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Wildlife species distribution modeling with unmanned aircraft

Modelado de la distribución de especies de fauna silvestre mediante aeronaves no tripuladas

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KEYWORDS

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unmanned aerial vehicle (UAV),
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protected forest,
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wildlife monitoring,
distribution model.

ABSTRACT

The use of drones and open-source software in Species Distribution Models (SDMs) represents an innovative approach for the study of wildlife fauna. This article reviews the current state of the art regarding their integration, identifying trends, challenges, and opportunities.

The methodology followed the PRISMA guidelines and included a literature search in databases such as Scopus, Web of Science, and Google Scholar. Articles published within the last decade were selected if they addressed the use of drones in wildlife monitoring and the application of open-source tools in spatial data analysis.

The results show a significant increase in the use of drones to collect precise geospatial data, improving the identification of habitats and species distribution patterns. Tools such as QGIS, R, and MaxEnt enable data processing without licensing costs, promoting accessibility and scientific reproducibility.

However, challenges remain in terms of methodological standardization, integration of heterogeneous data sources, and limited detection capability for certain species. Variability in image quality and environmental conditions also affects the accuracy of results.

In conclusion, the combination of drones and open-source software offers clear benefits: it enhances efficiency, improves model accuracy, and reduces costs. Nevertheless, greater standardization and technical validation are required to optimize its application in ecology and conservation.

PALABRAS CLAVE
Drones,
unmanned aerial vehicle (UAV),
topografía,
resolución,
reserva ecológica,
bosque protegido,
análisis geoespacial,
seguimiento de la fauna silvestre,
precisión,
modelo de distribución.

RESUMEN
El uso de drones y software libre en Modelos de Distribución de Especies (MDE) representa una alternativa innovadora para el estudio de la fauna silvestre. Este artículo revisa el estado del arte sobre su integración, identificando tendencias, desafíos y oportunidades.
La metodología siguió las directrices PRISMA, con búsqueda en bases como Scopus, Web of Science y Google Scholar. Se seleccionaron artículos publicados en la última década que aborden el uso de drones en monitoreo faunístico y el empleo de herramientas libres en análisis espacial.
Los resultados muestran un aumento notable en el uso de drones y tyopografía para obtener datos geoespaciales precisos, lo que mejora la identificación de hábitats y patrones de distribución. Herramientas como QGIS, R y MaxEnt permiten procesar estos datos sin costos de licencia, fomentando la accesibilidad y reproducibilidad científica.
No obstante, persisten desafíos en la estandarización metodológica, fusión de datos heterogéneos y detección limitada de ciertas especies. La variabilidad en calidad de imágenes y condiciones ambientales también afecta los resultados.
En conclusión, la combinación de drones y software libre ofrece beneficios claros: mejora la eficiencia, aumenta la precisión de los modelos y reduce costos. Sin embargo, se requiere mayor estandarización y validación técnica para optimizar su aplicación en ecología y conservación.

1. Introduction

Species Distribution Models (SDMs) help to identify and protect areas rich in biodiversity and predict changes in species distribution due to factors such as climate conditions, habitat alteration by human influence or other invasive species. In general, forest ecosystems are exposed to a wide variety of environmental, social and economic pressures that challenge their sustainability on a planetary scale.

The biodiversity they harbor can respond in many ways to these pressures, generating variable and complex impacts. Therefore, it is necessary to anticipate such impacts and future challenges with appropriate, proactive and adaptive management [1]. In this context, the efforts of researchers try to conceive increasingly efficient SDMs, incorporating computer vision techniques oriented to the analysis and processing of images of natural environments, since the objective is precisely the conservation of species in their habitat, allowing the interpretation and prediction of species situations.

For example, a recent study [2] demonstrates how advanced AI algorithms, such as Maximum Entropy (MaxEnt) and Random Forest (RF), can integrate large environmental and biological datasets to clearly predict species distributions. Likewise, other recent studies have demonstrated the importance of predictive models for the conservation of species such as the mountain tapir [3]. The *Journal of the Royal Society Interface* introduced a distribution model for multiple species that operates on presence-only data, which is valuable for maximizing the use of global biodiversity databases such as GBIF [4].

On the other hand, there is the problem of obtaining satellite images, which usually involves considerable expense, limiting accessibility for research projects, especially in developing countries. For example, commercial satellite images obtained from WorldView-3 provide high resolution, but the high cost restricts their use in ecological studies [5]. In response to this, several studies are encouraging the use of drones [6, 7, 8, 9].

Drone imagery, as an alternative to satellite imagery, offers several advantages in terms of accuracy and cost, but its inappropriate use, such as frequent flights at noticeable heights of noise and vision, can generate unexpected wildlife behaviors. Drones can capture high-resolution imagery needed to detect small species and perform detailed monitoring in specific areas [6]. In addition, they allow for real-time monitoring and data collection in low-connectivity conditions, which is crucial for the study of remote and hard-to-reach areas [7]. These capabilities would most likely improve the efficiency and accuracy of SDMs, enabling informed decision-making for biodiversity conservation and management.

Several studies have confirmed that the use of drones with machine learning (ML) algorithms improves wildlife detection, reducing reliance on manual assessments and increasing the accuracy of the data collected. This technology not only facilitates obtaining accurate data at lower cost, but also minimizes disturbance to monitored species, significantly improving conservation efforts [10]. The integration and processing of images obtained from drones using MaxEnt algorithms and their subsequent advanced analysis in `R` can be convenient to develop a detailed SDM.

The objective of the systematic literature review is to provide a method to assess variability in the conduct of studies and data analysis, identify and summarize studies already conducted, measure the consistency and quality of results, and target knowledge gaps to be investigated, using a systematic literature review approach in drone-based SDMs.

This paper presents proposals for future research in terms of the methods used, the systematic use of drones and satellites in data collection, the identification of best practices, and the establishment of standards to ensure the reproducibility and accuracy of SDM studies. The first part of this document details the importance and necessity of conducting a Systematic Literature Review for the development of SDMs. In the second part, the relevant definitions of the elements that compose the development and implementation of an SDM using data obtained from drones and analyzed with `R` software are presented.

Then, in the third part, the methodology for obtaining SDMs is described, structured in five phases derived from five research questions. The fourth part of the paper presents the systematic review used to conceptualize the research questions, providing a statistical summary of the literature reviewed and an analysis of similar work in the creation of SDMs with drones. In the fifth part, the research questions are discussed through a comparative analysis between drone-based and satellite-based imagery solutions. The paper concludes with the proposed solution.

2. Species Distribution Model

Forest ecosystems face growing environmental pressures, requiring sustainable and proactive conservation strategies. Species Distribution Models (SDMs) are valuable tools for estimating species' potential distributions and habitat availability by analyzing ecological niches through environmental data and raster images. These models help predict responses to environmental changes and support decision-making at multiple scales, including protected area designation and climate policies.

When built with current data and properly calibrated, SDMs can be adapted across different spatial and temporal contexts, making them essential for biodiversity monitoring and adaptive management [11, 12].

SDMs are key tools in biodiversity and conservation, but assessing their reliability at unsampled sites is difficult, especially where there are sampling biases [13]. There are numerous ecological niche modeling techniques, such as the Genetic Algorithm for Rule Set Prediction (GARP) or MaxEnt, which are the most widely used and generally employ, according to [13], two types of data:

1. Records of the occurrence of the species, such as geographical data (latitude and longitude) of the sites where specimens have been collected or recorded.

