Senecio inaequidens DC. will thrive in future climate: A case study in a Mediterranean biodiversity hotspot

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ABSTRACT

Monitoring the expansion of invasive non-native plants under current and future climatic conditions is crucial for understanding biodiversity threats, addressing the ecological impact, and developing effective management strategies. This study focuses on modelling the expansion and distribution of *Senecio inaequidens* DC. on the island of Sardinia (Italy) to address these environmental challenges. The objectives were to identify bio-climatically suitable areas under current conditions, project potential future distribution, and evaluate invasion dynamics on the island to localize suitable areas for effective management strategies.

Species data were collected from 1991 to the present, supplemented by global databases and analyzed using an ensemble species distribution model approach. This approach utilized presence data, high-resolution current bioclimatic variables (40 m^2), developed explicitly for our study area, and two future scenarios derived from the newly Coupled Model Intercomparison Project Phase 6 (CMIP6) under Shared Socio-economic Pathways (SSP2–4.5 and SSP5–8.5 for 2040 and 2060).

The ensemble model's findings suggest a close alignment between the currently documented occurrences of *S. inaequidens* and its bio-climatically suitable habitats in Sardinia. Moreover, predictions indicate high bioclimatic suitability for *S. inaequidens* in the western and southwestern coastal regions, contrasting with its known occurrences at higher altitudes. Notably, the model also forecasts high bio-climatic suitability across most small islands surrounding the region and in central-east Sardinia, potentially indicating habitats at lower altitudes compared to current records.

Under the SSP2–4.5 scenario, suitable areas are expected to nearly double by 2040 and more than double by 2060, compared to current conditions. Under the SSP5–8.5 scenario, the increase in suitable habitats is projected to be about 83.31% by 2040 and more than double by 2060. These results highlight the species' ability to thrive under climate change, with a more pronounced range expansion under the pessimistic management regime (SSP5–8.5) than under the intermediate one (SSP2–4.5), particularly in the central region of the island. This expansion under the more severe management scenario is particularly alarming as it reflects limited implementation of environmental management policies.

The study underscores the potential ecological risk posed by *S. inaequidens* due to its potential range expansion and ability to invade different habitat types, from coastal regions to mountainous areas, under current and future scenarios. Based on these findings, we propose targeted management actions for monitoring and eradicating the species, leveraging prior information and local experiences to mitigate its impact.

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1. Introduction

Invasive non-native species pose significant challenges to nature conservation, with newly established invasive species rapidly increasing worldwide (Seebens et al., 2018, 2021). Addressing the invasion of non-native taxa is an environmental challenge that requires effective predictive tools for assessing invasion dynamics (Buchadas et al., 2017). Identifying areas at risk of invasion is a management priority (Catterall et al., 2012; Henry et al., 2023; Vicente et al., 2016). To prioritize efforts and prevent future introductions that could harm biodiversity and ecosystem functions and services, global agreements such as the Convention on Biological Diversity (2022), IPBES (Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services, Roy et al., 2023), and European legislation (e.g., Regulation (EU) No. 1143/2014) are implementing countermeasures to control or eradicate invasive species and manage pathways to prevent the introduction and establishment of new invasive non-native species. These policy commitments can be supported by standardized and replicable tools implemented at different scales to achieve early detection, monitoring, and mapping (Lazzaro et al., 2016).

In this context, species distribution models (SDMs) serve as valuable tools for predicting the relative suitability of habitat when introductions occur outside the native range (Broennimann and Guisan, 2008; Chapman et al., 2019; Sofaer et al., 2019). Additionally, SDMs are recognized as efficient and replicable tools to forecast potential habitats under both current and future scenarios (Davis et al., 2024; Espíndola et al., 2012) supporting eradication and monitoring attempts (Vicente et al., 2013) even when based only on climatic predictors.

Climate is frequently deemed a critical factor for species' habitats and exhibits a stronger correlation compared to other factors (Luoto et al., 2007; Mandle et al., 2010), such as altitude and latitude (Austin, 2007). Other environmental factors, like soil type, undergo changes at varying rates over time (e.g., geologic timescales) and cannot be discernible within the timeframe of climate projections typically utilized in species distribution studies (Stanton et al., 2012). Remote sensing-derived factors, such as land cover classifications and productivity measures, have been demonstrated to be useful for estimating current species distributions (Buermann et al., 2008; Zimmermann et al., 2007) if available at high spatial resolutions (Bucklin et al., 2015; Shirley et al., 2013). Predicting changes in land cover at this resolution can be difficult because its patterns result from a confluence of many other factors (i.e., resource demand, human population density and available technology) (Stanton et al., 2012) which also influence the climate-system.

The concurrent effects of climate and these related factors have been implemented in an integrated framework within the sixth phase of the World Climate Research Program Coupled Model Intercomparison Project (CMIP6; Eyring et al., 2016) for developing a new generation of alternative plausible scenarios that covers a wide range of future climate forcing and trajectory of global environmental changes (Gidden et al., 2019; Hurtt et al., 2020; IPCC, 2023; Meinshausen et al., 2020; O'Neill et al., 2016; van Vuuren et al., 2017). These scenarios combine new datasets on emissions and concentrations (Meinshausen et al., 2020; Riahi et al., 2017), land use change (Hurtt et al., 2020; Popp et al., 2017), human population dynamics, other anthropogenic drivers and environmental policy implementation, harmonizing with the Shared Socioeconomic Pathways (SSPs), and the Representative Concentration Pathways (RCPs) previously described (Gidden et al., 2019). Supporting the Sixth Assessment Report (AR6) of the Intergovernmental Panel on Climate Change (IPCC, 2023) as well as other national and international assessments or special reports (Eyring et al., 2016), such scenarios can enable a new generation of biological studies by elucidating the consequences and impacts of future developments in absence of new climate policies beyond those in place today (Lenzner et al., 2019; Pörtner et al., 2021; Riahi et al., 2017).

The assessment of range expansion holds paramount importance in evaluating the impact of these future changes on the distribution of invasive plant species (Petitpierre et al., 2012). Distribution modelling frequently relies on this criterion to predict the range of invasive plants. Invasive non-native species offer excellent model systems for examining the expansion associated with biological invasions (Peterson et al., 2011; Sax et al., 2007). However, evidence indicating eco-evo adaptations occurring over relatively short time spans (Whitney and Gabler, 2008) suggests that shifts (i.e., species ability to occupy climate niches in a new range vastly distinct from its native range) might be more commonplace than previously acknowledged (Rodríguez-Verdugo et al., 2017; Saul et al., 2013).

Senecio inaequidens DC. (African ragwort) is a perennial herbaceous species (Fam. Asteraceae) native to austral Africa, primarily thriving in open habitats associated with sandy and gritty riverbeds at mountain elevations, ranging from 1400 to 2850 m a.s.l. (Hilliard, 1977; Lachmuth et al., 2011). Accidentally introduced in Europe during the late 19th century, the species was first recorded as escaped in Germany in 1889 (Ernst, 1998; Hilliard, 1977; Sans et al., 2004). Over the subsequent decades, *S. inaequidens* appeared in several European countries (Jäger, 1988), with an initial quite slow dissemination often linked to wool processing farmlands (Ernst, 1998). However, starting from the 1970s, African ragwort underwent swift naturalization in central and southern Europe (Bossdorf et al., 2008; Heger and Böhmer, 2005). Today, *S. inaequidens* is present in most of the European countries (Lachmuth et al., 2010). In Italy, the species is currently distributed across all regions (Sardinia and Sicily included), where it is predominantly considered invasive. Notably, it was recently considered naturalized in Apulia, Basilicata and Sardinia, while it remained casual in Calabria and Sicily (Galasso et al., 2018, 2024). More specifically, recent research over the last decade indicates a rapid expansion of the species in the northern regions and in mountainous areas of central-southern Italy (Eller and Chizzola, 2016; Galasso et al., 2018, 2024; Misuri et al., 2020; Vacchiano et al., 2013).

Senecio inaequidens is not comprised within the list of invasive alien species of Union concern, as outlined by EU Regulation no. 1143/2014. However, the species is enlisted in the European Plant Protection Organization (EPPO) in the List of Invasive Alien Plants (EPPO 2024; https://www.eppo). In Italy, it is currently featured in the "black-list" of the Aosta Valley regional law on the conservation of alpine flora (L.R. 45/2009) (Vacchiano et al., 2013). Other regions have recognized the significance of this taxon and have included it among those deserving attention, regulated by regional laws. This recognition has specifically occurred in Lombardy, Piedmont, Veneto and Friuli Venezia Giulia (Brundu et al., 2020). Given that *S. inaequidens* is considered a noxious invasive plant, particularly due to the presence of potentially toxic alkaloids affecting animals, humans and food products, control actions have been proposed (Leiss, 2011). The adverse effects of African ragwort are specifically associated with the existence of pyrrolizidine alkaloids, which can easily transfer from the plant to livestock, causing health issues (Giunti et al., 2014; Wiedenfeld and Edgar, 2011). The accumulation of substantial amounts of the plant's alkaloids in hay can result in intoxication or even fatalities in livestock (Dimande et al., 2007). Furthermore, there is potential for contamination and devaluation of human food products, including honey and milk (Eller and Chizzola, 2016; Kempf et al., 2011). From an economic standpoint, the African ragwort also inflicts direct damage as a weed species affecting crops and pastures, leading to a reduction in their commercial value (Scherber et al., 2003). Quantifying the economic impacts of the species is challenging. Nevertheless, the indirect damage associated with its effects entails costs for road maintenance (Reinhardt et al., 2003).

