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# Partial altitudinal movement of Himalayan Bulbul *Pycnonotus leucogenys* in Himalayan Siwalik range

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**Abstract**
Himalayan Bulbul *Pycnonotus leucogenys* is widely spread in the Himalayan Siwalik range but information is available on its migratory behavioural patterns. Hence, a two-year study was undertaken to investigate its distribution range of the species in the summer and winter seasons in Punjab and Himachal Pradesh. A total of twenty variables including 19 bioclimatic variables and elevation were selected for the development of Species distribution Modelling (SDM). Occurrence records of *P. leucogenys* in summer and winter were processed at the Maximum entropy model (MaxEnt) using the ENMeval data package. The results suggested a downward movement from the upper Siwalik Himalayan ranges to the lower Siwalik in winter, and with return migration movement in summer. However, a large fraction of the distribution range was found overlapping in both the models, which suggests partial altitudinal migration of *P. leucogenys.* The data recorded on the ground subordinate the finding of the model. A wide range of tolerance for bioclimatic variables was observed in *P. leucogenys,* however temperature-related factors played a vital role in the variation in the species distribution range in the annual cycle of partial migration. The finding of this study would be a valuable reference for future studies on ecological and behavioral aspects of partial-migration of bird species in the Himalaya.

**Keywords:** *Pycnonotus leucogenys,* Himalayas, Siwaliks, partial altitudinal migration, maximum entropy model (MaxEnt), species distribution modelling (SDM)

## Introduction

Birds of hilly regions show altitudinal migration as they can migrate much shorter distances than the birds of plains to reach regions with favourable climatic conditions (Boyle and Conway 2007) [6]. Altitudinal migration is the periodic movement of birds for wintering at different elevations, performed by 1238 species (about 10% of the total avian species) (Barcante *et al.* 2017) [3]. Although a plethora of information is available on bird migration, however information about on the distribution patterns of bird species undertaking altitudinal migration is still lacking with very few studies done in the Himalayan region (Renner and Rappole 2011, Kumar S and Kler T 2021, Singh G and Kumar S 2022) [42, 23, 15]. A substantial decline has been observed in generalist, forest, grassland and wetland avian species in recent times in India (SoIB 2020) [45], which makes it more crucial to have information seasonal distribution range shifts.

Long-term bio-monitoring studies are an acknowledged way of detecting variations in ecosystems due to climate change (Doran *et al.* 2003) [11], but however, monitoring all-inclusive system at regular intervals is very expensive and difficult even for a small area (Lawton *et al.* 1998) [24]. Recent advances in technology enable us to understand unknown migration distribution patterns of migrant species across their annual cycle (Norbu *et al.* 2013) [29]. Species distribution modeling (SDM) utilizes information on the occurrence records by using long-term average climate variables to reflect the environmental requirements and geographical distribution with suitable climatic conditions that disclose the ecological niche of an organism (Pearson and Dawson 2003) [34]. MaxEnt is one of the most advanced machine learning software for SDM than other predictive distribution methods (Merow *et al.* 2013) [25] such as GAM (Generalised Additive Models) and GLM (Generalised Linear Models) (Elith *et al.* 2006) [12]. Distribution modelling of a species in different seasons provides reliable sources of information for making conservation strategies.

Himalayan Bulbul *Pycnonotus leucogenys* is a fruitivorous that has wide-spread in Siwalik range (Grimmett *et al*. 2014) [18]. Climatic conditions of the Himalayan range are changing (Chopra 2013), and a recent report on the decline in the population of generalist species (SoIB 2020) [45] creates an essential need to investigate the distribution range of *P. leucogenys.* The present study was undertaken to investigate the distribution range shifts of *P. leucogenys* in the annual pattern of summer and winter seasons using (SDM) MaxEnt.

## 2. Materials and Methods
### 2.1 Study area and availability of data
Punjab and Himachal Pradesh were selected as the study area which includes the northern distribution range of *P. leucogenys.* Punjab has plain areas that are know for its intensive agricultural practices. It also has some hilly region along the border with Himachal Pradesh. The state of Himachal Pradesh is dominated by Himalayan-mountain ranges (1200-6000 m) and the siwalik hills (600-1200 m) (Fig. 1) (Chand 2013; Gosal 2004) [8, 14].