2. Layers of variables that are related to the distribution of the species. These may be climatic (e.g., temperature, precipitation), vegetation type, soil type, and terrain slope, among others.

SDMs use environmental data and species occurrence records to generate niche models that represent suitable conditions such as climate, altitude, and vegetation. These models can be projected geographically to predict where the species may occur, producing maps of potential distribution. By identifying environmental associations, SDMs define optimal conditions for viable populations, following the BAM framework proposed by [1].

The method identifies areas with similar environmental features to known presence sites, enabling spatial predictions based on mathematical similarity, although models retain a certain degree of uncertainty regarding species distribution patterns of species [2].

2.1. Biotic Abiotic Movement (BAM)

The BAM method for creating an SDM begins by identifying the biology of the species, then assessing the accessibility of areas, and finally incorporating environmental variables.

This allows for a holistic understanding of a species' likely distribution, facilitating robust models for conservation studies. The BAM diagram, as illustrated in Figure 1, is a conceptual tool for modeling species distribution, integrating biology (B), accessibility (A), and environment (M) [14].

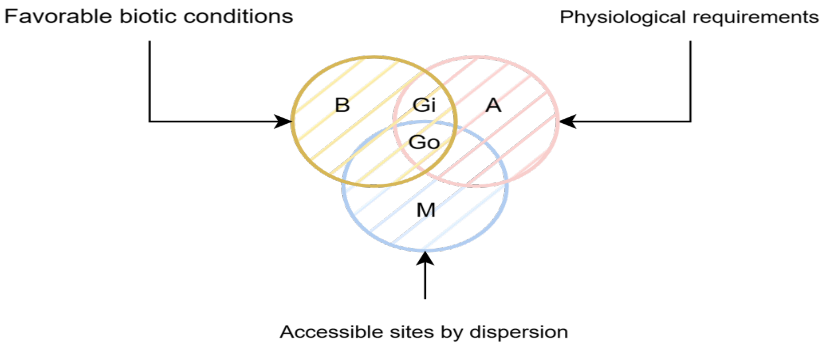

Figure 1: *The BAM diagram [14].*

In the BAM Diagram, shown in Figure 1, the occupied area of a species (G_o) is illustrated as the intersection of its three components: the biotic (B), abiotic (A), and movements (M), as:

$$G_o = B \cap A \cap M$$

The area G_i occurs at sites that are favorable both biotically and abiotically, but that the species has not been able to access ($B \cap A \cap M$) [14].

2.2. Ecological niche

The ecological niche encompasses the environmental conditions and resources a species needs to survive and thrive, including abiotic factors like temperature and humidity, and biotic factors such as food and competition [15].

Species Distribution Models (SDMs) predict a species' geographic distribution by modeling its ecological niche using environmental and occurrence data [2]. These models identify areas of high habitat suitability and quantify how environmental conditions influence species presence [16].

The ecological niche and SDMs are related through their connection to species distribution, but they differ in approach and use. The ecological niche focuses on a species' environmental requirements in theory, whereas SDMs are practical tools for mapping and predicting species distributions in real landscapes, aiding conservation and management decisions [17].

2.3. Raster images

A raster is a format for storing, analyzing, and displaying geographic data. It consists of a grid of cells or pixels arranged in rows and columns. Each cell, which can be rectangular (not necessarily square), contains information such as coordinates and attribute values. Rasters represent continuous surfaces and recognize areas with similar characteristics, though they do not define clear boundaries like vector polygons:

- Category: land use
- Magnitude: pollution, precipitation, etc.
- Height: distance, slopes, orientation, mass, hydrographic basin, etc.
- Spectral value: satellite images, aerial photographs, etc.

A raster image can cover an area of 100 km^2 using one hundred cells, each measuring 1 km^2 with equal width and height [1]. Raster and image data are useful for a wide variety of applications. In a geographic information system (GIS), raster and image data are typically used for the following:

- Images as base maps
- Raster as surface maps
- Raster as thematic maps

Raster images obtained via drones offer advantages over satellite-acquired data, as noted in studies like [18], which highlight their higher accuracy and ability to provide continuous data representation. Additionally, [19] emphasizes the importance of raster imagery in enhancing geospatial data storage and access to scientific information. This enables field researchers to obtain accurate and relevant data on species. The raster (or cell-based) data model is widely used in the GIS industry for detailed biodiversity research and assessment, as illustrated in Figure 2.

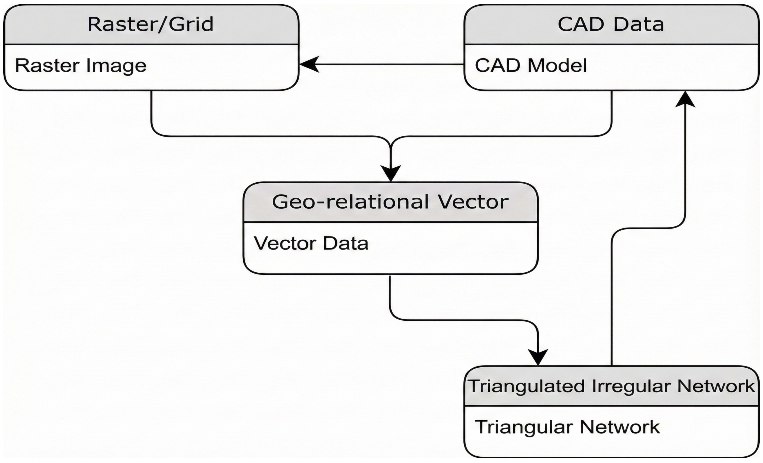

Figure 2: *Network diagram illustrating the data models: CAD data, Raster/Grid, Geo-relational Vector and Triangulated Irregular Grid [20].*

The network diagram in Figure 2 shows how geospatial data are combined to create a Triangulated Irregular Network (TIN). Raster and CAD data are converted into vector format to build the TIN, supporting detailed surface analysis. This is essential for surveying and civil engineering, enabling the integration and transformation of diverse geospatial data for advanced uses.

2.4. Drones and wildlife

Drones are aircraft that could fly unmanned and autonomously. The main advantages they offer over other methods of wildlife monitoring are:

1. High spatial resolution, as low-altitude flight allows images to be taken in detail, and
2. High temporal resolution, as their ease of deployment allows flights to be made as frequently as desired [21].

Currently, drones are being used to study various species of fauna. In the field of ornithology, there are several works of census of waterfowl and gregarious bird colonies, population monitoring of penguins, geese, and inspection of raptor and corvid nests, among others [22].

Four impacts are considered in this context and are shown below:

- **Technological impact.** By comparing the current approach to species distribution modeling using satellite imagery with the method employing drone-based data collection, the profitability of the product obtained is determined in terms of data availability, quality, accuracy, costs and safety.
- **Economic impact.** It offers the ability to reduce costs associated with traveling to remote and difficult-to-access areas [18], as well as improve processing efficiency and save time during project implementation [21]. Also, according to [6] there is an economic advantage of using data obtained by modeling images from drones compared to the high costs associated with the acquisition of data from satellite images.
- **Social and scientific impact.** Promotes conservation and scientific research in ecological reserves. Provides georeference data of protected environments without affecting social organizations [23]. The availability of updated data facilitates the study of biodiversity and promotes conservation in natural areas [18, 24].
- **Environmental impact.** The widespread use of drones can disturb wildlife and damage fragile habitats, causing stress and behavioral changes [25]. Repeated flights may harm biodiversity in areas like wetlands [26]. To reduce impacts, establish protocols limiting flight frequency and duration [25], and conduct environmental assessments beforehand [27]. Drone operations must be responsibly managed to avoid ecological harm [25].

