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Predicting the invasion potential of two alien plant species (*Parthenium hysterophorus* L., Asteraceae and *Salvia tiliifolia* Vahl, Lamiaceae) under the current and future climate change scenarios in Ethiopia

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Abstract

Background Invasive alien plants pose serious threats to native ecosystems, agricultural productivity, and biodiversity. *Parthenium hysterophorus* and *Salvia tiliifolia*, both originating from the Americas, have become aggressively invasive in Ethiopia since their introduction in the 1970s and 1980s, respectively. This study applies species distribution modeling (SDM) to predict their potential distribution across Ethiopia under current and future climate conditions. An ensemble modeling approach, combining 10 replications of seven algorithms (BRT, RF, GLM, GAM, MaxEnt, MARS, and SVM), was implemented using screened occurrence records and key environmental predictors. Projections were made for the present and for future periods (2050s and 2070s) under two Shared Socioeconomic Pathways: SSP2-4.5 and SSP5-8.5.

Results The ensemble model demonstrated high predictive performance, with AUC values of 0.90 for *P. hysterophorus* and 0.92 for *S. tiliifolia*, and corresponding TSS scores of 0.67 and 0.74. Key climatic predictors influencing habitat suitability included BIO9, BIO18, BIO13, BIO4, BIO14, and BIO15. Under current conditions, *P. hysterophorus* occupies approximately 73,155 km², while *S. tiliifolia* covers about 47,671 km². *P. hysterophorus* is projected to expand under a moderate climate scenario (76,977 km² in the 2050s) but decline sharply under a high-emissions scenario (26,768 km² in the 2070s). In contrast, *S. tiliifolia* shows continuous expansion under both scenarios, reaching up to 75,843 km² by the 2050s. Predicted distributions suggest a high invasion risk across central, northern, southern, eastern, northwestern, southeastern, and southwestern Ethiopia, with substantial overlap with major crop-producing areas, including key teff (*Eragrostis tef*, Poaceae) growing regions.

Conclusions The findings indicate that both invasive weeds are expected to expand across several regions of Ethiopia, highlighting the urgent need for strengthened control efforts. Continuous monitoring and improved management of forests, agricultural lands, and pastures are essential, as these landscapes remain especially vulnerable to invasion. Proactive measures, including stricter prevention strategies, are critical to limit further spread at both local and national scales. This is particularly important in key agricultural regions such as Amhara, Oromia, Sidama, Southern Nations Nationalities and Peoples Region, Harari, and Dire Dawa, where major crops like teff, sorghum, wheat, and coffee are widely cultivated. Special attention should be given to the major teff-producing regions, which are

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not only agriculturally important but also culturally significant, and where the impact of these invasive weeds may be especially severe due to the crop's short stature.

Keywords Climate change, Ensemble model, Invasive weeds, *Parthenium hysterophorus*, *Salvia tiliifolia*

Introduction

Global biodiversity loss is a widely recognized crisis, with species extinctions projected to occur at rates far exceeding natural background levels (Wood et al. 2013). Research confirms that the rate of biodiversity loss now surpasses earlier projections, emphasizing the urgent need for conservation (Lewis 2006; Jablonski 2008). The main drivers of this decline include land and sea use change (the most dominant factor), along with the direct exploitation of natural resources, pollution, climate change, and invasive alien species (Jaureguiberry et al. 2022). Although climate change has emerged as an increasingly urgent threat, it is not the sole factor; other drivers continue to significantly reduce genetic diversity, undermine species survival, and destabilize ecosystems (Malhi et al. 2020; Jaureguiberry et al. 2022). Land-use change has long been the leading driver, but climate change is projected to have the most profound impact on terrestrial biodiversity in the future (Sala et al. 2000). If current trends persist, Earth could be on the path to the sixth mass extinction within the next 240 years (Barnosky et al. 2011).

Invasive alien plant species are among the major threats to biodiversity, posing a significant global risk by disrupting ecological functions, services, and socio-economic systems (Didham et al. 2005; McGeoch et al. 2010). Over the past decades, invasive alien plants have severely impacted local biodiversity, ecosystem services, and environmental quality (Rai and Singh 2020), altering ecosystem processes (Raizada et al. 2008). They reduce native species abundance and richness through competition, predation, hybridization, and indirect effects (Blackburn et al. 2004; Gaertner et al. 2009), change community structures (Hejda et al. 2009), and modify genetic diversity (Schierenbeck and Ellstrand 2009).

Although biological invasions disrupt ecosystem functions and services, their trophic and taxonomic impacts on native species loss remain largely unexamined at the global scale (Mollot et al. 2017). Invasive species cause severe ecological and economic harm across many parts of the world. In the United States, invasive plants are considered the second-most serious threat to biodiversity conservation after habitat destruction, resulting in annual economic losses of approximately \$34 billion (Randall 1996; Pimentel et al. 2005). Similarly, in China, invasive alien species lead to losses estimated at \$14.45 billion each year, with indirect damages accounting for

over 80% of the total (Xu et al. 2006). In Ethiopia, invasive species usually come in the third place next to habitat loss and degradation and unsustainable utilization of biodiversity resources. Furthermore, in the face of escalating climate change, the impacts of invasive alien species are expected to be more and more significant (Gebretsadik 2016). Beyond economic costs, invasive species also pose serious threats to native biodiversity. For example, the rapid spread of *Eichhornia crassipes* (water hyacinth) in Dianchi Lake, Yunnan Province, caused the extinction of 13 native hydrophytes (Wu 1993). In Ethiopia, the impact of this species on Lake Tana is currently under investigation (Asmare et al. 2020).

The invasive weeds *Parthenium hysterophorus* and *Salvia tiliifolia* harm biodiversity, crops, and pasture lands, causing agricultural losses, degrading natural plant communities, and posing health risks, leading to significant economic impacts worldwide (Hu et al. 2013; Kumar and Aggarwal 2024). Native to the tropical Americas (Haseler 1976; Swati et al. 2013), *P. hysterophorus* poses a significant threat to natural ecosystems and agroecosystems in over 30 countries worldwide (Haseler 1976; Swati et al. 2013). This pioneer species is capable of spreading to grazing lands, degraded pastures, agricultural fields, orchards, summer crops, forests, roadsides, railway tracks, recreational spaces, and floodplains (Navie et al. 1996). *S. tiliifolia*, originally native to Central America (Hedberg et al. 2006), has spread as a weed to various regions worldwide. Its distribution now includes Mexico, the United States, Ethiopia, South Africa, and Australia, with its recent introduction to China (Demissew 1996; Hu et al. 2013). The plant is commonly found on hillslopes near roads in woodlands and is best suited to altitudes ranging from 1,700 to 2,500 m above sea level, which is right at the epicentre of the agroecological distribution zone (1500 to 2550 m a.s.l.) of teff cultivation (Melese et al. 2025).

P. hysterophorus was first introduced to Ethiopia in the 1970s (Tesema 2002) and was initially observed in the 1980s near food aid distribution centers, particularly around Dire-Dawa (Mekbib et al. 1996). Ethiopia is currently the most severely affected country in the region. According to Tana and Milberg (2000), this species is regarded as the most significant weed in both croplands and grazing areas by 90% of farmers in Ethiopia's lowlands, with sorghum yields reduced by up to 97% in experimental fields with high densities of the weed.

Likewise, *S. tiliifolia* was introduced to Ethiopia in the 1980s, likely through grain supplied during a humanitarian aid program following prolonged droughts. The weeds aggressively spread across various regions of the country, extending across different floristic zones. According to Demissew (1996), since it was introduced to Ethiopia, it has been spreading rapidly, replacing native herbs in some areas.

P. hysterophorus, and *S. tiliifolia* are annuals or short-lived perennial herbaceous plants. The former species often forms dense stands, reaching an average height of 1.5 m, or up to 2.0 m under favorable soil moisture conditions (Adkins and Shabbir 2014). Invasive weeds are known to release allelopathic chemicals that suppress crop and pasture growth (Kanchan and Jayachandra 1980), reducing yields and harming livestock (Bashar et al. 2021; Tilaye et al. 2023). Their ability to spread is further enhanced by human activities, as vehicles such as stock transporters, trucks, and graders disperse their seeds in mud, dust, or plant debris (Haseler 1976).

Moreover, invasive plants benefit from climate change by having a competitive advantage over native species due to rising temperatures and CO₂ levels (Liu et al. 2017). Invasion and its effects are exacerbated by synergies with other global changes (Pyšek et al. 2020). As a result, invasive weeds can tolerate a wide range of environments, including extreme soil moisture increasing their adaptability to various conditions (Navie et al. 2005), suggesting that they are highly adaptable plants under climate change. Thus, it is imperative to manage invasive species efficiently, conserve local biodiversity, and assess their establishment and spread under present and future climate scenarios.

Species distribution models (SDMs) are currently the most reliable tools used by biologists and environmental scientists to investigate the impact of climate change on the geographical distribution and range expansion of invasive species (Kleinbauer et al. 2010; Barbet-Massin et al. 2018; Adhikari et al. 2023). The information gained through predictive tools, will enable the early detection of invasive weeds (Srivastava et al. 2019), establish rapid response systems for controlling them, and guide the planning and implementation of effective control and eradication strategies under future climate change scenarios (Pyke et al. 2008; Briscoe Runquist et al. 2019; Beaury et al. 2020). In recent years, predicting the dynamic potential distribution of invasive species can be done with different species distribution models (Mainali et al. 2015). SDM links species occurrences with climatic and other environmental variables, using the principle of niche conservatism, to generate maps that depict the potential distribution of a given species (Peterson et al. 2011).

In the current study, we used ensemble modeling techniques for predicting the habitat suitability of invasive weeds, outperforming single-algorithm methods in accuracy and precision (Thuiller et al. 2016). The algorithm has been widely used to predict the current and future habitats of various invasive species (Stohlgren et al. 2010; Figuerola-Ferrando et al. 2025).

To the best of our knowledge, there is a lack of comprehensive research on the invasion potential of invasive weeds in Ethiopia, underlining the need for further investigation into their ecological impacts and management strategies. In this study, we aimed to (1) identify the most important environmental variables predicting the distribution of *P. hysterophorus* and *S. tiliifolia*, (2) map the current and future potential distribution of invasive weeds, taking into account the current and future scenarios (2050 and 2070), and (3) evaluate the spatiotemporal changes in invasive species' ranges and their implications for weed control and management.

We hypothesize that climate change increases the invasion potential of *P. hysterophorus* and *S. tiliifolia* by expanding the distribution of suitable habitats for these species. Overall, we identified areas that are at high risk of invasion by *P. hysterophorus* and *S. tiliifolia*. This study's findings will enhance our understanding of the current distribution and future expansion potential of *P. hysterophorus* and *S. tiliifolia* in Ethiopia and will help in creating a framework for developing management strategies to control their further spread and minimize impacts.

