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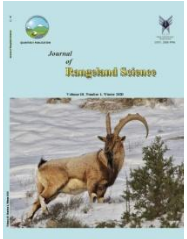

Research and Full Length Article:

Predicting the Distribution of *Leucanthemum Vulgare* Lam. Using Logistic Regression in Fandoghlou Rangelands of Ardabil Province, Iran

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Abstract. Species Distribution Modelling (SDM) is an important tool for conservation planning and resource management. Invasive species represent a good opportunity to evaluate SDMs predictive accuracy with independent data as their invasive range can expand quickly. Thus, the aim of this study was to investigate the relationships between presence of *Leucanthemum vulgare* Lam. and environmental variables in Fandoghlou rangeland, Ardabil, Iran using logistic regression model. Sampling was conducted in six sites as presence/absence of *L. vulgare* by a systematic random method in 2016. Physiographic, climatic, surface coverage and density of *L. vulgare* were measured in sampling sites. In the beginning, middle and end of each transect, soil samples were taken from the depth of rootstock of range plants including *L. vulgare*. Soil attributes were measured in the laboratory. The maps of physiographic and climate were derived from digital elevation model, and selected soil attributes were derived using Kriging interpolation method. Derived regression equation from the presence of *L. vulgare* was applied to map the effective environmental variables, and a prediction map was produced for the study area. The comparison between the predicted and actual maps was assessed using the Kappa coefficient. Results showed that the presence of *L. vulgare* had a positive relationship with temperature and volumetric soil water content factors and had a negative relationship with electrical conductivity, sodium, diffusible clay factors. Therefore, *L. vulgare* type is significantly affected by the presence of these factors ($p<0.01$). The Kappa coefficient was 0.55 for derived predicted map. The evaluation of the model indicated that logistic regression was able to predict the distribution of *L. vulgare* habitats. The results of this study gave more insight and understanding from the habitats and effective environmental factors in *L. vulgare* distribution.

Keywords: Species distribution modelling; Environmental factors; Invasive species; Namin County

Introduction

Identifying the factors which affect species distribution is an important unresolved issue in ecology (Araújo and Guisan, 2006; Bagheri *et al*., 2017; Mirzaei Mossivand *et al*., 2017). There are many combinations of predictors which can explain distribution of species, especially when environmental variables are correlated, and this presents vagueness over the effect of each variables (Platts *et al*., 2008; Murray and Conner, 2009; Bagheri *et al*., 2017; Mirzaei Mossivand *et al*., 2017). Species distribution modelling (SDM) based on their relationship with environmental variables is important for range management activities (Mirzaei Mossivand *et al*., 2017; Bagheri *et al*., 2017). Examples include management of threatened species and communities, risk assessment of invasive species in new environments, and the estimation of the extent of biological comebacks to environmental changes (Barry and Elith, 2006). Moreover, SDM is becoming an important tool for conservation planning, resource management and understanding the effects of changing environmental conditions on biogeographical patterns (Guisan and Thuiller, 2005; Austin, 2007; Esfanjani *et al*., 2018). Models are constructed from estimates of species responses to one or more environmental variables (Oksanen and Minchin, 2002; Esfanjani *et al*., 2017). Typically, these comprise habitat factors which affect the species either directly such as temperature and dissolved oxygen or indirectly such as topography and latitude (Austin, 2002).

Several methods have been advanced for building predictive SDM. Guisan and Zimmermann (2000) presented an inclusive review and classified the methods into two groups: 1) regression-based methods; and 2) environmental envelope methods. Regression methods relate species response to single or multiple environmental predictors, these include frequently used methods such as logistic regression (Hosmer and Lemeshow, 1980), generalized additive modeling (Hastie *et al*., 2009), and classification and regression tree (Breiman *et al*., 1984). Logistic regression is a statistical tool that relates a binary dependent variable to a set of discrete or continuous independent variables (Zare Chahoukia and Zare Chahouki, 2010). It is useful for making inductive inferences using a particular sample of data, in a way that the probability of occurrence of each state of the target variable may be inferred from the values of the predictor variables (Zare Chahouki *et al*., 2008). Logistic regression has shown to be a powerful tool which produces robust models, and it is broadly used in the predictive SDMs starting from presence/absence of data (Madsen and Prang, 2001; Merow *et al*., 2014). Many studies have been done by Vaz *et al.* (2008), West *et al.* (2016), Mirzaei Mossivand *et al.* (2017), Yilmaz *et al.* (2017); Piri Sahragard and Ajorlo (2018) on modeling and prediction of plant species using logistic regression with successful results. Borna *et al*. (2017) stated that modeling and prediction of *Astragalus gossypinus* habitat map using logistic regression, which elevation, pH, organic carbon, average temperature of the wet season and average temperature during the dry season were the most important environmental variables manipulating the distribution of this species. Moreover, Shojaee *et al*. (2017) in investigating the role of topographic factors on spatial distribution of plant species using logistic regression in Baghe-Shadi of Yazd province noted that elevation is the most important factor for predicting spatial distribution of plant species in the study area and predicts from 16 to 46 percent of variations in presence.