A total of 180 observations were recorded during surveys conducted in Punjab and Himachal Pradesh during the period of April 2018 to March 2020. Point count method is generally found suitable in both in plain and hilly terrains (Ralph et aj 1995) [41] therefore all possible areas assessable via roads were surveyed using point count method (Verner 1985) [47] comprising of twenty random points each (at least 500 meters) were taken in Punjab and border areas of Himachal Pradesh. Mobile phone- based Q-field application (Quantum geographic information system) was used for georeferencing (± 2 mt). As the data survey area and number of observations were low therefore presence data (352 records) was also obtained from the global biodiversity information facility (gbif.org) and grouped with the field recorded data.

To develop models for summer (Model-1) and winter (Model-2), observation records were divided into two groups, where April to July was taken as summer (n=215) season, and November to March as winter season (n=316).

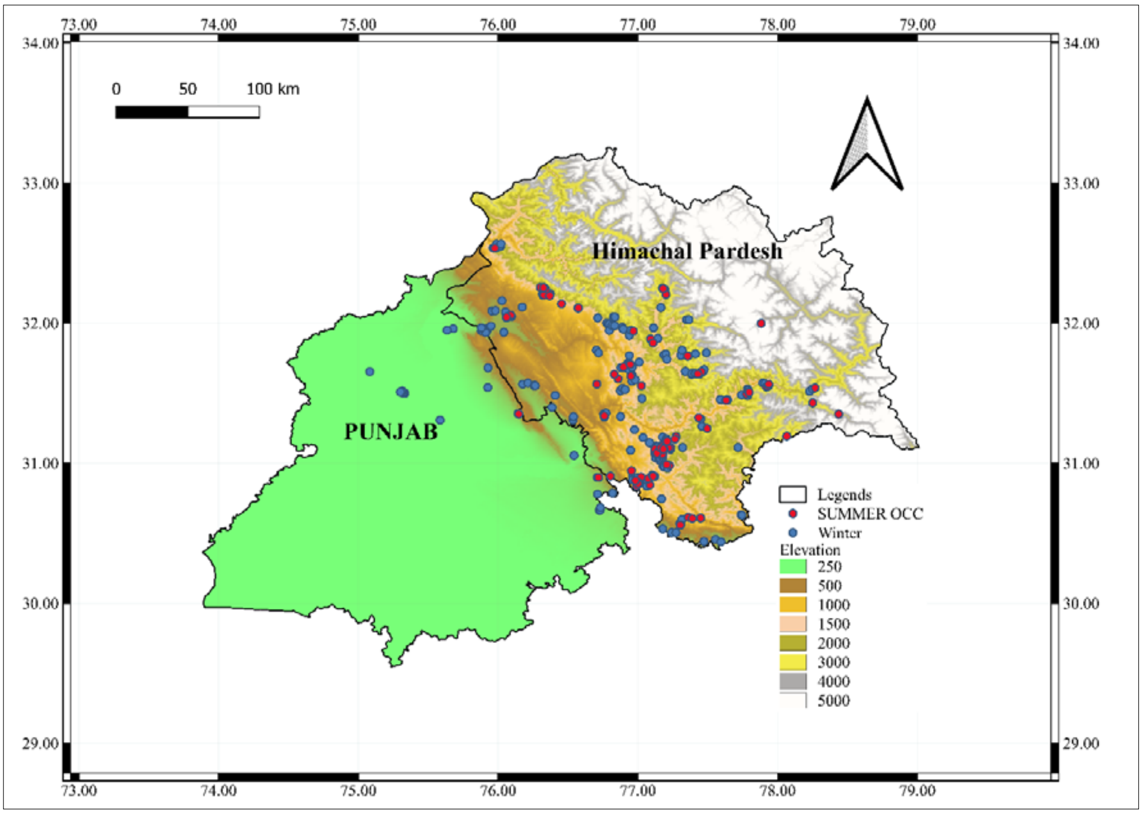


**Fig 1:** Study area with sampling points used for the distribution modelling.

### Climate Data Extraction and Analysis
Twenty environmental variables including nineteen bioclimatic variables and one elevation variable were collected from World Clim 2.1 at resolution of 2.5 minute arc (Fick *et al.* 2017) [16]. Climate layers were imported into the QGIS version 3.12 and clipped for the study area. The clipped layers were converted to ASCII format as required for MaxEnt software (Phillips *et al.* 2009) [38]. Presence-only data with georeferencing was incorporated with clipped layers to extract numeric values for all variables at each occurrence point using point sampling tool in QGIS. The maximum, minimum and standard deviation values of each variable are given in Table 1. Using large number of variables may lead to multicollinearity which may results in biased model predictions (Dormann *et al.* 2013) [11], therefore, all selected variables were tested for variance inflation factor (VIF) analysis to minimize the multicollinearity effect using R package ‘usdm’ with (Naimi *et al.* 2014) in R programming language version 1.2.5033 (2019). Variables having VIF values < 3 were included in the models (Zuur *et al.* 2010). Alt, Bio1, Bio2, Bio3, Bio4, Bio5, Bio12, Bio14, Bio15 were selected for summer model and Alt, Bio1, Bio3, Bio4, Bio7, Bio11, Bio15, Bio18, Bio19 were selected for model 2 based on prior knowledge of the species natural history and distribution range and VIF analysis (Zhang *et al.* 2019) [49].

