

REVIEW

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# Trends in species distribution modelling in context of rare and endemic plants: a systematic review

Ammad Waheed Qazi<sup>\*</sup> , Zafeer Saqib and Muhammad Zaman-ul-Haq

## Abstract

**Background:** Many research papers have utilized Species Distribution Models to estimate a species' current and future geographic distribution and environmental niche. This study aims to (a) understand critical features of SDMs used to model endemic and rare species and (b) to identify possible constraints with the collected data. The present systematic review examined how SDMs are used on endemic and rare plant species to identify optimal practices for future research.

**Results:** The evaluated literature (79 articles) was published between January 2010 and December 2020. The number of papers grew considerably over time. The studies were primarily conducted in Asia (41%), Europe (24%), and Africa (2%). The bulk of the research evaluated (38%) focused on theoretical ecology, climate change impacts (19%), and conservation policy and planning (22%). Most of the papers were published in publications devoted to biodiversity conservation, ecological or multidisciplinary fields. The degree of uncertainty was not disclosed in most studies (81%).

**Conclusion:** This systematic review provides a broad overview of the emerging trends and gaps in the SDMs research. The majority of studies failed to present uncertainties and error estimates. However, when model performance estimates are given, the model results will be highly effective, allowing for more assurance in the predictions they make. Furthermore, based on our systematic review, we recommend that in the future rare and endemic SDMs should represent uncertainty levels and estimates of errors in the modelling process.

**Keywords:** Species distribution modelling, Endemic, Rare, Uncertainty measures, Model validation

## Introduction

It is imperative to know the distribution of species for environmental management. However, it is hard to determine where the members of each species are at the exact moment. Therefore, species distribution models (SDMs) are applied to forecast a species' ecological and geographic location. If a species exhibits any of the following characteristics, it is viewed as a rare species: (a) raises naturally in a contracted geographical region; (b) inhabits only one or few particular habitats, and (c) has a small

population. In contrast, an endemic species raises naturally only in a specific geographic region, which can be limited or enormous in size. A species may be both rare and endemic at the same time if it lives in a narrow geographic region (Işik 2011; Orsenigo et al. 2018).

The SDMs methodology was developed based on Hutchinson's theory of ecological niche, which he introduced in the 1950s and then sophisticated by Booth et al. (1988). Through future Global Climate Model (GCM) and ecological information, SDMs are seen as a leading approach for analysing the most likely impacts of changing climate on the target species (Blanco et al. 2020; Pechi et al. 2019; Zurell et al. 2020). A variety knows the approach of distinct names: climate envelope, niche-based model, ecological niche model, habitat model, and

\*Correspondence: ammad.waheed@iiu.edu.pk

Department of Environmental Science, International Islamic University Islamabad, Islamabad 46000, Pakistan

environmental niche model (ENM) (Hamann and Wang 2006; Peterson et al. 2018; Zurell et al. 2020). Given the ambiguity concerning the definition of the term “niche”, the usage of SDM as synonymous with ENM is contentious (McInerney and Etienne 2013; Moukrim et al. 2019; Pecchi et al. 2019; Peterson and Soberón 2012).

To evade the misunderstanding, we followed the niche idea given by Mittelbach and Schemske (2015), which defines a species’ niche as “the combined description of an organism’s zero net growth isocline (ZNGI) and the impact factors on that ZNGI in the multivariate space defined by the pool of environmental variables present.” The correlative SDMs are extensively employed to calculate the impacts of climate change on the geographical distribution of species (Araújo et al. 2019; Kearney et al. 2010; Thomas et al. 2004; Yates et al. 2018). For example, Wan et al. (2021) modelled climate change’s influence on distribution patterns of six endemic species in Madagascar using averages of climatic variables like precipitation, temperature, wettest month, and driest month. A second method, known as the mechanistic model, based on physiological constraints and functional traits, determines the connection between a species’ environment and its wellness and, afterward, maps the results of species’ wellness onto a scene. For example, Sarychev et al. (2020) predicted the distribution and abundance of rare species based on landscape features in the Lipetsk Region. The species’ distribution was based on terrain characteristics, hydrography, and human impacts. The third method, known as the hybrid model, incorporates both mechanistic and correlative approaches. For example, de Queiroz et al. (2012) modelled the distribution of rare and endemic plant species and conservation planning in Nevada using a correlative modelling technique based on environmental predictors and a mechanistic model for the physiological response to climate-related aspects.

Many SDMs are currently being utilized to fulfil various research objectives. The majority of research has focused on the impacts of climate change, conservation planning and strategies, invasive alien species, and ecological problems (Yates et al. 2018). A previous literature review focused on SDM in forest management regarding the projected distribution of trees in the future (Janowiak et al. 2017). The study demonstrated that an adequate explanation of presence/absence information is critical to determining an ecological niche’s proper assessment. The study also recommends minimizing the uncertainties associated with the modelling stages (climate surfaces, dependability of species distribution data) (Pecchi et al. 2019).

