Modelling the global and regional niches of major invasive alien plant species of India

Sudhakar Reddy, C.[1*], Ramshida, K.[1], Jyoti Kumari.[1], Shijila, P.S.[1], Gulzar, R.[2] and Khuroo, Anzar, A.[2]

[1]Forest Biodiversity and Ecology Division, National Remote Sensing Centre, Indian Space Research Organisation, Balanagar, Hyderabad- 500 037, Telangana, India

[2]Centre for Biodiversity & Taxonomy, Department of Botany, University of Kashmir, Srinagar-190006, Jammu and Kashmir, India

*E-mail id: drsudhakarreddy@gmail.com

Abstract: *Biological invasions driven by invasive alien species, significantly contribute to biodiversity loss and are similar to natural disasters in their unpredictability and impact. Global initiatives are highlighting the need for systematic measures to prioritize and mitigate these invasions in order to safeguard biodiversity, ecosystems, and human livelihoods. Identifying invaded areas and predicting areas at high risk of invasion is critical to prioritizing management efforts. Species distribution models typically assume that the modelled species are in equilibrium with their environment, which can introduce bias when applied to alien species spreading into new areas. To overcome these issues, this study used the MaxEnt model and multiple data sources to predict the current global and regional potential niches of three major invasive alien plant species in India: Ageratina adenophora, Mesosphaerum suaveolens and Senna uniflora. Our results reveal that most of the natural ecosystems in India are predicted to have moderate to high climatic suitability for invasion hotspots, coinciding with sites of conservation significance. The global model effectively identified a wide range of highly suitable habitats for A. adenophora, M. suaveolens and S. uniflora in India. Both the regional and global niche models had good predictive performances. Looking ahead, our study offers a geo-spatial approach to generate extreme and conservative scenarios for invasive species, thereby aiding in prioritizing decision-making in invasion management.*

Keywords: Biodiversity, Habitat, Invasion, Remote sensing

Introduction

Invasive alien species pose a significant threat to ecosystems, economies, and human health. They can outcompete native species for resources, leading to a loss of biodiversity and disruption of ecological balance. It is estimated that one-sixth of the world's land surface is highly vulnerable to invasion, encompassing large areas in developing economies and biodiversity hotspots (Early et al. 2016). Global climate change, such as rising temperature and altered precipitation patterns, are expanding the range of invasive species across continents, while regional microclimates and species interactions shape their success within local ecosystems. It is essential to identify regions most vulnerable to invasions or hotspots, to effectively prioritize prevention and management strategies. The use of remote sensing techniques, combined with geographic information system (GIS) and machine learning algorithms, can significantly enhance the effectiveness of monitoring and managing invasive species. This integrated approach allows for improved detection and mapping of these species for efficient control interventions to reduce the presence and influences of these species. Species Distribution Models (SDMs) are predictive tools used in ecology, biogeography and conservation biology to understand the distribution of species across geographic areas. SDMs can be applied across different geographic scales and levels of ecological organization.

SDMs frequently encounter criticism for their substantial limitations, notably the frequent violation of the equilibrium assumption during the invasion process. In the study of Barbet-Massin et al., (2018) used the Asian hornet, *Vespa velutina nigrithorax*, as an example to evaluate the predictive accuracy of SDMs in the expansion of invasive species. The climate suitability predictions for independent validation points were highly accurate, suggesting that the spread of this invasive species is partially climatically driven (Barbet-Massin et al., 2018). According to Wolmarans et al. (2010), despite the environmental differences between the native and introduced ranges of invasive plant species, their core habitats are likely to be similar. Calibrating models with native range records reliably predicts emerging invaders, as geographical bias has little effect on performance. Bellard et al. (2018) found that climate change is likely to cause reductions in the range size more often than expansion; 233 studies found a decrease while 145 observed an increase. Global and large regional scales particularly reveal this trend. However, at the specific regional scale, the majority of the works expect an extension of plant ranges. The local circumstances and management practices may allow for species spread. Limitations in species dispersal capabilities and biotic interactions can introduce discrepancies between predicted and observed species distributions (Dormann et al. 2018).

A global model, which provides estimates of more general invasion threats, stands in contrast with a regional model that provides a more conservative assessment derived from the particular ecological setting (Pinna et al., 2024). The MaxEnt model is one of the most popular SDM because of its high accuracy in the prediction of occurrence and flexibility in the broader field of ecology and conservation. It operates on maximum entropy principles, aiming to predict distributions closest to uniform while accounting for environmental constraints. The strong statistical background of MaxEnt is due to the capability of incorporating various environmental data and keeping the differences in relative entropy between probabilities densities at the lowest (Elith et al., 2011). Maxent is presented by Phillips et al. (2006) as a valuable approach to the modelling of species geographic distributions based on presence-only data. This is so because it has a clear and straightforward mathematical structure to it, which makes it ideal for species distribution modelling. Padalia et al. (2014) modelled potential invasion range of *Hyptis suaveolens* (*Mesosphaerum suaveolens*) in India and concluded better performance of MaxEnt as compared to GARP. Panda and Behera (2018) applied Maxent to characterize and project alterations in the distribution of *Chromolaena odorata* and *Tridax procumbens*, incorporating a training dataset of 75% and a testing dataset of 25%. They found high-risk regions and future spread inside India, where there are different geographical and climatic modes for each of the species. Recent studies examined invasion trends by employing advanced spatial pattern mining tools (Pasha & Reddy, 2023; Devananda et al. 2024). Gulzar et al. (2024) prepared comprehensive list of invasive alien plant species of South Asia based on expert's knowledge, species history and invasiveness attributes. Saranya et al. (2024) incorporpated essential biodiversity variables framework for management of invasive alien species through Earth Observations. Pasha & Reddy (2024) applied multiple machine learning models to identify potential suitable habitats of *Prosopis juliflora* globally under current climate and future climate scenarios.

Ageratina adenophora (Sprengel) R. King and H. Robinson (syn: *Eupatorium adenophorum* Sprengel), (Asteraceae) is native of Mexico. *Ageratina adenophora* (Asteraceae) has successfully invaded forests, plantations and other human dominated landscapes of Himalayas and Western Ghats. It was introduced in India as a garden plant in about 1924 (Raizada, 1976; Tripathi et al. 2006). *Mesosphaerum suaveolens* (L.) Kuntze (*Hyptis suaveolens* (L.) Poit.) and *Senna uniflora* (Mill.) H.S. Irwin & Barneby (*Cassia uniflora* Mill.) are native speices of Mexico to Tropical America. In India, J.D. Hooker recorded *Hyptis suaveolens* (*Mesosphaerum* suaveolens) in 1885 and reports its occurrence in Deccan peninsula and Cachar. Singh (1979) and Raghavan (1980) reported *Senna uniflora* for the first time in India from Pune, Maharashtra. Later it was recorded from Karnataka, Andhra Pradesh (Reddy et al. 2000; Reddy, 2008), Telangana (Reddy et al. 2000; Reddy & Reddy, 2016), Kerala (Pradeep et al. 2008), Madhya Pradesh (Kumar et al. 2021), Rajasthan (Meena and Yadav, 2009; Arigela et al. 2024), Uttar Pradesh (Shukla et al. 2012) and Punjab (Kabila et al. 2023).