**Table 1:** Summary statistics of bioclimatic variables extracted for sampling the study areas based on georefenced data.

| Label | Variables | Model 1- Summer (n=215) | | | | Model 2- Winter (n=316) | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | Mean ± SE | SD | Min | Max | Mean ±SE | SD | Min | Max |
| Alt | Elevation from sea level (m) | 1724.9 ± 53.40 | 783.13 | 204.00 | 5448.00 | 1371.1 ± 36.83 | 654.85 | 227 | 3042.00 |
| Bio1 | Annual Mean Temperature ($^0$C) | 15.73 ± 0.32 | 4.78 | -7.43 | 24.09 | 18.09 ± 0.20 | 3.59 | 7.05 | 23.82 |
| Bio2 | Mean Diurnal Range ($^0$C) | 9.86 ± 0.058 | 0.85 | 8.49 | 13.94 | 10.12 ± 0.06 | 1.12 | 8.21 | 13.52 |
| Bio3 | Isothermality (BIO2/BIO7) | 36.28 ± 0.09 | 1.36 | 30.09 | 39.76 | 36.29 ± 0.07 | 1.31 | 32.95 | 40.02 |
| Bio4 | Temperature Seasonality ($^0$C) | 603.36 ±3.22 | 47.29 | 548.32 | 850.19 | 607.81 ± 2.77 | 49.30 | 549.60 | 749.24 |
| Bio5 | Max Temperature of Warmest Month ($^0$C) | 28.52 ± 0.35 | 5.17 | 8.71 | 40.70 | 31.93 ± 0.26 | 4.76 | 19.55 | 39.92 |
| Bio6 | Min Temperature of Coldest Month ($^0$C) | 1.35 ± 0.12 | 4.7 | -24.38 | 6.84 | 3.53 ± 0.14 | 2.64 | -6.78 | 7.46 |
| Bio7 | Temperature Annual Range (BIO5-BIO6) ($^0$C) | 27.16 ± 0.27 | 1.79 | 24.04 | 35.13 | 27.86 ± 0.14 | 2.54 | 24.42 | 34.60 |
| Bio8 | Mean Temperature of Wettest quarter ($^0$C) | 20.75 ± 0.38 | 4.06 | 2.73 | 30.37 | 22.86 ± 0.211 | 3.76 | 8.83 | 29.61 |
| Bio9 | Mean Temperature of Driest Quarter ($^0$C) | 13.12 ± 0.31 | 5.71 | -10.80 | 24.11 | 15.01 ± 0.23 | 4.15 | 4.90 | 26.34 |
| Bio10 | Mean Temperature of Warmest Quarter($^0$C) | 22.24 ± 0.31 | 4.61 | 2.81 | 32.22 | 24.66 ± 0.23 | 4.12 | 14.61 | 31.66 |
| Bio11 | Mean Temperature of Coldest Quarter($^0$C) | 7.66 ± 0.33 | 4.98 | -17.86 | 14.00 | 9.91 ± 0.17 | 3.16 | -0.97 | 14.39 |
| Bio12 | Annual Precipitation (mm) | 1454.8 ± 26.71 | 391.69 | 444.00 | 2532.00 | 1493.7 ± 22.13 | 393.40 | 691.00 | 2532.00 |
| Bio13 | Precipitation of Wettest Month (mm) | 376.24 ± 11.19 | 164.20 | 113.00 | 780.00 | 403.76 ± 7.86 | 139.79 | 127.00 | 780.00 |
| Bio14 | Precipitation of Driest Month (mm) | 17.04 ± 0.28 | 4.24 | 3.00 | 24.00 | 16.48 ± 0.28 | 5.11 | 5.00 | 25.00 |
| Bio15 | Precipitation Seasonality (Fraction) | 91.38 ± 2.11 | 31.06 | 37.09 | 128.32 | 99.67 ± 1.46 | 25.99 | 37.16 | 135.49 |
| Bio16 | Precipitation of Wettest Quarter (mm) | 877.50 ± 25.72 | 377.24 | 264.00 | 1810.00 | 935.19 ± 18.32 | 325.71 | 328.00 | 1810.00 |
| Bio17 | Precipitation of Driest Quarter (mm) | 106.33 ± 1.36 | 20.05 | 25.00 | 154.00 | 100.59 ± 1.35 | 24.07 | 37.00 | 154.00 |
| Bio18 | Precipitation of Warmest Quarter (mm) | 564.76 ± 11.38 | 166.87 | 167.00 | 953.00 | 581.36 ± 8.80 | 156.57 | 260.00 | 953.00 |
| Bio19 | Precipitation of Coldest Quarter (mm) | 268.09 ± 3.72 | 54.63 | 38.00 | 377.00 | 199.81 ± 3.40 | 60.56 | 62.00 | 377.00 |

