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Research Article

Long-term future prediction of potential suitable zones for *Calamus flagellum* Griff. (Arecaceae) in Assam, using Maxent and Artificial Neural Networks

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ABSTRACT

The present study utilised the Maxent model to predict the distribution of the rattan species *Calamus flagellum* in Assam to prepare potential distribution and future predictions of suitable zones using bioclimatic variables and CMIP6 environmental models within a GIS framework, focusing on the BCC-CSM2-MR-ssp126 model for the period 2021-2040. Along with the predicted variables, a land use and land cover prediction map of 2040 is also prepared using MOLUSCE plugins (ANN-Multi layer perception) from QGIS 2.8.2 version to anticipate and establish probable land use changes in the year 2040 as well as to detect the transition of land use changes in the study area for the three periods 2014, 2017 and 2020. The model demonstrates high significance with AUC validation statistics of 0.96 for current and 0.95 for future predictions. These results can be utilized to conserve the species under both present and future climatic scenarios.

Key words: Land Use prediction, models, rattan, Assam, ANN

INTRODUCTION

Rattans are important non timber forest product (Negi, 1996) belongs to the subfamily Calamoideae of the monocot family Arecaceae and is distributed in tropical and subtropical region of the world (Renuka *et al*., 2010). The Indian species of rattans belong to the genera *Calamus* L., *Daemonorops* Blume, *Korthalsia* Blume and *Plectocomia* Mart. confined primarily to North and North-eastern India, Andaman and Nicobar Islands, and Peninsular India (Renuka *et al*., 2010). The species under *Daemonorops* reported from India were merged under *Calamus melanochaetes* (Blume) Miquel by Henderson (2020).

The distribution range of *Calamus flagellum* Griff. (Figure 1 A-B) was recorded from different countries like Bangladesh, China, India, Myanmar, Laos, Thailand and Vietnam (Henderson, 2020). In India, the species was reported from the states of West Bengal, Assam, Meghalaya, Arunachal Pradesh and Manipur and holds significant value as NTFP as the stem is used in the manufacture of furniture (Renuka & Sreekumar, 2012). In Assam, the tender shoots and fruits of this species were also consumed (Patiri & Borah, 2007; Mehmud & Roy, 2021). The ethno-medicinal uses (Das *et al*., 2013) and nutrient content of the edible shoot (Manohora, 2013) were also reported. Appearance of adventitious branching from the injured stem of the species has also been observed in this species (Mehmud & Roy, 2020).

Considering the utilitarian value of the species, it is important to know the prominence of the species in the wild and also to predict the status in near future. The present study aims to understand the distant future of *C. flagellum* in the context of changing climate using the CMIP6 environmental variable BCC-CSM2-MR-ssp126 in combination with the Artificial Neural Networks (ANN) as a machine-learning method to facilitate the predictive analysis. By employing ANN with the selected environmental variable, we predict the long-term future of *C. flagellum* in the light of probable climate change. This analysis will help to estimate the availability of the species, formulate potential cultivation and conservation strategy. It is expected that the present study would be an important step to uphold the floristic diversity of Assam and also its values. Since rattans are important non-timber forest products and their numbers are gradually declining, it is crucial to predict their future trends. Maxent is a widely accepted model for the prediction and distribution of species on presence-only data. Combining ANN methods with Maxent enhances the predictability of the target species, especially when considering future land use and land cover.

