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Climate Change

Climate change and geographical distribution projections for major leaf beetles (Coleoptera: Chrysomelidae) in Saudi Arabia

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Climate change has a substantial impact on the quality and diversity of insect pests, which may have adverse ecological and economic effects. The family Chrysomelidae represents one of the most economically and ecologically important groups within Coleoptera, with species acting as agricultural pests and contributing substantially to biodiversity in arid regions. Based on bioclimatic, topographic, and vegetation data, the current and future distributions of 4 chrysomelids (*Caryedon acaciae* (Gyllenhal, 1833), *Chaetocnema pulla* Chapuis, 1879, *Phyllotreta cheiranthi* Weise, 1903, and *Spermophagus sericeus* (Geoffroy, 1785)) in Saudi Arabia were predicted using MaxEnt modeling for 2050 under 2 Shared Socioeconomic Pathways (SSPs), SSP126 (low emission) and SSP585 (high emission) scenarios. The leaf beetle models showed strong performance, with average area under the curve (AUC) values ranging from 0.86 to 0.96 and average TSS values ranging from 0.52 to 0.65. Five predictors were chosen for each species from 21 environmental variables. The results show that the key ecological factors that influence species distributions varied, with vegetation being the most influential. According to habitat suitability maps, in the future, such distribution will be severely altered, mostly by climate change. More precisely, *C. acaciae* will face minor range shifts, while *C. pulla*, *P. cheiranthi*, and *S. sericeus* will expand their ranges substantially, especially in the Eastern Province. Our results confirm the importance of implementing adaptive pest-management strategies to address the potential range expansions of various agricultural pests, which could intensify local ecological challenges and pose a heightened threat to agricultural systems.

Keywords: species distribution modeling, MaxEnt, geographic range shifts, pest management

Introduction

Climate change is significantly affecting the distribution and abundance of insect pests and is expected to expand their geographic range worldwide (Bebber et al. 2013). Insects are particularly susceptible to climate change because of their ectothermic nature, dependence on ambient temperature for survival and growth, as well as metabolic processes (González-Tokman et al. 2020). The leaf beetles are herbivorous insects comprising more than 37,000 species in over 2,500 genera (Song et al. 2018) and have been noted for their immense ecological and economic importance (Fernandez and Hilker 2007). Brassica crops in the areas of *P. cheiranthi* infestation experience a high level of yield loss (Lundin 2019). *Caryedon* beetles threaten the regeneration rate of Acacia woodlands, important for grazing and agroforestry, in Saudi Arabia and neighboring countries like Sudan and Oman (Shetta et al. 2016, El-Sheikh 2023). *Chaetocnema pulla* and *S. sericeus* are threatening food security due

to their attack on cereal grains and legume seeds, especially in these irrigated areas where such crops are increasingly grown (Nwilene 1999; Banwo et al. 2002, Mehdizadeh et al. 2018). However, they are not immune to climate effects (Olfert et al. 2017). These beetles, which are very important to ecosystem functions both as pest species and as bioindicators of environmental change, might face altered habitat suitability under future climate scenarios (Olfert et al. 2017, Zou et al. 2020, Lucio-García et al. 2022). The stability of ecosystems, agriculture, and natural vegetation in arid and semi-arid regions may be significantly affected by future climatic changes due to the potential redistribution of leaf beetles (Sánchez-Reyes et al. 2019).

In Saudi Arabia, climate change poses a particularly great threat due to the desert climate and sparsely populated agricultural areas (Sayed and Masrahi 2023). The Arabian Peninsula has experienced a significant warming trend, characterized by rising maximum and minimum temperatures and shifts in precipitation patterns during the recent period of global unprecedented warming (Almazroui 2020, El-Rawy et al. 2023, Labban et al. 2023). Concurrently, the projected scenario of climate change is intended to deteriorate further in the future. These changes in the climate have the potential both to create new ecological niches and cause loss of habitats for a number of species, among them insects like leaf beetles and can thus be expected to influence their ecology and distribution (Cerasoli et al. 2019, Skendžić et al. 2021). Understanding the potential responses of these beetles to these changes is crucial for the prediction of future ecological threats and the management of agricultural pest outbreaks. Modeling the future distribution of insects, such as leaf beetles, in a changing environment is increasingly important in order to support successful conservation plans, pest management practices, and biodiversity preservation initiatives. As expressed by Harvey et al. (2023), this would involve informed conservation strategy, management methods, and biodiversity conservation.

Recently, powerful ecological niche modeling tools have been developed to forecast the potential distribution of economically important insect species under various climate scenarios (Sillero et al. 2021). Of these, species distribution modeling—or SDM—using MaxEnt modeling has become a well-established and extensively applied approach, supported by a substantial body of research over the past 2 decades (Lissovsky and Dudov 2021). MaxEnt is a method that utilizes environmental variables such as temperature and precipitation, together with presence-only data, to determine the ecological niche of a species and predict its potential distribution (Bradie and Leung 2017). This method has a distinct advantage in arid regions, such as Saudi Arabia, where species records are often limited due to both the naturally sparse distribution of populations in harsh desert conditions and the logistical challenges of conducting comprehensive biological surveys across vast, remote areas (Soliman et al. 2023). In addition, while MaxEnt has demonstrated robustness across various ecological questions and biogeographical conditions, it is not without limitations. As noted by Lissovsky and Dudov (2021), frequent misuse by researchers, particularly in underestimating the influence of initial parameters and spatial bias in occurrence data, can impact model accuracy. Nevertheless, MaxEnt remains a widely used tool with broad applications in modeling insect species distributions under climate change scenarios (Li et al. 2021, Sutton and Martin 2022, Santos et al. 2024).

The four-leaf beetle species to be studied are *Caryedon acaciae* (Gyllenhal, 1833), *Chaetocnema pulla* Chapuis, 1879, *Phyllotreta cheiranthi* Weise, 1903, and *Spermophagus sericeus* (Geoffroy, 1785). All these species are of great economic importance because they are agricultural pests and ecological indicators. *Caryedon acaciae*, commonly known as the Acacia seed beetle, infests primarily the leguminous trees belonging to *Acacia* spp. through egg laying upon the seeds of said trees, where the larvae subsequently burrow into, creating serious damage to the seeds (Ramos and García 2008). It is considered a serious threat to both natural and cultivated ecosystems, including plantations of economically important *Acacia* species that are valuable for their timber, fuelwood, and fodder in parts of Africa and the Middle East (Walters and Milton 2003). Although *C. acaciae* primarily targets seeds, it disrupts natural and cultivated Acacia populations through reduced seed viability and regeneration, with knock-on effects on ecosystem services such as soil stabilization and grazing (Atta 1993). *Chaetocnema pulla* is a flea beetle with considerable reported impacts on rice and other cereal crops (Iannella et al. 2021). Flea beetles are notorious for jumping behavior and causing severe damage to the tender seedlings of plants through feeding on leaves, hence reducing yields. It is, therefore, of more serious concern in those areas of Africa where rice is one of the staple foods due to their enhancing food insecurity through aiding in crop disease diffusion, such as Rice Yellow Mottle Virus (RYMV) (Iannella et al. 2021). Although rice is not a staple crop in most KSA regions, the production takes place only in the few highly selective regions of the irrigated systems, such as that in the Eastern Province (Al-Mssallem et al. 2023). The potential invasion by *C. pulla* would, therefore, threaten the whole high-input agricultural ecosystem. *Phyllotreta cheiranthi* belongs to a group of flea beetles that are generally considered very injurious to cruciferous crops, such as cabbage and mustard, besides other economically important plants of the Brassicaceae family (Pollard 1956). These beetles basically feed on the foliage, characteristically causing shot-hole damage that leads to significant crop loss and thus requires extensive effort in pest management. This makes them an important pest in agriculture throughout Northeast Africa, Southwest Asia, and the Middle East, where Brassicae vegetables play a major role in local food production and export markets (Gentry 1965, Gruev and Döberl 1997). Brassica crops, such as mustard and cabbage, are grown increasingly for domestic consumption and export. In areas like the Asir highlands, where the climate is conducive to their cultivation, their economic value has increased (Nagmouchi and Alsubeie 2020). *Spermophagus sericeus* (Bruchinae, Chrysomelidae), a seed beetle, targets seeds of plants in the Convolvulaceae family, such as *Convolvulus arvensis*. The larvae develop inside the seeds, destroying their viability and causing severe effects on seed-based propagation efforts (Kergoat et al. 2015). This beetle, through its activities in agriculture, stands to impede the successful cultivation of economically valuable legumes and hence disrupts the seed trade industry. It has also been studied as a biocontrol agent against certain weeds, such as *Convolvulus arvensis*, which would reduce the application of chemical herbicides in weed control (Tóth and Cagáň 2005). Overall, these insects impose immediate financial burdens from plant and seed destruction and indirect effects via the heightened demand for the management and control of pests. Knowledge of their biology and distribution becomes the key to developing sustainable agricultural practices, thereby reducing their economic burden.

