Current and future invasion potential of *Senna didymobotrya* under the changing climate in Africa

Elias Cherenet Weldemariam[1], Dejene W. Sintayehu [2]

[1]Department of Geo-information Sciences, Haramaya University, Dire Dawa , Ethiopia

Email: eliachent@gmail.com

[2] College of Agriculture and Environmental Sciences, Haramaya University, Dire Dawa , Ethiopia

Email: sintekal@gmail.com

Abstract

Senna didymobotrya is an invasive flowering shrub native to Africa. Climate change is thought to facilitate the introduction and spread of invasive alien species. Following the ongoing climate and land-use changes, the potential invasion of *S. didymobotrya* species across the continent is expected to increase in the future. However, information on the extent of invasion is lacking. The present study aimed at examining the present and future invasive potential of *S. didymobotrya* under the changing climatic conditions using the Species Distribution Model. Two representative concentration pathways (RCP4.5, and RCP8.5), and seven bioclimatic including one topographic variables were used to simulate the current and future (2050s and 2070s) distribution of *S. didymobotrya* invasion in Africa. The model performance evaluation is done based on, the area under the receiver operating characteristic curve (AUC) and true skills statistics (TSS). The results of the study showed that under current climatic conditions 18% of the continent of Africa is suitable for *S. didymobotrya* establishment and invasion. Eastern Africa is seen as the most suitable habitats for *S. didymobotrya* invasion followed by southern Africa. The predicted model shows that in the 2050s under RCP4.5 and RCP8.5, 3.4% and 3.17% of the continent will be highly suitable for *S. didymobotrya* invasion, respectively. In the 2070s, the highly suitable area for the species is predicted to be 3.18 % and 2.73% in RCP4.5 and RCP8.5, respectively. The low to moderate suitability under RCP 4.5 and RCP8.5 in the 2050s is projected as 17.4 % and 20.5 % and this area is increased in the 2070s to19.11% and 22.82 for the RCP 4.5 and RCP 8.5, respectively. The results of this study indicate a significant increase in the vulnerability of habitat for *S. didymobotrya* invasion under the future climatic conditions. Moreover, our current finding suggests the future biodiversity conservation strategy and policy direction should focus on the means and strategy of limiting the rate of expansion of invasion and distribution in different ecosystem types, hence reduce the expected harm in the ecosystem services.

Keywords: *S. didymobotrya, Invasive species, climate change, Africa,* Ensemble Approach

Introduction

Invasive alien species are plants, animals, pathogens, and other organisms that are non-native to an ecosystem. They are posing a great threat to global biological diversity and many ecosystems types (Mainka & Howard, 2010a; Shiferaw et al., 2018),and agricultural productivity and economic growth (Simberloff et al., 2013). Human activities have greatly contributed to changing the habitat range of invasive alien species at a faster rate than ever before (Walther et al., 2009). The rapidly growing human populations, increased human mobility, tourism, transport, and technological advancement (Wilson et al., 2009; Wittenberg & Cock, 2001), and increasing international trade in agricultural and related products (Richardson & Rejmanek, 2011) have greatly facilitated the movement of many invasive alien species from their native ranges into new areas. Once established in their habitat, invasive species can flourish and extend quickly into the new area and tends to harm the ecosystem function and structure (Masters & Norgrove, 2010; Shiferaw et al., 2019), natural processes, and human activities (Luizza, et al., 2016).

The currently increasing spread and risk of invasive of alien plant species in Africa remain the most striking problem affecting the biological diversity losses and livelihood (Witt et al., 2018). This calls for an integrated approach. Over 164 invasive alien plant species were reported in Africa by Witt et al.(2018), of these, *Senna didymobotrya* is among the most frequently reported invasive species. *Senna didymobotrya,* also named as a bush encroacher. The species is known to suppresses the regeneration and growth of native plant species by creating large dense impenetrable brushes, and mono-cropping stands (Witt et al., 2018), and obstructing the movement of wild animals. It can easily establish itself in diverse habitats types, including grasslands, woodlands, forests, riparian zones, dumpsite, disturbed area, and coastal scrub (Tamiru, 2017; Witt & Luke, 2017). High invasion of *S. didymobotrya* was reported in forest reserves in Uganda (Winterbottom & Eilu 2006); in degraded land, urbanized land, coastline, Savanna, and Grassland of southern Africa (Nel et al., 2004; Rambuda & Johnson, 2004; Terzano et al., 2018) and in several parts of Ethiopia (Fessehaie & Tessema, 2014; Fufa et al., 2017; Shiferaw et al., 2018; Tamiru, 2017). Its further expansion would worsen the problem, leading to great environmental and socio-economic damage.

