Invasive ranges of *Ulex europaeus* (Fabaceae) in South Australia and Sri Lanka using species distribution modeling

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Abstract- The distribution of *Ulex europaeus* plants in South Australia has been modeled using presence-only location data as a function of six climate parameters. The predicted range of *U. europaeus* was mainly along the Mount Lofty Ranges in the Adelaide hills and on Kangaroo Island. Annual precipitation appeared to be the highest contributing variables to the final model formulation. The Jackknife procedure was employed to identify the contribution of different variables to *U. europaeus* model outputs and response curves were used to predict changes with changing environmental variables. Based on this analysis, we revealed that the combined effect of one or more variables could make a completely different impact to the original variables on their own to the model prediction. We found that Maxent acts as a robust model when projecting the fitted species distribution model to another area with changing climatic conditions, whereas we found GLM, Bioclim and Domain models to be less robust in this regard. These findings are important not only for predicting and managing invasive alien *U. europaeus* in South Australia and Sri Lanka but also in other countries of the invasive range.

Index Terms- invasive species, Maxent, species distribution modeling, *Ulex europaeus*

I. Introduction

An understanding of current and potential distribution patterns is fundamental for managing invasive alien species (Gormley et al 2011; Ward 2007). Preventing alien species invasion is hampered due to difficulties in predicting possible areas of invasion in space and time (Gertzen & Leung 2011). In this context, identification and recognition of effective methods and techniques to assess species distribution patterns are important in conservation planning (Baldwin 2009). Species distribution modeling (SDM), the prediction of species' geographic distributions based on environmental variables and available records of species occurrence, is an increasingly used technique that provide information about species ranges for conservation planning and related applications (Glor & Warren 2011; Graham & Hijmans 2006).

Hutchinson defined the species niche as n-dimensional hyper-volume within which a species can survive and reproduce; in the absence of biotic interactions this volume is equal to the species' fundamental niche (Franklin 2010). However, under a given circumstance, a species will usually only occupy a certain part of the fundamental niche, which is called the realized niche (Jiménez-Valverde et al 2011). Therefore, theoretically, SDM estimates a species' potential distribution rather than the actual distribution. When the species niche is projected to a geographical space, it yields a predictive map of species' presence (Phillips et al 2006; Tsoar et al 2007).

The Maximum - entropy algorithm or Maxent software (Phillips et al 2006) is one of the more accurate, increasingly popular and globally accepted machine-learning techniques currently in use for species distribution modeling (Graham & Hijmans 2006; Ramírez-Villegas & Bueno Cabrera 2009). It estimates the probability distribution of maximum entropy of each environmental variable across the entire study area (Graham & Hijmans 2006). Maxent performs extremely well in predicting distributions of species across landscapes compared to other popular approaches for presence-only data (Elith et al 2006).

Ulex europaeus L. (gorse) is a native of Europe (Atlan et al 2010; Ireson et al 2008; Ireson & Davies 2012; Markin & Yoshioka 1996) and the British Isles (Hill et al 2001). It is a nuisance weed in more than 15 countries in the world (Markin & Yoshioka 1996) including Australia and Sri Lanka. We modeled the distribution of *U. europaeus* in two climatically distinct countries in its invasive range, South Australia and Sri Lanka. We selected this species for modeling due to its long history of establishment in its invasive range and also its ecological and economic significance. Therefore, the aims of this study were to (i) predict the potential range of *U. europaeus* in South Australia using data on the current distributions, (ii) compare potential range of *U. europaeus* in South Australia using multiple SDM model comparison and (iii) forecast the possible range expansion of *U. europaeus* in Sri Lanka using the Maxent fitted model to South Australia. Information generated by distribution models is crucial to ensure successful control and management of *U. europaeus* in its invasive range.

