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Predictive modeling of Sungrass (*Imperata cylindrica*) invasion under changing climate scenarios in Raghunandan Hills Reserved Forest of Bangladesh

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Abstract

Sungrass (*Imperata cylindrica*), also known as Cogongrass, is one of the most invasive weeds globally, has been identified in the Raghunandan Hills Reserved Forest in Bangladesh. This species is known to outcompete native flora, causing significant harm to natural ecosystems and agricultural lands. This study employed the Maximum Entropy (MaxEnt) model to identify and predict the potential habitat of Sungrass, utilizing 22 environmental variable layers and 190 occurrence records. Projections for the species' distribution were made for the years 2050, 2070, and 2090, based on two Shared Socioeconomic Pathways (SSP 245 and SSP 585). Ten model replicates were executed, with an average used for analysis. Both threshold-dependent and threshold-independent methods were employed for model evaluation, resulting in test Area Under the Curve (AUC) values greater than 0.5, indicating superior performance to random models. The findings suggest that the forest currently supports Sungrass distribution in various areas, with an expected increase in habitat suitability under future climate scenarios. Key factors influencing habitat suitability included potassium, soil organic matter, nitrogen, and elevation, as indicated by the Jackknife test. This study provides critical insights for the management of the Raghunandan Hills Reserved Forest, highlighting the need for strategies to address the challenges posed by Sungrass invasion.

Keywords: Sungrass, Predictive modelling, Raghunandan Hills Reserve, MaxEnt, Climate change, Environmental variables, Habitat distribution

1 Introduction

Invasive alien plant species present a major global threat, disrupting ecosystems and socioeconomic systems by displacing native species, causing ecological imbalances, and leading to economic losses [1,2]. Projections suggest a further rise in alien species invasions, endangering currently non-invaded areas and amplifying these impacts [3]. Monitoring their spread through advanced technologies is crucial, especially in developing nations where financial and technical resources are limited [4]. Delayed action only exacerbates the problem [5,6]. Alien species, which evolve outside their natural habitats or are introduced intentionally or accidentally, often outcompete native vegetation, reducing biodiversity due to their rapid colonization and lack of natural predators [7]. While not all alien species are invasive, some demonstrate aggressive behaviors that disrupt ecosystems [8]. Bangladesh, with its history of introducing over 300 non-native species, faces challenges as many of these species have become invasive, threatening native biodiversity [9].

Sungrass (*Imperata cylindrica*), also known as Cogongrass, the world's 100 most invasive species (weeds), has severely impacted both agricultural and natural ecosystems [10]. Sungrass exists in five distinct varieties, with at least one successfully established on every continent except Antarctica [11]. This highly aggressive species is known for its ability to spread rapidly and colonize new areas, often outcompeting native vegetation and altering ecosystem dynamics [12]. This species competes effectively for water and nutrients, forming monocultures that are inhospitable to wildlife. Its ability to spread through seeds and rhizomes, along with allelopathic effects and pyrogenic behavior, enables it to dominate vast areas [12]. In Bangladesh, Sungrass has been reported as invasive in several forest ecosystems, including Rema-Kalenga Wildlife Sanctuary [13] and Raghunandan Hills Reserved Forest [14]. Severe invasions have also been documented in the Sitakunda Botanical Garden and Eco-Park in Chittagong, where the weed has harmed local biodiversity [15]. Despite these reports, data on the spread and extent of Sungrass infestation in Bangladesh's forests remain scarce, highlighting the need for more detailed studies to understand habitat requirements and invasive species spread [16].

The issue of ecosystem infestation by invasive weeds like Sungrass is a major concern to the global scientific community, posing a threat to biodiversity and causing economic damage. Modeling the future distribution of invasive species can help prioritize areas for monitoring and

control [17]. However, in Bangladesh, knowledge of invasive plants, particularly Sungrass, and their spatial distribution remains limited and is still evolving.

A proactive approach to invasion control involves predicting suitable habitats for invasive species and implementing timely, cost-effective interventions to prevent their spread [18]. Mapping existing invasions and predicting future suitable habitats using ecological models can provide critical insights for ecologists and policymakers [19-21]. Effective management of invasive species requires accurate monitoring systems that are both reliable and efficient [22]. Ecologists seek cost-effective tools for studying invasive species and predicting their spread [23].

Species Distribution Models (SDMs) use species presence and absence data, along with environmental variables, to predict potential distributions. SDMs are increasingly popular in fields such as forestry, ecology, and conservation biology [24]. Environmental factors like climate play a key role in determining species distribution, and SDMs incorporate statistical methods such as climatic envelopes, logistic regression, and boosted regression trees to estimate species-environment relationships [25]. Methods like Artificial Neural Networks (ANN), Generalized Additive Models (GAM), and Generalized Linear Models (GLM) require both presence and absence data, while tools like MaxEnt and Ecological Niche Factor Analysis (ENFA) rely solely on presence data [25].

MaxEnt (Maximum Entropy), a machine learning algorithm, is widely used to model species distributions based on presence-only data combined with environmental variables [26]. This approach has been shown to generate consistent and accurate distribution predictions, even with small datasets [27,28]. MaxEnt's ability to handle gaps in data and its built-in Jackknife test to assess variable importance make it a reliable tool for predicting habitat suitability [29]. The model produces geographically explicit habitat suitability maps, making it valuable for studying invasive species like *Imperata cylindrical* [28, 30, 31].

Spatial databases, such as those developed using earth observation satellite data and local environmental parameters, provide crucial information for managing the environmental impacts of invasive species like Sungrass [32]. The Raghunandan Hills Reserved Forest, a key tropical monsoon forest in Bangladesh, has been heavily infested by *Imperata cylindrica*. Although native to North America [13], this species has spread across more than 200 million hectares

globally, including a rapid annual increase of 150,000 hectares in Asia [33,34]. However, there has been little research in Bangladesh on the distribution of this invasive weed [15].

This study addresses the gap by conducting a spatiotemporal analysis of the current and future distribution of *Imperata cylindrica* in the Raghunandan Hills Reserved Forest under changing climatic scenarios. The MaxEnt model was used to identify areas at risk of Sungrass invasion. The research tests the hypothesis that the habitat distribution of *Imperata cylindrica* can be predicted significantly better than a random model using environmental variables (H_0 : AUC (train) and AUC (test) > 0.5 , H_1 : AUC (train) and AUC (test) ≤ 0.5).

2. Methodology

2.1 Study area

Raghunandan Hills Reserved Forest (6143 ha, approx.) is a protected area in the Madabpur Upazila of the Habiganj district, Bangladesh, located between 24°5'48"–24°16'11" latitudes and 91°21'40"–91°28'23" longitudes (Fig. 2). This reserved forest, consisting of six administrative beats, encompasses a variety of ecosystems, including natural and modified forests, plantations of native and non-native species, shrublands, grasslands, and fallow areas [35]. Due to illicit logging and subsequent silvicultural practices, much of the reserve, excluding the core zone of Satchari beat, has become managed secondary forests or plantations. The northern Shahjibazar area consists mainly of industrial rubber plantations. The Satchari beat in the south features most species-richness, old-growth trees and plantations, whereas Jagadishpur and Shahapur beats in the west consist extensive degraded habitats dominated by grasses and shrubs. Of the grasses, Sungrass (*Imperata cylindrica*), locally known as ‘Chon,’ is a highly invasive, colony-forming perennial grass characterized by its rhizomatous growth. This species has established a significant presence in the degraded areas of the reserve and is recognized as an invasive weed in various countries. Due to its high flammability, sungrass poses a considerable fire risk during the dry season, especially under intense sunlight. These grass-dominated areas are often used by local residents for cattle grazing.

Structurally, the natural forests in Satchari are uneven-aged and multi-storied, reflecting their ecological complexity. Ecologically, the vegetation of this natural forests represents a transition zone between the Indian subcontinent and the Indo-Chinese ecoregion [13].

The climate of the Raghunandan Hills Reserve is characterized by a subtropical monsoon system, with three distinct seasons: summer (March to June), monsoon (July to October), and winter (November to February) [36]. The region experiences its heaviest rainfall during June and July, with an annual average precipitation of 4,162 mm, while December and January are the driest months, often receiving no rainfall. The wet season spans from April to October, whereas the dry season is relatively shorter, lasting from November to March. Temperature variations remain minimal from April to September, with the average temperature hovering around 27°C.

