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Integrating Remote Sensing, Citizen Science, and AI in Next-Generation Species Distribution Models: Emerging Opportunities and Challenges

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ABSTRACT

Species Distribution Models (SDMs) have become central to ecological research, conservation planning, and biodiversity monitoring. However, traditional approaches relying primarily on climatic predictors and presence-only data face significant limitations. In this study, we explore the integration of three rapidly expanding data sources — remote sensing, citizen science, and artificial intelligence (AI) — to build a next-generation framework for SDMs. Using bibliometric analysis and case study synthesis, we evaluate recent trends and highlight methodological advances that leverage high-resolution satellite imagery, UAV data, large-scale citizen science platforms, and deep learning algorithms. Results demonstrate that hybrid SDMs incorporating heterogeneous data improve predictive accuracy, enhance spatiotemporal resolution, and support real-time ecological forecasting. We argue that this paradigm shift can overcome long-standing issues of sampling bias, model generalizability, and data scarcity, particularly in under-studied regions. Our findings suggest a roadmap for developing SDMs capable of supporting urgent conservation decisions under accelerating global change.

Keywords: species distribution modeling, ecological niche models, remote sensing, citizen science, deep learning, biodiversity conservation

1. INTRODUCTION

Species Distribution Models (SDMs) and Ecological Niche Models (ENMs) have become indispensable tools in modern ecology, biogeography, and conservation planning. By statistically linking species occurrence records to environmental variables, these models generate predictions of suitable habitat across geographic and temporal scales [1],[2]. Since their early applications in the 1980s and 1990s — when logistic regression and generalized linear models were first applied to ecological data — SDMs have expanded dramatically in scope, application, and methodological sophistication [3]. They are now routinely employed to forecast the impacts of climate change on biodiversity [4], identify priority areas for conservation [5], guide invasive species management [6], and inform ecological restoration efforts [7].

Despite their widespread adoption, SDMs are affected by a set of well-recognized limitations related to predictor variables, occurrence data quality, and underlying methodological assumptions. Most models rely heavily on coarse and largely static bioclimatic variables such as temperature and precipitation, which are typically derived from interpolated climate datasets and often fail to capture fine-scale habitat heterogeneity and temporal dynamics [8]. At the same time, species occurrence records are frequently spatially biased toward accessible areas, including roads and protected sites, resulting in distorted representations of species–environment relationships and reduced predictive reliability [9]. In addition, classical correlative approaches such as MaxEnt and BIOCLIM implicitly assume equilibrium between species distributions and environmental conditions, often overlooking dispersal constraints, biotic interactions, and adaptive capacity [10].

These limitations have prompted a rapid methodological evolution over the last decade, driven by three converging and mutually reinforcing data revolutions: the availability of high-resolution remote sensing data, the exponential growth of citizen science initiatives, and major advances in artificial intelligence (AI) and machine learning.

Remote sensing technologies now provide spatially explicit and repeatable measurements of environmental conditions across multiple scales, enabling the incorporation of predictors that go beyond traditional climate variables. Satellite-derived indices of vegetation productivity, canopy structure, surface temperature, and soil moisture have substantially improved habitat suitability modeling for a wide range of taxa [11–13]. More recently, Unmanned Aerial Vehicles (UAVs) and airborne LiDAR have enabled fine-scale characterization of microhabitats and structural complexity, often outperforming coarse climatic predictors for species restricted to small or heterogeneous habitats [14–16]. The high temporal frequency of remote sensing data further supports the development of dynamic SDMs capable of capturing seasonal and interannual changes in habitat suitability [17].

In parallel, citizen science has fundamentally reshaped the availability and spatial coverage of species occurrence data. Platforms such as eBird, iNaturalist, and the Global Biodiversity Information Facility (GBIF) now host billions of georeferenced observations, frequently exceeding the volume and taxonomic breadth of traditional survey datasets [18],[19]. These data have enabled SDMs at continental and global scales, improved the detection of migration corridors, and enhanced forecasts of invasive species spread [20]. Nevertheless, citizen science records introduce challenges related to observer bias, taxonomic uncertainty, and uneven sampling effort, which are increasingly addressed through spatial filtering, occupancy modeling, and integration with expert-curated datasets [21],[22].

