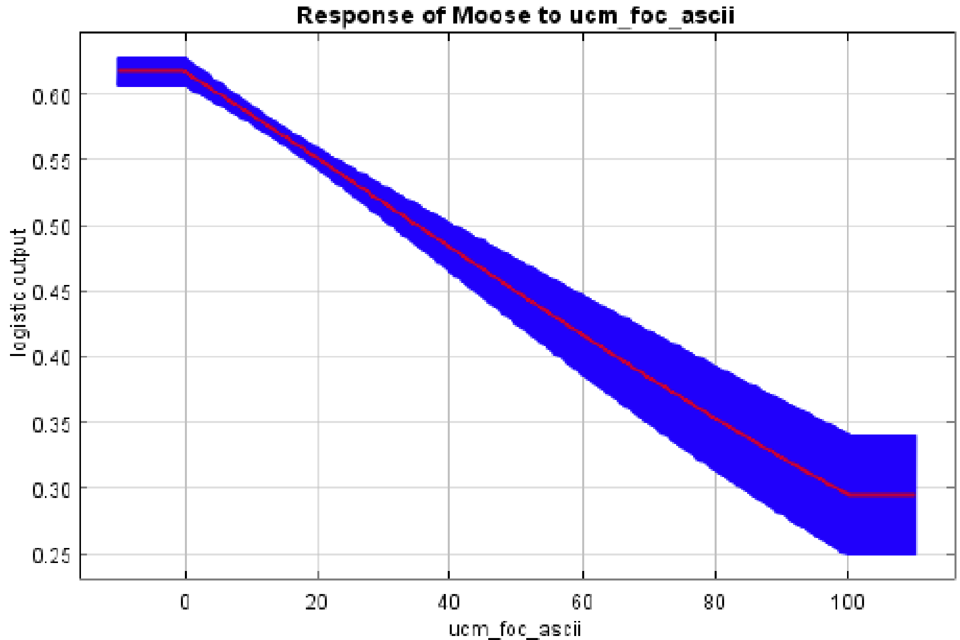
Non-Binary Input Run with Omitted Layers



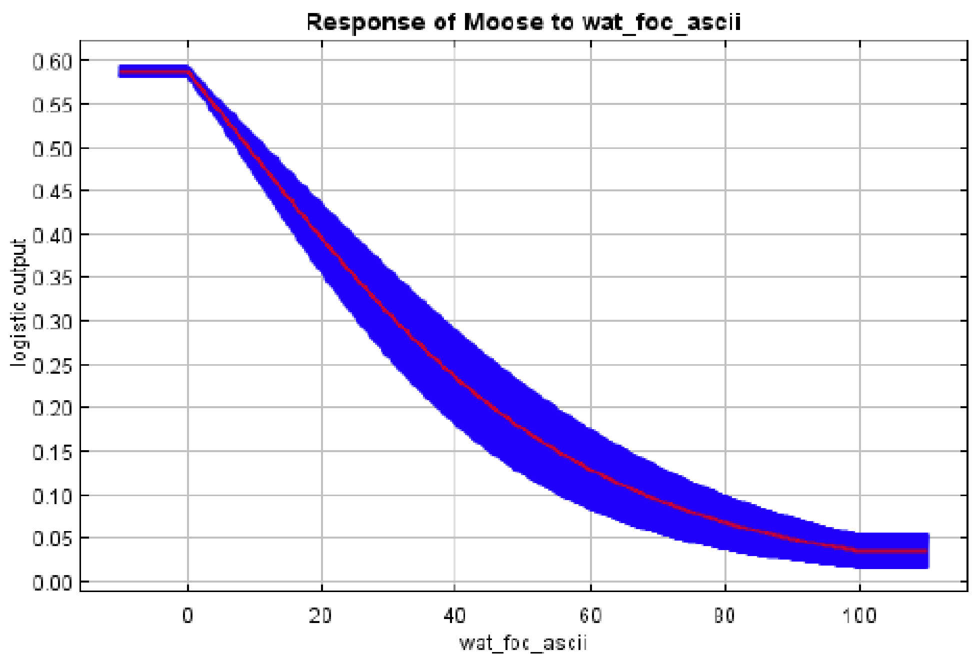
Appendix E-32. Response curve depicting the relative contribution of Open Muskeg to the non-binary model with non-contributing layers omitted.