This study aimed to address the following questions: (i) What are the potential spatial patterns of distribution of *Ageratina adenophora*, *Mesosphaerum suaveolens* and *Senna uniflora* under current climate conditions globally and regionally in India? (ii) Where are the high-invasion-risk regions are located? The main objectives are to map potential spatial distribution of the three invasive alien species in the world and India and to identify priority sites for invasive species management.

Methodology

Species occurrence data

Species occurrence data is information about the presence of a particular species at defined geographic coordinates. Such species occurrence data is vital to the functionality and performance of the MaxEnt model because this data is the core of the investigation of species distribution in connection with the environment.

Ageratina adenophora introduced into Algeria, Angola, Assam, Azores, California, Cambodia, Canary Is., Cape Provinces, Cape Verde, China South-Central, China Southeast, Corse, Costa Rica, East Aegean Is., East Himalaya, France, Germany, Greece, Hawaii, India, Jamaica, Jawa, Kriti, KwaZulu-Natal, Laos, Lebanon-Syria, Madeira, Morocco, Nepal, New South Wales, New Zealand North, Norfolk Is., Northern Provinces, Peru, Philippines, Portugal, Queensland, Society Is., South Australia, South China Sea, Spain, Thailand, Yugoslavia and, Zimbabwe (https://powo.science.kew.org/). *Mesosphaerum suaveolens* is introduced into Angola, Bangladesh, Benin, Borneo, Burkina, Burundi, Cambodia, Cameroon, China, Congo, East Himalaya, Equatorial Guinea, Gabon, Gambia, Ghana, Guinea, Guinea-Bissau, Hawaii, India, Ivory Coast, Jawa, Kenya, Laccadive Is., Laos, Lesser Sunda Is., Liberia, Malaya, Mali, Maluku, Marianas, Mozambique, Myanmar, Nansei-shoto, Nepal, New Guinea, Niger, Nigeria, Northern Territory, Philippines, Queensland, Senegal, Sierra Leone, Sulawesi, Sumatera, Taiwan, Tanzania, Thailand, Togo, Uganda, Vietnam, Australia, Zaïre, and Zimbabwe. *Senna uniflora* has been introduced into India, Mauritius, and Réunion from its native range (https://powo.science.kew.org/).

In this study, we utilized presence-only data for *Ageratina adenophora*, *Mesosphaerum suaveolens,* and *Senna uniflora* from India by leveraging the ISRO’s repository’s all-India database of invasive species from multiple projects (Reddy, 2008; Roy et al. 2012; Reddy et al. 2017) and the Global Biodiversity Information Facility (GBIF, https://www.gbif.org/) to obtain current distribution data. Distribution data at a worldwide scale, covering both native and non-native ranges, was acquired from GBIF. In MaxEnt, occurrence data should be in the form of a CSV file with species name, longitudinal and latitudinal coordinates with coordinates expressed in decimal degrees (Fig. 1). A total of 12,976 field-based occurrence points were used to model the global distribution of *Ageratina adenophora*. For *Mesosphaerum suaveolens*, 19,538 occurrence points were used, while 818 points were used for *Senna uniflora*.

Specifically, *Ageratina adenophora* was modelled with 122 points from India, compared to 919 points for *Mesosphaerum suaveolens* and 174 points for *Senna uniflora.*

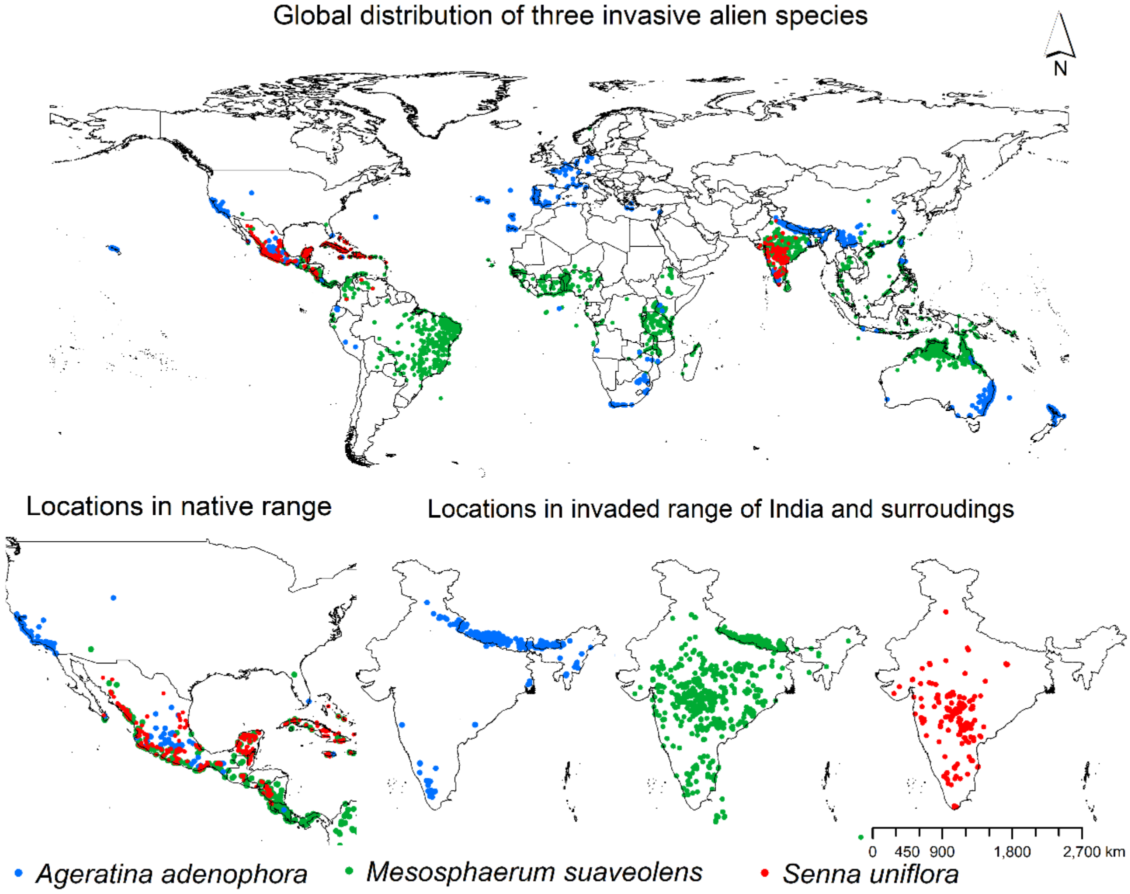

Fig.1. Species occurrence locations of *Ageratina adenophora, Mesosphaerum suaveolens* and *Senna uniflora*

Environmental variables

Bioclimatic variables are important environmental factors that describe climatic and ecological conditions essential for predicting species distribution models. These are the variables derived from climate data and include factors such as temperature, rainfall, and seasonality that define the preferred environment for species. In the present study, we used 19 bioclimatic variables extracted from the WorldClim 2.1 database, which contains climate data with a spatial resolution that is specifically 1 km (30 arc-seconds). (https://www.worldclim.org/).