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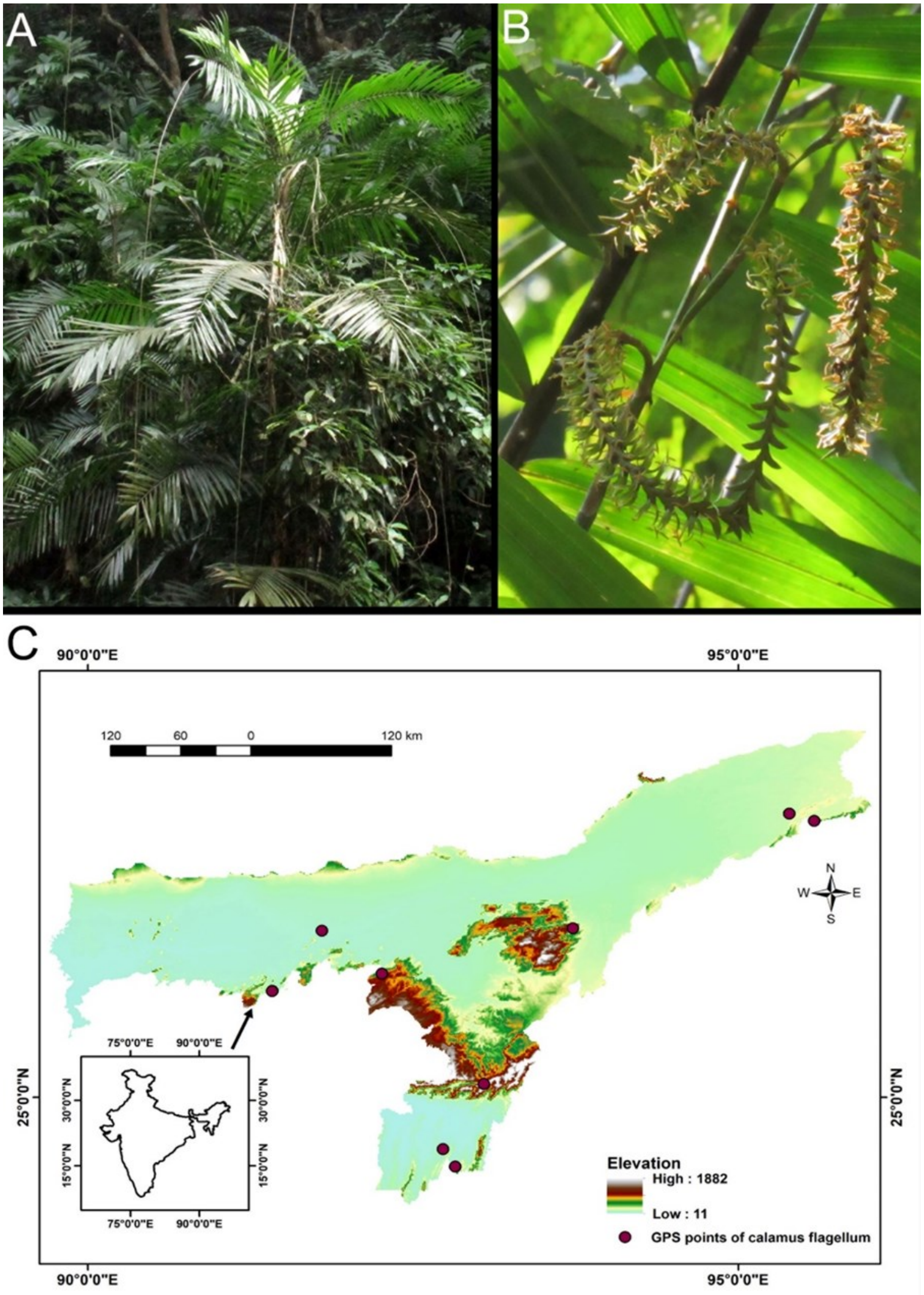

Figure 1. A. Habit of *Calamus flagellum*, **B.** Staminate inflorescence of *C. flagellum*, **C.** GPS locations of the species in Assam *C. flagellum*

MATERIALS AND METHODS

Study Area: Assam (Figure 1 C), one of the northeastern states of India nestling between the eastern Himalayan foothills and the Patkai & Barail ranges of hills. Though largely plain, the state is characterized by distinct habitats, landscapes, broad valleys and hills. The mountainous Barail range is positioned in such a way that both sides of this range are having two valleys i.e. the Brahmaputra and Barak Valleys. Situated between 24°2'-27°6' N latitude and 89°8' - 96° E longitude, the political boundary of Assam extends to an area of 78,438 sq km of which total forest area is about 28,312 sq km that is about 35.09% of the total geographical area of the state (Anonymous, 2021). The rapid increase in human population in the area over the past century has resulted in the loss of habitat for many species, and over time, many of these species have become fragmented and confined.

Distribution data: Extensive field surveys were conducted in Assam for documentation of palm species during the period from 2017 to 2022. Samples of *C. flagellum* collected and documented from different districts of Assam, locations were recorded by using GPS device (Garmin eTrex 10 model). The specimens were also processed for herbarium preparation by following Dransfield (1986) and the vouchers were deposited in the herbarium of Department of Botany, Cotton University, Assam. Identification was confirmed based on literature (Henderson, 2009; Renuka & Sreekumar, 2012; Henderson, 2020) and by visiting different herbaria houses such as Botanical Survey of India (ASSAM, ARUN and CAL), Gauhati University herbarium (GUBH), digital herbaria like NYBG, MICH, K as well as other virtual herbaria accessed through GBIF portal (www.gbif.org).

Land use and land cover: The study applies a categorization system, based on the leaf area index (Table 1). Supervised classifications of MODIS Terra and Aqua reflectance (Friedl & Sulla-Menashe, 2019) data are used to create the MCD12Q1 Version 6 data package. Using the study area mask in ArcGIS 10.6, the product has been trimmed. The LULC maps are used to create for future prediction of the selected species, as the forecast of LULC is critical in developing strategies to balance conservation and development. The LULC map for the year 2014, 2017 and 2020 is used. After reclassification of the selected LULC rasters, it is loaded in Qgis plateform for further analysis. The MOLUSCE plugin is used along with other spatial variable rasters like elevation (Figure 3 A), slope (Figure 3 B), road networks (Figure 3 C) and river networks (Figure 3 D) are used. These spatial data are downloaded from www.diva-gis.org.

