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ORIGINAL ARTICLE OPEN ACCESS

Modelling the Climatic Suitability of *Digitaria insularis*, a Global Invasive Species, Under Climate Change Scenarios

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Received: 15 July 2025 | **Revised:** 4 February 2026 | **Accepted:** 17 February 2026

Keywords: adaptability | ecological niche modelling | niche modelling | Poaceae biogeography | sourgrass

ABSTRACT

Grasses in the Poaceae family are major components of global ecosystems and agricultural systems, and their adaptive success has enabled some species to become highly competitive weeds. *Digitaria insularis* (sourgrass), a C4 perennial grass native to the Americas and now widely introduced elsewhere, has evolved herbicide resistance and poses an increasing threat to crop productivity. This study modelled the current and future climatic suitability of *D. insularis* using ecological niche models under two climate change scenarios (SSP126 and SSP585) for 2030 and 2090. After filtering 1329 occurrence records, 559 high-confidence records were used for modelling. A total of 19 bioclimatic variables from WorldClim were reduced via Principal Component Analysis, and four algorithms (Bioclim, Maxent, Random Forest, and SVM) were combined into an ensemble approach. Model performance was consistently high across metrics, and MOP analyses indicated limited strict extrapolation, supporting the robustness of projections. Results show extensive suitability across tropical and subtropical regions under current conditions, with substantial retention of suitable areas and progressive gains in future scenarios. Expansion was particularly pronounced under SSP585, with increased suitability in South America, Sub-Saharan Africa, Southeast Asia, northern Australia, and higher-latitude agricultural regions, including the U.S. Corn Belt and Mediterranean Europe. These expansions overlap with structurally vulnerable agricultural systems, indicating an elevated risk of invasive spread and potential impacts on food security. The findings highlight the need for proactive, integrated, and cross-regional management strategies to mitigate future spread and resistance-related agronomic losses.

1 | Introduction

Grasses (Poaceae) are among the most successful angiosperms, forming ecosystems that cover a large portion of the Earth's land surface and contributing substantially to global primary productivity (Beer et al. 2010; Linder et al. 2018). Their success is linked to high adaptive capacity and strategies that enable colonisation and persistence across diverse environments. Over geological time, grasses have reshaped the biosphere; during the Miocene, C_3 grasses replaced temperate forests, and later, C_4 grasses expanded into tropical regions, replacing C_3-dominated vegetation (Sage 2004; Vicentini et al. 2008).

The evolution of C_4 photosynthesis, initially driven by declining atmospheric CO_2 levels, was also influenced by factors such as aridity, high light, salinity, and disturbance. While C_4 metabolism in most plants is associated with water stress, in grasses it correlates strongly with high temperatures, explaining their dominance in tropical savannas and absence in cold temperate grasslands (Vicentini et al. 2008; Xu and Zhou 2017).

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This distribution pattern is particularly relevant in the context of global warming, which may shift the potential ranges of C_4 grasses and alter the composition of grass-dominated ecosystems (Beer et al. 2010; IPCC 2023).

Among the most vulnerable sectors, agriculture is directly impacted by extreme weather events and increasingly unpredictable meteorological conditions, compromising crop productivity and posing a growing threat to global food security. Agricultural practices have intensified rapidly over the past two centuries through the expansion of cultivated areas (Goldewijk et al. 2017), widespread monoculture planting (Crews et al. 2018), and increased use of agrochemicals (Malaj et al. 2020). Since the mid-20th century, the development of new high-yielding crop varieties, including wheat, cotton, maize, and soybean, resistant to herbicides has significantly boosted agricultural productivity (Borlaug 1983; Beckie 2020).

However, agriculture now faces a serious threat due to the proliferation of weed species, especially those that have evolved herbicide resistance. Sourgrass (*Digitaria insularis* (L.) Mez ex Ekman) is a grass in the Poaceae family with C_4 photosynthetic metabolism, native to the Americas and now introduced in regions of Asia, Africa, and Oceania. Each plant can produce up to 40 000 seeds per year, equipped with trichomes that facilitate long-distance wind dispersal (Gemelli 2012; Souza et al. 2024), promoting colonisation of new areas, particularly in human-altered environments.

D. insularis is a highly competitive perennial grass capable of rapid spread through vegetative propagation via rhizomes. Its prolific seed production and high germination potential enable establishment across diverse agricultural and non-agricultural environments. Its competitiveness is driven by efficient exploitation of light, water, and nutrients, and by its tolerance to a wide range of soil physical and chemical conditions. In Brazil and other South American countries, land-use changes and intensive agricultural practices, including continuous herbicide application, have favoured the selection of populations resistant to glyphosate and ACCase inhibitors, causing yield losses exceeding 80% in crops such as soybean crops. This resistance involves both target-site mechanisms (e.g., mutations in the ACCase gene) and non-target-site mechanisms (e.g., enhanced metabolism and vacuolar sequestration), which together reduce the efficacy of conventional chemical control. Such adaptive success is closely linked to genetic diversity and strong regional selective pressures, enabling rapid evolution in intensively managed agricultural systems (Sehgal et al. 2024; Souza et al. 2024).

Given its range expansion and impact on agricultural systems, understanding the species' potential geographic distribution becomes essential. Ecological niche models (ENMs) are powerful tools for predicting potential species distributions based on occurrence records and environmental variables. They have broad applications, from conservation and climate change studies to mapping invasive species and assessing biological risks (Wan et al. 2017; Solís-Montero et al. 2022). For highly adaptable and widely dispersing weed species like *D. insularis*, ENMs help identify environmentally suitable areas for occurrence and expansion, supporting the development of more effective management strategies.

In this context, this study aimed to model the current and future distribution of *D. insularis* under different climate change scenarios (SSP126 and SSP585) for the years 2030 and 2090, in order to identify environmentally suitable regions for its occurrence and potential expansion. Specifically, the objectives were to: (i) map the current climatic distribution of the species based on occurrence records and bioclimatic variables; (ii) project its potential future distribution; (iii) compare patterns of climatic suitability across scenarios and timeframes; (iv) identify areas at risk of invasion in vulnerable agricultural regions; and (v) provide insights to support monitoring, management, and policy-making efforts. It is hypothesized that *D. insularis* exhibits high ecological plasticity and will undergo significant geographic expansion under future climate conditions, especially under high-emission scenarios. Tropical and subtropical regions are expected to remain primary areas of suitability, with expansion into temperate zones such as the U.S. Corn Belt and southern Europe. Furthermore, the overlap between highly suitable areas and structurally vulnerable agricultural systems is anticipated to represent a growing threat to global food security, even under climate mitigation scenarios.

2 | Materials and Methods

2.1 | Data Collection and Filtering

Georeferenced occurrence data for the species were compiled from online herbarium databases using the **spocc** R package (https://github.com/ropensci/spocc). This tool aggregates occurrence records from several repositories, including the Global Biodiversity Information Facility (GBIF, https://www.gbif.org/), the New York Botanical Garden (https://www.nybg.org/), and SpeciesLink (https://specieslink.net/) (Figure 1).

Following data retrieval, a rigorous filtering process was conducted using the CoordinateCleaner package to ensure data reliability and spatial accuracy (Zizka et al. 2019). The filtering criteria included: (i) Missing and duplicate data—removal of records lacking geographic coordinates (latitude and/or longitude), duplicate entries, or those with coordinates equal to zero; (ii) Spatial validation—exclusion of records located within a 1000 m radius of national capitals, 10 000 m of country or municipality centroids, and 100 m of known biodiversity institutions (including GBIF headquarters). Points located in oceanic regions or urban areas were also removed; (iii) Outlier detection—the five most extreme geographic outliers were identified and excluded based on the quantile method; (iv) Taxonomic and georeferencing validation—potential errors in species identification or geolocation were manually reviewed and discarded (Figure 2).

Additionally, records dated before 1980 were excluded due to potential inaccuracies in georeferencing practices during that period. Entries with missing, null, or evidently incorrect year information were also removed from the dataset (Figure 3).

2.2 | Current and Future Climate Variables

To model the species' potential distribution under current climatic conditions, 19 bioclimatic variables (bio1 to bio19) were retrieved from the WorldClim database, version 2.1 (Table S1).