**2.2 Model Building**

Maximum entropy approach (MaxEnt version 3.4.1) general-purpose machine learning method (Phillips *et al.* 2017; Phillips and Dudik 2008; Phillips *et al.* 2006) [36, 37] was used for distribution modeling. Maximum number of background points (n=5000) were selected after calculating total number of points available for building the model. We used R package 'ENMeval' (Muscarella *et al.* 2014) [27] to evaluate the models using AIC (Akaike information criterion). AIC is a relative measures the goodness of statistical model fits where smaller the AIC value better the model fit to data.

Training and testing data was assigned in a ratio of 80:20. Training data was used to formulate the model parameters, whereas testing data points were used to assess its prediction accuracy. Duplicate presence records were removed using basic settings along with random seed feature. Ten replicates were run for both models and logistic outputs were selected using Baggenstoss 2018 [2]; Presse *et al.* 2013 [39]; Phillips and Dudik 2008.

Jackknife approach was adopted to determine the importance of the variables used in the model (Hoenes and Bender 2010; Yost *et al.* 2009) [20, 48]. Receiver operating characteristic (ROC) analyses was used to evaluate the reliability and predictive performance of the models (Pearce and Ferrier 2000) [33]. Area under cover (AUC) in ROC plot ranges from 0.5 (no discrimination ability) to 1.0 (perfect discrimination) (Fielding and Bell 1997) [17]. More robust predictive performance for ROC was calculated using average AUC of ten cross validations (mean± standard deviation).

The distribution range was calculated as the mean longitude and latitude of pixel cores where the species was predicted to be present. We assumed that *P. leucogenys* would be able to move through the landscape without physiological or environmental barriers.

**3. Results**

Omission and predicted graphs were prepared by MaxEnt to investigate the goodness of model by providing information regarding the independent nature of test and training data (Merow *et al.* 2013) [25]. The calculated omission rate (Fig. 2) was found closer to the predicted omission rate which suggested high suitability of data in both the models (Phillips and Dudik, 2009) [38]. The orange and blue shading surrounding the lines on the graph denoted variability. Omission on test samples (orange shading) was a good match to the predicted (black) omission rate and it was anticipated that the test and training data were independent (Merow *et al.* 2013) [25].

