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Integration of remote sensing and bioclimatic data for prediction of invasive species distribution in data-poor regions: a review on challenges and opportunities

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Abstract

Prediction and modeling using integrated datasets and expertise from various disciplines greatly improve the management of invasive species. So far several attempts have been made to predict, handle, and mitigate invasive alien species impacts using specific efforts from various disciplines. Yet, the most persuasive approach is to better control its invasion and subsequent expansion by making use of cross-disciplinary knowledge and principles. However, the information in this regard is limited and experts from several disciplines have sometimes difficulties understanding well each other. In this respect, the focus of this review was to overview challenges and opportunities in integrating bioclimatic, remote sensing variables, and species distribution models (SDM) for predicting invasive species in data-poor regions. Google Scholar search engine was used to collect relevant papers, published between 2005–2020 (15 years), using keywords such as SDM, remote sensing of invasive species, and contribution of remote sensing in SDM, bioclimatic variables, invasive species distribution in data-poor regions, and invasive species distribution in Ethiopia. Information on the sole contribution of remote sensing and bioclimatic datasets for SDM, major challenges, and opportunities for integration of both datasets are systematically collected, analyzed, and discussed in table and figure formats. Several major challenges such as quality of remotely sensed data and its poor interpretation, inappropriate methods, poor selection of variables, and models were identified. Besides, the availability of Earth Observation (EO) data with high spatial and temporal resolution and their capacity to cover large and inaccessible areas at a reasonable cost, as well as progress in remote sensing data integration techniques and analysis are among the opportunities. Also, the impacts of important sensor characteristics such as spatial and temporal resolution are crucial for future research prospects. Similarly important are studies analyzing the impacts of interannual variability of vegetation and land use patterns on invasive SDM. Urgently needed are clearly defined working principles for the selection of variables and the most appropriate SDM.

Keywords: Bioclimatic variables, Remote sensing, Species distribution modeling, Invasive species

Introduction

Invasive species are a serious worldwide threat to biodiversity (Paz-Kagan et al. 2019; Somers and Asner 2012; Truong et al. 2017). They moreover negatively affect livelihoods (Shackleton et al. 2014, 2015), density, richness, and diversity of native woody species, and quality and distribution of water (Bekele et al. 2018). They have also a huge capacity to invade all land use types at high

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invasion rates such as watercourses, highways, irrigated areas, forests, degraded lands, and agricultural land (Shiferaw et al. 2019c) in particular if the invaded areas have low diversity (Ilukor et al. 2016; Sun et al. 2015). The negative impact of invasive species is generally increasing over time as it usually requires huge amounts of labor and costs to eradicate infested areas (Bekele et al. 2018). In particular, relatively poor countries often don't have the necessary means to remove areas invaded by invasive species. Any deferment, however, further aggravates the problem (Vilà et al. 2011).

Currently, the adverse impacts of invasive species are in most countries by far greater than their positive return. In Ethiopia, the negative impact of *Prosopis Juliflora* (hereafter *Prosopis*) outweighs its positive contribution both to the ecosystem and livelihood (Iluker et al. 2014; Wakie et al. 2014). Currently, in Ethiopia, around 4.56 million hectares of land is highly suitable for Prosopis distribution (Sintayehu et al. 2020). In addition, in the Afar region, *Prosopis* has invaded about 1.17 million hectares of land and is expected to increase at a rate of 8.3% annually (Shiferaw et al. 2019b). It invades native species and grasslands that were an important source of fodder for the locality (Ayanu et al. 2014; Wakie et al. 2014). Economically, an expected 535 billion dollars net loss may occur under poor management (Iluker et al. 2014). Hence, as eradication of invasive species is difficult and costly, early detection and prevention, using an integrated data source, need to be prioritized for its management (Paz-Kagan et al. 2019; West et al. 2014; Zimmermann et al. 2007). Although mapping current distribution and modeling of suitable habitat for invasive species are of particular interest, published reports are limited (Fischer et al. 2013; Ng et al. 2018).

Species distribution modeling (SDM) has a great potential for the identification of suitable habitats and modeling prediction of invasive species (Bradley 2014; Filho et al. 2010; Feilhauer et al. 2012; Truong et al. 2017). They are also useful for planning and management of conservation efforts involving at a range of different scales. They also help to address important policy and strategic concerns on a global scale (Cayuela et al. 2009). Even though invasive SDM makes field inventories more efficient and effective, their prediction potential is often limited by spatial bias, lack of spatially explicit predictor variables, and unavailability of species absence data (Cayuela et al. 2009; Filho et al. 2010; He et al. 2015). In view of this, the prediction of invasive species requires great care (Václavík and Meentemeyer 2012).

Advancements in remote sensing technology and statistical modeling increasingly support the prediction efficiency of SDM by reducing SDM-inherent limitations (He et al. 2015). Remotely sensed rainfall and temperature data are available at the different temporal and spatial resolutions but are not yet widely used (Amiri et al. 2020; Deblauwe et al. 2016; Fernandez et al. 2013). Normalized Difference Vegetation Index (NDVI), Leaf Area Index (LAI), Enhanced Vegetation Index (EVI), and other EO derived data are still under-used in SDM though their potential is unquestionable (Feilhauer et al. 2012; He et al. 2015; Klerk and Buchanan 2017). This is particularly important for data-poor regions such as Ethiopia where weather stations are scarcely found (Deblauwe et al. 2016; Truong et al. 2017). Most studies in Ethiopia were carried out using survey data which is costly and time-consuming. Though the use of remote sensing data is at its infant stage, in recent years some few studies were carried out using remote sensing and bioclimatic variables (Ayanu et al. 2014; Shiferaw et al. 2019a; Wakie et al. 2014).

Besides the contributions of remotely sensed environmental variables, bioclimatic variables are equally important for predicting invasive species distribution (Amiri et al. 2020; Bradley et al. 2018; Deblauwe et al. 2016; Fernandez et al. 2013). Though it has the coarse resolution, climate variables alone have great potential to predict invasive species while the presence of remotely sensed environmental variables supports to provide spatial detail (Truong et al. 2017; Zimmermann et al. 2007). So far, several review articles have been published regarding SDM (e.g.; Kissling et al. 2018; Urbina-Cardona et al. 2019), and invasive species (e.g.; Bartz and Kowarik 2019; Kapitza et al. 2019; Shackleton et al. 2015; Vilà et al. 2011) and role of remote sensing in invasive SDM (e.g.; (Bradley 2014; He et al. 2015; Huang and Asner 2009; D. Rocchini et al. 2015a, b; Royimani et al. 2018; Transon et al. 2018)). For example, Thamaga and Dube (2018a, b) have provided an overview of remote sensing on water hyacinth. Similarly, Matongera et al. (2016) have reviewed the advancement and challenges of remote sensing in mapping and sensing *Bracken fern* invasive species. Bradley et al. 2014 also provides a detailed description of the spectral, textural, and phenological approach of remote detection of invasive plants. Some review papers also focused on the impacts of climate-based variables in invasive species distribution (e.g.; Tricarico 2016; Zhao et al. 2013). However, to the best of our knowledge, studies to highlight the integration of different disciplines for accurate prediction of SDM are still missing. In light of this, Cord et al. (2013) wrote a commentary on the need for bridging disciplinary perspective for better use of their full potential. As the integration of remotely sensed environmental data sources, bioclimatic variables and SDM could be an effective and reliable tool to predict and map invasive species distribution; this review paper provides a review of the state-of-the-art in this field.