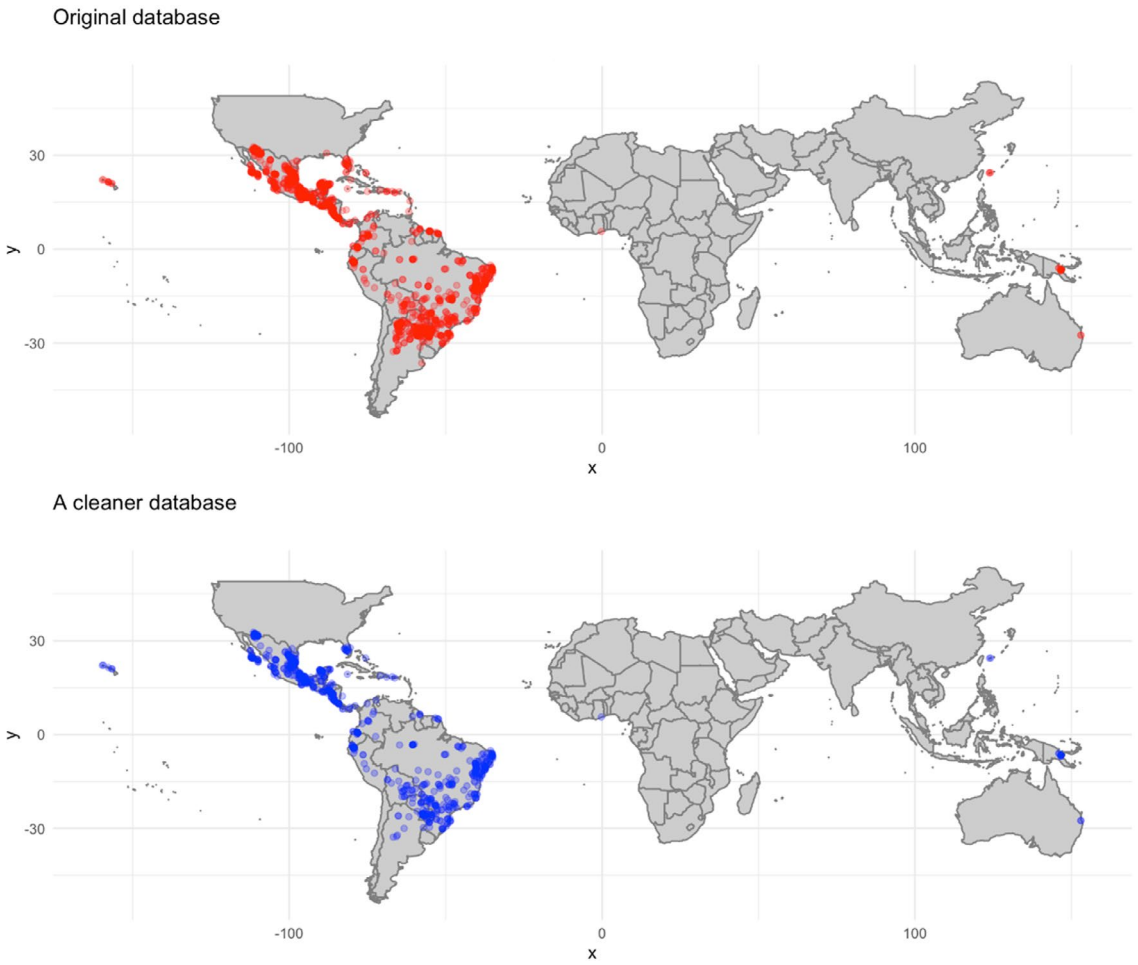

FIGURE 1 | Geographic distribution of *Digitaria insularis* occurrence records before (top, in red) and after (bottom, in blue) data cleaning. The original dataset (1329 records) included numerous spurious or unreliable occurrences, often clustered in urban areas, positioned at country centroids, or representing duplicated geographic coordinates, issues typically arising from imprecise georeferencing or data entry errors in global biodiversity databases. Data cleaning was performed using the CoordinateCleaner, applying filtering criteria to remove duplicates, points with low coordinate precision, and records outside the species' plausible range. The cleaned dataset (700 records) exhibits a more ecologically coherent spatial distribution, with a substantial reduction in outliers. This refined dataset provides higher spatial accuracy and reliability for subsequent ecological niche modelling and climate change impact assessments.

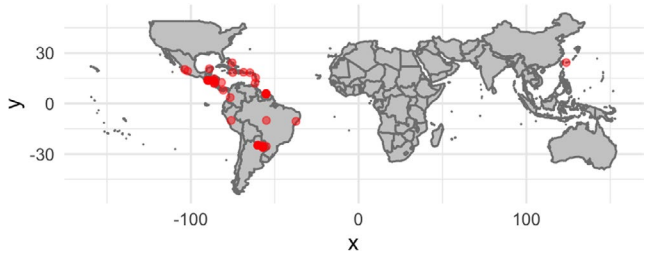

FIGURE 2 | Occurrence records of *D. insularis* removed during the filtering process. The excluded points include duplicated coordinates, locations in urban centers, capital cities, country or municipality centroids, entries with evident georeferencing errors, and records in unlikely areas such as oceans.

These layers correspond to the historical period of 1970–2000 and have a spatial resolution of 5 arcminutes. According to WorldClim, these variables capture key aspects of climate patterns, including annual means (e.g., temperature and precipitation), seasonality (e.g., temperature and precipitation ranges), and environmental extremes or constraints (e.g., minimum temperature of the coldest month, precipitation of the driest quarter).

To estimate the future potential distribution of the species, climate projections were generated using an ensemble of two general circulation models (GCMs): MPI-ESM1-2-HR and EC-Earth3-Veg (Gutjahr et al. 2019; Döscher et al. 2022). These projections were based on two distinct Shared Socioeconomic Pathways (SSPs), which represent plausible future trajectories of global development, greenhouse gas emissions, and climate policies. The SSP126 scenario reflects an optimistic pathway, characterised by a global transition toward sustainable development, reduced inequality, investments in education and health, and strong mitigation strategies that lead to low greenhouse gas emissions and limited climate change. In contrast, the SSP585 scenario represents a pessimistic trajectory, in which the world follows a fossil fuel-intensive path, with continued high population growth, limited international

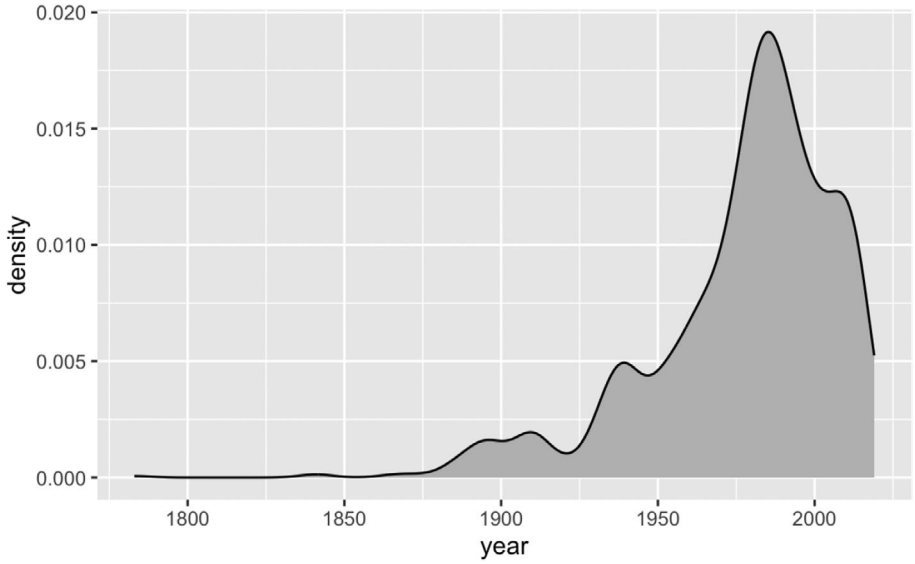

FIGURE 3 | Temporal distribution of occurrence records obtained from online herbaria prior to the initial filtering. Records dated before 1980 were excluded from the analysis due to low georeferencing reliability.

cooperation, and minimal efforts to curb emissions, resulting in severe global warming (Meinshausen et al. 2020). To capture potential temporal shifts in species distribution under these scenarios, two future timeframes were considered: the year 2030, representing the average climate conditions for the period 2021–2040, and the year 2090, corresponding to the average for 2081–2100.