Materials and methods

Study area

The study was undertaken in Ethiopia, located between 3°–15°N latitude and 33°–48°E longitude (Fig. 1). Ethiopia has a variety of landforms, land use patterns, soil types, and twelve primary vegetation types across its different altitudinal zones. The country covers an area of approximately 1.13 million km², within the elevation range of 125 m below sea level in the Danakil Depression to 4533 m above sea level in the Simien Mountains (Asefa et al. 2020). It consists of extensive areas of highland, surrounded by lowlands on all sides except to the north, where the Western highlands continue into Eritrea. The northern part of central Ethiopia is intersected by the East African Rift Valley, which includes the triangular Afar lowlands, part of the AF (Afar) floristic region (Friis et al. 2011). Invasive alien weeds, such as *P. hysterophorus* and *S. tiliifolia*, are distributed across the different floral regions of Ethiopia. These species have been observed in agricultural lands/crops, within forests and at their edges, grazing areas, and along roadsides (Fig. 2), where they pose significant challenges to native biodiversity

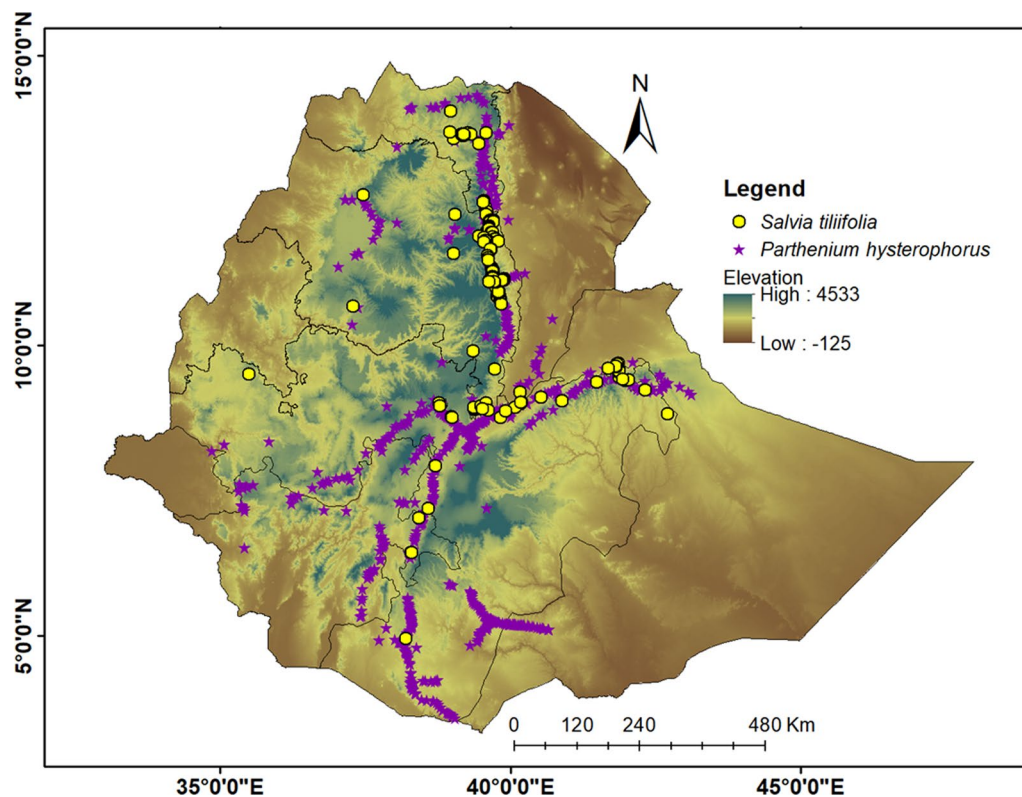


Fig. 1 Study area showing the occurrence points of *P. hysterophorus* and *S. tiliifolia* across various elevation ranges in Ethiopia. Elevation data were derived from a Digital Elevation Model (DEM) to represent topographic variation. The map indicates that both species are predominantly found in lowland and mid-elevation zones and are rarely recorded at the highest elevations. This altitudinal pattern reflects their ecological preference for warmer conditions typically associated with lower elevations, which may support their establishment and spread

and affect land-use systems, including those managed by farmers, herders, and park/protected area managers.

Species occurrence data

Voucher specimens of the invasive weeds (with collection number DA001 for *P. hysterophorus* and DA002 for *S. tiliifolia*) were collected from study sites, pressed, and transported to the National Herbarium (ETH) for further identification. The samples were compared with the authenticated specimen in the National Herbarium, identified, and finally confirmed by experts in the field and deposited there for further reference. The species occurrence data used for this study was collected from a field survey, from the Global Biodiversity Information Facility (GBIF, <https://www.gbif.org>) ($n=724$ for *P. hysterophorus* and $n=28$ for *S. tiliifolia*), and herbarium specimens ($n=24$ for *P. hysterophorus* and $n=6$ for *S. tiliifolia*, the National Herbarium). Field data were obtained from surveys conducted between October 2023 and December 2024 across various sites with high crop productivity. These sites included South Wollo (Kalu and Tehuledere districts) and Central Ethiopia (including Minjar Shenkora District). Field observations were recorded at 138

locations for *P. hysterophorus* and 200 locations for *S. tiliifolia*. Data were collected from farmland, grazing land, forests, surrounding environs, and roadsides, with a 1 km distance from each site.

The data from GBIF were carefully evaluated and cross-checked with herbarium and field records. We have used records with accurate geographic coordinates and excluded those with ambiguous locations. We used occurrence points of specimens collected from the 1980s onwards since the accuracy of location data tends to diminish with specimen age (Murphey et al. 2004; Bloom et al. 2018).

Prior to model fitting, these occurrence points were spatially rarified with 1 km² spatial resolution using SDM toolbox V2.6 (Brown 2014) to avoid spatial autocorrelations (Guisan et al. 2017). Thus, out of 2186 and 573 presence points, 948 and 172 occurrence points of *P. hysterophorus* and *S. tiliifolia* were retained (Tables S1 and S2), which were subsequently used to develop habitat suitability models for the species. We used ArcGIS and Google Earth to map the locations to check their accuracy. Moreover, misidentification and duplicate occurrences were checked by cross-referencing with different



Fig. 2 Field survey of invasive weeds conducted in 2023 and 2024. Images **A** and **B** show the invasion of *S. tiliifolia* in grasslands and along roadsides, where the species forms dense stands that suppress native vegetation. Image **C** presents a herbarium specimen of *S. tiliifolia*, collected from an infested site for documentation. Images **D** and **E** depict the invasion of *P. hysterothorus* in croplands, particularly in fields of *Allium cepa* (onion) and *Eragrostis tef* (teff), as well as in areas used for cattle grazing, indicating its effect on both crop and pasture lands. Image **F** shows a herbarium specimen of *P. hysterothorus*, prepared and archived using standard botanical methods. All photographs were taken by the first author during the fieldwork

sources, like floral books of Ethiopia and Eritrea, published articles, and books (Demissew 1996; Tana and Milberg 2000; Hedberg et al. 2006).

Ecological predictor variables

The combined effects of various environmental variables shape both the habitat suitability and spatial distribution of species (Peterson et al. 2011). We utilized 23 environmental factors to develop a model for invasive weed species, including 19 bioclimatic variables, as well as land cover, altitude, aspect, and slope. Bioclimatic variables (Bio1–Bio19) were extracted from the WorldClim 2.1 database (www.worldclim.org/bioclim), at a resolution of 30 arc-seconds ($\sim 1 \text{ km}^2$), which are based on interpolated representative data collected between 1970 and 2000 (Hijmans et al. 2005). In addition to bioclimatic variables, we included the following as candidate predictors: elevation, derived from the Shuttle Radar Topography

Mission digital elevation model (SRTM-DEM, <https://srt.csi.cgiar.org/>); the global land cover map was obtained from the Copernicus Climate Change Service (<https://cds.climate.copernicus.eu/>), which describes the land surface into 22 classes, defined using the United Nations Food and Agriculture Organization (UN FAO). Land Cover Classification System (LCCS) includes cropland, broad-leaved evergreen forest, broad-leaved deciduous forest, shrubland, grassland, urban areas, bare lands, and water bodies. The topographic attributes, such as elevation, aspect and slope, and land cover were resampled and clipped to fit a spatially resolved bioclimatic variable using ArcGIS 10.8.

The HadGEM3_GC global circulation model (GCM) from the Coupled Model Intercomparison Project (phase 6) (CMIP6) (Michaelides 2023) developed by the UK Met Office Hadley Centre was applied for future modeling, which included two shared socioeconomic pathways

(SSPs) for 2050 and 2070. The SSP2-4.5 (intermediate greenhouse gas emissions that CO₂ increase to the current until 2050 and then decrease but reach net zero by 2100) and SSP5-8.5 (very high greenhouse gas emissions where CO₂ emission tripled by 2100) (Riahi et al. 2017) were used to assess the future potential suitable habitats of *P. hysterophorus* and *S. tiliifolia*.

To establish a set of independent variables and reduce the risk of overfitting, we selected bioclimatic variables with low pairwise correlation ($r < 0.7$) and acceptable multicollinearity levels, indicated by variance inflation factors (VIF) below 10 (Hair et al. 1986; Guisan et al. 2017). This selection was performed using a stepwise approach, where at each iteration the variable with the highest VIF was removed. The procedure was conducted using the “usdm” package in the R environment (Naimi et al. 2014). Initially, we included 22 continuous environmental variables, which were evaluated for multicollinearity through the VIF procedure. The categorical variable (land use) was excluded from the VIF analysis due to its non-continuous nature. Among these, 11 variables showed collinearity problems, leaving 11 variables to be used in the model (Table 1). After the selection of non-collinear continuous variables, the land use variable was added to the final set of predictors, which was then used in the model prediction.

Species distribution modeling

The prediction and projection of species distribution were conducted using an ensemble model with various algorithms, categorized into three groups: profile

methods, classical regression techniques, and machine learning approaches (Hijmans and Elith 2019). Specifically, we applied three regression algorithms—Generalized Linear Models (GLM), Generalized Additive Model (GAM), and Multivariate Adaptive Regression Splines (MARS)—and four machine learning algorithms—Boosted Regression Trees (BRT), Maximum Entropy Model (MaxEnt), Random Forests (RF), and Support Vector Machines (SVM)—to enhance predictive performance (Meynard and Quinn 2007; Santini et al. 2021) (Table 2). These models are widely used in research and species conservation (Zhang and Li 2017) for their strong predictive accuracy (Elith et al. 2008; Wang et al. 2011; Kaky et al. 2020).

Prior to model development, we evaluated both default and customized parameter settings including background point generation, number of iterations, learning rate, feature types, and number of trees to enhance model reliability. Species distribution models were implemented using the sdm package in R (Naimi and Araújo 2016), which supports ensemble modeling with multiple algorithms. Models were trained using 70 percent of the occurrence dataset and evaluated with the remaining 30 percent through a tenfold subsampling approach (Wang et al. 2022). Algorithm-specific settings included a learning rate of 0.05, 500 trees, and a bag fraction of 0.75 for BRT; 500 trees for RF; a binomial family for GLM and GAM (Hastie et al. 2009); 1000 iterations and a regularization multiplier of 1 for MaxEnt (Kufa et al. 2025); a radial kernel with a cost parameter of 1 for SVM; and degree equal to 2 with nprune equal to 30 for MARS.

To generate absence data, 10,000 random background points were sampled across the study area using the gRandom method in the sdmData function. These points were used as background for MaxEnt and as pseudo-absences for algorithms that require absence data, ensuring consistency across models. Final ensemble predictions were generated by averaging the outputs of all models, weighted by their True Skill Statistic (TSS), following established practices to improve predictive performance and reduce uncertainty (Dormann et al. 2018).