This plugin allows to get a better understanding of the land use changes that have occurred between 2014, 2017 and 2020 by generating a transition matrix and producing an area change map. Moreover, it can forecast LULC transitions for 2040 by utilizing ANN (Multi Layer Perception) and predicting the future of land use based on present LULC patterns and dynamics. Moreover, Pearson's correlation, Crammer's coefficient and Joint information uncertainty are used to calculate the area's category and LULC changes between 2010 and 2020. Ultimately, the algorithm produces a transition matrix displaying the proportion of pixels shifting from one land use cover type to another.

Apart from artificial neural networks (ANN), there are other ways to create future predictions of land use in MOLUSCE plugin. The reason behind selecting ANN for prediction is that this computational intelligence aspect is good for dealing with huge amount of uncertain and complex raster data. (Kamaraj & Rangarajan, 2022)

In order to verify the accuracy of a classified image, an interpreted LULC map of 2020 was compared with a reference map of LULC 2020 using a measure known as a kappa coefficient. This kappa coefficient is a way to measure the difference between the rows and columns of the error matrix.

$$\boldsymbol{Khat} = \frac{(\mathrm{Obs} - \mathrm{exp})}{(1 - \mathrm{Exp})} \qquad \text{(Cohen, 1960)}$$

The methodology for LULC Prediction is given in Figure 2) .

Selection of environmental variables: To examine how different environmental conditions, influence the distribution and closeness of the *C. flagellum* in the Assam, 19 environmental variables from world climate data (Fick & Hijmans, 2017) with 30 arc seconds geographical resolution were employed. A shuttle radar topographic Mission (SRTM) (Rodriguez *et al*., 2005) DEM with a resolution of 30 meters is also retrieved and clipped with the research area. Using ArcGIS 10.6, this dataset is utilized to generate slope and aspect data for the given region. The Pearson's correlation coefficient was used to perform the multicollinearity test (r). The cross-correlation was computed, and variables exhibiting cross-correlations exceeding 8 (Mehmud *et al*., 2022) were eliminated from the model. Apart from the environmental variables from current estimation, BCC-CSM2-MR-ssp126 for the year 2021-2040 is taken into consideration. Future prediction of suitable zones is prepared in GIS using the bioclimatic variable as CMIP6 environmental model.

To get a glimpse into the future of *C. flagellum* in Assam, the Beijing Climate Centre's BCC-CSM2-MR model and the Coupled Model Intercomparison Project Phase 6's SSP126 pathways (Eyring *et al*., 2016). These pathways allow the prediction of different future climates and the varying levels of socio-economic development. SSP1 is projected to reach a sustainable development level, while SSP2 is predicted to continue on the current historical path. SSP3 and 4