2.3 | Ecological Niche Modelling

The occurrence coordinates were first filtered using the CoordinateCleaner package and subsequently processed with the ENMTML package to perform ENM (Andrade et al. 2020). As part of its preprocessing steps, the ENMTML package applies a spatial thinning procedure to reduce sampling bias by eliminating records that are closer than twice the resolution of the environmental variables, in this case, approximately 9 km. This step helps prevent overfitting and overestimation of suitable areas, particularly in regions with a high density of occurrence records.

A Principal Component Analysis (PCA) was applied to reduce multicollinearity among the bioclimatic variables. Principal components were retained until a cumulative variance threshold of at least 95% was reached, resulting in the selection of six components that together explained 96.8% of the total variance (Supplementary Table S2) (Destro et al. 2020). This procedure was implemented using the ENMTML package with the argument colin_var = c(method = "PCA"), ensuring the selection of informative and non-redundant environmental predictors. Loadings of the original bioclimatic variables on each principal component are provided in Supplementary Table S3.

To estimate the species' ecological niche, four algorithms were employed and grouped into three methodological categories based on the type of input data used:

i. Presence-only models, which rely solely on known occurrence records without requiring information on absences. These models assume that the absence of data does not necessarily indicate unsuitable conditions. Bioclim (Booth et al. 2014) was used as a representative of this approach.

ii. Presence-absence models, which require both presence and confirmed absence data, allow the algorithm to distinguish suitable from unsuitable environments more explicitly. In this study, random forest (RF) (Breiman 2001) and support vector machine (SVM) (Guo et al. 2005) were applied under this category.

iii. Presence-background models, which use known occurrences and generate background points (pseudo-absences) across the study area to contrast environmental conditions where the species is known to occur with those where it might not. Maxent v3.4.1 (Warren and Seifert 2011) was used to represent this group.

Pseudo-absences were generated using the geo_env_cost method implemented in the ENMTML package, which combines geographical and environmental constraints to explicitly address the uncertain nature of absences in species distribution modelling. This approach restricts pseudo-absence selection to areas that are simultaneously geographically distant from known occurrences and environmentally unsuitable, based on low suitability values predicted by the Bioclim model (Booth et al. 2014). By doing so, the method reduces the inclusion of environmentally suitable but unsampled locations (i.e., methodological or contingent absences), thereby minimising bias and improving model calibration (Lobo et al. 2010).

Model evaluation was conducted using a geographical block partitioning scheme (BLOCK), which divides the study area into two-dimensional spatial blocks (checkerboard). This strategy enforces spatial independence between

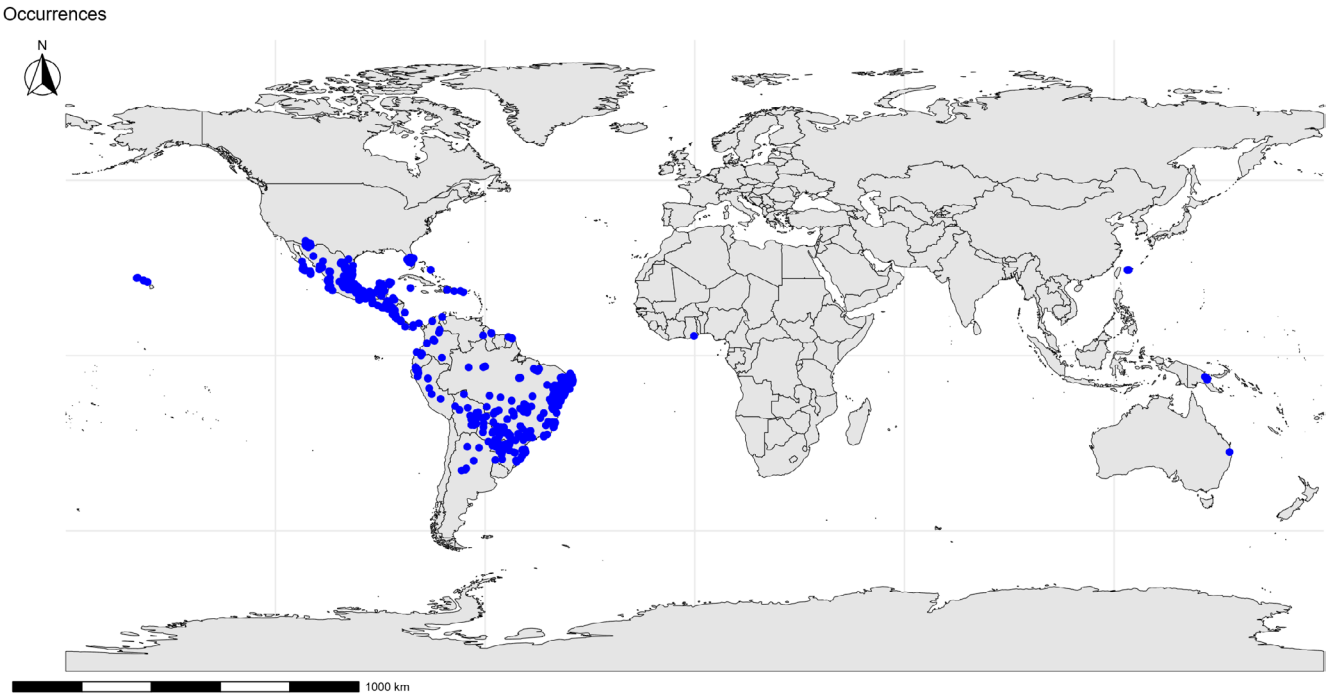

FIGURE 4 | Geographic distribution of the 508 validated occurrence records of *Digitaria insularis* after processing with the ENMTML package. The world map, in geographic coordinates, displays countries in grey, a grid of meridians and parallels, and a scale bar; blue points represent occurrences with high spatial reliability retained for niche modelling analyses. A higher concentration is observed in South America, especially in Brazil (Southeast, Central-West, and South), as well as in Paraguay, Bolivia, and northern Argentina; records are also found along Mesoamerica and the Caribbean and in northern South America (Colombia and Venezuela). Scattered occurrences appear in Sub-Saharan Africa, Southeast Asia (e.g., Indonesia, Philippines, Malaysia), Papua New Guinea, and eastern Australia. This final dataset served as the basis for the subsequent ecological niche modelling steps and projections under climate change scenarios.

calibration and validation datasets, reducing the effects of spatial autocorrelation and providing a more conservative and realistic assessment of model predictive performance (Roberts et al. 2017).

Model accuracy was evaluated using multiple evaluation metrics, including the area under the curve (AUC) (Metz 1986), Kappa, the true skill statistic (TSS) (Allouche et al. 2006), as well as the Jaccard and Sorensen similarity indices and the omission rate (OR). Only models with AUC >0.75 and TSS >0.7 were retained for ensemble forecasting. Ensemble was computed using the mean method ("MEAN") to combine suitability outputs.

Suitability maps and occurrence points were visualised using the raster (Hijmans 2025), ggplot2 (Wickham 2016), sf (Pebesma 2016), and gridExtra (Auguie and Antonov 2022) R packages. Global minimum and maximum suitability values across all raster layers were determined using the min() and max() functions in R.

3 | Results

A total of 1329 occurrence records of *D. insularis* were initially compiled from online biodiversity databases. Occurrences of *D. insularis* were geographically widespread, with the highest numbers of records observed in Mexico ($n=428$), Brazil ($n=320$), Argentina ($n=167$), and Paraguay ($n=88$). Additional records were distributed across Central and South America, North America, Oceania, Africa, and Asia (Supplementary Table S4). After data cleaning and quality control, 297 records were excluded due to redundancy and spatial uncertainty, and 332 records collected prior to 1980 were removed (Supplementary Table S5). A total of 700 occurrence points remained after these preprocessing steps and were used to initiate ENM (Supporting Information 1). Following internal ENMTML filtering and spatial thinning, 559 high-confidence occurrence records were retained for model calibration and validation (Supporting Information 2 and Figure 4).

After partitioning the suitable area for *D. insularis* into loss, stability and gain components (Table 1), our results show a high retention of climatically suitable areas across all future scenarios, with overlap values above 57 million km^2. Although some currently suitable areas are projected to be lost (between 2.17 and 2.64 million km^2), these losses are consistently outweighed by projected gains in newly suitable regions. These gains increase across time horizons, from 3.76 million km^2 under SSP126 in 2030 to 9.76 million km^2 under SSP585 in 2090, indicating not only the persistence of much of the current distribution but also the potential for geographic expansion in future climates.