This study uses the MaxEnt model to determine the impacts of future climate change on the distribution of targeted chrysomelids in Saudi Arabia. In this regard, the integration of present and future climate data would result in the identification of potential changes in the suitable habitat for these beetles under different RCP scenarios. More precisely, we have focused on the answer to the following questions: (i) How might climate change impact the studied leaf beetle population in Saudi Arabia with respect to geographical distribution? (ii) Which climatic factors have the most significant

impact on their suitable habitat? (iii) How do such distributional changes in species affect ecosystem stability and the local farming system?

It is such a study that will impart the necessary insights into the role that climate change may play in affecting the Saudi Arabian agricultural and biodiversity sectors. Besides, knowledge of the ecological responses of leaf beetles to changes in climate will provide management strategies at levels that help dampen negative impacts such beetles may have as pests yet wanted for contributing positively to ecosystem health.

Materials and Methods

Study Area

Saudi Arabia covers a vast area of about 2,250,000 km^2 of the Arabian Peninsula. The region has high temperatures and low precipitation; the climatic conditions prevailing throughout the entire nation comprise arid, semiarid, and forested regions (Sulaiman et al. 2021). The country's latitude ranges from 32° 12′ N along the Jordanian border in the north to 16° 00′ N along the Yemeni border in the south. It is bounded on the west by the Red Sea and on the east by the Arabian Gulf. It is broadly divided into 4 major regions: Hijaz, Najd, Asir, and the Eastern Province. These regions are further subdivided into 13 provinces (Alsafiah et al. 2017) (Fig. 1).

Distribution Data for Beetle Species

The occurrence data used in our modeling was based on 172 records of the 4 chrysomelid species collected within Saudi Arabia between 2007 and 2022. These records came from extensive field collections conducted by the authors and their research assistants during various insect pest surveillance across the country. Field collections were conducted across different localities, representing various altitudinal levels and habitats within 11 Saudi provinces: Asir, Baha, Jouf, Eastern Province, Jazan, Madinah, Makkah, Najran, Qassim, Riyadh, and Tabouk (Supplementary Table S1). Multiple collection methods were employed including, pitfall trapping, UV-light trapping, Malaise trapping, net sweeping, beating vegetation, vacuuming, and handpicking to ensure comprehensive sampling across different microhabitats. For recent specimens (2009 to 2022), geographic coordinates were recorded directly using GPS instrumentation. For older specimens, coordinates were derived using Google Earth based on the recorded collection localities. In order to reduce the likelihood of biases in the calibration of species distribution models (SDMs), we implemented spatial filtering to eliminate redundant entries within individual 2.5' pixels (approximately 5 km^2) (Syfert et al. 2013). Following spatial filtering, the number of occurrence points for each species was 16 for *C. acaciae*, 47 for *C. pulla*, 12 for *P. cheiranthi*, and 34 for *S. sericeus*. All collected specimens were sorted and deposited in the King Saud University Museum of Arthropods

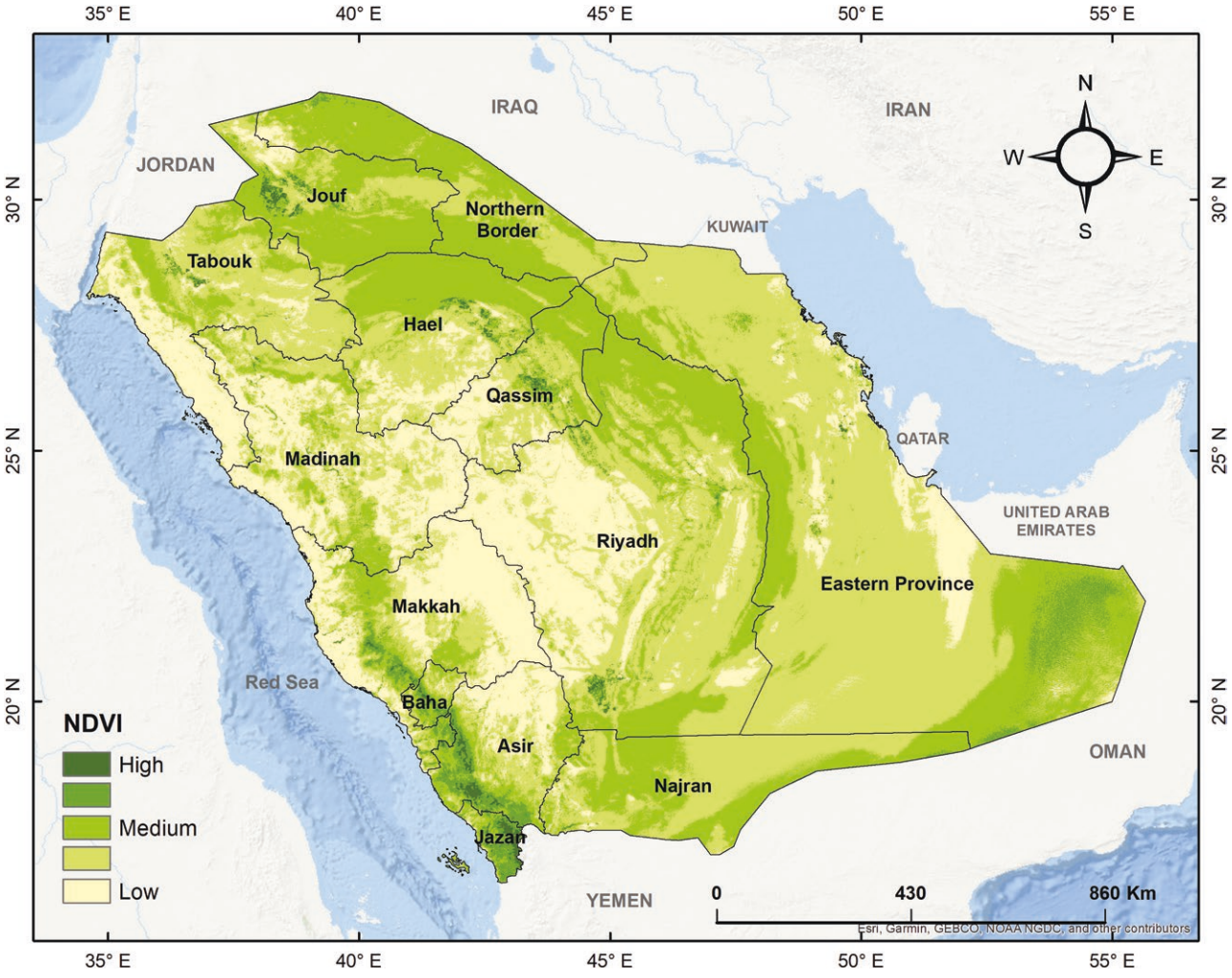

Fig. 1. Normalized Difference Vegetation Index (NDVI) map generated for Saudi Arabia.

