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Review

Remote Sensing and Invasive Plants in Coastal Ecosystems: What We Know So Far and Future Prospects

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Abstract: Coastal environments are highly threatened by invasive alien plants (IAP), and Remote Sensing (RS) may offer a sound support for IAP detection and mapping. There is still a need for an overview of the progress and extent of RS applications on invaded coasts that can help the development of better RS procedures to support IAP management. We conducted a systematic literature review of 68 research papers implementing, recommending, or discussing RS tools for IAP mapping in coastal environments, published from 2000 to 2021. According to this review, most research was done in China and USA, with *Sporobolus* (17.3%) being the better studied genus. The number of studies increased at an accelerated rate from 2015 onwards, coinciding with the transition from RS for IAP detection to RS for invasion modeling. The most used platforms in the 2000s were aircraft, with satellites that increased from 2005 and unmanned aerial vehicles after 2014. Frequentist inference was the most adopted classification approach in the 2000s, as machine learning increased after 2009. RS applications vary with coastal ecosystem types and across countries. RS has a huge potential to further improve IAP monitoring. The extension of RS to all coasts of the world requires advanced applications that bring together current and future Earth observation data.

Keywords: passive sensors; active sensors; invasion ecology; literature metadata; coastal ecosystem types; spatial and spectral resolution; life forms; analysis algorithms

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1. Introduction

Coastal environments are narrow belts that occupy transitional zones between terrestrial and marine ecosystems, hosting particularly specialized flora and fauna [1]. These ecosystems provide important ecological services such as the filtration of large volumes of seawater, nutrient recycling, flood control and storm protection [2–4]. Because of their relevant economic value, coastal zones are among the most densely populated regions of the world. Therefore, the dense population and frequent exchange of materials and energy in coastal areas make them particularly sensitive and vulnerable to natural and anthropogenic changes. Coastal areas have undergone severe environmental alterations imposed by human activities, climate change and extreme events [5].

One of the main threats to coastal biodiversity and ecological functioning is invasive alien plants (IAP) [6,7], which pose a particular threat in dune ecosystems [8]. IAP can deeply modify the structure and function of invaded ecosystems [9], alter biotic interactions [10], degrade soil properties (e.g., nutrient content and water surface) [11,12] and homogenize plant and animal communities at large spatial scales [13,14]. IAP, given their threat to genetic diversity, species and ecosystems IAP [15], can cause direct economic losses [6,7,15]. Furthermore, invasion management is challenging [16] and highly expensive, with costs that in some European countries may reach hundreds of billions of Euros (EUR) per year [17].

Given the negative economic and ecological impacts of IAP, methods for rapid detection and prediction of their arrival and spread are crucial to enable effective early assessment of the risk of species invasion [18] and to be ready to act quickly [19]. To properly apply proactive management of IAP, remote sensing can offer a set of effective tools [7].

Remote sensing, i.e., the process of remotely acquiring information about the Earth, has become increasingly important for environmental conservation and ecological monitoring, including IAP detection and modeling [20]. Remote sensing has been shown to offer a great opportunity for invasion biologists, resource managers and policy makers to develop predictive models for invasion risk analysis as well as early detection strategies. By integrating remote sensing products with field sampling data, significant progress can be made in identifying, mapping and modeling invasive taxa in a wide range of habitats and ecosystems [15,21].

Several studies on alien plant invasions using remote sensors have been done in different habitats [6,7,15,20,22,23] across the world, yet an overview of RS applications in coastal ecosystems is still missing. Indeed, although remote sensing appears to offer a very promising and efficient set of tools, a systematic survey of the literature available to date is needed to identify gaps to focus on and to develop better RS procedures to support IAP management. Accordingly, we performed a systematic review of published literature on the use of remote sensing to monitor IAP in coastal ecosystems. Specifically, our aims are to: i) analyze the main characteristics of the research articles that have adopted remote sensing tools to studying plant invasions in coastal ecosystems, with particular regard to their study areas, genera, life forms and IAP origin; ii) examine how the utilization of the different observation platforms, sensors and methodologies on RS coastal invasions studies have evolved in the last decade; iii) analyze the interaction between different remote sensing features (e.g., platforms, sensors, spatial and spectral resolutions, etc.) and the coastal ecosystem types where the studies were conducted.

2. Materials and Methods

We structured the review framework following two main steps: (a) systematic literature search, and (b) meta-data extraction, as outlined in the workflow (Figure 1). Subsequently, we analyzed temporal trends in the number of published papers on the topic and the statistical association between several remote sensing and plant species attributes occurring in the extracted meta-data.

2.1. Systematic Literature Search

To perform the systematic literature search, we accessed the Scopus database from December 2021 to March 2022 (at: https://www.scopus.com/). The search string used for the advanced search in Scopus was initially generated by considering all the possible combinations of the following keywords: "coastal ecosystems", "invasive alien plants", "management", "conservation", "remote sensing", "remotely sensed", "satellite", "UAV" (i.e., unmanned aerial vehicle), "hyperspectral", "multispectral", "lidar". The full string was generated with the R software. The initial keywords were selected using a participatory approach that involved a team of researchers with expertise in remote sensing, plant ecology and coastal ecosystems. The time frame of our literature search is from 2000 to 2021. We chose this time frame because previous remote sensing research to detect aliens along coastal ecosystems was almost entirely absent.

After dropping duplicates, the total number of records from Scopus was N = 745. Additional documentation was included after a first inspection of the references of the final Scopus database, along with Mendeley's email alerts which were grouped together as other sources (N = 123). Mendeley is an open-source bibliographic manager that was used to store and handle the final database (https://www.mendeley.com/ (accessed on 16 December 2022)). All articles from these searches (N = 868; Figure 1A) were first screened by examining title, abstract and keywords to exclude articles with information not relevant to the research objectives (Table S1). Subsequently, the full text of the remaining 109 studies that met the initial inclusion criteria (Table S1) were further assessed for eligibility, reducing the database to 86 articles for meta-data extraction (Table S2). Of these, 18 articles were removed because they lacked relevant information, maintaining a final pool of 68 articles for analysis (Table S3, Figure 1A).