Climate and land-use change have a profound effect on the introduction, establishment, and expansion of invasive species (Roura-Pascual et al., 2011). Climate warming could facilitate the dispersal and performance of invasive alien species, which would allow range expansion and new invasions (Thiney et al.,2019; Walther et al., 2009). Climate change is considered as the main driving factor assisting for the establishment and spread of invasive alien species (Burgiel & Muir, 2010). Moreover, climate change facilitates the distribution of alien spices into the new areas through removing constraints to species dispersal and survival such as temperature or moisture (Hellmann,et al.,2008; Mainka & Howard, 2010b). Recent studies showed that cimate change is one of the factor governing the inavsion of invasive species (Sintayehu et al. 2020a; Sintayehu et al. 2020b). Similarly, climate change may create an opportunity for the establishment and invasion of *S. didymobotrya*. Thus, examining the relationship between the invasion of invasive species and climate change is crucial to design appropriate strategies, hence to mitigate their expansion and potential adverse impacts. Therefore, this study examined the current and future habitat suitability for *S. didymobotrya* invasion in Africa under the current and future climatic scenarios. This study addresses the long-term projected impact of climate change in the distribution and spatial extent of alien invasive species at the continent level (Africa). Moreover, to our knowledge, this is the first-ever study that made use of species distribution modelling (ensemble model) to examine the current and future habitat suitability of S. *didymobotrya* invasion in Africa under changing climate conditions.

Materials and methods

Target species

Senna didymobotrya (Fresen) H.S. is flowering plant species in the family fabaceae. In several parts of Africa, the species named "African senna ", "candelabra tree", "popcorn senna ", and "peanut butter cassia" (Jaca & Condy, 2017). It is a hairy, aromatic shrub growing up to nine meters. It has been domesticated in many areas as an ornamental plant, a cover crop, and leguminous green manure. The plant commonly grows in the tropical climate on diverse habitats types and is native to eastern and central Africa (Orwa et al., 2009). The leaf extracts from *S. didymobotrya* are used as traditional medicinal (Jaca & Condy, 2017; Jeruto et al.,2017). The species is distributed from Congo east to Ethiopia and south to Namibia, Zimbabwe, Angola, Mozambique, Comoros, Madagascar, Mauritius ,and South Africa (Orwa et al., 2009; Tabuti, 2007). The species is capable of establishing itself under light frost up to 25 days in a year (Dlamini, 2016) but usually prefers a warmer climate. Its occurrence is favored by the presence of other species like *Sesbania punicea*, *Melia azedarach*, and *Psidium guajava* (Dlamini, 2016). The species often grow in ruderal areas with a steady water supply such as wetlands, and riparian areas (Dlamini, 2016; Tabuti, 2007), water bodies, damp localities, grassland and woodland (Nyaberi et al., 2013), with an altitude range from 900 up to 2500 m above sea level (Tabuti, 2007).

Species presence records

Species occurrence data were acquired from the Global Biodiversity Information Facility (GBIF: 105 https://www.gbif.org/), Vegetationmap4africa (597: https://vegetationmap4africa.org/), and the South African National Biodiversity Institute (SNABI: 11, http://ipt.sanbi.org.za/iptsanbi/) databases (figure 1). . A visual inspection was done using the acquired georeferenced points in ESRI ArcMap 10.7 software. The data were checked and duplicate records were removed from the dataset. Finally, a total of 515 presence points were used as input for species distribution modeling. Furthermore, to reduce the influence of false absence during modeling, we generated 800 randomly distributed pseudo-absence points over the geographical surface.

Figure 1. Spatial distribution of species occurrence across an elevation range

Environmental and climate data

To predict the current and future distribution 19 bioclimatic and one elevation variables were acquired from WorldClim (www.worldclim.com) database version 2.1. The data has a resolution of 5arc minutes which is approximately 10 km at the equator. The dataset was interpolated from the measurement taken in more than 10,000 weather stations across the world (Hijmans et al., 2005). Furthermore, the data was downloaded in GeoTiff (.tif) format using the getData raster package (Naimi,2018:https://cran.r-project.org) in R. The downscaling was into the boundary of Africa was performed by using the clip tool in ArcMap 10.7. Since the collinearity problem might result in model instability and wrong interpretation (Dormann et al., 2013), hence all the acquired bioclimatic data were undergone for the collinearity test. To determine collinearity between variables, we used variance inflation factors (VIF) in the sdm R package (Marquardt, 1970). A pearson's correlation coefficients was used to examine the correlation between environmental variables and variables with the highest correlation coefficient (r >0.7) were excluded from the model (Dormann et al., 2013) to avoid the effect of multi-collinarirty. Finally eight bioclimatic variables (consisting of four temperatures and four precipitations) and one topographic variable were maintained for modeling (Table 3).