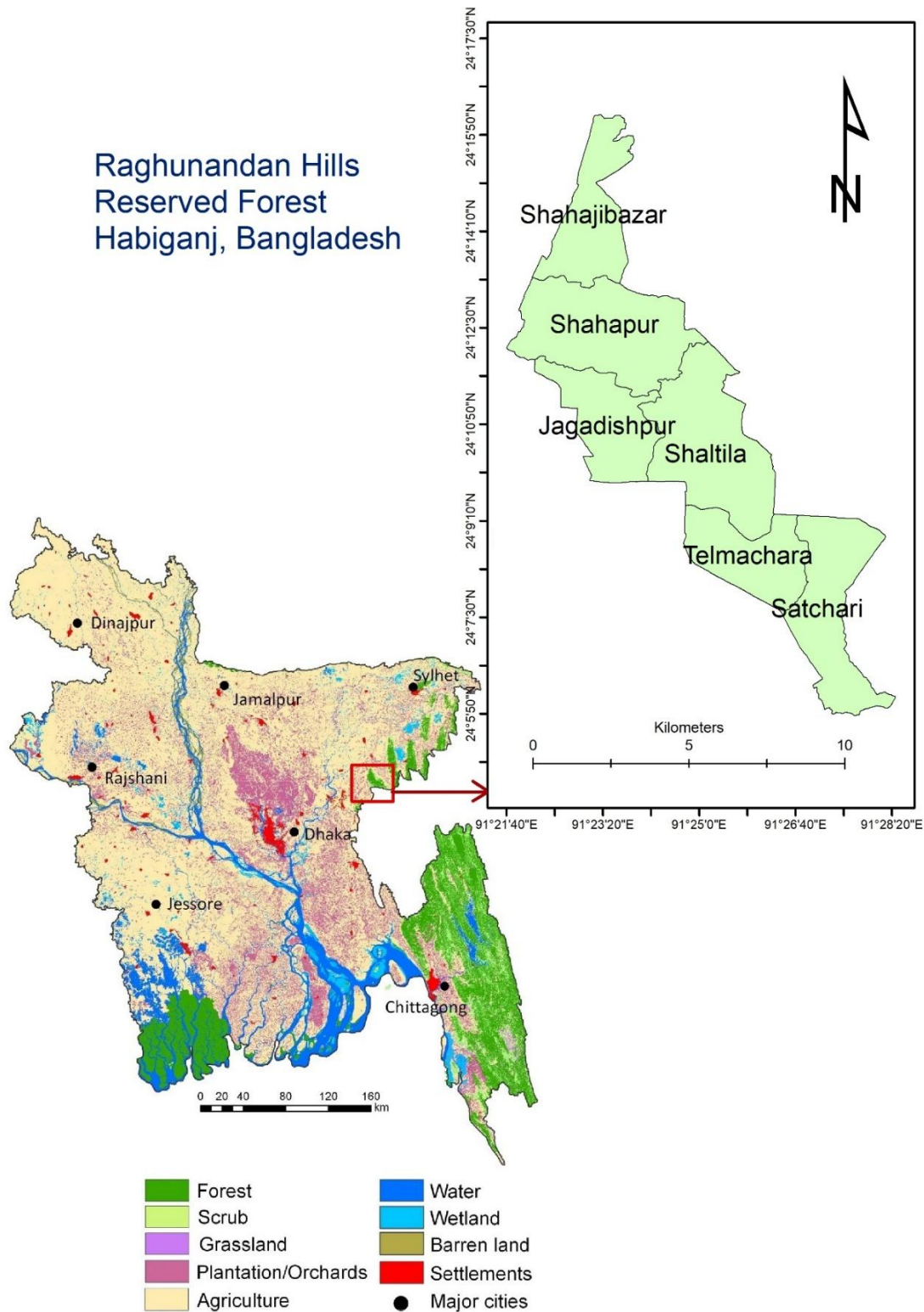


Fig. 1 Map of the Raghunandan Hills Reserved Forest with demarcated six forest beats. The Bangladesh map was adapted from Reddy et al (2016) [37].



Fig. 2 Glimpse of Sungrass (*Imperata cylindrica*) infestation at Raghunandan Hills Reserved Forest, Habiganj. Picture courtesy: Mohammad Redowan (Author).

2.2 Workflow and data

The overall methodology followed in this study is illustrated in Figure 1. Initially, Sentinel satellite images of the study area were downloaded from the USGS website and used to create a land cover map employing a machine learning algorithm. Subsequently, all other environmental variables—including bioclimatic, soil, topographic, land cover, and proximity data—were

extracted, projected, and processed to run in MaxEnt modeler to obtain the current and future distributions of Sungrass habitat.

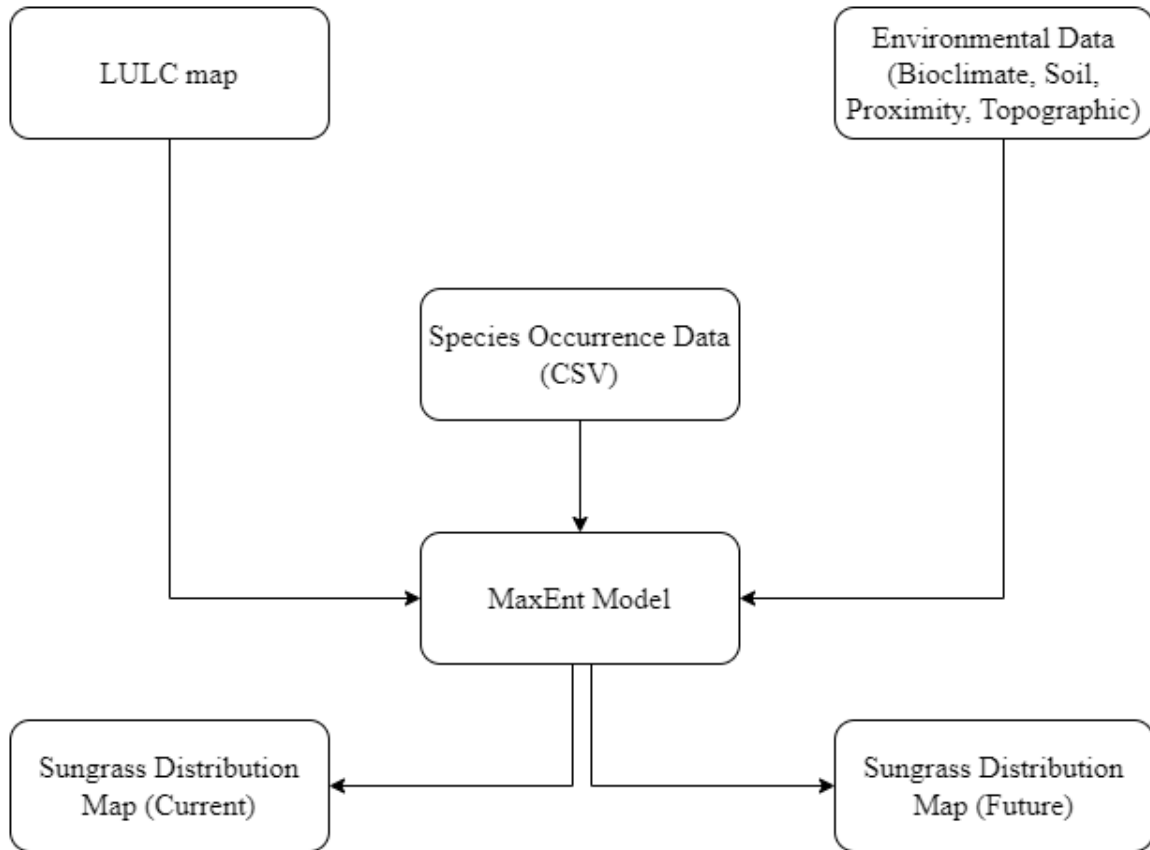


Fig. 3 Overall Workflow

2.2.1 Species occurrence data

Sungrass occurrence records were gathered from the study area through comprehensive field surveys. The species was found both as individual plants and in patches. However, information on patch size or connectivity was not included, as the MaxEnt model cannot accommodate such data [38]. The occurrence points were collected randomly using the QField mobile extension of QGIS and the standalone Gaia GPS Android app. In total, 250 occurrence points were recorded. After screening for duplicates and uncertain data, 192 valid records were selected for further analysis.

2.2.2 Environmental variables

The environmental variables used as model inputs were selected based on a thorough review of the relevant literature. Initially, 19 bioclimatic variables were sourced from the WorldClim (v2.1) dataset (<https://www.worldclim.org/>) for four time periods: current (1970s-2000s), 2050s (2040s-2060s), 2070s (2060s-2080s), and 2090s (2080s-2100s). These data were obtained at a 30-second (~1km) spatial resolution. The study employed the ACCESS-CM2 Global Climate Model (GCM) and two Shared Socio-economic Pathways (SSP245 and SSP585) to assess climate change impacts.

Topographic variables such as elevation, slope, and aspect were downloaded from the United States Geological Survey (USGS) and processed using ArcGIS 10.5. Proximity variables, including distance to roads and settlements, were generated using the Euclidean distance tool in ArcGIS, with estimations based on the methodology of Ervin and Holly (2011) [39] and Google Earth Pro.

For land cover data, cloud-free Sentinel images (2022) were acquired from the USGS website and processed into raster files using the Spatial Analyst tool in ArcGIS. Additionally, soil samples from the study area were analyzed at the laboratories of the Department of Forestry and Environmental Science at Shahjalal University of Science and Technology (SUST) and the Soil Resources Development Institute (SRDI) in Sylhet. These analyses provided values for variables such as pH, soil organic matter (SOM), sand content, nitrogen (N), phosphorus (P), potassium (K), and sulfur (S). The soil variable maps were then prepared, projected, and reclassified to fit the study area in ArcGIS.

Table 1 Pre-selected environmental variables

Categories	Different variables	Data	Resolution	Data source
Bioclimatic data	Min annual air	Raster	30 m	Worldclim data
	Mean temperature of the	Raster	30 m	
	Mean temperature of the	Raster	30 m	
	Mean temperature of the	Raster	30 m	
	Mean temperature of the	Raster	30 m	
	Temperature Seasonality	Raster	30 m	
	Annual precipitation	Raster	30 m	

	Precipitation of wettest	Raster	30 m	
	Precipitation of driest	Raster	30 m	
	Precipitation of wettest	Raster	30 m	
	Precipitation of driest	Raster	30 m	
	Precipitation of warmest	Raster	30 m	
	Precipitation of coldest	Raster	30 m	
	Precipitation seasonality	Raster	30 m	
Soil data	Soil pH	Raster	30 m	Sample collected from field
	Soil organic matter	Raster	30 m	
	Soil moisture content	Raster	30 m	
	Soil sand content	Raster	30 m	
	Nitrogen (N)	Raster	30 m	
	Phosphorus (P)	Raster	30 m	
	Potassium (K)	Raster	30 m	
	Sulphur (S)	Raster	30 m	
Topographic data	Slope	Raster	30 m	USGS DEM
	Aspect	Raster	30 m	
	Elevation	Raster	30 m	
Landcover	Landcover data	Raster	30 m	Sentinel-2
Proximity data	Distance to road	Raster	30 m	From satellite image & field observations
	Distance to Settlement	Raster	30 m	

2.3 Data preparation

The data processing methodology for this study is illustrated in Figure 4. The 192 occurrence points of Sungrass were processed using ArcGIS and converted into a CSV file for use in the MaxEnt model. Bioclimatic variables for the present and future periods (2050, 2070, and 2090) were downloaded in GeoTIFF format from the WorldClim 2.1 database. These files were then projected and resampled to the desired resolution of 30m x 30m. Soil sample data were

transformed into continuous soil maps using the Inverse Distance Weighting (IDW) interpolation technique in ArcGIS 10.5.

Topographic variables, including slope, aspect, and elevation, were generated from the global digital elevation model (DEM) data obtained from the USGS website. Proximity data were created using the Euclidean distance tool in ArcGIS, utilizing Google Earth Pro as a reference. Land cover data were generated through a combination of supervised and unsupervised classification methods in ArcGIS, as no comprehensive land use/land cover (LULC) dataset is available for tropical Asia.

All environmental layers were standardized to the same spatial extent, cell size (30m x 30m), and projection system (WGS 1984 UTM Zone 46N), and then converted to ASCII format for MaxEnt modeling. A multicollinearity test was performed to minimize the effect of correlated environmental variables using a Spearman's correlation test in RStudio. Based on the results, 22 environmental variables (8 bioclimatic, 8 soil, 3 topographic, 2 proximity, and land cover) were selected for the final model.