Methods

The Google Scholar search engine was used to identify relevant papers. The following keywords/phrases were used alone and in combination to search published articles in the past 15 years:

- SDM
- Remote sensing of invasive species
- Contribution of remote sensing in SDM
- Bioclimatic variables
- Invasive species distribution in data-poor regions
- Invasive species distribution in Ethiopia

In this way, 442 papers were retrieved, published between 2000–2020. Out of these papers, 112 studies, published between 2005–2020 (March), were finally selected (Fig. 1). The main aim of the review was to describe challenges and opportunities in combining (bio) climatic (both in situ and/or remote sensing based) and EO derived variables with SDM for predicting invasive species distribution. In particular, the role of EO in the prediction of invasive species was thoroughly examined. Varied views of integrating these datasets with SDM were also explored. Major challenges and opportunities associated with the process of integrating these datasets were highlighted. Finally, recommendations were distilled out of the body of published work, providing some guidance concerning the design of future studies. To prepare this review paper, we first define the methodology used to select and analyze published (SCI) papers. Thereafter, in two separate chapters, we summarize the sole use of either (bio) climatic or EO data for SDM. The next chapter follows a summary of the combined use of the two datasets for SDM, followed by a review chapter on the use of such data for invasive species modeling in Ethiopia. Finally, we highlight the challenges and opportunities offered by a combined analysis of EO and (bio) climatic data. The review concludes with chapters on recommendations and conclusions.

Results and discussion

Contribution of remote sensing in SDM

Remote sensing is the most cost-effective approach to monitor vegetation cover and its changes over time, as it provides wide spatial coverage and repeated measurements over a short period, which are difficult to achieve otherwise (Paz-Kagan et al. 2019; Rocchini et al. 2015a, b; Rocchini et al. 2015a, b). The availability of

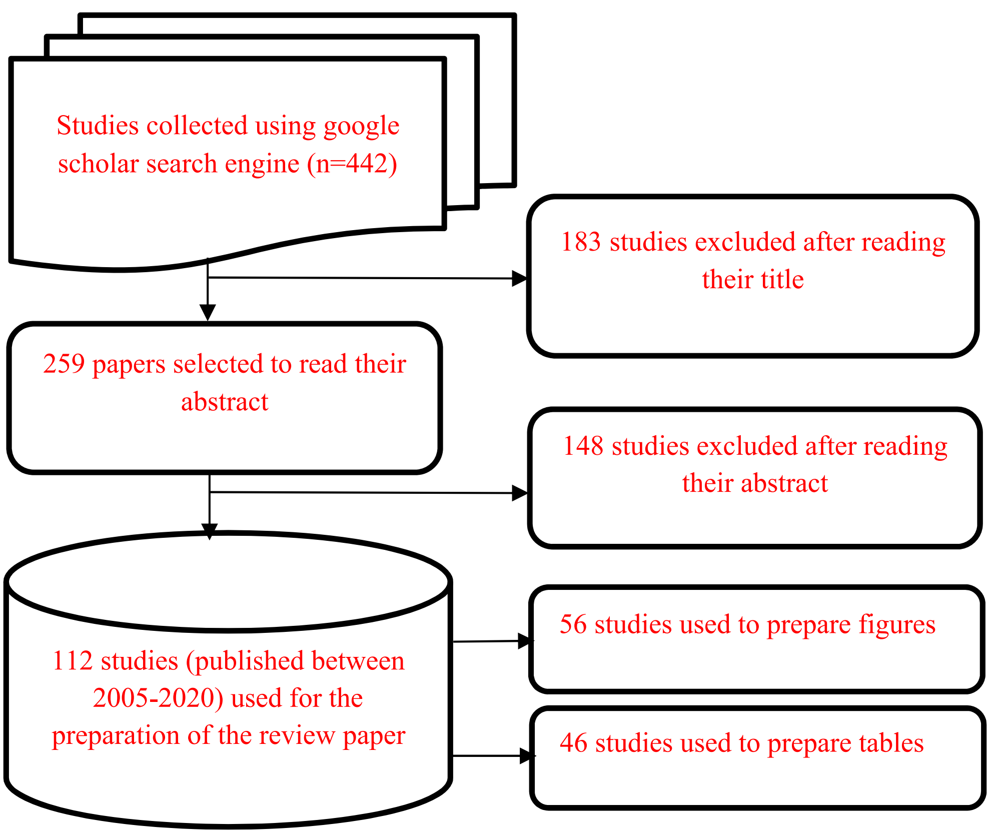

Fig. 1 Selection process of articles used for the review paper

multi-temporal satellite data at varied spatial resolution has immense importance in modeling the distribution of invasive species (Bradley 2014; Buermann et al. 2008; Paz-Kagan et al. 2019; Saatchi et al. 2008; Truong et al. 2017). Several studies used multi-temporal and high spatial resolution data for mapping and modeling of invasive species (Evangelista et al. 2008; Huang and Asner 2009; Ng et al. 2017; Shiferaw et al. 2019a; Somers and Asner, 2012; Wakie et al. 2014).

Importantly, ongoing developments in remote sensing technologies lead to steadily improved sensors that have the potential to better support predictions of invasive species (Buermann et al. 2008; Huang and Asner 2009; Leitão and Santos 2019; Truong et al. 2017). With the availability of freely available Copernicus satellites (in particular Sentinel-2), unprecedented detail is offered every 5 days at the equator, for the identification of invasive species, (Ng et al. 2017; Rajah et al. 2018, 2019; Thamaga and Dube 2018a, 2018b) as well as crop and vegetation mapping (Immitzer et al. 2019; Shoko and Mutanga 2017; Vuolo et al. 2018; Wessel et al. 2018). The tremendous additional potential is offered by a steadily growing fleet of commercial satellites, UAV, and hyperspectral sensors (Feilhauer et al. 2013; Piiroinen et al. 2018).

Spectral characteristics of remotely sensed images permit to identify invasive species from native ones (Asner et al. 2008; Bradley 2014; Ouyang et al. 2013; Singh et al. 2013; Somers and Asner 2012). This is possible as EO data capture distinct spectral features stemming from (subtle) spectral characteristics of leaves and canopies of *Morella faya* and *Psidium cattleianum* (Asner et al. 2008; Somers and Asner 2012), *Lantana camara* L. (Oumar 2016), and *Pteridium aquilinum* L. (Singh et al. 2013), *Spartina alterniflora* (Ouyang et al. 2013), and *Centaurea solstitialis* L. (Ge et al. 2006).

As an example, Fig. 2, presents the spectral characteristics of invasive (I), nitrogen-fixing invasive (IN), native (H), and nitrogen-fixing native (HN) species in Hawaii in varied seasons. It shows that invasive species have (I) higher reflectance than native species (H).

The provision of inter-annual satellite data offers additional profound advantages for the separation of individual species in different phenological cycles (Asner et al.