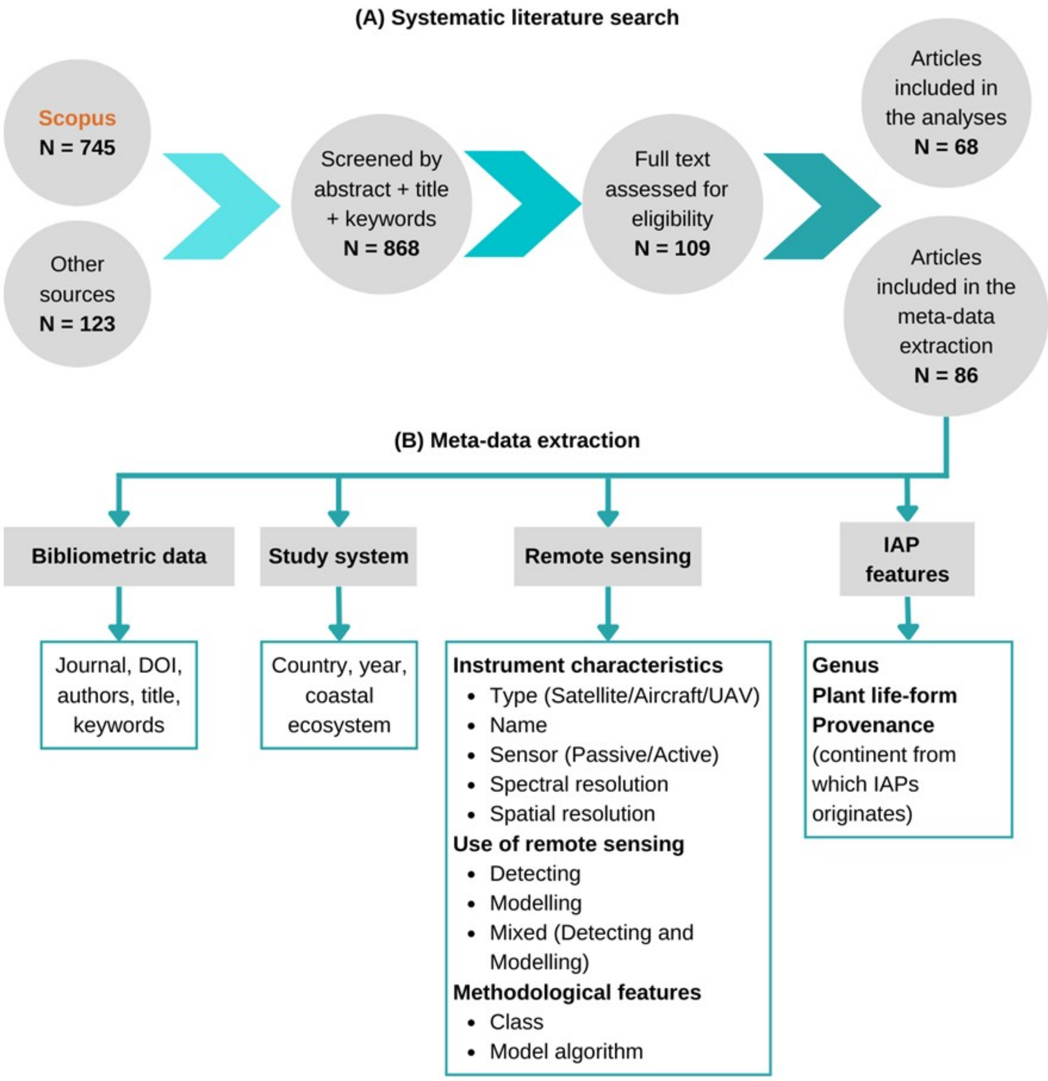

Figure 1. (**A**) Diagram describing the flow of information through the different phases of the systematic literature review. (**B**) Summary of the metadata collected for the database (UAV stands for unmanned aerial vehicle).

2.2. Meta-Data Extraction

Detailed information and meta-data were retrieved from all the articles included in the final dataset (Figure 1B). On the one hand, we extracted bibliometric details (i.e., journal, DOI, authors, title, keywords) and information related to the study system (i.e., country, year, and type of coastal ecosystem where the study was carried out). On the other hand, we recorded information concerning remote sensing features as well as data relating to the taxa analyzed in each study. The main remote sensing characteristics were determined and grouped into the following categories: "instrument characteristics", "use of remote sensing", and "methodological features" (Figure 1B). In the first category we identify the name and type of the instrument, whether the study used satellites, aircraft, UAVs or a combination of them. We also verified whether the sensor equipped in the instrument was passive, active or whether both sensors were used. The spectral and spatial resolutions of the sensors used in each study were also determined. Specifically, we considered hyperspectral, multispectral, panchromatic, LiDAR and SAR as different categories. Spatial resolution was rated as ultra-high (<5 m), very high (5–30 m) and fine resolution (30–100 m), based on general remote sensing science literature [24,25] as well as the authors' knowledge and expertise.

In the category "use of remote sensing" we classified the use of remote sensing as detection (i.e., remote sensing instruments are used directly to detect the species and remote sensing products are used as response variables in a statistical framework), modelling (i.e., remote sensing products are used as explanatory variables in a statistical framework), and mixed use. In the "methodological features" category we determined the modelling algorithm used (e.g., random forest, maximum likelihood classification, etc.) along with the class of methodology the algorithms belong to (e.g., machine learning, frequentist inference, etc.).

Finally, we classified the information about the IAP studied into three features: "genus", "plant life-form" and "provenance", the latter to identify the continent where the species originated (Figure 1B).

2.3. Data Visualization and Statistical Analysis

To carry out the analyses we only considered the following variables from our database: "year", "keywords", "instrument type", "instrument name", "spectral resolution", "spatial resolution", "RS sensor", "use of RS", "methodology", "model algorithm", "genus", "life-form", "provenance", "coastal ecosystem", "country". For plant genera, we extracted the whole list from our selected studies and then checked for synonyms according to https://powo.science.kew.org/ and used only the current accepted name in our analyses (for instance, *Sporobolus* is the current accepted name for *Spartina*).