To date, a few regional (Brundu et al., 2020; Galasso et al., 2024; Misuri et al., 2020; Vacchiano et al., 2013) and global scale (Caño et al., 2007; Delory et al., 2019; Heger and Böhmer, 2005; Van De Walle et al., 2022) studies have aimed at recognizing *S. inaequidens* as a harmful invasive species. Due to the limited number of previous studies on the invasive potential of this species in the insular Mediterranean context, we propose a study to assess and map the potential invasion dynamics of

the invasive non-native plant *S. inaequidens* in a Mediterranean hotspot of biodiversity, the island of Sardinia (Italy). We adopt a SDM approach and high-resolution bioclimatic layers specifically developed for our study area and two future CMIP6 scenarios from the last generation of CMIP6 models that underpin the IPCC AR6 (IPCC, 2023). The occurrence of *S. inaequidens* has been monitored on the island of Sardinia from 1991 to the present to employ the approach with the following objectives: (i) identification of bio-climatically suitable areas under current conditions; (ii) estimation of its potential distribution under two future climate and socio-economic scenarios for two temporal periods (2040 and 2060); (iii) identification of the invasion dynamics induced by future scenarios, with a specific emphasis on changes in the range size; (iv) to propose possible management actions aiming at the species mitigation.

The outcomes of this study can be used to implement management and control actions within protected areas and support monitoring campaigns under different management regimes. Additionally, SDMs have been used to highlight areas that have not yet been invaded or are in the early stages of invasion but are predicted by the model to be at high invasion risk. These areas should be prioritized for monitoring actions and resource allocation (Lozano et al., 2020, 2023). Therefore, the information and maps generated in this study will identify the distribution of *S. inaequidens* within the island, supporting the

implementation of regional policies, the evaluation of strategies, and the development of management measures under different scenarios. Moreover, potential future distribution maps can be used to identify habitats that may face increased risks, aiding in devising preventive measures to protect these vulnerable areas.

2. Materials and methods

2.1. Study area and target species

The research was conducted in Sardinia (Fig. 1), which stands as the second-largest island in the Mediterranean Basin, covering an area of about 24,100 km^2. Positioned at the center of the west-Mediterranean Sea, Sardinia extends along a North-South axis, with latitudinal coordinates ranging from approximately N 38.864044° (Capo Teulada) in the South to N 41.259150° (Punta Falcone) in the North. The island exhibits an irregular profile, characterized by elevated hills and low mountains, with the highest peak, Mount Gennargentu, reaching 1834 m a.s.l. Sardinia is mostly conditioned by a typically Mediterranean climate. The region encompasses two macro-bioclimates, seven thermometric belts, and 43 isobioclimates, reflecting the diverse environmental conditions (Canu et al., 2015). Specifically, the mountain tops of Sardinia host an Oceanic temperate bioclimate (Canu et al., 2015).
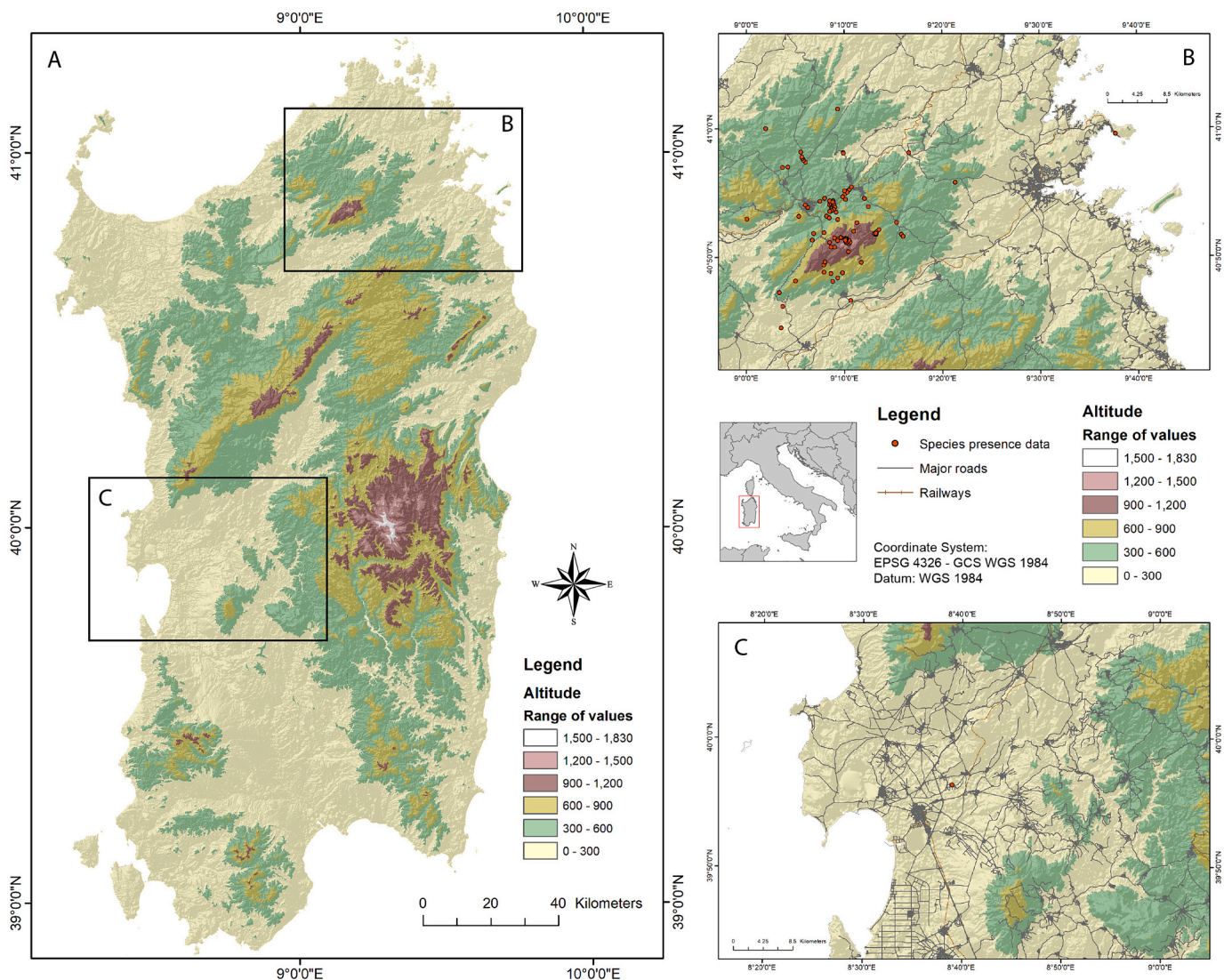

Fig. 1. The study area (A) located in Sardinia (Italy) and the distribution of *Senecio inaequidens* on the study area (B and C).

Sardinian-rich vegetation is mainly influenced by its high diversity of bioclimatic niches and complex geology (Carmignani et al., 2016). The plant communities include, among others, thermo- to meso-Mediterranean shrublands, Sardinian oak-managed woodlands (comprising holm-oak, cork oak and downy oak), supra-Mediterranean holm-oak and downy oak forests, Mediterranean riparian gallery forests (prevalently featuring alder and poplars), junipers' matorral, Mediterranean xeric garrigues and grasslands (Bacchetta et al., 2009). Sardinian flora comprises 2372 native species (Bartolucci et al., 2024). A recent study established that the island is home to 340 endemic plant taxa, representing approximately 15% of the total native flora (Fois et al., 2022). Due to this elevated endemicity rate, Sardinia has been classified as a meso-hotspot of plant diversity within the broader macro-hotspot that encompasses Tyrrhenian continental islands in the central-western Mediterranean, together with Corsica, Sicily, Balearic and Tuscan Archipelagoes (Cañadas et al., 2014).

Senecio inaequidens DC. was initially reported in Sardinia in 1990 (Bocchieri, 1990) on the topmost area of Mount Limbara (1359 m a.s.l.), along a road close to telecommunications and military centers. During the field surveys carried out from 1991 to 2023, it has been possible to observe that *S. inaequidens* has become sporadically diffuse in the area surrounding the first report, being found mostly along roads, in fallow lands and disturbed areas (e.g., Tempio Pausania industrial zone), along with dry pastures and clearcut woodlands, but also in more natural contexts such as garrigues, scrublands and scarps (Calvia and Ruggero, 2020, 2023). The areas where the species was recently observed extend from Punta Balestrieri (Mount Limbara) towards the North. In this context, *S. inaequidens* plants are invading primarily thanks to a network of country roads of approximately 720 km (provincial roads included).

The latest records of the species in Sardinia were collected close to urban centers at sea level (Golfo Aranci), along a railroad.

2.2. Analytical framework

Given the variability observed in model performance across species, regions, and applications (Elith et al., 2006; Pearson et al., 2006; Segurado and Araújo, 2004), our ensemble species distribution model approach (i.e., consensus modelling or ensemble forecasting) integrates multiple individual models into an ensemble framework. This strategy aims to capture the central tendency of the best-performing models, thereby enhancing predictive accuracy and reducing prediction uncertainty (Araújo and New, 2007; Hao et al., 2019, 2020; Marmion et al., 2009). The ensemble approach was applied through *biomod2* package (4.2–2 version) (Thuiller et al., 2020) using the software R (R core Team, 2020) and following a three-step method for modelling (Guisan et al., 2017; Peterson et al., 2011): (i) data collection and preparation, (ii) model fitting and evaluation, and (iii) prediction (Fig. 2).