Table 1. Percent contributions of the variables (bioclimatic and topographic) in the Maxent Models for the beetle species (10 replicated runs)

Variables	Description	% Contribution
Caryedon acacia		
Bio 2	Mean diurnal range (max temp – min temp) (monthly average)	45.8
NDVI	Normalized difference vegetation index	28.8
Bio 1	Annual mean temperature	19.8
Bio 3	Isothermality (Bio1/Bio7) × 100	2.8
Bio 13	Precipitation of wettest period	2.7
Chaetocnema pulla		
NDVI	Normalized difference vegetation index	41.9
Bio 7	Temperature annual range	34.5
Bio 14	Precipitation of driest period	16.9
Alt	Altitude in degrees	4.7
Bio 13	Precipitation of wettest period	1.9
Phyllotreta cheiranthi		
Bio 18	Precipitation of warmest quarter	65.7
Bio 2	Mean diurnal range (max temp – min temp) (monthly average)	21.6
NDVI	Normalized difference vegetation index	9.7
Bio 1	Annual mean temperature	2.1
Bio 15	Precipitation seasonality (coefficient of variation)	0.9
Spermophagus sericeus		
NDVI	Normalized difference vegetation index	83.8
Bio 2	Mean diurnal range (max temp – min temp) (monthly average)	9.6
Alt	Altitude in degrees	3.7
Bio 14	Precipitation of driest period	1.7
Bio 8	Mean temperature of wettest quarter	1.2

(KSMA). There, they were identified by comparing them with the reference chrysomelid collection in the KSMA museum, which was identified by the late Ashraf El-Torkey (Classification Department, Plant Protection Research Institute, Agriculture Research Center, Giza, Egypt) and Jan Bezděk (Mendel University, Department of Zoology, Zemědělská, Czech Republic). Host plants and associated flora were identified using Flora of Saudi Arabia by Chaudhary (1999). A color-coded network diagram illustrating the studied chrysomelid pests, along with their host plants and associated flora, is also provided (Supplementary Fig. S1).

Environmental Data

Three types of environmental variables were selected: bioclimatic (19 variables), topographic variables (altitude), and biological environmental variables (normalized difference vegetation index "NDVI"). Climatic and topographic variables were downloaded from the WorldClim database (https://worldclim.org/). The NDVI data were acquired from the Moderate Resolution Imaging Spectroradiometer (MODIS) MOD13A2 product. The NDVI data was sourced from the Google Earth Engine, GEE platform https://earthengine.google.com/, and preprocessed for the median range from 2000 to 2020. NDVI is a satellite-derived measure of vegetation density and health, ranging from –1 to + 1, where higher positive values indicate denser, healthier vegetation (Pettorelli et al. 2011). This index is particularly relevant for leaf beetles as it directly reflects food resource availability and microhabitat conditions. A total of 21 variable layers were downloaded at 30 arcsec (~1 km) spatial resolution each as per the requirement for the current climatic condition assessment. The details are shown in Supplementary Table S2.

Significant correlations between bioclimatic variables frequently account for their spatial variation (Currie et al. 2020). To mitigate the influence of the highly correlated environmental variables on the model prediction outcomes, a systematic approach was employed for each species under investigation (Li et al. 2020). Initially, we utilized ArcGIS software version 10.7 to drive values for each of the 19 bioclimatic variables at each occurrence point. Next, we employed IBM SPSS Statistics software v27 to perform principal component analysis (PCA) on these data, and the results are summarized in Table S3. A 2-step process was employed to refine the variable selection. First, we employ the jackknife function in MaxEnt to identify and exclude variables that did not make a significant contribution to the distribution of species. The second step was to conduct Pearson's correlation tests to address multicollinearity. Highly collinear variables were defined as those with a correlation coefficient $r \geq 0.7$ in such instances, we retained the variable that made the most significant contribution to the model and eliminated the variable that was the least influential (Soliman et al. 2023) (Supplementary Table S4). The primary factors that influence distribution patterns were identified through this exhaustive selection process, which resulted in the identification of 5 relatively uncorrelated environmental variables for each species (Table 1). These selected variables are representative of 1 to 2 factors from each of the 3 or 4 main components that were identified through PCA. To ensure that the variable layers were in accordance with the geographical boundaries of Saudi Arabia, we used ArcGIS software v10.7 to clip them.

To predict the effects of climate change on species distribution, we downloaded 5 general circulation models (GFDL-ESM4, IPSL-CM6A-LR, MPI-ESM1-2-HR, MRI-ESM2-0, and UKESM1-0-LL) with a resolution of 30 arcsec (~ 1 km) from the WorldClim database. These models simulate future climate conditions based on different greenhouse gas emission scenarios and provide robust and reliable projections, allowing us to assess how climate change might alter the distribution of leaf beetles in Saudi Arabia. Circulation models were downloaded for the year 2050 (2040–2060) for 2 contrasting Shared Socioeconomic Pathways (SSPs): SSP126 and SSP585. SSP126 represents a sustainable development pathway with low greenhouse gas emissions (equivalent to RCP2.6), characterized by global cooperation, improved education, rapid technological development, and reduced resource intensity. In contrast, SSP585 describes a fossil fuel-dependent development pathway with high emissions

(equivalent to RCP8.5), marked by rapid economic growth, high energy demand, and limited environmental policies (Leimbach and Giannousakis 2019). These scenarios were selected to represent both optimistic and pessimistic future trajectories of socioeconomic development and their associated climate impacts. Five climate models comprise the core set of the ISIMIP3b impact modeling protocol, which was implemented in the present study. The selection of these models was based on their climate sensitivity metrics, which were intended to represent the broader CMIP6 ensemble. The quality of the representation of the process of these models varies, with GFDL-ESM4, MRI-ESM2-0, and UKESM1-0-LL demonstrating robust performance, while IPSL-CM6A-LR and MPI-ESM1-2-HR exhibit satisfactory performance (Soliman et al. 2023). The detailed characteristics and specifications for each climate model utilized in this study are provided in Supplementary Table S5.

Habitat Suitability Model

To analyze and predict the current and future geographical distribution of the 4 species of beetles, we employed MaxEnt, a maximum entropy modeling technique, software v 3.4.4 (Phillips et al. 2024). MaxEnt is renowned for its robust performance with presence-only data and relatively limited occurrence records (Elith et al. 2006, Wang et al. 2007). Consequently, it is the preferred method for projecting the distributional shifts of species under climate change scenarios (Yan et al. 2020). In this method, mathematical models are developed to elucidate the relationship between probabilities of species presence and various environmental predictors. These models are subsequently transformed into potential distribution maps, which highlight the areas of environmental suitability that are suitable for species habitation. The scale of suitability values ranges from 0 (unsuitable) to 1 (highly suitable) (Khanum et al. 2013, Gebrewahid et al. 2020). Our modeling approach involved allocating 25% of the occurrence records as test data and the remaining 75% as training data. In order to improve the efficacy and robustness of the model, we implemented tenfold bootstrapped replicas with a random seed. Selection of an appropriate background is critical to ensuring unbiased model predictions, as highlighted by VanDerWal et al. (2009) and Elith et al. (2011). The background definition methodology employed in our MaxEnt models was designed to reflect the ecological requirements of the studied beetle species and the environmental heterogeneity of the study area. By including both high and low NDVI areas in the background definition, we ensured that the models captured the complete range of potential habitats, resulting in ecologically meaningful and unbiased predictions. This approach is consistent with best practices in species distribution modeling for arid and semi-arid regions, where vegetation patterns are often patchy and dynamic. For quantifying model performance, we used 2 established metrics: the AUC of the receiver operating characteristic curve, henceforth referred to as AUC (Phillips et al. 2006), and the true skill statistic, henceforth referred to as TSS (Allouche et al. 2006). Both vary between 0 and 1; the higher these values are, the more capability they reflect for discrimination, hence higher model precision and informativeness (Allouche et al. 2006, Phillips et al. 2006).

For each species, we generated 10 combinations of distribution models (5 Global Climate Models 'GCMs' × 2 SSPs) for the year 2050. We computed the mean values across all runs to provide a summary of the model outputs, which in turn provides an estimate of the ecological niche for each species under current conditions. In accordance with the methodology described by Kamal et al. (2018), we averaged the mean values of all GCMs within each SSP scenario. We estimated the uncertainty index for model predictions in accordance with Kamal et al. (2018). This index was developed for the current conditions by deriving the range (maximum-minimum) of predictions across 10 replicate MaxEnt runs, which utilized bootstrapped occurrence datasets. The range of all future model combinations within each SSP was used to calculate the uncertainty index for future conditions, which is indicative of the variation in predictions among the different GCMs.

