

Identifying Cultivation Hotspots of *Aquilegia fragrans* Benth.-an Endangered Medicinally Important Plant via Ensemble Modelling under Climate Change Scenarios

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Abstract

Climate change is one of the main drivers for species redistribution and biodiversity loss, especially for endemic and medicinally important plant species with a restricted distributional range. For that reason, it is vital to comprehend "how" and "where" priority medicinal and aromatic plants (MAPs) might be effectively used to address conservation-related issues under rapid climate change. In the current study, we used an ensemble modelling approach to investigate the present and future potential distribution coupled with the range dynamics of the *Aquilegia fragrans*—a medicinally important endangered plant species in the entire spectrum of the Himalayan biodiversity hotspot. The findings of the current study revealed that, under current climatic conditions, the northwest states of India (Jammu and Kashmir, Himachal Pradesh, and the northern part of Uttarakhand); the eastern and southern parts of Pakistan Himalaya have highly suitable and optimal climatic conditions for the growth of *A. fragrans*. The ensemble model exhibited high forecast accuracy, with temperature seasonality (BIO4) and precipitation seasonality (BIO15) as the main climatic variables responsible for the distribution in the biodiversity hotspot. Furthermore, the study predicted that future climate change scenarios will diminish habitat suitability for the species by -46.922% under RCP4.5 2050 and -55.052% under RCP4.5 2070. Likewise, under RCP8.5 the habitat suitability will decrease by -51.760% in 2050 and -94.351% in 2070. The current study also revealed that the western Himalayan area will show the most habitat loss. Some regions that are currently unsuitable such as the northern Himalayan regions of Pakistan will become more suitable under climate change scenarios. Hopefully, the current approach will provide a robust technique and showcases a model with learnings for predicting cultivation hotspots and devising scientifically sound conservation plans for this endangered medicinal plant in the Himalayan biodiversity hotspot.

Introduction

Biodiversity around the world is debilitated by human-induced alteration in climate and land use change (Barnosky et al., 2011). Medicinal plants have an essential role in the Himalayan ecosystems, subsistence, and civilizations (Grytnes and Vetaas, 2002; Olsen, 2005). Ethnographic and field research has emphasized these links for millennia, together with the financial worth of medicinal/aromatic plants for the regional population of Himalaya (Upreti et al., 2016; O'Neill et al., 2017). However, in recent years, the herbal industry's increased need for raw material has led to the indiscriminate collection of medicinal herbs from the Himalaya which is their natural habitat (Ganie et al., 2019). For example, recent research found 64 plant species in the Indian Himalaya that fall into various threatened groups, including critically endangered (13), endangered (28), and vulnerable (23) (Mehta et al., 2020b). These requirements, unfortunately, have put a significant impact on medicinal and aromatic species (MAPs) throughout the Himalaya (Gao et al., 2019). The strategic framework is required to secure long-term markets for these plants and to meet the future problems that global climate change will pose to MAPs (Rana et al., 2017).

According to the newly released global biodiversity assessment study, approximately ten lakh plant and animal species, at the moment are posed with extinction threats (IPBES, 2019). According to newly published Red List, roughly one-third of all evaluated species are threatened (IUCN, 2021). Looking into

these horrible situations biodiversity hotspots with a high number of endemics are more susceptible to species extinctions (Tali et al., 2015; Hamid et al., 2020). The likelihood of extinction is higher for endemic species with smaller distribution ranges than for those with wider ones (Manes et al., 2021). The chief factors driving the extinction of species worldwide comprise a change in the use of land, climate change, overexploitation, invasion of alien species, and pollution (IPBES, 2019). Alterations in ecological and physiological processes brought on by global warming cause the extermination or species loss, especially of those that are unable to cope with the changing climatic conditions (Santangeli et al., 2017; Gong et al., 2017).

Changing climate plays a pivotal role in shifting plant species to new habitats where they might not be protected or be plagued by other human activities, thereby bringing them one step forward toward extinction (Araujo et al. 2011). Investigating how climate change may affect the spatial and temporal distribution of species is very much imperative for effective conservation (Dawson et al., 2011; Li et al., 2015; Wang et al., 2015). Technological advancements especially SDM made it very easy for forecasting the impact of climate change on the distribution pattern of species (Zimmermann et al., 2010; Norberg et al., 2019).

Preservation of natural ecosystems and restoring degraded ones are of utmost priority to meet the global challenge of climate change and biodiversity loss; both of these are nature-based solutions and are equally important in terms of sustainability (IUCN, 2021). The era from 2021–2030 designated as the Decade of Ecosystem Restoration by the United Nations (Fischer et al., 2021), gives stress on the reinstatement of dented environments in addition to providing conservation to already existing ones worldwide (Abhilash, 2021). Figure out and give preference to those profligated habitats which possess the remarkable potential to harbor vulnerable biodiversity, especially species of endemic origin that are supposed to be at greater likelihood of loss (Padilla and Pugnaire, 2006; Chauhan and Bisht, 2020). Global climate change has made it difficult to design tactics that may affect the Himalayan MAPs' habitat, distribution, ecology, and phenology (Aryal, 2015; Hasan et al., 2021, 2022). By 2100, evidence shows that global warming would likely surpass 2.0°C in all scenarios (IPCC, 2014). Change of temperature at the global surface at the end of (2081–2100) i.e., the 21st century is anticipated to be more than 1.5°C relative to 1850–1900 at most (RCP) respective concentration pathways (IPCC, 2014). These temperature variations had quite a significant impact on species distributions in alpine habitats (Pearson and Dawson, 2003, Hamid et al., 2019). Overabstracting plants having medicinal holdings, particularly those uniquely in Himalaya, has pushed some of them towards extermination (Tali et al., 2015; Hamid et al., 2020). The unlawful with improper harvesting of medicinal plants, especially the subterranean parts (roots, rhizomes), has resulted in the deterioration of the ecological systems in the Himalaya (Mehta et al., 2020a). Furthermore, the warming of Himalaya is rising faster than the rest of the world (0.06°C/year) due to climatic alteration (Hassan et al., 2021), increasing the extinction risk in this region. Such human-governed biodiversity challenges, along with climate change, might turn the region into a recruiting ground for extinctions (Cardillo et al., 2004). In the coming time due to swift changes in climate in the Himalayas, it is predicted that it poses a heavy risk of extinction, especially to endemic and vulnerable species thereby making it compulsory to introduce the changes driven via climate into the

conservation policy related to biodiversity and approaches towards restoring ecosystems (Hamid et al., 2020; Mehta et al., 2020a, b; Manita, 2021; Chauhan and Bisht, 2020).

