Habitat Suitability of Globally Worst Invasive Weed, *Sphagneticola trilobata* (L.) Pruski in South Asia

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DECLARATION

I, Puspa Aryal, hereby declare that this dissertation entitled **"Habitat Suitability of Globally Worst Invasive Weed, *Sphagneticola trilobata* (L.) Pruski in South Asia"** is my original work, and credit has been given to all other sources of material used. I have not applied for any academic awards at any other university with it or any of its components.

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LETTER OF RECOMMENDATION

This document confirms that Ms. Puspa Aryal has completed the dissertation titled **"Habitat Suitability of Globally Worst Invasive Weed, *Sphagneticola Trilobata* (L.) Pruski in South Asia"** under our guidance. The research presented in this dissertation is original and conducted by the candidate. To the best of our knowledge, this work has not been submitted for any other academic qualification. We recommend the acceptance of this dissertation as a requirement for obtaining a M.Sc. Degree in Biodiversity and Environmental Management (BEM) from the Institute of Science and Technology, Tribhuvan University, Kathmandu, Nepal.

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LETTER OF APPROVAL

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ABSTRACT

Sphagneticola trilobata (L.) Pruski [Asteraceae], a native to the tropics of Central America, is one of the world’s 100 notorious invasive alien species invading the tropics and subtropics in Asia, Africa and Oceania. Since the weed is rapidly spreading in South Asian countries including Nepal, it is imperative to understand its climatic suitability in South Asia to prevent its future expansion and for better management. Using occurrence data that are publicly available in the Global Biodiversity Information Facility (GBIF) and the climatic variables derived from Worldclim, the study assessed the distribution of *S. trilobata* in South Asia and predicted the climatically suitable areas in this region under current and two future climate scenarios (Shared Socioeconomic Pathways SSPs 2-4.5 and 5-8.5 for 2030 and 2050) using ensemble models. *Sphagneticola trilobata* has been reported in six of the eight South Asian countries with a high frequency of occurrences in India, Sri Lanka and Maldives. Under the current climate scenario, suitable areas were predicted to lie mainly in Sri Lanka, Bangladesh, Maldives and southern Indian states (e.g., Karnataka and Kerala). Only a small proportion of the area was predicted to be suitable in the remaining South Asian countries. The climatically suitable areas for *S. trilobata* were projected to decline in all countries under both climate change scenarios. The decline will be pronounced in Bangladesh (45.7% under SSP 5-8.5) and Bhutan (25% under SSP 5-8.5). Similarly, the study also identified that the overall predicted area of the species will decrease but in current climatic conditions, as well as in future climate scenarios, Sri Lanka and Maldives were found to have a higher proportion of climatically suitable areas for *S. trilobata* compared to other South Asia countries. Analyses of the dynamics of the suitable areas in different scenarios indicate that some of the currently unsuitable areas will also be suitable in future. This information will be useful to prioritize management strategies so that potential negative impacts of this species on ecosystems, biodiversity and livelihood could be averted. By recognizing regions vulnerable to future invasion risks, this study provides valuable information for managers and policymakers with timely and relevant data to enact appropriate measures against the potential threat posed by *S. trilobata* about climate change

Keywords: Climate change, Ensemble models, Global Biodiversity Information Facility, Invasive alien species, Shared Socioeconomic Pathways.

शोधसार

सुर्यमुखी परिवार अन्तरगत पर्ने सिंगापुर डेजी *(Sphagneticola trilobata* (L.) Pruski) मध्य-अमेरिकाको उष्ण क्षेत्रको रैथाने प्रजाति हो, तर एशिया, अफ्रिका र ओशिनियामा उष्ण तथा उपोष्ण क्षेत्रहरूमा फैलिएको विश्वको सबैभन्दा हानिकारक १०० प्रजातिहरू मध्ये एक हो। नेपाल लगायत दक्षिण एसियाली देशहरूमा यो झार तिब्र गतिमा फैलिरहेको हुनाले भविष्यमा फैलिन नदिन र उपयुक्त व्यवस्थापनका लागि यसको जलवायु अनुकूलता बुझ्न जरुरी छ । Global Biodiversity Information Facility (GBIF) मा सार्वजनिक रूपमा उपलब्ध तथ्याङ्क र Worldclim मा उपलब्ध जलवायुका सुचकाङ्कहरू (Bioclimatical variables) प्रयोग गरी यस अध्ययनमा दक्षिण एसियामा सिंगापुर डेजीको उपयुक्त बासस्थानको मूल्याङ्कन र वर्तमान तथा भविष्यको जलवायु अन्तर्गत यस क्षेत्रमा जलवायु अनुकूल क्षेत्रहरूको भविष्यवाणी परिदृश्यहरू Shared socioeconomic pathways (SSPs) २-४.५ र ५-८.५ तथा २०३० र २०५० को लागि) Ensemble मोडेलहरू प्रयोग वाट गरिएको छ। सिंगापुर डेजी आठ दक्षिण एशियाली देशहरु मध्ये भारत, श्रीलंका र माल्दिभ्स गरी छ वटा देशहरुमा उच्च आवृत्ति (frequency) मा रिपोर्ट गरिएको छ। हालको जलवायु परिदृश्यमा यस प्रजातीको उपयुक्त क्षेत्रहरू मुख्यतया श्रीलंका, बंगलादेश, माल्दिभ्स र दक्षिणी भारतीय राज्यहरू (जस्तै, कर्नाटक र केरला) मा पर्ने देखिन्छ। बाँकी दक्षिण एसियाली देशहरूमा क्षेत्रफलको थोरै हिस्सा मात्र उपयुक्त हुने अनुमान गरिएको छ। सिंगापुर डेजीको लागि जलवायु अनुकूल क्षेत्रहरु भविष्यका दुबै जलवायु परिवर्तन परिदृश्यहरु अन्तर्गत सबै देशहरुमा घट्ने प्रक्षेपण गरिएको छ। दक्षिण एसियाली देशहरू बंगलादेशमा (SSPs ५-८.५ अन्तर्गत ४५.७%) र भुटान (SSPs ५-८.५ अन्तर्गत २५%) मा यो प्रजातिको अनुमानित क्षेत्र घट्नेछ। त्यसैगरी, अध्ययनले यो पनि पहिचान गर्यो कि वर्तमान जलवायु परिदृश्यमा यो प्रजातिहरूको समग्र अनुमानित क्षेत्र घट्नेछ तर, भविष्यको मौसम परिदृश्यहरूमा, केही दक्षिण एसियाली देशहरू जस्तै श्रीलंका र माल्दिभ्समा यो प्रजातिको उपयुक्त क्षेत्रहरूको अनुपात बढी रहनेछ। विभिन्न परिदृश्यहरूमा उपयुक्त क्षेत्रहरूको गतिशीलताको विश्लेषणले वर्तमान अनुपयुक्त क्षेत्रहरू भविष्यमा उपयुक्त हुने संकेत गर्दछ। यो जानकारी व्यवस्थापन रणनीतिहरूलाई प्राथमिकता दिन उपयोगी हुनेछ ताकि पारिस्थितिक प्रणाली, जैविक विविधता र जीविकोपार्जनमा पर्न सक्ने सम्भावित नकारात्मक प्रभावहरूलाई रोक्न सकियोस । भविष्यमा जोखिममा पर्न सक्ने क्षेत्रहरू पहिचान गरेर, यस अध्ययनले जलवायु परिवर्तनको सम्बन्धमा सिंगापुर डेजी थप क्षेत्रहरूमा फैलिदा हुने जोखिमलाई न्यूनीकरण गर्न समयमै र उपयुक्त कदम चाल्नका लागि व्यवस्थापकहरू र नीति निर्माताहरूलाई बहुमूल्य जानकारी प्रदान गरेको छ।

शब्दकुञ्जी: जलवायु परिवर्तन, Global Biodiversity Information Facility, मिचाहा प्रजाति, Ensemble मोडेलहरू, Shared Socioeconomic Pathways

ABBREVIATIONS AND ACRONYMS

ANN	Artificial Neural Network
ASCII	American Standard Code for Information Interchange
AUC	Area Under the Curve
CMIP	Coupled Model Intercomparison Project
CO_2	Carbon dioxide
CSV	Comma Separated Value
CTA	Classification Tree Analysis
EDRR	Early Detection and Rapid Response
GAM	General Additive Model
GBIF	Global Biodiversity Information Facility
GBM	Generalized Boosting Model
GCM	Global Circulation Model
GHGs	Green House Gases
GLM	General Linear Model
GRIIS	Global Register of Introduced and Invasive Species
KATH	National Herbarium & Plant Laboratories
MARS	Multivariate Adaptive Regression Splines
MaxEnt	Maximum Entropy
RCP	Representative Concentration Pathways
RF	Random Forest
ROC	Receiver Operating Characteristics
SA	South Asia
SDM	Species Distribution Model
SRTM	Shuttle Radar Topography Mission

SSP	Shared Socioeconomic Pathways
TSS	True Skill Statistic
TUCH	Tribhuvan University Central Herbarium

CHAPTER 1: INTRODUCTION

1.1 Background

Biological invasions of non-native species influence natural species by means of competition and/or alternation of habitat quality (Vilà and Hulme, 2017); an essential component direct cause of change, causing biodiversity loss and the extinction of local and global species (IPBES, 2023). The globalization of human activities, extensive alternation of land, and climate change all contribute to the ease with which invasive species are introduced, established, and dispersed on both regional and global levels (Mack et al., 2000; Foley et al., 2005; Svenning and Condit, 2008). According to Diagne et al. (2021), invasive alien species cause an economic loss of US$1.288 trillion (2017 US dollars) in the 50-year time period, with no sign of a decline in the loss. Consequently, managing invasive plants poses a considerable challenge in mitigating their expansion into novel landscapes.

A species has to pass several stages to become invasive. For understanding the invasion process, Blackburn et al. (2011) presented a unified approach that comprises four stages - transport, introduction, establishment, and spread. A species must overcome its own unique set of obstacles at each stage to move on to the next. In the transport stage, the species must be transported to a new area. This can happen intentionally or accidentally. In the introduction stage, the species must be introduced to a suitable habitat. This can happen through release, escape, or contamination (Hulme et al., 2008). In the establishment stage, the species must survive and reproduce in the new area. This can be difficult if the species is not adjusted to the new surroundings. In the spread stage, the species must disperse and colonize new areas. This can be facilitated by human activities or by natural processes.

A significant danger to native biodiversity arises from the introduction of alien species. They are capable of causing ecosystem disruption, population declines, and extinctions (Rai and Singh, 2020). Generally, protected areas are less invaded, but islands are especially vulnerable to biological invasion. Though islands are not as vulnerable as other regions, native plants are the most affected category. Although they do not always offset the negative effects, invasive species can sometimes benefit native species (Bacher et al., 2023).

Successful management of invasive species requires strategies encompassing prevention, eradication, containment, and mitigation (Blackburn et al., 2011). According to Simberloff et al. (2013), prevention measures include regulations on trade and transportation to minimize future introductions. Early detection and rapid response (EDRR) programs intend to detect novel invasions at an early stage to facilitate effective control measures. Control strategies may involve eradication or control of established populations and restoration of affected ecosystems. To mitigate the impact of biological invasions, managers rely on the EDRR programs, involving eliminating emerging invasions before they become established. Knowing the circumstances that lead to species invasions can help with early infestation detection, which improves effectiveness (Bradley and Marvin, 2011). Geographical ranges and environmental factors that are favourable for invasive plant species can be predicted by ecological niche models (Thuiller et al., 2005). Therefore, these models can guide land managers regarding the optimal locations for implementing EDRR programs.

The elements of proactive management, such as prediction, prevention, early detection, eradication, and other rapid responses, prove to be more cost-effective and efficient compared to reactive strategies (Leung et al., 2002; Lodge et al., 2006; Rout et al., 2014; Epanchin-Niell and Liebhold, 2015). Prediction is achieved through risk assessment and pathway analysis. Common methods for evaluating the risks linked with invasive species frequently prioritize the identification of pathways and mechanisms of introduction and spread. This involves assessing vulnerable hosts and suitable habitats, as well as determining the potential outcomes of their establishment in previously unaffected regions (Pheloung et al., 1999; Anderson et al., 2003). Invasive species have an important role in driving global change (Pejchar and Mooney, 2009). Numerous studies have successfully shown the ability of invasive species to harm biodiversity and ecosystems, as well as how nature benefits humans (e.g., Vilà et al., 2011; Bacher et al., 2023). Because of an increase in global trade (Seebens et al., 2015), population growth (Vitousek et al., 1997), and global climate change (Peterson et al., 2008), the spatial distribution of species invasions at the global, national, and regional levels may expand in the future.

Out of the 100 most problematic invasive species worldwide, 37 are vascular plant species (Lowe et al., 2000; Luque et al., 2014), with 21 of them being non-native and currently present in Asian countries (Shrestha et al., 2022). Among them, South Asia became the second most invaded region by those worst species counting 17 species (Shrestha et al., 2022). Over the nations in the South Asian regions, there are significant differences in the number of IAPS. India has the highest number (185), followed by Bhutan (53), Sri Lanka (45), Bangladesh (39), Nepal (30), Pakistan (29) and the Maldives (15) (Gulzar et al., 2024). Controlling invasive alien plant species in South Asia is difficult without baseline data, therefore knowing the existing prevalence and introduction pathways of these species is crucial. New approaches to management will be possible by this information (Bhatta et al., 2023).

Sphagneticola trilobata (L.) Pruski is recognized as one of the world's 100 most detrimental invasive species (Lowe et al., 2000). Due to its ability to rapidly spread across extensive areas, eradication and containment (i.e., preventing further expansion to new areas) of the species is most important. The study species *Sphagneticola trilobata* is in the early stage of "establishment" in Nepal (Shrestha et al., 2021) whereas the species is widespread in other South Asian countries such as India and Sri Lanka (GBIF: https://www.gbif.org/occurrence/; accessed on March 29, 2023).

The species distribution models (SDMs) are statistical models of species-environment relationships based on species occurrence data and measures of associated environmental variables which are widely used techniques for spatial predictions (Elith and Franklin, 2013). Studies using SDMs explore how invasive plants alter their ecological niche in response to changing climatic conditions, both in terms of spatial distribution and over time (Kariyawasam et al., 2019). In SDMs, the environmental variables utilized may differ across various scales (Bradley et al., 2012). The behavior of invasive plants in unfamiliar climates is expected to be distinct and unpredictable; thus, possible responses under scenarios of climate change should be studied to enhance our understanding (Ibanez et al., 2009). The SDM studies have also been carried out to forecast future suitable locations for invasive plant species. These studies aim to examine the potential expansion of specific invasive plant species or certain taxa groups at a local level, with the objective of identifying areas for future strategic management. (Kariyawasam et al., 2019).

1.2 Statements of the problem

Species distribution modeling (SDM) serves as a valuable tool for forecasting the potential new regions suitable for the expansion of invasive alien species. Numerous modeling techniques have been developed to evaluate regions vulnerable to invasion across different scales (Guisan and Zimmermann, 2000), including envelope models such as MaxEnt, CLIMEX, and GARP, as well as ensemble models (Beaumont et al., 2005). These approaches are commonly employed to forecast the potential distribution of invasive species by considering their ecological and climatic characteristics, under the assumption that climate primarily dictates plant species distribution (Baker et al., 2000; Kriticos et al., 2003; Phillips et al., 2006). In this study, an ensemble model was used to predict the distribution of *Sphagneticola trilobata*. Ensemble models combine outputs from different models, are reported to outperform an individual model (Crossman and Bass, 2008; Stohlgren et al., 2010) and have been used for the prediction of climatically suitable regions of several invasive alien invaders (e.g., Shrestha et al., 2018, Shrestha et al., 2022).

For the control of *Sphagneticola trilobata* before its' spread, different EDRR activities, as well as modelling techniques, have not been applied yet. This modelling exercise will identify regions in South Asian countries with high climatic suitability as well as a high vulnerability to invasion by this weed. Similarly, the study will also identify the regions where the probability of invasion by this weed is very low. This information will be useful in selecting appropriate management strategies so that potential negative impacts on ecosystems, biodiversity and livelihood can be averted.

1.3 Hypothesis

A hypothesis of the present research is: Climate change expands climatically suitable areas of *Sphagneticola trilobata* in South Asia.

1.4 Objectives

A general objective of the current research is to predict the climatically suitable region of the globally worst invasive weed, *Sphagneticola trilobata* in South Asia.

The specific objectives are

- To analyze the current distribution of *S. trilobata* in South Asia.
- To predict climatically suitable regions of *S. trilobata* in South Asia.
- To analyze the potential impacts of climate change on the distribution of climatically suitable regions of this weed in South Asia.

1.5 Limitations

A major limitation of the present study is that it depends on secondary occurrence data obtained from the GBIF. The accuracy of the data presented in the GBIF has a limit on the accuracy of the findings. The accuracy of the GBIF data can also affect the accuracy of the predicted suitable region. The accuracy of Species Distribution Model predictions heavily depends on the quality and quantity of occurrence data available for the species. Limited occurrence data may lead to less accurate predictions, especially in areas where the species is rare or underreported. Therefore, the results of this study should be interpreted in light of such limitations. Nevertheless, the findings of this study can be used for management decisions of invasive species.

CHAPTER 2: LITERATURE REVIEW

Biological invasion is regarded as a major global environmental alteration that poses a significant threat to biodiversity as well as ecosystems (IPBES, 2023). Invasive alien species exert pervasive and detrimental effects across all ecological levels, contributing to extinctions, particularly impactful in isolated ecosystems like islands, posing substantial threats to protected areas' biodiversity and ecosystems, affecting several aspects of the benefits that nature provides to human welfare, and significantly burdening Indigenous Peoples and Local Communities (IPLC) with predominantly negative impacts on water resources, human and livestock health, and traditional land access (Bacher et al., 2023). Vitousek et al. (1996) also suggests that biological invasion is a key factor driving global environmental change. Invasive species primarily affect the functioning of communities and ecosystems, leading to profound impacts (Braun et al., 2019; Papier et al., 2019). Richburg (2008) further highlights that invasive species not only impact the environment but also have social as well as cultural impacts. Therefore, invasion species has significant and widely recognized effects on the economy, ecology, and society. (Gallardo and Aldridge, 2013; Marbuah et al., 2014; Vilà and Hulme, 2017; Castro-Diez et al., 2019). An economic loss of US$1.288 trillion (2017 US dollars) has been attributed to invading alien species for 50 years, and there is no indication that this amount will decrease (Diagne et al., 2021). According to studies by Etana (2013) and Qureshi et al., (2014), invasive plants can lead to reduced agricultural productivity, alteration of native flora, and disturbance of ecosystem processes. Worldwide, invasive alien species rank among the top five major contributors to decline in biodiversity, sharing this critical role with alternations in land and sea use, direct exploitation of organisms, climate change, and pollution (Lopez et al., 2022).

2.1. Climate change and Plant invasion

In the current context, climate changes have a significant impact on the increase of biological invaders (Walther et al., 2009; Bradley et al., 2010). Changes in the climate system, particularly in temperature and precipitation conditions, and rise in atmospheric CO_2 level contribute to the promotion of invasiveness and expansion of invasive species in new areas (Stachowicz et al., 2002; Walther et al., 2009; Bradley et al., 2010; Bellard et al., 2013). Depending on how much these variables change, invasive plants may benefit or be negatively impacted by temperature and precipitation variations (Finch et al., 2021). Climate change induces alterations, such as temperature increase and unpredictable rainfall patterns, which result in negative impacts on the management strategies of invasive species, changes in seasonal phenology and range shifts (Sutherst et al., 2000; Hellmann et al., 2008; Chen et al., 2009; Dillon et al., 2010; IPCC, 2014; Shamsabad, 2018). Climate change influences the entire invasion process in three key ways: the source pools of invasive species, dispersal pathways, and the invasion process within new host ecosystems (Sutherst et al., 2000).

The mutually beneficial relationship between biological invasions and climatic change is obvious in the context of environmental dynamics. The process of invasion is facilitated by climate change, which creates new, favourable environments for the spread and establishment of invasive species (Bradley et al., 2009; Bellard et al., 2016). Studies suggest that shifting climate conditions result in an expansion of the range of invasive alien species rather than a reduction due to physical barriers, restricted dispersal, and the species' potential life history. Several invasive species notably experienced some degree of range shift as a consequence of climate change (Buckley et al., 2010). Allen and Bradley (2016) reported that 80% of existing invasive plant hotspots remained geographically stable despite changing climate conditions, while the remaining 20% shifted northward. Climate change might also widen pathways for the dissemination of invasive species through tourism and commerce (Hellmann et al., 2008). Additionally, invasive alien species are introduced to new territories through natural disasters like floods or cyclones, as well as human activities, whether accidental or intentional (Sandilyan, 2015). Global environmental shifts may elevate the global risks associated with biological invasions (Ricciardi et al., 2017). Climate changes also influence how quickly new species become established and how invasive existing species and dormant ones might become (Spear et al., 2021).

Research conducted at global, continental, and national scales, utilizing projected future climate scenarios, has examined the effects of climate change on the distribution of climatically suitable regions for invasive species (Poland et al., 2021). These studies employ various models to identify and forecast the influence of climate change on invasive species, leading to the expansion and altered distribution of certain invasive species. Broennimann and Guisan (2008) forecasted current and future biological invasions in both native and invaded ranges using an alternative prediction approach involving fitting models with pooled data from all ranges. They concluded that this pooled approach enhances the prediction accuracy of invasion extent.