To enhance the clarity and consistency of our modelling process, we also implemented the ODMAP protocol (Zurell et al., 2020) as outlined in Supplementary Appendix A1. We adopted ODMAP to align with standardized practices in species distribution modelling, ensuring that our methods are clearly communicated and easy to evaluate. Implementing this protocol is especially important for addressing potential concerns related to model transparency and uncertainty, which are crucial for the broader application and acceptance of models in environmental decision-making (Zurell et al., 2020).
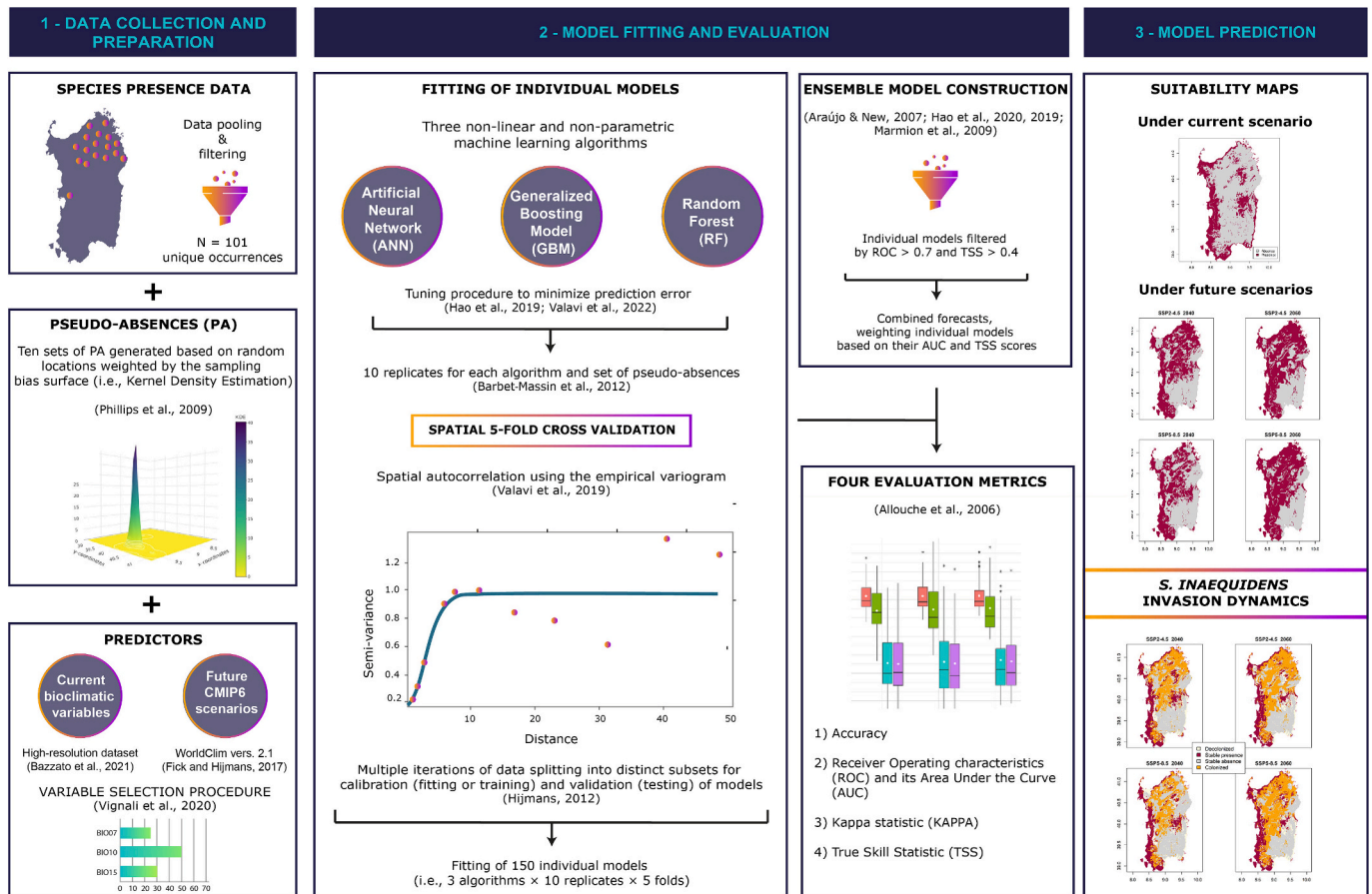

Fig. 2. Flowchart showing the ensemble species distribution model approach adopted to predict the potential distribution of *Senecio inaequidens* under current conditions and two Shared Socio-economic Pathways (SSPs) and Representative Concentration Pathways (RCPs) (Kriegler et al., 2016; O'Neill et al., 2017; van Vuuren et al., 2017) for two periods 2040–2060, under the Coupled Model Intercomparison Project Phase 6 (CMIP6; O'Neill et al., 2016).

2.2.1. Data collection and preparation

Species occurrences of *S. inaequidens* were retrieved from two primary sources. Firstly, a dedicated working group of botanists contributed observations of species presence points during a monitoring campaign spanning from 1991 to 2023. Additionally, we incorporated into the dataset data available on online platforms (i.e., www.iNaturalist.org; www.gbif.org, accessed on May 2023). To ensure data accuracy, we excluded records with potential errors, particularly duplicates falling within the same pixel (40 m²), as well as those with low positional accuracy (< 40 m). Consequently, we refined the number of georeferenced records available for this study to 101 (WGS84 coordinate reference system; EPSG:4326). As a result, the number of georeferenced records available for SDMs was 101. The prepared data used in this study are shared in Supplementary Appendix A2 to enhance transparency and support future research.

Occurrence data often shows spatial bias (Bowler et al., 2022), indicating that some sites are more likely to be studied than others. Such a bias could significantly affect model quality (Phillips et al., 2009). To account for sampling bias in occurrence data (Barbet-Massin et al., 2012), a sampling bias surface using Kernel Density Estimation was generated (Fig. A.1 in Supplementary Appendix A3) using the *sm* package (Bowman and Azzalini, 2021). Subsequently, ten sets of pseudo-absences (Fig. A.1 in Supplementary Appendix A3) were generated based on random locations weighted by the sampling bias surface, each with an equal number of pseudo-absence points as presence points (Barbet-Massin et al., 2012; Elith et al., 2010).For the current climate scenario, we retrieved 19 bioclimatic variables from a high-resolution dataset (40 m², approximately 1.69 arc-*sec*) developed specifically for Sardinia by Bazzato et al. (2021). This dataset (Table A.1 in Supplementary Appendix A3) relied on high-quality, long-term climate time series (averaged over the 1971–2000 period) sourced from the regional climatic database of the Weather and Climate Department (ARPA Sardegna). We employed the *SDMtune* R package (Vignali et al., 2020) to streamline model complexity and reduce collinearity among variables of the entire climate set through a variable selection procedure. This procedure involved the elimination of highly correlated variables ($R > 0.7$; Fig. A.2 in Supplementary Appendix A3) and those with minimal importance for individual model performance (percent contribution <5%; Fig. A.3 in Supplementary Appendix A3).

For future projections, we considered the two scenarios for two temporal horizons (2040 and 2060) as defined by SSPs and the RCPs (Kriegler et al., 2016; O'Neill et al., 2017; van Vuuren et al., 2017) under the CMIP6 (Eyring et al., 2016; Hurtt et al., 2020; O'Neill et al., 2016): (1) SSP2–4.5, referred to as Middle-of-the-road, represents an intermediate management regime characterized by socio-economic, and technological trends, greenhouse gas emissions and the land consumption do not significantly deviate from historical patterns, and environmental policy implementation remains limited; (2) SSP5–8.5, known as Fossil-fueled Development, depicts an unmitigated pessimistic management regime where the high economic growth, material overproduction and land consumption patterns elevate greenhouse gas emissions and energy, resulting in potentially high challenges to mitigation.

For a specific future year and scenario, diverse General Circulation Models (GCMs) have been formulated to project credible future climate forcing (Fajardo et al., 2020). While these GCMs share a common overall perspective, substantial variance exists among them (Zappa and Shepherd, 2017) owing to internal climate system variability, modeled climate response, and spatial structure (van den Hurk et al., 2014). Considering that the choice of the General Circulation Model (GCM) is recognized as a significant source of variability and uncertainty in species distribution models (Fajardo et al., 2020; Thuiller et al., 2019), we utilized the *GCM compareR* package (Fajardo et al., 2020) to compare the bioclimatic disparities among all GCMs within the CMIP6 framework (O'Neill et al., 2016). These GCMs are available at 30 arc-second resolutions (~1 km²) in the WorldClim database version 2.1 (Fick and Hijmans, 2017; last access 2023-08-24). The advantage of using the

WorldClim database is that it provides downscaled and calibrated (bias-corrected) climate data for GCMs, ensuring a consistent basis for comparison. The GCMs we compared include ACCESS-CM2, CanESM5-CanOE, CMCC-ESM2, CNRM-CM6–1, CNRM-ESM2–1, EC-Earth3-Veg, HadGEM3-GC31-LL, MIROC6, MPI-ESM1–2-HR, MRI-ESM2–0. Therefore, we selected the MRI.ESM2.0 model based on its minimal distance from the ensemble multi-GCM mean (Fajardo et al., 2020) to evaluate the potential distribution of *S. inaequidens* under two future climate and socio-economic scenarios for two temporal horizons (2040 and 2060).

Subsequently, we calculated different statistics (i.e., mean, standard deviation or SD, minimum and maximum values, and coefficient of variation or CV, expressed as a percentage) for each current and future variable contributing to the models. Additionally, we provided kernel density estimates to illustrate variable changes under current and future scenarios.

2.2.2. Model fitting and evaluation

Three non-linear and non-parametric machine learning algorithms [i.e., Artificial Neural Network (ANN); Generalized Boosting Model (GBM) and Random Forest (RF)] were used to calibrate individual models. A model tuning procedure was implemented using *BIOMOD_Tuning* function to identify optimal values for each algorithm for modelling, minimizing prediction error (Hao et al., 2019; Valavi et al., 2022). Tuning parameters for each algorithm are summarized in Fig. A.5, Supplementary Appendix A3. To account for potential variations in predictions due to modelling methods and the selection of pseudo-absences that can influence model accuracy, we replicated each algorithm for each set of pseudo-absences (i.e., 10 replicates; Fig. A.6 in Supplementary Appendix A3), assigning equal weight to occurrences and pseudo-absences (Barbet-Massin et al., 2012; Elith et al., 2010).

We assessed the predictive performance of individual models through a spatial block cross-validation procedure, involving multiple iterations of data splitting into distinct subsets for calibration (fitting or training) and validation (testing) of models (Hijmans, 2012). This procedure addresses potential spatial autocorrelation issues in model evaluation, enhancing independence between the two subsets (Hijmans, 2012; Muscarella et al., 2014; Roberts et al., 2017). To identify the optimal separation distance ensuring approximately independent residuals, the isotropic variogram was used (non-directional empirical variogram) from the *spatialAutoRange* function of the *blockCV* package (Valavi et al., 2019) on R (R core Team, 2020) (Fig. A.7 in Supplementary Appendix A3), assuming that the data meets necessary geostatistical criteria, such as stationarity and constant variance (Valavi et al., 2019). Consequently, we divided the data into 100 equal-sized square blocks for splitting the training and testing subsets. Then, we randomly allocated each block into five folds using the *spatialBlock* function in the *blockCV* package (Valavi et al., 2019), ensuring a similar number of occurrence and pseudo-absence records in each fold (Fig. A.8 in Supplementary Appendix A3).

