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RESEARCH ARTICLE

ASSESSMENT OF POTENTIAL DISTRIBUTION OF SHOREA ROBUSTA GAERTN. F. IN DUMKA DISTRICT OF JHARKHAND THROUGH ECOLOGICAL NICHE MODELLING

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ABSTRACT

Jharkhand is India's most biologically diverse state due to its location and different physiographical and climatic situations. It is well-known for its indigenous peoples, mineral riches, and extensive forest cover. Sal (*Shorea robusta*) is one of the essential and the most important Dipterocarp species in ecology and commerce, but it is also one of the most threatened species. Due to its socio-economic and cultural significance, it has been recognized as Jharkhand's" State Tree". The study entitled" Assessment of potential distribution of *Shorea robusta* Gaertn.f. in the District of Dumka, Jharkhand through Ecological Niche Modelling is aimed at assessing the potential distribution and forecasting the future distribution of *Shorea robusta* Gaertn.f. in the District of Dumka. The modelling and the MAXENT method are utilised for forecasting the present (2020) and future (2040) distribution of the *Shorea robusta* ecological niche. In order to examine the distribution of the target species, 19 bioclimatic variables were employed. The data were analysed from the jack knife test after running the 19 variables in the MAXENT. Then eight bioclimatic factors were eliminated in accordance with their contribution to the *Shorea robusta* distribution. Finally, just 11 bioclimatic variables were used to provide the actual contribution of the model. The potential distribution of the *Shorea robusta* in the study area was predicted by Max Ent model which involved multiple predictor variable is bioclimatic variables, elevation, slope, soil, LULC, and human influence index, where the maximum contribution of minimum temperature of coldest month was 33.9 % having followed by precipitation seasonality 11.9% respectively.

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INTRODUCTION

In ecology, a species' ecological niche defines how it responds to resource distribution and competition. A species' fitness and environmental circumstances are combined in the concept of ecological niche. HSM offers a correlation between environmental factors and the probability of species occurrence (Khatibi and Sheikholeslami, 2016). ENMs are used to forecast species dispersion. Their basic premise is that species distribution always follows the present climate (Ray *et al*., 2016). ENMs assess a species' ecological needs and probable geographic range by combining current data with environmentally appropriate layers (Menon *et al*., 2010). As a machine learning approach, MaxEnt uses the Grid to maximize the amount of information extracted from it. For example, to forecast species distribution, it simply uses data on species' presence (Elith *et al*., 2010).This software component quickly becomes one of the most popular due to its ease of use (Warren and Seifert, 2011). Cleanly and effectively, it solves species distribution modelling (Ortega-Huerta and Peterson, 2008). Each environmental variable's contribution to the prediction model is summarised in a table (Ortega-Huerta and Peterson, 2008). It also offers continuous predictions and delicate topographical data (Phillips *et al*., 2006). Because SDMs may be used to forecast the future geographic range of a species under shifting climatic scenarios, conservation biologists throughout the world use them often (Prates-Clark *et al*., 2008; Saatchi *et al*., 2008).

Use of statistical approaches based on the relationship between species occurrence records and environmental factors is used in SDM (Franklin *et al*., 2013; Guisan and Thuiller 2005). *Shorea robusta* is one of the essential Dipterocarp species in ecology and commerce, but it is also one of the most threatened. *S.robusta* forms dominant monospecific canopies in Jharkhand's dry and wet deciduous woods. Due to its socio-economic and cultural significance, it has been recognised as Jharkhand's "state tree" (Marandi *et al*. 2016). *S.robusta* is a timber-producing dominating tree found across the Himalayan plains and lower foothills, as well as in the tropical moist and dry deciduous forests of India, Nepal, Bhutan, and Bangladesh (Gautam & Devoe, 2006). Sal is found throughout India's plains, lower Himalayan foothills, and valleys (Champion and Seth, 1968). According to Tewari, 1995, it covers around 1 05,790 sq. km. or roughly 14.2 to 16 per cent of the country's total forest cover. Around 30 million forest inhabitants, primarily tribal, subsist on Sal leaves and seeds. Simultaneously, *S.robusta* distribution is mainly determined by climate; its local distribution is principally determined by geographical and soil conditions (Troup, 1921). Tropical tasar silkworm, *Antherea mylitta* Drury is exploited in India for the production of tasar silk and directly or indirectly, 3.5 lakh of tribal earn their livelihood through tasar culture. Rearing of tasar silkworm for the production of cocoon is also a tribal practice in Bihar, Andhra Pradesh, Chhattisgarh, Jharkhand, Madhya Pradesh, Odisha, West Bengal, Maharashtra, Uttar Pradesh, and Telangana. Large-scale collection of naturally formed cocoons in various tasar producing locations. These states are renowned for their traditional and one-of-a-kind Tasar silk weaving (Achary *et al*., 2019).