One of the most important conservation methods for heavily overexploited species for trade purposes is to find out ample habitat so that they can be cultivated commercially to address overharvesting difficulties caused by high trade demand (Rana et al., 2020). As a result, projecting existing and future appropriate habitats for significant MAPs is a prerequisite for undertaking agricultural planning that might incorporate mixed plantation systems. Ensemble species distribution modelling (eSDM) provides a significant strategy for the restoration of threatened species with restricted distribution (Rana et al., 2020; Rather et al., 2022; Kumari et al., 2022, Wani et al., 2022). SDM is greatly worth mentioning recently because of its comprehensive implications in conservation biology to forecast hotspots suitable for cultivation and conservation of endemic as well as medicinally vital species, besides restoration ecology to restore ecosystems (Zellmer et al., 2019; Banerjee et al., 2021; Zhong et al., 2021; Rather et al., 2021, 2022). Ensemble modelling can be a reliable approach for identifying potential ideal regions for MAPs restoration (Rana et al., 2020). Furthermore, it has many benefits in comparison to single model algorithms, as it accounts use of many algorithms, which reduces estimation uncertainty and hence increases the precision of species distribution forecasts (Gritti et al., 2013; Thuiller et al., 2009; Hamid et al., 2019; Rana et al., 2020; Rather et al., 2022; Kumari et al., 2022, Wani et al., 2022).

Aquilegia fragrans Benth is an endangered perennial medicinal herb belonging to the family Ranunculaceae, mainly distributed in Himalaya, particularly western region (Baig et al., 2014). For the first time, we constructed climatic envelope models for *A. fragrans* based on present and future climate data, intending to provide climate effect evaluations to enhance the conservation strategy for this commercially endangered species. More specifically, the current study intended to address the following research questions. (i) To investigate the present and future distribution patterns of *Aquilegia fragrans* under climate change in the entire spectrum of Himalayan biodiversity hotspot. (ii) To access the main climatic determinants that influence the distribution of *A. fragrans* and (iii) To quantify the range change patterns of *A. fragrans* under future climate change scenarios.

Materials And Methods

Study area

The Himalaya a global biodiversity hotspot represents the world's premier mountain system on earth and is thereby known to possess varied ecological, biogeographical, and evolutionary attributes giving rise to tremendous biodiversity of endemic origin (Joshi and Pant 2012; White et al., 2019; Rana et al., 2021). The Himalayan biodiversity hotspot falls within the geo-coordinates (34–36°N, 27°E) to (27–28° N, 90°E) involving north-western Pakistan and Northern Myanmar respectively, and is snuggled between the south Indian subcontinent and the northern highland of Tibetan (<https://www.cepf.net>) (Fig. 1). It has been divided into two categories biogeographically such as Western Himalaya including regions of Jammu and Kashmir, Uttarakhand and Himachal Pradesh while Eastern Himalaya comprises of north-eastern

Indian states (Sikkim, Assam, West Bengal, and Arunachal Pradesh), southeast Tibet, northern Myanmar, Nepal, and Bhutan (Hamid et al., 2019; Rather et al., 2022; Wani et al., 2022). It is located at a biogeographic crossroads amidst the Palearctic and Indo-Malayan regions. Furthermore, the Himalayas' geological, climatic, and altitudinal differences, besides complexity in topography (Troll 1972; Zurick and Pacheco 2006; Miehe et al. 2015), bestow Himalaya with abundant biodiversity.

Currently, Himalayan biodiversity hotspot is facing increased anthropogenic influences such as land use change, habitat loss, spreading of invasive alien species, and non-judicious ways of gathering natural resources which ultimately led to biodiversity loss, deprivation of fragile ecosystems as well as compromising ecosystem services and products (Ren et al., 2007; Khuroo et al., 2012; Roy and Srivastava, 2012; Palmer et al., 2014; Ahmad et al., 2019b; Upreti et al., 2021)

Target species

Aquilegia fragrans Benth, an endangered perennial medicinally important herb belonging to the family Ranunculaceae, are distributed predominantly in the Western Himalaya (Hussain et al., 2011; Baig et al., 2014). *Aquilegia fragrans*, prevalently known as “sweet scented columbine” and in Kashmir locally possess different names “Janglikuth”, “Kalumb” and “Zaoneel”. The plant grows naturally in India (Kashmir valley) at elevated altitudes (Mathew and Sinnott, 2003). Its stem is 30–80 cm in length, branched, densely hairy with glands below the flower. Leaflets are wedge-shaped to obovate and glaucous. Flowers are several, somewhat horizontal to slightly nodding. Sepal's 20–30×9–12 mm, whitish to purple, slightly velvety (Fig. 2). This plant finds its traditional use in treating diverse inflammatory ailments and wounds (Baig et al., 2014). Besides, the rhizome is found to be curative in kidney stones, eczema, psoriasis, blood sugar, cystitis, gout, and bovine mastitis (Ganie et al., 2019, Rani et al., 2013). For headache alleviation, dried flower paste is utilized, and jaundice and pneumonia are treated traditionally with seeds and the whole plant respectively (Khan et al., 2018). Recently its root has been found effective ethanomedicinally as an analgesic and antipyretic (Majid et al., 2020). For the treatment of boils plant flower paste in refined butter is made and subsequently massaged for one to two weeks (Lal and Singh, 2008). Overexploitation and habitat fragmentation due to the immense medicinal properties of *A. fragrans* has put enormous strain on the population of this endangered species in the Himalaya.

Species distributional records

A Comprehensive field survey was done from (2019–2021) in the entire Kashmir Himalaya to collect occurrence records of *Aquilegia fragrans*, which are supplemented with geographical records from herbarium reconstruction (KASH) and some of the well-known databases like BIEN, IBP, GBIF, and BBP (Botanical information Facility, Indian Biodiversity Portal, Global Biodiversity Information Facility and Bhutan Biodiversity Portal respectively). All the above-mentioned databases were accessed on 30 February 2022.

A total of 75 georeferenced records for its distribution were gathered from the aforementioned sources (S1) and subsequently reduced to 32 after clipping for the research area (Himalaya). The species distributional records are frequently oversampled from those areas which are physically suited and easily accessible (Hijmans et al., 2005). This led to geographic sample bias (Ahmad et al. 2019a; Hamid et al., 2019; Rather et al., 2022). We employed spatial thinning to reduce geographical autocorrelation and sample bias by dividing the research region into grid cells of 1×1 km and arbitrarily picking a lone point among every cell having single or multiple points of occurrence (Ahmad et al. 2019a; Hamid et al., 2019; Rather et al., 2022). The ultimate dataset is taken for modelling of *A. fragrans* comprised of 30 georeferenced records

Environmental data

To forecast the present distribution pattern of plant species under study across the research area, WorldClim database version 1.4 was utilized for the extraction of climatic variables at a geographical resolution of 30 arc seconds (Hijmans et al., 2005). Additionally, greater collinearity across bioclimatic variables may reduce model performance and can produce unreliable interpretations (Dormann et al., 2013). To solve this issue Pearson's correlation analysis was taken into account wherein we utilized only one variable from each pair of a highly interrelated variable having a correlation coefficient of ($r > 0.75$). Following correlation analysis, five variables were selected for the distribution modelling of *A. fragrans* under current climatic conditions (Table 1). For the prediction of distribution in future with respect to selected species, Hadley Global Environment Model 2-Earth System (HADGEM2-ES) simulations for two representative concentration pathways (RCP4.5 and RCP8.5) for time periods 2050 and 2070 were obtained from the Intergovernmental Panel on Climate Change (IPCC) fifth assessment report (AR5) (Moss et al., 2010). Future distributions of the target species were predicted using the same set of environmental variables that were used to estimate their current distribution.