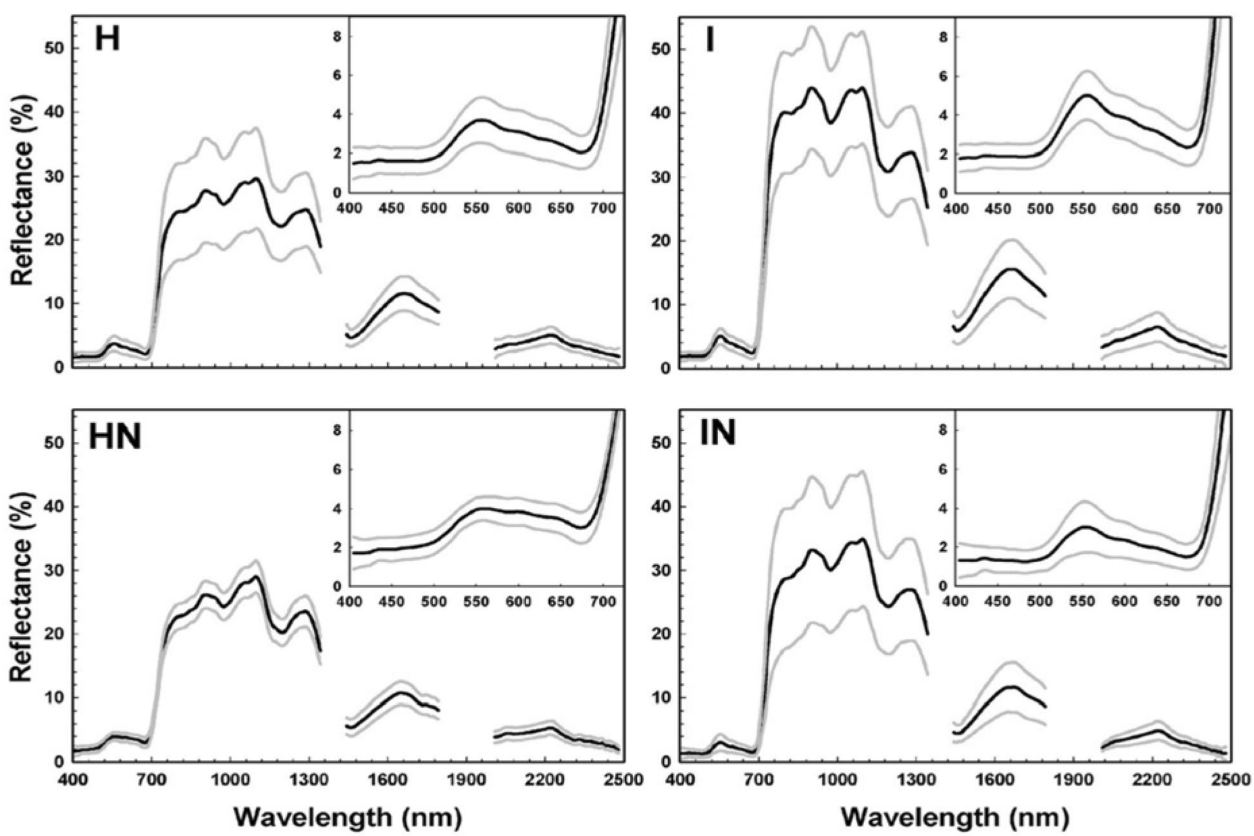

Fig. 2 Mean (± S.D.) spectral reflectance of Invasive (I), native Hawaiian non-nitrogen-fixer (H), and native nitrogen-fixer (HN), and invasive nitrogen fixer (IN) species (Asner et al. 2008). It clearly describes the spectral separability of invasive and native species and the role of remote sensing in its identification is very high

2008; Bradley 2014; Ge et al. 2006; Somers and Asner 2012). By observing the same target (pixel) multiple times during a growing cycle, additional (multi-temporal) indicators and features can be extracted, further benefiting the species identification. Understory invasive species that have a longer growing season in the early spring and late fall seasons for example can be identified from other trees using remote sensing (Bradley 2014).

Furthermore, EO data has a great potential to quantify environmental properties, biodiversity conservation, and detecting long-term change of ecosystem, often impossible to quantify otherwise (Cord et al. 2013; Prates-Clark et al. 2008; Taddese 2014). Moreover, the availability of multi-temporal remote sensing data permits ecologists to design SDM beyond climatic variables, by adding remotely sensed environmental variables (Cord and Rodder 2011). It has been pointed out that, incorporating remotely sensed environmental variables increases the acceptance of SDM for the prediction of invasive species (Leitão and Santos 2019). Climate and weather variables can also be derived from EO sensors and used for the prediction of invasive SDM, though published reports using this kind of application are limited (Deblauwe et al. 2016; Fernandez et al. 2013; Truong et al. 2017). Generally, the application of remote sensing products and their integration with climate data can create a better understanding of the field of SDM (Cord et al. 2013; Truong et al. 2017).

Contribution of bioclimatic data in SDM

For the better prediction of invasive species using SDM, it is necessary to include climate variables. Climate variables are one of the major contributing factors for predicting invasive species (Deblauwe et al. 2016; Fernandez et al. 2013; Re et al. 2020). SDMs perform better when climate data are used (either partially or completely) for model predictions (Ahmadi et al. 2020; Guisan et al. 2007; Truong et al. 2017; Zimmermann et al. 2007). Projection of invasive species distribution can also be possible using climate models (Heshmati et al. 2019). Unlike remote sensing, which mainly leverages the spectral signature of vegetation, climate data can provide information about environmental factors affecting species. Biophysical properties of vegetation can provide basic information on vegetation (Amiri et al. 2020; Deblauwe et al. 2016). For example, invasive species (*Acacia melanoxylon* R., *Gleditsia triacanthos* L.) often spread more widely in the dry season due to their unique biophysical characteristics to cope with water limitations (Godoy et al. 2011). Overlooking this will create inconsistencies in the prediction of invasive species distributions (Amiri et al. 2020; Bellard et al. 2018; Truong et al. 2017).

There are different sources of climate data sets that can be used for predicting invasive species. These data sources are either spatially interpolated (e.g.; WorldClim, Climatic Research Unit (CRU)), or satellite-based estimates of climatic variables (e.g.; Tropical Rainfall Measuring Mission (TRMM) and Moderate Resolution Imaging Spectrometer (MODIS). For example, in WorldClim, climate data is spatially interpolated using spline interpolation. This data is very popular to use for invasive SDM (Hijmans et al. 2005; Vega et al. 2017). However, there are some uncertainties in this product as it can be affected by closeness to weather stations, inter-annual variability, and topographic heterogeneity (Amiri et al. 2020; Fernandez et al. 2013). As a result, WorldClim as well as other station-based climate data is always uncertain for the prediction of invasive species distribution when ground weather stations are sparse (Amiri et al. 2020; Deblauwe et al. 2016). In such cases, the inclusion of satellite-based climate data improves the prediction of invasive species compared to models that only consider spatially interpolated climate data (Engler et al. 2013). Figure 3 describes a methodological flow chart on how to derivate bioclimatic variables from remotely sensed datasets. Even if remotely sensed climate data has great potential in providing better temporal and spatial resolution, the EO should always be examined and validated using station based climate data to check their accuracy (Loew et al. 2017; Richter and Hank 2012).