Model validation and mapping

The model's performance was evaluated using a receiver operating characteristic (ROC) curve (Fig. 3a and b), the threshold-independent area under the curve (AUC), and threshold-dependent metrics such as true skill statistics (TSS), sensitivity, and specificity (Allouche et al. 2006). The AUC score ranges from 0 to 1, where 0.5 indicates random performance, values between 0.7 and 0.8 are considered fair, 0.8 to 0.9 are deemed good, and scores above 0.9 are classified as excellent. Similarly, TSS ranges from -1 to $+1$, with a score of 1 representing perfect

Table 1 Selected ecological predictor variables used for modeling the habitat suitability of *P. hysterophorus* and *S. tiliifolia* and their Variance Inflation Factor (VIF)

No	Variables	Units	Code	VIF1*	VIF2**
1	Isothermality (BIO2/BIO7) ×100	°C	BIO3	6.58	6.64
2	Temperature seasonality	°C	BIO4	7.23	7.00
3	Temperature annual range (BIO5–BIO6)	°C	BIO7	2.14	2.10
4	Mean temperature of driest quarter	°C	BIO9	3.50	3.50
5	Precipitation of warmest month	mm	BIO13	6.96	6.40
6	Precipitation of driest month	mm	BIO14	2.84	2.78
7	Precipitation seasonality	×100	BIO15	3.07	3.00
8	Precipitation of warmest quarter	mm	BIO18	2.32	2.36
9	Precipitation of coldest quarter	mm	BIO19	4.03	3.76
10	Aspect	°		1.01	1.01
11	Slope	×100		1.21	1.22
12	Land-use (Categorical)	–		–	–

* VIF1, Variance Inflation Factor of *Parthenium hysterophorus*

** VIF2, Variance Inflation Factor of *Salvia tiliifolia*

Table 2 Predictive models from machine learning (BRT, RF, MaxEnt, and SVM), regression (GAM, GLM, and MARS) methods and their short description and common pieces of literature that have used these models in modelling invasive weeds distribution

Models	Descriptions
Boosted Regression Trees (BRT)	Methods relying on a relatively small number of trees effectively enhance the performance of predictive variables (Elith and Leathwick 2009), handle multiple predictors with high accuracy (Gu et al. 2019), and build models through iterative gradient boosting techniques (Friedman 2002)
Random Forest (RF)	Effective approach for predicting species occurrence data (Abdi 2020). It maintains effectiveness with minimal sensitivity to parameter tuning (Freeman et al. 2015) and minimizes over-fitting by randomly selecting variables to generate numerous classification trees (Jin et al. 2016)
Generalized Linear Model (GLM)	It handles non-linear data structures and is well-suited for ecological studies (Bunce 1985). It uses parametric functions, like linear or polynomial forms, to model predictor-response relationships and extend ordinary least squares regression
Generalized Additive Model (GAM)	GAM is a commonly used regression model in ecological research for handling non-normal distributions (Ravindra et al. 2019)
Maximum Entropy Modeling (MaxEnt)	It outperforms other modeling methods with small sample sizes (Perkins-Taylor and Frey 2020), was developed for modeling presence-only species data (Phillips et al. 2006), and is capable of constructing complex models based on the number of occurrence points and user-defined parameters (Elith et al. 2006)
Multivariate Adaptive Regression Splines (MARS)	A flexible nonparametric regression model that uses piecewise linear basis functions (Elith and Leathwick 2007), combines species data and presence information, considers local interactions between variables, and automatically selects predictors based on species presence data (Leathwick et al. 2006)
Support Vector Machine (SVM)	It is a non-parametric machine-learning technique used for regression and classification tasks (Cortes and Vapnik 1995). It employs nonlinear forms of predictor variables to provide greater flexibility (Hastie et al. 2009)

accuracy, 0 indicating random prediction, and values greater than 0.6 typically indicate good model performance. Negative TSS values suggest that the model performs worse than random classification (Zou et al. 2011; Bahn and McGill 2013).

Ensemble models predicted the suitable habitats and distribution ranges of *P. hysterophorus* and *S. tiliifolia* under current climate conditions, establishing a baseline for evaluating potential climate change impacts. Because of the continuous nature of the results, the optimal threshold for species occurrence was established after creating a predictive map. Maximizing the sum of sensitivity and specificity ($\max(\text{se} + \text{sp})$) determines the threshold that optimally balances accurate predictions for both the presence and absence of the species. The method aligns with maximizing the True Skill Statistic (TSS), making it effective for minimizing both omission

and commission errors, which is critical for ecological decision-making (Liu et al. 2005; Allouche et al. 2006; Jimenez-Valverde and Lobo 2007).

To further improve reliability and robustness, we used a weighted mean (Liu et al. 2013), incorporating corresponding TSS values instead of simply averaging thresholds. Values at this threshold were classified as suitable areas in the final prediction maps for the species. We then created a distribution map of *P. hysterophorus* and *S. tiliifolia* in Ethiopia using ArcGIS 10.8. Binary predictions (Figs. S1 and S2) were reclassified into four suitability levels: unsuitable, less suitable, suitable, and highly suitable (Qin et al. 2017; Zhang et al. 2019). We also projected changes in the species' range under current and future scenarios (Curr_2050 and Curr_2070), utilizing two thresholds best suited to the shared socioeconomic pathways, SSP2-4.5 (intermediate) and SSP5-8.5 (high

(See figure on next page.)

Fig. 3 a The Receiver Operating Characteristic (ROC) Curve of *Parthenium hysterophorus*. The ROC curves present the performance of species distribution models (SDMs) built using seven algorithms (BRT, RF, GLM, GAM, MaxEnt, MARS, and SVM) with subsampling replication (10 replicates, 30% test data). Sensitivity (true positive rate) is plotted against 1–specificity (false positive rate). The red and blue lines represent the average Area under the Curve (AUC) for training and test datasets, respectively. These curves evaluate the models' ability to discriminate between suitable and unsuitable habitats. Among the algorithms, Random Forest (RF) achieved the highest AUC, indicating a strong ability to predict habitat suitability. **b** The Receiver Operating Characteristic (ROC) Curve of *Salvia tiliifolia*. The ROC curves present the performance of species distribution models (SDMs) built using seven algorithms (BRT, RF, GLM, GAM, MaxEnt, MARS, and SVM) with subsampling replication (10 replicates, 30% test data). Sensitivity (true positive rate) is plotted against 1–specificity (false positive rate). The red and blue lines represent the average Area under the Curve (AUC) for training and test datasets, respectively. These curves evaluate the models' ability to discriminate between suitable and unsuitable habitats. Among the algorithms, Random Forest (RF) achieved the highest AUC, indicating a strong ability to predict habitat suitability

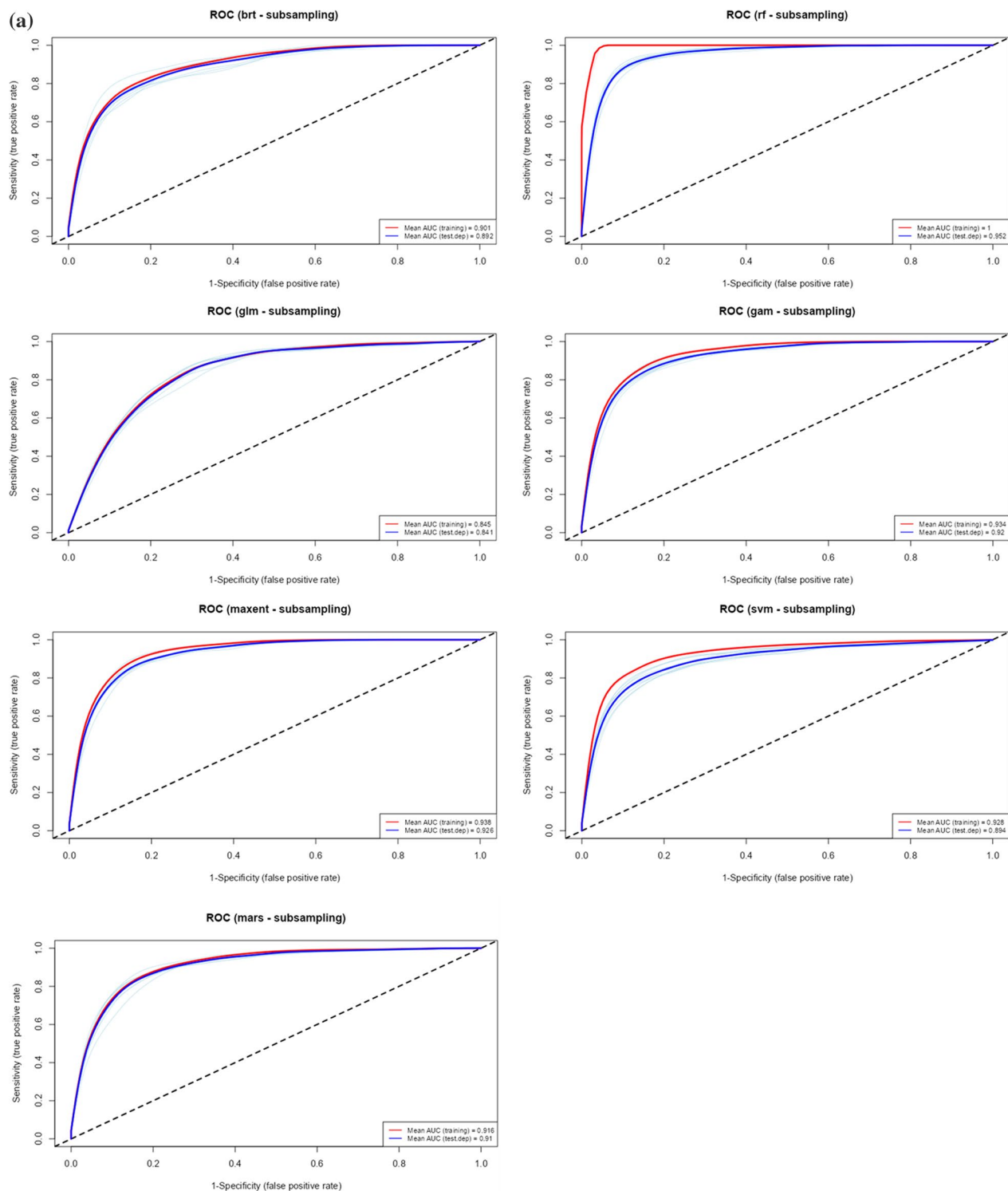


Fig. 3 (See legend on previous page.)

emissions). Using ArcGIS 10.8, we also calculated areas designated as unsuitable, suitable, loss, gain, remain suitable or unsuitable, range change, and projected future

range (Figs. S3 and S4), and assessed the impacts of climate change on the species' range, including gains, losses, and range shifts (Fordham et al. 2012).