To examine the temporal variation in the number of published papers on remote sensing and IAP in coastal ecosystems we fitted a Generalized Linear Model (GLM) with a Poisson distribution of errors. Specifically, the total number of published records per year was used as the response variable, while the publication year (i.e., between 2000 and 2021 that was the time span of our search) acted as explanatory variable. GLM goodness-of-fit was calculated by means of McFadden determination coefficient (R^2).

Then, we extended the temporal trend analysis by looking at how the different categories of the variables "coastal ecosystem", "platform", "plant life form", "methodology", "spatial resolution", "spectral resolution" and "use of remote sensing", varied through time. For this purpose, we fitted Multinomial Logistic Regressions (MLR), where the abovementioned variables acted as response term, while the year between 2000 and 2021 was used as explanatory variable. For MLR we calculated goodness-of-fit by means of Nagelkerke determination coefficient (R^2). Moreover, we assessed MLR predictive performance through a 10-fold cross-validation approach, calculating the percentage overall accuracy as evaluation metric, as implemented in the 'caret' R package [26].

Lastly, to explore interactions among variables we calculated the Cramer's V, i.e., a measure of statistical association between two nominal variables that ranges from 0 (no association) to 1 (full association). From all the analyzed variables we selected and discussed only the pairs that displayed Cramer's V values > 0.4, which were also represented through chord diagrams. All data analyses and visualization were conducted in R version 4.1.2 (R Core Team, 2021) using the following packages: "rsq" [27], "ggplot2" [28], "vegan" [29], "lmPerm" [30], "ggsignif" [31], "jtools" [32], "visreg" [33], "reshape2" [34], "nnet" [35], "chisq.posthoc.test" [36], "pbapply" [37], "MASS" [35], "caret" [26], and "circlize" [38].

3. Results

3.1. General Overview

According with our literature search the most mentioned keyword was "invasive species", followed by "hyperspectral" and "random forest", and less frequently "*Acacia longifolia*", "maxent", "invasive plant species", "invasive alien species", "phenology", "Landsat", "support vector machine", and "hyperspectral remote sensing" (word cloud in Figure 2). As for the geographic distribution of the published literature, most of the studies were carried out in China (22), followed by the United States of America (11), Italy

(8) and Portugal (7). Fewer studies were carried out in Spain (3), Germany (3), Israel (3), the Netherlands (2), South Africa (2), and Chile (2), while only one record was reported for Norway, Romania, France, Jordan, New Zealand, and Mexico (World map in Figure 2).

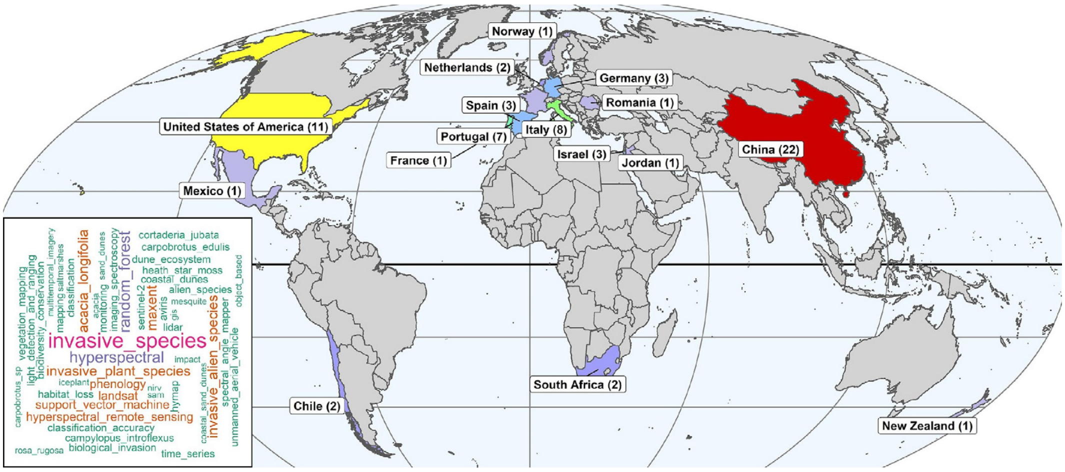

Figure 2. World map (EPSG:4326-WGS84) showing the number of studies carried out by each country along with a word cloud providing the most frequently used keywords in our database. Colors visualize countries with a comparable number of published papers.

Our literature search indicated as the most studied taxa with remote sensing in coastal ecosystems the genera *Sporobolus* (= *Spartina*; 17.3%), followed by *Acacia* (11.8%) and *Carpobrotus* (8.7%; Figure 3). In keeping with that our analyses also provided evidence that the continent of origin showing the highest frequency is North America (31.4%), followed by Australia (21.6%) and Africa (14.7%; Figure 4a). In terms of life forms, phanerophytes (33%) are the most studied, followed by geophytes (31.9%) and hemicryptophytes (16.5%; Figure 4b).