Globalization has led to an increase of nonnative species, a pattern likely to continue (Seebens *et al*., 2017). Besides being one of the biggest threat to biodiversity and ecosystems (Bellard *et al*., 2016), biological invasions are also very costly to the global economy (Bradshaw *et* *al*., 2016). This increase of invasive species and their consequences on biodiversity and ecosystems raise numerous management and control issues (Hulme, 2009). Preventing an invasive species formation and additional spread is recognized as a more efficient and less costly management strategy than eradication, containment and control that may be required when the invasive species has fully established (Simberloff *et al*., 2013). There is currently much worldwide interest in predicting distributions of invasive species, and many organizations will be faced with questions of whether and how to embark on such a task, or how to interpret predictions that others have provided. To that end, SDMs are increasingly being used in invasion biology, especially to predict invasion risk (Tingley *et al*., 2017) and optimize control strategies (Tulloch *et al*., 2014).

Leucanthemum vulgare Lam. (Oxeye daisy) is in the Asteraceae taxonomic family and is a perennial forb reproduced by seeds and rhizome (Jacob, 2008). The ecological, environmental, economical, and sociological impacts of *L. vulgare* are not well documented (Samadi, 2017). Mangold *et al.* (2009) reported the greatest impact of *L. vulgare* is on forage production of infested rangeland and meadows because livestock avoids grazing *L. vulgare* and carrying capacity of heavily infested rangeland is reduced. They also reported dense stands of *L. vulgare* that can decrease plant diversity and increase the amount of bare soil in an area and dense infestations exclude other plant species, leading to soil erosion and depletion of soil organic matter. It forms dense populations which are able to reduce native plant species diversity (Khuroo *et al*., 2010).

This study uses a small dataset with presence/absence of *L. vulgare* and therefore, it requires a method which can use these data. However, this study focuses on identifying species–environment relationships and on estimating the realistic potential distribution area of the species *L. vulgare*.

Fandoghlou rangeland of Ardabil province in Iran is one of the most important rangelands of the country and is important from ecological aspects such as existence of rangeland desirable species, genetic resources, economy and forage production (Azimi Motem *et al*., 2011; Teimoorzadeh *et al*., 2015). The main invasive species of this region is *Leucanthemum vulgare* Lam., a permanent weed, which has been widely spread in these rangelands, and is indicative of the degradation of rangelands and the reduction of flora and plant biodiversity (Azimi Motem *et al*., 2011; Teimoorzadeh *et al*., 2015). Due to the frequency and complexity of the presence of invasive species in natural ecosystems, our understanding of the distribution, spread and effects of this invasive plant (*L. vulgare*) in the present and future increases. Thus, the aim of this study was to evaluate the prediction power of regression logistic method for *L. vulgare* based on presence/absence data, and also to determine the most important effective environmental variables in *L. vulgare* distribution at the study area, which may recognize these variables to help natural resources experts and managers to good deal with this invasive plant species.