The integration of drones with SDMs represents a scientific advancement in ecological research. Drones capture high-resolution images for detailed habitat mapping. When used with models like MaxEnt, they support climate analysis and conservation planning.

Drones also help collect species presence and absence data, improving SDM accuracy through machine learning. Together, these tools boost data efficiency and enable faster biodiversity conservation responses, as recent studies demonstrate (see Table 1).

Table 1: *Research works on SDM using drones and the methodology applied*

Reference	**Drone Use Methodology**	**Focus on SDM**	**Species of Fauna Studied**
[27]	Drones are used for aerial imaging and habitat mapping, followed by SDM to analyze and compare different climate scenarios.	Comparison of climate scenarios using aerial imagery.	Oriental quoll (*Dasyurus viverrinus*).
[3]	Drones are used to collect high-resolution spatial data, which is then integrated with predictive SDMs and satellite image analysis.	Predictive models combined with satellite imagery.	Seagrasses (*Cymodocea nodosa*).
[28]	Drones used to collect species presence/absence data, incorporating machine learning algorithms to improve the accuracy of distribution models.	Machine learning algorithms to improve SDM accuracy.	Various species of terrestrial fauna.
[29]	Evaluation of the use of small drones for the collection of species distribution and behavioral data in different habitats.	Behavioral and distribution data collection.	Birds and small mammals.

3. Materials and Methods

It is essential to look for alternatives to face the problem of the high cost of the analysis of satellite images necessary for the generation of orthophotos and the creation of SDMs. It is also important to establish an adequate method for the detection of specific ecosystems for each species.

Therefore, an effective identification of biodiversity patterns and their trophic chains is required. Also, it is essential to have an accurate image analysis, without taxonomic bias, and using non-invasive mechanisms to the SDM. Based on these concerns, five questions are posed in search of evidence, descriptively, transversally and in the field, as follows:

- **Q1.** What tools are used for the processing and georeferencing of images from drones for the creation of SDMs?
- **Q2.** What variables are used to promote accuracy in the development of SDMs?
- **Q3.** How does geo-technology affect the creation of SDMs?
- **Q4.** Which data automation methods allow for efficient creation of SDMs?
- **Q5.** What is the feasibility of combining drones and satellites for SDM creation?

This document synthesizes the information currently available through a literature review in an orderly fashion. For this purpose, the inclusion and exclusion criteria and the combination of terms and keywords of the project with the search string (*"accuracy" OR "distribution model" OR "ecological niches" OR "drones" OR "monitoring"*) and (*"wildlife species"*) are defined to obtain better results in the literature review sources: EBSCO, SCIELO, SCOPUS and Web of Science (WoS). Research articles published from 2019 onwards are considered.

The PRISMA diagram in Figure 3 describes the process of selecting studies for a systematic review through several phases. In the identification phase, a total of 608 records were obtained from several databases: EBSCO (62), Web of Science (90), SciELO (22) and SCOPUS (434).

In the eligibility phase, 116 records were selected for eligibility assessment. During this phase, 492 records were excluded for various reasons:

1. not answering the research questions,
2. not being classified, and
3. being duplicates.

This resulted in the screening of forty-seven records. In the screening phase, ninety-one records were eliminated because they did not answer the research questions posed. Finally, the inclusion phase culminated in the selection of forty-seven studies for systematic review.

This meticulous process ensures that only the most relevant and high-quality studies are included, increasing the validity and reliability of the review results. Each stage of the process is designed to reduce bias and ensure that the included studies are relevant and meet the criteria established for the review (see Table 2).

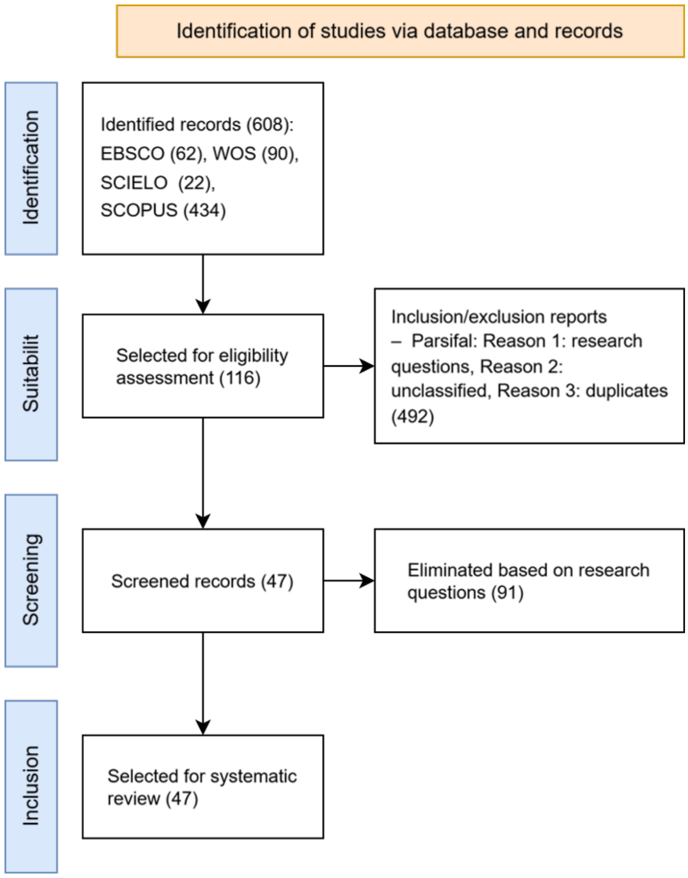

Figure 3: *Prism Diagram - Systematic Review [30].*

Table 2: *Summarizes two results obtained from the search and selection process of the scientific articles analyzed and shown in Figure 3.*

Search base	Found	(-) Rejected	(-) Non-classified	(-) Duplicate	(-) mc/exc	Accepted
EBSCO	62	33	1	9	8	11
WoS	90	68	8	0	5	9
SCIELO	22	0	22	0	0	0
SCOPUS	434	325	10	56	56	27
Total	**608**	**426**	**41**	**25**	**69**	**47**

On the other hand, in the review category there are some related articles such as the evaluation of camera trap data using artificial intelligence, the possibility of using camera traps to measure alterations induced by climatic changes in the activity patterns of elusive terrestrial vertebrates [31], successional habitat needs of at-risk species on privately owned land, and the use of drone imagery and machine learning-based algorithms for data collection. However, none of the topics presented here have already been addressed in those studies [7].

4. Analysis of Research Questions

4.1. Tools for georeferencing and processing of drone imagery in SDM creation

The use of GPS in wildlife habitat data collection allows the monitoring of bird migration routes and has revealed patterns critical to their survival [32]. In mammals, tracking bear territories [33] has provided valuable information on their behavior and habitat. In addition, sea turtle tracking [34, 35] has identified feeding areas, improving conservation strategies.