II. METHODOLOGY

2.1 Species distribution data

Our data represented 154 presence-only records from a 75-year period (from 1936 to 2011) of specimens held in State Herbarium of South Australia, Adelaide. Duplicate records were removed using 'exact match' option of the ENM tools (Warren Dan L. et al 2010). To reduce the effect of spatial sampling bias species occurrences were filtered using one of the environmental variables, enabling each grid cell to have only one occurrence record. Data cleaning reduced the number of available records resulting to a final set of 111 geo-referenced records. All available *U. europaeus* locational records in Sri Lanka were taken through field study as geo-referenced records for Sri Lankan *U. europaeus* was not located. In the models we used that considered presence-absence data, 'pseudo-absences' were used as absence data. Pseudo absences were selected randomly from all points within the studied area.

2.2 Environmental data

High resolution, 30 arc-seconds (~1 km^2) environmental rasters were downloaded from the Worldclim database (Hijmans et al 2005), version 1.4 (http://www.worldclim.org/) which were based on current time period. Environmental data were re-sampled for the South Australian geographic area of prediction representing the Mount Lofty Ranges, Kangaroo Island and York and Eyre Peninsula (134.29ºE, 140.5ºE, -36.11ºS, -32.2ºS) and for the Sri Lankan extent (79.66ºE, 81.89ºE, 5.92ºN, 9.84ºN). After exploratory modeling, we selected a subset of six highly contributing variables (Table 1) which included annual mean temperature (bio1), isothermality (bio3), maximum temperature of warmest month (bio5), mean temperature of warmest quarter (bio10), annual precipitation (bio12) and precipitation seasonality (bio15). Pearson correlations among variables were tested using ENM tools (Warren D. L. et al 2010).

2.3 Settings for running the model in Maxent

The Maxent, Maximum Entropy Modeling software package version 3.3.3k was employed for the study (Phillips et al 2009). We selected the "Do Jackknife to measure variable importance", "create response curves" and "make pictures of predictions" options. The cumulative output format instead of the default logistic output was chosen. We used 10-fold cross validation allowing Maxent to use all occurrences in the model since we had limited number of occurrence records. Other relevant default settings of the Maxent software were applied, including the maximum number of background points (10,000), replicated run type (crossvalidate), maximum iterations (500), convergence threshold (0.00001), and default prevalence (0.5). Auto features were activated as it is recommended for training samples greater than 80 records.

2.4 Development of potential suitable area maps

The Maxent generated average model output was imported into in ArcMap for suitability analysis. We used a non-fixed threshold approach, the widely used 10 percentile training presence logistic threshold of the Maxent as recommended by (Liu et al 2005). This logistic threshold provided ecologically meaningful better output for the selected species. Therefore, areas above this threshold were considered as 'suitable' and below 'not suitable'. All suitable areas were further categorized into three classes using ArcMap manual classification, 'highly suitable',' moderately suitable' and 'less suitable'.

2.5 Maxent projection to Sri Lanka using Maxent software

The aim of this task was to project the Maxent model for *U. europaeus* that we fit to data from South Australia to a climatically distinct geographic area, Sri Lanka. The same six environmental variables were used as projection layers. A binary presence-absence map was made at a 10 percentile training presence. The available few locality data of *U. europaeus* in Sri Lanka were overlaid on the image to test the prediction.

2.6 Multiple SDM model comparisons for *Ulex europaeus* in South Australia

Four different species distribution modeling methods, namely GLM, Bioclim, Domain, and Maxent, were run in the R statistical programming environment (R Development Core Team 2012) using packages 'dismo' (Hijmans et al 2013), 'raster' (Hijmans & van Etten 2013), 'rJava' (Urbanek 2013) and several model functions in R to compare the potential predicted distribution among modeling algorithms. The aim of this exercise was to investigate the relative ability of different algorithms to make predictions under current climate and to compare the robustness of predictions between these modeling techniques. The same environmental data layers (previously used in Maxent) were used in raster format and the same *U. europaeus* occurrence data were used. Models fit under each of the above modeling techniques were evaluated and predicted for South Australia. Maps of predicted presences and absences were generated under each model at 10 percentile training presence threshold.

