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RESEARCH ARTICLE

Ensemble Habitat Suitability Studies of *Vetiveria zizanioides* (Linn.): An Important Genetic Resources with Aromatizing, Medicinal and Land Restoration Properties

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Abstract

This study evaluated *Vetiveria zizanioides* habitat suitability to its current bio-climatic, root zone characteristics, and land use types to two projected climatic timeframes (2050 and 2070) and four future greenhouse gas scenarios (RCP 2.6, RCP 4.5, RCP 6.0, and RCP 8.5). We compared seven machine learning techniques for habitat suitability modeling of this species utilizing presence records using these predictors. With all RCPs, the random forest and support vector machine algorithms yielded high-quality models. Finally, we used ensemble modeling (averaging of several techniques) to quantify this species' habitat suitability. According to our model, this species' optimal and moderate habitat types are distributed over the southern, south-west, and south-eastern zones, with marginally suitable areas interspersed in between. This species was shown to be unsuited for extreme western, northern, and eastern India in our research. Under both the current and 2070 RCP 8.5 scenarios, isothermality had the biggest effect, but the latter dropped the optimum range from 45–55% to 25–35%. In the RCP 2.6 to 8.5 scenarios for 2050, the precipitation of the wetest quarter (PrWeQ) for this species ranged from 500 to 3000 mm. Precipitation seasonality increases the likelihood of a habitat being favorable for a species. The optimal area, according to this study, is progressively reducing and will be largely in the south and south-west by 2050, with RCPs ranging from 2.6 to 8.5. This research can be used to identify areas that foster vetiver oil quantity and qualities and support higher biomass for land restoration and reclamation.

Keywords: *Vetiveria zizanioides,* Species distribution modeling, Random forest, Ensemble model, Bio-climatic, Root zone, Landcover variables.

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Introduction

Vetiveria zizanioides (Linn.) Nash is a perennial C_4 grass (Figure 1A) that belongs to the Poaceae family, prized for its aromatic and highly valued adventitious roots. *Vetiver* grass has many applications in ecological engineering and environmental restoration, including slope stabilization (Figure 1B and C, Eab *et al.,* 2015), erosion management (Cao *et al.,* 2015), and phytoremediation (Wasino *et al.,* 2019; Abaga *et al.,* 2021). Since the 1980s, this species has been advocated by the World Bank as a way to improve water management (D'Souza *et al.,* 2019). Our current understanding suggests that this grass species can survive in a broad variety of environments, from those with high salt and heavy metal contamination to those with poor fertility and high pH, as well as extended periods of drought and frequent flooding (Itusha *et al.,* 2019; Holanda *et al.,* 2022).

Additionally, its fibrous roots (Figure 1D) contain about 3% of oil on a dry weight basis, making it a particularly useful plant. One litter of oil extract requires about 250 kg of *V. zizanioides* root (Belhassen *et al.,* 2015). Oil from Reunion Island (France) is so superior that it's known as Bourbon oil. Global *vetiver* oil output is projected to reach

300 to 350 tons per year by 2022 (Gupta *et al.,* 2015; Lal *et al.,* 2021a) and the vetiver oil market is forecast to grow to $ 169.5 million by that same year (Durge and Moon, 2021). The quantity used and interest in it both rise each year. The main exporters of vetiver oil are Indonesia and Haiti, each shipping out between 50 and 100 tons per year. China, meanwhile, imports about 20 tons per year.

Large quantities of vetiver can be found in the Indian states of Uttar Pradesh, the South, and the peninsula. The fragrance, masticatory, attar, and soap sectors (Figure 1E) rely heavily on Indian vetiver oil, and although the country has over 10,000 ha of land dedicated to growing and cultivating the plant (Lal *et al.,* 2018), it only produces 100 tons of oil each year (Lal *et al.,* 2021b). Essential oils from various parts of the world have varied qualities and aromas because of their origins. Numerous studies have been conducted to learn how the agro-climatic conditions of various regions affect the oil content of vetiver through time and space (Ghani, 2003; Pripdeevech *et al.,* 2006; Hammam *et al.,* 2019; Holanda *et al.,* 2022). Northern Indian vetiver oil, in particular, has a reputation for excellence (Gupta *et al*. 2015).

Unfortunately, we still don't know how this species will respond to bio-climatic variables in the context of potential future greenhouse gas scenarios. In light of this, the purpose of the present study was to compare the potential growth of *V. zizanioides* under two future climatic timeframes (2050 and 2070) and four future greenhouse gas scenarios (RCP 2.6, RCP 4.5, RCP 6.0, and RCP 8.5) to its growth under its existing bio-climatic, root zone variable, and land use settings. In this research, we explain and analyze the findings of an evaluation of multiple algorithms for modeling species distributions using presence records of this species, and we do so in terms of an existing criterion for evaluating model quality. The results of such studies on a national scale are useful for evaluating its current and future status and determining whether or not it is essential to preserve.

Materials and Methods

Data Collection

Distributional records for *V. zizanioides* were obtained from data repositories such as the Global Biodiversity Information Facility [9;https://www.gbif.org/], the Indian Biodiversity Portal (https://indiabiodiversity.org/species/show/33318), published literature Lal *et al.,* 1997; Dudai *et al.,* 2006; Babalola *et al.,* 2007; Edelsterin *et al.,* 2009; Mickovski and Beek, 2009; Lal, 2013; Li *et al.,* 2014; Yaseen *et al.,* 2014; Gupta *et al.,* 2015; Liu *et al.,* 2016; Jaikaew and Nokkaew, 2019; Aziz, 2020, Chintani *et al.,* 2021; Ondo Zue Abaga *et al.,* 2021; Shuai *et al*. 2022) as well as from our field-based inventories (Mathur, 2005; Mathur and Mathur and Sundaramoorthy 2013a b and 2019). Using high-resolution Google Earth satellite image data and GIS ArcMap (Coban *et al.,* 2020), the locations of these sites were determined relative to the WGS84 coordinate datum. In addition, when occurrence data was not available, precise geo-coordinates were determined by utilizing Google Earth (http://ditu.google.cn/) to get latitude and longitude values. The distributional locales were compiled into a comma-separated value (.csv) database using the aforementioned sources).

To determine its IUCN conservation category in India, we used a CSV database file to analyze its extent of occurrence and area of occupancy (Sq. km). To accomplish this, we utilized the ConR R-based program.

Bio-Climatic (BC) Variables

Machine learning methods can use the current distribution of species to project their future movements (Sarikaya *et al.,* 2018; Wei *et al.,* 2018). WorldClim version 1.4 (https://worldclim.org/data/cmip6/cmip6clim30s.html) provided the observational data (bioclimatic variables: precipitation and temperature accessed on 21st October, 2023) used to predict the present and future distributions of species. We

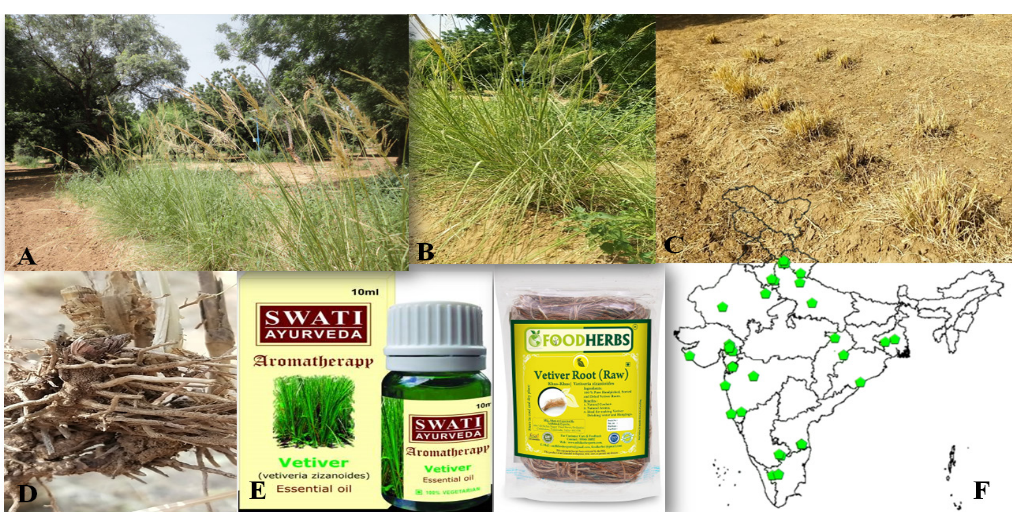

Figure 1: Pictorial representation of *Vetiveria zizanioides grass (A), use for slope stabilization (B), prevent sand movement (C),* its fibrous roots source of aromatic oil (D), marketed products of *V. zizanioides* (E) and *GPS points of natural population of this species (F).*

