

UNIVERSITY OF MOLISE
Department of Biosciences and Territory



DOCTORAL SCHOOL IN "ECOLOGY AND TERRITORY" – XXXVII CYCLE

Title of doctoral thesis:

**"Eyes in the Sky: Remote Sensing Approaches to Coastal Biodiversity
Monitoring and Ecosystem Health"**

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A.Y. 2024/2025

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ABSTRACT

Coastal ecosystems are dynamic transitional zones between terrestrial and marine environments, hosting specialized flora and fauna while providing essential ecosystem services, such as coastal protection and carbon sequestration. However, due to their high economic and ecological value, these regions are among the most densely populated areas worldwide. High population density and continuous exchange of materials and energy make coastal areas particularly sensitive and vulnerable to both natural and anthropogenic changes. These ecosystems have undergone severe environmental alterations caused by human activities, climate change, and extreme climate events. Human activities have significantly impacted these ecosystems, leading to habitat degradation and biodiversity loss. One of the most pressing threats to coastal biodiversity and ecosystem functioning is the spread of invasive alien plants (IAP). Regardless of intentional or unintentional introduction, IAP can disrupt ecosystems by altering communities, affecting trophic interactions, reducing animal and/or plant populations, thus reducing ecosystem resilience. Invasion processes are often facilitated by human-induced disturbances such as tourism, urbanization, agriculture, reforestation, and infrastructure development. The combined effects of anthropogenic coastal subsidence, along with increased erosion and flooding due to global climate change, have already caused significant damage to human settlements and a reduction in the provision of essential ecosystem services. Consequently, coastal ecosystems are included in the European Habitat Directive 92/43/EEC, which aims to preserve biodiversity by protecting natural habitats and wild fauna and flora.

Traditional field surveys for ecosystem monitoring, while valuable, present limitations in terms of cost, accessibility, and time. Remote sensing (RS), the process of acquiring information about the Earth from a distance, has become increasingly important for environmental conservation and ecological monitoring. These technologies have proved highly effective in assessing habitat changes and degradation, monitoring biodiversity, and identifying impacts and threats on ecosystems, including IAP and climate change.

In this context, the present PhD thesis aims to evaluate and enhance the use of RS for biodiversity monitoring in coastal ecosystems, with a particular emphasis on addressing the threat of IAP and climate change pressure. The research focused on two primary objectives:

1. To evaluate the use of remote sensing for mapping IAP in coastal ecosystems;
2. To apply different RS techniques to address ecological challenges in coastal ecosystems of Central and Southern Italy.

As a first step, a systematic review was conducted to analyze the progress of RS applications in detecting IAP in coastal environments. This review synthesizes findings from 68 studies published

between 2000 and 2021, highlighting the increasing role of unmanned aerial vehicles (UAV) platforms and machine learning analytical tools for IAP detection. The study highlighted the need to expand RS methodologies beyond dominant geographic regions (China and the USA) and to integrate predictive modeling approaches for enhanced conservation planning. To apply RS tools to real-world conservation challenges, two case studies were performed. Subsequently, I contributed to a first case study that utilized UAV imagery to identify and map *Carpobrotus* sp. pl. invasions in coastal dunes of Central Italy, proposing optimized mapping protocols for IAP management. High-resolution multispectral and RGB imagery significantly enhanced classification accuracy, demonstrating the effectiveness of UAV-based monitoring strategies for IAP management. The second case study focused on the Kentish Plover, an endangered shorebird species in Italy. This study used RS-derived environmental variables to model current and future nesting habitat suitability under climate change–driven coastline projections along the Molise coast (Southern Italy). Findings revealed a strong preference for open sandy areas near herbaceous vegetation, providing insights for conservation strategies. In addition, due to anthropogenic pressures and climate change-driven coastal modifications, potential nesting habitat is projected to decline by over 22%, emphasizing the urgent need for conservation measures to mitigate climate change effects.

This research contributes to advancing RS applications in biodiversity conservation by integrating remote sensing with ecological modeling and conservation planning. The findings have direct implications for environmental management, policymaking, and the development of data-driven strategies to mitigate biodiversity loss and habitat degradation in coastal ecosystems. Future research should focus on refining RS methodologies, incorporating additional ecological variables, and expanding predictive modeling efforts to enhance conservation outcomes and guarantee coastal ecosystems health. By demonstrating the effectiveness of RS technologies in monitoring IAP and modeling biodiversity, this research highlights the potential of RS as a fundamental tool for sustainable coastal management in the face of global environmental change.

INTRODUCTION

Coastal ecosystems, located at the dynamic interface between land and sea, represent one of the most important areas of the world's oceans from a human perspective (Lu et al., 2018). These ecosystems supply unique habitat assemblages due to a steep environmental sea-inland gradient, resulting in a high level of biodiversity compared to other natural ecosystems supporting a very specialized and distinctive flora and fauna (Bazzichetto et al., 2016; Carranza et al., 2007). Beyond their intrinsic ecological value, coastal environments provide several ecosystem services and essential benefits to society, such as groundwater stored in dunes, water purification, nutrient cycling, and coastal defense, which have value in the form of replacement coasts (Bazzichetto et al., 2016; Drius et al., 2019). As dynamic interfaces between land and ocean, coastal ecosystems act as buffer zones, protecting uplands areas from storms, flooding, wind and aerosols, and removing pollutants and other land-derived materials before entering the ocean, while also playing a crucial role in regulating climate at local and global scales (Drius et al., 2019; Lu et al., 2018). Coastal ecosystems also provide cultural services, including opportunities for recreation and tourism, as these zones are often perceived as natural spots and as a source of mental well-being offering a sense of escape and isolation (Drius et al., 2019).

Despite their high biodiversity value and numerous benefits, coastal ecosystems are among the most threatened habitats globally (Drius et al., 2019). Because of their important economic and ecological value, coastal regions are among the most densely populated worldwide, and dense populations along with the frequent exchange of materials and energy, make them particularly sensitive and vulnerable to both natural and anthropogenic changes (Lu et al., 2018). Tourism, along with associated activities such as mechanical cleaning and infrastructure development (Sperandii et al., 2019), industrial expansion and intensive agriculture have resulted in habitat loss and fragmentation, and biodiversity decline (Bazzichetto et al., 2016). Moreover, climate change exacerbates these threats, with phenomena such as sea-level rise, ocean acidification, and storm-induced coastal flooding that have intensified, causing severe damage to human settlements and reductions in the provision of crucial ecosystem services, including coastal defense, groundwater storage and climate regulation (Bazzichetto et al., 2020; Lu et al., 2018). As the potential impacts of coastal hazards continue to increase globally due to socio-economic development and population growth, erosion and flooding are expected to persist in the future due to global climate change and rising sea levels (Aucelli et al., 2018). Sea level rise will potentially pose a major threat to coastal areas, disrupt coastal ecosystems, and induce changes in breeding and feeding areas of shoreline-dependent organisms (AlRashidi et al., 2012), impacting overall ecosystem functioning. Global climate change reports have already alerted about the risks induced by sea-level rise and extreme weather events with critical

consequences on the functioning of coastal environments, particularly combined with anthropogenic coastal subsidence (Bazzichetto et al., 2020). Due to their unique geographical locations, coastal zones are the most vulnerable ecosystems to climate change impacts (Lu et al., 2018), reinforcing the urgent need for targeted mitigation measures.

One of the most pressing threats to ecosystem health is the invasion of alien species, which has become a major global conservation issue (Malavasi et al., 2019). Invasive alien plants (IAP), in particular, are present globally in most ecosystems and threaten biodiversity and ecosystem functioning, modifying communities and ecosystems, and generally decreasing animal abundance, diversity and fitness (Jackson et al., 2021). The introduction and spread of these species are closely linked to human activities, such as tourism, urban expansion, agricultural intensification, and infrastructure development, which provide pathways for their establishment (Carranza et al., 2010; Giulio et al., 2020). Fragmented and disturbed natural habitats are particularly vulnerable to invasion, as patches dominated by allochthonous species facilitate further colonization across the landscape (Carranza et al., 2010). European coastal dunes and sandy shores are among the most invaded habitats, where alien plants drive profound ecological transformations and impose significant socio-economic costs (Cascone et al., 2021; Giulio et al., 2020). Given that plant invasions are predominantly concentrated in anthropogenic habitats and landscapes undergoing human-induced transformation, their spatial coincidence underscores the urgent need for advanced methodologies to predict and manage their distribution (Basnou et al., 2015).

In response to the degradation of coastal ecosystems, many coastal habitats in Europe are included in the Habitats Directive 92/43/EEC of the European Union, which is at present one of the world's most effective legal instruments concerning biodiversity and nature conservation (Carranza et al., 2007). However, anthropogenic pressure continues to increase and due to the rapid environmental changes affecting coastal ecosystems, the development of efficient monitoring tools is essential for conservation and management strategies.

While traditional field surveys are crucial for validating data, they present significant limitations for regular biodiversity assessment, including high costs, the complexity or dynamism of some ecosystems, difficulties in accessing some sampling sites, excessive time consumption, and a lack of historical data (Marzialetti et al., 2021).

In response to these challenges, remote sensing (RS) has emerged as a powerful tool for environmental conservation and ecological monitoring (Vaz et al., 2018). RS involves collecting information about the Earth through recording, observing, and storing electromagnetic data, waves, or energies emitted or reflected by a target object or area (Okoye et al., 2020). Unlike traditional field-

based methods, RS provides frequent and complete spatial coverage, offering a cost-effective (free remotely sensed products) solution for monitoring several biodiversity features across multiple spatial scales (Marzialetti et al., 2021). This technology facilitates the study of complex geographic terrains and inaccessible ecosystems by utilizing a variety of range of sensor systems and platforms, such as aerial photographs, airborne multi-spectral scanners, satellite imagery, and ground-based spectrometer measurements, to maximize environmental monitoring (Joshi et al., 2002; Okoye et al., 2020). These sensors acquire imagery or data in varying conditions, multiple resolutions (such as spatial, spectral, and radio-metric resolution) and multiple bandwidths (Okoye et al., 2020), allowing for detailed environmental monitoring under diverse conditions.

Remote sensing techniques are particularly valuable for their ability to revisit specific geographic areas on a regular cycle, facilitating the detection of environmental changes over time, which allows to understand vegetation patterns and environmental changes, landscape conditions, and identifying the major causes of environmental degradation (Okoye et al., 2020). Additionally, RS technology has been proved to be one of the most effective ways in land cover/use monitoring, especially in coastal ecosystems classification due to the difficulties of field investigation, as it supports large-scale research, hard to carry out by modeling or field observations, such as assessing the global impacts of sea-level rise, for which predictive models are currently limited (Okoye et al., 2020; Ren et al., 2021).

Recent advancements in RS have demonstrated its potential to assess ecosystem functional attributes, properties, and services, as well as to identify biodiversity hotspots and model species distributions (Vaz et al., 2018). RS facilitates the mapping of key environmental parameters and biophysical properties that shape species distribution and abundance, driving significant progress in predictive distribution modeling and enhancing our understanding of ecosystem functioning (Bazzichetto et al., 2016). This enables ecologists and landscape planners to predict community responses to environmental and anthropogenic changes over extensive geographic areas (Andrew & Ustin, 2009; Vaz et al., 2018). The integration of remotely sensed data with in-situ field observations is particularly promising for filling gaps in biodiversity monitoring and enhancing our understanding of complex ecosystems (Marzialetti et al., 2021). Moreover, recent advances in RS and species distribution models offer promising tools for forecasting the expansion of IAP by incorporating ecologically relevant predictors derived from spectral and structural imagery (Malavasi et al., 2019). As biological invasions contribute to habitat degradation, economic losses, and potential public health concerns, enhancing our understanding of the drivers of IAP distribution remains a crucial objective in conservation biology (Bazzichetto et al., 2018).

In this context, the present PhD research aims to evaluate and improve the use of RS for biodiversity monitoring in coastal ecosystems, with a particular emphasis on addressing the threat of IAP and climate change pressure. The research focused on two main objectives:

1. **To evaluate the use of RS for mapping IAP on coastal ecosystems**, through a systematic review of scientific literature on the detection of IAP and its applicability in biodiversity conservation and environmental planning.
2. **To apply different remote sensing techniques to address ecological challenges in coastal ecosystems of Central and Southern Italy**, using UAV imagery to map *Carpobrotus* sp. pl. invasions in coastal dunes and employing remote sensing-derived variables to model current and future habitat suitability of the Kentish Plover (*Anarhynchus alexandrinus*).