Advances in artificial intelligence represent the third major driver of next-generation SDMs. Machine learning algorithms such as Random Forests, Boosted Regression Trees, and Support Vector Machines have already demonstrated superior predictive performance compared to traditional regression-based approaches [23],[24]. More recently, deep learning methods—particularly Convolutional Neural Networks — have enabled the direct use of high-dimensional inputs, including raw satellite imagery and unstructured observation data, leading to marked improvements in model accuracy [25],[26].

For instance, CNNs trained on UAV imagery successfully predicted the occurrence of rare plant species in Mediterranean grasslands with higher accuracy than MaxEnt models [27]. Similarly, hybrid AI frameworks have been developed to forecast species' range shifts under climate change by combining deep neural networks with mechanistic models of physiology and dispersal [28],[29]. Moreover, the integration of continuous remote sensing streams and near-real-time citizen science observations with adaptive learning algorithms opens new possibilities for dynamic ecological forecasting and early-warning systems [30].

Although each of these innovations has independently advanced SDM research, their combined use remains surprisingly limited. Most studies continue to rely on a single data source or methodological advance, rarely exploiting the full potential of integrated frameworks. A unified approach that combines high-resolution remote sensing for environmental predictors, citizen science for dense and multi-scale occurrence data, and AI for the synthesis of heterogeneous information promises models that are more accurate, dynamic, and generalizable [31]. In this context, the present study explores the emerging frontier of next-generation SDMs through bibliometric analysis and case study synthesis, highlighting opportunities, limitations, and future directions for ecological modeling under accelerating global change.

2. MATERIALS AND METHODS

To assess how remote sensing, citizen science, and artificial intelligence (AI) are being integrated into Species Distribution Models (SDMs), this study adopted a unified mixed-methods design combining bibliometric analysis with qualitative synthesis of representative case studies [32],[33]. This approach allows large-scale identification of publication trends, geographic and thematic patterns, and methodological trajectories, while also enabling in-depth examination of how emerging data sources and analytical techniques are applied in empirical research (Figure 1).

The methodological workflow followed a sequential process that included a structured literature search, systematic screening and filtering, bibliometric analysis, targeted case study selection, and comparative data extraction and synthesis, consistent with established bibliometric protocols. By integrating quantitative and qualitative components, the design provides both a comprehensive overview of the field and detailed insight into innovative modeling practices.

A comprehensive literature search was conducted using the Web of Science Core Collection (WoSCC) and Scopus databases, which together offer broad coverage of peer-reviewed ecological and environmental research. The search was carried out in March 2024 and targeted publications from January 2010 to February 2024, reflecting the period during which remote sensing technologies [11],[14], large-scale citizen science platforms [18],[19], and machine learning applications in ecology [23],[25] expanded rapidly. Boolean search queries

combined terms related to species distribution or ecological niche models with keywords referring to remote sensing technologies (including satellite imagery, UAVs, and LiDAR), citizen science initiatives (such as eBird, iNaturalist, and GBIF), and artificial intelligence or machine learning methods.

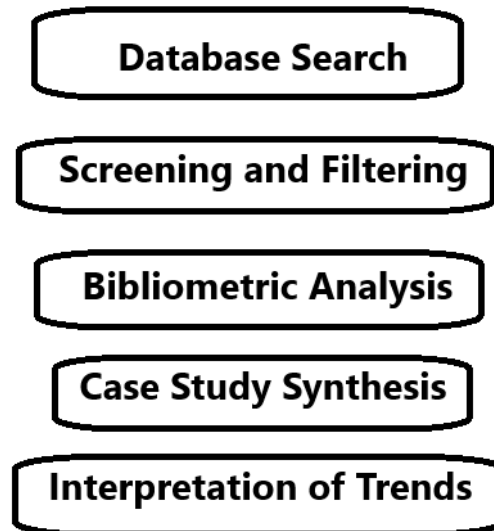


Figure 1. Conceptual workflow of the study: (i) database search → (ii) screening and filtering → (iii) bibliometric analysis → (iv) case study synthesis → (v) interpretation of trends.