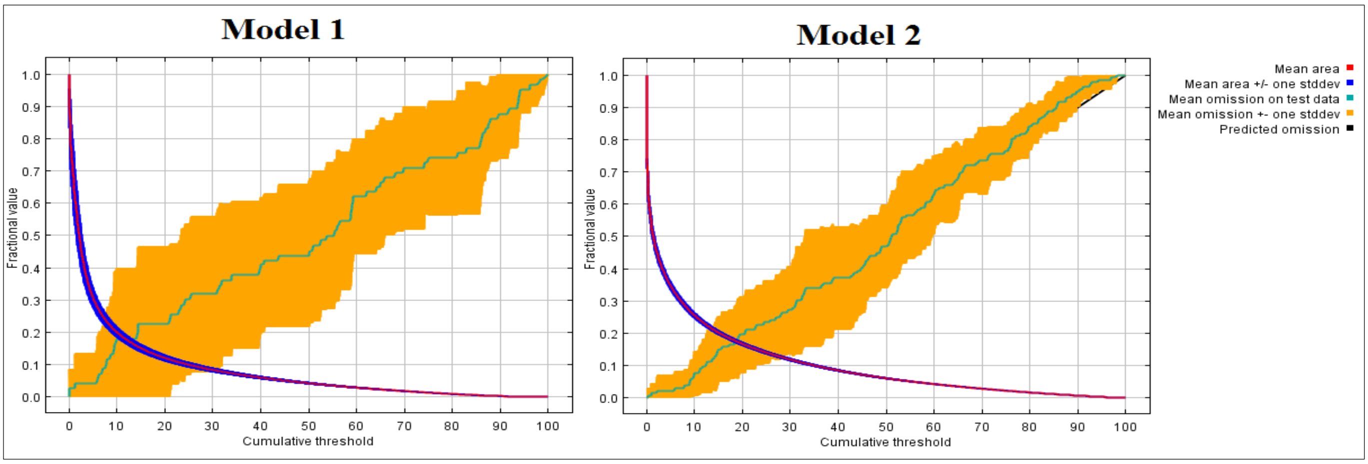


**Fig 2:** Average omission and predicted area for *P. leucogenys*

During this study, the ROC curve was averaged for ten cross validations (mean± SD) over the replicate runs for more robust predictive performance. The average test AUC for the replicate runs for model 1 and 2 was 0.902 and 0.905 with standard deviation 0.067 and 0.033 respectively (Fig. 3). AUC in ROC calculate the quality of a ranking and avoid the difficulties associated with threshold effects (Fielding and Bell 1997) [17]. AUC is probability where presence site are chosen and ranked randomly on chosen absence site (Phillips *et al.* 2017) [36]. Random ranking system provides average AUC of 0.5 whereas a perfect ranking accomplishes the AUC of 1.0 (Elith *et al.* 2002) [13]. Higher the AUC of ROC plot better is the model (Pearce and Ferrier 2000) [33]. The values of ROC were above 0.9 in both the models in the present study which suggests the well performance of the model with high predictive accuracy, thus information in models should be considered potentially very useful.

