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The role of remote sensing in species distribution models: a review

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ABSTRACT

Species distribution models (SDMs) are invaluable for delineating ecological niches and assessing habitat suitability, facilitating the projection of species distributions across spatial and temporal dimensions. This capability is crucial for conservation planning, habitat management and understanding the impacts of climate change. Remote sensing has emerged as a superior alternative to traditional field surveys in developing SDMs, offering cost-effective, repetitive data collection over comprehensive spatial and temporal scales. Despite the rapid advancements in remote sensing technologies and analytical methods, the specific contributions of remote sensing to SDMs historically, and the potential pathways for its integration with SDMs remain ambiguous. Therefore, our study has set forth two objectives: firstly, to conduct a thorough review of remote sensing's role in SDMs, focusing on environmental predictors, response variables, scalability and validation; secondly, to outline prospective research trajectories for remote sensing within SDMs. Our findings reveal that remote sensing offers a plethora of environmental predictors for SDMs, encompassing climate, topography, land cover and use, spectral metrics and biogeochemical cycles. A variety of remote sensing techniques, including random forest, deep learning and linear unmixing, facilitate the derivation of SDM response variables and the development of species distribution models across diverse scales. Furthermore, remote sensing enables the validation of SDMs through its mapping outputs.

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1. Introduction

Species distribution models (SDMs) are defined as empirical models that predict the species' distribution across a landscape by relating species occurrence or abundance with environmental gradients, based on statistically or theoretically derived response surfaces (Elith and Leathwick 2009; Guisan and Zimmermann 2000). SDMs mainly comprise two types of models, namely statistical models and machine learning models. Statistical models encompass generalized linear models with the logistic regression for presence/absence data and the Poisson regression for count data, generalized additive

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models and multivariate adaptive regression splines. Machine learning models include decision tree-based models, ensemble models, support vector machine, artificial neural networks, maximum entropy and genetic algorithms for rule-set production. The selection and performance of SDMs are influenced by species' geographic distributions (Segurado and Araujo 2004), species rarity (Franklin 2010), habitat specificity (Tsoar et al. 2007) and other ecological traits such as endemism and migratory status (McPherson and Jetz 2007). Rooted in the niche concept, SDM describes both the species niche and the species habitat suitability, and thus should be evaluated for ecological realism, the consistency with ecological knowledge of environmental factors and the species response curve (Franklin 2010). SDMs, also known as climate envelopes, bioclimatic models, ecological niche models, habitat models and resource selection functions, are widely used to interpolate sparse biological surveys in space and predict species geographic distributions for conservation planning, reserve design, habitat management and risk analysis (Elith and Leathwick 2009; Ferrier 2002; Franklin 2010; Nams, Mowat, and Panian 2006; Rodríguez et al. 2007; Thorn et al. 2009; Turner et al. 2004; Lu and Wang 2022). Besides, SDMs are being increasingly used to extrapolate species distributions in time and space for predicting the spread of disease organisms (DeVisser et al. 2010; Machado-Machado 2012; Peter et al. 2007), assessing the potential ranges of invasive species (Andrew and Ustin 2009; Diao and Wang 2014; Ibáñez et al. 2009; Peterson and Vieglais 2001; Zimmermann et al. 2011) and forecasting the impacts of climate change on biodiversity (Hijmans and Graham 2006; Pearson and Dawson 2003; Sinclair, White, and Newell 2010; Thuiller et al. 2008).

However, collecting sample data for SDMs presents significant challenges, especially as large-scale studies become increasingly necessary due to global climate change. Traditional field survey methods often fall short in providing accurate and randomly distributed samples, as biases are very likely to occur during the sampling process (Guillera-Arroita et al. 2015; Zurell et al. 2020). For instance, survey data from sources not specifically designed for SDMs, such as herbaria and museum specimens, often exhibit sampling biases towards easily accessible locations, like those near roads (Guillera-Arroita et al. 2015). These biases can compromise the reliability of the resulting models, leading to an overestimation of suitability in heavily sampled environments and an underestimation in less frequently surveyed areas (Guillera-Arroita et al. 2015). Additionally, detection errors, such as failing to record a species that is present or incorrectly noting its presence, can adversely affect the training of SDMs, especially when only presence data is used.

In this context, remote sensing has received increasing attention in mapping the species distribution and modelling habitat suitability, owing to its ability to capture spatially and temporally consistent observations from above. Compared to field surveys, remote sensing technology offers a more expedient means to obtain flexible and randomized occurrence records, especially in ecologically inaccessible areas. Furthermore, remote sensing images, derived from both airborne and satellite sensors, provide a considerable potential for measuring the characteristics of habitats in SDMs over different scales (Collingham et al. 2000; Fournier et al. 2017; Hallman and Douglas Robinson 2020; Ibáñez et al. 2009; Thierry, Joost, and Randin 2006). At regional to continental scales, the distribution of species is mostly affected by bioclimatic factors, such as precipitation and temperature. At the local scale, it is more affected by land use, land cover and topography (Elith and Leathwick 2009;

Franklin 2010). Remote sensing provides an inexpensive means of deriving continuous measurements of these environmental variables at varying spatial and temporal scales and testing their roles in predicting suitable habitats of species. Another strength of remote sensing is its wide temporal coverage. Time-series remotely sensed data have been widely used to extract the vegetation phenological attributes as environmental predictors in SDMs (Cord and Rödder 2011). By monitoring the landscape in a temporally consistent way, multi-temporal remote sensing images suggest a promising approach to updating the habitat information regularly and validating the predicted habitat suitability map accordingly (Diao and Wang 2014; Franklin 2010; Rocchini et al. 2015). The repeated and continuous monitoring of species distributions with time-series remotely sensed data facilitates the evaluation of the dynamic performance of SDMs over space and time, particularly for species not in equilibrium with the environment. Remote sensing characterizes the environmental conditions, obtains flexible occurrence records, monitors the landscape at various scales and validates the dynamic performance of SDMs. Remote sensing data, ranging from spectral reflectance to thermal emissivity, and derived products, encompassing land cover type, vegetation indices and topographical features, are frequently used as environmental gradients in SDMs to quantify the ecological niche of species and model their potential suitable habitats (Anderson et al. 2006; Evangelista et al. 2009; He et al. 2015; Leitão and Santos 2019; Muñoz and Felicísimo 2004; Parviainen, Luoto, and Heikkinen 2010; Prates-Clark, Saatchi, and Agosti 2008; Randin et al. 2020; Stohlgren et al. 2010; York et al. 2011; Zimmermann et al. 2011). With the increasing availability of high-spatial-resolution, hyperspectral and LiDAR data, more and more studies were conducted to map individual plants or associations of single species directly with their unique spectral, textual, structural and phenological signatures (Andrew and Ustin 2009; Diao and Wang 2014; He et al. 2015; Muñoz and Felicísimo 2004; Randin et al. 2020; Xie, Sha, and Yu 2008; Q. Zhang and Zhang 2012).

