No place to hide: Rare plant detection through remote sensing

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Abstract

Aim: Detection of rare species is limited by their intrinsic nature and by the constraints associated with traditional field surveys. Remote sensing (RS) provides a powerful alternative to traditional detection methods through the increasing availability of RS products. Here, we assess the capacity of RS at high and medium resolution to detect rare plants with direct and indirect approaches, and how the performance of RS can be influenced by the characteristics of species.

Methods: An extensive literature review was conducted to synthesize the use of RS to detect or predict rare plant occurrence at high and medium resolution (<30 m and 30–300 m, respectively). The concept of “rarity” was based on Rabinowitz’s rare species classification. The literature review was performed in Scopus for the period 1990–2020.

Results: While direct detection is often limited, it is possible with high and very high spatial resolution data for rare plants with distinctive traits. RS is also able to capture biophysical conditions driving rare plant distributions, which can indirectly provide accurate predictions for them. Both approaches have the potential to discover new populations of rare plants. RS can also feed SAMs of rare plants, which combined with SDMs can provide a valuable approach for rare plant detection. While direct detection is limited by the space occupied by a species within its habitat and its morphological, phenological and physiological characteristics, the predictive performance of RS-based SDMs (indirect detection) can be influenced by habitat size, habitat specificity and phenological features of rare plants. Similarly, model predictive performance can be influenced by the rarity form of the target species according to the rarity classification criteria.

Main conclusions.

With this synthesis, the strong potential of RS for the purposes of detection and prediction of rare plant has been highlighted, with practical applications for conservation and management.

KEYWORDS
direct detection, endemism, new populations, predictive models, rarity, remote sensing predictors, SDMs, sensor, spatial resolution

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1 | INTRODUCTION

Rare plants are recognized as a conservation priority as they are key components of biodiversity, increasing and promoting species richness and functional diversity at different scales (Bracken & Low, 2012; Kearsley et al., 2019; Leitao et al., 2016; Mouillot et al., 2013; Patykowski et al., 2018; Režek et al., 2016; Umana et al., 2017) and supporting ecosystem functioning and services (Dee et al., 2019; Hooper et al., 2012; Jolls et al., 2019; Soliveres et al., 2016; Xu et al., 2020; Zavaleta & Halvey, 2004). While rare plants are especially vulnerable to extinction (Sykes et al., 2019; Weisser et al., 2017; Zhang, 2019), implementing effective conservation measures is limited by the quality and quantity of data available on them. The low detectability often associated with rare plants due to their low prevalence (Lomba et al., 2010) and/or sparse and small populations (Guisan et al., 2006; Menon et al., 2010) results in notable knowledge gaps on important aspects of their ecology (Lyons et al., 2005; Wu & Smeins, 2000) or spatial distribution patterns (Gogol-Prokurat, 2011; MacDougall & Loo, 2002). Furthermore, remoteness of terrain, as well as economic and logistic constraints, can make field studies of rare plants unfeasible (Le Lay et al., 2010).

Remote sensing (hereafter “RS”; see Box 1) has become an important tool for the scientific community in addressing these field survey issues, offering an inexpensive method to assess biodiversity characteristics over large areas at regular intervals (Corbane et al., 2015; Kerr & Ostrovsky, 2003). RS allows both (i) detection of individual biological entities, species assemblages or ecological communities (direct approach) and (ii) acquisition of biodiversity-related information from environmental proxies (indirect approach; Turner et al., 2003). The indirect approach provides a powerful alternative that, in combination with species distribution models (hereafter “SDMs”), enables users to infer species’ habitat preferences or predict species distributions (Buechling & Tobalske, 2011; Guillaumet-Arroita et al., 2015).

RS has become a widely applied tool in plant studies (e.g. Asner, Hughes, et al., 2008; Asner et al., 2008; Kopeć et al., 2020; Wan et al., 2020) with the increasing availability of RS products that capture a wide variety of environmental features (Corbane et al., 2015; Kerr & Ostrovsky, 2003; Turner et al., 2003). Studies using RS to focus specifically on rare plants remain uncommon, although their number has been growing in recent years (e.g. Arenas-Castro et al., 2019; Gonçalves et al., 2016; Zhu et al., 2016). As an emerging research field, the potential benefits of RS for the detection of rare plants remain unclear. In this context, the objectives of this synthesis were i) to evaluate the capacity for RS to detect and predict the occurrence of rare plants, and ii) to assess how the main characteristics of rare plants influence the performance of RS. Our concept of “rarity” is based on Rabinowitz’s rare species classification (Rabinowitz, 1981), which discerns seven rarity types based on three dichotomous criteria: geographic distribution range (large versus. restricted), habitat specificity (wide versus. narrow), and local population size (large versus. small). Since these criteria are characterized by a continuous transition among the different rarity categories (absence of defined thresholds) and make abstraction of causes of rarity, it is a flexible

