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Modeling suitable habitats for *Aquilegia nivalis*, an endangered species of Kashmir Himalaya

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ABSTRACT
Restricted geographic ranges, high degree of habitat specialization and small population size of endangered species deserve exceptional consideration for their conservation. Prediction and mapping of potential suitable habitats for such species can aid in their conservation. We used species distribution modeling technique to predict the current suitable habitats of A.nivalis in Kashmir Himalaya. We used world clim data and Maxent software to perform distribution modeling. Our models successfully predicted current known habitats as well as new areas suitable for A.nivalis. We identified several new populations based on the model predictions and intensive field surveys. Our modeling approach can provide a baseline method for modeling rare and endangered species.
***Key words**: Endemic, Himalaya, Habitat, Maxent, Niche modelling, IUCN, Aquilegia nivalis*

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INTRODUCTION

The precise assessment of the conservation status of rare and endemic species attains fundamental significance in establishing conservation priorities for threatened elements of biological diversity. Rare and endemic species merit special attention as a conservation concern in view of being at a higher risk of extinction. Because of restricted geographic ranges, high degree of habitat specialization and small population size these species deserve exceptional consideration for conservation [1]. In this direction, prediction and mapping of potential suitable habitats for rare endemic species assumes pivotal importance for monitoring and restoration of their declining population status in natural habitats, artificial introductions, or selecting appropriate sites for their conservation and management [2-3]. Recent developments in Ecological Niche Modeling (ENM) have explored applications to diverse conservation issues, including suitable habitat and species range estimates [4-10], protected area prioritization and network design [11-18], effects of habitat disturbance on species distributions [19, 20], to aid in IUCN categorization of species [26] and projecting future distributions under climate change [21-24]. By definition, ecological niche is a set of ecological conditions that allows a species to persist and produce offsprings [25]. The ENM approach combines species occurrence data with ecological/environmental variables (temperature, precipitation, elevation, geology, and vegetation) to create a model representing species distributions compatible with the environment [27]. Availability of high resolution satellite imageries, downscaling tools for environmental variables and interpolated spatial datasets on climate and vegetation has enhanced the accuracy of prediction of the models manifold.

Species distribution data are now increasingly getting available due to various efforts to digitize historical distribution records obtained from national and local natural history collections [28, 29]. ENM facilitates interpolation as well as extrapolation of species distributions in geographic space across different time periods. This has made it possible to prepare species distribution maps with high level of statistical confidence and identify areas suitable for reintroduction of threatened species [30-35]. Species distribution modelling tools are becoming increasingly popular in ecology and are being widely used in many ecological applications [6, 36-40]. A variety of species distribution modelling methods is available to predict potential suitable habitat for a species [41-50]. Data on rare and endemic species usually have few observations, limited spatial accuracy and lack of valid absences [51], consequently relatively few predictive models have been applied to rare and endangered species [52]. These limitations of rare

species datasets make the application of the usual statistical approaches more difficult. However, at the same time the rare species utmost need predictive distribution modelling, for both monitoring and conservation management purposes.
Kashmir Himalaya occupies a pivotal position in representing a unique biospheric unit in the Western Himalayas, a biodiversity hotspot [54].The mountainous region lies between 32°20' to 34°50' North latitude and 73°55' to 75°35' East longitude [55] 2,000 plant species have been recorded from the region [3], grouped under 710 genera and 132 families out of which 8% species are exclusively endemic to Kashmir despite the region comprises of only 0.48% land mass of India [4]. Most of these endemic species are restricted to the alpine and sub-alpine habitats. A large number of species are facing threat due to various anthropogenic activities, such as habitat loss or modification, over-exploitation of economically important plants, alien species invasion, unchecked grazing, unplanned development, and influx of tourists [9], thus, substantiating the immediate need to undertake systematic conservation planning. Species distribution Modelling tools can serve a useful solution in solving the problems of conservation in this Himalayan region were no such efforts have been undertaken so far.
Notwithstanding the aforementioned 'rare species modelling paradox' [21], we realized the importance of using ENM as a conservation tool for rare species and modelled *A. nivalis*, an endangered and endemic species of Kashmir Himalaya [2].

MATERIAL AND METHODS

Study area

Kashmir Himalayan region constitutes an important biogeographic zone of north western Himalaya. It is located at 33∘20–34∘54N latitudes and 73∘55–75∘35E longitudes, covering an area of 16, 000 km^2(Fig 2.e). The region is rich in biodiversity, with lofty mountains of the Pir Panjal in the South and Southwest and by the Great Himalayan range in the North and East with a deep elliptical bowl-shaped Kashmir valley in the middle.

