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Projected Range Shifts of Emerging Agricultural Weeds Under Climate Change in Central Europe

Georg Hörmann[1] | Gilles Colling[1] | Swen Follak[2] | Zdenka Lososová[3] | Jana Bürger[4] | Serge Buholzer[5] | Filip Küzmič[6] | Nina Richner[7] | Urban Šilc[6] | Franz Essl[1] | Michael Glaser[1]

[1]Division of BioInvasions, Global Change & Macroecology, Department of Botany and Biodiversity Research, University of Vienna, Vienna, Austria | [2]Institute for Sustainable Plant Production, Austrian Agency for Health and Food Safety, Vienna, Austria | [3]Department of Botany and Zoology, Faculty of Science, Masaryk University, Brno, Czech Republic | [4]Landscape Ecology, Faculty of Agricultural and Environmental Sciences, University of Rostock, Rostock, Germany | [5]Agroscope, Research Division Agroecology and Environment, Zürich, Switzerland | [6]Research Center of the Slovenian Academy of Sciences and Arts (ZRC SAZU), Jovan Hadzi Institute of Biology, Ljubljana, Slovenia | [7]FORNAT AG, Forschung für Naturschutz Und Naturnutzung, Zürich, Switzerland

Correspondence: Georg Hörmann (georg.hoermann1@gmx.at) | Michael Glaser (michael.glaser@univie.ac.at)

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ABSTRACT

Assessing which weed species are likely to expand under climate change is essential for proactive management. While climate-driven range expansions of many weed species have been documented globally, projections for their future spread in Central Europe remain limited and poorly understood. We used ensemble species distribution models for 23 weed species that are currently emerging in Central Europe to evaluate their climatically suitable areas at present and future time periods (2041–2060, 2061–2080 and, 2081–2100) under four different future climate change scenarios (SSP1-2.6, SSP2-4.5, SSP3-7.0, SSP5-8.5). The climatic suitability of our study area is predicted to increase for all species in the two earlier time periods and under moderate climate change conditions. However, climate change is likely to reduce the potentially suitable area in later time periods and under more severe scenarios. The climatically suitable area is expected to decline or remain stable for 14 of the modelled species, of which two thirds show a decline by 2100, regardless of the climatic trajectory. Furthermore, hotspots of climatic suitability, where multiple emerging weeds overlap are shifting northwest under the two more moderate climate change scenarios, whereas under the two severe climate change scenarios, hotspots are likely to shrink by 2100. Additionally, we found that most of the modelled species whose suitable area increases are C_4 plant species, while those with decreasing suitability are predominantly C_3 plants. Our findings underscore the importance of monitoring and proactive management strategies to mitigate the impacts of emerging weeds, particularly those better adapted to future climatic conditions.

1 | Introduction

Emerging weeds compete with crops for resources such as light, water and nutrients and thus can cause substantial crop yield losses (Milberg and Hallgren 2004; Oerke 2006). Emerging weeds can also have impacts beyond agriculture, such as on human health by the highly allergenic pollen of *Ambrosia artemisiifolia* (Essl et al. 2015) or the highly toxic seeds of *Datura stramonium* (Rojas-Sandoval 2023).

Agricultural fields have long been hotspots for biological invasions (Chytrý et al. 2008). Yet, in recent decades, an increase in the number of emerging weed species on arable land in Central Europe has been documented (Colling et al. 2025; Pyšek et al. 2005)

Franz Essl and Michael Glaser are joint last authors.

and several emerging weeds that are difficult to control have become more widespread in Central Europe (Weber and Gut 2005). Changes in the prevalence and management of certain emerging weeds have largely been linked to changes in agricultural practices (Chytrý et al. 2008; Moss 2017; Storkey et al. 2010).

The spread and impact of emerging weeds is often associated with substantial time lags (Rouget et al. 2016); emerging weeds that are already present could become problematic for agriculture in the future. These species are considered emerging weeds (sensu Seebens et al. 2018), as they are currently spreading and increasing in impact.

Climate change is a major driver of shifts in plant species distributions (Peters et al. 2014; Shabani et al. 2020). It can lead to range expansions, changes in species phenology and population dynamics (Peters et al. 2014). The distribution of emerging weeds is influenced by temperature (Patterson et al. 1999) and may be further amplified by changes in precipitation patterns and increases in drought in many important agricultural areas due to climate change (Ramesh et al. 2017). These predicted effects of climate change pose a growing threat to crop production (Paterson et al. 2017; Ramos et al. 2019; Shabani and Kotey 2016). The changes of the Earth's atmospheric conditions, such as increased CO_2 (Zhu et al. 2016), prolong growing seasons (Mueller et al. 2015) and more drought periods (Naumann et al. 2018), create favourable conditions for weed proliferation and intensify competition with crops. These changes not only affect emerging weeds, but simultaneously cause substantial crop yield losses (Porter et al. 2014). Elevated CO_2 is expected to enhance weed growth by increasing photosynthetic efficiency and water-use efficiency, which can shift the competitive balance in favour of weeds and facilitate their invasion into managed ecosystems (Patterson 1995; Valerio et al. 2013). Climate change tends to favour C_4 emerging weeds over C_3 due to their higher water-use efficiency and better performance under high temperatures and drought conditions (Tubiello et al. 2007). The changing climate and rising CO_2 are creating selective pressures on emerging weeds, encouraging rapid adaptive evolution (Ziska et al. 2019).

Extending these patterns, climate change is expected to facilitate the spread of emerging weeds (Renteria et al. 2021). Through enemy release in new regions (Maron and Vilà 2001), non-native emerging weeds can allocate more resources to growth and reproduction, making them highly competitive (Blossey and Notzold 1995). Rising temperatures and shifting precipitation patterns are driving the spread of emerging weeds to higher latitudes and altitudes (Patterson et al. 1999; Ziska and Dukes 2011). Reduced rainfall and prolonged droughts further suppress crop growth, creating opportunities for drought-tolerant emerging weeds (McDonald et al. 2009; Sreekanth et al. 2023). Additionally, rising atmospheric CO_2 may reduce herbicide efficacy, which could complicate the management of both native and alien herbicide-tolerant emerging weeds (Ziska 2016).