**BOX 1** Remote sensing (RS)-related terms and abbreviations

- **Active sensor:** Emits radiation and measures the energy returned after being reflected.
- **Hyperspectral sensor:** Discriminates many narrow spectral bands across the electromagnetic spectrum.
- **Multispectral sensor:** Discriminates a few relatively broad spectral bands across the electromagnetic spectrum.
- **Multi-temporal imagery:** Multiple images of the same location acquired on different dates.
- **Passive sensor:** Measures energy emitted or reflected by the earth’s surface without emitting radiation.
- **Remote sensing:** Methods of detecting the electromagnetic radiation coming from the earth’s surface via aircraft or satellite sensors (Campbell & Wynne, 2011; Turner et al., 2003).
- **Spatial resolution:** Basic unit of captured information that corresponds to pixel or grain size and determines the minimum spatial scale at which variation can be observed. Categories of spatial resolution in this paper follow Corbane et al. (2015): very high resolution <3 m; high resolution 3–29 m; medium resolution 30–300 m; and low resolution >300 m.
- **Spectral resolution:** Width (and thus number) of bands into which the electromagnetic spectrum is divided.
- **Temporal resolution:** Measure of the revisit frequency of the sensor at the same location.
- **Sensors abbrev.:** AISA, Airborne Imaging Spectrometer for Applications; AMSR-E, Advanced Microwave Scanning Radiometer for Earth Observing System; ASTER, Advanced Spaceborne Thermal Emission and Reflection Radiometer; CMOS, Complementary Metal Oxide Semiconductor; HiFIS, High-Fidelity Imaging Spectroscopy; LiDAR, Light Detection and Ranging; LISS, Linear Imaging and Self Scanning; MERIS, Medium-Resolution Imaging Spectrometer; MODIS, Moderate-Resolution Imaging Spectroradiometer; SPOT, Satellite for Observation of Earth; SRTM, Shuttle Radar Topography Mission; SSM/I, Special Sensor Microwave Imager; TMI, TRMM Microwave Imager.
- **RS data/predictor abbrev.:** EVI, Enhanced Vegetation Index; GCC, Green Chromatic Coordinate; mNDWI, modified Normalized Difference Water Index; NCVI, Normalized Coastal Vegetation Index; NDVI, Normalized Difference Vegetation Index; NDWI, Normalized Difference Water Index; NGVI, Normalized Green Vegetation Index; NIR band, Near Infrared band; PRI, Photochemical Reflectance Index; RENDVI, Red Edge Normalized Difference Vegetation Index; SAVI, Soil-Adjusted Vegetation Index; SIPI, Structurally Insensitive Pigment Index; SWIR band, Shortwave Infrared band; Thermal IR band, Thermal Infrared band; TNDVI, Transformed Normalized Difference Vegetation Index.
concept for the continuous and complex nature of rarity. While we will discuss the capacity for RS to feed into and improve SDMs of rare plants, a comparative evaluation of the performance of different modelling techniques is beyond the scope of this synthesis and has been addressed in the literature (e.g. Elith & Burgman, 2002; Williams et al., 2009; Wiser et al., 1998). We will discuss the suitability of predictive performance measures for rare plant modelling studies, as well as the potential influence of rarity types on RS effectiveness and the detection of target species in the field (hereafter “practical utility”).

2  METHODS

An extensive literature review was conducted to synthesize the use of RS to detect or predict rare plant distributions. Although the term “remote sensing” is defined precisely in the literature, the concept of “remote sensing variables or predictors” remains ambiguous. Henceforth, RS predictors refer to: i) continuous spectral information obtained from aircraft or satellite sensors, either as raw spectral bands or as indices; ii) landcover products developed from the classification of spectral information; and iii) digital elevation models ("DEMs") developed from satellite or airborne sensor information as well as derived topographic indices. In cases where the information on the origin or generation process of the predictors were not provided nor accessible, they were considered as non-RS predictors, except for DEM-derived topographic indices. DEMs are commonly generated through RS techniques and their direct survey is rare; therefore, when the DEM source is other than RS, it is usually stated in the literature (e.g. Padalia et al., 2010; Sperduto & Congalton, 1996).

A literature review of peer-reviewed articles was carried out using the search engine Scopus by combining terms related to plant with keywords related to RS and rarity or species at risk for the period 1990–2020. Studies targeting species at risk were included with keywords related to RS and rarity or species at risk for the period 1990–2020. A total of 1,112 articles matched our search criteria. These articles were first classified by RS approach (direct or indirect) and then by spatial resolution used (Table 1).