Table 1
Bioclimatic variable for modelling the distribution of *A. fragrans* in the present study. Selected variables are in bold.

BIO-1 (Annual Mean Temperature)
BIO-2 (Mean Diurnal Range)
BIO-3 (Isothermality)
BIO-4 (Temperature Seasonality)
BIO-5 (Max Temperature of Warmest Month)
BIO-6 (Min Temperature of Coldest Month)
BIO-7 (Temperature Annual Range)
BIO-8 (Mean Temperature of Wettest Quarter)
BIO-9 (Mean Temperature of Driest Quarter)
BIO-10 (Mean Temperature of Warmest Quarter)
BIO-11 (Mean Temperature of Coldest Quarter)
BIO-12 (Annual Precipitation)
BIO-13 (Precipitation of Wettest Month)
BIO-14 (Precipitation of Driest Month)
BIO-15 (Precipitation Seasonality)
BIO-16 (Precipitation of Wettest Quarter)
BIO-17 (Precipitation of Driest Quarter)
BIO-18 (Precipitation of Warmest Quarter)
BIO-19 (Precipitation of Coldest Quarter)

Modelling technique

During the present study species distribution modelling and ensemble forecasting was executed by utilising “biomod2” package (Thuiller et al., 2009) within R software version 4.0.3 (R Development Core Team, 2021). A total of nine algorithms were utilised (Table 2) in the current study. Presence/absence data is required for modelling but acquiring accurate absence data is challenging. Subsequently, in accordance with Barbet-Massin et al. (2012), Guisan et al. (2017), and Rather et al., (2022) we generated five hundred pseudo-absences at random within the study area. Since our pseudo-absence selection procedure uses a stochastic approach that selects pseudo-absences at random, we carried out the operation 3 times for removing bias in the sample created during the production of pseudo-absence

(Guisan et al., 2017; Rather et al., 2022). We used 80% of the data (training set) to develop the models and evaluated on the remaining 20% (validation set). The whole approach was repeated thrice. As a consequence, we got a total of 81 models for each climate situation and time period combination (3 replicate pseudo-absence datasets $\times$ 9 algorithms $\times$ 3 replicates) (Rather et al., 2022). Two assessment metrics, such as area under the curve (AUC) of receiver operating characteristics and true skills statistics (TSS), were utilised for examining performance of model using a repeated data-splitting technique called cross-validation (Allouche et al., 2006; Marmion et al., 2009; Beaumont et al., 2016; Rather et al., 2022).

Using committee averaging as well as weighted-mean approach, the final ensemble model was constructed for each climate scenario along with time period combination based on various modelling results (Marmion et al., 2009). Those models having TSS scores of ≥ 0.8 were retained for the creation of final ensemble models. Consequently, five ensemble projections were created, one reciprocates with current climatic suitability and the remaining ones for anticipation of future prediction on habitat suitability for the time periods of 2050 and 2070 periods), representing 2 typical concentration trajectories RCP4.5 and 8.5 (Kumari et al., 2022, Rather et al., 2022).

Table 2
List of algorithms used in the present study

S. No	Model	Type	Reference
1	ANN Classification Tree Analysis (CTA)	Machine learning	(Breiman et al., 1984),
2	Generalised Linear Model (GLM)	Machine learning	(McCullagh and Nelder, 1989)
3	Surface Response Envelope (SRE)	Profile	(Busby, 1991)
4	Flexible Discriminant Analysis (FDA)	Statistical regression	(Hastie et al., 1994),
5	Artificial Neural Networks (ANN)	Machine learning	(Ripley, 1996)
6	Generalised Boosted Models (GBM)	Machine learning	(Ridgeway, 1999)
7	Random Forest (RF)	Machine learning	(Breiman, 2001)
8	Maximum Entropy (MAXENT)	Machine learning	(Phillips et al., 2006)
9	Generalised Additive Models (GAM)	Statistical regression	(Hastie and Tibshirani, 1990)

Variable importance

We employed a permutation method to determine the relative impact of each climatic condition in affecting the distribution of *A. fragrans* (Elith et al., 2005, Rather et al., 2022). Predictions were generated during this process by using a predetermined algorithm after changing just a solitary target variable

whilst holding other variables constant. The significance of a particular variable is estimated by subtracting the score of correlation (1-correlation score) from the difference between the original forecast and the permuted variable prediction (Rather et al., 2022; Ahmad et al., 2019a). Correspondingly, a zero value indicates, the predictor variable holds no connotation toward the model, whereas higher values indicate a predictor variable of more importance.

Species Range Change

In the biomod2 R package *RangeSize()* function was employed to measure and determine the range change shift for *A. fragrans* under projected future climate change (Thuiller et al., 2009). We get two outputs from the *RangeSize()* function: a table with summarized information on species range shifts and a geographical map showing whether species may gain or lose appropriate habitats (Guisan et al., 2017; Rather et al. 2022; Kumari et al., 2022).

Taking these output types into consideration one will come to know about absolute metrics such as "loss", "absent" and "stable". So far "loss" is concerned it denotes pixel in number forfeited by species under study owing to the fact of climate alterations; "absent" represents pixel resolution in number presently not engrossed through species under study besides having no prediction for suitability under a peculiar environmental scenario; and "stable," represents a pixel in number engrossed via species under research and additionally predicted to be appropriate beneath a particular climatic scenario (Guisan et al., 2017; Rather et al. 2022; Kumari et al., 2022).

We also get three additional relative metrics like: "percentage loss" indicating a loss in the percentage of sites inhabited presently and measured via $(\text{loss} / (\text{loss} + \text{stable}))$; "percentage gain" which is figured out through $(\text{gain} / (\text{loss} + \text{stable}))$; simply can be put as a percentage of new sites taking into account the present distribution size of species and "range change" expresses comprehensive projection output equivalent to percentage gain– percentage loss (Guisan et al., 2017; Rather et al. 2022).

