A SPECIES DISTRIBUTION MODEL FOR *LINARIA DALMATICA* IN THE KENDRICK MOUNTAIN WILDERNESS, ARIZONA

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ABSTRACT

A SPECIES DISTRIBUTION MODEL FOR *LINARIA DALMATICA* IN THE KENDRICK MOUNTAIN WILDERNESS, ARIZONA

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Geographical position such as slope and elevation coupled with wildfire facilitate the distribution of the aggressive invasive plant, *Linaria dalmatica,* across rangelands of the Kaibab National Forest (KNF). I used presence-only data to develop a species distribution model (SDM) for *Linaria dalmatica* in the Kendrick Mountain Wilderness area of the KNF. I used geographic information systems (GIS) data layers coupled with Maximum Entropy modeling (MaxEnt) to create a species distribution model for *Linaria dalmatica.*

According to the MaxEnt model, highly suitable habitats for *Linaria dalmatica* are predicted to occur at high elevations, steep slopes and burned areas of the Kendrick Mountain Wilderness. The jackknife of regularized training gain from MaxEnt showed elevation as the best variable for the model with a gain or goodness of fit to the model at 0.18. The elevation variable had a strong contribution to the presence on its own without adding other variables. Slope and burn severity variables were also good fits for the model. Slope had a gain of 0.14 and burn severity a gain of 0.13.

Species distribution modeling with MaxEnt may be another tool that allows land managers to focus their efforts on areas of potential invasive plant species risk.

Keywords Dalmatian toadflax, invasive plant species, MaxEnt, GIS

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PREFACE

This professional paper is written in journal format and the target journal is *Biological Invasions.*

Introduction and Background

Many forest and range ecosystems of the Southwest are threatened by the increase of invasive non-native plant species. Some invasive plants become dominant in their new environments, rapidly reproducing, spreading aggressively outside their native ranges (Richardson et al. 2000; Dodge et al. 2008). These aggressive invasive species often have negative effects on the native ecosystems, including replacing and often hybridizing with native vegetation, displacing wildlife, altering ecosystem functions including nutrient cycling and hydrology as well as natural disturbance regimes (Vitousek 1990; D'Antonio and Vitousek 1992; Daehler and Strong 1994; Williamson 1996; Vitousek et al. 1997; Wilcove et al. 1998; Ross and Lembe 1999; Richardson et al. 2000; Ehrenfeld 2003; Levine et al. 2003; McGranahan et al. 2012).

Invasive plants can also negatively affect ecosystem continuity (uninterrupted presence of native ecosystems), which is often associated with high biodiversity and habitat specialist species (Norden et al. 2014). Some invasive plants not only impact natural ecology but can impact human health, recreation and ranching activities (Di Tomaso 2000), which warrants noxious weed status where laws require control. Land managers must understand both current and future problems posed by invasive plant species to prioritize management actions.

Some studies report an increase in invasive non-native plant species after prescribed and wildland fires (D'Antonio 2000). The combined effects of large wildfires due to historical fire management practices coupled with the threat of changing climates makes understanding the dynamics between invasive species spread and fire critical to a successful management plan. Stand replacing wildfires have become more frequent in forests and rangeland areas of the Southwest, which have likely facilitated the establishment of opportunistic invasive plant populations (Dodge et al. 2008). In addition, dense stand conditions, increased fuel loads and global warming effects are often attributed to increases in crown fire numbers and sizes (Covington and Moore 1994; Walker and Smith 1997; Swetnam et al.1999; D' Antonio and Meyerson 2002; Korb and Springer 2003; Schoennagel et al. 2005; Westerling et al. 2006).

The ability to predict invasive plant spread with wildfire depends on many factors including invasive species traits, the ability to colonize burned areas, pre-fire population levels and propagule pressure, plant-plant competitive traits, and time since fire (Grace et al. 2001). In coniferous forests of the southwestern US, some studies show an increase in invasive species with burn severity (Keeley et al. 2003; Hunter et al. 2006; Kerns et al. 2006; Dodge et al. 2008), while other studies report low levels of invasive exotic species cover on severely burned sites (Huisinga et al. 2005; Kuenzi et al. 2008).

History and Morphology

Linaria dalmatica (L.) Mill (Dalmatian toadflax) is an aggressive invasive plant that spreads quickly in disturbed or post-fire systems. *L. dalmatica* is a Mediterranean species that was introduced to North America in the late 1800s as a nursery plant (Alex 1962). In 12 western states it has been legally designated as "noxious" due to its ability to grow outside of its native range (NRCS 2007). *Linaria dalmatica* populations increase quickly in response to disturbances (e.g., fire, disease, drought, flooding and erosion) as well as non-disturbance (anthropogenic introduction such as plant nurseries and natural seed dispersion). Fire was found to promote *Linaria dalmatica* invasion where severity of invasion was correlated with fire severity (D'Antonio 2000; Griffis et al. 2001; Keeley et al. 2003; Keeley 2004; Dodge et al. 2008; Garcia-Dominguez and Palacios 2009). New invasive populations can be initiated and pre-existing populations may increase by soil disturbance (Phillips and Crisp 2001).

Linaria dalmatica morphology is not unique in comparison to other plants as it reproduces using the same methods of seed and root sprouting (Vujnovic and Wein 1996). It is adaptive to a wide range of growing conditions. Researchers refer to it as an "opportunistic invader" as it will propagate in dry, open grasslands and forest sites as well as in disturbed areas with coarse, well-drained soils (Crawford et al. 2001; Griffis et al. 2001; Sieg et al. 2003; Wolfson et al. 2005; NRCS 2006).

Managing for *Linaria dalmatica* has become a challenge across rangelands in the western United States. Land managers could benefit from the use of geographic information systems (GIS) and species distribution modeling to create an effective early detection monitoring tool. Remote sensing has been widely used in research due to its ability to: 1) detect invasive plants without having to physically sample an area (Young et al. 2007), 2) detect invasive plants with spatial resolutions under 30 m (Lass et al 2005), 3) increase accuracy of predictive spatial modeling by improving capacities of data collection (Cohen and Goward 2004), and 4) accurately identify invasive species using time series (Peterson 2005). GIS datasets are also often created through the use of remotely sensed data making it easier for researchers to visually improve their data and place it within a GIS environment such as ArcGIS.

Species distribution models (SDM), also known as niche models or habitat suitability models, are used to predict a species probability of occurrence across a landscape, and relate a species location to environmental data for prediction of the species in unsampled locations (Guisan and Zimmerman 2003; Araujo and Luoto 2007; Elith and Leathwick 2009). There are many statistical approaches to SDMs, but one of the best performing SDM techniques for analysis of presence-only data is maximum entropy or MaxEnt (Elith et al. 2006; Williams et al. 2009).