III. RESULTS

3.1 Species distribution modeling with Maxent software for *U. europaeus* in South Australia

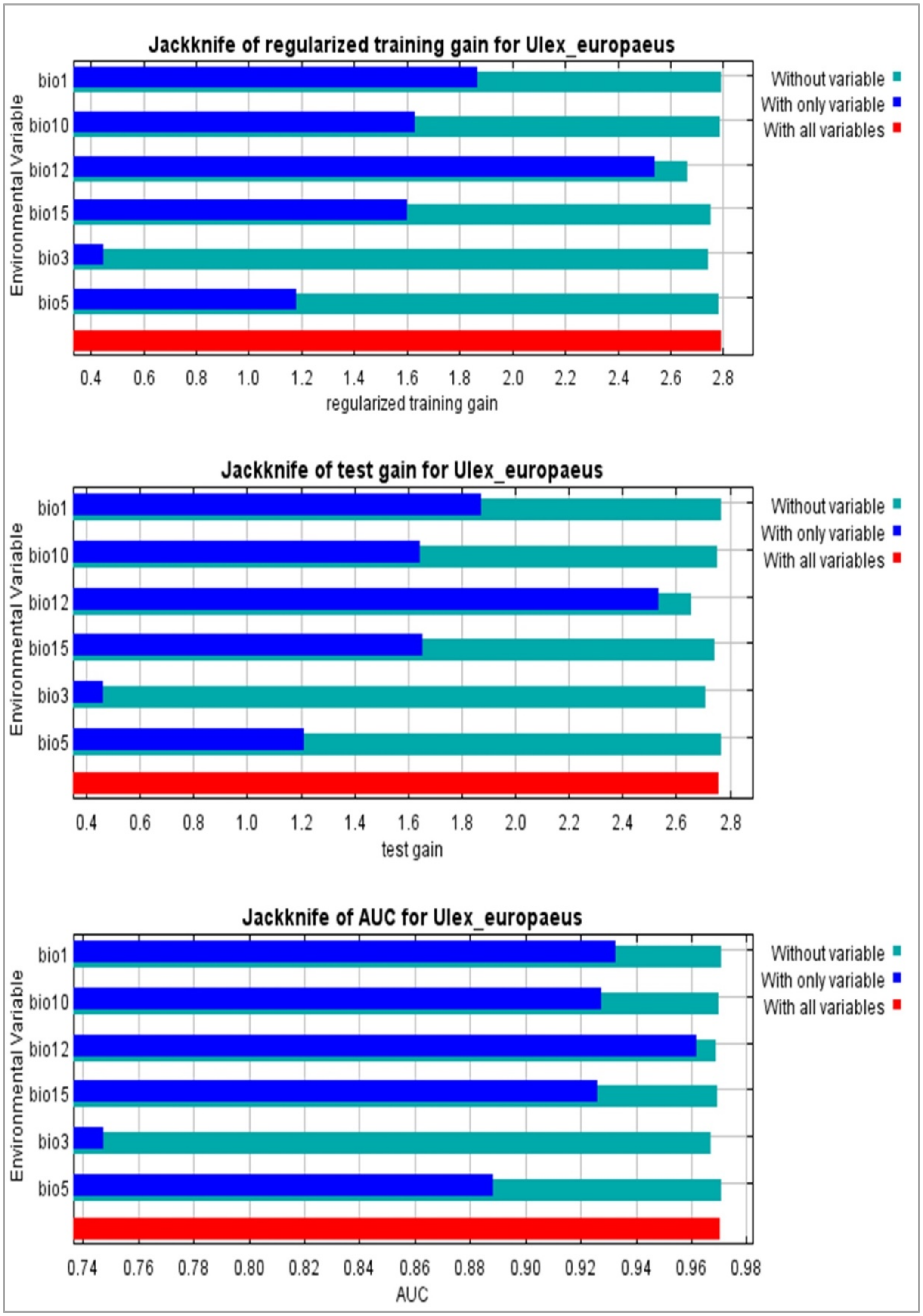
Figure 1 shows the potential range of *U. europaeus* in South Australia. All areas greater than the threshold value at 10 percentile training presence were predicted as areas where *U. europaeus* is predicted to occur under current climate conditions. The Mount Lofty Ranges in the Adelaide hills is predicted as high probability area for *U. europaeus* distribution in South Australia. In addition Kangaroo Island and scattered areas above York Peninsula were predicted as potential ranges. The potential area of suitability of *U. europaeus* under this threshold did not include the Eyre Peninsula but did include slight patches in the York Peninsula. However, a greater predicted area, comprising all of the York Peninsula and a considerable part of the Eyre Peninsula could be observed using the threshold derived from the minimum training presence. In general, AUC value >0.9 is considered as very good performance (Araújo et al 2005; Fielding & Bell 1997). Accordingly, the *U. europaeus* model was found to have a high predictive power or good discrimination ability, with very good mean AUC value of 0.971.