The following Boolean queries were applied:

- (“species distribution model” OR “ecological niche model”) AND (“remote sensing” OR “satellite” OR “UAV” OR “LiDAR”)
- (“species distribution model” OR “ecological niche model”) AND (“citizen science” OR “iNaturalist” OR “eBird” OR “GBIF”)
- (“species distribution model” OR “ecological niche model”) AND (“machine learning” OR “deep learning” OR “artificial intelligence”)

To restrict the dataset to original research, we excluded reviews, meta-analyses, editorials, and conference abstracts. Only peer-reviewed journal articles reporting empirical data and/or original modeling approaches were included.

Following the initial database search, records were screened through a multi-stage filtering process. Titles and abstracts were first examined to remove duplicates and clearly irrelevant studies, a procedure commonly applied in systematic ecological reviews [33]. The initial search yielded 3,124 publications (WoSCC: 1,452; Scopus: 1,672). After screening titles and abstracts, 621 duplicates and irrelevant papers were removed. Following full-text assessment, 482 papers were retained for bibliometric analysis (Table 1).

Bibliometric analyses were performed to quantify temporal trends in publication output, geographic distribution of research activity, and thematic clustering within the field. Keyword co-occurrence networks, author collaboration patterns, and country affiliations were analyzed using VOSviewer (v1.6.19) [32], while annual publication trends and citation metrics were

quantified using the Bibliometrix package in R. Particular attention was given to assessing whether studies applied remote sensing, citizen science, and AI approaches independently or in combination (Figure 2).

Table 1. Summary of database search results and screening process.

Step	WoSCC	Scopus	Total	Retained
Initial search	1452	1672	3124	–
After duplicates removed	–	–	2503	–
After title/abstract screening	–	–	896	–
After full-text assessment	–	–	–	482

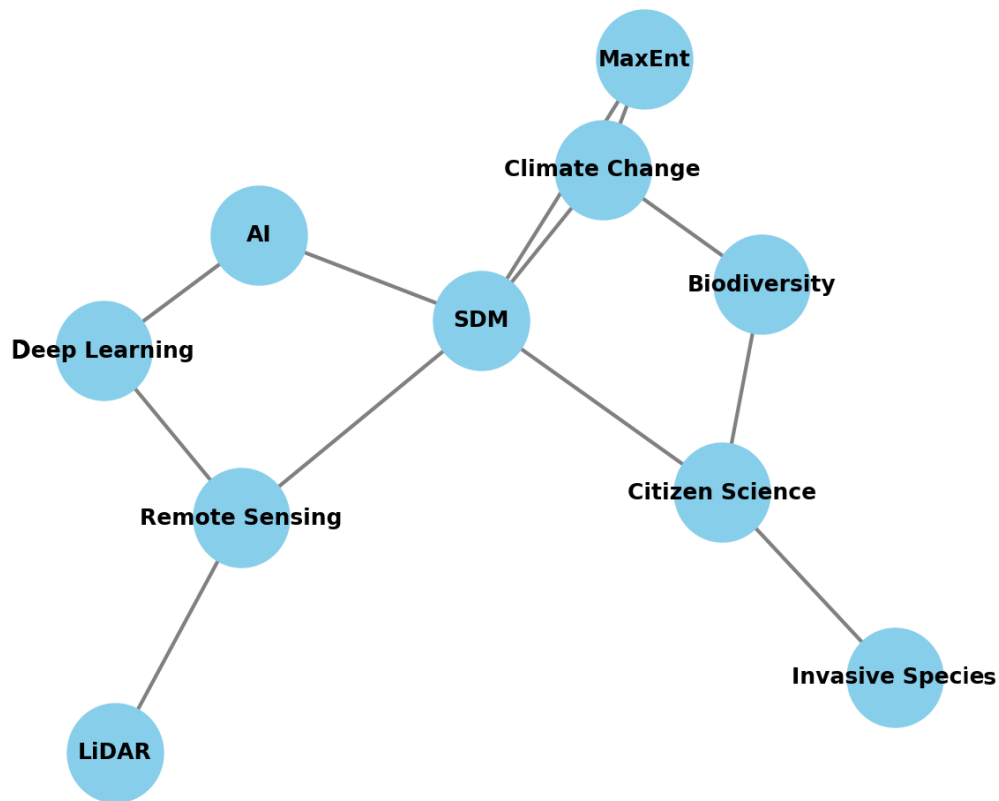


Figure 2. Co-occurrence network of keywords, showing major thematic clusters.