Table 1: List of nineteen bioclimatic variables derived from the WorldClim database

Bioclimatic variable	**Climatic parameter**	**Unit**
BIO1	Annual Mean Temperature	^{o}C
BIO2	Mean Diurnal Range (Mean of monthly (max temp - min temp)	^{o}C

BIO3	Isothermality (BIO2/BIO7) (×100)	^{o}C
BIO4	Temperature Seasonality (standard deviation ×100)	^{o}C
BIO5	Max.Temperature of Warmest Month	^{o}C
BIO6	Min. Temperature of Coldest Month	^{o}C
BIO7	Temperature Annual Range (BIO5-BIO6)	^{o}C
BIO8	Mean Temperature of Wettest Quarter	^{o}C
BIO9	Mean Temperature of Driest Quarter	^{o}C
BIO10	Mean Temperature of Warmest Quarter	^{o}C
BIO11	Mean Temperature of Coldest Quarter	^{o}C
BIO12	Annual Precipitation	mm
BIO13	Precipitation of Wettest Month	mm
BIO14	Precipitation of Driest Month	mm
BIO15	Precipitation Seasonality (Coefficient of Variation)	mm
BIO16	Precipitation of Wettest Quarter	mm
BIO17	Precipitation of Driest Quarter	mm
BIO18	Precipitation of Warmest Quarter	mm
BIO19	Precipitation of Coldest Quarter	mm

Modelling procedures and validation

To predict the species distribution of *Ageratina adenophora*, *Mesosphaerum suaveolens,* and *Senna uniflora*, current study adopted MaxEnt version 3.4.1. MaxEnt is a software package used to predict the potential distribution of species, by correlating species occurrence data with environmental information such as climate, topography, anthropogenic features, and soil data. The principle of maxent involves estimating a desired probability distribution by finding the distribution with the highest entropy, which is the most uniformly spread out while conforming to constraints that delineate the incomplete representation of the target distribution. Maxent became widely recognised for its ability to predict species distribution using limited presence-only data (Philips et al., 2006). MaxEnt is highly adaptable and capable of managing both continuous and categorical data, as well as interactions between different variables (Phillips et al., 2006), allowing for the integration of various types of data in invasive species ecology. Due to the lack of absence data for many species, this model generates pseudo-absence data for those species. Invasive alien species, show considerable flexibility in their environmental tolerances, making it difficult to use native range data alone to predict where they may invade.

So, the model is trained based on both native range and invaded range data to provide insights into the climatic factors that define the species ecological niche. When projected to new areas, this can reveal potential invasion hotspots.

To ensure model robustness, we used three replicates and incorporated 10,000 random background points as pseudo-absence data across the study area. The model was configured with a regularization multiplier of 1, a maximum of 500 iterations, and a convergence threshold of 105. We selected the cloglog output format for better interpretability of habitat suitability. To assess the model's predictive performance, species occurrence data was split into a training set (70% of the total records) and a test set (30% of the total records). Model performance was assessed with the Receiver Operating Characteristic (ROC) curve, plotting sensitivity against specificity at different thresholds, and summarized using the Area Under the Curve (AUC), which measures the model's ability to correctly rank positive instances above negative ones (Phillips et al., 2004). The AUC ranges from 0 to 1. A score of 1 means perfect prediction, 0.5 means the model is as good as random guessing, and scores below 0.5 suggest worse performance than random chance (Elith, 2006). We assessed the relative contributions of bioclimatic predictors to the distribution model using percentage variable contributions and the Jackknife test, identifying the variables with the greatest impact on the model. The Maxent output maps were imported into ArcMap 10.8 and converted to Tiff raster format for further analysis. These maps were classified into two suitability ranges: 0.00–0.50 (low suitability) and 0.50–1.00 (high suitability).

Results and Discussion

Model performance and main variables at global level

Global potential distribution maps of three species are presented in Figures 2-4. The AUC value obtained for *Mesosphaerum suaveolens* is highest (0.977), followed by 0.933 for *A. adenophora* and 0.862 for *Senna uniflora* , indicating excellent model performance. The jackknife test of the model indicated that the major variables contribute significantly to the potential suitability of invasion. For *A. adenophora* Isothermality (Bio3) is the most influencing variable with high percent contribution (37.7%), followed by Precipitation of Wettest Quarter (Bio16) (24.2%), Mean Temperature of Coldest Quarter (Bio11) (19.5%), Precipitation of Coldest Quarter (Bio19) (5.6%) and Temperature Annual Range (Bio7) (3.6%). For *M. suaveolens* Precipitation of Wettest Month (Bio13) is the most influencing variable with high percent contribution (43%), followed by Annual Mean Temperature (Bio1) (8.5%), Precipitation of Coldest Quarter (Bio19) (8.2%), Isothermality (Bio3) (7.6%) and Mean Temperature of Coldest Quarter (Bio11) (5.4%). For *Senna uniflora* Bio16 is the most influencing variable with high percent contribution (56.9%), followed by Precipitation of Wettest Month (Bio13) (10.7%), Mean Temperature of Coldest Quarter (Bio11) (9.1%), Annual Mean Temperature (Bio1) (7.4%) and Precipitation Seasonality (Bio15) (3.7%).