The predictive performance of 150 individual models (i.e., 3 algorithms × 10 replicates × 5 folds) was evaluated using four metrics (Allouche et al., 2006) as follows: Accuracy, Receiver Operating Characteristics (ROC) with the corresponding Area Under the Curve (AUC), the Kappa statistic (KAPPA), and the True Skill Statistic (TSS). To ensure the inclusion of well-calibrated and validated models, only those with AUC ≥ 0.7 and TSS ≥ 0.4 were considered in constructing the ensemble model, adhering to thresholds recommended by previous studies (Franklin, 2010; González-Irusta et al., 2015; Lahoz-Monfort et al., 2014; Manel et al., 2001; Osborne and Leitão, 2009).

2.2.3. Model prediction

We constructed the ensemble model through the assignment of weights to individual models based on their AUC and TSS scores, and we averaged the results following a technique referred to as EMwmean. This approach aimed to generate consensus distributions by considering the incorporating predictions from each individual model (Marmion et al.,

2009). The resulting ensemble model underwent evaluation utilizing the previously mentioned metrics. The ensemble model was employed to create spatially continuous bioclimatic suitability maps, illustrating the likelihood of species presence under current climate conditions, ranging from zero (minimum probability) to one (maximum probability). These probabilities are derived from the estimated overall prevalence and local favorability of the species within the analyzed climatic conditions (Real et al., 2017). Additionally, we assessed the relative contribution of each variable to the ensemble model through 999 permutations using the *biomod2* package (Thuiller et al., 2020).

We constructed species response curves to explore the relationship between the probability of species occurrence and current climate variables. Subsequently, we projected the potential distribution of the species under climate and socio-economic changes for two temporal periods (2040 and 2060), generating four future predictions of species occurrence probability (one for each temporal period in each scenario). To facilitate the interpretation of species occurrence probability, each current and future projected probability was converted into binary classification (presence and absence map). This classification was determined using the threshold that maximizes the True Skill Statistic (max TSS) as derived from the *PresenceAbsence* package (Freeman and Moisen, 2008), a recommended approach for models derived from presence-only data (Liu et al., 2015).

2.2.3.1. Senecio inaequidens invasion dynamics. The *BIOMOD_RangeSize* function (Thuiller et al., 2020) was employed on the binary classification maps outcome to quantify and assess the species' shift range compared to present conditions under each scenario and time period: the intermediate management regime (SSP2–4.5) for the 2040 and 2060 periods, and the pessimistic management regime (SSP5–8.5) for the 2040 and 2060 periods. These distribution shifts were calculated to identify (i) suitable or unsuitable areas where the species studied will remain present or absent under current and future scenarios (stable presence or stable absence) and (ii) the loss or gain of suitable habitats (i.e., areas where *S. inaequidens* will disappear or colonize new areas under future change scenarios).

Additionally, three relative metrics were computed to determine the percentage of loss (calculated using the formula loss/(loss + stable)), gain (evaluated as gain/(loss + stable)), and the overall range change (determined as gain percentage - loss percentage) under each scenario and time period compared to present conditions (Guisan et al., 2017).

3. Results

The following sections present the results of our ensemble species distribution model approach, implemented using presence data, high-resolution current bioclimatic variables (40 m^2), and future scenarios from the CMIP6 under Shared Socio-economic Pathways (SSP2–4.5 and SSP5–8.5) for two time periods (2040 and 2060). The results include model evaluations, predictions of current and future distributions of *Senecio inaequidens* on the island of Sardinia, and assessments of its invasion dynamics induced by future scenarios, focusing on changes in range size.

3.1. Model evaluation

The performances of individual models, assessed through spatial block cross-validation procedures and utilizing four evaluation metrics (Accuracy, ROC, KAPPA, and TSS), exhibited low variability between model algorithms (Fig. 3 and Table A.2 in Supplementary Appendix A3). The mean Accuracy varied from 0.86 ($\pm$ 0.03 SD) for GBM to 0.97 ($\pm$ 0.01 SD) for RF in the calibration and reached a value of 0.67 for all algorithms in the validation. Similarly, the mean ROC ranged from 0.84 ($\pm$ 0.05 SD) for ANN to 0.99 ($\pm$ 0 SD) for RF in the calibration and reached a value of 0.59 ($\pm$ 0.13 SD) for ANN and 0.6 for the other algorithms in the validation. According to TSS and Kappa values, when the
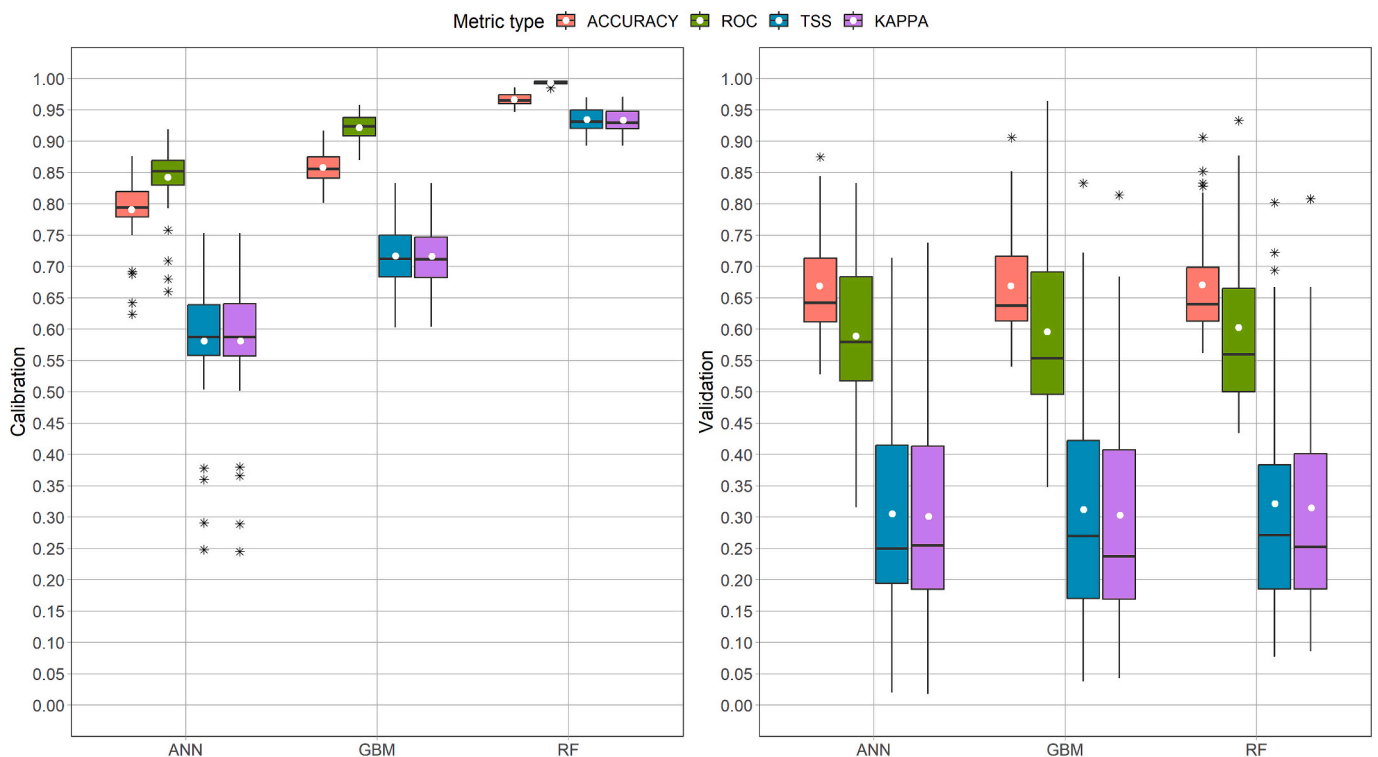

Fig. 3. Box plots representing Accuracy, Receiver Operating Characteristics (ROC), Kappa statistic (KAPPA), and True Skill Statistic (TSS) of 150 individual models (3 algorithms × 10 replicates × 5 folds) built using three different machine learning algorithms: artificial neural networks (ANN), generalized boosting model (GBM), and random forest (RF). Boxes span the 25th to the 75th percentile; whiskers span from the 10th percentile to the 90th percentile. The bar across the box shows the median value of each evaluation metric, the white point their mean values, and the star the outliers.

calibration was considered, the lowest mean values were obtained for ANN (0.58 ± 0.1 SD) and GBM (0.72 ± 0.05 SD), while RF reached the highest mean values (0.93 ± 0.02 SD). Considering the validation, all algorithms obtained the same performance with mean TSS and Kappa values of 0.3. Overall, these results highlighted that RF models were better calibrated than models based on other algorithms (ANN and GBM), considering all evaluation metrics (Fig. 3).

To construct the ensemble model, the best performing individual models (AUC ≥ 0.7 and TSS ≥ 0.4) were selected while poorly calibrated and validated ones were excluded, as determined by spatial cross-validation, resulting in strong performance of the ensemble model (Table 1). The ensemble model indicated high predictive accuracy, with evaluation metrics ranging from a minimum of 0.5 (± 0.02 SD) for Kappa to maximum values of 0.9 (± 0 SD) for ROC (Table 1 and Fig. A.9 in Supplementary Appendix A3).