In Europe, surface temperatures in the past decade (2013–2023) were over 2°C above pre-industrial levels and are projected to continue rising - up to 8.5°C (under SSP5-8.5) by 2071–2100 (compared to 1981–2010) at a rate higher than the global average (Masson-Delmotte et al. 2021). These complex interactions between climate change, weed dynamics and land management underscore the need to assess the future distribution of emerging weeds. Understanding these changes will help farmers implement targeted strategies, reduce herbicide use, limit environmental impacts and prevent further spread.

We project the climatically suitable area of 23 emerging weeds in Central Europe under four different climate change scenarios (SSP1-2.6, SSP2-4.5, SSP3-7.0, SSP5-8.5) and for three time periods until the end of the 21st century. We address two main research questions: (1) How will the potential distribution of the 23 selected emerging weeds change in Central Europe? (2) Which areas in Central Europe are at greatest risk from emerging weeds and how will hotspots be affected by climate change? Finally, we examine the broader agricultural implications of our projections.

2 | Material and Methods

2.1 | Study Area

Our study area encompasses Central Europe and adjacent regions: Austria, Croatia, the Czech Republic, Germany, Hungary, Northern Italy (Valle d'Aosta, Piemonte, Lombardy, Trentino-Alto Adige, Veneto, Friuli-Venezia Giulia, Liguria, Emilia-Romagna), Liechtenstein, Slovakia, Slovenia and Switzerland, see Figure 1. The study area covers a total of around 900 000 km^2 and has a temperate climate. The climatic gradient in Central Europe is characterized by oceanic conditions in the west, continental climates in the east and sub-Mediterranean influences in the south. Annual precipitation ranges from less than 450 mm in the driest regions of northern Bohemia and central Germany to over 1000 mm in mountainous areas (Fick and Hijmans 2017). Much of the study area is dominated by mountain ranges, that is, the German 'Mittelgebirge', Bohemian Massif, Northern Apennines, Dinaric Mountains, Western Carpathians and, in particular, the European Alps. Agricultural land is primarily located in valleys and in the forelands of these mountain ranges and in the Pannonian basin (Figure 1). The total arable land in our study area is around 46%. Hungary has the highest percentage of arable land compared to the total land size (55.6%, 50 437 km^2), followed by Germany (47.5%, 165 910 km^2) and the Czech Republic (45.8%, 35 298 km^2), whereas Slovenia has the lowest proportion with 26% (6110 km^2) (World Bank Group 2021).

2.2 | Species Selection

We selected emerging weeds for Central Europe, that is, weeds showing a recent increase in occurrences/abundance on arable land and increasing negative impacts (Glaser, Dullinger, et al. 2024). The selection was based on available literature about species that are likely to increase in the study area (e.g., Hanzlik and Gerowitt 2012), expert assessments and farmer surveys on perceived impacts (Glaser, Essl, Follak, 2024). For these 23 selected emerging weeds we modelled their potential future range in Central Europe (Table 1). The European and Mediterranean Plant Protection Organization (EPPO) lists seven of these species (*A. artemisiifolia*, *Asclepias syriaca*, *Cyperus esculentus*, *Reynoutria japonica*, *Reynoutria sachalinensis*, *Reynoutria ×bohemica*, *Helianthus tuberosus*) in the List of Invasive Alien Plants. Three others (*Amaranthus tuberculatus*, *Amaranthus palmeri*, *Solanum*