Integration of remote sensing and bioclimatic variables

Invasive SDM can benefit from using bioclimatic, survey, remote sensing data, and/or integration of all with SDM. Predicting the risk of invasive species at different scales can be quantified by readily available remote sensing products in conjunction with climate data and SDM (Wakie et al. 2014; Zimmermann et al. 2007). However, there is no consensus among scientists whether the integration of both datasets with SDM can enhance the prediction of species distribution or not. Some researchers argue that integration of both datasets with SDM has huge potential for efficient mapping of species distribution, compared to using remotely sensed or climate data alone (Arogoundade et al. 2019; Buermann et al. 2008; Prates-Clark et al. 2008). Other papers revealed that the integration of both datasets could even decrease the accuracy of modeling due to the quality of remotely sensed environmental variables (land cover) (Engler et al. 2013; Truong et al. 2017; Zimmermann et al. 2007).

In addition, a study by Truong et al. (2017), evaluated the performance of bioclimatic and remote sensing data separately and in combination using the MaxEnt model. They concluded that despite the challenges, the integration of both datasets had a promising future for

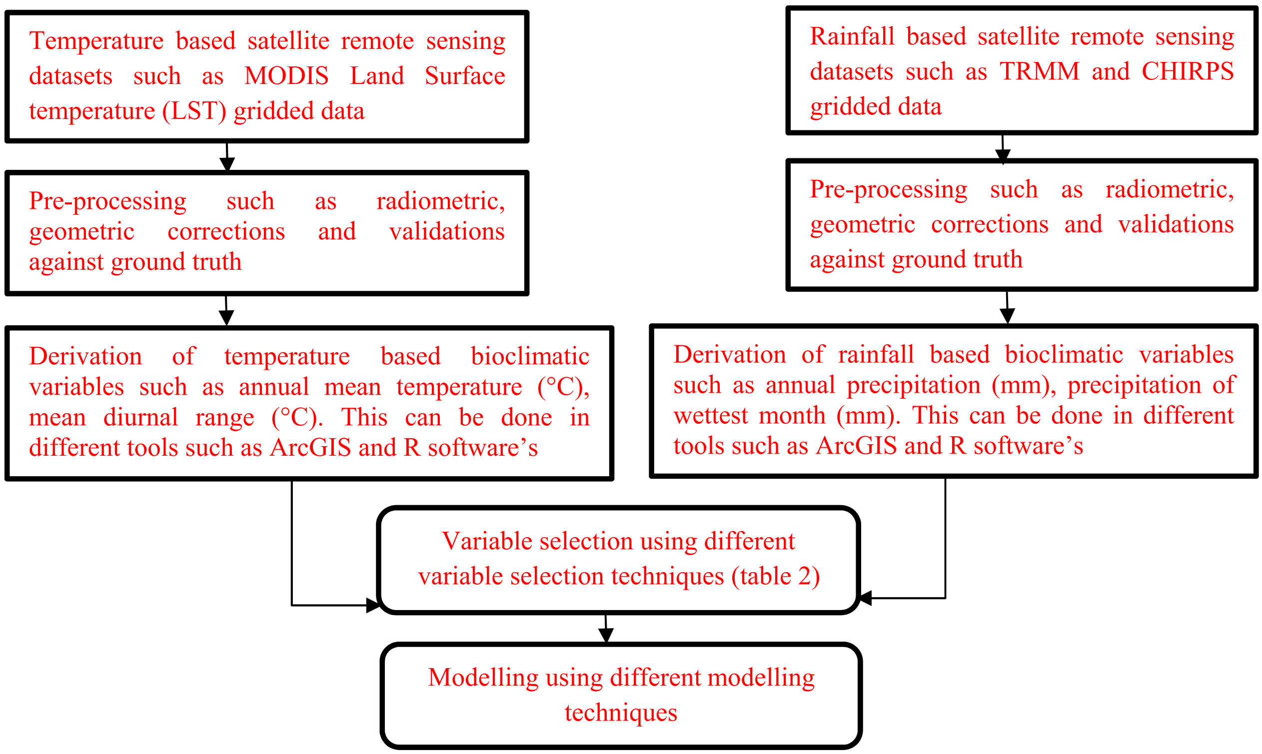

Fig. 3 Derivation of bioclimatic variables from remotely sensed data (adapted from Amiri et al. 2020; Deblauwe et al. 2016)

invasive SDM. Similarly, a study by Wakie et al. (2014), employed the MaxEnt model for integration of 19 bioclimatic variables with remotely sensed environmental parameters. Their study revealed that the integration of both datasets enhances the prediction of invasive species, particularly in areas where sufficient ground survey is difficult to undertake. Besides, a study by Feilhauer et al. (2012) combined 19 WorldClim bioclimatic data with MODIS NDVI time-series data to determine species distribution at coarse spatial resolution. They indicated that there is a strong improvement in species prediction when data are combined. However, completely ignoring EO variables and fully depending on climate data, or even excess of climate variables, might lead to unreliable results (Li et al. 2014). Hence, combining spatially interpolated ground stations with remotely sensed climate data has profound importance to accurately utilize their respective benefits sides while reducing their limitations. Besides, for an improved prediction of invasive species several requirements are of utmost importance:

- High spatial, temporal, and spectral resolution satellite products (Engler et al. 2013; Truong et al. 2017)
- Proper selection of environmental variables (Cord and Rodder 2011; Zimmermann et al. 2007), and
- Appropriate techniques to integrate both data sets (Cord et al. 2013; Guisan et al. 2007)

Several studies followed the below flowchart (Fig. 4) to integrate remote sensing and bio (climatic) variables for a particular species distribution modeling. The first requirement is to select remote sensing and bio (climatic) datasets. Once the datasets are selected the next step is to select the best-performed variables. After appropriate variables are selected the next step is to choose the modeling technique. Moreover, model performance can be computed using different approaches and best-performed variables from both models can be selected for the integration of remote sensing with bio (climatic) based model. The overall process to integrate both datasets is presented in Fig. 4.

Furthermore, a few papers are summarized in Table 1 that focuses on the prediction of species using both datasets. This yields insights on the kind of variables and SDM was most often used in combining the two datasets for the prediction of invasive species.

From Table 1, the following observations are extracted:

- There is poor agreement on the process of selecting variables and SDM for the prediction of invasive species distribution.