Given the unprecedented advent of remote sensing sensors and analytical techniques as well as SDM requirements, it is imperative to review the latest progress in this field. To the best of our knowledge, very limited reviews have been made available as of today. The most representative two were made by He et al. (2015) and Randin et al. (2020). He et al. (2015) provided a summary of remote sensing data in deriving response variables and environment predictors of SDMs and further discussed future opportunities. Randin et al. (2020) reviewed the development of remote sensing in SDMs focusing on the key biophysical processes. Existing studies were summarized in four aspects: climate, topography, physical disturbances and anthropogenic pressures. In addition, they emphasized the potential value of remote sensing in temporal coverage. However, in recent years, besides the traditional means of collecting predictor or response variables, remote sensing has gradually expanded to analysing the influence of spatial and temporal scales and deriving validation data for SDMs. Neither of the two aforementioned review studies has fully discussed these aspects. Therefore, in order to establish a comprehensive overview of existing studies, the objective of this study is 1) to summarize the up-to-date work of remote sensing in SDMs in four aspects: environment predictors, response variables, multi-scales, and validation. 2) to project future research directions of remote sensing in SDMs.

2. Existing studies

SDMs aim to unveil the relationship between environmental variables, such as climate, topography and land covers, and species distribution variables, such as the occurrence of species and environmental suitability indicators. In tradition, the independent environmental variables are defined as environmental predictors, while the species distribution variables are named as response variables. To explore their inter-relationship, records of the response variables and the corresponding environmental predictors are required. In addition, after the development of an SDM, validation is required to test its performance. Furthermore, depending on different observation scales, their relationship between the environmental variables and species distribution could be different. This is because, in coarse spatial resolutions, one observation record is an aggregated summary of the environment, while fine-spatial-resolution observations can offer us more detailed information. Thus, in SDM studies, environmental predictors, response variables, multi-scale analysis and validation are four critical aspects that need to be addressed.

In the field of remote sensing, their contributions in these four aspects are still unknown. However, remote sensing images are widely utilized by increasing numbers of SDM studies to provide information about species habitat characteristics at varying temporal and spatial resolutions. A summary of their applications in SDMs is illustrated in Figure 1 by highlighting the types and spatial resolutions of data used for different variables. This figure shows that multispectral images at medium and coarse spatial resolutions are the most utilized. Radar data, primarily used to capture topography, precipitation and wave wind strength, follow closely. In this section, we will discuss the

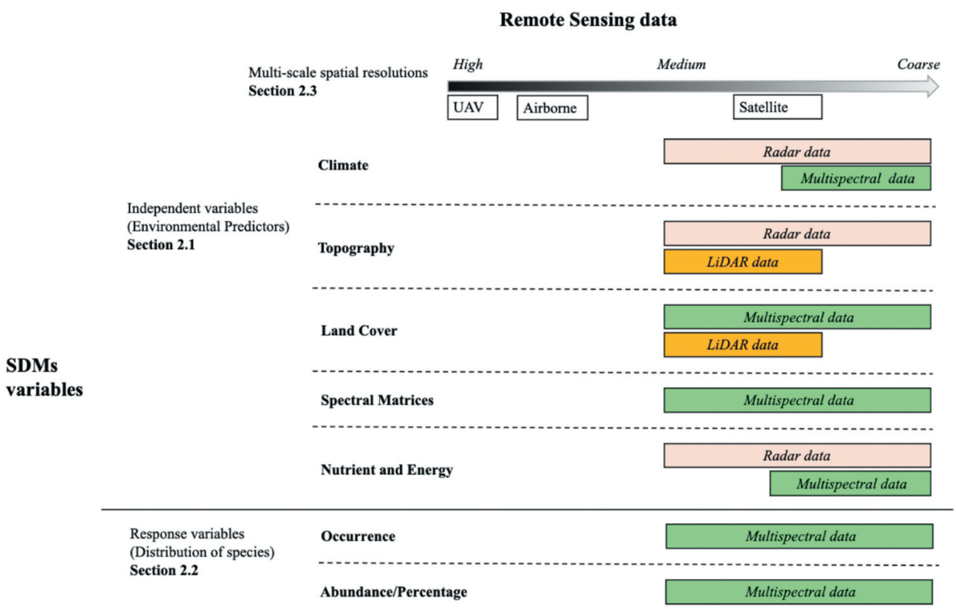

Figure 1. Application of remote sensing in SDMs: the vertical axis represents different types of variables in SDMs, while the horizontal axis shows the remote sensing data utilized, organized by spatial resolution from high to coarse. Pink, orange and green boxes indicate the types of remote sensing data that have been applied to each variable.

role of remote sensing in four aspects: environmental predictors, response variables, multi-scales and validation. Since this review was started at the beginning of 2023, we only included publications from 2016 to 2022.

2.1. Environmental predictors

Climate, topography, land cover, spectral metrics and nutrients and energy are the five major categories of remotely sensed environmental predictors. The Moderate Resolution Imaging Spectroradiometer data (MODIS) and the Shuttle Radar Topography Mission data (SRTM) are two major remote sensing products utilized as environmental predictors in SDM. Detailed information about the data and methods used for each category is listed in Table 1. Climate variables, such as sea surface temperature, wind speed and wetness, were considered in most SDM studies. This is because climate tolerances for different species are distinctive, making climate the primary proxy for accounting for species distributions (Bradie and Leung 2017; Gaston 2003). Remotely sensed climate information with high temporal resolutions can be publicly accessed, such as MODIS and the Advanced Very High-Resolution Radiometers data (AVHRR). Thus, remote sensing has been widely used to derive climate information in the last 5 years. Topography, such as slope, elevation and curvature, is utilized by more than half of the studies. Temperature, water availability and insolation for local areas are all related to land surface topography (Bennie et al. 2008; Elsen and Tingley 2015; Siegert et al. 2016). In remote sensing, topographic data are generally collected from digital elevation models (DEMs) derived from SRTM or airborne Light Detection and Ranging (LiDAR) imagery. Moreover, land cover maps directly describe land cover information on the ground surface. The distribution of species can be restricted by land covers, as different species have different food and water requirements, different predators and different breeding environments. Land cover information

Table 1. Remotely sensed data and processing methods for five major categories of environment predictors. TRMM stands for the tropical rainfall measuring mission dataset. CHIRPS stands for the climate hazards group infrared precipitation with stations dataset. NOAA/NCDC stands for the US National Oceanic and Atmospheric Administration's National Climatic Data Center. QuikSCAT stands for the NASA Quick Scatterometer dataset. ASCAT stands for the advanced scatterometer products. AVISO stands for the archiving, validation and interpretation of satellite oceanographic data. SeaWiFS stands for the Sea-viewing Wide Field-of-view Sensor. MERIS stands for a medium-resolution imaging spectrometer.