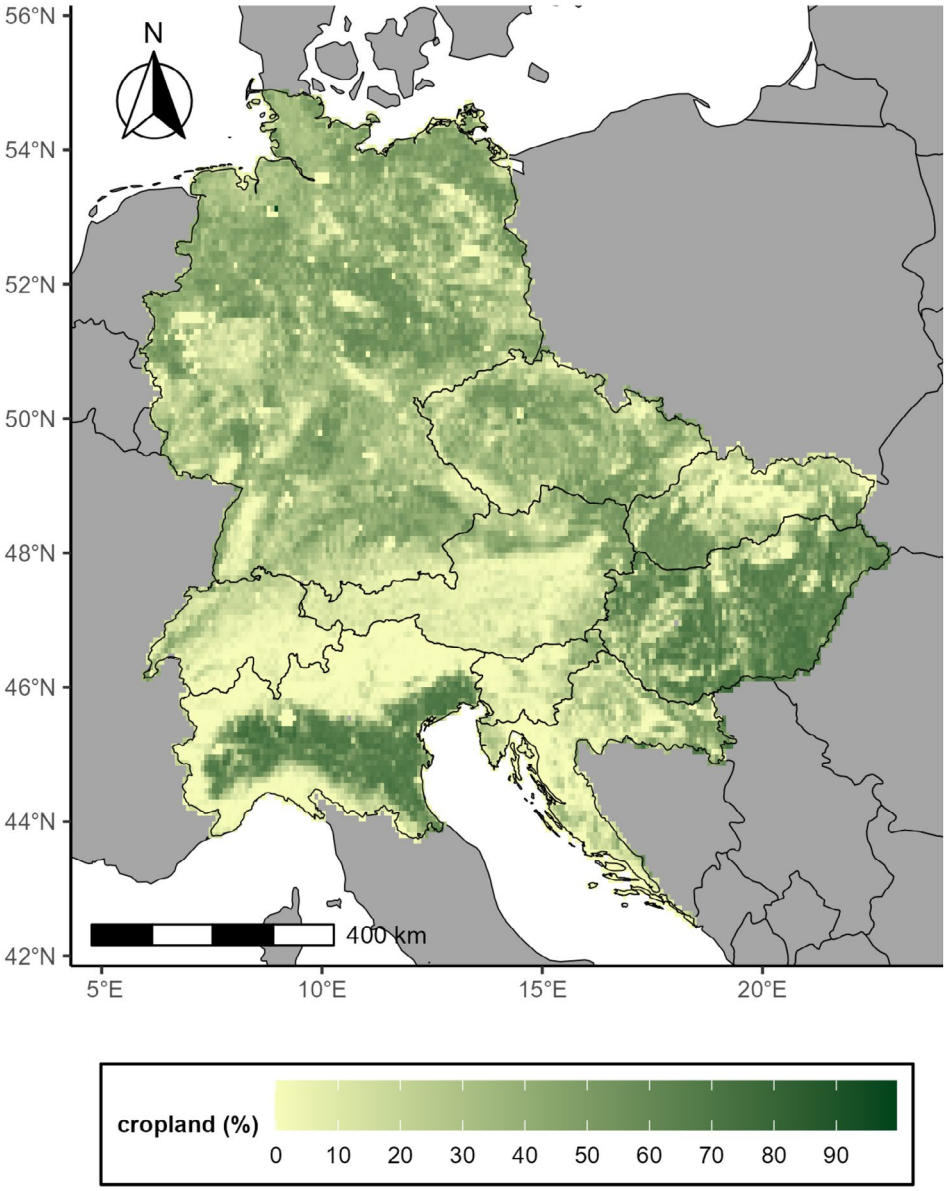

FIGURE 1 | The proportion of arable land (in %) in grid cells of 1 × 1 km size in the study areas, following World Bank Group (2021).

carolinense) are included in the list of pests recommended for regulation as quarantine pests (EPPO 2024). The selected species are highly competitive, grow rapidly, have high reproduction rates and, therefore, have a high potential for causing agricultural damage (CABI 2024). Most of our modelled species are neophytes (18), while only five are native species or archaeophytes. A total of 15 are C_3-plants and eight are C_4-plants (Pyankov et al. 2010).

2.3 | Occurrence Data

Occurrence data of the selected species was gathered from the largest repository of species occurrence data, the Global Biodiversity Information Facility database (GBIF 2024). Initially, we extracted a total of 1 588 212 species occurrence records representing each species' global distribution to avoid sampling only on parts of the species niche (i.e., only records from the study area) (Early and Sax 2014; Fernández and Hamilton 2015; Pearman et al. 2008). To identify and remove potentially erroneous entries, such as records located at biodiversity institutions, country centroids or zero coordinates, we used the 'CoordinateCleaner' package in R (Zizka et al. 2023), which flags common geolocation errors. All other settings from 'CoordinateCleaner' we used on default. Additionally, to mitigate spatial sampling bias, caused by uneven reporting frequencies across regions, we thinned species occurrences using the 'spThin' package on a 1 km scale (Aiello-Lammens et al. 2019). This step helps reduce overrepresentation of well-sampled areas, which can distort SDM outputs in the absence of true absence data. Further it helped to reduce sampling bias by limiting the influence of oversampled regions and increasing spatial independence among occurrence records.

2.4 | Species Distribution Modelling

Species distribution models (SDMs) relate species presence data to environmental variables to estimate areas of potential climatic

TABLE 1 | Modelled species and their attributes: life form is the form of persistence (The = Therophyte, Hem = Hemicryptophyte, Geo = Geophyte) according to Raunkiær (1907), life span (a = annual, p = perennial, b = biennial) is based on Chytrý et al. (2024), biogeographic status in Central Europe (nat = native, neo = neophyte) according to Chytrý et al. (2024) (we note here that some species may be differently classified by different sources/authors), photosynthetic pathway ($C_3 = C_3$ pathway, $C_4 = C_4$ pathway) based on Pyankov et al. (2010).

Family	Taxon	Life form	Life span	Photosynthetic pathway	BioGeo status in EU	First record in study area	Native and global distribution					
							NA	SA	EU	AS	AF	AUS
Malvaceae	*Abutilon theophrasti* Medik.	The	a	C_3	Nat	NA	X	X	X	O	X	X
Amaranthaceae	*Amaranthus palmeri S. Watson*	The	a	C_4	Neo	1908	O	X	X	X	X	
Amaranthaceae	*Amaranthus tuberculatus* (Moq.) J. D. Sauer	The	a	C_4	Neo	1945	O		X			
Asteraceae	*Ambrosia artemisiifolia* L.	The	a	C_3	Neo	1883	O	X	X	X	X	X
Apocynaceae	*Asclepias syriaca* L.	Hem, Geo	p	C_3	Neo	1786	O		X	X		
Cyperaceae	*Cyperus esculentus* L.	Hem, Geo	p	C_4	Nat	NA	O	O	X	O	O	X
Solanaceae	*Datura stramonium* L.	The	a	C_3	Neo	1550	O	X	X	X	X	X
Brassicaceae	*Descurainia sophia* (L.) Webb ex Prantl	The	a	C_3	Nat	NA	X	X	O	O	X	X
Asteraceae	*Helianthus tuberosus* L.	Geo	p	C_3	Neo	1627		X	X	X	X	X
Asteraceae	*Lactuca serriola* L.	Hem, The	a, b, p	C_3	Nat	NA	X	X	O	O	O	X
Poaceae	*Panicum barbipulvinatum* Nash ex Rydb.	The	a	C_4	Neo	1862	O	X	X	X		X
Poaceae	*Panicum dichotomiflorum* Michx.	The	a	C_4	Neo	1889	O	O	X	X		X
Poaceae	*Panicum miliaceum* L.	The	a	C_4	Neo	1864	X	X	O	X	X	X
Poaceae	*Panicum schinzii* Hack.	The	a	C_4	Neo	1980			X	X	O	
Phytolaccaceae	*Phytolacca americana* L.	Hem, Geo	p	C_3	Neo	1700	O	X	X	X	X	
Polygonaceae	*Reynoutria japonica* Houtt.	Geo	p	C_3	Neo	1870	X		X	O		X
Polygonaceae	*Reynoutria sachalinensis* (F. Schmidt) Nakai	Geo	p	C_3	Neo	1869	X		X	O		X
Polygonaceae	*Reynoutria ×bohemica* Chrtek & Chrtková	Geo	p	C_3	Neo	1946	X		X	O		
Solanaceae	*Solanum carolinense* L.	Hem	p	C_3	Neo	1985	O		X	X		
Poaceae	*Sorghum halepense* (L.) Pers.	Hem, Geo	p	C_4	Neo	1853	X	O	X	O	O	X
Asteraceae	*Xanthium orientale* agg. L.	The	a	C_3	Neo	1850	O	O	X	O	X	