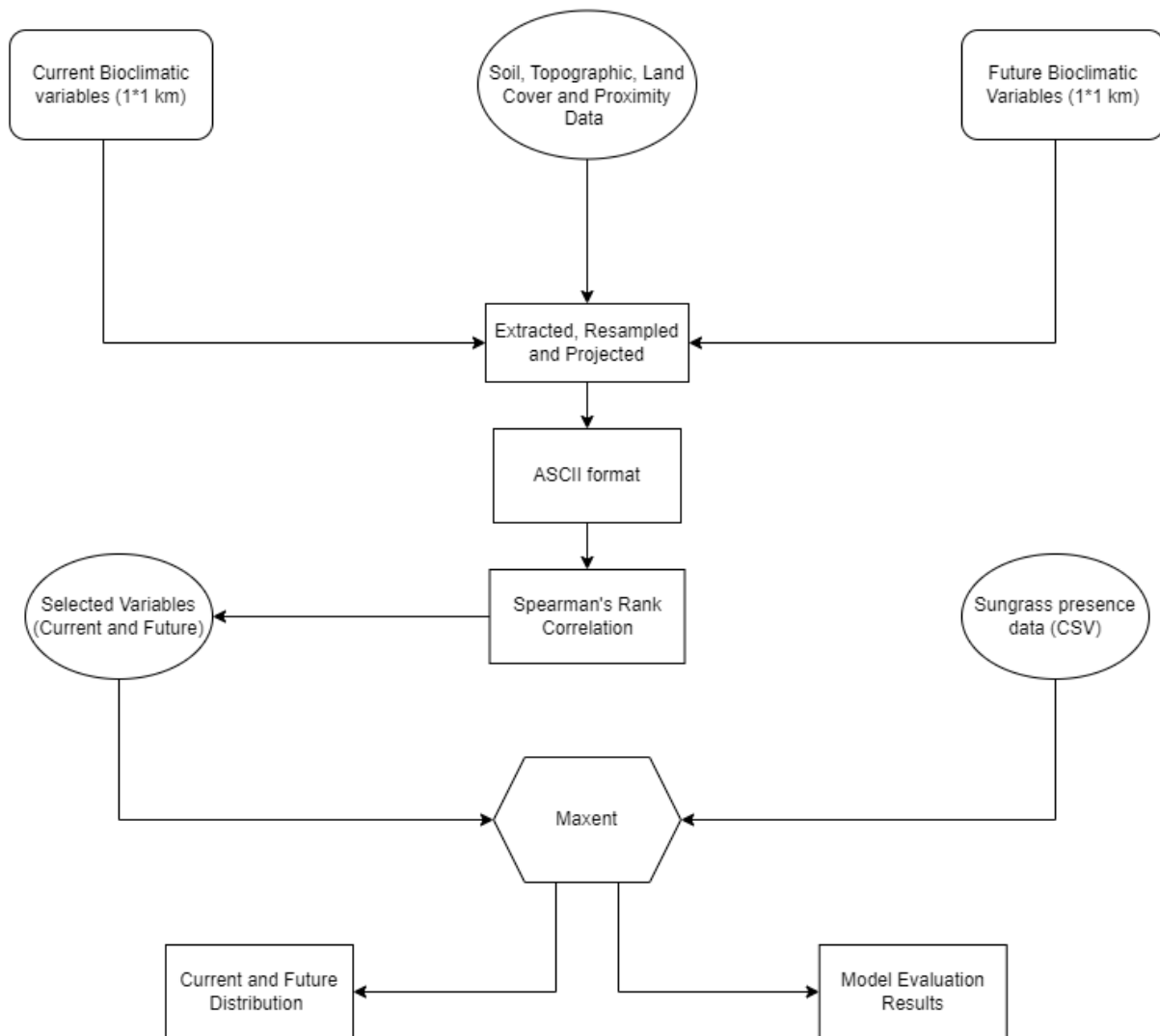


Fig. 4 Data processing and modelling method at a glance

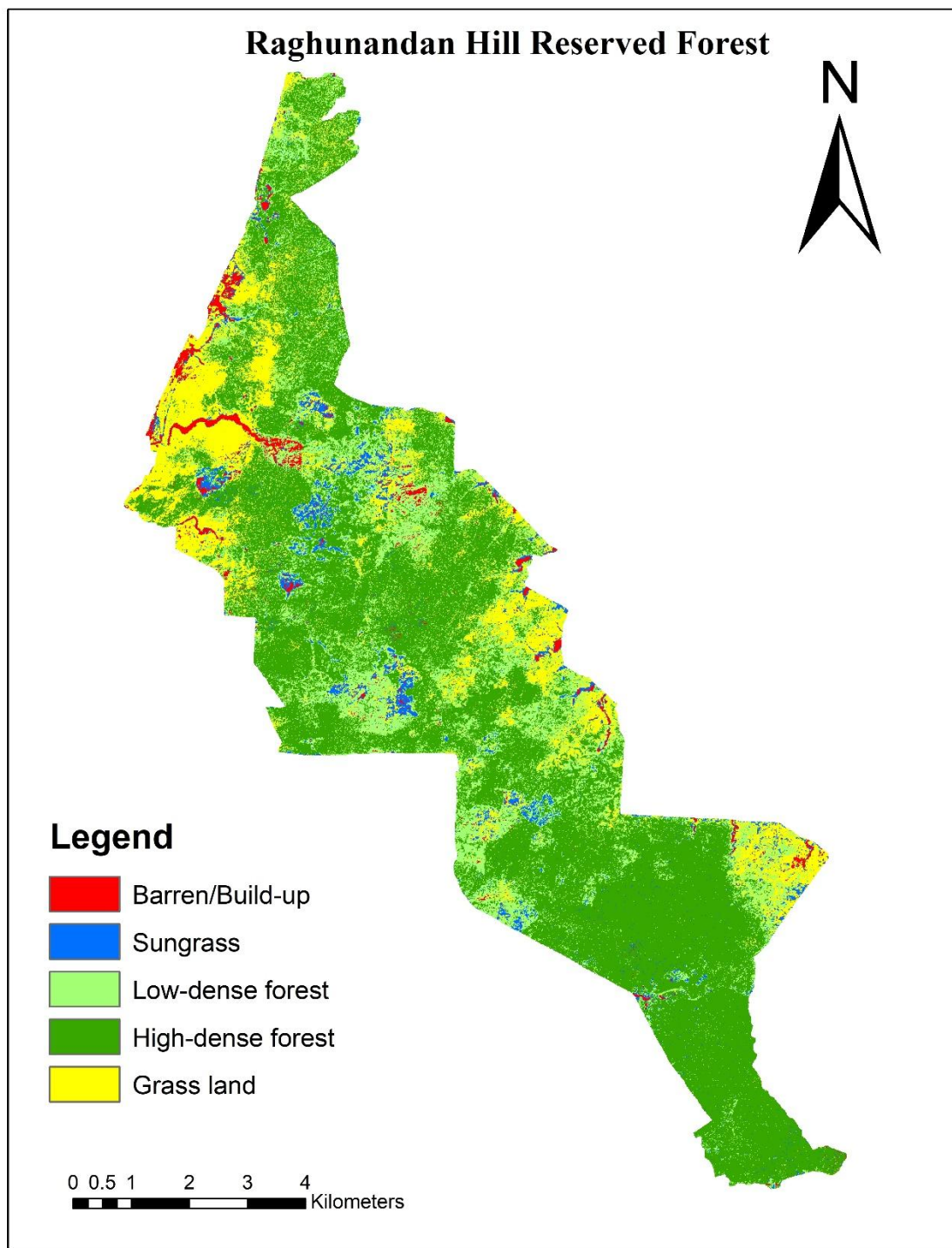


Fig. 5 Produced landcover map (Raghunandan Hills Reserved Forest)

2.4 Modelling

The species distribution modeling was conducted using MaxEnt software, with the optimal settings determined via the ENMevaluate package in RStudio. This function is specifically designed to identify the best configuration for MaxEnt modeling for a given case. According to the evaluation (results not shown for brevity), the Hinge feature with a regularization multiplier of 2 was identified as the most suitable. The maximum number of background points was set at 10,000 for sampling. The options to ‘create response curves’, ‘perform jackknife tests’, and set the output format to cloglog were selected, as they offer results that are straightforward to interpret and explain. All other settings were left at default. The model was run 10 times, and the average of these runs was used for final interpretation.

To address the potential impact of sampling bias—a common issue in presence-only distribution models—a bias file was created in RStudio to limit background points to areas where species occurrences were recorded [40]. Based on the multicollinearity test results, Sungrass distribution and areas at risk were modeled using bioclimatic, topographic, soil, land cover, and proximity data, combined with georeferenced occurrence data [16,17]. The MaxEnt analysis was utilized to predict future Sungrass spread under different climate scenarios [41,42].

MaxEnt generated habitat suitability maps in ASCII format, which were reclassified into presence-absence maps to quantify changes in species occupancy under current and future climate conditions. Using the Reclass tool in ArcGIS, the model output was divided into four habitat suitability categories based on natural breaks (Jenks): unsuitable (0-0.25), poorly suitable (0.25-0.50), moderately suitable (0.50-0.75), and highly suitable (0.75-1.0). Finally, changes in habitat under future climate change scenarios were analyzed by calculating the area for each suitability class.

2.5 Model evaluation

To evaluate the model's performance, a threshold-independent technique was applied, utilizing receiver operating characteristic (ROC) curves with the area under the curve (AUC) as the evaluation metric (Table 2). An AUC value between 0.5 and 0.6 indicates that the model's predictive ability is inadequate, 0.6 to 0.7 reflects poor performance, 0.7 to 0.8 suggests an average effect, 0.8 to 0.9 indicates good performance, and an AUC between 0.9 and 1 demonstrates outstanding model accuracy [43].

Table 2 AUC range and interpretation

AUC Range	Interpretation
0.90-1	Excellent
0.80-0.90	Good
0.70-0.80	Fair
0.60-0.70	Poor
0.50-0.60	Fail

Identifying environmental factors that potentially influence the modeled distribution of a species is crucial. In MaxEnt, the influence of individual variables was determined through the percentage contribution of each variable and the Jackknife test.

3 Results

3.2 Habitat distribution of Sungrass under current scenario

The MaxEnt-generated map of the current distribution of Sungrass in the Raghunandan Hills Reserved Forest (Fig. 6) provides valuable insights into habitat suitability. According to the model, the forest encompasses 460 ha (9%) of highly suitable habitat, 1042 ha (20%) of moderately suitable habitat, and 1707 ha (33%) of poorly suitable habitat for Sungrass. In contrast, the area deemed unsuitable for the species covers 1985 ha (38%) (Fig. 7). Both the suitable and unsuitable habitat areas for the species are spread across different sections of the forest. The only predicted unsuitable areas were found in the Shahajibazar beat, while all other beats show varying degrees of suitability for Sungrass. Shahpur, Sathchari, Jagadispur, along with Shaltila and Telmachara beats, were identified as highly suitable for the species (Fig. 7).