Materials and methods

Study area

Fandoghlou natural rangelands are located in northwest of Iran in 24 km northeast of Ardabil city along the mountains of Talesh between 38˚23′55″ to 38˚24′55″N and 48˚33′05″ to 48˚34′16″E (Fig. 1). The maximum altitude at the selected study area is 1588 masl and minimum is 1438 masl. The average rainfall of the area using the information of the nearest station (Namin synoptic station with the elevation of 1345 masl) is 272.21 mm and the average temperature is 10.9°C. The area has moderate summers and cold winters. For 3 to 4 months a year, which is covered by snow and ice, and most rainfall occurs in autumn and winter and early spring (Azimi Motem *et al*., 2011; Teimoorzadeh *et al*., 2015; Aslami and Ghorbani, 2018). Study area in the classification of ecosystems of Iran is the ecotone between the Europe-Siberian and Iran-Turonian regions (Assadi, 2006; Teimoorzadeh *et al*., 2015). These rangelands have changed from forest ecosystems and present physiognomic structure is meadow, which is considered as one the best rangeland ecosystems of Iran (Assadi, 2006; Teimoorzadeh *et al*., 2015; Aslami and Ghorbani, 2018). These rangelands are threatened and destroyed by invader species especially *L. vulgare* (Magharri *et al*., 2015; Samadi, 2017). The main part of the forage of these rangelands harvested in the spring and summer and used in winter for livestock. Each year, these rangelands by the local livestock, (sheep, goats and cattle) from mid-May to mid-November are grazed for almost seven months.

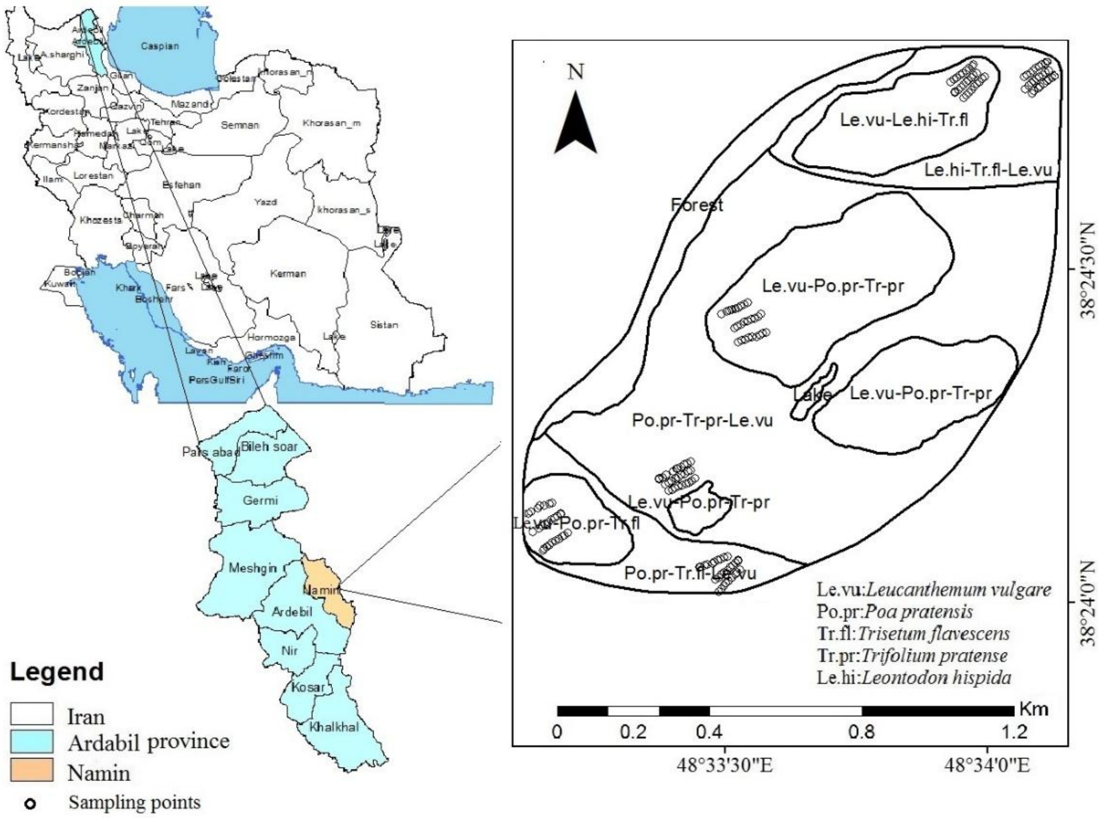

Fig. 1. Location of the study area and vegetation types, in Namin county, Ardabil province and Iran