(Continues)

TABLE 1 | (Continued)

Family	Taxon	Life form	Life span	Photosynthetic pathway	BioGeo status in EU	First record in study area	Native and global distribution				
							NA	SA	EU	AS	AF	AUS
Asteraceae	*Xanthium sibiricum* Patrin ex Widder	The	a	C_3	Neo	1952			O	O	O	X
Asteraceae	*Xanthium strumarium* agg. L.	The	a	C_3	Nat	NA			O	O	O	O

Note: First Records of the species in the study area with the year of the first record according to Seebens et al. (2017) and the native range and current global distribution (O = native, X = current distribution, NA = North America, SA = South America, EU = Europe, AS = Asia, AF = Africa, AUS = Australia) following POWO (2024). Nomenclature and taxonomy follow POWO (2024).

suitability. These relationships are then projected across geographic space to identify regions where climate conditions may support the species' occurrence (Elith and Leathwick 2009; Franklin and Miller 2010; Guisan and Thuiller 2005). With such models and the data available for them, it is not possible to model the realized niche of each species, which is why we only modelled the physiological niche in this study. For our models we used raster-based data for spatially explicit predictions on future climate scenarios, including multiple variables, resulting in a raster of occurrence probabilities. A range of SDM methods exist, each based on different assumptions and statistical methods, which can lead to substantially different predictions depending on the modelling approach and data structure (Guisan et al. 2017; Peterson et al. 2011). To avoid the pitfalls of individual SDM methods, we used ensemble models that provide an integrated perspective by combining multiple modelling techniques (Araújo and New 2007; Friedman and Popescu 2008; Seni and Elder 2010) using the R package 'biomod2' that uses twelve different models (Thuiller et al. 2024). Since most SDM algorithms rely on both presence and absence data to differentiate suitable from unsuitable conditions, we generated pseudo-absences to compensate for the lack of true absence records. This approach allowed us to apply presence–absence modelling techniques within the biomod2 ensemble framework, which includes algorithms such as GLM, GAM and Random Forest that require binary response data. The selection of pseudoabsences (method and amount) has been shown to potentially substantially influence model results and accuracy (Iturbide et al. 2015; Wisz and Guisan 2009). To achieve the highest possible accuracy, we followed the approach of Barbet-Massin et al. (2012) and selected the same number of randomly placed pseudoabsences to the number of occurrences used for modelling. Finally, we assigned equal weight to presence and pseudoabsence data points to ensure balance in model training (Barbet-Massin et al. 2012). We assessed the predictive performance of each model by splitting the occurrence data, using 80% of the occurrence data for calibration and the remaining 20% for evaluation (Kumar et al. 2014; Lozano et al. 2020; Tang et al. 2019). We created ensemble suitability predictions by model averaging, using the Boyce Index of every individual model as weight, as a threshold-independent evaluator for our SDMs predictions (Hirzel et al. 2006; Di Cola et al. 2017). We projected the ensemble models to current and future scenarios of climate change using bioclimatic variables, which represent temperature and precipitation-based predictors relevant to plant distributions. More detailed information on the ensemble SDMs is provided in Table S1, following the ODMAP protocol by Zurell et al. (2020).

A careful selection of bioclimatic variables is important to obtain better and more realistic prediction models of weed distributions (Sheppard 2013). We retrieved 19 bioclimatic variables from the WorldClim Global Climate database (WorldClim 2023) with a high spatial resolution of 30 arc-seconds (~1 km^2). From this initial set, we retained four bioclimatic variables: BIO1 (Annual Mean Temperature), BIO6 (Min Temperature of Coldest Month), BIO10 (Mean Temperature of Warmest Quarter) and BIO18 (Precipitation of Warmest Quarter)—chosen because they represent key gradients of thermal stress, thermal opportunity and water availability that are known to strongly influence plant distribution (Root et al. 2003). As most of the modelled species are thermophilic and characterized by rapid growth, the chosen variables specifically capture

conditions during critical phases of establishment and reproduction. For all subsequent modelling analyses, only these four bioclimatic variables (BIO1, BIO6, BIO10 and BIO18) were included. To avoid issues with collinearity among predictors, we selected the largest possible subset of the chosen variables for every species with a Pearson correlation coefficient below 0.7 (Dormann et al. 2013). We parametrized our models on the climatic average from 1970 to 2000. To capture the full range of climate change, we used four different climate change scenarios until the end of the 21st century ranging from mild (SSP1-2.6) to severe (SSP5-8.5) climate change. The assumption for SSP1-2.6 is that global warming would increase the average temperature by 1.7°C between 2041 and 2060 and by 1.3°C–2.4°C between 2081 and 2100. For SSP5-8.5 it is assumed that global warming increases average temperature by 2.4°C (2041–2060) and by 3.3°C-5.7°C between 2081 and 2100 (O'Neill et al. 2017; Riahi et al. 2017). We modelled future potential species distributions for three time periods (2041–2060, 2061–2080, 2081–2100).

2.5 | Definition and Identification of Potential Future Hotspots

We produced risk maps through binarizing the results of ensemble projections with the Boyce Index as a cutoff and then summed up for every combination of climate scenario and time step. We evaluated the potential suitability of a species under the future climatic scenarios in relation to the current climatic conditions by comparing the predicted areas. We examined the location and distribution of current and future hotspot areas, defined as grid cells suitable for at least 75% of the modelled species (more than 18 species).

3 | Results

3.1 | Performance of Species Distribution Models

Given the complexity of modeling potential range shifts of 23 species across four future climate scenarios and four time steps, we focus here on the two most extreme scenarios (SSP1-2.6 and SSP5-8.5) to capture the range of possible outcomes. All ensemble models calibrated well, with a mean Boyce Index above 0.92, highest for *Reynoutria japonica* (0.99) and lowest for *Helianthus tuberosus* (0.75), indicating adequate model performance (Hirzel et al. 2006). Based on the four chosen bioclimatic variables, the minimum temperature in the coldest month (BIO6) showed the highest variable importance (for nearly two thirds [15] of the species), followed by the mean annual temperature (BIO1, in 7 species) and the mean temperature of the warmest quarter (BIO10, in one species). BIO18 (precipitation of the warmest quarter) was never the most important variable for any of the modeled species (Figure 2). These results indicate that, among the four bioclimatic variables considered, minimum temperature in the coldest month and mean annual temperature had the strongest influence on the potential suitability of our modeled species.