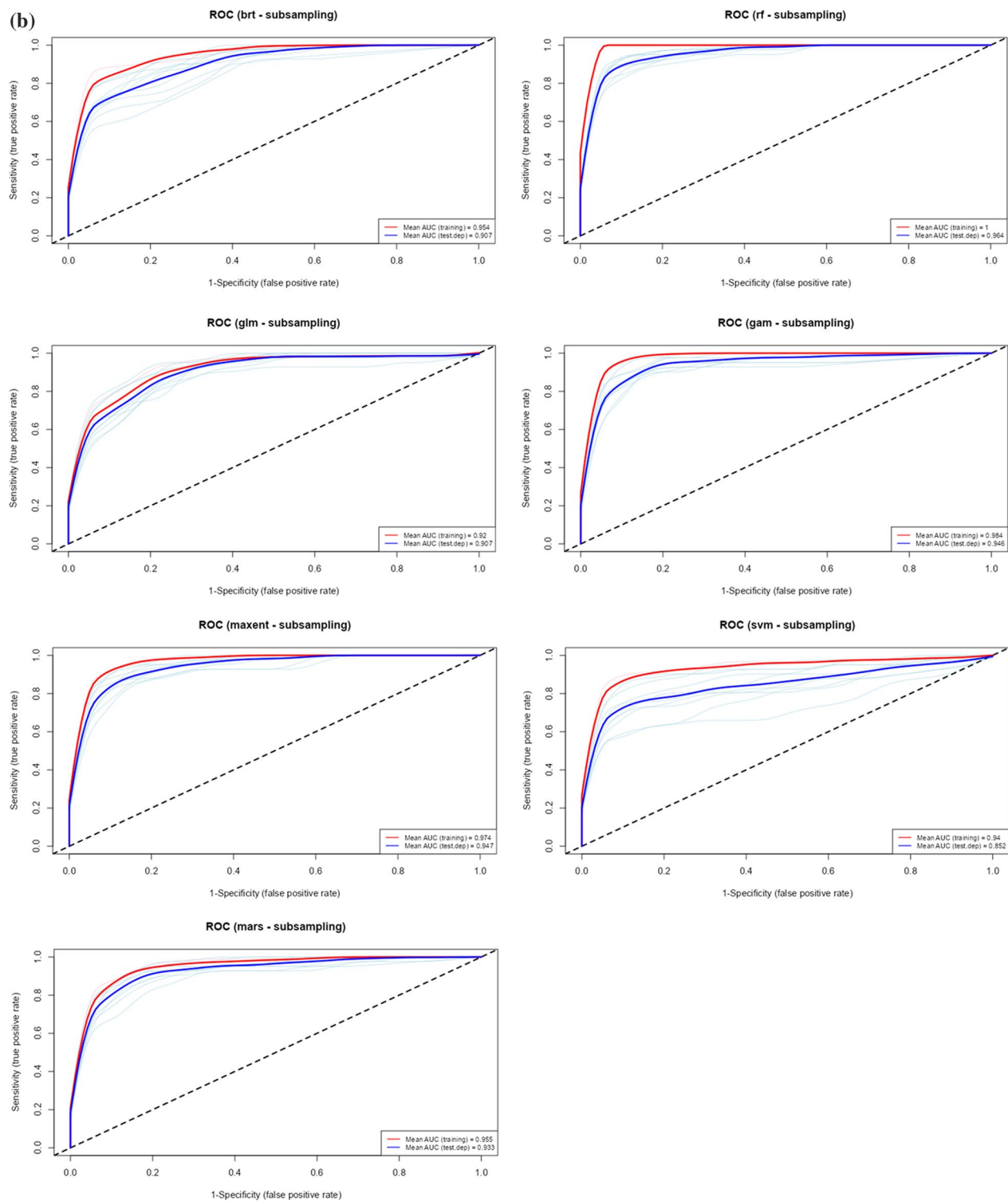


Fig. 3 continued

To assess the impact of invasive weeds on Ethiopia's major crop production, we overlaid the habitat suitability map with the regional map and analyzed areas

of overlap. Additionally, we generated a spatial map of teff production zones using national data from the Central Statistical Agency (CSA 2021) and examined

its intersection with invasive weed distributions. As a tiny-seeded grass crop, teff requires intensive hand weeding and proper fertilization, yet invasive species compete for critical resources such as sunlight, nutrients, and water. Identifying regions where invasive weeds and teff cultivation coincide reveals areas most at risk and supports the development of targeted and effective weed management strategies.

A graphical representation of the comprehensive methodology employed in this study is presented, as shown in Fig. 4.

Results

Model performance and variable importance

Seven SDM algorithms (GLM, GAM, SVR, MARS, RF, BRT, and MaxEnt) were used to build an ensemble model based on their predictive performance, assessed using AUC and TSS. The average AUC and TSS values across all algorithms and scenarios were 0.90 ± 0.03 and 0.67 ± 0.07 for *P. hysterophorus*, and 0.92 ± 0.03 and 0.74 ± 0.06 for *S. tiliifolia*. Among the models, machine learning algorithms, particularly RF, showed the highest performance (AUC: 0.95 and 0.96; TSS: 0.68 and 0.74), while regression-based models like GLM had lower performance (AUC: 0.84 and 0.90; TSS: 0.57 and 0.67) for the two species, respectively (Table 3).

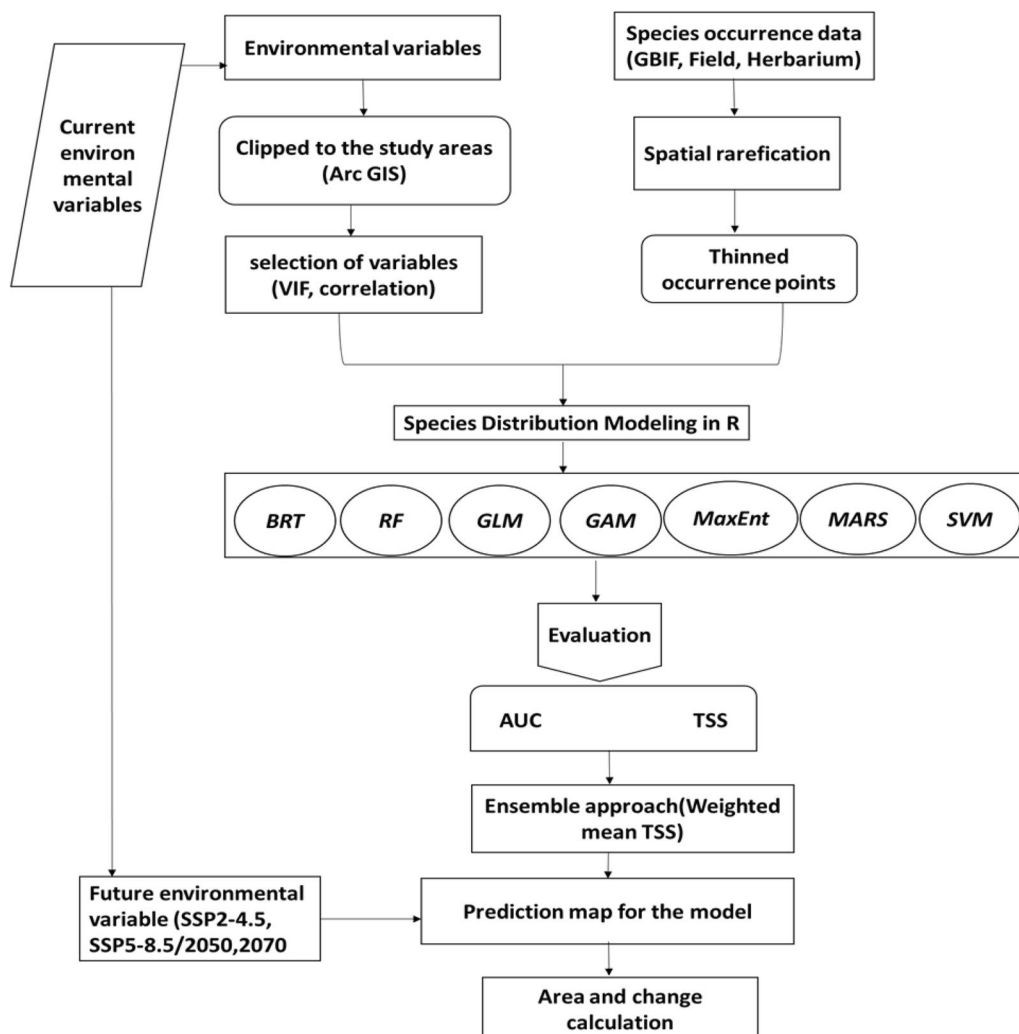


Fig. 4 Methodological schematic illustrating the modeling procedures for invasive weed species. A schematic diagram illustrating the methodological steps involved in modeling the distribution and habitat suitability of invasive weed species. The figure outlines the procedures followed in data collection, environmental variable selection, model development, and validation, ultimately leading to the calculation of area change in habitat suitability for the invasive species across the study area

Table 3 AUC and TSS values for the seven models and their averages and standard deviations

Species	Evaluation metrics	Models								
		BRT	RF	GLM	GAM	MaxEnt	SVM	MARS	SD*	Ensemble
<i>P. hysterophorus</i>	AUC	0.89	0.95	0.84	0.92	0.93	0.89	0.91	0.03	0.90
	TSS	0.64	0.80	0.57	0.70	0.72	0.67	0.69	0.07	0.68
	Sensitivity	0.81	0.91	0.87	0.86	0.88	0.82	0.85	0.03	0.86
	Specificity	0.83	0.89	0.70	0.84	0.84	0.85	0.84	0.05	0.83
<i>S. tiliifolia</i>	AUC	0.91	0.96	0.91	0.95	0.95	0.85	0.93	0.03	0.92
	TSS	0.67	0.83	0.67	0.79	0.78	0.66	0.75	0.06	0.74
	Sensitivity	0.77	0.90	0.88	0.91	0.89	0.75	0.89	0.06	0.86
	Specificity	0.90	0.93	0.79	0.89	0.89	0.92	0.86	0.04	0.88

* SD: Standard deviation

No notable differences were observed between training and test data for AUC and TSS. The low standard deviations (AUC: 0.03; TSS: 0.07 for *P. hysterophorus*; AUC: 0.03; TSS: 0.06 for *S. tiliifolia*) indicate limited variability, suggesting the dataset is sufficiently robust for predicting habitat suitability. Overall, model predictions were consistent across complexity levels, repetitions, and input data.

Our results also revealed that the mean temperature of the driest quarter (BIO9), precipitation of the warmest quarter (BIO18), precipitation of the wettest month (BIO13) are the most influential factors affecting the distribution and suitable habitats of *P. hysterophorus*, while temperature seasonality (BIO4), precipitation of driest

month (BIO14) and precipitation seasonality (BIO15) are the most influential factors affecting the distribution and suitable habitats of *S. tiliifolia* (Fig. 5).

Spatial and temporal dynamics of potentially suitable habitats for invasive species

Current invasion risks

Four habitat suitability classes were distinguished for *P. hysterophorus* and *S. tiliifolia*, categorized as highly suitable, suitable, less suitable, and unsuitable, with varying proportions of area mapped for each class (Figs. 6 and 7). Suitable and highly suitable habitats represent regions with favorable conditions for the species under current climate conditions, while less suitable habitats indicate

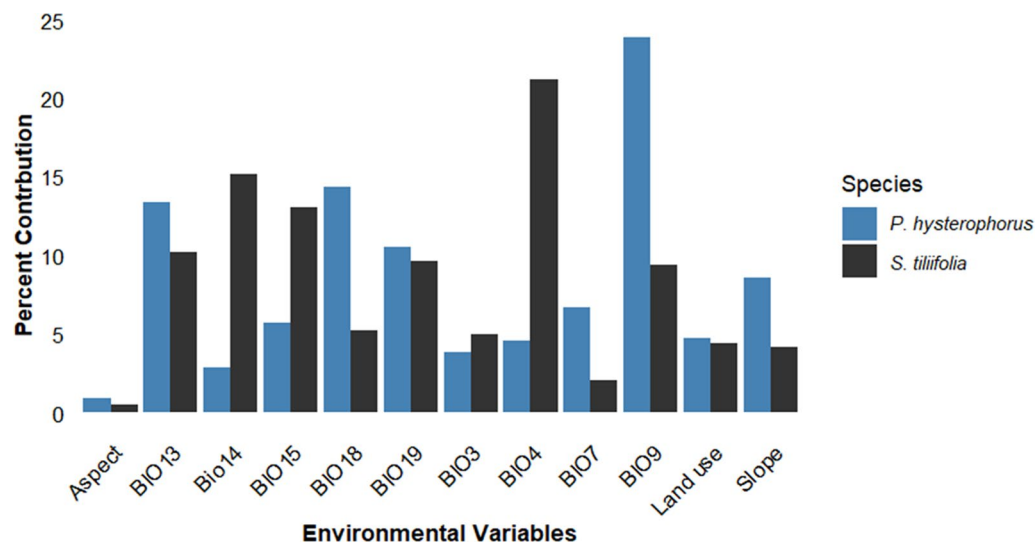


Fig. 5 The relative predictive power of different environmental variables (bioclimatic variables, slope, land use, aspect) for *P. hysterophorus* and *S. tiliifolia*. The steel blue and dark grey bars represent the weighted mean influence of these variables for *P. hysterophorus* and *S. tiliifolia*, respectively. The height of each bar indicates the relative contribution of each predictor to the model, with taller bars signifying a greater contribution to species distribution