The use of camera traps allows the collection of data on the habitat of vertebrate species in wildlife studies. In Africa, camera traps have made it possible to study how human activity affects the behavior of African elephants in Kasungu National Park, Malawi, by assessing factors such as distance to water bodies and vegetation cover [9]. In Namibia, camera traps have been used to estimate the density and abundance of unmarked ungulates, such as roan and sable, using Poisson binomial models [36]. Furthermore, a study on motion-based video compression has optimized the use of camera traps in resource-limited environments, improving monitoring duration and reducing storage requirements [37].

The combined use of camera traps, GPS, and drones has revolutionized the study of wildlife and their responses to climate change. Camera traps have enabled the identification of behavioral patterns in species such as guenons in the Congo, contributing to the conservation of endangered species [38]. GPS technology has been used to track migratory movements, as in the case of raptors in Europe, providing crucial data on changes in their habitats [39]. Finally, drones equipped with thermal cameras have been used to map coral reefs, helping to assess the impact of global warming on these ecosystems [40].

Table 3: *Tools for georeferencing and processing of images from drones in the creation of SDMs.*

Appearance	**Tools / Programs**	**References**
Georeferencing	GPS and Drone	[4]
Image Processing	Pix4Dmapper, Agisoft Metashape	[5]
Geospatial Analysis	ArcGIS, QGIS	[3]
Species Distribution Modeling (SDM)	MaxEnt, Random Forest	[6]

Table 3 provides a detailed overview of the aspects of image processing and the various tools and techniques used in georeferencing and image processing. In addition, relevant literature references supporting the use of these technologies are included, thus facilitating a broader and more informed understanding of their efficacy and applicability in wildlife conservation and study (see Figure 4).

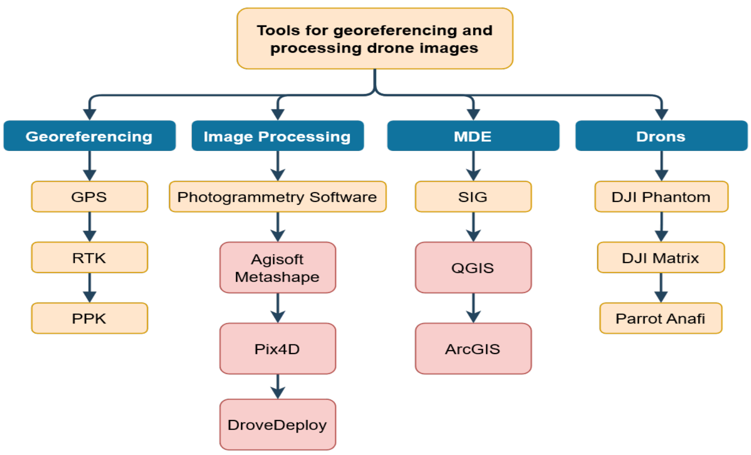

Figure 4: *Graph diagram illustrating existing methods for georeferencing and processing drone imagery in the creation of SDMs [3].*

On the other hand, it is important to emphasize that the use of images captured by drones, processed with the MaxEnt algorithm and analyzed in R software, offers an effective solution to develop SDMs. This technique combines the high spatial resolution of drone imagery with the predictive capability of MaxEnt. Recent studies confirm that this method can predict areas of high probability of species presence with an accuracy comparable to traditional methods, but at a significantly lower cost and with greater operational flexibility.

4.2. Tools for georeferencing and processing of drone imagery in SDM creation

SDMs also attempt to predict whether a species will be present or absent in a specific area based on some environmental variables; the most common environmental variables include temperature, precipitation, topography, vegetation cover, soil type, elevation, moisture, and land use patterns.

Table 4 presents a detailed compilation of the variables used in various SDM studies employing drone imagery. This table highlights both the independent and dependent variables used in such studies, providing a comprehensive overview of the methodologies applied and analytical approaches adopted.

The independent variables include environmental and geographic factors such as altitude, vegetation cover, slope, and proximity to water bodies. These variables allow us to understand how different habitat elements influence the distribution of species. For example, studies such as [35] have used aerial imagery to capture accurate data on vegetation and topography, which has allowed more accurate modeling of species distribution. On the other hand, the dependent variables are usually presence/absence or abundance data of the species under study. These variables are derived directly from field observations and analyses of images captured by drones. [6] have shown that the use of drones to collect presence/absence data significantly improves the spatial and temporal resolution of SDMs.

The integration of these variables into models provides insight into ecological relationships and helps predict changes in species distribution under different environmental scenarios. The accuracy and high resolution of drone imagery facilitates the capture of fine details of the habitat, which is fundamental for the development of SDMs.

Table 4: *Variables used in different SDM studies with drone imagery, highlighting independent and dependent variables.*

Article / Project	Independent Variables	Dependent Variables	Variables Not Considered
Use of drones for biodiversity monitoring [41]	- Vegetation Cover - Soil Type - Elevation (SDM) - Surface Temperature	- Species presence - Species distribution	- Soil Moisture - Precipitation
Analysis of bird distribution in urban areas [24]	- Vegetation Cover - Land Use - Distance to Water Bodies - Human Pressure	- Presence of endemic plants - Plant distribution	- Soil type - Competition with other species
Forest health assessment using drones [9]	- Vegetation index NDVI - Canopy cover - Soil type - Soil moisture	- Tree health - Distribution of tree species	- Elevation - Surface Temperature
Analysis of amphibian distribution in protected areas [42]	- Vegetation cover - Proximity to bodies of water	- Presence of amphibians - Diversity of amphibian species	- Land Use - Human Pressure

SDMs require accurate and detailed data on a variety of environmental variables. Fortunately, there are multiple open and accessible data sources that provide information for these models. Some of the most relevant and reliable sources for downloading data on environmental variables, the tools used, and a possible re-search project using these databases are described below in Table 5.

Table 5: *Sources for downloading environmental data for use in SDMs.*

Tool	**Description of the database**	**Possible scientific project**
WorldClim	Global database offering high-resolution climate data.	Species distribution modeling, precipitation and historical climate analysis.
Global Biodiversity Information Facility (GBIF)	Comprehensive source of biodiversity data including species distribution and patterns.	Analysis of species distribution patterns and their changes.
EarthExplorer (USGS)	Access to satellite data and derived products.	Building databases, land cover, and remote sensing analysis.
Copernicus Open Access Hub	Provides access to high-resolution satellite data.	Study of ecosystem dynamics and water resources through remote sensing.
TerraClimate	Provides climate and water balance data on a monthly scale from 1958 to the present.	Research on the impact of climate change on water availability.
CHELSA	High-resolution climate data from 1979 to the present.	Species distribution modeling based on high-resolution climate data.

Some of these sources may have restrictions and/or licenses for their use; therefore, it is advisable to review the policies of each source before using them to obtain data [1]. After the systematic review carried out for this document, and considering several parameters derived from multiple investigations on Species Distribution Models (SDMs), Figure 5 illustrates the variety of data required to build an accurate and robust model.

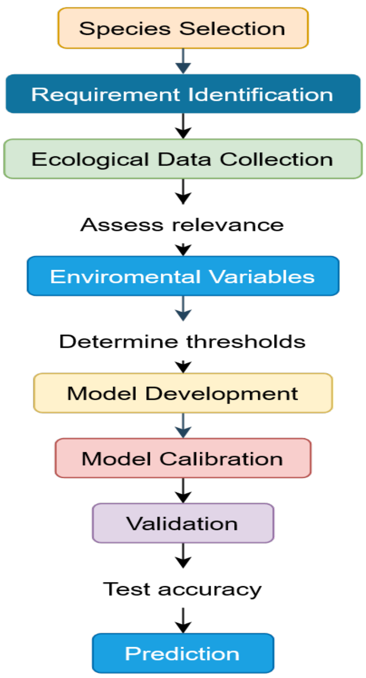

Figure 5: *Requirements for species selection and subsequent distribution model development [7]*

As can be seen in Figure 5, each type of data contributes significantly to the understanding of the habitat and the conditions necessary for the presence of the target species.