Results

Model assessment

The final ensemble models constructed through committee averaging had AUC and TSS of 0.98 and 0.90, respectively. Similarly, the weighted mean ensemble models had a TSS and AUC of 0.92 and 0.98 respectively. These two findings demonstrated that the final models were reliable and accurate at predicting the spread of the target species in the target area. At the individual algorithm level, the prediction accuracy investigated was again outstanding, but varied, with RF, GBM, ANN, and FDA performing well, followed by GLM, CTA, and GAM, while algorithms such as CTA, Maxent Phillips, and SRE performed poorly as compared to other employed algorithms (Fig. 3).

Variable importance

The proportionate relevance of various predictor variables varied significantly between algorithms. The most significant contributing factor impacting species distribution was BIO-04 (Temperature Seasonality), with significance values of 0.28 to 0.83 (mean = 0.53), followed by BIO-15 (Precipitation Seasonality), with significant scores of 0.36 to 0.62 (mean = 0.51). Other factors' responses varied between algorithms, and hence their role showed greater variation in shaping the distribution of species (Table 3).

Table 3
The relevance scores of the selected bioclimatic variables, both overall and algorithmically.

Variable	GLM	GBM	GAM	CTA	ANN	SRE	FDA	RF	MAXENT. Phillips	Mean
BIO-01	0.11	0.02	0.40	0.00	0.20	0.27	0.01	0.03	0.18	0.14
BIO-02	0.03	0.02	0.44	0.03	0.13	0.20	0.00	0.06	0.26	0.13
BIO-04	0.61	0.43	0.83	0.42	0.57	0.63	0.45	0.28	0.60	0.53
BIO-12	0.11	0.03	0.33	0.00	0.13	0.41	0.00	0.06	0.25	0.15
BIO-15	0.48	0.51	0.62	0.54	0.60	0.60	0.47	0.36	0.44	0.51

Current distribution

So far the results of ensemble modelling are contemplated it has revealed under the present conditions of climate, the Himalaya western part of which includes the Indian states of the north-west side like Himachal Pradesh, Jammu and Kashmir, and the northern part of Uttarakhand, and the eastern and southern part of Pakistan, has climatic conditions that are both ideal and optimal for growth of *A. fragrans* (Fig. 4). Nepal (north-western and central portions), on the other hand, have fairly appropriate areas, but Bhutan (central and southern parts), Sikkim and Arunachal Pradesh (northern and north-eastern parts) has poor suitability for *A. fragrans*.

Future potential distribution

Taking *A. fragrans* habitat suitability into consideration, it will shrink under the changing future climatic conditions. Nonetheless, presently some satisfactory areas including majority of western Himalaya-eastern and southern Pakistan, northwest states of India like Himachal Pradesh (HP), Jammu and Kashmir (J&K), and the northern part of Uttarakhand will continue to be suitable during all climate changes in future (Fig. 5).

Species range change

The findings from the distributional change investigation demonstrated that the studied species will experience large distributional changes in the event of future climatic conditions (Table 4), and it will be guided majorly via decreasing habitat suitability in the future. In terms of committee averaging, habitat suitability for *A. fragrans* could well be lowered by approximately 46.922% (under RCP4.5 2050), 55.052%

(RCP4.5 2070), 51.760% (RCP8.5 2050) and around 65.417% under RCP8.5 for 2070 while comparing it to present habitat suitability (Table 3). Also, for *A. fragrans*, the habitat suitability may decline by 77.977% (under RCP4.5 2050), 80.590% (RCP4.5 2070), 84.035% (RCP8.5 2050), and by about 94.351% under RCP8.5 for the year 2070 (Table 4) in terms of weighted mean. In the future those areas that seem to be incompatible are primarily positioned towards Pakistan's southern region of Himalaya, J&K (central and southern parts), HP and the central part of Uttarakhand (Fig. 6).

Some currently unsuitable locations, on the other hand, will become suitable following the future change in climate with a range expansion of 2.053% (under RCP4.5 2050), 1.994% (RCP4.5 2070), 2.048% (RCP8.5 2050), and 2.242% (RCP8.5 2070) (Table 4), in terms of committee averaging and mostly include the northern region of Pakistan Himalaya (Fig. 6). Likewise, in terms of weighted mean, certain unsuitable regions at current will become compatible under future climatic conditions, with a range expansion of 0.171% (under RCP4.5 2050), 0.136% (RCP8.5 2050), 0.079% (RCP4.5 2070), and 0.084% (RCP8.5 2070) (Table 3) and mostly covers the northern region of Pakistan Himalaya (Fig. 6).

Table 4
Range change statistics for *A. fragrans* under climate change scenarios compared to current climatic conditions.

Scenario	Ensemble type	Loss	Absent	Stable	Gain	Loss (%)	Gain (%)	Range change (%)
RCP4.5 2050	Committee averaging	47822	841379	49823	2005	48.975	2.053	-46.922
RCP4.5 2050	Weighted mean	61549	862135	17210	135	78.149	0.171	-77.977
RCP8.5 2050	Committee averaging	52541	841384	45104	2000	53.808	2.048	-51.760
RCP8.5 2050	Weighted mean	66292	862163	12467	107	84.171	0.136	-84.035
RCP4.5 2070	Committee averaging	55703	841437	41942	1947	57.046	1.994	-55.052
RCP4.5 2070	Weighted mean	63534	862208	15225	62	80.669	0.079	-80.590
RCP8.5 2070	Committee averaging	66065	841195	31580	2189	67.658	2.242	-65.417
RCP8.5 2070	Weighted mean	74376	862204	4383	66	94.435	0.084	-94.351

Discussion

To our best knowledge, the present study is the first attempt from the Himalayan biodiversity hotspot to investigate the current and future potential distribution of the *A. fragrans* under ongoing climate change by using Biomod ensemble approach, thereby identifying the potential cultivation hotspots of this endangered medicinal plant in the entire spectrum of the Himalaya.

Predicting the climatic space of medicinal plants using a species distribution model might be important for sustainable habitat protection and species management (Profirio et al., 2014; Rana et al., 2020; Rather et al., 2022, Wani et al, 2022). As a result, appropriate MAPs species must be chosen for growth in both natural and ex-situ environments (Rana et al., 2020). This not only gives the major drivers of geographical range area, but also allows us to comprehend the interaction between species distribution range and extinction (Purvis et al., 2000; Cardillo et al., 2008; Kumari et al., 2022). Ensemble species distribution modelling has shown to be a beneficial and cost-effective approach for assessing species potential distribution under ongoing rapid climate change (Ranjitkar et al., 2016; Rana et al., 2020; Rather et al., 2022). The ensemble modelling approach used in the current study reduces the predictive uncertainty of single models like Maxent (Araujo and New, 2007; Ahmad et al., 2019a; Hamid et al., 2019; Rana et al., 2020; Rather et al., 2022, Wani et al, 2022) and addresses the limitations and uncertainties inherent in SDM techniques (Barry and Elith, 2006).