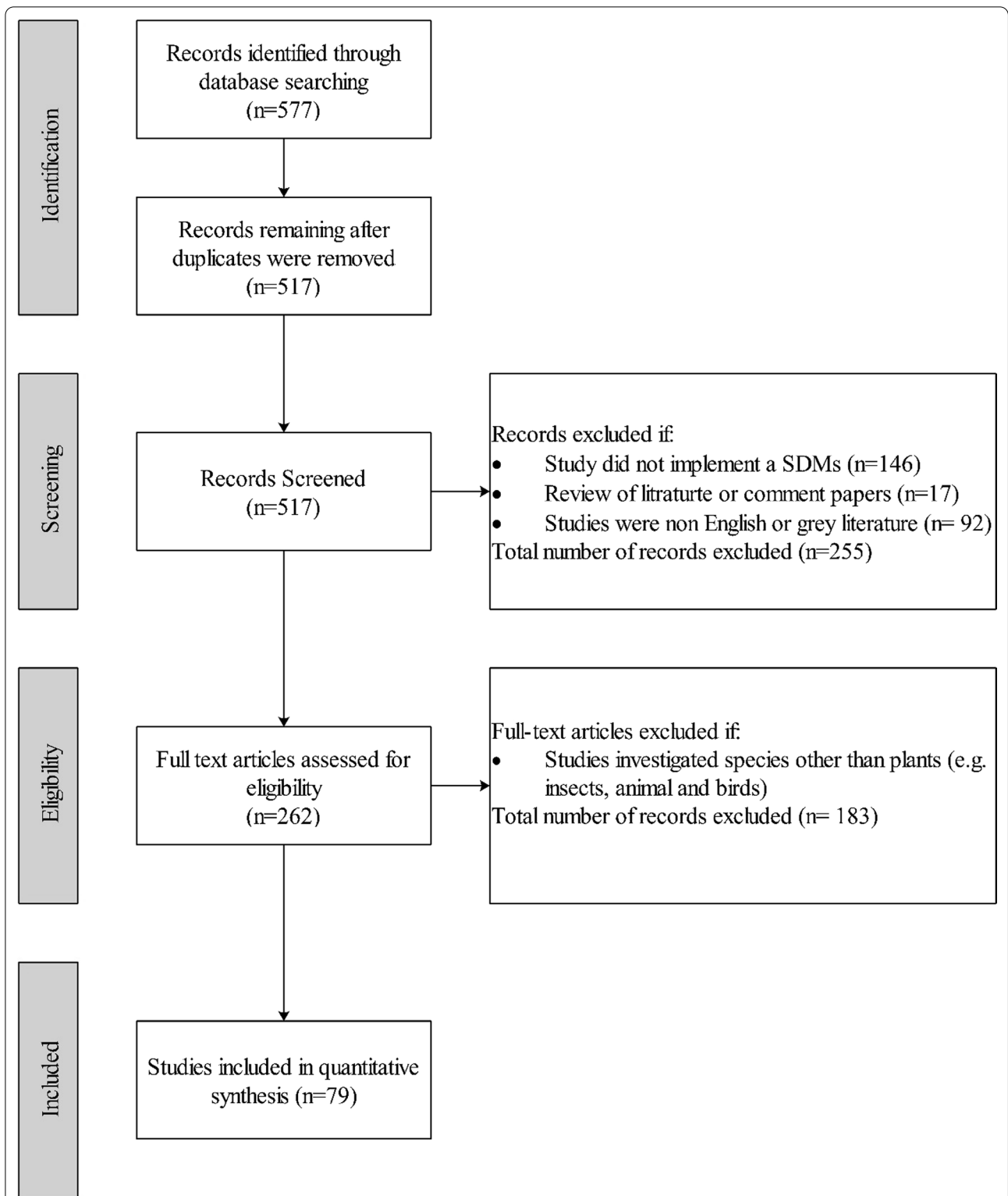
Many studies focused on a multi-model group approach for executing SDMs. For example, studies

conducted by Yun et al. (2017) and Ahmed et al. (2019) have demonstrated that accumulating many SDMs provides a structure for combining key model variables such as agreement levels and uncertainty outcomes. From the perspective of Species Distribution Models, model uncertainty or error valuation includes measuring model faults and mistakes and the accurate idea of variation (Barry and Elith 2006; Guélat and Kéry 2018). Generally, revealing such model uncertainties is significant for SDMs, specifically for research aimed at monitoring endemic and rare species, assessing biodiversity risks, and analysing climate change impacts. Nonetheless, most of the research failed to assess the model’s uncertainty level and error estimates adequately. The SDMs should ideally be based on well-established sample conventions and extensive information on quality control measures. Instead, a presence-only data approach has been utilized by numerous SDMs (Pacifiçi et al. 2017). Though this is a practical solution in most studies, developing models utilizing these data may disregard some of the models’ conventions (Morales et al. 2017). In this way, proposals for best practices in the development of SDMs are essential. In this study, we reviewed how the SDMs are used for the distribution of rare and endemic species to suggest best practices for future examinations. Important aspects examined from each research publication are systematized into two groups: (1) the key elements of the article and (2) SDMs parameters used in each study. Recommendations are presented to ensure SDMs users can comprehend the fundamental elements of SDMs and identify possible limitations with data.