3.2 | Climate Response of the Modelled Species

Under current climate conditions, *Abutilon theophrasti* and *Descurainia sophia* have the largest potentially suitable areas (94.4% and 94.3% of the study area), while *Solanum carolinense* and *Xanthium sibiricum* have the smallest (1.2% and 2.0%). When considering all 23 modelled species, the mean area of current potential suitability based on the four chosen climatic variables is 58.4% (for details on all scenarios see Figure S2). However, potential predicted ranges varied substantially between the species. In response to moderate climate change (SSP1-2.6), the highest increase in suitability are predicted for *Amaranthus palmeri* (+40% of the study area), *Phytolacca americana* (+27%) and *Cyperus esculentus* (+21%) until 2100. In contrast, *Panicum miliaceum* (−12%), *Panicum barbipulvinatum* and *Datura stramonium* (both −8%) showed the largest decreases. Six species showed decreases whereas 10 showed an increase in their potentially suitable areas and seven remained stable (< ±+2% change), under SSP1-2.6 until 2100. Under severe climate change (SSP5-8.5), however, eight species are projected to decline (ranging from −4% to −82%), while nine are projected to increase (ranging from +3% to +50%) and seven predicted to remain stable (< ±2% change), until 2100. Similar to SSP1-2.6, the highest increases in potentially suitable areas are projected for *A. palmeri* (+50%), *P. americana* (+28%) and *C. esculentus* (+25%). In contrast, the largest declines are predicted for *R. japonica* (−82%), *D. sophia* (−68%) and *Ambrosia*

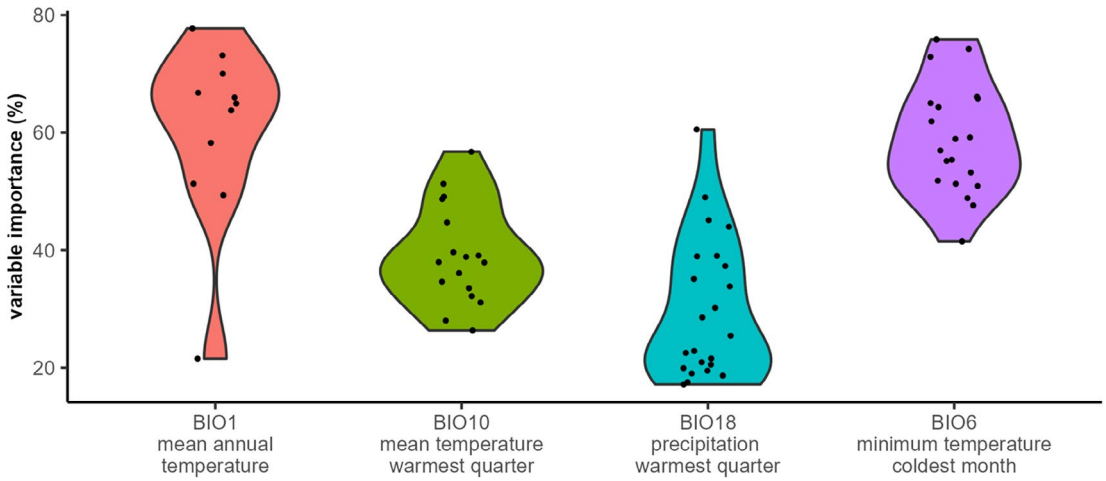

FIGURE 2 | Variable importance of the four bioclimatic variables of the modelled species used in the analyses. For improving readability, points have been jittered.