Table 1: Description of predictive bio-climatic variables use in this study (downloaded from WorldClim related to four timeframes: current, 2050 and 2070 Shared Socioeconomic Pathways (RCPs 2.0, 4.5, 6.0 and 8.5)

Code	*Environmental variables and their abbreviations*	*Scaling Factor*	*Unit*
BC-1	Annual mean temperature (AMT)	10	°C
BC-2	Mean diurnal range (MeDR)	10	°C
BC-3	Isothermality (BC2/BC7) (×100) (Iso)	100	Percentage
BC-4	Temperature seasonality (standard deviation ×100) (TempS)	100	°C
BC-5	Max temperature of warmest month (MaTWaM)	10	°C
BC-6	Min temperature of coldest month (MiTCM)	10	°C
BC-7	Temperature annual range (BC 5BC 6) (TAR)	10	°C
BC-8	Mean temperature of wettest quarter (MeTWeQ)	10	°C
BC-9	Mean temperature of driest quarter (MeTDQ)	10	°C
BC-10	Mean temperature of warmest quarter (MeTWaQ)	10	°C
BC-11	Mean temperature of coldest quarter (MeTCQ)	10	°C
BC-12	Annual precipitation (AnPr)	1	mm
BC-13	Precipitation of wettest month (PrWeM)	1	mm
BC-14	Precipitation of driest month (PrDM)	100	mm
BC-15	Precipitation seasonality (Coefficient of Variation) (PrS)	1	Percentage
BC-16	Precipitation of wettest quarter (PrWeQ)	1	mm
BC-17	Precipitation of driest quarter (PrDQ)	1	mm
BC-18	Precipitation of warmest quarter (PrWaQ)	1	mm
BC-19	Precipitation of coldest quarter (PrCQ)	1	mm

used DIVA-GIS version 7.5 (Coban *et al.,* 2020) to convert 19 bioclimatic variables (Hijmans *et al.,* 2005) for the present and two future climate scenarios to ASCII (or ESRI ASCII) at a spatial resolution of 10 arc seconds for India. In 2050 timeframe represents the mean values from 2041 to 2060 and the 2070 timeframe represents the mean values from 2061 to 2080 (Hijmans *et al.,* 2001; Zhang *et al.,* 2021). These are related to four RCPs (RCP 2.6, RCP 4.5, RCP 6.0, and RCP 8.5) and were downloaded. Table 1 lists the various bioclimatic parameters, their respective units, and their respective mathematical expressions and abbreviations.

Non-Bio-climatic variables

Root zone variables

The Global Climate Observation System's (GCOS) Terrestrial Observation Panel for Climate highlighted the 95% rooting depth as a critical variable required to quantify the relationships between climate, soil, and plants. The data on vertical root distribution was provided by the International Land Surface Climatology Project (ISLSCP), and it includes points of data from a wide variety of land coverings (evergreen needle leaf forest, evergreen broadleaf forest, deciduous broadleaf forest, mixed forest, wooded grassland, cropland, urban built-up and open shrub land, closed shrub land, bare ground, Schenk *et al.,* 2009). Data on this parameter was downloaded from http://daac.ornl.gov Rooting zone water storage (mm H_2O) was applied in the current research, which was calculated using the assimilation of NDVI-fPAR (fraction of Absorbed Photosynthetically Active Radiation) and atmospheric forcing data. In this research, estimations of the global distribution of the rooting zone's total plant-available soil water storage capacity ("rooting zone water storage size") on a 1.0-degree global grid (Ramankutty *et al.,* 2010a and b; Kleidon, 2011) were downloaded from https://daac.ornl.gov/ISLSCP II/guides/root water storage 1deg.html.

Land-Use-Land Cover Variables

For this study, we downloaded a geographical dataset at a resolution of 5 meters, which included information about five land cover/land use categories: barren and very sparsely vegetated land; irrigated cultivated land; rain-fed cultivated land; forest; and grass/scrub/wood land (Fischer *et al.,* 2008). Details of these variables are available at https://www.fao.org/soils-portal/data-hub/soil-maps-and-databases/harmonized-world-soil-database-v12/en/#jfmulticontent_c284128-4

Issue of multicollinearity

In order to look at cross-correlation, we employed the Pearson Correlation Coefficient (r), and we ran a multi-collinearity test to make sure we weren't over-fitting. Also, the Niche Tool Box was used to gradually eliminate variables

Table 2: Model qualities parameters with current bio-climatic and non-bio-climatic (solar and land cover) variables

Current BC, Solar and Landcover	*AUC*	*sensitivity*	*specificity*	*Kappa*	*TSS*
GLM	0.78	0.64	0.92	0.3	0.56
GAM	0.83	0.88	0.79	0.2	0.67
MARS	0.78	0.79	0.77	0.16	0.56
CTA	0.81	0.77	0.85	0.62	0.62
RF	0.85	0.82	0.9	0.69	0.7
ANN	0.8	0.85	0.76	0.02	0.61
SVM	0.84	0.92	0.76	0.69	0.68
ESDM	0.83	0.87	0.88	0.61	0.66

with cross-correlation coefficient values greater than or equal to 0.85 (Pradhan, 2016; Osorio-Olivera *et al.,* 2020 https://github.com/luismurao/ntbox). In this study, model training and model validation were assigned to 70 and 30% of the data, respectively (Obiakara and Fourcade, 2018).

Projection Assignment and their Transformations

Before extracting data and making predictions using the ensemble model, it is necessary to correct the projections of the Bio-Climatic (BC) and Non-BC variables, which were received from different sources and at different resolutions. In our analysis, we did this by following a set procedure in ArcMap with the help of ArcToolbox. The projection was initially outlined in the "projection and transformation" tab of the Data Management Tools interface. For this, we relied on the World Geodetic System 1984 EASE Geographic Coordinate System (GCS). We transformed the projections of the habitat class raster file to WGS 1984 web Mercator (auxiliary sphere-3857) in order to use the "calculate geometry" window of Arc Map to quantify area under each habitat suitability class (see below). To proceed, let's say we want to determine the region under a certain class using a measurement system of the user's choosing (we utilized square kilometers).

Species Distribution Modeling

The following algorithms from the Dismo 1.1-4 package (Hijmans *et al.,* 2017) were used for modeling: Generalized Linear Models using Gaussian distribution (GLM), generalized additive model (GAM) (Wood 2019), support vector machines (SVM), random forest (RF) (Breiman, 2001; Cutler, 2018), multivariate adaptive spline (MARS), and maximum entropy (Maxent v. 3.4.1; Phillips *et al.,* 2017; Layola *et al.,* 2022). Artificial neural network (ANN) (Ripley and Venables, 2020), and classification tree analysis (CTA) (Therneau *et al.,* 2019), the last two being executed through the biomod-2 package (Thuiller *et al.,* 2009). We used the default for all studied algorithms. We split up the SDM analysis into two parts: (a) determining which model or algorithm performed best based on predetermined evaluation criteria (discussed further down), and (b) doing modeling using an ensemble approach that included both climatic and non-climatic predictors.