Indigenous peoples are mainly responsible for silk production. Nearly 30 million (77%) of the entire tribal population of over 38 million reside in tasar farming states in the tropical zone (25.67 million) and temperate zone (4.23 million). However, 13.2 million and 3.2 million indigenous people reside in tropical and temperate tasar growing districts. Thus, around 1.23 lakh families in a tropical zone are active in tasar silkworm raising (Achary *et al*., 2019). *S.robusta* is one of the major food plants of tasar silkworm and it is utilized for the production of tasar cocoon with high silk yield. SDMs are a popular technique among conservation biologists around the globe because they may assist estimate the future geographic distribution of a species under changing climatic scenarios (Prates-Clark *et al*., 2008; Saatchi *et al*., 2008). SDM uses statistical approaches based on the correlation between the species occurrence records and their environmental factors (Franklin *et al*., 2013; Guisan and Thuiller 2005). SDM-based Spatio-temporal maps assist conservationists to identify ecological priority regions that need immediate attention (Zhang *et al*., 2012). SDM insights aid the preservation of endangered plants and wildlife through supporting conservation science, policy and field impacts (Engler *et al*., 2017). Researchers worldwide create SDMs for endangered flora and animals to support policymakers and conservation biologists. Many SDM research utilised the representative concentration pathways (RCPs) of the IPCC and Maximum Entropy Algorithm, commonly known as MaxEnt. Kamyo and Asanok (2020), for instance, utilised MaxEnt to locate appropriate habitats in Thailand for Dipterocarpus alatus. Qin *et al*. (2017) utilised Max Ent in China to predict possible future habitats outside its present distribution for Thuja sutchuenensis.

S.robusta is impacted by anthropogenic causes like ineffective silvicultural management, habitat fragmentation, encroachment, the overall effect of climate change, and insect pests (Kulkarni *et al*., 2018; Tripathy *et al*., 2020; Mathur and Singh 1961). These insects feed on the roots, seeds, seedlings, mature timbers, storage, leaves, bark, and inflorescences of Sal trees, wreaking havoc on tree health and wood quality (Mathur and Singh 1961). Furthermore, vulnerability of *S.robusta* is increasing with abiotic stresses through climate change. In 76 % of the global land area,significant increase in temperature were observed in the 20th century and further predicted to increase of 2.4–4.0 degree C by 2100. Simultaneously, forest pathogens and pest also continue to show increasing trends (Nahrang and Carnogen 2020). Therefore, the current study aims to model the potential distribution areas of *S.robusta* under the current environmental condition and to predict its distribution under various future climatic change using Maxent Model.

MATERIALS AND METHODS

STUDY AREA

The geographical coordinates of the study area comprise of Latitude 23 º 58' 56'' N to 24 º 38' 25''N and Longitude 86º 52' 50''E to 87º 41' 48'' E, whereas total geographical area roughly is 3,771 km² (Figure 1). The elevation varies from 27 to 491 m from the mean sea level. The administrative headquarters of this district is Dumka which is primarily rural dominated area with the large population still residing in the villages. The decadal rainfall average varies from 1088 mm to 1244 mm. The total population of the district 2011 census has been recorded as 1,321,096 whereas the tribal population is 43% of the total population. Agriculture practices are the main source of economy for the rural people of thedistrict.

SATELLITE DATA: The Landsat 8 OLI and DEM was used in this study area. Erdas Imagine 9.1 and Arc GIS 10.2 software was used for digital image processing and spatial database. Aster DEM data with district boundary was clipped. A digital elevation was developed from ASTER data of 30-meter resolution. GIS layers of areas of occurrence for *S.robusta* and elevation was created. This map along with Survey of India topographical sheet of 1:50,000 was used for ground truth verification as per GPS location.