Data collection

Using the land use map and field observations of Fandoghlou rangelands in 2016, the main habitats of *L. vulgare* were selected (Samadi, 2017; Aslami and Ghorbani, 2018; Hassanzade *et al*., 2018). In the determination of sampling sites (systematic random), two groups of sites with presence (three sites) and absence (three sites) of *L. vulgare* species (Fig. 1) by considering the altitude classes and the presence/absence of *L. vulgare* species and literature researches such as Teimoorzadeh *et al*. (2015) and Hassanzade *et al*. (2018) were selected. Method of measuring and evaluating of vegetation based on the structure and characteristics of vegetation (dominant species is forb and grass) and according to past research (Arzani, 1997) was done. In each site, three sampling transects (Mirzaei Mossivand *et al*., 2017) with a length of 200 m (Parker *et al*., 2011) and distance of 100 m from each other and perpendicular to the slope direction were located. Along each sampling transect, 10 plots ($1m^2$) with distance of 20 m were established. In the site of presence of *L. vulgare* that include 90 plots, density and percentage of canopy cover of *L. vulgare* were measured.

Vegetation types were determined, which was: in the first site; *Leucanthemum vulgare- Poa pratensis-Trisetum flavescens* and *Poa pratensis-Trisetum flavescens-Leucanthemum vulgare*; in the second sites, *Leucanthemum vulgare- Poa pratensis-Trifolium pratense* and *Poa pratensis-Trifolium pratense-Leucanthemum vulgare*; in the third sites, *Leucanthemum vulgare -Leontodon hispidus- Trisetum flavescens* and *Leontodon hispidus- Trisetum flavescens-Leucanthemum vulgare* (Fig.1). Plot location was recorded using global position system. In the beginning, middle and end of each transect, soil samples were taken from the depth of rootstock of species (Aghajanlou *et al*., 2018). Soil attributes such as pH, Electrical Conductivity (EC), soil texture, lime, calcium, magnesium, sodium (Na), phosphorus, potassium, organic matter, Diffusible Clay (DC) and Volumetric soil Water Content (VWC) using standard methods were measured in the laboratory (Samadi, 2017; Hassanzade *et al*., 2018).

Data Analysis

Multicollinearity between independent variables was examined through the calculation of Variance Inflation Factor (VIF). Logistic regression was applied by the following regression equation (Equation 1), in which presence/absence of an object is transformed into a continuous probability ranging from 0 to 1. Occurrence probability of *L. vulgare* is calculated with respect to the combined effect of site conditions with the following equation (Equation 1):

$$Y = \frac{exp\ (LP)}{(1+exp(LP))} = \frac{exp\ (b0+b1x1+b2x2+\cdots+bnxn)}{1+exp\ (b0+b1x1+b2x2+\cdots+bnxn)} \qquad \text{(Equation 1)}$$

Where y is the probability; x_n is explanatory variable; b_0 is the constant; and exp is an exponential function.

Mapping Prediction Models

Topographic data (elevation, slope, and aspect) and climate data (rainfall and temperature) were derived using gradient equation and DEM (Bagheri *et al*., 2017; Esfanjani *et al*., 2018). To map soil characteristics, spatial statistics including variogram analysis and Kriging interpolation were used by GS^+5 (Esfanjani *et al*., 2017) and point map of selected soil characteristics using acquire models were prepared. Based on obtained predictive models for *L. vulgare* related predictive variables map were derived in ArcGIS10. After the determination of optimal threshold using the equal sensitivity and specificity methods, continuous predicted maps were converted into presence and absence maps (Piri Sahragard and Zare Chahouki, 2016).

Model evaluation

The agreement between predicted and documented maps was calculated with Kappa index in IDRISI 32. Monserud and Leemans (1992) suggested the following ranges of agreement for the statistic: no agreement, <0.05; very poor, 0.05–0.20; poor, 0.20–0.40; fair, 0.40–0.55; good, 0.55–0.70; very good, 0.70–0.85; excellent, 0.85–0.99; and perfect, 0.99–1.00. We used these ranges to describe the levels of agreement.