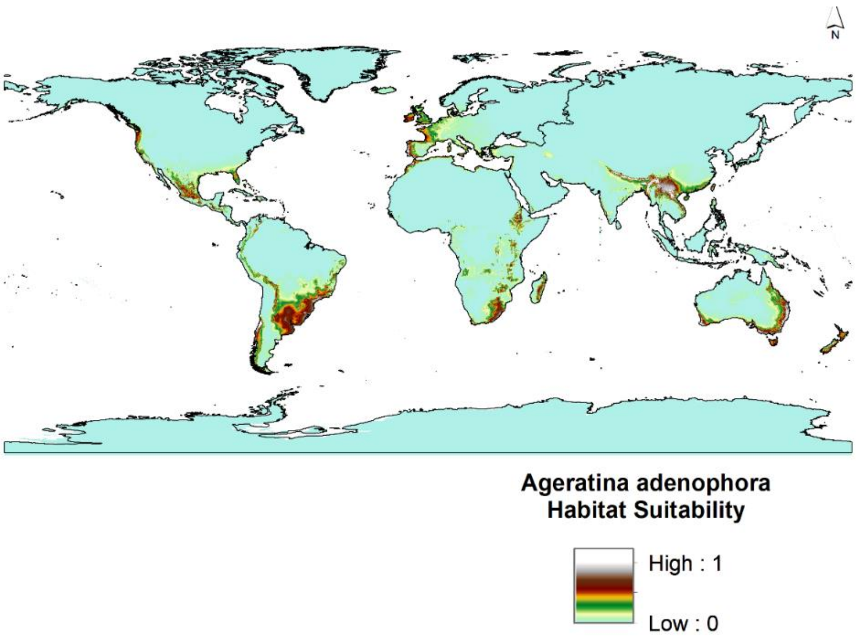

Fig.2. Global potential distribution map of *Ageratina Adenophora*

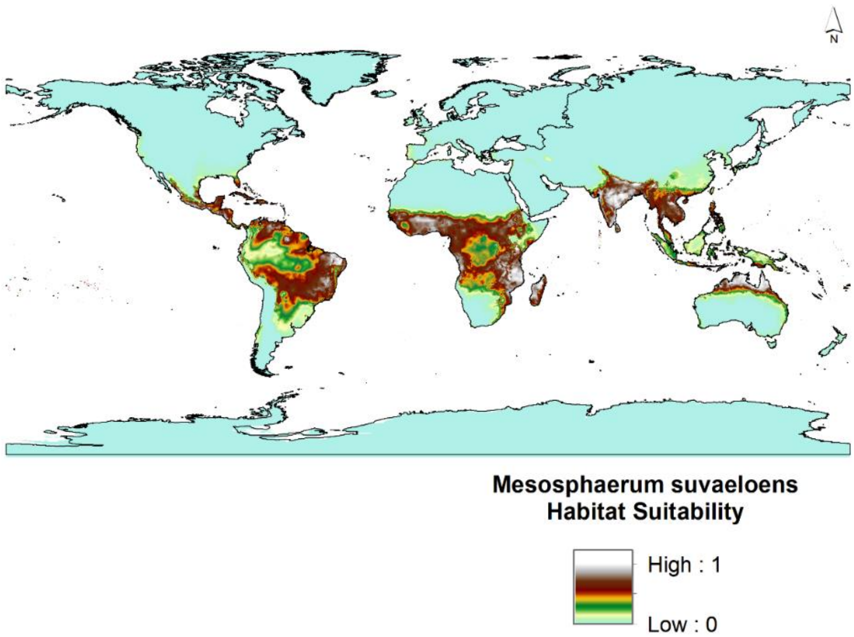

Fig.3. Global potential distribution map of *Mesosphaerum suaveolens*

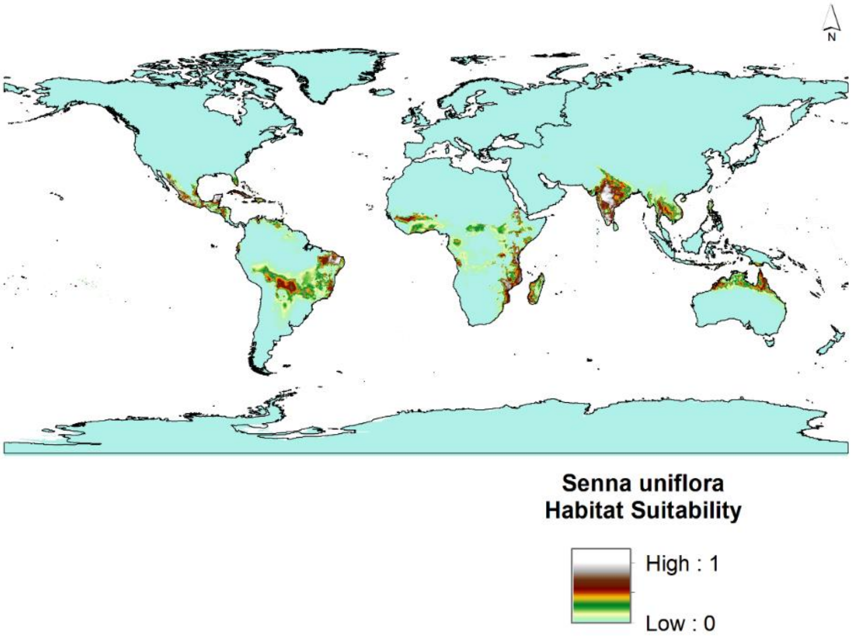

Fig.4. Global potential distribution map of *Senna uniflora*

Model performance and main variables at regional level (India)

The AUC value obtained for *A. adenophora* is highest for *A. adenophora* (0.983), followed by and 0.905 for *S. uniflora and* 0.887 for *M. suaveolens*, indicating excellent model performance. The jackknife test of the model indicated that the major variables contribute significantly to the potential suitability of invasion. For *A. adenophora* (Bio7) is the most influencing variable with high percent contribution (24.8%), followed by (Bio18) (22.8%), (Bio5) (19.3%), (Bio9) (13.1%) and (Bio6) (12.0%). For *M. suaveolens* (Bio13) is the most influencing variable with high percent contribution (20.2%), followed by (Bio5) (17.7%), (Bio8) (13.5%), (Bio14) (11.4%) and Mean Temperature of Coldest Quarter (Bio11) (9.6%). For *S. uniflora* (Bio5) is the most influencing variable with high percent contribution (27.1%) followed by the mean temperature in the coldest quarter (Bio11, 13%), mean diurnal range (Bio2, 12.3%), total annual precipitation (Bio12, 9.5%), and precipitation seasonality (Bio15, 9.3%).

Dynamics in potential suitable area under global niche and regional niche scenarios

Global and regional niche maps of *A. adenophora*, *M. suaveolens* and *S. uniflora* are presented in figure 5. According to the global niche map of potential suitable areas of *A. adenophora*, the total area of India found to be high suitable was 167,297 km^2 which represents 5.1% of total geographic area of India. According to the regional niche map of potential suitable areas of *A. adenophora*, the total area of India found to be high suitable was 85,688 km^2 which represents 2.6% of total geographic area of India. Global and regional niche overlap between two modelled products of *A. adenophora* was estimated 67,404 km^2 (36.3%). According to the global niche map for *M. suaveolens*, the high-suitability area in India is 220,070 km², representing 67% of the country's total geographic area. For *A. adenophora*, the regional niche map indicates a high-suitability area of 182,279 km² in India, which is 5.5% of the country's total area. The global and regional niche overlap for *M. suaveolens* is estimated at 182,263 km² (8.3%). For *S. uniflora*, the global niche map identifies a high-suitability area of 1,200,570 km² in India, covering 36.5% of the country's total area. The regional niche map for *A. adenophora* shows a high-suitability area of 219,862 km² in India, representing 6.7% of the total area. The global and regional niche overlap for *Senna uniflora* is estimated at 182,263 km² (17.9%).

