



## Statistical And Machine Learning Models Applied To Species Distributions Under Climate Change Scenarios: A Systematic Review

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### Abstract

**Objectives:** Climate change is altering species distribution worldwide, causing shifts in geographic ranges and disruptions in ecosystems. To understand these changes and develop conservation strategies, species distribution models (SDMs) have become increasingly relevant. **Methods:** This systematic review analyzes 47 studies published from 2015 to 2024 that have applied statistical models and machine learning techniques to model species distribution under climate change scenarios. The study examines the methodological approaches used, the main climatic factors considered, and the most studied taxonomic groups. **Results:** The results highlight the growing adoption of machine learning techniques, such as MaxEnt and Random Forest, due to their ability to capture complex relationships between environmental variables. Temperature and precipitation emerge as key climatic factors, while the area under the curve (AUC) is the most used validation metric. **Conclusions:** Despite advancements in modeling, gaps remain in the representation of certain geographic regions and underrepresented taxonomic groups, emphasizing the need to expand future research to enhance the understanding of climate change impacts on biodiversity.

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## Introduction

Climate change has become one of the greatest global environmental challenges, rapidly transforming patterns of temperature, precipitation and other fundamental climatic factors. These variations induce modifications in the availability and quality of habitats, leading to shifts in geographic ranges, alterations in ecological interactions and, ultimately, loss of biodiversity [1],[2]. In this regard, species distribution modelling (SDM) is an indispensable tool for predicting the response of species to future environmental scenarios and for guiding decision-making in conservation and adaptive management.

Recent years have seen a progressive transition from traditional statistical methods such as Generalized Linear Models (GLM) and Generalized Additive Models (GAM) to more advanced machine learning techniques such as MaxEnt, Random Forest and ensemble models. These emerging methods offer greater flexibility, allowing complex, non-linear relationships to be modelled without requiring predefined functional assumptions, which is especially valuable in contexts of high environmental variability [3], [4].

In addition, the inclusion of proxy variables such as grazing pressure, habitat fragmentation or binary representation of certain land cover types has enriched models, allowing the assessment of how anthropogenic activities modify landscape structure and thus influence species distributions[5], [6]. The application of multi-scale analysis, combining remote sensing, time series and GIS data, facilitates the capture of spatial heterogeneity and landscape dynamics, which are crucial for projecting distributions in a changing world [4],[7].

In this context, the main objective of this study is to analyze the application of statistical and machine learning models in the modelling of species distribution under climate change scenarios, evaluating their performance in terms of accuracy, validation (using metrics such as AUC, sensitivity, specificity and cross-validation) and comparing them with traditional approaches. This analysis focuses on studies published from 2015 to 2024, ensuring the timeliness and relevance of the evidence presented to support conservation strategies

## Theoretical framework

Species distribution modelling is based on ecological niche theory, which differentiates between the fundamental niche (the environmental conditions that a species can tolerate) and the realized niche (the conditions actually occupied, influenced by biotic interactions and spatial constraints)[8]. Traditional methods, such as GLM and GAM, have established links between the presence or absence of species and specific environmental variables, providing interpretability and a robust framework for inferring ecological relationships[9]. However, these approaches may be insufficient in the face of the complexity of modern ecosystems and climate change-induced perturbations.

### Advanced Machine Learning Methods and Ensemble Models

In recent years, machine learning methods have revolutionized species distribution modelling. Algorithms such as MaxEnt and Random Forest allow complex relationships to be modelled without the need to establish a predetermined functional form, identifying nonlinear interactions between multiple variables [3]. The integration of ensemble models, which combine the outputs of several algorithms, has been shown to reduce uncertainty in projections and improve the robustness of predictions, which is critical when projecting future scenarios under unprecedented environmental conditions [10].

A prominent example is Campbell's study [11] in which ensemble models were used to predict changes in amphibian distribution under different climate change scenarios, demonstrating substantial improvements in the accuracy and practical utility of the models.

### Multi-scale Analysis and Spatial Resolution

Spatial scale is a determining factor in modelling, as species respond differently to their environment depending on the level of resolution of the analysis. The integration of environmental variables at fine and broad scales allows the identification of local (e.g. microhabitats and soil structure) and regional (e.g. landscape connectivity or fragmentation) determinants. Recent studies, such as Rather[4], have shown that multi-scale analysis significantly improves the accuracy of distribution projections by capturing spatial variability more adequately. In addition, the use of high-resolution remotely sensed data, combined with GIS techniques, has enabled the generation of more detailed and updatable environmental predictors, essential for monitoring habitat change over time [7].

### Integration of Indirect Variables and Ecological Processes

The inclusion of proxy variables, which capture factors such as grazing pressure, habitat fragmentation and biotic interactions, has proven to be essential to improve the explanatory power of SDMs. Fern[5] has shown how incorporating grazing pressure into grassland bird distribution models increases predictive accuracy by reflecting the indirect effects of anthropogenic activities on habitat structure. In addition, hybrid approaches have been developed which combine correlative components with mechanistic elements to simulate fundamental ecological processes, such as dispersal and population dynamics, allowing a more realistic projection of the effects of climate change on species distributions [12].

### Future Scenario Projection and Dynamic Modelling

Projecting future distribution scenarios involves significant challenges, especially due to the emergence of non-analogue climates, where combinations of environmental variables exceed what is observed in the present. The use of dynamic models that integrate time series and remotely sensed data has become essential to capture long-term trends and assess climate velocity, i.e. the rate at which environmental conditions move across the landscape. A recent example is Campbell's [11] study of amphibians in the Upper Missouri River Basin, which illustrates how the integration of climate projections and land-use changes allows accurate anticipation of transformations in species distributions.