3 | REMOTE SENSING DIRECT APPROACH—DETECTION OF RARE PLANTS

The direct detection of rare plants and their traits through RS requires previous knowledge of a species’ ecology and distribution, as well as the use of high spatial resolution imagery. Despite these constrains, 19 articles following this RS approach were found (Table 1; Figure 1). Direct detection can be carried out either by visual identification or by image classification methods that allow the detection of distinctive spectral features of the target species. Specifically, Fletcher and Erskine (2012) and Rominger and Meyer (2019) showed the usefulness of very high spatial resolution traditional colour aerial imagery for the detection of the rare plant *Boronia deanei* Maiden & Betché (Deane’s Boronia) and the endangered and gypsophile endemic plant *Arctomecon humilis* Coville (dwarf bear-poppy), respectively. The uniqueness of the morphological characteristics exhibited by these two species at detection was key to their identification. Likewise, the classification of traditional colour aerial imagery allowed the detection of the endemic cactus *Neobuxbaumia tetetzo* (F.A.C. Weber ex K. Schum.) Backeb. in the Tehuacan–Cuicatlan Valley in Mexico with high validation accuracy (0.95; López-Jiménez et al., 2019). When morphological features extracted from traditional colour imagery are not enough to discriminate rare plants, spectral bands and derived indices, either alone or in combination with other types of RS indices, has proven to be an effective alternative approach for their direct detection (Liu et al., 2018). For instance, the endangered *Allium trioccum* Aiton (wild leek) and the endemic *Agathis australis* (D.Don) Lindl. ex Loudon (kauri) were successfully detected using vegetation and wetness indices derived from multi- and hyperspectral airborne sensors, respectively (Leduc & Knudby, 2018; Meiforth et al., 2019). Likewise, the rare plant *Fimiana daxianensis* H.H.Hsue & H.S.Kiu, J. S. was detected in Danxia Mountain (China) using multispectral bands and RS-derived vegetation, topographic, texture and geometric indices (Liu et al., 2018).