The use of an adequate number and combination of bioclimatic variables are required for modelling unique and endangered plant species (Kumari et al., 2022; Salam et al., 2020). Our findings revealed that the key bioclimatic factors influencing the distribution of *A. fragrans* in the Himalaya were temperature seasonality and precipitation seasonality. Several previous research studies have found that the aforementioned bioclimatic variables predominate in the distribution of other Himalayan plant species (Cao et al., 2016; Hamid et al., 2019; Mir et al., 2020; Sofi et al., 2021; Rather et al., 2022; Kumari et al., 2022, Wani et al., 2022., Wani et al., 2021). The possible reason for this might be that most precipitation in this mountainous landscape comes during the monsoon between June and October, which corresponds with the growing period of *A. fragrans* (Ranjitkar et al., 2013; Hamid et al., 2019, Wani et al., 2022). The final ensemble models constructed through committee averaging had an AUC and TSS of 0.98 and 0.90, respectively. Similarly, the weighted mean ensemble models had a TSS and AUC of 0.92 and 0.98 respectively. These two findings revealed that the final models were reliable and accurate at predicting the distribution of the target species.

The results of the ensemble model revealed that the north-west states of India like Jammu and Kashmir, Himachal Pradesh, the northern region of Uttarakhand, and the eastern and southern part of Pakistan, have extremely appropriate and best possible growth conditions for *A. fragrans*. Our results are in accordance with numerous previous studies which have shown the restricted distribution of many Himalayan plants (for instance *Betula utilis* – Hamid et al., 2019; Sofi et al., 2021 – *Trillium govanianum*; Rather et al., 2022 – *Trillium govanianum*; Kumari et al., 2022– *Valerianawallichii*, Wani et al., 2022– *Swertia petiolata*). This is mostly due to increased snow cover in subalpine and alpine zones, as well as more precipitation in the western Himalaya compared to the eastern Himalaya, which favors the growth and development of *A. fragrans* (Hamid et al., 2019; Sofi et al., 2021; Kumari et al., 2022). Another

possible factor might be the temperature of western Himalaya, to which most of the endemic Himalayan plant species have adapted, as opposed to the tropical climate found in the eastern Himalaya (Sofi et al., 2021, Wani et al., 2022).

Climate change is emerging as another serious hazard to Himalayan plants, with the current study revealing a reduction in habitat suitability reaching its peak (94.351%) under RCP 8.5 2070. Under future climate change scenarios, suitable habitats for *A. fragrans* are predicted to decrease in southern Pakistan, Jammu and Kashmir (central and southern parts), Himachal Pradesh (HP), and the central part of Uttarakhand, while as northern Himalayan part of Pakistan shows an increase in the habitat suitability of *A. fragrans* in the future. The latter region can be identified as the best cultivation hotspot for *A. fragrans*. Our results are in concordance with several other previous studies (Hamid et al., 2019; Sofi et al., 2022; Rather et al., 2022; Kumari et al., 2022). The rapid warming trends reported in the sub-alpine zones in the region where *A. fragrans* is usually found may explain the decreasing habitat appropriateness of *A. fragrans* in western parts of the Himalaya under climate change (Adhikari et al., 2018; Mariani et al., 2019; Rather et al., 2022). Another probable explanation for this shift is that the central Himalaya receives lower temperatures and more rainfall for a longer period of time than the western area, allowing the species to flourish and survive under shifting climatic circumstances (Rana et al. 2017). Our findings have important implications for developing successful conservation strategies and restoration sites for this endangered medicinal plant species in high-altitude Himalayan ecosystems in an era of fast land-use change and climate change.

From the biodiversity conservation point of view species distribution models are considered an indispensable tool. They produce geographical maps by making use of connections involving environmental variables and known distribution records of species. Ecological insights and the predicting distribution of species across different habitats are attained from these maps (Elith and Leathwick 2009). Prediction of Species distribution through modelling is treated nowadays as a vital component of conservation planning, and several modelling techniques have been developed in this regard (Guisan and Thuiller, 2005). Development in SDM has aided biodiversity conservation by connecting science to policy and decision-making processes. SDM allows stakeholders to make informed decisions on where to focus their effort. Besides conservation several other applications like climate change perception, species diversity identification, and revealing suitable areas for conservation and species reintroduction. (Casey et al., 2002; Philips et al., 2009; Champman et al., 2016; Mainali et al., 2015; West et al., 2017; Kraemer et al., 2017; Sundblad et al., 2011). SDM takes into account the correlation of provided environmental variables and selects the most important variable that mostly governs its distribution. Simultaneously SDM can anticipate a species' occurrence probability and environmental requests. This serves as a link between science and wildlife management in the conservation of species.

Conclusion

The current work is the first to apply BIOMOD ensemble technique to map current habitats and anticipates influence on the suitability of habitat through climate change in *Aquilegia fragrans*, an

important endangered medicinal plant in the Himalayan biodiversity hotspot. Ecosystem restoration for sweet-scented columbine conservation is the prime focus of the current study by finding appropriate sites in the Himalaya. Under the circumstances of climate change in the future, our findings estimated a decline in habitat appropriateness for the species ranging from – 46.9% under RCP4.5 2050 to -94.3% under RCP8.5 2070. The majority of habitat loss will take place in the western Himalayan area. In contrast, certain currently unfavorable Himalayan regions, such as the northern regions of Pakistan, would be more suited in the event of future climate change. The current study's findings can help in identifying conservation measures or reintroduction spots for this plant species having medicinal significance in the data-deficient Himalayan biodiversity hotspot and similar mountainous places throughout the world for such plant species. This technique will not only recover the target species, but also guarantees the achievement of bigger restoration goals such as ecosystem stability, structure, and functioning, besides the continued provision of life-sustaining ecosystem commodities and services in natural habitats

Declarations

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Author contribution

IAB and MF perceived the research idea. RQ, SR, JQ and ZAK supervised the research work. IAB, MF, and SR collected field and herbarium data. IAB, MF, and TW conducted modelling and data analysis; validation and visualization were carried out by TW, ZAK, and KG. The original draft was written by IAB and KG with a detailed review, editing and inputs from TW, ZAK, JQ and RQ. All the authors reviewed and approved the final draft for submission.

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Availability of data and material

The distributional data analysed in the current study are available from the Global Biodiversity Information Facility (GBIF) ([https:// www. gbif.org/ occurrence](https://www.gbif.org/occurrence)), and bioclimatic data were obtained from the WorldClim database ([http:// www. worldclim. org](http://www.worldclim.org)). All the data supporting the results and R codes are available from the corresponding author upon reasonable request.

Ethical approval Not applicable

Consent to participate Not applicable

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Competing interests The authors declare no competing interests

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Supplemental File

Supplemental file S1 is not available with this version.