- **Species Occurrence Data:** Provides direct information on where the species has been found, helping to define its current and potential distribution.
- **Soil Data:** Is vital for understanding the edaphic conditions that may favor or limit the presence of the species.
- **Vegetation Data:** Helps identify plant associations that are critical to the species in terms of food availability, shelter, and other ecological requirements.

- **Topographic Data:** Allows understanding how the topography of the area influences species distribution by affecting factors such as solar exposure, slope, and elevation.
- **Climate Data:** Is important for evaluating how climatic conditions, such as temperature and precipitation, affect species distribution.

Careful selection of variables in the generation of Species Distribution Models (SDMs) is essential to improve the robustness and transferability of the models due to their direct and indirect effects. Environmental variables, such as climate, topography, and vegetation, determine suitable habitats for species and their geographic distribution [2]. The inclusion of bioclimatic and edaphic variables allows for more accurate predictions of changes in species distribution driven by factors such as climate change [8].

4.3. Impact of geo-technology on the automation of SDMs

Advanced tools such as the `R` software environment enable the automation of SDM construction and evaluation processes, improving both reproducibility and analytical accuracy. In addition, the application of machine learning techniques, such as ensemble models, has enhanced the predictive capability of SDMs by combining multiple algorithms to increase the robustness and accuracy of predictions [9]. These advances facilitate the integration of spatial and environmental data, thereby optimizing biodiversity management and conservation [10].

Table 6 presents in detail how geo-technology has revolutionized the automation of SDMs by providing advanced tools for the collection and analysis of geospatial data. The combined use of drones and satellites enables the acquisition of high-resolution imagery in near real time, leveraging the strengths of each technology. Satellites provide wide and continuous coverage of large geographic areas and long-term datasets that support the monitoring and analysis of large-scale environmental changes. In contrast, drones operate at low altitudes and capture very high-resolution imagery, allowing detailed analyses of specific areas and the precise identification of microhabitats with distinct terrain features. Furthermore, the integration of machine learning algorithms and Geographic Information Systems (GIS) facilitates the processing of large volumes of data, optimizing the prediction of species distribution.

Table 6: *Geo-technology in the automation of SDMs.*

Research Study	Description of the Study	Impact of Geo-Technology
[11]	Use of machine learning algorithms to improve the accuracy of SDMs in Australia.	Improved accuracy and robustness of models facilitating biodiversity management.
[12]	Integration of remote sensing data and predictive models to map the distribution of endemic plants in the Swiss Alps.	Increased accuracy in the identification of critical habitats and vulnerable species.
[13]	Application of MaxEnt and high-resolution drone data to model bird distribution in U.S. national parks.	Real-time, high-resolution data acquisition to optimize species conservation.
[14]	Implementation of geoprocessing techniques and satellite data to assess the impact of climate change on amphibian distribution in India.	Detailed evaluation of environmental changes and their influence on species distribution to support conservation strategies.

Figure 6 shows the relationship between geo-technology and the creation of Species Distribution Models (SDMs). Geo-technology encompasses Geographic Information Systems (GIS), remote sensing, and photogrammetry, all of which are fundamental for generating SDMs. GIS enables the integration and analysis of geospatial data, while remote sensing technologies, such as satellites and drones, provide elevation and altitude-related data [43].

Photogrammetry uses aerial imagery to construct accurate topographic maps [15]. The resulting SDMs are essential for various applications, such as urban plan-ning, environmental studies and agriculture, where specific analysis tools are used to assess and manage the terrain [16].

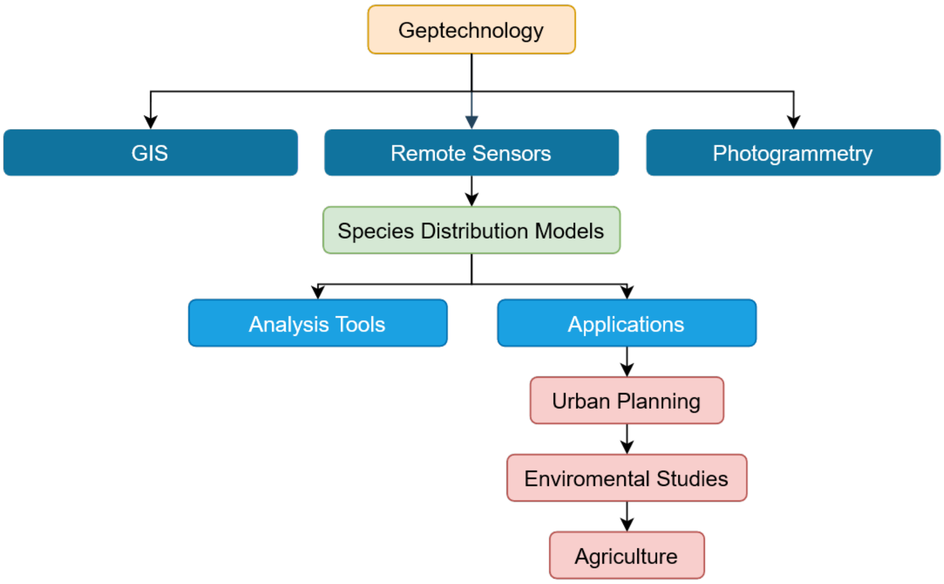

Figure 6: *Relationship diagram between geo-technology and the creation of Digital Elevation Models (SDM).*

4.4. Data automation methods for efficient creation of SDMs

Each method is different for a variety of reasons, as shown in Table 7, which identifies techniques, biological data types, and environmental variable formats used in the creation of SDMs. This table highlights the differences in data automation techniques, allowing a clear view of how each approach handles different types of biological information and environmental variables. This comparative analysis allows understanding the applicability of each method in SDMs, helping researchers to select the most appropriate methodology for their studies [2].

Table 7: *Data automation methods for creating SDMs.*

Method	**Techniques Used**	**Type of Biological Data**	**Environmental Variables Format**
Generalized Linear Models (GLM)	Regression and statistical analysis	Presence data, abundance data	Continuous variables, categorical variables
MaxEnt	Maximum entropy	Presence data	Continuous variables, categorical variables
ML	Neural Networks, Random Forest, SVM	Presence data, abundance data	Continuous variables, categorical variables
Other Data Automation Method	Machine learning algorithms	Presence data, abundance data	Continuous variables, categorical variables
Other Methods	Varies by method	Varies by method	Mainly continuous variables

Generalized Linear Models (GLM) use regression and statistical analysis techniques and are suitable for presence and abundance data with continuous and categorical variables [2]. MaxEnt, based on the principle of maximum entropy, is particularly effective for presence data and also handles continuous and categorical variables [17].
Machine Learning, which includes techniques such as neural networks, Random Forest and Support Vector Machines (SVM), has been noted for its ability to handle both presence and abundance data, with continuous and categorical environmental variables [6]. Another data automation method also uses machine learning algorithms, adapting to presence and abundance data, and continuous and categorical variables [18]. Other methods vary according to the technique used, but generally focus on continuous variables [11]. This diversity of methods and techniques allows a

more appropriate selection according to the specific needs of the study and the types of data available.
The methodological approach in Species Distribution Models (SDMs) is based on the nature of the occurrence data. The techniques used fall into three main categories. Table 8 details these categories, shows the differences in the types of data employed, and provides specific examples of methods in each. This comparative analysis provides a better understanding of the applicability of each technique, facilitating the selection of the most appropriate method based on the available data and the objectives of the study.