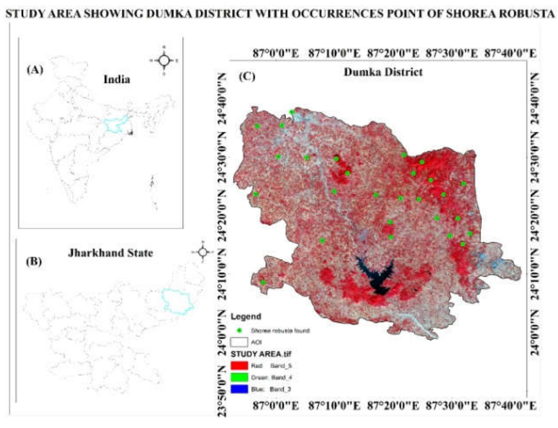

Figure 1. Study area map showing Dumka district with occurrences of *Shorea robusta* overlaid on LANDSAT satellite image of standard False Colour Composite (FCC)in RGB: B5B4B3. The red colour represents vegetation

MODELING PROCEDURE

S.robusta occurrence point data were divided into training data (90 % of occurrence point data was used for model prediction) and test data (10 % of occurrence point data was used for model prediction) (25 % occurrence point data used for model validation). The model will be duplicated 20 times, with a sub-sample as the replicated run type. The regularisation multiplier will be set to 1 by default. The maximum number of background points be 10000. The maximum iterations were taken 500 with a 0.00001 convergence threshold. The replicated run type was set as 'Bootstrap'. The 'Adjust sample radius' is taken 'zero' and default prevalence as 0.5. The Logfile was taken as ‘maxent log’. For reliable evaluation of model outputs, the area under the receiver operating curve (AUC) is used. It runs from 0 to 1, with an AUC of more than 0.8, indicating a good prediction. Multiple sample points using GPS over the entire Dumka district was collected. All the sample points were derived from different sample plots of 500x500m plots dimension.

ENVIRONMENTAL VARIABLES: In order to generate the bioclimatic indices, the best feasible spatial resolution requires reliable climatic records. Interpolated climate records were obtained from a global network of 4000 climate stations, using current 1970–2020 climate data (http://www.worldclim.org). More biologically relevant variables were produced using the BIOCLIM model implemented in DIVA-GIS (version 7.1.7.2), i.e., 19 bioclimatic indicators including precipitation and temperature data. Bioclimatic indices evaluate energy and water balances at a particular location as a substitute term. Annual trends (e.g., annual rainfall, average annual temperature), seasonality (e.g., precipitation ranges and annual temperature) and severe environmental circumstances (e.g., the temperature of the coldest and warmest month and precipitation of the wet and dry quarters).

METHODOLOGY

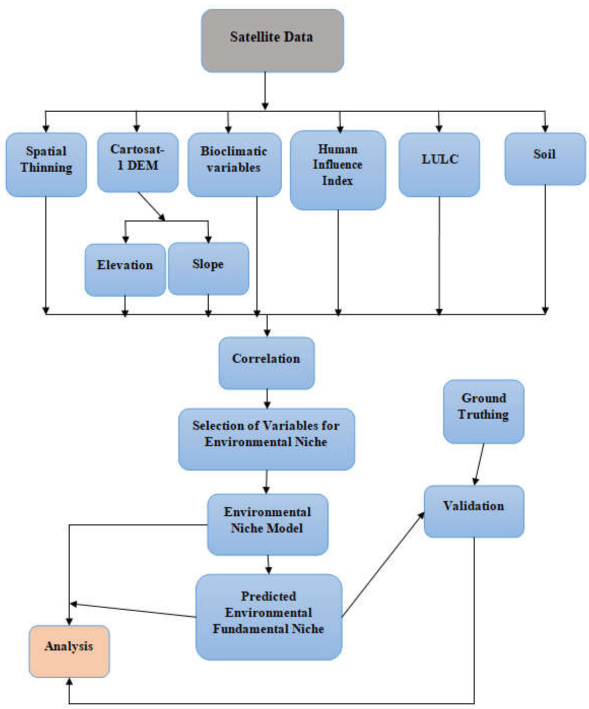

Figure 2. Methodology flowchart for assessing the present distribution of *Shorea robusta* in Dumka district

S.robusta potential distribution is calculated using Ecological Niche modelling and the Max Ent Model, representing the target species' occurrence pattern across the region. Multiple sample points of the target species, *S.robusta* were acquired using GPS over the whole Dumka district area. All sample points were derived from a plot dimension of 5km x 5km. The MaxEnt Model, which included numerous predictor variables such as bioclimatic factors, elevation, slope, soil, land use and land cover, and human influence index, projected the possible distribution of *S.robusta* in the research region.