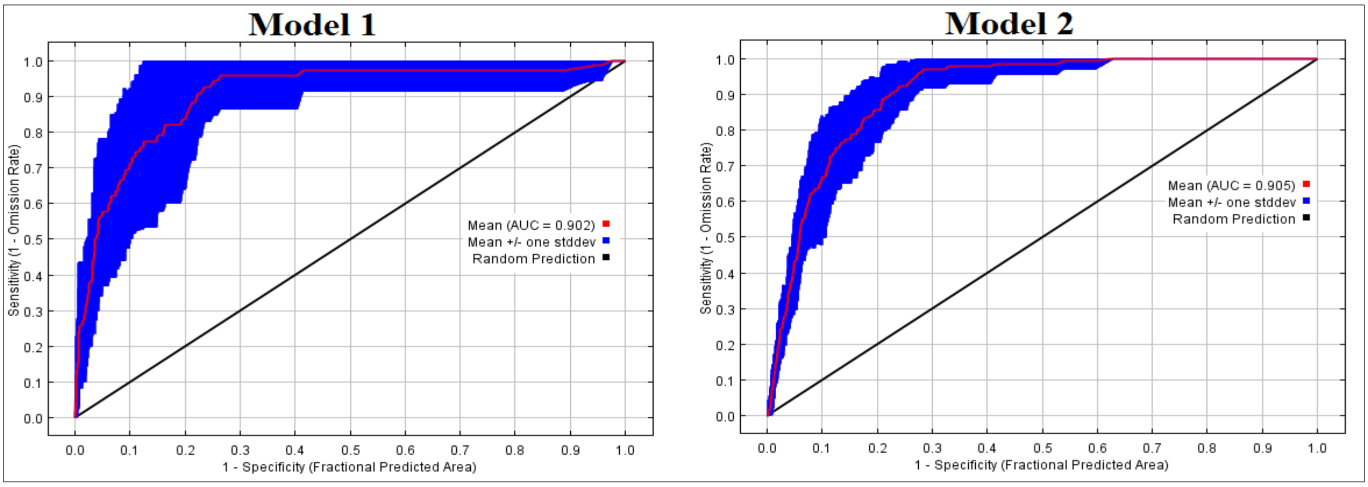


**Fig 3:** Average sensitivity vs 1-specificity for *P. leucogenys*

Jackknife analysis of both model exposed that Bio 4 and alt (elevation) contributed most in developing both model when used in isolation (Fig. 4). Minimum contribution to both models was contributed by Bio 15 in both the models. Bio 4 is modus of temperature seasonality which reveals that temperature plays an important role in the distribution of *P. leucogenys* in both the seasons.