Study species

A. nivalis is a perennial endangered species which is endemic to Kashmir Himalayan region (Dar et al. 2008) (Fig 2.a) and grows along an altitudinal range from 3000 to 4000m (amsl). It is found in rocky habitats and grows as high as 25cm with stems simple, scapose, short, leafless or one-leaved. Flowers are solitary, terminal, drooping and dark purple in colour. Flowering and fruiting season ranges from June–July. Due to small size of its populations, very few individuals reach the reproductive stage. The species is not only over exploited in view of myriad medicinal uses but its individuals are also damaged by herbivores in various populations. These factors in conjunction with hostile habitat conditions and enhanced anthropogenic pressures contribute to the present threat status of this endemic species.

Table 1: Early records of *A.nivalis* at the beginning of the study and the new localities sampled during successive field trips based on model thresholds.

Species	**Early Locations**	**Status of Individuals**				
		Plants found at Flowering stage	Plants at vegetative stage	Plants at seedling stage	Total	Altitude (m)
Aquilegia nivalis	Thajwas	90	13	8	111	3700
	Apharwat	156	20	16	192	3800
	Khillanmag	65	5	5	75	3600
	Vishnosar	189	17	23	229	3950
	Gangbal	143	14	20	177	3800
	Sarsoon	87	12	9	108	3800
	Harmuk	123	25	20	168	3850
	Seeryadi	421	37	35	493	3850
	Newly Locations					
	Sinthan Top	223	42	35	300	3700
	Pehjan	200	37	16	253	3750
	Peer Ki Gali	150	24	27	201	3800
	Kousar Nag	135	25	24	184	3800

Species distribution modeling

We used sixteen distribution records of *A. nivalis* for modeling its suitable habitats.We carried spatial autocorrelation with the help of 'SDM tool box' (Brown 2014)in order to remove overlapping and non relevant records.

Environmental data

For modeling purpose we used bioclimatic and topographic variables for *A. nivalis.* These GIS data sets characterize global climates from 1950–2000 using average monthly weather station data and are available at different spatial resolutions. [34] and are known to influence species distributions [62]. We downloaded environmental variables from WorldClim [34] with a spatial resolution of 30 arc-seconds (http:// worldclim.org/current) . All environmental layers were resampled to a 500 m cell size for usage in the regional scale models. All spatial procedures were implemented in ArcGIS 10.1. In order to remove highly correlated variables we used Spearman's rank correlation test, and only those with a correlation coefficient lower than 0.85 were taken [6, 7].