Model performance metrics indicate consistently high predictive ability across algorithms (Table 2). The Bioclim model yielded a mean AUC of 0.963 (±0.014), with corresponding TSS and Kappa values of 0.907 (±0.029) and high similarity indices (Jaccard $=0.909\pm0.028$; Sorensen $=0.952\pm0.015$). The Maxent

TABLE 1 | Spatial partitioning of climatically suitable areas for *Digitaria insularis* under future climate scenarios. The table presents the area exclusively suitable under current conditions ("Loss"), the area of persistence between current and future projections ("Stable/Overlap"), and the newly suitable area predicted under each scenario ("Gain"). Total current and future suitable areas were calculated by summing the exclusive and overlapping fractions. Values are expressed in square kilometres.

Scenario	Loss (Current exclusive) km²	Stable (Overlap) km²	Gain (Future exclusive) km²	Total current km²	Total future km²
SSP126–2030	2 172 658	57 875 087	3 757 472	60 047 745	61 632 559
SSP585–2030	2 231 056	57 816 689	3 688 668	60 047 745	61 505 357
SSP126–2090	2 291 259	57 756 486	4 636 616	60 047 745	62 393 102
SSP585–2090	2 636 397	57 411 348	9 758 127	60 047 745	67 169 475

TABLE 2 | Mean values and standard deviations of performance metrics for ecological niche models of *Digitaria insularis*.

Algorithm	AUC	Kappa	TSS	Jaccard	Sorensen	OR
BIO	0.9628 ± 0.0135	0.9066 ± 0.0287	0.9066 ± 0.0287	0.9086 ± 0.0279	0.9520 ± 0.0153	0.0721 ± 0.0258
MXS	0.9873 ± 0.0022	0.9255 ± 0.0129	0.9255 ± 0.0129	0.9262 ± 0.0123	0.9617 ± 0.0066	0.0659 ± 0.0061
SVM	0.9930 ± 0.0041	0.9312 ± 0.0169	0.9312 ± 0.0169	0.9333 ± 0.0170	0.9655 ± 0.0091	0.0353 ± 0.0263
RDF	0.9948 ± 0.0031	0.9446 ± 0.0021	0.9446 ± 0.0021	0.9462 ± 0.0027	0.9724 ± 0.0015	0.0261 ± 0.0151
MEAN	0.9975 ± 0.0002	0.9543 ± 0.0157	0.9543 ± 0.0157	0.9561 ± 0.0144	0.9775 ± 0.0076	0.0072 ± 0.0007

Note: Performance metrics of ecological niche models for *Digitaria insularis*, obtained through bootstrap partitioning and using the maximum TSS threshold (MAX_TSS). Mean values and respective standard deviations (SD) for each metric are presented across replicates. AUC (Area Under the ROC Curve), Kappa (concordance coefficient), TSS (True Skill Statistic), Jaccard and Sorensen (similarity indices), OR (Omission Rate) are reported. AUC, Kappa, and TSS indicate the models' discriminative capacity, while Jaccard and Sorensen quantify the overlap between predicted presence areas and actual occurrence points. Variability across replicates is expressed by the standard deviation values of the metrics. MEAN corresponds to the ensemble model produced using the mean approach, whereby suitability predictions from all individual algorithms are averaged to generate a consensus distribution. Accordingly, MEAN does not represent a distinct algorithm, but rather the final ensemble output derived from the mean of individual model predictions.

model with simple features (MXS) showed improved performance, with a mean AUC of 0.987 (± 0.002) and TSS of 0.926 (± 0.013).

Among machine-learning approaches, the SVM and RF models achieved the highest accuracy, with mean AUC values of 0.993 (± 0.004) and 0.995 (± 0.003), respectively, and TSS values exceeding 0.93. Ensemble predictions generated using the mean approach (MEAN) presented the best overall performance, with a mean AUC of 0.998 (± 0.0002), TSS of 0.954 (± 0.016), high similarity indices (Jaccard = 0.956 ± 0.014; Sorensen = 0.978 ± 0.008), and the lowest omission rate (OR = 0.007 ± 0.001), with the contribution of each retained principal component to model performance summarised in Supplementary Table S6.

The Mobility-Oriented Parity (MOP) analysis showed that most regions included in the global projections were characterised by environmental conditions analogous to those represented in the calibration area (Figure 5). Areas with low MOP values, indicating potential environmental novelty and strict model extrapolation, were spatially limited and primarily concentrated in the Amazon Basin, with additional localised regions observed in parts of Southeast Asia and Oceania. Overall, the restricted extent of extrapolation suggests that the projected suitability patterns are largely supported by environmental conditions represented in the occurrence dataset.

The ENM revealed a broad potential distribution for *D. insularis* across tropical and subtropical regions worldwide. The areas with the highest environmental suitability are concentrated in South America, particularly Brazil, especially in the Central-West, Southeast, and South regions, as well as large parts of Paraguay, Bolivia, Colombia, Venezuela, and northern Argentina. In Central America and the Caribbean, the species also finds highly favourable conditions for occurrence (Figure 6).

Outside the Americas, the model indicated high suitability across vast areas of Sub-Saharan Africa, encompassing both tropical and subtropical zones. In Southeast Asia, countries such as Indonesia, Malaysia, the Philippines, and parts of Thailand and Vietnam showed a high probability of occurrence. Similarly, in Australia, the northern and eastern regions exhibited strong potential for the species' suitability.

Conversely, temperate or cold climate areas such as northern North America, northern Europe, most of Central Asia, and high-altitude regions showed low or no environmental suitability for *D. insularis*, according to the model projections.

Climate-based modelling under the SSP126 scenario for the year 2030 indicates significant expansion of environmental suitability for *D. insularis* across tropical and subtropical regions. Brazil and other South American countries continue to exhibit high suitability for species occurrence, while new environmentally favourable areas are projected in Central America, the southern United States, Sub-Saharan Africa, Southeast Asia, the Indian subcontinent, and northern Australia (Figure 7).

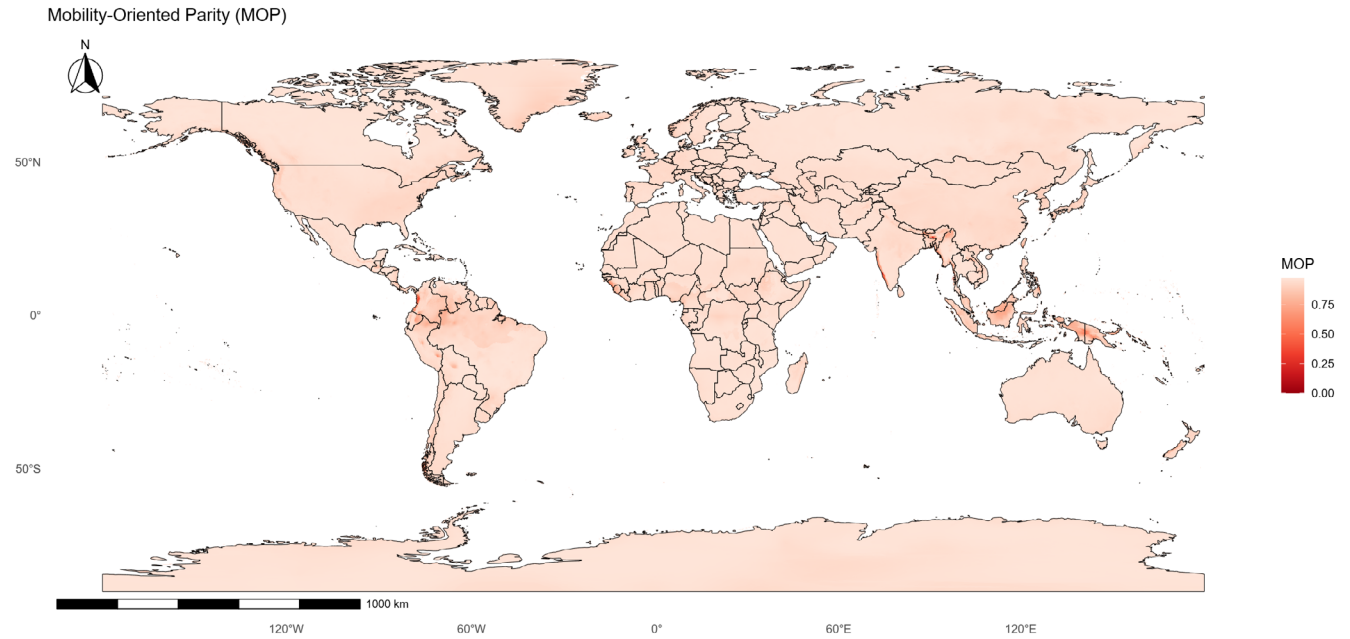

FIGURE 5 | Global Mobility-Oriented Parity (MOP) analysis used to assess environmental similarity between the calibration area and the projection space for *Digitaria insularis*. Lighter colours indicate areas with higher environmental similarity to the calibration conditions, whereas darker colours represent regions with lower similarity, suggesting potential environmental novelty and model extrapolation. The analysis highlights that most projected areas fall within environmentally analogous conditions, with limited regions of potential extrapolation.