For more accurate predictions, models were evaluated using K-fold cross-validation with ten folds and ten replications for each algorithm (Rajamanickam *et al*. 2021). For each replication, the data is randomly split into ten folds, and the model is evaluated using the other nine folds for calibration (Elith *et al.,* 2011). We measured the predictive algorithm's efficacy with six different metrics: overall accuracy (the percentage of correctly classified data), sensitivity (the probability of predicting the presence of a species), specificity (the probability of predicting the absence of a species), Cohen's Kappa (a measure of the correctness of predictions), true skill statistic (TSS), and area under the receiver operating curve (AUC). The TSS and KAPPA values typically range from 0.40 to 0.75, with values exceeding 0.75 indicating excellent model performance. The performance of a model is likely to be subpar if the value is less than 0.40. (Beaumont *et al.,* 2016; Ahmad *et al.,* 2019). The AUC was used to evaluate the classifier's performance on presence/absence datasets. When evaluating the AUC statistic, the following grades are used: exceptional (0.90–1.00), very good (0.8–0.9), good (0.7–0.8), fair (0.6–0.7), and poor (0.5–0.6).

A model's specificity measures accuracy in detecting absences. The sensitivity of a model is measured by how often it correctly identifies the existence of a target. Using their respective variable importance rankings, the contributions of bio-climatic and non-bio-climatic variables were determined (Irving *et al.,* 2019). To estimate the upper bound of the most influential predictors on the habitat appropriateness of this fungus, we used the getResponseCurve function of the sdm program in the R language (Naimi and Araujo, 2016).

Post Ensemble Analysis

Habitat suitability

ASCII raster outputs from the ensemble were imported into ArcMap, and cell values (0 to 1) were used to categorize habitats for this species. Based on the continuous point break criteria for each class (Khan *et al.,* 2022), we divide algorithms into four distinct categories based on their level of suitability: optimal, moderate, marginal, low, and absent/inappropriate. We used the raster calculator to determine the total area (in square kilometers) that falls into these categories (spatial Analyst Tool/Map Algebra/ Raster Calculator).

Non-Parametric Assessment of Internal Matrix of Habitat Classes

Each of the examined projections was subjected to a regression analysis to determine the link between the number of polygons and the total area covered by the four

Table 3: Model qualities parameters with 2050 bio-climatic times frames and four Representative Concentration Pathways

Algorithms	*2050 RCP 2.6*					*2050 RCP 4.5*				
	AUC	*Sensitivity*	*Specificity*	*Kappa*	*TSS*	*AUC*	*Sensitivity*	*Specificity*	*Kappa*	*TSS*
GLM	0.78	0.78	0.78	0.16	0.56	0.78	0.82	0.75	0.15	0.57
GAM	0.78	0.77	0.79	0.16	0.56	0.79	0.82	0.76	0.15	0.58
MARS	0.78	0.8	0.76	0.16	0.56	0.78	0.75	0.81	0.18	0.56
CTA	0.79	0.76	0.82	0.58	0.58	0.81	0.82	0.73	0.55	0.55
RF	0.85	0.93	0.87	0.7	0.7	0.85	0.84	0.9	0.68	0.74
MAXENT	0.79	0.85	0.73	0.02	0.58	0.78	0.82	0.75	0.02	0.57
ANN	0.82	0.87	0.76	0.64	0.64	0.77	0.79	0.76	0.55	0.55
SVM	0.85	0.92	0.77	0.6	0.7	0.84	0.94	0.74	0.61	0.68
ESDM	0.82	0.91	0.84	0.62	0.71	0.81	0.85	0.85	0.56	0.7
Algorithms	*2050 RCP 6.0*					*2050 RCP 8.5*				
	AUC	*Sensitivity*	*Specificity*	*Kappa*	*TSS*	*AUC*	*Sensitivity*	*Specificity*	*Kappa*	*TSS*
GLM	0.79	0.82	0.76	0.14	0.58	0.78	0.82	0.75	0.15	0.57
GAM	0.82	0.89	0.76	0.16	0.65	0.80	0.82	0.76	0.15	0.58
MARS	0.78	0.8	0.76	0.15	0.56	0.78	0.75	0.81	0.18	0.56
CTA	0.82	0.91	0.71	0.62	0.62	0.77	0.82	0.73	0.55	0.55
RF	0.85	0.91	0.87	0.67	0.78	0.83	0.89	0.89	0.69	0.78
MAXENT	0.79	0.82	0.76	0.02	0.58	0.78	0.82	0.75	0.02	0.57
ANN	0.81	0.89	0.69	0.58	0.58	0.77	0.79	0.76	0.55	0.55
SVM	0.83	0.91	0.75	0.62	0.66	0.84	0.94	0.74	0.61	0.68
ESDM	0.82	0.86	0.81	0.57	0.67	0.82	0.91	0.84	0.69	0.75

analyzed habitat suitability classes: optimal, moderate, marginal, and low.

Network analysis, a graphical statistical tool, allows for easy visualization and comprehension of relationships between many different variables. In contrast to latent variable modeling, where the structure of the variables is attempted to be reduced to their shared information, we instead directly estimate the relationship between all variables (refers to a diverse group of statistical techniques that employ one or more unobserved variables to explore and explain relationships between a larger set of observed variables, such as regression analysis, principal component analysis and structural equation modeling). Networks are graphical structures comprised of nodes, which are typically circles representing variables. Connections between nodes are represented by lines called edges. Both un-weighted and weighted networks exist. While in unweighted networks, an edge just indicates a connection between nodes, in weighted networks, it also indicates the strength of that connection. A thicker link between two nodes indicates a stronger bond between them.

Both directional and non-directional networks exist. In the former, edges that represent a line of influence or a route between nodes are marked with arrows. Without arrows, a non-directional network's edges are just straight lines that don't indicate anything about the order in which the variables' interactions should be explored (Epskamp *et al.,* 2018). To better comprehend the connections between the four habitat suitability classes and their respective predictors—the present BC+NBC, 2050, and 2070 with RCPs ranging from 2.6 to 8.5, we used the non-directional weighted network analysis in JASP software (Love *et al.,* 2019).

Results

Based on data gathered from a variety of sources, we were able to pinpoint the exact GPS coordinates of 46 distinct natural populations of this species across India. We used these locations to evaluate the ecological niche of this species under a range of climatic and non-climatic conditions. Figure 1F shows a graphical representation of various locations. The current extent of occurrence (EOO) and area under occupation (AOO), according to our IUCN assessment, were 2123159 and 126 sq. km. These findings indicated a least concern category with EOO greater than 20,000 km^2, but with AOO it might be considered an

Table 4: Model qualities parameters with 2070 bio-climatic times frames and four Representative Concentration Pathways.