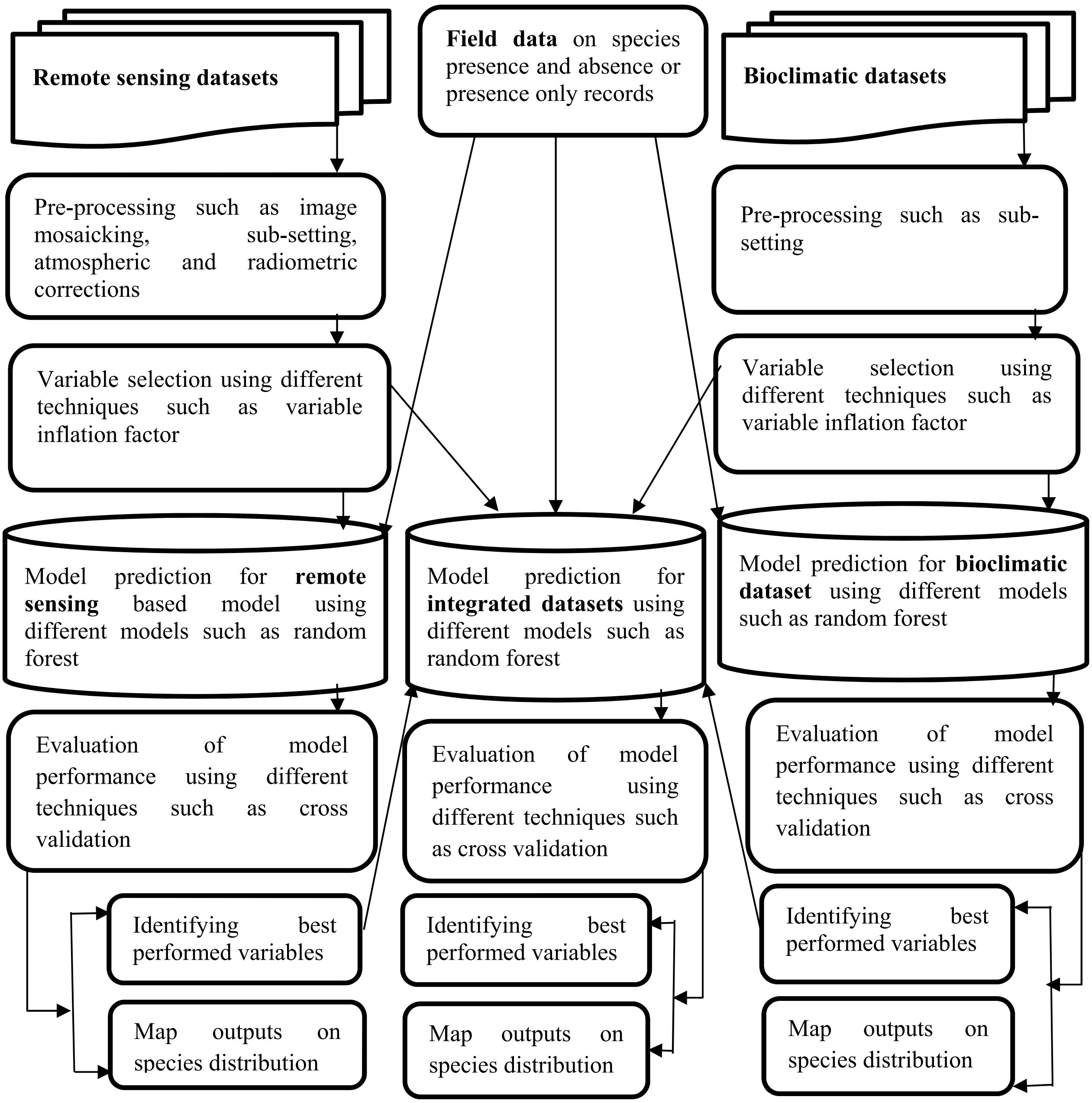

Fig. 4 Methodological flowchart used in several studies to integrate remote sensing and bioclimatic based models (adapted from Engler et al. 2013; Truong et al. 2017; Zimmermann et al. 2007)

- Justifications to select (or ignore) variables and SDM are overlooked.
- Although integration of remotely sensed environmental variables, bioclimatic variables, and SDM are highly valuable for studying species distribution, methods that specifically work on the integration of EO and bioclimatic variables are requiring.

Experiences in Ethiopia

More than 35 invasive alien species are reported in Ethiopia (Shiferaw et al. 2018; Tamiru 2017). However, only a few attempts were made to map their distribution. For example, *Prosopis* (Ayanu et al. 2014; Hundessa and Fufa 2016; Shiferaw et al. 2019a; Wakie et al. 2014), *Mimosa diplotricha* (Wakjira 2011); *Parthenium hysterophorus*

Table 1 Variables, SDM, and species used in combination of both datasets of some researches

Variables	SDM	References
Climate variables (mean annual rainfall, mean monthly temperature, monthly land surface temperature during day and night time) *Remote sensing variables* (monthly land surface temperature during the day and nighttime, panchromatic reflectance, red reflectance, near-infrared reflectance, shortwave infrared band 6 reflectance, NDVI, elevation, slope, relief, landform, rugged, and distance to River) Survey data (distance to road, distance to village)	Random Forest (RF)	Shiferaw et al. (2019a)
Climate variables (temperature seasonality) *Remote sensing variables* (elevation, landform, lithology, distance to water, distance to urban areas) *Survey data* (distance to road)	RF, MaxEnt, logistic regression, Bayesian networks, Ensemble	Ng et al. (2018)
Climate variables (19 WorldClim bioclimatic variables) *Remote sensing variables* (bedrock, bulk density, cation exchange capacity, soil texture fraction clay, coarse fragments volumetric, soil organic carbon stock, soil organic carbon content, soil pH, soil texture fraction silt, soil texture fraction sand, land cover, gross primary productivity, coefficient of variation, gross primary productivity, elevation)	MaxEnt	Truong et al. (2017)
Climate variables (WorldClim variables and MODIS land surface temperature) *Remote sensing variables* (long term EVI, surface reflectance including blue, red, near-infrared, and middle infrared wavelengths and land cover data)	MaxEnt	Cord et al. (2014a, b)
Climate variables (WorldClim bioclimatic variables) *Remote sensing* variables (monthly NDVI and EVI), elevation and slope	MaxEnt	Wakie et al. (2014)
Climatic variables (growing degree days, mean temperature of the coldest month, summer moisture index, summer sum of precipitations, winter sum of precipitations, yearly solar radiation, summer solar radiation, soil water balance, topographic wetness index, topographic position *Remote sensing variables* (NDVI, Renormalized Difference Vegetation Index (RDVI), Modified Simple Ratio index (MSR), Modified Chlorophyll Absorption Ratio Index 1 (MCARI1), blue band, green band, red band, near-infrared band, slope and topographic position, distance to the nearest water body)	9 SDM including Generalized Linear Model (GLM), RF, Artificial Neural Network, and Ensemble model	Engler et al. (2013)
Climatic variables (WorldClim bioclimatic variables) *Remote sensing variables* (NDVI)	Partial Least Squares regression	Feilhauer et al. (2012)
Climatic variables (WorldClim bioclimatic variables) *Remote sensing variables* (LAI, vegetation density, seasonality, and net primary productivity, forest cover, and heterogeneity, surface moisture, and roughness (forest structure), seasonality, topography, and ruggedness)	MaxEnt	Buermann et al. (2008)
Climatic variables (WorldClim bioclimatic variables) *Remote sensing variables* (monthly NDVI, monthly LAI, percent tree cover, scatter meter backscatter monthly composites at 1 km, elevation)	MaxEnt	Prates-Clark et al. (2008)
Climatic variables (Bioclimatic variables derived from DAYMET) *Remote sensing variables* (NDVI)	GLM	Zimmermann et al. (2007)

L. (Beyene and Tessema 2015) are to mention most. Out of the papers retrieved for this review, 23 focused on the distribution of invasive species in Ethiopia. However, only seven of those studies employed satellite data or bioclimatic data and/or a combination of both datasets. The rest used survey data to map the distribution of invasive species, which is very difficult and time-consuming. For example, (Beyene and Tessema 2015; Hundessa and Fufa 2016; Tola and Tessema 2019; Wakjira 2011) followed the same methodology for various invasive species. These authors gathered survey data at 10 km intervals; ignoring remote sensing and bioclimatic variables.

