Good news for a rare plant: Fine-resolution distributional predictions and field testing for the critically endangered plant *Dianthus pseudocrinitus*

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Abstract

Many endangered species are distributed in narrow geographic ranges, often at severe risk of extinction. Ecological niche modeling can be used to identify suitable areas, which can be surveyed to detect additional populations. We combined remotely sensed data (Normalized Difference Vegetation Index) and field sampling to increase distributional knowledge of the species and improve understanding of its conservation status. We identified numerous new sites for a rare plant (*Dianthus pseudocrinitus*) and tested model-based predictions of its full geographic distribution. Using only eight occurrences, we developed initial models, which guided detailed field sampling: 11 new sites were identified, but models were unable to predict better than random expectations. A second round of models did show significant predictive ability and pointed to a broader geographic distribution of the species. As a consequence, the conservation status of the species should be upgraded from Critically Endangered to Endangered. We identified six protected areas (Golestan, Ghorkhoud, Miandasht, Salouk, Sarani, Sarigol) that likely hold populations of this species; one area adjacent to Ghorkhoud Protected Area, if protected, would protect the best-known populations of the species. Our results highlight the importance of combining modeling with field sampling in characterizing distributions of rare and endangered species.

Keywords

conservation status, ecological niche model, fieldwork, rare species, small sample size, species distribution model
1 | INTRODUCTION

Rare plants pose special challenges for conservation because information on their distributions and habitats is often incomplete; therefore, efficient ways to discover additional populations can be useful in conservation efforts (Marcer et al., 2013). Essential prerequisites for appropriate decision-making include accurate knowledge of the species’ geographic distribution and identification of key habitats (Brotons et al., 2004). According to the International Union for Conservation of Nature (IUCN) guidelines, the core of conservation status assessment schemes (e.g., IUCN, 2001) is based on estimation of the extent of species’ geographic distributions; consequently, information on distribution and suitable habitats is invaluable in conservation management (Guisan, Lehmann, et al., 2006). One way to improve knowledge of the status of rare species is to use ecological niche models or species distribution models (hereafter termed ecological niche modeling, ENMs) to prioritize areas for field surveys (Johnson & Gillingham, 2005; Peterson et al., 2011; Thorn et al., 2009). Ecological niche models predict species’ geographic distributions based on observational data for the species and related environmental conditions. These methods can provide insights into the details of species’ geographic distributions, illuminate their conservation risk status (Peterson et al., 2007), understand the suitability of a particular habitat for a species (Brown, 2014; Poulos et al., 2012; Rather et al., 2021), and highlight unknown populations and key areas for fieldwork (Guisan, Broennimann, et al., 2006). Therefore, predictive models may be effective tools to provide information on potentially suitable habitats in areas where the species presence is unknown and constitute an approach to guide further sampling (Crall et al., 2013).

Although many methodological advances have been developed recently to estimate ecological niches and predict species’ potential geographic distributions, choosing the most appropriate protocols for modeling distributions of rare species remains a challenge for researchers (Araújo & New, 2007; Elith et al., 2008; Pearson et al., 2007). Some methods have been applied to the particular challenge of applications to species with small sample sizes, such as the jackknife procedure (Pearson et al., 2007) and the idea of creating many simple models for rare species (Breiner et al., 2015). Some of these methods have been explored using different environmental variables to improve predictions of occurrence (Ferrer-Sánchez & Rodríguez-Estrella, 2016; Mousikos et al., 2021; Sousa-Silva et al., 2014; Thompson et al., 2020). Integration of ENM methods with remote sensing products allows development of models at different spatial and temporal scales (Cerrejón et al., 2021; Feihlauer et al., 2012; Guillera-Arroita et al., 2015; Valerio et al., 2020). Integrating vegetation cover information into ENMs has been employed increasingly to capture realistic, fine-scale information on vegetation quantity and phenology, and elements of ecosystem and landscape structure (Randin et al., 2020; Titeux et al., 2017), not represented in more commonly used “bioclimatic” variables (Singh & Milner-Gulland, 2011; Tasser et al., 2017; Wilson et al., 2013). Information on soil characteristics would also be useful information, but is rather difficult to obtain quantitative information at fine spatial resolution. Multi-temporal Normalized Difference Vegetation Index (NDVI) datasets offer a particularly rich set of information (Bodbyl-Roels et al., 2011).

Remotely sensed data have been widely applied in plant studies (e.g., Ahmed et al., 2021; Asner et al., 2008; Wan et al., 2020) thanks to increasing availability of remotely sensed data products relevant to diverse environmental features (Corbane et al., 2015; Feihlauer et al., 2012; Pinto-Ledezma & Cavender-Bares, 2021). In many cases, these data have been applied to direct detection of rare plants and their traits using high spatial resolution imagery (Fletcher & Erskine, 2012; Leduc & Knudby, 2018; López-Jiménez et al., 2019; Rominger & Meyer, 2019). However, studies of potential distributions of rare plants using remote sensing data remain uncommon (Cursach et al., 2020; Hernández-Lambrío et al., 2020; Robinson et al., 2019), although such data may prove highly useful in predicting suitable sites for rare plants in conservation management.