Algorithms	*2070 RCP 2.6*					*2070 RCP 4.5*				
	AUC	*Sensitivity*	*Specificity*	*Kappa*	*TSS*	*AUC*	*Sensitivity*	*Specificity*	*Kappa*	*TSS*
GLM	0.79	0.85	0.74	0.14	0.59	0.78	0.86	0.7	0.14	0.56
GAM	0.77	0.78	0.77	0.14	0.55	0.78	0.86	0.7	0.14	0.56
MARS	0.80	0.8	0.78	0.16	0.58	0.80	0.79	0.78	0.19	0.57
CTA	0.78	0.8	0.77	0.57	0.57	0.81	0.73	0.89	0.62	0.62
RF	0.87	0.9	0.88	0.74	0.78	0.82	0.88	0.85	0.68	0.73
MAXENT	0.8	0.84	0.77	0.02	0.61	0.78	0.82	0.73	0.01	0.55
ANN	0.82	0.86	0.77	0.64	0.63	0.82	0.91	0.73	0.64	0.64
SVM	0.83	0.89	0.77	0.67	0.66	0.82	0.92	0.71	0.64	0.63
ESDM	0.81	0.88	0.82	0.58	0.7	0.81	0.84	0.86	0.58	0.7
Algorithms	*2070 RCP 6.0*					*2070 RCP 8.5*				
	AUC	*Sensitivity*	*Specificity*	*Kappa*	*TSS*	*AUC*	*Sensitivity*	*Specificity*	*Kappa*	*TSS*
GLM	0.78	0.79	0.78	0.18	0.57	0.75	0.64	0.87	0.2	0.51
GAM	0.81	0.82	0.81	0.25	0.63	0.76	0.73	0.78	0.14	0.51
MARS	0.80	0.73	0.85	0.21	0.58	0.81	0.82	0.73	0.13	0.55
CTA	0.81	0.84	0.78	0.62	0.62	0.82	0.82	0.82	0.64	0.64
RF	0.84	0.88	0.87	0.75	0.75	0.84	0.89	0.87	0.67	0.76
MAXENT	0.79	0.77	0.81	0.03	0.58	0.8	0.82	0.79	0.02	0.61
ANN	0.87	0.81	0.79	0.75	0.6	0.8	0.91	0.7	0.61	0.61
SVM	0.86	0.84	0.85	0.68	0.69	0.81	0.82	0.81	0.6	0.63
ESDM	0.81	0.84	0.83	0.64	0.67	0.82	0.87	0.79	0.58	0.66

endangered species due to its AOO being less than 500 km^2. Of the 46 sites in the natural population identified by our research, 32 can be classified as subpopulations. We were able to rule out one of the bio-climatic variables that were part of a strongly correlated pair using a multi- collinearity test.

Comparative Assessment of Various Algorithms

We used AUC, Kappa, and TSS to compare the predictive abilities of different machine learning algorithms, including GLM, GAM, MARS, CTA, RF, ANN, SVM, and an ensemble approach (ESDM). For the current set of BC and NBC variables (Table 2), we observed that random forest (RF) performed best. When comparing the aforementioned algorithms, we found that while their AUC values were comparable, their Kappa values varied considerably. Random Forest and SVM both achieved the highest value (0.69). Conversely, ANN yielded the lowest value (0.02). In addition, RF has the highest TSS value. Tables 3 and 4 presented outcomes of model quality parameters for the 2050 and 2070 climatic timeframes using different RCPs. All RCP values greater than 0.80 were observed for the RF and SVM algorithms, indicating excellent model qualities. Both of these methods had TSS values above 0.60, indicating that they produced satisfactory models. In contrast, the lowest Kappa values were found for GLM, GAM, and MARS, indicating that these machine learning tools are not well suited for making predictions about the habitat suitability of this species. Both the AUC and TSS for the ensemble model, including all of the studied factors, were over 0.80 and 0.65, respectively, showing excellent predictive power.

Assessment of Variables Importance for Habitat Suitability Model

The current bio-climatic, root-zone, and land-cover variables that regulate the different types of habitat suitability for this species are shown in Table 5. Grassland/scrub/forest cover (VIP = 18.86) and isothermality (VIP = 10.6; which is reliant on temperature), were the two most influential bio-climatic indicators. The total plant-available soil water storage capacity in the rooting zone (TPASWSCRZ) was found to have a moderate effect on root zone variables, with a variable importance percentage (VIP) value of 7.7. Other than the above parameters, minimum temperature of the coldest month (BC-6); annual temperature range (BC-7); annual precipitation (BC-12); precipitation seasonality (BC-15); irrigated and rain-fed cultivated lands had VIP values greater than 4.0, implying that both bio-climatic and non-

Table 5: Percentage contribution (or Variable Importance Percentage) of different current Bio-climatic, solar and landcover variables

Current BC, Solar and Landcover Variables		*VIP*
Bio-Climatic Variables	Isothermality (BC-3)	10.6
	Maximum Temperature of Warmest Month (BC-5)	4.82
	Minimum Temperature of Coldest Month (BC-6)	5.50
	Temperature Annual Range (Bc-7)	5.36
	Mean Temperature of Driest Month (BC-9)	3.40
	Mean Temperature of Warmest Quarter (BC-10)	1.77
	Mean Temperature of Coldest Quarter (BC-11)	2.40
	Annual Precipitation (BC-12)	7.91
	Precipitation Seasonality (BC-15)	5.74
Root Zone Variables	Ecosystem (95%) Rooting Depth (ERD)	4.27
	Total Plant-Available Soil Water Storage Capacity of the Rooting Zone (TPASWSCRZ)	7.7
Landcover Variables	Barren and very sparsely vegetated land	3.45
	Irrigated Cultivated Land	6.89
	Rain-Fed Cultivated Land	6.25
	Forest	4.97
	Grass/Scrub/Woodland	18.86

bioclimatic factors control its current habitat types.

Table 6 displays the VIP values of bio-climatic variables for the years 2050 and 2070 under different RCPs. Precipitation of the wettest quarter (BC-16 PrWeQ) was found to be the most influential variable for this species in 2050 across all four RCPs. Using this information, the results showed that annual precipitation (BC-12; AnPr) and isothermality (BC-3) were the next most influential elements, with RCPs of 2.6 and 4.5, and RCPs of 6.0 and 8.5, respectively (Table 6).

Moreover, under RCP 2.6 and 6.0 for the 2070s, precipitation seasonality (Coefficient of Variation (BC-15 PrS) was found to be the most relevant component, with VIPs of 24.74 and 24.80, respectively. Nonetheless, the most important components for RCP 4.5 and 8.5 were found to be precipitation of the coldest quarter (BC-18; PrCQ) and isothermality (BC-3), with VIPs values of 22.79 and 22.66, respectively (Table 5). It was shown that the driest month precipitation (BC-14; PrDM) had the lowest relative contribution to change (RCPs of 2.6, 6.0, and 8.5). Maximum temperature in warmest month (BC-5; MaTWaM) is an example of an energy variable that RCP4.5 finds to be the least relevant. These findings suggest that water-related factors will ultimately determine whether or not this species' current habitat will continue to be suitable for it in the future. Using response curves, we were able to quantify the relationship between the presence of *V. zizanioides* and a range of environmental variables, thereby enhancing our understanding of the species' ecological niche. (Figure 2). Although isothermality was found to be an influential factor in both the present and 2070 RCP 8.5 scenarios, the optimal isothermality ranged from 25 to 35% under the current conditions and 45 to 55% under the 2070 RCP 8.5 scenarios. Analyses using RCP 2.6 to 8.5 for the year 2050 showed a greater range (500–3000 mm) of precipitation of the wettest quarter (PrWeQ) for this species (Figure 2). The unpredictability of precipitation is reflected in the seasonality of precipitation (BC-15), with higher percentages indicating greater variability. Our research shows that the species under study is able to thrive in areas with a wider range of precipitation variability and that the suitability of habitat for this species increases rapidly with increasing precipitation seasonality. 2070 RCP 4.5 warmest quarter (BC-18; PrWaQ) precipitation projections showed a significant improvement in habitat for this species, up to 500 mm.