2.2. Status of Biological Invasion in South Asia

South Asia is a region with diverse climatic zones and physical landscapes, which exposes it to a wide range of impacts from climate change. These impacts either create a favourable environment for invasive alien species to thrive or even without climate change, numerous regions remain suitable for IAS (Hasnat et al., 2018). In South Asian regions, a significant proportion of the population relies on agriculture for their livelihoods. However, the agriculture and biodiversity sectors in this area have been increasingly susceptible by global environmental changes, including climate change (Fatima et al., 2020), and biological invasions in recent decades (Bang et al., 2022; Pathak, 2023). Numerous invasive weeds pose a serious threat to agricultural and pasture plants in agroecosystems, as they compete for soil moisture and nutrients (Mausam et al., 2022). Aquatic habitats are also confronted with considerable threats from both climate change and biological invasions, particularly on a broader geographic scale (Gallardo et al., 2016; Gillard et al., 2017). The consequences posed by invasive aquatic plant species in response to climate change, such as rising temperatures, increased CO_2 levels, and alterations in precipitation patterns, are of grave concern globally (Gallardo et al., 2013). These impacts extend to aquatic biodiversity, ecosystem services, agriculture, and food security, highlighting the urgency of addressing this issue in many countries (Kariyawasam et al., 2021).

Invasive alien species, along with land use and climate changes, collectively exacerbate global environmental degradation, resulting in synergistic, adverse effects on ecosystems, biodiversity and agricultural production (Ravi et al., 2022; Lopez et al., 2022).

India, a mega-bio-diverse country with four global biodiversity hotspots, is home to hundreds of alien species. Among them, 185 alien plant species were being invasive in India (Gulzar et al., 2024). Between 1960 and 2020, invasive alien species caused significant economic losses to India's economy, totaling US$ 182.6 billion overall and US$ 127.3 billion when considering observed and high-reliability costs (Bang et al., 2022). Over the past two decades, India's extensive infrastructure projects have led to the destruction of natural habitats and the formation of disturbance corridors, creating favorable conditions for the introduction and spread of alien species (Sharma et al., 2005). The influx of alien species and their rate of introduction are closely linked to the scale of merchandise imports, a significant factor in India (Levine and D'Antonio, 2003; Westphal et al., 2008). Notable instances of Invasive Alien Species (IAS) in India include *Parthenium hysterophorus*, *Leucaena leucocephala*, and *Oreochromis mossambicus* (Ganie et al., 2013; Ahmad et al., 2019; Sankaran et al., 2021).

According to Paini et al., (2016) and Kariyawasam et al., (2017), Sri Lanka is facing a major challenge to agricultural production and food security due to invasive alien plant species (IAPs). Global environmental changes, such as increasing concentrations of atmospheric CO_2, temperature changes, and rainfall patterns, are major factors affecting the management of weed populations in agroecosystems (Varanasi et al., 2016). These changes pose a heightened risk of biological invasions on a global scale (Ricciardi et al., 2017). As Sri Lanka heavily relies on the agriculture sector for rural livelihood development (Central Bank, 2019), it is crucial to comprehend the effects of climate change on the distribution and persistence of weeds and invasive alien plant species (IAPS) in agriculture, particularly in food crop production.

There are 179 naturalized flowering plants in Nepal, and 30 of them are considered invasive (Adhikari et al., 2022; Shrestha, 2022, Gulzar et al., 2024). Notable invasive species in Nepal include *A. adenophora, Ageratum houstonianum, Chromolaena odorata, E. crassipes, L. camara, M. micrantha*, and *P. hysterophorus*. Gulzar et al. (2024) identified 15 invasive alien plant species, including *E. crassipes, L. camara, L. leucocephala, and Sphagneticola trilobata* in the Maldives.

As per the GRIIS database, the count of naturalized species is 107, 203, and 56 for Bangladesh, Maldives, and Afghanistan respectively (Bhatta et al., 2023). The relatively low number in Afghanistan could be due to insufficient assessment and research. From the study of Mukul et al., (2020) 69 IAPS were reported, including

Chromolaena odorata, Lantana camara and *Mikania micrantha* from Bangladesh, which are listed among the world's worst invasive alien species. Similarly, Dorjee et al. (2020) found that out of 964 alien plant species in Bhutan, 335 were observed outside cultivated areas, comprising 101 invasive species, 103 naturalized aliens, and 131 accidental aliens. Among these invasive species, *Tithonia diversifolia*, *A. adenophora*, *C. odorata*, *P. hysterophorus*, and *M. micrantha* are notable ones (Yangzom et al. 2018).

Gulzar et al., (2024) identified 29 IAPS in Pakistan, with notable invaders including *Eicchornia crassipes*, *Leucaenea leucocephala*, *Lantana camara, Broussonetia papyrifera*, *Eucalyptus camaldulensis*, *Xanthium strumarium*, *Prosopis juliflora*, *Parthenium hysterophorus* and *Salvinia molesta.*

2.3. Species Distribution Modeling (SDM)

Species Distribution Modeling (SDM) integrates ecological and biogeographical principles to analyze the interaction between species distributions and environmental factors (Holdridge, 1947; Whittaker et al., 1973). Also referred to as ‘Habitat Suitability’ or ‘Environmental Niche Modeling’, the SDM employs species-location data, environmental variables, and statistical techniques to establish equations describing species-environment relationships (Elith and Leathwick, 2009). These models are quantitative and empirical, aiming to quantify the influence of environmental characteristics on species occurrence (Franklin, 2010).

The SDMs forecast species distribution by extrapolating environmental conditions from known habitats to potential new areas (Srivastava et al., 2020). They are applied to predict rare, threatened, or invasive species' distributions (Engler et al., 2004; Pearson et al., 2007). SDM's versatility encompasses various applications such as biogeographic studies, conservation planning, and addressing climate change impacts (Guisan and Zimmerman, 2000; Padalia et al., 2014). SDMs have been globally adopted for predicting invasive species, especially exotic plants, aiding in prioritizing monitoring, control, and resource allocation (Peterson, 2003; Zhu et al., 2007; Rameshprabu and Swamy, 2015). Moreover, SDMs unveil factors promoting invasion, allowing for targeted management strategies (Loo, 2009). These models also predict how climate change will impact the spread of invasive species, providing valuable insights for proactive management strategies (Catford et al., 2016).

Over the past two decades, significant progress has been made in the field of species distribution modeling, resulting in a variety of methods that vary in their utilization of species data (Underwood et al., 2013). One of the commonly used approaches is ensemble modeling. Ensemble modeling techniques are employed to offer a more precise evaluation of habitat suitability for invasive species and their potential expansion within a specified timeframe. This approach comprises combination forecasts from multiple SDM models into a single binary map by weighting the average model predictions with an evaluation metric, such as AUC (Thuiller et al., 2004; Araújo and New, 2007; Marmion et al., 2009). In other words, the ensemble models are generated by applying specific algorithms that are produced from diverse methods, including Principal Component Analysis (Thuiller, 2004; Araújo et al., 2005a) and statistical criteria (Johnson and Omland, 2004), or simple mathematical functions such as averaging and medians of prediction ensembles (Gregory et al., 2001; Araújo and New, 2007). Theoretically, the ensemble model is expected to offer more precise and reliable forecasts compared to any single model by itself (Araújo and New, 2007; Marmion et al., 2009). Various research works have demonstrated that ensemble modeling has the potential to enhance model predictions (Stohlgren et al., 2010; Grenouillet et al., 2011; Oppel et al., 2012). Ensemble modeling is also recommended as a superior approach compared to single models for projecting future climate changes involving numerous species (Araújo and New, 2007). Nonetheless, there remains uncertainty regarding the efficacy of ensemble modeling. The selection of initial species distribution models (SDMs) employed for averaging significantly impacts model performance (Araújo et al., 2005a; Diniz-Filho et al., 2009).

The use of ensemble forecasting emphasizes the improved accuracy that can be achieved through combining models in risk analysis of invasive species, specifically in habitat mapping of invasive species (Stohlgren et al., 2010). Araujo et al., (2005b) also advocated that the use of ensemble forecasting improved the accuracy of modelling. Several studies have employed this approach and reported promising results. For example, Crossman and Bass (2008) utilized ensemble modeling to delineate the distribution of *Olea europaea* L. (European olive) in southern Australia. They discovered that the ensemble model outperformed individual models in terms of accuracy. According to Poulos et al. (2012), they conducted ensemble forecasting to predict potential habitats for three invasive species. Their studies suggest that ensemble modelling can be a useful tool for mapping invasive species as compared to other models and helps in identifying the regions that are at high risk of invasion both under current and in future scenarios, which is beneficial for implementing Early Detection and Rapid Response (EDRR) measures for managing aquatic biodiversity.

Similarly, Shrestha et al. (2022) employed ensemble modeling and a hotspot approach to delineate the present and future range of medicinal and aromatic plants in the Nepal Himalayas, aiming to guide environmental conservation efforts and adaptation policies.

Species distribution models serve as valuable tools in managing invasive species by enabling the prediction and mapping of potential suitable habitats on a spatial scale (Anderson et al., 2003; Qin et al., 2014). These models help in identifying areas where invasive species might exist but remain undetected, as well as areas where they could spread in the future. By forecasting habitat suitability spatially, species distribution models aid in determining the scope and effectiveness of a given management approach and prioritize locations for surveillance and control efforts (Ward, 2007).

2.5. Introduction history, dispersal pathway and impacts of *Sphagneticola trilobata*

Sphagneticola trilobata (L.) Pruski [Asteraceae] is a groundcover species indigenous to the tropical regions of Central America. Initially brought into South China during the 1970s for ornamental purposes, it has now emerged as a significant invasive weed, quickly proliferating across the area (Li and Xie, 2002). It is also considered one of the most dominant invasive plants in many Pacific islands (Meyer, 2000) and has been classified among the top 100 worst invasive alien species globally (Lowe et al., 2000). According to Thaman (1999), *S. trilobata* has become naturalized in many Pacific Island countries and regions, including high volcanic islands, limestone islands and islands, spreading up to 700 m in elevation and was also used for erosion control and landscaping purposes in various locations. It is easy-to-maintained and energetically growing nature, as well as dynamic vegetative reproduction, made it an attractive option for such purposes (Thaman, 1999). Randall (2017) suggests that significant pathways for the introduction of *Sphagneticola trilobata* may involve its utilization as a decorative plant and its presence as a contaminant in agricultural and floricultural products. Sankaran et al. (2012) reported that *S. trilobata* reproduces through both seeds and stem fragments.

Sphagneticola trilobata hinders the regrowth of other species by creating a dense ground cover in the shape of a mat, and it competes with crops for nutrients, water, and light in a plantation, lowering crop productivity (https://iucngisd.org/gisd/species.php?sc=44, GISD, 2023 (August 4, 2023)). It is known to prevent the regeneration of other species and form mono-specific communities at forest edges, resulting in a decline in species diversity and richness (Wu et al., 2005a, b). The plant has been found to have allopathic effects on native plants, reducing their germination and growth rate (Zhang et al., 2004**,** Wu et al., 2008). *Sphagneticola trilobata* has also been observed to demonstrate greater growth stimulation and higher photosynthetic energy-use efficiency than its native congener under high CO_2 concentrations in Southern China (Li et al., 2010; Song et al., 2010). The plant's greater heat tolerance and lower energetic cost for biomass constitution contribute to its invasive success (Song et al., 2010). Additionally, *S. trilobata* has been found to destroy riverbanks and wetlands, further contributing to its negative impacts on the ecosystem (Yu et al., 2009). While it is often found in disturbed sites, it can also thrive in relatively undisturbed areas along shorelines and the margins of mangroves and swamplands, of out-competing native coastal herbaceous species, some of which have significant cultural value.

2.5.1. *Sphagneticola trilobata* in South Asia

The status and impacts of this study species should be known as one of the most severe invasive alien species worldwide. To know the status and impacts of this study species *S. trilobata* fewer studies have been done in recent. In South Asian countries, this invasive species was recorded from India, Sri Lanka, Nepal and Maldives (Shrestha et al., 2022). In other countries like Bangladesh, Bhutan and Pakistan, this species is in its initial stages (According to GBIF records).

According to the findings of Shrestha et al. (2021), the first documented occurrence of *S. trilobata* in Nepal was observed in the Panchkhal municipality of the Kavrepalanchowk district. At present, the invasive plant is in its "establishment" phase, spreading across an estimated area of 15 square kilometers along the Jhiku Khola, a tributary of the Sunkoshi River, from Panchkhal bazaar to the Sunkoshi

River (Shrestha et al., 2021). Furthermore, initial investigations conducted in Panchkhal Municipality indicate that *S. trilobata* was intentionally introduced as part of a development project aimed at mitigating soil erosion (Shrestha et al., 2021).

Figure 1: *Sphagneticola trilobata* invasion in Tamaghat village of Panchkhal Municipality, Kavreplanchok, Nepal (26th August 2023)

The above figure represents the current status of this species in Panchkhal Municipality, which has currently invaded the cropland area. While interacting with the local people of this area, the species is likely to invade the crops mainly in the rainy season in comparison to other seasons. According to the local people, this species spreads like a mat-forming cover (personal observation); and is used as fodder but this species was not preferred by the livestock.

2.6. Research Gap

Several studies have used SDMs for the prediction of suitable areas for invasive alien species. Araújo and New (2007) suggest ensemble modeling as a superior option compared to single models for modeling future climate projections. In recent studies, many of the research used SDM tools for the prediction of suitable habitats from

South Asian countries (Kariyawasam et al., 2017; Maharjan et al., 2019; Poudel et al., 2020) despite such recommendations. Different kinds of studies related to invasive species were done in South Asian countries i.e., the Study area of this research. Very few studies were available related to the ensemble model but from the South Asian region, none of the studies were found. Although considered one of the most problematic invasive alien plant species (IAPs), there has been a lack of research conducted on management practices for this species. Therefore, this study is primarily focused on addressing this gap.

Sphagneticola trilobata, ranks among the world's 100 most notorious invasive species. Several studies reviewed the status, its allelopathic effects (Wang et al., 2012; Junhirun et al., 2018) as well as impacts of this species (Macanawai, 2013) but not about management perspectives. There is lacking of the management aspects of this species in South Asia. Using the SDM tools especially, the ensemble model, will be more effective in predicting the suitable habitat of invasive species in South Asian regions as well as all around the world. Being rich in biodiversity/hotspots of several endemic species, the South Asian region is at great risk of invasion as it impacts/affects the valuable resources as well as the life cycle of several species resulting in an imbalance in the ecosystem. In this research, the study mainly focused on the current occurrence, predicted present as well as future suitable habitat of the invasive plant species in South Asian regions regarding the management perspective.

Thus, predicting the suitable potential habitat of the world's worst invasive species is crucial to protect biodiversity from its impact. Therefore, it is argued that addressing in major gap in research involves how the occurrence data and several SDM tools help to identify the suitable habitat of these invasive species and help the environmental managers in biodiversity conservation efforts.

CHAPTER 3: MATERIALS AND METHODS

3.1. Study Area

The present study encompassed South Asia; a vast landmass situated in the southern part of the Asian continent. This region comprises eight countries: Afghanistan, Pakistan, India, Maldives, Sri Lanka, Nepal, Bangladesh and Bhutan. Spanning nearly 5.1 million km^2, South Asia accounts for approximately 11.51% of the Asian continent's total area (SACEP, 2016). This region is the most populous of all the sub-regions of Asia, with a population that accounts for around 25.2% of the world's population (https://www.worldometers.info/world-population/southern-asia-population/, assessed on 9 Aug 2023).

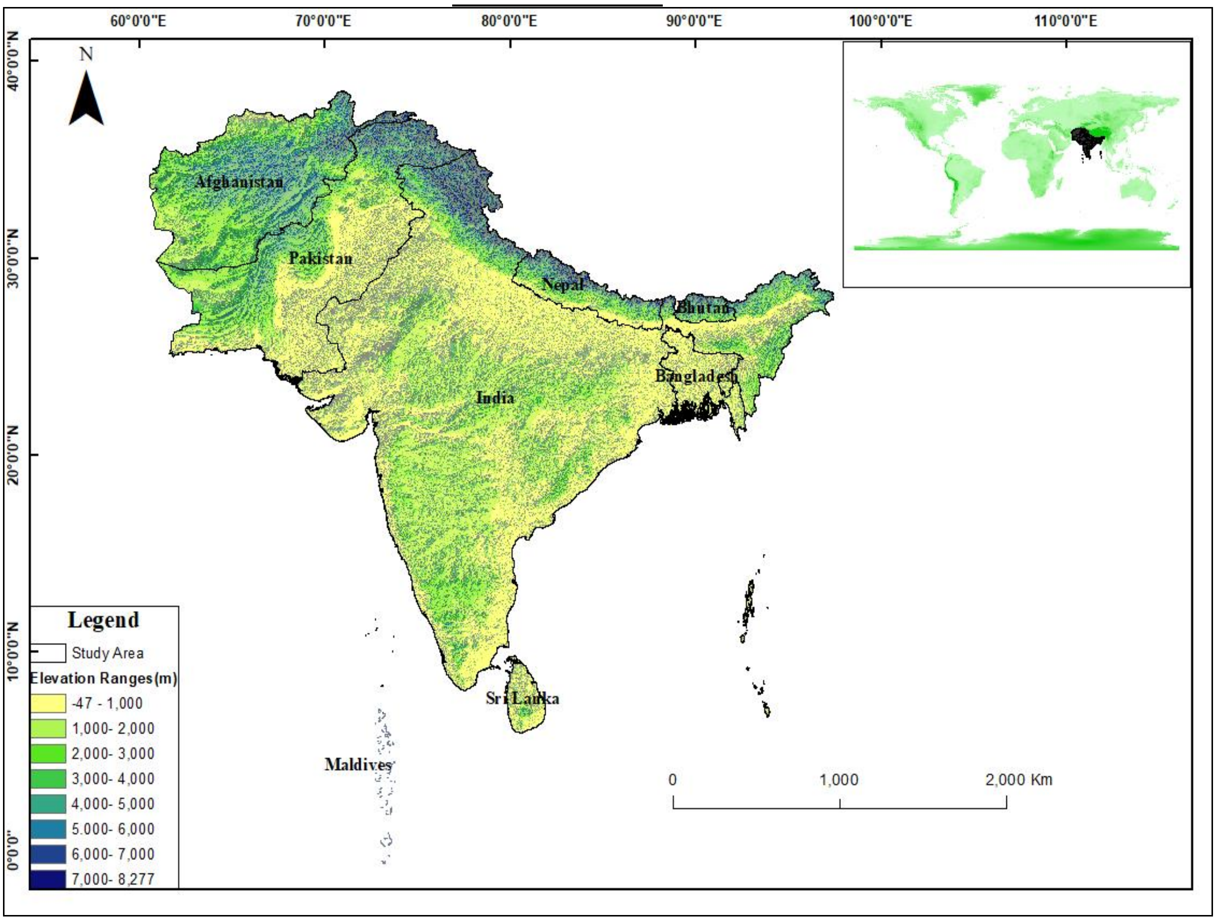


Figure 2: Map of the Study Area

Due to its diverse natural resources and ecosystems, South Asia holds significant ecological importance globally. The region's total forest coverage accounts for 2.73% of the world's forests and supports approximately 15.5% of the world's flora and 12% of its fauna (Hasnat et al., 2018). It host a rich floral diversity, including 39,875 species of flowering plants, 66 conifers and cycads, and 764 ferns (Hasnat et al., 2018). South Asia is home to four of the world's 35 biodiversity hotspots, namely the Eastern Himalayas, Sundaland, Indo-Burma, and Western Ghats, and India ranks among the world's 17 most biodiverse nations (Chowdhury et al., 2022).

The immense climatic diversity of South Asia, encompassing nearly half the world's zones, presents unique challenges and opportunities for native as well as alien species. With diverse climatic zones and varied physical landscapes, the region faces a wide array of impacts from climate change. The rapid industrialization and human activities in South Asia have fostered conducive environments for numerous invasive species (Hasnat et al., 2018). Agriculture serves as a vital component of the economy in most South Asian countries, supporting the livelihoods of approximately half the population. The region's agricultural sector has, however, faced challenges from global changes to the environment like climate change and biological invaders in recent decades (Bang et al., 2022; Pathak, 2023). According to a study by Paini et al., (2016), Nepal and Bangladesh are the third and fourth most vulnerable countries in the world, respectively, to the invasive alien species in the agriculture sector.

Despite being rich in biodiversity, South Asian regions face several challenges triggered by global trade and anthropogenic activities along with climate change and biological invasions (IPBES, 2018, Shrestha et al., 2022). Since trade, travel, and tourism are all on the rise and are unlikely to slow down anytime soon (Early et al., 2016), it is critical to monitor biodiversity-rich places to assess the presence of invasive species and put appropriate management measures in place (Bhatta et al., 2023).

3.2. Species occurrence data

The occurrence data for *Sphagneticola trilobata*, including geographic coordinates of both its native and introduced regions, was obtained from the Global Biodiversity Information Facility (GBIF), an open-access and extensive biodiversity database.