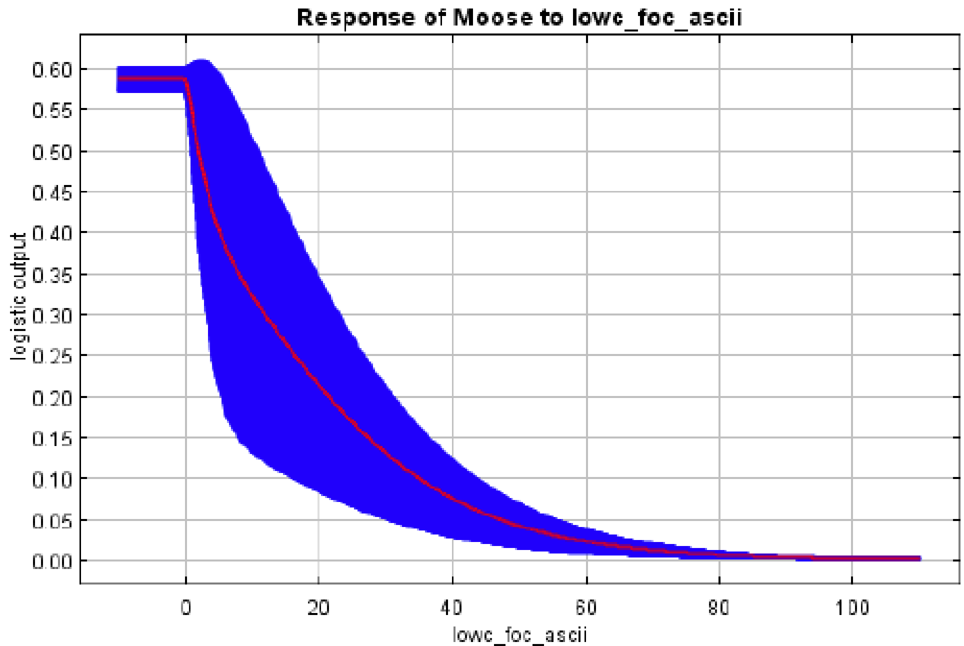
Appendix E-33. Response curve depicting the relative contribution of Treed Muskeg to the non-binary model with non-contributing layers omitted.



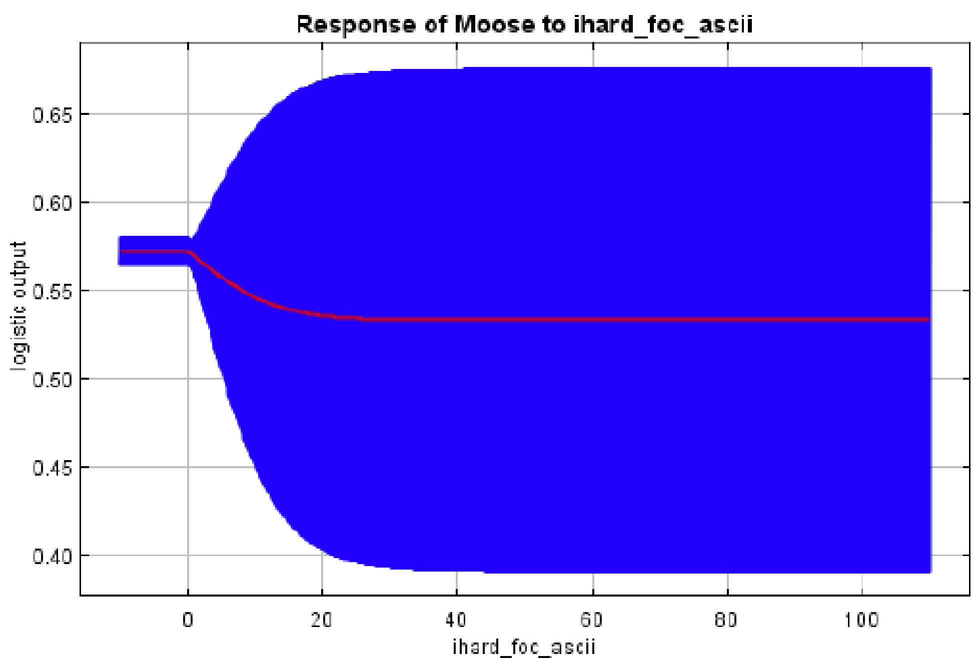
Appendix E-34. Response curve depicting the relative contribution of Mature to Late Upland Conifer & Mixed to the non-binary model with non-contributing layers omitted.