Results

Variance inflation factor was less than 10 for all independent variables. Predictive models of mentioned vegetation types are represented in equation 2. Regarding the equation 2, occurrence of *L. vulgare* type is inverse in relation with temperature, electrical conductivity (EC), sodium (Na), diffusible clay (DC) and volumetric soil water content (VWC). Therefore, *L. vulgare* type is significantly affected by the presence of these factors ($p<0.01$). The presence of *L. vulgare* had a positive relationship with temperature and VWC factors and had a negative relationship with EC, Na and DC factors.

$$Y = \frac{\exp(170.24\text{Temperature} - 93.63\text{EC} - 4.39\text{Na} - 5.39\text{DC} + 0.88\text{VWC} - 1336.29)}{(1 + \exp(170.24\text{Temperature} - 93.63\text{EC} - 4.39\text{Na} - 5.39\text{DC} + 0.88\text{VWC} - 1336.29))} \quad \text{(Equation 2)}$$

For mapping soil attributes, spatial structure of data and component of variogram was presented in Table 1. The variogram of DC is shown in Fig. 2 and the map of diffusible clay using spherical model was mapped and classified in 5 layers (Fig. 3).

Table 1. Components of variogram analysis for selected soil attributes

Characteristic	Model	Nugget effect (%)	Sill (%)	Effective range (m)	Proportion	R^2	RSS
Electrical conductivity (ds/m)	Exponential	0.08	0.25	12330.00	0.66	0.60	0.13
Sodium (meq/l)	Exponential	36.20	72.41	4110.00	0.50	0.50	0.41
Diffusible clay (%)	Spherical	0.10	201.10	3798.00	1.00	0.72	0.98
Volumetric soil water content (%)	Spherical	11.87	23.75	4110.00	0.50	0.48	0.31

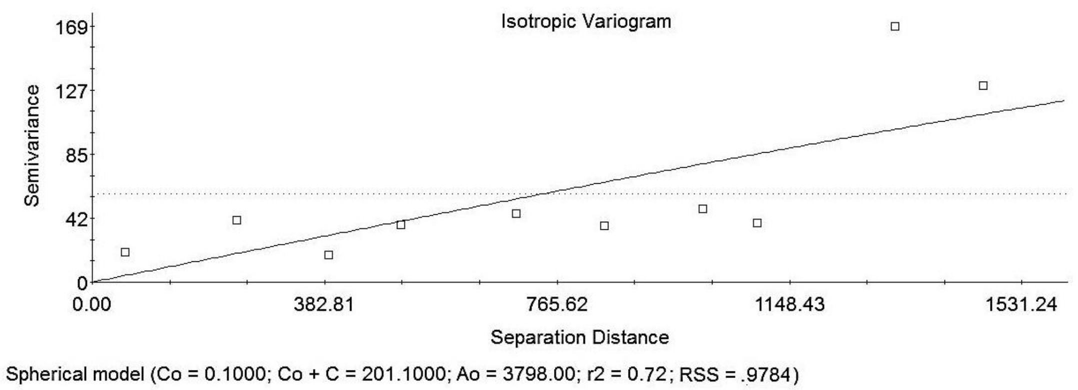

Fig. 2. Variogram model diffusible clay (%) in Fandoghlou rangelands

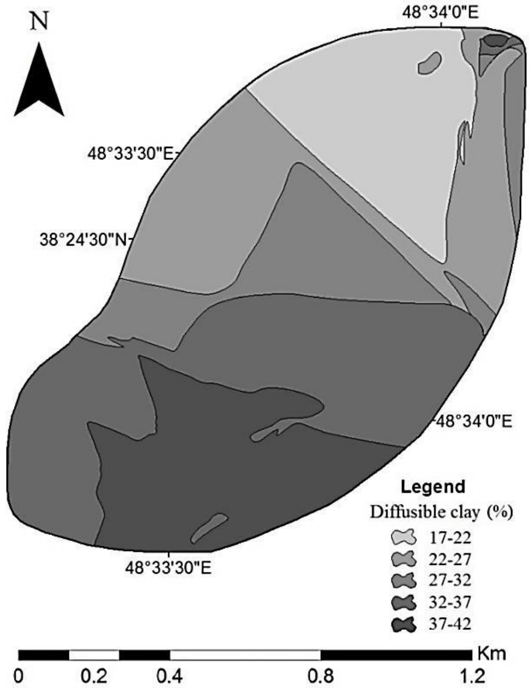

Fig. 3. Map of diffusible clay (%) in Fandoghlou rangelands

Finally, using component variogram and kriging interpolation, the predicted map of distribution *L. vulgare* in 1: 50000 scale was prepared (Fig. 4). Final prediction map was based on two levels: the presence of *L. vulgare* habitat with a probability value of 1 and the absence of *L. vulgare* habitat with a probability value of 0.