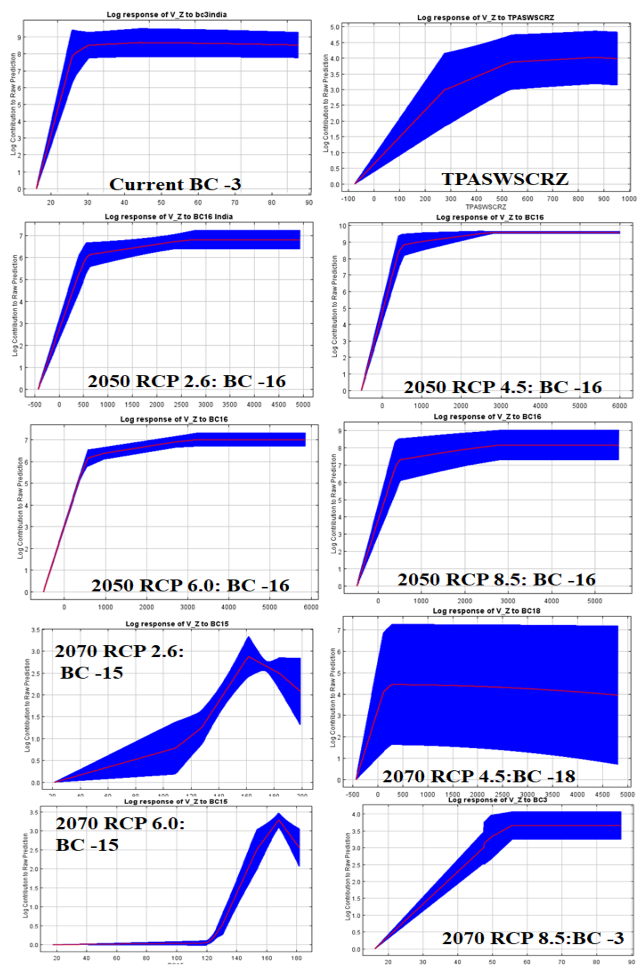

Figure 2: Response curves showing dependence of habitat suitability of *V. zizanioides* with most important variables pertains to different climatic timeframe, RCPs and non-climatic variables

Table 6: Percentage contribution (or Variable Importance Percentage) of Bio-climatic variables of two-time frames with four RCPs. Bioclimatic variables with higher VIP values were used to make the link between species and their environment

Variables	2050				2070			
	RCP 2.6	RCP 4.5	RCP 6.0	RCP 8.5	RCP 2.6	RCP 4.5	RCP 6.0	RCP 8.5
BC-1	7.21	x	x	x	x	x	x	x
BC-3	x	6.90	14.96	13.86	13.81	12.83	11.32	22.66
BC-4	8.20	x	x	x	x	x	x	x
BC-5	x	3.78	6.08	5.10	7.78	6.10	x	12.88
BC-6	x	4.37	10.40	7.79	x	9.45	4.49	x
BC-7	3.75	x	x	x	x	7.06	x	x
BC-8	3.44	6.0	6.84	6.19	7.69	9.5	x	12.86
BC-9	x	11.32	9.17	7.63	10.57	x	14.72	x
BC-10	5.24	3.47	7.09	5.57	x	x	5.0	x
BC-11	x	x	x	x	x	x	x	x
BC-12	17.67	16.13	x	x	x	x	x	x
BC-13	x	x	x	x	x	22.15	19.54	x
BC-14	6.99	12.57	5.13	4.69	5.73	x	6.65	4.20
BC-15	14.4	x	x	10.85	24.74	10.0	24.80	12.19
BC-16	18.50	21.09	20.79	19.29	13.78	x	x	19.50
BC-17	6.77	5.65	6.59	5.83	6.91	x	x	4.52
BC-18	7.74	8.78	12.91	13.19	8.96	22.79	13.43	11.16

x =eliminated variables due to their significant co-linearity with other variables

Table 7: Area under different habitat suitability classes of --- with studied bio-climatic and non-bioclimatic variables

	Habitat Suitability Classes (Sq. Km.)			
Projections	Optimum	Moderate	Marginal	Low
Current BC+NBC*	137595.41	1196523.70	1122624.31	500677.47
2050 RCP 2.6	91910.45	1380420.14	1206374.25	330904.42
2050 RCP 4.5	51140.08	865688.25	1154459.85	867698.00
2050 RCP 6.0	116271.13	1255448.17	1217124.55	531528.35
2050 RCP 8.5	51049.55	658782.93	1701987.07	505182.51
2070 RCP 2.6	73212.83	826888.05	1608108.96	358589.61
2070 RCP 4.5	123293.74	1251106.89	1286825.39	198589.61
2070 RCP 6.0	106214.45	718015.16	1704007.06	535545.43
2070 RCP 8.5	133593.34	1069453.86	1402216.93	511527.66

NBC* root zone and Landcover variables

Spatial Extent (Square Kilometres) of different Habitat Classes under various Projections

Table 7 shows the area (square kilometers) that falls into each of the four analyzed habitat suitability classes (optimum, moderate, marginal, and low). Their spatial range suggests that the optimum area is largest with current BC, root zone, and land cover variables (13,7595.41 km^2), and the smallest with 2050 RCP 8.5 (51,094.95). The marginal habitat class showed the opposite pattern, with the largest area (1701987.07) reported for 2050 RCP 8.5 and the smallest area (1122624.31) recorded under current BC, root zone, and land cover variables. The largest area covered by the moderate category (1380420.14) was found for 2050 RCP 2.6, while the smallest area (65872.93) covered by this category was found for 2050 RCP 8.5.

Figure 3 (current BC and 2050) and Figure 4 (2070) depict

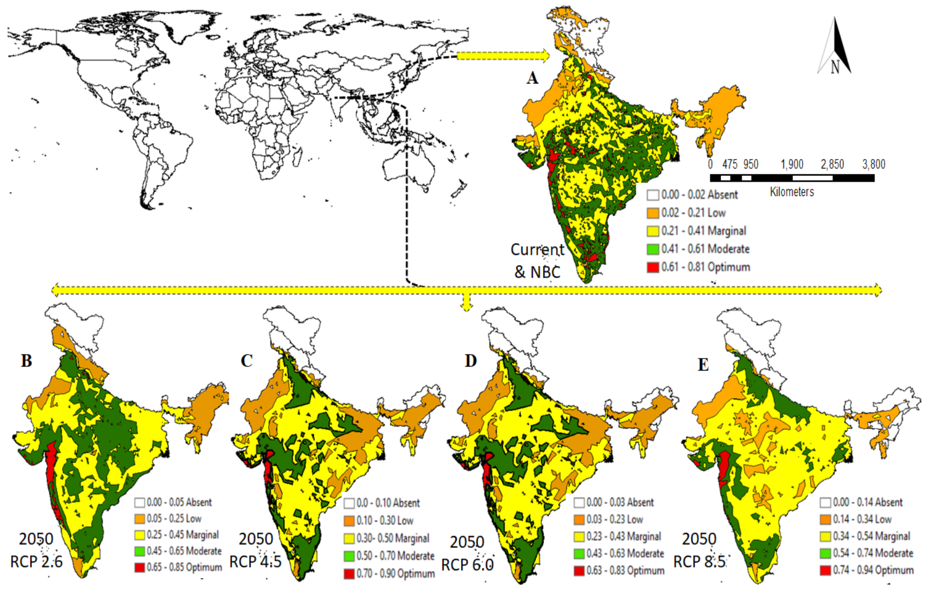

Figure 3: Habitat suitability of *V. zizanioides current bioclimatic and non-bioclimatic (A) as well as* with 2050 bio-climatic predictors (B) RCP 2.6; (C) RCP 4.5; (D) RCP 6.0 and (E) RCP 8.5.