Results

The performance of the models for leaf beetles was good; AUC ranged between 0.86 and 0.96, and TSS was between 0.52 and 0.65 (Supplementary Table S6). Performance metrics indicate that the models showed a strong discriminatory capacity and predicted the potential geographic distribution of beetles well using the chosen environmental predictors. The modeled spatial distributions of leaf beetles are as follows: the MaxEnt model for *C. acaciae* performed very well, with an average AUC of 0.88 and an average TSS of 0.52. The mean diurnal range (Bio 2) and the normalized difference vegetation index (NDVI) were the key predictors influencing the distribution of *C. acaciae*. These variables contributed 45.8% and 28.8% to the species habitat model, respectively (Fig. 2 and Table 1). Habitat suitability for *C. acaciae* decreases as the mean diurnal range increases (Fig. 3). For the species, about 50.8% of the total area in Saudi Arabia was a suitable habitat (Fig. 4). The main focuses of these suitable areas were the Eastern Province, the eastern half of Riyadh, Najran, the Red Sea coastline from Tabouk to Jazan, and some localities within Jouf (Fig. 4). The projected distribution of *C. acaciae* under future climate scenarios is not very different from the current estimated range. However, the models indicate a minor expansion in the northern areas of the country, alongside a slight contraction in the northeastern area of the Riyadh Province and the northern area of the Eastern Province (Figs 5 and 6). In both scenarios, accordingly, the area with suitable conditions where *C. acaciae* could be distributed in 2050 has been calculated to increase by 4.37% and decrease by 6.04%, respectively, compared to the present time.

The MaxEnt model for *C. pulla* was highly predictive, as evidenced by the average AUC of 0.92 and an average TSS of 0.58. Among the environmental variables analyzed, NDVI and temperature annual range (Bio 7) were the major predictors influencing the distribution of *C. pulla*. These variables contributed 41.9% and 34.5%, respectively, to the species' habitat suitability model (Fig. 2 and Table 1). Figure 3 demonstrates a positive correlation between habitat suitability for *C. pulla* and increasing values of the NDVI. Approximately 16.8% of the total area in Saudi Arabia was suitable habitat for *C. pulla* (Fig. 4). The region with the highest suitability is located in the southwestern area along the Red Sea, encompassing parts of Makkah, Baha, Asir, and Jazan provinces. A moderately suitable zone is present in the Eastern Province (Fig. 4), including the central-eastern area and the mountainous southern border with Yemen. The expansion of *C. pulla* under future climate scenarios is notably significant in the Eastern Province and Najran (Figs 5 and 6). As a result of the model, the area of suitable habitat is predicted to grow significantly from 321,452 km² (16.8%) to an average of 541,445 km² (28.3%) by 2050. Compared to the current conditions, under the 2 SSPs-SSP126 (low emission pathway) and SSP585 (high emission pathway), the potential distribution area of *C. pulla* is projected to increase by about 67.21% and 69.76%, respectively, by 2050.

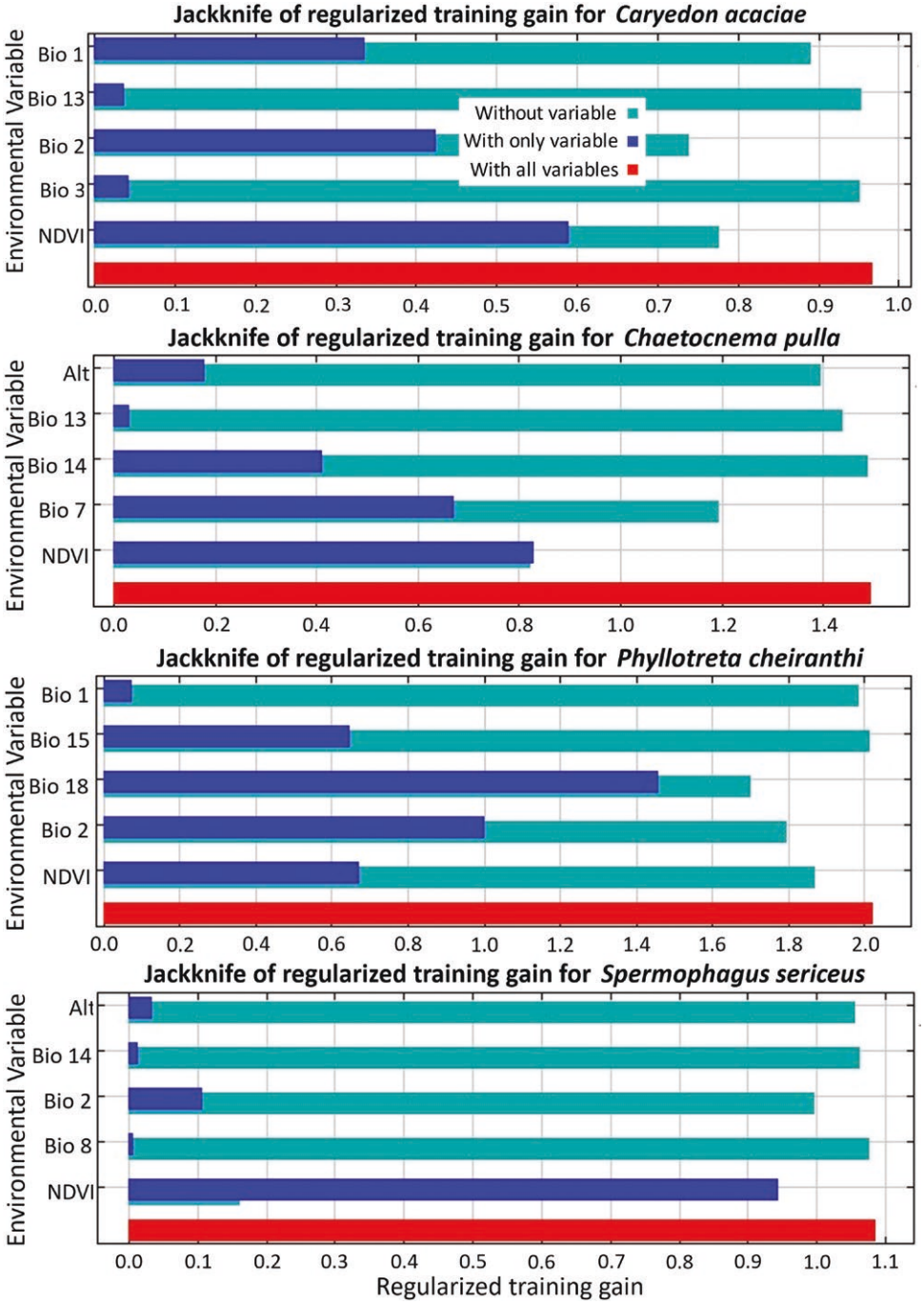

Fig. 2. Jackknife test results for the 4 beetle species, showing the relative predictive power of environmental variables.

The MaxEnt model performed well for *P. cheiranthi*, with an average AUC of 0.96 and an average TSS of 0.65. Precipitation of the warmest quarter (Bio 18) had greater effects on the distribution of *P. cheiranthi* than any other bioclimatic variables. This variable contributed 65.7% to the species' suitability model (Fig. 2 and Table 1). The probability of the presence of *P. cheiranthi* increased with an increase in precipitation in the warmest quarter (Fig. 3). Presently, 14.0% of the total area in Saudi Arabia constitutes suitable habitats for *P. cheiranthi* (Fig. 4). The southwestern region along the Red Sea, including parts of Makkah, Baha, Asir, and Jizan provinces, has the highest suitability index (Fig. 4). A substantial expansion of *P. cheiranthi* habitats is indicated by the projection of future climate conditions, notably in areas south of the Eastern Province and toward Najran Province (Figs 5 and 6). It follows from the model that the possible increase in habitat under SSP126 might constitute up to 84.67% and reach 92.49%, which, in turn, means an increase in suitable areas from 269,107 km² (14.0%) to an average of 507,509 km² (26.6%) by 2050 in relation to current conditions.