The contribution of different predictor variables to the overall model prediction was analyzed. Annual precipitation (bio12) appeared to be the highest contributing variable for the model formulation under the "percent contribution" criterion (Supplementary material S1). Annual mean temperature (bio1) appeared to be the least contributing variable to determine climatic suitability of *U. europaeus*. Annual precipitation showed highest fit in jackknife test too (Supplementary material S2); however, annual mean temperature showed relatively high importance. Therefore, it is hard to say that annual mean temperature is not important to the model, even though Maxent has used this variable least out of all the six predictor variables. We found that isothermality (bio3) achieves little fit in all three jackknife plots; however, it was a relatively important variable in the final model. None of the six predictor variables contained useful information that is not contained in other five variables. Looking at the response curves of important predictor variables, we noticed that the *U. europaeus* model responded highly to the annual precipitation (bio12) variable and predicted probability of suitable conditions increases continuously with increasing long range of values. The second response curve considering only the corresponding variable behaved similarly to the first.

S1 Contribution of environmental variables for *Ulex europaeus* model

Variable	Percent Contribution
Annual precipitation	85.9
precipitation seasonality	4.7
Isothermality	4.3
Mean temperature of warmest quarter	2.6
Maximum temperature of warmest month	1.8
Annual mean temperature	0.8

S2 Results of Jackknife test of variable importance in the regularized training gain (a), test gain (b) and AUC (c) for *Ulex europaeus* model



3.2 Maxent projection to Sri Lanka using Maxent software

Maxent model projected to Sri Lanka identified the central mountain areas of Sri Lanka as areas with a high predicted occurrence of gorse and the rest of the country with low probabilities of predicted occurrences. Figure 2 shows the Maxent model predicted areas of *U. europaeus* in Sri Lanka at 10 percentile training presence threshold level. The central mountain area of Sri Lanka is predicted occurrence of *U. europaeus.* The *U. europaeus* location data collected from Sri Lanka during our field work were overlaid on this predicted area and all points fell within the predicted area.

3.3 Multiple SDM model comparison with R for South Australia

Figure 3 shows predictions of the distribution of *U. europaeus* in southern South Australia under four modeling algorithms; GLM, Bioclim, Domain and Maxent, individually run in the 'dismo' package in R. The four models performed slightly differently, with the highest model AUC of 0.9632 achieved with the Maxent model, suggesting that this model best fit the data. Maxent showed relatively higher model robustness and its prediction was comparatively more conservative in comparison with the other three models suggesting that the latter three models might have overestimated the suitable climate space. Three models, Bioclim, Domain and Maxent predicted the presence of *U. europaeus* on the Yorke and Eyre peninsulas at varying levels of magnitude. The GLM model did not predict the presence of *U. europaeus* in these regions.