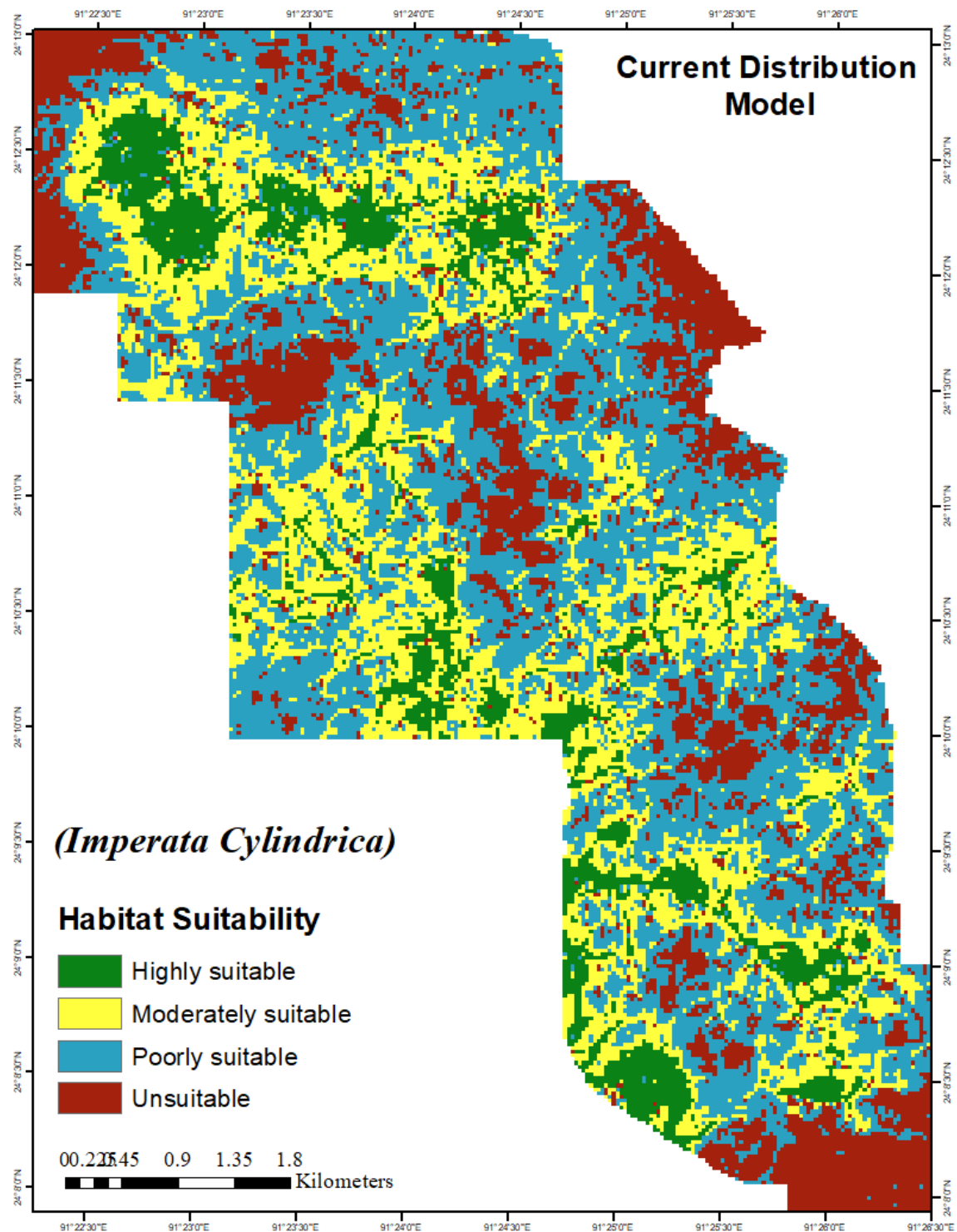


Fig. 6 Current distribution of Sungrass at Raghunandan Hills (zoomed in view)

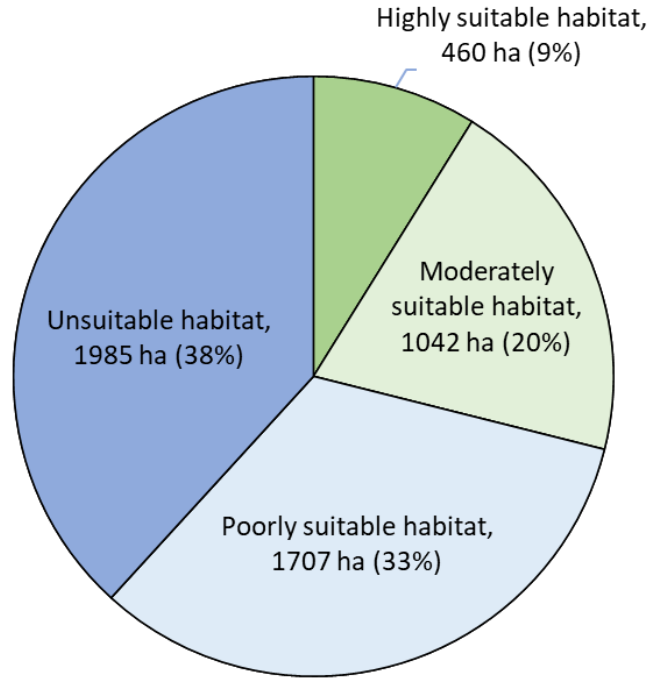


Fig. 7 Current distribution of Sungrass at Raghunandan Hills (zoomed in view)

3.2.1 Threshold-independent evaluation

3.2.1.1 ROC/ AUC analysis

The results of the threshold-independent evaluation model are presented in Table 3. It is clear that the current distribution model for Sungrass (average) surpassed the performance of a random model ($AUC = 0.5$). According to the AUC interpretation outlined in Table 2, the current distribution model is categorized within a good performance range. Additionally, the low standard deviation of the AUC further indicates the high reliability and robustness of the model's performance (Table 3).

Table 3 Results of threshold-independent evaluation

Model	Training AUC	Test AUC	AUC Standard Deviation
Sungrass_0	0.89	0.78	0.06
Sungrass_1	0.88	0.88	0.03
Sungrass_2	0.88	0.79	0.04
Sungrass_3	0.88	0.86	0.03

Sungrass_4	0.88	0.87	0.03
Sungrass_5	0.89	0.84	0.04
Sungrass_6	0.89	0.79	0.04
Sungrass_7	0.88	0.87	0.04
Sungrass_8	0.88	0.85	0.04
Sungrass_9	0.89	0.85	0.03
Sungrass (average)	0.88	0.84	0.04

3.1.1 *Relative contribution of environmental variables*

Table 5 presents the estimates of the relative contributions of environmental variables to the MaxEnt model. Elevation emerged as the variable with the highest percentage contribution (15.1%) for the current distribution model of Sungrass. Soil organic matter (SOM), potassium (K), and land cover contributed 15%, 11.9%, and 8.7% to the model, respectively. Among the bioclimatic variables, bio6 and bio4 contributed 8.4% and 3.1%, respectively, to the model.

Table 4 Variable contribution of current distribution model

Variables	Description	Contribution to Maxent model (%)
Elevation	Elevation	15.1
SOM	Soil Organic Matter	15
K	Potassium	11.9
Landcover	Land Cover Data	8.7
Sand	Soil sand content	8.4
bio6	Temperature Seasonality	8.4
Aspect	Aspect	8.4
Slope	Slope	6.6
N	Nitrogen	6.6
bio4	Mean temperature of the driest quarter	3.1
S	Sulphur	2.9
bio1	Min Annual Air	2.3

3.1.2 Jackknife test of important variables

The Jackknife test function in MaxEnt was employed to determine the significance of various environmental variables affecting the current distribution of Sungrass in Raghunandan Hills Reserved Forest. Average gains, both with and without each variable, were calculated from the ten random distributions generated during modeling. The results of the Jackknife test ranked potassium (K) as the most important variable, followed by soil organic matter (SOM) as the second most important and nitrogen (N) as the third. Potassium (K) exhibited the highest gain when used in isolation, indicating it contains the most valuable information for predicting Sungrass distribution. Conversely, elevation was identified as the variable that, when omitted, led to the most significant decrease in gain, suggesting it provides unique information not captured by other variables (Fig. 8).

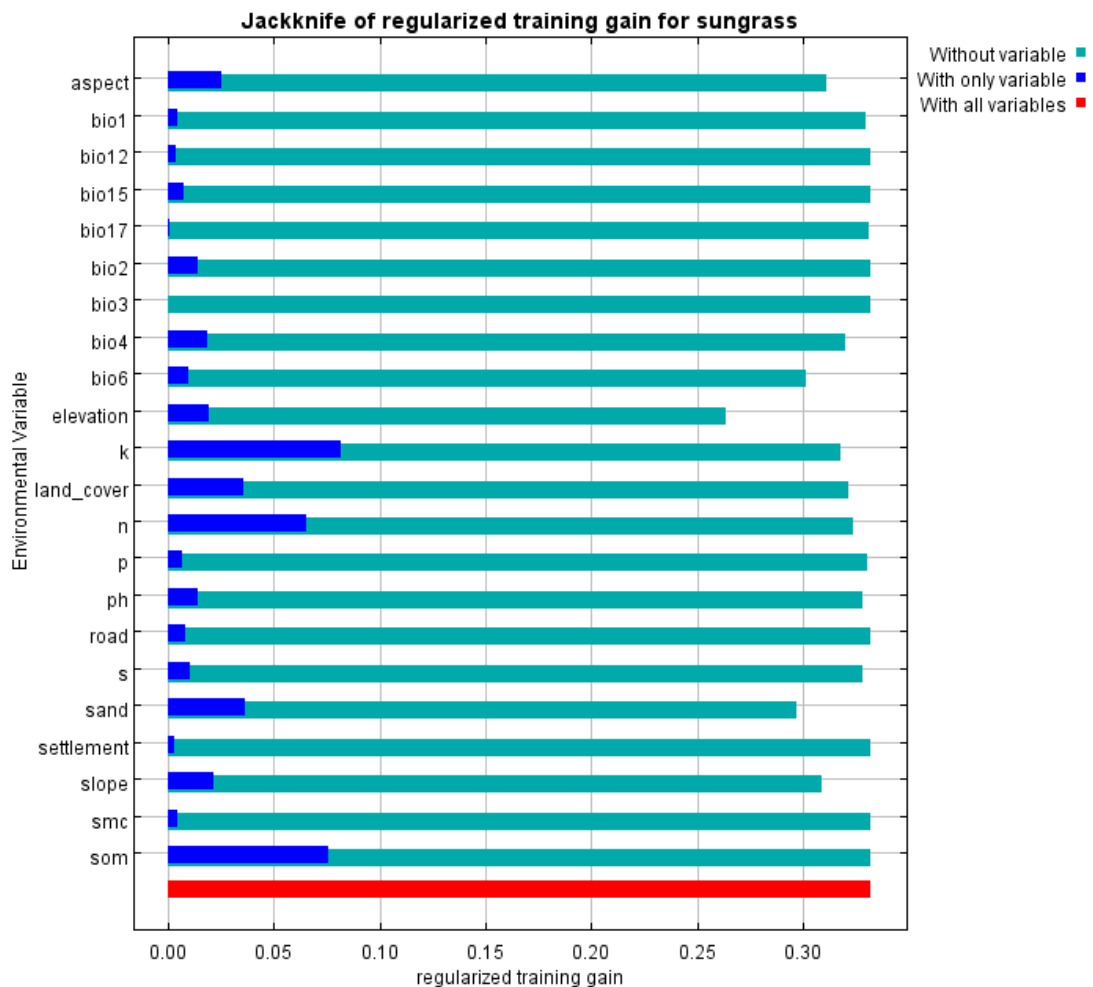


Fig. 8 Average gains for each variable (Current distribution model)