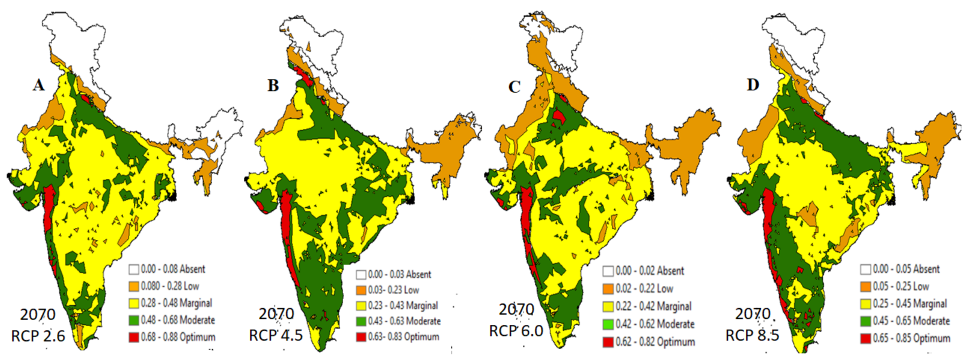

Figure 4: Habitat suitability of *V. zizanioides* with 2070 bio-climatic predictors (A) RCP 2.6; (B) RCP 4.5; (C) RCP 6.0 and (D) RCP 8.5.

the spatial extents of these classes. Using current bio-climatic, root zone, and land cover variables (Figure 3A), this analysis concluded that parts of Gujarat (Somnath, Anand, Vadodara, Surat), Maharashtra (Vapi, Silvasa, Nasik, Mumbai, Kolhapur, Chandoli National Park, Malkapur), and Karnataka (Topinkatti, Khnapur, Nandgad) are the best places for this species. Similarly, southern locations such as Thuraiyur, Mayanur, Pallapatii, and Chennimalai in Tamil Nadu, as well as some northern places such as Ayodhya, Kanpur, Pryagraj, and Etowah in Uttar Pradesh, have been identified as optimal areas. While the majority of eastern Indian states, such as West Bengal, Odisha, Chhattisgarh, and Jharkhand, as well as parts of Bihar, provide a moderate habitat for this species (Figure 3). Tamil Nadu, Karnataka, western territories such as Gujarat, and sections of Madhya Pradesh (Central India) have also been recognized as moderate sites. The majority of Madhya Pradesh, Haryana, and Uttar Pradesh are marginal areas for this species, whereas Nagaland, Arunachal Pradesh, Assam, Manipur, Mizoram, and western dry areas of Rajasthan have been recognized as low suitable habitats for this species under present climatic circumstances.

With a 2050 estimate and RCPs from 2.6 to 8.5 (Figure 3 B to E), the analysis shows that the optimum area is shrinking and becoming more concentrated to the south-west. Specific tendencies for modest area contraction and marginal area expansion were also observed. We found optimum habitats in Uttar Pradesh, Bihar, Uttarakhand, Madhya Pradesh, Punjab, Haryana, and the Southern Ghats using 2050 RCP2.6. From RCP 4.5 to RCP, such optimum zones will erode and be replaced by marginal areas. This analysis demonstrates the emergence of low-appropriate habitat types in various parts of central India with 2050 RCP 8.5 as

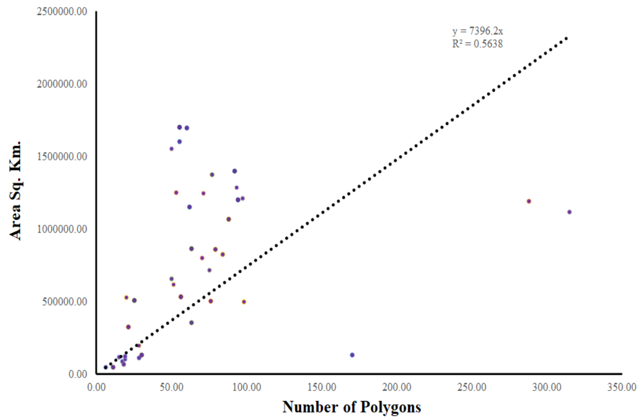

Figure 5: Regression analysis between number of polygons and areas under different suitability class with studied climatic and non-climatic projections (Includes all RCPs)

compared to the current condition (Figure 3). The south-western regions of a country are predicted to be optimum under all RCP scenarios from 2.6 to 8.5 in 2070 (Figure 4 A to D). Intriguingly, RCP2.6 and 6.0 showed higher moderate-area loss than RCP4.5 and 8.5. (Figure 4).

The optimal habitat for this species is just 4.19% of India's total land area, while the lowest value for this category (1.55%) was recorded with 2050 RCP 8.5. (Table 8). From the current BC, root zone, and land cover variables to other climatic epochs and the RCPs projection, it has been documented that the area occupied by this optimum category is steadily decreasing. Although this group has seen minimal land area expansion since 2050, this trend does not appear to have reversed by 2070. Moderate (41.99%) and low (26.40%) habitat types both had significant increases in area with a 2050 climate time frame but with RCP 2.6 and RCP 4.5, respectively (Table 8). Across all variables tested, we found a linear relationship between the number of polygons and their total area (square kilometers) and it can be equated as area (Sq. Km.) = 7396.20 x number of polygons ($R^2 = 0.56$ $p > 0.01$; Figure 5).

Figure 6 depicts the results of the network analysis. This non-parametric test for assessing the internal matrix of different habitat classes identified with different bio-climatic projections and RCPs. It revealed a significant negative relationship between current habitat classes (optimum, moderate, marginal, and low) and all RCPs of optimum and moderate habitat types in 2050 and 2070. However, such connections were only documented for the marginal class with 2070 and RCPs. For all habitat classes, we found substantial intra-RCP connections of bio-climatic time frame with distinct RCPs.

Table 8: Per cent of total land area of India

Projections	Habitat suitability classes			
	Optimum	Moderate	Marginal	Low
Current BC+NBC	4.19	36.40	34.15	15.23
2050 RCP 2.6	2.80	41.99	36.70	10.07
2050 RCP 4.5	1.56	26.33	35.12	26.40
2050 RCP 6.0	3.54	38.19	37.03	16.17
2050 RCP 8.5	1.55	20.04	51.78	15.37
2070 RCP 2.6	2.23	25.15	48.92	10.91
2070 RCP 4.5	3.75	38.06	39.15	6.04
2070 RCP 6.0	3.23	21.84	51.84	16.29
2070 RCP 8.5	4.06	32.53	42.66	15.56

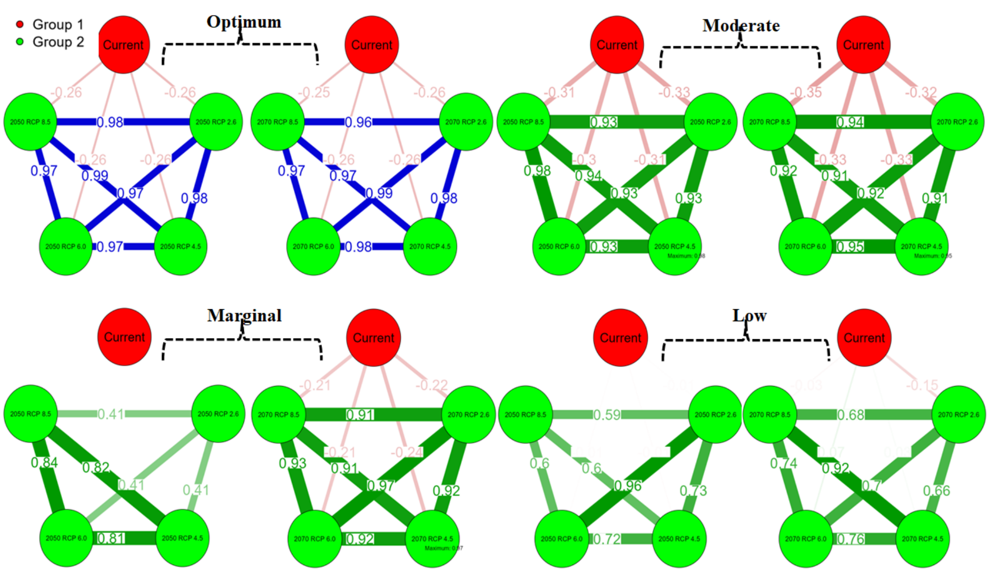

Figure 6: Network comparison between the areas (Sq. km.) classified under different suitability classes with different projections. Circle represent the projection; line or edge showed relationship with different nodes (edge width also corresponds to the strength of their