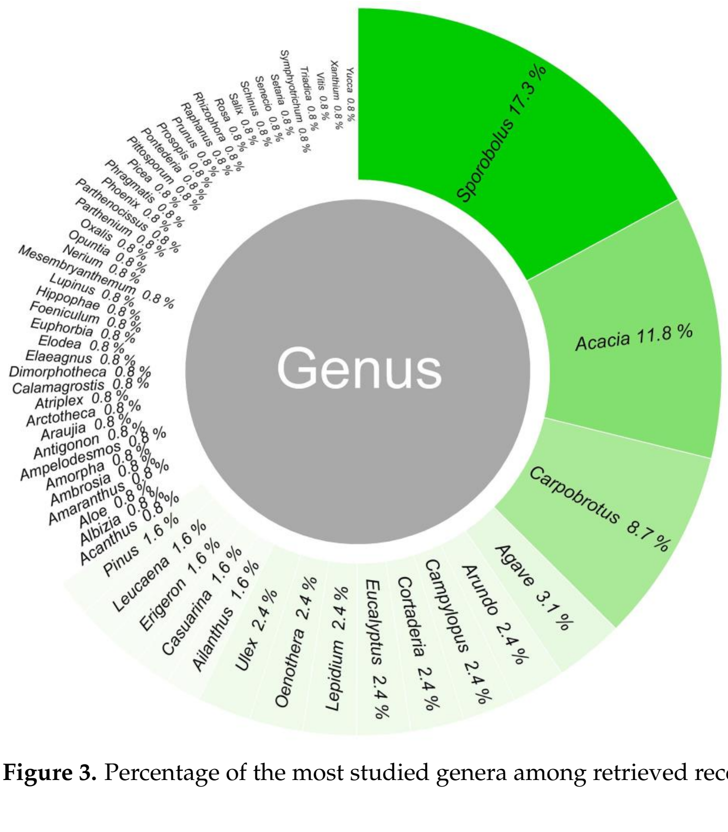

Figure 3. Percentage of the most studied genera among retrieved records.

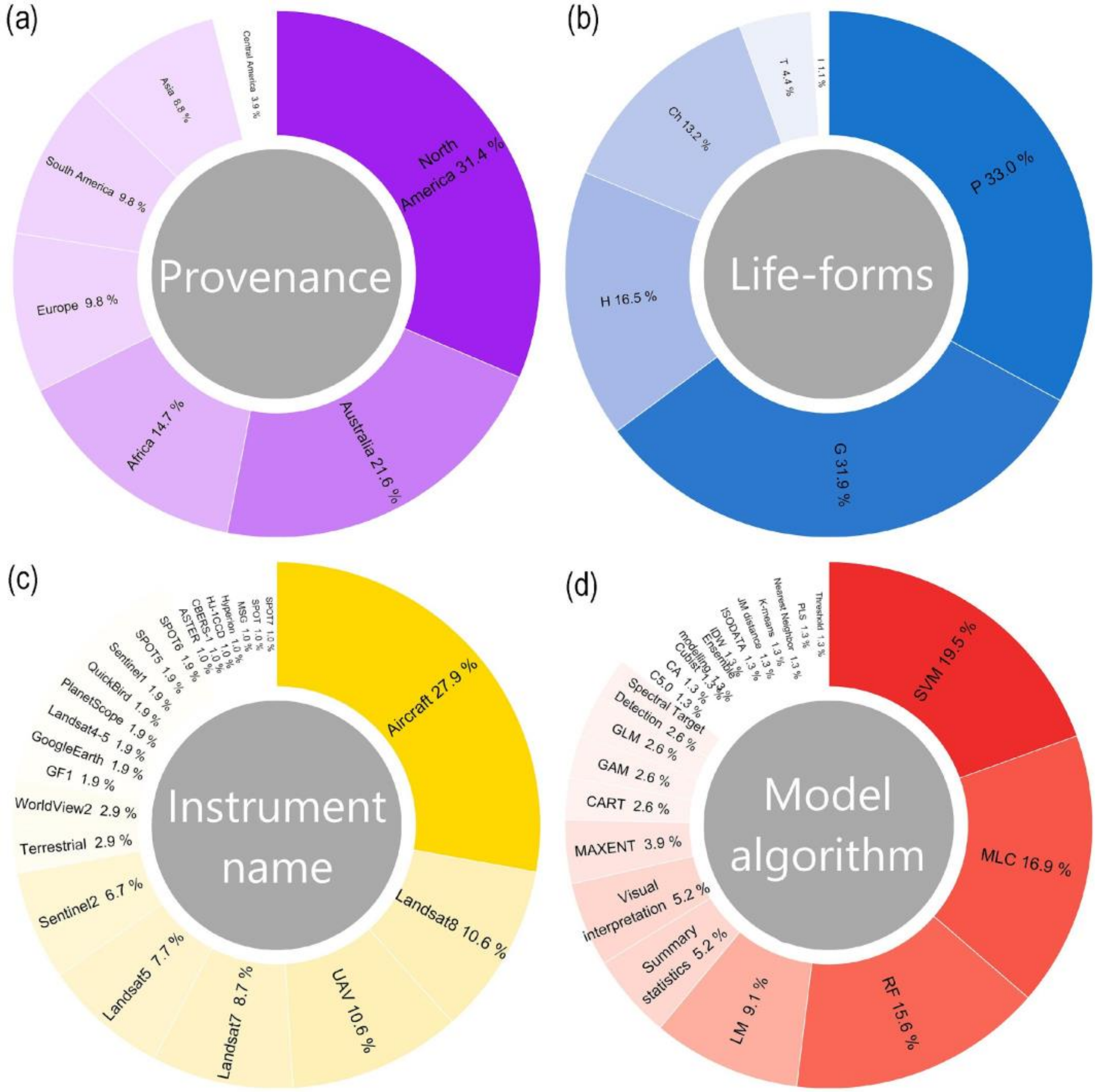

Figure 4. (**a**) Country of origin of the most studied IAP, represented in percentage per continent of origin. (**b**) Percentage of the life forms found in the database (P: Phanerophytes, G: Geophytes, H: Hemicryptophytes, Ch: Chamaephytes, T: Therophytes, I: Hydrophytes). (**c**) Percentage of the most frequent remote sensing instruments found in our database. (**d**) Percentage of the main modelling and classification algorithms preferred to analyze remote sensing data (SVM refers to Support Vector Machine, MLC refers to Maximum Likelihood Classification, RF refers to Random Forest, and LM refers to Linear Models).

As for the remote sensing instrument used in each study, our results pointed out Aircraft as the most recurrent (27.9%), followed by Landsat 8 (10.6%) and UAV (10.6%; Figure 4c). In terms of modelling and classification algorithms, Support Vector Machine (19.5%), Maximum Likelihood Classification (16.9%) and Random Forest (15.6%) are the most selected options to analyze remote sensing data (Figure 4d).