MaxEnt is a general purpose modeling approach, which is suitable for many applications, especially for data sets involving presence-only data (Phillips et al. 2006). The general idea of this approach is to estimate a target probability distribution by finding "the probability of maximum entropy (i.e., that is most spread out, or closest to uniform), subject to a set of constraints that represent our incomplete information about the target distribution (Phillips et al. 2006)." Phillips et al. (2006) describe the advantages of maximum entropy modeling (MaxEnt) over other modeling methods used in species distribution models, which include:

> "(1) It requires only presence data, together with environmental information for the whole study area. (2) It can utilize both continuous and categorical data, and can incorporate interactions between different variables. (3) Efficient deterministic algorithms have been developed that are guaranteed to converge to the optimal (maximum entropy) probability distribution. (4) The MaxEnt

> probability distribution has a concise mathematical definition, and is therefore amenable to analysis. For example, as with generalized linear and generalized additive models (GLM and GAM), in the absence of interactions between variables, additivity of the model makes it possible to interpret how each environmental variable relates to suitability. (5) Over-fitting can be avoided by using regularization. (6) The output is continuous, allowing fine distinctions to be made between the modeled suitability of different areas. If binary predictions are desired, this allows great flexibility in the choice of threshold. (7) MaxEnt could also be applied to species presence/absence data by using a conditional model. (8) MaxEnt is a generative approach, rather than discriminative, which can be an inherent advantage when the amount of training data is limited."

MaxEnt modeling coupled with the use of GIS data can be a powerful tool to identify species occurrence. GIS data were used to develop a MaxEnt species distribution model (more specifically a habitat suitability model) to identify the occurrence of *Linaria dalmatica* in the Kendrick Mountain Wilderness of the Kaibab National Forest. This distribution model was useful in determining what factors were associated with its distribution by using on-the-ground presence-only data and slope, aspect, elevation, forest type and burn severity predictor variables. I hypothesized that *Linaria dalmatica* populations would occur on south-facing slopes and severely burned areas in the Kendrick Mountain Wilderness study area as this had been shown in the literature (Dodge et al 2008; Blumenthal et al 2012).

Methods

Study Area

This study was conducted on Kendrick Mountain within the Kaibab National Forest, which is approximately 56 km northwest of Flagstaff, AZ (Fig. 1). The study area boundary contains 2,696 ha (6,664 ac.) of national forest lands including the Kendrick Mountain Wilderness. This wilderness is co-managed by both the Kaibab (1,706 ha, 4,217 ac.) and Coconino (990 ha, 2,447 ac.) National Forests. Importantly, this area was the location of a large-scale, lightning induced, forest fire. The fire occurred over a month from May 24-June 24, 2000. The Pumpkin Fire, named for its location along the Pumpkin trail, burned 5,968 ha.

The Kendrick Mountain Wilderness area is a high elevation site where elevations range from 2,133 m to 3,175 m and are characterized by steep rock land, talus slopes and a variety of tree species. The most common tree species include *Pinus edulis* and *Juniperus monosperma* at the lower elevations; *Pinus ponderosa* and *Quercus gambelii*, at the mid-elevations and *Picea engelmannii*, *Abies lasiocarpa* and *Populus tremuloides* at the highest elevations. There are many small grasslands and montane meadows interspersed among the forest canopy throughout the study area.

The Pumpkin Fire of 2000, discussed above, created burn severities ranging from unburned to high-severity crown fires within much of the study boundary and the Kendrick Mountain Wilderness (Fig. 2).

Data Collection/Sampling

Presence-only *Linaria dalmatica* location polygon data were collected (Fig. 3) via Trimble Juno GPS device (±9 m) and organized sampling occasions across a 39 day sampling period from May to August 2012.

An invasive plant inventory was compiled over four years: 2009, 2010, 2011 and 2012. GIS vector datasets corresponding to each of these years of survey have been compiled by the Kaibab National Forest. A survey was also conducted before the fire in 1997 but *Linaria dalmatica* was not detected. It was not until 2009 that the forest began detecting *Linaria dalmatica* west and south of Kendrick Peak as well as north on the Bull Basin trail. A crew of three to four KNF range staff conducted the invasive plant inventory using on-the-ground surveys both on and off trail surveys directed at determining the distribution of *Linaria dalmatica*. Visual observations included binoculars over longer distances allowing the technicians to effectively survey in difficult terrain (Rew et al. 2006, Higman et al. 2012). Fifty-one presence-only *Linaria dalmatica* presence polygons were compiled and used for analyses and modeling.

Analyses and Modeling

Five variables were used as potential predictors of *Linaria dalmatica* presence: slope, aspect, elevation, burn severity and forest type. Slope, aspect and elevation variables were generated from a 10 m digital elevation model (Joe Crouse, Northern Arizona University, Ecological Restoration Institute, GIS and remote sensing research specialist, personal communication). Burn severity and forest type (30 m) pdf and shape files were obtained from the Kaibab National Forest (Christopher MacDonald, Kaibab National Forest, soils scientist, personal communication). All variables were assigned the same resolution (cell size) of 10 m x 10 m, registered in the same map projection (NAD

1983 UTM Zone 12N), and extent, and then each variable was converted to a grid format and clipped to the study boundary within ArcMap 10.3 (ESRI 2015).

It can be problematic to use data layers originally created at 30 m x 30 m cell resolution (such as the burn severity map from this study) and change the cell resolution to 10 m x 10 m. For example, a 30 m x 30 m resolution or cell size has a lower resolution or diminished detail in the dimensions represented by each cell or raster pixel. A 10 m x 10 m resolution has a higher resolution or detail in the dimensions represented by each cell or raster pixel.

I used maximum entropy modeling to examine the distribution of *Linaria dalmatica* presence as a function of elevation, slope, aspect, burn severity, and forest type. I used MaxEnt modeling because it is one of the most popular tools for species distribution (suitable habitat or niche) modeling, it outperforms other methods based on predictive accuracy, and the software is user-friendly (Merow et al. 2013). I used MaxEnt version 3.3.3k (Phillips et al. 2006) for this project.

The MaxEnt software allows the user to make a number of decisions about the input data and settings as the species distribution (or habitat suitability) model is built from the data. For example, one can assign the number of replicate model runs. For my Linaria *dalmatica* model 10 model replicates were run. I used the MaxEnt model predictions as an index of *Linaria dalmatica* habitat suitability. MaxEnt has many rigorous assumptions about sampling (and sampling bias) and probabilistic interpretation of model output. Even if these sampling assumptions are violated, it is still possible to interpret MaxEnt's predictions as indices of habitat suitability, which is useful for qualitative and exploratory analyses (Merow et al. 2013).

Here I list the general steps I used to build a *Linaria dalmatica* MaxEnt model. First I built a *Linaria dalmatica* presence-only list with locations. Then, I prepared the set of predictor variables (elevation, slope, aspect, burn severity, and forest type) as grid cells across the Kendrick Mountain Wilderness study area. Then, I followed the MaxEnt modeling steps, making user-defined decisions regarding number of predictor variables, background data (random data set), training data and test data.

Presence Observations for Target Species

Presence-only polygon data were compiled or "lumped" due to project time constraints. Fifty-one *L. dalmatica* polygons were collected over the entirety of the study area. The data overlapped due to *L. dalmatica* being present during multiple sampling years. To deal with the overlap between polygons, a definition query for *Linaria dalmatica* was conducted. Presence-only polygons were then disaggregated to points so they could be utilized in MaxEnt modeling (Fig. 4). There are a few issues that can come up when disaggregating polygons to points though: 1) one may recognize that two points have fallen into a polygon and overlap ending in duplicated points and 2) converting to centroids results in a shapefile format, giving the correct geometry but changing the attribute names. Generating points from polygons is necessary in order to run MaxEnt as it will only accept point inputs. A total of 12,111 points were used to determine the MaxEnt distribution (background points and presence points).