We conducted a systematic literature review to provide an overview of the progress and scope of RS applications on invaded coastal areas. This review aims to facilitate the development of improved RS methodologies to support the management of IAP which pose a significant threat to coastal biodiversity and ecosystem functioning. We subsequently focused on specific remote sensing applications to comprehend and predict ecological patterns in response to various threats to coastal ecosystems. The first case study examines the use of unmanned aerial vehicles (UAV) images to identify *Carpobrotus* sp. pl. invasions on coastal dunes of Central Italy and improve mapping protocols. The second study investigates remote sensing's role in modeling current and future nesting habitat suitability for the endangered Kentish Plover (*Anarhynchus alexandrinus*) in Southern Italy, considering climate change scenarios.

The present PhD thesis is divided into two main sections:

Section 1 (**Chapter 1**) presents a systematic literature review of 68 research papers published between 2000 and 2021 that explore RS applications for IAP mapping in coastal environments. This review provides an overview of current methodologies, challenges, and future directions for improving RS-based IAP management.

Section 2 (**Chapter 2**) focuses on specific RS applications to address key ecological challenges in coastal ecosystems of Italy.

- **Chapter 2.1**, investigates the use of UAV imagery to identify and map *Carpobrotus* sp. pl. invasions on coastal dunes in Central Italy, proposing optimized mapping protocols for improved IAP management.

- **Chapter 2.2**, examines the potential of RS-derived environmental variables to model current and future nesting habitat suitability of the Kentish Plover in Southern Italy, providing insights into habitat conservation and climate change adaptation strategies.

By integrating RS tools with ecological modeling and conservation planning, this research contributes to advancing the use of RS for coastal biodiversity monitoring and promoting the health of coastal ecosystems.

Chapter 1 – “Systematic review of remote sensing applications for mapping invasive alien plants in coastal environments”

In this first chapter, my aim was to examine the advancements and applications of various remote sensing techniques for detecting and mapping IAP in coastal ecosystems, as it is one of the main threats that is leading to biodiversity loss and environmental degradation of these landscapes on a global scale.

This study enabled me to understand the strengths and limitations of different remote sensing technologies for identifying and mapping the spatial distribution of IAP in coastal ecosystems worldwide. This contribution could help to improve methodologies aimed at mitigating this threat. Furthermore, this research highlighted the critical role of remote sensing and geographic information systems (GIS) in monitoring these ecosystems, which are often characterized by inaccessibility and logistical challenges associated with fieldwork, due to their extensive spatial coverage.

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



Citation: Villalobos Perna, P.; Di Febbraro, M.; Carranza, M.L.; Marzialetti, F.; Innangi, M. Remote Sensing and Invasive Plants in Coastal Ecosystems: What We Know So Far and Future Prospects. *Land* **2023**, *12*, 341. <https://doi.org/10.3390/land12020341>

Academic Editor: Krish Jayachandran

Received: 21 December 2022

Revised: 17 January 2023

Accepted: 24 January 2023

Published: 27 January 2023



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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).

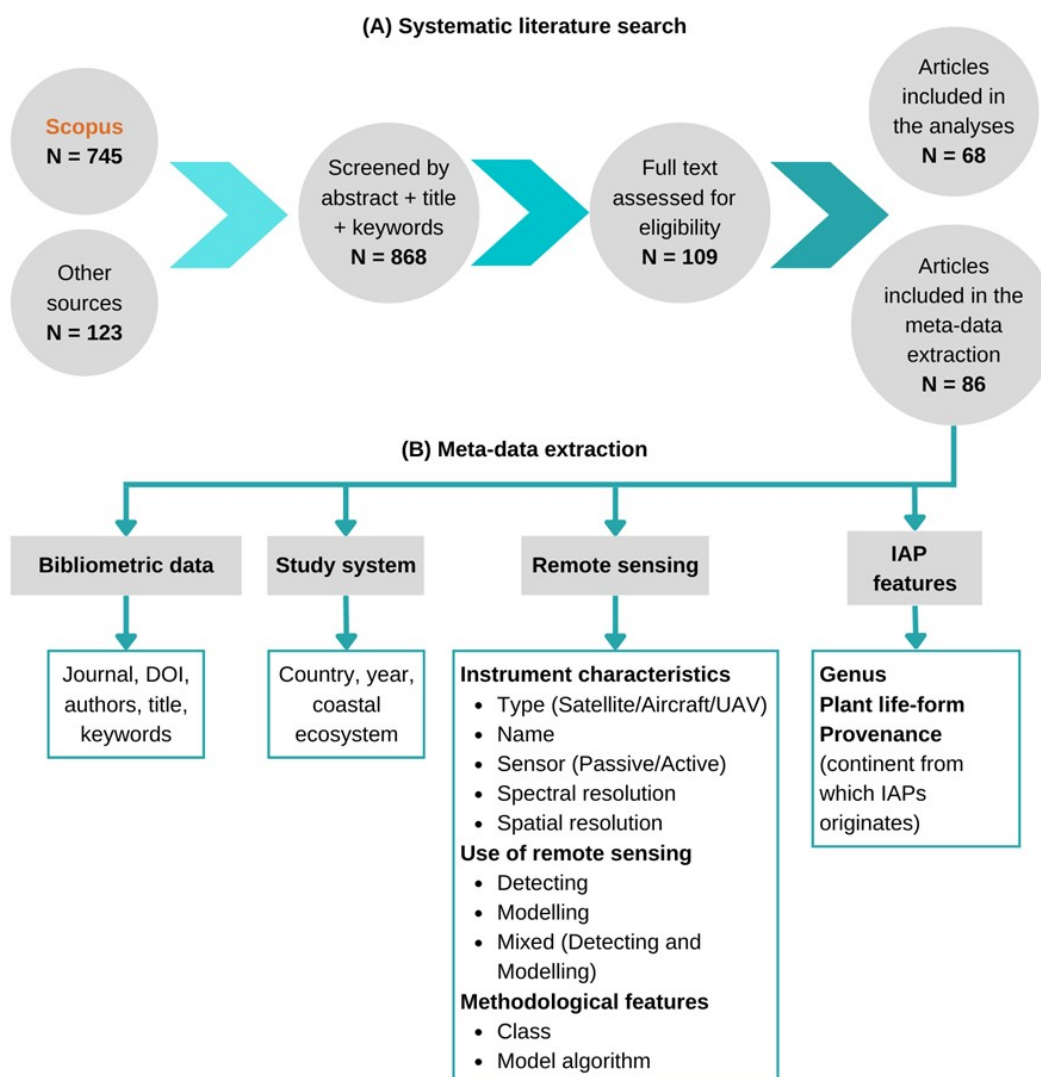


Figure 1. (A) Diagram describing the flow of information through the different phases of the systematic literature review. (B) Summary of the metadata collected for the database (UAV stands for unmanned aerial vehicle).

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

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).

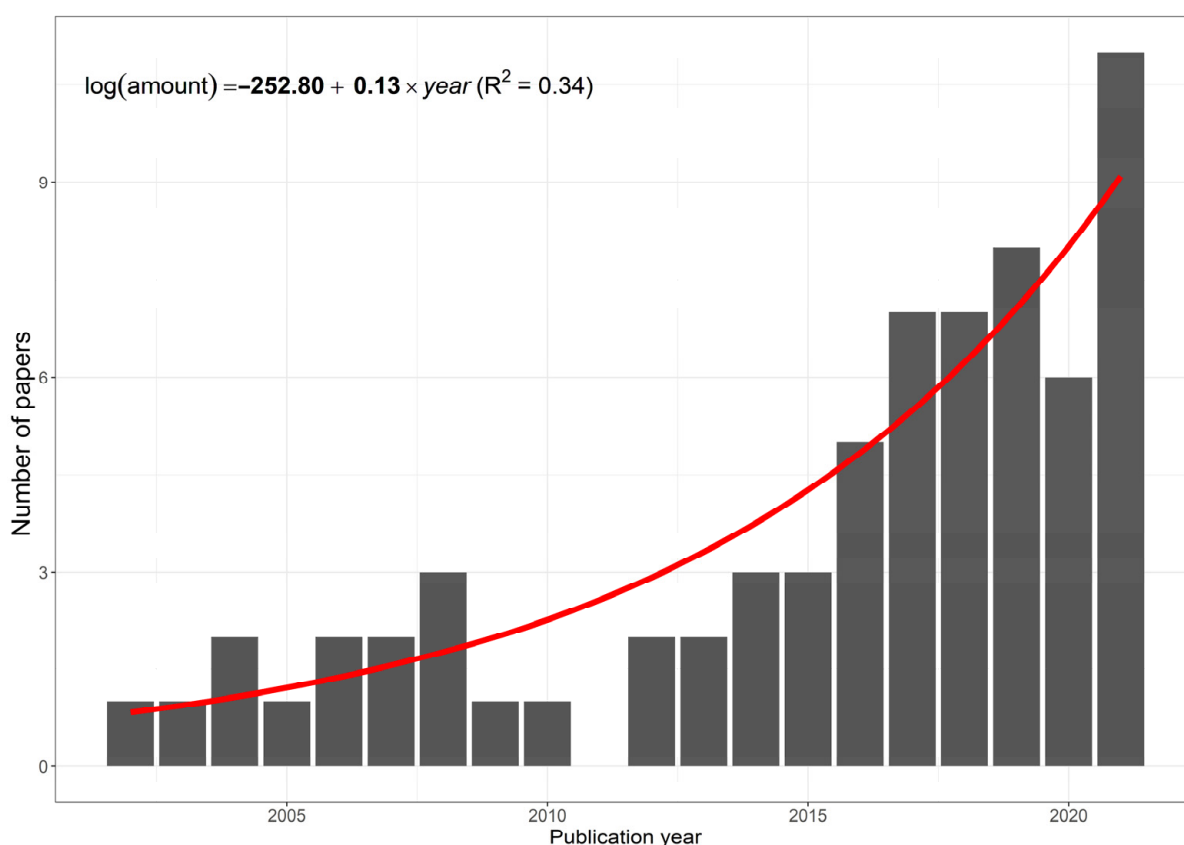


Figure 5. Temporal trends in the number of published records per year (2000–2021; source scopus).

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).