3.2. Model prediction

Following the variable selection process, it was determined that three out of the 19 bioclimatic variables constituted the optimal subset size for the individual models. These findings indicate that the current distribution of *S. inaequidens* is influenced by many complex interplays of many climate variables (Fig. A.2 in Supplementary Appendix A3). Among these, the variable selection procedure retained three uncorrelated variables with a significant contribution to the individual model performance (Fig. A.3 in Supplementary Appendix A3). The primary contributor to the current distribution of the *S. inaequidens* was identified as the Mean Temperature of Warmest Quarter, which accounted for an average contribution of 73% to the ensemble model (mean = 0.73 ± 0.03 SD; BIO10 in Fig. 4). The remaining variance was attributed to Temperature Annual Range and Precipitation Seasonality, contributing a mean of 21% (mean = 0.17 ± 0.01 SD and mean = 0.25 ± 0.01, respectively; BIO07 and BIO15 in Fig. 4).

The response curves derived from the ensemble models depict the correlation between the probability of occurrence of *S. inaequidens* and bioclimatic variables under the current climate (Fig. 5). The response curve of the most important variables indicates a direct increase in the occurrence probability of *S. inaequidens* as a result of decreasing the annual range of temperature (BIO07) and Mean Temperature of Warmest Quarter (BIO10 in Fig. 5). Specifically, the probability of species occurrence surpassing 51% - the threshold that maximizes TSS - appeared favored by low values of temperature range (< 23 °C; BIO07 in Fig. 5). These low values were in relation to continentality observed in the study area (mean ± SD = 26.02 ± 1.89; Table A.3 in Supplementary Appendix A3). Moreover, the probability of species occurrence exceeding 51% was confined to locations with Mean Temperature of Warmest Quarter lower than 23 °C, aligning closely to the mean values (24.30 °C ± 0.98 SD) under current climate conditions (BIO10 in Table A.3 in Supplementary Appendix A3). The likelihood of species presence >50% seemed limited by a narrow range of precipitation seasonality values, ranging from 45% to 48% (BIO15 in Fig. 5).

The distribution of the most important climatic variables across both

Table 1
Summary statistics of mean ± standard deviation (SD), minimum (min) and maximum (max) values of each evaluation metric: Accuracy, Receiver Operating Characteristics (ROC), Kappa statistic (KAPPA), and True Skill Statistic (TSS). These metrics were used to assess the performance of the ensemble model built by weighting the individual models according to their calculated AUC and TSS scores and averaging the result (EMwmean) to obtain the current and future bioclimatic suitability (Marmion et al., 2009).

Metric type	SDM ensemble rule	Mean ± SD (min – max)
ACCURACY	EMwmean	0.89 ± 0 (0.89–0.9)
KAPPA	EMwmean	0.5 ± 0.02 (0.49–0.52)
ROC	EMwmean	0.9 ± 0 (0.9–0.9)
TSS	EMwmean	0.69 ± 0.01 (0.69–0.7)

present and future scenarios is shown in Fig. 6. The projections indicate significant shifts in almost all climatic variables under the scenarios examined, but the most substantial changes should occur in the more pessimistic ones (SSP5–8.5), irrespective of the considered temporal horizon. Mean Temperature of Warmest Quarter will clearly shift towards higher values in the future (BIO10 in Fig. 6), respectively reaching average values of 27.60 °C (±25.52 SD) in the intermediate scenario (SSP2–4.5) and 27.80 °C (±26.06 SD) in the pessimistic ones (SSP5–8.5) by 2060 (Table A.3 in Supplementary Appendix A3). Conversely, the temperature ranges are expected to experience a marginal decrease under both intermediate (SSP2–4.5) and pessimistic (SSP5–8.5) management scenarios by 2040 and 2060 (BIO07 in Fig. 6).

3.2.1. Current and future binary maps

The outcomes of the ensemble model revealed that the current bioclimatically suitable habitats in Sardinia align closely with the collected occurrence records of *S. inaequidens*, predominantly in higher altitude areas (compare Fig. 1 and Fig. 7). Furthermore, the ensemble model predicted high bioclimatic suitability (probability values > 51%, according to the threshold that maximizes TSS) for *S. inaequidens* in the western and south-western coastal areas. Additionally, high bioclimatic suitability (probability values > 51%) was also predicted for nearly all small islands around the region and in central-east Sardinia, indicating potential habitats at lower altitudes under the current climate conditions (Fig. 7).

3.2.2. Senecio inaequidens invasion dynamics under future scenarios

The results of the shift range analysis indicated that the potential distribution of *S. inaequidens* will undergo significant shifts under future climate and socio-economic scenarios (Fig. 7 and Fig. 8). According to predictions, suitable habitats for *S. inaequidens* will significantly increase to spatial extent, particularly by 2060 (Fig. 8 and Table 2). This range change will be governed mostly by the gain of suitable habitats on the central side of the region in future change scenarios (Fig. 8). More specifically, there will be an expansion in suitable areas for *S. inaequidens* of about 103.13% and 120.11% under SSP2–4.5 scenario by 2040 and 2060, respectively, when compared to current bioclimatic suitability (Table 2). The gain of suitable habitats under SSP5–8.5 scenario will be about 83.31% and 123.58% by 2040 and 2060, respectively. The gain of potential distribution will be more evident under the pessimistic management regime (SSP5–8.5) than under the intermediate management regime (SSP2–4.5) (Table 2).

4. Discussion

In this study, we endeavored to predict the potential distribution of *Senecio inaequidens* under current climate conditions and two future climate scenarios, considering two timeframes (2040 and 2060) within the Mediterranean island of Sardinia. Employing an ensemble modelling methodology, which integrates predictions from diverse individual models (Araújo and New, 2007), we mitigated the inherent uncertainty in predictions (Marmion et al., 2009).

The ensemble model's outcomes demonstrated a notably elevated predictive accuracy compared to singular models. This was achieved by constructing the ensemble model using the weighted mean of the most accurate individual models, thereby circumventing the challenge of selecting a singular modelling method (Hao et al., 2019; Marmion et al., 2009). The heightened predictive accuracy was not only evident through conventional statistical metrics such as Accuracy, AUC, TSS, and Kappa, but was also substantiated by the precise prediction of the current documented distribution of *S. inaequidens*.

The implemented modelling approach, grounded in the correlation between plant occurrence and high-resolution bioclimatic characteristics tailored to the island of Sardinia, effectively delineated the invasion risk within current scenarios. Our models revealed that various interconnected climate parameters significantly influenced the present
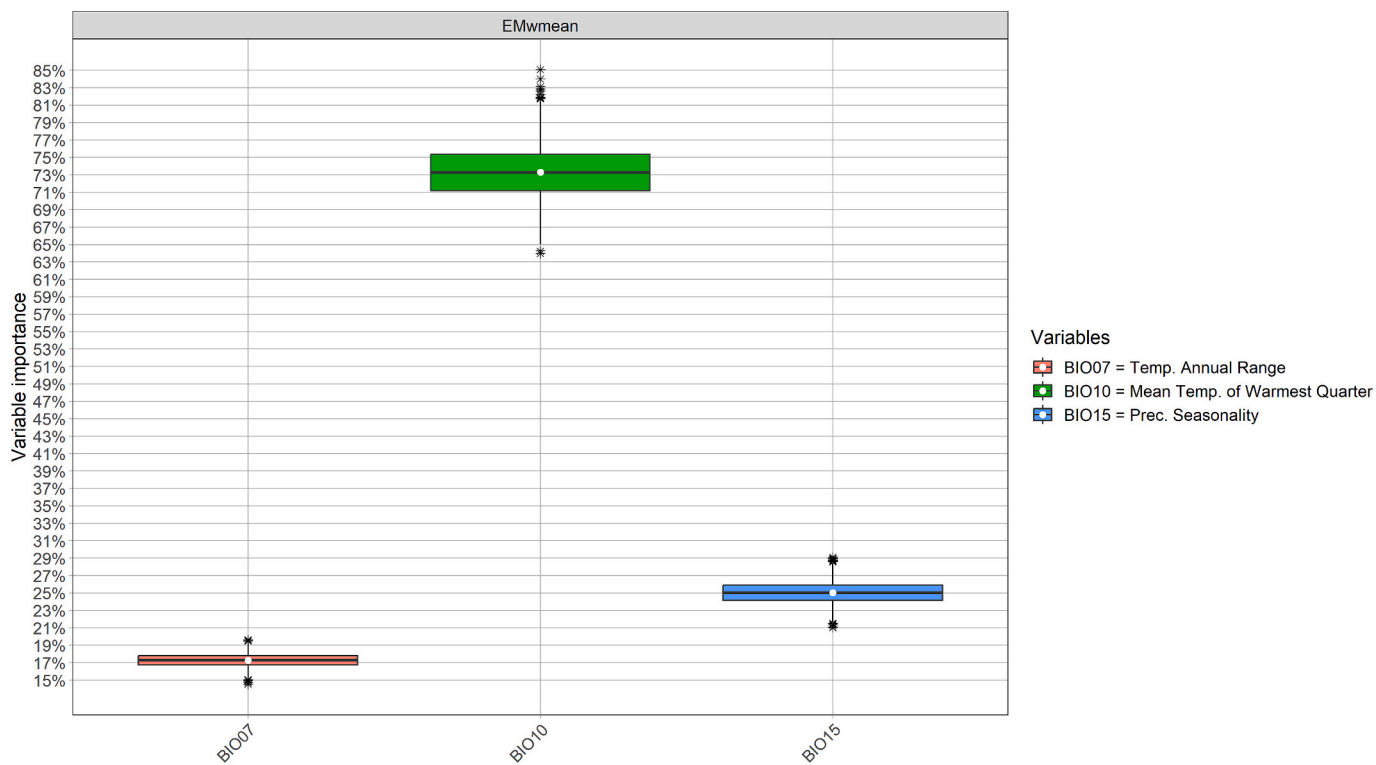
Fig. 4. Box plots depict the relative contributions of bioclimatic variables to the ensemble model, computed using 999 permutations. Each box covers the inter-quartile range from the 25th to the 75th percentile, while the whiskers extend from the 10th to the 90th percentile. The horizontal line within each box indicates the median value of the relative contribution, while the white point represents the mean values, and any outliers are denoted by stars.
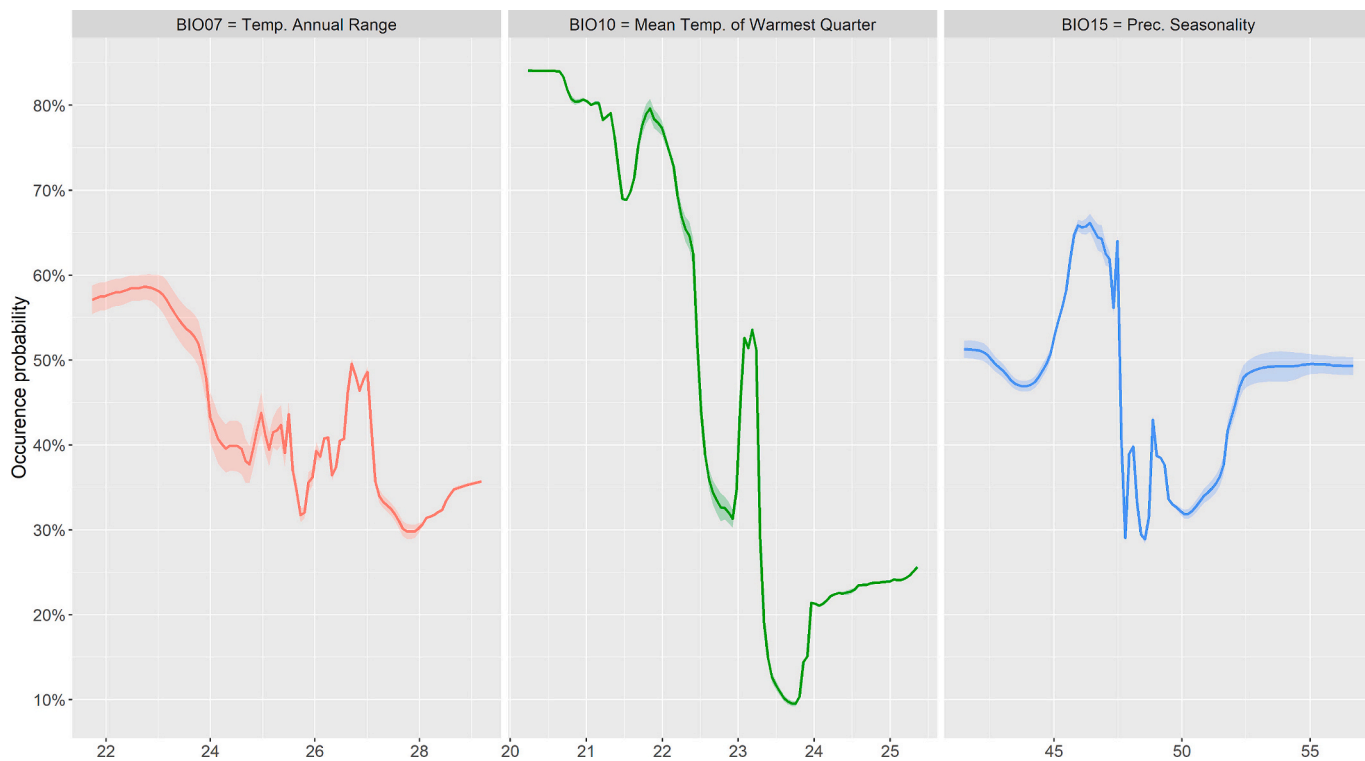