## Methods

### Search of literature

As a guide, the present systematic review used the PRISMA (Preferred Reporting Items for Systematic Reviews) statement (Moher et al. 2016). Three databases were used for bibliographic searches, i.e., ScienceDirect ([www.sciencedirect.com](http://www.sciencedirect.com)), Web of Science ([www.webofscience.com](http://www.webofscience.com)), and Google Scholar ([www.scholar.google.com](http://www.scholar.google.com)). The research papers published between 2010 and 2020 with the keywords “Endemic” or “Rare” and “Species Distribution Models” in the title, abstract, or keywords were included. Review or comment papers, non-English articles, and papers presenting marine environments were also excluded from the search. The screening of abstracts was the first step in selecting research papers for inclusion in our study. The articles were eliminated (34%,  $n = 164$ ) if they: (a) used the term SDMs for discussion or justification without actually using SDMs in the research; and (b) did not contain real research (i.e., comment papers, review papers, or perspectives) (Fig. 1). As a result, only articles that presented applications of



**Fig. 1** The methodology and selection process used in the systematic review are depicted in a flow diagram. It adheres to PRISMA's (Preferred Reporting Items for Systematic Reviews) rules and templates (Moher et al. 2016)

SDMs of rare and endemic plant species or those whose contents were ambiguous depending on just reviewing the abstracts were kept for future research. An additional 183 studies were eliminated after further review because they addressed the distributions of animals or insects ( $n=104$ ), birds ( $n=23$ ), and marine ( $n=56$ ) species. The quantitative study included 79 papers in all. All references used in this study can be found in Additional file 1: Appendix S1.

**Data analysis**

The parameters and features of each paper were considered and assembled into a database of SDM of rare and endemic species publications. The appendices were also evaluated if needed. We combined the findings for SDM development to characterize the main aspects of SDMs. We analysed the information given in the 79 peer-reviewed articles. We offered a detailed outline of the necessary features that must be presented in SDM of rare and endemic plant species.

**Results**

**Annual trends of publications**

The papers published from 2010 to 2020 were reviewed in this study, and each year at least one paper was included. From 2010 to 2014, the average number of

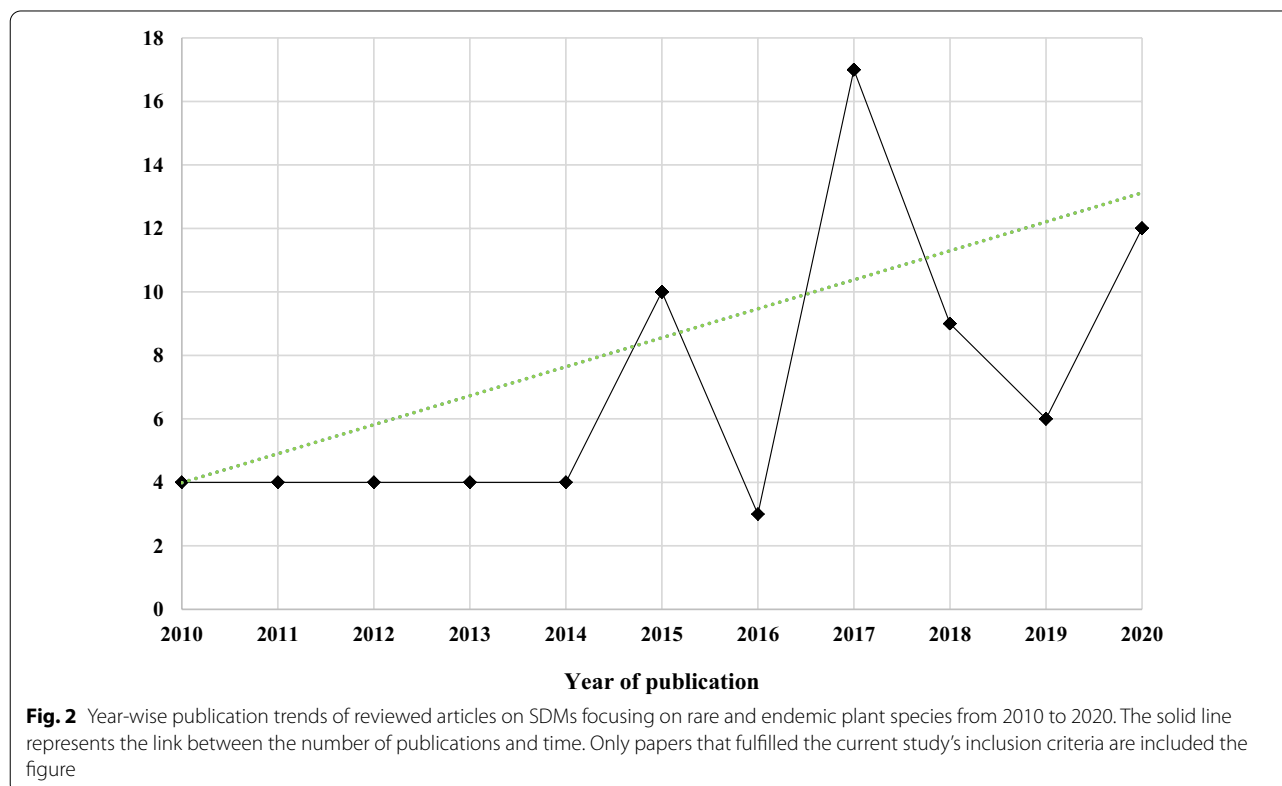
research articles published per year was 4. The use of SDMs for rare and endemic plant species gradually increased after 2015 and reached 17 papers per year in 2017 (Fig. 2). SDMs were applied only thrice in 2016. The most common approach used for studies was correlative models (83%), followed by mechanistic models (15%) and hybrids (12%).

**Uncertainty and error estimation**

Only 15 papers (Table 1) explicitly incorporate errors and uncertainty measures in their modelled distributions. In contrast, 81% ( $n=62$  papers) did not consider any error or uncertainty measures in their modelled distributions.