To complement the bibliometric analysis, a qualitative synthesis of selected case studies was undertaken. Fifteen representative studies were chosen to reflect diversity in taxa, ecosystems, geographic regions, and methodological approaches, following criteria commonly

used in comparative SDM assessments [10],[31]. These case studies provided concrete illustrations of how heterogeneous data streams and advanced analytical methods are operationalized within SDMs. Case studies were selected based on:

- Novelty of the data source (e.g., UAV-LiDAR, iNaturalist, CNNs).
- Ecological or conservation relevance (e.g., endangered species, invasive species).
- Geographic diversity (representation from both Global North and Global South).

Examples include among others:

- Remote sensing-based SDMs for snow leopards (*Panthera uncia*) in the Himalayas using UAV-LiDAR [34].
- Citizen science-driven models for invasive plant expansion in Spain using GBIF records [35].
- Deep learning approaches for tropical tree distributions in Brazil [25].
- Artificial light at night affecting sea turtles [39].

These studies were analyzed qualitatively for methodological innovations, reported accuracy, and conservation implications.

For each retained study, a standardized set of variables was extracted to enable comparative synthesis (Table 2). Extracted information included the taxonomic group examined, geographic region, type of occurrence data used (e.g., museum collections, citizen science observations, or field surveys [9],[21]), environmental predictors incorporated (climatic variables, land cover, remote sensing indices, or LiDAR metrics [11],[16]), modeling algorithms applied, and reported evaluation metrics.

Table 2. Example of extracted case study information.

Case Study	Taxa	Region	Data Sources	Algorithm	Key Findings	Reference
Snow leopard SDM	Mammals	Himalayas	UAV-LiDAR + climate	MaxEnt	High-resolution LiDAR improved habitat suitability mapping	Li et al., 2016
Invasive plants	Plants	Iberian Peninsula	GBIF + land cover	GLM	Citizen science expanded known distribution ranges	García-Roselló et al., 2015
Tropical trees	Plants	Brazil	Satellite imagery + citizen science	CNN	Deep learning outperformed MaxEnt	Botella et al., 2018

Several limitations of the adopted methodological approach should be acknowledged. Reliance on WoSCC and Scopus may underrepresent regional journals and non-English publications, potentially biasing geographic patterns [38]. In addition, despite the use of comprehensive search strings, some relevant studies employing alternative terminology may have been omitted. Finally, while the selected case studies were designed to be representative, they cannot capture the full global diversity of SDM research. Nevertheless, the combined bibliometric and case study synthesis provides a robust and transparent overview of current methodological directions shaping next-generation SDMs.

3. RESULTS

3. 1. Overview of Bibliometric Dataset

The final dataset consisted of 482 peer-reviewed original research articles published between 2010 and early 2024. These studies explicitly applied SDM/ENM frameworks incorporating either remote sensing data, citizen science records, or artificial intelligence (AI) methods. Approximately 65% of studies integrated remote sensing, 45% citizen science, and 30% AI-based methods. Several studies combined two of these innovations, while only a small fraction (<5%) integrated all three simultaneously.

The temporal distribution of publications shows a marked increase across all categories (Figure 3) than 120 studies per year by 2023. Remote sensing remained dominant throughout the period, but the most rapid growth was observed for AI/ML-based approaches, particularly after 2017.