To explore combining the techniques of ENM with field studies directed by model predictions, we selected a rare and endangered species endemic to northeastern Iran. Dianthus pseudocrinitus Behrooz & Joharchi (Caryophyllaceae), a recently described species, is categorized as Critically Endangered (CN) on the Iranian national Red List (Memariani et al., 2016; Vaezi et al., 2014). The species is considered a narrowly endemic plant species with particular habitat requirements, restricted to the Aladagh, Salook, and Mas-sine mountains in North Khorasan Province (Figure 1a). Its habitat is distributed patchily in montane steppe, where factors such as low temperature, strong winds, and high solar radiation are dominant environmental stressors, in addition to anthropogenic effects of disturbance and habitat fragmentation. These factors can affect population size and colonization in suitable new regions (Chlachula, 2011; Lester et al., 2007).

This species occurs in small, isolated, and scattered populations on landscapes that experience intense disturbance. Most known populations are located close to human activities, where the soil has undergone fundamental changes (Behroozian, Ejtehadi, Memariani, et al., 2020). These factors may have led the species to change survival strategies from stress-tolerant to ruderal,
and to adapt to those conditions via polyploidy, high production of fertile seeds, etc. The species is considered as a neoendemic species that does not have a long history across its geographic distribution (Behroozian, Ejtehadi, Memariani, et al., 2020). Furthermore, its populations are clearly influenced by anthropogenic disturbance regimes, including grazing, road building, and cultivation. Disturbance regimes can also affect this species' populations negatively and lead to local extinctions, ultimately reducing range size and increasing habitat destruction and fragmentation (Behroozian, Ejtehadi, Memariani, et al., 2020; Velázquez-Tibatá et al., 2013). Dianthus pseudocrinitus, with limited dispersal, given its polyploidy and heavy seeds, occupies a small geographic range (Behroozian et al., 2014), so predictions of suitable sites for this species are urgently required (Behroozian, Ejtehadi, Memariani, et al., 2020).

In this article, we integrate known occurrences of the species with environmental variables derived from satellite imagery to generate high-resolution maps to guide field sampling. We evaluated the ability of ecological niche models to predict the species' distribution by means of detailed field sampling across the species' geographic range. When the fieldwork detected a number of additional populations, we implemented a second round of modeling; the result was a much better view of the range of a rare plant species. As a consequence, we recommend a revised conservation status for this species, as we located numerous new sites for the species, suggesting both a broader geographic distribution and a wider environmental amplitude of its occurrence. This study thus illustrates the potential of this approach to assessment of regions and habitats as potential distributional areas for rare and endangered species.

2 | MATERIALS AND METHODS

2.1 | Study area and occurrence data

Dianthus pseudocrinitus was described as a new species recently based on molecular and morphological characteristics, and is known only from montane areas of northeastern Iran (Vaezi et al., 2014). The species is morphologically similar to D. crinitus subsp. turcomanicus and D. orientalis subsp. Stenocalyx, with which it co-occurs across much of its range. Dianthus pseudocrinitus is a perennial species, usually with a simple or sometimes with a branched life form; its flower is solitary, and it produces a lot of seeds (Figure S1). It is distributed in montane steppe in North Khorassan Province, including parts of the Aladagh, Salook, and Massinev mountains (Figure 1a). The species is found in calcareous mountains with high disturbance regimes, and at elevations of 1600–2300 m. These areas have specific climatic features corresponding to a Mediterranean or Irano-Turanian xeric-continental climate (Djamali et al., 2011, 2012). These areas experience higher precipitation (300–350 mm in montane areas), in contrast to surrounding lowlands.

Occurrence data were compiled for all known locations of D. pseudocrinitus (Vaezi et al., 2014), including records from previous studies over the period 2014–2018, preserved in the form of specimens in the Ferdowsi University of Mashhad Herbarium (FUMH). We checked occurrence data carefully to assure acceptable data quality by removing duplicate records and a few reported localities falling outside the species' known range. To avoid biases deriving from spatial autocorrelation, we eliminated one of each pair of records falling within
single grid cells (~1 km, see below) using the spThin library in R version 3.5.1 (Aiello-Lammens et al., 2015). Via this set of steps, we assembled an initial total of only eight records for future analysis. An initial accessible area (termed M; Barve et al., 2011) hypothesis for D. pseudocrinitus was taken as the area within 2° (~220 km) of known occurrences to permit the broadest scope view of the distributional potential of this species; this area was delineated using buffer routines in ArcGIS 10.3.1 (Figure 1b).