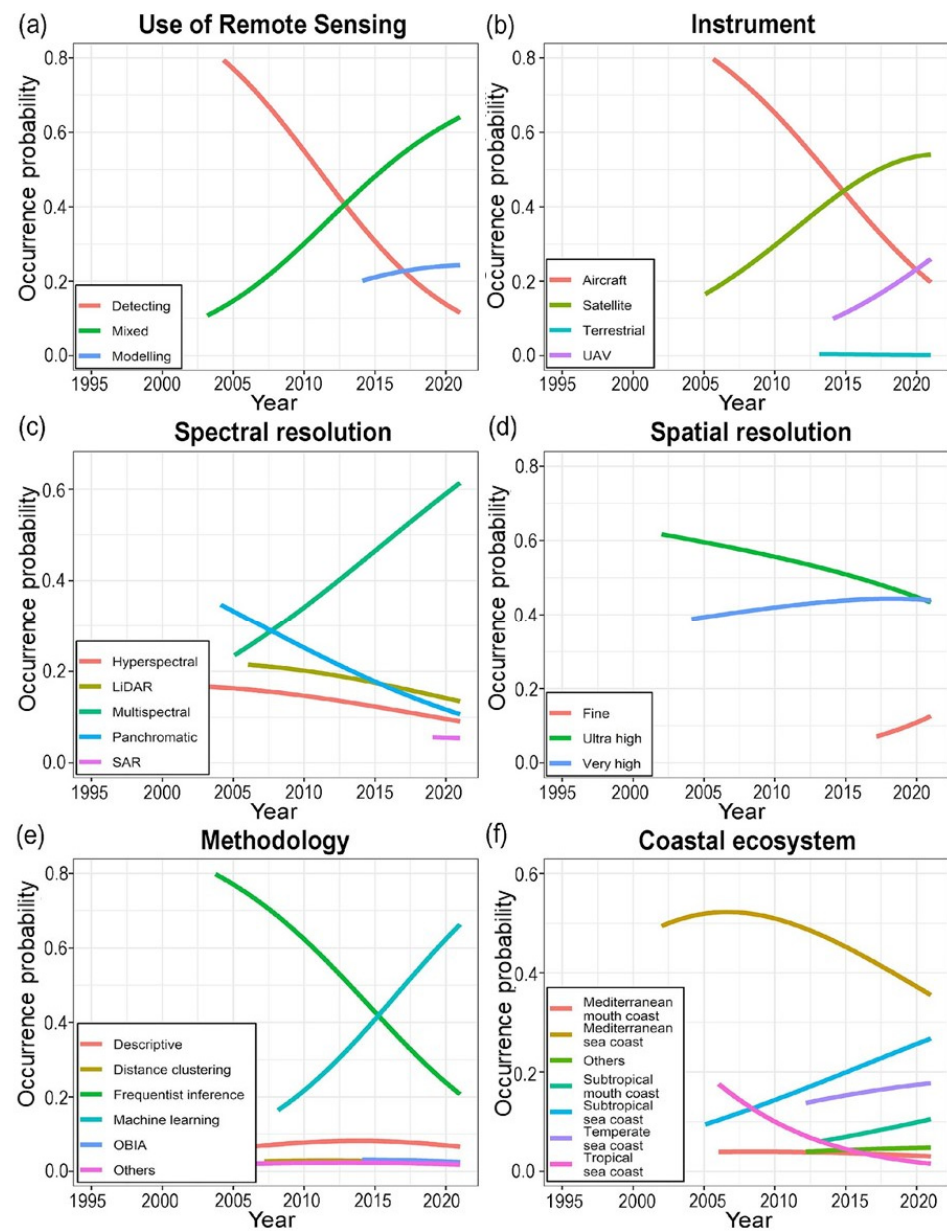


Figure 6. Temporal trends (2000–2022) of the proportion of scopus indexed papers using RS support for AIP mapping organized by (a) the type of use of remote sensing; (b) the type of instrument; (c) the spectral resolution; (d) the spatial resolution; (e) the methodology of analysis; and (f) the analyzed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

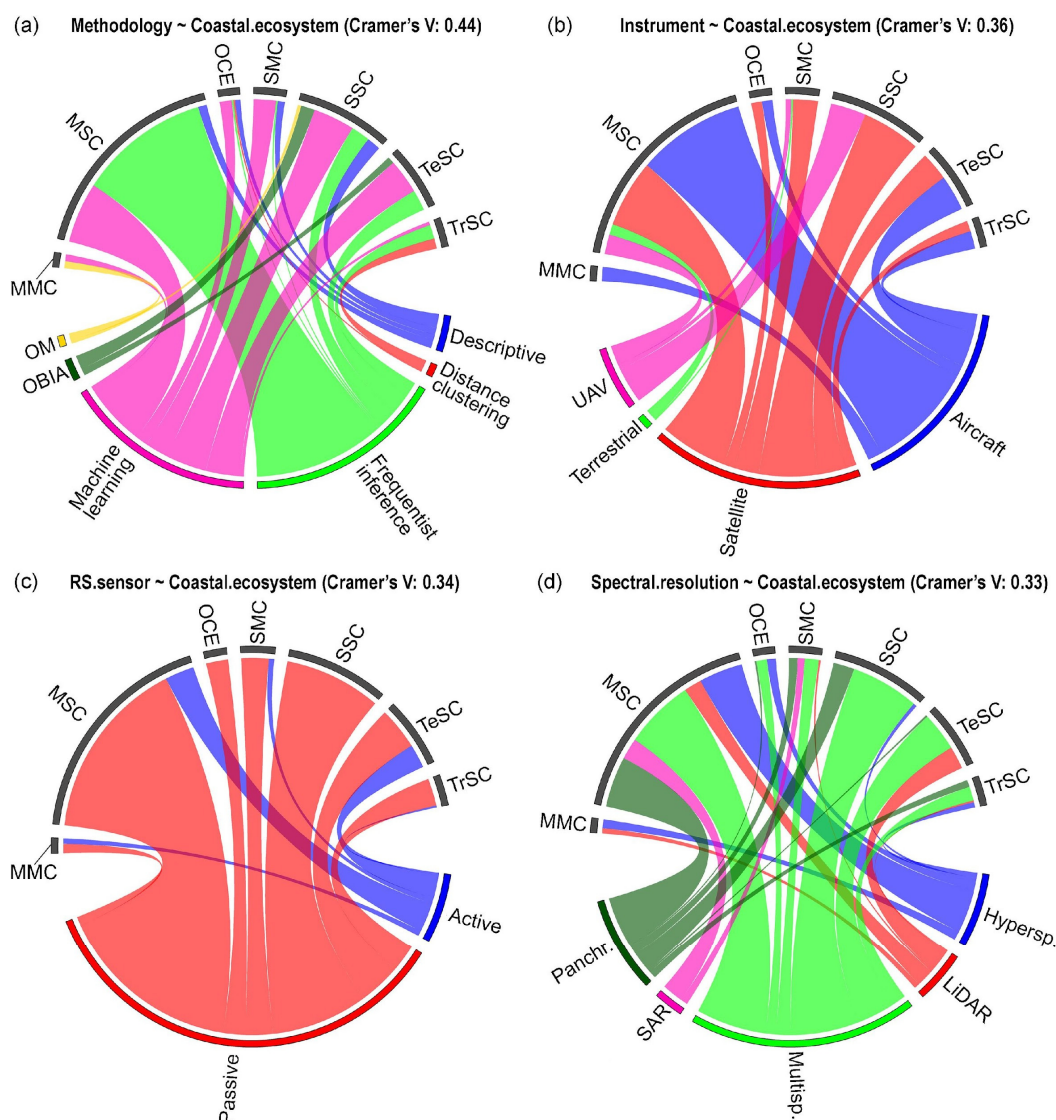


Figure 7. Chord diagrams depicting interactions between (a) class of methodology—coastal ecosystem; (b) type of instrument—coastal ecosystem; (c) RS sensor—coastal ecosystem; (d) spectral resolution—coastal ecosystem (MMC: Mediterranean mouth coast; MSC: Mediterranean Sea coast; OCE: other coastal ecosystems; 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 sea coast 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 Mediter-

ranean 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.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The data presented in this study are available on request from the corresponding author while the whole list of references used is provided as Supplementary Material.

Acknowledgments: This research was supported by Project DM 1062-10 August 2021, RTD-A (Action IV.6: Green. Code: 39-G-13537-2), PON-AIM (Programma Operativo Nazionale ricerca e innovazione 2014–2020; ID AIM1897595-2), PON “Green” D.M. n. 1061 PhD Programme and bilateral program Italy–Israel DERESEMII (Developing state-of-the-art remote sensing tools for monitoring the impact of invasive plant The authors acknowledge the editor and the four anonymous reviewers for the appreciation and helpful comments that help us to improve the manuscript.

Conflicts of Interest: The authors declare no conflict of interest.

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Chapter 2 – “Remote sensing applications for addressing key ecological challenges in coastal ecosystems of Italy”

*2.1 – UAV for identifying and mapping *Carpobrotus sp. pl.* invasions on coastal dunes of the Central Italy*

The findings presented in the first chapter demonstrated that UAVs have been the most extensively utilized platforms since 2014, as they provide high-resolution imagery that is particularly effective for detecting and modeling IAP, as well as for analyzing the intricate dynamics of coastal environments (Villalobos Perna et al., 2023). Building on these findings, this second chapter explores the strengths and limitations of UAV technology, with a particular emphasis on a case study aimed at identifying and proposing improved protocols for mapping *Carpobrotus sp. pl.* invasions in coastal dune ecosystems of Central Italy.

This research not only highlights the advantages and challenges associated with the use of UAVs but also identifies the most effective methodological approach for detecting *Carpobrotus sp. pl.*, considering its ecological traits and specific growth patterns in coastal environments. Additionally, this study contributes to the development of innovative protocols for managing IAP in coastal ecosystems, offering a detailed framework of critical factors to consider for their implementation in future management and conservation initiatives.



Article

Coastal Dune Invaders: Integrative Mapping of *Carpobrotus* sp. pl. (Aizoaceae) Using UAVs

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Abstract: Coastal dune ecosystems are highly threatened, and one of the strongest pressures is invasive alien plants (IAPs). Mitigating the negative effects of IAPs requires development of optimal identification and mapping protocols. Remote sensing offers innovative tools that have proven to be very valuable for studying IAPs. In particular, unmanned aerial vehicles (UAVs) can be very promising, especially in the study of herbaceous invasive species, yet research in UAV application is still limited. In this study, we used UAV images to implement an image segmentation approach followed by machine learning classification for mapping a dune clonal invader (*Carpobrotus* sp. pl.), calibrating a total of 27 models. Our study showed that: (a) the results offered by simultaneous RGB and multispectral data improve the prediction of *Carpobrotus*; (b) the best results were obtained by mapping the whole plant or its vegetative parts, while mapping flowers was worse; and (c) a training area corresponding to 20% of the total area can be adequate for model building. Overall, our results highlighted the great potential of using UAVs for *Carpobrotus* mapping, despite some limitations imposed by the particular biology and ecology of these taxa.

Keywords: alien early detection; GNDVI; HIS; LSMS; monitoring protocol; OBIA; random forest classification; SAVI; ultra-high spatial resolution



Citation: Innangi, M.; Marzialetti, F.; Di Febbraro, M.; Acosta, A.T.R.; De Simone, W.; Frate, L.; Finizio, M.; Villalobos Perna, P.; Carranza, M.L. Coastal Dune Invaders: Integrative Mapping of *Carpobrotus* sp. pl. (Aizoaceae) Using UAVs. *Remote Sens.* **2023**, *15*, 503. <https://doi.org/10.3390/rs15020503>

Academic Editors: Francisco Javier Mesas Carrascosa, José Emilio Meroño-Larriva and María Jesús Aguilera-Ureña

Received: 15 December 2022

Revised: 3 January 2023

Accepted: 12 January 2023

Published: 14 January 2023



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1. Introduction

Coastal ecosystems, due to their transitional nature between terrestrial and marine environments, are among those with the highest primary and secondary productivity and provide a large number of ecosystem services [1]. At the same time, human activities have had considerable direct and indirect impacts on coastal ecosystems, including habitat reduction, overexploitation, eutrophication, and pollution [2–6]. Beaches and coastal dune systems are among the coastal ecosystems most impacted by human activities, especially tourism-related ones [3,7,8]. Coastal dunes make up about three-quarters of the world's coastline and represent one of the most dynamic landscapes on earth [9,10], providing a multi-service nature of ecosystem services [11]. Under natural conditions, dune systems are characterised by marked gradients in chemical and physical characteristics from the coastline inland, favouring the establishment of highly specialised flora and fauna that follow one another in well-structured and defined communities [8,12–15].

Among the various threats to dune ecosystems, invasive alien plants (IAPs) represent one of the most serious [16]. IAPs are non-native taxa introduced voluntarily or involuntarily by humans, originating breeding populations in places far from their native ranges, resulting in negative economic and/or ecological impacts [17,18]. Indeed, IAPs are considered the second major threat to biodiversity globally, affecting species composition

and jeopardizing the conservation status of invaded habitats [18,19]. Early identification and accurate mapping of the presence of IAPs are basic prerequisites of any containment or eradication plans against these plants [17,20–22], as well as modelling their future invasion risks [23]. Traditional detection and mapping of IAPs usually involve intensive field investigations, which can be time-consuming and costly [24]. Nowadays, the availability of remote sensing technologies enables acquisition of data with more and more spatial and temporal resolution, and have expanded the range of applications in the field of IAPs mapping and detection [25–28]. However, the resolution of most of the satellite data was still recognised as the main cause for classification inaccuracies when discriminating IAPs from native vegetation [29]. An even more innovative frontier is offered by the use of unmanned aerial vehicles (UAVs) that are capable of low flying and acquiring RGB, multispectral, and hyperspectral images at higher resolution than satellite data [30–32]. When it comes to IAPs, resolution of satellite images may not be high enough to detect isolated individual plants or even small populations of plants [33]. In recent years, UAVs have been successfully employed in studying IAPs [32,34–37], sometimes in tandem with satellite imagery or as a high-resolution training dataset for upscaling satellite data [38–41]. Hitherto, despite their potential, the use of UAVs for invasion management of IAPs remains vastly outmatched by satellite and airborne imagery or even field measurements [29].