**Table 1** A summary of errors and uncertainty measures reported in literature

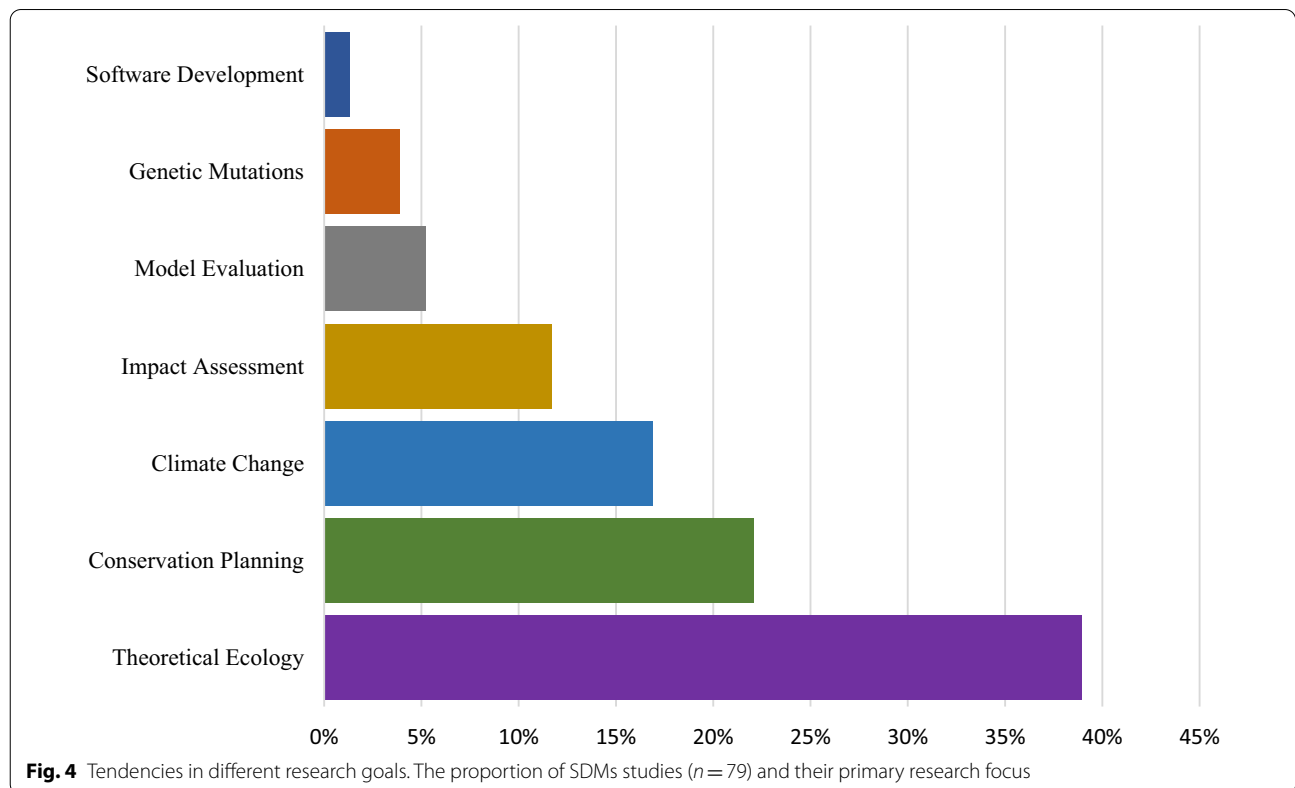
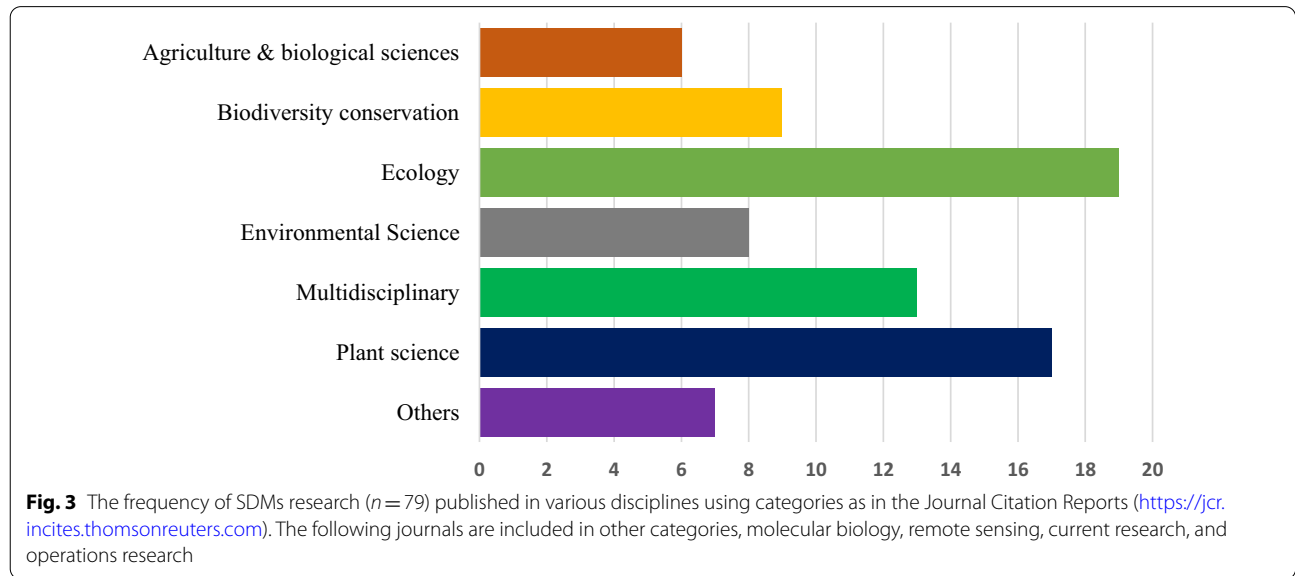
Category	Frequency
Not reported	64
Multi-model comparison	13
Bounding box method	1
Prediction similarity	1