Traits	Remote Sensing Data	Processing Methods
Climate	Temperature: MODIS, AVHRR; Precipitation: TRMM, CHIRPS; Topographic wetness index: SRTM; Winds: NOAA/NCDC Blended Sea Winds, QuikSCAT, ASCAT	Values (maximum, minimum values in a time period), convolution filters, spectral index
Topography	SRTM, AVISO, airborne Lidar/laser data	Values (time series), convolution filters
Land cover	Landsat, MODIS, Airborne lidar data	Classification, spectral indexes, thresholding, spectral unmixing
Spectral matrices	Landsat, MODIS	Values, spectral index
Nutrient and energy	Chl-a: MODIS, SeaWiFS, MERIS; Eddy Kinetic Energy: AVISO; Solar energy/sunshine duration: SRTM, MERIS	Values, mathematical equation, convolution filters

derived from Landsat, MODIS or LiDAR images was proven to be effective in various studies from 2016 to 2022. On the other hand, spectral metrics, including vegetation indices, spectral radiance values and water indices, were creatively utilized by several studies. Generally, spectral metrics can also inform land cover information, as different land covers have different spectral radiances. The availability of remotely sensed spectral products facilitates the acquisition of spectral metrics with high temporal and spatial resolutions. Remote sensing images, such as Landsat and MODIS, are widely used in SDMs to obtain the spectral radiance of land surface, from which the most widely used one is the Normalized Difference Vegetation Index (NDVI). Moreover, nutrient and energy predictors, such as chlorophyll-a concentration, Eddy Kinetic Energy (EKE) and solar insolation, can be easily obtained through remote sensing. These predictors indicate the vegetation concentration, nutrient availability and temperature of the environment. Thus, they were widely used by the majority of SDM studies.

2.1.1. Climate predictors

A majority of SDM studies collect their climate predictors from climate models or products, not directly from weather stations or remote sensing data. This is primarily due to the fact that station observations are not spatially continuous. Climate observations are unavailable in many locations. Alternatively, remote sensing data measures the strength of signals reflected by the earth's surface. However, further analysis is needed to extract relevant climate information for SDM. Thus, climate models are widely utilized to convert these raw data into some information that can be used.

The utilization of remote sensing in climate models can be divided into three major categories. For the most traditional methods, climate information was primarily collected from station observations. In order to make a spatially continuous climate map, digital elevation models, such as SRTM, were utilized. For these datasets, remote sensing is only considered as supplementary data to facilitate the process of interpolation. One representative data is Global Aridity and Global PET. Then, with the development of remote sensing techniques, climate information can be derived from satellite images, especially MODIS. Currently, a great number of climate products derived from MODIS have been established by NASA, such as MODIS Evapotranspiration and MODIS Sea Surface Temperature. However, both station or remote sensing methods have their pros and cons. For instance, for the estimation of rainfall, satellite data provide areal averages that suffer from biases due to complex terrain, which often underestimate the intensity of extreme precipitation events. Conversely, precipitation grids produced from station data suffer in more rural regions where there are fewer rain-gauge stations. Thus, a lot of climate products or models start to combine the advantages of both remote sensing and station observations. A representative one is CHIRPS.

Temperature, wetness and wind speed are the three major climate predictors collected from the remote-sensing-derived climate products. Among them, temperature is the most commonly used one due to the fact that different species have different requirements for environmental temperature (Bradie and Leung 2017; Pradervand et al. 2014). Detailed information on remote sensing data used in deriving climate predictors is listed in Table 2. In most cases, AVHRR and MODIS were used to derive temperature data. Wetness, such as precipitation and topographic wetness index, was used by several plant, bird and insect studies. This is because water

Table 2. Remote sensing data used for climate predictors.

Traits	Remote Sensing data	Spatial Resolution	Temporal Resolution	Sensors
Temperature	MODIS	250–1000 m	1–2 days	Passive
	AVHRR	1.1 km	0.5 day	Passive
Precipitation	TRMM	5 km	16 times per day	Active
	CHIRPS	0.05 degrees	daily, pentadal and monthly	Combination of satellite images and station records
Topographic wetness index	SRTM	30–90 m		Active
Winds	Blended Sea Winds	0.25 degrees	six-hourly, daily, monthly	Combination of satellite images and station records
	QuikSCAT	20 degrees	1 day	Active
	ASCAT	12.5 km, 25 km	1.5 days	Active

availability is a significant factor for species habitats' selection. Precipitation was mostly collected from TRMM. Topographic wetness indices were derived from DEM images. Wind speed, a significant driver for the change of surface temperature and wetness, was also considered as a climate variable in several publications (Afán et al. 2019; Coll et al. 2019; Gómez et al. 2018; Hazen et al. 2018; Louw, Doucette, and Voges 2017). The wind speed information can be obtained from a variety of remote sensing data, such as Blended Sea Winds, QuikSCAT and ASCAT. Generally, wind speed is used together with temperature to represent the climate of a local area. In summary, remote sensing images are capable of providing various climate information for SDM studies.

The most representative study using both temperature and wind speed was published by Roberts et al. (2016). They built habitat-based density models for cetacean species with unprecedented taxonomic coverage (26 cetacean species and 3 multi-species cetacean) and temporal resolution (at monthly or yearly resolution). The three climate predictors they used were all collected from remote sensing images. The Group for High-Resolution Sea Surface Temperature was used to derive sea surface temperature and sea surface temperature front. Wind speed was derived from NOAA NCDC 1/4° Blended Sea Winds. Besides the climate predictors, a total of 21 remotely sensed predictors were also considered. They can be classified into two categories: topography predictors, such as slope and depth, and nutrient and energy predictors, such as chlorophyll concentration and primary production. They found that small delphinoid densities had high regional differences, large delphinoid cetaceans were mainly distributed in the continental slope and beaked and sperm whales were mainly distributed in canyons and seamounts.

In addition, a noteworthy study using temperature and precipitation was carried out by Deblauwe et al. (2016). They compared the performance of station-interpolated climate data and remotely sensed data in SDM by modelling the distributions of 451 plant species in Atlantic Central Africa, the Western Ghats and the Amazon Basin. Different combinations of temperature and precipitation data have been tested. Two station-interpolated data, WorldClim and the Climatic Research Unit, were utilized. They can provide both temperature and precipitation information. For remotely sensed data, MODIS was used as the temperature data source. Two remote-sensing derived datasets, TRMM and CHIRPS, were selected as data sources for precipitation information. In order to limit the influence of models, two kinds of models, MaxEnt and generalized linear modelling, were calibrated. They found that the remotely sensed climate data outperformed the interpolated station observations regardless of which model or study site was selected.