Background Data

From this study area grid, with all predictor variables, MaxEnt extracts a sample of background locations (where presence/absence data is unmeasured) that it contrasted against the *Linaria dalmatica* presence. The background data were created by sampling 1000 random sample points through ArcMap 10.3, and placing these points 100 m apart across the extent of the study boundary.

Predictor Variables

I limited the predictor variables to those listed in Alex (1962) as suitable habitat for *Linaria dalmatica*. The predictor variables chosen for this study were: slope, aspect, elevation, forest type and burn severity. I did not conduct a correlation analysis to remove highly correlated predictors. Instead, I followed the alternative school of thought based in machine learning (where MaxEnt originated), which suggests that the user includes all reasonable predictors in the model and allow the MaxEnt algorithm to decide which variables are important via the regularization process.

Regularization

MaxEnt selects predictor variables that contribute most to model fit using regularization, which is conceptually similar to the AIC (and BIC) diagnostics for model comparisons and reduces (and penalizes) model over-fitting.

Training and testing data

I used 2,147 presence records as training data to train the MaxEnt model. I used 239 presence records as testing data.

Evaluating and Validating Models in MaxEnt

I evaluated and validated my model in MaxEnt three different ways. First, I used MaxEnt's jackknife of regularized training gain (Fig. 5). Second, I evaluated my MaxEnt model using the analysis of testing and training omission and predicted area (Fig. 6). Third, I validated my MaxEnt model using the area under the receiver operating curve ROC or AUC (Fig. 7).

First, in the MaxEnt model evaluation I used the jackknife of regularized training gain or the "leave-one-out" approach that shows the training gain of each variable if the model was run in isolation and compares it to the training gain with all the variables. This is useful in identifying which variables contribute the most to the model individually and is analogous to the measure of variance or goodness of fit.

Second, for the model evaluation method, the analysis of testing and training omission and predicted area was utilized to determine whether presence data fell in suitable or unsuitable habitat in relation to the given threshold by MaxEnt.

Third, for the model evaluation/validation method the receiver operating curve (ROC) or the area under the ROC curve (AUC) was utilized. This method shows how well the model fits the training and testing data while also explaining the predictive power of the model.

Response curves (Figs. 8 and 9) were also important in this analysis as they showed the probability of species occurrence and 1) averaged values of all other variables and 2) excluded all other variables from the model.

Results

According to the MaxEnt model, suitable habitats for *Linaria dalmatica* have higher elevations, steeper slopes and occur more often on burned areas.

The jackknife approach (Fig. 5) showed when all the predictor variables were run altogether (red line) that the model explained 38% of the variation in the data. Elevation explained 18% of the variation, slope 14% and burn severity 13%. Aspect only explained 1-2% of the variation in the data and was not important to the model whether run on its own or if it was removed.

The omission/commission analysis (Fig. 6) results showed the omission on test samples (green line) matched the predicted omission rate (black line) from the MaxEnt distribution suggesting suitable habitat exists above the threshold. MaxEnt allows the researcher to set a cumulative threshold value. The omission on training samples (blue line) fell below the threshold or predicted omission (black line).

For the receiver operating curve (ROC) or area under the ROC curve (AUC) results (Fig. 7) the model performed better than a random model as the AUC values are larger than the random prediction of 0.5 (training AUC= 0.760 and testing AUC=0.727), but risk being unreliable in how well they explained the model’s predictive power.

Because the presence data were split into training and testing partitions, the AUC values were slightly higher among training values then among testing values.

Discussion

The MaxEnt model predicted elevation, slope and burn severity as drivers of *L. dalmatica* invasion. Steep slopes and the burn severity of wildfires have been shown to be influential in the facilitation of this species through other research (McKenzie et al 2004; Schoennagel et al. 2005; Westerling et al. 2006; Dodge et al. 2008; Blumenthal et al. 2012). *Linaria dalmatica* is an opportunistic invader across the landscape from highly disturbed to pristine areas (Crawford et al. 2001; Griffis et al. 2001; Sieg et al. 2003; Wolfson et al. 2005; Lemke et al. 2011; Blumenthal et al. 2012) but appears to prefer disturbed, south-facing slopes.

The relationship between elevation and presence of *Linaria dalmatica* in the Kendrick Mountain Wilderness may be a function of several factors. One explanation is that elevation is often correlated with other factors such as temperature or precipitation (Liston et al. 2007; Dodge et al. 2008). Liston et al. (2008) found that temperature related factors predicted the presence of *L. dalmatica* in another system. Liston et al. hypothesized that dense toadflax infestations may have been associated with winter temperatures and areas of high snow accumulation due to northwest winter winds blowing snow onto south-facing slopes. Future SDMs should include precipitation and temperature in factors associated with *Linaria dalmatica* presence in the Southwest.

The MaxEnt model used in this study indicated that elevation was a good predictor of *Linaria dalmatica* presence and could be explained by dispersal patterns in that *L. dalmatica* can be found across broad elevations. Dispersal strategies could explain the pattern of invasion found in relation to increasing elevation either via wind or animal dispersal. Southwestern aspects were weakly associated with the presence of this plant owing to the possibility that predominantly western winds (Blumenthal et al. 2012) may have aided in the upslope distribution of this plant. Another explanation may be seed dispersal patterns although Dodge et al. (2008) found that *L. dalmatica* seeds are likely to disperse shorter distances from the mother plant which turns this explanation on its head.

There is a clear relationship between *L. dalmatica* and steep slopes and was demonstrated in the research of Blumenthal et al. (2012) where they quantified relationships between toadflax cover through high-resolution aerial imagery and relative snow deposition. Blumenthal et al. (2012) found that toadflax occurred in 742 of 1,861 of their images implying that it was very common throughout their 400 ha site. *Linaria dalmatica* presence can be found on flat meadow openings but responds greatly to steep slopes. The steeper the slope, the greater the plant will spread.

There is also a relationship of *L. dalmatica* with burn severity, which was demonstrated in Dodge et al. (2008). Areas that had received medium to high severity burns had experienced greater numbers of this species. *L. dalmatica* does not require fire to establish, but medium to high severity burns can and often will influence plant spread.

Potential issues with Species Distribution Models

There are some potential issues with the MaxEnt species distribution model I created, and most of these issues are common to all modeling approaches. These issues include transferability, the model species' range is still expanding, sampling distribution bias, model evaluation, and model selection.

Over-estimates of potential impact

Distribution models of invasive plants over-estimate potential impact (Bradley 2013). This is quite common amongst species distribution models for example MaxEnt can over-estimate potential impacts of invasive plants when presence and background data come from the same source.

Transferability

One potential problem with the MaxEnt model is the ability to transfer findings from the sampled area of Kendrick Mountain Wilderness to other unsampled areas. The environmental variables that were important in this study may change when modeling *Linaria dalmatica* in other areas. Therefore, results from this study should be considered limited in scope and would not transfer to other areas of the Kaibab National Forest or beyond.