For *S. sericeus*, the average AUC for the MaxEnt model was 0.86 and the TSS was 0.52, indicating better performance than random. Among the environmental variables analyzed, NDVI was the most influential, with a contribution of 83.8% to the habitat suitability of the species (Fig. 2, Table 1). Figure 3 illustrates a positive correlation between *S. sericeus* habitat suitability and increasing NDVI

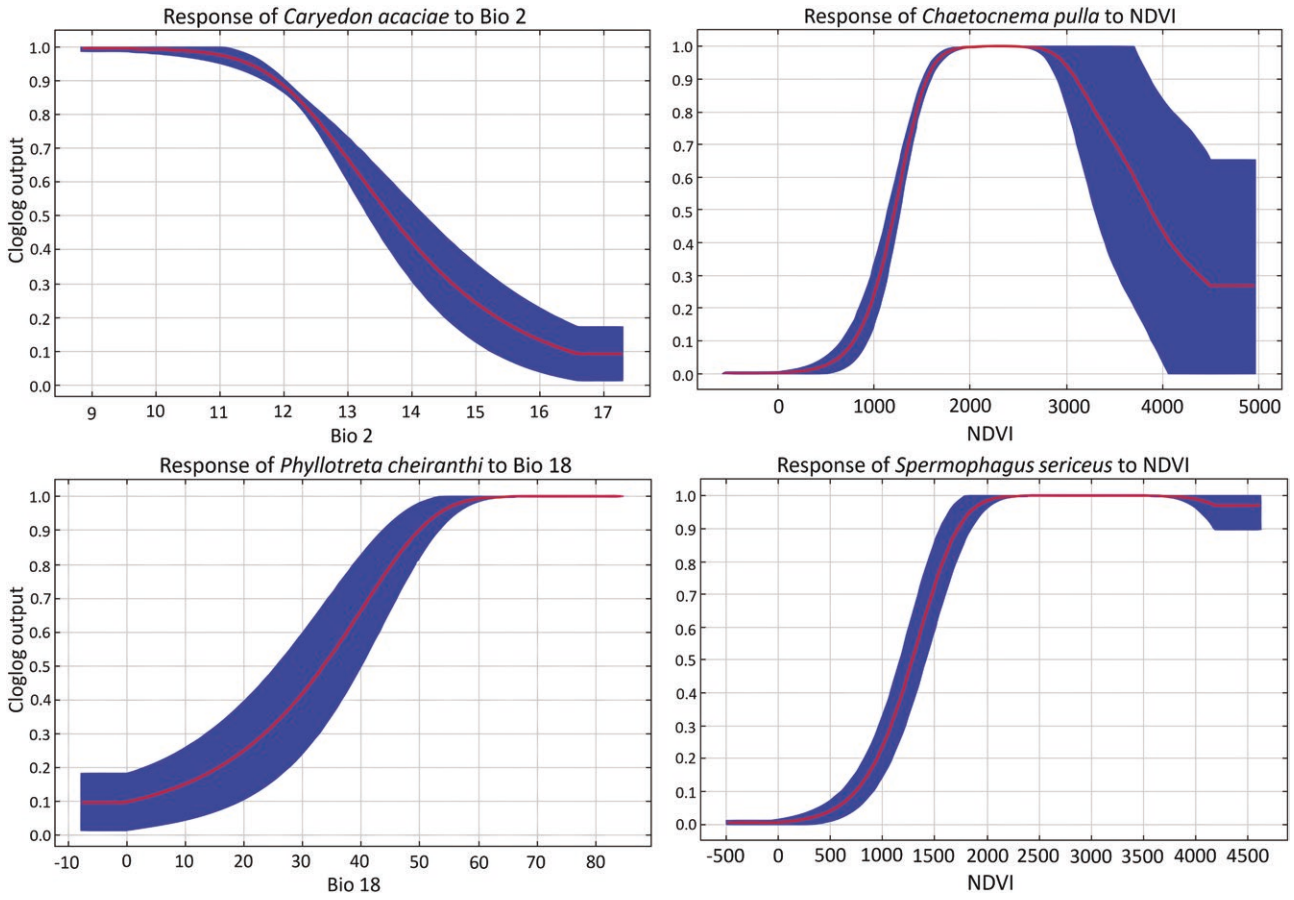

Fig. 3. Response curves showing the relationships between the probability of presence of a species and one top bioclimatic predictor: values shown are average over ten replicate runs.

values. Currently, 39.7% of Saudi Arabia provides suitable habitats for *S. sericeus* (Fig. 4), with the highest suitability in the Eastern Province near the Arabian Gulf, extending inland, in the southeastern area bordering Oman and Yemen, and in the central-eastern area. Furthermore, the southwestern coastal region, which includes parts of Makkah, Baha, Asir, and Jizan provinces suitable habitats, contains suitable habitats (Fig. 4). Under future climate scenarios, the models predicted significant expansion for *S. sericeus*, particularly in the eastern and southeastern areas, along with a moderate contraction in the northeastern areas (Figs 5 and 6). By 2050, the model projects that suitable habitat will increase significantly, averaging 877,089 km² over the current 759,127 km², representative of 45.9% and 39.7%, respectively. Under both the SSP126 and SSP585 scenarios by 2050, it was projected that the *S. sericeus* potential distribution area would increase by 23.33% and 20.24%, respectively.

Considering the distribution pattern, *C. acaciae* and *S. sericeus* may have adapted to a variety of climatic conditions in Saudi Arabia, ranging from coastal areas to mountainous terrain. These species exhibit a preference for regions with more vegetation, higher humidity, or moderate temperatures, as opposed to the extremely arid environments of the central and western interior. These species may be able to thrive in diverse ecosystems across the country due to a wide distribution of habitats suitable for them. However, the realized distribution of these species ultimately depends on the availability of specific host plants. Even if climate change expands the potential range of suitable habitats, these beetles are unlikely to establish populations in new areas without the presence of their essential host plants. In contrast, *C. pulla* and *P. cheiranthi* seem to prefer cooler, more humid climates, more prevalent in the southwestern highlands, and are less suited to the hot, arid conditions that dominate throughout Saudi Arabia.

In their current and future predicted distributions within Saudi Arabia, leaf beetle species exhibit varying levels of uncertainty, as shown in the uncertainty visualization maps (Supplementary Figs S2 and S3). Costal and mountainous areas along the Red Sea, extending from Jazan to Tabouk, exhibit the highest uncertainty. In contrast with SSP585, the uncertainty visualization maps for the SSP126 future scenario demonstrate lower levels of uncertainty, thus suggesting more consistent model predictions across the various GCMs.

Discussion

This study emphasizes the substantial effects of climate change on the geographical distribution of 4 Chrysomelidae species in Saudi Arabia. Some of these species are expected to expand their ranges under future climate scenarios, while others may experience contraction. Understanding where agricultural pests are and why is extremely important—especially now that the climate is changing so fast (Skendžić et al. 2021). The findings of this study allow a more realistic view of the current and potential future distributions of the 4 studied leaf beetles in Saudi Arabia, supported by previous studies from all over the world concerning arid zone research. Using MaxEnt, we developed a habitat suitability model based on