In the Afar region Ayanu et al. (2014), employed long term satellite data to provide basic information on the historical distribution of *Prosopis* and land-use changes and conclude that the role of long term remote sensing data has great contribution to manage invasive *Prosopis* distribution. In addition, Shiferaw et al. (2019a) used long term satellite data to quantify *Prosopis* distribution and its impact on land-use changes and ecosystem services and conclude that remote sensing data has a great contribution to quantify land cover changes and ecosystem services. Similarly, Wakie et al. (2014) and Shiferaw et al. (2019a) took into account both bioclimatic and remotely sensed variables for prediction of invasive *Prosopis* using MaxEnt and RF models respectively, and conclude that the use of integrated datasets has great importance in studying invasive species distribution and prediction. Shiferaw et al. (2019a) provided a comparison study on the performance of SDM in the prediction of *Prosopis* and conclude that the use of the best-performing machine learning algorithm provides better accuracy than the ensemble model. Moreover, West et al. (2014) provided extensive information on the potential distribution of *Prosopis* in Ethiopia using the Landsat 8 and MaxEnt model (Fig. 5). Overall, remotely sensed satellite data and bioclimatic variables have been scarcely used for mapping invasive species distribution in Ethiopia, indicating that the use of these data is still in its infancy in the country.

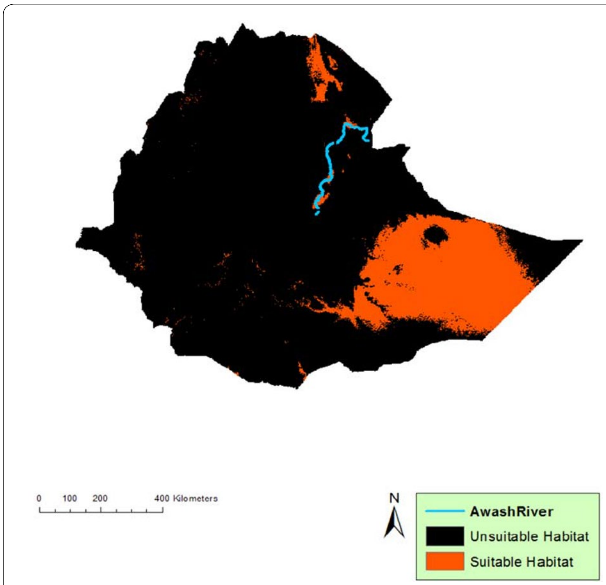

Fig. 5 Habitat suitability for distribution of *Prosopis* in Ethiopia using combined (EO and climate parameters) and MaxEnt model (West et al. 2014)

Challenges in the combination of EO and climate datasets

Combining EO and climate data is not without challenges. Major problems relate to:

1. The nature of species (invasive species are more difficult than native ones) (Evangelista et al. 2008; Václavík and Meentemeyer 2012),
2. Poor methodology in the selection of variables (Guisan et al. 2007),
3. Inappropriate selection of models (Guisan et al. 2007),
4. Quality issues of the data (Cord and Rodder 2011; Truong et al. 2017; Tuanmu and Jetz 2014), and
5. The difficulty of interpretation of remotely sensed data (Cord and Rodder 2011).

Unlike other species, mapping and modeling of invasive species require the highest care as it violates major assumptions known in SDM (Václavík and Meentemeyer 2012). Besides, remote sensing limitations such as failure to detect all plants, the trade-off between spatial with temporal and spatial with spectral resolutions negatively affects SDM application (He et al. 2015). It is also pointed out that, it is difficult to find reliable, high-quality land cover remotely sensed information at any time is also a great challenge (Bradley and Fleishman 2008; Prates-Clark et al. 2008). In addition to quality concern, the interpretation of remotely sensed signals is also challenging and disturbs the accuracy of other variables (Cord and Rodder 2011; Zimmermann et al. 2007).

Another major challenge relates to the fact that remote sensing toolset consists of sensors with widely varying sensor characteristics (Saatchi et al. 2008; Tuanmu and Jetz 2014). For example, the spatial resolution has a strong impact on the prediction of invasive species. The coarse spatial resolution of satellites limits certainly details of the map, whereas fine resolution brings its own problem in relation to cost, preprocessing, and intra-class variability (Boyd and Foody 2011).

Sample size and design in presence and absence data is also another challenge in SDM (Fithian et al. 2014; Rocchini et al. 2015a, b). Most researchers used the only presence or pseudo absence data for modeling prediction of species distribution as absence data for invasive species are difficult to obtain (Ng et al. 2018; Václavík and Meentemeyer 2012). In addition, employing a reasonable sample size using appropriate techniques can enhance the prediction of species distribution (Xie et al. 2008).

Proper selection of SDM can significantly increase the efficiency of prediction. Selecting a specific model needs to provide justifiable criteria as it can affect the result (Sakate and Kashid 2016). However, in most cases, models are selected without providing significant justification.

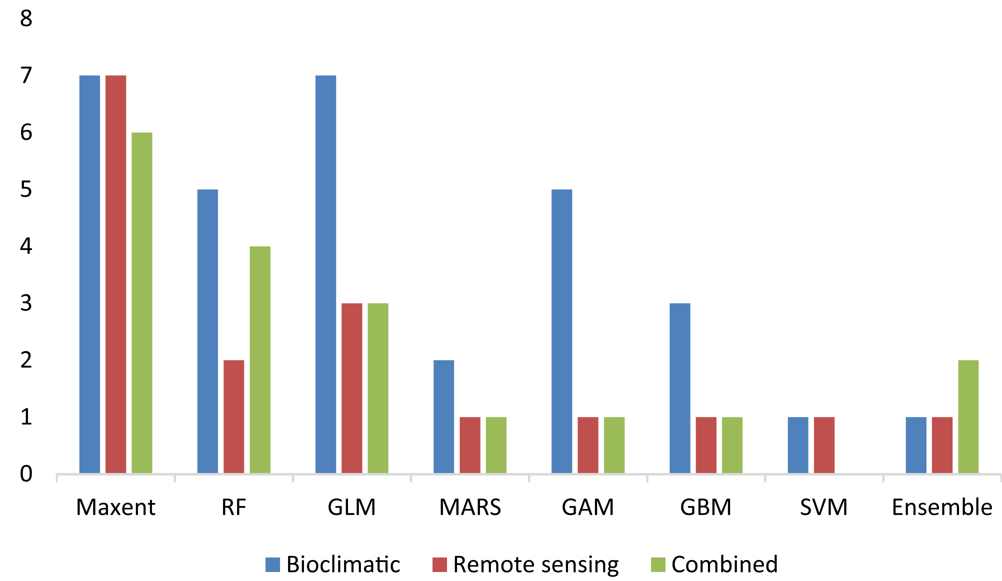

Fig. 6 Species distribution models (SDM) and their use of bioclimatic, remote sensing, and combined data. Maxent, GLM, MARS, GAM, and GBM use presence-only data whereas RF and SVM use both presence and absence data