In coastal dune landscapes, UAVs have proven effective tools in the identification and mapping of IAPs, since the use of satellite imagery alone cannot always yield effective results due to both the dynamic and heterogeneous nature of the landscape and the too coarse spatial resolution compared to the very fine grain of the dunes [34]. Nevertheless, coastal dunes in Europe are more successfully invaded by relatively small species, such as annuals including *Xanthium orientale* L. (Asteraceae) and *Erigeron canadensis* L. (Asteraceae) or several taxa of the genus *Oenothera* L. (Onagraceae) that are biennial hemicryptophytes [42,43]. A recent study showed that 49% of remote sensing applications dealt with the management of herbaceous plant invaders [29], yet most studies addressing herbaceous IAPs are focused on agricultural weeds [44–46]. Moreover, less than 4% of the IAP research has focused on marine coastal sand dune ecosystems, while even less information is available for succulent invaders, which account for about 1.5% of the total IAP studies [29].

Among the succulent IAPs that most seriously threaten dune environments is the genus *Carpobrotus* N.E.Br. (Aizoaceae). Despite their prominent role as invaders on coastal dunes, there is little research on *Carpobrotus* using remote sensing applications [47–50] and, to the best of our knowledge, no studies have ever attempted a detailed, high-resolution mapping of single *Carpobrotus* patches on coastal dunes using a combination of object-based image analysis (OBIA) and machine learning classification based on ultra-high-resolution UAV images.

In this study, we address several technical issues concerning the application of UAVs for identifying and propose potential mapping protocols of *Carpobrotus* invasions on coastal dunes. In particular, we aim to: (a) evaluate the most suitable RS set of variables to predict the presence of *Carpobrotus* among those derived from RGB and multispectral sensors; (b) evaluate the best approach to predict the whole plant or only the green parts or flowers using an OBIA–machine learning approach; and (c) establish the minimum training area in which to carry out photointerpretation of species presence to minimise manual effort when designing monitoring plans in new areas.

2. Materials and Methods

2.1. Study Species

A prominent example of IAP heavily affecting coastal dunes is the genus *Carpobrotus* (Figure 1). *Carpobrotus* are succulent, trailing perennial grasses, native to South Africa with a great propensity for clonal reproduction [51–53]. They have been introduced to Europe for ornamental and soil stabilisation purposes since the early 17th century and they are now widely naturalised in coastal habitats of southern and western Europe [53]. Two different species are typically found in Europe: *C. edulis* (L.) N.E.Br. and *C. acinaciformis* (L.) L.Bolus,

which are often difficult to distinguish from each other and can easily hybridise [49,53]. Although it is problematic to discriminate between the two species (especially in the absence of flowers), their ecological impact is essentially the same [54]; thus, from now onwards, we refer to *Carpobrotus* indicatively.



Figure 1. UAV image of a single patch of *Carpobrotus* about 6 m in diameter, with details of the plant as a whole, the green parts, and the flowers. Pictures by Michele Innangi.

Carpobrotus can invade sandy coastal ecosystems—from embryonic dunes to juniper groves—and rocky coastal ecosystems with equal success [53]. *Carpobrotus* represents one of the most important plant invaders in the Mediterranean [53,55], where their spread in coastal ecosystems is seriously threatening the conservation of biodiversity on both local and global scales, and numerous eradication initiatives have been implemented [56], especially on small islands [55,57,58].

2.2. Study Area

The area under investigation was a sector of central Italy on the Tyrrhenian coast (41.909461°N, 12.148823°E, Passoscuro, Fiumicino, Rome; Figure 2). In this area, it is possible to recognise the typical dune zonation characterised by a strong environmental gradient from the coastline inland that contributes to the formation of a sequence of habitats, many of which are of conservation importance [3,13,14]. In spite of the presence of a well-formed dune structure, the Passoscuro area has also been subject to tourist exploitation, encouraging a strong colonisation of alien species, in particular *Carpobrotus* [41].

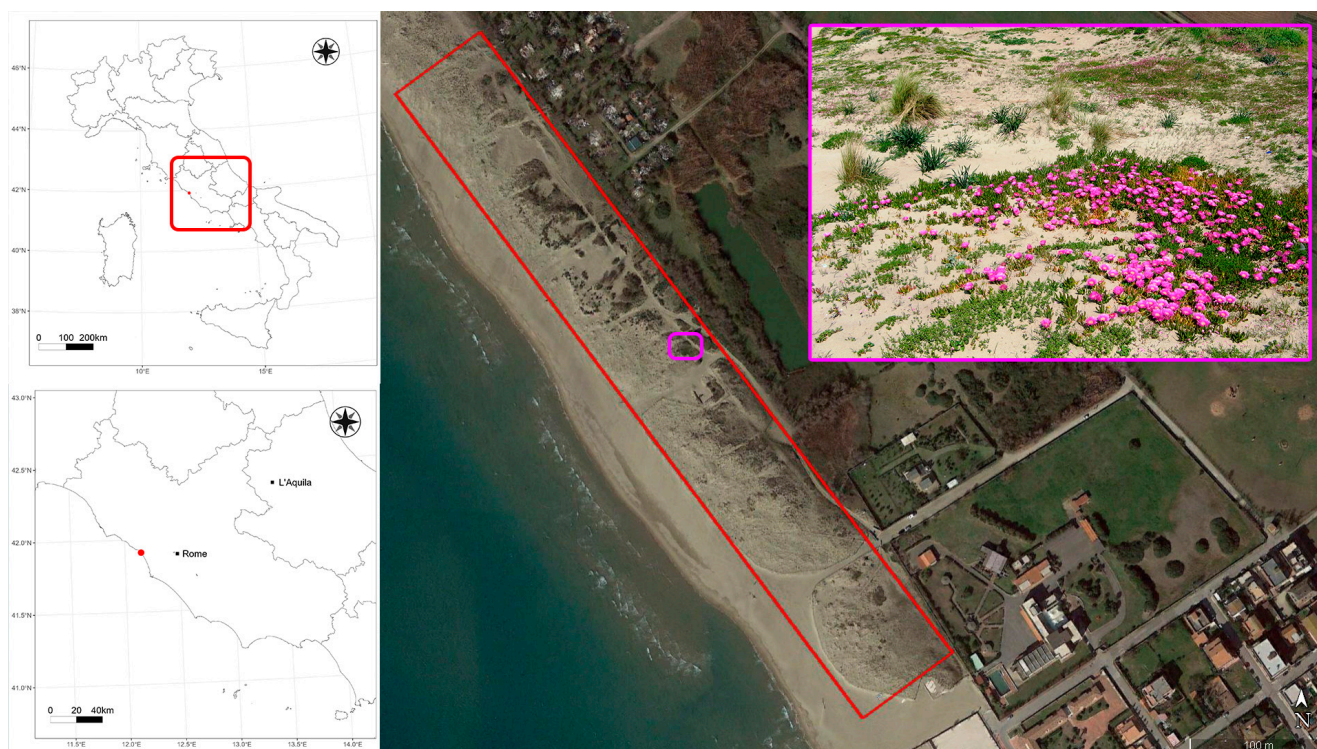


Figure 2. Map of the study area (41.909461°N, 12.148823°E, Passoscuro, Fiumicino, Rome, EPSG:4326-WGS84). The location of the Passoscuro shoreline where the UAV surveys were carried out is shown in the red boxes on the left on a map of Italy and a map of the region Latium where Passoscuro is located. The 5-hectare area surveyed is outlined in red in the central air photo (image acquired in March 2022 © Maxar Technologies and visible on the © Google Earth platform). The top right inset shows detail of the Passoscuro dune, highlighting a *Carpobrotus* bloom (Picture by Alicia Teresa Rosario Acosta).

2.3. Data Acquisition and Pre-Processing

We implemented a semi-automatic classification approach based on OBIA followed by machine learning classification for mapping *Carpobrotus*. An outline of the whole methodology can be seen in Figure 3. In May 2021 (i.e., during the peak flowering period of *Carpobrotus*), images were acquired by a UAV equipped with two different sensors over an area of approximately 5 hectares. We employed a multirotor quadcopter DJI Phantom 4 Pro V2.0 equipped with CMOS (complementary metal oxide semiconductor) sensor, i.e., a Red–Green–Blue (RGB) camera with 20 Mpx and 24 mm of equivalent focal length (EFL), and Parrot Sequoia multispectral camera with four bands, each with 1.2 Mpx and 30 mm EFL: Green (G, bandwidth: 550 nm ± 40 nm), Red (R, bandwidth: 660 nm ± 40 nm), Red Edge (RE, bandwidth: 735 nm ± 10 nm), and Near Infrared (NIR, bandwidth: 790 nm ± 40 nm).

Flights were planned via the freeware mobile application PIX4Dcapture (version 4.11.0 for Android, <https://www.pix4d.com/product/pix4dcapture/>, accessed on 18 November 2022). All UAV surveys were standardized using the same settings: time of acquisition between 10:00 and 12:00 PM, altitude of 35 m above the take-off point and speed of 5 m/s. The image overlap was set to 80% for both forward and lateral overlap. For setting up the Parrot Sequoia camera, we used the dedicated HTML interface, accessible by connecting the camera to the smartphone via Wi-Fi. Within the HTML interface, we entered the same flight altitude and image overlay values described for the PIX4Dcapture application. The two sensors captured images simultaneously during the flights; the CMOS sensor was activated by PIX4Dcapture, while the Parrot Sequoia camera was activated by the HTML interface. Before the flights, 12 ground control points (GCPs) of 50 cm² were placed in the flight area. The coordinates of the GCPs (longitude, latitude, and

altitude) were measured with a high-precision GNSS receiver (Trimble R2) connected to the HxGN SmartNet GNSS positioning services for RTK correction (nearest) with nominal and estimated horizontal accuracies of 1 and 7 cm, respectively. All aerial images were processed using Agisoft Metashape Professional's Structure for Motion (SfM) approach (version 1.6.2, <https://www.agisoft.com/>, accessed on 18 November 2022). We produced, for each flight, the RGB orthomosaic and the digital surface model (DSM) using the aerial images derived from the RGB CMOS sensor and the orthomosaics of the G, R, RE and NIR bands from the aerial images of the multispectral Parrot Sequoia sensor. These orthomosaics were georeferenced with the coordinates of the GCPs [34,59,60]. The spatial resolutions were 2 cm in RGB orthomosaics, 2.5 cm in DSM, and 5 cm in multispectral orthomosaics. All orthomosaics were up-scaled by means of bilinear interpolation to a resolution of 5 cm, which was the coarsest resolution available from the multispectral data [34,61].