Species range could still be expanding

Species distribution model predictions may under predict leading to a reduced distribution of the species. However, the data for this model were collected 10 years or more after the Pumpkin Fire occurred in the study area, so it is likely that *Linaria dalmatica*'s range is beginning to stabilize on Kendrick Mountain (Phillips and Crisp 2001).

Sampling distribution bias

The accuracy of any model is influenced by the sampling distribution. If the sampling distribution is biased because of the sampling method (for example, targeted sampling near trails, roads, etc.) then the resulting model will not accurately predict the species' distribution across the landscape.

Model evaluation

Model evaluations provide information regarding whether a model can predict distributions that are different than random. I used the jackknife test to assess the importance of predictor variables in my training data, testing data, and AUC. The jackknife approach relies on threshold values to predict presence-pseudo-absence locations. Threshold values differ for each model, and are selected at the discretion of the modeler. I was interested in identifying any possible area where *Linaria* might occur, so I wanted to minimize commission error. Once a threshold has been identified, locations can be classified as suitable or unsuitable for the species of interest.

Model selection

The best model out of a subset of potential models is model selection. I chose the best model using the jackknife due to its robustness and ability to look at variable contributions individually, without and in conjunction with other variables.

Management Implications

The establishment of the aggressive, exotic, noxious *Linaria dalmatica* in rangelands is a problem many southwestern land managers face with limited methods to control population spread. The Kaibab National Forest has experienced invasion of this species over large areas in rangelands throughout the Forest, and land managers are concerned that *Linaria* populations may keep spreading into the Kendrick Mountain Wilderness and Kendrick Peak. This makes for difficulty in monitoring these invasive populations through ground survey because of the difficult terrain and the inability to reach many areas by foot.

Since these control efforts can be ineffective, land managers could benefit by using MaxEnt coupled with geographic information systems (GIS) to survey these areas. This will help guide monitoring efforts and to place emphasis on the places suitable for establishment. Without these methods monitoring is unguided and efforts can be wasted as well as time that can be spent on other management efforts. Remote sensing coupled with the utility of GIS has greatly facilitated managers in geospatially collecting and disseminating datasets (Pearson et al. 2007). Species distribution models (SDMs) such as

Maximum entropy (MaxEnt) have been widely used by managers to predict areas of suitable plant invasion as well as global climate change.

Young et al. (2007) utilized GIS and MaxEnt to predict areas of invasive plant establishment within Big Bend National Park and created an early detection management tool. Holcombe et al. (2010) generated an efficient global climate change model utilizing MaxEnt that helped identify the leading edge or areas of potentially suitable habitat of *Lepidium latifolium*. This type of modeling is extremely important for natural areas and allows managers to keep better track of populations through more targeted surveys and monitoring. Much effort has been put into monitoring *Linaria dalmatica* populations in the Kaibab National Forest and with these implementations the on the ground monitoring effort can be more effective to verify and control populations (Everitt et al. 1996; Osborn et al. 2002; Goslee et al. 2003; Parker-Williams and Hunt 2004).

There were some lessons learned during the process of creating this MaxEnt modeling tool. First, goals and objectives of the invasive plant survey need to be made clear. Will the survey be used as a rapid assessment of invasive plant establishment or will it be used to monitor plants and predict new ones? Second, the sampling design needs to be planned and well structured. If the purpose of the survey is for monitoring, then a fixed, systematic sampling design should be implemented and the same points visited each year. Data should be collected to determine presence and absence of invasive species over time. Third, it was important to keep all data at the same resolution (e.g., 30 m) during the analyses to keep data intact. Fourth, more predictor variables could have been used to explore the relationship of *L. dalmatica* presence to environmental factors; variables such as precipitation, temperature, soil type, geological features, and distance to trails and water sources.

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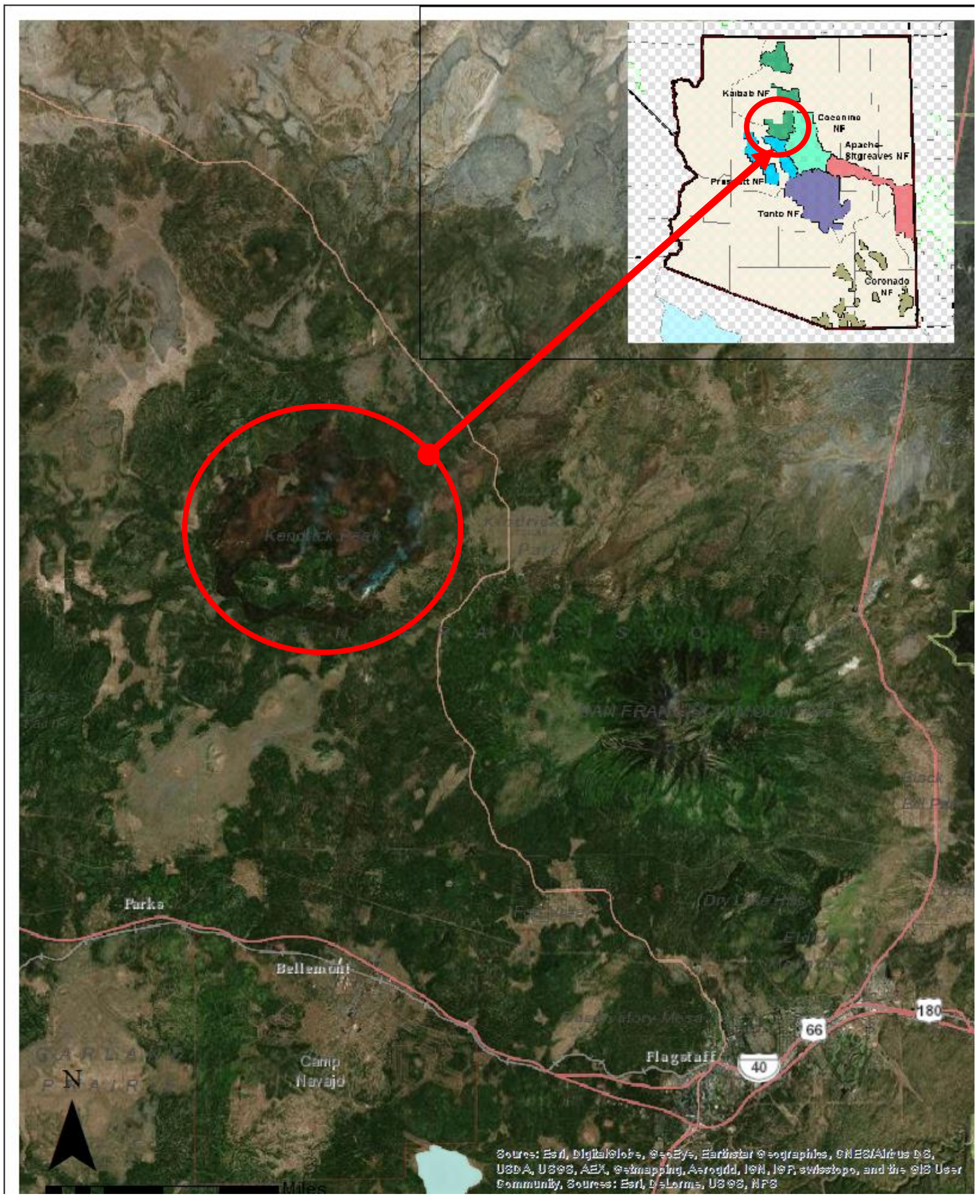

Fig. 1 Study was conducted in Kendrick Mountain Wilderness within the Kaibab National Forest, which is approximately 56 km northwest of Flagstaff, AZ. Kendrick Peak or Kendrick Mountain is one of the highest peaks in the San Francisco volcanic field at 3,176.93 m. Area marked with large red circle shows the Kendrick Mountain Wilderness location in reference to the city of Flagstaff. The smaller red circle shows inset location of the wilderness area within the state of Arizona.