**Discipline**

Endemic and rare SDM publications were found to have a strong presence in ecology and plant sciences (as categorized in the Web of Science). The majority of research was published in ecology, plant sciences, and multidisciplinary sciences journals ( $n = 19, 17,$  and  $13$  publications,

respectively) (Fig. 3). Biodiversity conservation and environmental sciences comprised 22% of the reviewed publications. Other fields, such as agriculture and biological sciences, accounted for less than 10% of the analysed publications (Additional file 2: Appendix S2).



### Study goal

In our study, seven classes of research approaches were characterized (Fig. 4). The majority of the research ( $n=30$ , 39%) was done to answer theoretical problems, conservation policy and planning ( $n=17$ , 22%), and the impacts of climate change ( $n=15$ , 18%). Publications on the following research areas were also included in the reviewed literature: impact assessment, model evaluation, and genetic mutations ( $n=9$ , 4, and 3 papers, respectively). A single publication was conducted for new software development.

### Species distribution model

Seven SDMs were reported from the reviewed literature (Fig. 5). The most frequently used model was MaxEnt, used in 49% ( $n=38$ ) of studies, followed by Ensembles ( $n=19$ ) and GLMs ( $n=10$ ). We found that only 12% of the studies were conducted by the following models: BRT, GARP, and CAR. A single study also reported the SMOTE Model for species distribution modelling.

### Selection procedure

A total of 10 selection parameter measures were executed in our study (Additional file 2: S2). The most common were cross-validation, multi-model inference, and stepwise selection approaches ( $n=30$ , 18, and 18 publications, respectively). On the other hand, 20% of the model selection approaches were executed twice (e.g.,

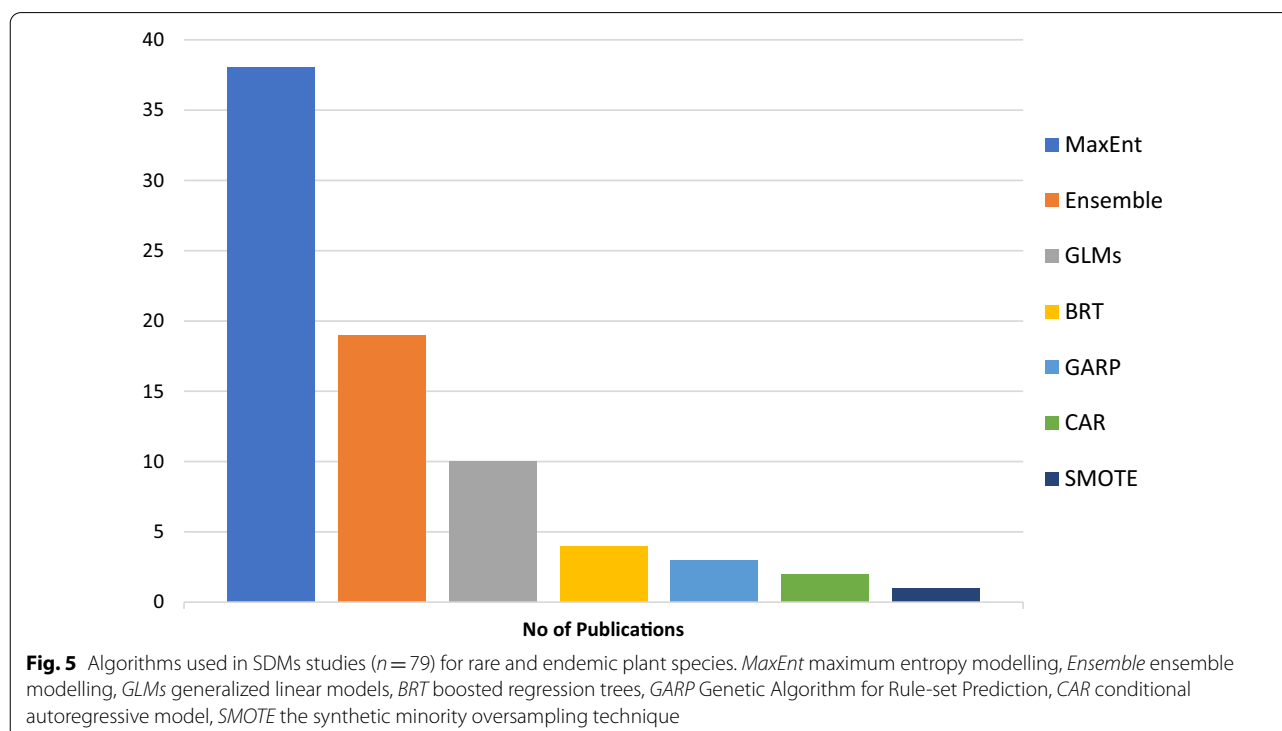
the information theory approach, boosting methods, and independent datasets). We examined that 5% of the studies had not executed a selection procedure.