3.2. Temporal Trends

GLM results indicated a significant increase in the number of studies in the 2000–2021 time span ($p < 0.05$; $R^2 = 0.34$), with a more pronounced rise from 2015 (Figure 5). As for temporal trends of the single categories, MLR indicated a significant decrease in the studies that focused primarily on detecting IAP while detection combined with a modelling approach has shown a significant increase. Specifically, the use of remote sensing only for modelling purposes emerged around 2014 and kept rising (R^2 = 0.22; accuracy = 0.50; for *p*-values see Table S4; Figure 6a). Aircraft were the most used instruments at the beginning of the analyzed period, but later started to significantly decrease as satellites were used more frequently after 2005. The use of UAVs gained importance around 2014 showing a significant increase, while terrestrial instruments emerged around 2013 but seem to be the least preferred with a slight decline observed in their use according to our database (R^2 = 0.21; accuracy = 0.55; for *p* values see Table S4; Figure 6b).

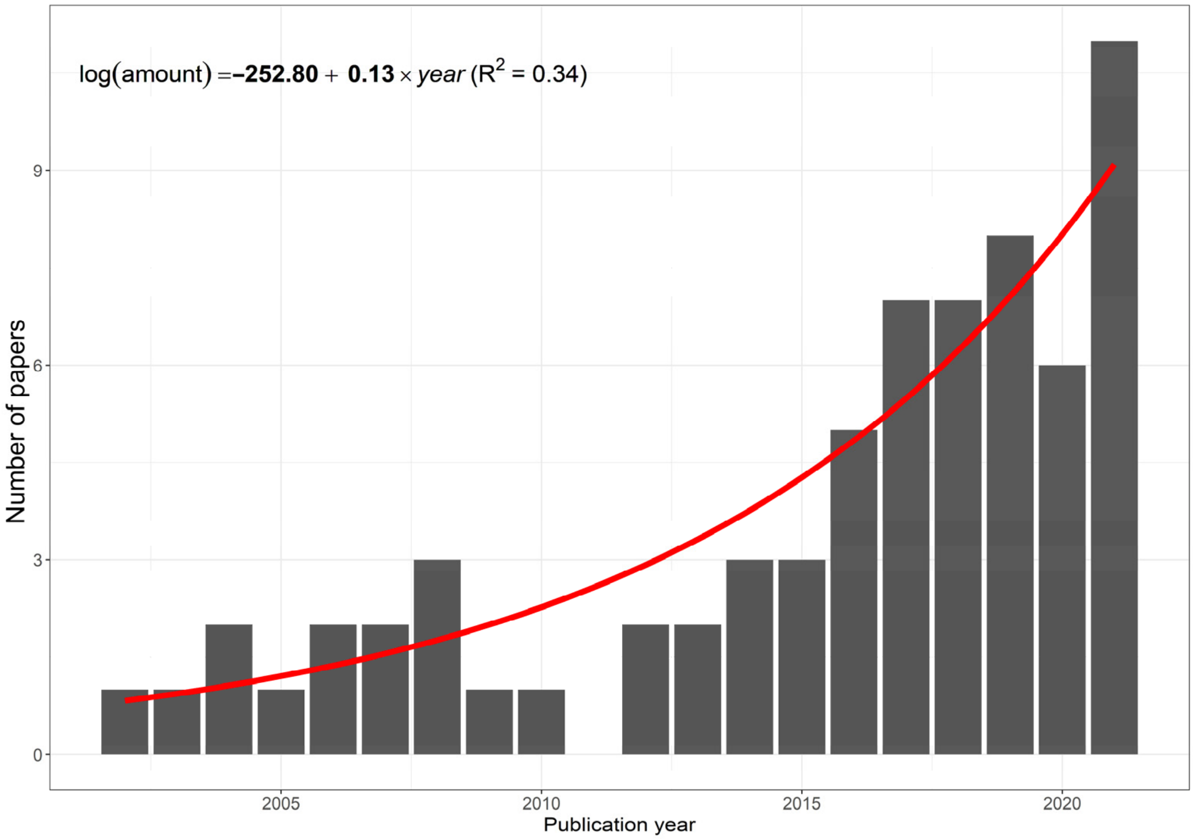

Figure 5. Temporal trends in the number of published records per year (2000–2021; source scopus).

MLR results (Figure 6) also evidenced that multispectral resolution images were adopted in a large volume of research and that their use significantly increased from 2005. The number of papers using panchromatic, hyperspectral and LiDAR data resulted low with a decreasing trend over time. The introduction of SAR data was recent (year 2019) and its use remained not very common (R^2 = 0.72; accuracy = 0.48; for *p* values see Table S4; Figure 6c). In terms of images spatial resolution (e.g., ultra-high: < 5 m; very high: 5 m–30 m; fine resolution: 30 m–100 m) for alien species detection on coastal systems, ultra-high and very high were the most used ones. Our analyses showed the introduction by 2017 of fine resolution data with a modest increase until 2021 (R^2 = 0.75; accuracy = 0.35; for *p* values see Table S4; Figure 6d). Concerning classification methodologies (e.g., frequentist inference, machine learning), we registered as the most adopted approach in the first years the frequentist inference that was replaced progressively over time by machine learning (R^2 = 0.18; accuracy = 0.54; for *p* values see Table S4; Figure 6e). Among the analyzed coastal ecosystem types Mediterranean is the best studied one, and most of such studies were carried out between the years 2000 and 2010. The first research in our database using RS for alien plants mapping on subtropical coasts date back to the year 2005, and such application increased until today (R^2 = 0.13; accuracy = 0.34; for *p* values see Table S4; Figure 6f).