Based on the initial search, the GBIF currently has more than 18,000 global occurrences records for *S. trilobata*, and the records were downloaded on March 28 of the year 2023 (https://doi.org/10.15468/dl.se9q9q). South Asian countries' shape files were collected from an open-source website and designated as the study's focus area.

The occurrence of *S. trilobata* in Nepal was obtained from Shrestha et al. (2021). This research utilized 1870 occurrence points collected from South Asian countries. The elevation for each point was determined using elevation data sourced from Shuttle Radar Topography Mission (SRTM) and processed using ArcGIS software. Sampling biases in location data can lead to increased spatial auto-correlation of localities, potentially causing overfitting of models. To address this, Boria et al. (2014) suggest that applying spatial filtering to occurrence data can enhance model accuracy by decreasing autocorrelation. In this study, spatial filtering was implemented by eliminating multiple points situated within a one-kilometre grid. This process ensured that only a single presence point was retained per 30-arc-second grid (approximately 1×1 km), aligning with the spatial resolution of the environmental factors (Elith et al., 2010). Specifically, 1,282 presence points were employed from the original 1,870 points for modelling the distribution of *S. trilobata*.

3.3. Environmental variables

3.3.1. Bioclimatic variables

For the current and future time periods, a total of 19 gridded bioclimatic variables (Table 1) were used in models to predict climatically suitable areas of *Sphagneticola trilobata* in South Asia. These variables were sourced from WorldClim version 2.1 (https://www.worldclim.org/data/worldclim21.html; Fick and Hijmans, 2017) at a spatial resolution of 30 arc-seconds, or a pixel size of roughly 1 km^2.

Table 1: List of 19 bioclimatic variables from the WorldClim database (Hijmans et al., 2005)

VARIABLES	EXPLANATIONS
BIO1	Annual Mean Temperature
BIO2	Mean Diurnal Range
BIO3	Isothermality(BIO2/BIO7)(*100)
BIO4	Temperature Seasonality
BIO5	Max Temperature of Warmest Month
BIO6	Min Temperature of Coldest Month
BIO7	Temperature Annual range (BIO5-BIO6)
BIO8	Mean Temperature of Wettest Quarter
BIO9	Mean Temperature of Driest Quarter
BIO10	Mean Temperature of Warmest Quarter
BIO11	Mean Temperature of Coldest Quarter

BIO12	Annual Precipitation
BIO13	Precipitation of Wettest Month
BIO14	Precipitation of Driest Month
BIO15	Precipitation Seasonality
BIO16	Precipitation of Wettest Quarter
BIO17	Precipitation of Driest Quarter
BIO18	Precipitation of Warmest Quarter
BIO19	Precipitation of Coldest Quarter

Data on precipitation and global temperature from 1970 to 2000 have been used to calculate bioclimatic variables within the WorldClim dataset. According to Hijmans et al. (2005), future bioclimatic variables for 2030 are calculated by averaging the expected values for 2021–2040; 2050 is calculated by averaging the projected values for 2041–2060; and 2070 is calculated by averaging the projected values for 2061–2080. Projected greenhouse gas emission scenarios were used to derive future bioclimatic variables.

3.3.2. Non-climatic variables

Elevation is a significant non-climatic factor that is considered when defining the geographic distribution of invasive alien species. The elevation data were obtained from WorldClim version 2.1 (https://www.worldclim.org/data/worldclim21.html; Fick and Hijmans, 2017) with a spatial resolution of 30 arc-seconds, equivalent to approximately 1 km^2 per pixel. In South Asian nations, elevation greatly influences species distribution, thus it was considered in the analysis.

3.4. Species distribution modelling

3.4.1. Selection of optimal environmental variables

To reduce multi-collinearity among numerous environmental variables (comprising 19 bioclimatic and one non-climatic variable, 'elevation'), as well as to prevent overfitting of the model, correlation analyses were conducted using SDM Toolbox v2.5. and variables showing high correlation, with a Pearson's correlation coefficient greater than or equal to 0.8, were subsequently removed. The Appendix I displays the Pearson's correlation coefficient between the variables. The variables with the highlighted text are the ones that are eliminated from the study due to their low study utility, while the correlation values highlighted indicate variables with high correlation. Ultimately, 8 bioclimatic variables (Annual mean temperature (Bio 1), temperature seasonality (Bio 4), minimum temperature of the coldest month (Bio 6), temperature annual range (Bio 7), mean temperature of the warmest quarter (Bio 10), mean temperature of the coldest quarter (Bio 11), Annual Precipitation (Bio 12), and Precipitation of Wettest Month (Bio 13)) were selected as predictors for constructing the habitat suitability model.

3.4.2. Model selection

The study utilized the open-source R-4.2.2 software (R Core Team, 2021) to conduct the modeling. The Biomod 2 package was installed within the R environment to facilitate ensemble modeling, a technique known to outperform single algorithm approaches (Araujo and New, 2007; Marmion et al., 2009). This ensemble model comprised seven algorithms: three regression methods (GAM: Generalized Additive Model, GLM: Generalized Linear Model, and MARS: Multivariate Adaptive Regression Splines), three machine learning methods (ANN: Artificial Neural Network, GBM: Generalized Boosting Model, and RF: Random Forest), and one classification method (CTA: Classification Tree Analysis). According to Hao et al. (2019), these are the models that ensemble modelling most usually uses.

Ensemble models are utilized to mitigate the uncertainty inherent in single-model predictions by aggregating the forecasts of multiple models, thus ameliorating the limitations of individual model predictions (Hao et al., 2019). To make these predictions, projected bioclimatic variables for the years 2030 and 2050 were utilized, based on the Shared Socioeconomic Pathways (SSPs) scenario from the Coupled Model Intercomparison Project Phase 6 (CMIP6) as outlined by the Intergovernmental Panel on Climate Change (IPCC, 2021). Gridded bioclimatic variables for future climate scenarios were generated using the outputs of Global Circulation Models (GCMs) covering various periods in the twenty-first century (Kriticos et al., 2012). Bioclimatic data for all present scenarios except 'GFDL-ESM4' GCM were sourced from WorldClim (Fick and Hijmans, 2017) due to the absence of SSP2-4.5 and SSP5-8.5 data, which were the main focus of this study. To enhance reliability, an ensemble of the 24 GCMs was created by averaging their values, with the ensemble values used as predictors.

Barbet-Massin et al. (2012) method was employed where 5,000 pseudo-absences were randomly selected for each iteration, positioned beyond a 10 km buffer from the presence points due to the unavailability of true absence data. The models were trained using 70% of the occurrence points (comprising both presence and pseudo-absence data) and tested using the remaining 30% (Araujo et al., 2005a). Three evaluation rounds were conducted for each study species during the pseudo-absence generation process, resulting in a total of 63 models per species (seven models per species, three evaluation rounds, and three pseudo-absence selection procedures) for each climate scenario.

True Skills Statistics (TSS) and Area Under Curve (AUC) were used as test statistics to evaluate the accuracy of the model's prediction abilities. According to Allouche et al. (2006) and Beaumont et al. (2016), a TSS value of 0.4 suggests poor model discrimination, whereas a TSS value of +1 shows perfect agreement. The projection outputs were used to form an ensemble using models with strong predictive accuracy (TSS > 0.6) (Thuiller et al., 2009; Gallien et al., 2012; Bellard et al., 2013). An ensemble model was created from the 63 individual models using a weighted-mean technique, where weights are assigned based on the evaluation metrics scores of each model. This ensures equitable discrimination in the ensemble model (Marmion et al., 2009). During the cross-validation process, binary maps (suitable and unsuitable) were created by utilizing the optimal threshold that maximizes the TSS score. This threshold prioritizes sensitivity (the number of false positives) over specificity (the number of false negatives) and remains unaffected by the species occurrence frequency (Allouche et al., 2006; Marmion et al., 2009; Liu et al., 2013).

ArcGIS (version 10.8) was used to visualize the binary map into two categories, appropriate habitat and unsuitable habitat. A binary habitat suitability map was produced in this manner for the present climate and all potential future climatic scenarios. For both present and future climate scenarios, the climatically suitable region was determined.

3.5. Model evaluation and validation

3.5.1. Accuracy Assessment

3.5.1.1. Threshold Independent ROC and AUC

Generating a plot of sensitivity (1-omission rate) against fractional expected area (1-specificity) across various thresholds results in the receiver operating characteristics (ROC) curve (Jafari et al., 2022). Correctly anticipated presence records and absence records are used to define sensitivity and specificity, respectively. Both the area under the receiver-operating characteristics curve (AUC) and the ROC will be used to evaluate and validate the model's accuracy (Pearsons, 2010). The AUC value, which spans from 0 to 1, serves as a threshold-independent method to distinguish between presence and absence to assess model performance (Thuiller et al., 2005). According to Peterson et al., (2011), the model performance will be assessed based on the following categories: exceptional (0.9-1), highly satisfactory (0.8-0.9), satisfactory (0.7-0.8), moderate (0.6-0.7), and unsuccessful (0.5).

3.5.1.2. True skill statistics (TSS)

The TSS values, ranging from -1 to 1, take into account both sensitivity and specificity to detect both commission and omission errors (Allouche et al., 2006; Lobo et al., 2008). According to Allouche et al. (2006), values nearing 1 indicate agreement between observation and forecast, whereas values nearing -1 suggest agreement as random as possible.

The threshold criterion for the tenth percentile of training presence was determined using both the true skill statistic (TSS) and the area under the curve (AUC). Utilizing the tenth percentile training presence is highly cautious when evaluating species tolerance towards individual climatic variables (Svenning et al., 2008), as it excludes the bottom 10% of locations or training presence records with the lowest projected values.

3.5.2. Sensitivity analysis

It was employed to compare the training gain achieved by the model when all predictor variables were taken into account with the relative importance and training gain of each individual predictor variable utilized in training the model.

3.6. Potential distribution under future scenarios

Climatically suitable areas of *S. trilobata* in South Asia were predicted under future climate change scenarios. To make these forecasts, anticipated bioclimatic factors for the years 2030 and 2050 were employed based on the Shared Socioeconomic Pathways (SSPs) scenario from the Coupled Model Intercomparison Project Phase 6 (CMIP6), as outlined by the Intergovernmental Panel on Climate Change (IPCC, 2021). The SSPs were developed to describe future societal and environmental changes. The five Shared Socioeconomic Pathways (SSPs) - SSP1 emphasizing sustainability; SSP2 representing a moderate path; SSP3 centered around regional competition; SSP4 addressing issues of inequality; and SSP5 focusing on fossil fuel-driven development - depict various challenges related to adaptation and mitigation, potentially mirroring future socioeconomic trends (O'Neill et al., 2014 and 2017). Among these scenarios, SSP1-1.9, SSP4-3.4 and SSP3-7.0 are the new scenario combinations, and SSP1-2.6, SSP2-4.5, SSP4-6.0 and SSP5-8.5 are the updated versions of the RCP scenarios from CMIP5.

To predict climatically suitable areas in future climate scenarios SSP2-4.5 and SSP5-8.5 were used for this study. The average temperature that will increase by 2100 under the SSP2-4.5 scenario is projected to be around 2.4°C to 2.7°C above pre-industrial levels. In contrast, under the SSP5-8.5 scenario, the average temperature that will increase by 2100 is projected to be higher, ranging from approximately 3.3°C to 5.7°C above pre-industrial levels. These temperature projections reflect the different levels of greenhouse gas emissions and socio-economic pathways associated with each scenario, highlighting the importance of mitigation and adaptation efforts in shaping future climate outcomes. (Huang et al., 2019; IPCC, 2021). To indicate the range shift of the study species during projections, three major terms were used; Gain, Loss and Stable. The "Gain" indicates the predicted increase in range that will be suitable for *S. trilobata*, the "Loss" indicates the projected decrease in range that will be unsuitable for *S. trilobata*, and the "Stable" indicates the projected stability of the range that will be suitable for *S. trilobata*.

CHAPTER 4: RESULTS

4.1. The current distribution of *Sphagneticola trilobata* in South Asia

The occurrence of *Sphagneticola trilobata* revealed that the species was the most abundant in India, the largest country in the South Asian region (Figure 3). The species was also widespread in Sri Lanka and Maldives whereas it appeared to be in the early stage of invasions in Pakistan, Nepal, and Bangladesh. The species has not been reported from Afghanistan and Bhutan.

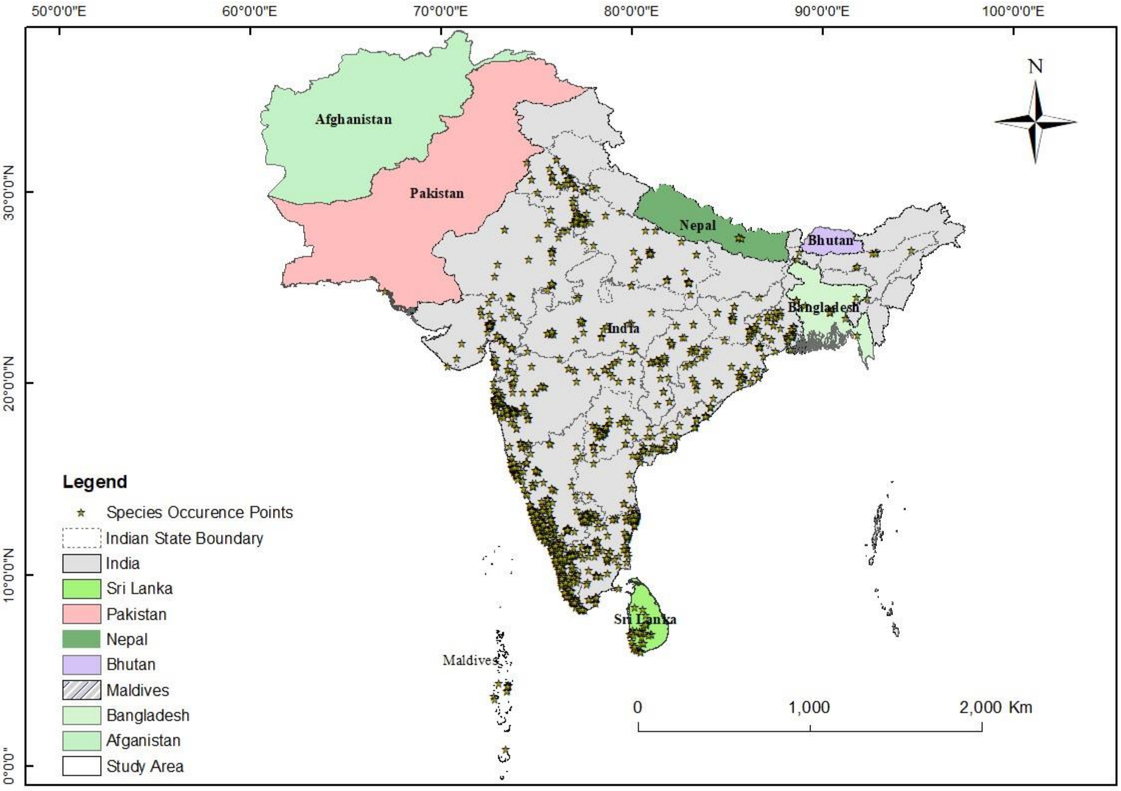


Figure 3: Current distribution of *Sphagneticola trilobata* in South Asian countries. (Data sources for species occurrence: GBIF, https://www.gbif.org/)

4.1.1 Occurrence along latitude gradient

The current distribution of *Sphagneticola trilobata* was significantly influenced by latitude. The highest number of occurrence points were identified within the latitude range of 10 to 14 degrees. This was followed by the ranges of 15 to 19, 20 to 24, 25 to 29, 30 to 34, and 0 to 4 degrees (Appendix II). After normalizing the occurrence points based on the area, the normalized species count was relatively elevated in the latitude range of 0 to 4 degrees (Figure 4).

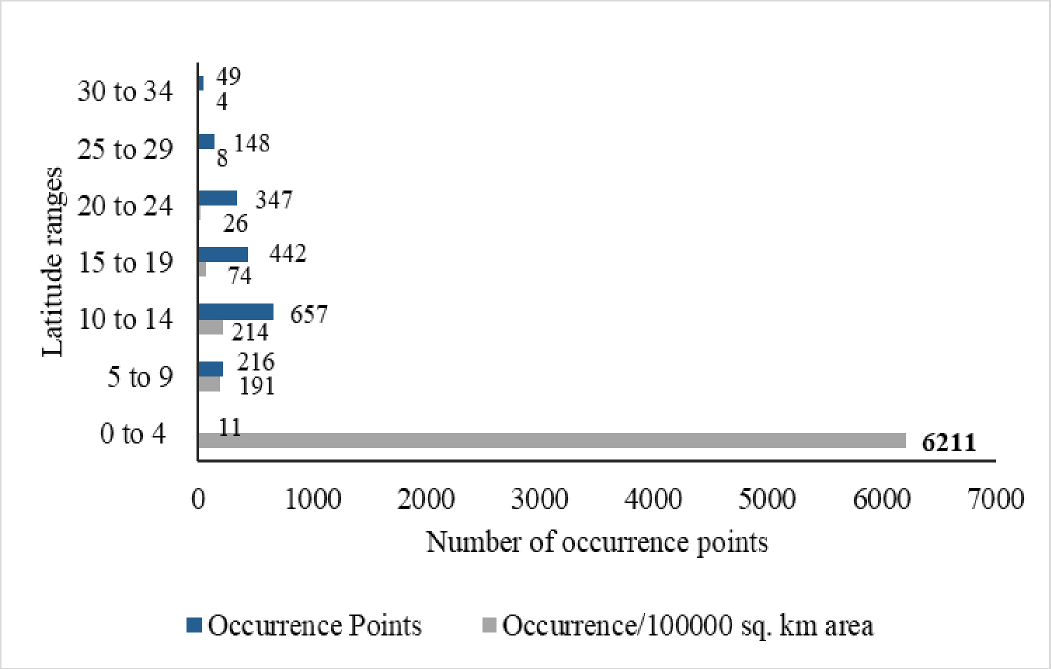


Figure 4: Normalized occurrence points (#occurrence /10^5 km^2 area) of *Sphagneticola trilobata* along latitude range in South Asia

4.1.2. Occurrence along elevation gradient

The most frequent occurrences were recorded in the elevation range of 0-500 m. This range with the highest number of occurrences was then followed by the 501-1000, 1001-1500, and 1501–2000 m (Figure 5). This pattern changed after the occurrence points were normalized. The new pattern showed the highest points in the 501–1000 m elevation range, followed by 0-500, 1001-1500, and 1501–2000 m.

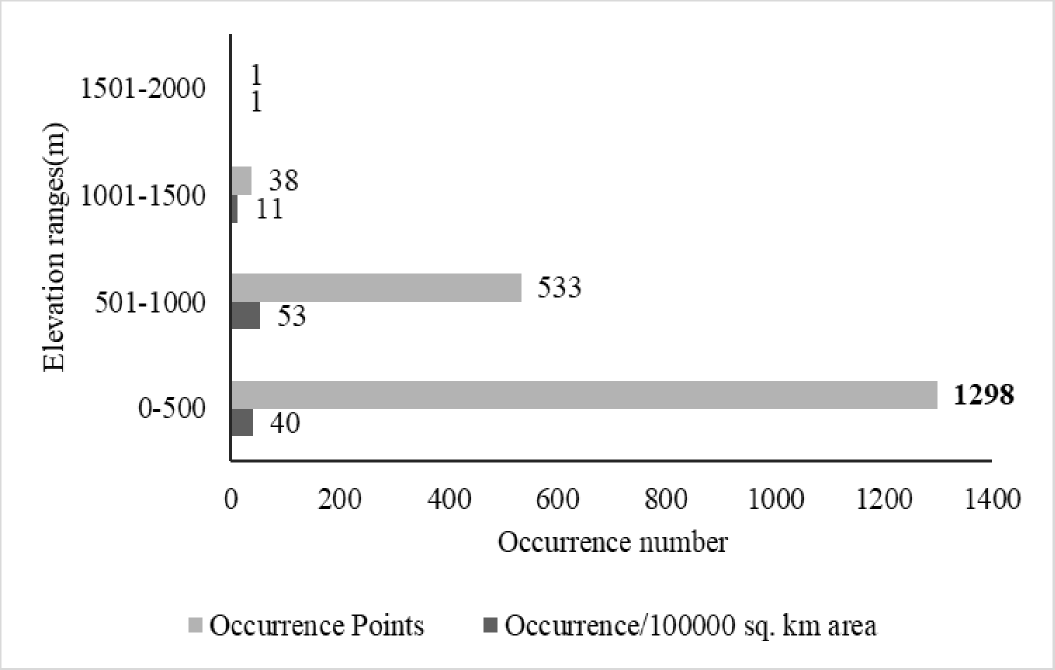


Figure 5: Occurrence of *Sphagneticola trilobata* along elevation ranges in South Asia

4.1.3. Occurrence along South Asian countries and Indian States

The species' occurrence points varied across different countries in South Asia. Among the recorded species numbers, India had the highest count of occurrence points (1796 points). Following India were other South Asian countries like Sri Lanka (38), Bangladesh (15), Maldives (9), Nepal (5), and Pakistan (2). However, after adjusting the occurrence points based on each country's area to make the comparison accurate, Maldives emerged as the country having the highest occurrence of species (3067/10^5 km^2) among South Asian countries. On the other hand, Pakistan had the lowest occurrence of species (0.2/10^5 km^2) (Figure 6). Notably, the study species was not been recorded in Afghanistan and Bhutan.