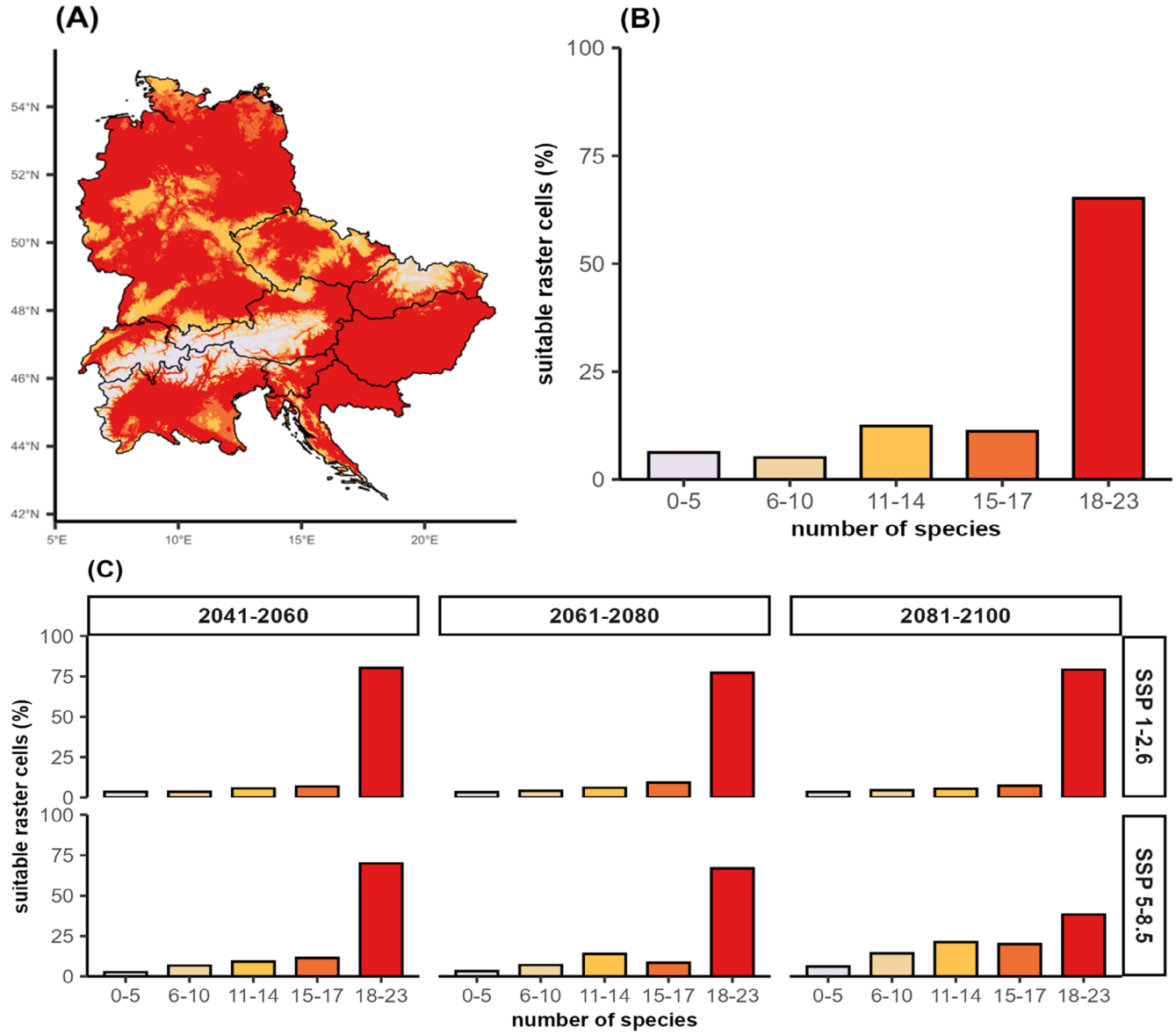

FIGURE 3 | (A) Cumulative map of climatically suitable areas of 23 emerging weeds under current (1970–2000) climate. Darker colours indicate higher number of species per grid cell. (B) Proportion of raster cells that are suitable for different numbers of the study species (*x*-axis) under current climate. (C) Proportion of climatically suitable raster cells under two different climate change scenarios and for three different time periods until the end of the 21st century.

artemisiifolia (−57%). Across scenarios, 39% of species (9) gain climatic suitability by 2100, 22% (5) remain stable and 39% (9) decline. At present, 65.2% of the study area is suitable for >18 species, whereas only 2.3% is unsuitable for all (Figure 3, for details on all scenarios see Figure S3). Under the low-emission pathway SSP1-2.6, these suitable zones expand continuously until 2100, whereas under SSP5-8.5 they contract earlier and markedly. *D. sophia* shows the steepest decline, especially under SSP5-8.5. Instead, *A. palmeri*, *Panicum schinzii* and *P. americana* experience major suitability expansions in every scenario.

Most C_4 species (e.g., *Sorghum halepense*, *P. schinzii*, *Amaranthus tuberculatus*, *A. palmeri*, *C. esculentus*) are projected to expand their suitable geographic range, particularly until 2080 under all SSPs, with the exception of *P. miliaceum*. By comparison, projections for some C_3 species (e.g., *Asclepias syriaca*, *Xanthium orientale*) show early gains (2041–2060), but later declines, especially in southern regions. By 2100, six of eight C_4 species are projected to gain suitable area under all scenarios, compared to only three of 15 C_3 species. Among the nine species losing projected suitable area, seven are C_3 and two are C_4. Stability in suitability is seen in five species, four of which are C_3. Finally, for all modelled species notable increases in suitability were projected in the Alpine Mountain regions and to the north of the Alpine ridge.

3.3 | Hotspots of Emerging Weeds

Under current conditions, much of the study area, especially the south, is predicted to be suitable for >18 species (Figure 3A), as estimated from our ensemble models (BIO2,