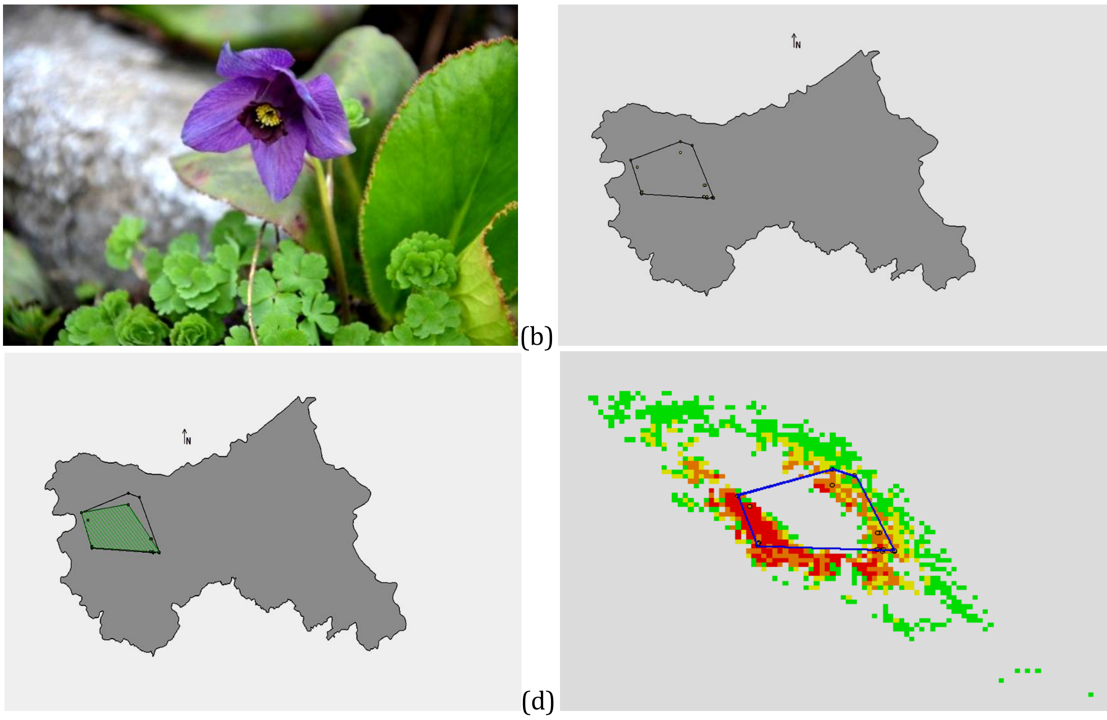
Modeling Software

We used Maxent 3.3.2 [15] to model suitable habitats for *A.nivalis* in Kashmir Himalaya. Maxent is one of the best performing tools particularly at low sample sizes. It is one amongst the 'presence-only' group of species distribution modelling methods which has been widely used. The strong attributes of Maxent are:(i) It holds a strict mathematical definition (ii) gives a continuous probabilistic output (iii) can simultaneously handle both continuous and categorical environmental data (iv) can investigate variable importance through Jackknife procedure (v) has the capacity to handle low sample sizes and (vi) simplicity for model interpretation [45, 46, 23, 24]. It also facilitates replicated runs to allow cross-validation, bootstrapping and repeated sub sampling in order to test model robustness.

To avoid over prediction of our SDMs we used Binary Models application of SDM tool box with a buffer distance of 100km.These tools clip DMs by a buffered minimum convex polygon (MCP) generated from the input point data of each species following the approach of Kremen *et al*. [42]. In this method suitable habitats are generated within an area of species known occurrences (based on a buffered MCP), excluding suitable habitat greatly outside of observed range and unsuitable habitat through the landscape.

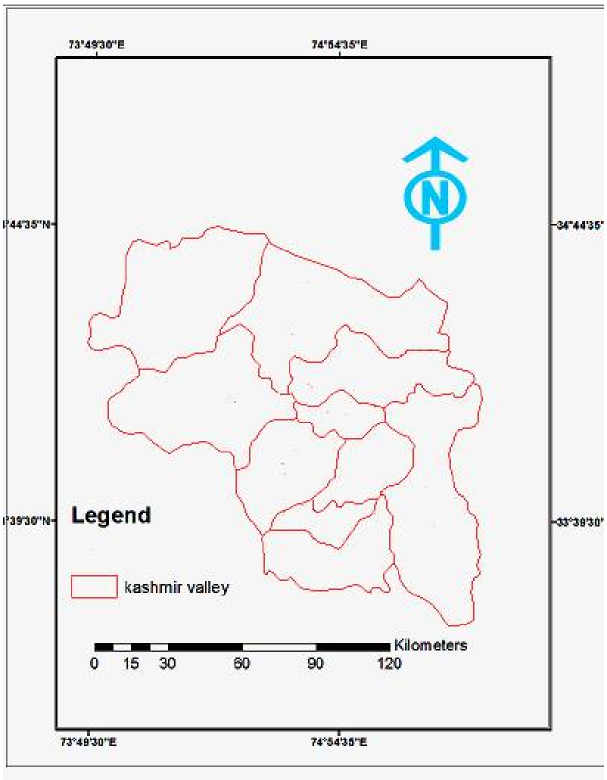
Extent of Occurrence

Convex hull method (IUCN 2005) was used to calculate the extent of occurrence for *A. nivalis*.This method involves producing Delauney triangulations of species occurrence points and at the same time removing all sides that are α times longer than the median of the original sides. We initially calculated the area of occurrence taking secondary data into consideration. Our final EOO was based on the secondary records as well as new occurrences.



(a) (b)

(c) (d)



(e)

Figure 2: (a) Study species *A. nivalis* (b) Area of extent for *A. nivalis*based on final records (c) Shaded portion represents area of occupancy which was calculated using initial distributional records. AOO overlaid on the distributional map (d) Map of Kashmir valley (e).

RESULTS

Habitat suitability modeling

Maxent model successfully predicted the current distribution besides predicting additional habitats like northern parts of Pakistan (Pakistan occupied Kashmir), Uttrakhand and Himachal Pradesh as suitable for areas for *A. nivalis*(Fig 1.a). Using primarily species distribution modeling approach aided by Convex hull method we were able to extend the range *A. nivalis*(extent of occurrence) in Kashmir Himalaya from 210 to 380 Km^{2}thus increasing the overall range for *A.nivalis* by 170 Km^2 (Fig 2,b,c and d).