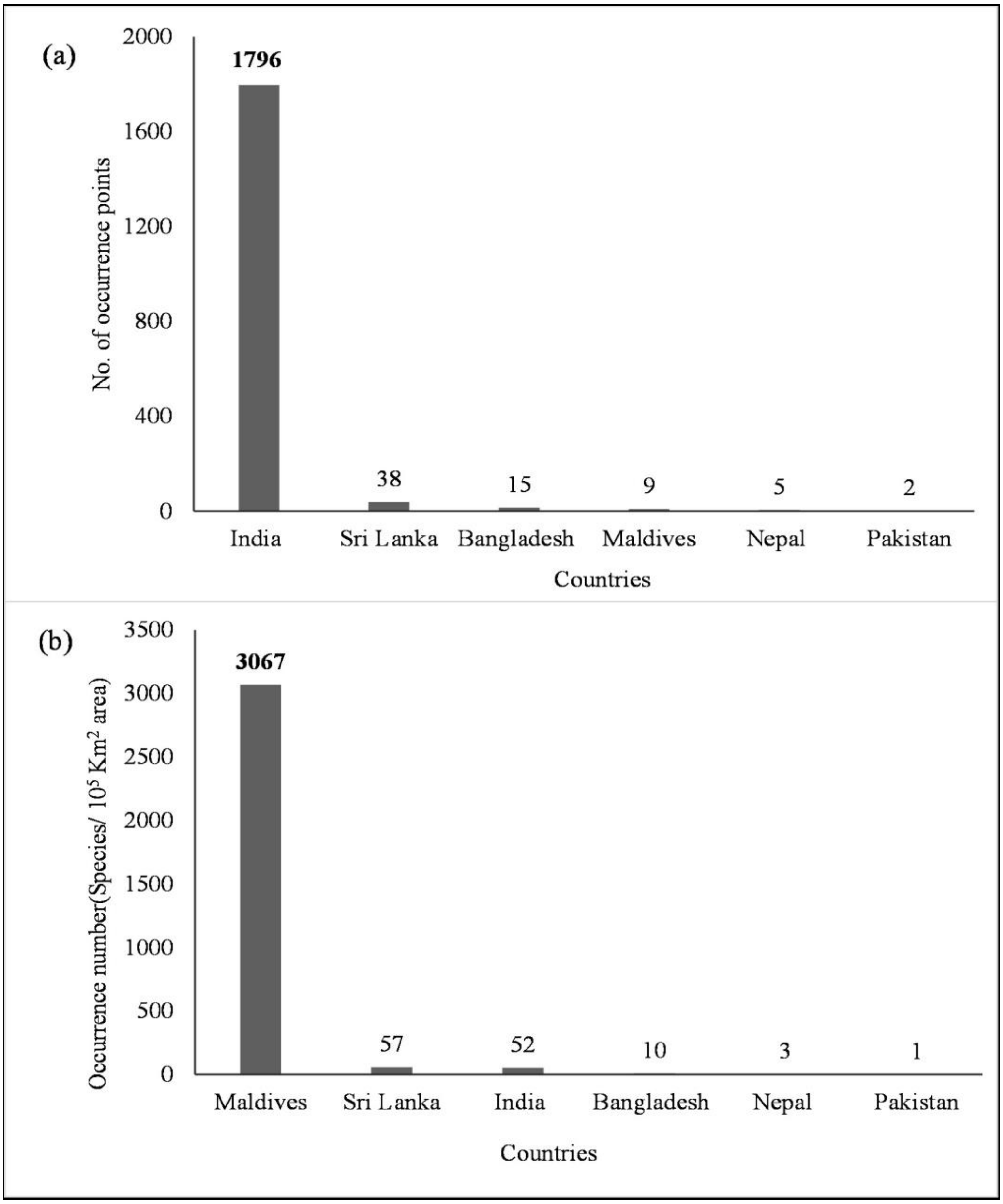


Figure 6: Occurrence of *Sphagneticola trilobata* along South Asian Countries (a) recorded number of species (b) the normalized species number (Species/ 10^5 Km^2 area)

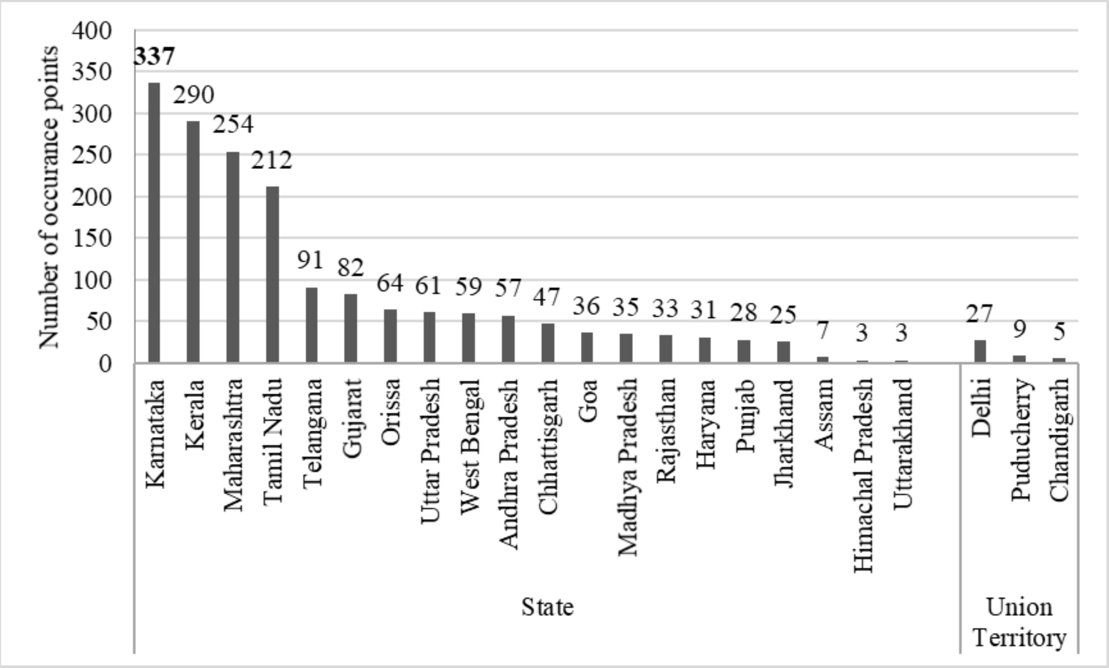


Figure 7: Number of occurrences points along the States and Union territory of India

The highest number of occurrence points was found in India. Of the 36 states and union territories of India, among the 23 states and union territories where the species was recorded, Karnataka, one of India's largest states, had the most occurrence points (337). It was followed by Kerala (290), Maharashtra (254), and Tamil Nadu (212) (Figure 7). The Indian states as well as union territory from where the species were not recorded were Arunachal Pradesh, Bihar, Manipur, Meghalaya, Mizoram, Nagaland, Sikkim, Tripura, Andaman and Nicobar, Dadra and Nagar Haveli and Daman and Diu, Jammu and Kashmir, Ladakh, Lakshadweep respectively.

4.2. Climatically suitable regions

4.2.1. Model performance and Suitable Habitat of Study species

The current model for *Sphagneticola trilobata* showed greater performance compared to random chance, with an average AUC value of 0.95 and a TSS value of 0.73. The mean AUC and TSS values of this model indicate good predictive accuracy. The models with AUC value < 0.8 and TSS value <0.6 were omitted from building the ensemble models. By Modeling, 26.7 % (which is 1,505,267 km^2) of the whole study area was considered suitable region for *S. trilobata* in the present climate scenario (Figure 8).

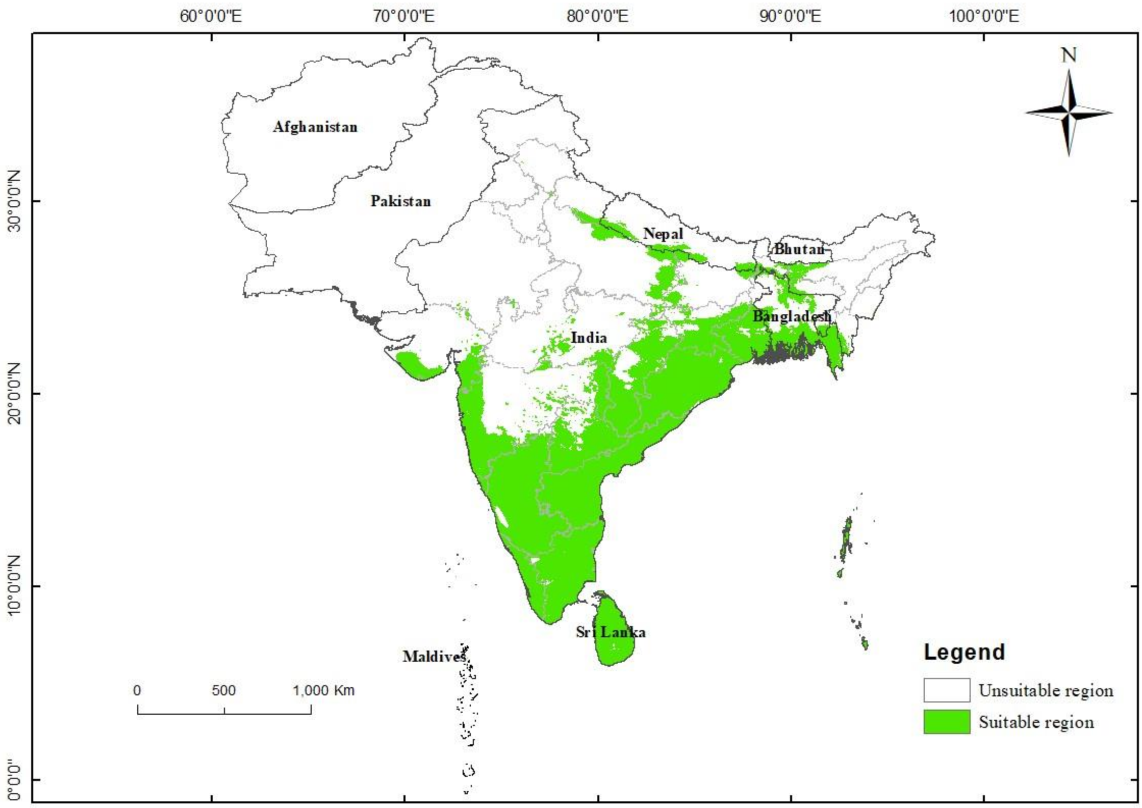


Figure 8: Current suitable region of *Sphagneticola trilobata in* South Asia

Out of the total suitable areas obtained by modelling, India occupies the maximum suitable areas of study species which are 1,329,859 km^2. i.e., 88.34 % of total suitable areas. Among the entire area of India, 39% of it is expected to be a suitable region for *Sphagneticola trilobata* in current climatic conditions. Of the suitable areas occupied in India, Karnataka (190,859 km^2) have the highest suitable area followed by Andhra Pradesh (166,150 km^2), Orissa (164,621 km^2), and Tamil Nadu (130,685 km^2) (Figure 9).

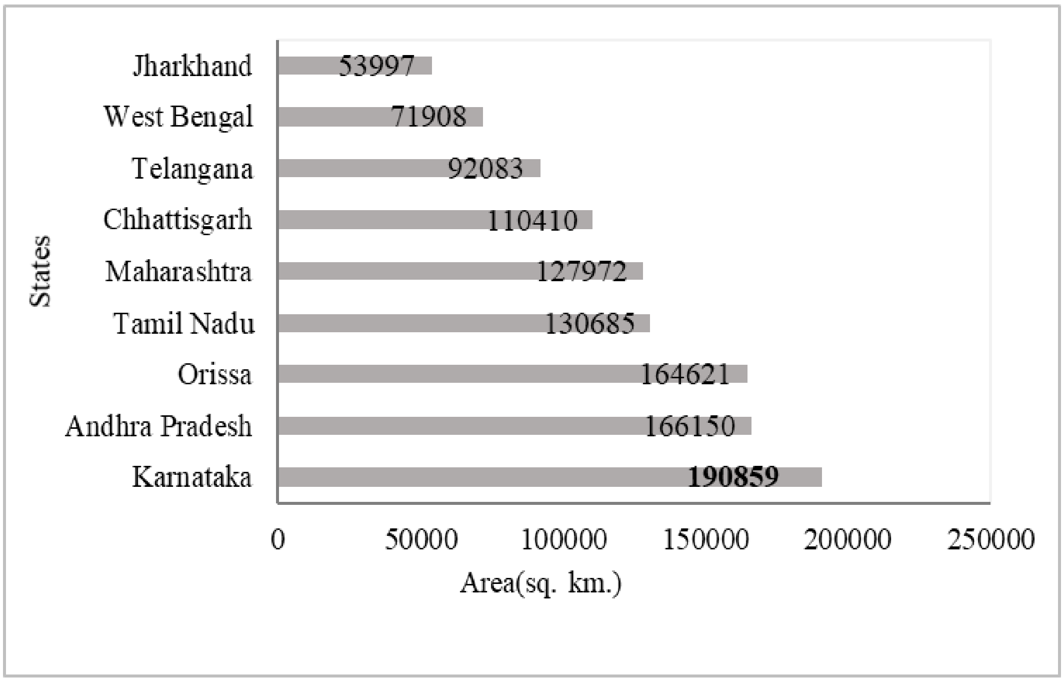


Figure 9: Current suitable region for *Sphagneticola trilobata* in the top nine Indian States

4.2.2. Climate change impacts on climatically suitable regions

The potential predicted suitable area for *Sphagneticola trilobata* was found to be decreased in both scenarios i.e., SSP 2-4.5 and SSP 5-8.5 under for both the years 2030 and 2050. The current suitable potential area for the study species was found to be 1,297,715 km^2 and 1,353,727 km^2 in the years 2030 and 2050 respectively under the scenario SSP2-4.5 (Figure 10). The figure shows that there is a slight difference in suitable potential habitats of species in two different periods.

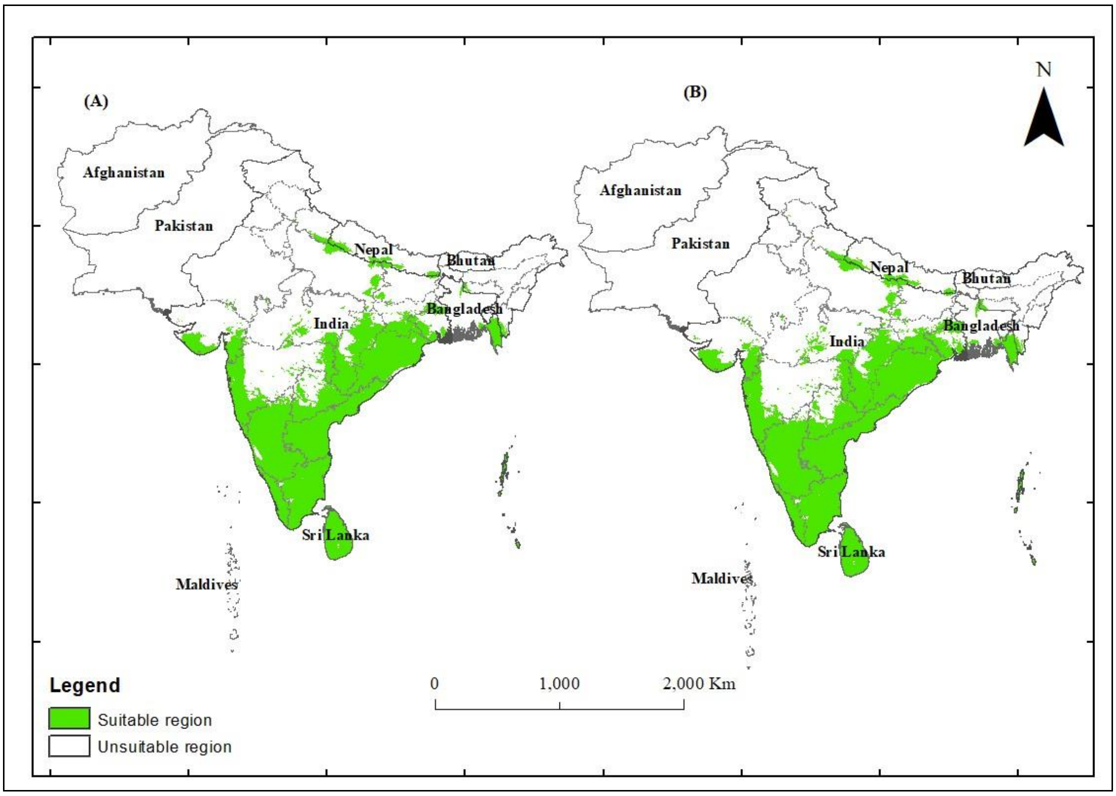


Figure 10: Predicted habitat of *Sphagneticola. Trilobata* under SSP2-4.5 Scenario (A) in 2030 (B) in 2050

In the SSP2-4.5 scenario, the species was predicted to be suitable in the maximum region of Maldives, Sri Lanka, India and a very few regions of Nepal (mainly Terai regions) and Bangladesh. In this projection, the suitable predicted area of the study species was found to be 23% and 24 % of the total area in the years 2030 and 2050 respectively (Figure 10).

Similarly, the current suitable potential area for the study species was found to be 1,262,198 km^2 and 1,335,703 km^2 in the years 2030 and 2050 respectively under the SSP5-8.5 scenario (Figure 11). The figure indicates a minor variation in the potential suitable habitat of the species between two distinct time periods.

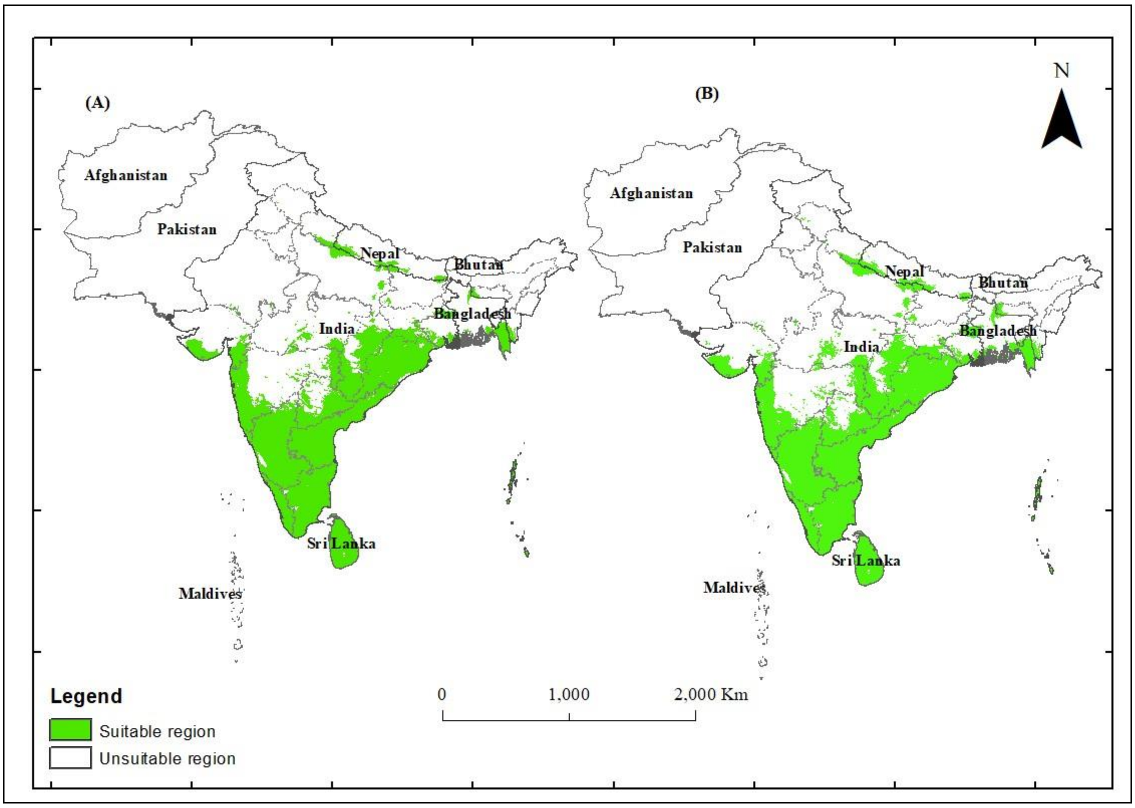


Figure 11: Predicted habitat of *Sphagneticola. trilobata* under SSP5-8.5 Scenario (A) in 2030 (B) in 2050

In the SSP5-8.5 scenario, the species was projected to be suitable in the maximum region of Maldives, Sri Lanka, India and a very few regions of Nepal (mainly Terai regions) and Bangladesh (Figure 11). In this projection, the suitable predicted area of the study species was found to be 22.35% and 23.65 % of the total area in the years 2030 and 2050 respectively.