The utility of high and very high spatial resolution satellite sensors for direct detection of rare plants has also been highlighted. Omer et al. (2015) detected with high accuracy 5 of the 6 target endangered tree species in Dukuduku forest in South Africa using WorldView-2 satellite spectral imagery at 2 m spatial resolution. Similarly, the use of 5 m resolution SPOT imagery allowed to map the endangered and endemic alpine tree *Larix chinensis* Beissn. (Shaanxi larch) on Mount Taibai in China (Zhao et al., 2016). Other studies have also tested the combined use of RS data from passive and active sensors for direct detection purposes. This combination provides a powerful approach, since active sensors, which allow the assessment of rare plant structural properties, can provide valuable information complementary to the optical
| Reference study                          | Location on map | No. and type of rare species | Sensor(s)                           | Pixel size (m) | Data/Predictors | Non-remote sensing | Practical utility |
|----------------------------------------|----------------|-----------------------------|-------------------------------------|----------------|-----------------|-------------------|-------------------|
| Landenberger et al. (2003)             | 1              | 1: S                         | Airborne optical sensor (Nikon N90s) | 0.04 to 0.05   | Traditional colour imagery | NA                | No                |
| Jones et al. (2011)                    | 2              | 1: T                         | LiDAR; Airborne optical sensor (AISA) | 2              | Structural (Canopy height; Canopy volume profiles); Spectral bands | NA                | No                |
| Fletcher and Erskine (2012)            | 3              | 1: H                         | Airborne optical sensor (Sony NEX5) | 0.041 x 0.096  | Traditional colour imagery | NA                | Yes               |
| Chávez et al. (2013)                   | 4              | 1: T                         | WorldView−2                         | 0.5            | Panchromatic band | NA                | No                |
| Omer et al. (2015)                     | 5              | 6: T                         | WorldView−2                         | 2              | Spectral bands | NA                | No                |
| Chávez et al. (2016)                   | 6              | 1: T                         | Quickbird2                          | 0.6            | Panchromatic band | NA                | No                |
| Murfitt et al. (2016)                  | 7              | 1: T                         | WorldView−2                         | 0.5            | Spectral bands; Panchromatic band | NA                | No                |
| Leduc and Knudby (2018)                | 8              | 1: H                         | Airborne optical sensor (CMOS)      | 0.05           | Vegetation index (GCC) | NA                | No                |
| Liu et al. (2018)                      | 9              | 1: T                         | Airborne optical sensor (Sony A6000) | 0.12           | Topographic; Spectral bands; Vegetation indices (NDVI; PRI; RENDVI; SIPI); Texture indices; Geometric indices | NA                | No                |
| Paz-Kagan et al. (2018)                | 10             | 1: T                         | LiDAR; HiFIS                        | 2              | Structural (Canopy height; Canopy volume profiles); Spectral bands | NA                | No                |
| Poursanidis et al. (2018)              | 11             | 1: H                         | WorldView−2                         | 0.46           | Spectral bands; Panchromatic band; Wetness index (NDWI); Water transparency | NA                | No                |
| López-Jiménez et al. (2019)            | 12             | 1:T                          | Airborne optical sensor (CMOS)      | 0.1 to 0.15    | Traditional colour imagery | NA                | No                |
| Madéra et al. (2019)                   | 13             | 1: T                         | Pleiades                            | 0.5 to 1       | Vegetation index (NDVI) | NA                | No                |
| Meiforth et al. (2019)                 | 14             | 1: T                         | Airborne optical sensor (AISA)      | 1              | Spectral bands; Wetness indices (mNDWI) | NA                | No                |
| Rominger and Meyer (2019)              | 15             | 1: H                         | Airborne optical sensor (CMOS)      | 0.0191; 0.0232 | Traditional colour imagery | NA                | No                |
| Slingsby and Slingsby (2019)           | 16             | 1: T                         | Pleiades                            | 0.5            | Traditional colour imagery | NA                | No                |
| Lobo Torres et al. (2020)              | 17             | 1: T                         | Airborne optical sensor (CMOS)      | 0.01           | Traditional colour imagery | NA                | No                |
| Reference study | Location on map | No. and type of rare species | Sensor(s) | Pixel size (m) | Data/Predictors | Non-remote sensing | Practical utility |
|-----------------|-----------------|-----------------------------|---------|---------------|----------------|-------------------|------------------|
| High spatial resolution (3–29m) | | | | | | | |
| Pasqualini et al. (1998) | 18 | 1: H | Airborne optical sensor | 5 | Traditional colour imagery | NA | No |
| Zhao et al. (2016) | 19 | 1: T | SPOT | 5 | | Topographic; Spectral bands | NA | No |
| Indirect approach (prediction) | | | | | | | |
| Very high spatial resolution (<3m) | | | | | | | |
| Ishii et al. (2009) | 20 | 8: H | Airborne optical sensor (AISA) | 1.5 | Spectral bands; Vegetation index (NDVI) | NA | No |
| Robinson et al. (2019) | 21 | 5: H; S | LiDAR | 2 | | | |
| Cursach et al. (2020) | 22 | 1: H | LiDAR; Airborne optical sensor (camera) | 2 | | | |
| High spatial resolution (3–29m) | | | | | | | |
| Sellars and Jolls (2007) | 23 | 1: H | LiDAR | 3 | | Topographic | NA | No |
| Varghese et al. (2010) | 24 | 8: T | LISS IV | 5.8 | | Topographic; Vegetation type | Soil | No |
| Pouteau et al. (2012) | 25 | 3: S, T | Quickbird | 5 | | Topographic; Vegetation type | NA | No |
| Baker et al. (2016) | 26 | 1: S | LiDAR; Landsat | 9.327 | Topographic; Spectral bands; Band ratio; Normalized band ratios; Vegetation indices (NDVI; Greenness); Soil (Brightness; Yellowness); Wetness index | | |
| Traganos and Reinartz (2018) | 27 | 1: H | Sentinel-2 | 10 | Bathymetry; Spectral bands; Water transparency | NA | No |
| Medium spatial resolution (30–300m) | | | | | | | |
| Lauver and Whistler (1993) | 28 | 2: H | Landsat | 30 | Vegetation indices (NDVI; Greenness); Soil brightness index; Wetness indices (including raw SWIR1 and SWIR2 bands) | NA | Yes |
| Sperduto and Congalton (1996) | 29 | 1: H | Landsat | 30 | Topographic; Vegetation index (raw NIR band) | Topographic; Soil Land-use | Yes |
| Wu and Smeins (2000) | 30 | 8: H, S | Airborne optical sensor (Exploranium GR–820); Airborne optically pumped magnetometer sensor (Scintrex CS2) | 30 | Topographic; Vegetation type | Soil | No |
| Crase et al. (2006) | 31 | 2: S | Airborne optical sensor (Exploranium GR–820); Airborne optically pumped magnetometer sensor (Scintrex CS2) | 100; 250 | Topographic; Geological (Radiometric data) | NA | No |
| Reference study            | Location on map<sup>a</sup> | No. and type of rare species<sup>b</sup> | Sensor(s)<sup>c</sup>                                      | Pixel size (m)<sup>d</sup> | Data/Predictors<sup>e</sup>                                                                 | Non-remote sensing<sup>f</sup> | Practical utility<sup>g</sup> |
|----------------------------|-------------------------------|----------------------------------------|-----------------------------------------------------------|--------------------------|-----------------------------------------------------------------------------------------------|-------------------------------|-------------------------------|
| Zimmermann et al. (2007)   | 32                            | 12: T                                  | SRTM; Landsat                                            | 90                      | Topographic; Spectral bands<sup>e</sup>; Vegetation indices<sup>*</sup> (NDVI; Greenness); Surface temperature index<sup>*</sup>; Soil brightness index<sup>*</sup>; Wetness index<sup>*</sup> | Climatic                      | No                            |
| Williams et al. (2009)     | 33                            | 6: H, S                                | MODIS                                                    | 150                     | Topographic; Vegetation index (NDVI)                                                            | Climatic; Geological           | Yes                           |
| Ishihama et al. (2010)     | 34                            | 4: H                                   | Airborne optical sensors (ADS40; RC30)                  | 100                     | Topographic; Spectral bands<sup>*</sup>; Vegetation index (Vegetation height<sup>*</sup>)         | NA                            | No                            |
| Padalia et al. (2010)      | 35                            | 1: T                                   | LISS IV                                                 | 150                     | Vegetation type; NDVI-derived density class; Land-use                                          | Topographic; Soil              | No                            |
| Buechling and Tobalske (2011) | 36                         | 4: H                                   | Landsat                                                 | 30                      | Topographic; Spectral bands<sup>*</sup>; Vegetation indices<sup>*</sup> (TNDVI; Greenness); Soil brightness index<sup>*</sup>; Wetness index<sup>*</sup> | Climatic; Soil                | Yes                           |
| de Queiroz et al. (2012)   | 37                            | 6: H                                   | Landsat                                                 | 30                      | Topographic; Geological (Gypsum spring mound occurrence probability)                           | NA                            | Yes                           |
| Zucchetta et al. (2016)    | 38                            | 1: H                                   | SRTM<sub>30</sub>; PLUS; MERIS; MODIS; SSM/I; TMI; AMSR-E; SeaWinds | 300                     | Bathymetry; Surface temperature index; Water transparency; Wind induced disturbance (Relative Exposure Index) | Water salinity                 | No                            |
| Adhikari et al. (2018)     | 39                            | 1: T                                   | MODIS                                                   | 250                     | Vegetation index (EVI<sup>*</sup>)                                                             | NA                            | Yes                           |
| Kim et al. (2018)          | 40                            | 1: H                                   | LiDAR; Landsat                                          | 30                      | Topographic; Vegetation index (NDVI); Wetness index (NDWI)                                     | Climatic; Soil; Flood area     | No                            |
| Attanayake et al. (2019)   | 41                            | 9: H, S                                | Landsat                                                 | 30                      | Spectral bands                                                                               | NA                            | No                            |
| Borfecchia et al. (2019)   | 42                            | 1: H                                   | Landsat                                                 | 30                      | Bathymetry; Vegetation indices (NCVI; NVGVI)                                                  | NA                            | No                            |
| Hernández-Lambrano et al. (2020) | 43                        | 1: H                                   | LiDAR; Landsat                                          | 30                      | Topographic; Vegetation index (SAVI); Surface temperature index; Wetness index                 | NA                            | Yes                           |