Moreover, using remote sensing data as the data source of the environmental predictors, Sinka et al. (2020) predicted the possible spatial distribution of *An. Stephensi*, an important transmitter of parasites closely related to malaria mortality and morbidity in human beings, in Africa. Enhanced Vegetation Index, Tasseled Cap Wetness, crop coverage and temperature in the study site were collected from MODIS images or products. CHIRPS was utilized to collect seasonal precipitation. Finally, they proved that there is a high probability of the presence of the *An. Stephensi* within urban cities in Africa, which provides a strong base of information for the surveillance and targeted vector control for urban malaria.

In summary, the remote sensing data, which are continuous in spatial coverage, are suitable for tracing the spatially different climate information.

2.1.2. Topographic predictors

The topographic predictors are different for terrestrial and aquatic species studies. Land surface topography is used for terrestrial species. The commonly used data sources for land surface topography are SRTM and airborne Lidar/laser data (Table 3). In contrast, for aquatic species, bathymetry and sea surface height are considered important. However, as the absorption capability of water is much stronger than air, it is hard to penetrate the seawater and detect the sea floor with the commonly used light energy for the ground, such as sunlight and Lidar. Thus, the modelling of bathymetry primarily utilizes the sonar measurements made by hydrographic survey. In addition, for some shallow water areas, airborne LiDAR data is also utilized (Table 3). In terrestrial species studies, elevation, slope, aspects and curvature of the land surface were the four commonly used predictors, which were mainly collected from airborne LiDAR or SRTM products. This is because different species have different tolerance for land surface topography. Alternatively, for aquatic species, bathymetry and sea surface height are considered as they influence the underwater environmental conditions, such as light penetration, sedimentation, current movements and thus temperature and oxygen gradients (Costello, Cheung, and De Hauwere 2010; Tong et al. 2012). In aquatic species studies, depth, slope and sea surface height were the three major predictors derived from remote sensing data, such as SRTM and AVISO. To sum up, all these indicate that remote sensing techniques ease the way to collect topographic information, since they are capable of generating spatially continuous high-resolution topographic products over large spatial scales.

A characteristic study of terrestrial species was made by Ziółkowska et al. (2016). Three topographic predictors were utilized: elevation, elevation range and slope collected from SRTM. They compared the effectiveness of habitat suitability models and movement models on the resistance and connectivity estimation for brown bears in the Carpathians. Six spatial scales were considered: 0.25, 0.5, 1, 2, 4 and 8 km. Besides the

Table 3. Remote sensing data used for topographic predictors.

Remote Sensing data	Spatial Resolution	Temporal Resolution	Sensors
SRTM	30–90 m	–	Active
AVISO	1/4°	Near real time/delayed time	Active
Airborne LiDAR data	On request	–	Active

topographic predictors, eight vegetation cover predictors from Landsat images and four artificial land cover predictors from an existing map product were considered. The results revealed that movement models performed better than habitat models in general.

For aquatic species, one of the significant publications was generated by Hazen et al. (2018). They developed a novel, data-driven, multispecies approach to predict both catch probability and bycatch risk at previously unachievable spatial and temporal scales for the California fishery, including one target species, broadbill swordfish, and three non-target species, leatherback turtle, blue shark and California sea lions. The refinement in temporal and spatial resolution was attributed to the integrated multiple data stream, especially the environmental predictors collected from remote sensing, including the sea surface temperature from Pathfinder and the Group for High-Resolution Sea Surface Temperature, zonal wind speed from QuikSCAT and ASCAT, chlorophyll-a concentration from SeaWiFS and MODIS Aqua, and sea surface height anomaly and EKE from AVISO+ and the Copernicus Marine Environment Monitoring Service. In particular, the topographic predictor, sea surface height anomaly, has proven to be useful, because it indicates thermocline depths which is effective in identifying vertical habitats of fish species. The results reveal that the current static closure of California fishery is well-placed spatially and sometimes overly conservative.

In summary, the remotely sensed topographic data are suitable sources for topographic predictors, since they are continuous in spatial dimension. In addition, for aquatic species, remotely sensed data not only provide surface information of water but also information below the surface which helps identify vertical habitats of aquatic species.

2.1.3. Land cover predictors

Remotely sensed vegetation, artificial land and water covers are the three major land cover predictors. Besides, the influences of snow, cloud and surface geology were tested by three studies. Vegetation covers were utilized in terms of vegetation types or coverage of each type. These vegetation maps directly represented the distribution of plant species, which further inferred the distribution of animals. A variety of remote sensing images, such as Landsat or MODIS, were used to satisfy different requirements of spatial resolutions. Artificial land covers, an indicator of anthropogenic disturbances that threaten the distribution of species, were used in three studies. These disturbances can change land cover types, fragment environment habitats, increase the risk of species invasions and release pollution. The artificial land covers were generated from either Landsat or MODIS images as percentages of artificial lands or distances to the nearest artificial lands. In addition, water covers are another important concern for species distributions, especially for terrestrial species, since water is essential for life. In some cases, water covers are foraging areas for terrestrial species. Distances to water or water coverages were measured in three terrestrial species studies from multispectral images (MODIS, Landsat and digital aerial orthophotos). In addition, snow, clouds and surface geology were studied to investigate their influence on species distribution in four articles. Snow was measured by classifying Landsat images, or visually interpreting aerial and satellite images. Cloud frequency derived from MODIS was used to test the influence of clouds on one bird study and two

Table 4. Remote sensing data used for land cover predictors.

Remote Sensing data	Spatial Resolution	Temporal Resolution	Sensors
Landsat	15–100m	16 days	Passive
MODIS	250–1000 m	1–2 days	Passive
Airborne LiDAR data	On request	–	Active
Land cover products	–	–	–

vegetation studies. Distance to shoreline derived from SRTM and a digital seafloor geomorphic features map was utilized in one oceanic study to predict cetacean density. Detailed information on the remote sensing images is listed in Table 4. In summary, Remote Sensing, measuring the characteristics of the earth surface with high spatial and temporal resolution, is effective in deriving land cover predictors.

A highly cited publication in this section was made available by Wilson and Jetz (2016). They analysed the influence of cloud cover dynamics on species distributions by making a probabilistic occurrence prediction for the montane woodcreeper in northwestern South America, and the king protea in the Mediterranean shrublands of South Africa. The only remotely sensed predictor used in this study was cloud covers, which were measured from MODIS. By comparing the two contrasting prediction models with/without remotely sensed cloud covers, they demonstrated that cloud cover can improve the predictions of habitats, ecosystems and species distributions with less spatial autocorrelation than the commonly used interpolated climate data.

In addition, Bazzichetto et al. (2018) exploited the causal relationship between the environmental characteristics and the occurrence of an invasive species, *Carpobrotus sp*, in the Mediterranean based on a land cover map derived from a panchromatic digital aerial orthophoto. The distribution of *Carpobrotus sp* was obtained from the land cover map. Moreover, the land cover map can provide environment information, such as percentages of artificial lands, agricultural areas vegetation land covers as well as the distance to the sea. They found that the invasive species favours areas with median elevation and low vegetation coverage through modelling the association between the distribution of *Carpobrotus sp* and the environment information derived from the land cover map, topographic information derived from airborne LiDAR imagery and distance to roads measured from OpenStreetMap. Their study revealed that land cover maps derived from remote sensing images can provide both response variables and environmental predictors for SDM, which are all difficult to collect through field measurements.