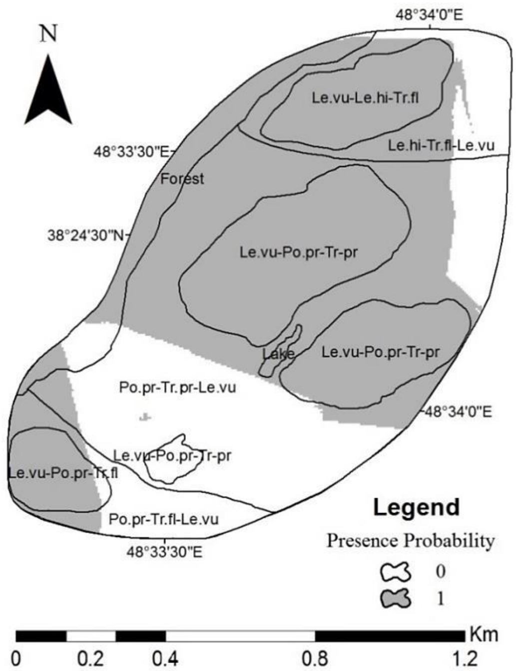

Fig. 4. Predicted map of *L. vulgare* species provided by logistic regression

The accuracy of the predicted maps was tested with actual vegetation maps. In this study, the adequacy of vegetation type mapping was evaluated using Kappa statistics. The values of Kappa coefficient based on LR of predicted and actual maps of vegetation cover indicate that the accordance of predicted map for *L. vulgare* habitat is good (Table 2).

Table 2. Kappa coefficient and accordance classes for predicted *L. vulgare*

Vegetation type	Kappa coefficient	Accordance class
L. vulgare	0.55	good

Discussion

Invasive species represent a good opportunity to evaluate SDMs predictive accuracy with independent data, as their invasive range can expand quickly. Indeed, invasive species whose invasion was closely monitored can be used to test whether records from the later stage of the invasion could have been predicted by a model calibrated with records only from the early stages of the invasion. Only very few studies have taken advantage of this opportunity to carry out validation studies with independent data (West *et al*., 2016), but they were carried out with simplistic envelop models or at small spatial scales.

Logistic regression is a kind of generalized linear model suitable for analysis when response data are binary. It uses a login link to describe the relationship between the response and the linear sum of the predictor variables (Miller and Franklin, 2002). Regression equation values close to 1 represent high probability *y* of presence whereas values close to 0 represent high probability of absence. In order to discrete *y* into presence and absence, a posterior threshold is assigned. Regression methods flexible enough to fit ecologically plausible relationships tend to perform well. Comparisons for invasive species modelling are more difficult because the truth about the potential distribution in the invaded range is unknown. It seems to be a general opinion emerging that smoother models (ones less tightly fitted to the known records) are more likely to predict well because they do not focus on details of the sampled distribution that might result from survey biases, local responses to biota and so on. Smoother models can be fitted for methods capable of highly complex fits by limiting degrees of freedom and model complexity (Falk and Mellert, 2011; Merow *et al.*, 2014; Elith, 2016). Numerous studies on invasive species distribution have been advocated to use distribution data from both the native and the invasive range (Mainali *et al*., 2015).

Jacobs (2008) reported that oxeye daisy (*Leucanthemum vulgare* Lam.) is predominantly a weed of rangelands and hay lands where it crowds out preferred forage species reducing carrying capacity for livestock and the value of hay and where it spreads onto rangelands, it will reduce livestock forage and plant community diversity. Due to the importance of this species, until now, comprehensive modeling of the distribution of *L. vulgare* species has been not done. The results showed that the presence of *L. vulgare* was related to climate and soil factors. In general, the most important ecological factors on habitats of *L. vulgare* species of Fandoghlou rangelands are temperature, electrical conductivity (EC), sodium (Na), diffusible clay (DC) and volumetric soil water content (VWC).

Temperature was one of the most effective climate variables in modelling habitats of *L. vulgare* because this factor had the highest coefficient (170.24) in the regression equation. Moreover, the presence of *L. vulgare* had a direct relationship with temperature. Plant species distributions are constrained by local climate. The influence of temperature and precipitation on plants is modified by slope, aspect, topographic position, and geologic substrate, giving rise to complex patterns of species distributions at finer scales. Temperature plays an important role in start of growing season, growth period and the type of vegetation. Borna *et al.* (2017) reported that average temperature of the wet season and average temperature during the dry season were the most important environmental factors influencing the distribution of *Astragalus gossypinus* in summer rangelands of Baladeh Nour.