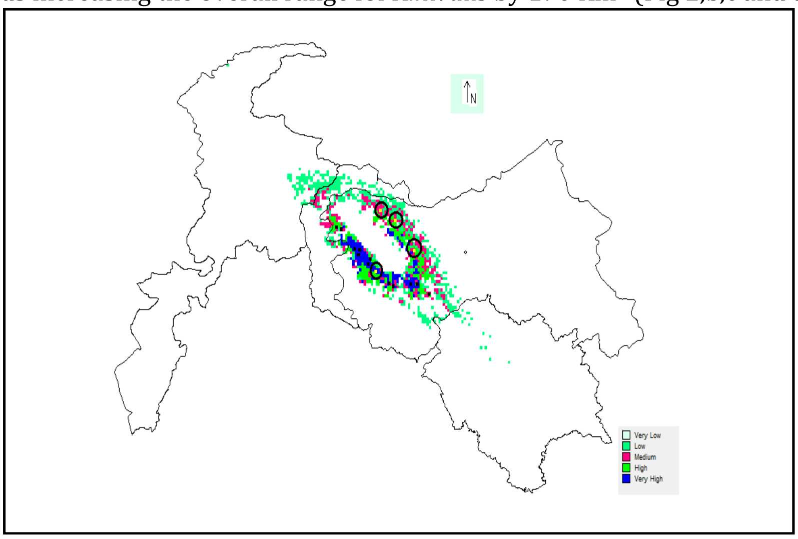


Fig.1: Habitat suitability map for *A.nivalis*

Model calibration andfactors determining species distribution

Maxent model attained an AUC value of>0.90 (0.99 ± 0.0009, 0.99±.0004) which is considered as excellent (Elith and Leathwick 2007).Precipitation Seasonality had highest contribution in followed by Mean Diurnal Range and Precipitation of Coldest Quarter (Fig 3, Table 3). The response curves for the environmental predictors most determinant for the species distribution of *A.nivalis* are presented in Figure 4. Overall, the response curves reveal that the species is mainly distributed in areas with lower values of Precipitation of Coldest Quarter,Precipitation Seasonality and low to medium temperatures, which is coherent with the known distribution of the species along the north-western Himalaya (Kashmir Himalaya).

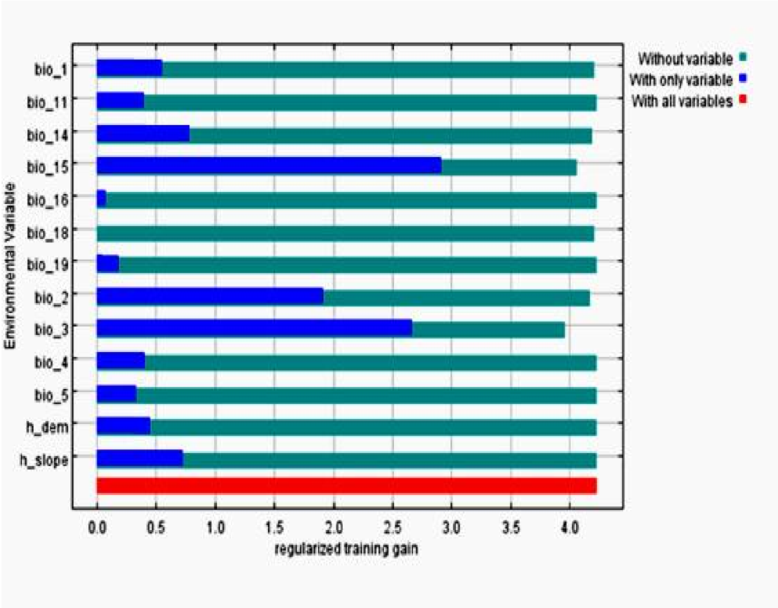


Fig. 3: Results of jackknife evaluation procedure on the relative importance of predictor variables for *A.nivalis*.

Habitats for reintroduction

A. nivalis occupies the alpine slopes with moist and rocky habitats. It sometimes grows in rock crevices and prefers pebbled and sandy soils at an altitudinal range of 3000-4000m. Suitable areas for reintroduction include alpine patches of north Western Himalayan region.

Table 2: Environmental variables used in modelling *A.nivalis*.

Predictors	**Source**
Annual Mean Temperature	World clim ; Hijmans et al., [34]
Mean Diurnal Range (Mean of monthly (max temp - min temp)	World clim ; Hijmans et al., [34]
Isothermality (BIO2/BIO7) (* 100)	World clim ; Hijmans et al., [34]
Max Temperature of Warmest Month	World clim ; Hijmans et al., [34]
Mean Temperature of Coldest Quarter	World clim ; Hijmans et al., [34]
Precipitation of Driest Month	World clim ; Hijmans et al., [34]
Precipitation Seasonality (Coefficient of Variation)	World clim ; Hijmans et al., [34]
Precipitation of Wettest Quarter	World clim ; Hijmans et al., [34]
Precipitation of Warmest Quarter	World clim ; Hijmans et al., [34]
Elevation	USGS Hydro-1K dataset)
Slope	USGS Hydro-1K dataset

DISCUSSION

Currently a large number of Species Distribution Models (SDMs) are used for addressing various ecological and evolutionary issues. However, the accuracy of these models depends to a large extent on how species occurrence data and environmental data are processed for model building, and if not done properly it can lead to erroneous predictions. In our study we considered several important issues prior to fitting the data to our model for instance Spatial autocorrelation among the occurrence localities is a serious issue to be taken care of. If occurrence points are spatially autocorrelated, often it leads to model overfitting and inflated values of model performance [47, 34, 9]. The removal of clustered locations particularly for species with limited occurrence records is important for model calibration and evaluation. Prior to fitting the occurrence localities in our models we considered issue of spatial autocorrelation and filtered the locations at 10km^2 resolutions. In our study we dropped several occurrences from the original data set to reduce spatial autocorrelation. We used 'Spatially Rarefy