Fig. 5. Response curves of the most important bioclimatic variables under current conditions: Temperature Annual Range (BIO07), Mean Temperature of Warmest Quarter (BIO10), Precipitation Seasonality (Coefficient of Variation in percentage, BIO15).
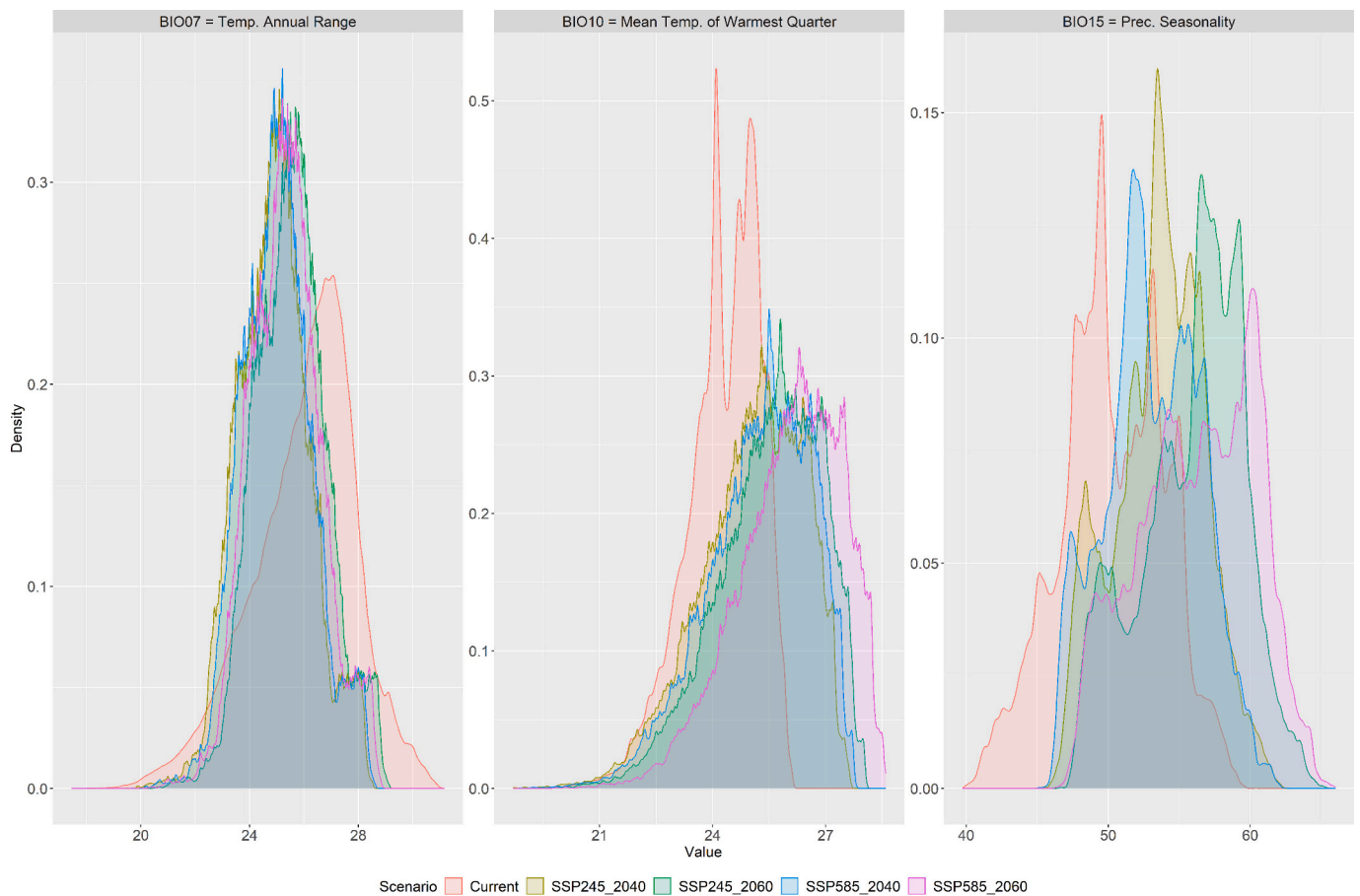
Fig. 6. Distribution of the bioclimatic variables that most contributed to the ensemble model, explaining the potential distribution of the species under (i) the current climate, (ii) the intermediate management regime (SSP2–4.5) for the 2040 and 2060 periods, and (iii) the pessimistic management regime (SSP5–8.5) for the 2040 and 2060 periods.

distribution of *S. inaequidens*. Notably, the mean temperature of the warmest quarter, annual temperature range, and precipitation seasonality emerged as the most influential predictors of its potential current distribution. These findings align with previous research (Misuri et al., 2020; Vacchiano et al., 2013; Van De Walle et al., 2022), highlighting *S. inaequidens*' broad ecological tolerance to a wide range of climatic conditions that can allow it to thrive and colonize a wide range of environments and altitudes from mountains to coasts in current and future scenarios.

This information is of strategic importance for decision makers, underlining the need to formulate early detection strategies and surveillance campaigns in regions and areas with greater climatic susceptibility to the invasion of this species.

4.1. Senecio inaequidens invasion dynamics

Given the projections of future change scenarios indicating an increase in temperatures and drought stress, presently constraining the altitudinal spread of invasive non-native plants (Pérez et al., 2022), new habitats' colonization is anticipated and warrants preventive measures. Our findings indicate that future climate and socio-economic changes will lead to a discernible shift in suitable habitats (Mahmoodi et al., 2022) throughout Sardinia, revealing a quite rapid expansion of *Senecio inaequidens* into previously unoccupied sites. The highlighted invasion dynamic was observed across all examined management regimes (SSP2–4.5, SSP5–8.5) and time periods (2040 and 2060), indicating that *S. inaequidens* is predicted to benefit from climate and socio-economic changes. Our findings indicate that under the intermediate

management regime (SSP2–4.5), suitable areas for the species are expected to nearly double by 2040 and more than double by 2060 compared to current conditions. However, under the more severe management regime (SSP5–8.5), the increase in suitable habitats is projected to be about 83.31% by 2040 and more than double by 2060. This expansion under the pessimistic scenario is particularly alarming because it reflects future developments in absence of new climate policies beyond those in place today.