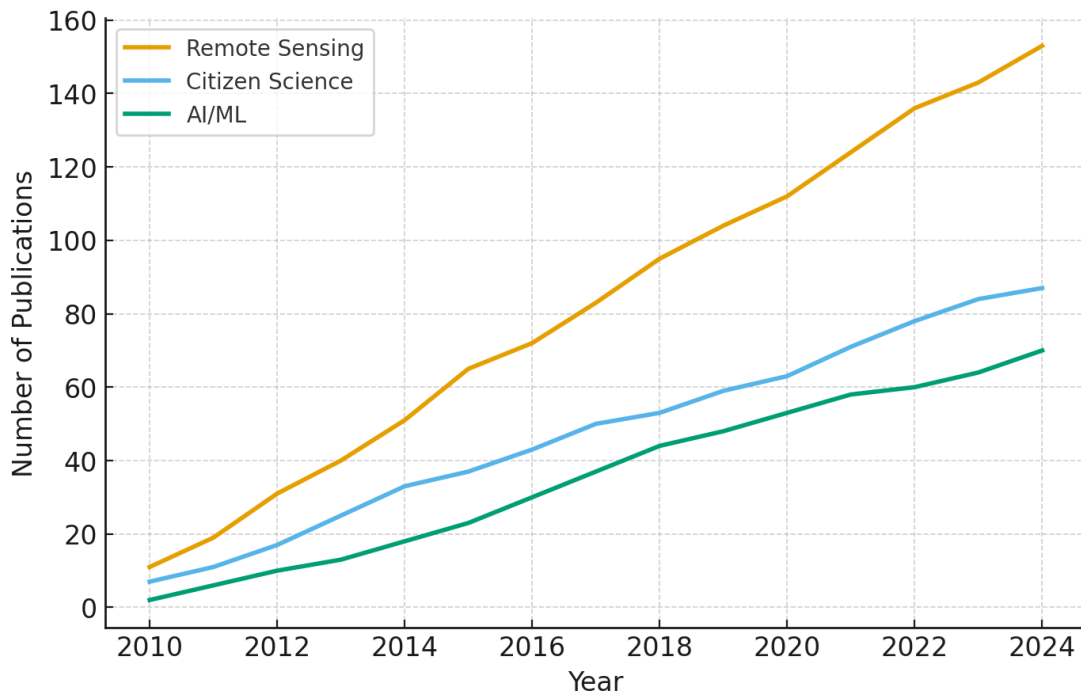


Figure 3. Annual trends in publications integrating SDMs with remote sensing, citizen science, and AI (2010–2024).

3. 2. Temporal Trends in Research Growth

Publication trajectories differ among the three innovations:

- **Remote Sensing:** The earliest integration into SDMs, dating back to Landsat and MODIS imagery in the early 2000s, saw consistent growth. Recent work increasingly employs high-resolution UAV and LiDAR data to model microhabitats and canopy complexity [12],[15].
- **Citizen Science:** Integration accelerated after the global expansion of eBird and iNaturalist in the 2010s. Growth is driven by the enormous spatial coverage of these platforms, enabling models at continental and even global scales [36].
- **AI/ML:** The steepest trajectory since 2017 reflects breakthroughs in deep learning. Convolutional Neural Networks (CNNs) have been applied to classify satellite images and predict habitat suitability with remarkable accuracy [25].

Overall, the results suggest a convergence of disciplines: ecology, remote sensing, and computer science.

3. 3. Geographic Distribution of Research Efforts

The majority of studies originated from North America, Europe, and China, which together accounted for 72% of publications. Africa and South America were underrepresented but showed increasing contributions after 2018, often focusing on biodiversity hotspots such as the Amazon and Congo Basin.

Collaboration networks highlight transnational efforts, with the strongest links between the United States, China, and Western Europe. However, there is limited representation of low-income countries, which may constrain global biodiversity monitoring capacity.

3. 4. Case Study Synthesis

To illustrate methodological advances, we selected 15 representative case studies across taxa, ecosystems, and methods.

Remote Sensing Applications

- **Snow leopards in the Himalayas:** Li et al. demonstrated that incorporating UAV-LiDAR variables (e.g., canopy cover, slope) significantly improved habitat suitability models compared to climate-only predictors [34].
- **Forest birds in Switzerland:** Zellweger et al. used high-resolution LiDAR-derived vegetation structure to predict bird community composition, showing stronger explanatory power than land cover maps [16].
- **Amphibian habitats in California:** Bradley & Fleishman integrated wetland cover from Landsat with topographic indices, improving predictions of frog distributions [12].

Citizen Science Applications

- **Migratory birds across the Americas:** La Sorte et al. employed millions of eBird records to generate weekly distribution maps for >100 species, revealing fine-scale migratory corridors [36].