Table 8: *Categories of techniques used in the development of MOUs.*

Method Category	**Description**	**Type of Data Used**	**Examples of Techniques / Methods**	**References**
Descriptive	Based solely on presence information.	Presence data	First methods used in species modeling.	[19]
Discriminants	They require presence and absence data to build the classifier.	Presence and absence data	Generalized Linear Models (GLMs), Support Vector Machines (SVMs)	[19, 20]
Hybrid or mixed	They combine descriptive and discriminant methods, generating pseudo-absences to improve accuracy.	Presence and pseudo-absence data	MaxEnt with pseudo-absences	[21]

The literature shows that the first automation methods used in SDM are characterized by using only presence data, disregarding absence or background data; these methods are grouped into three types: profile, classical regression and Machine Learning, as shown in Table 9.

Table 9: *SDM automation methods Category Methods.*

Category	**Methods**	**Description**
Profile methods	BIOCLIM, ANUCLIM	Classical techniques based on geographical or environmental contexts [22].
Profile methods	Mahalanobis, DOMAIN	Mathematical distance methods [22].
Profile methods	ENFA methodologies based on expert opinions	Similarity-based methods and deductive approaches [23].
Classical regression methods	Linear regression	Identification of relationships between environmental variables and species presence [11].
Classical regression methods	Linear regression	Predictions of species distribution [11].
ML Methods	Classification and Regression Trees (CART), Artificial Neural Networks (ANN)	Flexible nonparametric regression models including older techniques [13].
ML Methods	Random Forest (RF), Genetic Algorithm for Rule Set Production (GARP), Support Vector Machines (SVM), Maximum Entropy modelling (MaxEnt)	Popular and versatile models in the last decade [24].

The use of ML in the development of SDMs has proven to be a powerful tool for biodiversity conservation [10]. Advanced techniques such as random forests and deep neural networks allow the integration of large volumes of environmental and species occurrence data, improving the accuracy of predictions [14]. Recent studies have shown that the use of ML algorithms outperforms traditional methods in terms of predictive ability and handling of complex data [9]. This facilitates the identification of critical habitats and the planning of effective conservation strategies [5].

4.5. Feasibility of combining drones and satellites to create SDMs

For example, [25] demonstrate that the synergy between drones and satellites allows obtaining SDMs with unprecedented resolution, facilitating detailed monitoring of habitats and species in inaccessible or extensive areas. In addition, the study of [4] highlights how the combined use of these technologies can improve species management and conservation by providing more accurate data on their distribution and abundance.
The choice between satellite imagery and drone imagery for SDMs depends on several factors, such as required image resolution, coverage area, cost, timeliness, detail specificity, among others. As a result, the discussion typically focuses on the advantages and disadvantages of each technology.

Table 10 shows the comparison between the use of drones and satellites, revealing specific advantages and disadvantages for each method in the capture of SDM data [26]. Drones offer high spatial resolution and flexibility in real-time data capture, being more economical at small scales [27]. However, their use is limited by weather conditions and requires flight permits [44]. Satellites, on the other hand, provide global coverage and systematic monitoring, although at a high cost and with less detail in small areas [29].

Table 10: *Comparative table of the use of drones and satellites in the creation of SDMs.*

Drones	Satellites	Comparison	References
High spatial resolution	Global coverage	Drones provide greater detail in small areas compared to satellites.	[19]
Flexibility in data capture	Regular and systematic monitoring	Drones offer flexibility while satellites provide systematic monitoring.	[41]
Low cost of operation on a small scale	High cost for high resolution images	Drones are more economical on a small scale, while satellites have high costs.	[31]
Real-time data capture	Delay in obtaining data	Drones allow real-time data; satellites have delays.	[27]
Limited by weather conditions	Reduced impact due to weather conditions	Drones are more affected by weather than satellites.	[32]
Greater detail in small areas	Less detail in small areas	Drones offer greater detail in small areas; satellites cover large areas.	[29]
Flight permits required	No specific permissions required	Drones require flight permits, satellites do not.	[44]
Coverage limited to small areas	Suitable for large areas	Drones have limited coverage; satellites cover large areas.	[33]

The choice between drone or satellite imagery for developing Species Distribution Models (SDMs) depends on the needs of the study, scale, budget and data availability. Combining both sources can provide a more complete and accurate perspective. Drones are especially useful for identifying microhabitats and traces of small species, such as tracks and nests, that satellite imagery does not detect [15]. This information is important [34].

5. Discussion

In the development of SDMs using MaxEnt, significant advantages over other modeling tools stand out. MaxEnt offers high accuracy and is especially effective for working with presence-only data due to its maximum entropy approach. Unlike logistic regression or decision trees, MaxEnt better handles nonlinear relationships and interaction effects between variables [6]. Recent studies confirm its superior ability to model species distributions accurately and effectively [36]. However, the choice of the modeling tool also depends on the dataset, its characteristics and the objective of the study, where methods such as Random Forest or Boosted Regression Trees may be more appropriate in certain contexts [6].

In addition to R, other tools such as Python are also widely used for analyzing species distribution data. However, R offers advantages in these cases due to its extensive collection of specialized packages for ecological and biological analyses, such as `dismo` and `ecospat`. These packages are specifically designed to handle species presence-absence data and to develop robust predictive models. R also offers an active community and abundant resources for data visualization and advanced statistical analysis, which facilitates interpretation and informed decision making [37].

Replication of SDMs is possible due to several scientific and methodological factors:

- Methodological Consistency,
- Data Quality,
- Standard Algorithms,
- Environmental Variables,
- Code Scripts,
- Documentation and Publication.

Unlike traditional methods, SDMs are better when advanced geo-technology, such as Machine Learning, is used. The use of ML algorithms makes it possible to manage large volumes of data and to relate environmental variables and species presence, improving the accuracy and robustness of SDMs [38].
The combined use of satellite and drone technology largely depends on the methodology employed, the spatial coverage required, and the climatic conditions of the study area. From a climate-related perspective, drones offer greater control under specific weather conditions, whereas satellites provide more consistent data across varying climates. However, the effectiveness of drone usage may be limited if proper protocols for non-invasive data collection are not followed. Economically, the choice between drones and satellites should be guided by the project's specific needs, aiming to optimize resources and maximize benefits through a contextualized analysis.
This study contributes to the field of species distribution modeling by integrating drone-based remote sensing with open-source tools to develop high-resolution ecological models [42]. Compared to traditional approaches such as satellite-based MaxEnt or generalized linear models, the use of UAV-derived imagery combined with free and open-source software (FOSS) allows for greater spatial precision and adaptability at local scales [45].
Unlike coarse-resolution satellite data, drone-acquired images provide fine-scale habitat details that are essential for detecting microhabitat preferences and localized environmental changes [46]. Additionally, this approach reduces costs and technical barriers compared to proprietary GIS platforms, promoting accessibility and reproducibility in biodiversity research [47].
While conventional methods often rely on historical or interpolated environmental data, our workflow enables real-time monitoring and rapid model updating, enhancing responsiveness to dynamic ecological conditions. This methodology is particularly relevant for conservation planning in data-poor regions, where high-resolution, site-specific models are needed but resources are limited [48].
Future research should focus on the integration of UAV-based remote sensing with open-source software to enhance the accuracy and accessibility of SDMs. While UAVs offer high-resolution spatial data ideal for local-scale biodiversity assessments, their full potential can only be realized through scalable workflows that combine image acquisition, processing, and modeling in a unified framework. Recent studies have shown promising results using open-source tools such as QGIS, GRASS GIS, and Python-based libraries (e.g., GDAL, GeoPandas, scikit-learn) for habitat mapping and species detection [42], [49].
However, there is still a need for standardized protocols that ensure reproducibility and interoperability across platforms. Additionally, future work should explore the integration of deep learning techniques with UAV imagery to automate species classification and improve model generalization [45].
The use of freely available environmental raster layers, combined with cloud computing platforms like Google Earth Engine, could further expand the applicability of SDMs to larger geographic areas while maintaining high resolution [50]. These advancements will not only democratize access to advanced modeling tools but also support conservation planning in data-poor regions.