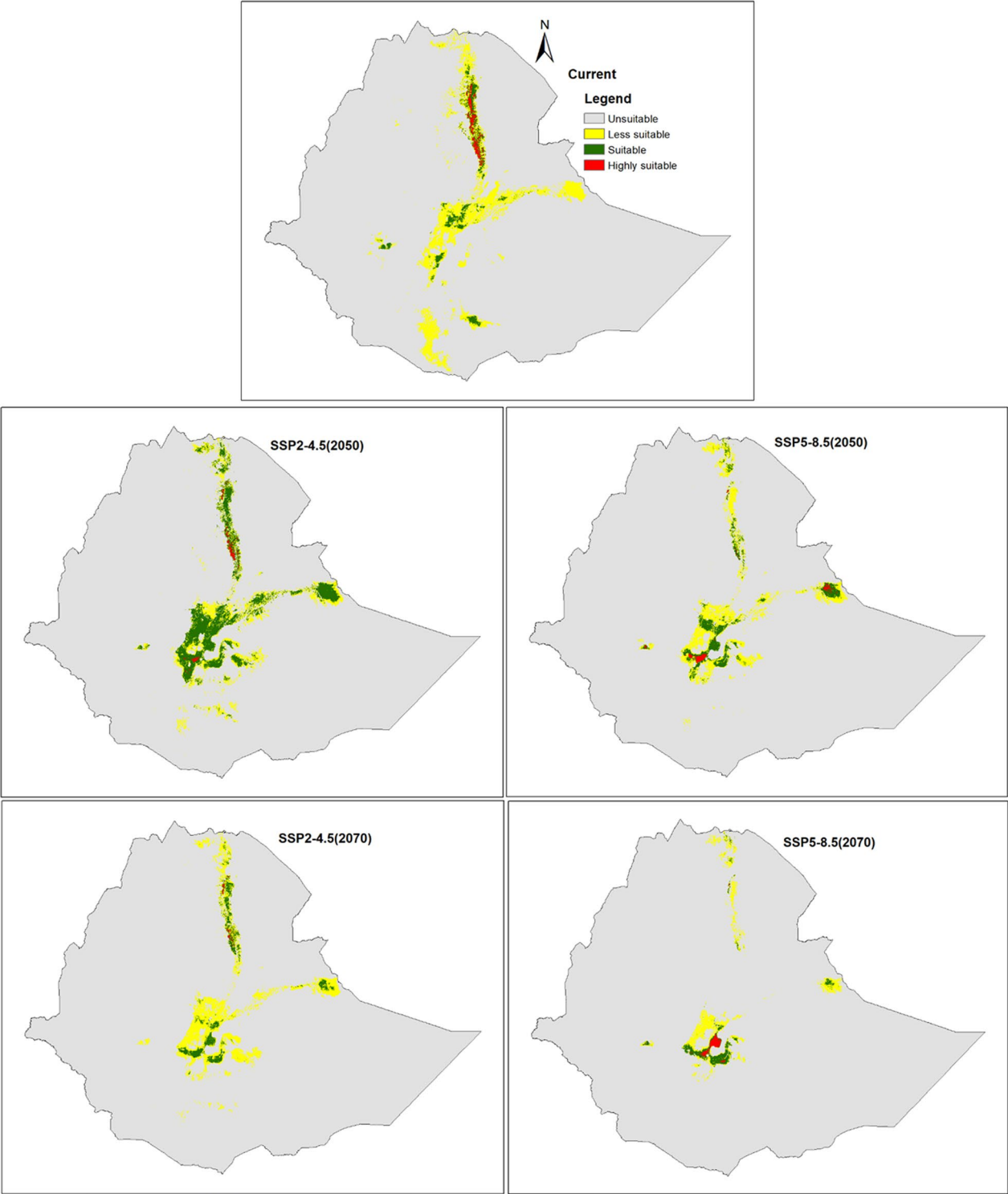


Fig. 6 Spatial prediction models of habitat suitability distributions for *P. hysterothorus* under current and future climate scenarios. The maps display the predicted habitat suitability for *P. hysterothorus* based on species distribution models (SDMs) under current climate conditions and future projections for the SSP2-4.5 (2050 and 2070) and SSP5-8.5 (2050 and 2070) scenarios. The color gradients indicate varying degrees of habitat suitability, from highly suitable (red) to unsuitable (grey)

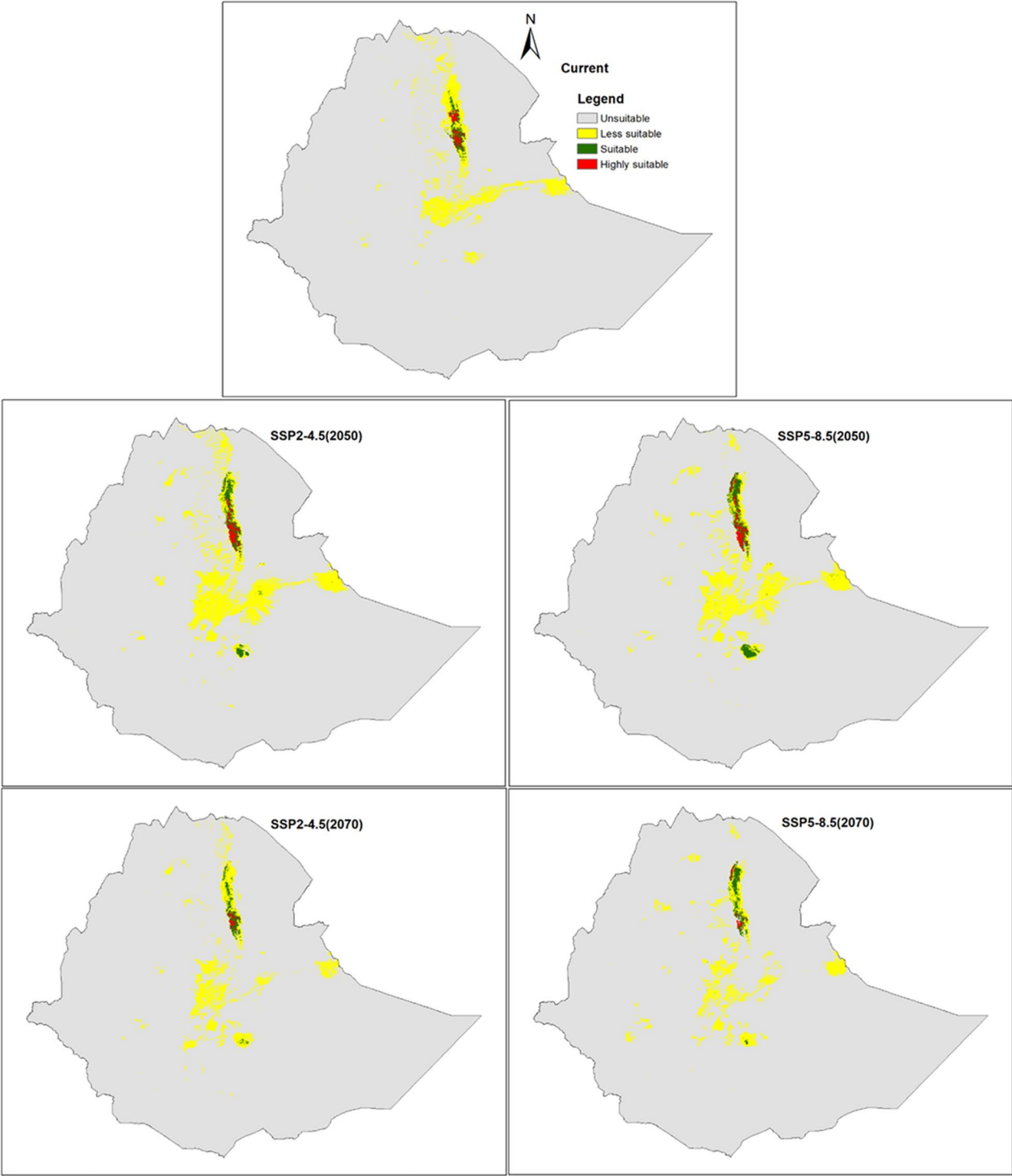


Fig. 7 Spatial prediction models of habitat suitability distributions for *S. tiliifolia* under current and future climate scenarios. The maps display the predicted habitat suitability for *S. tiliifolia* based on species distribution models (SDMs) under current climate conditions and future projections for the SSP2-4.5 (2050 and 2070) and SSP5-8.5 (2050 and 2070) scenarios. The color gradients represent varying degrees of habitat suitability, from highly suitable (red) to unsuitable (grey)

suboptimal conditions. Under these classes, the invasive species covered 73,155.2 km² (6.45%) and 47,670.86 km² (4.21%), respectively (Table 4). The high-risk areas of *P. hysterophorus* were mainly concentrated in central, southern, northern, and southwestern parts of Ethiopia, covering 13,638.19 km² or 18.64% of suitable habitats. The central parts include the lowlands of Shewa, following the Rift Valley and encompassing areas such as Minjar Shenkora, West Shewa around Ambo and its surroundings, and extending southward to Moyale, near the Kenya border. The northern part includes areas in Wollo and Tigray regions, while the southwestern part covers Tepi and its surrounding areas (Fig. 6).

High-risk areas for *Salvia tiliifolia* (4963.44 km²) were predominantly concentrated in the Wollo and Tigray floristic regions, overlapping mostly with those of *P. hysterophorus*. Simultaneously, regions with less favorable conditions for *S. tiliifolia* are distributed across the central, eastern, and parts of the southern region (Fig. 7).

Projected habitat suitability in future climate change scenarios

We predicted the change in the distribution of suitable habitats of *P. hysterophorus* and *S. tiliifolia* under a moderate scenario for future greenhouse gas emissions pathway (SSP2-4.5) and the upper boundary of the range of scenarios (worst scenario) (SSP5-8.5) developed by global climate model systems. Compared to the current baseline, *P. hysterophorus* is projected to gain suitable habitats under moderate climate change but lose them under more extreme scenarios, while *S. tiliifolia* is expected to gain suitable habitats initially, with a slight reduction as time progresses.

By 2050, the model predicts an expansion of suitable habitat for *P. hysterophorus* from 73,155.2 km² to

76,976.87 km² (Table 4, Fig. 6), with a gain of 50,728.70 km² (>100%) under the moderate scenario (Table 5, Fig. 8). However, under the worst-case scenario (SSP5-8.5), the net change in suitable habitats indicates a decline of 27.43% by 2050 and 67.72% by 2070 (Table 5; Fig. 8), with the total area shrinking to 26,768.27 km² (Table 4).