### Measures of model validation

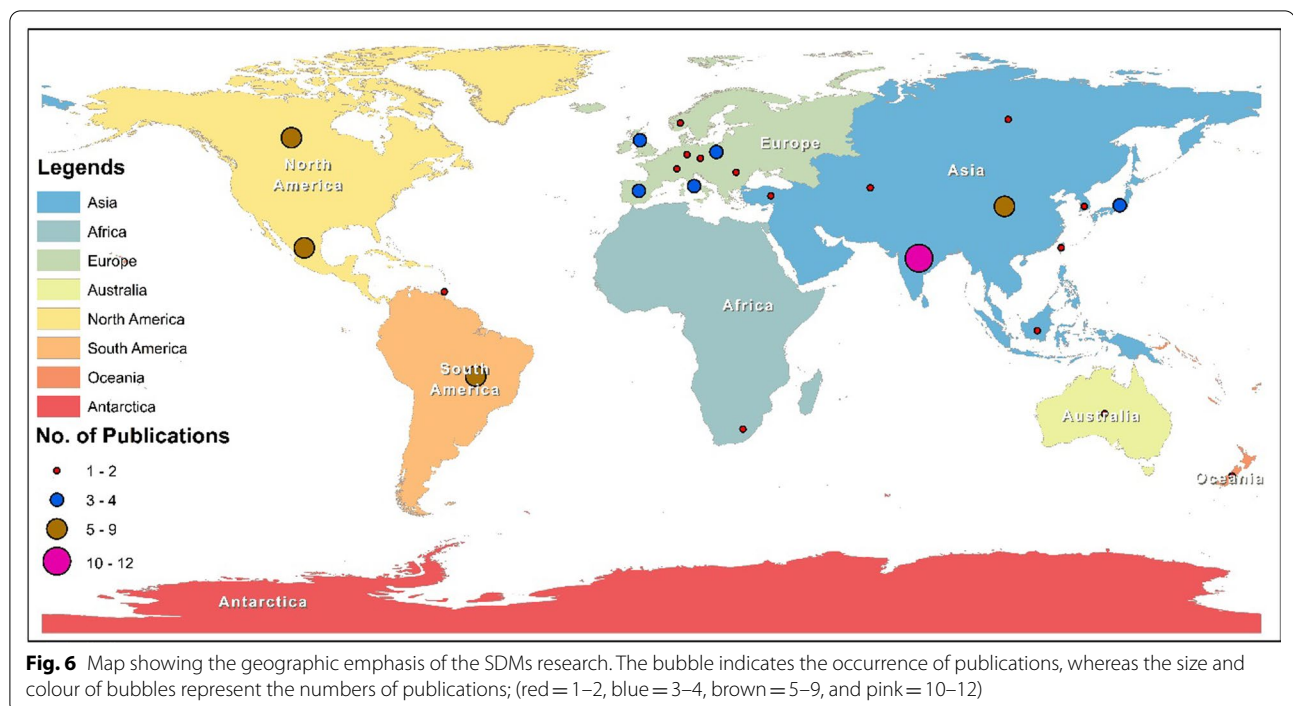
Model validation implies offering a quantifiable assessment of model “accuracy” or “performance” as well as sensitivity, precision, and specificity. Our sample determined that nine validation methods were applied (Additional file 2: S2). The most common method was threshold independent data measurement, used in 57% ( $n=44$ ) of the publications, followed by cross-validation methods, used in 26% ( $n=20$ ) of the papers. Only 5% of the papers compared their SDM results to independent datasets. The sole validation methods utilized in a single article were probability distribution and spearman rank correlation. We also discovered that 3% ( $n=2$ ) of the studies did not use a model validation approach to specify a measure of model performance.

### Geographic distribution

The rare and endemic SDMs covered all continents except Antarctica. Figure 6 illustrates the geographic focus of reviewed studies. The size and colour of the bubble represent the number of studies conducted. A total of 33 papers (42%) focused on SDMs of rare and endemic plant species of Asia (India  $n=12$ , China  $n=8$ , Japan  $n=4$  publications), followed by Europe with 23% (Poland,







Spain  $n=4$ , 4 and United Kingdom, Italy  $n=3$ , 3 publications, respectively). Both South America and North America also investigated rare and endemic plant species using SDMs ( $n=12$  and 11 publications, respectively). The countries/regions with fewer studies were Indonesia, Russia, South Korea, Taiwan (China), New Zealand, Czech Republic, Germany, Romania, Switzerland, Turkey, Uzbekistan, Australia, Norway, Trinidad and Tobago, and South Africa ( $n$  = between 1 and 2 papers each).