Global climate models (GCMs) for two representative concentration paths such as RCP4.5 and RCP8.5 of the periods 2050 (2041-2060) and 2070 (2061-2080) were obtained from WorldClim open sources database (https://worldclim.org/data/v1.4/cmip5.html) representing the future climate projections (Fick & Hijmans, 2017). According to van Vuuren et al. (2011) Representation Concentration Pathways (RCP) scenarios are developed to illustrates climate situations in which radioactive forcing can be anticipated to rise by 4.5 and 8.5 in Watts per square meter (W/m-2) in the year 2100 and are commonly used for historical climate change modelling(IPCC, 2014).

Species Distribution Modeling

Species distribution models (SDMs) is a powerful tool, and is used in many disciplines such as regional conservation planning, climate change impact assessment, and produce invasion risk mapping, ecology (Naimi, 2015), and phylogeography (Alvarado-Serrano & Knowles, 2014). It has a robust capability for predicting species probability of occurrence in geographical areas using the presence and absence data (Srivastava et al., 2019). SDMs model can be run in the sdm package in R statistical software and through the ensemble approach which combines several statistical and machine learning algorithms (Marmion et al., 2009; Naimi & Araújo, 2016). In our study, we used a total of eight SDM models using three regression models: generalized linear model (GLM), generalized additive model (GAM), and multivariate adaptive regression splines (MARS). Besides, we also used two classification models; flexible discriminant analysis (FDA) and mixed discriminant analysis, (MAD). Lastly, three machine learning models random forest (RF), boosted regression trees (BRT), and support vector machine (SVM), were also used. The selected model types are among the most powerful models in handling presence and absence data, hence predicting the species habitat suitability by generating a binary map (Naimi & Ara, 2016).

In this study, an ensemble modelling approach which combines the eight modelling results was used for predicting the current and future suitability map of invasion by *S. didymobotrya* species. An ensemble modelling was suggested as among the robust approaches in distribution modeling (Araújo & New, 2007; Gómez et al., 2018; Hao et al., 2020; Marmion et al., 2009). The ensemble modelling approach has the potential in minimizing the expected modelling result variability which may occur when using a single algorithm(Alfaro et al., 2019; Buisson et al., 2010; Turner et al., 2019). An ensemble model has been reported as the most efficient model in predicting different alien invasive species by Stohlgren et al.(2010), by Ng, et al.(2018). A proper selection of parameters is critical in the ensemble approach still required to reduce the possible model uncertainties.

Model performance, current and future suitability area analysis

The model predicting performance for the future and current area suitability for *S. didymobotrya* was evaluated based on the area under the curve (AUC) of receiver operating characteristics (ROC) (Fielding & Bell, 1997) and true skills statistics (TSS) (Allouche et al., 2006) measure of the metric. The AUC values range from 0 to 1, and while the TSS measuring metric ranges from -1 to 1 (Naimi, 2015). The different model AUC and TSS classification index are shown in Table1 (Thuiller et al., 2009). The classification index illustrates the model prediction efficacy from low/fail to excellent ranges. We calibrated the models using the default setting which shares the data into 70% for the training the model and the remaining 30% of the data were used for assessing the performance of the model (Araújo, et al., 2005).

Table 1. Index for classifying model prediction accuracy

Accuracy	**AUC**	**TSS**
Excellent /High	0.9 -1	0.8 - 1
Good	0.8 -0.9	0.6- 0.8
Fair	0.7- 0.8	0.4- 0.6
Poor	0.6- 0.7	0.2 -0.4
Fail/null	0.5- 0.6	0 - 0.2

Source (Thuiller et al., 2009)

In this study, the habitat suitability change analysis of *S. didymobotrya* was performed based on the future scenarios (2050 and 2070) under the two Representation Concentration Pathways (RCPs) 4.5 and 8.5. The final map generated from the ensemble model was classified into four different suitability classes, that is not suitable (0.0–0.25), low suitability (0.25–0.50), moderately suitable (0.50–0.75) ,and highly suitable (0.75–1.00) following the method of Hamid et al.(2019). A total of five maps, consisting of four maps for the two RCPs for the year 2050 and 2070 and one map for the current period (2020) were produced to show the current and future potential distribution of *S. didymobotrya* species at the continental level of Africa. We used a weighted averaging method to create the final ensemble maps. Finally, for each range of suitability classes, the area percentage was calculated in ArcMap version 10.7 (ESRI, 2011).