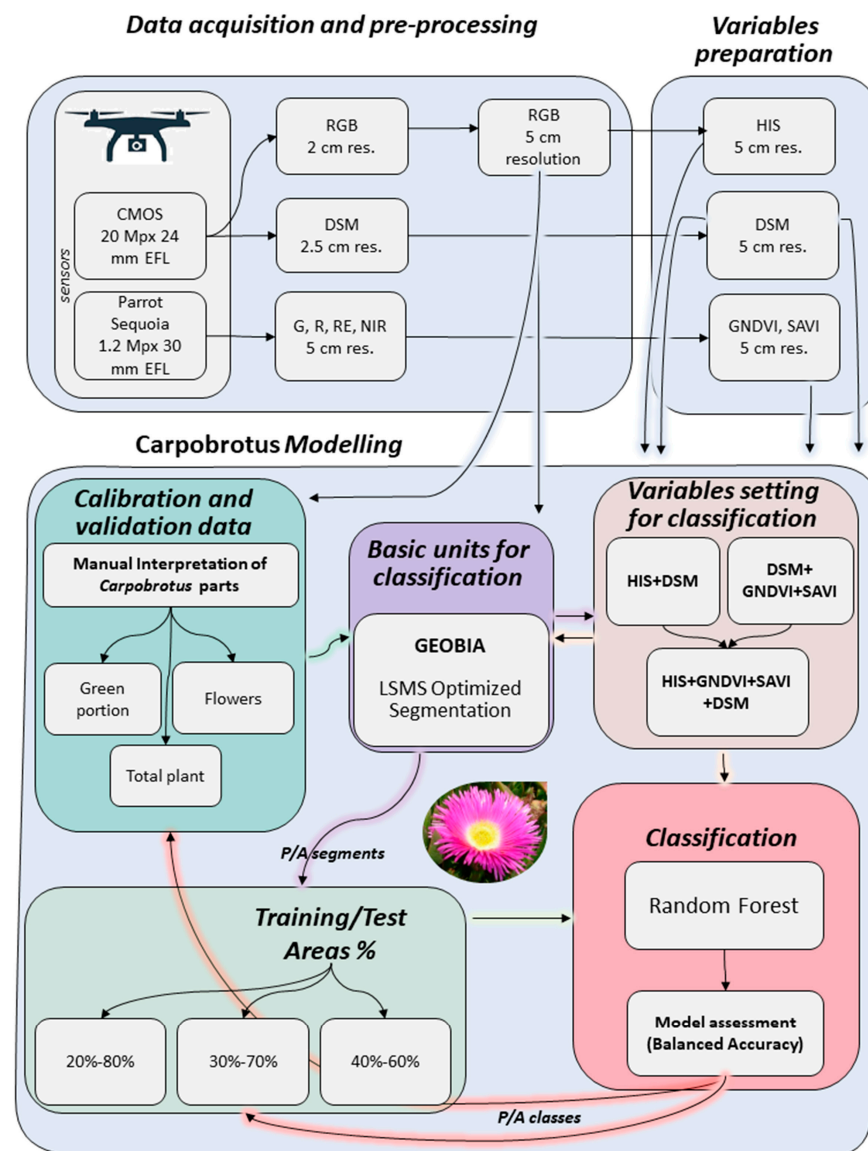


Figure 3. Simplified outline of the semi-automatic classification approach based on OBIA followed by machine learning classification adopted in this study. For details, see Section 2.

2.4. Preparation of Variables

Based on the up-scaled RGB orthomosaic, we derived hue, intensity, and saturation metrics (HIS) using the *i.rgb.his* tool within GRASS GIS 8.2 (<https://grass.osgeo.org/>, accessed on 19 November 2022), where hue (HUE) refers to the dominant wavelength of

light within the pixel, intensity (INT) refers to the total brightness of a colour measured as the relative degree of black or white, while saturation (SAT) refers to the purity of colour defined as the absence of blending in a fully saturated pixel devoid of other frequencies [34, 62]. Based on the multispectral orthomosaics, we derived two indexes that have been listed among those useful for detecting alien species [27], i.e., green normalized difference vegetation index (GNDVI, Equation (1)) and soil adjusted vegetation index (SAVI, Equation (2)). GNDVI is derived from the normalized difference vegetation index (NDVI) but, while NDVI involves NIR and R bands, GNDVI involves NIR and G bands [63]. GNDVI was shown to have a larger dynamic range than the NDVI, strong sensitivity to chlorophyll concentration across vegetation [63], and was successfully employed to study biodiversity and alien species [32,64]. SAVI was also introduced as a modification of NDVI, yet this index aimed to reduce soil brightness influences from spectral vegetation indices involving R and NIR wavelengths [65]. This correction is made by introducing the L factor into the index, which is set at 0.5 when there is little or intermediate vegetation [65]. SAVI was shown to be the most important spectral indices in predicting alien species distribution in arid ecosystems [66], aridity that also characterises dune systems.

$$\text{GNDVI} = \frac{\text{NIR} - \text{G}}{\text{NIR} + \text{G}} \quad (1)$$

$$\text{SAVI} = \frac{\text{NIR} - \text{R}}{\text{NIR} + \text{R} + \text{L}} \times (1 + \text{L}) \text{ with } \text{L} = 0.5 \quad (2)$$

HIS, multispectral indexes (GNDVI and SAVI, which we refer to simply as multi) and DSM data were all rescaled between the values of 0 and 255 [34,67] to reduce potential errors in the classification algorithm due to the different units of measurement of the variables.

Calibration and validation data were produced through photointerpretation of the original RGB image at a resolution of 5 cm. After masking artificial infrastructures (e.g., buildings or previously built-up areas, construction sites, roads, etc.) all recognisable *Carpobrotus* plants were manually interpreted on video with the help of QGIS 3.28 (<https://www.qgis.org/>, accessed on 17 November 2022), distinguishing between the flowers and green parts of the plant. In this way, we obtained a dataset able to depict the whole plant (i.e., Total plant), the green parts only (i.e., Green), and the flowers (i.e., Flowers).

2.5. *Carpobrotus* Modelling

We ran a total of 27 classification models, combining three different sets of RS variables (i.e., HIS + DSM, Multi + DSM, HIS + Multi + DSM), the different parts of the plant (i.e., Total plant, Green portions, and Flowers), and incremental calibration areas (i.e., 20–30–40% of the whole area). Specifically, calibration was implemented using incremental belts of the study area starting from the centre (i.e., 20–30–40% of the whole area), while the remaining portions were used for model validation (i.e., 80–70–60% of the whole area).

For every model, we generated the basic units for the classification by image segmentation of the original RGB orthomosaic using a geographic object-based image analysis approach (GEOBIA) [34,68]. Specifically, we used the large scale mean shift (LSMS) algorithm implemented in the open-source software Orfeo Toolbox for image classification [69]. The LSMS is a non-parametric, iterative clustering algorithm that groups image regions based on spatial and spectral proximity into homogeneous segments. The algorithm needs three parameters for optimal performance: spatial radius (sr), defining the maximum Euclidean spatial distance between pixels to be grouped in the same polygon; range radius (rr), the maximum Euclidean spectral distance between pixels to be grouped in the same polygon; and minimum segment size (ms), the minimum number of pixels per segment to define a polygon. We optimised the selection of segmentation parameters using an iterative algorithm. Initially, we created all possible combinations of the three LSMS parameters considering the following ranges: sr 1–14, rr 1–14, and ms 30–140 for total and green parts of *Carpobrotus* and sr 1–10, rr 1–10, and ms 10–50 for flowers. These values have been

chosen based on previous literature [30,34,68,70] to account for the different sizes of the plant's parts. From this set of combinations, we selected a random 20% and used it as an initial screening by performing the segmentation of the original RGB orthomosaic over the largest training area (40%). Then, we selected only the five combinations of LSMS parameters that gained the highest internal validation metric (mean balanced accuracy 0.835 ± 0.077) and we repeated the previous step. At the end of the process, we identified the best LSMS parameters per each model. Subsequently, the optimised segments were classified *Carpobrotus* presence when at least 50% of the pixels in them had been photo-interpreted as *Carpobrotus*, while the remaining segments were classified as absences.

Subsequently, for each model, 20% of the whole segment was used for calibration using random forest (RF), a machine learning regression/classification algorithm that works by constructing a large number of decision trees to generate spatial classifications and predictions [15,34,71]. We used the method 'ranger' as RF algorithm, implemented in the 'caret' R package [72]. RF classification models were optimally-tuned through internal 10-fold cross validation [73]. Specifically, the number of uncorrelated decision trees (Ntree) was set to 1000, while we tested for the highest accuracy in terms of optimal split rules and for the number of variables randomly selected at each node of decision trees (Mtry, ranging from two to the max number of variables within each model). The Gini index for classification (impurity) was used to assess variable importance. Finally, the calibrated model was projected on the test areas.

The accuracy of the models was quantified by assessing model predictions against the *Carpobrotus* presence-absence segments on the test areas (i.e., that were held out from the model calibration). In particular, given the strong class imbalance occurring between *Carpobrotus* presence and absence segments, we chose to rely on the balanced accuracy (BA) as an overall predictive performance metric. BA is an unbiased metric ranging from 0 to 1 and it is computed as the arithmetic mean between the true positive rate (sensitivity) and the true negative rate (specificity). BA values below 0.5 can be considered as indicating a random prediction. BA was shown to be a reliable metric when there is a strong class imbalance in several binary classification scenarios, including with remote sensing data [74–76]. From a computational point of view, BA is equivalent to true skill statistics (TSS), which is the sum of sensitivity and specificity minus one, and as a consequence, TSS can also assume negative values [77,78]. BA values can be computed from TSS by a simple linear equation ($BA = \frac{1}{2} \times TSS + \frac{1}{2}$).

Lastly, we assessed which factor (i.e., the combination of RS variables, the part of the plant analysed, and the percentage of the training area) was more decisive in influencing BA values by fitting a linear model that included BA as the response variable and the different factors and their combinations as covariates. The residuals of this model were checked for linearity and homoscedasticity. All statistical analyses were performed using R version 4.2.1. [79] using packages 'caret' [72], 'SegOptim' [80], and 'terra' [81].

3. Results

The results for the LSMS optimization can be seen in Figure 4. The parameters were very similar with regard to the analysis of the plant in its entirety (Total), with few differences depending on the type of variables used. In particular, sr was optimal between 1 and 2, rr between 10 and 12, and ms between 110 and 150. The analysis on the green parts of the plant alone (Green), on the other hand, resulted in a change about rr, which was lower (between 2 and 4) when multispectral data were present in the dataset, while sr and ms were comparable at Total. Finally, the case of flowers showed the greatest variability with different results depending on the type of dataset used and characterised above all by higher sr values, up to 10 in the case of Multi + DSM.

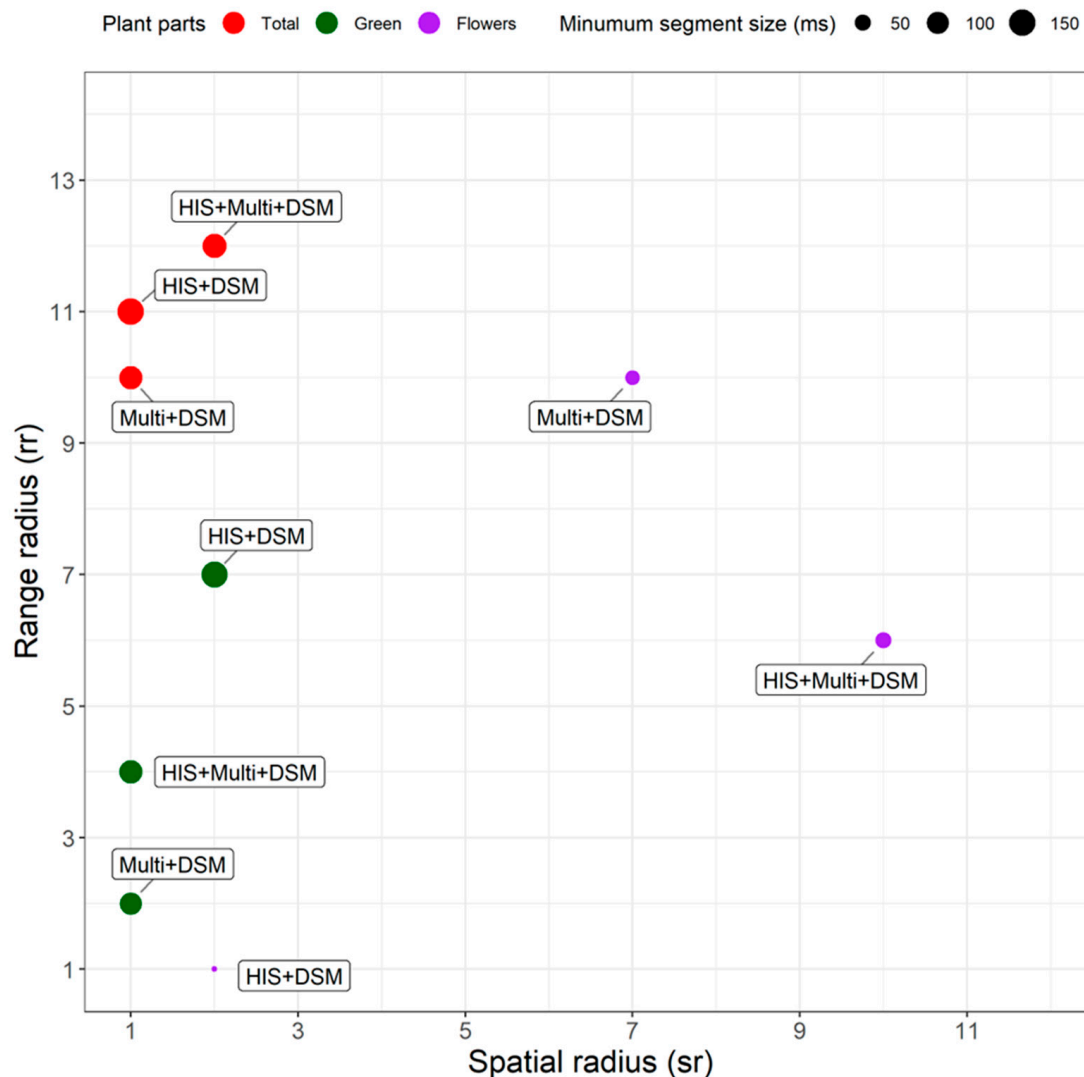


Figure 4. Graphical representation of optimised LSMS segmentation parameters. The x and y axes represent spatial radius (sr) and range radius (rr), respectively, while the point size is given by minimum segment size (ms). The points are also coloured according to the different parts of the plant analysed and bear the labels for the variable dataset used for optimisation.