In this comparison, the reference point is the current potential habitat of species (Appendix IV). When we compare the first scenario, SSP2-4.5 in the year 2030, with the current potential habitat, a decrease of 3.7 % in suitable area of study species was observed. Similarly, in the second time frame of SSP2-4.5, in the year 2050, there is a decrease of 2.7 %. Likewise, in the case of the second scenario, SSP5-8.5 in the year 2030, there is a decrease of 4.4 % in the year 2030 and a decrease of 3.1 % in the year 2050 (Figure 12).

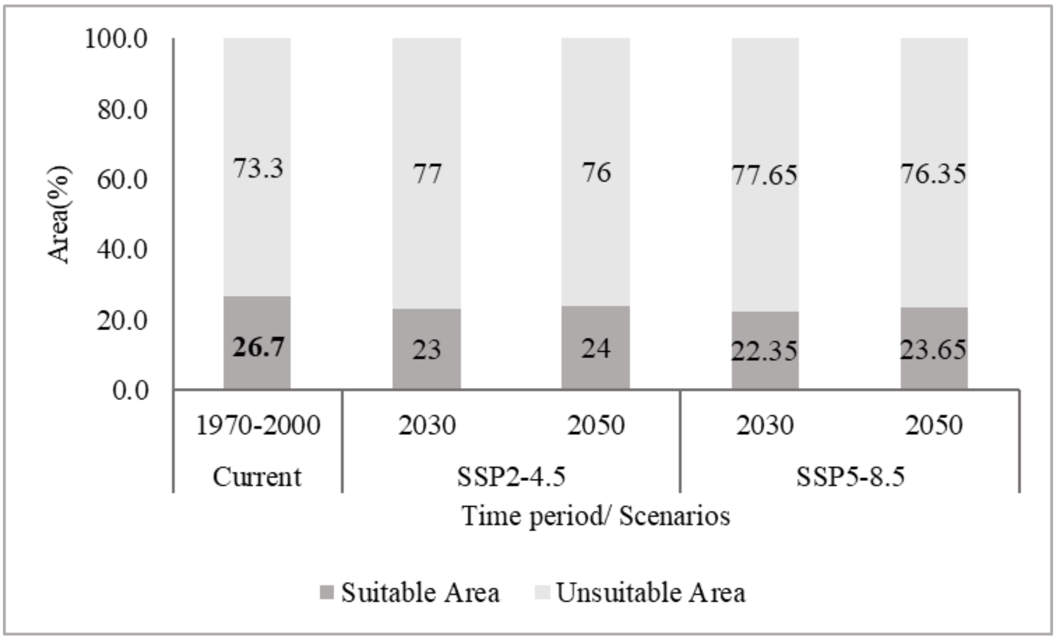


Figure 12: Climatically suitable and unsuitable areas for *Sphagneticola triloboata* under current (1970-2000), near future (2030) and mid-century climate scenarios (2050) in the South Asian region

The results show the projected area of suitable habitat for the study species *S. trilobata* in South Asian countries under two distinct climate change scenarios: SSP2-4.5 and SSP5-8.5. SSP2-4.5 denotes a moderate climate change scenario, while SSP5-8.5 represents a more severe climate change scenario. The figure shows that the area of suitable habitat for *S. trilobata* is projected to decline in all countries under both climate change scenarios (Figure 13). This decline is most significant in Bangladesh, with a projected reduction of 45.7% under SSP5-8.5. Bhutan also experiences a notable decline, with a projected decrease of 25% under SSP5-8.5.

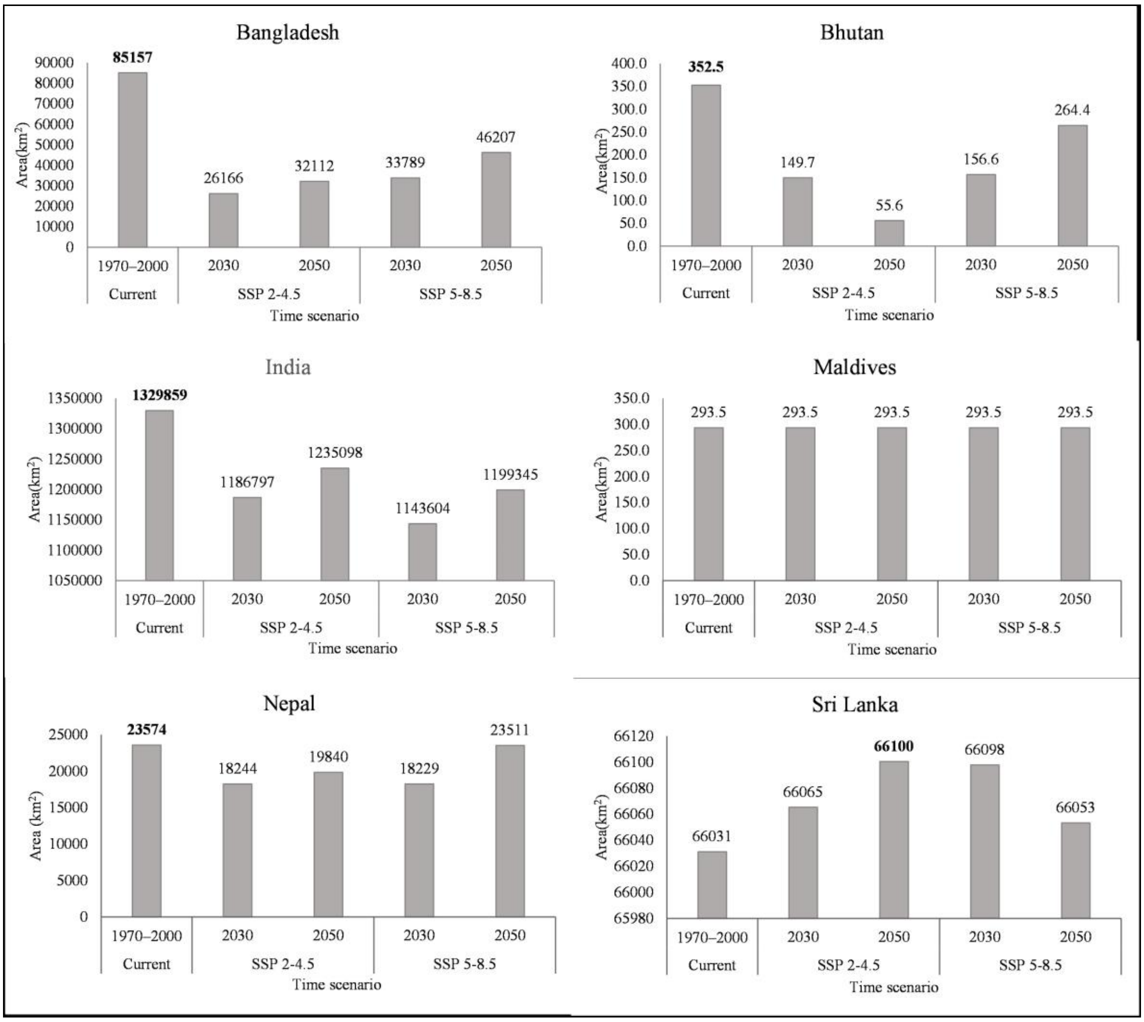


Figure 13: Comparison of projected suitable areas for *Sphagneticola trilobata* in South Asian countries

The only country, where the suitable area is projected to increase is Sri Lanka (SSP2-4.5 Scenario). The figure also shows that the decline in suitable habitat is projected to be more pronounced in the future. Overall, the study shows that climate change is expected to considerably affect the area of suitable habitat for *S. trilobata* in South Asia. The decline in suitable habitat is projected to be most pronounced in Bangladesh, and the expected to decrease more in future.

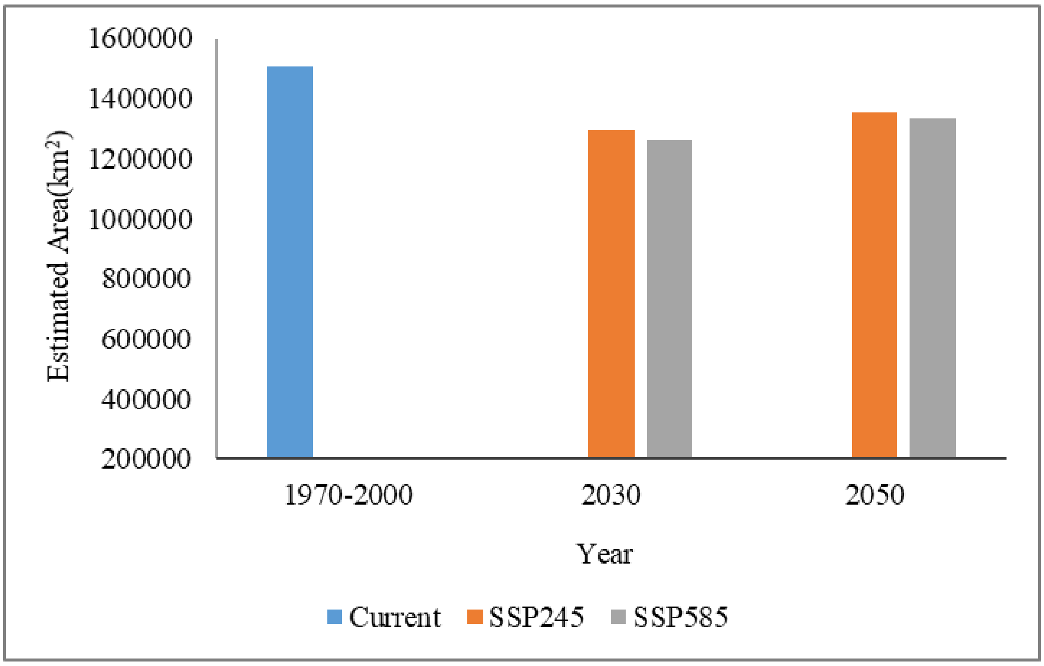


Figure 14: Potential habitat estimation of *S.trilobata* in South Asian countries under the current climate (1970–2000) and future climate scenarios (SSP2-4.5 and SSP5-8.5; 2021–2040 and 2041–2060). Blue, Orange and Grey bars indicate Current, SSP2-4.5 and SSP5-8.5, respectively.

Above mentioned figure shows that the overall estimated suitable habitat of the study species was found to decrease in area as compared to the predicted current environment scenarios.

4.2.3. Range shifts for future climate change projected scenarios (Gain, Loss or Stable)

In two distinct climate change scenarios, SSP2-4.5 and SSP5-8.5, climatically suitable regions of *Sphagneticola trilobata* may shift in South Asia. According to projections, there will be a gain in the suitable area of the species from the current to SSP2-4.5 for the year 2030 but found to decline as compared to the gain. In comparison among two time periods (from 2030 to 2050) under the SSP2-4.5 scenario, predicted suitable region was found to increase marginally from 2030 to 2050 (Figure 15).

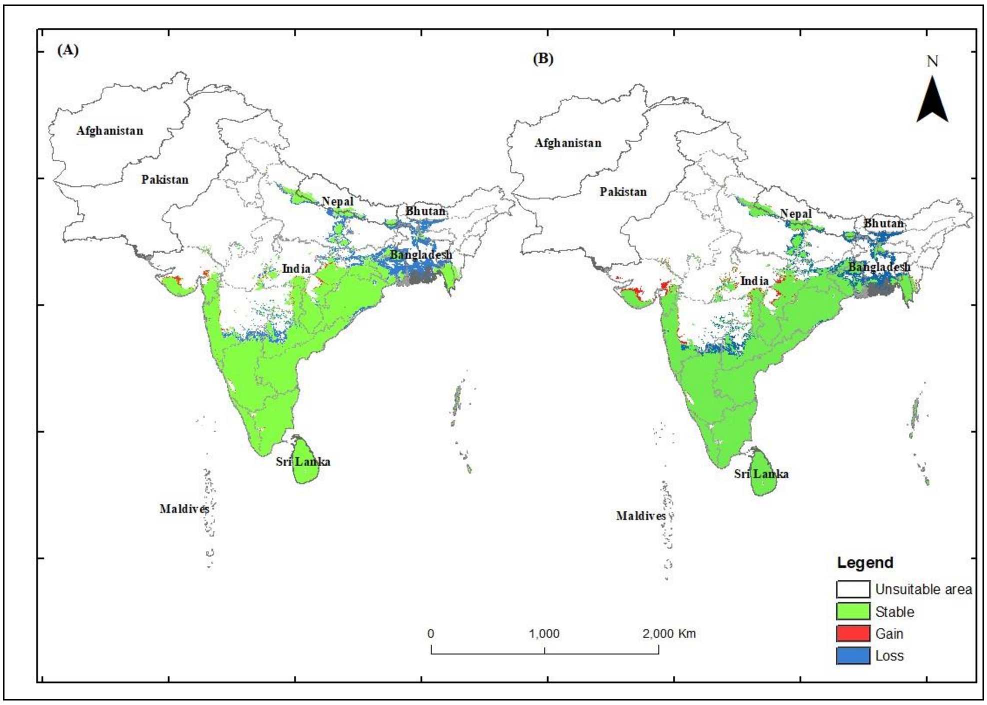


Figure 15: Predicted area of *Sphagneticola trilobata* in South Asia under SSP2-4.5 Scenario (A) in 2030 (B) in 2050

Similarly, from the current SSP5-8.5 scenario, loss areas were found to increase in comparison to gain areas. In the year 2030 under this scenario, the suitable habitat for species was found to decrease as compared to the current predicted habitat and again found to increase in the year 2050 as compared to 2030 (Figure 16).

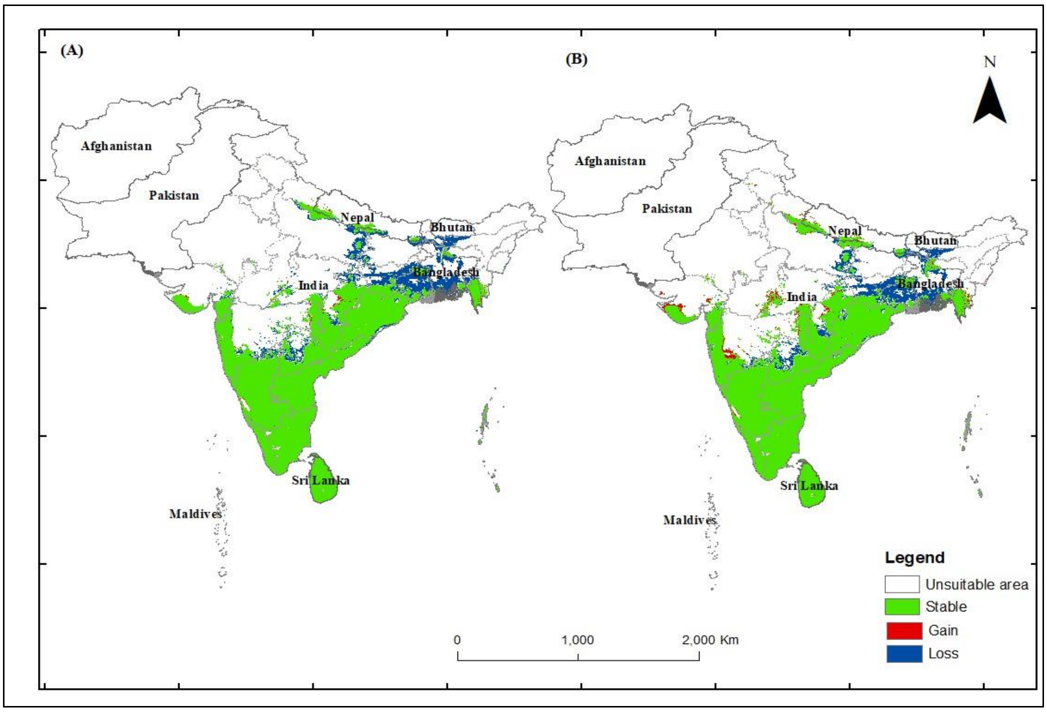


Figure 16: Predicted area of *Sphagneticola trilobata* in South Asia under SSP5-8.5 Scenario (A) in 2030 (B) in 2050

The highest stable, as well as the gain area of this species, is predicted in the scenario SSP2-4.5 in the year 2050 and the lowest stable as well as gain area is predicted in the scenario SSP5-8.5 in the year 2030, which is shortly (Figure 17).

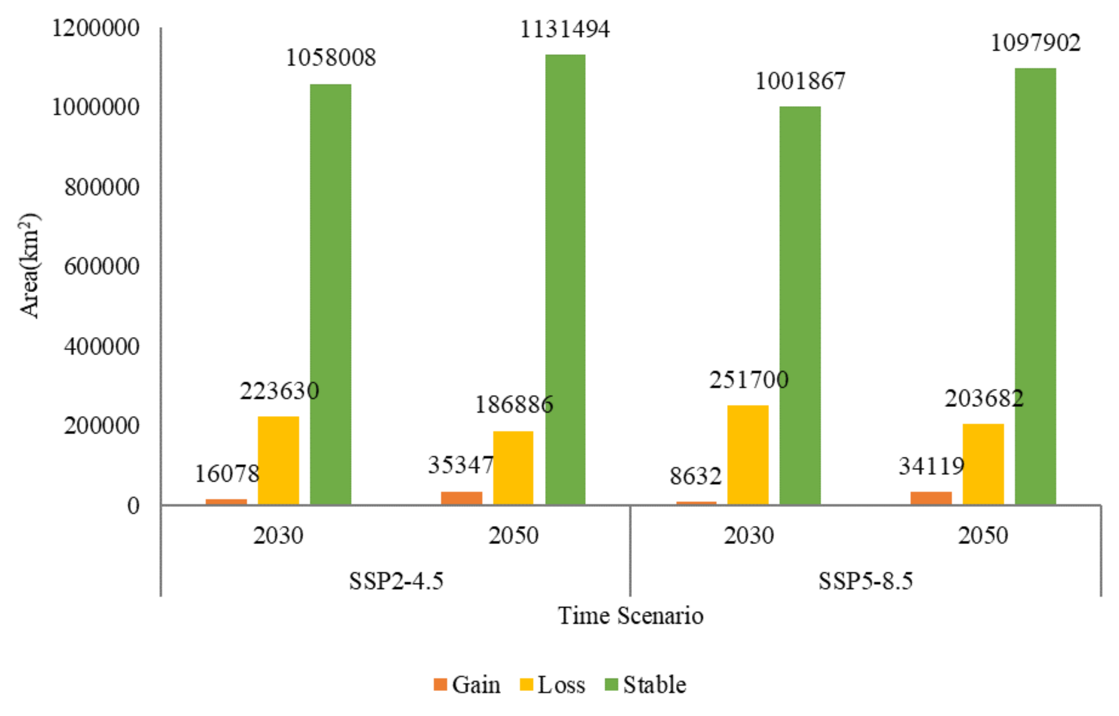


Figure 17: Gain, Loss and Stable areas of *S. trilobata*, in South Asia in different future climatic scenarios.

CHAPTER 5: DISCUSSION

Sphagneticola trilobata, one of the globally worst invasive weeds, has become a prominent concern in South Asia due to its abundant presence and rapid spread in the region. Using occurrence data of this species in South Asia, climatically suitable regions under both current and future climate conditions have been predicted. The results (Figure 8) indicate that nearly one-fourth of the region exhibits climatic suitability for this species, with significant variability observed across countries. Additionally, the analysis predicts potential losses and gains of climatically suitable regions due to climate change in the future. The results have direct implications for the prevention of this species from spreading to climatically suitable regions, where the species is currently absent.

5.1 Current distribution in South Asia

India, being the largest country in South Asia, has a very high occurrence of *Sphagneticola trilobata*. The rapid spread of this invasive species is also a threat to Bangladesh, Nepal, Sri Lanka, and the Maldives. Additionally, the expansion of *S. trilobata* poses a possible risk to Afghanistan, Bhutan, and Pakistan. The number of occurrence points was found to be the highest in the latitude range between 10-14°N (Figure 4) . However, the number of occurrence locations per 10^5 km^2 was the highest in the altitude range between 0 to 4° N. The highest number of occurrence locations lies in 0-500 meters elevation ranges (Figure 5) indicating that these elevation ranges are more favorable for the distribution of the studied species. From the South Asian Countries, the number of normalized species is notably high in island country Maldives. Maldives exhibits primarily a tropical climate varying from tropical to subtropical, which provides favorable habitats for *S. trilobata (*Thaman, 1999).

Because of its ability to flourish in both dry and wet conditions, the species has been able to colonize a variety of regions in Maldives and Sri Lanka with different levels of precipitation and humidity. Because *S. trilobata* can thrive in both sunny and shaded environments (Thaman, 1999), it has spread successfully over the whole country. India also offers a wide range of soil types, such as limestone that is bare, sandy beaches that are devoid of nutrients, and land that has been flooded or marshy. *S. trilobata* has expanded throughout various areas of India (Figure 3) as a result of its robust development in different soil types and versatility in a range of conditions. Thaman (1999) described the distribution of this study species in previous research using an identical environment. This species' invasion in South Asian nations has important ecological and economic consequences. Efficient management techniques are urgently needed to address the invasion of aquatic environments, destruction of natural habitats along roadsides and trails, and the designation as a noxious weed in agricultural regions, highlighting the pressing need to minimize the impacts of this invasive plant (PIER, 2003).