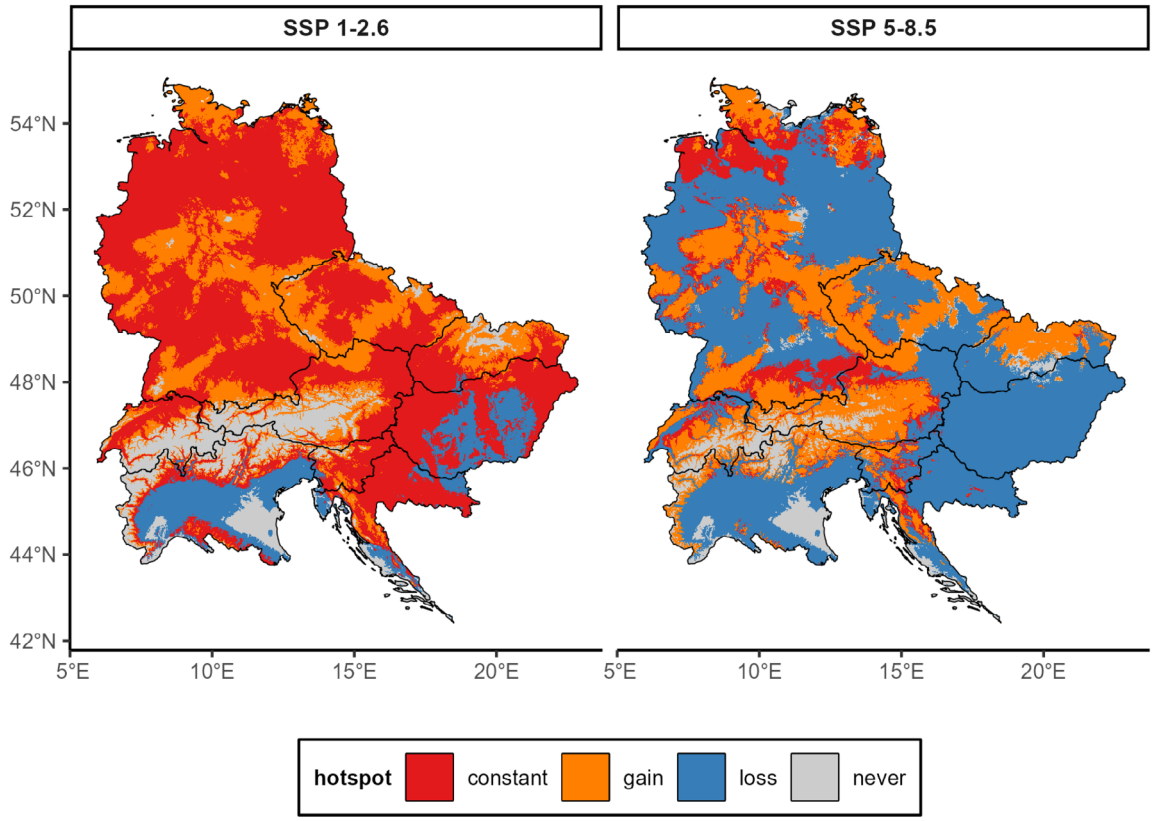

FIGURE 4 | Projected hotspot changes under mild (SSP 1–2.6) and severe (SSP 5–8.5) climate change in 2100 compared to current climate, colours corresponding to changes: 'constant' (red): hotspot currently and in 2100, 'gain' (orange): no hotspot in current climate, hotspot by 2100, 'loss' (blue): current hotspot but no future hotspot, ''never' (grey): hotspot neither in current nor future climate.

BIO4, BIO10, BIO18). However, these species are projected to lose suitability by 2100, while others like *A. palmeri* and *P. schinzii* are predicted to contribute increasingly to hotspot formation. Hotspot extent increases under all scenarios until 2041–2060. Under SSP1-2.6, this growth continues through 2061–2080 before declining by 2081–2100 to levels comparable to present conditions. Under SSP5-8.5, declines start after 2041–2060 and intensify by 2100 (Figure 3C), when most areas are suitable for only 6–15 species. Major declines are projected in Northern Italy, much of Hungary, Slovenia, Croatia and parts of the Czech Republic. Conversely, predicted suitability in the Alps rises from 2041 to 2060, beginning in inner-Alpine valleys and expanding to mountainous regions by 2081. By 2100, areas north of the Alps are projected to become highly suitable for many species, posing increased risk (Figure 4, for details on all scenarios see Figures S4 and S5). The Alps will see rising suitability, especially during 2061–2080 and 2081–2100, while southern areas like the plains of Northern Italy will decrease in suitability. North of the Alps, > 18 species could establish under all SSPs. Regardless of scenario, predicted suitability increases substantially in the near future (for details on all scenarios see Figure S1).

The size of hotspot areas is projected to decline by 2100 (Figure 5) as well, similarly to the decline of species suitability. The largest declines are also under the conditions of SSP5-8.5, while under the conditions of SSP1-2.6, the proportion of cropland in hotspots remains stable until 2100, only showing a minor decrease around 2080. The highest share of cropland in hotspot areas is projected to occur under SSP3-7.0 by 2030, with more than 80%.

4 | Discussion

In our ensemble modelling approach, we projected the current and future potential climatically suitable area of 23 emerging weeds in Central Europe using four key bioclimatic variables (BIO2, BIO4, BIO10, BIO18) and species occurrence data from GBIF. The models indicated increasing suitable areas in the near future and decreasing suitable areas later, especially under severe climate change. Species' contributions to hotspot regions changed over time, with species currently showing lower suitability beginning to contribute substantially to hotspot formation in later time periods. With warming up to 5.8°C, both hotspot and arable land areas are likely to shift substantially, intensifying pressure on already limited land resources. These changes, driven by shifting weed dynamics under climate change, are likely to pose major challenges for land management and agricultural productivity.

4.1 | Limitations of the Study

Apart from climate, many factors will influence the distribution of the 23 modelled species, such as dispersal (Lawton 2000),

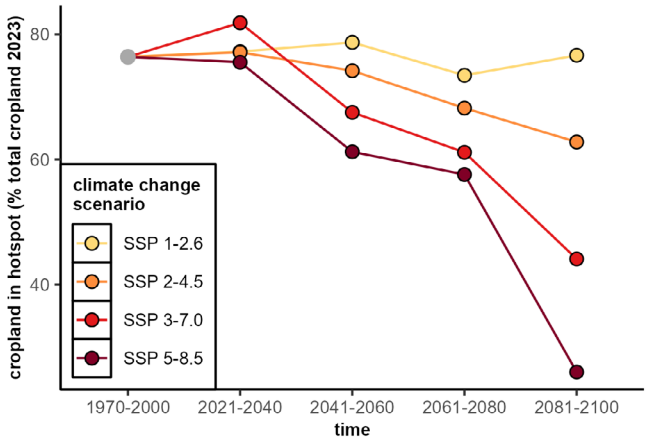

FIGURE 5 | Projected changes in the proportion of Central European cropland overlapping with hotspots (areas suitable for > 18 species out of 23 modelled species) under four future climate change scenarios (SSPs) across four future time periods. Values are expressed as a percentage of total cropland area in 2023.

competition (Davis et al. 1998; Mack 1996) and disturbance (Guisan and Thuiller 2005). Specifically in arable habitats, management practices play a significant part in avoiding the occurrence and invasion by emerging weeds, for example through choice of cultivated crops and crop rotations or respecting field hygienic measures to prevent the dispersal between fields through machinery.

As these factors are hard to incorporate into SDMs (Guisan et al. 2017), we restricted our conclusions to those clearly supported by our chosen method, ensemble SDMs. Current species distribution modelling methods do not account for how weeds will adapt to novel climate conditions or how farmers will change their cropping systems, potentially leading to an overestimation of the effect of future climate on weed distribution (Early and Sax 2014; Fitzpatrick and Hargrove 2009). Further, because it is not possible to model the realized niche of a species, these modellings focus on the physiological niche of the species. Nevertheless, SDMs are essential for assessing potentially suitable areas and invasion risks (Barbet-Massin et al. 2018; Runquist et al. 2019).

As warming intensifies, many regions in Central Europe may face climates similar to those in today's southern Europe or even parts of North Africa (Bulut et al. 2025). Southern Germany, for instance, could experience conditions like those in Lombardy, Italy (Fitzpatrick and Nakov 2019). A world with up to 5.8°C of warming would see major shifts—not only in climate and land use, but also in many interconnected natural and human systems. While such changes would impact the dynamics studied here, capturing their full complexity lies beyond this study's scope.