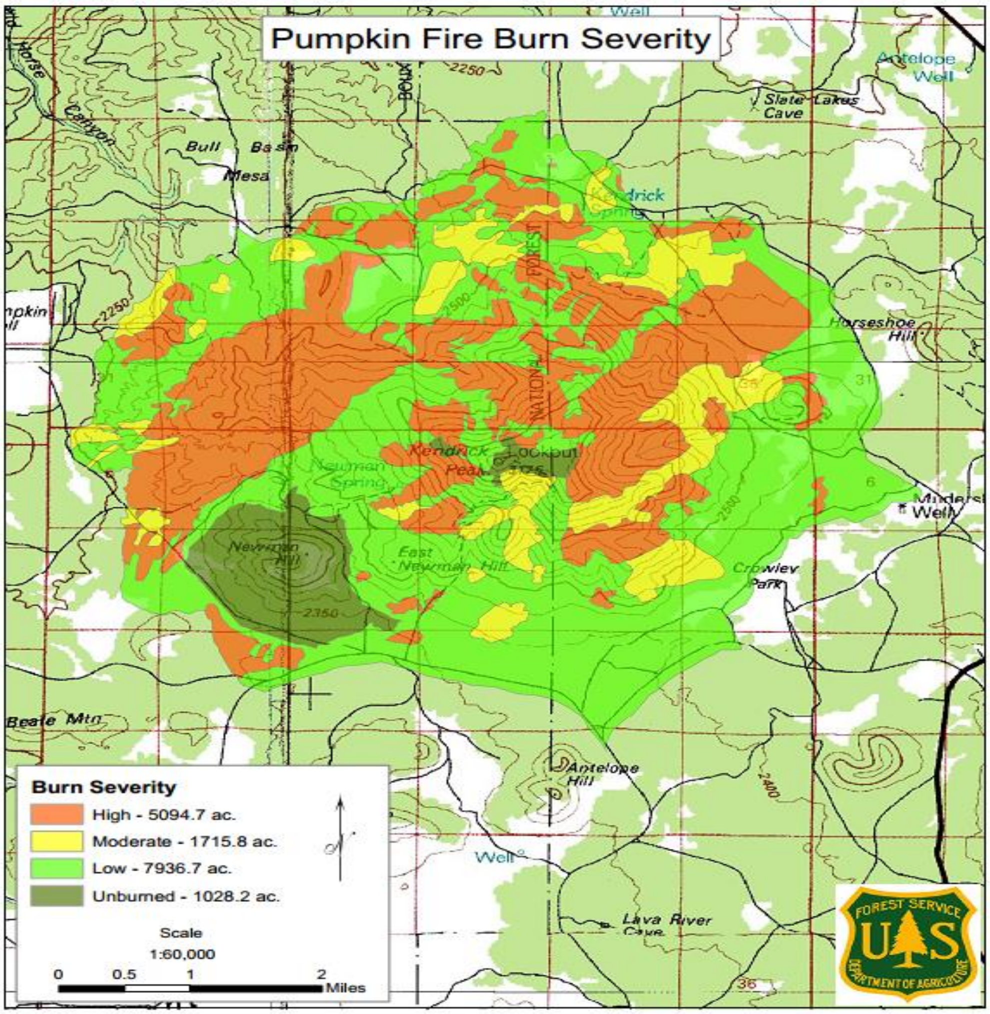

Fig. 2 Pumpkin Fire burn severity map created by USFS Kaibab National Forest. Levels of burn severity are color coded with acreage amounts affected by Pumpkin Fire. Olive green is unburned (416 ha, 1028.2 ac.), lime green is low severity burn (3,211 ha, 7936.7 ac.), yellow is moderate severity burn (694 ha, 1715.8 ac.) and orange is high severity burn (2,061 ha, 5094.7 ac.).

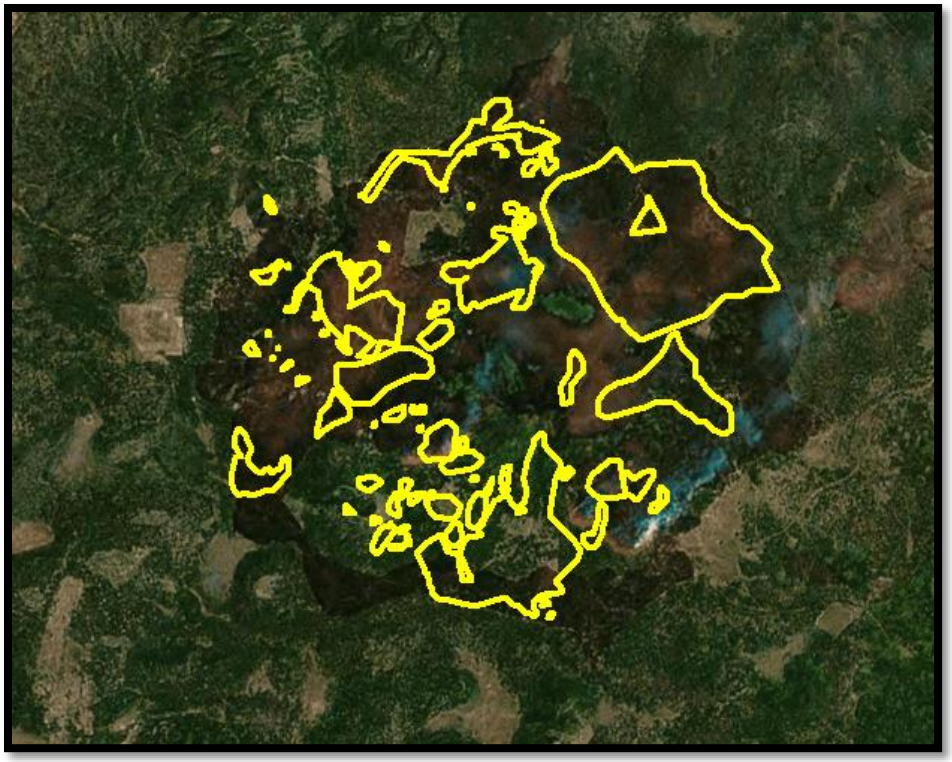

Fig. 3 ArcMap 10.3 map of presence-only polygon locations for *Linaria dalmatica* constrained within the study area of Kendrick Mountain Wilderness. Fifty-one polygons in all were collected to compile presence-only locations.