5.2 Potential Distribution in South Asia

The current climatic model projects that nearly one-fourth of the South Asian region is the suitable climatical region for *S. trilobata* growth with the southern parts of India, Nepal, and Bangladesh and almost 95% of the parts of Sri Lanka and whole area of Maldives, which are projected to be highly suitable (Figure 8). *Sphagneticola trilobata* was observed in all mainland South Asian countries except Afghanistan, Pakistan and Bhutan, certain areas of Bhutan are predicted to be suitable for its growth, particularly under changing climate conditions.

The current distribution data of the study species in India, Sri Lanka, Nepal, Bangladesh, and the Maldives closely match the predicted distribution that the study area was predicted to have the current as well as future potential suitable region for this species. For instance, *S. trilobata* has been documented in numerous states across India, with a higher frequency of occurrence observed in the southern states. Similar study was done by Shabbir et al. (2023) in which parthenium weed was predicted more suitable region was found in the southern states.

In Bangladesh and Nepal, *S. trilobata* is now regarded as an "up-coming weed," and, the weed is currently in the stage of "establishment" in Nepal (Shrestha et al., 2021). Locals have started to notice some socioeconomic effects of this plant, most likely in the paddy field (Figure 1) in the Tamaghat village of Panchakhal Municipality of Nepal (personal observations on 26th August, 2023) though it is still in the early stages of invasion. However, in the invasion areas where dense mats have formed on the ground and displaced the majority of other plant species, ecological effects were already noticeable (Shrestha et al., 2021). The model predictions also aligned with the current distribution observed in Nepal.

Overall the suitable area of the study species is found to decrease in future scenarios than that of in current predicted potential area. In this note, the result of this study is not aligned with the hypothesis that climate change expands climatically suitable areas of *Sphagneticola trilobata* in South Asia. A similar trend was reported in *Salvinia molesta* by Kariyawasam et al. (2021).

5.3 Impacts of climate change on the extent of climatic suitability

The evidence indicating that climate change is likely to exacerbate the risk of plant invasions is well-established, as it creates more favorable conditions for invasive species in the future (Bradley et al., 2010). However, the projections from this study indicate a decrease or fluctuation in climatically suitable areas for *S. trilobata* in the future. The weed is projected to either gain or lose suitable areas under four future climate scenarios: SSP2-4.5 (2030 and 2050) and SSP5-8.5 (2030 and 2050).

To reduce uncertainties associated with Species distribution models (SDMs) used for predicting future habitat suitability of invasive plant species, this study employed multiple algorithms, multiple global climate models (GCMs), and multiple shared socio-economic pathway (SSP) scenarios (Thuiller et al., 2019). The choice of algorithm can introduce significant uncertainty due to varying assumptions and limitations of each algorithm (Pearson et al., 2006). However, the combination of regression and machine-learning techniques used in this study, which relied on both presence and pseudo-absence data, produced similarly effective illustrations of the system (Araujo and New, 2007).

Species Distribution Models (SDMs) are frequently employed to forecast alterations in habitat suitability for invasive species; however, these models have assumptions and constraints that can result in over- or under-estimation of potential suitable habitat. One such assumption is that the species is in equilibrium within its environment, a condition that invasive species often do not meet (Gallien et al., 2012; Barbet-Massin et al., 2018).

Invasive species may not fully occupy their current potentially suitable habitat, and barriers to dispersal may prevent them from realizing their projected future range. Moreover, the climatic conditions linked to the locations of species records utilized in SDMs might not accurately represent the present or future climates, resulting in potential underestimation or overestimation of suitable habitat (Catford et al., 2019). It is important to acknowledge these uncertainties when interpreting SDM forecasts.

The potential habitat for *Sphagneticola trilobata* is anticipated to decrease in both SSP2-4.5 and SSP5-8.5 scenarios by the years 2030 and 2050. The current distribution of the species was used as the reference point for this comparison. In the SSP2-4.5 2030 scenario, the species distribution is expected to decrease by 3.66%. This is followed by a decrease of 2.66% in the SSP2-4.5 2050 scenario. In the SSP5-8.5 2030 scenario, the species distribution is expected to decrease by 4.31%, and by 3.01% in the SSP5-8.5 2050 scenario (Figure 12). Kariyawasam et al. (2021) conducted a similar study where they projected the potential distribution of aquatic invasive alien plants, *Eichhornia crassipes* and *Salvinia molesta* under two emissions scenarios, Representative Concentration Pathways (RCP) 4.5 and 8.5, for the periods 2050 and 2070. Their findings indicate that suitable aquatic habitats for *E. crassipes* are expected to decline notably by 2050 before experiencing a subsequent increase by 2070.

According to the findings, the projected habitat for the species is predicted to decrease overall. However, both Sri Lanka and Maldives are identified to have a higher proportion of climatically suitable areas for *S. trilobata* compared to other South Asian countries, under both current and future climate scenarios. Similar findings were reported by Kariyawasam et al. (2021) regarding the potential risks of plant invasions on native plant biodiversity differ significantly under projected climate change in Sri Lanka. From the above-mentioned results, it is found that the species distribution may expand or decrease along the GHG emission and the time. The study doesn’t mean that only the GHGs and time indicate the distribution or suitable habitat of invasive species. Several other factors may differ in the distribution of species and suitable habitat of certain species along the different periods.

To assess the potential effects of climate change on the distribution of suitable habitats for the study species in South Asia, forecasting its future distribution is essential to understand its potential impacts; which helps to know the suitable area either expands or shrinks in further climatic scenarios. Such results can inform decision-makers and communities about the optimal areas to implement EDRR initiatives aimed at conserving biodiversity and fostering a favourable environment for native species.

As the species suitable habitat decreases from the current potential to future scenarios, there is also an increase or decrease in gain, loss and stable area of study species regarding different scenarios. As in this study, three key terms were used to describe the study species' range movement during projections: Gain, Loss, and Stable. From this study, the highest gain and stability of the study species habitat was predicted to be found in the SSP5-8.5 in the year 2030. These indicators of growth, decline, and stability imply various interpretations in terms of biodiversity management and conservation. In those locations where invasive species may eventually spread, people should be aware of its effects and take steps to prevent their presence before it becomes established. In this manner, it might be possible to stop the spread of the area where the gain area is anticipated. When a studied species is lost or disappears from a region, it indicates that those places are good candidates for the regrowth of native species, which may be the best rivals for invasive species. The fact that the study species remained consistent in one place could mean that those regions are the hotspots which also favoured the invasive species to spread and disperse dominating native species; which is the main cause of the loss of biodiversity because its presence causes the native species to become extinct.

A similar study was done by Maharjan et al. (2019) to predict suitable habitat for an invasive plant species *Parthenium hysterophorus* in the Chitwan Annapurna Landscape, Nepal, under future climate scenarios. Similarly, Poudel et al. (2020) also predicted the current and future distribution of the invasive weed *Ageratina adenophora* in the same landscape and obtained similar findings, including areas of gain, loss, and stability. These analyses serve as valuable tools for managers and policymakers to promptly and effectively mitigate the risk of *A. adenophora* invasion associated with climate change by identifying potentially vulnerable areas in the future.

The proliferation of invasive species and their effects on native biodiversity is a growing concern for both present and future ecosystems. To address this issue, this study utilizes SDM tools i.e. ensemble model, which can be particularly effective in modelling the distribution of recently introduced, harmful invasive species that may not have yet colonized all suitable environments. By employing these tools, we can gain a deeper insight into and forecast the potential consequences of invasive species on local ecosystems, and develop effective strategies to mitigate their negative effects.

CHAPTER 6: CONCLUSION AND RECOMMENDATION

6.1. Conclusion

Analyses of the current distribution of *Sphagneticola trilobaota*, a globally worst invasive seed, suggest that it is already widespread in India, Sri Lanka and Maldives. However, considering future climate scenarios (SSP2-4.5 and SSP5-8.5), the habitat of *S. trilobata* is projected to expand further in Sri Lanka and whole region of Maldives, while most Indian states would become new invasion hotspots. These results also imply that the spread of this weed into new locations is likely to be facilitated by global warming brought on by climate change. In Bangladesh, a substantial portion of the country (40-50%) is expected to experience a decrease in *S. trilobata* presence under future climate conditions. For Nepal, this study species was expected to spread over the southern region. Overall, South Asia, excluding Sri Lanka and the Maldives in the southern region, is anticipated to witness a decline in *S. trilobata* habitat. Furthermore, based on existing forecast scenarios, this analysis of habitat suitability shows that the central South Asian regions are extremely conducive to *S. trilobata* invasion. Therefore, to stop the spread of this notorious weed, it is essential to apply rigorous planning and long-term management methods at the global, national and local levels.

6.2. Recommendation

- Based on the findings of the study, it is predicted that the suitable habitat for *Sphagneticola trilobaota* will shrink more than initially anticipated in future scenarios. This indicates that the negative effects caused by invasive species can be effectively reduced by accurately identifying them in our environment and implementing efficient control techniques.

- For smaller and easily accessible areas that have been invaded, management strategies can involve either mechanical control, such as manual pulling, or chemical control using herbicides. To ensure effectiveness, integrated weed management approaches should be adopted, accompanied by regular monitoring of suitable habitats.

- The scientific community and policymakers can utilize our study to evaluate the likelihood of *S. trilobata* spreading from its current locations to noninvaded areas, considering both present and future climatic conditions. This knowledge can assist in planning and implementing effective management strategies aimed at minimizing the ecological and economic impacts associated with this invasive species.

- Considering the scarcity of research on *S. trilobata* in South Asia, it is suggested to explore potential directions for future investigation. This may involve investigating into its population dynamics, dispersal mechanisms, genetic diversity, or its interactions with indigenous species across various habitats. Such endeavors could significantly contribute to our understanding of this species and its ecological impact in the region.

REFERENCES

Adhikari, B., Shrestha, B. B., Watson, M. F., Sharma, L. N., Bhattarai, S., Pendry, C. A., & Paudel, E. (2022). Invasive alien plants of Nepal: a field guide to 27 problematic species. Nepal Academy of Science and Technology, Khumaltar, Lalitpur, Nepal.

Ahmad, R., Khuroo, A. A., Hamid, M., Charles, B., & Rashid, I. (2019). Predicting invasion potential and niche dynamics of *Parthenium hysterophorus* (Congress grass) in India under projected climate change. *Biodiversity and Conservation* **28**: 2319-2344.

Allen, J. M., & Bradley, B. A. (2016). Out of the weeds? Reduced plant invasion risk with climate change in the continental United States. *Biological Conservation* **203**: 306-312.

Allouche, O., Tsoar, A., Kadmon, R. (2006). Assessing the accuracy of species distribution models: prevalence, kappa and the true skill statistic (TSS): Assessing the accuracy of distribution models. *Journal of Applied Ecology* **43**:1223–1232.

Anderson, R. P., Lew, D., & Peterson, A. T. (2003). Evaluating predictive models of species' distributions: criteria for selecting optimal models. *Ecological Modelling* **162**(3): 211-232.

Araújo, M. B., & New, M. (2007). Ensemble forecasting of species distributions. *Trends in Ecology & Evolution* **22**(1): 42-47.

Araujo, M. B., Pearson, R. G., Thuiller, W., & Erhard, M. (2005a). Validation of species–climate impact models under climate change. *Global Change Biology* **11**(9): 1504-1513.

Araújo, M. B., Whittaker, R. J., Ladle, R. J., & Erhard, M. (2005b). Reducing uncertainty in projections of extinction risk from climate change. *Global Ecology and Biogeography* **14**(6): 529-538.

Bacher, S., Galil, B. S., Nuñez, M. A., Ansong, M., Cassey, P., Dehnen-Schmutz, K., Fayvush, G., Hiremath, A. J., Ikegami, M., Martinou, A. F., McDermott, S. M., Preda, C., Vilà, M., Weyl, O. L. F., Fernandez, R. D., and Ryan-Colton, E.

(2023). Chapter 4: Impacts of invasive alien species on nature, nature's contributions to people, and good quality of life. In: Thematic Assessment Report on Invasive Alien Species and their Control of the Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services. Roy, H. E., Pauchard, A., Stoett, P., and Renard Truong, T. (eds.). IPBES secretariat, Bonn, Germany. https://doi.org/10.5281/zenodo.7430731

Baker, R. H., Sansford, C., Jarvis, C., Cannon, R. J., MacLeod, A., & Walters, K. F., (2000). The role of climatic mapping in predicting the potential geographical distribution of non-indigenous pests under current and future climates. *Agriculture, Ecosystems & Environment* **82**(1-3):57–71.

Bang, A., Cuthbert, R. N., Haubrock, P. J., Fernandez, R. D., Moodley, D., Diagne, C., Turbelin, A. J., Renault, D., Dalu, T. & Courchamp, F. (2022). Massive economic costs of biological invasions despite widespread knowledge gaps: a dual setback for India. *Biological Invasions* **24**(7): 2017-2039.

Barbet- Massin, M., Jiguet, F., Albert, C. H., & Thuiller, W. (2012). Selecting pseudo- absences for species distribution models: How, where and how many? *Methods in Ecology and Evolution* **3**(2): 327-338.

Barbet-Massin, M., Rome, Q., Villemant, C., & Courchamp, F. (2018). Can species distribution models really predict the expansion of invasive species? *PloS One* **13**(3): e0193085.

Beaumont, L. J., Graham, E., Duursma, D. E., Wilson, P. D., Cabrelli, A., Baumgartner, J. B., Hallgren, W., Esperón-Rodríguez, M., Nipperess, D. A., Warren, D. L., Laffan, S. W. & VanDerWal, J. (2016). Which species distribution models are more (or less) likely to project broad-scale, climate-induced shifts in species ranges? *Ecological Modelling* **342**: 135-146.

Beaumont, L. J., Hughes, L., & Poulsen, M. (2005). Predicting species distributions: use of climatic parameters in BIOCLIM and its impact on predictions of species' current and future distributions. *Ecological Modelling* **186**(2): 251-270.

Bellard, C., Cassey, P., & Blackburn, T. M. (2016). Alien species as a driver of recent extinctions. *Biology Letters* **12**(2): 20150623.

Bellard, C., Thuiller, W., Leroy, B., Genovesi, P., Bakkenes, M., & Courchamp, F. (2013). Will climate change promote future invasions? *Global Change Biology* **19**(12): 3740-3748.

Bhatta, S., Shrestha, B. B., & Pyšek, P. (2023). Invasive alien plants in South Asia: Impacts and management. *NeoBiota* **88**: 135-167.

Blackburn, T. M., Pyšek, P., Bacher, S., Carlton, J. T., Duncan, R. P., Jarošík, V., Wilson, J. R. U. & Richardson, D. M. (2011). A proposed unified framework for biological invasions. *Trends in Ecology & Evolution* **26**(7): 333-339.

Boria, R. A., Olson, L. E., Goodman, S. M., & Anderson, R. P. (2014). Spatial filtering to reduce sampling bias can improve the performance of ecological niche models. *Ecological Modelling* **275**: 73-77.

Bradley, B. A., & Marvin, D. C. (2011). Using expert knowledge to satisfy data needs: mapping invasive plant distributions in the western United States. *Western North American Naturalist* **71**(3): 302-315.

Bradley, B. A., Blumenthal, D. M., Wilcove, D. S., & Ziska, L. H. (2010). Predicting plant invasions in an era of global change. *Trends in Ecology & Evolution* ***25***(5): 310-318.

Bradley, B. A., Olsson, A. D., Wang, O., Dickson, B. G., Pelech, L., Sesnie, S. E. (2012). Species detection vs. habitat suitability: are we biasing habitat suitability models with remotely sensed data? *Ecological Modelling* **244**:57–64. doi: 10.1016/j.ecolmodel.2012.06.019

Bradley, B. A., Oppenheimer, M., & Wilcove, D. S. (2009). Climate change and plant invasions: restoration opportunities ahead? *Global Change Biology* **15**(6): 1511-1521.

Braun, K., Collantes, M. B., Yahdjian, L., Escartín, C., & Anchorena, J. A. (2019). Increased litter decomposition rates of exotic invasive species Hieracium pilosella (Asteraceae) in Southern Patagonia, Argentina. *Plant Ecology* **220**: 393-403.

Broennimann, O., & Guisan, A. (2008). Predicting current and future biological invasions: both native and invaded ranges matter. *Biology Letters* **4**(5): 5-8.5-589.

Buckley, L. B., Urban, M. C., Angilletta, M. J., Crozier, L. G., Rissler, L. J., & Sears, M. W. (2010). Can mechanism inform species' distribution models? *Ecology Letters* **13**(8): 1041-1054.

Castro- Díez, P., Vaz, A. S., Silva, J. S., Van Loo, M., Alonso, Á., Aponte, C., Bayón, A., Bellingham, P. J., Chiuffo, M. C., DiManno, N., Julian, K., Kandert, S., Porta, N. L., Marchante, H., Maule, H. G., Mayfield, M. M., Metcalfe, D., Monteverdi, M. C., Núñez, M. A., Ostertag, R., Parker, I. M., Peltzer, D. A., Potgieter, L. J., Raymundo, M., Rayome, D., Reisman-Berman, O., Richardson, D. M., Roos, R. E., Saldaña, A., Shackleton, R. T., Torres, A., Trudgen, M., Urban, J., Vicente, J. R., Vilà, M., Ylioja, T., Zenni, R. D. & Godoy, O. (2019). Global effects of non- native tree species on multiple ecosystem services. *Biological Reviews* **94**(4): 1477-1501.

Catford, J. A., Baumgartner, J. B., Vesk, P. A., White, M., Buckley, Y. M., & McCarthy, M. A. (2016). Disentangling the four demographic dimensions of species invasiveness. *Journal of Ecology* **104**(6): 1745-1758.

Catford, J. A., Smith, A. L., Wragg, P. D., Clark, A. T., Kosmala, M., Cavender- Bares, J., & Tilman, D. (2019). Traits linked with species invasiveness and community invasibility vary with time, stage and indicator of invasion in a long- term grassland experiment. *Ecology Letters* **22**(4): 593-604.

Central Bank (2019). Annual Report 2019. Colombo: Central Bank of Sri Lanka.

Chen, I. C., Shiu, H. J., Benedick, S., Holloway, J. D., Chey, V. K., (2009). Elevation increases in moth assemblages over 42 years on a tropical mountain. *Proc Natl Acad Sci* **106**:1479–1483.

Chowdhury, S., Alam, S., Labi, M. M., Khan, N., Rokonuzzaman, M., Biswas, D., Tahea, T., Mukul, S. A. & Fuller, R. A. (2022). Protected areas in South Asia: Status and prospects. *Science of the Total Environment* **811**:152316.

Crossman, N. D., & Bass, D. A. (2008). Application of common predictive habitat techniques for post- border weed risk management. *Diversity and Distributions* **14**(2): 213-224.

Diagne, C., Leroy, B., Vaissière, A. C., Gozlan, R. E., Roiz, D., Jarić, I., Salles, J., Bradshaw, C. J. A. & Courchamp, F. (2021). High and rising economic costs of biological invasions worldwide. *Nature* **592**(7855): 571-576.

Dillon, M. E., Wang, G., and Huey, R. B. (2010). Global metabolic impacts of recent climate warming. *Nature* **467**:704–706.

Diniz- Filho, J. A. F., Mauricio Bini, L., Fernando Rangel, T., Loyola, R. D., Hof, C., Nogués- Bravo, D., & Araújo, M. B. (2009). Partitioning and mapping uncertainties in ensembles of forecasts of species turnover under climate change. *Ecography* **32**(6): 897-906.

Dorjee, Johnson, S. B., Buckmaster, A. J., & Downey, P. O. (2020). Weeds in the land of Gross National Happiness: Knowing what to manage by creating a baseline alien plant inventory for Bhutan. *Biological Invasions* **22**(10): 2899-2914.

Dukes, J. S., & Mooney, H. A. (1999). Does global change increase the success of biological invaders? *Trends in Ecology & Evolution* **14**(4): 135-139.

Early, R., Bradley, B. A., Dukes, J. S., Lawler, J. J., Olden, J. D., Blumenthal, D. M., Gonzalez, P., Grosholz, E. D., Ibañez, I., Miller, I. 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* **7**(1): 12485.

Elith, J., & Franklin, J. (2013). Species Distribution Modeling. *Encyclopedia of Biodiversity* **6**:692–705. doi:10.1016/b978-0-12-384719-5.00318-x.

Elith, J., & Leathwick, J. R. (2009). Species distribution models: ecological explanation and prediction across space and time. *Annual Review of Ecology, Evolution, and Systematics* **40**:677-697.

Elith, J., Kearney, M., & Phillips, S. (2010). The art of modelling range- shifting species. *Methods in Ecology and Evolution* **1**(4): 330-342.

Engler, R., Guisan, A., & Rechsteiner, L. (2004). An improved approach for predicting the distribution of rare and endangered species from occurrence and pseudo- absence data. *Journal of Applied Ecology* **41**(2): 263-274.

Epanchin-Niell, R. S. & Liebhold, A.M. (2015). Benefits of invasion prevention: effect of time lags, spread rates, and damage persistence. *Ecological Economics* **116**:146–153.

Etana, B. (2013). Distribution and challenges of an invasive exotic species, Prosopis juliflora (Sw.) DC. (Fabaceae) in Ethiopia, East Africa. *International Journal of Green and Herbal Chemistry* **2**(1): 110-120.