6. Conclusions

The development of a SDM benefits the care of the environment and biodiversity development, but also the participating areas are benefited. Thus, for example, computing is strengthened by the boost in the development and application of advanced Machine Learning algorithms and geospatial data processing. For biology, SDMs offer tools for understanding and predicting species distribution, aiding in biodiversity conservation and ecosystem management. Collaboration between the two disciplines facilitates interdisciplinary approaches, improving the accuracy and applicability of models in ecological and environmental studies.
Clear documentation and well-defined guidance facilitate accurate replication of studies of more species in different ecological reserves, ensuring consistency and comparability of results. This promotes a better understanding of ecological dynamics and contributes to the development of conservation strategies. In addition, accessibility to standardized methodologies fosters collaboration among researchers, accelerating scientific progress and the practical application of findings in diverse computational, ecological, and geographic contexts.
To replicate the study in another ecological reserve and for other species, it is necessary to have a clear methodology, robust and processed data sources, machine learning tools algorithms, environmental variables and code scripts preferably in R or Python. In summary, SDM replication is based on the application of standardized methodologies, the use of high-quality data and the implementation of widely accepted scientific algorithms and tools. This ensures that the results obtained are reliable and comparable in different ecological scenarios.
Machine learning algorithms and data processing techniques in platforms like R and Python enable the integration of diverse data sources. These tools not only streamline the handling of large datasets but also enhance the accuracy

and robustness of predictive models through libraries such as `scikit-learn` and `caret`. Combining remote sensing and environmental data significantly improves the performance of SDMs, as shown by recent studies [39]. This multidimensional approach advances the analysis and interpretation of complex data in ecological and conservation studies. The hybrid use of drones and satellites is more feasible than using either technology alone for developing SDMs. Combining both allows researchers to leverage the high accuracy of drones and the broad temporal coverage of satellites [40].

Referencias

[1] A. Jiménez-Valverde, P. Acevedo, A. M. Barbosa, J. M. Lobo, and R. Real, "Maximum entropy modeling of species geographic distributions: A review of recent developments and applications," *Ecosphere*, vol. 12, no. 1, p. e03320, 2021.

[2] E. Gutiérrez and I. Trejo, "Application of different types of data in the distribution modeling of tree species in mexico," *Colombia Forestal*, vol. 26, no. 1, pp. 48–63, 2023.

[3] M. Mo and K. Bonatakis, "Approaching wildlife with drones: using scientific literature to identify factors to consider for minimising disturbance," *Australian Zoologist*, vol. 42, no. 1, pp. 1–29, 2022.

[4] Y. Huang *et al.*, "Realized ecological forecast through an interactive ecological platform for assimilating data (ecopad, v1.0) into models," *Geoscientific Model Development*, vol. 12, no. 3, pp. 1119–1137, 2019.

[5] R. G. Mateo *et al.*, "Hierarchical species distribution models in support of vegetation conservation at the landscape scale," *Journal of Vegetation Science*, vol. 30, no. 2, pp. 386–396, 2019.

[6] R. Valavi, J. Elith, J. J. Lahoz-Monfort, and G. Guillera-Arroita, "Modelling species presence-only data with random forests," *Ecography*, vol. 44, no. 12, pp. 1731–1742, 2021.

[7] N. Millner, A. M. Cunliffe, M. Mulero-Pázmány, B. Newport, C. Sandbrook, and S. Wich, "Exploring the opportunities and risks of aerial monitoring for biodiversity conservation," *Global Social Challenges Journal*, vol. 2, pp. 2–23, 2023.

[8] D. Zurell, S. A. Fritz, A. Rönnfeldt, and M. J. Steinbauer, "Predicting extinctions with species distribution models," *Cambridge Prisms: Extinction*, vol. 1, 2023.

[9] M. Rashid, B. S. Bari, Y. Yusup, M. A. Kamaruddin, and N. Khan, "A comprehensive review of crop yield prediction using machine learning approaches," *IEEE Access*, vol. 9, pp. 63 406–63 439, 2021.

[10] D. Boral and S. Moktan, "Modelling current and future potential distribution of medicinal orchids in darjeeling eastern himalaya," *Plant Ecology*, vol. 225, no. 3, pp. 213–226, 2024.

[11] J. Elith and J. R. Leathwick, "Species distribution models: Ecological explanation and prediction across space and time," *Annual Review of Ecology, Evolution, and Systematics*, vol. 40, pp. 677–697, 2009.

[12] A. Guisan, T. C. Edwards, and T. Hastie, "Generalized linear and generalized additive models in studies of species distributions," *Ecological Modelling*, vol. 157, no. 2–3, pp. 89–100, 2002.

[13] S. B. Phillips, V. P. Aneja, D. Kang, and S. P. Arya, "Modelling and analysis of the atmospheric nitrogen deposition in north carolina," *International Journal of Global Environmental Issues*, pp. 231–252, 2006.

[14] S. Mohanty, S. Mustak, D. Singh, T. Van Hoang, M. Mondal, and C. T. Wang, "Vulnerability and risk assessment mapping of bhitarkanika national park, odisha, india using machine-based embedded decision support system," *Frontiers in Environmental Science*, vol. 11, pp. 1–19, 2023.

[15] C. Waldock *et al.*, "A quantitative review of abundance-based species distribution models," *Ecography*, 2022.

[16] F. E. Rodríguez-Manzo and L. Juárez González, "Exploración cualitativa sobre el ruido ambiental urbano en la ciudad de méxico," *Estudios Demográficos y Urbanos*, vol. 35, no. 3, pp. 803–838, 2020.

[17] J. Elith, S. J. Phillips, T. Hastie, M. Dudík, Y. E. Chee, and C. J. Yates, "A statistical explanation of maxent for ecologists," *Diversity and Distributions*, vol. 17, no. 1, pp. 43–57, 2011.

[18] Y. Zhang, Y. Feng, S. Wang, H. Li, and J. Chen, "Predicting the spatiotemporal dynamics of invasive species using ensemble machine learning and remote sensing data," *Ecological Informatics*, vol. 71, p. 101756, 2022.