The highest balanced accuracy values were gained for both Total (BA 0.689 ± 0.006) and Green parts (BA 0.686 ± 0.007) using the combination of HIS + Multi + DSM, which was marginally better than HIS + DSM (BA 0.677 ± 0.008 and 0.680 ± 0.005 for Total and Green parts, respectively), although differences were not significant (Figure 5; Table 1). Multi + DSM showed the lowest BA values (BA 0.565 ± 0.012 and 0.575 ± 0.014 for Total and Green parts, respectively), although the model highlighted that this set of variables significantly increased the BA for Flowers (BA 0.530 ± 0.010 compared to 0.513 ± 0.006 with HIS + DSM and similar to 0.530 ± 0.022 for HIS + Multi + DSM; Figure 5; Table 1).

The factor that most affected BA was the part of the plant analysed, with comparable values between the Total and the Green parts, while average values were significantly lower by a factor of 0.16 for the Flowers. Regarding the type of data used to calibrate the models, the results show no significant difference between HIS + DSM and HIS + Multi + DSM, while the results obtained by Multi + DSM were significantly lower, reducing BA by 0.11. Finally, despite some differences visible in Figure 5, the differences due to the size of the calibration area were not statistically significant.

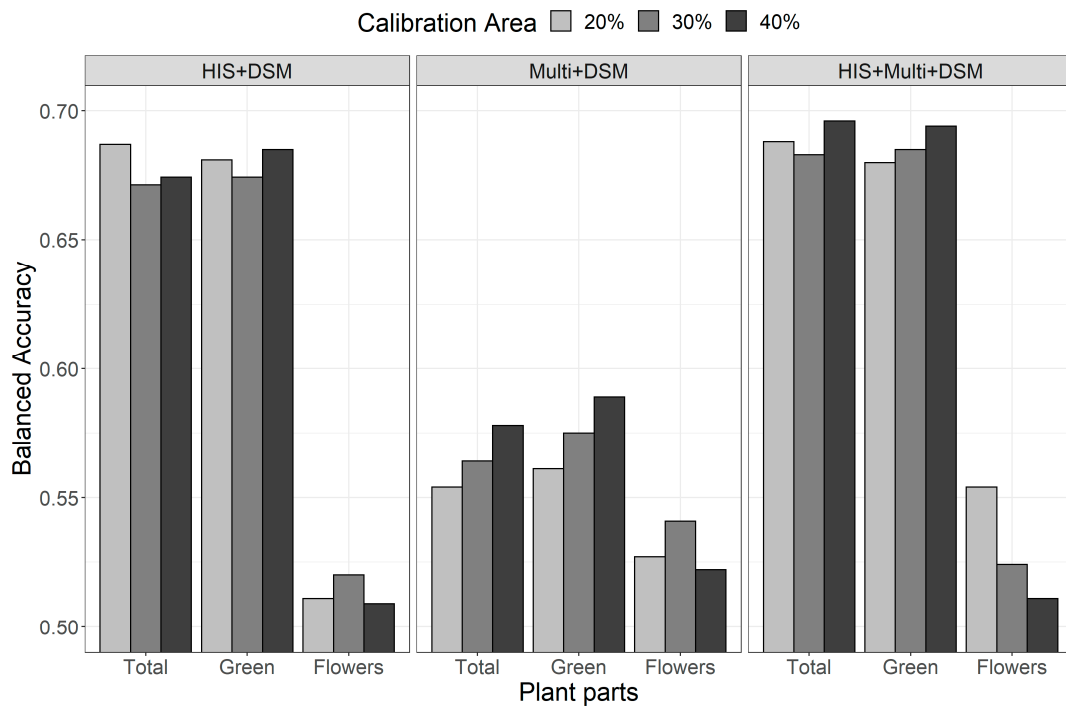


Figure 5. Outcomes of the assessment of the 27 models expressed as balanced accuracy (BA).

Table 1. Results of the linear model using balanced accuracy (BA) as the response variable and the dataset factors of variable (*Set*), plant part (*Part*) and percentage of calibration area (*Cal. Area*) as covariates. Values are reported as mean estimate and 95% confidence interval. Only the interactions between the factors that were found to significantly affect BA are shown. The reference levels are HIS + DSM for *Set*, Total for *Part* and 30% for *Cal. Area*. Significance is reported as *** $p < 0.001$.

	Mean	95% CI
<i>Set</i> Multi + DSM	−0.112 ***	−0.131, −0.093
<i>Set</i> HIS + Multi + DSM	0.012	−0.007, 0.031
<i>Part</i> Green	0.003	−0.016, 0.022
<i>Part</i> Flowers	−0.164 ***	−0.183, −0.145
<i>Cal. Area</i> 30%	−0.001	−0.012, 0.010
<i>Cal. Area</i> 40%	0.002	−0.009, 0.013
<i>Set</i> Multi + DSM: <i>Part</i> Green	0.007	−0.020, 0.034
<i>Set</i> HIS + Multi + DSM: <i>Part</i> Green	−0.005	−0.032, 0.022
<i>Set</i> Multi + DSM: <i>Part</i> Flowers	0.129 ***	0.102, 0.156
<i>Set</i> HIS + Multi + DSM: <i>Part</i> Flowers	0.005	−0.022, 0.032
Constant	0.677 ***	0.662, 0.692
Observations	27	
R ²	0.984	
Adjusted R ²	0.974	
Residual Std. Error	0.012 (df = 16)	
F Statistic	98.114 *** (df = 10; 16)	

Considering the original RGB image and the manual photointerpretation, it can be appreciated that all three models tend to correctly predict the presence of *Carpobrotus* in larger areas (Figure 6). The main shape of the largest *Carpobrotus* patches was identified by all three models. At the same time, it can be seen that all models tended to predict as *Carpobrotus*, a group of plants visible in the bottom right-hand corner, which are, however, other species (Figure 6). Finally, it can be seen that the HIS + DSM and especially Multi +

DSM models, identified many patches—especially very small ones—as *Carpobrotus*, a trend that was visually less pronounced in the HIS + Multi + DSM model.

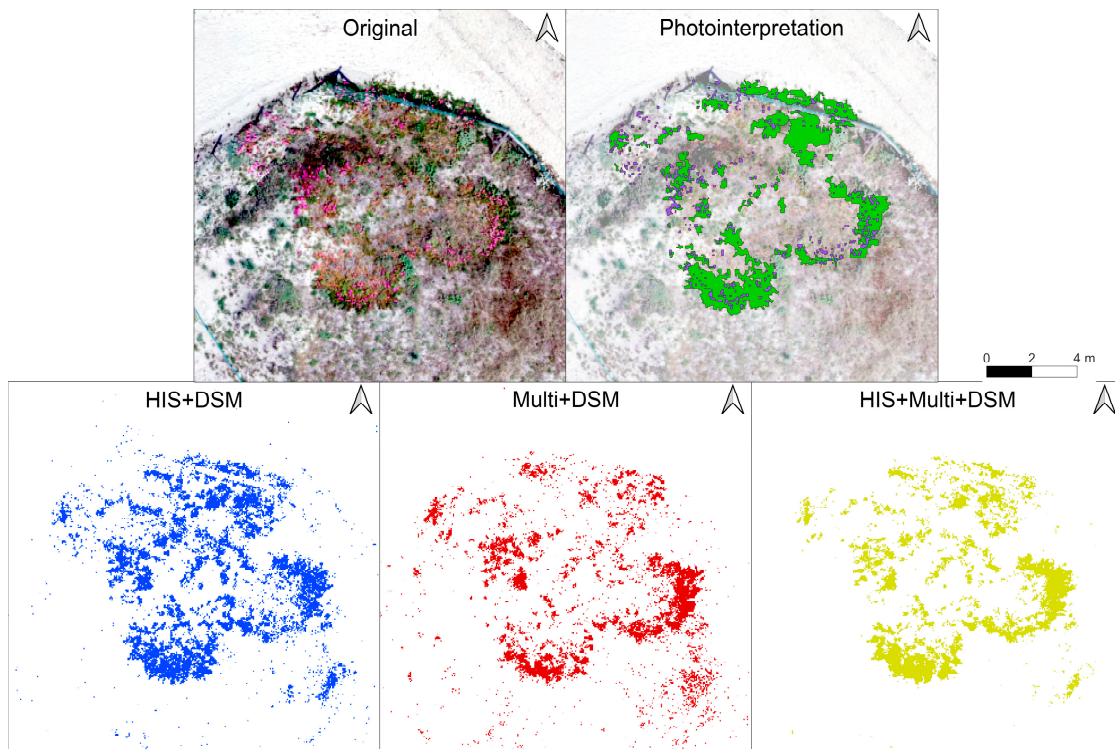


Figure 6. Example image showing results of the prediction of total *Carpobrotus* using the intermediate training area (30%) and the datasets HIS + DSM, Multi + DSM, and HIS + Multi + DSM. All images have the same scale, while the different colours are used only to aid visualization. The original orthomosaic at 5 cm resolution is shown in the top left, while the manual photointerpretation is visible in the top right. The figure shows a typical *Carpobrotus* patch surrounded by bare sand and other dune vegetation. Compared with the original RGB mosaic and manual photointerpretation, several parts of the image were misinterpreted as *Carpobrotus*, especially by the models based on HIS + DSM and Multi + DSM, while HIS + Multi + DSM retained the overall shape of the *Carpobrotus* patch.

In terms of variable importance (Figure 7), when using HIS + DSM data, intensity (INT) was the most important variable in predicting both Total and Green parts, while saturation (SAT) was predominant for Flowers. Concerning the Multi + DSM dataset, the importance of the variables was comparable between the different parts of the plant, with GNDVI marginally more important than SAVI. Finally, for the more complex dataset, HIS + Multi + DSM, intensity, saturation and GNDVI each contributed 1/5 of the importance of the overall variables in the case of Total and Green parts, while GNDVI was more relevant in the case of Flowers. Although DSM was the only variable included in all models, its importance was always marginal, exceeding 25% only in the case of Flowers in Multi + DSM.