### Emerging Technologies and High-Resolution Data

Access to remote sensing and GIS technologies has made it easier to obtain high-resolution environmental predictors, which has improved the quality and accuracy of SDMs. The use of satellite imagery, LiDAR data and other emerging sources allows capturing landscape complexity, identifying critical microhabitats and monitoring temporal changes in habitat. These tools are essential for updating models and continuously monitoring the impacts of climate change on biodiversity .[13]

### Consideration of Intrinsic Species Characteristics

In addition to general environmental variables, it is essential to recognize that each species has intrinsic characteristics such as tolerance to temperature ranges, dispersal strategies, adaptability and specific habitat requirements that condition its ecological niche. These characteristics determine how a species responds to environmental changes and thus affect the accuracy of distribution models. For example, generalist species may exhibit greater flexibility to environmental variation, while specialists are more vulnerable to perturbations and changes in their environment [14]. Including these aspects in SDMs allows refining variable selection and adjusting projections to more realistically capture heterogeneity in biological responses, which is crucial for targeted conservation strategies.

### Influence of Ecological Interactions on Species Distribution

Another essential component is the consideration of biotic interactions, such as competition, predation and mutualism, which can significantly modify the distribution of a species. These interactions, which vary in intensity and direction depending on the ecological context, can alter the realized niche of a species and consequently affect projections of distribution models. Incorporating variables that indirectly capture these effects, for example through indicators of habitat fragmentation or anthropogenic pressure, can improve the explanatory power of SDMs and adjust predictions based on food web dynamics and species interactions [14]. This holistic approach is particularly relevant in a context of climate change, where community disruption and reorganization of ecological interactions are increasingly evident.

The proposed systematic review is crucial for the following reasons:

1. **Integration of advanced methodologies:** The evolution from traditional methods to machine learning and ensemble modelling techniques has significantly improved the predictive capacity of SDMs. This review will synthesize these advances, identifying the most robust and relevant methodologies to address current challenges in biodiversity conservation .[3], [4]
2. **Relevance for Conservation and Adaptive Management:** The ability to project changes in species distributions is fundamental for designing adaptive management strategies in a context of accelerated climate change. The integration of direct and indirect variables and multi-scale analysis allows for a comprehensive understanding of how anthropogenic activities and environmental changes affect habitats, which is essential for prioritizing areas for intervention and efficiently allocating conservation resources .[7], [11]
3. **Overcoming Constraints in Data-Scarce Regions:** In many areas of high conservation need, the availability of robust data is limited. This review will address strategies and methodologies to maximize the use of heterogeneous information, providing a methodological framework applicable even in data-poor contexts, which is crucial for areas with high biodiversity but few information resources .[13]
4. **Use of Emerging Technologies to Improve Model Quality:** The incorporation of high-resolution remote sensing and GIS data has enabled the generation of detailed and updatable spatial models, facilitating the continuous monitoring of landscape change and assessing the effectiveness of protected areas. This has direct implications for the formulation of long-term conservation policies.
5. **Contribution to Conservation Policy Decision Making:** By synthesizing and comparing different methodological approaches, this review will provide managers and policy makers with evidence-based tools, enabling the implementation of more effective conservation strategies adapted to the challenges of climate change. Taken together, this systematic review not only advances the theoretical and methodological field of SDM but also offers a practical and robust framework for the conservation and adaptive management of biodiversity in a changing world.

In order to understand current trends in the use of models to predict species distributions under climate change scenarios, this systematic review poses the following research questions:

1. What types of statistical and machine learning models have been most used in studies of species distributions in the face of climate change and what are their main characteristics and methodological advantages?
2. What environmental variables and climatic factors are most frequently incorporated into species distribution modelling, and how do they influence model accuracy and validation?
3. Which taxonomic groups and geographic regions have been most represented in the recent literature, and what gaps or thematic biases are evident in the studies reviewed?

## Materials and methods

To ensure transparency and methodological rigor in this systematic review, the PRISMA 2020 methodology[15] was adopted. The application of the PRISMA framework in this research allowed us to establish clear inclusion and exclusion criteria, optimizing the search, screening and selection process of articles related to the use of statistical models and machine learning in the distribution of species in the face of climate change.

### Search strategy

To ensure completeness and rigor in the identification of relevant literature, a systematic search of high-impact scientific databases was conducted. The search focused on studies related to modelling species distribution under climate change scenarios, considering approaches based on statistical modelling and machine learning. The databases used were Scopus, Web of Science (WoS), SpringerLink and ScienceDirect (Elsevier), selected for their broad scope of peer-reviewed scientific research. Advanced search strategies were applied with Boolean operators (AND, OR) in the title, abstract and keyword fields.

### Inclusion and exclusion criteria

To ensure the quality and relevance of the articles selected for the systematic review, the following criteria were applied:

#### Inclusion Criteria

- Articles indexed in Scopus, Web of Science, SpringerLink and ScienceDirect.
- Studies published from 2015 to 2024.
- Written in English or Spanish.
- Open access and full-text articles available.
- Research analyzing the application of statistical models and machine learning in the distribution of species under climate change scenarios.
- Studies including validation metrics and accuracy of the models used.

#### Exclusion Criteria

- Studies outside the context of species distribution modelling.
- Articles that do not include statistical models or machine learning.
- Studies focused on genetics, microbiology, health or agriculture, unrelated to ecological modelling.
- Experimental research in animal models.
- Narrative reviews without meta-analysis or quantitative approach.
- Papers without complete information (e.g. conference abstracts, letters to the editor, expert commentaries).

### Search strategies

The search strings and filters applied in each database can be found at Table 1

**Table 1.** Search strings and results

Database	Search string	Number of studies
Scopus	ALL ( ( "species distribution modeling" OR "habitat modeling" OR "ecological niche modeling" ) AND ( "climate change" ) AND ( "statistical models" OR "machine learning" OR "predictive models" OR "deep learning" ) AND ( "model validation" OR "accuracy assessment" OR "performance metrics" ) ) AND ( LANGUAGE ( "English" ) OR LANGUAGE ( "Spanish" ) ) AND PUBYEAR > 2014 AND PUBYEAR < 2025 AND ( LIMIT-TO ( OA , "all" ) ) AND ( LIMIT-TO ( PUBSTAGE , "final" ) ) AND ( LIMIT-TO ( DOCTYPE , "ar" ) ) AND ( LIMIT-TO ( SUBJAREA , "AGRI" ) OR LIMIT-TO ( SUBJAREA , "ENVI" ) OR LIMIT-TO ( SUBJAREA , "EART" ) OR LIMIT-TO ( SUBJAREA , "MULT" ) OR LIMIT-TO ( SUBJAREA , "COMP" ) OR LIMIT-TO ( SUBJAREA , "MATH" ) )	283