Occurrence Data Tool' of SDM tool box developed by Brown 2014 to remove spatially autocorrelated localities. Initially we had eighteen locations and we were left with twelve final locations for first model.
Correlation among environmental variables also can bias model predictions. Highly correlated variables can expose models to multicolinearity. In our case variable selection was based on Pearson´s correlation test r Pearson < 0.85 and Maxent result (Those variables which had the highest contribution to the Maxent model).
Over prediction is a problem commonly associated with species a distribution that seriously affects the precision of predictive models, especially when we are dealing with rare and endemic species. In the present study help was taken from SDM tools Binary Models application of SDM tool box. Since the target species is endemic to Western Himalayan region and our purpose was to identify new populations of the target species we kept the buffering distance to 100km.These tools clip DMs by a buffered minimum convex polygon (MCP) generated from the input point data of each species following the approach of Kremen et al. [42]. In this method suitable habitats are generated within an area of species known occurrences (based on a buffered MCP), excluding suitable habitat greatly outside of observed range and unsuitable habitat through the landscape.
Our results are important in addressing many conservation issues such as reintroduction, identification of new populations and assessment of threat status for *A. nivalis*. Maxent modelling approach, an effective modelling tool even with relatively low occurrence records, was used in the present study because such models provide excellent discriminatory ability following Thuiller *et al*. [46] scales with AUC values above 0.90 for *A. nivalis*. Rare and endemic species have acquired top priority to conserve biodiversity worldwide because these species are assumed to undergo higher risk of extinction. Our models show that a mixture of climatic and non-climatic variables are needed to explain endemic species distributions in Western Himalaya, with Precipitation Seasonality, Mean Diurnal Range and Precipitation of Coldest Month being the most important predictor variables. Although we tried to overcome major problems associated with SDMs, there are still many issues particularly while modelling rare species with few occurrence records. It is difficult for low occurrence species to model actual and projected distributions [64, 65, 39]. At the same time distinction of important variables becomes difficult for models when the data are sparse. Although the best predicted subsets of the *A. nivalis* SDM are able to explain the potential habitat requirements for the species, they need to be interpreted with caution due to the implications of the model accuracy, model assumptions and fundamental vs. realized niches. They are informative, but have their limitations and should be used for conservation planning only in concert with targeted field survey. There are numerous bioclimatic variables used in species distribution models, but it has been observed in ecological science that a few variables account for about 95% of the variation in distribution. The results derived from the 'best models' must be interpreted with caution due to absence of high-resolution spatial climatic data. The inclusion of Climatic and topographic information, to a certain extent, minimize the potential source of error in prediction. However, with the improvement in technology both spatially and temporally, there could be better availability of data on vegetation, bioclimatic and topography for reliable prediction on the species distribution pattern. Furthermore, species occurrence records should be collected randomly across the region and the locations georefrenced precisely to avoid any error in the accuracy of the niche prediction. Taking these criteria into account, modelling algorithms can predict reliably species' macro distributions using the present environmental data.
Our model fitted with both climatic predictors and non-climatic variables, depicts, from a robust modelling approach, the potential range of the species besides identifying the most suitable areas for its occurrence. Moreover, our models were successful in predicting the previous distribution range of the species and were able to identify highly suitable areas which are coincident with grid cells where the species has not been recorded yet. Four new populations of *A. nivalis* were located based on model thresholds thus validating our spatial projections. Our spatial projections can support targeted surveys to collect additional records for the species, help identifying source and sink populations, and support the selection of populations to target urgent conservation measures. We were able to increase area of occupancy by *A. nivalis* from 210 to 380 Km^2, thus our modals also can aid in IUCN categorization of species. Species habitat assessments carried through field visits and by secondary surveys using Google Earth satellite imageries revealed that the predicted potential areas of the species under all suitability threshold levels i.e. low to very high suitability, include high altitude moist alpine habitats with varied ecological conditions. Thus while taking species reintroduction plans into consideration, appropriate habitats should be carefully selected. Our model can also inform in advance the range dynamics of the target species under climate change scenarios as reflected clear involvement of climatic variables in delimiting the distribution of *A.nivalis*. Climate change will definitely have an impact on distributions of endemic and critically endangered species like *A.nivalis*. Specifically for our test species the model highlighted a larger dependence on features of the precipitation regime and low temperatures, which

would support more accurate forecasts if climate change scenarios are applied. The model development in this study presents also some limitations since the species occurrence data are often affected by sampling intensity and records are often higher in easily accessible areas [61, 62]. It is also likely that various environmental variables that we used for our modelling are not the only factors to influence species distribution. Other factors such as dispersal and biotic interactions may also determine species distributions [63, 64, 65]. Overall, our results highlight the importance of combining multiple sets of predictors, with possible synergistic effects, when compared with models based on a very low amount of information when only few predictors were allowed in a single model due to too limited sample size. This stresses the importance of this novel ensemble modelling framework as a possible baseline for the establishment of efficient model-based management plans and optimized monitoring programs targeted at rare species. Whilst providing information on individual rare species, this approach is flexible enough to be combined with additional levels of information, and thus be applied in the improvement of broader conservation strategies at distinct spatial and temporal scales.