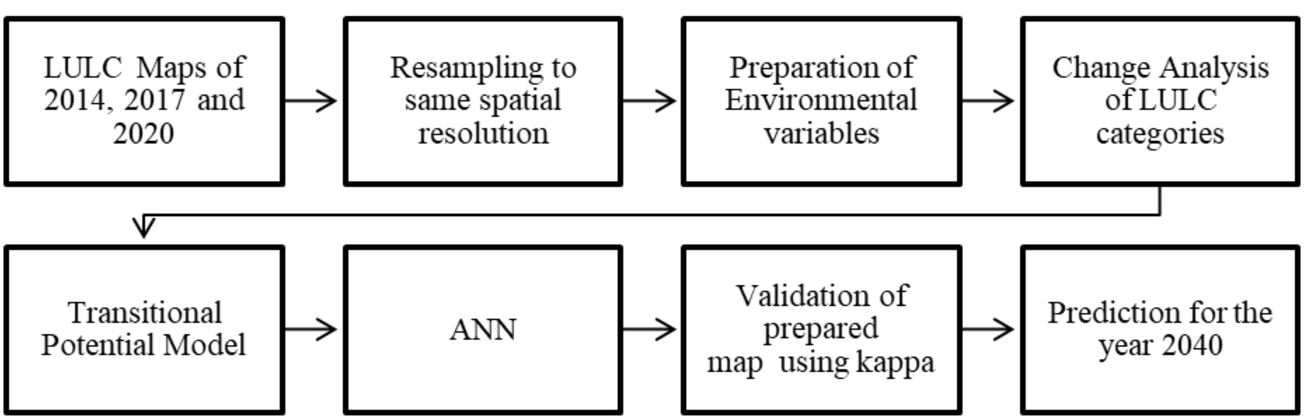

Figure 2. Methodology flowchart

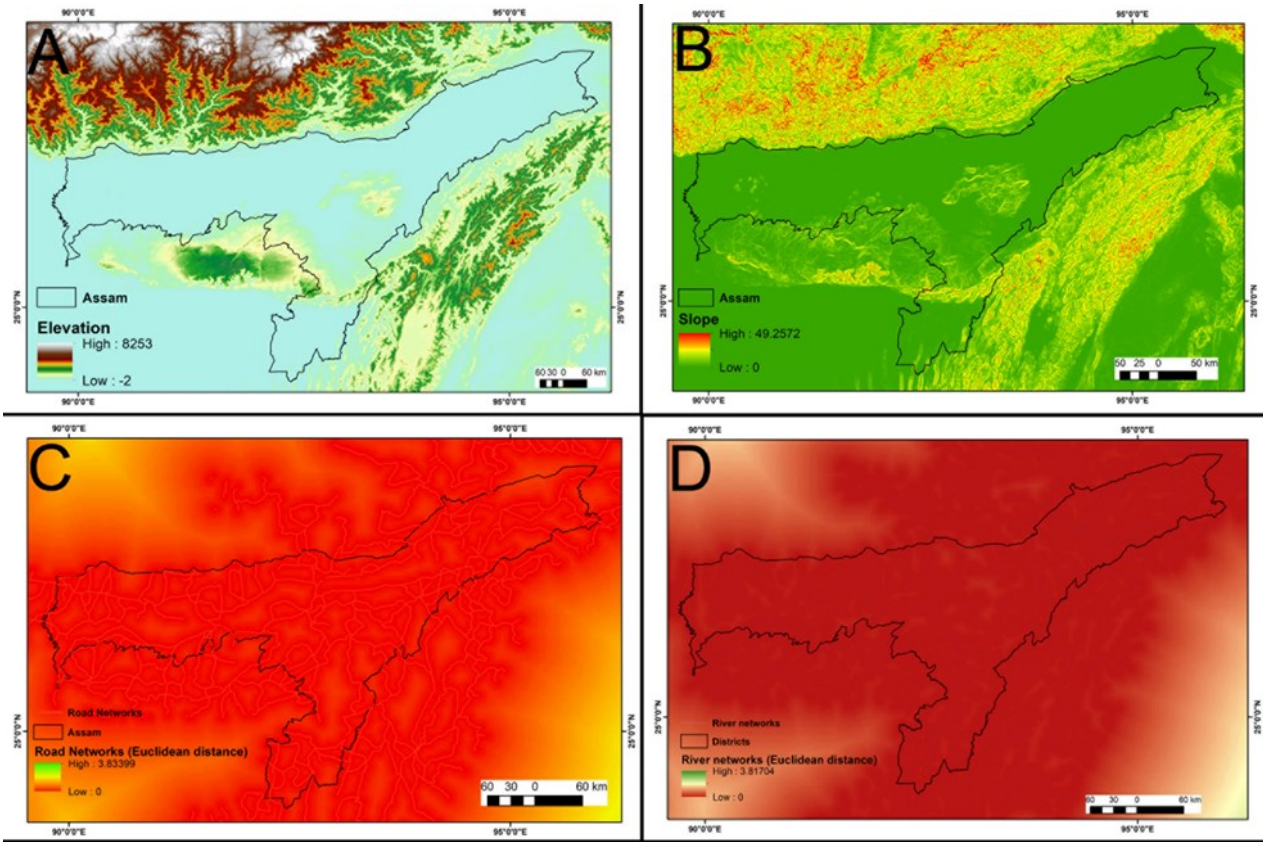

Figure 3. A. Elevation **B.** Slope **C.** Road networks **D.** River networks.

Table 1. LULC Changes in Assam. Areas are in Sq miles and negative signs denote a decrease

Class Names	Area in Sq miles (2014)	Area in Sq miles (2017)	Area in Sq miles (2020)	Area in Sq miles (2040)	Percent Change (2014-17)	Percent change (2017-20)	Percent Change (2020-40)
Water Bodies	1324.32	1312.74	1390.19	1308.77	-0.874411018	5.899873547	-5.856753393
Grassland	9287.95	9021.44	8410.66	8772.01	-2.869416825	-6.770316047	4.296333463
Broadleaf Croplands	1176.74	986.458	1023.36	954.135	-16.17026701	3.740858709	-6.764481707
Savannas	11532.6	12042.4	12847.4	12416.6	4.420512287	6.68471401	-3.353207653
Evergreen Broadleaf Forests	4887.77	4999.68	5341.51	4936.56	2.289592186	6.83703757	-7.581189589
Deciduous Broadleaf Forests	1683.23	1547.84	980.969	1527.71	-8.043464054	-36.623359	55.73478876
Evergreen Needleleaf Forests	0.304933	0.609866	1.21973	0.609866	100	99.99967206	-49.99991801
Non-Vegetated Lands	674.512	654.386	569.615	651.947	-2.983786797	-12.95428081	14.4539733
Urban and Built-up Lands	106.117	107.946	108.556	105.202	1.723569268	0.565097363	-3.089649582
Total Area	30673.54393	30673.49987	30673.47973	30673.54387			