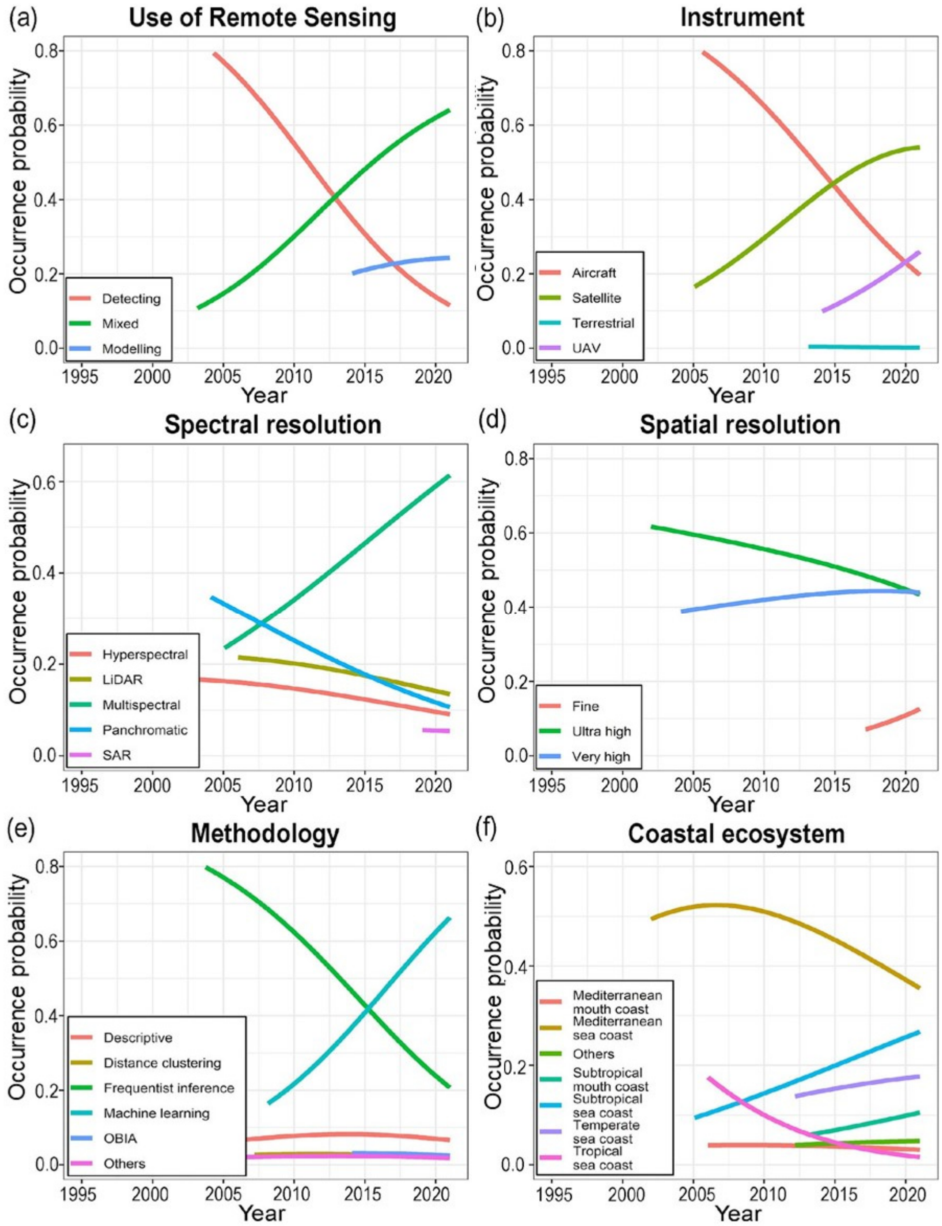

Figure 6. Temporal trends (2000–2022) of the proportion of scopus indexed papers using RS support for AIP mapping organized by (**a**) the type of use of remote sensing; (**b**) the type of instrument; (**c**) the spectral resolution; (**d**) the spatial resolution; (**e**) the methodology of analysis; and (**f**) the analyzed coastal ecosystem.

3.3. Interactions

Our results showed that most of the variables exhibited a strong association with the "coastal ecosystem" variable. Specifically, the methodology class presented the highest Cramer's V value (Figure 7a), with machine learning being used in all types of coastal ecosystems though its use was more frequent in Mediterranean and subtropical seacoast ecosystems. Frequentist inference occurred in more studies than machine learning, but its use was mainly restricted to Mediterranean seacoast ecosystems (Figure 7a).