Habitat vulnerability assessment

The potential habitat vulnerability change for the future climatic scenarios was assessed basing on the approaches by (Dai et al., 2019; Duan et al., 2016; Li et al., 2018; Li et al., 2017; Yan et al., 2020). The key for vulnerability evaluation criteria are i) unsuitable habitats: these are areas which presently and in the future (2050 and 2070) will remain unsuitable; ii) new suitable habitats: areas that are currently unsuitable habitats but are predicted to be suitable by the 2050 and 2070; iii) suitable habitats that have not changed: these are areas that are currently suitable habitats and will remain so in future (2050 and 2070), and iv) vulnerable areas: currently suitable areas which are projected to become unsuitable by the year 2050 and 2070.

The following different measure of indicator was used to calculate the effect of climate changes on the potential habitat suitability of *S. didymobotrya* invasion rate under current and future climatic conditions: suitable habitat invasion change rate in percentage (AC) equation 1; percentage of currently suitable habitat invasion area loss (SH_c) equation 2; and percentage of increased suitable habitat invasion rate under the future climate scenario (2050 and 2070) (SH_f) equation 3 (Dai et al., 2019; Duan et al., 2016; Li et al., 2018; Li et al., 2017; Yan et al., 2020).

$$AC = \frac{(Af - Ac)}{Ac} * 100 - - - - - - - - - - - eq.1$$

$$SHc = (Ac - Acf)/Ac * 100\% - - - - - - -eq.2$$

$$SHf = (Af - Acf)/Af * 100\% - - - - - - eq.3$$

Where A_f is the area predicted as suitable habitat under 2050 and 2070 climatic conditions; A_c is the current suitable habitat area predicted; and A_{cf} is the suitable habitat found/overlapping in both the current and future climatic conditions(2050 and 2070), respectively.

Results

Model performance statistics

The overall models mean value of AUC and TSS were 95% and 81%, respectively, and are higher than the expected random value of the model (Table 2). According to model evaluation results, the performance of ensemble model performance was very good for predicting the invasion *S. didymobotrya* in Africa. The highest model AUC value was attained from RF algorithms (AUC=99%), while the lowest performance was obtained from FDA and GLM algorithm (AUC=92%). The minimum and maximum TSS value from the eight algorithms was 76% (and 92%, respectively. The lowest was recorded from FDA and the highest was obtained from GLM algorithms.

Table 2 Mean model performance statistics of the eight models for predicting the current and future area suitability of *S. didymobotrya* under different climatic scenarios

Environmental variables relative importance

The relative contributions of each environmental variable to the model are shown in Table 3. Elevation accounted for 33% of the relative contribution to determine the distribution of *S. didymobotrya*, followed by bio3 (27.3%) and bio1 (20.6%). The contribution of bio12 was 10.8%. On the other hand, the environmental factors mean temperature of the wettest quarter (boi8), mean temperature of the driest quarter (bio9), and precipitation of the warmest quarter (bio18) were the least explaining factors for this species with the overall contribution of 5.3%, 3.5%, and 3.1%, respectively.

Table 3 . The relative contribution (%) of the environmental variables for determining the distribution of current and future *S. didymobotrya*

Current and future distribution of s*enna didymobotrya*

According to our model, about 18.22% of the continent of Africa is presently climatically suitable for *S. didymobotrya* (4.0% highly suitable, 3.8% moderately suitable and 10.3% low suitabile). However, the largest portion of the continent (81.88%) is not suitable for *S. didymobotrya.* The high suitable areas were generally observed in Rwanda, Uganda Western Kenya, Burundi, Tanzania, and most of Ethiopia. On the other side, Zambia, northeastern Zimbabwe, Mozambique, the central part of Angola, Lesotho, Central Madagascar, Eastern broader of South Africa, Malawi, DRC eastern side, south Sudan bordering Kenya and Eritrea have low to moderately suitable for invasion of *S. didymobotrya.* Furthermore, the species suitable habitat range is observed in the elevation range between 750m to 3000m a.s.l., however, a few patches of suitability range at a lower elevation beyond 750 m a. s.l. was also visualized.