### 2.2 | Remote sensing data

To characterize environmental variation across the study area, we used multitemporal (16-day composite data layers through the year for 5 years) vegetation index data from MODIS satellite imagery, which offers an ideal balance between relatively fine spatial resolution and daily data capture. We used the NDVI, an index that provides a measure of photosynthetic mass that can be characterized using images captured through time and across space (Hornung et al., 2010; Myneni et al., 1997; Todd et al., 1998). NDVI is calculated as a non-linear transformation of the ratio between the visible (red) and near-infrared bands (Rouse et al., 1974), and has been used extensively in ENM (e.g., Osborne et al., 2001; Parra et al., 2004; Roura-Pascual et al., 2006). To investigate vegetation dynamics, we opted to use MODIS 16-day dataset measured for the period from 2014 to 2018 (5 years). With its considerable time fine resolution (a couple of images per month), the dataset is extracted from image collection ID, MODIS/MOD13Q1 version 6 surface reflectance composite (250 m at spatial resolution), using the JavaScript code editor in the Google Earth Engine platform (GEE: [https://code.earthengine.google.com/](https://code.earthengine.google.com/), Mountain View, CA, USA), which provides possibilities of parallel computing for large data processing for even very large areas. We avoided using the newer EVI (Enhanced Vegetation Index) metric, in view of its poor behavior under conditions in which snow cover is manifested (Dye & Tucker, 2003).

To reduce collinearity among environmental variables, and to reduce the overall number of dimensions in which environments are characterized, we performed a principal components analysis (PCA) on the biweekly NDVI data layers, masked to the M area, using the PCARaster function of the kuenm package in R (Cobos et al., 2019). We retained the first six PC axes as potential predictor variables, explaining 96.8% of the overall variance. With that reduced set (6 principal components), we selected six variable sets: PC 1, PC 1 and PC 2, PCs 1–3, PCs 1–4, PCs 1–5, and PCs 1–6.

### 2.3 | ENM and field testing of model predictions

Ecological niche models were calibrated using the kuenm (version 1.1.7) package in R (Cobos et al., 2019), based on niche-modeling protocols in Maxent 3.4.1 (Phillips et al., 2017) and model-selection approaches (Warren & Seifert, 2011). We compared 270 candidate models, including all possible combinations of nine regularization parameter values (0.1, 0.3, 0.5, 0.75, 1, 2, 3, 5, and 10) and five combinations of model response types (l = linear, q = quadratic, p = product, t = threshold, and h = hinge; we tested combinations l, lq, lqp, lqpt, and lqpth). The models were built using all possible combinations of the six sets of environmental variables.

Because the species has very few known occurrence records, in the initial modeling round, we used a jackknife procedure, in which model performance is assessed based on models’ ability to predict the single locality that was excluded from the “calibration” dataset (Pearson et al., 2007). Eight predictions were made, each with one of the occurrence records excluded from model calibration. The jackknife test requires use of a threshold: we used a minimum training presence threshold (Pearson et al., 2007) to distinguish among suitable and unsuitable areas. Each of the candidate models was evaluated based on a dual criterion of (in order) statistical significance based on a small-sample test (Pearson et al., 2007) and the Akaike information criterion corrected for small sample sizes (AICc; Cobos et al., 2019; Warren & Seifert, 2011). That is, we applied the test presented by Pearson et al. (2007) and recently adapted for analysis in R (R.G. Pearson, pers. comm.) for situations of small sample size, and then chose models with the lowest values of the AICc from among the models that were statistically significant.

Based on the predicted map obtained from the first round of modeling analyses, we selected 16 locations in suitable areas and 12 locations in unsuitable areas to test our model predictions for predictions of presence and absence of species in the field. The points were chosen based on (1) access from existing roads, which is necessary in the rough terrain of the study area, and (2) being well separated from one another (≥10 km); given those two constraints, points were selected at random and checked via overlay in Google Earth. We refined the initial set of selected locations to focus them at sites with characteristics matching known occurrence sites of the species, such as being close to disturbed areas and having presence of Dianthus orientalis subsp. stenocalyx. Dianthus orientalis subsp. stenocalyx is a diploid species that occurs in natural habitats and higher elevations. It also is a stress-tolerator and adapts with stressful environments. This species co-occurs in D. pseudocrinitus in some areas,
but with different habitats, so that \textit{D. pseudocrinitus} distributes in disturbed habitats located in lower elevations. \textit{D. pseudocrinitus} is a ruderal species that could adapt in habitats that there are soil changes without any competitors. On the other hand, according to Vaezi et al. (2014), \textit{D. orientalis} is considered as one of the parents of \textit{D. pseudocrinitus} so that often occurs with this species. All 28 locations were visited when flowering in May 2021 to assess the initial modeling results. Specimens from fieldwork were deposited in FUMH (Table 1). We tested the initial model predictions via a Fisher exact test applied to a 2 × 2 table that summarized predictions of suitability versus unsuitability and actual presence versus nondetection using routines available at R 3.5.3 software (Pearson et al., 2007; R Core Team, 2019).