Figures

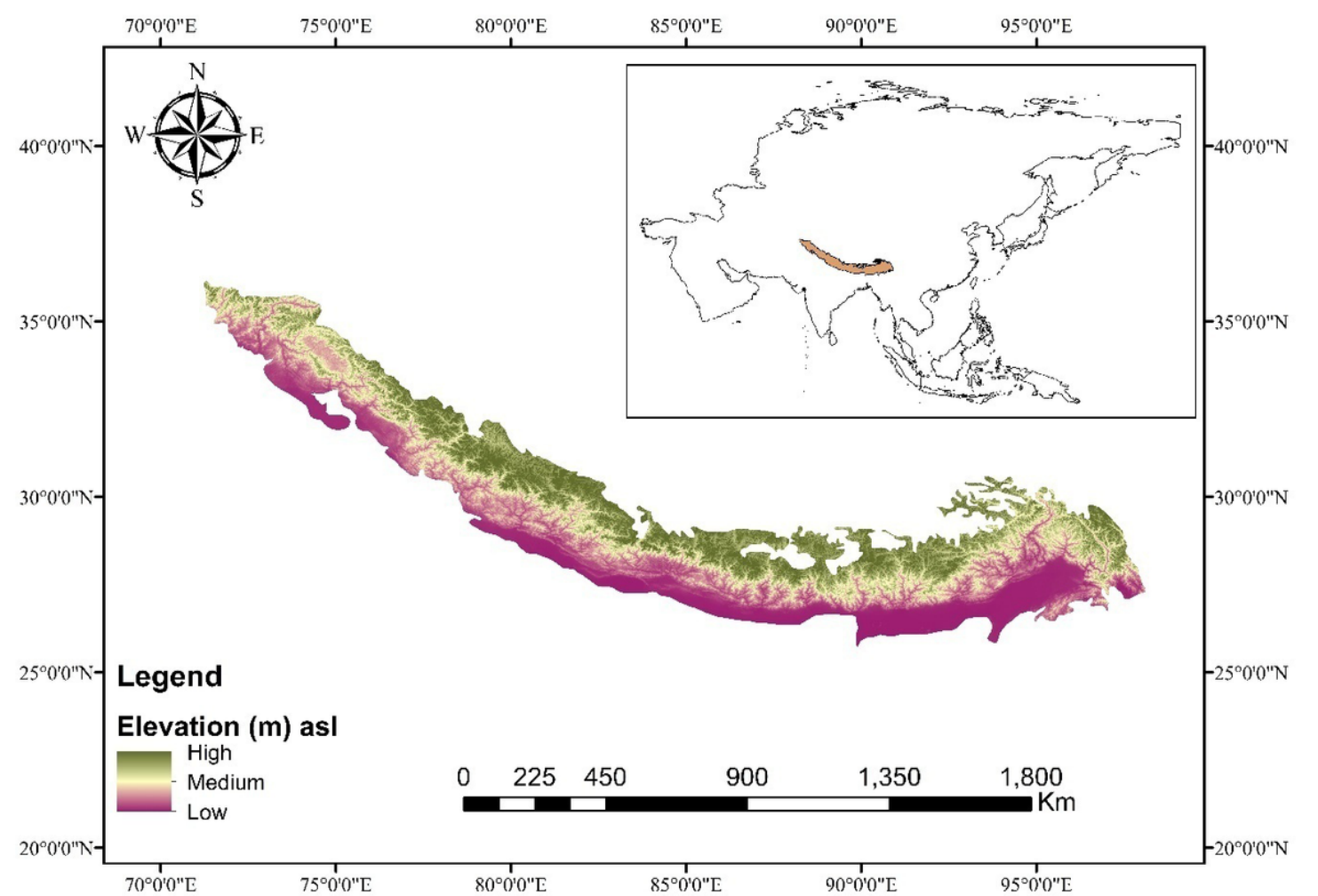


Figure 1

Study area Map



Figure 2

Aquilegia fragrans; (a) Habit and habitat; (b) Inflorescence; (c) Fruit and (d) Seed