Figure 2 *S. didymobotrya* invasions under current climatic conditions

Future model projections revealed that the climatically suitable for *S. didymobotrya* invasion would increase in the 2050s and the 2070s (figure 3). The total share of habitat categorized as a low and moderate class in the climatic scenarios of RCP 4.5 and RCP8.5 for the year 2050 was projected to be 16.98 % and 20 %, respectively. A similar trend was revealed for 2070, with an increase in the suitability of 18.62% and 21.98% for the RCP 4.5 and RCP 8.5 (Table4, figure3), respectively. The total area of the highly suitable area for *S. didymobotrya* will decrease by 15 % and 20.75% under RCP4.5 and RCP8.5, respectively by the year 2050 (table 4). Similarly, highly suitable area will decrease by 20.5% and 31.75% under RCP4.5 and RCP8.5 climate scenario in 2070, respectively (table 4).

Figure 3 S. didymobotrya invasion suitability under the future projected climatic conditions under RCP 4.5 and RCP 8.5.

Under RCP4.5 & RCP8.5 for the two considered period (2050 and 2070), Angola (southeastern), Zambia, Zimbabwe, DRC(northeast and central, partly to west), south African including Lesotho and Swaziland, Congo Brazzaville, western Namibia, southern Cotdivore, southern Ghana, and Cameron are among the hotspot areas for *S. didymobotrya* potential future invasion(figure 3). On the other hand, Mozambique and Ethiopia (northeastern) show a progressive loss in the current suitability of *S.didymobotrya* invasion. Likewise, a progressive decrease in the total suitability is observed for the eastern African countries which were previously considered the main hotspot area for *S. didymobotrya* (figure3, table4). However, in RCP8.5 (2050 and 2070), the percentage of areas invaded by the species is predicted to increase at a higher rate than that of RCP4.5. This increase is directed toward southern and slightly into central Africa. Nevertheless, under both future climatic scenarios the continent, except Sub-Saharan countries is not suitable for S. *didymobotry* invasion.

Table 4. Percentage of total suitable habitat change for the current distribution

Our model predicted a significant increase in the vulnerability of habitat for the invasion of *S. didymobotrya* under the future climatic scenarios. Our result demonstrations by the 2050s, an increase in the new invasion areas by 61.57% and 79.82% was projected under RCP 4.5 and RCP8.5, respectively (table 5). Similarly, this situation remains a rose in suitability in the 2070s with 73.12% and 95.62 % under RCP4.5 and RCP8.5, respectively. However, our assessment suggests a progressive decrease in suitability for *S. didymobotrya* invasion under future climatic scenarios for the not suitable and highly suitable class (table5).

Table 5 the percentage of future suitable habitat increase rate

Discussion

This study estimated current potential and future predicted habitat for *S. didymobotrya* in Africa using Ensemble Approach. We applied both AUC and TSS values to evaluate the model performance and the model predicted the distribution of the distribution of the species very well. The ensemble model for the first time showed the potential impact of current and future climate on the distribution of S. *didymobotrya* in Africa. Under the current climatic scenarios high habitat suitability of invasion is observed in countries like Rwanda, Burundi, Uganda, Kenya, Tanzania, and Ethiopia. On the contrary North African countries were projected to be the non-suitable habitat for *S. didymobotrya* invasion under current and future climatic conditions. Our present result is in agreement with the report made by Witt & Luke,(2017), which put *Senna* spp. as among the most occurring alien invasive species in many habitats of east African and southern African countries. Similarly, our current invasion distribution model result reaches an agreement with studies conducted in different parts of Africa (Dlamini, 2016; Fessehaie & Tessema, 2014; Fufa et al., 2017; Jaca & Condy, 2017; Nel et al., 2004)Given that, the climate change has affected the distribution of invasive species causing expansions in climatically suitable habitats worldwide (Bellard et al., 2013), our study shows that future climate change will cause similar increase in the climatically suitable areas of *S. didymobotrya* in Africa. The predicted maps provided by this study will be helpful for prevention and early detection of the species in the new areas.