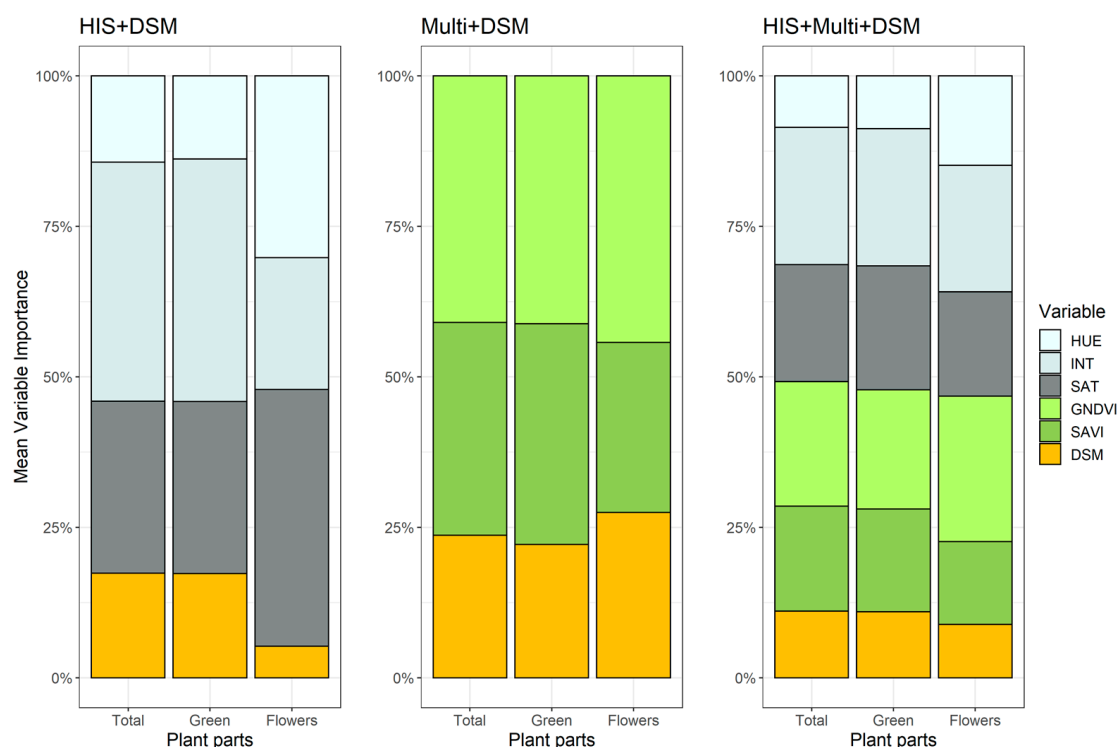


Figure 7. Importance of variables in different datasets and for different parts of the plant. Data for the intermediate calibration set (30%) are shown.

4. Discussion

4.1. On the Best Set of Variables to Predict the Presence of *Carpobrotus*

Balanced accuracy (BA) is one of the most robust metrics when class imbalance is present in the data [74,82]. As the average of sensitivity and specificity, BA is an unbiased metric ranging between 0 and 1 that outperforms classic metrics such as overall accuracy or Kappa with imbalanced data [82]. In our case, the class imbalance was conspicuous, as absences were more than 50 times more abundant than presences for Total and Green parts, and up to 4000 times for Flowers. Moreover, when the target species (e.g., an invasive alien plant) covers only a small portion of the studied area and there is no interest in mapping other classes, general agreement metrics (such as overall accuracy and Kappa) can be misleading [39,83].

Our results showed that the highest BA was reached by using a combination of RGB-derived variables along with data derived from multispectral sensors, with only a partial contribution from terrain morphology (DSM).

Both intensity and saturation were important variables in explaining the presence of *Carpobrotus*, while in comparison, for *Acacia saligna* (Labill.) H.L.Wendl. (Fabaceae) hue was more important in the absence of flowers, and saturation during flowering [34]. In general, even simple RGB images without the contribution of multispectral data have been shown to be viable instruments in detecting IAPs when the ultra-high-definition of UAVs is available [37,39,84,85]. Nevertheless, the integration of multispectral-derived indexes improved the prediction, as was also shown for other IAPs [34,39,85–87]. Even though NDVI was used in several cases [34,38,40,68,87], we used a modified version of NDVI based on near-infrared and green bands rather than near-infrared and red bands. This index (GNDVI) contributed to improving our predictions, and was also shown to be an effective and promising predictor when dealing with direct and indirect effects of invasive species, as it has even been used in monitoring vegetation health following invasion of pests [40,88,89]. Mallmann et al. found that spectral indexes that have a biochemical purpose, such as GNDVI, were the most effective in predicting the presence of invasive trees such as *Psidium*

guajava L. (Myrtaceae) and *Ligustrum lucidum* W.T.Aiton (Oleaceae; [32]). Similarly, GNDVI was shown to be a good predictor for monitoring the invasive *Acacia mangium* Willd. (Fabaceae) given its capability to differentiate active photosynthetic vegetation from other surface types, such as bare soils [33].

In contrast with previous research, DSM did not substantially contribute to discriminating *Carpobrotus* from the surrounding vegetation. Given its creeping habit, *Carpobrotus* does not rise substantially above the surrounding vegetation and at least based on our results, it does not appear to be particularly correlated with areas of higher or lower dune morphology. Moreover, invasion from *Carpobrotus* has been shown to homogenize horizontal vegetative cover [90]. In comparison, DSM was shown to be an important predictor for invasive trees, especially when flowers are not present, as the tree-like habitus raises the plants above the surrounding vegetation [34]. Accordingly, DSM was shown to be pivotal in discriminating between trees and shrubs [68] and even for identifying weeds from crops in precision agriculture applications [44].

Deriving BA from TSS values, in predicting the presence of the invasive alien *Acacia saligna* using UAV images, Marzioletti et al. reached values between 0.77 and 0.82 in pre-flowering and between 0.83 and 0.88 in flowering plants [34]. These BA values were larger than we achieved with *Carpobrotus*, but the differences in life-form and plant size must be considered.

Hamylton et al. used UAV-derived imagery at a spatial resolution of 3 cm and machine learning (convolutional neural network) to map the presence of a tussock native species (*Lomandra longifolia* Labill., Asparagaceae) introduced following invasive alien species eradication operations [91]. Their approach (which also compared pixel-based and manual digitisation techniques) produced optimal results using machine learning, highlighting the advantages of the latter approach in mapping individual plants [91]. Although our results also showed that a machine learning approach is appropriate for a species such as *Carpobrotus*, it should be borne in mind that a species such as *L. longifolia* forms very well-defined patches in terms of shape and size compared to a creeping herbaceous species such as *Carpobrotus*.

UAV was also used to monitor the invasive climbing vine *Mikania micrantha* Kunth. (Asteraceae) that forms large and compact patches on the cliffs of a small island off the southern coast of China [37]. Using only an integrative approach of 2D and 3D RGB imagery, Wu et al. demonstrated that, despite limited spectral information, ultra-high resolution UAV mosaics could effectively improve texture effectiveness in invasive mapping plants [37], a result that was not matched in our case although the morphology of our dunes was much less articulated than the steep walls of an island. The area under investigation was a sector of central Italy on the Tyrrhenian coast (41.909461°N, 12.148823°E, Passoscuro, Fiumicino, Rome; Figure 2). In this area, it is possible to recognise the typical dune zonation characterised by strong environmental gradients from the coastline inland that contribute to the formation of a sequence of habitats, many of which are of conservation importance [3,13,14]. In spite of the presence of a well-formed dune structure, the Passoscuro area has also been subject to tourist exploitation, encouraging a strong colonisation of alien species, in particular *Carpobrotus* [41].

4.2. On the Prediction of the Whole Plant or Its Vegetative/Reproductive Parts

We implemented an iterative procedure to optimize the segmentation of an herbaceous IAP such as *Carpobrotus*, which led to consistent results, especially regarding the whole plant or only the green parts. The LSMS algorithm implemented in Orfeo Toolbox is designed for the segmentation of very high resolution images by returning a segmented image that contains the radiometric mean and variance of each band [68]. There is still comparatively scarce literature on LSMS applied to UAV images [34,68], especially on an extremely fine scale as the one we adopted. The three optimized parameters (spatial radius, range radius, and minimum segment size) can be considered functional to image smoothing (based on spatial detail), segmentation (based on spectral detail) and merging of segments,

respectively [68,80,86]. In more detail, the spectral radius is the spectral signature distance between the bands and is expressed in radiometric units based on the Euclidean distance between the spectral signature values of the pixels [68]. De Luca et al. found that the optimal range radius for segmenting cork oak woodlands was six, because lower values led to over-segmentation and higher values to under-segmentation [68]. Marzialetti et al., instead, used a value of five for segmenting the invasive alien species *Acacia saligna* [34]. Both cases can be compared to our study as they used LSMS segmentation based on UAV images, yet they were both based on segmenting larger objects such as trees. The segmentation of smaller objects such as *Carpobrotus* plants led to results that varied according to the dataset used and the parts analysed. In particular, *Carpobrotus* flowers are showy and comparatively large for Aizoaceae, with a mean reported diameter of 7 cm [49], but can reach up to 12 cm in their invasive areas [92]. However, single flowers could be reduced to one or two pixels even with our 5 cm spatial resolution, resulting in inconstant LSMS parameters according to the dataset used and poorer results in terms of the performance of the models.

4.3. On the Minimum Size of the Training Area

Photointerpretation was carried out over the entire area to obtain the best overview of the calibrated model using machine learning to optimise and automate the procedure and minimising manual digitisation. In fact, although expert-based photointerpretation is certainly one of the best approaches, it is undoubtedly also one of the most time-consuming and operationally demanding compared to semi-automatic machine-learning-based classification systems, thus it is necessary to identify an optimal trade-off between the two methods depending on the study system [85,87,91,93]. Consequently, identifying the minimum area where manual digitisation should be carried out appears to be of great importance. Values of training objects ranging between 22% and 30% of the total surveyed area have been reported in literature when dealing with invasive plants [39,44], although in the case of larger plants (such as trees) this value can be as low as 2% [34]. In our case, we found that the effect of incrementing the training data from 20% to 40% was not significant. Therefore, especially when the area to be monitored is very large and the effort required for photointerpretation is to be reduced, values of approximately 20% may be adequate to calibrate optimal models. However, it seems more prudent and in line with previous literature on herbaceous plants to recommend the intermediate threshold of 30%.

4.4. Remarks on Previous RS Research on *Carpobrotus* and Some of Their Biological/Ecological Features

Carpobrotus can have severe negative effects on invaded ecosystems [53,54] and, as it happens also with other alien species on sandy beaches, its presence may have detrimental effects on ecosystem services [3,11,16]. Thus, effective and low-cost early detection strategies by means of RS remain pivotal for containing IAPs [29,34–36], including *Carpobrotus*. Yet, research on *Carpobrotus* through remote sensing is limited. Some studies used field collected surveys on dune ecosystems invaded by *Carpobrotus* and explored them by means of remote sensing data. Marzialetti et al. used field data of dune communities (both invaded and not-invaded by *Carpobrotus*) in order to explore whether spectral diversity can provide reliable information for monitoring floristic diversity even in ecosystems altered by plant invasions [48]. Similarly, Malavasi et al. used data from field surveys to explore the effect of high-resolution optical imagery and three-dimensional topographic models obtained from LiDAR on the presence of five IAPs, including *Carpobrotus* [41].

However, studies aimed at directly surveying *Carpobrotus* by remote sensing are still very few, especially regarding the use of UAVs, and in this respect, our contribution represents a turning point. Bogdan et al. studied the population size of *Carpobrotus* invading cliffs in Israel [49]. On a smaller area (about 2 ha) but with a higher spatial resolution (35 mm), Bogdan et al. used UAV images to study the population size of *Carpobrotus*

through manual digitizing of the main patches during two years of observation, in order to develop parameters for a demographic model [49].

Underwood et al. used hyperspectral imagery derived from an airborne visible/infrared imaging spectrometer to map *Carpobrotus edulis* and another invasive grass (*Cortaderia jubata* (Lemoine) Stapf, Poaceae) along the central coast of California [47,50]. Although the approach of Underwood et al. gave very encouraging results, especially since the hyperspectral data made it possible to more accurately identify the presence of water in succulent leaves, their method was at a larger spatial scale (4.5 m) and resulted primarily in classifying habitats with different degrees of *Carpobrotus* invasion rather than individual plants [47]. Moreover, it must be taken into account that the use of aircrafts is more expensive and requires greater technical experience when compared to UAVs, which are light, inexpensive and require minimal experience to operate [29,36,49,60].

Looking at the predictive comparison of the different models applied to a typical *Carpobrotus* patch, neither HIS + DSM nor Multi + DSM was able to provide sufficient discriminatory power to distinguish consistently between *Carpobrotus* and other vegetation with a similar spectral response. This effect was remarkably less evident with HIS + Multi + DSM, despite the BA values not being much higher than HIS + DSM. On a mere visual inspection of HIS + Multi + DSM results, plants of *Carpobrotus* were identified correctly in most cases.