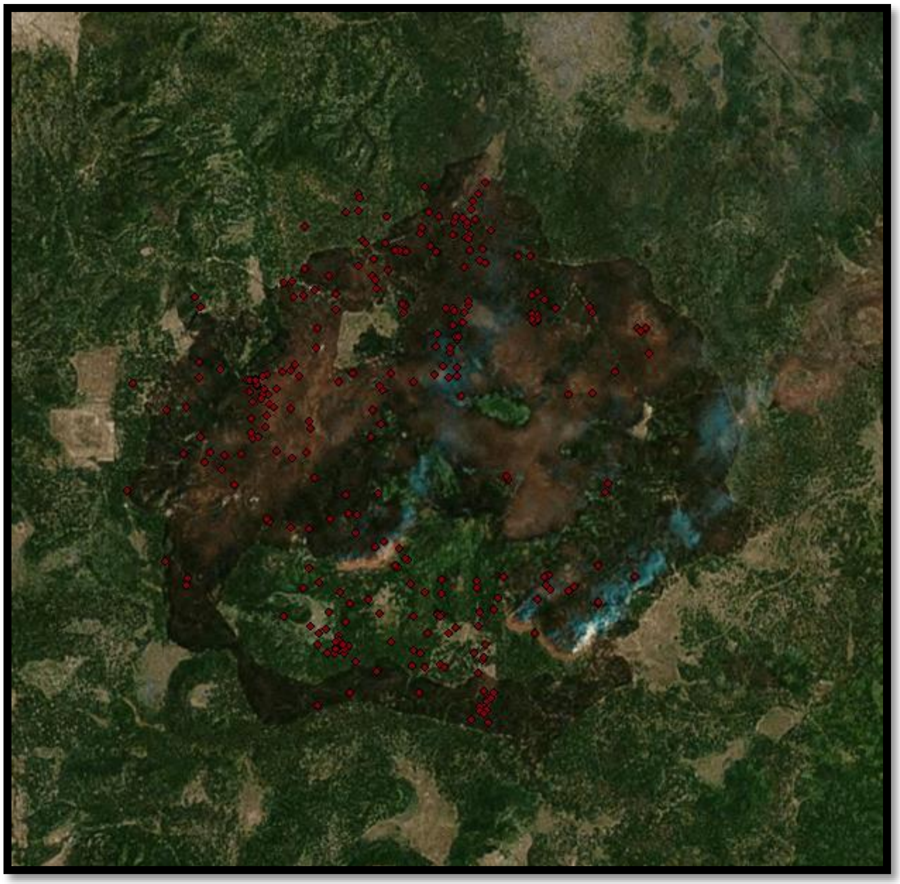

Fig. 4 Map showing boundary of Kendrick Mountain Wilderness with converted *L. dalmatica* polygons to sample points shown in red

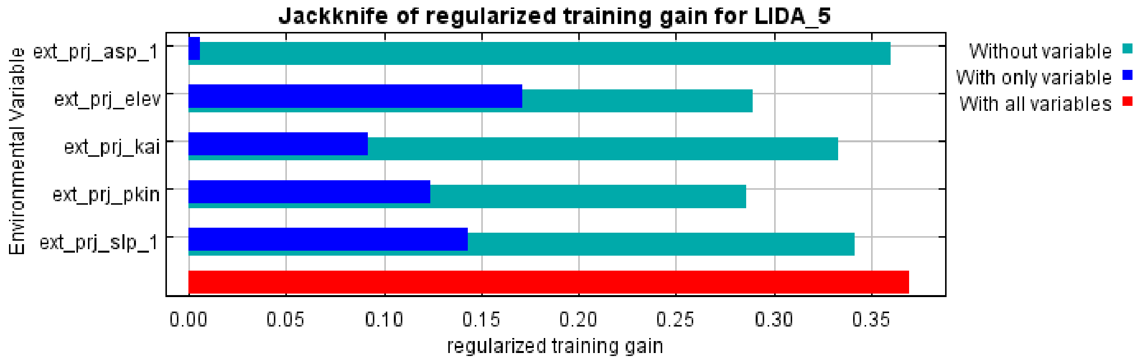

Fig. 5 Jackknife of regularized training gain or "leave-one-out" approach for *Linaria dalmatica* ranks importance of predictor variables (ext_prj_asp_1=aspect, ext_prj_elev=elevation, ext_prj_kai=forest type, ext_prj_pkin=burn severity and ext_prj_slp_1=slope) and is analogous to a measure of variance. A more robust analysis of variable contributions which account for dependencies between predictor variables by building two sorts of models: one involving a given feature by itself, and the other involving all features EXCEPT for the given feature. The x-axis is a measure of model predictive ability, using either 1) training gain; 2) test gain; or 3) AUC on test data. Dark blue bars indicate how well a model performs using only that feature compared to the maximal model (red bar), and light blue bars indicate how well a model performs excluding that feature. Thus, important variables can either have 1) large dark blue bars, indicating strong (but perhaps non-unique) contribution to presences; 2) short light blue bars, indicating no other variable contains equivalent information; or 3) both, indicating the variable is independently predictive.

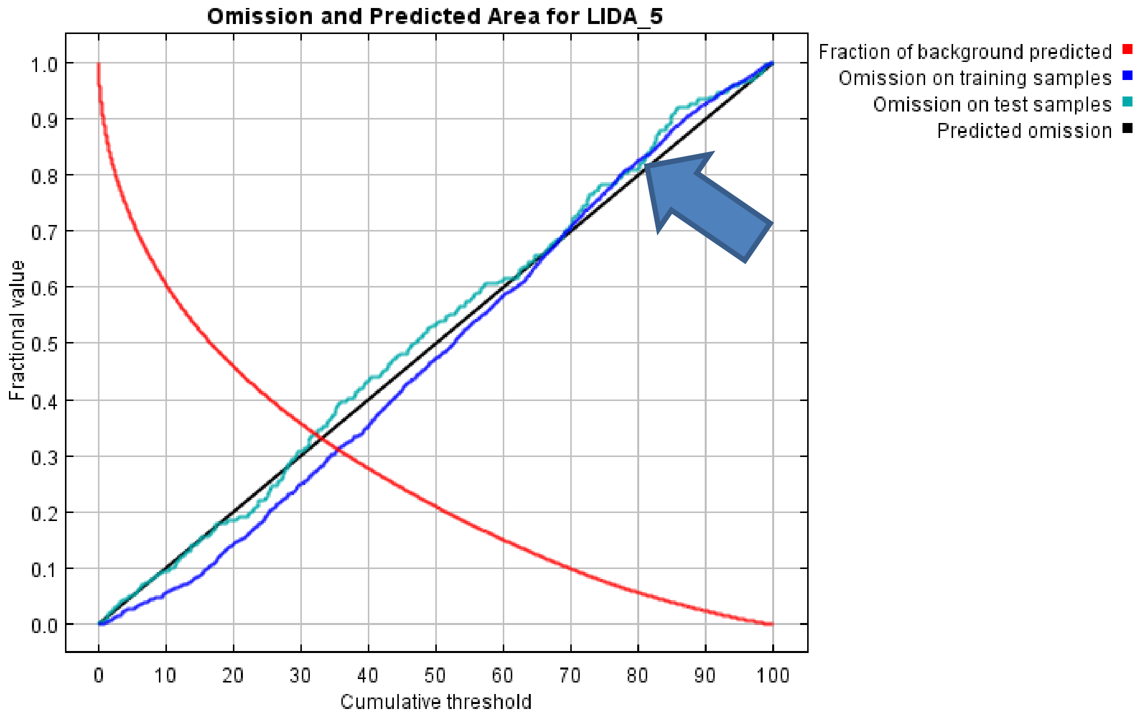

Fig. 6 MaxEnt testing and training omission analysis and predicted area for *Linaria dalmatica*. The omission on test samples (green line) matched the predicted omission rate or threshold (black line) from the Maxent distribution suggesting suitable habitat exists above the threshold. Threshold is indicated by blue arrow. The omission on training samples (blue line) fell below the threshold or predicted omission (black line).