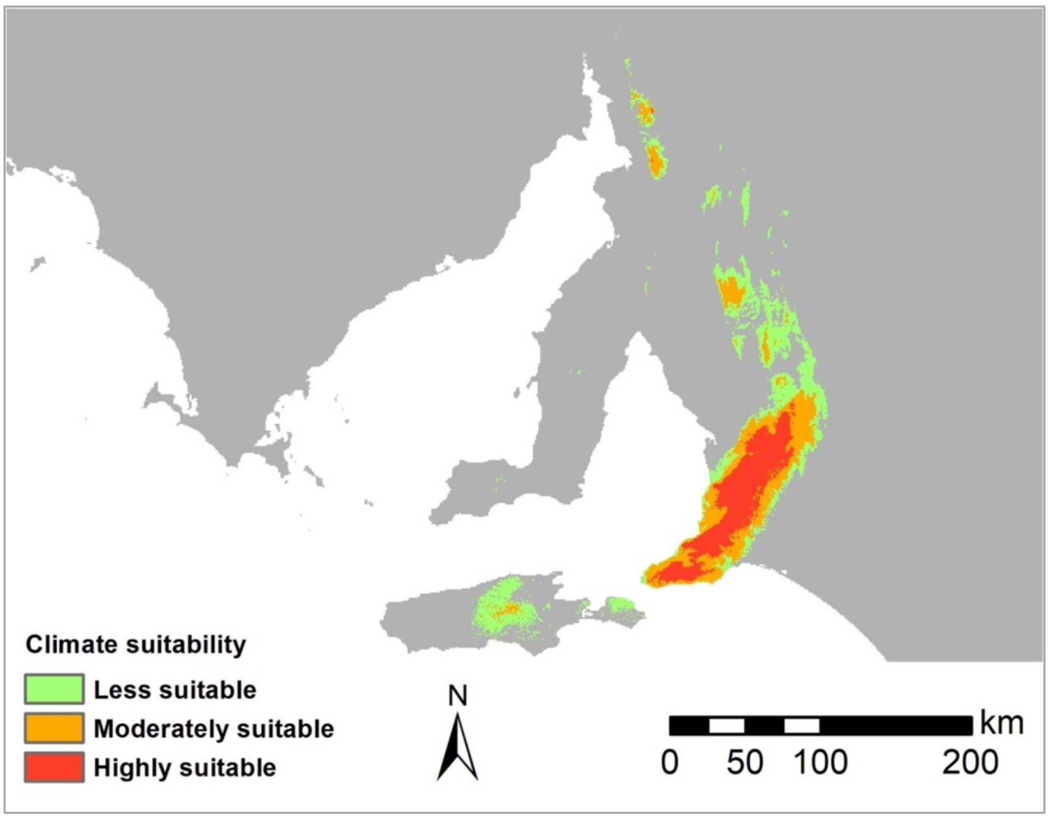


Fig. 1 Potential range of *Ulex europaeus* in South Australia under current climate.