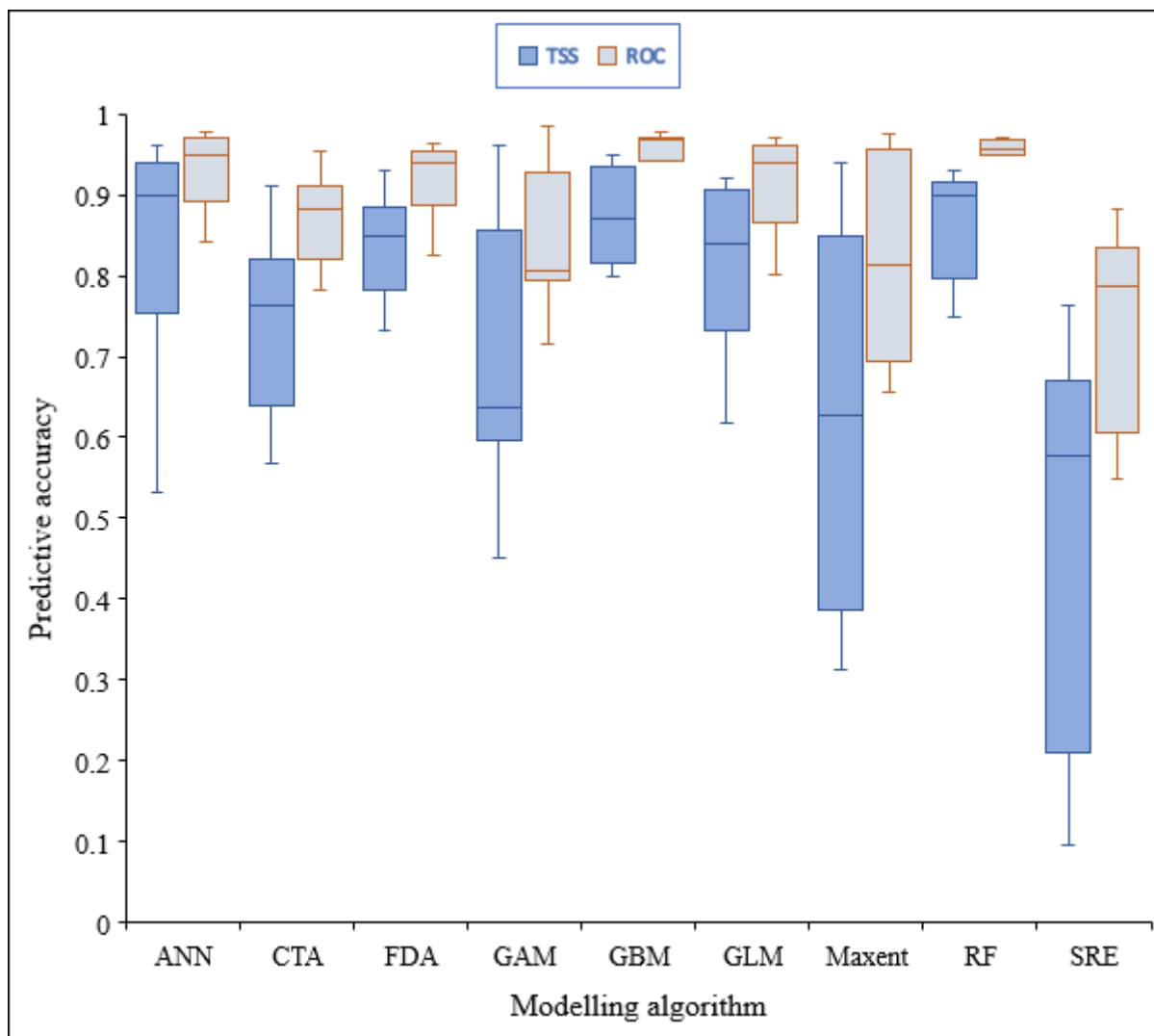


Figure 3

Mean model assessment scores for *A. fragrans* based on two separate evaluation measures, ROC (AUC) and TSS.

Aquilegia fragrans current projections

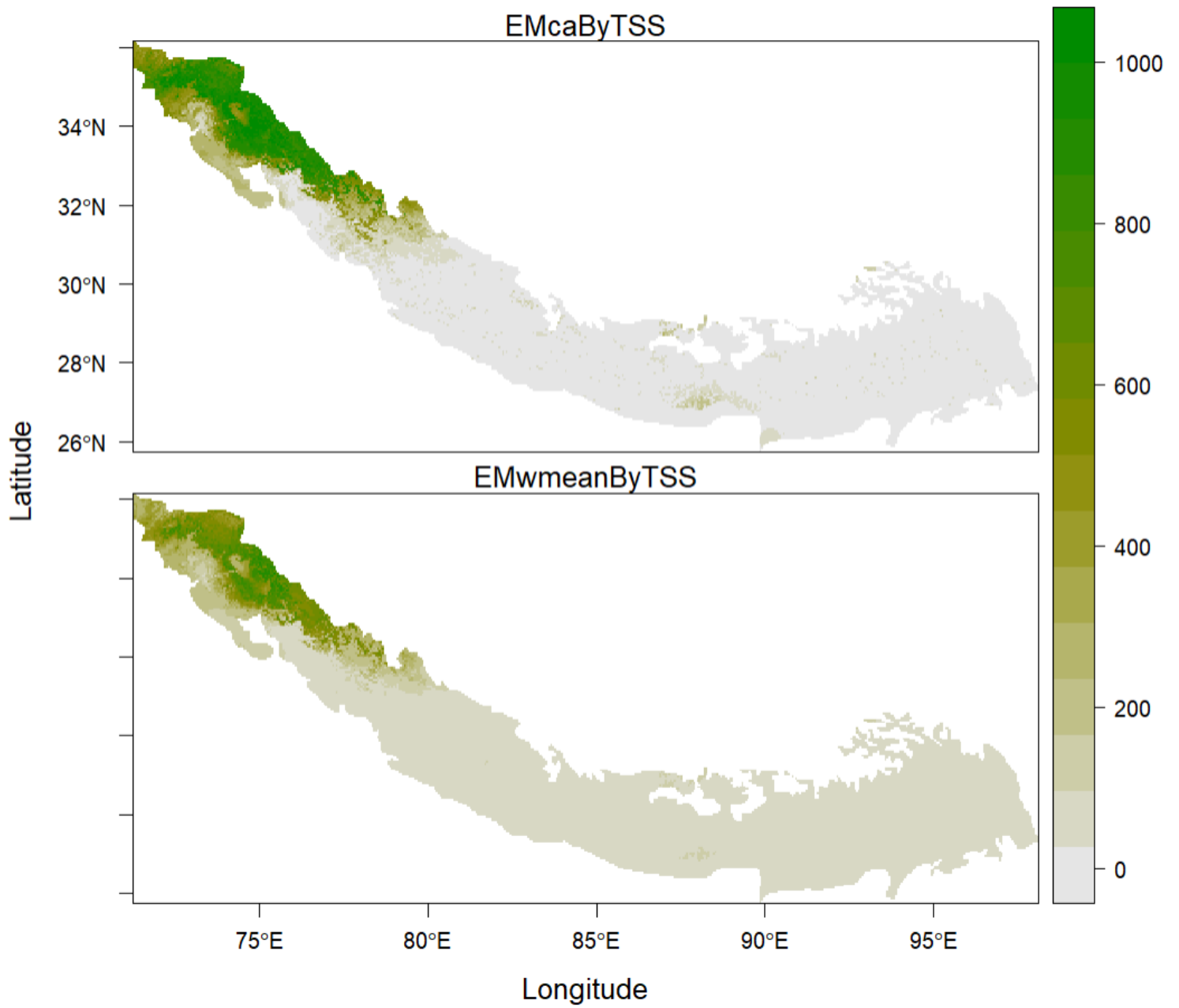


Figure 4

Map shows the pattern of the current distribution of *A. fragrans* in the Himalayan biodiversity hotspot; ca – upper and wm – lower. (Note: ca = committee averaging, wm = weighted mean)