Under the moderate emission scenario for 2050, the suitable habitat for *S. tiliifolia* is predicted to expand from 47,670.86 km² to 75,843.41 km². A continued increase is projected under the high-emission scenario for the same year, reaching 68,739.76 km² (Table 4). By 2070, however, suitable habitat is expected to decline moderately to 43,248.39 km² and 43,812.81 km² under the moderate and high-emission scenarios, respectively (Table 4; Fig. 7). This corresponds to a net loss of 4,682.07 km² (10.04%) and 3,758.38 km² (8.33%) by 2070 under the respective scenarios (Table 5; Fig. 9).

Invasion risk to crop production

By overlaying the regional map of Ethiopia, we illustrated the invasion risks of weeds in key crop production zones, including areas where teff, sorghum, wheat, and coffee are cultivated. The map indicated that habitat-suitable regions for *Parthenium hysterophorus* span Amhara, Oromia, Tigray, Dire Dawa, Harari, Sidama, the Southern Nations, Nationalities and Peoples Region (SNNPR), and, to a lesser extent, the South West Ethiopia Region. Similarly, *Salvia tiliifolia* has expanded across Amhara, Tigray, Dire Dawa, Harari, Oromia, and Sidama, and is also present in parts of SNNPR, showing a comparable level of infestation in crop-growing areas (Fig. 10).

Notably, major crop production zones coincide with regions affected by invasive weeds. Teff and sorghum are primarily cultivated in the Amhara, Oromia, Dire Dawa, and Harari regions, while coffee is mainly grown in the

Table 4 Predicted areas (km²) of habitat suitability with their percentage for *P. hysterophorus* and *S. tiliifolia* under different climate change scenarios

Scenarios	Prediction area (km ²)							
	Un-suitable	%	Less suitable	%	Suitable	%	Highly suitable	%
Current	1060060.81	93.54	59517.01	5.25	10660.59	0.94	2977.60	0.26
SSP2-4.5 (2050)	1056238.45	93.21	34468.23	3.04	41035.57	3.62	1473.07	0.13
SSP5-8.5 (2050)	1079384.517	95.25	37853.338	3.34	14396.304	1.27	1579.698	0.14
SSP2-4.5 (2070)	1077670.76	95.10	44527.98	3.93	10611.62	0.94	406.02	0.04
SSP5-8.5 (2070)	1106448.94	97.64	18575.82	1.64	6411.38	0.57	1781.07	0.16
Current	1085545.52	95.79	42707.42	3.77	3264.95	0.29	1698.49	0.15
SSP2-4.5 (2050)	1057366.97	93.31	67504.60	5.96	6043.75	0.53	2295.06	0.2
SSP5-8.5 (2050)	1064472.09	93.93	59122.90	5.22	7046.86	0.62	2570.00	0.23
SSP2-4.5 (2070)	1089966.86	96.18	38123.52	3.36	4389.09	0.39	735.78	0.06
SSP5-8.5 (2070)	1089399.53	96.13	39601.67	3.49	3483.53	0.31	727.61	0.06

Table 5 The ensemble model for the species range size change in each scenario for *P. hysterothorus* and *S. tiliifolia*

Species	Scenarios	Loss (km ²)	Remain suitable (km ²)	Gain (km ²)	% loss	% gain	Species range change (%)	Current range size (km ²)	Future range size (km ²)
<i>P. hysterothorus</i>	SSP2-4.5 (2050)	27191.82	22611.53	50728.70	54.60	101.86	47.26	49803.36	73340.24
	SSP5-8.5 (2050)	43453.73	20503.92	25910.23	67.94	40.51	27.43	63957.64	46414.15
	SSP2-4.5 (2070)	43071.05	25910.59	21218.79	62.44	30.76	31.68	68981.65	47129.39
	SSP5-8.5 (2070)	59757.90	10140.73	12418.65	85.49	17.77	67.72	69898.63	22559.38
<i>S. tiliifolia</i>	SSP2-4.5 (2050)	10758.39	31974.96	42652.98	25.18	99.9	74.72	42733.35	74627.94
	SSP5- 8.5 (2050)	14303.21	27527.45	40038.85	34.19	95.72	61.53	41830.66	67566.30
	SSP2-4.5 (2070)	22079.03	24556.15	17396.96	47.34	37.30	10.04	46635.17	41953.11
	SSP5-8.5 (2070)	25827.89	19294.16	22069.51	57.24	48.91	8.33	45122.05	41363.66

Bold values are used to visually emphasize habitat suitability gain and loss percentages

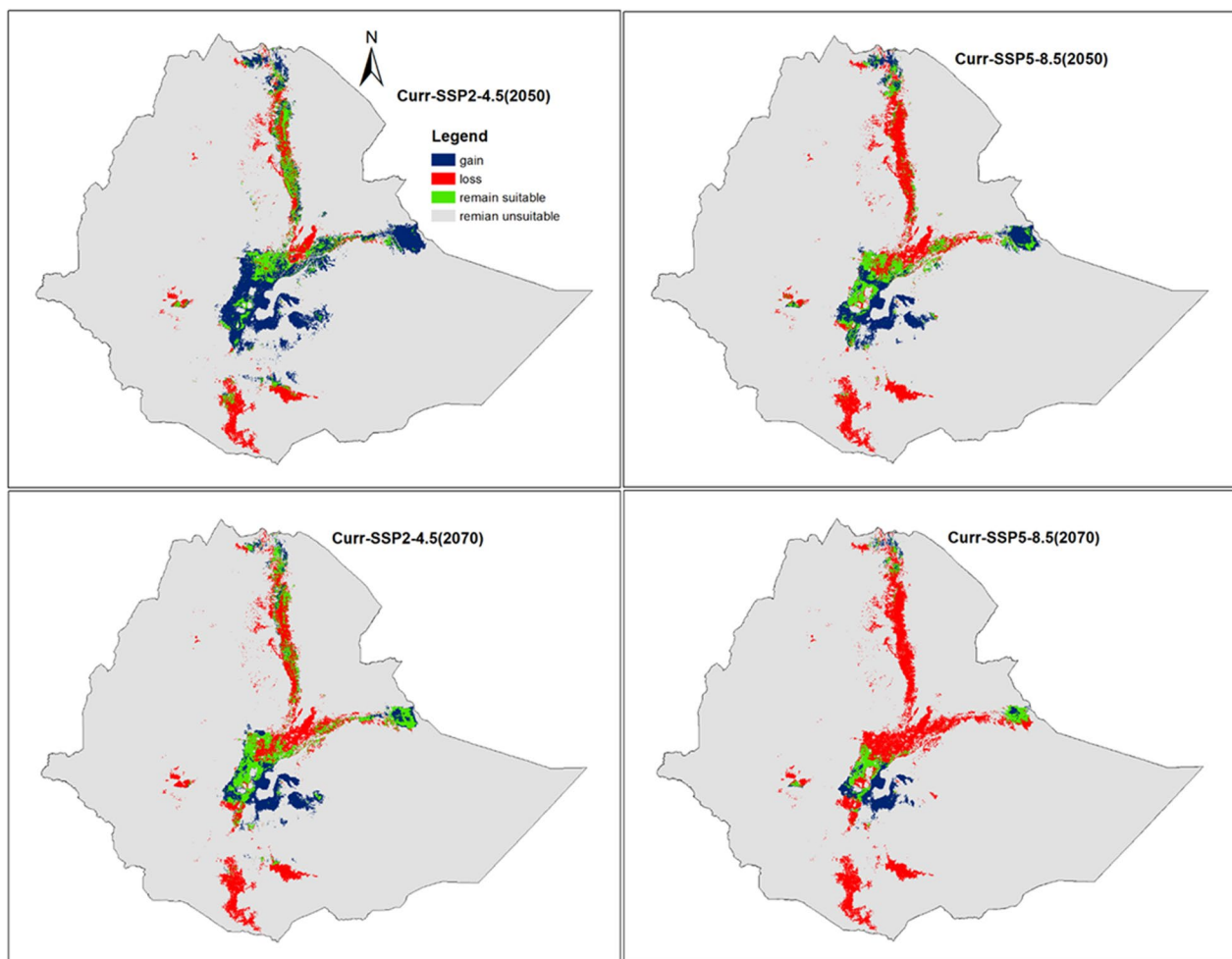


Fig. 8 The intersection of current habitat suitability maps with future climate projections shows projected changes in habitat suitability for *P. hysterophorus* from current to future periods. The first two maps illustrate the overlap of current habitat suitability with the 2050s projections under SSP2-4.5 (moderate) and SSP5-8.5 (worst-case) greenhouse gas emissions scenarios. The second set of maps shows the intersection with the 2070s projections. Areas of gain (new suitable habitat, blue), loss (loss of suitable habitat, red), remain suitable (areas that stay suitable, green), and remain unsuitable (areas that remain unsuitable, grey) are indicated using distinct color gradients. These visualizations highlight shifts in habitat suitability due to climate change, offering insights into potential future distributions of *P. hysterophorus*

South West Ethiopia, SNNPR, Oromia, and Dire Dawa regions. Wheat production is concentrated in the Oromia and Amhara regions. The overlay analysis revealed that teff-producing areas, in particular, extensively overlap with the distribution of both invasive weeds (Fig. 10).

Under projected future scenarios, the impact of invasive weeds is expected to intensify further, with *S. tiliifolia* expanding into key crop-producing regions, including teff, sorghum, wheat and coffee-growing areas in the Oromia, Amhara, Tigray, and to some extent South West Ethiopia, as well as Afar region (Figs. S5 and S6). This projection underscores the increasing risk of invasion in major agricultural landscapes, highlighting the

significant overlap between major crop production areas and regions vulnerable to invasive weed expansion.

Discussion

Globally, *P. hysterophorus* and *S. tiliifolia* are among the worst invasive weeds. This study pioneered the assessment of climatically suitable habitats for the potential invasion of *P. hysterophorus* and *S. tiliifolia* weeds in Ethiopia under current and future climate scenarios. Developing accurate and updated maps of *P. hysterophorus* and *S. tiliifolia* suitable distribution within Ethiopia, along with identifying areas at risk of invasion, is crucial for mitigating its impact.