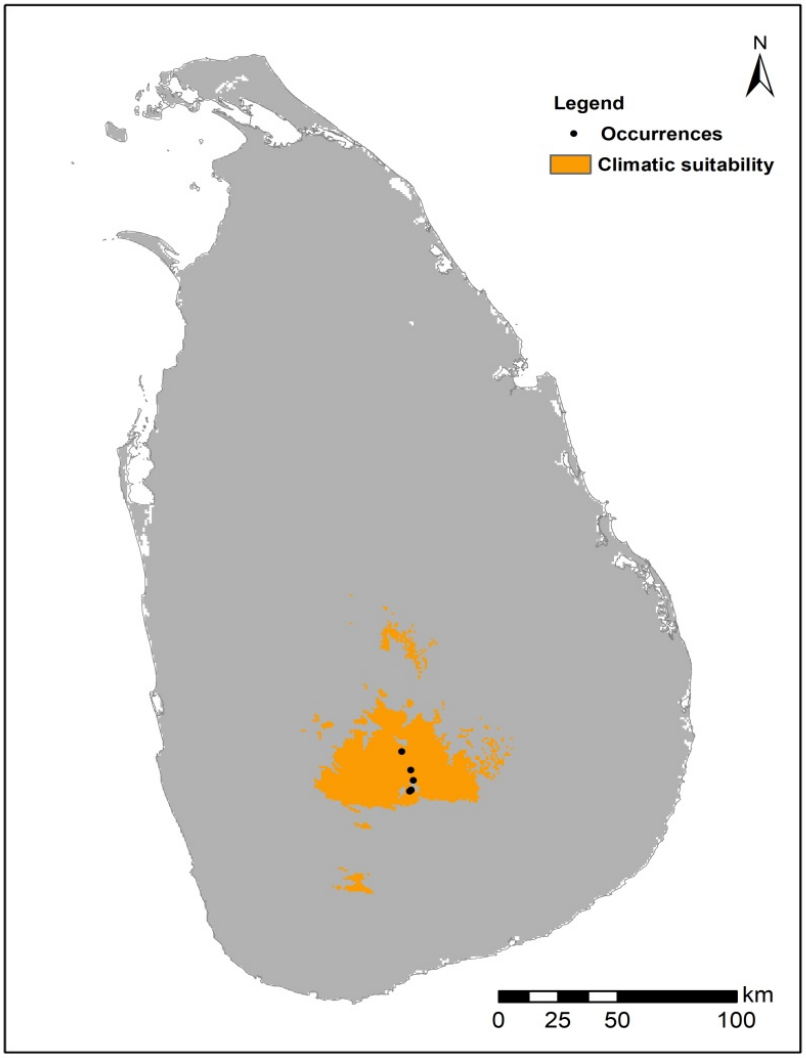


Fig. 2 Predicted areas of *Ulex europaeus* in Sri Lanka at 10 percentile training presence. Black dots indicate occurrence records of *U. europaeus* in Sri Lanka.