[19] F. Fischer, É. Joetzjer, I. Maréchaux, I. F. Sun, and J. Chave, "Transferability of an individual- and trait-based forest dynamics model: A testcase across the tropics," *bioRxiv*, 2021.

[20] V. F. Frans, T. H. Oliver, T. H. August, N. J. B. Isaac, and L. V. Dicks, "Integrated sdm database: Enhancing the relevance and utility of species distribution models in conservation management," *Methods in Ecology and Evolution*, vol. 13, no. 1, pp. 243–261, 2022.

[21] H. L. Kopsco, R. L. Smith, and S. J. Halsey, "A scoping review of species distribution modeling methods for tick vectors," *Frontiers in Ecology and Evolution*, 2022.

[22] A. Hua *et al.*, "Protecting endangered megafauna through ai analysis of drone images in a low-connectivity setting: a case study from namibia," *PeerJ*, vol. 10, 2022.

[23] C. Guillaumot, B. Danis, T. Saucède, G. Guillou, B. David, and T. Saucède, "Species distribution modelling of the southern ocean benthos: A review on methods, cautions and solutions," *Antarctic Science*, vol. 33, no. 4, pp. 389–406, 2021.

[24] J. Aguirre-Gutiérrez, F. Bisanzio, C. Capinha, and H. M. Pereira, "Mapping the gaps in alien species richness across contrasting european regions," *Diversity and Distributions*, vol. 28, no. 5, pp. 946–958, 2022.

[25] A. Iqbal, M. S. Mondal, W. Veerbeek, M. S. A. Khan, and H. Hakvoort, "Effectiveness of uav-based dtm and satellite-based sdms for local-level flood modeling in jamuna floodplain," *Journal of Flood Risk Management*, vol. 16, no. 4, pp. 1–19, 2023.

[26] D. Phiri, M. Simwanda, S. Salekin, V. R. Nyirenda, Y. Murayama, and M. Ranagalage, "Sentinel-2 data for land cover/use mapping: A review," *Remote Sensing*, vol. 12, no. 14, 2020.

[27] J. C. Padró, F. J. Muñoz, J. Planas, and X. Pons, "Comparison of four uav georeferencing methods for environmental monitoring purposes focusing on the combined use with airborne and satellite remote sensing platforms," *International Journal of Applied Earth Observation and Geoinformation*, vol. 75, pp. 130–140, 2019.

[28] M. D. Meza Castro, "El recurso de información y comunicación visual: imagen. apuntes en torno a las ciencias de la información y bibliotecología," *e-Ciencias de la Información*, vol. 8, no. 2, 2018.

[29] J. J. López and M. Mulero-Pázmány, "Drones for conservation in protected areas: Present and future," *Drones*, vol. 3, no. 1, 2019.

[30] PRISMA Group, "Prisma 2020 flow diagram," https://www.prisma-statement.org, 2020, accessed: 2024.

[31] X. Huang, L. Wang, and Y. Li, "Integrating remote sensing and geospatial modeling for forest management: A review of current approaches and future trends," *Remote Sensing*, vol. 14, no. 18, p. 4567, 2022.

[32] M. M. Quamar, B. Al-Ramadan, K. Khan, M. Shafiullah, and S. El Ferik, "Advancements and applications of drone-integrated geographic information system technology—a review," *Remote Sensing*, vol. 15, no. 20, p. 5039, 2023.

[33] J. Detka, H. Coyle, M. Gomez, and G. S. Gilbert, "A drone-powered deep learning methodology for high precision remote sensing in california's coastal shrubs," *Drones*, vol. 7, no. 7, 2023.

[34] J. C. Hernández Hernández, "La tecnología y la conservación de especies: el poder de las cámaras-trampa," *Revista Digital Universitaria*, vol. 24, no. 4, 2023.

[35] C. Merow *et al.*, "What do we gain from simplicity versus complexity in species distribution models?" *Ecography*, vol. 37, no. 12, pp. 1267–1281, 2014.

[36] D. Zurell, J. Franklin, C. König, and V. Bahn, "The machine learning-based species distribution models: Are they good for real-world predictions?" *Diversity and Distributions*, vol. 26, no. 8, pp. 852–864, 2020.

[37] B. Deneu, M. Servajean, P. Bonnet, C. Botella, F. Munoz, and A. Joly, “Convolutional neural networks improve species distribution modelling by capturing the spatial structure of the environment,” *PLoS Computational Biology*, vol. 17, no. 4, 2021.

[38] A. Anand, M. K. Pandey, P. K. Srivastava, A. Gupta, and M. L. Khan, “Integrating multi-sensors data for species distribution mapping using deep learning and envelope models,” *Remote Sensing*, vol. 13, no. 16, 2021.

[39] B. Bansod, R. Singh, R. Thakur, and G. Singhal, “A comparision between satellite based and drone based remote sensing technology to achieve sustainable development: A review,” *Journal of Agriculture and Environment for International Development (JAEID)*, 2017.

[40] M. P. Corcoran, M. L. Hobi, V. A. Barber, and A. Mathys, “Applications and implications of unmanned aerial vehicles (uavs) in ecology,” *Methods in Ecology and Evolution*, vol. 12, no. 9, pp. 1564–1577, 2021.

[41] S. Ecke *et al.*, “Uav-based forest health monitoring: A systematic review,” *Remote Sensing*, vol. 14, no. 13, 2022.

[42] H. R. Gomes, M. Zortea, L. M. Carvalho, N. P. Ferreira, and R. A. da Silva, “Use of uav-based remote sensing for plant species distribution mapping in a tropical savanna,” *Remote Sensing*, vol. 14, no. 18, p. 2938, 2022.

[43] B. S. Krishnan *et al.*, “Fusion of visible and thermal images improves automated detection and classification of animals for drone surveys,” *Scientific Reports*, vol. 13, no. 1, 2023.

[44] G. M. Mori *et al.*, “Predictive modelling of current and future potential distribution of the spectacled bear (tremarctos ornatus) in amazonas, northeast peru,” *Animals*, vol. 10, no. 10, pp. 1–21, 2020.

[45] X. Zhu, Y. Zhao, W. J. Platt, and H. Liu, “Deep learning applications in species distribution models using remotely sensed data: A review,” *ISPRS Journal of Photogrammetry and Remote Sensing*, vol. 203, pp. 1–15, 2023.

[46] D. Rocchini, C. Ricotta, G. Bacaro, and S. Schmidtlein, “High-resolution mapping of plant diversity using uav-based spectral metrics,” *Ecological Informatics*, vol. 73, p. 102014, 2023.

[47] K. Witt and R. R. Dunn, “Open-source tools in ecology: Bridging the gap between accessibility and scientific rigor,” *Frontiers in Ecology and Evolution*, vol. 10, p. 881845, 2022.

[48] W. Turner, I. Costello, and A. Soria-Barreto, “Low-cost tools for biodiversity monitoring in under-resourced regions: Opportunities and challenges,” *Biodiversity and Conservation*, vol. 30, no. 10, pp. 2649–2666, 2021.

[49] J. Torres, R. Cárdenas, and K. Rojas, “Open-source tools for drone image analysis in ecological monitoring: A case study in andean ecosystems,” *Ecological Informatics*, vol. 75, p. 102067, 2023.

[50] J. Fernández-López and F. J. Ariza, “Assessing the performance of open-access environmental data for species distribution modeling using uav imagery,” *Land*, vol. 12, no. 10, p. 1869, 2023.