In conclusion our models promise to be of great help in identifying the true endemic range for *A. nivalis* and reconsider its current threat status in light of IUCN criteria. Our predictions of the most suitable habitats have important conservation implications for this rare endemic species. We believe that well designed extensive field surveys in the predicted regions will further improve the estimates of range size, which may likely reduce the current threat status for *A.nivalis*. Our results complement the growing body of literature that indicates the significance of SDMs to predict potential species distributions, identify new populations of rare and endemic species and to locate suitable habitats for species reintroductions.

Table 4: Contribution of various environmental variables to maxent model

Variable	Percent contribution
Mean Diurnal Range (Mean of monthly max temp - min temp)	30
Precipitation Seasonality (Coefficient of Variation)	32
Mean Temperature of Coldest Quarter	5.5
Temperature Annual Mean	7.2
Isothermality (BIO2/BIO7) (* 100)	15.2
Precipitation of Driest Month	.6
Elevation	2.1
Max Temperature of Warmest Month	0.7
Precipitation of Warmest Quarter	1.8
Precipitation of Wettest Quarter	0.5
slope	1.2

REFERENCES

1. Banks SC, Finlayson GR, Lawson SJ, Lindenmayer DB, Paetkau D, Ward SJ, Taylor AC (2005) The effects of habitat fragmentation due to forestry plantation establishment on the demography and genetic variation of a marsupial carnivore, *Antechinus agilis*. Biological Conservation122:581–597.
2. Chefaoui RM, Hortal J, LoboJM (2005). Potential distribution modelling, niche characterization and conservation status assessment using GIS tools: A case study of Iberian Copris species. Biological Conservation 122: 327–338.
3. Dar AR, Dar GH, Reshi Z (2008). Narrow endemic angiosperms of the Kashmir Himalaya: threat assessment and conservation. In Science for Better Tomorrow (eds.). Chisti MZ and Fayaz A. Universal Printers, Khanyar, Srinagar. pp. 31-39.
4. Dar GH (2008) Special Habitats and Threatened Plants of Kashmir Himalaya.Envis Bulletin11: 49-56.
5. Dar GH, Bhagat RC, Khan MA (2002). Biodiversity of the Kashmir Himalaya. Valley Book House, Srinagar, Kashmir.
6. Elith J, Graham CH, Anderson RP, Dudik M, Ferrier S, Guisan A, Hijmans RJ, Huettmann F, Leathwick JR, Lehmann A, Li J, Lohmann LG, Loiselle BA, Manion G, Moritz C, Nakamura M, Nakazawa Y, Overton JMM, Peterson AT, Phillips SJ, Richardson K, Scachetti-Pereira R, Schapire RE, Soberón J, Williams SE, Wisz MS, ZimmermannNE (2006). Novel methods improve prediction of species' distributions from occurrence data. Ecography 29: 129–151.
7. Elith J, Leathwick JR (2009). Species distribution models: ecological explanation and prediction across space and time. The Annual Review of Ecology, Evolution, and Systematics 40: 677–697.
8. Elith J, Phillips SJ, Hastie T, Dudík M, Chee YE, Yates CJ (2011). A statistical explanation of MaxEnt for ecologists. Diversityand Distributions 17: 43–57.
9. Engler R, Guisa A, Rechsteiner L(2004). An improved approach for predicting the distribution of rare and endangered species from occurrence and pseudo-absence data. Journal of Applied Ecology 41: 263-274.
10. Franklin J (2009). Mapping Species Distributions: Spatial inference and prediction.Cambridge University Press, 338.