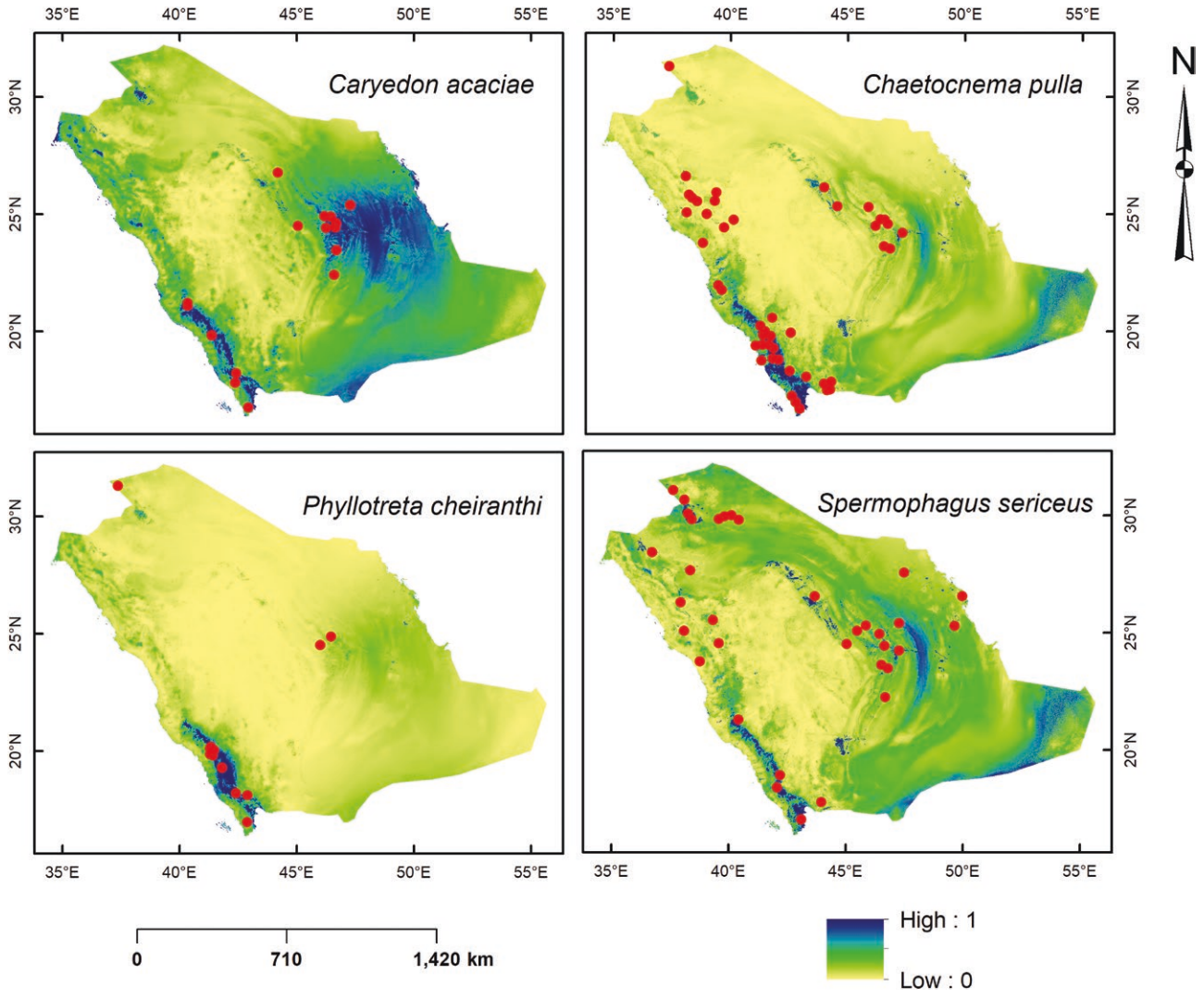

Fig. 4. Occurrence records and current climatic suitability for the 4 beetle species in Saudi Arabia.

environmental variables and occurrence records for the leaf beetle species. This model attempts to predict the geographic distribution of these species based on their suitable climatic conditions. MaxEnt modeling operates on the principle of maximum entropy, which means it produces the most uniform (or least biased) prediction possible while still conforming to the known environmental constraints of species occurrences (Li et al. 2020). This approach helps avoid overfitting and produces more reliable predictions of species distributions based on available environmental conditions (Soliman et al. 2023).

Strong values of both AUC and TSS indicate that the environmental predictors selected, namely temperature, precipitation, and vegetation indices, are adequate for modeling habitat suitability for *C. acaciae*, *C. pulla*, *P. cheiranthi*, and *S. sericeus*. There was a little variation in the robustness of the models between species, with *P. cheiranthi*'s model ranking first place in terms of accuracy.

The study reveals that the 4 species of leaf beetles have varied habitat distributions throughout Saudi Arabia. The distribution patterns are indicative of the general trend that is found in the Chrysomelidae in areas with arid conditions, where climate and vegetation are highly essential factors for habitat suitability. Generally, all beetle species are closely associated with regions offering higher moisture and moderate temperatures. However, notable differences were observed in their geographic distribution across Saudi Arabia. For instance, *C. acaciae* is highly associated with both the lowlands (hotter environments and cooler) and the highlands of the country. The availability of its host plants influences its distribution across both low and high lands, particularly Acacia species like *Vachellia tortilis* (Forssk.) Galasso & Banfi, which thrive in a wide range across varying altitudes (Al-Farhan and Al-Turki 2004, Al-Rowaily et al. 2012). This agrees with the previously reported association of other *Caryedon* spp. with desert-coastal distribution (Delobel, 2017). The bruchid beetles, like *Caryedon* spp., have a high tolerance for temperature variability in diverse habitats (Southgate 1979), so their geographic distribution has been documented in Africa and across the Middle East and Australia (Tuda 2007, Delobel 2012 and 2017).

From the strong association between both *C. pulla* and *S. sericeus* with NDVI, vegetation availability represents a critical driver of their habitat preferences. Indeed, previous studies on Chrysomelidae, such as Linzmeier and Ribeiro-Costa (2013), Sánchez-Reyes et al. (2016), and Lucio-García et al. (2022), demonstrated that leaf beetles, especially those adapted to xeric habitats, strongly rely on vegetative cover for nutritional requirements and protection. Often, these beetles and other related species can be found where vegetation is

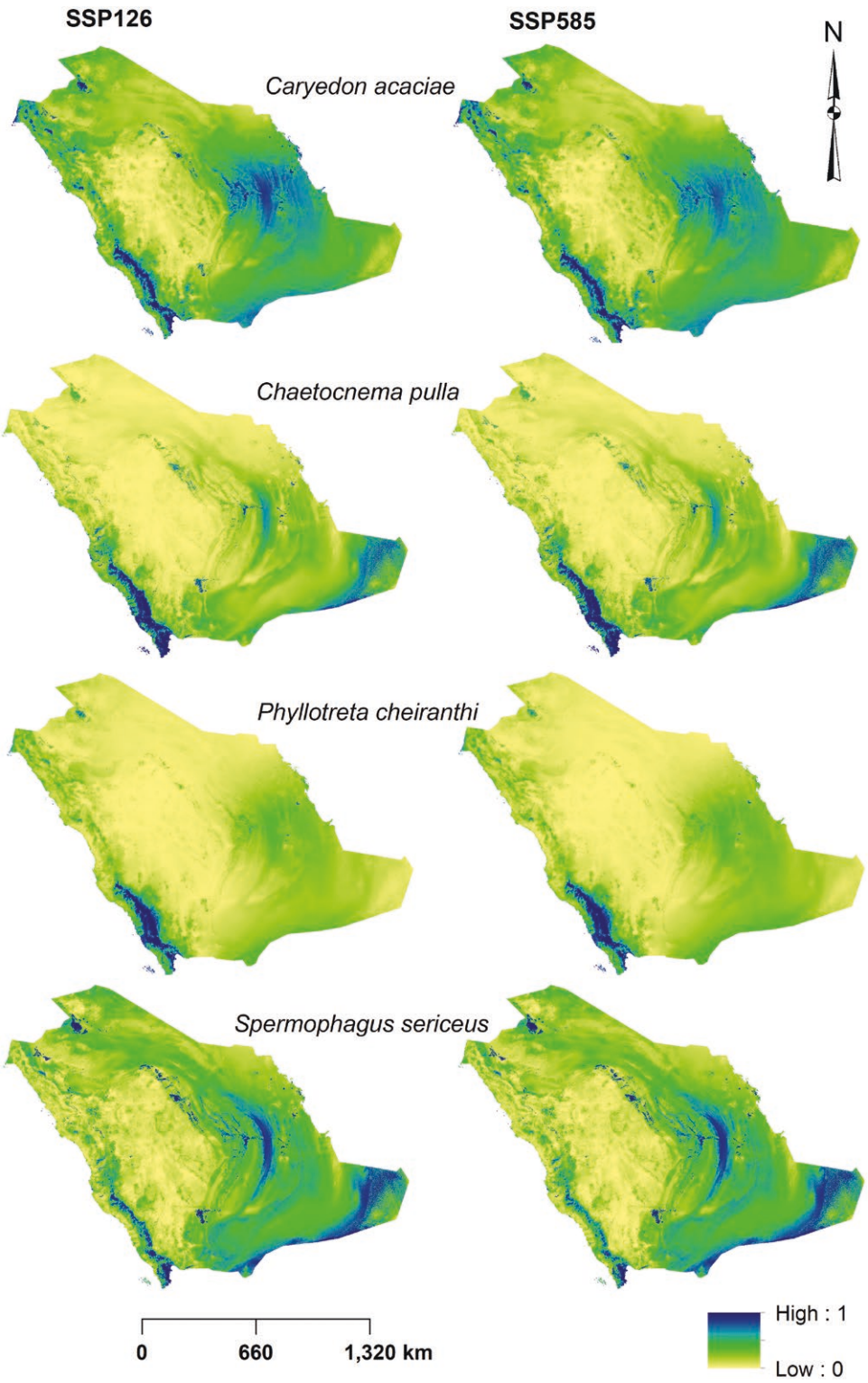

Fig. 5. Projected habitat suitability of the 4 beetle species in Saudi Arabia for the year 2050 (2041–2060) according to SSP126; SSP1-RCP2.6 low emission scenario and SSP585; SSP5-RCP8.5 high emission scenario.

at least moderate, and this often occurs quite frequently in areas where plant communities are highly adapted to oscillations of arid conditions (Austin et al. 2004, Nagler and Glenn, 2013, Gómez et al. 2021).