<sup>a</sup>The number indicates the location of the reference study in Figure 1.

<sup>b</sup>Total number of target rare plants with capital letters indicating the type of species based on their growth form (H: herbaceous; S: shrub; T: tree).

<sup>c</sup>Sensors from which remote sensing information was extracted.

<sup>d</sup>Spatial resolution of analysis

<sup>e</sup>Only data/predictors used for detection/prediction purposes are included.

<sup>f</sup>Vegetation indices refer to continuous spectral information, while vegetation type refers to classified information.

<sup>g</sup>NA, not applicable.

<sup>h</sup>Discovery of new rare plant localities using remote sensing information.
information derived from passive sensors. Specifically, the use of hyperspectral information along with LiDAR-derived structural data, namely canopy height and canopy volume profiles, allowed a successful detection of the rare trees *Quercus garryana* Douglas ex Hook. (Garry oak) in southern Gulf Islands (British Columbia) and *Sequoiadendron giganteum* (Lindl.) J. Buchholz (giant sequoia) in the western Sierra Nevada of California (Jones et al., 2011; Paz-Kagan et al., 2018). On the other hand, RS has also allowed the direct detection of rare plants in aquatic environments, as demonstrated by Pasqualini et al. (1998) and Poursanidis et al. (2018), who detected and mapped the species *Posidonia oceanica* (L.) Delile (Neptune grass) endemic to the Mediterranean Sea using aerial traditional colour imagery and WorldView-2-derived information, respectively.

The RS direct approach not only offers the possibility to detect and map rare plants but also to assess their status (e.g. water stress, health; Chávez et al., 2013, 2016; Murfitt et al., 2016). This ability may allow the implementation of monitoring systems for these species, which can provide valuable additional information for management and conservation purposes. The studies reviewed here well exemplify the potential of a direct RS approach not only to detect rare plants, but also to monitor them in space and time (Landenberger et al., 2003; McGraw et al., 1998), or even to discover new populations (Fletcher & Erskine, 2012).

### 4 | REMOTE SENSING INDIRECT APPROACH—PREDICTION OF RARE PLANT DISTRIBUTIONS

The indirect RS approach allows the prediction of rare plants under environmental conditions where their direct detection is not possible (Levin et al., 2007). Most of the studies included in this section were performed in the Northern Hemisphere, while only three were conducted in the Southern Hemisphere (Figure 1). RS has been used to spatially characterize different biophysical conditions at multiple spatial, spectral and temporal resolutions related to topography, vegetation, structure, climate, soil, geology, moisture, bathymetry and water transparency, as well as to anthropogenic and natural disturbances (Table 1). RS information has been acquired primarily from passive satellite sensors, although active satellite sensors, and airborne sensors both active and passive, have also been used.