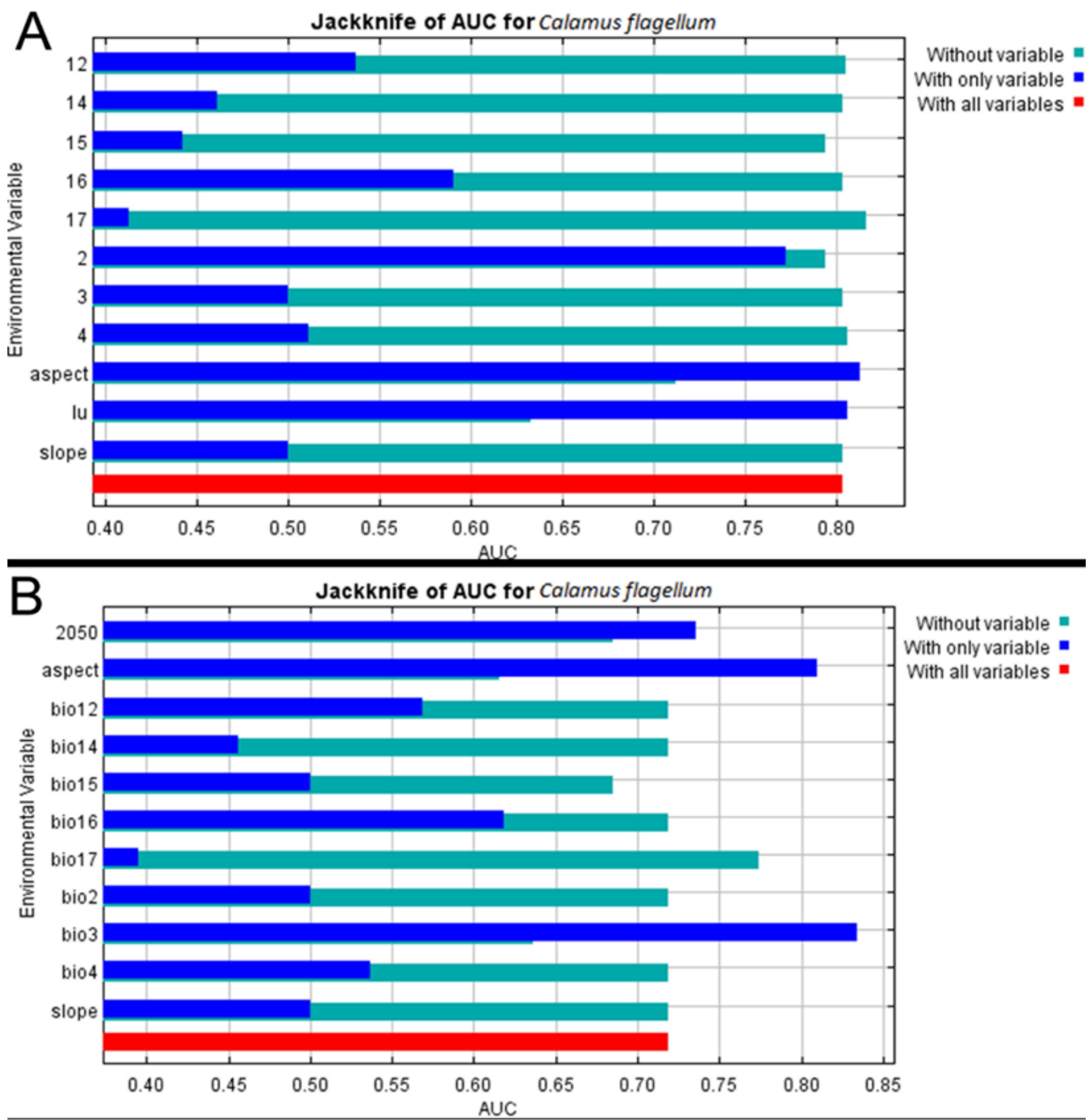

Figure 4. A-B. Jackknife of AUC test for *C. flagellum* evaluating relative importance of environmental variables for current and future prediction.