Concerning *P. cheiranthi*, its distribution was strictly related to the amounts of precipitation, outlining the necessity for places with more predictable moisture and plant resources. This beetle is closely allied with coastal regions, thriving in areas with high precipitation and low temperatures, such as the southwestern parts of Saudi Arabia. Indeed, these regions provide environmental conditions useful for the survival and further reproduction of leaf beetles, hence agreeing with previous local studies on arid-zone beetle distributions

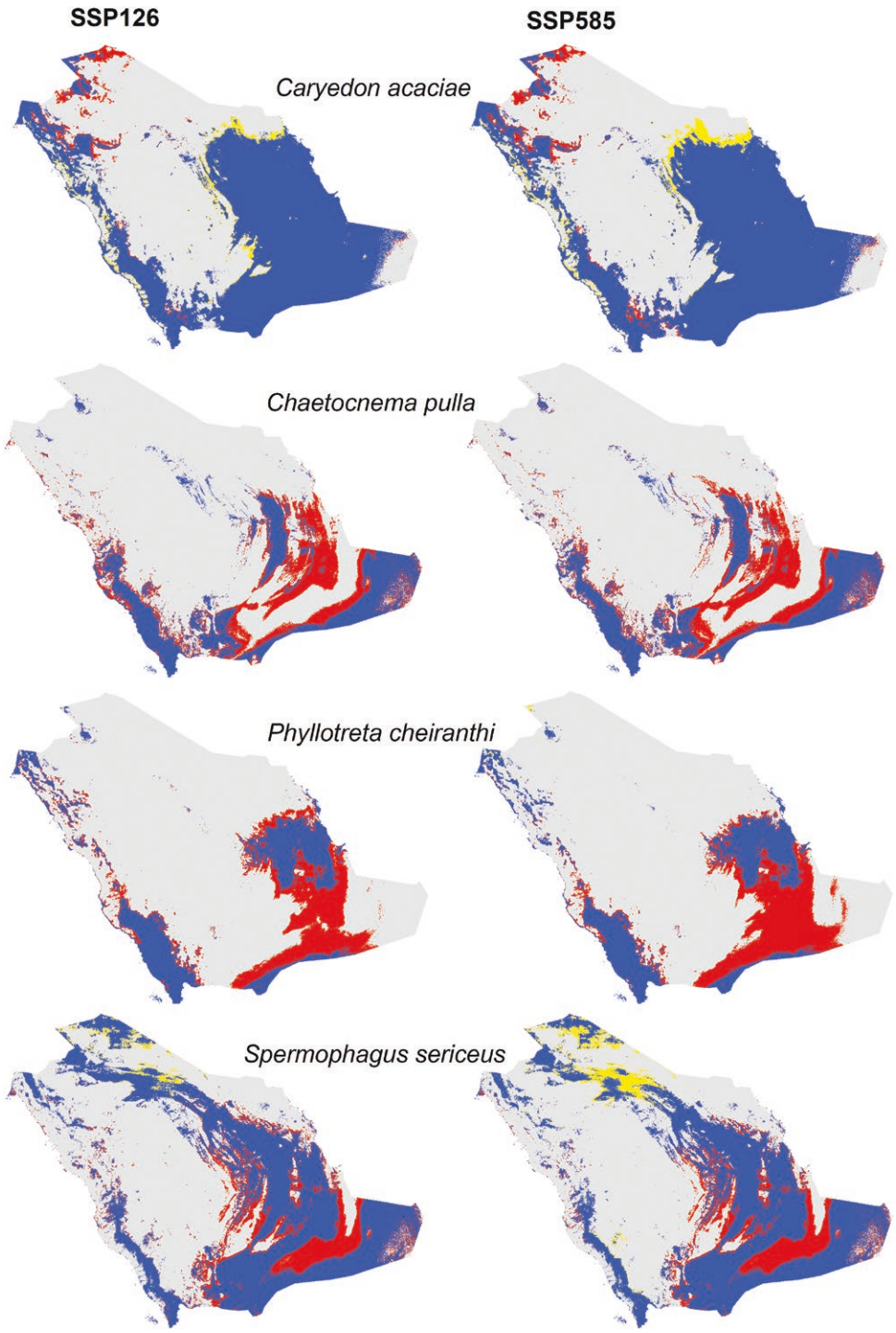

Fig. 6. Summary of the predicted distribution of the 4 beetle species in Saudi Arabia under both current conditions and future scenarios in 2050, exhibiting the modeled distributional changes and contrasts between Shared Socioeconomic Pathways (SSP126 [low emission pathway] and SSP585 [high emission pathway]). Blue denotes agreement between present and future predictions, while red indicates potential expansion, and yellow indicates contraction of distributional areas in the future. This is a simplified binary representation derived from the continuous suitability values shown in Figs 4 and 5. The reader is referred to the web version of this paper for the color representation of this figure.

(Rasool et al. 2017, Ziani et al. 2019, Abdel-Dayem et al. 2020). In these studies, beetles have generally been recorded as more abundant and diverse in cooler, moisture-retentive areas than in hyper-arid zones. This trend suggests that even in arid regions, Chrysomelidae beetles are taking advantage of microhabitats where the vegetation and climatic conditions are more predictable in their resources.

The distribution and abundance of Chrysomelidae insects are significantly influenced by the microclimate. The relationship between microclimate and beetles is not consistent across species (Lucio-García et al. 2022). Certain species, such as *C. acaciae*, are considered generalists because of their ability to tolerate a range of microclimatic conditions (Southgate 1979, Wagner et al. 1984).

Other species, such as *P. cheiranthi*, have a small niche breadth and might be categorized as specialists with more specific requirements for changes in microclimatic conditions. Therefore, specialists can only disseminate in localities with certain environmental conditions (Lucio-García et al. 2022). In general, vegetation acts as an intermediary between the microclimate and the beetles, with different types of plants offering a variety of microclimates that may or may not be suitable for them (Linzmeier and Ribeiro-Costa, 2013). For instance, in the southwestern mountains, beetle species are associated with juniper, acacia, and olive trees, which supply the necessary microclimatic conditions (Rasool et al. 2017, Ghazanfar, 2024). Lucio-García et al. (2022) suggest that extensive vegetation cover can offer shade and maintain the necessary humidity for beetle survival.

The distribution of these species in Saudi Arabia depicts more extensive biogeographical tendencies in the Chrysomelidae of arid regions worldwide. Hence, various studies conducted in arid parts of Africa, Australia, and Central Asia have demonstrated that vegetation cover and seasonal rainfall are the most crucial factors determining the richness and distribution of species (Chen and Wang 1962, Jolivet 2004, Iannella et al. 2021). This reliance on vegetation indices such as NDVI agrees with the outcome of the studies regarding Chrysomelidae in Mediterranean ecosystems, where leaf beetles have been found to thrive in relatively moist, vegetation-rich microhabitats within a largely dry climate. For instance, it is well documented that most of the leaf beetles, especially those of the *Chrysolina* species, are mainly restricted to habitat zones with moderate humidity and partial vegetation cover along river courses or in highland areas where reliable moisture availability can be more reasonably assured in Australia (Adair and Scott 1997). This further corresponds with the southwestern highlands in Saudi Arabia being highly suitable for the leaf beetle species, indicating that the ecological behavior of these species may be similar in arid and semi-arid regions globally.

Future climate change scenarios SSP126 and SSP585 for Chrysomelidae indicate shifting distributions of these species—a pattern that is suggested to be an overall global pattern of climate change to shift the ranges of beetle species in arid and semi-arid environments. In view of that, for *C. acaciae*, the forecast migration into northern regions is in line with predictions of poleward and altitudinal shifts in species distributions with rising temperatures. Such trends have also been recorded concurrently in studies of other insect taxa in Europe and North America, such as defoliating moths, bark beetles, and flea beetles, where species are expected to shift toward cooler and more favorable environments since climates have become more extreme, rising temperatures, and increased incidence of droughts (Olfert et al. 2017, Gómez et al. 2021). This is in contrast to the suitable habitats in the northeast parts of Saudi Arabia under the more extreme SSP585 scenario, which is in line with the global models that predict increased desertification and habitat loss in arid regions. The resulting contraction under such conditions does raise concerns over the long-term viability of Chrysomelidae species adapted to relatively cooler and vegetated environments. This contraction is particularly significant in arid ecosystems and points toward range restrictions for species, loss of genetic diversity, and possible local extinctions (McNeely 2003).