Web of Science	TX ("species distribution modeling" OR "habitat modeling" OR "ecological niche modeling") AND TX ("climate change") AND TX (("statistical models" OR "machine learning" OR "predictive models" OR "deep learning")) AND TX (("model validation" OR "accuracy assessment" OR "performance metrics"))  <b>Applied Filters:</b> Academic publications, years (2015-2024), language: English and Spanish link to full text, full text in PDF, apply equivalent subjects	148
SpringerLink	("species distribution modelling" OR "habitat modelling" OR "ecological niche modelling") AND ("climate change") AND ("statistical models" OR "machine learning" OR "predictive models" OR "deep learning") AND ("model validation" OR "accuracy assessment" OR "performance metrics")  <b>Applied Filters:</b> Original articles, Years (2015-2024), Open Access, Disciplines: Life Sciences, Environment, Earth Sciences, Sub-disciplines: Ecology, Environmental Management, General Environment	14
ScienceDirect	"species distribution modelling" OR "habitat modelling" OR "ecological niche modelling" AND "climate change" AND ("statistical models" OR "machine learning" OR "predictive models" OR "deep learning") AND ("model validation" OR "accuracy assessment" OR "performance metrics")  <b>Applied Filters:</b> Original articles, years (2015-2024), open access, disciplines: Environmental Sciences, Agricultural and Biological Sciences, Earth and Planetary Sciences, Computer Sciences.	173

### Study selection process

The study selection strategy followed the PRISMA flow, starting with an advanced search of the selected databases. Initially, 618 articles were identified, which were managed and cleaned in Zotero to eliminate duplicates, resulting in a total of 594 unique documents.

### Screening of studies using Natural Language Processing in R

After the elimination of duplicates, a screening process was implemented based on thematic and exclusion criteria, using Natural Language Processing (NLP) techniques in R. This procedure allowed us to filter the most relevant articles for the systematic review, ensuring that only those aligned with the research objectives were considered. The screening process was carried out in three main phases:

**Application of Thematic and Relevance Filters.** In the first phase, an automatic filtering was performed by searching for keywords in the titles and abstracts of the articles. For this, the packages `dplyr` and `stringr` in R were used, which allowed us to identify relevant studies in the following areas:

- **Species distribution modelling**, including terms such as species distribution modelling, ecological niche modelling, habitat modelling.
- **Climate change and environmental variables**, considering climate change, temperature, precipitation, altitude, altitude, land use.
- **Statistical and machine learning methods** applied to species distribution prediction: statistical models, machine learning, predictive models, deep learning, MaxEnt, GLM.
- **Validation and assessment of models** to ensure accuracy of results: model validation, accuracy assessment, performance metrics, AUC, kappa.

Only articles whose titles or abstracts contained at least one of these key terms were retained, resulting in a total of 458 articles for the next stage of screening.

**Exclusion of Non-Relevant Studies** In the second screening phase, specific criteria were applied to eliminate studies that did not contribute relevant information to the research. The following exclusions were established:

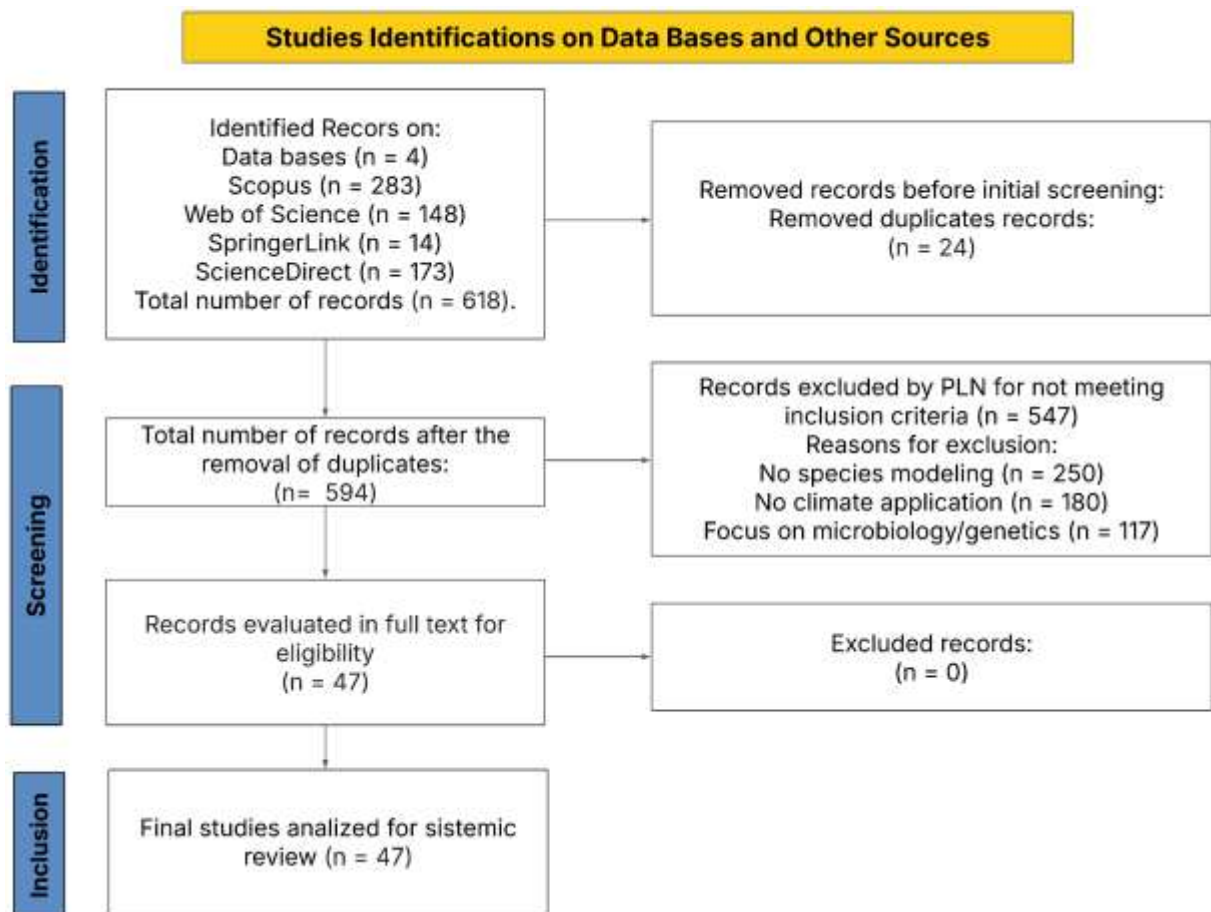
- **Exclusion of studies without species modelling:** Articles that did not include ecological modelling or species distribution approaches, i.e. those that focused exclusively on taxonomy, descriptive biodiversity or conservation without the application of predictive models, were discarded.
- **Exclusion of studies without climate application:** Articles that did not consider environmental variables such as temperature, precipitation, altitude or land use in modelling species distributions were filtered out.
- **Exclusion of studies focusing on microbiology, health, genetics or biomedicine:** Research related to biomedical and genetic areas was eliminated as it was not relevant to the objective of the study.