Fatima, A., Farid, M., Safdar, K., Fayyaz, A., Ali, S. M., Adnan, S., Nawaz, M., Munir, H., Raza, N., & Zubair, M. (2020). Loss of agro-biodiversity and productivity due to climate change in continent Asia: a review. *Plant ecophysiology and adaptation under climate change: mechanisms and perspectives I: general consequences and plant responses*, 51-71.

Fick, S. E., & Hijmans, R. J. (2017). WorldClim 2: new 1- km spatial resolution climate surfaces for global land areas. *International Journal of Climatology* **37**(12): 4302-4315.

Finch, D. M., Butler, J. L., Runyon, J. B., Fettig, C. J., Kilkenny, F. F., Jose, S., Frankel, S. J., Cushman, S. A., Cobb, R. C., Dukes, J. S., Hicke, J. A., & Amelon, S. K. (2021). Effects of climate change on invasive species. Invasive species in forests and rangelands of the United States: a comprehensive science synthesis for the United States forest sector, 57-83.

Foley, J. A., DeFries, R., Asner, G. P., Barford, C., Bonan, G., Carpenter, S. R., Chapin, F. S., Coe, M. T., Daily, G. C., Gibbs, H. K., Helkowski, J. H., Holloway, T., Howard, E. A., Kucharik, C. J., Monfreda, C., Patz, J. A., Prentice, I.C., Ramankutty, N. & Snyder, P. K. (2005). Global consequences of land use. *Science* **309**:570-574.

Franklin, J. (2010). *Mapping species distributions: spatial inference and prediction*. Cambridge University Press.

Gallardo, B., & Aldridge, D. C. (2013). Priority setting for invasive species management: Risk assessment of Ponto-Caspian invasive species into Great Britain. *Ecological Applications* **23**(2): 352–364.

Gallardo, B., & Aldridge, D. C. (2013). The 'Dirty Dozen': socio- economic factors amplify the invasion potential of 12 high- risk aquatic invasive species in Great Britain and Ireland. *Journal of Applied Ecology* **50**(3): 757-766.

Gallardo, B., Clavero, M., Sánchez, M. I., & Vilà, M. (2016). Global ecological impacts of invasive species in aquatic ecosystems. *Global Change Biology* **22**(1): 151-163.

Gallien, L., Douzet, R., Pratte, S., Zimmermann, N. E., & Thuiller, W. (2012). Invasive species distribution models–how violating the equilibrium assumption can create new insights. *Global Ecology and Biogeography* **21**(11): 1126-1136.

Ganie, M. A., Bhat, M. D., Khan, M. I., Parveen, M., Balkhi M. H and Malla, M. A. (2013). Invasion of the Mozambique tilapia, Oreochromis mossambicus (Pisces: Cichlidae; Peters, 1852) in the Yamuna River, Uttar Pradesh, India. *Journal of Environmental Microbiology* **1**(1):061–068.

Gillard, M., Thiébaut, G., Deleu, C., & Leroy, B. (2017). Present and future distribution of three aquatic plant taxa across the world: decrease in native and increase in invasive ranges. *Biological Invasions* **19**: 2159-2170.

Global Invasive Species Database. Species profile: *Sphagneticola trilobata.* http://www.iucngisd.org/gisd/species.php?sc=44. 27 August, 2023.

Gregory, A. W., Smith, G. W., & Yetman, J. (2001). Testing for forecast consensus. *Journal of Business & Economic Statistics* **19**(1): 34-43.

Grenouillet, G., Buisson, L., Casajus, N., & Lek, S. (2011). Ensemble modelling of species distribution: the effects of geographical and environmental ranges. *Ecography* **34**(1): 9-17.

Guisan, A., & Zimmermann, N. E. (2000). Predictive habitat distribution models in ecology. *Ecological Modelling* **135**:147-186.

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., Sujanapal, D. P., Rashid, I. & Khuroo, A. A. Looking beyond the political boundaries: an integrated inventory of invasive alien flora of South Asia. *Biological Invasions* **26**: 57–78 (2024). https://doi.org/10.1007/s10530-023-03165-6

Hao, T., Elith, J., Guillera- Arroita, G., & Lahoz- Monfort, J. J. (2019). A review of evidence about the use and performance of species distribution modelling ensembles like BIOMOD. *Diversity and Distributions* **25**(5): 839-852.

Hasnat, G. T., Kabir, M. A., & Hossain, M. A. (2018). Major environmental issues and problems in South Asia, particularly Bangladesh. *Handbook of Environmental Materials Management*, 1-40.

Hellmann, J. J., Byers, J. E., Bierwagen, B. G., & Dukes, J. S. (2008). Five potential consequences of climate change for invasive species. *Conservation Biology* **22**(3): 534-543.

Hijmans, R. J., Cameron, S. E., Parra, J. L., Jones, P. G., & Jarvis, A. (2005). Very high-resolution interpolated climate surfaces for global land areas. *International Journal of Climatology: A Journal of the Royal Meteorological Society* **25**(15): 1965-1978.

Holdridge, L. R. (1947). Determination of world plant formations from simple climatic data. *Science* **105**(2727): 367-368.

Huang, J., Qin, D., Jiang, T., Wang, Y., Feng, Z., Zhai, J., Cao, L., Chao, Q., Xu, X., Wang, G., & Su, B. (2019). Effect of fertility policy changes on the population structure and economy of China: from the perspective of the shared socioeconomic pathways. *Earth's Future* **7**(3): 250-265.

Hulme, P. E., Bacher, S., Kenis, M., Klotz, S., Kühn, I., Minchin, D., Nentwig, W., Olenin, S., Panov, V., Pergl, J., Pyšek, P., Roques, A., Sol, D., Solarz, W. & Vilà, M. (2008). Grasping at the routes of biological invasions: a framework for integrating pathways into policy. *Journal of Applied Ecology* **45**(2): 403-414.

Ibanez, I., Silander, J., Jr., Allen, J. M., Treanor, S. A., & Wilson, A. (2009). Identifying hotspots for plant invasions and forecasting focal points of further spread. *Journal of Applied Ecology* **46**(6):1219–1228. doi:10.1111/j.1365-2664.2009.01736.x.

IPBES (2018): Summary for policymakers of the regional assessment report on biodiversity and ecosystem services for Asia and the Pacific of the Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services. Karki, M., Senaratna Sellamuttu, S., Okayasu, S., Suzuki, W., Acosta, L. A., Alhafedh, Y., Anticamara, J. A., Ausseil, A.-G., Davies, K., Gasparatos, A., Gundimeda, H., Ibrahim, F.-H., Kohsaka, R., Kumar, R., Managi, S., Ning, W., Rajvanshi, A., Rawat, G. S., Riordan, P., Sharma, S., Virk, A., Wang, C., Yahara, T., & Yeo-Chang, Y. IPBES secretariat, Bonn, Germany. 41 pages.

IPBES (2023). Summary for Policymakers of the Thematic Assessment Report on Invasive Alien Species and their Control of the Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services. Roy, H. E., Pauchard, A., Stoett, P., Renard Truong, T., Bacher, S., Galil, B. S., Hulme, P. E., Ikeda, T., Sankaran, K. V., McGeoch, M. A., Meyerson, L. A., Nuñez, M. A., Ordonez, A., Rahlao, S. J., Schwindt, E., Seebens, H., Sheppard, A. W., and Vandvik, V. (eds.). IPBES secretariat, Bonn, Germany. https://doi.org/10.5281/zenodo.7430692.

IPCC (2014) Climate Change 2014: Synthesis report. Contribution of working groups I, II and III to the fifth assessment report of the Intergovernmental Panel on Climate Change. IPCC, Geneva, Switzerland.

IPCC (2021) Summary for Policymakers. In: Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change [Masson-Delmotte, V., P. Zhai, A. Pirani, S.L. Connors, C. Péan, S. Berger, N. Caud, Y. Chen, L. Goldfarb, M.I. Gomis, M. Huang, K. Leitzell, E. Lonnoy, J.B.R. Matthews, T.K. Maycock, T. Waterfield, O. Yelekçi, R. Yu, and B. Zhou (eds.)]. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA, pp. 3−32, doi:10.1017/9781009157896.001.

Jafari, R., Amiri, M., Asgari, F., & Tarkesh, M. (2022). Dust source susceptibility mapping based on remote sensing and machine learning techniques. *Ecological Informatics*, **72**:101872.

Johnson, J. B., & Omland, K. S. (2004). Model selection in ecology and evolution. *Trends in Ecology & Evolution* **19**(2): 101-108.

Junhirun, P., Pluempanupat, W., Yooboon, T., Ruttanaphan, T., Koul, O., & Bullangpoti, V. (2018). The study of isolated alkane compounds and crude extracts from *Sphagneticola trilobata* (Asterales: Asteraceae) as a candidate botanical insecticide for lepidopteran larvae. *Journal of Economic Entomology* **111**(6): 2699-2705.

Kariyawasam, C. S., Kadupitiya, H. K., Ratnayake, R. S. S., Hettiarchchi, A. K., & Ratnayake, R. M. C. S. (2017). Identification of High-Risk Agro-Ecological Regions using Species Distribution Modeling of Priority Invasive Species in Sri Lanka. *Indian Journal of Plant Genetic Resources* **30**(03): 228-231.

Kariyawasam, C. S., Kumar, L., & Ratnayake, S. S. (2019). Invasive plant distribution modelling: A tool for tropical biodiversity conservation with special reference to Sri Lanka. *Tropical Conservation Science* **12**: 1940082919864269.

Kariyawasam, C. S., Kumar, L., & Ratnayake, S. S. (2021). Potential distribution of aquatic invasive alien plants, *Eichhornia crassipes* and *Salvinia molesta* under climate change in Sri Lanka. *Wetlands Ecology and Management* **29**:531-545.

Kariyawasam, C. S., Kumar, L., Ratnayake, S. S., & Wijesundara, D. S. A. (2021). Potential risks of Invasive Alien Plant Species on native plant biodiversity in Sri Lanka due to climate change. *Biodiversity* **22**(1-2): 24-34.

Khuroo, A. A., Ahmad, R., Hamid, M., Rather, Z. A., Malik, A. H., & Rashid, I. (2021). An annotated inventory of invasive alien flora of India. *Invasive Alien Species: Observations and Issues from Around the World* **2**: 16-37.

Kriticos, D. J., Sutherst, R. W., Brown, J.R., (2003). Climate change and the potential distribution of an invasive alien plant: *Acacia nilotica* ssp. *indica* in Australia. *Journal of Applied Ecology* **40**:111–124.

Kriticos, D. J., Webber, B. L., Leriche, A., Ota, N., Macadam, I., Bathols, J., & Scott, J. K. (2012). CliMond: global high- resolution historical and future scenario climate surfaces for bioclimatic modelling. *Methods in Ecology and Evolution* **3**(1): 53-64.

Leung, B., Lodge, D. M., Finnoff, D., Shogren, J. F., Lewis, M. A., & Lamberti, G. (2002). An ounce of prevention or a pound of cure: bioeconomic risk analysis of invasive species. *Proceedings of the Royal Society of London. Series B: Biological Sciences* **269**(1508): 2407-2413.

Levine, J. M., & D'Antonio, C. M. (2003). Forecasting biological invasions with increasing international trade. *Conservation Biology* **17**(1): 322-326.

Li, Z. H., Wang, Q., Ruan, X., Pan, C. D., Jiang, D. A. (2010). Phenolics and plant allelopathy. *Molecules* **15**: 8933–8952. doi: 10.3390/molecules15128933.

Li, Z. Y., & Xie, Y. (2002). Invasive species in China. China Forest Publishing House, Beijing.

Liao, C. C., & Chen, Y. H. (2022). The effects of true and pseudo-absence data on the performance of species distribution models at landscape scale. *Taiwania* **67**(1): 9-20.

Liu, C., White, M., & Newell, G. (2013). Selecting thresholds for the prediction of species occurrence with presence- only data. *Journal of Biogeography* **40**(4): 778-789.

Lobo, J. M., Jiménez-Valverde, A., Real, R. (2008). AUC: a misleading measure of the performance of predictive distribution models *Global Ecology of Biogeography* **17**: 145–151.

Lodge, D. M., Williams, S., MacIsaac, H. J., Hayes, K. R., Leung, B., Reichard, S., McMichael, A. (2006). Biological Invasions: Recommendations for U.S. Policy and Management. *Ecological Applications* **16**(6): 2035–2054.

Loo, S. E., Mac Nally, R., O’Dowd, D. J., Thomson, J. R., & Lake, P. S. (2009). Multiple scale analysis of factors influencing the distribution of an invasive aquatic grass. *Biological Invasions* **11**: 1903-1912.

Lopez, B. E., Allen, J. M., Dukes, J. S., Lenoir, J., Vilà, M., Blumenthal, D. M., Beaury, E. M., Fusco, E. J., Laginhas, B. B., Morelli, T. L., O'Neill, M. W., Sorte, C. J. B., Maceda-Veiga, A., Whitlock, R. & Bradley, B. A. (2022). Global environmental changes more frequently offset than intensify the detrimental effects of biological invasions. *Proceedings of the National Academy of Sciences* **119**(22): e2117389119.

Lowe S., Browne M., Boudjelas S., De Poorter M. (2000). 100 of the World's worst invasive alien species. A selection from the global invasive species database.

Luque, G. M., Bellard, C., Bertelsmeier, C., Bonnaud, E., Genovesi, P., Simberloff, D., & Courchamp, F. (2014). The 100th of the world's worst invasive alien species. *Biological invasions* **16**: 981-985.

Macanawai, A. R. (2013). Impact of *Sphagneticola trilobata* on plant diversity in soils in South-East Viti Levu, Fiji. *Journal of Life Sciences* **7**(6): 635.

Mack, R. N., Simberloff, D., Mark Lonsdale, W., Evans, H., Clout, M., & Bazzaz, F. A. (2000). Biotic invasions: causes, epidemiology, global consequences, and control. *Ecological Applications* **10**(3): 689-710.

Maharjan, S., Shrestha, B. B., Joshi, M. D., Devkota, A., Muniappan, R., Adiga, A., & Jha, P. K. (2019). Predicting suitable habitat of an invasive weed *Parthenium hysterophorus* under future climate scenarios in Chitwan Annapurna Landscape, Nepal. *Journal of Mountain Science* **16**(10): 2243-2256.

Marbuah, G., Gren, I. M., & McKie, B. (2014). Economics of harmful invasive species: a review. *Diversity* **6**(3): 500-523.

Marmion, M., Parviainen, M., Luoto, M., Heikkinen, R. K., & Thuiller, W. (2009). Evaluation of consensus methods in predictive species distribution modelling. *Diversity and Distributions* **15**(1): 59-69.

Masum, S. M., Halim, A., Mandal, M. S. H., Asaduzzaman, M., & Adkins, S. (2022). Predicting current and future potential distributions of *Parthenium hysterophorus* in Bangladesh using maximum entropy ecological niche modelling. *Agronomy* **12**(7):1592.

Meyer, J. Y. (2000). Preliminary review of the invasive plants in the Pacific islands (SPREP Member Countries), in G. Sherley, (Ed.), Invasive species in the Pacific: A Technical Review and Draft Regional Strategy, South Pacific Regional Environment Programme, Samoa.

Mukul, S. A., Khan, M. A. S. A., & Uddin, M. B. (2020). Identifying threats from invasive alien species in Bangladesh. *Global Ecology and Conservation* **23**: e01196.

O'Neill, B. C., Kriegler, E., Ebi, K. L., Kemp-Benedict, E., Riahi, K., Rothman, D. S., Van Ruijven, B. J., Van Vuuren, D. P., Birkmann, J., Kok, K., Levy, M., & Solecki, W. (2017). The roads ahead: Narratives for shared socioeconomic pathways describing world futures in the 21st century. *Global Environmental Change* **42**: 169-180.

O'Neill, B. C., Kriegler, E., Riahi, K., Ebi, K. L., Hallegatte, S., Carter, T. R., Mathur, R., & Van Vuuren, D. P. (2014). A new scenario framework for climate change research: the concept of shared socioeconomic pathways. *Climatic Change* **122**: 387-400.

Oppel, S., Meirinho, A., Ramírez, I., Gardner, B., O'Connell, A. F., Miller, P. I., & Louzao, M. (2012). Comparison of five modelling techniques to predict the spatial distribution and abundance of seabirds. *Biological Conservation* **156**: 94-104.

Padalia, H., Srivastava, V., & Kushwaha, S. P. S. (2014). Modelling potential invasion range of alien invasive species, *Hyptis suaveolens* (L.) Poit. in India: Comparison of MaxEnt and GARP. *Ecological Informatics* **22***:*36-43. doi: 10.1016/j.ecoinf.2014.04.002

Paini, D. R., Sheppard, A. W., Cook, D. C., De Barro, P. J., Worner, S. P., & Thomas, M. B. (2016). Global threat to agriculture from invasive species. *Proceedings of the National Academy of Sciences* **113**(27): 7575-7579.

Papier, C. M., Poulos, H. M., & Kusch, A. (2019). Invasive species and carbon flux: the case of invasive beavers (*Castor canadensis*) in riparian Nothofagus forests of Tierra del Fuego, Chile. *Climatic Change* **153**(1-2): 219-234.

Pathak, H. (2023). Impact, adaptation, and mitigation of climate change in Indian agriculture. *Environmental Monitoring and Assessment* **195**(1): 52.

Pearson, R. G., Raxworthy, C. J., Nakamura, M., & Townsend Peterson, A. (2007). Predicting species distributions from small numbers of occurrence records: a test case using cryptic geckos in Madagascar. *Journal of Biogeography* **34**(1): 102-117.

Pearson, R. G., Thuiller, W., Araújo, M. B., Martinez- Meyer, E., Brotons, L., McClean, C., Miles, L., Segurado, P., Dawson, T. P., & Lees, D. C. (2006). Model- based uncertainty in species range prediction. *Journal of Biogeography* **33**(10): 1704-1711.

Pearsons, R. G. (2010). Species distribution modelling for conservation educators and practitioners. *Lessons Conservation* **3**: 54–58.

Pejchar, L., & Mooney, H. A. (2009). Invasive species, ecosystem services and human well-being. *Trends in Ecology & Evolution* **24**(9):497-504.

Peterson, A. T. (2003). Predicting the geography of species' invasions via ecological niche modelling. *The Quarterly Review of Biology* **78**(4):419-433.

Peterson, A. T., Soberon, R. G., Pearson, R. P., Anderson, E., Martinez-Meyer, M., Nakamura, and Araujo, M. B. (2011). Ecological Niches and Geographic Distributions. Princeton University Press, Princeton, New Jersey, USA.

Peterson, A. T., Stewart, A., Mohamed, K. I., & Araújo, M. B. (2008). Shifting global invasive potential of European plants with climate change. *PLoS One* **3**(6): e2441.

Pheloung, P. C., Williams, P. A., Halloy, S. R. (1999). A weed risk assessment model for use as a biosecurity tool evaluating plant introductions. *Journal of Environmental Management* **57**(4):239–251.

Phillips, S. J., Anderson, R. P., & Schapire, R. E. (2006). Maximum entropy modelling of species geographic distributions. *Ecological modelling* **190**(3-4): 231-259.

PIER (Pacific Island Ecosystems at Risk), 2003. *Wedelia trilobata.*

Poland, T. M., Patel-Weynand, T., Finch, D. M., Miniat, C. F., Hayes, D. C., & Lopez, V. M. (2021). Invasive species in forests and rangelands of the United States: a comprehensive science synthesis for the United States forest sector (p. 455). Springer Nature.

Poudel, A. S., Shrestha, B. B., Joshi, M. D., Muniappan, R., Adiga, A., Venkatramanan, S., & Jha, P. K. (2020). Predicting the current and future distribution of the invasive weed *Ageratina adenophora* in the Chitwan–Annapurna Landscape, Nepal. *Mountain Research and Development* **40**(2): R61.

Poulos, H. M., Chernoff, B., Fuller, P. L., & Butman, D. (2012). Ensemble forecasting of potential habitat for three invasive fishes. *Aquatic Invasions* **7**(2).

Qin, Z., DiTommaso, A., Wu, R. S., & Huang, H. Y. (2014). Potential distribution of two A mbrosia species in China under projected climate change. *Weed Research* **54**(5): 520-531.

Qureshi, H., Arshad, M., & Bibi, Y. (2014). Invasive flora of Pakistan: a critical analysis. *International Journal of Biosciences* **4**(1): 407-427.

R Core Team (2021). R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. URL https://www.R-project.org.

Rai, P. K., & Singh, J. S. (2020). Invasive alien plant species: Their impact on environment, ecosystem services and human health. *Ecological Indicators* **111**:106020.

Rameshprabu, N., & Swamy, P. S. (2015). Prediction of environmental suitability for invasion of *Mikania micrantha* in India by species distribution modelling. *Journal of Environmental Biology* **36**(3): 565.

Randall, R. P. (2017). *A Global Compendium of Weeds* (No. Ed. 3). RP Randall.

Ravi, S., Law, D. J., Caplan, J. S., Barron- Gafford, G. A., Dontsova, K. M., Espeleta, J. F., Villegas, J. C., Okin, G. S., Breshears, D. D., & Huxman, T. E. (2022). Biological invasions and climate change amplify each other’s effects on dryland degradation. *Global Change Biology* **28**(1): 285-295.