Moreover, Macdonald et al. (2019) mapped the core habitat and conservation opportunities for mainland clouded leopards in Southeast Asia using two Land Cover and Land use products, Forest cover (Hansen et al. 2013) and FRAGSTATS Land Cover layer (McGarigal et al. 2002). Although some other environmental predictors were utilized, e.g. topography information from SRTM, climate information from WorldClim and human footprint from Wildlife Conservation and Center for International Earth Science Information Network, the closed-canopy forest information is proven to be the most effective predictor for the distribution of clouded leopards.

In summary, thanks to the availability of various remote sensing images with wide temporal coverage, it was more convenient to extract the land cover information from them than from field measurements or historical maps.

2.1.4. Spectral matrices

Vegetation indices, spectral radiance values and water indices are the three types of remotely sensed spectral matrices adopted in SDM publications (Table 5). They are collected either from Landsat or MODIS (Table 6). Vegetation indices were utilized by most of the publications since they help delineate habitats for plant species and identify feeding, breeding and inhabiting areas for animal species. Specifically, four frequently used remote sensing vegetation indices were as follows: NDVI, the Enhanced Vegetation Index, Tasseled Cap and the Soil-adjusted Vegetation Index. Meanwhile, spectral radiance values, such as visual, near-infrared, short-wave infrared and thermal infrared band values, were employed by several SDM studies given their capability to reveal the presence of suitable ecosystems in landscapes that influenced the distribution of species. Moreover, water indices, capable of distinguishing foliar cover and measuring surface water, were deemed essential in four habitat suitability studies. Two kinds of water indices were used: the Normalized Difference Water Index and the Modified Normalized Difference Water Index. In these three studies, water indices were used together with vegetation indices. In summary, spectral matrices collected from Landsat and MODIS can provide continuous and objective observations of the land surface, which subsequently improves the SDMs' performance.

The most cited work using remotely sensed spectral matrices is made by West et al. (2017). In order to find a universally applicable SDM, they modelled the distribution of an invasive species, *Bromus tectorum*, in a post-wildfire landscape in the Medicine Bow National Forest, US. Time-series vegetation and water indices, such as NDVI, the Soil-adjusted Vegetation Index, Tasseled cap and the Modified Normalized Difference Water Index, were derived from Landsat images. SRTM was used to provide topographic information about the environment. Then, four SDMs (Boosted Regression Trees,

Table 5. Spectral matrices utilized in SDMs.

Type	Index	Description
Vegetation indices	NDVI	(NIR - R)/(NIR + R)
	Enhanced Vegetation Index	G * ((NIR - R)/(NIR + C1 * *R* – C2 * B + L)) L represents a value to adjust for canopy background, C values are coefficients for atmospheric resistance, and coefficients for the blue band (B)
	Tasseled Cap	−0.2848 * B – 0.2435 * G– 0.5436 * R + 0.7243 * NIR + 0.0840 * SWIR1– 0.1800 * SWIR2
	Soil-adjusted Vegetation Index	((NIR - R)/(NIR + R + L)) * (1 + L) L is a soil brightness correction factor
Water indices	Normalized Difference Water Index	(Green - NIR)/(Green + NIR)
	Modified Normalized Difference Water Index	(Green - SWIR)/(Green + SWIR)
Spectral radiance values	Visual, near-infrared, short-wave infrared and thermal infrared band values	

Table 6. Remote sensing data used for spectral matrices.

Remote Sensing data	Spatial Resolution	Temporal Resolution	Sensors
Landsat	15-100m	16 days	Passive
MODIS	250-1000 m	1-2 days	Passive

Random Forests, Generalized Linear Model and Multivariate Adaptive Regression Spline) were calibrated using an iterative approach. Their results revealed that the brightness of the Tasseled cap was the most significant predictor for the four SDMs among which Random Forests performed the best. In the end, they concluded that the time-series indices derived from Landsat images were effective in calibrating SDMs.

In addition, Álvarez-Martínez et al. (2018) established a significant work using vegetation indices and spectral radiance values. They mapped the area of occupancy for 24 habitat types in northern Spain by implementing the maximum entropy algorithm in MaxEnt. Three kinds of predictors were used in this study. Among them, spectral matrices and topographic predictors were derived from remote sensing images, while climate predictors were generated by interpolating data from meteorological stations. In the spectral matrices, the spectral radiance values they used were visual bands, the near-infrared band and the short-wave infrared bands from Landsat 8 images. Additionally, vegetation indices, which were NDVI and Tasseled Cap components, were also derived from these Landsat images. The seven topographic predictors were derived from the LiDAR data at 5-m resolution. They found that the two kinds of remotely sensed predictors contributed the most to predicting the habitat types.

In summary, spectral matrices derived from remote sensing make it viable to trace the Earth's surface across large regions through a wide spectrum of temporal coverage. Moreover, when we combine them with other remotely sensed predictors, such as the climate and topographic predictors, the existing SDMs have a high potential to be applied to large spatial scales.

2.1.5. Nutrient and energy predictors

Besides the aforementioned predictors, remote sensing can also be used to derive nutrient and energy predictors, among which the three representative ones were chlorophyll-a concentration, solar radiation and oceanic eddies. Chlorophyll-a concentration represents the biomass and productivity of phytoplankton, indicating the trophic status of water (Dall'olmo and Gitelson 2005; Tyberghein et al. 2012). Thus, it was widely utilized by aquatic species studies (16 publications). In addition, it was also used to predict the distribution of two bird species distribution studies, for which the ocean environment was important. The MODIS-Aqua, revisiting the same location on the earth every 2 days, is considered a major source of chlorophyll-a concentration information. Moreover, oceanic eddies were proven to be important for six oceanic species distribution studies. Because the oceanic eddies transport heat, biogeochemical substances and energy throughout the ocean, which change the environment for ocean species (Dawson, Strutton, and Gaube 2018; Mkhinini et al. 2014; Z. Zhang et al. 2019). As remote sensing images are continuous in space, they are suitable for observing the presence of oceanic eddies through indicators such as EKE and geostrophic surface velocities (Ioannou et al. 2019). Solar radiation, the primary energy source of life, was considered by a variety of SDM studies (six publications). This is because changing land surface temperature and humidity affects evapotranspiration and the photosynthesis process of vegetation (Wild et al. 2005). Solar radiation is affected by topography, solar illumination angle and atmospheric transmittance (Dubayah and Rich 1995), and it is thus mainly derived from DEM data, such as SRTM. The remote sensing data used in nutrient and energy predictors is listed in Table 7.