Discussion

Given the rapid pace of climate change, SDM has emerged as the most important method for predicting species' distributions and informing management decisions. In addition, the IUCN has started to formally incorporate SDMs for determining the frequency of occurrence as a proxy for extinction risk and for studying the impacts of climate change on species distribution (Cassini, 2011). Researchers in the Indian subcontinent have mostly relied on a single model approach, such as Maxent, when simulating the patterns of plant species' distributions. This has the potential to lower prediction accuracy and consequently lower confidence in projected species distributions (Bhandari *et al*., 2020; Boral and Moktan, 2021; Purohit and Rawat, 2021; Shekhar *et al*., 2022). In contrast to the standard practice, which relies solely on one algorithm (Maxent), we use a suite of seven algorithms (including Maxent) to predict the distribution dynamics of *V. zizanioides* and conduct a risk assessment across the entirety of India. When compared to single-model algorithms, the ensemble modeling approach provides several benefits (Ahmad *et al.,* 2019; Hamid *et al.,* 2019). (Mathur and Mathur, 2023). This study adds to the findings of Kumari *et al*. (2022), showing that using an ensemble approach to predict species distributions improves both the accuracy and confidence with which those predictions can be made. AUC, Kappa, and TSS were used to compare GLM, GAM, MARS, CTA, RF, ANN, SVM, and ESDM. SVM algorithms had good model quality, but RF performed best with BC and NBC variables. AUC and TSS of ensemble models with all predictors > 0.80 and > 0.65 indicate very good model predictive power.

From the perspective of protecting biodiversity, models of species distribution are crucial. They make maps by drawing on relationships between environmental factors and occurrence data on species' distributions. These maps are useful for gaining ecological understanding and making predictions about the distribution of species in various habitats. The evolution of SDM has aided biodiversity conservation by bridging the gap between research and policymaking. With the help of SDM, interested groups can determine with precision where to direct their efforts. Other uses include understanding the effects of climate change, cataloging species diversity, and pinpointing prime locations for preservation and reintroduction efforts. We found no previous research that attempted to predict whether or not the entire range of *V. zizanioides* in India would contain a variety of habitat types that were conducive to the survival of this species. Our findings have direct implications for identifying areas that support higher above- and below-ground biomass, which is significant because vetiver has the potential to be a candidate for land restoration and reclamation, as well as for selecting appropriate habitats that foster vetiver oil quantity and quality.

By using data from 46 natural population sites, we determined the EOO and AOO according to IUCN criteria, and our analysis places this species in the least concern and endangered categories, respectively and providing vital information to conservationists about the species' distribution and how to best ensure its survival. Khan *et al*. (2022) found analogous things for *Pinus geradiana* in the Himalayas.

In present, our model predicts that this species' optimal and moderate habitat types are dispersed across the southern, south-west, and south-eastern zones, with marginally suitable areas presented here and there in between the aforementioned two classes. However, as we progressed through the climatic time frame and RCPs, we noticed two distinct patches of optimum and moderate areas located in opposite directions (Figures 3 and 4), roughly northern and southern. In contrast, marginal habitat types occupy the majority of central India. Based on our research, it appears that the western, northern, and eastern parts of the country are not good places to grow this species. SDM modeling of such patchy behavior for various plant species has been reported by researchers from different regions of the country, including Song *et al*. (2004), Xiaodan *et al*. (2011), Rashid *et al*. (2015), Manish *et al*. (2016), and Hamid *et al*. (2018). Such studies, however, reported the likelihood of a shift in vegetation and a rearrangement of plant assemblages to the north, both of which can be linked with future warming as predicted. Based on the predators we've studied, we know that this particular species prefers to head in a south-westerly direction.

There are two different kinds of vetiver. Unlike its southern Indian counterpart, the northern Indian variety is typically smaller and is gathered from the wild rather than farms. Even in wet conditions, it will reliably bloom and produce seed. The other variety is a staple in agriculture and is thought to have originated in southern India, where it was domesticated. It produces almost no usable seeds and has a low flowering rate, so it must be grown from cuttings (Lal *et al.,* 2021b). The use of vetiver as a permanent field boundary and in contour strips in southern India has been shown to be effective in reducing soil erosion. Due to low night-to-day temperature swings and an early start to the monsoon season, February and April are ideal for planting in South India (Lal *et al*., 2018).

In North Indian varieties, self-sown seeds lead to abundant seeding and natural regeneration. The typical seed yield per hectare is between 400 and 650 kilograms. The newly harvested spikelets are underdeveloped and will need to sit for an additional three months. Taking the caryopsis out of its shell helps the seed germinate. Most spikelets on south Indian varieties are sterile, and the thin, short-germinating seeds that are occasionally produced are not very hardy. The rhizome is not disturbed when propagating these non-seeding varieties; instead, the 15 to 20 cm long aerial portion is used to produce slips for further growth. North Indian varieties take only 35 to 40 hours to distill due to their high boiling point and low volatile oil content, while south Indian varieties take 72 to 96 hours. Two different oil fractions can be extracted from vetivers, one of which is lighter than water and the other of which is heavier. Oil's quality rises as its density rises. Finding out what traits this species possesses that will allow it to thrive in the central Indian plains and other moderately favorable sites in 2050 and 2070 under RCP 2.6, 4.5, and 6.0 would be a top priority for researchers based on the results of this study (Figures 3 and 4). In addition to assessing the influence of climatic predictors, we also evaluated the effect of landcover and root zone variables in our study, which is something that hasn't been done before for grass or Poaceae genera. Grassland/scrubland/woodland land cover type is the strongest predictor for this species, followed by isothermality and then barren, irrigated, rain-fed, and forest. In agreement with Lu *et al.* (2019) this finding suggests this species as a possible candidate for grassland restoration and management. To the best of our knowledge, this study was the first to apply Total Plant-Available Soil Water Storage Capacity of the Rooting Zone (TPASWSCRZ) to the modeling of the distribution of any indigenous Indian plant species. When precipitation is spotty and intermittent, as is typical in tropical countries like India, TPASWSCRZ values have a significant impact on grain crop yields.

Crop response to nutrient applications is influenced by a number of factors, including the efficiency with which nutrients are taken up by the plant and used by the plant (Leenaars *et al.,* 2015). According to the TPASWSCRZ response curves (Figure 2), the species' habitat becomes more and more suitable at an exponential rate. It rises to a maximum of 600 mm and then levels off at 900 mm. Therefore, one must guarantee this minimum level of soil water storage to boost its biomass. Dudai *et al.* (2006), who found that it thrives in regions with a moderately humid climate and annual rainfall of 1000 to 2000 mm, reached the same conclusion. Conventional wisdom holds that climate is the single most important factor in determining where species can be found, as it reveals crucial details about the kinds of environments in which they can thrive (Marino *et al.,* 2011). Furthermore, three precipitation-related variables (Precipitation of Driest Month, Precipitation Seasonality, and Precipitation of Warmest Quarter) were found to significantly influence the distribution of *Betula utilis* by Hamid *et al.* (2019).

Among temperature-related factors, the diurnal temperature range and isothermality were the most important. *Vetiveria* can grow in temperatures as low as -15°C and as high as +55°C. At 25°C, soil is at its most conducive to root development. Temperatures below 5°C trigger root dormancy. The shoots may turn purple and wither or even die in cold weather, but the underground growing points remain alive and will quickly sprout again once the weather warms up.

Visualizing the responses of key bio-climatic variables to *V. zizanioides* suitability, as indicated by the Variable Importance (VI) score and their response curves, can shed light on this species' ecological niche. Under both the current and 2070 RCP 8.5 scenarios, isothermality was found to have the greatest effect; however, under the latter, the optimal range for this climatic parameter is reduced from 45–55% to 25–55%. The precipitation of the wettest quarter (PrWeQ) for this species varied more widely, from 500 to 3000 mm, across the range of representative concentration pathways (RCP) 2.6 to 8.5 for the year 2050. (Figure 2). The BC-15 seasonality of precipitation metric is a reflection of the rainfall variability, with larger percentages indicating more pronounced swings. Our findings demonstrated that this species does well in regions with a greater degree of precipitation variability and that the suitability of habitat for this species raises precipitation seasonally. With 2070 RCP 4.5 warmest quarter (BC-18; PrWaQ) precipitation, up to 500 mm, the suitability of this species significantly increased.