After applying these filters, the total number of articles was reduced to 47 studies that met all the criteria.

### Manual Validation and Final Selection

In the final phase of the screening, a manual full-text review of the 47 selected articles was carried out to confirm their relevance and methodological quality. During this process, each study was checked to ensure that it met the established inclusion criteria and addressed the following key aspects: species modelling under climate change scenarios, application of statistical models or machine learning in species distribution, and evaluation of model performance through validation metrics such as AUC, precision and predictive performance. This process allowed us to confirm that the 47 selected articles were relevant and of high quality, which were stored in BibTeX and CSV, facilitating their organization and analysis in the following phases of the study.

The final number of studies included in the systematic review, represented by the Figure 1 forms the basis for the development of this work. These studies will allow us to evaluate the methodological approaches most used in modelling species distributions under climate change scenarios and will contribute to the analysis of their implications for conservation and environmental management.



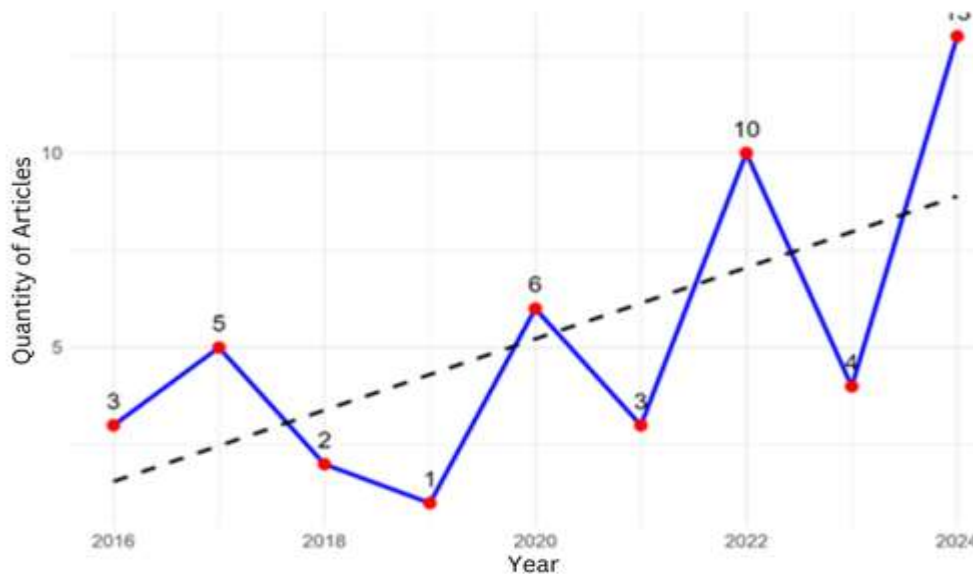
**Figure 1.** Diagram of study selection according to PRISMA methodology.

Source: Own elaboration.

## Results

The temporal analysis of the selected studies reveals variability in the number of publications on species distributions in the context of climate change over the last few years. As shown in Figure 2, between 2016 and 2019, the number of annual studies remained relatively low, with a minimum in 2019. From 2020 onwards, an increase in scientific production is evident, reaching a peak in 2022 and 2024.

This trend suggests a growing interest in species distribution modelling and its implications for climate change. The increase in the number of publications could be attributed to increased access to modelling tools, the availability of long-term climate data and the urgency to understand the effects of climate change on biodiversity. The fitted trend line indicates an upward trajectory, suggesting that interest in this topic will continue to increase in the coming years.



**Figure 2.** Trend of Publications by Year. Source: Own elaboration.

### **Classification of Species Distribution Models and their Application to Climate Change**

Analysis of the 47 papers included in this systematic review reveals the diversity of approaches used to model species distributions under climate change scenarios. Five main categories of models were identified, the application of which varies according to data availability, the complexity of relationships between environmental variables and the need to reduce uncertainty in predictions.

Each model has advantages and limitations depending on the type of data used, the ability to fit non-linear relationships and the ease of interpretation. The general trend indicates a preference for machine learning approaches and ensemble models, which improve the stability and accuracy of predictions.

#### **Maximum Entropy Based Models (MaxEnt)**

MaxEnt is the most widely used model, with 17 studies using it to predict species distributions. Based on the principle of maximum entropy, it requires only presence data, which makes it especially useful in studies where absence data are unreliable. It is simple to implement and has robust validation tools, such as the Area Under the Curve (AUC) and the True Skill Statistic (TSS), to assess its accuracy. However, it is sensitive to sampling biases and collinearity of variables, which can affect its predictions.

#### **Random Forest Based Models (Random Forest)**

The Random Forest (RF) algorithm was employed in 6 studies (plus 2 that also used MaxEnt). It is based on the combination of multiple decision trees to improve the accuracy of species distribution prediction. Its main advantage is its robustness to complex data and its ability to handle non-linear relationships. In addition, it allows the importance of each variable in the prediction to be assessed. However, RF requires more computational power, and its interpretation is less intuitive compared to simpler models such as MaxEnt or GLM.