The prediction range of *S.robusta* in the MaxEnt Model ranges from 0-1

- 0 suggesting no potential for occurrence
- 1 shows high potential for the occurrence

The MaxEnt model also enables an internal jack-knife test to assess the relevance of the variables that influence the *S.robusta* distribution.

RESULTS AND DISCUSSION

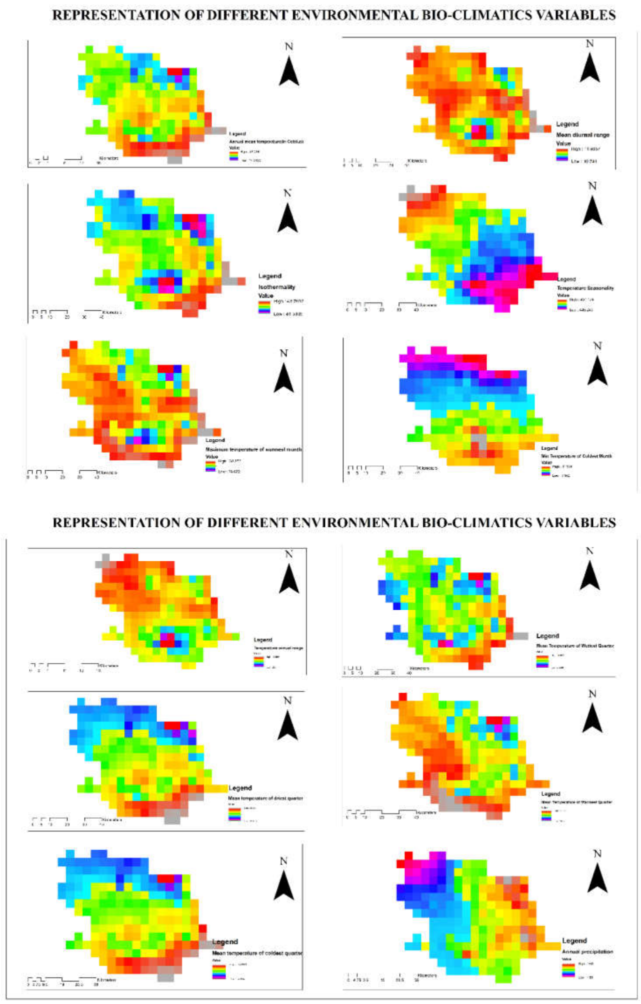

Figure 3. Representation of different environmental variables viz.(a)Annual mean temperature, (b) Mean diurnal range, (c) Isothermality, (d)Temperature Seasonality, (e) Maximum temperature of warmest month, (f) Minimum temperature of coldest month, (g)Temperature annual range, (h)Mean temperature of Wettest Quarter, (i)Mean temperature of driest quarter, (j)Mean temperature of warmest quarter, (k)Mean temperature of coldest quarter, (l)Annual precipitation

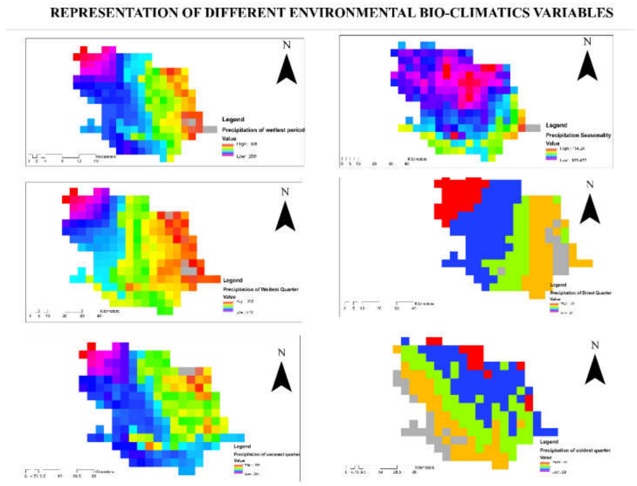

Figure 4. Representation of different environmental variables viz.(a) Precipitation of wettest period, (b) Precipitation seasonality, (c) Precipitation of wettest quarter, (d) Precipitation of driest quarter, (e) Precipitation of warmest quarter, (f) Precipitation of coldest quarter