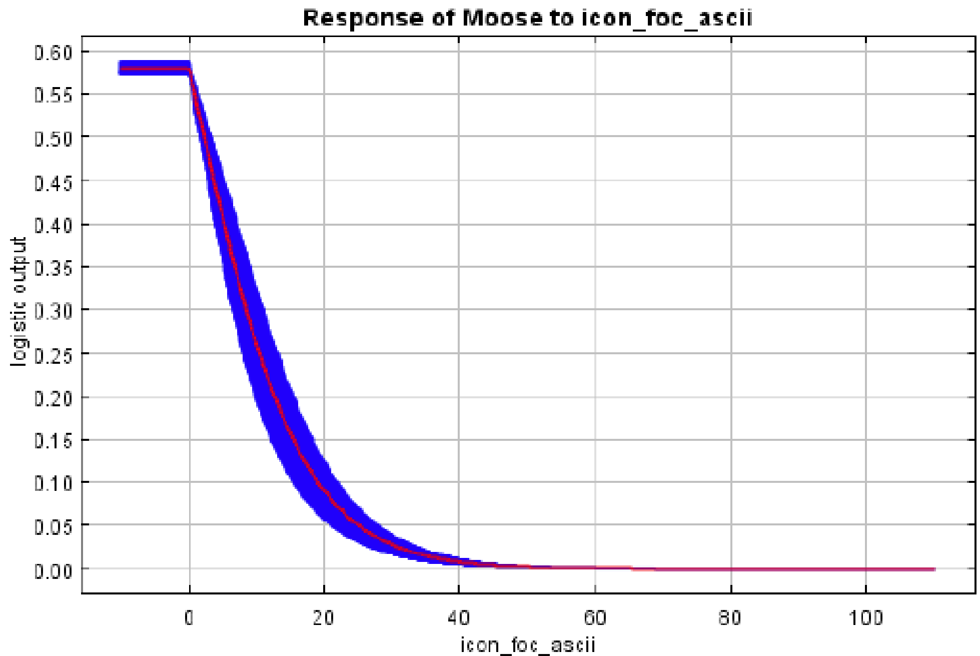
Appendix E-35. Response curve depicting the relative contribution of Water to the non-binary model with non-contributing layers omitted.