Only three studies have used very high-resolution RS to model the distribution of rare plants, being limited exclusively to LiDAR-derived topographic predictors, NDVI and hyperspectral data. The usefulness of 2 m resolution topographic predictors alone to predict rare plants was proven by achieving excellent accuracies (AUC = 0.99–1) for five rare plants modelled in semiarid south-western Australia (Robinson et al., 2019). Similarly, high predictive performance (AUC = 97) was obtained for the endemic plant *Euphorbia fontqueriana* Greuter by combining 2 m resolution topographic and NDVI predictors, with almost no contribution from the non-RS soil type variable (Cursach et al., 2020). More modest predictions were however obtained in the mapping of habitat types for 8 threatened species in Watarase wetland (Japan) using hyperspectral data (Ishii et al., 2009).

A higher diversity of RS predictors has been tested in models developed at high resolution, while topographic (or bathymetric) variables have been the common element in all of them. One example used LiDAR-derived elevation at 3 m resolution to predict up to 88% of *Amaranthus pumilus* Raf. (seabeach amaranth) occurrences across the North Carolina coastline (Sellars & Jolls, 2007). The integration of a Quickbird-derived vegetation type map along with topographic variables also provided accurate predictions (AUC = 89–97.9) for three endangered or endemic plant species on the island of Moorea (Pouteau et al., 2012). Likewise, the endemic plant *Schoenocrambe suffrutescens* (Rollins) S.L. Welsh & Chatterley...
(shrubby reed-mustard) was successfully mapped (AUC = 0.85) by combining a wide variety of RS predictors, including topographic variables, spectral bands (and ratios), as well as vegetation, wetness and soil indices (Baker et al., 2016).

Rare plant studies using medium resolution RS are more common and have used a much wider diversity of RS predictors than those developed at high and very high resolutions (Table 1). The variety of RS predictors that can be successfully integrated into rare plant models at this resolution was exemplified by Zimmermann et al. (2007). The authors modelled 19 tree species distributions ranging from rare to common and found that models combining RS and non-RS predictors consistently provided better performance for all species, and more so for rare species. Medium resolution RS-only SDMs are also very useful for predicting rare plant occurrences. Suitable habitats for the endemic tree Adinandra griffithii Dyer were accurately predicted (AUC = 0.99) by using EVI time series (Adhikari et al., 2018). Similarly, robust predictions were achieved for the narrow-range endemic species Antirrhinum lopesianum Rothm. in the Iberian Peninsula using RS-derived topographic, vegetation, surface temperature and wetness indices (Hernández-Lambráno et al., 2020). RS can also provide useful geology-related information for predicting rare plants. The Landsat-derived geological predictor “Gypsum spring-mound occurrence probability” alone was able to successfully predict habitat suitability (AUC = 0.92) for 6 edaphic endemic plants in White River Valley, Nevada (de Queiroz et al., 2012). Robust models were also developed for the rare sandstone shrubs Melaleuca triumphalis Craven and Stenostegia congesta A.R. Bean using a RS radiometric map representing thorium, uranium and potassium in combination with two and one topographic predictors, respectively (Crase et al., 2006). Likewise, the usefulness of the indirect RS approach to characterize aquatic habitats of rare plants has been demonstrated by several studies (Borfeccchia et al., 2019; Traganos & Reinartz, 2018; Zucchetta et al., 2016). While all these studies focused on the same species, the endemic plant P. oceanica, they exemplify the variety of RS predictors that can be employed for predictive mapping purposes in aquatic environments (Table 1).

Overall, RS has provided valuable information on rare plant niches with good predictability at high and medium resolution. These results highlight the potential of RS to not only characterize the habitats of rare plants but also to monitor them spatially and temporally (Bartel & Sexton, 2009; Neumann et al., 2015). Several authors have also demonstrated the practical utility of predictive models built partially (Buechling & Tobalske, 2011; Sperduto & Congalton, 1996; Williams et al., 2009) or completely (e.g. Hernández-Lambráno et al., 2020; Lauver & Whistler, 1993; de Queiroz et al., 2012) with RS predictors at those resolutions by discovering previously unknown populations of rare plants (Table 1). While SDM-based predictions are valuable tools to guide the search for rare plants in the field, the integration of abundance estimates derived from species abundance models (“SAMs”) could further facilitate their detection. Likewise, when probability of occurrence estimated from SDMs and predicted abundance are uncorrelated and determined by different sets of predictors, SAMs can provide valuable additional information on habitat quality or ecological species preferences (Duff et al., 2012). Since RS also has the ability to feed SAMs (e.g. Arenas-Castro et al., 2019; Duff et al., 2012; Guarino et al., 2012), abundance estimates can also be obtained at high or medium resolutions. Therefore, the combination of both RS-based SDM and SAM model types may represent a new and strong practical approach for detection of rare plants, by guiding field search efforts towards predicted habitats where higher plant abundance makes them more detectable.