3.1.3 Response curves of environmental variables

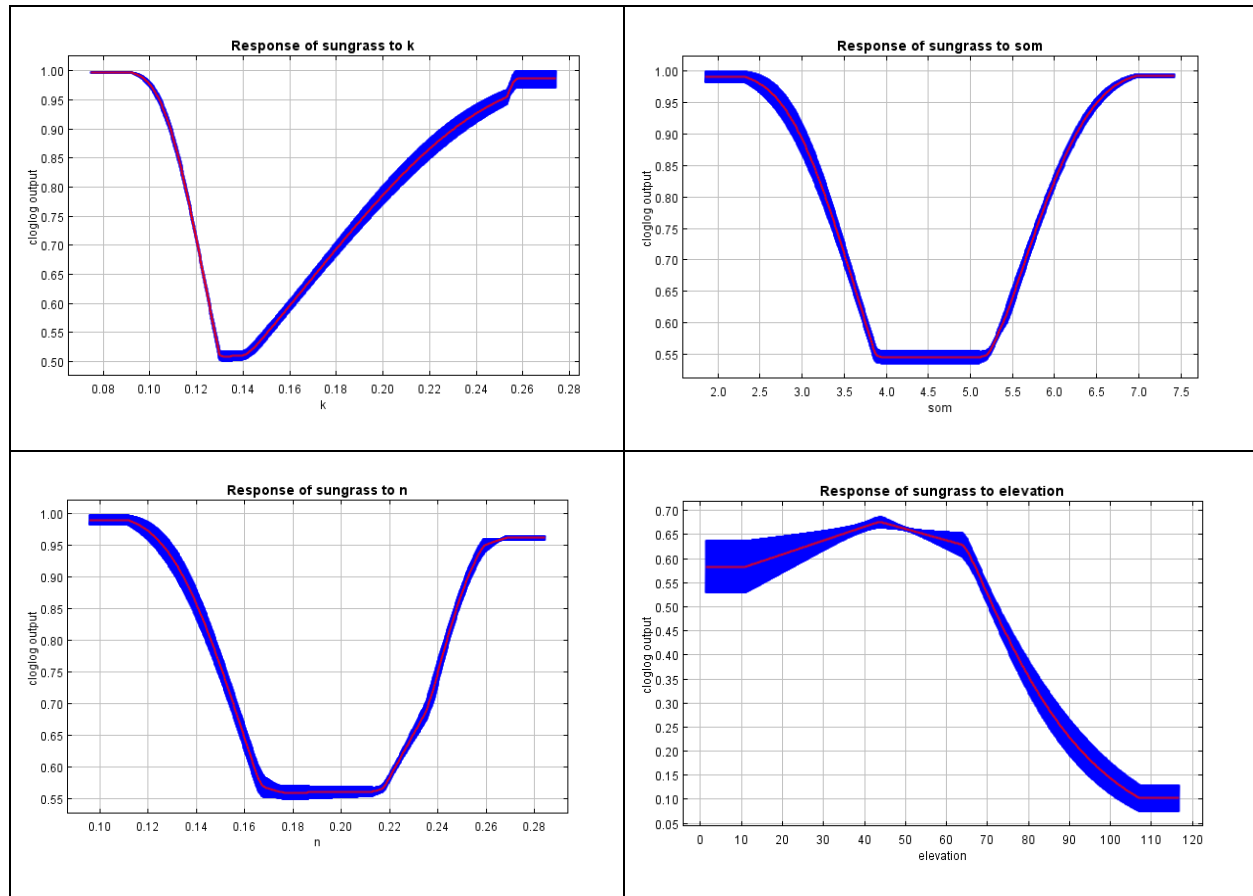


Fig. 9 Response curves of Sungrass (Current distribution model)

Figure 9 illustrates the response curves for potassium (K), soil organic matter (SOM), nitrogen (N), and elevation. The response curve for potassium indicates that areas with K values above 0.13 exhibit an increased probability of Sungrass occurrence. Similarly, the response curves for SOM and nitrogen reveal that higher concentrations of these variables correlate with a greater likelihood of Sungrass presence beyond certain thresholds. In contrast, higher elevations are associated with a lower probability of Sungrass occurrence. The elevation curve initially shows a gradual increase in the probability of occurrence, which subsequently declines sharply as elevation rises. The response curves for the other environmental variables are not displayed.

3.2 Habitat distribution of Sungrass under climatic scenarios

Visual analysis of the projected future maps (Fig. 10, 11, and 12) of Sungrass distribution in the Raghunandan Hills Reserved Forest highlights both positive and negative trends in suitable habitat areas under different climate change scenarios for 2050, 2070, and 2090. These projections indicate fluctuations in the potential habitat of *Imperata cylindrica* in response to varying climatic conditions. The habitat distribution under SSP245 and SSP585 scenarios shows broadly consistent trends for 2050 and 2090, though notable deviations are observed in 2070.

In 2050, both poorly suitable and moderately suitable habitats showed significant increases compared to the current distribution. Poorly suitable habitats expanded by 300 ha (16%) in SSP245 and 100 ha (5%) in SSP585, while moderately suitable habitats increased by 200 ha (21%) in SSP245 and 200 ha (16%) in SSP585. Conversely, unsuitable habitats decreased sharply by 500 ha (27%) in SSP245 and 200 ha (12%) in SSP585. Highly suitable habitats showed mixed results, increasing slightly by 30 ha (7%) in SSP245 but declining by 10 ha (1%) in SSP585.

In 2070, trends in habitat suitability varied slightly. Poorly suitable habitats grew modestly, with an increase of 30 ha (2%) in SSP245 and no significant change (0 ha) in SSP585. Moderately suitable habitats followed suit, increasing by 40 ha (4%) in SSP245 and 10 ha (1%) in SSP585. However, highly suitable habitats declined in both scenarios, shrinking by 20 ha (5%) in SSP245 and 30 ha (6%) in SSP585.

By 2090, patterns largely mirrored those observed in 2050. Poorly suitable habitats expanded by 200 ha (15%) in SSP245 and 200 ha (14%) in SSP585. Moderately suitable habitats grew by 200 ha (15%) in SSP245 and 100 ha (14%) in SSP585. Unsuitable habitats continued to decline, reducing by 400 ha (21%) in SSP245 and 400 ha (19%) in SSP585. Meanwhile, highly suitable habitats showed mixed trends, with a slight increase of 10 ha (2%) in SSP245 but a decrease of 20 ha (3%) in SSP585.

Overall, future scenarios project a consistent decline in unsuitable habitats alongside increases in poorly and moderately suitable habitats. The suitable habitats of Sungrass at Raghunandan Hills Reserved Forest are likely to increase in the future. However, the dynamics of highly suitable habitats remain variable across different scenarios and timeframes.

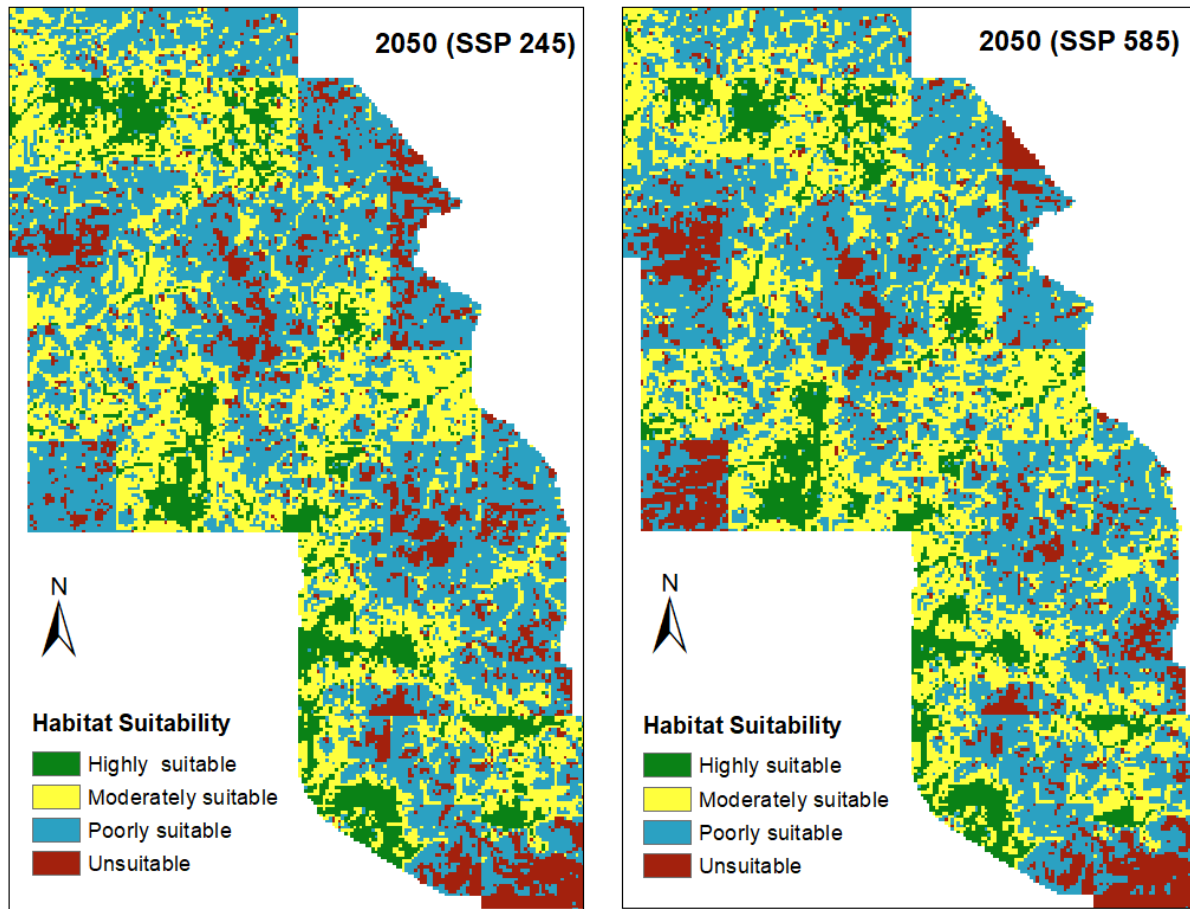


Fig. 10 Future distribution of Sungrass for 2050 (SSP 245 & SSP 585)