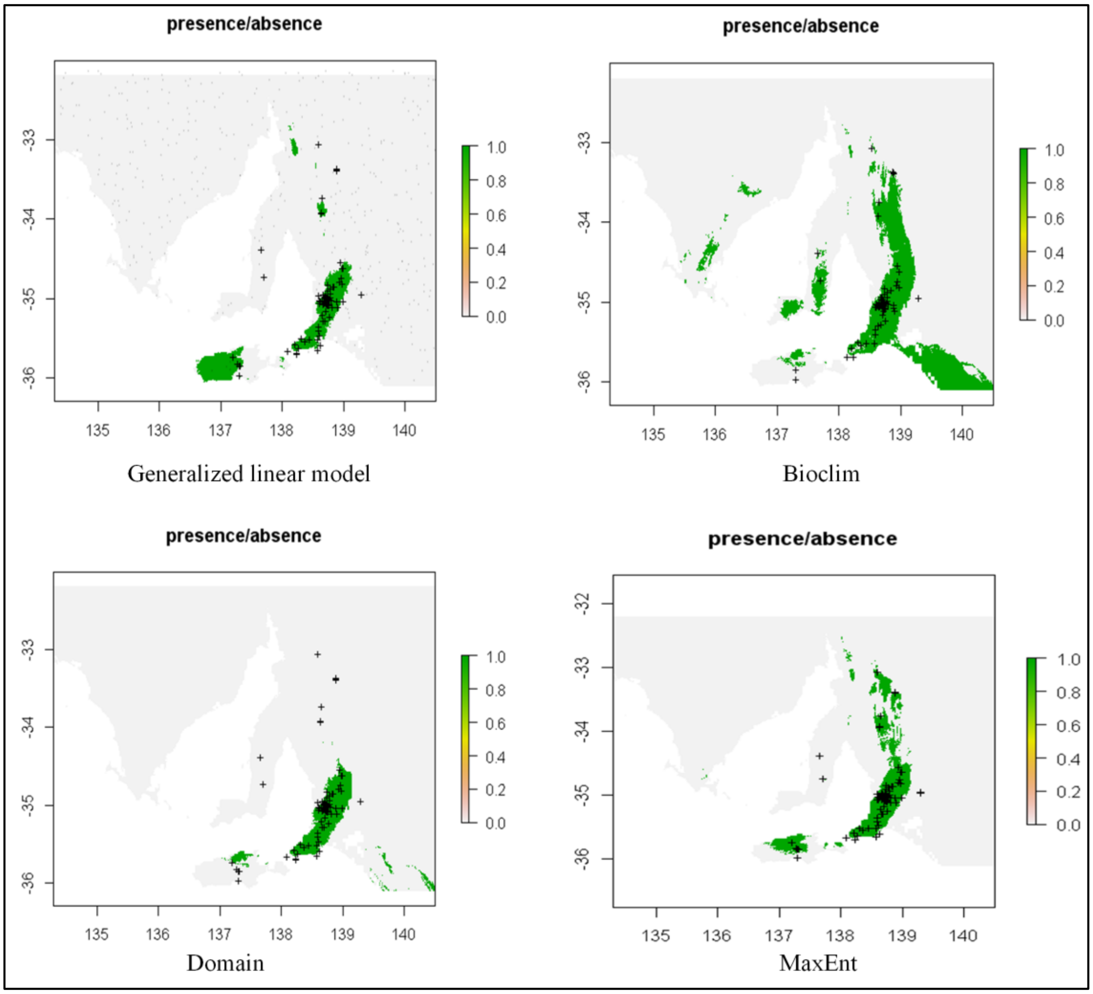


Fig. 3 Model projections for the potential distribution of *Ulex europaeus* using four modeling techniques in the 'dismo' package in R for South Australia. Small crosses indicate occurrence records of *U. europaeus* in South Australia.

IV. DISCUSSION

Ulex europaeus is an alien invasive species in many countries in the world. Thus, prediction of the potential distribution patterns of *U. europaeus* using bioclimatic modeling is an important aspect of understanding the likely impact of this noxious species in countries of its invasive range such as South Australia and Sri Lanka.

4.1 Species distribution modeling with Maxent software for *Ulex europaeus* in South Australia

Our *U. europaeus* model performed well with selected subset of environmental variables. Maps from SDM represent the potential distribution of the species based on the postulated links between species data and environmental variables, and since invasive species tend to expand their habitat to acquire all climatically suitable habitats, such models are likely to be useful predictors of the ultimate range of invasive species (Wilson et al 2011). *U. europaeus* was established both in South Australia and Sri Lanka more than 100 years ago. Based on our predicted presence-absence map at our selected threshold, *U. europaeus* is predicted to be widely distributed in the Mount Lofty Ranges and Kangaroo Island areas in South Australia. We found that our herbarium occurrence points were distributed in most of the suitable areas of the presence-absence map, showing that this species has already occupied most of its favorable climatic gradient in South Australia. Having confidence that SDM models capture key determinants of the fundamental niche is important to properly apply them to understand species invasions (Webber et al 2011). The majority of our species environmental data obtained from the Worldclim database are averaged over a long time period (1960-1990), therefore we believe that data are likely to represent the relevant environmental variability experienced by *U. europaeus* and so provide a realistic prediction.

SDM predictions can over-estimate ranges if they omit factors that limit the spread of species such as natural barriers, soil type, predators and competition by closely related species (Scheldeman & Zonneveld 2010). However, *U. europaeus* can grow on a wide range of soil types including sands, clays and clay loams other than soils rich in calcium (Gorse Control Strategy 1999). Honey bees (*Apis mellifera* L.), the primary pollinators of *U. europaeus* (Bowman et al 2008) are widespread in every continent except Antarctica (Goulson 2003). Therefore, neither of these factors would likely contribute to overestimating the range of this species. The threshold value which was set for model prediction is an arbitrary value (Liu et al 2005) hence the prediction of potential area could vary with the selected threshold. For example our *U. europaeus* model prediction very much increased when we used the "minimum training presence" criterion in Maxent.

Analysis of our jackknife tests revealed that annual rainfall was a critical factor in affecting the distribution of *U. europaeus* in South Australia. The contribution of all other variables was not significant to the model. Isothermality, which is a measure derived from temperature values (mean diurnal range /temperature annual range * 100), weakly influences the distribution of *U. europaeus* in this climate regime.