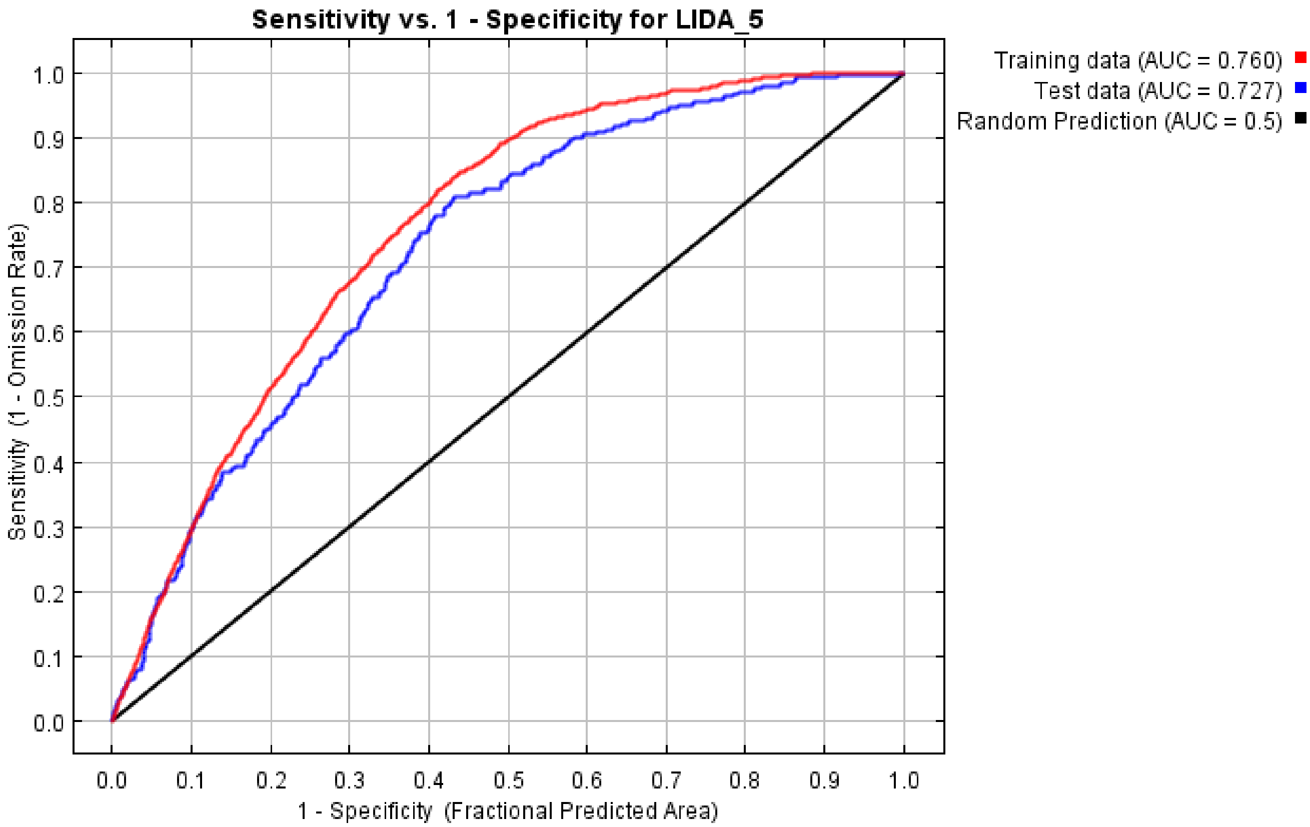

Fig. 7 The test for validation and evaluation of Maxent models is the receiver operating curve (ROC) or area under the ROC curve (AUC). Y-axis shows sensitivity of prediction to data and x-axis is predicted area to data. AUC values larger than the random prediction of 0.5 (training AUC= 0.760 and testing AUC=0.727) are desired but risk being unreliable in how well they explain the model's predictive power. In this study, the presence data were split into training and testing partitions and the AUC values were slightly higher among training values then among testing values. The red line (training) shows how well the model fits the training data. The blue line (testing) indicates how well the model fits the testing data while also explaining the predictive power of the model.

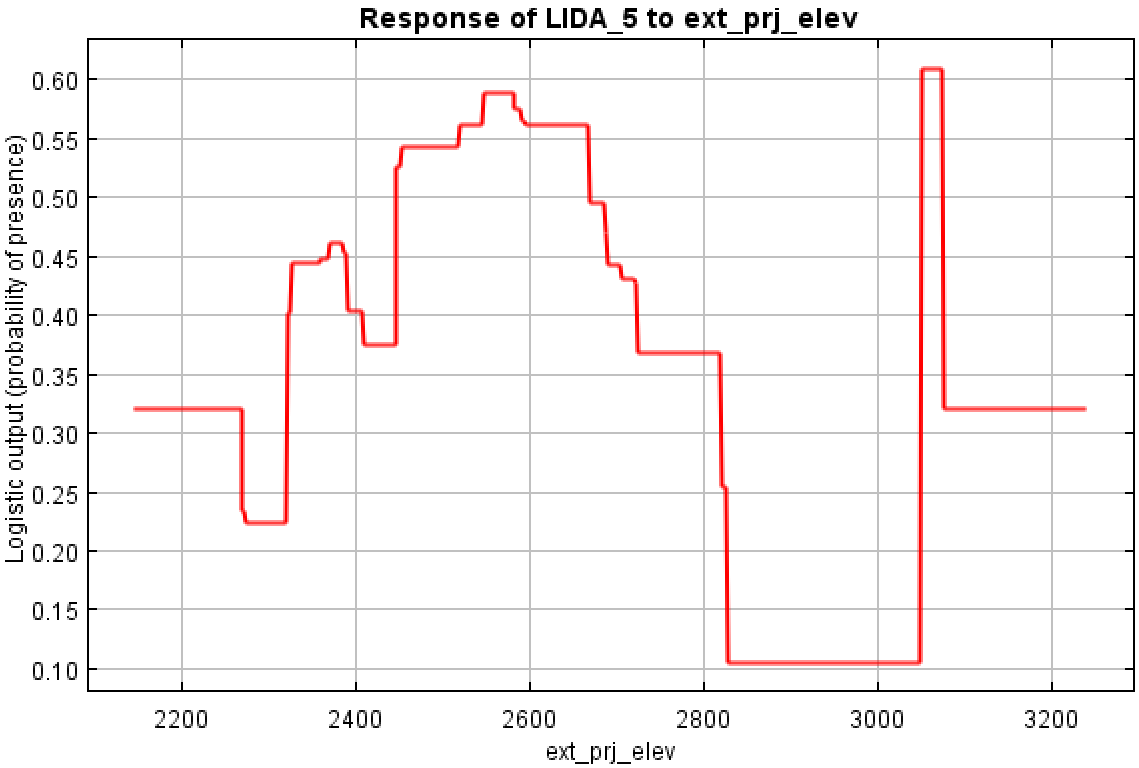

Fig. 8 Response curve for elevation and *Linaria dalmatica* showing on y-axis probability of presence and on x-axis levels of elevation. An increase of elevation correlates with an increase in the probability of *Linaria dalmatica* presence. The drop in probability from 2900 m to 3100 m may be an artifact of *L. dalmatica* not being present at those elevations.