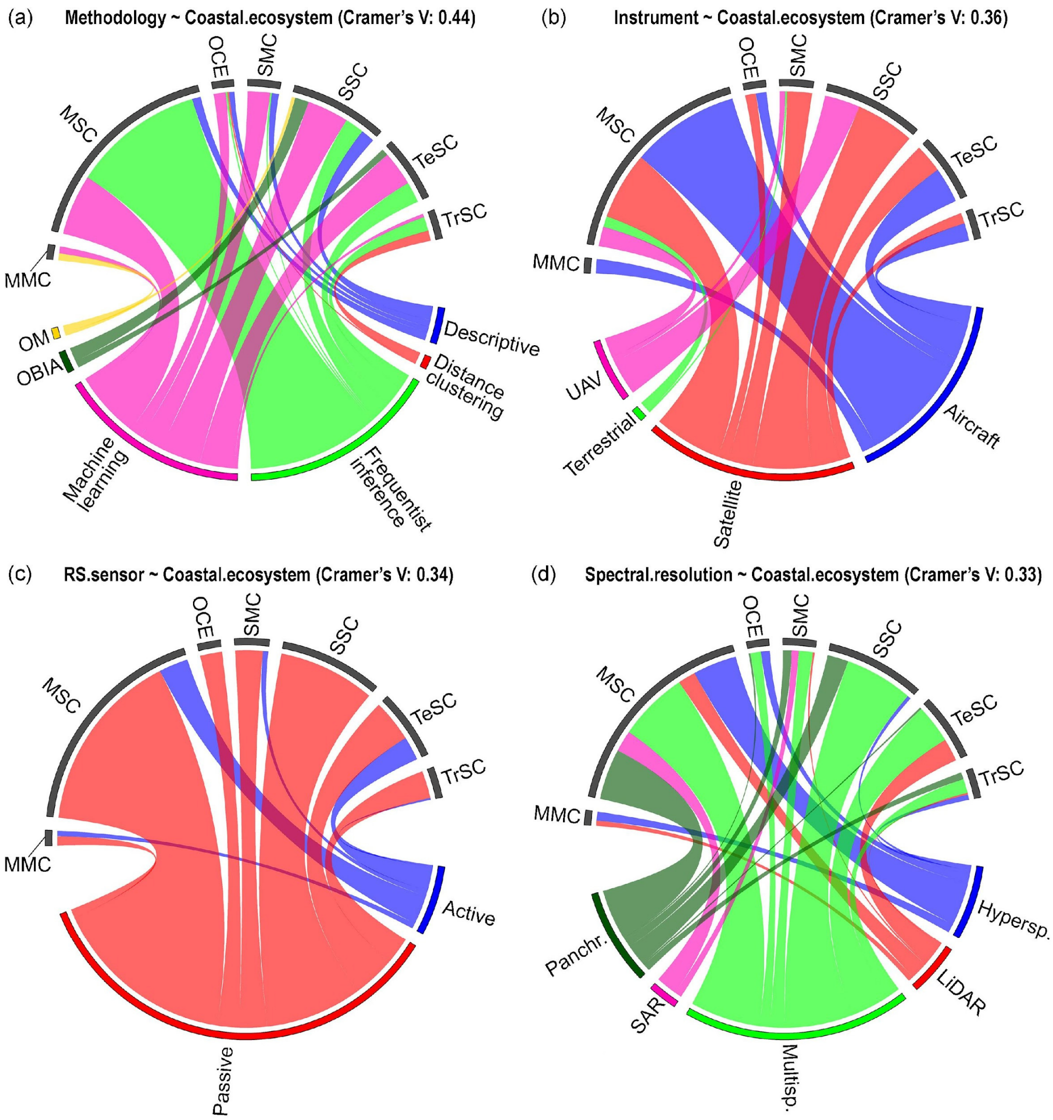

Figure 7. Chord diagrams depicting interactions between (**a**) class of methodology—coastal ecosystem; (**b**) type of instrument—coastal ecosystem; (**c**) RS sensor—coastal ecosystem; (**d**) spectral resolution—coastal ecosystem (MMC: Mediterranean mouth coast; MSC: Mediterranean Sea coast; OCE: other coastal ecosystems; SMC: subtropical mouth coast; SSC: subtropical sea coast; TeSC: temperate sea coast, TrSC: tropical sea coast).

The type of instrument (e.g., aircraft, satellite, terrestrial, UAV) also presented a high degree of association with the variable "coastal ecosystem", with satellites emerging as the most used instruments to carry out remote sensing studies in all types of coastal ecosystems, except in Mediterranean mouth coasts (Figure 7b). Aircraft were also used in many studies, though mostly pertaining to Mediterranean seacoast ecosystems. Few studies have used UAVs, which were mostly conducted in subtropical coastal ecosystems (Figure 7b).

Also, the sensor type showed a strong association with the variable "coastal ecosystem". Passive sensors proved to be the most preferred ones and were used across different types of invaded coasts. Active sensors, instead, were less used and the few existing applications were implemented in the Mediterranean and temperate coasts (Figure 7c).

As the association between "spectral resolution" and "coastal ecosystem", our results revealed that most of the analyzed RS studies on IAP invasions used multispectral resolution and panchromatic resolution in most of the coastal ecosystems (Figure 7d). Hyperspectral resolution seemed to be less preferred and was used particularly in Mediterranean seacoasts. On the other hand, the use of LiDAR and SAR data was less frequent and restricted mainly to Mediterranean and temperate seacoasts ecosystems (Figure 7d).

4. Discussion

Although the generic keyword 'invasive species' is very recurrent in the scientific literature, detailed studies that rely on remote sensing to investigate invasion events by IAP on coastal ecosystems are mostly recent and their worldwide coverage is still limited. As IAP are a major threat to biodiversity and ecological functioning on coastal ecosystems worldwide [6,7], RS applications for invasions detection, mapping and modelling remains limited to a relatively small number of studies carried out in a few countries.

Even if the research starts with a limited number of contributions, the increased production of research using different remotely sensed data registered from the early 2000s [7,39] reflects the enhanced awareness of the scientific community on the negative impacts of IAP on biodiversity [19,40] as well as the greater availability of RS data and the enhanced computational calculation facilities.