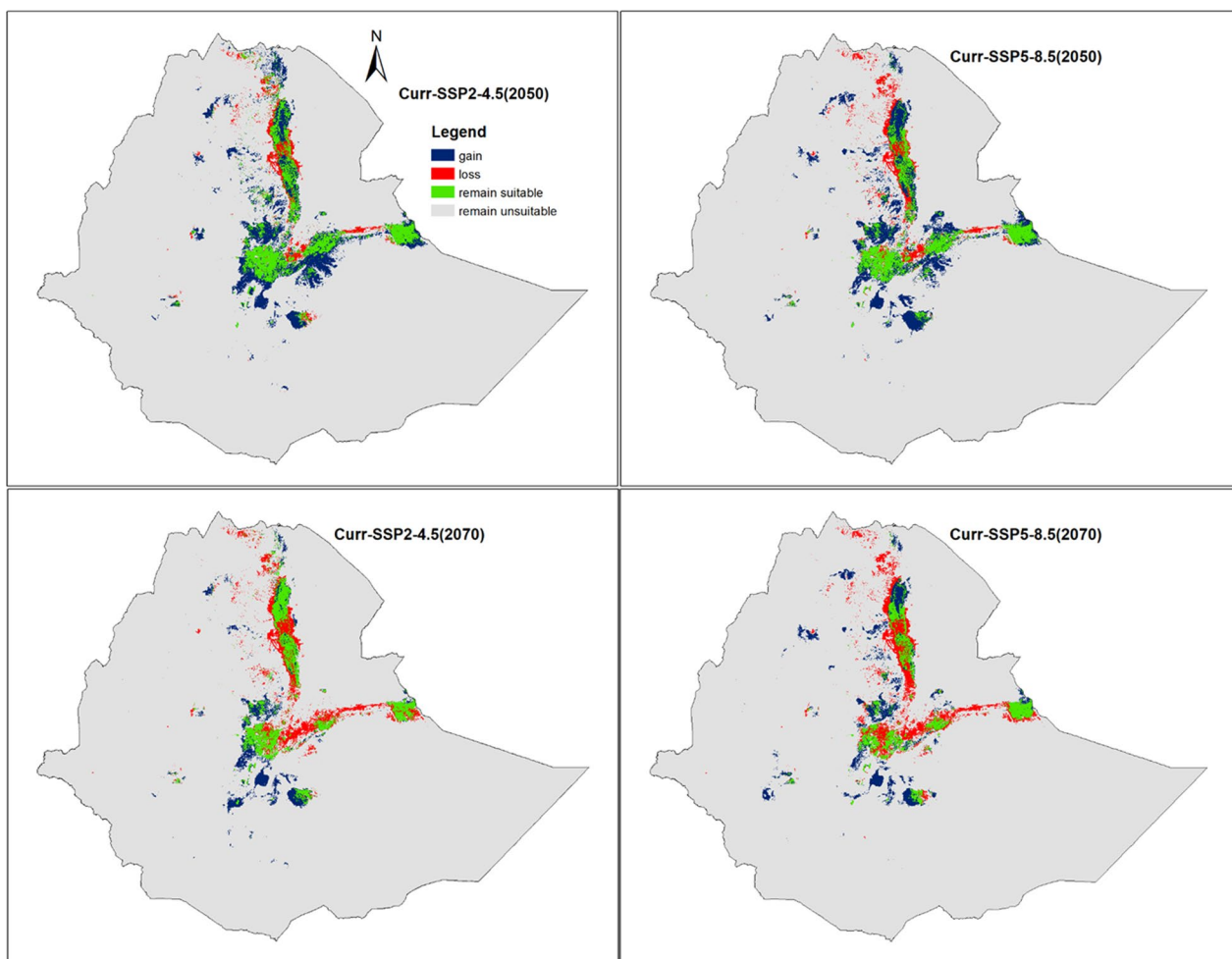


Fig. 9 The intersection of current habitat suitability maps with future climate projections shows projected changes in habitat suitability for *S. tiliifolia* from current to future periods. The first two maps illustrate the overlap of current habitat suitability with the 2050s projections under SSP2-4.5 (moderate) and SSP5-8.5 (worst-case) greenhouse gas emissions scenarios. The second set of maps shows the intersection with the 2070s projections. Areas of gain (new suitable habitat, blue), loss (loss of suitable habitat, red), remain suitable (areas that stay suitable, green), and remain unsuitable (areas that remain unsuitable, grey) are indicated using distinct color gradients. These visualizations highlight shifts in habitat suitability due to climate change, offering insights into potential future distributions of *S. tiliifolia*

Our study shows that strong performance across all averaged evaluation metrics improves the ability to identify distribution and priority suitable habitat areas accurately. The average AUC and TSS values derived from the ensemble models were consistent with those observed in well-fitted models and showed no significant differences from earlier studies, reaffirming their reliability in distinguishing between suitable and unsuitable areas (Ahmed et al. 2021; Dorji et al. 2022). The ensemble average modeling approach is considered effective in reducing model uncertainty and enhancing robustness (Araújo and Mark 2007; Marmion et al. 2009), thereby improving the accuracy of invasive weeds' distribution modeling.

Major environmental factors influencing the potential distribution of *P. hysterophorus* and *S. tiliifolia*

While many species distribution modeling studies primarily focus on climatic variables, this study also incorporates topographic and land use factors—such as slope, aspect, and land cover—to better capture a broader range of environmental influences on species distribution. Although the statistical models (BIO9, BIO13, BIO14, BIO15, BIO18, and BIO19) have been identified as key predictors, their ecological relevance is reinforced by the known physiological traits of the two invasive species.

For *Parthenium hysterophorus*, the importance of BIO9 (mean temperature of the driest quarter), BIO13 (precipitation of the wettest month), BIO18 (precipitation

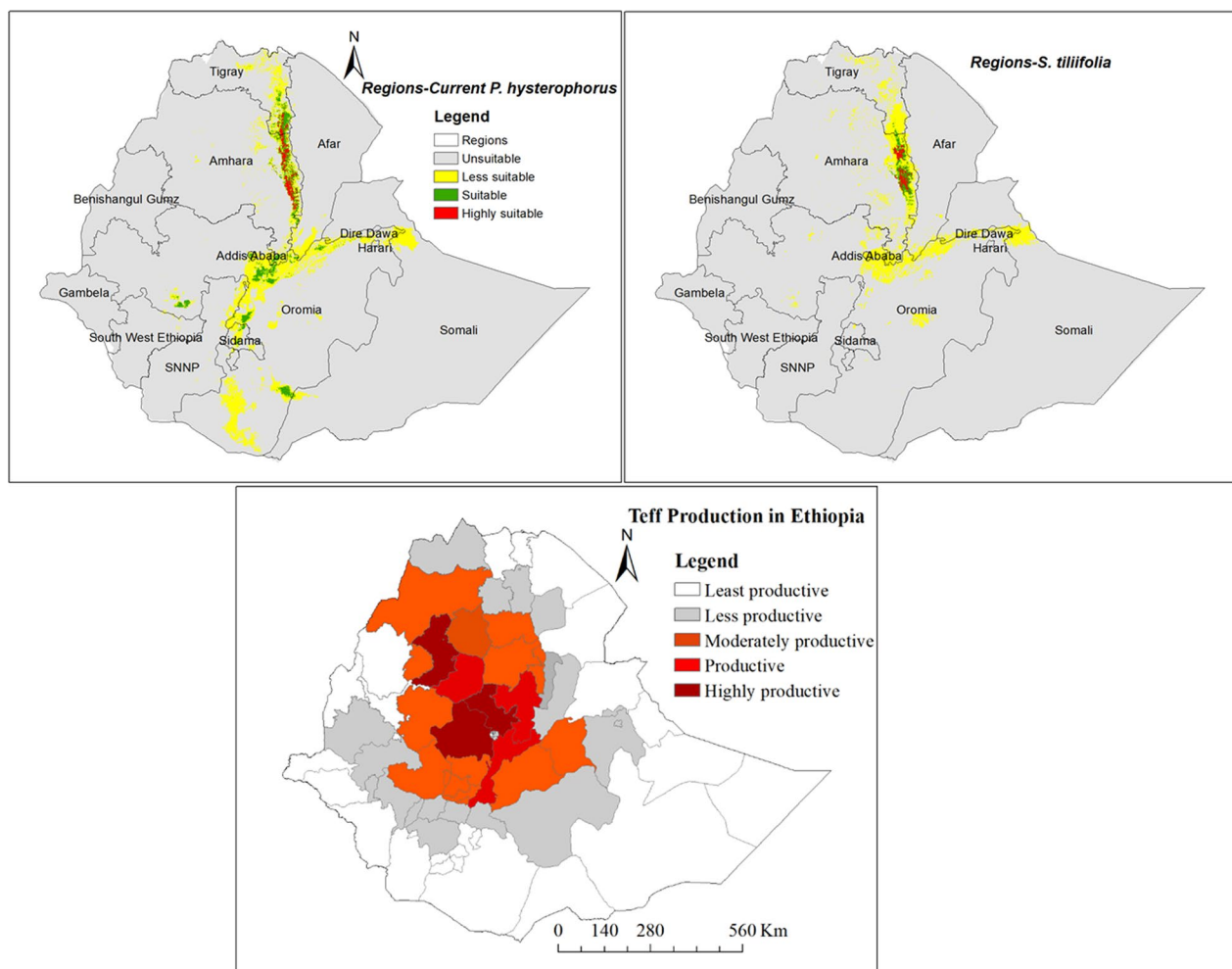


Fig. 10 Overlay of invasive weed habitat suitability with regional maps of Ethiopia to illustrate potential impacts on major crop production under current climate conditions. The first two maps display the predicted distributions of *P. hysterophorus* and *S. tiliifolia*, while the third map shows the spatial distribution of teff production across Ethiopia (adapted from CSA data, 2021). The overlay reveals that highly productive teff-growing areas substantially overlap with regions predicted to be suitable for invasive weed establishment. This spatial intersection underscores the potential threat posed by invasive species to key agricultural zones and highlights the need for targeted monitoring and control strategies

of the warmest quarter), and BIO19 (precipitation of the coldest quarter) underscores its sensitivity to seasonal variations in temperature and precipitation. This climatic responsiveness aligns with the species' capacity to withstand drought and high temperatures, facilitated by its rapid life cycle and efficient seed dispersal, which enable it to exploit brief periods of moisture availability. *P. hysterophorus* can germinate, grow, and flower across a broad range of temperatures and photoperiods, and mature plants can survive short frost events down to -2°C (Williams and Groves 1980). It performs best under warm-season temperatures between 35 and 45°C but shows poor growth during colder periods (7°C to 15°C) (Kapoor 2014). Such climate-driven distribution patterns are consistent with earlier studies identifying

temperature and precipitation as key drivers of invasive plant spread (Flores-Tolentino et al. 2020; Al Ruheili et al. 2022; Zheng et al. 2024). These environmental factors are closely tied to physiological processes that influence establishment and growth, particularly in invasive species reliant on favorable seasonal conditions (Kathiresan and Gualbert 2016).

Under moderate climate change scenarios (SSP2-4.5, 2041–2060), its expansion is likely driven by increased seasonal rainfall during warmer periods. However, under more extreme scenarios (SSP5-8.5, 2041–2080), the combination of rising temperatures and reduced precipitation during key growth phases may exceed its physiological limits, thereby reducing habitat suitability. This trend is consistent with observations in Ethiopia, where

P. hysterothorus is most abundant in areas with moderate temperatures and high soil moisture, with optimal growth occurring between 10 and 25 °C (Tana et al. 2002).

For *S. tiliifolia*, the most influential variables—BIO4 (temperature seasonality), BIO13 (precipitation of the warmest month), BIO14 (precipitation of the driest month), and BIO15 (precipitation seasonality)—highlight its sensitivity to climatic variability. Its response to both temperature fluctuations and rainfall extremes indicates broad ecological flexibility. The species is projected to expand under moderate and high emission scenarios by the 2050s, likely benefiting from shifting rainfall patterns and seasonal changes. Although a slight contraction in suitable habitat is anticipated by the 2070s, this decline remains modest, suggesting that *S. tiliifolia* retains a relatively broad tolerance to future climate conditions.

Experimental data on the physiological traits of *S. tiliifolia* are limited, but field observations suggest that it shares ecological characteristics with *P. hysterothorus*. Both species are commonly found in lowland areas with high temperatures and can extend into mid-altitude zones under favorable conditions. While they tolerate dry environments, increased rainfall enhances soil moisture availability, promoting germination and establishment. This pattern supports earlier research emphasizing the role of soil moisture in shaping invasive plant distribution (Shrestha et al. 2015), which may explain *S. tiliifolia*'s projected expansion under future climate scenarios.

In addition to climatic influences, land use, slope, and aspect contribute to distribution patterns. Land use reflects anthropogenic pressures such as agriculture, grazing, and disturbance, which can either inhibit or facilitate invasion. Managed landscapes may suppress invasion, whereas disturbed or abandoned lands often provide favorable conditions for establishment. Slope and aspect influence microclimatic conditions such as solar radiation, soil moisture, and erosion, all of which affect germination and growth success.