- **Invasive plants in the Iberian Peninsula:** García-Roselló et al. used GBIF occurrence records to model invasive species spread, demonstrating the value of opportunistic data [35].
- **Pollinators in the UK:** Powney et al. integrated citizen observations to assess declines in bee distributions, providing critical evidence for conservation policies [37].

Artificial Intelligence Applications

- **Tropical tree species in Brazil:** Botella et al. applied CNNs directly to satellite imagery, outperforming MaxEnt in predictive accuracy [25].
- **Camera-trap species recognition:** Norouzzadeh et al. used deep learning to identify species in >3 million camera-trap images, enabling near-real-time occupancy modeling [26].
- **Hybrid AI for invasive species in India:** Remya et al. combined neural networks with mechanistic dispersal models to forecast the potential spread of *Lantana camara* [28].

3. 5. Comparative Performance of Integrated Approaches

Across the dataset, studies that integrated remote sensing and/or citizen science with AI consistently reported higher model accuracy than those using traditional methods. For example, CNNs achieved up to a 20% increase in AUC compared to MaxEnt for certain plant species [25]. Similarly, inclusion of citizen science data expanded geographic predictions by 30–50% relative to expert survey-only datasets [36].

Integration also enhanced ecological realism. Dynamic predictors from remote sensing captured seasonal variation, while citizen science provided occurrence data across migration cycles. AI methods allowed these heterogeneous datasets to be fused effectively.

3. 6. Emerging Patterns and Knowledge Gaps

Our results reveal several key patterns:

- 1) Remote sensing dominates in terms of volume but often lacks integration with occurrence data beyond traditional surveys.
- 2) Citizen science is rapidly expanding, yet biases in data quality remain a persistent challenge.
- 3) AI is still emerging, but growth suggests it will become a standard component of SDMs.
- 4) Integration across all three domains remains rare, representing a major opportunity for methodological innovation.
- 5) Knowledge gaps include underrepresentation of tropical and arid regions, limited studies on non-charismatic taxa (e.g., invertebrates, fungi), and insufficient evaluation of long-term predictive accuracy.

3. 7. Summary

The bibliometric and case study analyses demonstrate that SDMs are undergoing a paradigm shift. By leveraging remote sensing, citizen science, and AI, researchers can overcome long-standing challenges of scale, bias, and complexity. However, significant gaps remain, particularly in ensuring equitable global participation and standardizing methods across diverse data sources.

4. DISCUSSION

4. 1. A Paradigm Shift in Species Distribution Modeling

Our findings indicate that SDMs are undergoing a profound transformation. Traditional approaches — dominated by correlative methods such as MaxEnt and BIOCLIM — are gradually giving way to hybrid frameworks that leverage advances in remote sensing, citizen science, and AI. This represents a paradigm shift from static, climate-driven models toward dynamic, data-rich, and adaptive modeling frameworks.

Remote sensing provides fine-scale, temporally continuous environmental predictors; citizen science supplies large-scale, distributed occurrence records; and AI offers powerful algorithms capable of integrating heterogeneous datasets and capturing nonlinear relationships. Together, these three innovations address some of the most persistent limitations of SDMs, including sampling bias, low resolution of predictors, and poor generalizability [10],[30].

4. 2. Contributions of Remote Sensing

Remote sensing has emerged as the most widely adopted innovation in SDMs. Studies consistently show that environmental variables derived from satellites and UAVs increase predictive accuracy compared to climate-only models. For example, LiDAR-derived vegetation structure explained bird species richness more effectively than land-cover classes in Swiss forests [16]. Similarly, UAV-LiDAR integration improved snow leopard habitat models in the Himalayas [34].

Beyond accuracy, remote sensing also allows dynamic modeling, capturing phenological changes, disturbance regimes, and land-use transitions [17]. This is particularly relevant for migratory species and ephemeral habitats, where conditions vary rapidly across space and time. However, access to high-resolution imagery remains uneven, often limited by costs or restricted licensing.

4. 3. Role of Citizen Science Data

Citizen science has democratized biodiversity data collection, producing unprecedented volumes of occurrence records [40]. eBird alone has contributed over one billion bird observations worldwide, revolutionizing avian SDMs [18]. By expanding spatial and temporal coverage, these datasets help overcome long-standing gaps in under-sampled regions [36].