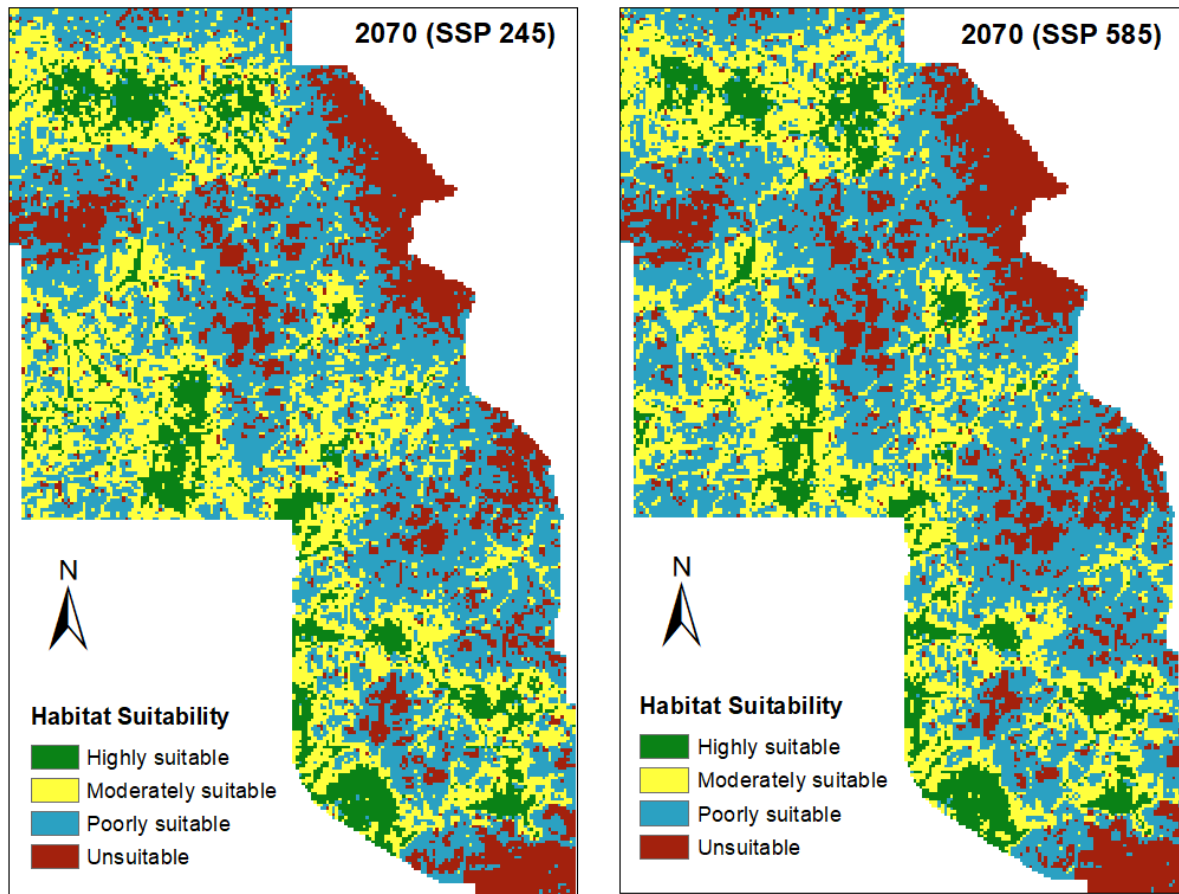


Fig. 11 Future distribution of Sungrass for 2070 (SSP 245 & SSP 585)

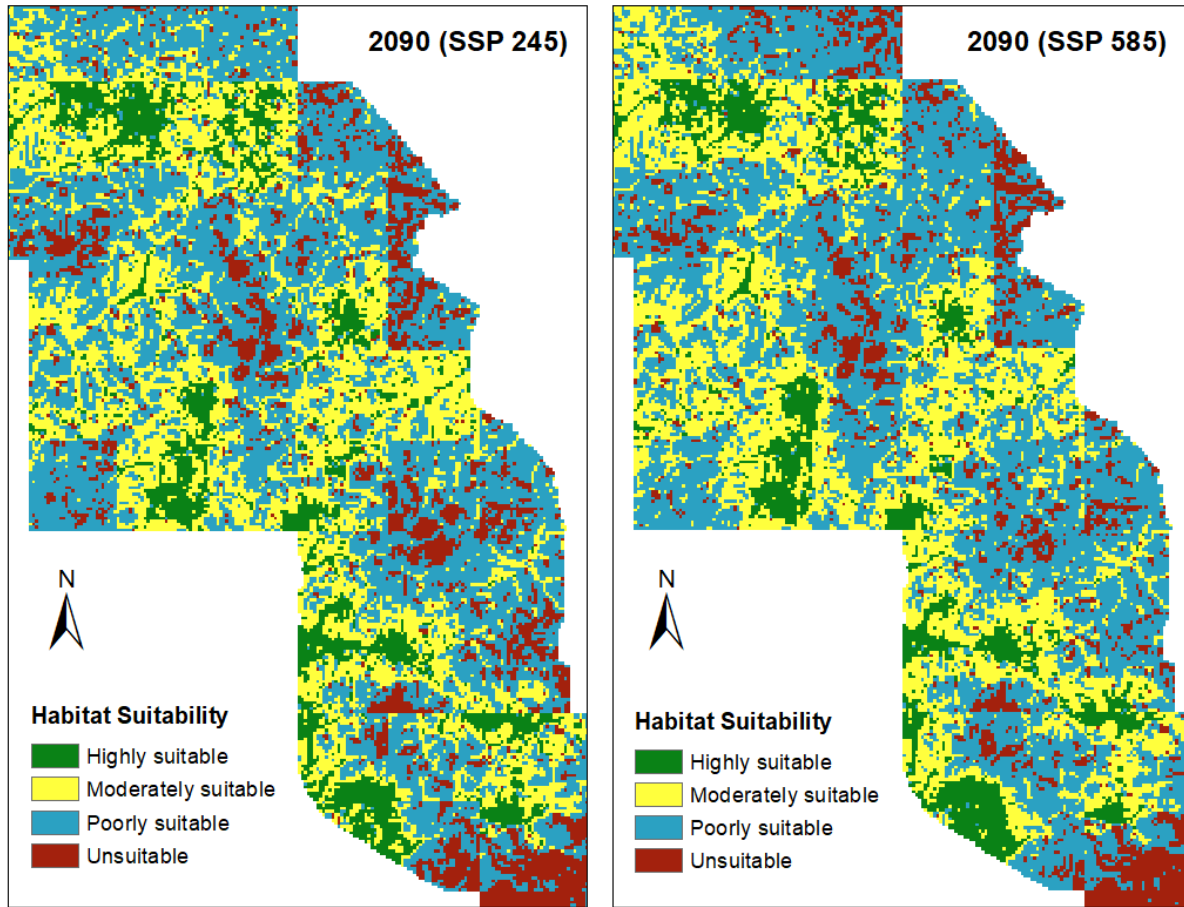


Fig. 12 Future distribution of Sungrass for 2090 (SSP 245 & SSP 585)

Table 4 Changes in habitat distribution areas under climate change scenarios

Climate Scenarios	Unsuitable habitat (ha)	Changes (%)	Poorly suitable habitat (ha)	Changes (%)	Moderately suitable habitat (ha)	Changes (%)	Highly suitable habitat (ha)	Changes (%)
Current	1,985	0	1,707	0	1,042	0	460	0
SSP 245 (2050)	1,456	-27	1,987	16	1,257	21	491	7
SSP 585 (2050)	1,742	-12	1,784	5	1,210	16	455	-1
SSP 245 (2070)	1,940	-2	1,733	2	1,081	4	438	-5
SSP 585 (2070)	2,003	1	1,710	0	1,050	1	430	-6
SSP 245 (2090)	1,569	-21	1,956	15	1,201	15	467	2
SSP 585 (2090)	1,612	-19	1,951	14	1,184	14	445	-3

3.2.1 Threshold-independent evaluation

3.2.1.1 ROC/AUC analysis

The results of the threshold-independent evaluation (Table 5) indicate that all future models for 2050, 2070, and 2090 performed well under both climate scenarios. The test AUC and training AUC for each future model exceeded 0.8, demonstrating strong performance. Additionally, the low standard deviation across the models further supports their overall high reliability.

Table 5 Results of threshold-independent evaluation for future model

Model	Training AUC	Test AUC	AUC Standard Deviation
SSP 245 (2050)	0.88	0.84	0.04
SSP 585 (2050)	0.88	0.83	0.04
SSP 245 (2070)	0.89	0.84	0.04
SSP 585 (2070)	0.89	0.83	0.04
SSP 245 (2090)	0.88	0.84	0.04
SSP 585 (2090)	0.87	0.84	0.034

3.2.2 Relative contribution of environmental variables

Tables 6 and 7 illustrate the estimates of variable contributions to the models for SSP 245 (2050) and SSP 585 (2050), respectively. In the SSP 245 (2050) model, elevation and soil organic matter (SOM) accounted for 16% and 15.2% of the contributions, respectively. In the SSP 585 (2050) model, potassium (K) was the leading contributor at 19.8%, followed by elevation at 14.4%.