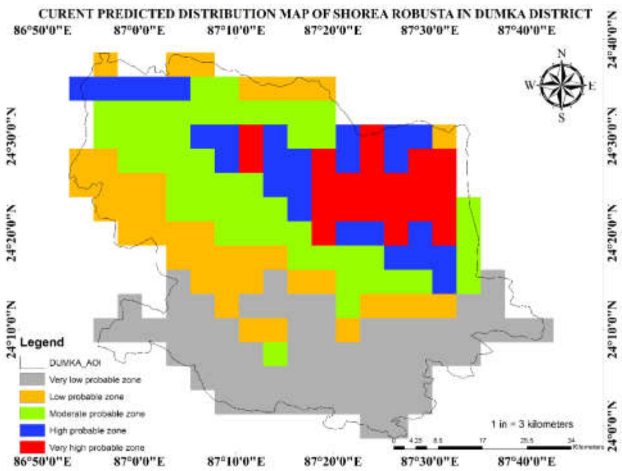

Figure 5. Current predicted distribution map of *Shorea robusta* in Dumka district

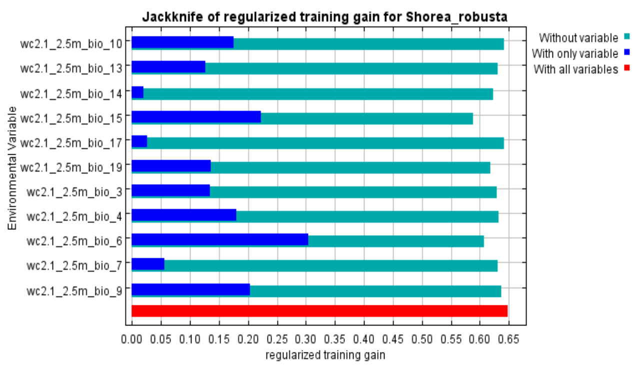

Figure 6. Jac knife of regularized training gain for Shorea robusta

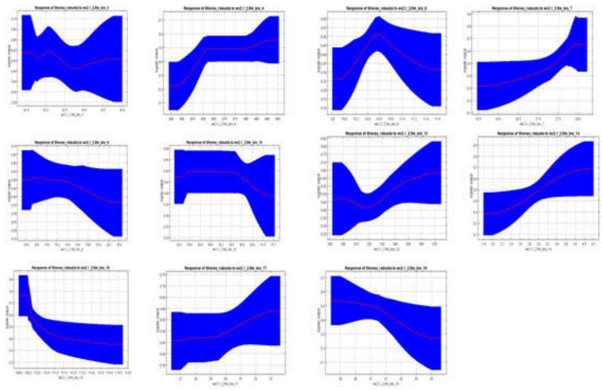

Figure 7. Response curve of (a)Temperature seasonality, (b)Precipitation of driest period, (c)Precipitation of wettest period. (d) Precipitation of driest quarter, (e) Precipitation seasonality, (f) Isothermality, (g) Minimum temperature of coldest month, (h) Mean temperature of driest quarter, (i) Precipitation of coldest quarter, (j) Temperature actual range, (k) Mean temperature of Warmest Quarter

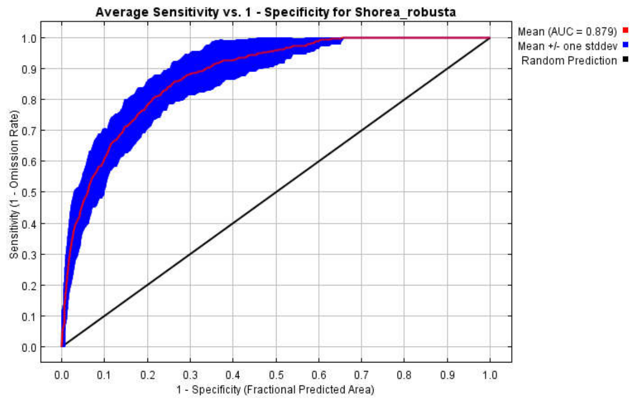

Figure 8. Area under the receiver operating curve (AUCs) for the prediction of ecological niche of *S.robusta*