suggests populations will continue to grow and have low investments, and SSP5's social economy is mainly based on fossil fuels and energy (Zhou *et al*., 2021). The RCPs (Representative Concentration Pathway) are reduced in level of emission and increased absorption of carbon to match the situation of the SSPs. RCP is a standardized approach used to represent different scenarios of future emissions and concentrations of greenhouse gases, aerosols and other trace species in the atmosphere (Zhou *et al*., 2021). RCP 8.5 reflects the worst-case emissions scenario in the framework of SSP126, in which greenhouse gases stay at current, high levels throughout the twenty-first century. Future bioclimatic data for this scenario can be used to identify possibly high climatic stress zones and measure the effects of climate change in various parts of the planet.

Spatial modelling: The Maxent model, which uses a maximum entropy-based machine learning algorithm to estimate the likelihood of species dispersion based on the environmental parameters employed, has grown in popularity among academics working on species distribution modelling. The nearest neighbour resampling technique is used to clip and resample environmental parameters including land use, slope, and aspect data to a spatial resolution of 1 km. Furthermore, every data later has been transformed to an ASCII grid in order to make the model work. The maximum number of background points and regularization multiplier values were both set to 10000. In the model, 70% of the data were used, while the remaining 30% were saved for model testing. The model underwent a total of 100 runs.

The area under the receiving operating curve (AUC) was in use as a measure to assess the model's goodness of fit, and the model exhibiting the highest AUC was selected for further analysis. The jackknife test (Figure 4 A-B) was conducted to determine the significance of the factors. Four distinct levels of habitat suitability were established: high potential, good potential, moderate potential, and low potential.

RESULTS AND DISCUSSION

For the current prediction, the model was operated with 500 iterations using 16 training samples and 6 test samples. The training AUC is 0.96 and test AUC is 0.80. Additionally, 10,000 background points were utilized in the model. Among the variables, Land use and variable 15 contribute 49.1% and 23.3% respectively. Variable 17 and aspect also make significant contributions to the model. Out of the total area, 13,126.03 km^2 has been identified as highly potential, and 8,653.5 km^2 is considered as good potential area.

For the future prediction, the model was similarly operated with 500 iterations using 16 training samples and 6 test samples. The training AUC is 0.95, while the test AUC is 0.72. The model incorporated 10,000 background points. Among the variables, bio 17 (Precipitation of Driest Quarter) and bio 15 [Precipitation Seasonality (Coefficient of Variation)] contribute 54.8% and 22.5% respectively. Variable aspect, bio 3 [Isothermality (BIO2/BIO7) (×100)], and 2040 land use are notable contributors to the model. Out of the total area, 29,184.5 km^2 has been designated as highly potential, and 9,263.3 km^2 is regarded as good potential area.

In order to predict the future land use and land cover changes, differently dated LULC maps are considered as it is a necessity to consider their spatial distribution. In this study LULC maps of three years i.e., 2014 (Figure 5 A), 2017 (Figure 5 B) and 2020 (Figure 5 C) are considered. Although the prepared maps look similar for all these years, but the changes of LULC classes are apparent from the table 1. The land cover modifications can be seen widely in the land use classes. There are continuous ups and downs in changes of land use categories throughout these years. Before predicting the final LULC map for 2040 (Figure 5 D), a model validation test is conducted for predicted and observed LULC map of 2020 (Figure 6). Which gives an overall 74.84% of correctness with overall kappa statistics value of 0.67, which implies that 67% of the mistake that a purely random categorization would produce were prevented by the classification procedure. According to various studies (Rahman *et al*., 2017; Perovic *et al*., 2018; Aneesha *et al*., 2020; Alam *et al*., 2021; Kamaraj & Rangarajan, 2022) the highest kappa value of 0.63 indicated a high level of accuracy.

The spatial distribution modelling (Figure 7 A) shows that the species is scattered mainly in the hilly tract of Lakhimpur, Dhemaji, Dibrugarh, Sivasagar, Jorhat, few parts of Golaghat, hilly tracts of East Karbi Anglong, few patches in West Karbi Anglong, Dima Hasao, Cachar, Karimganj and Hailakandi districts. A fewer suitable zone can also be seen in present in middle and lower Assam.