4.1 | Considerations of predictive performance measures for rare plants

Currently, there is still no consensus on which are the most suitable metrics to evaluate the predictive performance of SDMs, which has the use of multiple metrics as the best solution (Amini Tehrani et al., 2020; Breiner et al., 2015). However, since each accuracy metric provides a type of information, the choice should ideally be based on their intended use (Fielding & Bell, 1997) rather than on the arbitrary selection of different metrics. As rare plants typically show low prevalence (i.e. high absences/presences ratio), overall predictive performance metrics (e.g. accuracy or AUC) can lead to overly optimistic results about model accuracy (Buechling & Tobalske, 2011; Lobo et al., 2008). Furthermore, those metrics are not sensitive to overprediction, which can be common for rare plant presence. Based on these drawbacks, we propose the use of two complementary metrics to evaluate isolation the ability of the model to predict presences of rare plants, namely sensitivity and precision. Sensitivity is the proportion of true positives correctly predicted, while precision is the proportion of positive predictions corresponding to true positives (Fawcett, 2004). The use of both metrics provides information on the proportion of actual presences correctly predicted and possible instances of overestimation. Therefore, sensitivity and precision are ultimately metrics indicative of the practical utility of models to find new localities of rare plants.

5 | Remote sensing based on the characteristics of rare plants

Rare plants, like all plant species, have distinct features that allow their differentiation and identification, but is it possible to capture some of the distinguishing features of rare plants through RS? Can these features influence the performance of RS to detect or predict rare plants? In this section, rare plant features related to morphology, phenology, physiology, and ecological niche are discussed. Since rare and common plants are not categorized as such based on the plant features presented, we are aware that some aspects of our discussion may also apply to common plants.
5.1  |  Morphology

Morphological features of rare plants can provide decisive information for their direct detection. Two conditions must be met to ensure the success of this approach (also applicable to common plants): i) very high spatial resolution is required to capture morphological characters considered important, and ii) the date on which RS imagery is taken must correspond to a time when the target plant exhibits distinctive morphological characters that allow its discrimination. The direct detection of the rare shrub *Boronia deanei* based on its pink flowers and growth form exemplifies these criteria (Fletcher & Erskine, 2012).

5.2  |  Phenology

Multi-temporal RS imagery at high temporal resolution has the potential to capture phenological traits of rare plants, such as flowering, fruiting or leaf growth/fall (Campbell & Wynne, 2011; Turner et al., 2003). This phenological information can be advantageous for both RS approaches. Direct detection can benefit from phenological processes as long as the conditions mentioned in the previous subsection are met. However, multi-temporal imagery can only provide useful information when morphologically and phenologically similar target and cohabitating species display these features at different times. By contrast, single-date images provide similar information if the detection date captures the uniqueness of morphological characters derived from phenological features.

In the indirect approach, the spectral radiation associated with phenological features of rare plants can directly influence the information captured from remote sensors during the characterization process of their ecological niche, which is subsequently used to model rare plant occurrence. This fact has been defined as a source of unintentional bias when predicting potentially suitable habitats of plants, since the captured information is associated with their actual distribution (Bradley et al., 2012). However, this type of bias can be considered advantageous when RS-based predictions are used to locate actual rare plant occurrences. For instance, predictions of rare trees improved with the inclusion of multi-temporal predictors whose spectral information was directly influenced by their leaf phenological features (Zimmermann et al., 2007). Similarly, the detection of leaf phenological changes in the Watarase wetland allowed to accurately predict the occurrence of two of four rare plants studied (Ishihama et al., 2010). The authors highlighted that one of these species, *Ophioglossum namegatae* Nish. & Kurita, because of its sprouting period (early spring) and rapid growth, could directly contribute to the spectral information captured in early May, which was one of the most important predictors for both species. Likewise, the flowering phenological stage of the endemic tree *A. griffithii* played an important role in predicting its distribution, since the EVI for the periods of June and July were the most influential predictors (Adhikari et al., 2018).

5.3  |  Physiology

Plant spectral information is influenced by plant physiological traits such as concentration and distribution of biochemical components (Peñuelas & Filella, 1998), which can be identifiable and quantifiable based on their spectral absorption features (Asner & Vitousek, 2005; Blackburn, 1998; Sims & Gamon, 2003). The use of multispectral bands and physiological indices at high spatial resolution has been shown to significantly contribute to the detection of rare tree species (Liu et al., 2018; Omer et al., 2015). However, the detection of rare plants could also benefit from hyperspectral bands and LiDAR sensors, which have the capacity to assess plant physiological traits in more detail (Andrew & Ustin, 2006; Asner, Jones, et al., 2008; Ustin & Gamon, 2010).

5.4  |  Ecological niche

The vertical position occupied by rare plants in their respective habitats (e.g. overstory or understory) influences their direct detection by RS. Active airborne sensors (e.g. LiDAR) are required to detect subcanopy plants (Asner, Hughes, et al., 2008; Hernandez-Santín et al., 2019). On the other hand, the effectiveness of the RS indirect approach in characterizing species’ ecological niches depends on two conditions. First, sensor spatial resolution must be adapted to habitat size. This is especially important for rare plants that are associated with small habitat patches (e.g. de Queiroz et al., 2012), which can remain indistinguishable if they are smaller than the RS imagery pixel (Luoto et al., 2002). Secondly, habitat specificity of rare plants has been shown to influence prediction accuracy (Buechling & Tobalske, 2011; Parviainen et al., 2013). Prediction accuracy of rare plants can increase when their habitat specialization increases (Hernandez et al., 2006), making habitats where they occur more distinct than habitats where they are absent. For rare plants with wider habitat specificity and few occurrences, insufficient prior knowledge seems to be the main limiting factor rather than capacity of RS to successfully discriminate between suitable and unsuitable habitats.