Table 2 Variable selection techniques used in the integration of remote sensing and bioclimatic based variables

S.no	Variable selection methods	References
1	Correlation (Pearson, Kendall, Spearman)	Buermann et al. (2008); Engler et al. (2013); Gormley et al. (2011); Ng et al. (2018); Saatchi et al. (2008); Truong et al. (2017); Wakie et al. (2014); West et al. (2014); Zimmermann et al. (2007)
2	Principal component analysis	Deblauwe et al. (2016); Feilhauer et al. 2012; Jensen et al. (2020)
3	Variance inflation factor	Ahmadi et al. (2020); Ng et al. (2018); Shiferaw et al. (2019c)
4	Weighted mean fitted analysis approach	Shiferaw et al. (2019a)
5	Permutation importance	Wilson et al. (2013)
6	Expert knowledge	Beaumont et al. (2005); Jones (2012); Ng et al. (2018)

Some researchers use single models for mapping and predicting invasive species distribution (e.g.; MaxEnt model used by Truong et al. 2017; Wakie et al. 2014). Some other researchers first compare different models and then use the best performing model for prediction (e.g. Engler et al. 2013; Ng et al. 2018; Shiferaw et al. 2019a). Other papers suggest that ensemble models are preferable over single models (e.g.; Früh et al. 2018; Ng et al. 2018)). Figure 6 depicts various SDM employed bioclimatic data, remote sensing data, or their combination. Maximum entropy (MaxEnt), RF, GLM, Multivariate Adaptive Regression Splines (MARS), Generalized Additive Model (GAM), Gradient Boosted Model (GBM), ensemble model, and Support Vector Machine learning (SVM) are analyzed within about 49 studies.

As indicated in Fig. 5, GLM and MaxEnt are largely used in bioclimatic and remote sensing based research. This might be attributed to the challenge of collecting absence data for invasive species (Ng et al. 2018; Václavík and Meentemeyer 2012). MaxEnt is popular in SDM, through evaluating the quality of SDM is difficult (Filho et al. 2010; West et al. 2014). From the presence and absence of data models, the RF is the most employed model in bioclimatic, remote sensing, and integrated datasets.

Variable selection methods

To ensure a non-bias variable selection, it is important to determine variable correlation through a set of standardized tests (Phillips et al. 2006). It is hard to know; however, in which environmental variables are most appropriate and useful for predicting species distribution (Aranda and Lobo 2011). The importance of environmental variables is dependent on the type, nature of species, and its topography (Cord et al. 2013). Due to this, we can't see consistent variables used by researchers for

Table 3 Variables and their data sources used for integrating (bio) climatic and remote sensing data

Variables	Data sources	References
Bioclimatic variables	WorldClim database	Buermann et al. (2008); Cord et al. (2014a, b); Feilhauer et al. (2012); Ng et al. (2018); Prates-Clark et al. (2008); Truong et al. (2017); Wakie et al. (2014)
Long term NDVI	Landsat, MODIS, Airborne Digital Sensor	Engler et al. (2013); Evangelista et al. (2008); Feilhauer et al. (2012); Ng et al. (2018); Shiferaw et al. (2019a); Shiferaw et al. (2019c); Wakie et al. (2014)
Long term EVI	MODIS	Cord et al. (2014a, b); Wakie et al (2014)
LAI	MODIS	Buermann et al. (2008); Engler et al. (2013); Prates-Clark et al. (2008); Saatchi et al. (2008)
Near-Infrared band	Landsat, Airborne Digital Sensor	Engler et al. (2013); Shiferaw et al. (2019a); Zimmermann et al. (2007)
Land cover	Tuanmu and Jetz 2014	Truong et al. (2017); Tuanmu and Jetz (2014)
Vegetation density	Tuanmu and Jetz 2014	Truong et al. (2017); Buermann et al. (2008)
Elevation	SRTM, ASTER, GTOPO30	Bradley and Mustard (2006); Buermann et al. (2008); Ng et al. (2018); Prates-Clark et al. (2008); Saatchi et al. (2008); Shiferaw et al. (2019a); Truong et al. (2017)
Slope	SRTM, ASTER	Ng et al. (2018); Shiferaw et al. (2019a)
Distance from road	Survey data	Ng et al. (2018); Shiferaw et al. (2019a)
Distance from water	SRTM	Engler et al. (2013); Ng et al. (2018); Shiferaw et al. (2019a)
Distance to Village	Landsat, Survey data	Ng et al. (2018); Shiferaw et al. (2019a)

the prediction of species distribution even with similar climate, species, and study locations. The selection of significant variables is a crucial step and can determine the accuracy of models (Beaumont et al. 2005; Elkind et al. 2019). The following are (Table 2) among the variable selection methods used in several studies.

Furthermore, the following variables were selected in many invasive species prediction studies using the above variable selection techniques.

From Table 3, bioclimatic variables, long-term NDVI, EVI, elevation, and slope are most widely used for the prediction of invasive species. Generally, challenges in integrating bioclimatic and remote sensing variables with SDM are the results of the overall problems listed above.

Opportunities for combining climate and EO datasets

Despite its challenges, integration of climate and EO data sets with SDM for invasive species has a promising future. The availability of fine resolution and multi-temporal remote sensing data is a unique opportunity for SDM (Cord et al. 2014a, b). This is particularly the case as more and more EO data become freely available, and both data quality and information content increase through time (Saatchi et al. 2008).

The development of techniques to check and validated the accuracy of SDM is also an important research opportunity (Václavík and Meentemeyer 2012). Many SDM that support the adoption of remote sensing data for invasive species distribution are available. Ensemble SDM is considered as a major way forward in the field of SDM (Früh et al. 2018; Ng et al. 2018).

The application of Unmanned Aerial Vehicle (UAV) in SDM is a great asset as it provides fine resolution at minimum cost for species-level monitoring (Fritz et al. 2018), as long as the area of interest is relatively small (< 1km^2). An image fusion technique that integrates different sensors to provide better temporal and spatial resolution is considered as a good forward for better prediction (Xie et al. 2008). Advancements in satellite-based (bio) climate data, and techniques to integrate with ground-based weather stations, are also considered useful for better prediction of invasive species (Amiri et al. 2020; Deblauwe et al. 2016; Fernandez et al. 2013) (Table 4).

Recommendations

Through advancements in remote sensing science, technology, application, and machine learning provide a better prediction of invasive species, more research in ecology and remote sensing experts is needed. This includes on one hand a better understanding of distribution patterns of invasive species and on the other hand an improved knowledge about the most important spectral bands and acquisition times to permit an effective and robust identification of the target species. There is moreover a strong need to develop basic working principles and procedures in the selection of environmental variables and SDM. Such a selection needs to consider the nature of species, SDM, and available datasets.