#### **Generalized Linear Models (GLM) and Generalized Additive Models (GAM)**

GLM and GAM models were applied in 4 studies (plus 1 that also used RF). These traditional statistical models establish a relationship between species presence/absence and environmental variables by means of linear functions (GLM) or smoothed functions (GAM). Their simplicity and ease of interpretation make them valuable tools for exploratory studies. However, their ability to capture non-linear relationships is limited compared to machine learning models, which may reduce their accuracy in complex scenarios.

#### **Assembly-Based Modelling**

Ensemble models were used in 14 studies, reflecting a growing trend towards combining multiple models (MaxEnt, RF, GLM, BRT, among others). This approach allows for reduced uncertainty in predictions and improved stability of results. However, it is computationally more expensive to implement and more complex to interpret due to the integration of several models.

#### **Other Models (MARS, BRT, GARP, etc.)**

Less conventional models, such as MARS (Multivariate Adaptive Regression Splines), BRT (Boosted Regression Trees) and GARP (Genetic Algorithm for Rule-set Prediction), were applied in 6 studies (plus 3 that also used other models). These approaches have proven useful in specific contexts, especially when required to capture highly non-linear relationships or work with limited data. However, their lesser documentation and comparison with more widely used approaches limit their widespread adoption.

Table 2 presents the classification of the models used in the studies analyzed, together with the evaluation metrics used and their main advantages and limitations.

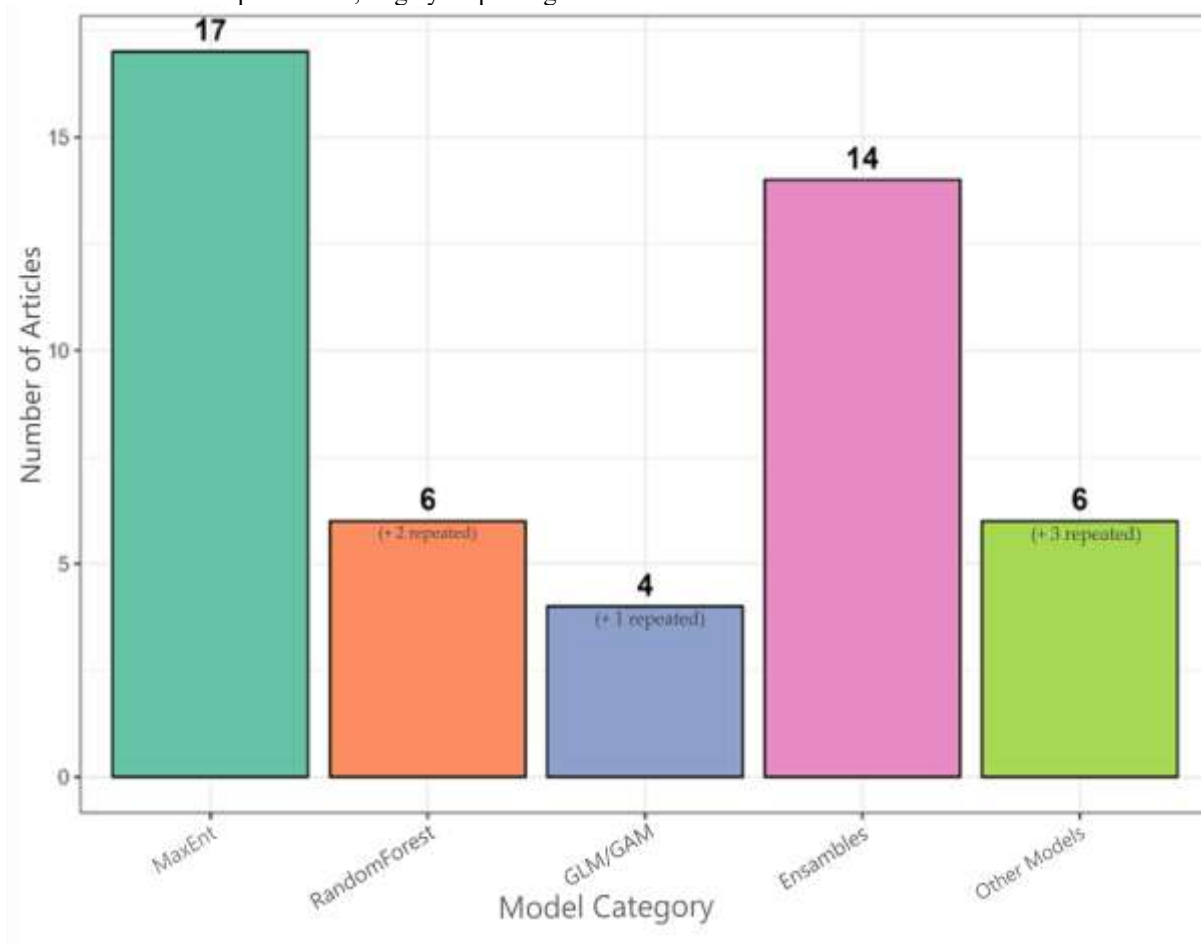
**Table 2.** Classification of the species distribution models used in the studies analyzed.