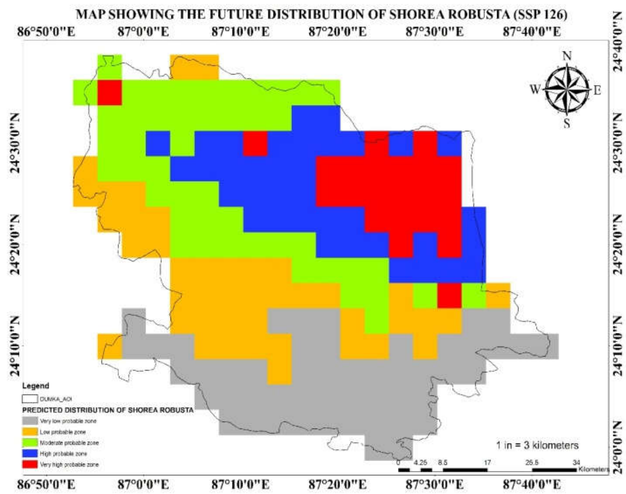

Figure 9. Predicted distribution map of Shorea robusta for the year 2040 under SSP 126 climate change scenarios in Dumka district

The possible distribution of *Shorea robusta is* done with the aid of the MaxEnt model, which shows the occurrence pattern of the target species across the dumka district. We have gathered manysample points utilising GPS of the target species in research region, the AUC was above 0.879 for all variables indicating very high accuracy (Swets *et al*. 1988).

The prediction ranged from 0 to 1, 0 suggesting no potential for the occurrence and 1 showed high potential for the occurrence. (Figure-8). Ecological niche modelling aids and improves endangered species research by enabling fast field surveys led by niche model projections to find additional populations of rare and poorly known species (Menon *et al*., 2010).

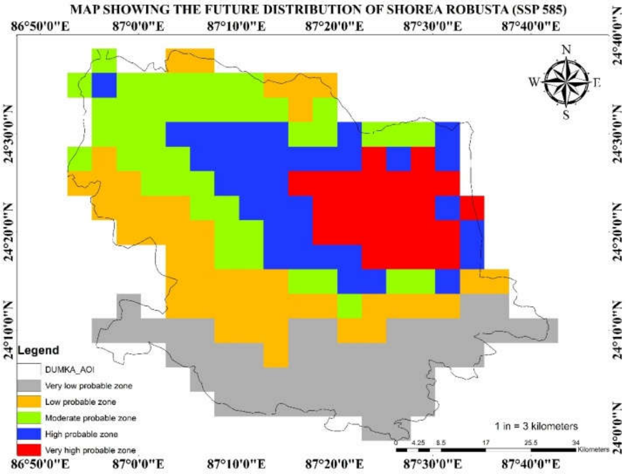

Figure 10. Predicted distribution map of Shorea robusta for the year 2040 under SSP 585 climate change scenarios in Dumka district

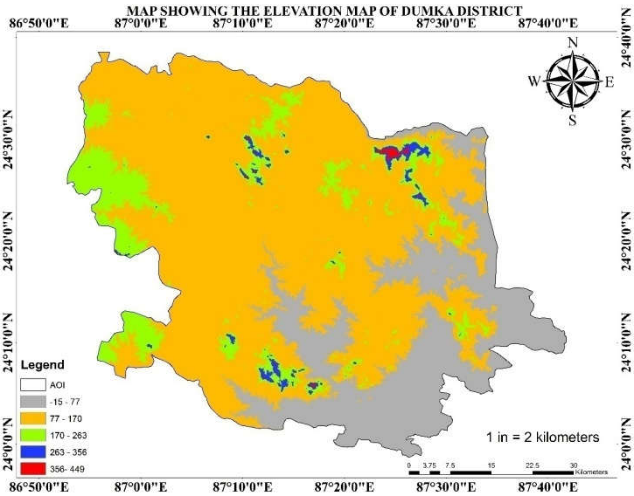

Figure 11. Representation of Elevation map of the study area (Dumka district)

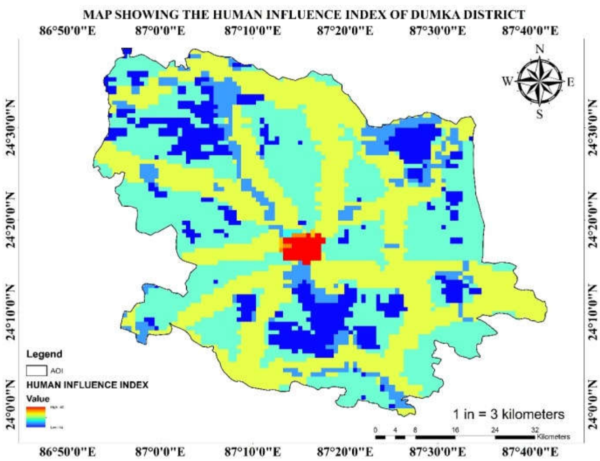

Figure 12. Representation of Human Influence Index map of the study area (Dumka district)

Shorea robusta was mostly found in tropical deciduous woods in Dumka eastern and central sections, according to data. Using a combination of bioclimatic parameters, relief, slope, land use/land cover, soil, and a human influence index, these field records were used to anticipate the current distribution pattern of *S.robusta* in Dumka.