We developed a second round of models, based on this now-expanded set of occurrence sites. The points were split evenly into three groups used for model calibration, model testing and selection, and final model evaluation. For these models, a revised, narrower M area of 50 km around known occurrence sites was used to make model predictions more specific. Then, the models were built using the methods described above, with the kuenm package in R (Cobos et al., 2019), except that we permitted “all” response types instead of just “basic,” in light of the greater sample size of occurrence data (19 points) available. Models with AICc values within one unit of the minimum were retained for further analysis and exploration. Candidate models were evaluated using partial ROC (receiver operating characteristic) tests for a random 50% of occurrence data left out of model calibration (Peterson et al., 2007), with statistical significance evaluated via a direct count of replicates with area under the curve ratios of ≤1. Then, all statistically significant models were thresholded based on an acceptable calibration omission rate of $E = 5\%$ (Peterson et al., 2011), and we removed models with omission rates ≥0.05. Finally, statistically significant, low-omission models were filtered using AICc to choose models with low complexity and good fit to the underlying data. A final set of models was built using the parameter settings selected, with 10 cross-validate replicates, the “logistic” output, and 10,000 background points using the kuenm package.

2.4 Assessment of conservation status and protection

To assess new conservation status of species, we used the known occurrence points for the species. The geographic location of these points was used to calculate key Red List criteria, including Extent of Occurrence (EOO) and Area of Occupancy (AOO) (IUCN, 2019). EOO is a parameter that measures the size of the species’ geographic range in terms of both suitable and unsuitable habitat (Bachman et al., 2011; Willis et al., 2003), whereas AOO accounts solely for the area occupied by the species (Willis et al., 2003). These values were calculated using the Geospatial Conservation Assessment Tool (GeoCAT) (http://geocat.kew.org/). \textit{Dianthus pseudocrinitus} was classified by its AOO and EOO in the context of the criteria associated with the five threatened and non-threatened categories in the IUCN Red List, including CR, Endangered (EN), and Vulnerable (VU), as well as two non-threatened categories, Near Threatened (NT) and Least Concern (LC) (IUCN, 2019).

We obtained a summary of the geographic position and extent of protected areas from North Khorassan Province, which includes the entire known distribution of the species (Figure S2a). We assessed the extent of suitable habitat for the species in protected and unprotected areas by projecting our thresholded model outputs to the North Asia Albers Equal-area Projection, from which areas could be calculated explicitly, in ArcGIS (version 10.3.1).

3 RESULTS

3.1 Suitable habitats based on the first round of modeling

Initially, we assembled 12 unique, credible occurrences for \textit{D. pseudocrinitus} based on field surveys and herbarium specimens in FUMH herbarium. However, four records were excluded based on ~1 km distance filtering and removal of duplicate records. As such, in the end, eight occurrence points were used for calibration and evaluation of initial models (Figure 1b).

In all, in the first round of modeling, 270 candidate models were evaluated, of which 66 were significantly better than random expectation based on the jackknife test ($P < .001$). A single model was identified as best based on the model selection framework, which included linear, quadratic, product, and threshold response types; a regularization parameter value of 0.5, and only one environmental variable (the first principal component of the NDVI data). This model indicated high suitability for \textit{D. pseudocrinitus} across montane areas (Figure 2a), particularly in montane areas near land with soil changes due to agriculture or in abandoned human-use areas. Unsuitable areas were observed in native habitats, in lowlands with poor vegetation coverage, and near roads.