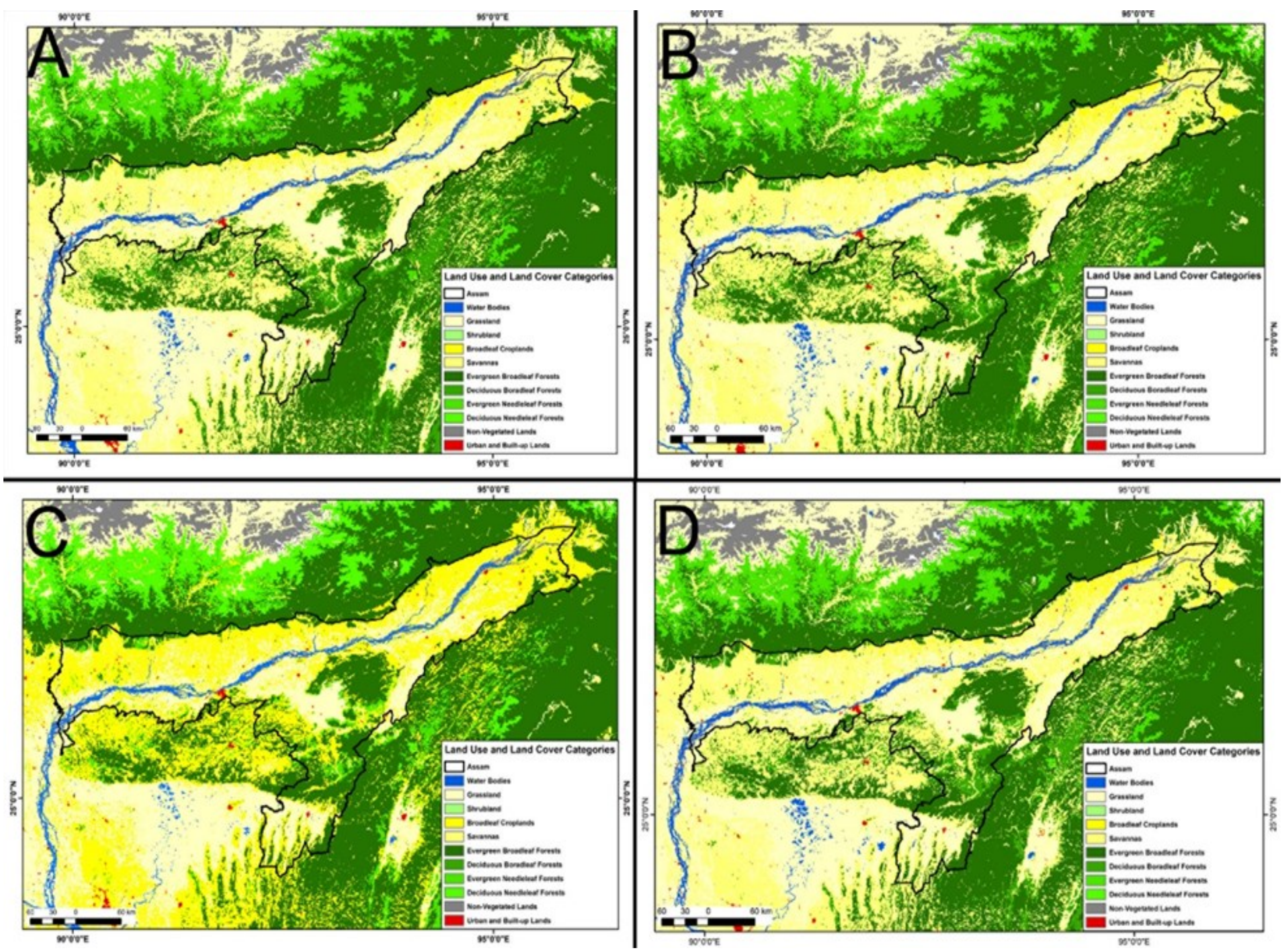

Figure 5. A. LULC Maps for the year 2014, **B.** LULC Maps for the year 2017, **C.** LULC Maps for the year 2020, **D.** LULC Maps for the year 2040.

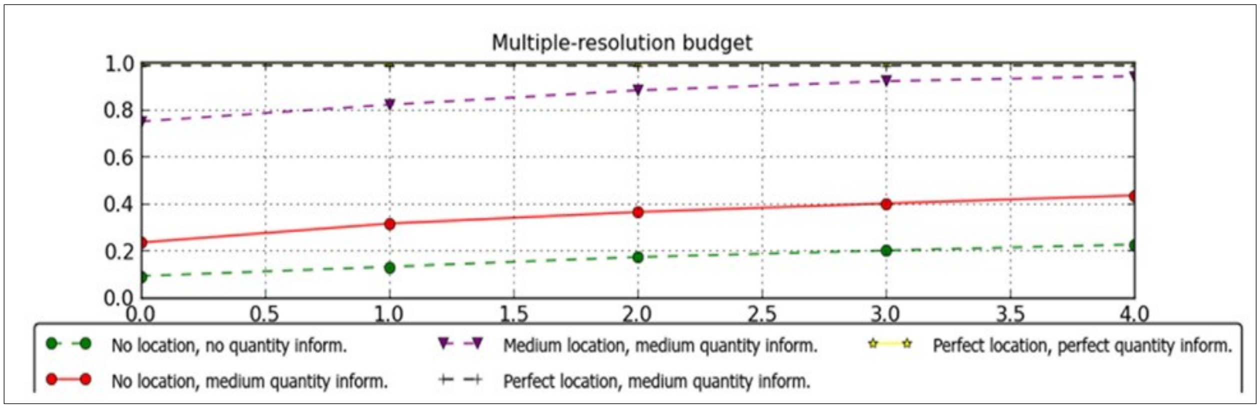

Figure 6. Validation graph between observed and predicted 2020 LULC map.