On the remote sensing side, detailed information can be obtained at high spatial and temporal resolution owing to the open access policy of most satellite data owners. Freely available Sentinel-2, Landsat, and MODIS data are particularly necessary for developing countries as the cost of high-resolution images are difficult to justify. The fusion of image data from multiple sensors will lead to an

Table 4 Climate and EO datasets are used for the prediction of species distribution modeling

Climate and EO datasets	Description	Spatial resolution	Accessibility	References
WorldClim	It is a world gridded climate data that contains 19 bioclimatic variables. It is designed based on the spline interpolation of long-term station climate data	$1 km^2$	Free	Bucklin et al. (2016); Fernández and Hamilton (2015); Heshmati et al. (2019); Truong et al. (2017)
TRMM	It is a joint mission from NASA and Japan developed in 1997 to provide precipitation data	5 km	Free	Saatchi et al. (2008)
MODIS	It is an instrument that collects remotely sensed data starting from 2000 to the present using both Terra and Aqua satellites	250 m to 1 km	Free	Cord and Rodder (2011); Feilhauer et al. (2012); Truong et al. (2017);
Landsat 5	It is launched in 1984, provides an earth image that can be helpful for different applications	30 m	Free	Dubula et al. (2016); West et al. (2014)
Landsat 7	It is launched in 1999, equipped with an enhanced thematic mapper plus provides earth observation using 8 bands	30 m	Free	Evangelista et al. (2008); Lima et al. (2019)
Landsat 8 OLI (Operational Land Manager)	It, is launched in 2013, has 9 spectral bands with 16-day temporal resolution using Landsat 8 OLI and Thermal Infrared Sensor	30 m	Free	Khare et al. (2019); Meroni et al. (2017)
Sentinel 1	It is designed and developed by the European satellite agency and funded by the European Commission	5 m to 40 m	Free	Rajah et al. (2019)
Sentinel 2	It was launched in 2015 (Sentinel 2A) and 2017 (Sentinel 2B) providing data at five days (at the equator) temporal resolution having 13 spectral bands	10–60 m	Free	Arogoundade et al. (2019); Fritz (2018); Kiala et al. (2019); Lima et al. (2019); Ng et al. (2017)
Spot 6	SPOT 6 an optical imaging was launched in 2012 aimed for different applications	1.5–6 m	Commercial	Khare et al. (2019)
SRTM	Shuttle Radar Topographic Mission (SRTM) aimed to provide topographic data for 80% of the land surface was launched in 2000. It can be used for different applications including hydrology and vegetation	30–90 m	Free	Girma et al. (2015); Hernandez et al. (2006); Václavík and Meentemeyer (2012); Wakie et al. (2014)
GTOPO30	Global Topographic Data (GTOPO30) is a Global Digital DEM since 1993	1 km	Free	Truong et al. (2017)
World view 2	It provides high-resolution imagery of panchromatic and eight multispectral bands. It is used for different applications	1.8 m	Commercial	Elkind et al. (2019); Paz-Kagan et al. (2019)
LiDAR	Light Detection And Ranging (LiDAR) commonly used to provide high-resolution maps using laser light	On-demand	Commercial	Sankey et al. (2017)
Aerial photograph	The aerial photograph is defined as taking photographs from aircraft or flying objects. It provides high-resolution imagery for different applications	On-demand	Commercial	Müllerová et al. (2017)

Table 4 (continued)

Climate and EO datasets	Description	Spatial resolution	Accessibility	References
SAR	Synthetic Aperture Radar (SAR) is a type of radar aimed to provide fine resolution radar data that can be used for different applications	It depends on the type of SAR	Commercial	Rajah et al. (2018)
Rapid Eye	It is a group of five earth observation satellites aimed at providing high-resolution images at five spectral bands	6.5 m	Commercial	Khare et al. (2019)
Pleiades	The Pleiades is a group of two satellites that provide global data at 26 days of temporal resolution	0.5–2 m	Commercial	Ng et al. (2017)
QuikSCAT	QuikSCAT satellite is a microwave radar aimed to measure near-surface wind speed and direction	2.25 km	Free	Prates-Clark et al. (2008); Saatchi et al. (2008)
Earth observing-1 Hyperion (EO-1)	It was launched in 2000 aimed at providing different applications including the spectral definition of forest canopy and structure. Hyperion and Advanced Land Manager are the two main instruments used in EO-1	30 m	Free	Somers and Asner (2012)

important advancement, as the integrating of different sensors will not only permit a better temporal and spatial resolution but will also leverage synergies from different band settings (Rajah et al. 2018). Furthermore, evaluating and boosting the capability of machine learning algorithms for the prediction of invasive species is necessary.

Bioclimatic variables derived from the WorldClim database are a good source of information for the prediction of invasive species. However, these records need to be updated using recent climate data as the latest version considers interpolation of climate data only from 1970 to 2000. Besides, there is also a need to integrate bioclimatic variables of WorldClim with remotely sensed bioclimatic variables to obtain a better spatial and temporal resolution. Moreover, evaluating the integration of remotely sensed environmental variables with bioclimatic variables in the prediction of invasive species is also necessary. Several studies (Truong et al. 2017; Cord et al. 2014a, b; Engler et al. 2013; Buermann et al. 2008) tried to evaluate the efficiency of bioclimatic and remote sensing variables separately and in combination. However, similar studies should be motivated for different species and geographic areas.

Conclusion

The integration of remote sensing and bioclimatic variables with SDM has the potential to play a key role in mapping and prediction of invasive species especially in arid and semi-arid areas where accessibility of environmental data is a challenge. Both datasets have their own advantages and hence it can be expected that the integration of both datasets provides richer and more predictive information. In data-poor regions where survey data is sparse, remote sensing can provide useful information due to its multi-temporal, spatial, and spectral resolution, and the resulting possibility to identify invasive species and to map certain environmental variables. On the other side, bioclimatic variables can solve some of the limitations of remotely sensed variables in relation to climate data. Hence, persistent information can possibly be obtained through the integration of both data sets. The integration of both datasets should in our opinion—and supported by the research community—be considered as a viable tool to increase the efficiency of SDM even though more research is required. It is also necessary to give due attention to presenting the guiding principle that helps to select variables and models for better accuracy of SDM. Furthermore, it is also necessary to validate remotely sensed (bio) climatic datasets and their integration with (spatially interpolated climate) data.

Abbreviations

SDM: Species Distribution Modelling; EO: Earth Observation; NDVI: Normalized Difference Vegetation Index; LAI: Leaf Area Index; EVI: Enhanced Vegetation Index; CRU: Climatic Research Unit; TRMM: Tropical Rainfall Measuring Mission; MODIS: Moderate Resolution Imaging Spectrometer; MSR: Modified Simple Ratio Index; RDVI: Renormalized Difference Vegetation Index; MCARI1: Modified Chlorophyll Absorption Ratio Index; GLM: Generalized Linear Model; RF: Random Forest; GAM: Generalized Additive Model; GBM: Gradient Boosted Model; SVM: Support Vector Machine; MARS: Multivariate Adaptive Regression Splines; UAV: Unmanned Aerial Vehicle; OLI: Operational Land Manager; SRTM: Shuttle Radar Topographic Mission; GTOP30: Global Topographic data; LiDAR: Light Detection and Ranging; SAR: Synthetic Aperture Radar.

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Authors' contributions

All authors made a valuable contribution. NA designed and wrote the methodology, collect literature, carried out data analysis, and wrote the draft manuscript; CA refines the methodology, support in collecting additional literature, rewrite the manuscript; and WZ supports in refining methodology, collection of additional literature, and refining the manuscript. All authors read and approved the final manuscript.

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The authors declare that there is no conflict of interest.

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