Electrical conductivity (EC) is one of the selected soil characteristics in distribution of *L. vulgare* and had an inverse relationship with the presence of this species. In places with more distribution of *L. vulgare*, EC is low. Thus, this species cannot tolerate the salinity. Plant physiology, growth, and development are closely associated with the environmental conditions and nutrient supply (Signore *et al*., 2016). EC is an index of salt concentration and an indicator of electrolyte concentration of the solution. EC of the nutrient solution is related to the amount of ions available to plants in the root zone (Nemali and Van Iersel, 2004). The optimal EC is crop specific, and depends on environmental conditions (Sonneveld and Voogt, 2009). In general, too low EC levels indicate low available nutrients, and too high EC levels indicate an excess of nutrients (Fourie, 2017). Low EC's are often found in sandy soils with low organic matter levels whereas high EC levels are usually found in soils with high clay content (Fourie, 2017). According to Samadi (2017) *L. vulgare* prefer poor soils with low minerals. It confirms the results of this research. Zare Chahuki *et al.* (2008) reported that the EC is one of the effective factors in the division of vegetative types of Garizat rangelands of Yazd province, Iran and expressed that the presence of the *Artemisia sieberi* with EC of the second depth has an inverse relationship. Moreover, Zare Chahuki and Zare Chahuki (2010) expressed EC is the most effective factors in presence of *Tamarix ramosissima* in Garizat rangelands of Yazd province.

Sodium (Na) is most effective soil factors in modelling the distribution of *L. vulgare* and had an inverse relationship with the presence of this species. Therefore, in places where the amount of Na is low, this species is more distributed. So, this species do not choose salty soils for growth and distribution. Soils of high salinity possess two main problems to plants i) the accumulation of sodium ions can lead to the poisoning of the plant and ii) high levels of NaCl cause the water potential of the soil to become very negative (Mamedov *et al*., 2010). Increased salinity level may cause effects on plant growth, rate of germination and production (Hasanuzzaman *et al*., 2012). According to this subject that *L. vulgare* is an invasive species with a large dispersal power, selected soils for distribution which had no limits to growth and development. Rezai Poorbaghedar *et al.* (2014) concluded that sodium in addition to other factors, had the most effect on *Dorema ammoniacum* and *Rheum ribes* in rangelands of Baghedar region in Bafgh city, Iran.

Diffusible clay (DC) was also an effective factor in the distribution of *L. vulgare* and by increasing the amount of this factor, the probability of the presence of this species decreases. Soil erosion has been directly linked to the rate and volume of water dispersible clay in a soil (Calero *et al*., 2008). Potential soil erosion in areas of very high rainfall has been estimated using water dispersible clay and its indices (Calero *et al*., 2008). DC when soils are submerged in water affect a lot of soil physical and chemical properties (Heathwaite *et al*., 2005). The fraction of clay dispersed in water which is known as water dispersible clay has been shown by Kjaergaard *et al.* (2004) as an important property with respect to predicting soil erosion and colloid leaching. Molaei *et al.* (2017) noted that water dispersion clay is one of the effective factors in the distribution of *Artemisia aucheri* Boiss. in southeast faced slopes of Sabalan Mountain, Iran and the numerical value of this parameter in locations with presence of *A.aucheri* was less than locations with absence of *A.aucheri*, it shows less erosion of the habitats of this species.

Volumetric soil water content (VWC) had a significant effect on the presence and distribution of the *L. vulgare* and directly influenced the growth of this species. The effect of VWC on the distribution of *L. vulgare* can be explained by soil texture. In fact, VWC are mainly controlled by soil texture. Sandy soils can provide considerable amount of water to plants (Tavakoli Neko *et al*., 2012). According to Samadi (2017), the species of *L. vulgare* prefers loam-sandy texture regions. Regions with high VWC and great amount of available nutrients provide a good condition for vigor growth of *L. vulgare*. Piri Sahragard *et al.* (2014) presented that available moisture is one of the effective factors in the predicted model for *Tamarix passerinoides* in the Hoze sultan west rangelands and by increasing this variable, the probability of the presence of the species increases. This study confirms the results of this research.