Model Category	Frequency of Use	Articles that use it	Evaluation Metrics	Advantages	Limitations
<b>Maximum Entropy Based Models (MaxEnt)</b>	17	[16], [17], [18], [19], [20], [21], [22], [23], [24], [25], [26], [27], [28], [29], [30], [31], [32].	Area Under the Curve (AUC), True Skill Statistic (TSS) for sensitivity and specificity, Jackknife Test, Response Curves, Omission Rate and Regularized Gain.	Requires only presence data, high accuracy in the absence of reliable absence data .	Sensitive to sampling bias and collinearity of variables.
<b>Random Forest Based Models (Random Forest)</b>	6 (+2 already counted in MaxEnt)	[33], [21], [34], [35], [36], [37], [11], [31].	Model Accuracy Score, Root Mean Square Error (RMSE), Variable Importance Scores, AUC, TSS and ROC Curve.	Resistant to overfitting, high performance with complex data.	Requires more computational data, difficult to interpret, less effective on unbalanced data without adequate pre-processing and difficult to extrapolate to conditions not seen in training.
<b>Generalised Linear Models (GLM) and Generalised Additive Models (GAM)</b>	4 (+1 already counted in Random Forest)	[33], [38], [39], [40], [41].	Deviance Explained, Akaike Information Criterion (AIC), Adjusted R <sup>2</sup> , AUC, TSS, Likelihood Ratio Test and Deviance Residuals.	Simple, interpretable, useful in exploratory studies.	Reduced ability to capture complex non-linear relationships.
<b>Assembly-Based Modelling</b>	14	[42], [43], [44], [45], [46], [47], [48], [12], [49], [50], [51], [52], [53], [54].	AUC, TSS, Weighted Mean Model Performance, Cohen's Kappa, RMSE, Between-Model Variance and Confidence Intervals on Predictions.	Reduced uncertainty, greater stability in predictions.	It requires more computational time, greater implementation complexity, possible redundancy between models and difficult interpretation due to the combination of multiple approaches.
<b>Other Models (MARS, BRT, GARP, etc.)</b>	6 (+3 already counted in other categories)	[17], [21], [38], [55], [56], [57], [58], [59], [60].	AUC, TSS, Deviance Explained, Sensitivity and Specificity, Cross-validation.	Depending on the model, they can capture complex relationships or adapt to limited data.	Less documentation and comparison with other more widely used approaches, higher uncertainty compared to more standardised models, and some can be computationally expensive on very large datasets.

Source: Own elaboration.

Figure 3 graphically represents the frequency of use of the models in the studies analyzed. It can be seen that MaxEnt is the most frequently used model, followed by ensemble and Random Forest models, while the more traditional approaches (GLM/GAM) have been less frequently used. The last bar in the graph corresponds to the "Other Models" category, reflecting its lower frequency of use.

This trend confirms that species distribution modelling has evolved towards machine learning approaches and combinations of multiple models, largely displacing traditional statistical methods.



**Figure 3.** Frequency of Use of Species Distribution Models.

Source: Own elaboration.

### Geographical Regions Studied and Distribution of Studies

Analysis of the reviewed studies reveals an uneven distribution of research on modelling species distributions in the context of climate change. While some regions have been widely explored due to their biodiversity, ecological relevance and visible impacts of climate change, others have received considerably less attention, indicating possible knowledge gaps in the scientific literature. Most studies have concentrated on Asia, followed by North America, Africa and Europe. Latin America, Australia and Oceania, as well as oceans and seas, have received less attention compared to the other regions.

### Regions with the highest number of studies

Asia is the region with the highest concentration of research, reflecting the growing interest in modelling the effects of climate change in one of the most biologically diverse regions with ecosystems that are highly sensitive to climatic variations. China, India and Southeast Asia have been the main foci of study, with research focusing on the redistribution of plant, mammal and insect species under different climate change scenarios. The main variables analyzed include temperature, precipitation and humidity, key elements in determining the viability of habitats in this region.

North America also ranks as one of the most studied regions, with research focusing on species response to extreme weather events, habitat availability and the effects of climate change on temperate and mountain ecosystems. In this region, studies have focused on the impact on mammals, insects and amphibians, reflecting concerns about habitat fragmentation and changes in species phenology.

Africa, particularly South Africa and Ethiopia, has also been the subject of multiple studies, although to a lesser extent compared to Asia and North America. Research in this region has addressed the relationship between temperature, precipitation and land use, with a particular focus on key conservation species and those of agricultural and ecological importance. In this case, studies have mainly looked at mammals, insects and plants,

in order to assess the adaptive capacity of species in the face of global warming and modification of their environment.

Europe, although with a smaller number of studies, has been a region where research has been more oriented towards the impact of climate change on invasive species and the transformation of temperate ecosystems. Particular interest has been identified in the behavior of insects and plants under climate change scenarios, with studies focusing on the validation of predictive models to assess species expansion.

### Regions with the lowest number of studies

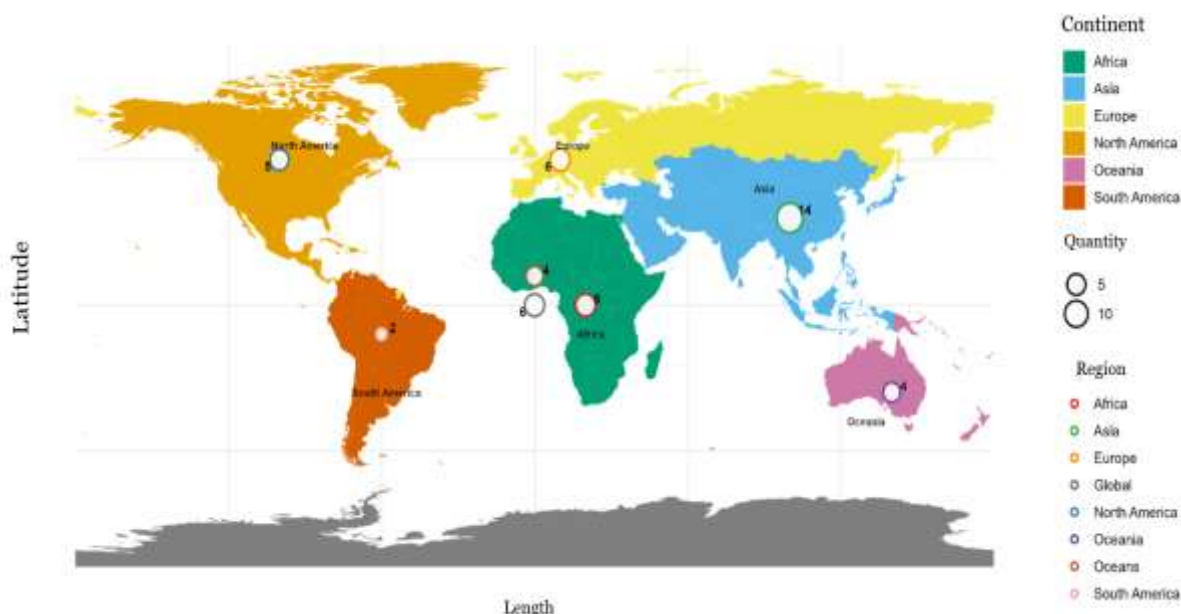
In contrast, Latin America, despite its high biodiversity and the importance of its tropical forests and mountain ecosystems, has received less attention in the scientific literature on species modelling under climate change. Research in this region has mainly focused on the influence of temperature, deforestation and precipitation on plant and mammal species in tropical and Andean ecosystems.