The ability of *S. inaequidens* to thrive and expand more rapidly under such conditions highlights the critical importance of proactive and robust management strategies to mitigate its spread. The success of *S. inaequidens* invasion can also be increased in the future by a synergy of ecological factors during initial establishment and life-history traits and evolutionary changes facilitating spread (Caño et al., 2007). Our findings emphasize the urgent necessity for monitoring this invasive and noxious species to curtail further expansion, especially within biodiversity hotspots like the island of Sardinia. The potential distribution map delineates the susceptibility of the Sardinian coastal sectors to the establishment and expansion of *S. inaequidens*. Although the model predicts stable presences in extensive areas near the coast, it is crucial to highlight that the species is not confined solely to coastal sectors. On the contrary, its initial presence in the Limbara massif and its current predominant diffusion in the hillside and low mountain environments lead to extending concerns to a wider spectrum of potentially invaded habitats, as also shown by our models. Consequently, areas potentially susceptible to *S. inaequidens* invasion also encompass mountain environments within the larger area identified as favorable for the species' establishment under future management regimes. The scenarios used in
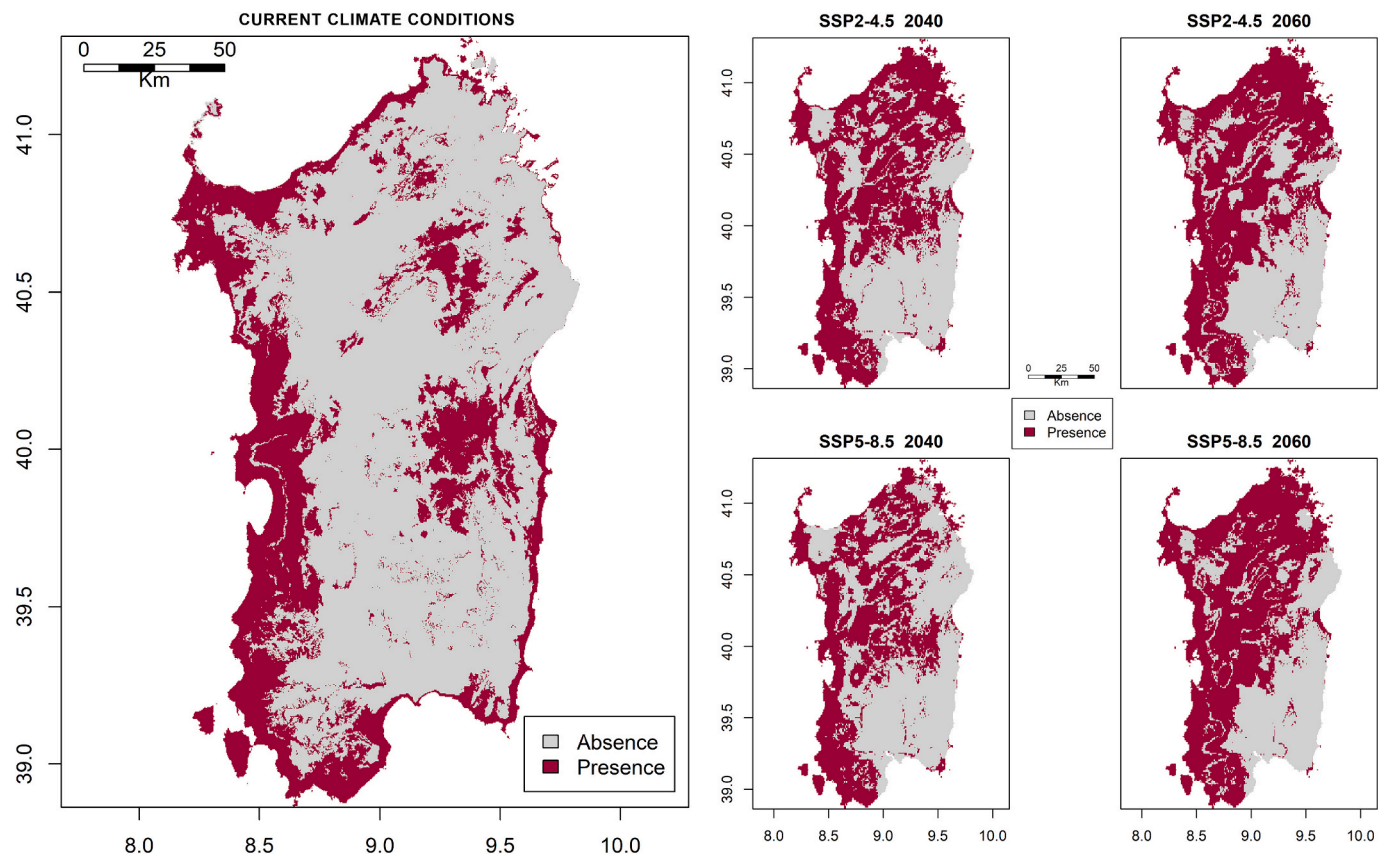
Fig. 7. Binary maps (i.e., absence and presence) indicating geographical areas with potentially high suitability under the current and future scenarios for *Senecio inaequidens* in the Mediterranean island of Sardinia (i.e., occurrence probability values > 0.51, equal to 51%, according to the threshold that maximizes TSS).

this study not only illustrate potential futures but also help identify key uncertainties, allowing for the incorporation of alternative perspectives and theories into the analysis of potential outcomes (Peterson et al., 2003).

This approach provides a more comprehensive understanding of the possible expansion of *S. inaequidens* under varying climate and socio-economic conditions, informing policymakers and conservationists about the necessary steps to face the ecological consequences of the growth of this species. The noteworthy aspect of the species' behavior lies in the fact that, over the course of 35 years since its first documentation in Sardinia, it remains mostly localized to the northeastern sector of the island. Simultaneously, its presence is now evident across an elevational gradient exceeding 1300 m, indicating its capability to proliferate in diverse altitudinal and bioclimatic conditions. This observation underscores the species' increasingly remarkable adaptability to thrive even in less favorable climatic conditions.

Historically, Italian records highlight that, in 1982, the species was predominantly found in lowlands and hillsides up to an elevation of 500 m a.s.l. (Pignatti, 1982). By 1989, it had extended its range to elevations of 1000 m in alpine areas (Büscher, 1989). After another decade, it reached 1420 on Monte Baldo (Trentino; Brandes, 1999). In the last two decades, the species has exhibited an upward expansion along the mountain flanks, successfully establishing itself in pre-alpine and alpine environments, at even 1600–1695 m (Monty and Mahy, 2009; Vacchiano et al., 2013) and then up to 1850 m a.s.l. (Prosser et al., 2019; personal observations in Trentino during autumn 2023). This trajectory underscores the species' dynamic response to environmental conditions and its ability to adapt to progressively higher altitudes, making *S. inaequidens* one of the most successful neophytes regarding the span of altitude. In this context, considering the favorable ecological and bioclimatic conditions prevalent in Sardinian Mountain areas, the

hypothesis that the species could even readily colonize the Gennargentu mountain massif becomes a plausible consideration.

4.2. Management actions associated with the expansion of Senecio inaequidens

The outcomes of this study provide a basis for implementing management and control measures to support monitoring campaigns. By designating high priority areas for intervention, we can target and strategize management actions to optimize resource allocation and improve overall effectiveness (Hama and Khwarahm, 2023). Additionally, SDMs have identified areas that have not yet been invaded or are in the early stages of invasion but are predicted to face a high risk of invasion in the near future.

External evidence from outside the island indicates *S. inaequidens'* competitive edge over certain herbs, such as *Epilobium angustifolium*, *E. hirsutum* and *Cirsium arvense* (Boehmer et al., 2001). While potential negative impacts on biodiversity have been suggested by Bornkamm (2002), testing of these effects, especially regarding pyrrolizidine alkaloid (PA) adverse effects on other plant species, gave contrasting results (Van De Walle et al., 2022). Nonetheless, the production and release of PA pose a threat to grazing animals and humans. This risk is especially significant if the species enters the alimentary chain and is consumed with food (Altaee and Mahmood, 1998; Edgar et al., 2011). Given this, the precise mapping and modelling of the potential distribution of this considered plant species become an urgent need that deserves consideration for future mitigation programs.

Monitoring and eradication actions are imperative to contrast the rising issues due to invasive plant species such as *S. inaequidens*, along with handling the associated costs of implementing control programs (Zamora et al., 1989). Among the essential actions required, in addition
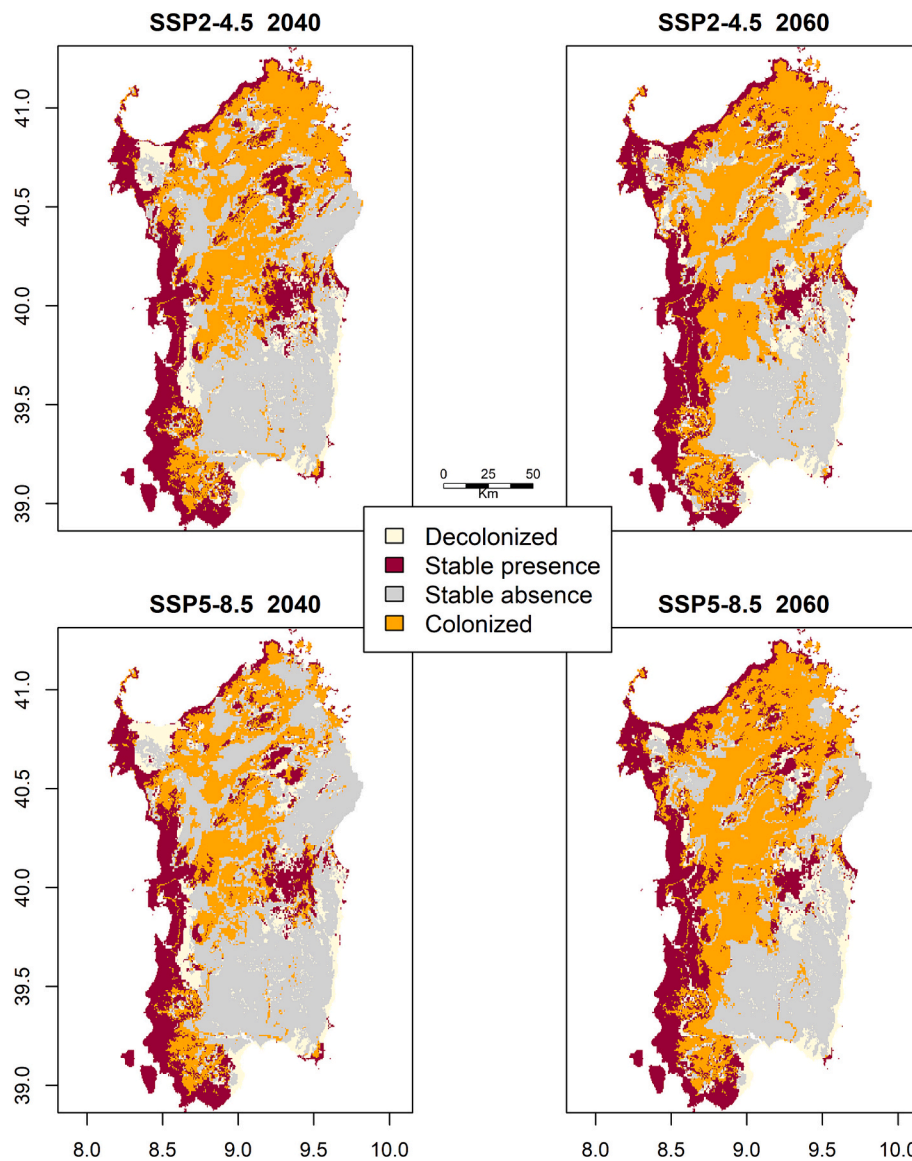
Fig. 8. Suitable (i.e., stable presence) or unsuitable areas (i.e., stable absence) where *Senecio inaequidens* will remain present or absent under current and future scenarios, and the loss (i.e., decolonized areas) or gain (i.e., colonized areas) of suitable habitats where the species will disappear or colonize new areas under the analyzed future change scenarios: the intermediate management regime (SSP2–4.5) and the pessimistic management regime (SSP5–8.5) for the 2040 and 2060 periods. Maps were produced using the binary classification maps (coordinate systems WGS 84, EPSG: 4326) with the *BIOMOD_RangeSize* function (Thuiller et al., 2020).