Table 7. Remote sensing data used for nutrient and energy predictors.

Traits	Remote Sensing data	Spatial Resolution	Temporal Resolution	Sensors
Chl-a	MODIS	250–1000 m	1–2 days	Passive
	SeaWiFS	4.5km –1.1km	1day	Passive
	MERIS	300 m	3 days	Passive
Eddy Kinetic Energy /Current velocity	AVISO	1/4°	Near real time/delayed time	Active
	Bio-ORACLE			
Solar energy/sunshine duration	SRTM	30–90 m	–	Active
	MERIS	300 m	3 days	Passive
Salinity & Dissolved oxygen	Bio-ORACLE			

Oceanic eddies were generally used together with chlorophyll-a concentration in SDM studies. A significant study was put forward by Hazen et al. (Hazen et al. 2017). They predicted the habitat preference and seasonal densities for blue whales in the Gulf of California and the eastern tropical Pacific. A satellite-telemetry-based habitat model was developed using remotely sensed nutrient and energy predictors, climate predictors and topographic predictors. Chlorophyll-a concentration was derived from SeaWiFS and MODIS. EKE was collected from AVISO. They found that blue whales were distributed in inshore areas with high rugosity and low surface temperature in summer, and offshore areas with low rugosity and warm temperature in winter.

In addition, Hu et al. (2022) investigated the distribution of 21 fish species in China using remotely sensed nutrients, energy, topography and climate predictors. Bio-ORICLE data, a compilation of pre-processed remotely sensed (MODIS and SeaWiFS) and in situ measured oceanographic data, was utilized to collect the current velocity, mean salinity and dissolved oxygen in the study area. Additionally, the mean temperature from the MODIS-Aqua L3 product and bathymetry from the ETOPO1 data were collected. They found that if the climate keeps changing, as predicted by IPCC, 9 out of 21 fish species have a high potential to be endangered.

Moreover, an important work considering the incoming radiation was done by Gunnar et al. (2017). In order to investigate the importance of low-altitude mountains for the endemic *Ornduffia calthifolia* and *O. marchantii*, they built SDMs to predict the distribution of these species at different scales. Besides the commonly used climate predictors, such as temperature and precipitation, and topographic predictors, such as elevation, slope and aspect, they calculated total solar radiation from LiDAR data obtained by airplane. The rationale is that the total solar radiation quantifies the solar energy arriving at the earth surface, which is significant for plants. They found that topographic predictors and total solar radiation are important determinations for the distribution of *Ornduffia calthifolia* and *O. marchantii* at the local scale. At the regional scale, climate predictors demonstrate paramount importance. This is because different topographic conditions and income solar energy can create significantly different local climate environments which may not be able to be detected by climate stations or climate satellites. In this circumstance, remotely sensed images with high spatial resolution, such as the LiDAR data used in their study, are feasible to detect the change of environment over small distances.

In summary, remote sensing, given its ability to repeatedly observe the earth, can provide unprecedented measures of SDM environmental predictors, which are hard to acquire through traditional in situ observations, such as nutrient and energy predictors.

2.2. Response variables

Remotely sensed response variables are not widely utilized in SDM. For the majority of SDM studies, the response variables were still collected from in situ surveys either established by themselves or shared by other researchers and organizations. However, there are still some vegetation studies creatively making use of remote sensing in deriving response variables. This is caused by the fact that wide and continuous coverage in spatial and, sometimes, temporal remote sensing eases the way to derive the vegetation distribution information through generating spatially continuous land cover maps. Nevertheless, there are still gaps in obtaining the distribution of animals with Remote Sensing due to the fact that the location of individual animal is often temporally uncertain, not to mention that evidence of animal species is likely to be covered under associated land covers, such as plants, rocks and soil. It is difficult to capture the distribution of animals with remote-sensing images. Thus, remote sensing was more suitable for deriving vegetation response variables.

Percentage and presence of vegetation species were the two major response variables derived from Remote Sensing. Percentage is defined as the proportion of a region covered by the target species, while presence is binary data that describes the occurrence and absence of species. The two representative studies were presented by Tredennick et al. (2016) and Long et al. (2017). In order to predict the impact of climate change on large-scale plant distributions, Tredennick et al. (2016) tracked the percentage of *sagebrush* in each 30 m × 30 m area for every year from 1984 to 2011 by unmixing three sources of optical imagery (QuickBird, Landsat and the Advanced Wide Field Sensor). A new approach using spatiotemporal population modelling was introduced to fit a population model with five climate variables to the large-scale *sagebrush* covers. It was the first time that the future response of *sagebrush* to climate changes was predicted at the landscape scale. They found that the response of *sagebrush* to climate change was consistent with the existing individual-level studies, which demonstrated the feasibility of using remote sensing data to model population responses to environmental change at large scales. Additionally, Long et al. (2017) explored the relationship between an invasive species, *phragmites*, and its environmental factors, such as land use and nutrient levels in the Great Salt Lake, US. Their response variables were the presence or absence of *phragmites* derived from the classification of a 10-m resolution aerial image. They found that the distribution of *phragmites* was highly related to the pollution level, elevation and inundation of the environment. Moreover, they concluded that remote sensing data with high resolutions and wide coverage can benefit SDM studies of invasive species.

In summary, thanks to the availability of images with diverse spatial, spectral and temporal resolution, and different spatial and temporal coverage, remote sensing can be used to map the species distribution at different scales. In addition, various classification and unmixing methods, such as random forest, deep learning and linear unmixing, the coverage or occurrence of plant species can be derived from remote sensing images.

2.3. Multi-scales

The most common approach in SDMs is to link species distribution data with environmental variables at coarse spatial resolutions. Climate predictors, in particular, are often used at a resolution of approximately 1 km or coarser (Lembrechts, Nijs, and Lenoir 2019). This approach may be effective in flat terrains with stable land use and long-term climate stability but falls short in capturing species distributions in regions with significant spatial and temporal climate heterogeneity, known as microclimates (Lembrechts, Nijs, and Lenoir 2019; Scales et al. 2017). For instance, in forest systems, sub-canopy temperatures in the understory can be more than 5°C lower than in nearby clear-cuts (Chen et al. 1999). This partial decoupling from free-air temperatures creates microclimates that provide opportunities for species unable to tolerate the average temperatures measured at coarse spatial resolutions. However, this spatial heterogeneity of temperatures often goes undetected in environmental data derived from interpolated weather station data or field data collected at discrete spatial points, such as WorldClim (Fick and Hijmans 2017; Lembrechts, Nijs, and Lenoir 2019). By contrast, remote sensing images are by nature spatially continuous. As such, they provide flexibility in spatial resolutions to meet the different requirements of SDMs. At different resolutions, observations of an environmental variable can be significantly different. For instance, an environmental record at coarse resolutions is a summary of the environment in a large region. Alternatively, high-resolution data are instrumental in tracing the change of microrefugia spatially (Leempoel et al. 2015). In addition, remote sensing data provide extensive temporal records, offering opportunities to analyse the temporal dynamics of the environment. However, acquisition and processing of remotely sensed environmental data is complicated. Thus, in order to avoid missing essential information or getting lost in unnecessary details, it is imperative to define a suitable observation scale before the optimal SDMs can be constructed (Levin 1992).