#### Associations between categories

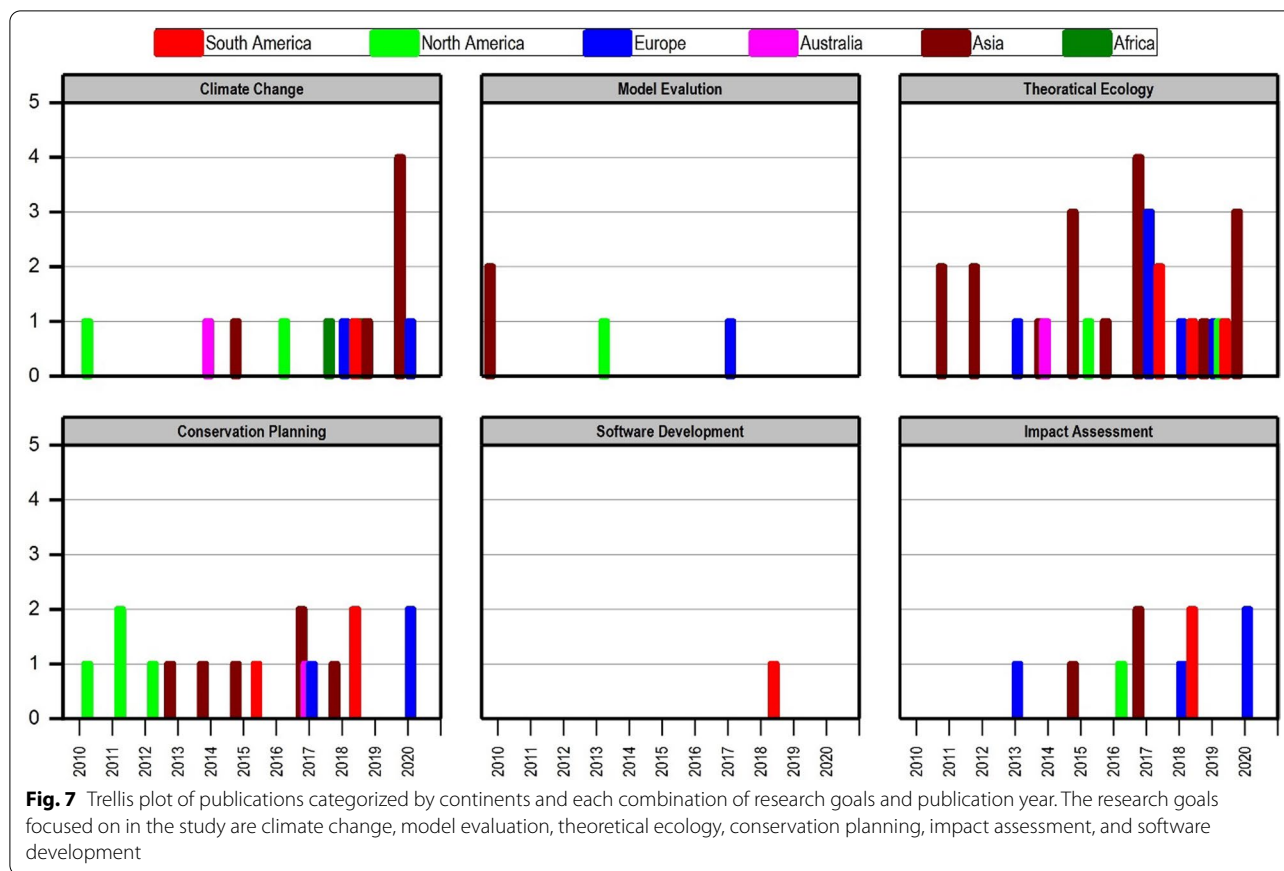
The strong association witnessed was between the algorithms and the goals/approach. MaxEnt was a standard algorithm for theoretical ecology and climate change ( $n=16$  and 10 publications, respectively). Although a significant association was observed between some categories, the association among most of the classes was weak. A demonstration of the combination of each study approach/goal and publication year by continent can be seen in Fig. 7. The representation of climate change, conservation planning, theoretical ecology, and impact assessment in all continents is shown in the trellis plot. In contrast, only a single study on software development has been conducted in South America.

#### Discussion

The previous literature reviews of SDM have discussed the effectiveness of species distribution modelling for forest management (Pecchi et al. 2019), evaluated the

performance of ensemble models (Hao et al. 2019), and considered the spatial–temporal issues with species distribution (Martinez-Minaya et al. 2018). Although the objectives and aims of previous studies vary from those of this study, after conducting this systematic review, identical conclusions have been reached.

This study highlighted many challenges related to the applications of SDMs for the distribution of rare and endemic species. First, the present research has revealed the effectiveness of MaxEnt, applied in 49% of studies conducted on the distribution of rare and endemic plant species. It is the most frequently used model due to its convenience as it performs on presence-only data (Wan et al. 2021). The MaxEnt model is well known today, which has been employed in research on the impacts of climate change on species distribution, species richness, invasive species, endemism hotspots, and to estimate the extent of occurrence and quality of protection of rare species (Cunningham et al. 2009). Compared to other models such as GARP and BIOCLIM, the MaxEnt performed better in prediction accuracy (Elith et al. 2011). 25% of studies followed the multi-model ensemble approach as an alternative to the single-model approach. Second, only 18% of the reported SDMs offered uncertainty measures or estimates of errors (Guélat and Kéry 2018). For spatial data planning, species distribution predictions are critical. However, conservation planning and resource management strategies based on SDMs might harm the environment due to unacknowledged and undiagnosed



weaknesses and high degrees of uncertainty. As a result, knowing the interactions between the ecological mechanisms that control the distribution of species and the input variables used to characterize and simulate them is a critical stage in the modelling process. Our quantitative review of the research has allowed us to find similarities across study fields and model components that have frequently been neglected by earlier studies (Table 2).

One of the most challenging considerations in developing SDMs is deciding the statistical algorithm(s) to utilize in the modelling. Previously published research on similar datasets can guide the most appropriate technique.