Australia and Oceania have also been less explored compared to other regions, with studies focusing mainly on the effects of climate change on marine biodiversity and ocean acidification. These studies have mainly analyzed fish and plants, with the aim of understanding the vulnerability of these ecosystems to changes in ocean temperature and sea level rise.

On the other hand, the oceans and seas have been studied in terms of the effects of global warming on fish and marine invertebrates, especially in relation to sea level rise and the occurrence of extreme weather events. However, there remains a significant knowledge gap regarding the redistribution of species in these ecosystems at the global level.

Finally, methodological studies with a global approach have been identified, which do not focus on specific regions, but seek to develop and evaluate predictive models to improve the accuracy of species distribution modelling. These studies have been fundamental to the advancement of discipline, providing new tools and metrics for model validation.

Figure 4 presents the distribution of the studies reviewed, highlighting the regions with the largest amount of species distribution modelling research. The size of the bubbles represents the number of studies conducted in each region, while the colors indicate the different geographical areas addressed in literature.



**Figure 4.** Distribution of Articles by Continent.

Source: Own elaboration.

Analysis of the most studied climatic factors shows that temperature and precipitation are the predominant variables in all regions, indicating their critical role in species distribution under climate change scenarios. In addition, in coastal and oceanic regions, there is a greater emphasis on factors such as sea level and ocean acidification, reflecting concerns about the impact of climate change on marine ecosystems.

In terms of the taxonomic groups studied, plants are the most studied organisms, especially in Asia and Latin America, due to their ecological and economic importance. Mammals and insects have also received significant attention, particularly in studies on species of conservation interest or with key roles in ecosystems, such as pollinators and seed dispersers. In marine regions, studies have focused mainly on fish and invertebrates, reflecting interest in assessing the impact of climate change on aquatic biodiversity. Table 3 summarizes the distribution of the studies analyzed, together with the main climatic factors considered and the taxa studied in each region.

**Table 3.** Distribution of studies, climatic factors analyzed and taxa studied by region.

Region	Quantity	Articles	Climatic factors analyzed	Taxa studied
North America (USA, Canada)	5	[16], [50], [30], [11], [49]	Temperature, precipitation, extreme events	Mammals (2), Insects (2), Amphibians (1)
Asia (China, Japan, South Korea, Himalayas, Southeast Asia, Indonesia)	14	[40], [25], [26], [27], [28], [37], [17], [19], [22], [23], [44], [54], [60], [36]	Temperature, precipitation, humidity, seasonal changes	Plants (6), Mammals (3), Insects (2), Fish (3)
Latin America (Mexico, Brazil, Ecuador, Tropical Andes)	2	[20], [56]	Temperature, deforestation, precipitation	Plants (1), Mammals (1)
Africa (South Africa, Ethiopia, Kenya)	6	[18], [46], [48], [12], [58], [32]	Temperature, precipitation, land use	Mammals (3), Insects (1), Plants (2)
Europe (Mediterranean, Balkans, Germany)	6	[47], [38], [34], [31], [39], [52]	Temperature, habitat changes, extreme events	Insects (3), Plants (2), Fish (1)
Australia, Oceania and the Pacific	4	[21], [29], [51], [43]	Temperature, precipitation, acidification of oceans	Fish (2), Plants (2)
Oceans and Seas (Arctic, Pacific, Adriatic)	4	[45], [55], [41], [57]	Temperature, sea level, extreme events	Fish (3), Marine invertebrates (1)
Global (Methodological Studies or Model Review)	6	[33], [42], [35], [24], [59], [53]	Methodological analysis, predictive models	Not applicable (Focus on methodology)

Source: Own elaboration.

This analysis highlights the importance of considering regional variability in research on species distribution and climate change, as well as the need to extend studies to under-represented taxonomic groups and to regions that have received less scientific attention.

## Discussion

The results of this systematic review indicate that, over the last decade, there has been a remarkable transition towards the use of machine learning techniques in species distribution models (SDMs), outperforming traditional statistical approaches. This trend is attributed to the ability of these models to handle non-linear relationships and process large volumes of environmental data [61]. Among the most prominent techniques, MaxEnt remains the predominant model, followed by Random Forest and ensemble approaches, suggesting a preference for hybrid strategies that seek to improve predictive accuracy [62].

In terms of model validation, metrics such as Area Under the Curve (AUC) and cross-validation are commonly used to assess the performance of SDMs. However, recent studies have questioned the exclusive reliability of these metrics, pointing out that they may overestimate the predictive ability of models [61]. For example, Woelmer [63] demonstrated that process-based models provide better predictions of water temperature and dissolved oxygen in lakes compared to null models, emphasizing the importance of considering temporal and depth variability in assessments. In addition, Williams [64] highlighted the relevance of identifying the most influential predictor variables in suitability models for terrestrial invasive plants, suggesting the need to explore additional metrics to improve the robustness of assessments.

A significant challenge in species distribution modelling is the presence of geographical and environmental biases in occurrence data, which can affect the accuracy of models. Several studies have proposed methods to correct these biases, such as the aggregation background technique, which has been shown to improve predictions by

addressing geographic and environmental biases in SDMs[65]. In addition, geographic filtering and the use of multi-species data have been suggested as effective approaches to mitigate the impact of sampling biases in models[66].

Another relevant finding is the uneven geographical distribution of studies, with a higher concentration in Asia, North America and Europe, while regions such as Latin America, Africa and marine ecosystems remain under-represented. This disparity may be due to limitations in data availability, less access to funding and the absence of long-term monitoring programs. This geographical bias could compromise the ability to project climate change impacts in regions with high biodiversity and affect the implementation of effective conservation strategies. For example, Xie[65] identified changes in the spatial and temporal patterns of the endangered tree *Toona ciliata* in China due to climate change, highlighting the urgency of increasing studies in under-represented ecosystems. Similarly, Vinha [67] used ensemble models to predict the distribution of indicator taxa of vulnerable marine ecosystems in data-limited seamounts in Cape Verde, highlighting the need to expand monitoring in less studied regions.