Under future climate change scenarios, suitability for S. *didymobotrya* will expand towards lower elevations. Higher species richness of invasive alien species was reported in the lower elevation ranges than higher elevation (Averett et al., 2016; Ibanez et al., 2019; Pauchard, 2017). Similarly, some invasive species are shifting their geographic distribution towards high altitude as the climate warms (Bradley, Blumenthal, Wilcove, & Ziska, 2010; Shrestha, Sharma, Devkota, Siwakoti, & Shrestha, 2018), and new invasive species are adding to those currently being successfully controlled. This is could be because higher elevation ranges are assumed to be isolated and distant from weed populations subsequently hindering accessibility by vehicular traffic and less human disturbance, lead to the less propagule pressure across the landscape resulting in a low establishment. This means that in the long-run, the inherent characteristic of the species and lack of native competitors may cause a niche shift in new ranges towards lower elevations; and it is more possible that climate variability will facilitate the spread of the species into new areas.

Following topographic information, temperature variables (accounting 47.9%) (bio6: min temperature of coldest month and bio1: annual mean temperature) were among variables predicted to be important for S. *didymobotrya* establishment. Similarly, our ensemble model predicted precipitation variables which are accounting 26.8% (bio12: Annual precipitation; bio14: precipitation of driest month; and bio17: precipitation of driest quarter) as the third most important environmental variables affecting S. *didymobotrya* distribution. Ibanez et al.(2019) also reported positive effects of mean annual precipitation on alien species coverage. Similarly, Averett et al. 2016 reported in their study the influence of temperature variables (minimum temperature records over 30yr) as the most predictor variables limiting the distribution of non-native species richness.

Our future projection model showed a substantial increase in the new invasion areas both for the considered RCPs (4.5 and 8.5). Nevertheless, it is visualized that areas which are highly suitable under current climatic condition tend to lose their suitability into moderately and low suitability ranges under the future climatic condition. The model predicted compared to the current suitability, the southern Africa countries are expected to gain more new invaded areas than countries located in the eastern African and central Africa in the future climatic scenarios. This trend indicated a shift in the future hotspot area invasion by *S. didymobotrya* into these countries as a result of climate change. Nevertheless, despite the loss in a higher range of suitability, east African countries remain the main hotspot location of *S. didymobotrya* future invasion. According to Witt & Luke (2017) and Witt et al.(2018) the future alien invasive plants species distribution including *S. didymobotrya* in mots habitat range of East African countries is high facilitated by increased land degradation, overgrazing, deforestation of native forest and the associated impact of climate change.

Climate change can cause alien species to migrate into new place from the currently growing habitats Walther et al.(2009), similarly, in our study, we found a significant shift in the future range of niche of *S. didymobotrya* invasion from the current growing range, which is articulated as the effect of climate change. Moreover, our result suggests in the long run due to the ongoing climate changes potential shift in species habitat ranges. Furthermore, the movement of invasive species into the new areas at the global and local scale is favored by other mechanisms such as wind (cyclone), severs weather events, global circulation air, and water and climate changes (Burgiel & Muir, 2010).

Conclusion

This study confirms for the first time the distribution of *S. didymobotrya*. Both the present and future projections show the presence of *S. didymobotrya* in most of the African countries. We found that eastern Africa countries are more vulnerable to *S. didymobotrya* invasion in the future, followed by southern African countries. The current status and future trend of *S. didymobotrya* indicate a precautionary note calling for coordinated, inter-country, and large scale interventions. Additionally, the outputs of this study will support the management of the species through early detection of future potentially suitable areas. Based on our study, we urge that the future conservation strategy and policy direction should target on how to limit the increasing expansion of invasion mainly by focusing the hotspot areas through designing more feasible management and control measures through early identification and eradication actions. There is a need for more studies to provide more information on the distribution of *S. didymobotrya* at the local scale, by incorporating other variables such as land cover/use, population, proximity to water, and proximity to roads, and population parameters.

List of abbreviations

IPCC= Itnetrantional Panel for Climate Change

RCPs= Representative Concentration Paths

GCM= Global climate models

SDM= Species distribution model

Data Accessibility Statement

The authors fully confirm that, if the manuscript is accepted in this journal, the bioclimatic species occurrence data and the R code/script used to generate this manuscript will be uploaded in "Dryad" and "GitHub" repository for publicly accessible.

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Author information

Affiliations

Haramaya University, School of Geography and Environmental Studies, Department of Geo-information Sciences, Ethiopia

Elias Cherenet weldemariam

Haramaya University, College of Agriculture and Environmental Sciences, Ethiopia

Sintayehu Workeneh Dejene (PhD)

Contributions

EChW, designed the study, analyzed data, review literature and write the manuscripts.

SWD, initiated the work, edited the manuscript, and read the final manuscript,

Corresponding author

Correspondence to Elias Ch. Weldemariam

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