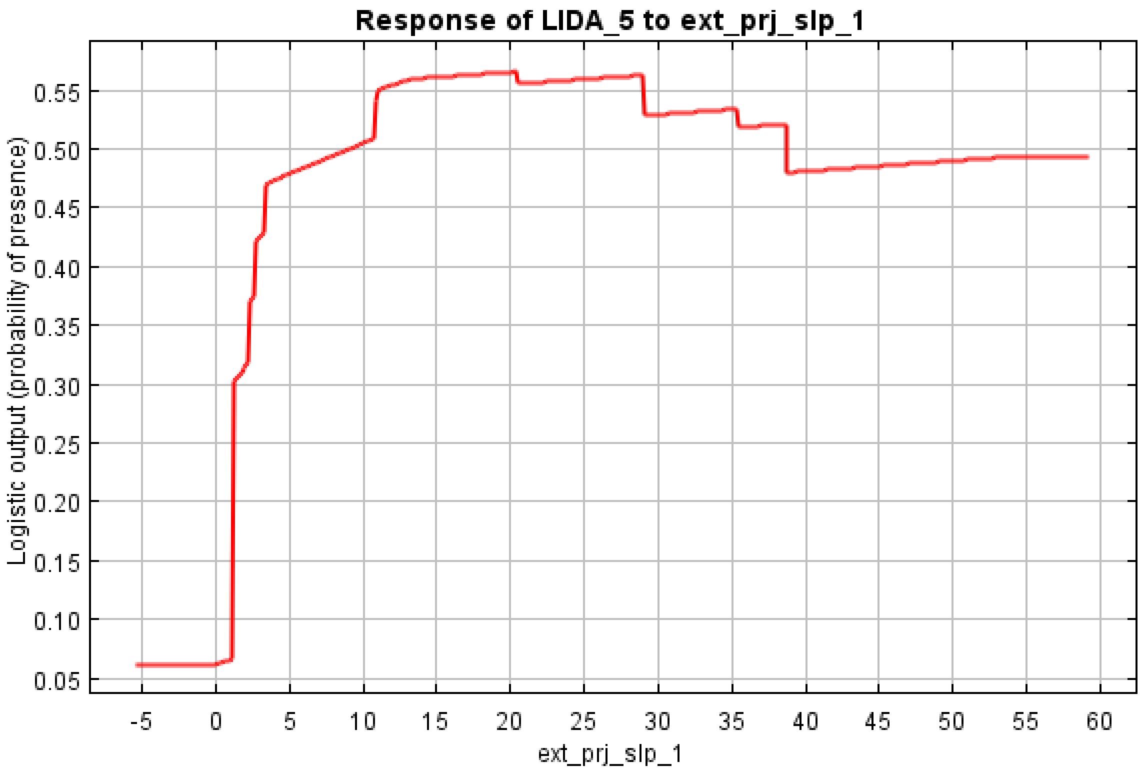

Fig. 9 Response curve for slope and *Linaria dalmatica* showing on y-axis probability of presence and on x-axis degrees of slope. Slope increases the probability of *Linaria dalmatica* presence.

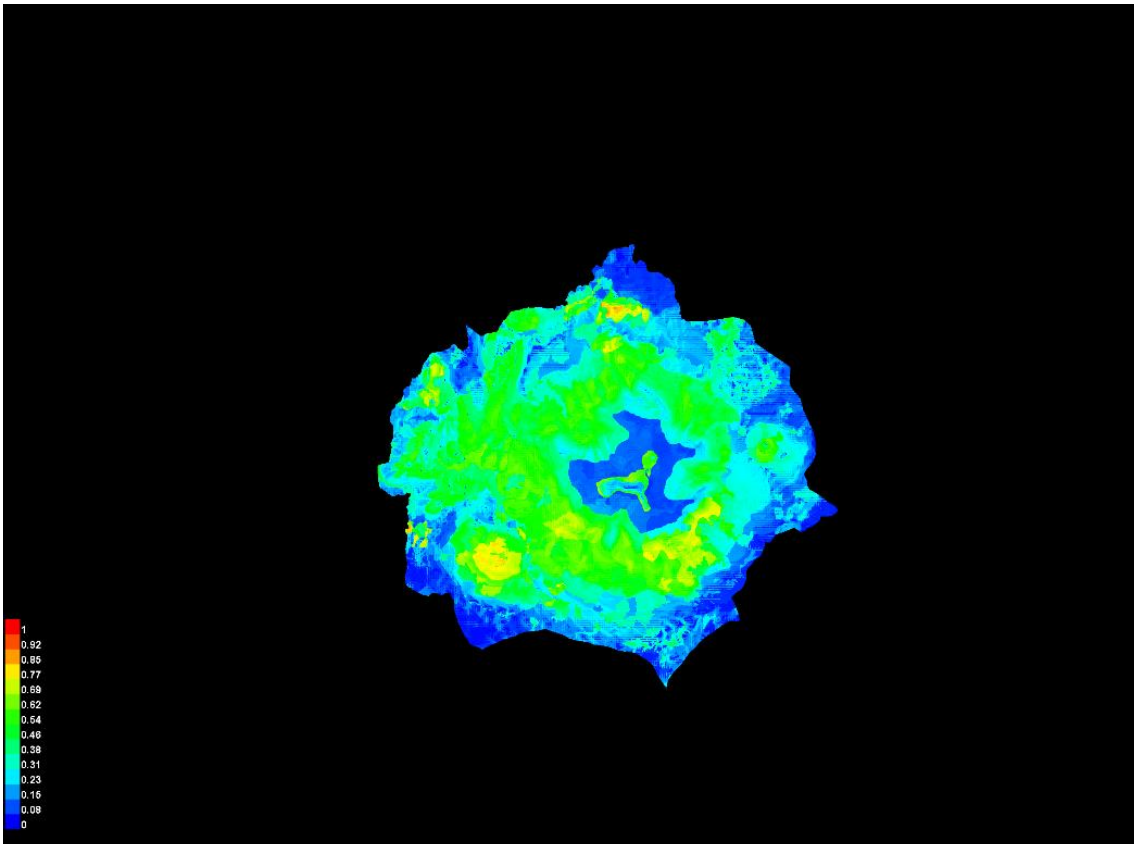

Fig. 10 MaxEnt map of predictive probability for *Linaria dalmatica* showing a probability scale from 0-1. Areas of blues and greens exhibit a low probability of presence where oranges and reds are a high probability of presence. This model shows that areas southeast, southwest and north of Kendrick Peak have high probabilities of presence specifically in the Newman Hill/East Newman Hill areas, southeast in Crowley Park area as well as north of the wilderness area around Kendrick Spring area.