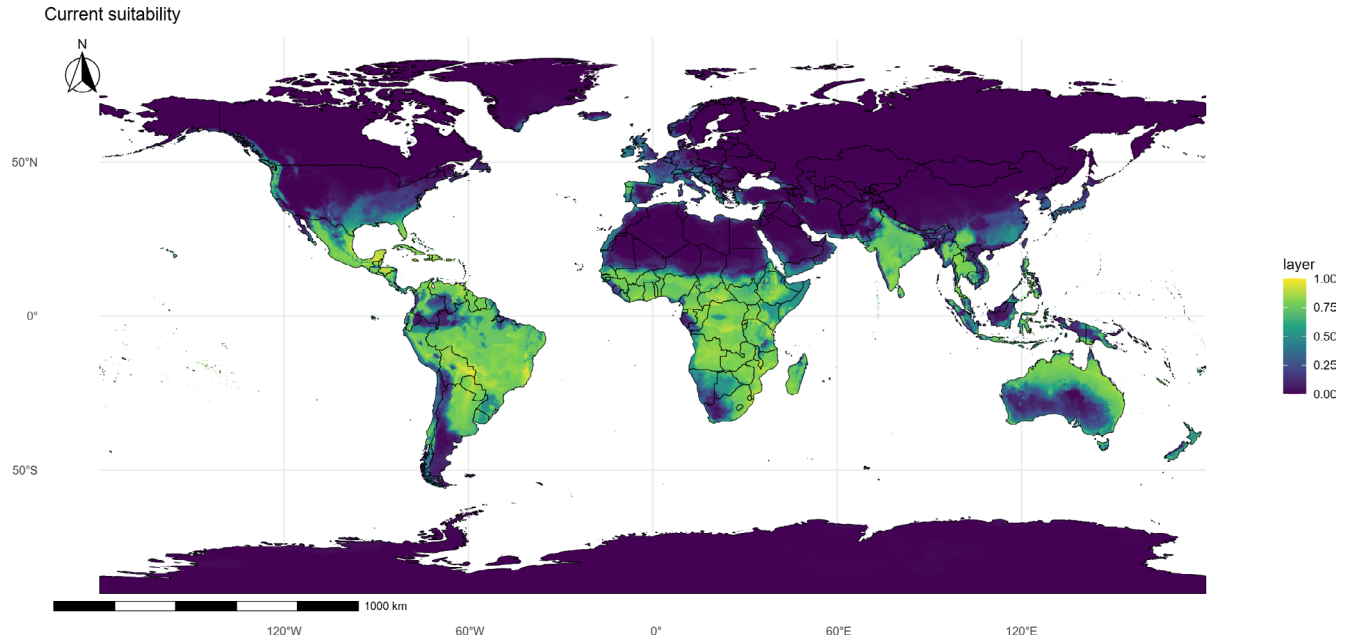

FIGURE 6 | Global map of current climatic suitability for *Digitaria insularis*, obtained through ecological niche modelling. The colour scale ranges from dark purple (low suitability) to yellow (high suitability), with higher values indicating more favourable climatic conditions, based on present-day climatic conditions and encompassing both native and introduced areas of the species.

Comparisons with projections for SSP126 (2090) and SSP585 (2030) reveal similar patterns, with the species maintaining a high likelihood of occurrence across these same regions and exhibiting slight expansions into transitional climatic zones (Figures 8 and 9).

Despite differences in time horizon and emission intensity, both scenarios result in a comparable expansion of the species' potential area of occurrence. Notably, both scenarios show slight to moderate increases in suitability toward parts of the Corn Belt, one of the world's most important agricultural regions. Even under the climate-controlled SSP126 scenario for 2090, environmental suitability persists in vulnerable agricultural areas, suggesting that *D. insularis* will remain a significant threat to agriculture even in contexts of climate mitigation.

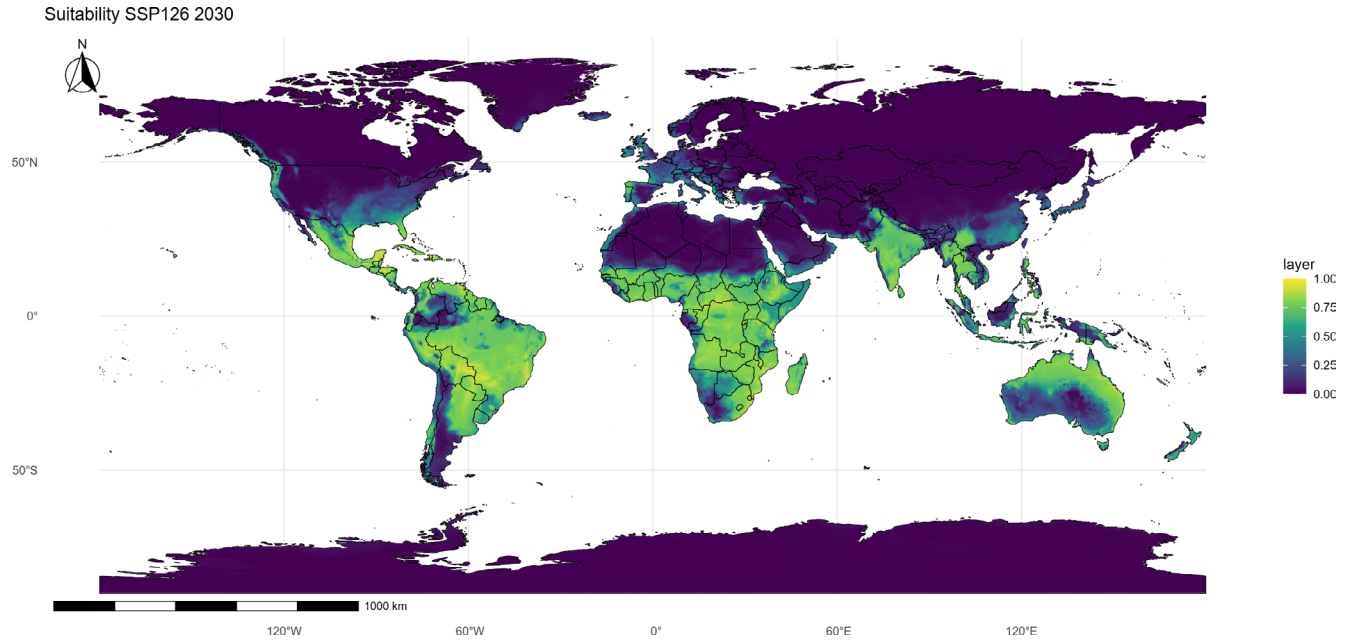

FIGURE 7 | Projected climatic suitability for *Digitaria insularis* in 2030 under the SSP126 scenario, based on ecological niche modelling. The colour scale ranges from dark purple (low suitability) to yellow (high suitability). Green–yellow areas indicate regions with favourable climatic conditions for the species, while purple areas represent low or no suitability. SSP126 represents a sustainable development pathway characterised by low greenhouse gas emissions and effective climate mitigation measures.