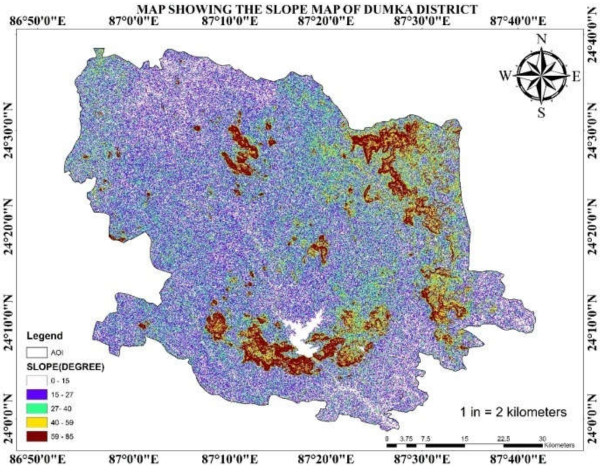

Figure 13. Representation of Slope map of the study area (Dumka district)

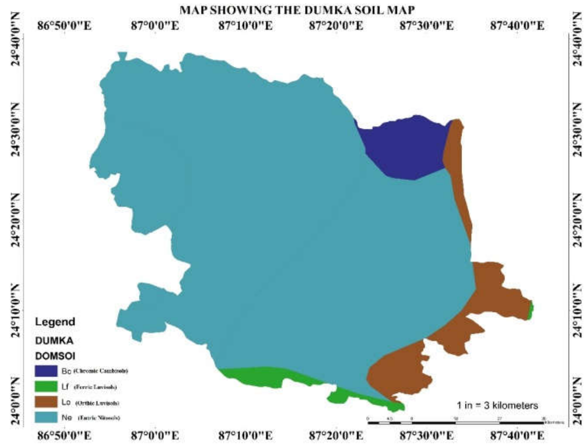

Figure 14. Representation of Slope map of the study area (Dumka district)

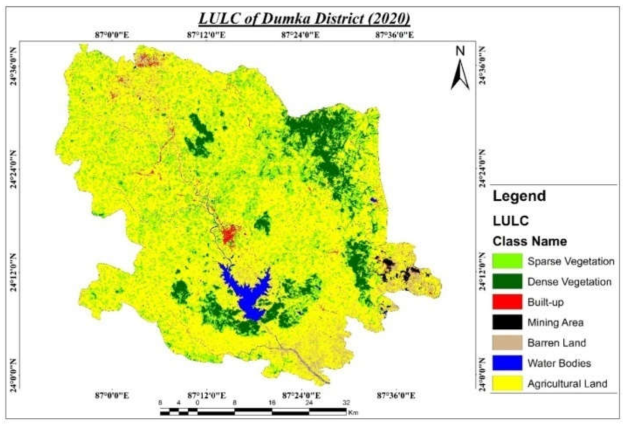

Figure 15. Representation of Land Use Land Cover map of the study area (Dumka district)

The red colour showed the maximum potential, the grey colour showed the minimum potential whereas all the in between colours showed the varying potential distribution of the target species. TheNorth – Eastern region of the study area has shown the higher potential, followed by the South – Western. TheSouthern region has shown the minimum support for the distribution of the *S.robusta* in the study area.(Figure-5) The MaxEnt model also allowed to perform an internal jack-knife test to quantify the importance of the variables on influencing the distribution of *S.robusta.* The distribution showed that the

Sl.No.	Environmental variables	Code	Unit
1.	Temperature Seasonality	BIO_4	°C
2.	Precipitation of driest period	BIO_14	mm
3.	Precipitation of wettest period	BIO_13	mm
4.	Precipitation of Driest Quarter	BIO_17	mm
5.	Precipitation Seasonality	BIO_15	Fraction
6.	Isothermality ((Bio2/Bio7) × 100)	BIO_3	Dimensionless
7.	Min Temperature of Coldest Month	BIO_6	°C
8.	Mean temperature of driest quarter	BIO_9	°C
9.	Precipitation of coldest quarter	BIO_19	mm
10.	Temperature annual range (Bio5-Bio6)	BIO_7	°C
11.	Mean Temperature of Warmest Quarter	BIO_10	°C