Table 2
Predicted changes in potential range size of *Senecio inaequidens* for the 2040 and 2060 periods, according to the intermediate management regime (SSP2–4.5) and the pessimistic management regime (SSP5–8.5) on the binary classification maps: suitable or unsuitable areas (i.e., stable presence or stable absence, expressed in km²), the loss or gain of suitable habitats (i.e., decolonized and colonized areas, expressed in km²), percentage of loss, gain and overall range change by the species compared to present conditions under each scenario and time period.

Future SSPs and RCPs scenarios	Decolonized areas (km^2)	Stable absence (km^2)	Stable presence (km^2)	Colonized areas (km^2)	Loss (%)	Gain (%)	Overall range change (%)
SSP2–4.52040	2030.00	8578.78	5294.16	7553.55	27.72	103.13	75.42
SSP2–4.52060	2183.68	7335.04	5140.48	8797.28	29.81	120.11	90.30
SSP5–8.52040	2394.80	10,030.85	4929.35	6101.47	32.70	83.31	50.61
SSP5–8.52060	2002.02	7081.12	5322.13	9051.20	27.33	123.58	96.25

to those specifically applicable in the field (such as surveys, manual and/or mechanical plant removal, followed by restoring invaded sites), others can be strategically programmed through the integration of field and remote activities (Ghiani et al., 2023). These include early detection and circumscription of the invasive species, assessment of its noxious potential and key drivers of spread, study of its biology and evolutionary history, and development of technologies aimed at formulating comprehensive strategies to contrast or remove the species (Caplat et al., 2012; Foxcroft et al., 2013; Heger and Trepl, 2003; Saul et al., 2013; Veitch and Clout, 2002).

Invasive species management aims to prevent introductions, eradication or contain populations, and mitigate their negative environmental, economic, and social impacts (Simberloff, 2014). Interventions, including legislation, trade regulation, border controls, eradication, population controls, and restoration, generate both positive and negative impacts (Crowley et al., 2017). While some communities may benefit from damage reduction or increases in native biodiversity, others might be negatively affected by trade restrictions or the loss of valued plants (Marshall et al., 2011; Norgaard, 2007). Nevertheless, the significance of prevention and monitoring cannot be overstated, as they play a fundamental role in containing the costs associated with mitigation actions. Consequently, the modelling of the expansion of invasive plants under future conditions is increasingly recognized as a pertinent and valuable research tool in different sectors (Barney, 2014; Lázaro-Lobo et al., 2021; Lindgren, 2013). To accomplish these goals, a coordinated effort involving various stakeholders, including the scientific community, political entities, and citizens, is crucial. Unfortunately, achieving a unified intention often proves challenging (Foxcroft et al., 2013). In fact, the governance and processes of management can also create social impacts; excluding stakeholders from meaningful participation in deliberation and decision-making can produce distrust and animosity, as well as anxiety if people feel they lack control over decisions that affect them (Crowley et al., 2017). Similar findings have been reported in studies addressing sustainable environmental practices and management policies (Agarwal et al., 2023; Alvarado et al., 2021). Moreover, planning eradication programs with the ambitious goal of a total elimination strategy demand meticulous monitoring and a readiness for plant recognition and sampling techniques by potential personnel (Zamora et al., 1989). Additionally, eradication actions cannot be limited to the removal of all plants from a determined area, in relation to the presence of seed banks (Panetta, 2015). Monitoring actions should be reiterated over time, even for many years, both to check the possible regrowth of plants from root remnants (Leiss, 2011) and to prevent the resurgence of new plants through the germination of dormant seeds triggered by disturbance events (Panetta, 2004).

A recent instance pertains to the ongoing invasion of *S. inaequidens* within a former pasture located in North Sardinia. This area underwent excavation in 2023 to facilitate the establishment of a photovoltaic park, and presently hosts a substantial population of the species. Considering the escalating frequency of such occurrences throughout North Sardinia, characterized by the abundant proliferation of plants colonizing disturbed sites, including but not limited to roadsides, industrial areas, and a multitude of worksites, along with the predictions highlighted in this work, the status of this plant in Sardinia should be reassessed as an invasive species in Sardinia. Among the possible field actions to mitigate the expansion of *S. inaequidens* in Sardinia, a good strategy has recently involved initiating manual eradication of individuals (adults, juveniles, and seedlings), mostly in isolated, small, and sparse patches. Eradication efforts are most effective and economical in these cases (Simberloff, 2009). For larger, denser patches, a monitoring approach from the periphery towards the center, targeting areas with the highest individual density, can help contain the species' expansion (Simberloff, 2009). However, local eradication efforts may face challenges due to the yearly production of even thousands of seeds per plant (Misuri et al., 2020), whose pappuses facilitate wind dispersal, serving as a very potent tool for invasion (Monty et al., 2008).

In northern Sardinia, in the absence of regional laws protecting native plant species, along with categorizing, monitoring and controlling the expansion or commercialization of invasive non-native ones, to contrast these issues, autonomous activities in numerous locations were achieved (*personal communication*). Such activities were conducted where the species was identified, and entailed the eradication of plants, following the removal and destruction of all mature capitula. This approach aimed to prevent potential dispersal phenomena due to the potential ability of achenes to reach maturity from fertile flowers even after eradication. Consequently, most of the settlement sites have witnessed the subsequent disappearance of the species. Such actions have predominantly targeted small populations, consisting of scattered individuals. However, in one instance, in autumn 2018, over 200 plants of different ages were eradicated from an infested holm oak forest that had been indiscriminately felled in 2014, situated at elevations between 700 and 900 m a.s.l. Following the systematic removal of all identified plants and the destruction of all mature capitula, the species did not reappear in that area in the following five years.

5. Conclusions

Our study underscores the urgent need to understand and anticipate the spread of *Senecio inaequidens* in Sardinia under both current and future climatic conditions. Utilizing an advanced ensemble species distribution model (SDM) approach, we provide insights into the bioclimatic suitability of Sardinia for this invasive species, identifying areas where proactive management efforts are needed. One of the standout aspects of our research is the use of an ensemble modelling method, which integrates multiple individual models to reduce the uncertainties associated with single-model predictions. Our study offers predictions for the potential distribution of *S. inaequidens* under current climatic conditions, leveraging high-resolution bioclimatic data specifically tailored for Sardinia. This high-resolution bioclimatic data enhances our understanding of the present invasion risk and allows for immediate and targeted management actions.

The model accurately identifies bio-climatically suitable areas for the species, closely aligning with the documented occurrences on the island under the current conditions. Incorporating the latest climate and socio-economic scenarios from the Coupled Model Intercomparison Project Phase 6 (CMIP6), our research provides projections under both intermediate (SSP2–4.5) and severe (SSP5–8.5) future conditions. The projections indicate the spread of *S. inaequidens*, with an increase in suitable habitats expected by 2040 and 2060. The severe scenario is particularly concerning, as it suggests a pronounced expansion, highlighting the critical need for proactive management strategies.

However, our approach has some caveats. The reliance on presence-only data, due to the scarcity of high-quality absence data, can limit the model predictions. Additionally, the limited availability of future data, especially for non-climate variables, can hinder a clear and complete understanding of the future spread of non-native species. This poses challenges for scientists and managers in developing effective management and adaptation strategies. Addressing the identified limitations through enhanced data collection and the inclusion of additional ecological factors will be crucial for improving model predictions and management effectiveness. For example, the positive effect of road dissection of the landscape and fragmentation on the non-native species spread is widely acknowledged. Developing future projections of these environmental drivers in coherence with the latest generation of future scenarios could improve the understanding of future invasion dynamics of non-native species and provide better predictions of high-risk areas for invasiveness, supporting the development of management plans. Detailed management plans will be essential for efficient resource allocation and timely interventions to mitigate the spread and ecological impact of non-native invasiveness.

CRediT authorship contribution statement

Erika Bazzato: Writing – review & editing, Writing – original draft, Visualization, Validation, Methodology, Formal analysis, Conceptualization. **Giacomo Calvia:** Writing – review & editing, Writing – original draft, Resources, Investigation, Data curation. **Michela Marignani:** Writing – review & editing, Resources, Conceptualization. **Alessandro Ruggero:** Resources, Investigation, Data curation. **Vanessa Lozano:** Writing – review & editing, Writing – original draft, Resources, Investigation, Data curation, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data are shared in Supplementary Appendix A2.

Acknowledgements

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ecoinf.2024.102783.

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