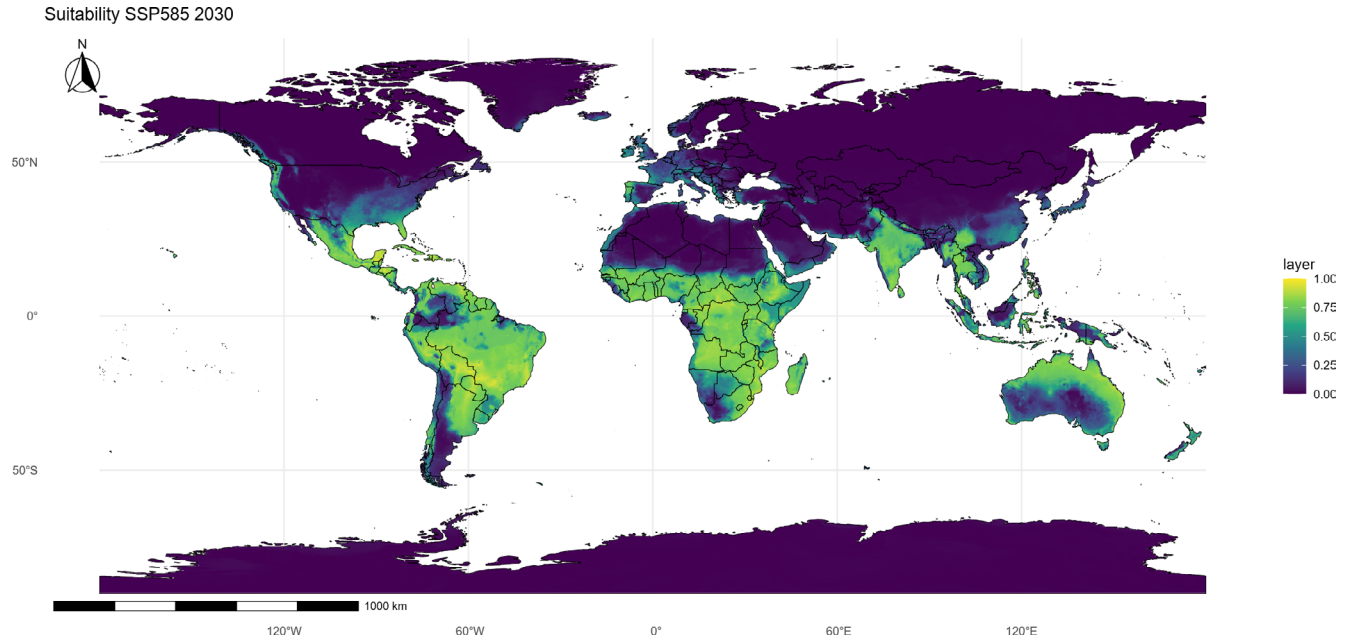

FIGURE 8 | Projected climatic suitability for *Digitaria insularis* in 2030 under the SSP585 scenario, based on ecological niche modelling. The colour scale ranges from dark purple (low suitability) to yellow (high suitability). Lighter areas indicate regions that will remain or become more suitable for the species. SSP585 represents a high-emission pathway characterised by carbon-intensive economic growth and limited implementation of climate mitigation measures.

The projection for 2090 under the SSP585 scenario indicates a substantial expansion in environmental suitability for *D. insularis*. The model reveals a pronounced increase in favourable areas, not only across regions previously identified such as South America, Sub-Saharan Africa, and Southeast Asia but also extending into new zones, including Central America, the southern United States, the Indian subcontinent, and Australia. Notably, several of these areas show intensified zones of high suitability compared to earlier scenarios (Figure 10).

The expansion of suitability toward higher latitudes and altitudes becomes more evident in this scenario, reflecting the amplified effects of environmental change on the species' climatic niche.

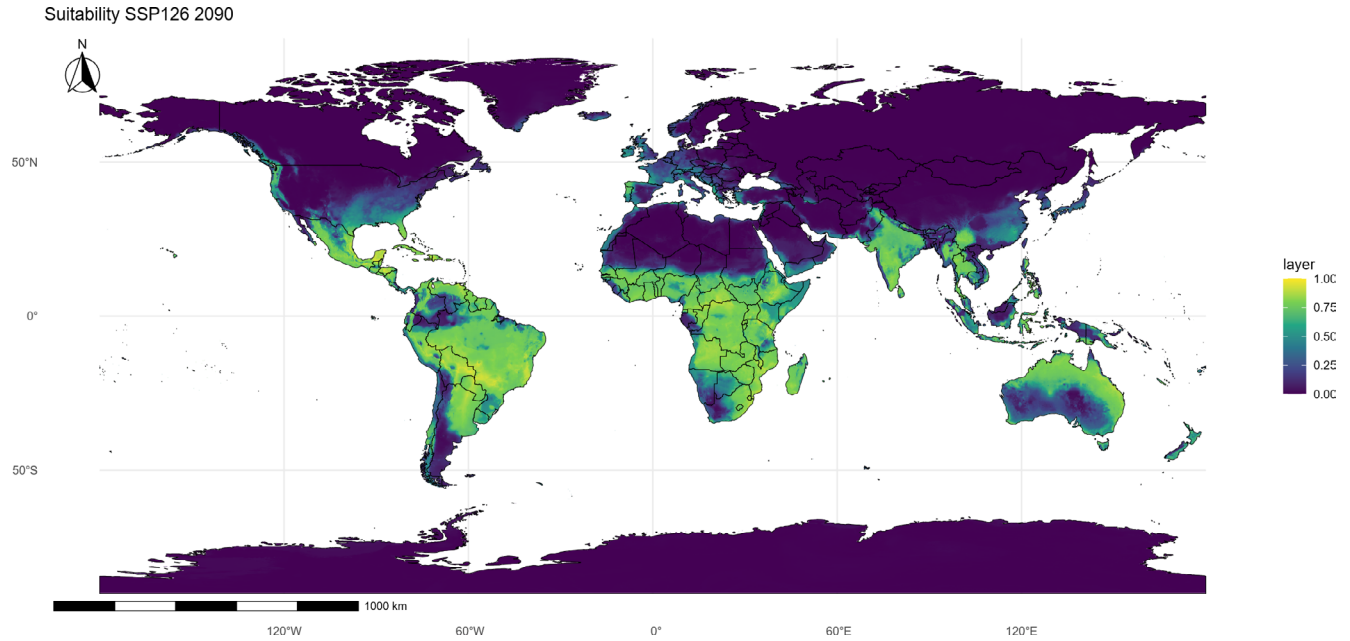

FIGURE 9 | Projected climatic suitability for *Digitaria insularis* in 2090 under the SSP126 scenario, based on ecological niche modelling. The colour scale ranges from dark purple (low suitability) to yellow (high suitability). Despite the temporal advancement, this low-emission pathway shows limited changes in the species' potential distribution, with highly suitable areas persisting mainly in South America and parts of Sub-Saharan Africa, alongside smaller favourable regions in other tropical and subtropical zones.

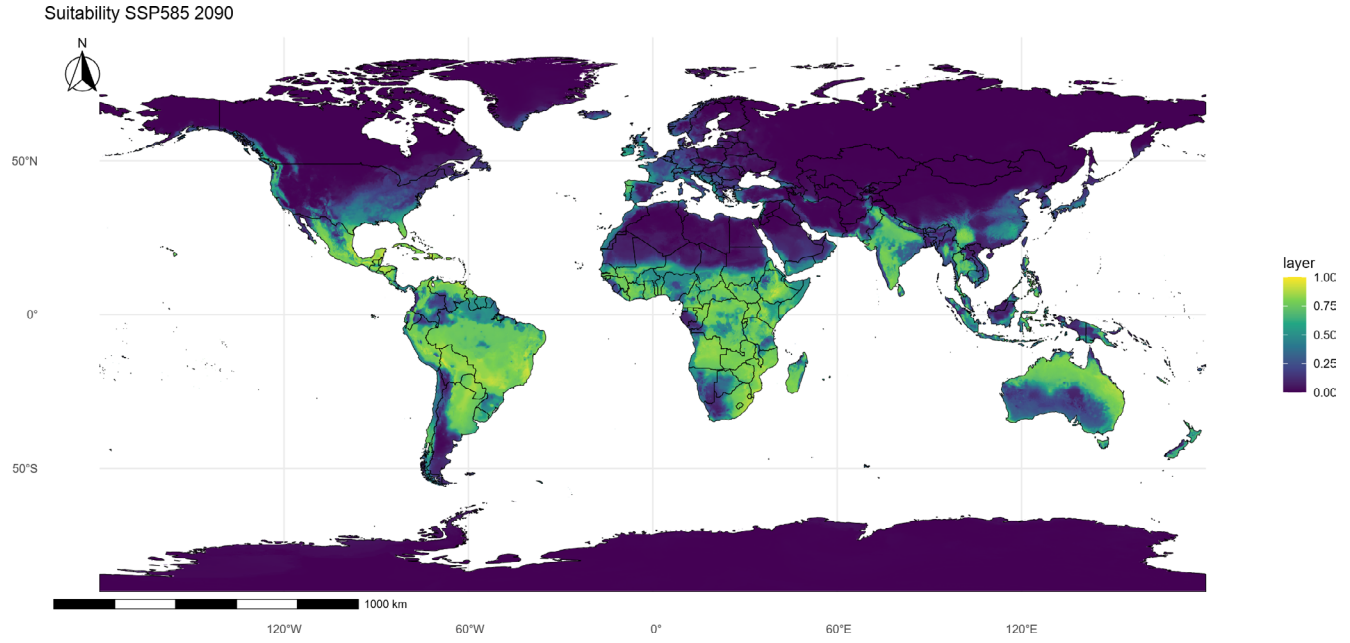

FIGURE 10 | Projected climatic suitability for *Digitaria insularis* in 2090 under the SSP585 scenario, based on ecological niche modelling. The colour scale ranges from dark purple (low suitability) to yellow (high suitability). This extreme high-emission pathway projects a substantial expansion of suitable areas across tropical and subtropical regions, including significant increases in zones that are currently less favourable, and an extension toward higher latitudes and altitudes.