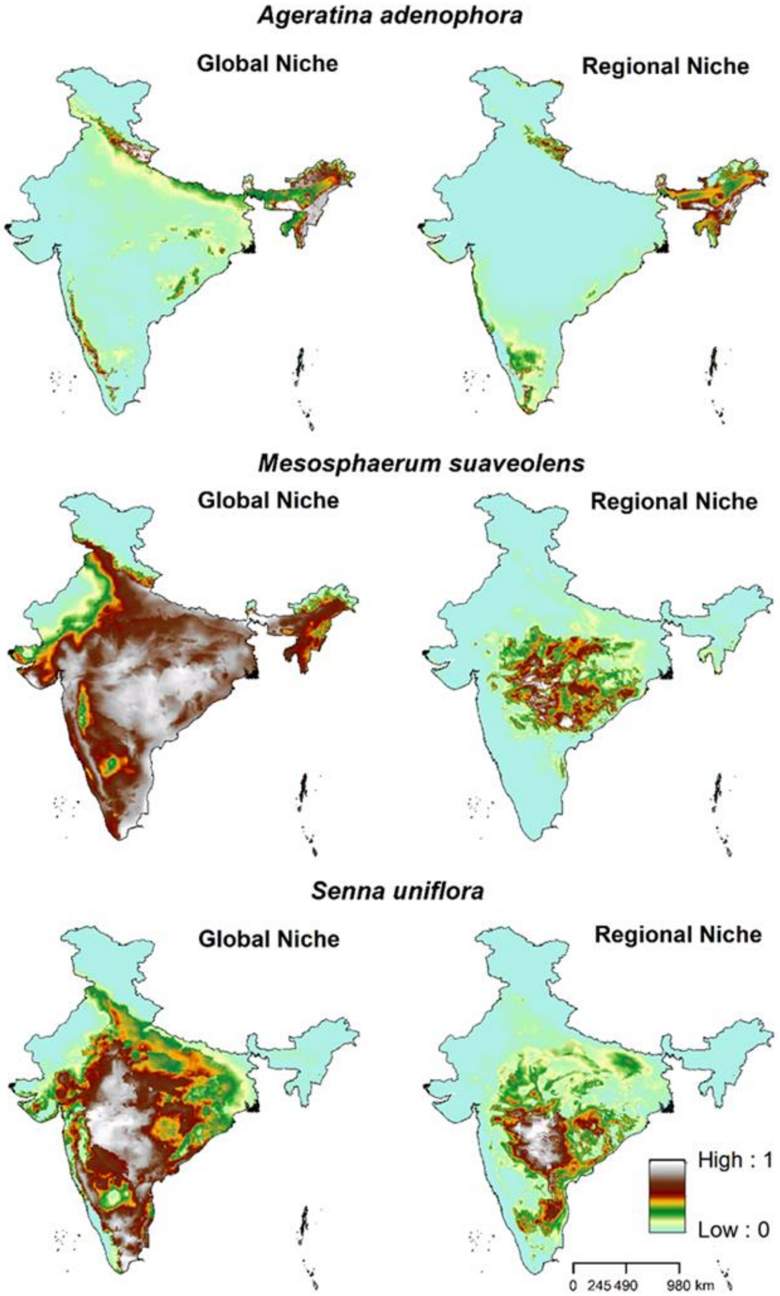

Fig.5. Global and regional niche of *Ageratina adenophora*, *Mesosphaerum suaveolens* and *Senna uniflora*

The comparison of highly suitable habitats for *A. adenophora*, *M. suaveolens*, and *S. uniflora* is based on global and regional niche models (Fig. 6). Rising global temperatures, changing precipitation patterns, and altered seasonality can expand or shift the range of climates where invasive alien species can thrive. The dynamics in potential suitable area under global and regional niche scenarios highlight the importance of considering the appropriate spatial scale and niche concept when using SDMs for predicting species distributions. Global niche models are useful for identifying regions at risk of invasion, while regional niche models provide more accurate predictions of realized niche within a specific region. Combining spatial information from both niche scenarios can lead to a more comprehensive understanding of a species potential distribution and invasion dynamics.