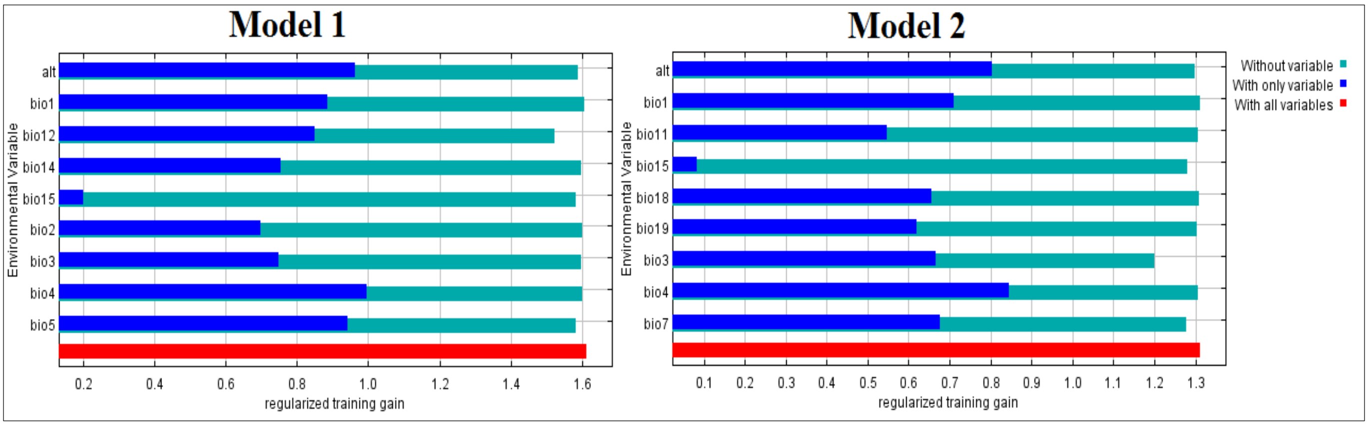


**Fig 4:** Jackknife of regularized training gain for *P. leucogenys*

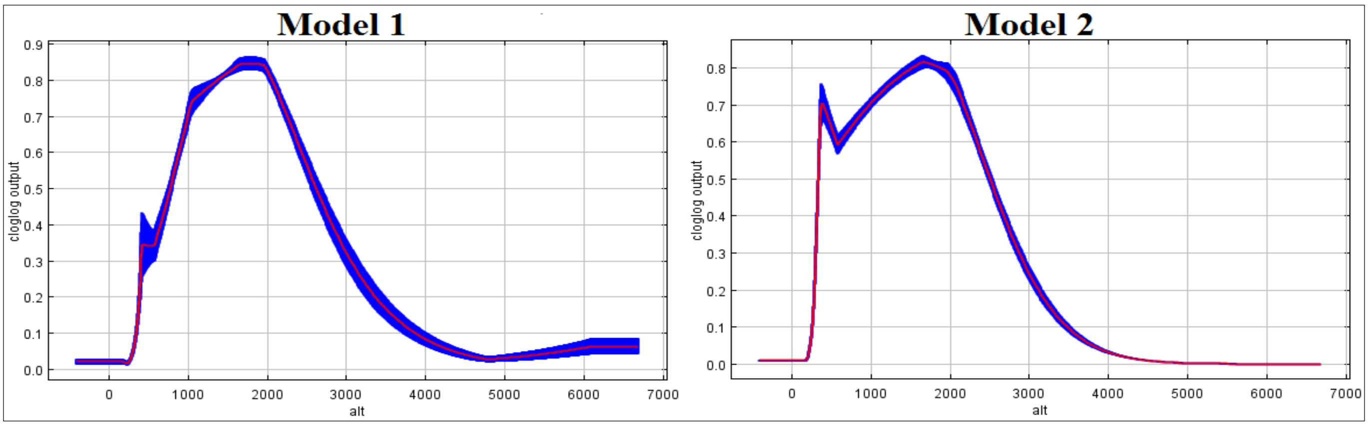


**Fig 5:** Response to alt (Elevation) for *P. leucogenys*

The results show that the optimal/suitable habitat has expanded downward due to similar and favorable habitat conditions at lower altitudes in winters. This phenomenon may have resulted in only partial migration of *P. leucogenys* towards Siwalik Hills-since the conditions in the upper elevation areas are still suitable. Suitable habitat range shift with bearable conditions at existing habitat range offers conditions for partial migration. Variation in migratory behavior within a population is less studied has been subject to little studies despite its potential to provide information on the evolutionary origin of migration (Chapman *et al.* 2011). Environmental and genetic factors also play a significant role in partial migration (Chapman *et al*. 2011; Pulido 2011) [40]. During the field visits, *P. leucogenys* was observed in both the seasons at different heights with variation in abundance in summer and winter. Abundance was maximum in upper mountainous regions ranging 500 to 3000 m in summer, whereas downwards partial local altitudinal migration was observed towards lower hills, valleys, and plains of Siwalik, ranging 180-2500m in winter. Similar and well explained results were observed in the form of map using SDM (Maxent).

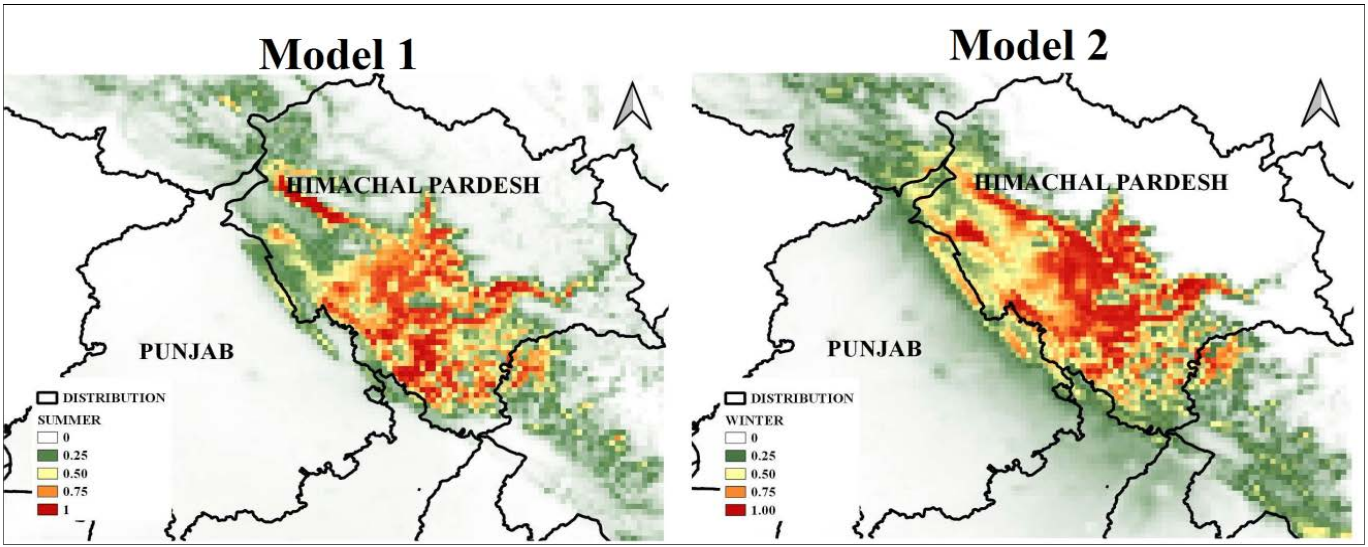


**Fig 6:** Predicted distribution maps of *P. leucogenys* in summer and winter based on maxent models.

## 4. Discussion

The temperature in winters is an important factor that affects migration patterns of birds (Schaefer *et al.* 2008) [43] but food shortage may be linked to the association between has been altitudinal migration (Barcante *et al.* 2017) [3]. The second contributing factor was altitude (Elevation) which showed wide range of distribution for *P. leucogenys* ranging 158 to 6000 m for annual range however maximum optimal distribution was between 500 to 3000 m in summer whereas it decreased to 180 to 2500 m in winter (Fig. 5).