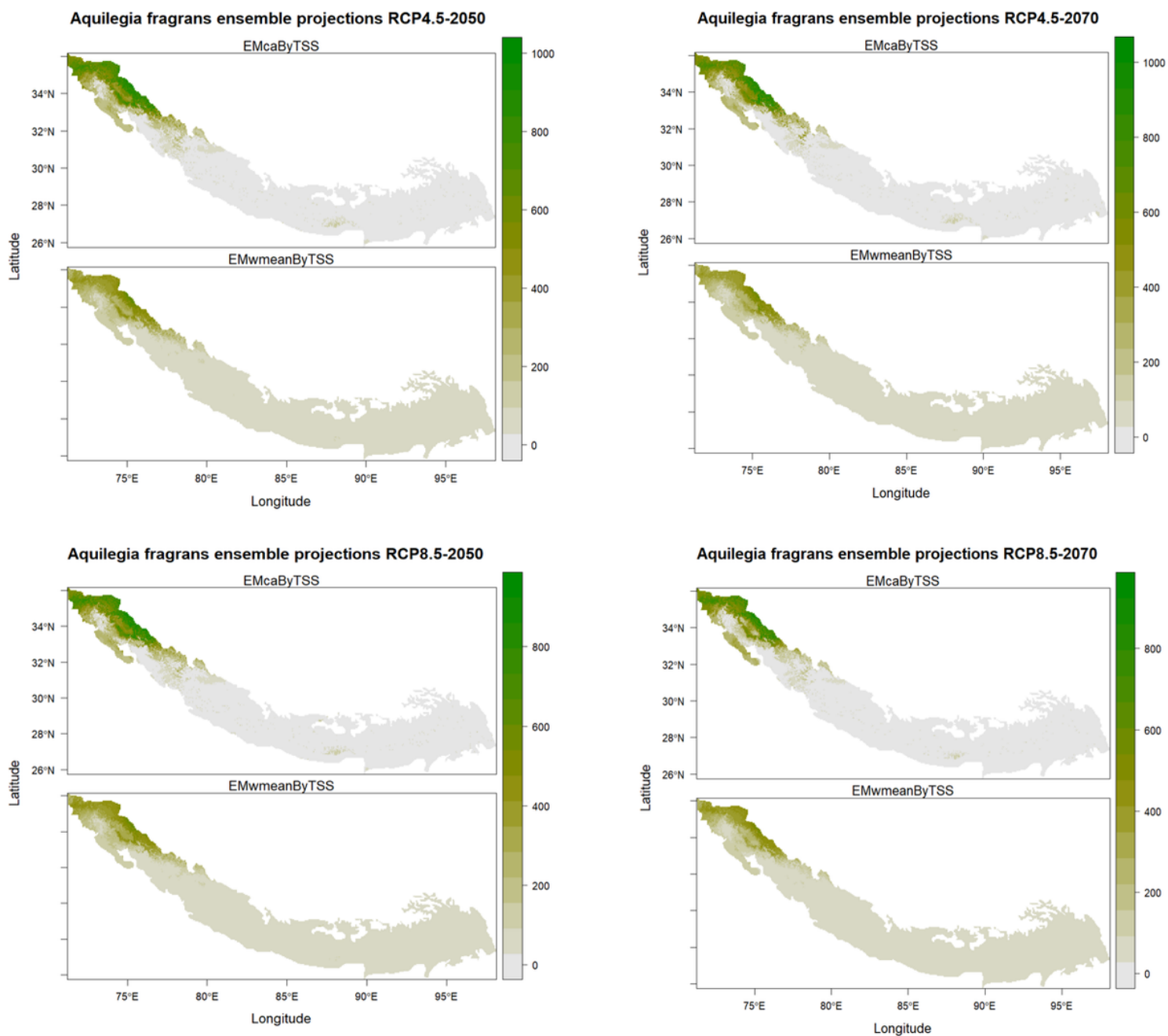


Figure 5

Potential appropriate habitats of *A. fragrans* in the event of future climate change scenarios anticipated by a ca – upper and wm – lower. (Note: ca = committee averaging, wm =weighted mean)

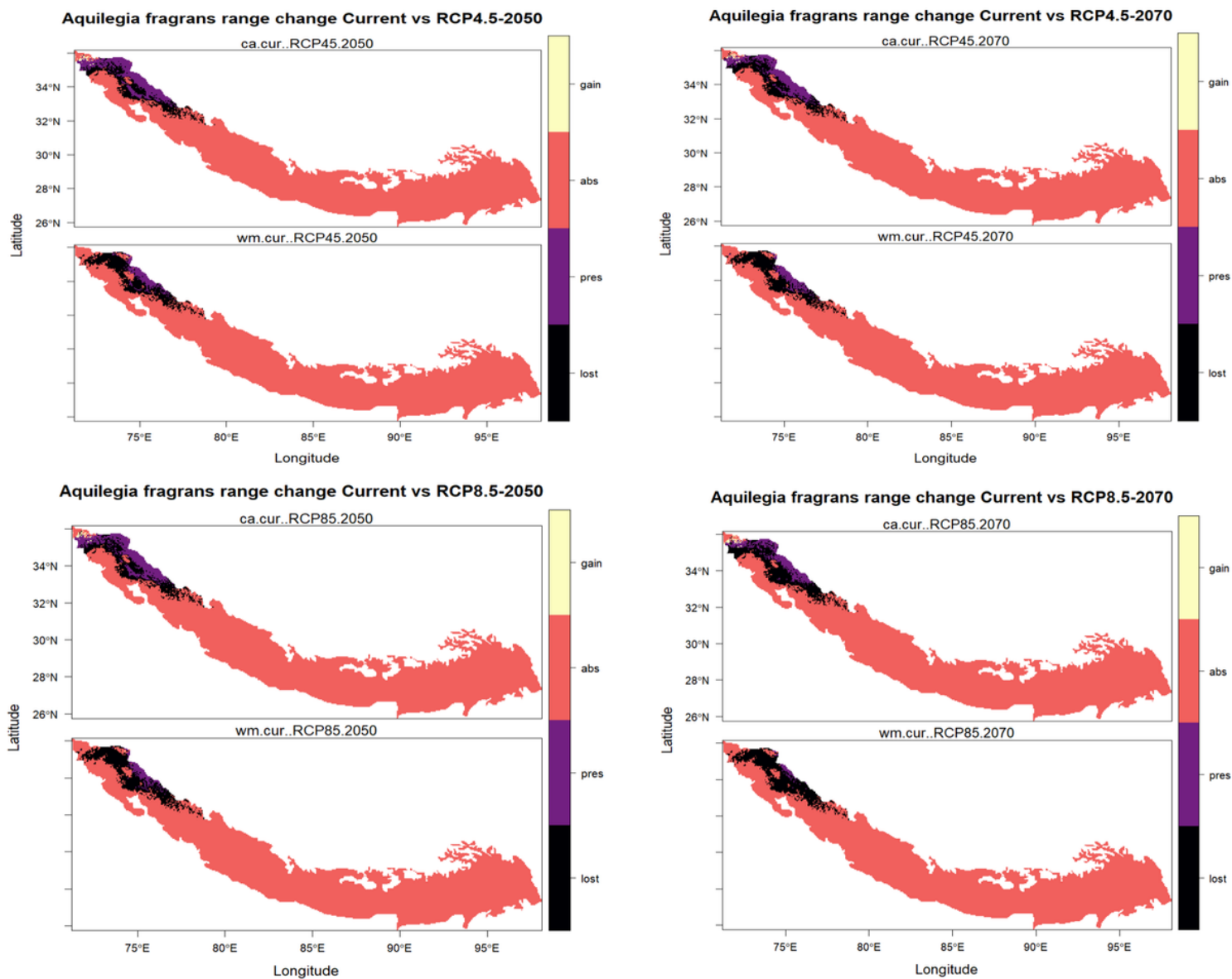


Figure 6

Range change in the suitability of habitat for *A. fragrans* owing to the fact of climate alteration between current and future climate; ca– upper and wm – lower. (Note: ca = committee averaging, wm =weighted mean)