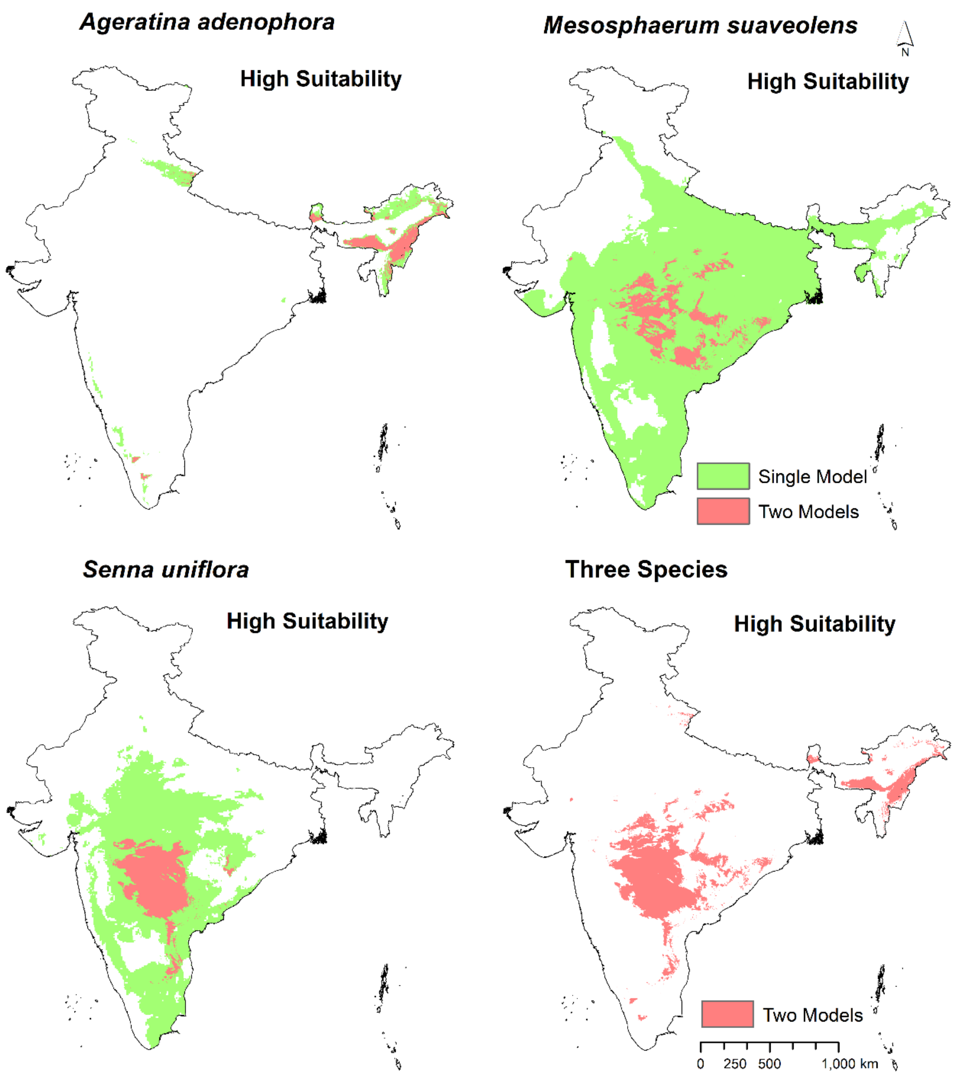

Fig.6. Comparison of highly suitable habitats of *Ageratina adenophora*, *Mesosphaerum suaveolens* and *Senna uniflora* based on global and regional niche models

Invasion in sites of conservation significance

Our results reveal that most of the natural ecosystems of India are predicted to have moderate to high climatic suitability for invasion hotspots, coinciding with sites of plant invasion hotspots in protected areas (Fig. 7). In the present study, sites represented as highly suitable in both global and regional models were identified 'hotspots of alien plant invasion'. Hotspots of *Ageratina adenophora* are distributed in protected areas of Arunachal Pradesh (Kamlang, Mehao, Mouling, Namdapha, Pakke (Pakhui)) Assam (Barail, East Karbi Anglong), Himachal Pradesh (Churdhar), Kerala (Anamudi Shola, Chinnar, Eravikulam, Kurinjimala, Mathikettan Shola, Pambadum Shola, Silent Valley), Manipur (Keibul-Lamjao), Meghalaya (Balphakram, Nokrek, Nongkhyllem, Siju), Mizoram (Khawnglung, Lengteng, Murlen, Phawngpui Blue Mountain,Tawi), Nagaland (Fakim, Puliebadze), Sikkim (Barsey Rhododendron, Fambong Lho, Khangchendzonga, Kitam, Pangolakha), Tamil Nadu (Indira Gandhi (Anamalais), Mukurthi)), Uttarakhand (Askot Musk Deer, Binsar, Kedarnath), and West Bengal (Buxa, Mahananda, Neora Valley, Senchal and Singalila).

Hotspots of *Mesosphaerum suaveolens* are distributed in protected areas of Andhra Pradesh (Papikonda), Chhattisgarh (Bhairamgarh, Bhoramdev, Guru Ghasi Das (Sanjay), Kanger Valley, Pamed Wild Buffalo, Sitanadi, Udanti Wild Buffalo), Gujarat (Balaram Ambaji, Jessore, Shoolpaneswar), Madhya Pradesh (Bandhavgarh, Bori, Gandhi Sagar, Pench, Kheoni, Noradehi, Pachmarhi, Panna, Ratapani, Sanjay Dubri, Satpura, Singhori, Van Vihar), Maharashtra (Amba Barwa, Andhari, Bhamragarh, Bor, Dhyanganga, Gautala-Autramghat, Gugamal, Karanja Sohal Blackbuck, Melghat, Narnala Bird, Nawegaon, Painganga, Tadoba, Tipeshwar, Wan, Yawal), Odisha (Baisipalli, Chandaka Dampara, Karlapat, Kothagarh, Satkosia Gorge, Sunabeda), Rajasthan (Mount Abu), Telangana (Eturnagaram, Kawal, Kinnerasni, Sivaram, Pakhal, Pocharam), and Uttar Pradesh (Kaimur and Ranipur).

Hotspots of *Senna uniflora* are distributed in protected areas of Andhra Pradesh (Gundla Brahmeswaram, Kaundinya, Papikonda, Nagarjunasagar-Srisailam, Sri Lankamalleswara, Sri Penusila Narasimha, Sri Venkateswara), Karnataka (Nagarhole), Madhya Pradesh (Pench), Maharashtra (Amba Barwa, Andhari, Aner Dam, Bor, Chaprala, Dhyanganga, Gautala-Autramghat, Gugamal, Karanja Sohal Blackbuck, Katepurna, Lonar, Melghat, Naigaon Peacock, Narnala Bird, Nawegaon, Painganga, Tadoba, Tipeshwar, Wan, Yawal, Yedsi Ramlin Ghat), Odisha (Karlapat, Sunabeda), Telangana (Amrabad, Eturnagaram, Kasu Brahmananda Reddy NP, Kawal, Kinnerasni, Sivaram, Mahaveer Harina Vanasthali NP, Manjira, Mrugavani, Pakhal, Pocharam, and Pranahita).