For the SSP 245 (2070) model, elevation and SOM continued to be the most significant contributors, with elevation contributing 15% in the SSP 245 condition and 13.4% in the SSP 585 condition. SOM contributed 15.4% in the SSP 585 condition and 11.6% in the SSP 245 condition, while K was the second-highest contributor in both models, contributing 13.9% and 14.5%, respectively.

In the SSP 245 (2090) and SSP 585 (2090) models, elevation and K contributed 15.2% and 14.2%, respectively, while K and SOM contributed 15.5% and 13.7%, respectively.

Table 6 Variable contribution to the model (SSP 245- 2070)

Variable	Contribution (%)
Elevation	15
K	13.9
SOM	11.6
Landcover	9.2
N	8.8
Aspect	7.7
Slope	7.4
Sand	7.2
Bio6	7.1
Bio4	4.1
pH	1.5
Bio2	1.4
S	1.2

Table 7 Variable contribution to the model (SSP 585- 2070)

Variable	Contribution (%)
SOM	15.4
K	14.5
Elevation	13.4
Sand	8.8
Landcover	8.3
Slope	6.9
Aspect	6.6
N	5.8
Bio3	5.4

Bio4	3.6
Bio6	2.9
S	2
pH	1.8

3.2.3 *Jackknife test of important variables*

The Jackknife test results for identifying important variables in the future models for both climate scenarios in 2050, 2070, and 2090 are presented in Figures 13, 14, and 15. The findings reveal that potassium (K) emerged as the most significant variable influencing the potential habitat of Sungrass across all future models, followed by soil organic matter (SOM) as the second most important variable and nitrogen (N) as the third in both climatic scenarios. Among the environmental variables, K demonstrated the highest gain when assessed in isolation, indicating it contains the most valuable information by itself. Conversely, elevation was identified as the variable that, when omitted, resulted in the most substantial decrease in gain, suggesting it holds critical information not captured by the other variables.

The response curves for all future models under both climate scenarios in 2050, 2070, and 2090 exhibited similar patterns (Fig. 15). These curves indicated that, beyond a certain threshold, areas with higher potassium (K) values are associated with an increased probability of Sungrass occurrence in Raghunandan Hills Reserved Forest under specific conditions. Conversely, the response of soil organic matter (SOM) initially shows a lower probability of Sungrass presence in areas with higher SOM values. However, after reaching a certain point, regions with elevated SOM values demonstrate a greater likelihood of supporting Sungrass populations.

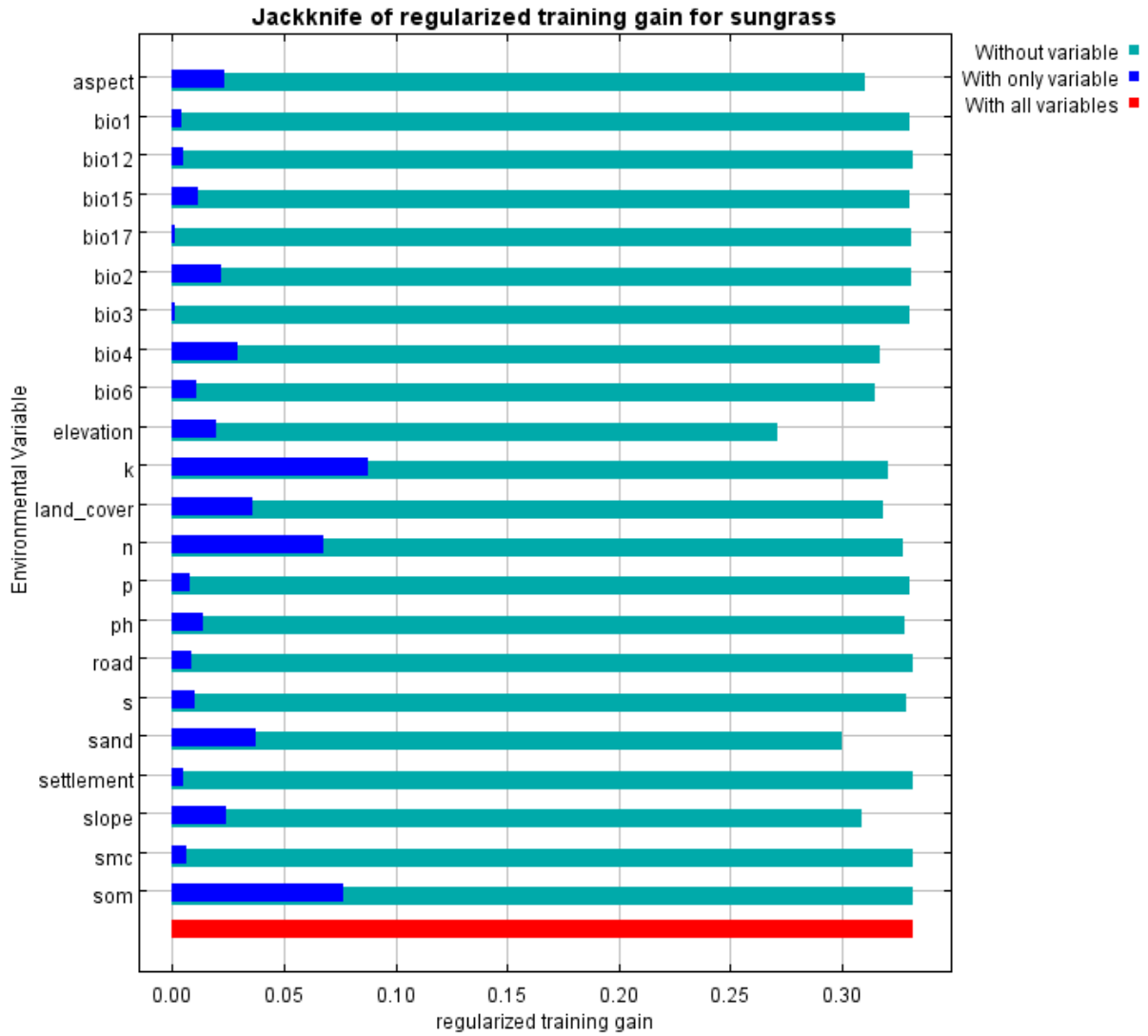


Fig. 13 Average gains for each variable (SSP 245- 2070)

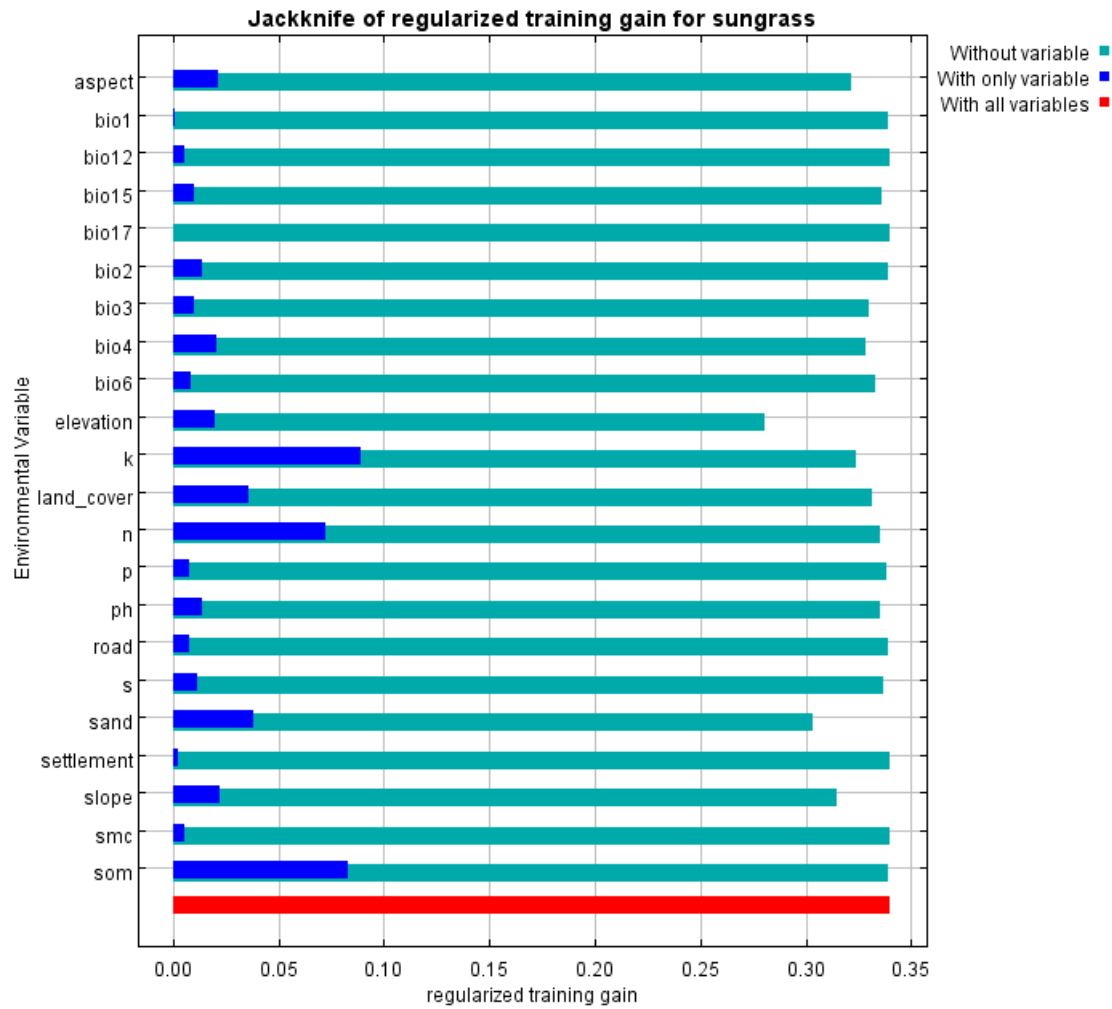


Fig. 14 Average gains for each variable (SSP 585- 2070)