In relation to the diversity of taxa studied, there is a predominance of research focusing on plants and mammals, while groups such as insects, fish and marine invertebrates have received less attention. This bias limits a comprehensive understanding of the effects of climate change on biodiversity. For example, Yao [68] assessed the habitat suitability of *Danaus gientia* using an optimized MaxEnt model, highlighting the importance of including insects in modelling studies. In addition, Vinha [67] highlighted the need to improve distribution models for marine and freshwater species, especially in less studied ecosystems. On the other hand, Yimam [69] developed a model to map the spatial distribution of *Eucalyptus globulus* in the upper Blue Nile basin, using Sentinel-2 multispectral data and environmental data, demonstrating the effectiveness of machine learning algorithms in modelling invasive plant species.

The integration of machine learning approaches into SDMs has enabled significant advances in predicting extinction risks and assessing the impacts of climate change on various species. For example, Estopinán[70] demonstrates that deep learning-based models can effectively predict plant extinction risk and assess future climate impacts, providing valuable tools for proactive conservation. Furthermore, the application of mechanistic models based on biophysical ecology offers promising prospects for predicting species responses to climate change, by considering in detail the interactions between organisms and their physical environment [71]. These methodological advances, together with interdisciplinary collaboration and investment in long-term monitoring programs, are essential for developing effective conservation strategies to mitigate the adverse effects of climate change on global biodiversity.

These findings reinforce the importance of further optimizing predictive models and integrating climatic, topographic and ecological information to improve accuracy in identifying critical areas for conservation. They also highlight the need to strengthen monitoring in under-represented regions and expand the diversity of species analyzed to obtain a more complete picture of the effects of climate change on global biodiversity.

Despite notable progress in the application of statistical models and machine learning in species distribution modelling, this systematic review identifies several limitations that should be considered. Firstly, there is a marked geographical unevenness in the studies analyzed, with a strong concentration in Asia, North America and Europe, and a notable absence of research in regions of high biodiversity such as Latin America, Africa and marine ecosystems. This skewed distribution restricts the generalizability of findings and limits the applicability of models in less studied ecological contexts.

Secondly, a taxonomic bias is evident, with a prevalence of studies focusing on plants and mammals, and under-representation of key groups such as insects, fish and marine invertebrates. This lack of taxonomic balance may lead to an incomplete picture of the effects of climate change on global biodiversity.

In addition, most of the reviewed studies employ validation metrics such as AUC and cross-validation, without complementing these analyses with additional measures of sensitivity, specificity or independent validations, which may overestimate the predictive capacity of the models. Limited consideration of biotic interactions and dynamic ecological processes, which are essential to realistically capture species responses to environmental change, is also identified.

Finally, methodological heterogeneity between studies - in terms of spatial scales, environmental variables, algorithms used and modelling approaches - complicates the direct comparison between results and hinders the quantitative synthesis of evidence, which represents a barrier to the development of replicable and consistent standards in this field of research.

## Implications

The limitations identified have direct implications for the future development of species distribution models and for the formulation of adaptive conservation strategies in the face of climate change. First, there is a need to expand geographic and taxonomic coverage, encouraging studies in under-represented regions and on less-studied biological groups, which is crucial for a more holistic and equitable understanding of global environmental impacts.

Further integration of ecological proxy variables, such as habitat fragmentation, anthropogenic pressure and biotic interactions, as well as the incorporation of hybrid models combining correlative and mechanistic approaches, is also required to improve the accuracy and robustness of predictions under non-analogue future scenarios.

From a methodological point of view, it is essential to strengthen validation schemes by using multiple metrics, independent data and spatial and temporal validation techniques to ensure the reliability of models in different ecological contexts.

Finally, this review highlights the importance of promoting open access to environmental data, algorithms and modelling platforms, as well as the standardization of methodologies, as key pillars to foster reproducibility, knowledge transfer and interdisciplinary collaboration. These elements are essential to transform distribution models into effective tools to support decision-making in conservation, territorial planning and public policy in the face of climate change.

## Conclusions

This systematic review allowed to analyze the application and effectiveness of statistical and machine learning models in modelling species distributions under climate change scenarios, providing a framework for the most used methodologies and their implications in different ecological contexts. It was identified that the most widely used models have been MaxEnt, Random Forest and ensemble approaches, which have proven to be highly effective in predicting species distributions due to their ability to handle large volumes of data and capture non-linear relationships. However, traditional statistical models, such as GLM and GAM, are still relevant in studies where interpretability of results is a priority.

In relation to the environmental variables used, temperature, precipitation and altitude were found to be the most influential factors in habitat modelling, highlighting their role in the accuracy of predictions. However, there was variability in the selection of variables according to the taxonomic group analyzed, with marked differences between plants, mammals and insects. This heterogeneity underlines the need for adaptive approaches that take into account the ecological particularities of each taxon to improve model accuracy.

Regarding model validation, the most commonly used methods have been AUC and cross-validation, although some studies have pointed out that these metrics may overestimate the accuracy of the models. In this sense, it is recommended to incorporate complementary approaches to assess performance more rigorously, considering metrics such as sensitivity, specificity and independent validation with external data.

From a geographical perspective, it was observed that most studies are concentrated in Asia, North America and Europe, while regions such as Latin America, Africa and marine ecosystems have been less explored. This lack of representativeness limits the generalizability of the models and highlights the urgency of strengthening research in these areas to improve understanding of the effects of climate change on global biodiversity.

A bias in the diversity of analyzed taxa was also identified, with a predominance of studies on plants and mammals, while groups such as insects, fish and marine invertebrates have received less attention, despite their ecological importance. This finding highlights the need to broaden the range of species studied to obtain a more comprehensive view of changes in biodiversity distribution under climate change scenarios.

As future lines of research, it is recommended to continue exploring hybrid models that integrate statistical and machine learning approaches, allowing better adaptation to different ecological scenarios. In addition, it is essential to develop more robust validation methods and promote access to open data and advanced computational tools to improve the quality and replicability of studies. Finally, it is crucial that the results of these models are used in decision-making in conservation and environmental management, ensuring that the strategies implemented respond effectively to the challenges posed by climate change on biodiversity.

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