Regions that currently exhibit low likelihood of occurrence may begin to offer favourable conditions, increasing the risk of invasion and reinforcing the need for long-term preventive and management strategies. Additionally, a limited but noticeable increase in environmentally favourable areas is observed in climatic transition regions, including portions of southern Europe. These changes are particularly evident in some Mediterranean zones, such as southern Spain, Italy, Greece, and restricted areas along the southern coast of France. Previously unsuitable areas now exhibit greater potential for species establishment, possibly due to gradual increases in temperature and reductions in soil moisture over the century, highlighting the importance of monitoring and prevention strategies in regions not previously considered at risk.

The overlay of the current distribution of *D. insularis* with the four projected future scenarios (SSP126 and SSP585 for 2030 and 2090) reveals a clear trend of expanding environmental suitability over time, especially under the high-emission scenario (SSP585). The maps show that, as early as 2030, new favourable areas emerge under both scenarios, particularly in Central America, Sub-Saharan Africa, Southeast Asia, and northern Australia (Figure 11).

As time progresses toward 2090, this expansion becomes even more pronounced. Under the SSP585 scenario, for instance, areas that are currently unoccupied become highly suitable, including zones at higher latitudes, reflecting the direct impact of global warming on the species' climatic niche. The SSP126 scenario, in contrast, presents a more restrained expansion, yet still significant, keeping the species as a potential threat in various tropical regions. Even under climate mitigation scenarios, *D. insularis* will remain a threat for agriculture, especially in environmentally vulnerable regions.

4 | Discussion

The high and consistent accuracy obtained across all modelling algorithms indicates that the selected environmental predictors adequately represented the ecological niche of *D. insularis*. Agreement across different statistical approaches reinforces the modelling framework's robustness, suggesting that predicted distribution patterns are not an artefact of a single method but rather reflect genuine environmental associations. The superior performance of the ensemble model compared with individual algorithms further supports the use of consensus approaches, which tend to reduce method-specific biases and improve generalisation capacity.

Although the extremely high AUC values observed (up to 0.998) could raise concerns regarding potential overfitting, this risk was mitigated using spatial block cross-validation and multiple complementary performance metrics. Moreover, such high accuracy likely reflects the strong climatic signal and broad ecological tolerance of *D. insularis*, rather than model overparameterization.

Moderate spatial autocorrelation observed in the residuals suggests that part of the spatial structure in the species' distribution is not fully explained by the selected environmental variables, indicating that additional biotic interactions, dispersal processes, or anthropogenic factors may also contribute to its realised distribution.

The MOP analysis indicated that most projected areas for *D. insularis* are characterised by environmental conditions well

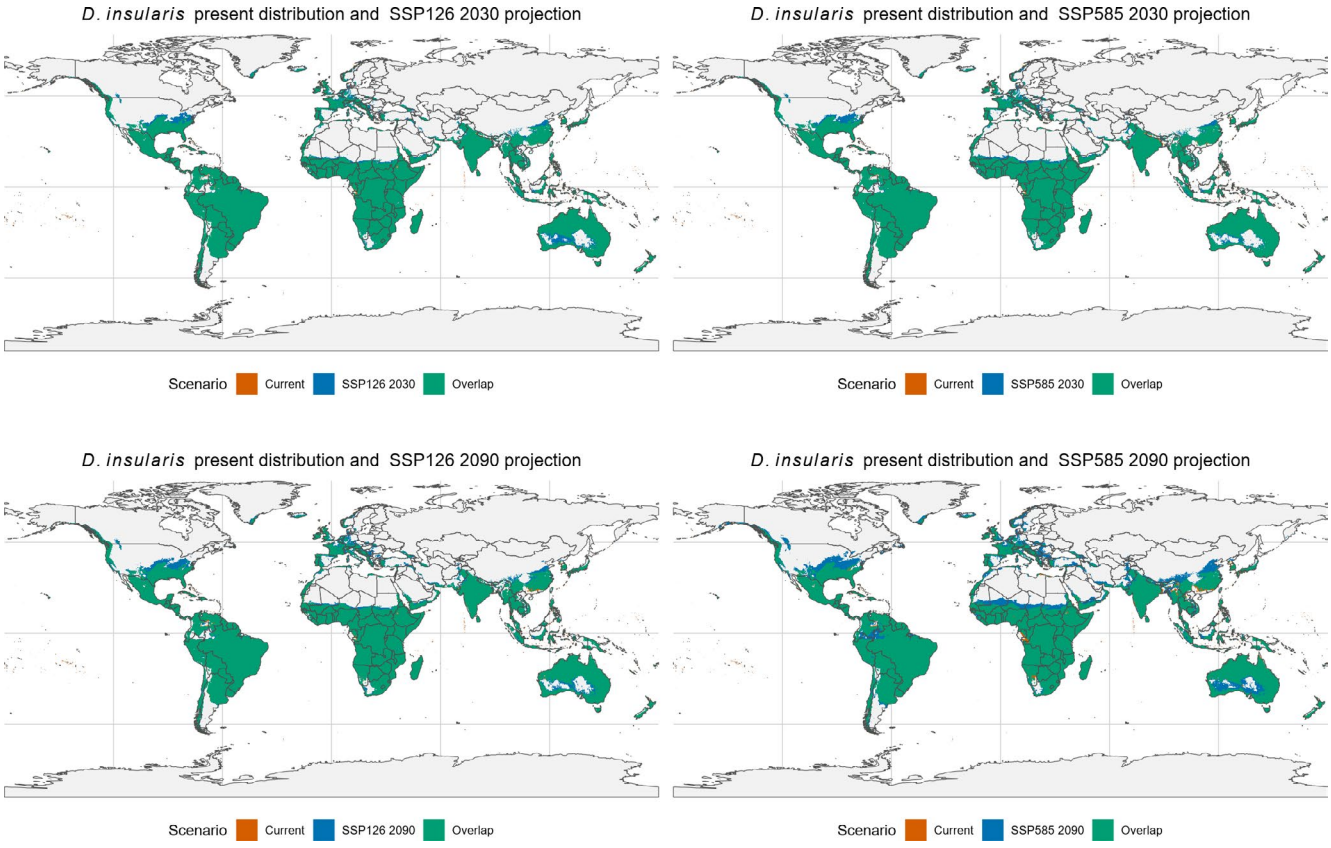

FIGURE 11 | Binary overlay maps comparing the current climatic distribution of *Digitaria insularis* (green) with projected environmental suitability under different climate scenarios and time horizons: SSP126 in 2030 (red, upper left), SSP585 in 2030 (blue, upper right), SSP126 in 2090 (yellow, lower left), and SSP585 in 2090 (cyan, lower right). In these binary maps, each grid cell is classified as either suitable or unsuitable based on model thresholds. Overlapping areas (green plus scenario colour) indicate regions that remain suitable over time, while uniquely coloured areas represent potential expansions or contractions in the species' distribution according to each scenario.

represented in the calibration domain, with only limited and spatially restricted regions of environmental novelty (Figure 4) (Owens et al. 2013). Areas of low environmental similarity were primarily confined to localised portions of the Amazon Basin, Southeast Asia, and Oceania, whereas most projected suitable areas exhibited high environmental similarity to the calibration conditions. The restricted extent of strict extrapolation supports the robustness of the projected suitability patterns under future climate scenarios. Importantly, these regions of environmental dissimilarity largely fall outside major global agricultural production systems commonly affected by *D. insularis*, indicating that extrapolation is unlikely to influence crop-based weed risk assessments. Consequently, the projected suitability patterns remain both robust and agronomically relevant under future climate conditions.