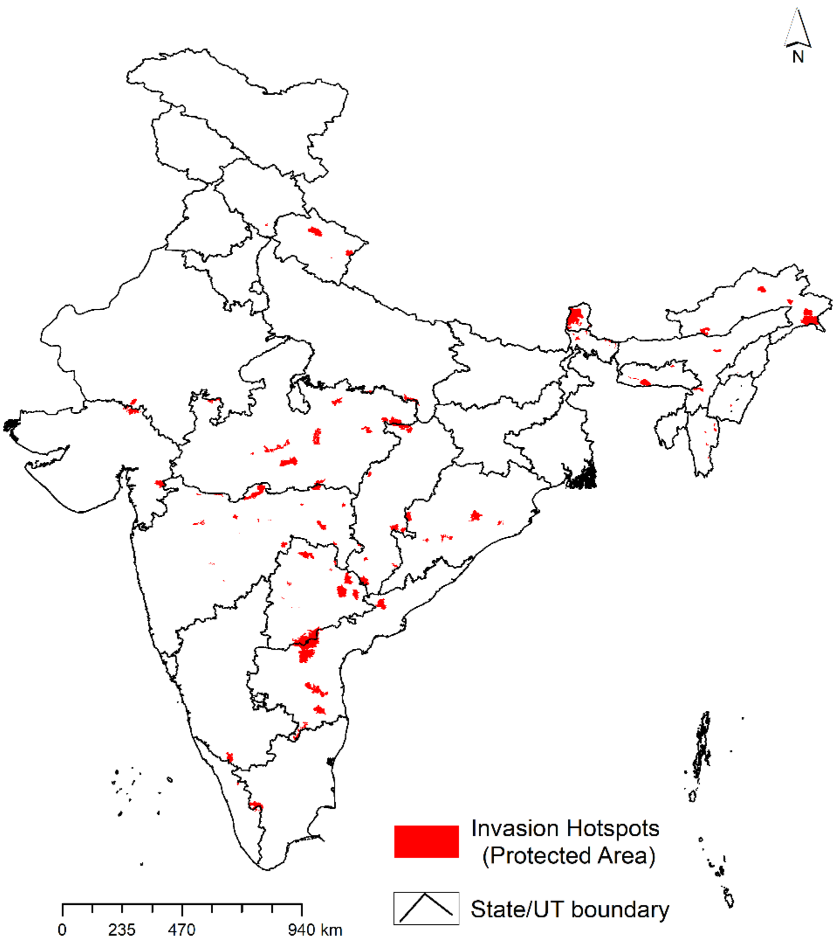

Fig. 7. Distribution of Protected Areas with hotspots of alien plant invasion (*Ageratina adenophora*, *Mesosphaerum suaveolens* and *Senna uniflora*) in India

Conclusion and Recommendation

The study aimed to improve the understanding of habitat suitability of invasive alien plant species by using environmental data and the MaxEnt model at both global and regional levels, incorporating both native and invaded ranges. This research demonstrates the value of integrating remote sensing and GIS technologies with modelling techniques to effectively manage and mitigate the impacts of invasive species. The study's results emphasize the importance of targeted interventions and management strategies to minimize the ecological and socio-economic consequences of these species, particularly in the context of ongoing climate change.

Acknowledgement

Authors are thankful to Director, NRSC, Deputy Director (RSA), NRSC, Group Director, Forestry and Ecology Group, NRSC and Head, Department of Botany, University of Kashmir for suggestions and encouragement. Thanks are due to GBIF for providing global occurrence locations of invasive species.

References

1. Arigela, R.K., Harikrishna, P., Deroliya, P.K., Singh, R.K. & Reddy, C.S. (2024). Invasive alien plant species of Rajasthan, India. Ambika Prasad Research Foundation, Odisha. ISBN: 978-81-970898-3-1.
2. Barbet-Massin, M., Rome, Q., Villemant, C., & Courchamp, F. (2018). Can species distribution models really predict the expansion of invasive species? PLoS ONE, Vol.13(3), 1-14. https://doi.org/10.1371/journal.pone.0193085
3. Bellard, C., Jeschke, J. M., Leroy, B., & Mace, G. M. (2018). Insights from modeling studies on how climate change affects invasive alien species geography. Ecology and evolution, Vol. 8(12),1-13.http://dx.doi.org/10.1002/ece3.4098
4. Devananda, K., Reddy, C.S. & Arigela, R.K. (2024). Tracking five decades (1972-2024) of spatio-temporal dynamics and hotspots of Prosopis juliflora in Keoladeo national park, a World Heritage Site. Spatial Information Research. DOI :10.1007/s41324-024-00598-6.
5. Dormann, C. F. et al. (2018). Biotic interactions in species distribution modelling: 10 questions to guide interpretation and avoid false conclusions. Global Ecology and Biogeography, 27(9), 1004-1016. DOI: 10.1111/geb.12759
6. Early, R., Bradley, B. A., Dukes, J. S., Lawler, J. J., Olden, J. D., Blumenthal, D. M., Gonzalez, P., Grosholz, E. D., Ibanez, I., Miller, L. P., Sorte, C. J. B. & Tatem, A. J. (2016). Global threats from invasive alien species in the twenty-first century and national response capacities. Nature communications, Vol. 7(1), 12485. https://doi.org/10.1038/ncomms12485
7. Elith, J., Graham, C. H., Anderson, R. P., Dudı´k, M., Ferrier, S., Guisan, A., Hijmans, R. J.,Huettmann, F., Leathwick, J. R., Lehmann, A., Li, J., Lohmann, L. G., Loiselle, B. A., Manion, G.,Moritz, C., Nakamura, M., Nakazawa, Y., Overton, J. McC., Peterson, A. T., Phillips, S. J.,Richardson, K. S., Scachetti-Pereira, R., Schapire, R. E., Sobero´n, J., Williams, S., Wisz, M. S. and Zimmermann, N. E. (2006). Novel methods improve prediction of species' distributions from occurrence data. Ecography, Vol. 29, 129 -151. http://dx.doi.org/10.1111/j.2006.0906-7590.04596.x
8. Elith, J., Phillips, S.J., Hastie, T., Dudik, M., Chee, Y.E. and Yates, C.J. (2011) A Statistical Explanation of MaxEnt for Ecologists. Diversity and Distributions, Vol. 17, 43-57. http://dx.doi.org/10.1111/j.1472-4642.2010.00725.x

9. Global Biodiversity Information Facility. (7 July 2024). GBIF Occurrence Download for *Ageratina adenophora*. https://doi.org/10.15468/dl.3pqpmp
10. Global Biodiversity Information Facility. (7 July 2024). GBIF Occurrence Download for *Mesosphaerum suaveolens.* https://doi.org/10.15468/dl.27dxfz
11. Global Biodiversity Information Facility. (2 July 2024). GBIF Occurrence Download for *Senna uniflora.* https://doi.org/10.15468/dl.29hyk9
12. Gulzar, R., Wani, S. A., Hassan, T., Reddy, C. S., Shrestha, B. B., Mukul, S. A., Shabbir, A., Iqbal, I. M., Ranwala, S. M. W., Dorjee, N., Sujanapal, P., Rashid, I., & Khuroo, A. A. (2023). Looking beyond the political boundaries: an integrated inventory of invasive alien flora of South Asia. Biological Invasions, Vol. 26(1), 57–78. https://doi.org/10.1007/s10530 023-03165-6
13. Hooker, J. D. (1885). The Flora of British India (Vol. 5). L. Reeve.
14. Kabila, B., Sidhu, M. C., & Ahluwalia, A. S. (2023). A Biological Report on *Senna uniflora* (Mill.) HS Irwin & Barneby from Rupnagar, Punjab, India. J. Indian bot. Soc, Vol, 103(4), 298-301. https://doi: 10.61289/jibs2023.25.01.1114
15. Kumar, V., Khare, P. K., & Khan, M. L. (2021). Growth performance and invasive attributes of Cassia uniflora Mill., a recently introduced plant in central India. International Journal of Ecology and Environmental Sciences, Vol. 47(2), 145-151. https://nieindia.org/Journal/index.php/ijees/article/view/2226
16. Meena, K.L. & Yadav, B.L. (2009). *Senna uniflora* (Mill.) Irwin & Barneby (Caesalpiniaceae) A new record for Rajasthan. Natural Product Radiance, Vol. 8(5) 525-527.https://nopr.niscpr.res.in/bitstream/123456789/6352/1/NPR%208%285%29%20525-527.pdf
17. Padalia, H., Srivastava, V., & Kushwaha, S. P. S. (2014). Modeling potential invasion range of alien invasive species, Hyptis suaveolens (L.) Poit. in India: Comparison of MaxEnt and GARP. Ecological informatics, Vol. 22, 36-43 . https://doi.org/10.1016/j.ecoinf.2014.04.002
18. Panda, R. M., & Behera, M. D. (2019). Assessing harmony in distribution patterns of plant invasions: a case study of two invasive alien species in India. Biodiversity and Conservation, Vol. 28, 2245-2258. https://link.springer.com/article/10.1007/s10531-018-1640-9
19. Pasha, S.V., & Reddy, C.S. 2023. Trends in Hotspots of Alien Plant Invasion in Kachchh Biosphere Reserve, India Using Spatial Pattern Mining Tool. Journal of the Indian