4.2 | Projected Species Range Shifts Under Climate Change

Our results indicate that predicted climatically suitable areas of most of the modelled species will shift to higher altitudes (from the mountain valleys to higher elevations, i.e., in the Alps) and higher latitudes (shifting northwards, i.e., from Northern Italy to Germany), especially under more severe future climate change. Some of the studied species are already found north of the Alps (e.g., *A. artemisiifolia*, *D. stramonium*), whereas others are assumed to spread northward in the future. These possible shifts may occur through natural dispersal, however anthropogenic dispersal is more likely to play a dominant role (Ansong 2024) particularly via agricultural practices, roadsides and contaminated agricultural machinery and equipment (Petit et al. 2013). Consequently, the locations of hotspots of emerging weeds are also moving northwards. Furthermore, in the southern regions (i.e., Northern Italy, Croatia, Slovenia, Hungary) the potentially suitable areas will decrease for some species, particularly in later time steps, presumably due to extreme heat and drought. In line with our findings, Bellard et al. (2013) projected a decline in invasive alien plants in the future in south-west Europe under climate warming. This trend, characterized by an increase in the near future followed by a decrease in the distant future, has also been shown in various contexts worldwide (Cunze et al. 2013; Taylor et al. 2012; Wei et al. 2017). Rising temperatures are likely to promote range expansions of thermophilic species (Ju et al. 2015; Sobrino Vesperinas et al. 2001), as shown in our results for species such as *A. tuberculatus* or *C. esculentus*. This is further underscored by the high variable importance of BIO6 (minimum temperature of coldest month) and BIO1 (mean annual temperature) for our modelled species. The same trend is also reflected in the projections of the species predominating the future hotspot areas. Under current climate conditions, *D. stramonium*, *A. theophrasti* and *D. sophia* are among the dominant species shaping hotspot patterns but are projected to decline under all scenarios by 2100. These projections are driven by climate alone and do not incorporate biotic interactions (e.g., competition among weeds or impacts of natural enemies), nor land use change, what can further constrain or facilitate range shifts and alter hotspot composition of emerging weeds (Guisan and Thuiller 2005).

4.3 | Increasing Competitive Advantage of C_4 Species and Neophytes Under a Warmer Climate

Of the 23 emerging weeds modelled, eight follow a C_4 pathway and 15 a C_3 pathway. The majority of the C_4 weeds of this study show gains in climatic suitability compared to the C_3 species, which show mainly losses or remain stable. Furthermore, most of the species projected to predominantly shape future hotspot areas are C_4 species. Under elevated temperature, plants with a C_4 photosynthetic pathway outcompete crop plants with a C_3 pathway (Yin and Struik 2008), because C_4 weeds are better adapted (Sreekanth et al. 2023). Simultaneously, the most important crops in the study area are C_3 plants (e.g., common wheat, spelt, barley, potatoes, sugar beets, canola, sunflower, soybean), with the main exception being maize as a C_4 plant. These findings suggest a competitive advantage for C_4 pathway weeds, potentially causing greater competitive imbalance, damage and yield losses, depending on the crops planted. Since C_4 plants are climatically more competitive, they could also become more resilient to management methods.

Among the 23 modelled emerging weeds, 18 are neophytes and five natives (incl. archaeophytes). Several, such as *S. carolinense* and *A. artemisiifolia*, have already expanded in arable fields in parts of the study area and are continuing to do so (Follak et al. 2017, 2023). They have shown large range expansions in the past (Glaser, Dullinger, et al. 2024) for the past and many neophytes are listed on pertinent watchlists (EPPO 2024) as they pose a substantial threat for agricultural production.

4.4 | Projected Future Hotspots and Affected Agricultural Areas

Many regions north of the Alps are predicted to offer high climatic suitability for more than 18 of the emerging weeds under current and future conditions. These areas should therefore be prioritized for monitoring. Southern Germany, northern Switzerland and north-western Austria are threatened by > 18 species, regardless of the climate change scenario. These regions are important for agricultural production (Statistik Austria 2021; Statistische Ämter des Bundes und der Länder 2010). Furthermore, nearly 46% of the land area of the Czech Republic is used for agriculture (World Bank Group 2021), which will also be at high risk of negative impacts from these species in the future.

Under mild climate change, more arable land falls within hotspot areas of emerging weeds, but species' potential ranges change little. Farmers will face these new weeds, which will also lead to adjustments and changes in management. In addition, more than half of the areas that were considered highly productive in the past are no longer as productive due to periods of drought (Torbensen et al. 2024). Severe climate change is likely to lead to major shifts in the distribution of species.

4.5 | Implications for Farmers

The results of this study raise awareness among farmers regarding the first occurrences consequences of emerging weeds and the influence of climate change. For species encountering favourable climatic conditions in specific regions, nascent populations must be targeted for control before they establish and spread (Moody and Mack 1988). Existing populations must be rigorously controlled using all applicable weed management strategies (e.g., EPPO (2021), for *A. artemisiifolia*). Continuous monitoring of these species remains imperative, particularly with respect to their occurrence and potential expansion. Adapting agricultural practices in response to the impacts of climate change could help farmers to maintain resilience against emerging weeds.

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Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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Supporting Information

Additional supporting information can be found online in the Supporting Information section. **Table S1:** Summary table with information on the calculated species distribution models ('biomod2') following the ODMAP protocol by Zurell et al. (2020). **Figure S1:** Suitability changes under all different scenarios (SSPs) and three different time steps. **Figure S2:** Percentage of suitable raster cells in the study area per modelled species under different climate change scenarios (per panel) and time periods (in yellow, current time period repeated in every panel in grey). **Figure S3:** Proportion of climatically suitable raster cells under four different climate change scenarios and for three different time periods until the end of the 21st century (2081–2100). **Figure S4:** Projected changes in location and extent of hotspots under four climate change scenarios (SSPs) in 2100 compared to current climate, colours corresponding to changes.