During the study, *P. leucogenys* as least observed in Punjab whereas it remained similar in Himachal Pradesh during summer. In winter, the encounter rate increased in border areas of Punjab. The models showed increased in suitable distribution range during the winter in study area as compared to summer distribution (Fig. 6). The model predicts that the central area of Himachal Pradesh is consistent with distribution in both the seasons. It can be seen from the models that the distribution remained same in Himachal Pradesh however the suitable distribution range has increased towards Punjab in winter which has comparatively lower elevation. Thus some observations were recorded up to the central regions of Punjab in winter while at the same time the distribution range also dispersed to larger area in Himachal Pradesh. In winters, the temperature in the higher mountain ranges decreases to freezing, and the area become difficult to survive (Bassler *et al.* 2010) [4]. However a significant area of suitable distribution range remained similar in both the models suggests that the total population movement may not have occurred. If survival of migrant populations is higher and survival of winter residents is density dependent, then it leads to the evolution of migratory trends within species (Norris and Taylor 2006) [30]. Highland birds can migrate much shorter distances than lowland birds to reach regions that differ in temporal patterns of food resource availability (Boyle and Conway, 2007) [6]. The above discussion signifies that the habitat suitability decreases on higher elevations for *P. leucogenys* in winter lead to the movement of population towards lower areas of Punjab and Himachal Pradesh.

Other than bioclimatic factors, partial migration can get triggered by variables like food, watershed, predation risk and competition for resources (Barcante *et al.* 2017) [3]. Often various factors act synergistically to create complex patterns of movement within populations (Chapman *et al.* 2011). Various strategies of partial migration have been observed by both temperate and tropical birds (Boyle *et al.* 2011) to avoid competition due to changes in conditions at a location for some time. Extreme winter conditions and intraspecific competition for limited food resources promotes migration and avoids costly aggressive struggles in some bird species (Nilsson *et al.* 2008) [28]. The body size and temperature are interrelated and play an important role in migration (Alonso *et al*. 2009) [1].

The selection of feeding behavior in migratory birds may link to trade between energy, diet, and digestion (Molokwu *et al.* 2011) [26]. Most studies propose that environmental factors play a vital role in partial migrations (Ogonowski and Conway, 2009; Olsson *et al.* 2006; Skov *et al.* 2010) [31, 32, 44]. Migratory behavior of birds is significantly linked with temperature variations (Hsiung *et al.* 2018) [21] and the same has been observed in this study. The model provided that the temperature related variables contribute a significant role in the change in distribution range over two seasons (Fig. 4) but factors like food and competition for resources may also had played some role in partial distribution. Bioclimatic variables alone may not provide all information about the causes of migrations and suitable habitat conditions for an organism however the information derived on the basis of SDM cannot be neglected. New techniques like General-purpose machine learning programs (MaxEnt, ENMeval etc.) are economical and less time-consuming methods and can provide significant information about the distribution range of a species.

Comparative studies on migrant and resident populations of the same species may shed some light on the behavioral, physiological, and genetic adaptations to migration and residency. It is also important to understand the impacts of anthropogenic disturbance and environmental variation on the dynamics of partial migration to provide information on ecological and evolutionary causes of partial altitudinal migration.

This study reveals that *P. leucogenys* has a wide range of tolerance for various environmental factors but also shows partial migration in winters. This study provides important insights between environmental change and partial migration however more studies will be required to shed light on other ecological factors contributing towards partial migration. The study concludes that *P. leucogenys* shows partial altitudinal migration towards lower Shiwalik hills in winter. The data recorded on ground and SDM both suggest increase in abundance in lower Shiwalik ranges in winter and the population moves upward in summer season. A large segment of distribution range was overlapping in both the models which suggest partial altitudinal migration of *P. leucogenys*. Temperature related variables contributed vital role in the variation in distribution range in annual cycle of partial migration. We suggests further comparative studies on migrant and resident populations of the same species which may shed more light on behavioral, physiological, and genetic dynamics of species to provide information on ecological and evolutionary causes of partial altitudinal migration.

**5. Acknowledgments**

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