Phyllotreta cheiranthi and *C. pulla* are likely to play an increasingly important ecological role in the Eastern Province and Najran under future climate scenarios. This agrees with a suggestion that species adapted to arid conditions might benefit from future climate change as many regions become more desert-like (Silva et al. 2018). By contrast, *S. sericeus* is predicted to lose some of its areas in certain regions but gain suitable habitats within other regions, especially the eastern and southeastern parts of Saudi Arabia. This result agrees with ecological theories, suggesting that species with narrow habitat requirements suffer most due to climatic shifts but can, at the same time, also exploit new opportunities when conditions turn favorable (Lucio-García et al. 2022). In newly suitable habitats, monitoring programs should be initiated to detect and manage potential outbreaks, thus minimizing economic damage. Furthermore, the habitat contraction of species like *C. acaciae* can result in a reduction in pest pressure in some areas, allowing the revision of pesticide applications and resource allocations.

Native beetles of Saudi Arabia, such as these, might interact with agricultural systems and local vegetation in ways that affect ecosystem dynamics. For instance, Chrysomelidae beetles are known to have varying impacts on native and cultivated plants based on densities and feeding behavior (Tuda 2007). Such an expansion of these beetles to new areas may lead to increased herbivorous pressure on the local plant communities, especially under conditions of aridness that have resulted in sparse vegetation. Also, the introduction of alien beetle species to regions of high biodiversity levels, such as the southwestern highlands, could result in interference in ecosystem relationships, especially competition with other herbivorous insects or modifications in predator-prey relations.

Our models reveal that climate change directly influences these beetle species through mechanisms independent of vegetation shifts. For instance, while *P. cheiranthi* is strongly associated with precipitation in the warmest quarter (65.7% contribution); this relationship extends beyond simple host plant availability. Even in areas where suitable host plants persist, our models predict range contractions where temperature-precipitation combinations exceed the species' physiological tolerances. This is particularly evident in the northeastern regions under SSP585, where despite the predicted presence of Brassicaceae host plants, *P. cheiranthi* shows reduced habitat suitability due to increasing temperature extremes. Similarly, *C. pulla*'s strong response to temperature annual range (34.5% contribution) suggests direct thermal constraints on its biology, as the species shows reduced presence in areas where host plants remain viable but temperature fluctuations exceed its physiological limits. *C. acaciae*'s sensitivity to the mean diurnal range (45.8% contribution) indicates that daily temperature variations directly affect its survival and reproduction, independent of its primary host, *Vachellia tortilis*, which shows broader temperature tolerance. These patterns demonstrate that while vegetation availability remains crucial, climate change directly impacts these species through physiological stress, altered reproductive timing, and modified activity periods.

While our study focused on Saudi Arabia, these findings have important regional implications across the Arabian Peninsula and neighboring regions. The predicted range shifts of these beetle species likely extend beyond Saudi Arabia's political boundaries, particularly along the continuous ecological zones that span multiple countries. For instance, the southwestern mountains of Saudi Arabia are part of a larger highland system continuing into Yemen and Oman, while the eastern coastal regions share similar environmental conditions with other Gulf countries. The predicted expansion of species like *C. pulla* and *P. cheiranthi* into the Eastern Province suggests potential range extensions into similar habitats in neighboring Kuwait, Bahrain, Qatar, and the UAE. Similarly, the suitable habitats identified along the Red Sea coast likely continue into Sudan and Egypt, though verification would require dedicated studies in these regions.

The index of uncertainty is helpful to researchers and conservationists because it indicates where further sampling or refined models could improve prediction accuracy for species

distributions. Here, varying levels of uncertainty were associated with different Chrysomelid predicted distributions across multiple climate models rather than within single model internal uncertainty estimates (Kamal et al. 2018). The highest emissions scenario of SSP585 had higher levels of uncertainty in the maps compared to low-emission SSP126. The fact that the GCMs provide more predictable model projections for all different GCMs under the SSP126 emission pathway signifies a future with global collaboration and sustainable growth. On the other hand, the SSP585 scenario has the greatest uncertainty in climate projections as it describes a future with high CO2 emissions from continued reliance on fossil fuels (Leimbach and Giannousakis 2019) and exhibits unpredictable habitat suitability. Furthermore, species are potentially more ecologically resilient under low emissions, and distribution predictions may show less variance as well (Iverson et al. 2019). However, the consistently high uncertainty in both coastal and mountainous areas, regardless of the emission scenarios, can be recognized as a characteristic of these environments, which exhibit microclimate variability, difficult local topography, and dynamic land-sea interaction, posing challenges for accurate species distribution modeling (Lembrechts et al. 2019). Examining patterns in these uncertainties suggests that while the model had high overall predictive power, there was considerable uncertainty, especially in its predictions for coastal regions along the Red Sea.

A notable limitation of our study concerns the treatment of vegetation cover (NDVI) in future projections. While NDVI emerged as a crucial predictor for all studied species, our models used contemporary NDVI values for future projections due to the challenges of accurately modeling vegetation changes in arid environments. Future vegetation patterns will likely be influenced by complex interactions between changing climate conditions, water availability, land use changes, and human interventions in agriculture and urban development. The absence of projected NDVI changes in our models may affect the accuracy of our future distribution predictions, particularly for species strongly associated with vegetation cover, such as *C. pulla* and *S. sericeus* (which showed 41.9% and 83.8% NDVI contribution to their models, respectively). This limitation underscores the need for a cautious interpretation of our future distribution predictions, particularly in regions where vegetation changes might be substantial. Nevertheless, our results provide valuable insights into potential distribution shifts based on our current understanding of species–habitat relationships and projected climate changes.

Based on our results, the study provides a critical overview of the current and future distributions of 4 Chrysomelidae species in Saudi Arabia: *C. acaciae*, *C. pulla*, *P. cheiranthi*, and *S. sericeus*, under changing climatic conditions. By combining advanced species distribution models with key environmental predictors, we could identify significant habitat suitability patterns that are closely related to vegetation cover and regional climate dynamics. While some species, such as *P. cheiranthi*, would benefit from a range expansion because of future climate scenarios, others, such as *C. acaciae* are at risk of severe habitat contractions, particularly under more extreme climate pathways (SSP585). The findings suggest the need for adaptive pest-management strategies and biodiversity conservation plans since range expansions of various species, especially agricultural pests, could exacerbate local ecological problems and the threat to agriculture. In Saudi Arabia, the loss of forage poses numerous threats to native and migratory wildlife species. To address the ecological and economic impacts of these changes in the context of continuously changing climate conditions, proactive tracking and habitat management will be necessary. Further studies using other environmental drivers and additional samplings would be useful, particularly in zones with high uncertainty rates, such as coastal and alpine areas. This will improve the accuracy of predictions and facilitate better pest control and conservation strategies in a changing climate.

Author contributions

Mahmoud Abdel-Dayem (Conceptualization [equal], Data curation [lead], Formal analysis [supporting], Funding acquisition [supporting], Investigation [lead], Methodology [lead], Validation [supporting], Visualization [equal], Writing—review & editing [lead]), Hathal Al Dhafer (Conceptualization [equal], Investigation [equal], Project administration [lead], Resources [lead], Supervision [lead], Writing—review & editing [equal]), Ahmed Soliman (Data curation [equal], Investigation [equal], Writing—review & editing [equal]), Amin Al Ansi (Data curation [equal], Investigation [equal], Writing—review & editing [equal]), Saad El-Sonbati (Data curation [equal], Investigation [equal], Writing—review & editing [equal]), Alrabea Adam Ebaid Ishag Ishag (Data curation [equal], Resources [supporting], Writing—review & editing [equal]), Amr Mohamed (Conceptualization [equal], Formal analysis [equal], Methodology [equal], Supervision [supporting], Visualization [equal], Writing—original draft [equal], Writing—review & editing [equal]), and Mustafa Soliman (Conceptualization [equal], Data curation [equal], Formal analysis [lead], Investigation [equal], Methodology [lead], Software [lead], Validation [equal], Visualization [lead], Writing—original draft [lead], Writing—review & editing [equal])

Supplementary material

Supplementary material is available at *Journal of Economic Entomology* online.

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Ethics approval

This article does not contain any studies with human participants or animals performed by any of the authors

Consent for publication

All authors read and approved the manuscript.

Data availability

The datasets generated during and/or analyzed during the current study are available from the corresponding author on reasonable request.

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