The northwest Himalayan perennial herb *Rheum webbianum* was found to be most sensitive to the amount and timing of precipitation during the driest month and the seasonality of precipitation (Wani *et al.,* 2021). Global habitat suitability for the annual grass *Cenchrus spinifex* was predicted by Cao *et al.* (2021) in light of present and future climate change scenarios. Under the RCP 2.6 and RCP 8.5 scenarios, they found that *C. spinifex* would have less suitable habitats than it does now in 2050 and 2070. The seasonality of precipitation (bio15), the mean temperature of the warmest quarter (bio10), the mean temperature of the coldest quarter (bio11), and the precipitation of the driest quarter (bio17) together accounted for 96.8% of the variance, indicated that optimal conditions for *C. spinifex* growth appear to be determined by temperature and precipitation. Previous research (Liang *et al.,* 2016 and 2018; Wang *et al.,* 2018 and 2021) and our own results agree that the annual total precipitation and its seasonal variation pattern, as well as temperature variations and their seasonality, are the most influential variables for its habitat suitability. Consistent with our findings, Chen *et al.* (1991) determined that the optimal temperature range for vetiver grass growth in the current bioclimatic conditions is between 25 and 30℃. According to Verma (2020) findings, the optimal range of isothermality would rise from 25 to 35% under current conditions to 45 to 55% by 2070 under RCP 8.5 scenarios.

This is in line with the well-known trait and biogeographical differences between the distributions of C_3 and C_4 species (Pau *et al.,* 2013), which show that C_4 species, on average, have a higher optimal temperature and water-use efficiency and thus prefer drier habitats at lower latitudes. In their modeling of C_3 and C_4 grass species' distributions, Havrilla *et al.* (2022) found that these species' distributions are extremely sensitive to seasonality in precipitation. These variations may be explained, at least in part, by the fact that the various functional groups experience the seasons differently. C_3 grasses typically benefit more from cool-season and stored soil moisture than C_4 grasses, which are more reliant on summer rainfall due to their later seasonal phenology.

To ensure the survival of these valuable species, habitats must be conserved and regularly monitored, as future climate change will have significant effects on such species across all GHG projections (Khan *et al.,* 2022; Mathur and Mathur, 2023). Multiple studies, consistent with one another, attribute this species' limited distribution to the far north and east because of the extensive and prolonged snow-covered landscape in temperate climates (Sofi *et al.,* 2022; Rather *et al.,* 2022). The northern and eastern Himalayas have cooler temperatures and more precipitation over a longer period of time than the hot, arid and semi-arid western areas of India, which both pose threats to the species' survival (Rana *et al.,* 2020).

Comparing the spatial extent of the four habitat suitability classes—optimum, moderate, marginal, and low under different projections reveals that the optimum area is largest under the current BC, root zone, and land cover variables, while the lowest area under this class was recorded with the 2050 RCP 8.5. The marginal habitat class, on the other hand, recorded the highest area with 2050 RCP 8.5 and the least with current BC, root zone, and land cover variables. The largest region falling within the moderate category was found for 2050 RCP 2.6, while the smallest was found for 2050 RCP 8.5.

This research shows that the optimal area is consistently decreasing and is concentrated in the south and west based on projections to 2050 and RCPs 2.6 to 8.5. There were also discernible patterns noted for the decline of intermediate-sized regions and the growth of small- and very-small-sized regions. We found the best conditions in the states of Uttar Pradesh, Bihar, Uttarakhand, Madhya Pradesh, Punjab, Haryana, and the Southern Ghats using the 2050 RCP2.6 scenario. Such optimal regions will deteriorate between RCP 4.5 and RCP 6.0, and be replaced by marginal regions. Based on the current trends and the 2050 RCP 8.5 scenario, this study predicts the emergence of low-suitable habitat types in a portion of central India (Figure 3). The south-western regions of a country are predicted to be the best places to live under all RCP scenarios from 2.6 to 8.5 by 2070. Interestingly, RCP2.6 and 6.0 showed more moderate-area shrinkage than RCP4.5 and 8.5 (Figure 4).

The optimal habitat for this species is only 4.19 percent of India's total land area, and the lowest value for this category (1.55 percent) was recorded with 2050 RCP 8.5. (Table 8). From the present-day BC, root zone, and land cover variables to other climatic epochs and RCPs projection, the area occupied by this category has been steadily decreasing. There has been minimal growth in land area for this category between 2050 and 2070. Under the 2050 climate scenario, however, RCP 2.6 and 4.5 showed the greatest increase in moderate (41.99%) and low (26.40%) habitat types, respectively (Table 8).

Currently, *V. zizanioides* is more common in the south (including the western and eastern ghats) and in the center of India, but it is less common in the west and east, where it faces stiffer competition. Our ensemble model predicted that the climatically suitable area for *V. zizanioides* would shrink or become unsuitable by the end of the century under both the 2050 and 2070 climate change scenarios. Part of Gujarat, Maharashtra, Karnataka, Ayodhya, Kanpur, Pryagraj, and Etowah are ideal sites for future research based on existing bio-climatic, root zone, and land cover variables. Eastern areas, such as Nagaland, Arunachal Pradesh, Assam, Manipur, and Mizoram, and western arid areas of Rajasthan are low suitable habitats.

Using a variety of projections, our network analysis shows how the space utilized by this species is distributed internally across size classes. The presence of intra-RCP correlation denotes the extent to which a certain set of predictors influences a particular class of habitat; identifying such regions and taking measures to preserve or restore them would have an undeniable impact on future time periods and RCPs.

Conclusion

To our knowledge, this is the first study to assess the risk posed by *V. zizanioides*, map its current distribution, and speculate on its possible future distribution in the Indian subcontinent. This study used ensemble modeling to predict the distribution dynamics of *V. zizanioides* in the Indian subcontinent. Results showed that the optimum places for this species are located in the south, the south-west, and the south-east, with marginal spots strewn about in between. The root zone's total plant-available soil water storage capacity (TPASWSCRZ) was found to be strongly related with its current habitats. In both the current and 2070 RCP 8.5 scenarios, isothermality was found to have the greatest impact, but under the latter, the optimal range for this climatic parameter is reduced from 45–55% to 25–35%. *V. zizanioides* is a species that does well in regions with a wider range of precipitation variability, and the suitability of habitat for this species is determined by the annual total precipitation and, its seasonal variation pattern and the seasonality of temperature variations. Studies show that the optimal area is steadily shrinking and is concentrated in the south and some portions of the north, with intermediate-sized regions declining and small and very small regions expanding according to a discernible pattern. Low suitable habitats can be found in the eastern regions of Nagaland, Arunachal Pradesh, Assam, Rajasthan and Gujarat. The traits (aromatic oil quality and quantity, root biomass) now existing in northern and southern India vetiver varieties would be used to set research targets for future regionally unique types with varying climate projections.

Ethics approval and consent to participate

Not applicable.

Consent for publication

Not applicable.

Availability of data and materials

The data sets used and/or analysed during the current study are available from the corresponding author on reasonable request.

Competing interests

The authors declare that they have no competing interests

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Not available.

Author Contribution

Senior author conceptualized the chapter theme and interpretation of output of various machine learning techniques. Co-Author prepared various types of language codes in python, Java and in R scripts and convert the various file format from ASCII to KMZ, Raster, dbf, CSV etc. for software's like QGIS 3.10.0; Wallace; DIVA-GIS version 7.5; MaxEnt 3.4.1 software; SDM toolbox; Map Comparison Kit; ENMTools and Ntbox; SSDM R packages.

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