The still limited use of RS data on coastal ecosystems invaded by IAP may be due to the interaction of several aspects, such as the limited extent and fast ecological dynamic of coastal landscapes that require an accurate study of detailed spatial data registered with high frequency. Indeed, mapping coastal ecosystems characterized by tiny mosaics occurring on linear and narrow strips (usually less than 500 m) between sea and inland systems [41], requires the use of sensors with ultra-high spatial resolution regardless of the differences among satellites [42,43], aircraft [44–46], and UAVs [47–50]. The use of RS for the detection, mapping and modelling of invasive plants becomes even more difficult due to the characteristics of invasion processes that often occur on very small patches of IAP [51–53] interspersed with open areas such as bare sand or water [54]. The use of hyperspectral data with ultra-high spatial resolution, such as aircraft data (e.g., AVIRIS data), responds well to the vegetation complexity and fine scale required to IAP detection, modelling and mapping on coastal areas [44–46]. Yet, hyperspectral aircraft missions need accurate programming of non-recurrent, expensive and time-consuming data collection, which, combined with the high storage, management, and computation efforts, restrict their use to few study cases [44]. Similarly, other aircraft data (e.g., multispectral, panchromatic/RGB data and active LiDAR and SAR) registered on single missions, being unable to depict phenological vegetation features, are little used for IAP detection, mapping and modelling [55–58]. The use of free satellite data, despite the coarse spatial resolution (fine as Landsat, very-high as Sentinel-2), has gained in importance especially after 2014, also thanks to their high temporal resolution. The increasing accessibility to free and improved satellite data available worldwide [47,59,60], with short revisit period (e.g., Landsat 8 from 8 to 16 days, Sentinel-2 from 5 to 10 days) [61,62], effective support time series analysis able to depict vegetation phenology and seasonality which can help to distinguish IAP from native vegetation [53,63–65]. Indeed, as IAP tend to avoid the overlap of blooming and vegetative periods with native vegetation, temporal variability of spectral values may allow the discrimination between IAP and native species [66,67]. Most of the multispectral satellite-based studies of IAP on coastal areas are supported by Landsat data [68–71]. Landsat mission with 30 m spatial resolution, launched for the first time in the early 1970s, offers the longest temporal series with adequate spectral resolutions (11 bands in Landsat-8) [63]. However, the use of Landsat images to detect and model IAP on coastal areas could decrease in the future and be replaced by the latest satellite images with finer spatial resolution and similar revisit period (e.g., Sentinel-2, PlanetScope, etc.) [58–60,72]. The most recent RS platforms as UAVs with ultra-high spatial resolution (below 1 m) certainly offer adequate images to detect and model IAP and to analyze the entire complexity of coastal environments [50]. UAVs utilization may be limited by severe technical constraints such as the short battery life and flight duration, the survey restrictions, and the huge data processing and management effort, all reducing its potential of application at regional or national scale [14,48,73,74]. However, the invasion maps derived by UAV images may supply accurate IAP occurrences data aiding satellite data classification and modelling (e.g., Sentinel-2, PlanetScope, etc.) [42,75,76]. UAV derived occurrence data improve the detection and mapping of IAP in complex areas with low invasion degree, filling the gap between the continuous field spectral values and those of the coarser multispectral satellite images [49,75–77]. As for SAR images, while they offer a sound support for delineating coastline, mapping sea level, wind direction and ground displacements, their potential for detecting and mapping single plant species is very limited [78–81]. As a matter of fact, SAR images are used for IAP detection mainly in combination with hyper/multispectral images [59,82].

In addition to the increased availability of free images with high spatial resolution, another fact that has contributed to extend the production of RS IAP studies in coastal areas has been the improvement in classification and modelling algorithms as well as the increased computer processing power. The most recent machine learning algorithms (e.g., SVM, RF) are implemented in most of the current studies across different coastal ecosystem types [67,83,84]. The newest machine learning algorithms tend to be more accurate than the traditional parametric classifiers, especially for complex data with a high-dimensional feature space [85]. Furthermore, these algorithms are programmed to reduce the computation efforts to classify and model many remote sensing images with ultra/very high spatial resolution and/or hyper/multispectral spectral resolution [85,86]. The large number of old research projects carried out in the Mediterranean coast adopting Frequentist inference classification algorithms may reflect the long tradition of local researchers on adopting such approach for RS applications.

Our results also evidenced the limited number of countries where IAP in coastal ecosystems were detected, mapped and modelled using RS data (only 16 countries, with Asia—except for China—and the Southern hemisphere almost absent), even if the threats posed by invasion processes impact coastal areas at global scale [6,7,87]. This limited number of countries seems to be unrelated to the extent of the coastline within each state, suggesting that future efforts are needed to achieve a global cover of coastlines monitored by RS data. The large research effort that has been done in these areas, which provided results addressing several issues regarding IAP in coastal ecosystems [44,55,57,69,71,88], may be extended to other countries and regions. Undoubtedly, many nations with extensive coastlines may benefit from remote sensing analysis of IAP, such as the case of South Africa, which is under the pressure of *Acacia* but has not yet adopted remote sensing to monitor its invasion [89]. Furthermore, this limited number of countries constrained the number of studied IAP using RS platforms providing a partial picture of the invasions on a global scale. A large number of IAP impinging coastal ecosystems worldwide are still needed of specific RS research and applications [52,90,91], albeit the research in this field is progressing as shown by promising results in 2022 [92–95].

5. Conclusions

Our systematic review on the progress, current state and opportunities of RS for mapping and modelling plant invasions on coastal systems evidenced its increased utilization over time. So far, studies on this topic are still incomplete and limited to certain regions of the world. The narrow extent of coastal systems and their dynamic nature, combined with their characteristic tiny landscape pattern, require very fine resolutions and short return time of RS platforms. Despite such limits, RS applications to IAP detection and modelling registered a consistent increase, especially due to new improved RS technologies and computational power. The improvement in IAP detection, modelling, and mapping techniques in recent years, along with new RS data, are providing an improved support to invasion management also in coastal systems. For instance, the latest hyperspectral data now available with fine or very high spatial resolution (PRISMA, EnMap, Chime) are very promising for IAP detection and modelling. New data with higher spatial, temporal and spectral resolution may have an even greater potential to improve classifications and to better distinguish and monitor IAP coastal invasions. Taking example from the existing pioneer case studies, further efforts are needed to properly test and refine RS analysis of ecological invasions across all coastal countries, providing standardized and comparable information for increasingly larger areas.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/land12020341/s1, Table S1: Search terms and respective number of retrieved records; Table S2: Table of all the 86 references used for metadata extraction; Table S3: Table of all the 68 references used for analysis; Table S4: p values corresponding to the different levels of each variable under study.

Author Contributions: Conceptualization, M.D.F., M.I. and M.L.C.; methodology, P.V.P., M.D.F. and M.I.; software, M.I., P.V.P. and M.D.F.; validation, M.I., F.M. and M.D.F.; formal analysis, P.V.P., M.I. and M.D.F.; investigation, F.M., P.V.P., M.I. and M.D.F.; resources, M.L.C. and M.D.F.; data curation, P.V.P., M.I. and M.D.F.; writing—original draft preparation, P.V.P., M.I. and M.D.F.; writing—review and editing, P.V.P., M.I., F.M., M.D.F. and M.L.C.; visualization, M.I., M.D.F., F.M. and M.L.C.; supervision, M.I., M.D.F. and M.L.C.; project administration, M.D.F. and M.L.C. All authors have read and agreed to the published version of the manuscript.

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