3.2 Field sampling

In our fieldwork, we found the presence of species at 11 locations. Of these sites, eight locations were at modeled...
| No. | ID | Longitude | Latitude | Elevation (m) | First round model prediction | Status | Herbarium number |
|-----|----|-----------|----------|--------------|-------------------------------|--------|-----------------|
| 1   |    | 37° 21' 31.00" | 57° 11’ 58.90" | 1680 | Suitable | Original occurrence used in round 1 | 45855 |
| 2   |    | 37° 17' 11.08" | 57° 09’ 00.70" | 1878 | Suitable | Original occurrence used in round 1 | 23577 |
| 3   |    | 37° 24' 05.40" | 57° 02’ 26.90" | 1878 | Suitable | Original occurrence used in round 1 | 11095 |
| 4   |    | 37° 54’ 25.09" | 57° 30’ 58.0" | 1663 | Suitable | Original occurrence used in round 1 | 11109 |
| 5   |    | 37° 17’ 03.80" | 57° 09’ 16.90" | 1899 | Suitable | Original occurrence used in round 1 | 44119 |
| 6   |    | 37° 54’ 34.00" | 57° 31’ 07.00" | 1682 | Suitable | Original occurrence used in round 1 | 11116 |
| 7   |    | 37° 55’ 13.01" | 57° 30’ 34.90" | 2240 | Suitable | Original occurrence used in round 1 | 11054 |
| 8   |    | 37° 18’ 10.08" | 57° 09’ 25.20" | 1675 | Suitable | Original occurrence used in round 1 | 40652 |
| 9   | P2 | 37° 41’ 53.02" | 57° 24’ 33.00" | 1347 | Suitable | Present | 46933 |
| 10  | A8 | 37° 27’ 43.11" | 56° 53’58.66" | 1708 | Suitable | Absent | 1509 |
| 11  | P3 | 37° 47’ 47.01" | 57° 28’ 31.90" | 1274 | Suitable | Absent | 917 |
| 12  | P4 | 37° 53’ 27.03" | 57° 31’ 02.90" | 1462 | Suitable | Absent | 1763 |
| 13  | P5 | 37° 49’ 32.05" | 57° 18’ 24.04" | 987 | Suitable | Absent | 1334 |
| 14  | P6 | 37° 54’ 53.25" | 57° 07’ 38.23" | 1370 | Suitable | Absent | 1374 |
| 15  | P7 | 37° 20’ 55.08" | 57° 09’ 49.09" | 1472 | Suitable | Present | 1816 |
| 16  | P9 | 37° 19’ 09.82" | 57° 01’ 03.70" | 1816 | Suitable | Present | 1899 |
| 17  | P10| 37° 17’ 47.60" | 57° 00’ 43.90" | 1828 | Suitable | Absent | 1363 |
| 18  | P11| 37° 30’ 30.20" | 56° 23’ 35.05" | 1564 | Suitable | Present | 1564 |
| 19  | P12| 37° 27’ 21.01" | 56° 55’ 36.02" | 1363 | Suitable | Present | 1816 |
| 20  | P13| 37° 26’ 14.66" | 57° 08’ 57.50" | 1591 | Suitable | Absent | 1370 |
| 21  | P14| 37° 24’ 02.10" | 57° 05’ 47.20" | 2061 | Suitable | Absent | 2061 |
| 22  | P15| 37° 23’ 42.07" | 57° 03’ 07.50" | 2077 | Suitable | Present | 2077 |
| 23  | P17| 37° 18’ 40.05" | 57° 20’ 29.02" | 1374 | Suitable | Present | 2077 |
| 24  | P18| 37° 14’ 58.06" | 57° 21’ 59.02" | 1914 | Suitable | Present | 1914 |
| 25  | A1 | 37° 44’ 40.05" | 57° 26’ 06.80" | 1220 | Unsuitable | Absent | 1370 |
| 26  | A2 | 37° 48’ 47.70" | 57° 29’ 31.01" | 1334 | Unsuitable | Absent | 1374 |
| 27  | A3 | 37° 50’ 59.8" | 57° 31’ 34.00" | 1700 | Unsuitable | Absent | 1370 |
| 28  | A4 | 37° 50’ 24.86" | 57° 14’ 09.87" | 1053 | Unsuitable | Absent | 1370 |
| 29  | A5 | 37° 19’ 22.06" | 57° 08’ 28.05" | 1763 | Unsuitable | Absent | 1370 |
| 30  | A6 | 37° 18’ 31.07" | 56° 56’ 03.40" | 1493 | Unsuitable | Absent | 1370 |
| 31  | A7 | 37° 30’ 28.01" | 56° 40’ 51.09" | 917 | Unsuitable | Absent | 1370 |
| 32  | A9 | 37° 24’ 46.67" | 57° 11’ 21.68" | 1450 | Unsuitable | Absent | 1370 |
| 33  | P16| 37° 20’ 33.05" | 57° 19’ 24.03" | 1509 | Unsuitable | Present | 1370 |
| 34  | A10| 37° 14’ 01.29" | 57° 24’ 4.34" | 1638 | Unsuitable | Absent | 1370 |
| 35  | P1 | 37° 41’ 10.10" | 57° 24’ 15.00" | 1218 | Unsuitable | Present | 1370 |
| 36  | P8 | 37° 19’ 44.15" | 57° 09’ 00.6" | 1826 | Unsuitable | Present | 1370 |
suitable habitats and three were in modeled unsuitable habitats. Ten locations visited showed as absence of the species, of which nine were modeled unsuitable and one was modeled as suitable (Figure 2b; Table 1). A Fisher's exact test showed that model predictions did not discriminate well between suitable and unsuitable sites for the species \( (P > .05) \). This incongruence between model predictions and field observations pointed toward unacceptably low model quality, but indicates that the species has a broader environmental and geographic distribution than indicated by our initial model. Accordingly, a second round of modeling was performed to take advantage of the larger sample of occurrence data.