Case studies demonstrate the transformative impact of citizen science. For example, invasive plant distributions in Spain were better predicted using GBIF records than using herbarium data alone [35]. Similarly, long-term citizen science monitoring revealed alarming declines in UK pollinators, influencing national conservation policy [37].

Nevertheless, citizen science introduces biases in sampling effort, taxonomic identification, and spatial accuracy [21]. These issues necessitate statistical corrections such as spatial filtering, effort-based weighting, or hierarchical occupancy models [22]. Future advances will depend on tighter integration between citizen and expert datasets, as well as improved data validation protocols.

4. 4. The Promise of Artificial Intelligence

AI and machine learning represent the newest and fastest-growing frontier in SDM research. Algorithms such as Random Forests and Boosted Regression Trees already

outperform traditional regression models in many contexts [2], [24]. More recently, deep learning—particularly Convolutional Neural Networks (CNNs) — has demonstrated exceptional capacity to handle high-dimensional data, including raw imagery and unstructured citizen science observations [25].

A notable advantage of AI methods is their ability to fuse heterogeneous datasets. For example, hybrid neural networks have been developed to combine satellite imagery, LiDAR data, and citizen science records in a unified predictive framework [29]. These models are capable of capturing complex interactions among variables, leading to more ecologically realistic predictions.

Furthermore, AI enables real-time ecological forecasting. Coupling citizen science uploads and satellite-derived vegetation indices with online learning algorithms has the potential to provide early warning systems for invasive species outbreaks or habitat degradation [26],[30]. However, computational demands, lack of interpretability, and the need for large training datasets remain significant challenges.

4. 5. Integration Across Disciplines: Opportunities and Challenges

Although each innovation has advanced SDM research independently, full integration remains rare. Only a handful of studies combine remote sensing, citizen science, and AI simultaneously. Yet, our results suggest that such integration offers the greatest gains in predictive power and ecological realism.

Opportunities:

- **Enhanced spatiotemporal resolution:** Remote sensing can provide near-real-time environmental layers, while citizen science delivers continuous species records.
- **Improved generalizability:** AI methods allow models to scale across regions, taxa, and data types.
- **Policy relevance:** Integrated SDMs can inform dynamic conservation decisions, such as adaptive protected area design or rapid response to invasions.
- **Challenges:**
- **Data quality and accessibility:** Citizen science records often require validation, while high-resolution remote sensing data may be costly or restricted.
- **Computational barriers:** Training deep learning models requires substantial computing power, which may limit accessibility in developing countries.
- **Interdisciplinary silos:** Ecologists, computer scientists, and remote sensing specialists often work separately, limiting knowledge exchange.

Addressing these challenges will require investment in open data infrastructures, cross-disciplinary training, and equitable access to technology.

4. 6. Regional and Taxonomic Biases

Our bibliometric analysis revealed stark geographic imbalances. Most integrated SDM studies are conducted in North America, Europe, and China, with limited contributions from biodiversity-rich but resource-poor regions such as Africa, Southeast Asia, and South America. This bias risks reinforcing global inequalities in conservation science [38]. Taxonomically, research remains heavily biased toward birds, mammals, and plants, while invertebrates, fungi,

and microorganisms are underrepresented. Expanding SDMs to these groups will be critical for achieving a holistic understanding of biodiversity patterns and ecosystem functioning.

4. 7. Toward Next-Generation SDMs

Taken together, the results highlight the emergence of next-generation species distribution models (SDMs) defined by integrated data approaches that combine remote sensing, citizen science, and AI within unified frameworks; dynamic updating through real-time data streams that enable adaptive predictions; scalability that leverages AI to manage global datasets while preserving local ecological relevance; and accessibility through open-source tools and democratized data access to reduce global inequities. These advances hold transformative potential for biodiversity science, with real-time SDMs offering applications such as informing adaptive migration corridor management under climate change or enabling early detection of invasive species before they become widespread.