Society of Remote Sensing, 51(3), 469-481. https://link.springer.com/article/10.1007/s12524-022-01637-1

20. Pasha, S.V. & Reddy, C.S. (2024). Global spatial distribution of *Prosopis juliflora* - one of the world's worst 100 invasive alien species under changing climate using multiple machine learning models. Environmental Monitoring and Assessment, Vol. 196, 196. https://doi.org/10.1007/s10661-024-12347-1.
21. Phillips, S. J., Dudík, M., & Schapire, R. E. (2004). A maximum entropy approach to species distribution modeling. In Proceedings of the twenty-first international conference on Machine learning, Vol. 83. .http://dx.doi.org/10.1145/1015330.1015412
22. Phillips, S. J., Anderson, R. P., & Schapire, R. E. (2006). Maximum entropy modeling of species geographic disiptributions. Ecological modelling, Vol. 190(3-4), 231-259. https://doi.org/10.1016/j.ecolmodel.2005.03.026
23. Plants of the World Online. (n.d.). *Ageratina adenophora* (Spreng.) R.M.King & H.Rob . https://powo.science.kew.org/taxon/urn:lsid:ipni.org:names:30003158-2
24. Plants of the World Online. (n.d.). *Mesosphaerum suaveolens* (L.) Kuntze. https://powo.science.kew.org/taxon/urn:lsid:ipni.org:names:21028-1
25. Plants of the World Online. (n.d.). *Senna uniflora* (Mill.) H.S.Irwin & Barneby. https://powo.science.kew.org/taxon/urn:lsid:ipni.org:names:30000132-2
26. Pradeep S V, Balan A P and Prasad V P (2008). *Senna uniflora* (Mill.) Irwin & Barneby (Fabaceae–Caesalpiniaceae) – A New Record to Kerala. Indian Journal of Forestry, Vol. 31(3), 435-436. https://doi.org/10.54207/bsmps1000-2008-WHW3VE
27. Raizada, M.B. (1976). Supplement to Duthie's Flora of the Upper Gangetic Plain and of Adjacent Siwalik and Sub Himalayan Tracts. Bishen Singh Mahendra Pal Singh, Dehradun, 358 pages.
28. Raghavan, R. S. (1980). *Cassia uniflora* Mill. (Caesalp1niaceae)- A new record for India. Nelumbo-The Bulletin of the Botanical Survey of India, Vol. 22(1-4), 225. https://doi.org/10.20324/nelumbo/v22/1980/75478
29. Reddy, C.S. (2008). Catalogue of invasive alien flora of India. Life Science Journal, Vol 5(2), 84-89.
30. Reddy, C.S., Bhanja, M.R. & Raju, V.S. (2000). *Cassia uniflora* Miller: A new record for Andhra Pradesh, India. Indian Journal of Forestry, Vol. 23 (3): 324-325
31. Reddy, C. S., Diwakar, P. G., & Murthy, Y. V. N. K. (2017). Sustainable Biodiversity Management in India: Remote Sensing Perspective. Proceedings of the National

Academy of Sciences, India. Section a, Physical Sciences, Vol. 87(4), 617–627. https://doi.org/10.1007/s40010-017-0438-6

32. Reddy, K.N. & Reddy, C.S. (2016). Flora of Telangana State, India. Bishen Singh Mahendra Pal Singh, Dehra Dun. pp 1-819. ISBN: 978-81-211-0935-2.
33. Roy, P.S., Kushwaha, S.P.S., Murthy, M.S.R., Roy, A., Kushwaha, D., Reddy, C.S., Behera, M.D., Padalia, H., Mathur, V.B., Singh, S., Jha, C.S. & Porwal, M.C. (2012). Biodiversity Characterisation at Landscape Level: National Assessment. Indian Institute of Remote Sensing, Dehra Dun. pp 1-254. ISBN 81-901418-8-0.
34. Saranya, K.R.L., Satish, K.V. & Reddy, C.S. (2024). Remote sensing enabled essential biodiversity variables for invasive alien species management: towards the development of spatial decision support system. Biological Invasions, Vol. 26(4):1-9 https://doi.org/10.1007/s10530-023-03240-y.
35. Shukla, B. K., Tiwari, A. P., & Shukla, A. N. (2012). *Senna uniflora* (Mill.) HS Irwin & Barneby (Caesalpiniaceae) and Sida tiagii Bhandari (Malvaceae): new records for the flora of Uttar Pradesh. *Journal of Non-Timber Forest Products,* 19(2), 157-158.
36. Singh, N.P. (1979). *Cassia sericea* Sw - A new record for India. Bulletin of the Botanical Survey of India, Vol. 21, 203-205.
37. Tripathi, R. S., Kushwaha, S. P. S., & Yadav, A. S. (2006). Ecology of three invasive species of *Eupatorium:* A review. International Journal of Ecology and Environmental Sciences, 32(4), 301-326.
38. Pinna, L. C., Gallien, L., Pollock, L. J., Axmanová, I., Chytrý, M., Malavasi, M., Acosta, A. T. R., Campos, J. A., & Carboni, M. (2024). Plant invasion in Mediterranean Europe: current hotspots and future scenarios. Ecography, 2024(5). https://doi.org/10.1111/ecog.07085
39. WorldClim.(n.d.). https://www.worldclim.org/
40. Wolmarans, R., Robertson, M. P., & Van Rensburg, B. J. (2010). Predicting invasive alien plant distributions: how geographical bias in occurrence records influences model performance. Journal of Biogeography, Vol. 37(9), 1797–1810. https://doi.org/10.1111/j.1365-2699.2010.02325.x