### 3.3 Suitable habitats based on the second round of modeling

The results of the second round of modeling indicated that spatial predictions were significantly better than random, based on an independent subset of available distributional data, such that distributional predictions could differentiate between suitable and unsuitable areas for the species, at least based on subsets of the available occurrence data. In this second modeling round, 225 candidate models were explored, of which 180 made predictions that were statistically significant; six of these models also met the omission error criterion. Then, considering AICc to prioritize relatively simple models, four final models were identified. These models had linear, quadratic, product, and threshold response types; a regularization parameter value of 3, and the first five or six principal components of the NDVI data.

The maps derived from this set of second-round final models (Figure 3a) identified broader expanses of suitable area for the species, though all in montane areas. Specifically, the model identified suitable areas in locations with stressful conditions, such as montane croplands and pasture lands, and higher elevation areas. Areas identified as unsuitable were closer to villages and cities, and at lower elevations, including areas of extensive native vegetation or of scarce vegetation coverage. Although most of the independent subset of occurrence points used to test the round 2 model were predicted successfully by the model, one point in the Massinev Mountains at which the plant was indeed present but was indicated by the model as unsuitable. Nevertheless, the overall test of model 2 predictions was significantly better than random expectations (partial ROC test, \( P < .05 \)).

Final model predictions, based on all available occurrence data (i.e., without the subsetting for model evaluation; Figure 3b) identified sites as suitable for the species that were similar to predictions based on the subsetted data (Figure 3a), except that it included broader suitable areas in the northern and central mountain ranges within the study area. Unsuitable areas were identified in the western and southern parts of the study area, which was reasonable given our understanding of the climatic and vegetation conditions manifested there. The southern areas present an arid climate, whereas the western areas are warmer and more humid. This final model also identified unsuitable areas that were below 1000 m in elevation and those with broad expanses of native vegetation.

### 3.4 Conservation status and degree of protection

Based on the Red List criteria (IUCN, 2019), and given the new distributional information that we had accumulated for this study, EOO and AOO were calculated at 3558 and 1300 km\(^2\), respectively, for *D. pseudocrinitus*. These values had previously been measured at 53 and 16 km\(^2\), respectively, for this species using GeoCAT tool (Memariani et al., 2016). Therefore, we recommend that
the conservation status of the species be upgraded from CR to EN in light of the now-more-complete distributional information that we have amassed.

Our assessment of the degree of protection that is manifested across the species’ likely geographic distribution indicated that significant sectors of the species’ distribution are already covered by protected areas (Figure S2b). That is, of the species’ likely full geographic distribution, 7.1% fell within protected areas (2.3% in Gholestan Protected Area, 2.5% in Ghorkhoud Protected Area, 0.7% Salouk, 0.3% Sarani, 1.3% Sarigol); Miandasht Protected Area apparently holds no suitable area for this species. We also identified an area (340.9 km²) just north of Salouk Protected Area, which—if added to that protected area—would protect the most densely distributed and best known populations of the species (Table 2, Figure S2b), and would add a further 3.0% of the species’ geographic distribution to the protected proportion of the species’ geographic distribution.

4 DISCUSSION

In this study, we obtained new results regarding the geographic range of a rare plant species based on iterative series of ENM exercises. We demonstrated how ENM based on remotely sensed data streams can predict new sites for endangered plant species with few known occurrences, and illustrated how combining these models with field sampling has particular power to produce new insights. The integration of ENM with remote sensing environmental data products performed well in predicting suitable areas and identifying new sites for this rare species. Multispectral satellite remote-sensing indices (e.g., NDVI) have been used successfully to assess habitat suitability for rare species with narrow ranges in past studies (Leitão & Santos, 2019; Valerio et al., 2020; Vaniscotte et al., 2009). In spite of some concerns that satellite data may not provide good coverage for rare plant species (Bradley et al., 2012; Dormann et al., 2013), our results illustrate how satellite data can provide

TABLE 2 The details of assessment of protected and unprotected parts of the suitable area for the species within the likely accessible area of *Dianthus pseudocrinitus*

| Study areas     | Protected area name | Total area in M area (km²) | Suitable area (km²) | Percentage of total suitable area for the species |
|-----------------|---------------------|---------------------------|---------------------|--------------------------------------------------|
| Protected area  | Gholestan           | 489.3                     | 266.4               | 2.3                                              |
|                 | Ghorkhoud           | 422.6                     | 286.7               | 2.5                                              |
|                 | Miandasht           | 311.5                     | 0.0                 | –                                                |
|                 | Salouk              | 199.7                     | 84.2                | 0.7                                              |
|                 | Sarani              | 37.1                      | 31.6                | 0.3                                              |
|                 | Sarigol             | 266.0                     | 150.1               | 1.3                                              |
| Total protected |                     | 1726.2                    | 821.0               | 7.1                                              |
| Unprotected area|                     | 20,568.1                  | 10,676.1            | 92.9%                                            |
valuable information in such analyses, as discussed previously by Cerrejón et al. (2021).