A representative study investigating the impact of multi-scale is made by Scales et al. (2017). To investigate the effects of spatial and temporal resolutions in SDMs, Scales et al. (2017) predicted the presence and habitat suitability of pelagic predator species in the California Current System at six spatial resolutions (3, 4, 9, 25, 50 and 111 km) and five temporal resolutions (daily, weekly, monthly, seasonal and climatological). They found that temporal resolution was more important for SDMs than spatial resolution. In addition, Mateo-Sanchez et al. (2016) tested the impact of temporal and spatial scales on SDMs. They focused on modelling the distribution of brown bears in the Cantabrian Range. Based on LiDAR data, a topographic map and a transport infrastructure map, SDMs with nine spatial scales ranging from 0.25 to 64 km were built. In addition, as food availability is changing seasonally, habitats for animals are also changing. Thus, temporal resolution is vital for SDM. In this study, four different temporal resolutions were considered: each season, a time period from 2000 to 2004, a time period from 2005 to 2010 and the entire 2000 to 2010. They found that environmental predictors describing foraging resources and human pressures affect the SDM at broad scales. However, predictors related to the shelters of brown bears are effective at different spatial scales. In addition, Atzeni et al. (2020) implemented a univariate scaling method to find suitable scales for environmental variables when they predict the distribution of snow leopards in two landscapes of western China. SRTM and ESA GlobCover 2009 were the two remote sensing data they utilized. Environmental predictors were collected at two different scales: class level and landscape level. They found that landscape attributes at broad scales can better express the distribution of snow leopards. Additionally, they revealed that the multi-scale modelling approach was better than the unscaled counterparts in almost all cases.

In summary, remote sensing is feasible to investigate the influence of scales in SDMs. Remote sensing images divide the land surface into spatially connected cells with the same side length, which enables researchers to change the spatial scales and then, investigate the effective spatial scales of different environment predictors.

2.4. Validation

Key challenges in validating SDMs include ensuring that the validation data are independent of the training records, accurate and randomly distributed across the study area (Guillera-Arroita et al. 2015; Julie et al. 2022). Without these, assessing the model's effectiveness becomes difficult. However, during traditional field surveys, meeting these criteria is challenging, as the detectability of samples often depends on environmental variables (Guillera-Arroita et al. 2015), which can distort our understanding of species distribution. Alternatively, remote sensing images offer significant potential to alleviate these issues in SDM validation, as they provide consistent spatial detection and direct observations for each pixel. Additionally, remote sensing offers observations in places where human beings have a hard time getting access to. In the two studies in section 2.2 (response variables), the remotely sensed species maps were also used to validate their SDMs. In these studies, the derived SDMs can be evaluated in more sites, or even in each pixel area of the remote sensing images, compared with the validations using limited field or station observations. In addition, Hazen et al. (2017) also used remotely sensed data to examine the track data of blue whales. The movement of blue whales was identified by switching state space models using images captured by dynamic cameras. These movement data can be used to validate the accuracy of blue whale tracks collected from tags attached to the whales. Thus, using Remote Sensing, we can gain a more comprehensive and objective assessment of the SDMs' performance.

3. Discussion

Through the above review, we found that remote sensing has been widely employed in SDMs to replicate environmental predictors, whereas it is still understudied for generating response variables, testing the multi-scale effects and validating the resultant models. In the following four sub-sections, we will discuss current gaps and potential research directions for the four aspects, respectively.

3.1. Environmental predictors

Remote sensing is widely used in collecting samples for environmental predictors. The benefits of remote sensing images manifest in three aspects: samples can be collected at various spatial resolutions; it is easy to collect random samples using remote sensing data; and remote sensing makes it easy to collect samples at large scales. First, suitable scales for different environment predictors in SDMs are different. Some factors, such as temperature, are almost consistent at local scales. By contrast, others, such as artificial landscapes, change significantly within a small distance. Thus, the suitable spatial resolution for environment factors can be different. Since remote sensing data are spatially continuous, environment data in different scales can be collected from remote sensing images.

Second, random samples can be easily collected in remote sensing images. A remote-sensing image provides information for each pixel in it. Thus, for all randomly collected points, their information can be collected. At last, remote sensing makes it possible to collect samples at large scales at the same time. A remote sensing image can cover a large area of the earth. For instance, the size of a Landsat 8 scene is 185 km × 180 km. The data of each pixel in the image is collected on the same day, which is hard to accomplish using in-situ data.

Nevertheless, there is still some environment information that is difficult to collect using remote sensing. First, environment information under the earth surface cannot be captured in remote sensing images. For example, nutrients in soil, which are significant factors for vegetation distribution, are hard to be detected using remote sensing images. This is because remote sensing images only collect information on the earth's surface. Nutrient components under the surface of soil are hard to detect in remote sensing images. Second, remote sensing images which are freely available have coarse spatial resolution. For SDM studies that require high-spatial-resolution environment factors, a large budget may be needed to buy the required images. At last, there are time lags among environment factors collected by remote sensing. According to Table 1, different environmental predictors need to be collected from different data sources. Remote sensing images are not updated in real-time. For example, the temporal resolution of Landsat images is 16, while for SRTM, the latest data is for the year 2000. During the time lag, environment factors and the distribution of species may change a lot, which decreases the accuracy of SDMs.

3.2. Response variables

In SDMs, the response variables of species occurrence or abundance are conventionally acquired by field observations (or published species records). Compared to the field (or opportunistic) data, remote sensing maintains several advantages in obtaining the response variables: the data flexibility in spatial distribution, the access to the impractical areas of ecological field studies and the extensive coverage of species occurrences and dynamics. First, the species sampling points acquired from remote sensing images are flexible and more prone to be randomly distributed, which is required for most statistical or machine-learning SDMs. In field surveys, due to the limited time and effort, random and sufficient samplings can be difficult to collect. Appropriate sample designs can be challenging, especially when the ecosystem is complicated. Also with remote sensing images, a variety of random samplings can be utilized repeatedly to diminish the uncertainty in SDMs caused by a single sample set. Second, remote sensing images are beneficial to derive the species samplings in ecologically inaccessible and impractical areas, such as the Amazon basin (Chambers et al. 2007). Sampling points are extremely hard to collect in those inaccessible areas, which have plagued ecological studies all the time. Advances in remote sensing have overcome some of those obstacles and enabled progress towards tackling difficult ecological problems. Third, remote sensing provides a means of measuring the habitat characteristics and species occurrences across broad areas and potentially entire landscapes. In SDMs, the species occurrence data should be geographically and environmentally representative of the species distribution in the study area. The extent of species occurrence should encompass the whole range of species, the degree of which largely affects the SDM performance (Franklin 2010). However, the field data rarely allow the true species niche to be fully specified or confirmed, especially for the wide-ranging species. Remote sensing images can expand the scope of analysis from small field plots to regional understanding, as well as monitor dynamic features of species and landscapes over space and time.