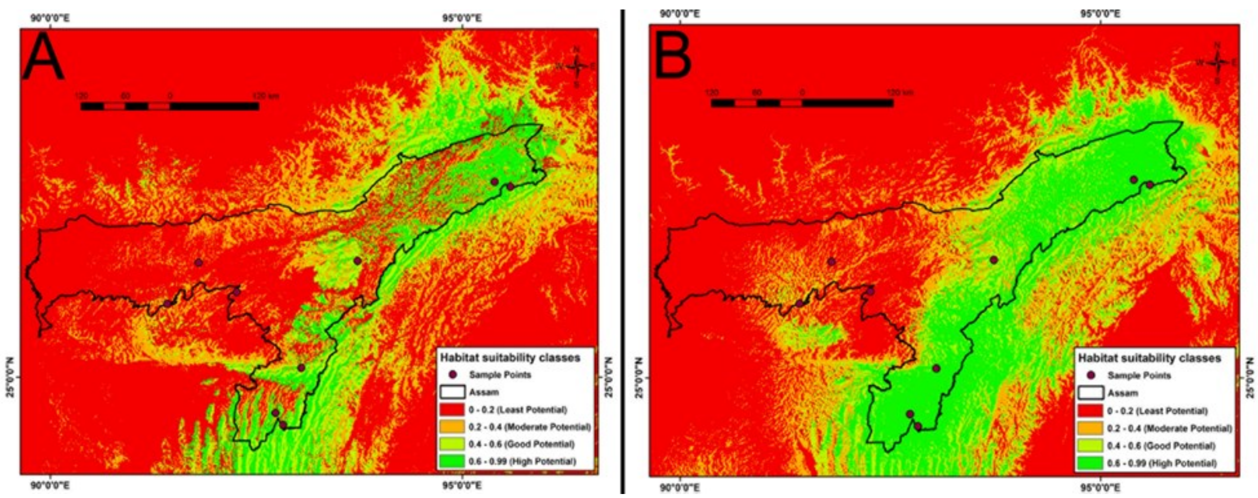

Figure 7. A. Habitat suitability class of *C. flagellum* in Assam; **B.** Future prediction of *C. flagellum* in Assam.

For future distribution of the species, the model predicts (Figure 7 B) covering almost entire upper Assam including Lakhimpur, Dhemaji, Dibrugarh, Sivasagar, Jorhat, few parts of Golaghat, hilly tracts of East Karbi Anglong, few patches in West Karbi Anglong, Dima Hasao, Cachar, Karimganj and Hailakandi districts has shown growth in these areas. The neighbouring state like Mizoram, Arunachal Pradesh and few areas of Meghalaya are also suitable for the species.

CONCLUSION

The ability to accurately predict the future of Land Use and Land Cover is imperative for the preservation of certain plant species. The Molusce plugin of QGIS is using a sophisticated ANN Cellular Automation model that takes into account four key spatial variables viz., elevation, slope, road networks, and river networks. The model has shown to be highly effective, achieving an impressive Kappa value of 0.67 i.e., the highest level of accuracy possible between the observed and predicted LULC maps. The land use and land cover categories i.e., Water Bodies, Grassland, Broadleaf Croplands, Savannas, Evergreen Broadleaf Forests, Deciduous Broadleaf Forests, Evergreen Needleleaf Forests, Non-Vegetated Lands, Urban and Built-up Lands have shown dynamics for the year 2014, 2017, 2020 and 2040. The Beijing Climate Centre's BCC-CSM2-MR model under the Coupled Model Intercomparison Project Phase 6's SSP126 pathways model is incorporated with projected land use and land cover map is capable to give us an idea of changing trajectory of *C. flagellum* for the year 2040. As *C. flagellum* is a NTFPs and economically as well as culturally very important, therefore the present study will help in proper conservation and as well as cultivation of the species in Assam or in neighbouring states of northeast India.

AUTHOR CONTRIBUTIONS

Taxonomic study is conducted by SM, HR, and PB; Spatial modelling using MAXENT and GIS is conducted by NK and DS.

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