Figure 16. Environmental variables and their percentage contribution (Current Scenario: 2021)

S.No.	Environmental variables	Code	Unit	% Contribution
1	Temperature Seasonality	BIO_4	°C	8.6
2	Precipitation of driest period	BIO_14	mm	3.3
3	Precipitation of wettest period	BIO_13	mm	7.7
4	Precipitation of Driest Quarter	BIO_17	mm	3.9
5	Precipitation Seasonality	BIO_15	Fraction	11.9
6	Isothermality ((Bio2/Bio7) × 100)	BIO_3	Dimensionless	5.2
7	Min Temperature of Coldest Month	BIO_6	°C	33.9
8	Mean temperature of driest quarter	BIO_9	°C	8.9
9	Precipitation of coldest quarter	BIO_19	mm	7.9
10	Temperature annual range (Bio5-Bio6)	BIO_7	°C	3.2
11	Mean Temperature of Warmest Quarter	BIO_10	°C	5.8

Minimum Temperature of Coldest Month contributed the most that is 33.9%, followed by Precipitation Seasonality with 11.9%respectively (Figure-6). The SSP 126 indicates that if no external factor or forces act on the *S.robusta* species, how will the distribution vary. (Figure-9) Whereas, the SSP 585 indicates that if all the external factors act on the species distribution of *S.robusta*, how will the distribution vary.(Figure-10) The land use and land cover map were generated after running a maximum likelihood supervised classification as well as a post classification algorithm. The maximum region of human influence index is very low because there is no direct human influence on terrestrial ecosystem such as human settlement, accessibility, and landscape transformation and minimum part is covered with high values as shown in (Figure 12). Slope was derived from Digital Elevation Model with thirty-meter resolution using geographical information system software. Its value ranges from minimum of 0° to a maximum 85 °slope as per the derived Digital Elevation Model (Figure 13).The land use land cover of dumka district for the year 2020 showed various classes in which maximum contribution was agricultural land (2733.94 sq.km) followed by sparse vegetation (816.239 sq.km), dense vegetation (389 sq.km), barren land (247.686 sq.km), water bodies (86.299 sq km), built up (settlement) is 84.88 sq km respectively.(Figure-15).

CONCLUSION

The prospective application of ecological niche modelling can be seen in this study, which maps the potential distribution of *S.robusta* in the Dumka district. This study has made an attempt to understand the relationship between the predictor variables including bioclimatic variables, elevation, slope, soil, land use land cover, and human influence index and target species. This study has also tested the efficiency of the MaxEnt model as it has given accurate and précised result about the species distribution.

MaxEnt has provided a number of outputs, such as the contribution of each predictor variables. The study was focused on the potential distribution of the *S.robusta* in the Dumka district of Jharkhand using Ecological Niche modelling and the MAXENT algorithm. The area of the whole study area was estimated to be 4404 sq. km by the LULC model, which matches the administrative area of the Dumka district from the official website (https://dumka.nic.in/).The study area is divided into five zones: 'Very Low probable Zone', 'Low Probable Zone', 'Moderate probable Zone', 'High Probable Zone', and 'Very High Probable Zone'. The result of the modelling predicted that the 'Very high probable zones were found in the area of Karbindha, Katikund, Gopikandar which covers the north-eastern region of Dumka district. Also, the 'High probable zones' were present around the very high probable zones in the north-eastern part. Some 'High probable zones' were found in the north-western region of Raksa, Sareya, and Hansdiha. In addition, the 'Moderate probable Zones' were found of *Shorea robusta* found surrounding the 'High probable zones' starting from the northern Dumka then to the north-western part then crossing the study area diagonally to the central part of Dumka district. Some Low probable zones were found in the Northern part of the district, then in the eastern part in Orma and the Western region covering Jarmundi, Chorkata, Dumka, Baramasia and Sikariapara. The southern parts have found to be 'Very low probable zones' covering from Masalia (in the west) to Pirargaria (in the east). Suppose no external impact or factor affects the distribution in 2040. In that case, the distribution of Sal will remain in the central and northern regions with a shift of 'High Probable zone' to north-western regions. Suppose all the external factors impact its distribution in the next 20 years. In that case, the 'Very High Probable Zones will only be confined to the eastern part of the Dumka district, and gradually the density of *S.robusta* will decrease surrounding it.

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