6  |  RELATING RARITY FORMS WITH MODEL PREDICTIVE PERFORMANCE

The rare species classification developed by Rabinowitz (1981) suggests that predictive performance of models could vary by type of rare species. This section addresses this assumption starting at the criterion level.

The geographic distribution of species has an indirect rather than direct effect on model predictive performance through the acquisition of RS products. Availability and cost of RS imagery could restrict analyses to coarser spatial resolutions unable to capture species-environment relationships, especially when dealing with widely distributed rare plants. A practical solution to this drawback would be to guide modelling studies to smaller areas within a species'
distribution range where their conservation status is most critical or their study is more urgently required.

Habitat specificity can positively influence model predictive performance, with increases in model predictive performance as habitat specificity increases. Local population size can also strongly affect model predictive performance. Species with smaller populations are more vulnerable to demographic, environmental, and genetic stochastic events as well as anthropic pressure, which can reduce their probability of persistence (Fischer & Stöcklin, 1997; Matthies et al., 2004; Ouborg, 1993; Thomas, 1994). This can result in lower proportion of occupied suitable sites or “fidelity,” which can lead to an increase in false positives and thus decrease model predictive accuracy. In contrast, species with larger populations are more resistant to stochastic events and therefore more stable over time, which would increase their probability of presence and fidelity.

Summarizing the previous ideas regarding the influence of Rabinowitz’s rarity classification criteria on model predictive performance, predictive performance can be negatively influenced by geographic distribution range and positively influenced by habitat specificity and local population size (Figure 2). Nonetheless, predicting widely distributed rare plants throughout their entire distribution range is not practical for their detection; thus, the effect of the geographic distribution range on model performance becomes negligible when prioritizing smaller areas for predictions. At this point and using the same classification as Rabinowitz (1981), better results in terms of predictive performance can be expected for predictable and endemic rarity forms showing large local population size (Figure 2). However, because the assumption initially raised in this section has been only theoretically addressed, the veracity of these final conjectures must be tested empirically.

**7 | CONCLUSION**

Direct and indirect RS provide great potential for the detection and prediction of rare plants in both terrestrial and aquatic environments. While direct detection is often limited, it was shown to be possible with high and very high spatial resolution data for species with distinctive traits. Remote sensors were also able to capture important biophysical conditions that drive rare plant distributions at very high to medium resolutions. Generally, RS predictors contributed positively to the predictive performance of SDMs when they were combined with non-RS predictors. RS predictors by themselves also provided accurate predictions of rare plant occurrences and allowed the discovery of new locations, highlighting the practical utility of these tools for conservation purposes. Likewise, the capacity for RS to feed SAMs and provide abundance estimates at high resolutions can offer, in combination with traditional SDMs, a valuable approach to guide future field surveys and facilitate the detection of new populations, as well as for monitoring these species and their populations in space and time. Additionally, accuracy metrics were proposed for future modelling studies that focus on predicting actual rare plant occurrences.

Some characters of rare plants can influence the capacity for direct RS to detect them. The effectiveness of this RS approach will depend on the space occupied by a species within its habitat and the distinctive morphological, phenological and/or physiological features that facilitate its identification. On the other hand, the predictive performance of RS-based SDMs can be influenced by the habitat size, habitat specificity and phenological features of rare plants. The spatial resolution of RS imagery must match the habitat size occupied by species; otherwise, small habitats can remain indistinguishable at coarse resolutions. Likewise, higher habitat specificity for rare species facilitates the capture and integration of environmental variability associated with the species, and better discrimination between suitable and unsuitable habitats. In addition, the influence of phenological features of rare plants on the spectral information captured by remote sensors can improve SDM performance for predicting actual occurrences. Similarly, model predictive performance can be influenced by the rarity form of the target species according to the rarity classification criteria, but this requires empirical testing.

In conclusion, RS is a powerful information source to generate predictions and guide the discovery of new rare plant populations. New rare plant occurrences can subsequently be used as inputs for improving predictive models, to acquire better knowledge on ecological requirements and restrictions of species to help understand
the causes of their rarity, and to review and update when necessary their conservation status. With this synthesis, we have highlighted the strong potential of RS for the purposes of detection and prediction of rare plants, with practical applications for rare species conservation and management.

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**BIOSKETCH**

Carlos Cerrejón is a PhD student interested primarily on the study of bryophytes, including taxonomy, phylogeny, ecology and distribution. He is currently working on the development of biodiversity and species distribution models of bryophytes and lichens using remote sensing data.

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