Due to the Kappa coefficient for habitats of *L. vulgare* species, we can say that this model was successful for *L. vulgare* habitat and locations of distribution of this species was predicted with average accuracy. This could benefit the early control and proactive management strategies to a large extent. However, predicting the full potential invasive range of an invasive species may not be as relevant as accurately predicting the areas that are more likely to be colonized next. Indeed, given the cost of species monitoring and surveillance for the early detection of invasive species, it is more relevant to predict areas that might be invaded next rather than all potential areas that could be reached by the invader. Information regarding the areas that might be invaded next could indeed be used by managers for a cost-effective effort on monitoring and controlling such areas. Monitoring efforts need to be implemented within the highest suitable areas within the already invaded range as well as the highest suitable areas that are the closest to the already invaded range. Improved detection techniques would further increase the efficiency and decrease the costs of monitoring/controlling the invasion (Milanesio *et al*., 2017). Therefore, even if invasive SDMs cannot predict the full potential invasion range of an invasive species that has just established (Rodrigues *et al*., 2016), they can still be very valuable for invasive species management. Yet, validation is needed for model reliability and credibility, especially when management decisions are based upon it (Mouquet *et al*., 2015).

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پیش بینی توزیع گونه *Leucanthemum vulgare* Lam. با استفاده از رگرسیون لجستیک در مراتع فندوقلوی استان اردبیل، ایران

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چکیده: مدل‌سازی توزیع گونه (SDM) یک ابزار مهم برای برنامه‌ریزی حفاظت و مدیریت منابع است. گونه‌های مهاجم نشان‌دهنده یک فرصت خوب برای ارزیابی دقت پیش‌بینی SDM ها با داده‌های مستقل هستند، زیرا دامنه تهاجم آنها می‌تواند به‌سرعت تغییر کند. بنابراین هدف از این مطالعه بررسی روابط بین حضور گونه *Leucanthemum vulgare* Lam. و متغیرهای محیطی در مراتع فندوقلو، اردبیل، ایران با استفاده از مدل رگرسیون لجستیک بود. نمونه‌برداری در سال ۱۳۹۵ در شش سایت حضور/ عدم حضور *L. vulgare* به‌روش تصادفی سیستماتیک انجام شد. فیزیوگرافی، اقلیم، تاج پوشش و تراکم L. *vulgare* در سایت‌های نمونه برداری اندازه‌گیری شد. در ابتدا، میانه و انتهای هر ترانسکت، نمونه‌های خاک از عمق ریشه‌دوانی گیاهان مرتعی شامل *L. vulgare* برداشت شد. ویژگی‌های خاک در آزمایشگاه اندازه‌گیری شد. نقشه‌های فیزیوگرافی و اقلیم از نقشه مدل رقومی ارتفاع استخراج شد و ویژگی‌های خاک انتخاب شده با استفاده از روش درون یابی کریجینگ به‌دست آمد. معادله رگرسیون استخراج شده از حضور گونه *L. vulgare* بر روی نقشه متغیرهای محیطی موثر اعمال شد و نقشه پیش‌بینی برای منطقه مورد مطالعه تهیه شد. مقایسه بین نقشه‌های پیش‌بینی شده و واقعی با استفاده از ضریب کاپا مورد ارزیابی قرار گرفت. نتایج نشان داد که حضور *L. vulgare* با فاکتورهای درجه حرارت و رطوبت حجمی خاک ارتباط مثبت و با فاکتورهای هدایت الکتریکی، سدیم، رس قابل انتشار ارتباط منفی دارد. بنابراین تیپ *L. vulgare* به‌طور معنی‌داری تحت تاثیر حضور این عوامل قرار دارد (P<0/01). ضریب کاپا برای نقشه پیش‌بینی شده ۰/۵۵ درصد بود. ارزیابی مدل نشان داد که رگرسیون لجستیک قادر به پیش‌بینی توزیع زیستگاه‌های *L. vulgare* بوده است. نتایج این مطالعه بینش و درک از زیستگاه و عوامل محیطی موثر در توزیع *L. vulgare* را ارائه می‌دهد.

واژگان کلیدی: مدل‌سازی توزیع گونه؛ فاکتورهای محیطی؛ گونه مهاجم؛ شهرستان نمین