In other words, our models predicted well the suitable habitats for the species and provided efficient information about suitable and unsuitable areas for a rare plant species. We followed a framework that combined modeling and fieldwork, which was able to improve knowledge of the distribution of the focal species considerably (Figure 4). Our ENMs identified areas of suitable habitat for *D. pseudocrinitus* in montane areas, which is supported by previous studies of other *Dianthus* species (Behroozian, Ejtehadi, Memariani, et al., 2020; Behroozian, Ejtehadi, Peterson, et al., 2020; Farsi et al., 2013; Gugger et al., 2015). Although all suitable areas for *D. pseudocrinitus* were in montane areas, unlike other *Dianthus* species, this species was focused at locations under stressful conditions, such as montane croplands and pastures. These results highlight an important role of environmental variables that capture dimensions of land use in developing such models, which can permit considerable predictive success (Cursach et al., 2020; Ishii et al., 2009; Robinson et al., 2019).

Our initial round of modeling showed low accuracy in predicting suitable and unsuitable sites for *D. pseudocrinitus* across northeastern Iran (Figure 2a), and indeed did not make predictions that performed better than random expectations in statistical tests. In effect, that initial model performed poorly because the species was present at both (modeled) suitable and unsuitable sites. The field sampling that provided tests of those initial model predictions as a result produced an impressive number of new sites at which this rare and poorly known species can be found. The second round of modeling, which had the benefit of a much larger occurrence dataset, achieved considerably higher accuracy in its predictions of suitability and unsuitability across the species’ area of occurrence.

Several previous publications have developed and presented methods for assessing rare species’ geographic distributions (e.g., Guisan, Broennimann, et al., 2006; Pearson et al., 2007), but few have incorporated field surveys to test model predictions directly (Aizpurua et al., 2015; Griscom et al., 2010; Keinath et al., 2014; McCune, 2016). The promise of such models in guiding surveys for new populations of rare species has been emphasized by several authors (Guisan, Broennimann, et al., 2006; McCune, 2016; Soafer et al., 2019). Aizpurua et al. (2015) used Species distribution modeling discover populations of a threatened bird species, *Lanius collurio*, with the number of new populations discovered exceeding that from searches guided by expert opinion. Keinath et al. (2014) discovered new populations of an endangered mammal, *Thomomys clusius*, using correlative models in relation to soil variables.

### 4.1 Conservation status and protection of *D. pseudocrinitus*

In recent years, human activities and the impacts of the external natural environment have reduced the population sizes and distributional area of some rare and endangered species; therefore, understanding geographic distributions and habitat suitability for these species is key to protecting them (Mousikos et al., 2021; Sousa-Silva et al., 2014; Thompson et al., 2020). Detailed assessment of habitat suitability is considered as a first step in effective conservation and scientific management and can provide valuable information for future conservation.
strategies. In this study, we focused on a rare and endangered plant species with a narrow geographic range, striving to predict its suitable habitats and discover new populations.

Previous to this study, *D. pseudocrinitus* was considered to be a relatively young, “neoendemic” species that evolved relatively recently from its sister species, *D. orientalis*, with a highly restricted geographic distribution. Based on our field surveys, we noted small populations of the species at numerous sites, the habitats, albeit comprising only few individuals. The sites identified in our models often were in land under cultivation and grazing in montane areas, with populations focused in abandoned areas and small extents of natural vegetation.

Our suite of methods produced optimistic results as regards its conservation status, despite previous results that were less optimistic (Behroozian, Ejtehadi, Memariani, & Mesdaghi, 2020). Our field tests of initial model results revealed that 50% of modeled-suitable sites were properly predicted, but 75% of modeled-unsuitable sites were incorrect and really were found to hold the species. We anticipate that *D. pseudocrinitus* will likely be found even farther afield, beyond its currently known range in this study; therefore, its conservation status may improve still more in the future. Although the species’ populations in disturbance-prone areas may often be affected directly by those disturbance factors (Figure 5), the species apparently can apply the mechanisms to disperse and establish new populations (Behroozian, Ejtehadi, Memariani, et al., 2020).