4. 8. Limitations of the Current Study

Several caveats must be acknowledged. First, our bibliometric analysis was limited to English-language publications in Scopus and WoSCC, potentially excluding regional research. Second, while case studies were selected to maximize diversity, they cannot capture the full breadth of global innovation. Finally, our synthesis focused on three key innovations; other advances, such as mechanistic physiological modeling and genomic data integration, also play important roles in the future of SDMs.

4. 9. Future Research Directions

To fully realize the potential of next-generation species distribution models (SDMs), future research should focus on developing hybrid modeling frameworks that seamlessly integrate multiple data sources and algorithms, while also improving data quality controls for citizen science platforms through AI-assisted validation.

Expanding geographic representation, particularly in biodiversity hotspots of the Global South, will be crucial for capturing global ecological patterns. At the same time, enhancing the interpretability of AI models is necessary to ensure that outputs provide ecological insights rather than solely statistical accuracy.

Finally, strengthening interdisciplinary training will empower ecologists to effectively harness advanced computational tools, fostering innovation and collaboration across biodiversity science. By pursuing these directions, SDMs can evolve from descriptive tools into predictive, policy-relevant instruments capable of guiding conservation in an era of rapid environmental change.

4. 10. Synthesis

The integration of remote sensing, citizen science, and AI is reshaping species distribution modeling. These innovations complement one another: remote sensing provides fine-scale predictors, citizen science expands occurrence data coverage, and AI synthesizes complexity. While challenges remain, particularly regarding biases, accessibility, and computational demands, the trajectory is clear: the future of SDMs lies in integration, dynamism, and inclusivity.

5. CONCLUSIONS

Species Distribution Models (SDMs) have advanced from simple correlative approaches based on coarse climate predictors to complex, integrative frameworks capable of incorporating heterogeneous data streams. The bibliometric and case study evidence presented here underscores a paradigm shift in SDM research, driven by the convergence of remote sensing, citizen science, and artificial intelligence (AI).

Remote sensing technologies provide temporally dynamic and spatially detailed environmental predictors, from global satellite imagery to fine-scale UAV and LiDAR data. Citizen science initiatives supply unprecedented volumes of species occurrence records, democratizing biodiversity monitoring and expanding geographic coverage. AI methods, particularly deep learning, offer the computational power and flexibility needed to synthesize these diverse data sources and uncover complex species–environment relationships.

When considered independently, each of these innovations improves SDM performance; when combined, they promise transformative advances. Integrated frameworks can produce models that are not only more accurate, but also dynamic, generalizable, and policy-relevant. Such next-generation SDMs have the potential to support real-time biodiversity monitoring, adaptive conservation planning, and early-warning systems for invasive species and disease outbreaks.

Yet, significant challenges remain. Remote sensing data are often costly or inaccessible, citizen science records may suffer from observer bias and uneven coverage, and AI methods require high computational resources and improved interpretability. Moreover, geographic and taxonomic biases persist, with most studies concentrated in the Global North and focused on charismatic taxa.

Addressing these gaps will require investment in open data infrastructures, equitable access to technology, and capacity building in underrepresented regions.

Looking ahead, future research should prioritize the development of hybrid frameworks that bring together remote sensing, citizen science, and AI within a unified modeling architecture. Equally important is the expansion of global participation to ensure that biodiversity-rich regions of the Global South are adequately represented in ecological analyses. At the same time, greater emphasis should be placed on promoting transparency and interpretability in AI-driven models so that ecological relevance is maintained alongside statistical accuracy.

Finally, advancing open and interoperable platforms for data sharing, validation, and collaborative modeling will be essential to foster integration, reproducibility, and innovation across biodiversity research.

By embracing these priorities, SDMs can evolve into truly next-generation ecological forecasting systems, capable of informing conservation decisions at the speed and scale required in the Anthropocene. This transformation will not only enhance our scientific understanding of species distributions but also provide actionable insights to mitigate biodiversity loss under accelerating global change.

In conclusion, the integration of remote sensing, citizen science, and AI marks a turning point in species distribution modeling. It represents not just an incremental improvement, but a shift toward a new era of dynamic, inclusive, and globally relevant ecological modeling. The challenge now lies in translating these innovations into practice, ensuring that the benefits of next-generation SDMs are realized equitably across taxa, regions, and societies.

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