11. Gaston KJ (1996). What is biodiversity? in K.J. Gaston (ed.), Biodiversity: a biology of numbers and difference. Blackwell Science, Oxford, pp. 1–9.
12. Gaubert P, Papes M, Peterson AT (2006). Natural history collections and the conservation of poorly known taxa: ecological niche modeling in central African rainforest genets (*Genetta* spp.).BiologicalConservation130: 106–117.
13. Bellard C, Bertelsmeierm C, Leadley P, Thuiller W, Courchamp F (2012). Impacts of climate change on the future of biodiversity. Ecology Letters 15: 365–377.
14. Blach-Overgaard A, Svenning JC, Dransfield J, Greve M, Balslev H (2010). Determinants of palm species distributions across Africa: The relative roles of climate, non-climatic environmental factors, and spatial constraints. Ecography 33: 380–391.
15. Boria RA, Olson LE, Goodman SM, Anderson RA (2014). Spatial filtering to reduce sampling bias can improve the performance of ecological niche models. Ecological Modeling 275: 73–77.
16. BrownJ L (2014). SDM toolbox: A python-based GIS toolkit for landscape genetic, biogeographic and species distribution model analyses. Methods inEcology and Evolution5: 694–700.
17. Buisson L, Thuiller W, Casajus N, Lek S, Grenouillet G (2010) Uncertainty in ensemble forecasting of species distribution. Global Change Biology 16: 1145–1157.
18. Cardoso P, Borges PAV, Triantis KA, Ferrández MA, Martín JL (2011). Adapting the IUCN Red List criteria for invertebrates. Biological Conservation 144: 2432– 2440.
19. Martinez-Meyer E, Peterson AT, Servin JL, Kiffo LF (2006). Ecological niche modelling and prioritizing areas for species Reintroductions Oryx:411-418.
20. McKinney (1999). High rates of extinction and threat in poorly studied taxa. Conservation Biology 13:1273–1281.
21. Morueta-Holme N, Flojgaard C, Christian J (2010). Climate Change Risks and Conservation Implications for a Threatened Small-Range Mammal Species. PloS One 5: e10360
22. Papes M, Gaubert P (2006) Modelling ecological niches from low numbers of occurrences: assessment of the conservation status of poorly known viverrids (Mammalia, Carnivora) across two continents. Diversity and Distributions13: 890–902.
23. Pearson RG, Dawson TP (2004) Bioclimate envelope models: what they detect and what they hide – response to Hampe. Global Ecology and Biogeography13: 471– 473.
24. Pearson RG, Raxworthy CJ, Nakamura M, Peterson AT (2007) Predicting species distribution from small occurrence records: a test case using cryptic geckos in Madagascar. Journal of Biogeography 34: 102–117.
25. Pena JCC, Kamino LHY, Mariano-Neto, MRE, Siqueira MF (2014) Assessing the conservation status of species with limited available data and disjunct distribution.Biological Conservation170: 130–136.
26. Global Biodiversity Information Facility, 2013. <http://www.gbif.org/>(accessed 03.2013)
27. Grenouillet G, Buisso L, Casajus N, Lek S (2011)Ensemble modelling of species distribution: the effects of geographical and environmental ranges.Ecography 349–17.
28. Grinnell J (1917). Field tests of theories concerning distributional control. The American Naturalist 51:115–12.
29. Gritti ES, Gaucherel C, Crespo-Perez MV, Chuine I (2013). How can model comparison help improving species distribution models? PloS One23:86-88.
30. Guisan A, Graham CG, Elith J, Huettman F (2007). The NCEAS Species Distributions Modelling Group Sensitivity of predictive species distribution models to change in grain size. Diversity and Distributions 13: 332–340.
31. Guisan A, Thuiller W (2005). Predicting species distribution: Offering more than simple habitat models. Ecology Letters 8: 993–1009.
32. Guisan A, Zimmermann NE (2000). Predictive habitat distribution models in ecology. Ecological Modelling135:147–186.
33. Hegel MT, Cushman SA, Evans J, Huettmann F (2010).Current State of the Art for Statistical Modelling of Species Distributions. F., S.A. Cushman and F. Huettmann (eds.), Spatial Complexity, Informatics, 273 and Wildlife Conservation.
34. Hijmans RJ, Cameron SE, Parra JL, Jones PG, Jarvis A (2005). Very high resolution interpolated climate surfaces for global land areas. International Journalof Climatology 25: 1965–1978.
35. Hijmans RJ (2012) Cross-validation of species distribution models: removing spatial sorting bias and calibration with a null model. Ecology 93: 679–688.
36. Huisman JM, Millar AJK (2013) Australian seaweed collections: use and misuse. Phycologia 52: 2–5.
37. Hussain M(2002) Exploration of legume diversity endemic to salt range in the Punjab. Annual technical report submitted to HEC. Islamabad, Pakistan.
38. IUCN (2005)Guidelines for using the IUCN Red List Categories and Criteria. Prepared by the Standards and Petitions Subcommittee of the IUCN SSC Red List Programme Committee. IUCN, Gland, Switzerland, and Cambridge, United Kingdom.
39. Jenness J (2003) Mahalanobis distances extension to Arc View GIS 3x. Available at http://www.jennessent. com/arcview/arcview_extensions. htmorhttp://arcscripts.esri.co/.
40. Jiménez-Alfaro B, Draper D, Nogués-Bravo D (2012) Modeling the potential area of occupancy at fine resolution may reduce uncertainty in species range estimates. Biological Conservation 147: 190-196.
41. Kearney M, Porter WP (2009) Mechanistic niche modelling: combining physiological and spatial data to predict species' ranges. Ecology Letters 12:334–350.