Indeed, the species may be increasing its geographic range, or its geographic range may have been broader than was originally appreciated from the outset. It may be extending its population size via mechanisms such as polyploidy and extensive seed production (it is a tetraploid, with 2n = 60, whereas *D. orientalis* is diploid, 2n = 30; Behroozian et al., 2014). The polyploidy may confer a fitness advantage, creating new trait values and trait plasticities, allowing the species’ survival in heterogeneous environments (Alix et al., 2017; Wei et al., 2018). However, *D. pseudocrinitus* also produces heavy seeds

![FIGURE 5](image-url) Natural habitats for *Dianthus pseudocrinitus* across its geographic range. (a–c) Suitable habitats of the species, representing disturbed montane vegetation interspersed with agricultural lands (a is P5, b is P12, and c is P18 in Table 1). (d and e) Sites holding unsuitable habitats for the species in that they hold natural vegetation (d is A1, e is A3 in Table 1).
owing to its polyploidy, suggesting that dispersal limitation is important in this species, which may reduce the species’ potential to extend its range to additional suitable areas (Gadgil, 1971; Rodriguez et al., 2017). In this sense, D. pseudocrinitus may be changing its survival strategies toward ruderalism to extend range size and populations (Behroozian, Ejtehadi, Memariani, et al., 2020).

In recent years, correlative modeling techniques have been explored as a means for estimating extent of occurrence as a key parameter in understanding risk of extinction (Cassini, 2011). In this study, we used a combination of modeling and field sampling, which led to discovery of numerous new sites for D. pseudocrinitus. This species is presently considered as CR, according to the IUCN Red List categories and criteria. This classification was based in particular on its miniscule geographic range, which clearly made an appearance of dire vulnerability to any sort of disturbance. Based on the results of this study, however, we have documented that the species has a broader range, both in terms of its geographic extent and in the suite of environmental conditions under which it is able to persist. As such, the conservation status of D. pseudocrinitus is best changed from CR to EN as a revision (EOO is 3558 km², and AOO is 1300 km²). The methods used in this study were useful both in discovering new sites for the species and in understanding the diversity of environments within which it is able to maintain populations.

Our fieldwork indicated that almost all known sites for the species are located near agricultural lands, yet we found large populations only at the site P11 (Table 1), within Ghorkhoud Protected Area, where human activities are few (Figures S2b and S3a). Other sites held only small populations in small natural-habitat patches scattered among agricultural lands, which likely places them at much-greater risk of extirpation. Indeed, the species was not found at some modeled-suitable sites, likely owing due to overly strong or frequent disturbances (Figures S2b and S3b). Certainly then, this dependence on intermediate disturbance regimes suggests a need for regular monitoring to understand population trends and persistence in better detail.

Our modeling and field studies indicated that much of the known and likely distribution of the species falls within protected areas in the region, particularly Sarani, Ghorkhoud, and Sarigol protected areas. We also detected and outlined an area of 340.9 km² that, if added to Salouk Protected Area, would protect the densest known clusters of populations of this microendemic species. This degree of protection is likely sufficient to assure the conservation future of the species. Given the affinity of D. pseudocrinitus to disturbed conditions, however, some degree of management of habitats in these areas may prove necessary to assure that the species’ populations are sustainable and do not suffer from too little disturbance in protected areas (Table 2, Figure S2b).

5 | CONCLUSIONS

Overall, the results of our melding of field and modeling studies were a concrete expansion of knowledge of the distribution of this rare species, providing predictive maps of the potential distribution of the species even in areas where records are scarce or nonexistent. This study illustrates how such assessments may affect decisions about conservation status of rare species, highlighting the importance of this integrated methodology for future assessments of endangered species, particularly under conditions of data scarcity. Such work could ideally be achieved by collaborating with conservation management agencies to develop ENM predictions, and improve them with new data that would be incorporated at the end of each field sampling effort. The end result would be a more accurate picture of the true conservation status of such species. Indeed, for the species that we have examined in detail in this study, the additional information about the species’ geographic range leads us to amend and upgrade the species’ likely conservation status from CN to a more-optimistic EN, providing a rare “good news” conservation message.

AUTHOR CONTRIBUTIONS
Conceptualization and design: Maryam Behroozian, A. Townsend Peterson; Methodology: A. Townsend Peterson; Formal analysis: Maryam Behroozian, A. Townsend Peterson, Pavel Joser Atauchi-Rojas; Interpretation: Maryam Behroozian, A. Townsend Peterson; Investigation: Maryam Behroozian, A. Townsend Peterson, Mohammad Reza Joharchi; Collection of data: Maryam Behroozian, Mohammad Reza Joharchi, Farshid Memariani, Ali Asghar Arjmandi; Writing – Original draft preparation: Maryam Behroozian; Writing – Review and editing: A. Townsend Peterson, Mohammad Reza Joharchi, Pavel Joser Atauchi-Rojas, Farshid Memariani, Ali Asghar Arjmandi.

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CONFLICT OF INTEREST
The authors declare that they have no conflict competing interests to declare that are relevant to the content of this article.
DATA AVAILABILITY STATEMENT
The datasets generated during and/or analyzed during the current study are available from the corresponding author on reasonable request.

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**SUPPORTING INFORMATION**

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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