3.2.4 Response curves of environmental variables

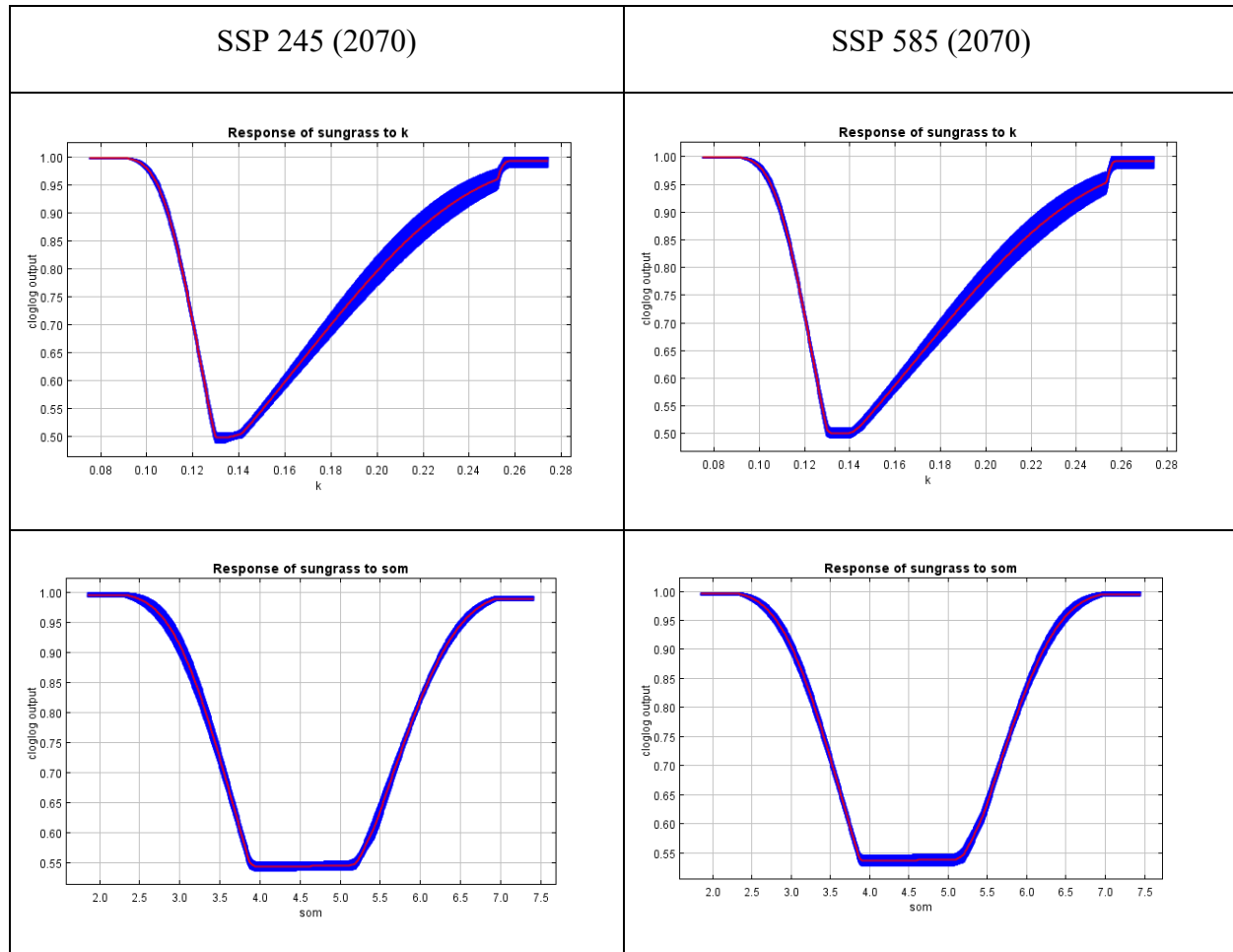


Fig. 15 Response curve of future model 2070 (SSP 245, SSP 585)

4 Discussion

The present study employed the MaxEnt model to predict the potential distribution of Sungrass habitats in both current and future periods in the Raghunandan Hills Reserved Forest, Bangladesh. The objective was to assess the influence of various environmental variables on the habitat distribution of Sungrass. To enhance the model's accuracy and relevance, the analysis incorporated Sentinel satellite data alongside locally collected environmental variables.

This analysis utilized the ACCESS-CM2 Global Climate Model (GCM) and two Shared Socio-economic Pathways (SSP245 and SSP585) to assess climate change impacts. These scenarios represent the latest conditions compared to the previous RCP 4.5 and RCP 8.5 from CMIP5 [44].

The choice of this model was driven by its relevance, data availability, and suitability for the study.

The distribution of species is often constrained by environmental factors [45]. Identifying these factors is crucial for enhancing species distribution models. In this study, among 22 environmental variables considered for the current distribution model, elevation (15.10%), soil organic matter (SOM, 15.00%), and potassium (K, 11.90%) emerged as the most significant contributors. The Jackknife test further confirmed that K was the most critical variable, followed by SOM and nitrogen (N).

For future projections, elevation remained a key variable across different scenarios. In the SSP 245 (2050) model, elevation contributed 16.00%, followed by SOM (15.20%) and K (14.70%). In contrast, K was the leading variable in the SSP 585 (2050) model, contributing 19.80%, followed by elevation (14.40%) and nitrogen (0.20%). Similar patterns were observed for SSP 245 and SSP 585 models for 2070 and 2090.

The current distribution model indicated that the Raghunandan Hills Reserved Forest generally provides suitable habitats for Sungrass, with the exception of the Shahajibazar beat. The analysis revealed 460 ha as highly suitable, 1042 ha as moderately suitable, 1707 ha as poorly suitable, and 1985 ha as unsuitable for Sungrass. Although the area classified as unsuitable was significant, the majority of the forest exhibited some degree of suitability for Sungrass, supporting the notion that the species can rapidly expand and colonize new areas [7]. The Satchchari, Jagadispur, and Shahpur beats were identified as particularly favorable habitats.

The threshold-independent evaluation demonstrated good performance for the current distribution model, with training AUC at 0.88 and test AUC at 0.84. These results confirm the feasibility of predicting Sungrass habitat distribution under current climate conditions, leading to the acceptance of the alternative hypothesis.

Future distribution models project notable changes in habitat suitability under various climate scenarios for 2050, 2070, and 2090. For 2050, the models anticipate a reduction in unsuitable areas and an expansion of poorly and moderately suitable habitats. The SSP 245 (2050) scenario projects 491 ha of highly suitable habitat, 1257 ha of moderately suitable habitat, and 1987 ha of poorly suitable habitat, with unsuitable areas declining to 1456 ha. In contrast, under the SSP 585

(2050) scenario, highly suitable habitats decrease to 455 ha, moderately suitable areas increase to 1210 ha, poorly suitable areas reach 1784 ha, and unsuitable areas decline to 1742 ha.

Model projections for 2070, considering both the SSP 245 and SSP 585 climate scenarios, demonstrate a consistent trajectory of habitat suitability change. Specifically, the SSP 245 scenario predicts a decline in highly suitable habitat to 438 ha, while moderately suitable and poorly suitable habitats increase to 1081 ha and 1733 ha, respectively. Similarly, under the SSP 585 scenario, highly suitable habitat is projected to decrease further to 430 ha, with corresponding expansions in moderately and poorly suitable categories.

The trends observed in 2090 mirrored those of 2050, indicating fluctuations in habitat suitability. In SSP 245 (2090), highly suitable habitats increased to 467 ha, moderately suitable habitats to 1201 ha, and poorly suitable habitats to 1956 ha, while unsuitable habitats decreased to 1569 ha. The SSP 585 (2090) condition revealed a decrease in highly suitable habitats to 445 ha, with increases in moderately and poorly suitable habitats.

While specific reasons for these changes were not within the scope of this study, the results indicate that climate change is likely to affect the distribution range of Sungrass in the Raghunandan Hills Reserved Forest.

5 Conclusions

This study employed the MaxEnt model to predict the current and future distribution of Sungrass (*Imperata cylindrica*) at Raghunandan Hills Reserved Forest in Habiganj, utilizing various environmental and locally collected variables. The potential current distribution was estimated using Sentinel satellite data, revealing that the entire reserved forest, except for one beat, exhibited some degree of suitability for Sungrass. Specifically, the current distribution model indicated 460 km² of highly suitable habitat, 1042 km² of moderately suitable habitat, 1707 km² of poorly suitable habitat, and 1985 km² of unsuitable habitat.

The potential future distribution of Sungrass was assessed for the years 2050, 2070, and 2090 using two climate change scenarios (SSP 245 and SSP 585). The accuracy of the predicted distributions was significantly higher than a random model, with threshold-independent

evaluation methods confirming that both current and future models (2050, 2070, and 2090) performed well ($AUC > 0.5$) under both climate scenarios.

While the current distribution model suggested that Sungrass could potentially thrive in various areas of the forest, the future distribution models indicated fluctuations in suitable habitat areas. In both climate scenarios, the likelihood of habitat increases and decrease for Sungrass was observed, reinforcing the possibility of predicting its distribution using environmental variables. Thus, the null hypothesis was rejected, and the alternative hypothesis was accepted.

Elevation emerged as the most influential variable in the current distribution model (15.1%), followed closely by soil organic matter (SOM) and potassium (K) at 15.0% and 11.9%, respectively. These variables consistently contributed significantly to Sungrass distribution across the future models (2050, 2070, and 2090) under both climatic scenarios. According to the Jackknife test, potassium (K), soil organic matter (SOM), nitrogen (N), and elevation were identified as the key determinants of Sungrass presence in the Raghunandan Hills Reserved Forest.

The analysis of habitat area distribution in 2050 and 2090 revealed similar trends in both SSP245 and SSP585 scenarios, although 2070 exhibited slightly different results. This suggests a potential alteration in the species' range due to changing climatic conditions.

Future research should explore additional local-scale variables influencing distribution, such as other soil nutrients and disturbance presence in the forest. Since the bioclimatic data used represent mean values from 1950 to 2000, they may not accurately reflect current conditions. Accessing local and reliable datasets can enhance model precision. Additionally, while bioclimatic data were utilized with a spatial resolution of 30 m², higher resolution data have been shown to yield better predictive models. Incorporating finer resolution bioclimatic data would likely improve the accuracy of the conclusions drawn from this study.

Author contributions

Mohammad Redowan: Conceptualization, Methodology, Supervision, Writing – original draft, Writing – review & editing, Resources. Md. Mokshedur Rahman: Writing – review & editing,

Methodology, Data curation, Software, Visualization. Akbar Hossain Kanan: Writing – review & editing, Investigation, Formal analysis.

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Data availability

The datasets generated during and/or analyzed during the study are available from the corresponding author on reasonable request.

Declarations

Ethics approval and consent to participate

No plant specimens were collected, removed, or destructively sampled during this study. Field investigations were conducted in accordance with applicable institutional, national, and international guidelines for plant research and biodiversity conservation. Necessary permissions to access and conduct vegetation surveys in the study area were obtained from the appropriate authorities before fieldwork. The research did not involve endangered or protected plant species requiring special collection permits. Plant species identification was conducted by Dr. Mohammad Redowan of the Department of Forestry and Environmental Science, Shahjalal University of Science and Technology, Sylhet.

Consent to publication

Not applicable.

Competing interests

The authors declare no competing interests.

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