With the increasing availability of high resolution (e.g. PlanetScope), hyperspectral (e.g. the DLR Earth Sensing Imaging Spectrometer), LiDAR and radar remote sensing data, mapping the individual species with its characteristic spectral, textural, structural and phenological signatures becomes more prospective (Ferraz et al. 2016; Lu and Wang 2024; Yin et al. 2024). In addition, the spectral unmixing methods in remote sensing can quantify the percentages (or abundances) of species within each pixel, which further facilitates the use of medium (or coarse) spatial resolution imagery for species characterization in SDM studies. Satellite tracking data are increasingly being employed to trace the movement of animal species. Tags can be deployed on animals to monitor their locations, which makes it efficient for collecting animal occurrence data. Depending on the target species, remotely sensed species occurrences may be affected by image quality (e.g. cloud contamination) and uncertainties of species identification. Yet with the rapid advancement of remote sensing, the accuracy of remotely sensed species occurrences continues to be improved. Collecting response values of species from remote sensing shows great promise for future studies.

However, remote sensing is still unable to replace field observations. There are three major challenges in using remote sensing data: it is hard to select proper classification methods and training samples for vegetation species, vegetation species vertically covered by other land covers are hard to detect in remote sensing and the remote sensing techniques of detecting the occurrences of animal species are underdevelopment. First, in remote sensing, there are a great number of classification methods, such as random forests and deep learning, and training data collection methods, such as field collection and visual interpretation of high spatial-resolution images. A certain classification method may have quite different performances in different study areas and use different training data. In order to ensure the high quality of the results, plenty of time and effort have to be made in trial and error to find a suitable classification method and effective training samples. It is hard for researchers without a remote sensing background. Second, a large part of remote sensing images only records the surface layer of the earth. Short trees or shrubs under the canopy of other trees are hard to be detected. At last, the special resolution of commonly used remote sensing data is too coarse to trace the occurrences of animals. In addition, the locations of animals are changing, and they are always staying in shelters, which increases the difficulty of detecting them using remote sensing. Although a few studies exist, further studies are required to widely implement remote sensing in animal occurrence detection.

3.3. Multi-scales

Different environmental predictors are likely to affect the species' occurrence at markedly different spatial scales. For instance, in terrestrial systems climate dominates species distributions at regional to global scales, whereas at meso- and topo-scales (a few to hundreds of kilometres), topography, land cover and land use create finer-scale variations in climate, nutrient availability and water flows (Elith and Leathwick 2009). Therefore, one challenge in SDMs is to combine different types of predictors with varying scales in a single model. Several approaches have been put forward recently for addressing the scale problem such as creating models with hierarchical structure, possibly by Bayesian approaches, which incorporate different predictors into sub-models separately to consider the relationships at disparate scales (Latimer et al. 2006; Mackey and Lindenmayer 2001). However, the relative advantages and performances of those hierarchical approaches need to be evaluated both theoretically and practically.

According to the multi-scale studies in SDMs, researchers are starting to recognize the importance of spatial scales. It has been proven in recent studies that environmental predictors collected at different spatial scales have different effects in modelling the species distributions. Remote sensing data, which are spatially continuous, make it possible to investigate the influence of spatial scales to a large extent.

Nevertheless, the influence of temporal scales is rarely discussed. Plenty of remote sensing satellites, such as Landsat and MODIS, have long-term historical observations. They can generate a new image of the Earth's surface in a short period of time. For instance, Landsat images cover the Earth's surface every 16 days. These historical images of rich temporal information have not been fully studied. Thus, how to fully use these temporally and spatially continuous remote sensing data is still a question to be answered in future studies.

3.4. Validation

Remote sensing provides a new direction for validating the performance of SDMs. For the aforementioned SDM studies, in-situ field samples or published records are usually divided into two parts: the training samples and the validation samples. Those validation samples are typically restricted in size, time and location. By contrast, remote sensing enables us to expand the size and the extent of the validation samples over both space and time and promises to evaluate the interpolation and extrapolation capabilities of SDMs in predicting the habitat suitability of species. The distributions of vegetation species across locations and years can be obtained with remote sensing images and are usually more accurate than the spatially interpolated data obtained from in-situ point observations. The distributions of animal species can be tracked using satellite tracing data and aerial data (e.g. unmanned aerial vehicle-based images). A method was recently developed to count songbirds using unmanned aerial vehicles by Wilson, Barr, and Zagorski (2017), which opens a new direction to generate the validation data. Instead of capturing spectral reflectance of the land surface, they utilized unmanned aerial vehicles to record bioacoustic information across their study areas. Although their methods were only tested in a small area in Gettysburg College, Pennsylvania, U.S.A., they have a high potential to be widely used. Additionally, the validation data from the repeated remote monitoring of species distributions promises to evaluate the extrapolation abilities of SDMs, particularly for the species not in equilibrium with the environment. The main challenge in non-equilibrium settings is that the species occurrence data in the current environment may not represent those in the new conditions, such as in the forecasting of species invasion or climate impacts on species distributions. By monitoring the species distributions repeatedly and consistently, remote sensing can potentially assess the performance of SDMs over space and time in a dynamic fashion and provide insights into the extrapolation process of SDMs. The use of remote sensing to validate the SDMs is a direction to be further explored in future studies.

4. Conclusion

This review article delineates four pivotal domains within SDM where remote sensing is poised to make significant contributions: environmental predictors, response variables, multi-scales and validation. Our analysis reveals that remote sensing provides an extensive array of measurements for SDM environmental predictors, including climate, topography, land use and cover, spectral indices and metrics referring to energy and nutrients. Furthermore, remote sensing images offer the advantage of spatial and temporal consistency, enabling detailed monitoring of microclimates or microrefugia across large study areas. This significantly enhances the capability of SDM studies to analyse species distributions across different spatial and temporal scales. Additionally, remote sensing allows for data collection in locations inaccessible to humans, reducing the sampling bias often encountered in field surveys, making it an invaluable resource for SDM validation. Thus, while traditional SDM studies have predominantly relied on in situ surveys for response variable collection and validation, our review reveals a growing trend in vegetation studies where remote sensing is being innovatively utilized. In summary, this review not only delineates the current applications of remote sensing in SDMs but also emphasizes the emerging potential of remote sensing to revolutionize the field. By offering novel insights and expanding the capabilities of SDMs, remote sensing stands as an invaluable tool that enhances our understanding of species distributions.

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