42. Kremen C, Cameron A, Moilanen A, Phillips SJ, Thomas CD, Beentje H (2008) . Aligning conservation priorities across taxa in Madagascar with high-resolution planning tools. Science 320: 222–226.
43. Solano E, Feria TP (2007)Ecological niche modeling and geographic distribution of the genus *Polianthes* L. (Agavaceae) in Mexico: Using niche modeling to improve assessments of risk status. Biodiversity and Conservation 16:1885–1900.
44. Tali BA, Ganie AH, Nawchoo IA, Wani AA, Reshi ZA (2014). Assessment of threat status of selected endemic medicinal plants using IUCN regional guidelines: A case study from Kashmir Himalaya.Journal for Nature Conservation 23:80-89.
45. Thorn JS, Nijman V, Smith D, Nekaris KAI (2009). Ecological niche modelling as a technique for assessing threats and setting conservation priorities for Asian slow lorises (Primates: Nycticebus). Diversity and Distributions 15:289-298.
46. Thuiller W, Richardson DM, Pyˇsek P, Midgley GF, Hughes GO, Rouget M (2005). Niche based modelling as a tool for predicting the risk of alien plant invasions at a global scale. Global Change Biology 11: 2234–2250.
47. Veloz SD (2009). Spatially autocorrelated sampling falsely inflates measures of accuracy for presence-only niche models. Journalof Biogeography 36: 2290–2299.
48. Watson JEM (2014). Human responses to climate change will seriously impact biodiversity conservation: it's time we start planning for them. Conservation Letters, 7, 1–2.
49. Watson JEM, Iwamura T, Butt N (2013) Mapping vulnerability and conservation adaptation strategies under climate change.Nature Climate Change 3: 989–994.
50. Wisz MS, Hijman RJ, Peterson AT, Graham CH (2008) Effects of sample size on the performance of species distribution models. Diversity and Distributions 14: 763–773.
51. Kumar S, Stohlgren TJ (2009) Maxent modeling for predicting suitable habitat for threatened and endangered tree Canacomyrica monticola in New Caledonia .Journal of Ecology and Natural Environment 1: 094-098.
52. Lomba L, Randin C, Vicente J, Moreira F, Honrado J, Guisan A (2010) Overcoming the rare species modelling paradox: A novel hierarchical framework applied to an Iberian endemic plant. Biological Conservation 143: 2647–265.
53. Margules, Austin(1994) Biological models for monitoring species decline: The construction and use of data basesPhilosophical Transactions of the Royal Society B: Biological Sciences 344: 69–75.
54. Peterson AT (2006).Uses and requirements of ecological niche models and related distributional models. Biodiversity Informatics 3: 59–72.
55. Phillips SJ, Elith J (2010). POC plots: calibrating species distribution models with presence-only data. Ecology91: 2476–2484.
56. Phillips SJ, Anderson RP, Schapire RE (2006). Maximum entropy modeling of species geographic distributions. Ecological Modelling 190: 231–259.
57. Phillips SJ, Dudik M (2008). Modelling of species distribution with Maxent: New extensions and a comprehensive evaluation. Ecography 31:161−175.
58. Phillips SJ, Dudik M, Schapire RE (2004). A maximum entropy approach to species distribution modelling. Appearing in proceedings of the 21st international conference on machine learning, Banff, Canada.
59. Rana CS, RawatDS (2012). New floral distribution records of *Aquilegia nivalis* (Baker) Falc.ex B.D.Jacks distribute and *Doronicum falconeri* C.B. Clarke ex Hook. f. from the Valley of Flowers National Park, Uttarakhand, IndianJournal of Threatened Taxa 3: 2100–2103.
60. Rogers WA, Panwar PS (1988). Planning a Wildlife Protected Area Network in India. Vols. 1-2. Wildlife Institute of India, Dehra Dun (Mimeographed).
61. Rondinini C, Stuart S, Boitani L (2005).Habitat suitability models reveal shortfall in conservation planning for African vertebrates. Conservation Biology 19: 1488–1497.
62. Root TL, Price JT, Hall KR, Schneider SH, Rosenzweig C, Pounds JA(2003). Fingerprints of global warming on wild animals and plants.Nature 421: 57-60.
63. Roura-Pascual N, Brotons L, Peterson A, Thuiller W (2009). Consensual predictions of potential distributional areas for invasive species: a case study of Argentine ants in the Iberian Peninsula. Biological Invasions 11: 1017-1031.
64. Sanchez-Cordero V, Cirelli V, Munguía M, Sarkar S (2005). Place prioritization for biodiversity representation using ecological niche modeling. Biodiversity Informatics2: 211–223.
65. Sergio C, Figueira R, Draper D, Menezes R, Sousa AJ (2007) Modelling bryophyte distribution based on ecological information for extent of occurrence assessment. Biological Conservation 135: 341-351.

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