4.2 Maxent projection to Sri Lanka using Maxent software

At present, U. europaeus distribution in Sri Lanka is restricted to a small patch in the central mountains. The occurrence points we collected during our field works in Sri Lanka were quite close to each other and therefore, these species data are not quite enough on their own to directly derive a Maxent model for Sri Lanka. Nevertheless, we were able to project a Maxent model derived from South Australian records to predict the potential range expansion for *U. europaeus* in Sri Lanka, even though the areas for *U. europaeus* in South Australia and Sri Lanka are climatically distinct. The prediction we received for Sri Lanka was realistic because our few occurrence points were overlaid on the prediction area (Fig. 2). This also implies that the Maxent fitted model for *U. europaeus* in South Australia has captured the considerable environmental gradient of the species to make a prediction in a climatically distinct area. In Sri Lanka, *U. europaeus* is restricted to a few very small patches in central highland area. However, the prediction we received was larger than the actual distribution we observed. Therefore, we believe that *U. europaeus* has the potential to spread further in Sri Lanka and hence that management should consider relevant precautionary actions to control the spread of this species in central highlands in Sri Lanka. During our field visits we observed isolated *U. europaeus* plants which were flowering and fruiting in several places in the central highlands, indicating the climatic suitability for the *U. europaeus* distribution in these areas.

Selection of suitable environmental parameters is an important and challenging step of the modeling process. Our first attempt to transfer the *U. europaeus* model fit with Worldclim monthly data was not successful. In this analysis, the prediction we received for South Australia was similar as with the Bioclim variables we used later, but the algorithm reversed the prediction areas when we projected the model to Sri Lanka. In comparison to the monthly climatic parameters in the Worldclim database (monthly maximum and minimum temperature and precipitation), the derived Bioclim variables, such as "annual precipitation" or "mean temperature of warmest quarter" do not specify a particular time of the year or month. This is extremely important when projecting a model to a different hemisphere where the climatic conditions in a particular period may be completely reversed.

Webber et al (2011) point out that projection of correlative models especially to novel climates should be done carefully because they can make biologically unrealistic projections when the response functions of certain parameters exceed model behavior. We investigated the values of each variable applicable to these two countries which indicated the ranges of values were quite different. Therefore, same variables may perform in a different manner in climatically distinct areas.

4.3 Multiple SDM model comparison with R

Our study found quite similar and realistic projected range limits for *U. europaeus* in South Australia using four different modeling techniques, GLM, Bioclim, Domain and Maxent. AUC is considered as an important metric to quantify model performance (Syphard & Franklin 2009). The overall mean of AUC values across all models we received was 0.95 and all models individually exceeded a model AUC of 0.93, indicating that all models provided a good fit to the data. In multiple model comparisons using the 'dismo' package in R, the GLM, Bioclim and Domain models predicted comparatively greater predicted areas as suitable for *U. europaeus* distribution than did the Maxent model. However, model evaluation shows Maxent as the most robust model with relatively better discrimination ability. In our exercise we received the highest AUC value with Maxent where the predicted area map is smaller compared with other three models. The lowest model performance out of the above four models was observed in Bioclim where the prediction map extent is highest. The other two models GLM and Domain have moderate levels of AUCs. The AUC represents a probability for observations where prediction for presence observations is higher than the prediction for absence observation (Syphard & Franklin 2009). However, we get higher AUC in Maxent where we have relatively less prediction. This may be due to some other factors, such as model prevalence or map correlation, that vary with the modeling method used.

V. CONCLUSION

Based on the Maxent model predicted potential distribution map, *U. europaeus* is predicted to be widely distributed in the Mount Lofty Ranges and Kangaroo Island areas in South Australia. Our work demonstrated the need for a careful approach when selecting environmental variables for projecting correlative models to climatically distinct area and the utility of relativized, rather than absolute, measures of climatic conditions. Our projection of a Maxent model trained with environmental variables of South Australia to relevant layers of Sri Lanka brings valuable insight for applications in changing climate conditions. The prediction we received for Sri Lanka encompassed our known occurrence localities which were restricted to a few patches but was larger than the actual area of *U. europaeus* distribution, suggesting a capacity for *U. europaeus* to expand its range. These findings are important not only to predict and manage invasive alien *U. europaeus* in South Australia and Sri Lanka but also in other countries of the invasive range.

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Conflicts of interest

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