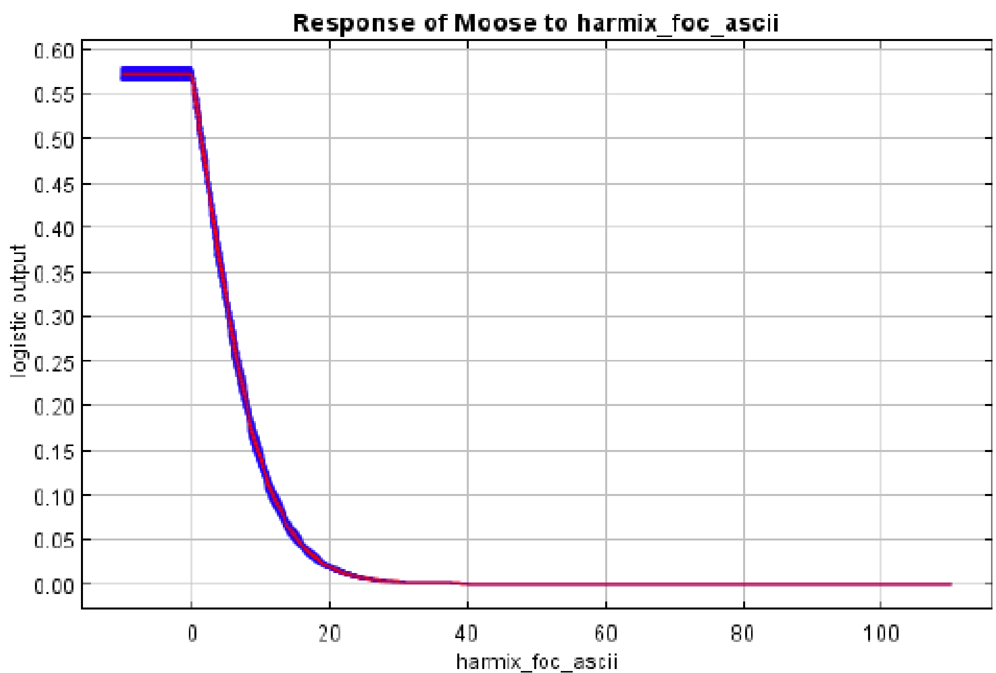
Appendix E-36. Response curve depicting the relative contribution of Mature to Late Lowland Conifer to the non-binary model with non-contributing layers omitted.



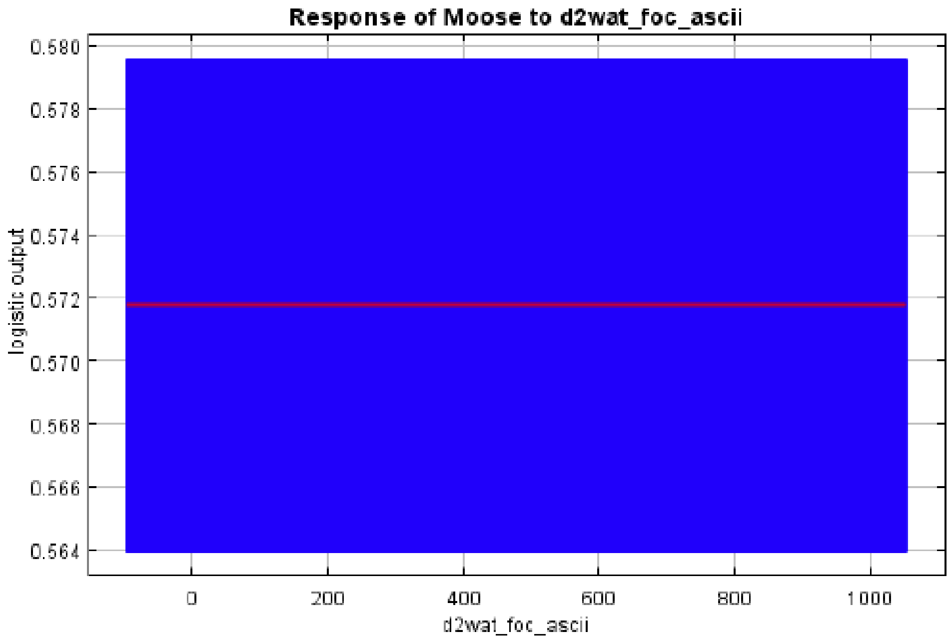
Appendix E-37. Response curve depicting the relative contribution of Immature Hardwood to the non-binary model with non-contributing layers omitted.