However, more research into algorithms that work with existing environmental data is necessary. While previous studies primarily focused on single-model approaches (Deb et al. 2017; Yilmaz et al. 2017), according to particular research (Cotado and Munne-Bosch 2020; Shaareef et al. 2015), one model outperforms the others. We recommend employing multi-model ensemble strategies that consider the similarity level or variation across model results and outputs. It is feasible to compare the results of several algorithms by applying numerous methodologies (Yun et al. 2017). To choose an appropriate explanatory model, the reported SDMs analysed input

**Table 2** A checklist of model characteristics that must be explicitly mentioned in published SDMs

- The geographical location of the study
- Methodological approach followed in the study: mechanistic, correlative, or hybrid
- What is the type and degree of errors?
- How can the absence record be addressed?
- What is the association between fitted models and estimated models?
- What are the outcomes of putting the model predictions to the test against independent datasets?
- What are the outcomes of spatial and temporal extrapolation of model outputs?
- Do the outcomes of various algorithms agree or contradict across geographical spaces?



data using the matrices that quantify the model fitness (variable importance, residual plots, covariate response curves, and goodness-of-fit). While these metrics estimate model fitness, using a single model to do that might result in the selection of a model that does not accurately represent the natural environment. As a result, we suggest employing a multi-model approach that considers the degree of uncertainty in model selection (Gillingham et al. 2018).

The outputs of models are verified, which means they are evaluated based on their performance. Several studies merely use one or a few validation metrics to validate models (e.g., percent deviation, *p*-value, AUC/ROC curve). We suggest evaluating model precision using many validation metrics (Sugali and Rao 2014). We were able to determine model components that should be mentioned in reported SDMs by conducting a systematic review (Table 2) and model elements that need to be studied more in the future. This checklist includes several questions concerning different areas of model development. The evaluated literature's key characteristics include research information like the objective or goal, geographical region, and methodological technique used (mechanistic, correlative, or hybrid). The questions about data deficiency, how to validate findings, and how to choose the best model should be answered during the modelling procedure.

The impact of sample size on creating reliable models has gained special attention in SDM. Interestingly, little was discussed about the role of sample size in determining the accuracy of models. The critical step in SDM is validation, and understanding the effects of sample size on it is of great importance. The gap between reported and factual accuracy shrinks as the sample size grows (Bean et al. 2012). It is challenging to recommend precise sample sizes since many factors influence the precision of the estimates. A sample size of at least 30 is recommended, whereas samples fewer than 20 should raise concerns (Chernick and Labudde 2011). A sample size of 20 may still be sufficient, and therefore the interval (20–30) appears to be a comfortable lower limit (Jiménez-Valverde 2020). SDMs with a limited environmental range can be reliable and highly stable even with few presences. Species with a wide environmental range and few presences creating numerous replicable models that break up the preliminary data and develop a consensus model (Mateo et al. 2010). Because of difficulty in finding new individuals or small population size, presence data for endemic and rare species are frequently limited. Therefore, SDMs for endemic and rare species are frequently developed by the MaxEnt algorithm, which has

been shown to generate significant results with narrow and spatially biased presence data (Rovzar et al. 2016).

Species frequently have physiological restrictions that extend the wide variety of environmental conditions faced in their current realized niche. For instance, essential traits for species to persist in novel climates, including phenotypic plasticity (Hoffmann and Sgrò 2011), evolutionary processes (Etterson 2004), and thermal tolerance (Early and Sax 2014; Overgaard et al. 2014; Sunday et al. 2012) are likely to influence responses of species to climate change. Catullo et al. (2015) created a framework for integrating significant physiological restrictions and responsive parameters into the SDMs and the impacts of changing climate. The framework defined four parameters: the rate at which adaptive evolution occurs, the realized limit, the physiological limit at the moment, and the evolutionary physiological limit. The above parameters can be predicted or calculated using multiple data sources and applied to numerous modelling approaches. This framework is broad enough to apply to single species and multiple species modelling, as well as mechanistic modelling and correlative modelling approaches.

## Conclusions

This study is based on a systematic review protocol applied to a set of 79 research publications in SDMs from 2010 to 2020 and provided a broad overview of the emerging trends and gaps in the SDMs research. The most obvious finding of this review is that the SDMs are gaining recognition as a tool for sustainable biodiversity management. The majority of studies were carried out to answer theoretical problems, conservation planning, and impacts of climate change. The correlative approach was the most common approach, and MaxEnt is the most frequently used model due to its convenience, but the majority of studies failed to present uncertainties. However, when model performance estimates are given, the model results will be highly effective, allowing for more assurance in their predictions. To compare model findings, for example, between locations, through organism groups, time, and for duplication, a systematic framework combining multi-model methods and clear reporting of errors and uncertainty is required. The present study will assist future research on the effective application of SDMs for endemic and rare plant species.

## Abbreviations

SDMs: Species distribution models; PRISMA: Preferred Reporting Items for Systematic Reviews; MaxEnt: Maximum entropy modelling; GARP: Genetic algorithm for rule-set prediction; GLMs: Generalized linear models; BRT: Boosted regression trees.

## Supplementary Information

The online version contains supplementary material available at <https://doi.org/10.1186/s13717-022-00384-y>.

**Additional file 1:** List of research journals and their fields/discipline as categorized in ISI Web of Science.

**Additional file 2:** Different terms and their explanation used in present systematic review.

### Author contributions

AWQ collected all the data, ZS supervised the complete study, and MZH performed the analysis. AWQ wrote the manuscript. All authors reviewed and approved the manuscript. All authors read and approved the final manuscript.

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### Declarations

#### Ethics approval and consent to participate

Not applicable.

#### Competing interests

The authors declare that they have no financial and non-financial competing interests.

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