The projected expansion of *P. hysterothorus* and *S. tiliifolia* under future climate scenarios highlights the broader trend of invasive species benefiting from climate change. Rising temperatures may shorten the dry season and shift plant phenology, enabling earlier germination and establishment of invasive weeds (Williams and Groves 1980; Karlsson et al. 2015). These species, shaped by temperature and precipitation patterns, possess broad environmental tolerance and high phenotypic plasticity, allowing them to rapidly adapt and spread. This supports findings that invasive species are well suited to thrive under warmer temperatures, altered rainfall, and elevated CO₂, posing increasing risks to native ecosystems and land use systems (Liu et al. 2017; Pyšek et al. 2020).

Potential invasive range of *P. hysterothorus* and *S. tiliifolia* under the current climate

The climatically suitable distribution areas of invasive weeds for the period 1970–2000 suggest that approximately 6.45% and 4.21% of Ethiopia's total area were suitable for each species, respectively. More specifically, the central part, along and within Great Rift Valley, northern Ethiopia, and the lowlands of western to southwestern Ethiopia, was identified as a hotspot for the climatically suitable distribution of *P. hysterothorus* weed. The invasion mostly intensifies following the main road to the towns of Adama, Minjar Shenkora, Dire Dawa, Ambo, Ataye, Kombolcha, Woldia, Adigrat, and Tepi, emphasizing the importance vehicles in seed dispersal of the weed. The finding is consistent with the previous studies (McConnachie et al. 2011; Bekeko et al. 2012). The intensification and distribution of *P. hysterothorus* gradually decrease at higher altitudes, with its presence primarily concentrated in low and mid-altitude areas characterized by high temperatures. Native to the American tropics (Kohli et al. 2006), the species prefers sunny, moist environments and is classified as a lowland species (Tana and Milberg 2000).

Similarly, *S. tiliifolia* is concentrated in the low and mid-altitude ranges, primarily in the northern and central regions of Ethiopia. It is mainly found in the Wollo, Tigray, and Shewa floristic regions, which aligns with previous studies (Friis 2006). The altitudinal range of the weed is similar to that of *P. hysterothorus*. While less research has been done on *Salvia tiliifolia* compared to *P. hysterothorus*, it spreads vigorously, replacing native herbs in various locations (Demissew 1996).

The two invasive weed species were recently introduced in Ethiopia, but their impact is already being felt through decreased agricultural yields and loss of native biodiversity. They possess various seed dispersal mechanisms, including movement via vehicles, water, animals, and crop seeds. Domestic animals consume *P. hysterothorus*, while *S. tiliifolia* is not palatable to them. However, *S. tiliifolia* has hairy fruits that facilitate its dispersal, in contrast to *P. hysterothorus*, which relies on other spread mechanisms. Therefore, in the future, measures such as regularly removing weeds from river channels, weeding crops along main roads, and early identification of areas at risk of invasive species seed spread should be implemented.

Projected invasion dynamics under future climate conditions

Future climate change is likely to promote the habitat expansion of *P. hysterothorus* and *S. tiliifolia*, consistent with similar findings on the spread of invasive weeds (Adhikari et al. 2023).

Compared to the current suitable habitats, the area suitable for *P. hysterophorus* is projected to expand under future climate conditions, particularly under the medium-emission scenario. Similarly, the suitable habitat for *S. tiliifolia* is expected to expand considerably by the 2050s under both climate change scenarios, with only a slight contraction projected by the 2070s. The projected expansion of suitable habitats suggests an elevated risk of invasion into previously unaffected ecosystems, potentially leading to the displacement of native flora and disruption of ecological balance (Hoffmeister et al. 2005).

The study also examined variations in projected range changes, including both gains and losses in suitable areas, to better understand the future expansion of invasive weeds under different climate change scenarios. The results reveal a declining trend in habitat suitability from moderate to extreme scenarios. For instance, *Parthenium hysterophorus* shows a 47.26% net expansion in suitable habitat by 2050 under SSP4.5, but under the worst-case scenario (SSP8.5), it is projected to lose up to 67.72% of its currently suitable area. Similarly, *Salvia tiliifolia* is projected to expand by up to 74.72% under SSP4.5, yet experiences only a small loss (8.33%) under SSP8.5. These findings indicate that while moderate climate change may promote the spread of invasive weeds, extreme scenarios could reduce their suitable habitats—especially for *P. hysterophorus*. This highlights the species-specific nature of responses to climate change, which has critical implications for future invasive species management and the conservation of native ecosystems (Ramesh et al. 2017).

The projected range map indicates that climate change is likely to have a substantial effect on the distribution and suitability of habitats for invasive weeds. *P. hysterophorus* is projected to expand more towards central, eastern, southeastern, and to some extent northern Ethiopia under the medium scenario, while the loss of suitable habitats is relatively concentrated in central northern and southern Ethiopia under the worst-case scenario. Since this study incorporated land use among the predictor variables, the observed habitat loss in certain regions may be partially attributed to effective weed control and land management practices, as supported by previous research (Barman et al. 2014).

S. tiliifolia is projected to expand its suitable habitat both longitudinally and latitudinally, gaining ground in the central, northern, northeastern, northwestern, southeastern, and southwestern highlands of Ethiopia. It expands aggressively across all climate change scenarios, particularly during the 2050s, with only a slight loss in the northern and eastern parts of the country. The species' survival in hot and dry areas suggests that it could potentially withstand more extreme high-temperature conditions than previously assumed. This is consistent

with the findings of Zheng et al. (2024), who observed an upward trend in mid- to high-performing areas of invasive weeds, with distributions expanding from low- to high-latitude districts under future climate change.

Invasion risk in Ethiopian agricultural systems: implications for major crops

In this study, we paid particular attention to the potential invasion risk of *P. hysterophorus* and *S. tiliifolia* in croplands, particularly those cultivating major crops such as teff, coffee, sorghum, and wheat in Ethiopia. Although the exact loss due to invasive weeds in Ethiopia is not fully documented, some studies and reports indicated significant crop yield reductions (Bogale and Tolossa 2021). The most noxious invasive weeds, such as *P. hysterophorus* and *S. tiliifolia*, have been shown to cause considerable damage, particularly in cereals like teff, maize, and sorghum (Negewo et al. 2024).

The impact of these invasive species is further intensified by their overlap with Ethiopia's most productive agricultural regions for teff (Fig. 10), sorghum, coffee, and wheat, posing a serious threat to food security and economic stability. This spatial overlap aligns with previous findings that identify Amhara and Oromia as the primary teff-producing regions in Ethiopia (Tadele and Hibistu 2021; Melese et al. 2025), highlighting the heightened vulnerability of these key agricultural zones. In addition to the spread of invasive weeds, climate change has further reduced the suitable habitats for teff (Bezabih et al. 2020), posing a compounded threat to the crop.

Salvia tiliifolia is a common weed in maize, sorghum, and coffee plantations, as well as among native plant species and grasses. As stated by Daba et al. (2023), it is one of the most aggressive weeds and is classified as herbicide-resistant in the West Hararghe zone. The spread of these invasive species could severely impact crop production by competing for resources, reducing yields, and increasing management costs for farmers (Eschen et al. 2021). Their presence may also lead to shifts in land use practices and threaten the country's food security due to their overlap with major crop production areas. Furthermore, reduced yields of key crops could lower export earnings and increase dependency on food imports, putting additional pressure on the country's currency.

Limitation of the study

Although ensemble modeling was employed to reduce uncertainty, one limitation of this study is the reliance on a single global circulation model (GCM), which may not fully capture the range of possible climate futures. In addition, anthropogenic variables such as road density, human footprint, land-use change, soil types, and grazing pressure were not explicitly included in the models.

Integrating these key drivers in future analyses could enhance the accuracy and ecological realism of predictions, especially in regions where human activities strongly influence species distributions. Future studies should also incorporate more detailed physiological investigations, particularly for *S. tiliifolia*, a species for which ecological data remain scarce.

Conclusions

This research predicts the habitat suitability of *P. hysterophorus* and *S. tiliifolia* in Ethiopia, using an averaged ensemble model to assess their invasion potential. The model was based on the species' occurrence data and related environmental variables. Key environmental factors affecting both invasive weeds include the mean temperature of the driest quarter (BIO9), precipitation of the warmest quarter (BIO18), temperature seasonality (BIO4), and precipitation of the driest month (BIO14). Our analysis of dispersal routes revealed distinct patterns, highlighting the significant role of human activity in the spread of *P. hysterophorus* and *S. tiliifolia* across the country.

Under current climate conditions, the lowlands of central Ethiopia, including areas in the Rift Valley, as well as southern, western, and southwestern regions, are identified as primary invasion zones for *P. hysterophorus*. *S. tiliifolia* is likewise predicted to invade low- and mid-altitude regions, particularly in northern and central Ethiopia. Although each species shows distinct invasion tendencies, they overlap in several areas, collectively posing significant ecological and economic threats to the country.

Under future climate scenarios, the suitable habitat for both invasive weeds is projected to expand substantially. *S. tiliifolia* is expected to spread widely under both medium and worst-case scenarios, whereas *P. hysterophorus* shows a notable expansion primarily under the medium scenario. Both species are projected to overlap with key crop production zones, including areas cultivated with teff, raising serious concerns for agricultural sustainability.

Continuous monitoring and improved management of forests, agricultural lands, and pastures are vital, as these landscapes are particularly susceptible to invasion. Based on our findings, we recommend prioritizing surveillance and early detection efforts in teff, wheat, sorghum, and coffee-producing regions of Amhara, Oromia, Sidama, SNNPR, Harari, and Dire Dawa, where future habitat suitability for invasive species is projected to rise significantly. Regular removal of invasive weeds along riverbanks and major roadways should be carried out to reduce seed dispersal into productive agricultural zones.

Farmers should be encouraged to manually remove these and other weeds before seeding to disrupt the life cycle. Strengthening the role of local agricultural extension systems by integrating invasive weed identification and control techniques can further support early intervention, particularly in areas where these species overlap with major crops. Stricter regulation of the movement of agricultural equipment, livestock, and crop materials is also necessary to prevent cross-regional spread. In West Hararghe, Amhara, and Tigray, *S. tiliifolia* presents significant management challenges due to herbicide resistance in West Hararghe and high infestation levels in Amhara and Tigray. In these regions, community-based manual removal and ecological restoration should be prioritized. Developing a national-level risk mapping system using remote sensing and field data can guide policy decisions and timely responses. Ultimately, successful management requires collaboration among researchers, policymakers, land managers, and local communities to translate these findings into actionable, climate-resilient strategies.

Supplementary Information

The online version contains supplementary material available at <https://doi.org/10.1186/s13717-025-00626-9>.

Additional file 1.

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Author contributions

DM was responsible for data compilation, modeling, analyzing the output, and drafting the manuscript. ZW, ZA, and BW contributed to title selection, data analysis, revising the manuscript, and providing supervision during the study. We confirm that the work presented here is original research, which has not been previously published and is not under consideration for publication elsewhere, in whole or in part. All authors made substantial contributions to the research and have read and approved the final manuscript for submission/publication.

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Data availability

The datasets analyzed during this study are included in this manuscript as supplementary information files.

Declarations

Ethics approval and consent to participate

Not applicable.

Consent for publication

Not applicable.

Competing interests

The authors have no competing interests to declare that are relevant to the content of this article.

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