The projected changes in suitable area across all scenarios indicate a gradual expansion of climatically favourable environments for *D. insularis* rather than a reduction. Short-term projections under SSP126 and SSP585 for 2030 already show moderate increases in suitability, while long-term forecasts reveal even more pronounced expansions, particularly under the SSP585 scenario. This progressive increase underscores the species' capacity to benefit from higher temperatures and altered precipitation regimes, as warming trends tend to relax climatic constraints in transitional and subtropical regions. Such findings are consistent with broader evidence showing that several C_4 invasive grasses can capitalise on rising temperatures and reduced water availability, extending their potential range under future climates despite increasing environmental stressors.

Although our projections indicate an expansion of climatically suitable areas for *D. insularis*, it is important to recognise that invasive species do not respond uniformly to climate change. In regions where extreme warming and intensified aridity prevail, especially under high-emission scenarios, the availability of suitable habitats can decline. Such reductions have been documented for other invasive grasses, illustrating that increased temperature and reduced moisture can constrain establishment and persistence in certain environments. This reinforces the notion that climatic change can either facilitate or limit invasive potential depending on species-specific physiological traits and regional environmental pressures (Khwarahm 2025).

Building on these considerations, projections into environmentally suitable yet currently unoccupied areas must be interpreted with caution, as the intrinsic constraints of correlative species distribution models exclude critical non-climatic determinants of establishment. Factors such as propagule pressure, dispersal barriers, and human-mediated introduction pathways can strongly influence realised distributions but are not captured in purely climatic models. For *D. insularis*, these pathways may involve unintentional spread through routine agricultural operations and the inadvertent movement of seeds or other propagules via international trade in agricultural commodities and machinery, underscoring the need to integrate such drivers into future modelling frameworks for more robust and realistic predictions.

The high climatic suitability projected for *D. insularis* across Sub-Saharan Africa is particularly noteworthy given the ongoing agricultural expansion in the region. The Sub-Saharan Africa has been identified as an emerging frontier for global food production, characterised by extensive land-use expansion, a strong presence of smallholder systems, limited access to credit, and constrained technical assistance (Livingston et al. 2011; Sakho-Jimbira and Hathie 2020). These structural conditions may increase the vulnerability of production systems to the establishment and spread of highly competitive weed species.

In such contexts, limited institutional support and restricted access to agricultural inputs can indirectly favour higher weed incidence and dispersal, potentially intensifying management challenges. Although the present models do not explicitly account for socioeconomic drivers, the overlap between climatically suitable areas for *D. insularis* and regions with low adaptive capacity suggests an elevated risk of agronomic impacts, particularly where management options are constrained (Bain et al. 2017).

At broader scales, climate change is expected to reduce the availability of highly productive cropland in Sub-Saharan Africa, especially in regions suitable for multiple annual harvests (FAO 2025). These projected losses coincide with areas already characterised by limited resilience to climatic and economic stressors. Within this framework, the expansion or persistence of a competitive weed such as *D. insularis* may represent an additional pressure on agricultural sustainability, potentially increasing management costs and reducing crop productivity.

The establishment of *D. insularis* in newly converted or intensively managed agricultural areas may also be facilitated by environmental changes associated with climate variability, including altered precipitation regimes, increased drought frequency, and soil salinization in irrigated systems (Zambão et al. 2020; Corwin 2021). Together with the species' high ecological plasticity and efficient anemochorous dispersal, these factors highlight that projected suitability patterns should be interpreted as indicators of increased exposure and management risk rather than direct predictors of socioeconomic outcomes.

Overall, the spatial coincidence between high climatic suitability for *D. insularis* and structurally vulnerable agricultural regions underscores the importance of integrating invasion risk into climate adaptation planning. While broader socioeconomic impacts remain inferred and dependent on local management capacity, our results identify priority regions where preventive monitoring and integrated weed management strategies may be particularly relevant under future climate scenarios.

The intensification of agriculture, when conducted unsustainably, often involves practices such as excessive herbicide use for weed control, which can exacerbate environmental degradation and undermine long-term sustainability goals (Viana et al. 2022). In Brazil, the economic consequences of *D. insularis* interference are already evident in major grain crops. In soybean, a single clump per square meter can reduce yields by approximately 500 to 1400 $kg\,ha^{-1}$, and losses may exceed 2000 $kg\,ha^{-1}$ under higher infestation levels, depending on plant origin and growth stage (Gazziero et al. 2019). In maize, coexistence with sourgrass throughout the crop cycle can lead to yield reductions of up to 86%, while even a 30-day interference period after sowing may still result in losses of about 5% (Piazentine et al. 2024). These

substantial reductions illustrate how sourgrass can rapidly erode farm profitability and intensify reliance on herbicides, reinforcing the urgency of early intervention and integrated management measures in Brazilian production systems.

Genomic studies have revealed weak genetic structure among *D. insularis* populations in Brazil and a predominant south-to-north gene flow, associated with the movement of agricultural machinery across soybean-producing regions (Gonçalves Netto et al. 2021). This pattern of gene flow suggests that human-mediated dispersal plays a central role in the spread of *D. insularis*, facilitating the establishment of new populations across distant agricultural landscapes. Such connectivity not only accelerates the colonisation of new areas but also contributes to the homogenization of genetic variation, potentially enhancing the species' adaptability to diverse environmental conditions and herbicide regimes.

The high connectivity among populations also poses a substantial challenge for herbicide resistance management. Once resistance alleles emerge in a local population, whether through de novo mutation or selection from standing variation, human-mediated dispersal can rapidly disseminate these traits across vast agricultural areas. This process undermines localised control efforts and reduces the efficacy of herbicide rotation strategies, as resistant genotypes can be reintroduced from neighbouring regions. Furthermore, the homogenization of genetic backgrounds across populations may promote the fixation of resistance-conferring alleles and the emergence of multiple resistance mechanisms within the same biotype, complicating chemical control. Effective mitigation therefore requires not only field-level interventions but also coordinated, landscape-scale strategies that integrate machinery hygiene protocols, regional monitoring networks, and restrictions on the movement of contaminated equipment between farms (Busi et al. 2011).

The spatial patterns identified in this study provide a strategic basis for optimising management interventions against *D. insularis*. Areas showing both high climatic suitability and elevated agricultural vulnerability should be prioritised for early detection, targeted control measures, and intensive monitoring. This spatial prioritisation enables more efficient allocation of financial and technical resources, maximising the impact of available budgets while reducing the likelihood of further range expansion. By directing extension services, biosecurity measures, and resistance management programs to these high-risk zones, stakeholders can shift from reactive containment to proactive risk mitigation, ultimately safeguarding crop productivity and supporting long-term agricultural resilience.

5 | Conclusions

Climate suitability projections for *D. insularis* indicate that the species has a high potential for geographic expansion under climate change scenarios, both in the short term (2030) and in the long term (2090). Even under extreme conditions, such as the SSP585 scenario, suitability is maintained and intensified across large regions of South America, Sub-Saharan Africa, Southeast Asia, and northern Australia, highlighting a trend of both latitudinal and longitudinal spread.

These results complement and extend approaches based on genetic connectivity by demonstrating that the expansion is not limited to gene flow between populations: it also represents an ecologically viable trajectory. The ENM shows that areas of high climatic suitability extend beyond Brazilian territory, indicating a potentially global threat.

This ecological plasticity may pose additional challenges for species management, especially in tropical agricultural environments, and reinforces the importance of preventive strategies in regions that, although currently free from infestation, are becoming increasingly suitable. Given the high genetic connectivity reported in previous studies and the expansion of climatically favourable areas identified here, the effectiveness of isolated local or national management efforts may be limited.

Funding

This work was supported by Coordenação de Aperfeiçoamento de Pessoal de Nível Superior (CAPES).

Acknowledgements

The Article Processing Charge for the publication of this research was funded by the Coordenação de Aperfeiçoamento de Pessoal de Nível Superior - Brasil (CAPES) (ROR identifier: 00x0ma614).

Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

The datasets generated and analysed during the current study, including PCA results, model projections, MOP analyses for each future scenario, as well as binary and continuous suitability maps, are available in the Zenodo repository (DOI: https://doi.org/10.5281/zenodo.17939210).

Peer Review

For transparency, the peer review documents associated with this article are available at https://doi.org/10.1111/wre.70076.

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Supporting Information

Additional supporting information can be found online in the Supporting Information section. **Data S1:** Supporting Information.