Ricciardi, A., Blackburn, T. M., Carlton, J. T., Dick, J. T., Hulme, P. E., Iacarella, J. C., Jeschke, J. M., Liebhold, A. M., Lockwood, J. L., MacIsaac, H. J., Pyšek, P., Richardson, D. M., Ruiz, G. M., Simberloff, D., Sutherland, W. J., Wardle, D. A, & Aldridge, D. C. (2017). Invasion science: a horizon scan of emerging challenges and opportunities. *Trends in Ecology & Evolution* **32**(6): 464-474.

Richburg, J. (2008). *Invasive Plant Management: Guidelines for Managers*. The Trustees of Reservations.

Rout, T., M., Moore, J.L, McCarthy. M.A. (2014). Prevent, search or destroy? A partially observable model for invasive species management. *Journal of Applied Ecology* **51**(3): 804–813.

Roy, H. E., Pauchard, A., Stoett, P., Renard Truong, T., Bacher, S., Galil, B. S., Hulme, P. E., Ikeda, T., Sankaran, K., McGeoch, M. A., Meyerson, L. A., Nuñez, M. A., Ordonez, A., Rahlao, S. J., Schwindt, E., Seebens, H., Sheppard, A. W., & Vandvik, V. (2023). IPBES Invasive Alien Species Assessment: Summary for Policymakers (Version 3). Zenodo. https://doi.org/10.5281/zenodo.10127924

SACEP, (2016). South Asia Co-operative Environment Programme December 2016. South Asia's Biodiversity: Status, Trend and Challenges.

Sandilyan, S. (2015). Highways of India: A heaven to invasive alien plants. *Science India*, **18**(12): 33-36.

Sankaran, K. V., Khuroo, A. A., Raghavan, R., Molur, S., Kumar, B., Wong, L. J., & Pagad, S. (2021). Global Register of Introduced and Invasive Species-India. Version 1.5. Invasive Species Specialist Group ISSG. Checklist dataset.

Sankaran, K. V., Suresh, T. A., & Sajeev, T. V. (2013). *Handbook on invasive plants of Kerala*. Kerala State Biodiversity Board.

Seebens, H., Essl, F., Dawson, W., Fuentes, N., Moser, D., Pergl, J., Pyšek, P., Van Kleunen, M., Weber, E., Winter, M., & Blasius, B. (2015). Global trade will accelerate plant invasions in emerging economies under climate change. *Global Change Biology* **21**(11): 4128-4140.

Shabbir, A., Zalucki, M. P., Dhileepan, K., Khan, N., & Adkins, S. W. (2023). The current and potential distribution of parthenium weed and its biological control agent in Pakistan. *Plants* **12**(6): 1381.

Shamsabad, M. M. (2018). The impact of climate change implies the northward shift in the distribution of the Irano-Turanian subalpine species complex *Acanthophyllum squarrosum*. *Journal of Asia Pacific Biodiversity* **11**: 566-572.

Sharma, G. P., Singh, J. S., & Raghubanshi, A. S. (2005). Plant invasions: emerging trends and future implications. *Current science* 726-734.

Shrestha, B. B. (2019). Management of invasive alien plants in Nepal: Current practices and future prospects. *Tropical ecosystems: Structure, functions and challenges in the face of global change,* 45-68.

Shrestha, B. B. (2022). Invasive alien weeds problem in South Asia: Challenges and prospects of their management.

Shrestha, B. B., Witt, A. B., Shen, S., Khuroo, A. A., Shrestha, U. B., & Naqinezhad, A. (2022). Plant invasions in Asia. In *Global Plant Invasions* (pp. 89-127). Cham: Springer International Publishing.

Shrestha, H. S., Adhikari, B., & Shrestha B. B. (2021). *Sphagneticola trilobata* (Asteraceae): first report of a naturalized plant species for Nepal. *Journal of the Indian Association for Angiosperm Taxonomy* **31**(2): 77–81.

Shrestha, U. B., & Shrestha, B. B. (2019). Climate change amplifies plant invasion hotspots in Nepal. *Diversity and Distributions* **25**(10): 1599-1612.

Shrestha, U. B., Lamsal, P., Ghimire, S. K., Shrestha, B. B., Dhakal, S., Shrestha, S., & Atreya, K. (2022). Climate change- induced distributional change of medicinal and aromatic plants in the Nepal Himalaya. *Ecology and Evolution* **12**(8): e9204

Shrestha, U. B., Sharma, K. P., Devkota, A., Siwakoti, M., & Shrestha, B. B. (2018). Potential impact of climate change on the distribution of six invasive alien plants in Nepal. *Ecological Indicators* **95**:99-107.

Simberloff, D., Martin, J. L., Genovesi, P., Maris, V., Wardle, D. A., Aronson, J., Courchamp, F., Galil, B., García-Berthou, E., Pascal, M., Pyšek, P., Sousa, R., Tabacchi, E., & Vilà, M. (2013). Impacts of biological invasions: what's what and the way forward. *Trends in Ecology & Evolution* **28**(1): 58-66.

Sivakumar, M. V., & Stefanski, R. (2011). Climate change in South Asia. *Climate Change and Food Security in South Asia*, 13-30.

Song, L. Y., Li, C. H., & Peng, S. L. (2010). Elevated CO2 increases the energy-use efficiency of invasive *Wedelia trilobata* over its indigenous congener. *Biological Invasions **12***: 1221-1230.

Spear, M. J., Walsh, J. R., Ricciardi, A., & Zanden, M. J. V. (2021). The invasion ecology of sleeper populations: prevalence, persistence, and abrupt shifts. *BioScience* 71(4): 357-369.

Srivastava, V., Roe, A. D., Keena, M. A., Hamelin, R. C., & Griess, V. C. (2020). Oh, the places they'll go: improving species distribution modelling for invasive forest pests in an uncertain world. *Biological Invasions* **23**:297–349. doi:10.1007/s10530-020-02372-9

Stachowicz, J. J., Terwin, J. R., Whitlatch, R. B., & Osman, R. W. (2002). Linking climate change and biological invasions: ocean warming facilitates nonindigenous species invasions. *Proceedings of the National Academy of Sciences* **99**(24): 15497-15500.

Stohlgren, T. J., Ma, P., Kumar, S., Rocca, M., Morisette, J. T., Jarnevich, C. S., & Benson, N. (2010). Ensemble habitat mapping of invasive plant species. *Risk Analysis: An International Journal* **30**(2): 224-235.

Sujanapal, P., & Sankaran, K. V. (2016). Common plants of Maldives. *Bangkok: Food and Agriculture Organization of the United Nations and Kerala Forest Research Institute*.

Sutherst, R. W., Maywald, G. F., & Russell, B. L. (2000). Estimating vulnerability under global change: modular modelling of pests. *Agriculture, Ecosystems & Environment* **82**(1-3): 303-319.

Svenning, J. C., & Condit, R. (2008). Biodiversity in a warmer world. *Science* **322**(5899): 206-207.

Svenning, J. C., Normand, S., & Kageyama, M. (2008). Glacial refugia of temperate trees in Europe: insights from species distribution modelling. *Journal of Ecology* **96**(6): 1117-1127.

Thaman, R. R. (1999). *Wedelia trilobata*: Daisy invader of the Pacific islands. Institute of Applied Science, University of the South Pacific Suva, Fiji Islands.

Thuiller, W. (2004). Patterns and uncertainties of species' range shifts under climate change. *Global Change Biology* **10**(12): 2020-2027.

Thuiller, W., Guéguen, M., Renaud, J., Karger, D. N., & Zimmermann, N. E. (2019). Uncertainty in ensembles of global biodiversity scenarios. *Nature Communications*, **10**(1): 1446.

Thuiller, W., Lafourcade, B., Engler, R., & Araújo, M. B. (2009). BIOMOD–a platform for ensemble forecasting of species distributions. *Ecography* **32**(3): 369-373.

Thuiller, W., Richardson, D. M., Pyšek, P., Midgley, G. F., Hughes, G. O., & Rouget, M. (2005). Niche- based modelling as a tool for predicting the risk of alien plant invasions at a global scale. *Global change biology*, **11**(12): 2234-2250.

Underwood, M. C., Allan, D. H., & James, F. Q. (2013). Geospatial tools for identifying and managing invasive plants. *Invasive Plant Ecology. CRC Press, Boca Raton*: 175-202.

Varanasi, A., Prasad, P. V., & Jugulam, M. (2016). Impact of climate change factors on weeds and herbicide efficacy. *Advances in Agronomy* **135**: 107-146.

Vilà, M., & Hulme, P. E. (2017). Non-native species, ecosystem services, and human well-being. *Impact of Biological Invasions on Ecosystem Services* **12**: 1-14.

Vilà, M., Espinar, J. L., Hejda, M., Hulme, P. E., Jarošík, V., Maron, J. L., Pergl, J., Schaffner, U., Sun, Y., & Pyšek, P. (2011). Ecological impacts of invasive alien plants: a meta- analysis of their effects on species, communities and ecosystems. *Ecology letters* **14**(7): 702-708.

Vitousek, P. M., DAntonio, C.M., Loope, L.L. & Westbrooks, R. (1996). Biological invasions as global environmental change. *American Scientist* **84**: 468-478.

Vitousek, P. M., Mooney, H. A., Lubchenco, J., & Melillo, J. M. (1997). Human domination of Earth's ecosystems. *Science* **277**(5325): 494-499.

Walther, G. R., Roques, A., Hulme, P. E., Sykes, M. T., Pyšek, P., Kühn, I., Zobel, M., Bacher, S., Botta-Dukat, Z., Bugmann, H., Czu´ cz, B., Dauber, J., Hickler, T., Jarosik, V., Kenis, M., Klotz, S., Minchin, D., Moora, M., Nentwig, W., Ott, J., Panov, V. E., Reineking, B., Robinet, C., Semenchenko, V., Solarz, W., Thuiller, W., Vila`, M., Vohland K., & Settele, J. (2009). Alien species in a warmer world: risks and opportunities. *Trends in Ecology & Evolution* **24**(12): 686-693.

Wang, R. L., Staehelin, C., Dayan, F. E., Song, Y. Y., Su, Y. J., & Zeng, R. S. (2012). Simulated acid rain accelerates litter decomposition and enhances the allelopathic potential of the invasive plant *Wedelia trilobata* (creeping daisy). *Weed Science* **60**(3): 462-467.

Ward, D. F. (2007). Modelling the potential geographic distribution of invasive ant species in New Zealand. *Biological Invasions* **9**: 723-735.

Westphal, M. I., Browne, M., MacKinnon, K., & Noble, I. (2008). The link between international trade and the global distribution of invasive alien species. *Biological Invasions* **10**: 391-398.

Whittaker, R. H., Levin, S. A., & Root, R. B. (1973). Niche, habitat, and ecotope. *The American Naturalist* **107**(955): 321-338.4

Wu, J., Peng, S., Zhao, H., & Xiao, H. (2008). Allelopathic effects of *Wedelia trilobata* residues on lettuce germination and seedling growth. *Allelopathy Journal* **22**(1): 197-203.

Wu, Y. Q., Hu, Y. J., Chen, J. N. (2005a). Reproductive characteristics of alien plant Wedelia trilobata. *Acta Scientiarum Naturalium Universitatis Sunyatseni* **44**: 93–96.

Wu, Y. Q., Hu, Y. J., Liao, F. L. (2005b). *Wedelia trilobata*- a species from introduced to potential invasive. *Guihaia* **25**: 413– 418.

Yangzom, R. (2018). *A pictorial guide to major invasive plant species of Bhutan*. National Biodiversity Centre, Ministry of Agriculture and Forests, Royal Government of Bhutan.

Yu, F. H., Wang, N., Alpert, P., He, W. M., Dong, M. (2009). Physiological integration in an introduced, invasive plant increases its spread into experimental communities and modifies its structure. *American Journal of Botany* **96**: 1983–1989.

Zhang, Y. H., Liu, M. F., Ling, T. J., Wei, X. (2004). Allelopathic sesquiterpene lactones from *Wedelia trilobata*. *J. Trop. Subtrop. Bot.* **12**: 533–537.

Zhu, L., Sun, O. J., Sang, W., Li, Z., & Ma, K. (2007). Predicting the spatial distribution of an invasive plant species (*Eupatorium adenophorum*) in China. *Landscape Ecology* **22**: 1143-1154.

APPENDIX

Appendix I

Table 2: Correlation matrix of 19 bioclimatic and 1 topographic variable.

Layer	Altitude	Bio 1	Bio 2	Bio 3	Bio 4	Bio 5	Bio 6	Bio 7	Bio 8	Bio 9	Bio 10	Bio 11	Bio 12	Bio 13	Bio 14	Bio 15	Bio 16	Bio 17	Bio 18	Bio 19
Altitude	1																			
Bio 1	-0.97	1																		
Bio 2	-0.95	0.95	1																	
Bio 3	-0.91	0.97	0.84	1																
Bio 4	-0.23	0.22	0.00	0.36	1															
Bio 5	-0.27	0.27	0.09	0.39	0.93	1														
Bio 6	0.13	-0.11	-0.22	-0.03	0.33	0.13	1													
Bio 7	-0.53	0.54	0.55	0.50	0.09	0.32	-0.40	1												
Bio 8	-0.28	0.28	0.09	0.40	0.96	0.99	0.16	0.29	1											
Bio 9	0.12	-0.11	-0.24	-0.02	0.41	0.21	0.95	-0.39	0.24	1										
Bio 10	-0.11	0.07	-0.09	0.15	0.76	0.59	0.31	-0.09	0.65	0.39	1									
Bio 11	0.06	-0.07	-0.13	-0.01	0.33	0.33	0.25	-0.15	0.31	0.27	0.02	1								
Bio 12	-0.11	0.08	0.35	-0.12	-0.69	-0.55	-0.44	0.27	-0.58	-0.51	-0.52	-0.26	1							

Bio 13	-0.50	0.59	0.38	0.72	0.36	0.34	0.18	0.13	0.32	0.17	0.15	0.25	-0.28	1						
Bio 14	0.46	-0.57	-0.28	-0.76	-0.62	-0.58	-0.20	-0.23	-0.59	-0.23	-0.35	-0.13	0.62	-0.82	1					
Bio 15	-0.88	0.88	0.98	0.75	-0.12	-0.01	-0.29	0.58	-0.02	-0.32	-0.23	-0.16	0.49	0.27	-0.15	1				
Bio 16	-0.88	0.94	0.79	0.99	0.41	0.43	0.03	0.43	0.43	0.04	0.18	0.04	-0.22	0.76	-0.80	0.69	1			
Bio 17	0.27	-0.36	-0.05	-0.57	-0.69	-0.59	-0.34	0.02	-0.61	-0.39	-0.49	-0.23	0.82	-0.75	0.94	0.11	-0.64	1		
Bio 18	-0.82	0.87	0.77	0.86	0.27	0.31	-0.04	0.52	0.32	0.00	0.21	-0.12	-0.04	0.50	-0.59	0.69	0.83	-0.41	1	
Bio 19	-0.81	0.79	0.84	0.71	0.01	0.09	-0.20	0.45	0.08	-0.23	-0.18	0.02	0.29	0.44	-0.26	0.84	0.70	-0.07	0.48	1

Appendix II

Table 3: Number of occurrence points along the latitude range

Latitude ranges (In degree)	**S_{Inv} (Species)**	**S_{Inv}/A (* 10^5) (Species per 100,000 Km^2)**
0 - 4	11	6210.7
5 - 9	216	190.7
10 - 14	657	213.9
15 - 19	442	73.8
20 - 24	347	26.4
25 - 29	148	8.1
30 - 34	49	4.3

Appendix III

Table 4: Number of occurrence points along the elevation range

Elevation ranges (In meter)	**S_{Inv} (Species)**	**S_{Inv}/A (* 10^5) (Species per 100,000 Km^2)**
0 - 500	1298	40.3
501 - 1000	533	52.5
1001 - 1500	38	11.3
1501 - 2000	1	0.4

Appendix IV

Table 5: Occurrence points observed within different countries

Species occurring in SA Countries	**S_{Inv} (Species)**	**S_{Inv}/A (* 10^5) (Species per 100,000 Km^2)**
India	1796	52.3
Sri Lanka	38	57.2
Maldives	9	3066.7
Bangladesh	15	9.8
Nepal	5	3.0
Pakistan	2	0.2

Appendix V

Table 6: Suitable area of *S. trilobata* in different scenarios

Scenario	Suitable area (Km^2)	Suitable area (%)	Change in Suitable area (%)
Current	1,505,266.84	26.66	-
SSP245 2030	1,297,715.32	23	-3.66
SSP245 2050	1,353,727.09	24	-2.66
SSP585 2030	1,2621,98.32	22.35	-4.31
SSP 585 2050	1,335,703.35	23.65	-3.01

Appendix VI

Table 7: Summary of Change in the suitable habitat (Km^2) of *S. trilobata* in different South Asian countries in future compared to the current climatic condition (1970–2000).

SA Countries	Current climatic condition (Km^2)	SSP 245 (Km^2)		SSP 585 (Km^2)	
		2030	**2050**	**2030**	**2050**
Nepal	23574.18	18243.64	19840.23	18229.09	23510.86
India	1329858.58	1186797.22	1235098.11	1143603.56	1199344.96
Bangladesh	85156.93	26165.87	32112.46	33788.63	46207.17
Bhutan	352.52	149.73	55.62	156.58	264.39
Sri Lanka	66031.15	66065.37	66100.45	66097.89	66053.39
Maldives	293.48	293.48	293.48	293.48	293.48
Afghanistan	0	0	0	0	0
Pakistan	0	0	0	0	0

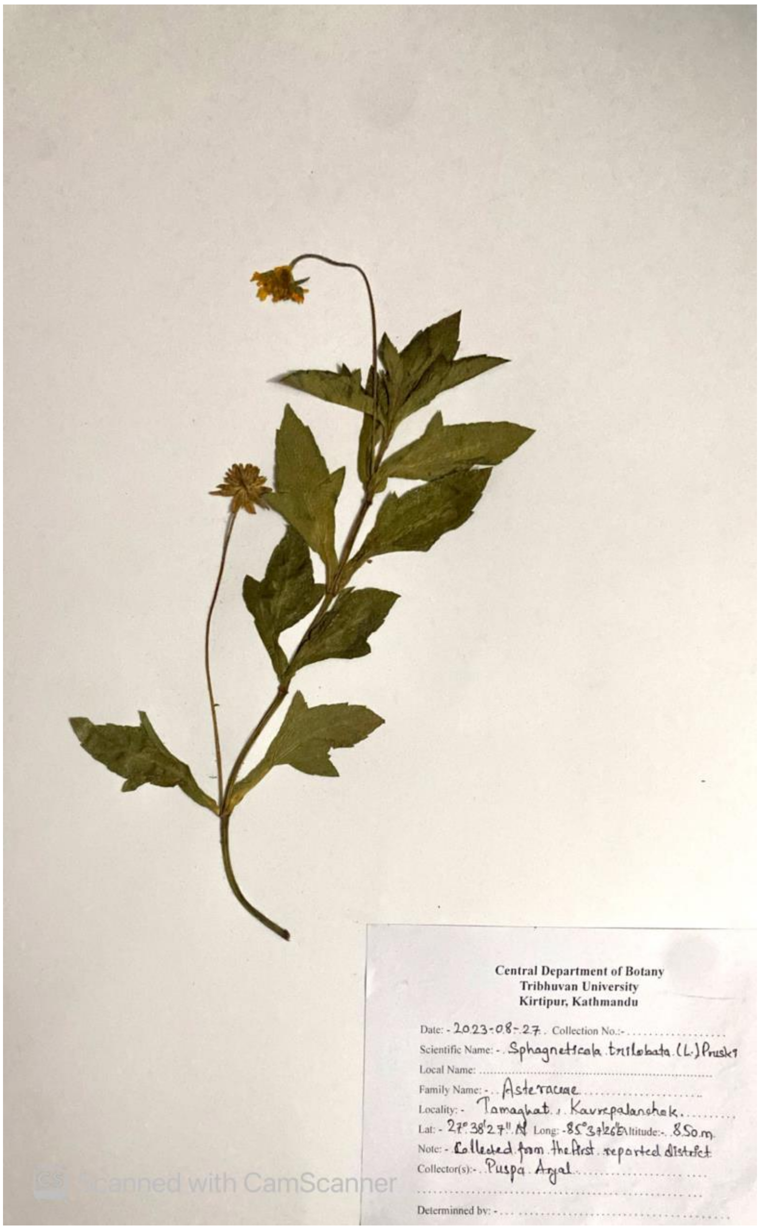
PHOTOS PLATES

Figure: Current status of *Sphagneticola trilobata* in Kavrepalanchowk, Nepal

. **Figure :** *Sphagneticola trilobata* along with *Mimosa sp*

Figure*:* Extracting species for herbarium from

Figure*:* Mat forming *Sphagneticola trilobata* species site



Central Department of Botany
Tribhuvan University
Kirtipur, Kathmandu

Date: - 2023-08-27. Collection No.:-
Scientific Name: - Sphagneticola trilobata (L.) Pruski
Local Name:
Family Name: - Asteraceae
Locality: - Tamaghat, Kavrepalanchok.
Lat: - 27°38'27" N Long: - 85°37'26"E Altitude:- 850 m.
Note: - Collected from the first reported district
Collector(s):- Puspa Aryal

Determinned by: -

Figure: Herbarium of study species from the first reported site from Nepal