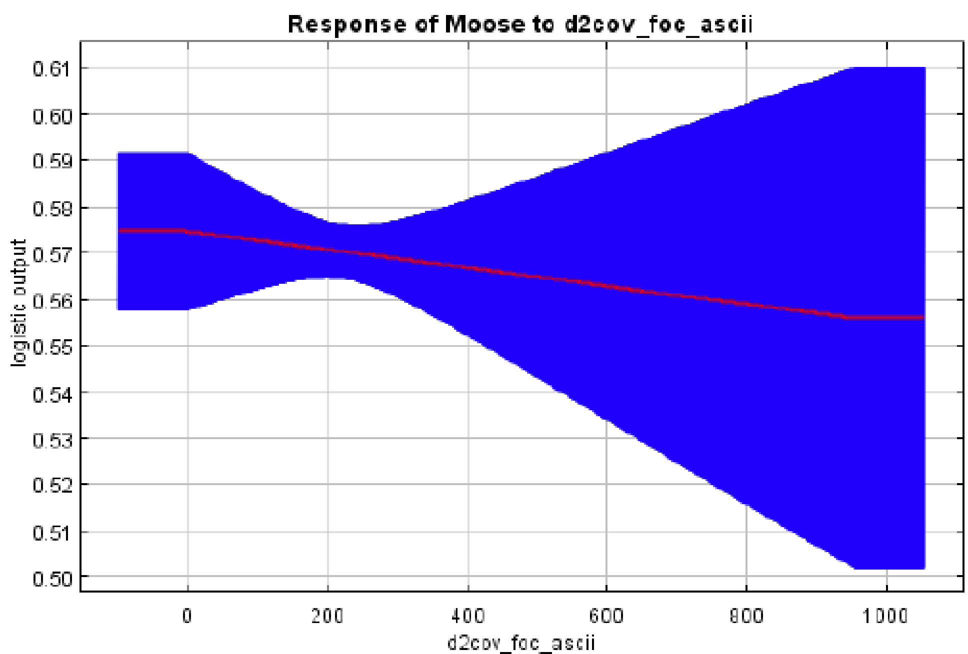
Appendix E-38. Response curve depicting the relative contribution of Immature Conifer to the non-binary model with non-contributing layers omitted.



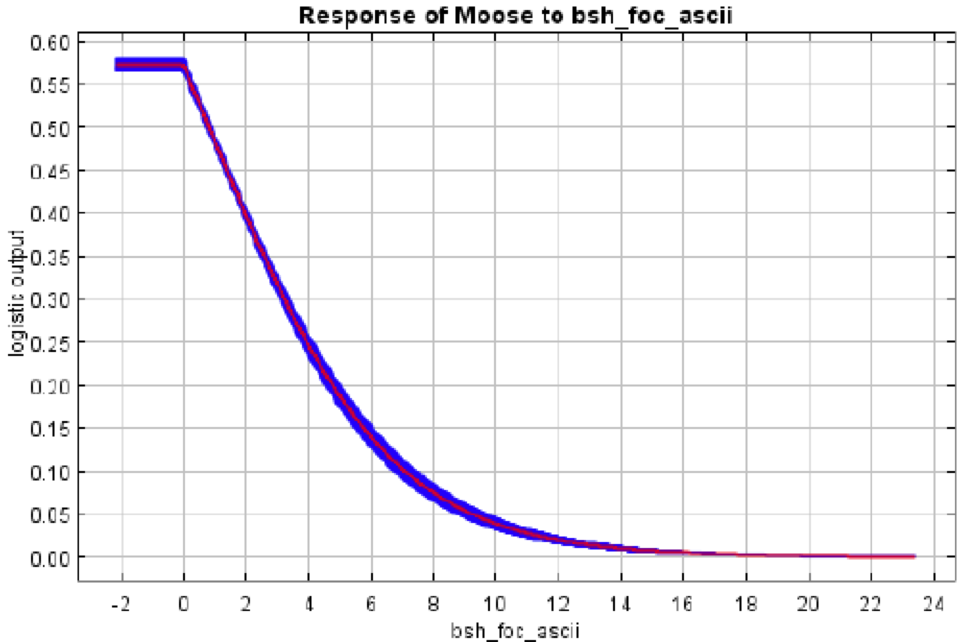
Appendix E-39. Response curve depicting the relative contribution of Mature to Late Hardwood and Mixed to the non-binary model with non-contributing layers omitted.



Appendix E-40. Response curve depicting the relative contribution of Distance to Water (m) to the non-binary model with non-contributing layers omitted.



Appendix E-41. Response curve depicting the relative contribution of Distance to Cover (m) to the non-binary model with non-contributing layers omitted.



Appendix E-42. Response curve depicting the relative contribution of Brush to the non-binary model with non-contributing layers omitted.