Carpobrotus is a difficult species to map and, especially when vegetation is dense, individual plants may be hard to identify even with expert-based manual digitizing [49]. Given its growth habit and the complexity of discriminating between taxa and hybrids, *Carpobrotus* plants tend to vary both in shape and colour, depending on age and site disturbance [53,54]. Typical plants growing under ideal conditions form an almost circular shape, progressing from the centre to the edges and reaching peak growth when the plants are about 50 years old [94]. As the plants age, the older branches in the middle die off and become greyish, sometimes leaving only a torus of active vegetation (see Figure 1). Similarly, young leaves tend to have brighter colours, while older plants become more yellowish according to a change in light use efficiency, also considering that *Carpobrotus* shows a facultative C3-CAM photosynthetic strategy [54,95,96]. Moreover, some colour differences have also been attributed to the species (i.e., *C. edulis* vs. *C. acinaciformis* [53,54]). Given *Carpobrotus* strong propensity toward clonal reproduction over seed dispersal [52,53,95], even a few plant fragments can give rise to new patches. In disturbed environments, there can thus be numerous small patches of *Carpobrotus* [54], often without flowers, making them difficult to identify. In addition, because *Carpobrotus* depletes dune vegetation and, consequently, also the presence of dune-stabilizing species such as *Thinopyrum junceum* (L.) Á.Löve and *Calamagrostis arenaria* (L.) Roth subsp. *arundinacea* (Husn.) Banfi, Galasso & Bartolucci [53,54,97], individual *Carpobrotus* plants can often appear fragmented or masked because they have been covered by sand after adverse weather events.

Considering all the above information regarding the particular challenges posed by *Carpobrotus*, the results of this study represent an excellent trade-off for a mapping protocol that is rapid, inexpensive, and can be easily repeated over time (e.g., before and after management or eradication programs). In addition, the results provided by the UAV can be seen as a solid basis to extend IAP monitoring to satellite data with metric spatial resolution, such as PlanetScope [38,98], or even satellites that can achieve sub-metric resolution such as WorldView-2 or Pleiades 1B PMS [39,40].

5. Conclusions

Given its ecology and the peculiar features of its growing environment, the case of mapping the presence of *Carpobrotus* through UAV images presented some challenges and limitations. Yet, our study represents the first comprehensive contribution to mapping *Carpobrotus* in dune ecosystems using an integrative approach of image segmentation, photointerpretation, and classification using machine learning based on UAV images. Our results allowed us to determine that a mapping protocol using UAVs must take into account

the following factors: (a) results offered by a synergistic presence of RGB and multispectral data (i.e., HIS + Multi + DSM) improve *Carpobrotus* prediction, offering better BA values and presence maps more congruent with photointerpretation, although results based only on RGB-derived data were not significantly different from those including multispectral information; (b) prediction of flowers does not appear robust when compared with the whole plant and green parts alone at a 5 cm spatial resolution, thus we recommended considering the whole plant, thus facilitating identification and mapping even during periods when the plant is not in anthesis; and (c) we found no significant differences due to the size of the training area, so even a training area corresponding to 20% of the total area appears adequate for building the models, although we recommend a more conservative threshold of 30%.

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

Funding: This research received no external funding.

Data Availability Statement: The data presented in this study are available on request from the corresponding author.

Acknowledgments: This research was supported by Project DM 1062-10/08/2021, RTD-A (Action IV.6: Green. Code: 39-G-13537-2), PON-AIM (Programma Operativo Nazionale ricerca e innovazione 2014–2020; ID AIM1897595-2), and bilateral program Italy–Israel DERESEMII (Developing state-of-the-art remote sensing tools for monitoring the impact of invasive plant). The authors are grateful to Federica Pontieri for her support. The authors acknowledge the editor and the three anonymous reviewers for the appreciation and helpful comments that help us to improve the manuscript.

Conflicts of Interest: The authors declare no conflict of interest.

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2.2 – Remote sensing variables for modelling current and future nesting habitat suitability of the Kentish Plover

The results presented in the previous chapters demonstrated the negative impact of IAP on coastal biodiversity. However, IAP represents only one of multiple threats affecting coastal ecosystems, which also face significant pressures from human disturbances and climate change consequences. Therefore, the main objective of this chapter was to assess the potential role of environmental and anthropogenic variables derived from remote sensing in modelling the current and future nesting habitat suitability of the Kentish Plover, an endangered shorebird species in Italy, under climate change scenarios.

This study enabled me to address several environmental challenges on a larger scale, since we examined the entire coast of the Molise region (Southern Italy). In addition, it allowed me to identify the nesting preferences of the species under study by improving monitoring protocols and informing management and conservation strategies in the region. Moreover, our findings highlighted the importance of dune conservation, along with their associated flora and fauna, not only for preserving the Kentish Plover's nesting habitat, but also for mitigating the adverse effects of climate change, which compromise the ecosystem services provided by coastal ecosystems.

The approach employed in this study also demonstrates the substantial potential of integrating remote sensing tools combined with field-based observations to model biodiversity and support the development of effective conservation strategies.



OPEN Anthropogenic and climate change-driven coastline dynamics will erode future nesting habitats of the kentish plover on the central adriatic coast

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Shorebirds play a crucial role in assessing the health of coastal ecosystems due to their life history, behaviour, migratory patterns, and feeding preferences. Many shorebird species are experiencing population declines worldwide, driven by habitat loss and climate change. Understanding these challenges requires extensive data on their distribution and breeding ecology. The Kentish Plover (*Anarhynchus alexandrinus*) is a small shorebird that constructs its nests on sandy beaches. However, there is a scarcity of data regarding the reproductive ecology of this species in many areas, including the Molise region of Southern Italy. This study aimed at assessing the potential role of environmental variables derived from remote sensing to model current and future Kentish Plover nesting habitat suitability accounting for future scenarios of coastal dynamics in 2040. Data on Kentish Plover nests were collected along the Molise coast over several years and used to calibrate ecological niche models (ENMs) relying on environmental variables derived from coastal images. Kentish Plover nesting habitat suitability was mostly affected by distance from open sand, artificial surfaces, shoreline, and herbaceous vegetation and forested areas. The study predicts an average decline of more than 22% in suitable nesting environments for the Kentish Plover within the next two decades. Results indicated that our modelling approach can offer valuable insights for the conservation strategy of Kentish Plover in the region. In conclusion, we assert that preserving the nesting habitat of the Kentish Plover will not only safeguard this species, but also other species that inhabit similar environments, along with providing protection for coastal landscapes and associated ecosystem services.

Shorebirds, by virtue of their life history, behaviour, migratory and foraging habits are important indicators of the integrity of coastal environments, which are currently pinpointed as one of the most threatened ecosystems, as well as being prone to biodiversity loss^{1–3}. Coastal sandy ecosystems have undergone severe environmental alterations imposed primarily by human activities⁴. Many shorebird populations are facing a global decline, driven mainly by human disturbance, though other impacts such as climate change, antagonistic species interactions, and predation have been implicated^{2,5}.

The Kentish Plover, *Anarhynchus alexandrinus* (Linnaeus, 1758), is a small ground-nesting shorebird in the family Charadriidae that breeds in Europe, Asia and Northern Africa, mainly in coastal habitats, especially sandy beaches⁶. This species has an extremely large geographic distribution range and is currently evaluated as “Least Concern” (LC) by the International Union for the Conservation of Nature (IUCN), both globally

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and at European level⁷. Although Kentish Plovers do not currently approach the threshold for the population decline criterion of the IUCN Red List⁷, their populations are known to be declining in much of their range². For instance, the last Red List of Italian breeding birds evaluated the species as “Endangered (EN)” in Italy⁸, due to the sharp reduction in numbers of the national population (i.e., -50% for the years 2000–2010)⁹. Because of its conservation status, in Europe the Kentish Plover is included in Annex I of the Birds Directive 2009/147/EEC, Appendix II of the Bern Convention, Appendix II of the Bonn Convention, and it is classified as a Species of European Concern (SPEC) at level ‘3’, with negative population trends^{10–12}. In Italy, the species is protected by Art. 2 of L. 157/92^{8,13}.

The ongoing decline in the Kentish Plover population in Italy, like other Mediterranean areas, is driven by coastal alterations due to urban expansion, seashore erosion, tourism, and recreational activities, as well as by predation of eggs and chicks (e.g., by crows, rats, yellow-legged gulls, dogs, and cats)^{9,14}. This highlights the urgent need for effective conservation strategies accounting for the most vulnerable phases of the Kentish Plover life cycle. Since the Kentish Plover tends to choose the same nidification sites across the years, monitoring their nests is crucial for its conservation and management^{15,16}. Furthermore, analyzing nest spatial distribution can enhance the understanding of the species’ reproductive ecology and the relationship between nest location and environmental and threat factors. Although standardized nest monitoring protocols are widely implemented¹⁷, new research efforts are needed to further develop spatially explicit models that describe nesting habitat preferences and the related threats over time. Previous studies in Europe, Africa, and North America have proposed models depicting the relationship between nesting habitat and environmental and anthropogenic variables derived from remotely sensed data^{2,4,5,15,16,18}. While these studies promoted the use of remotely sensed products as potentially valuable environmental predictors for modelling suitable habitats of various bird species, including the Kentish Plover, they were mainly focused on current habitat conditions. Starting from this evidence, we propose a study aimed at exploring the potential role of environmental variables derived from remote sensing to model current and future Kentish Plover nesting habitat suitability in Southern Italy (i.e., Molise region), explicitly accounting for future scenarios of coastal dynamics. In particular, we focused on addressing the following questions: (a) is there a combination of environmental variables that is particularly conducive to nesting? (b) how would shoreline future dynamics influence the distribution and extent of suitable nesting locations?

In order to answer these questions, we set an analytical framework (Fig. 1) around the following three main objectives:

1. Collect georeferenced observations of Kentish Plover nests and map landscape characteristics derived from remote sensing data along Central Adriatic beaches.
2. Quantify and map species nesting habitat suitability under an ecological niche model (ENM) framework, quantifying the importance of environmental variables in defining nesting preferences.
3. Predict 2040 nesting habitat suitability considering future scenarios of coastline modifications due to climate change and anthropogenic pressure, also calculating range net change (RNC) between current and future modelled nesting habitats.

Methods

Study species

The Kentish Plover is a ground nesting shorebird that belongs to the *Anarynychus* genus¹⁹.

It belongs to the family Charadriidae, which includes plovers, dotterels, and lapwings, usually with compact bodies and short, thick necks²⁰. The Kentish Plover is a small bird within its family, with sizes ranging between 15 and 17 cm for a weight of about 39–48 g, making it one of the smallest breeding plovers in Italy¹⁶. The species follows the typical colouring pattern that characterizes the family Charadriidae, sandy upperparts and sandy white lower parts^{16,21}. Adult males and females have dimorphic plumage; males having incomplete black breast-bands, black eye-stripes, and a black frontal head bar, whereas these areas are pale brown in females (Fig. 2)²². The cryptic colouration of the Kentish Plover makes the species difficult to distinguish from the substrate on which it nidifies and feeds¹⁶.

The main source of food of the Kentish Plover consists of small aquatic and terrestrial invertebrates such as insects, larvae, arachnids, small crustaceans, bivalve and univalve molluscs, and polychaete worms^{6,16}. The bird usually finds these invertebrates on the coastline, lakes or lagoons, where it picks them up directly from the ground or digs small wells in the sand^{16,23}. Although most of the Kentish Plover populations are fully migratory, this species is partially sedentary in Molise^{7,24}. It is a bird that exhibits a high degree of loyalty to its nesting site, resulting in the pairs consistently constructing their nests in the same locations as in prior years¹⁵. The nesting period begins around March and ends in August. The modal clutch size is three small eggs, very mimetic, sand-greyish colour spotted of black (Fig. 2), that hatch after 25–26 days of incubation. Both sexes incubate the eggs; females incubate mostly during the day, and males incubate mostly during the night^{16,22}. The chicks are nidifugous and after about 2 h from hatching are ready to leave the nest to follow the movements of the parents that attend, brood, and defend them for about 4–5 weeks, but they do not provide food for them^{15,22}.

Study area

The Molise coast (Southern Italy) extends for over 30 km along the Adriatic Sea and falls entirely in the physiographic unit of Punta Penna (Abruzzo region) – Punta Pietre Nere (Apulia region)^{25,26}. This area is mainly composed of sandy beaches, a few river mouths and channels, and one rocky promontory. Dunes occupy a narrow strip (approximately 50–70 m large) parallel to the seashore, being low, simple in structure, and relatively recent (formed in the Holocene period^{25,27}). Along a sea-to-land gradient, the typical vegetation zonation ranges from embryonic dunes in the seashore, followed by mobile dunes with perennial herbaceous vegetation,

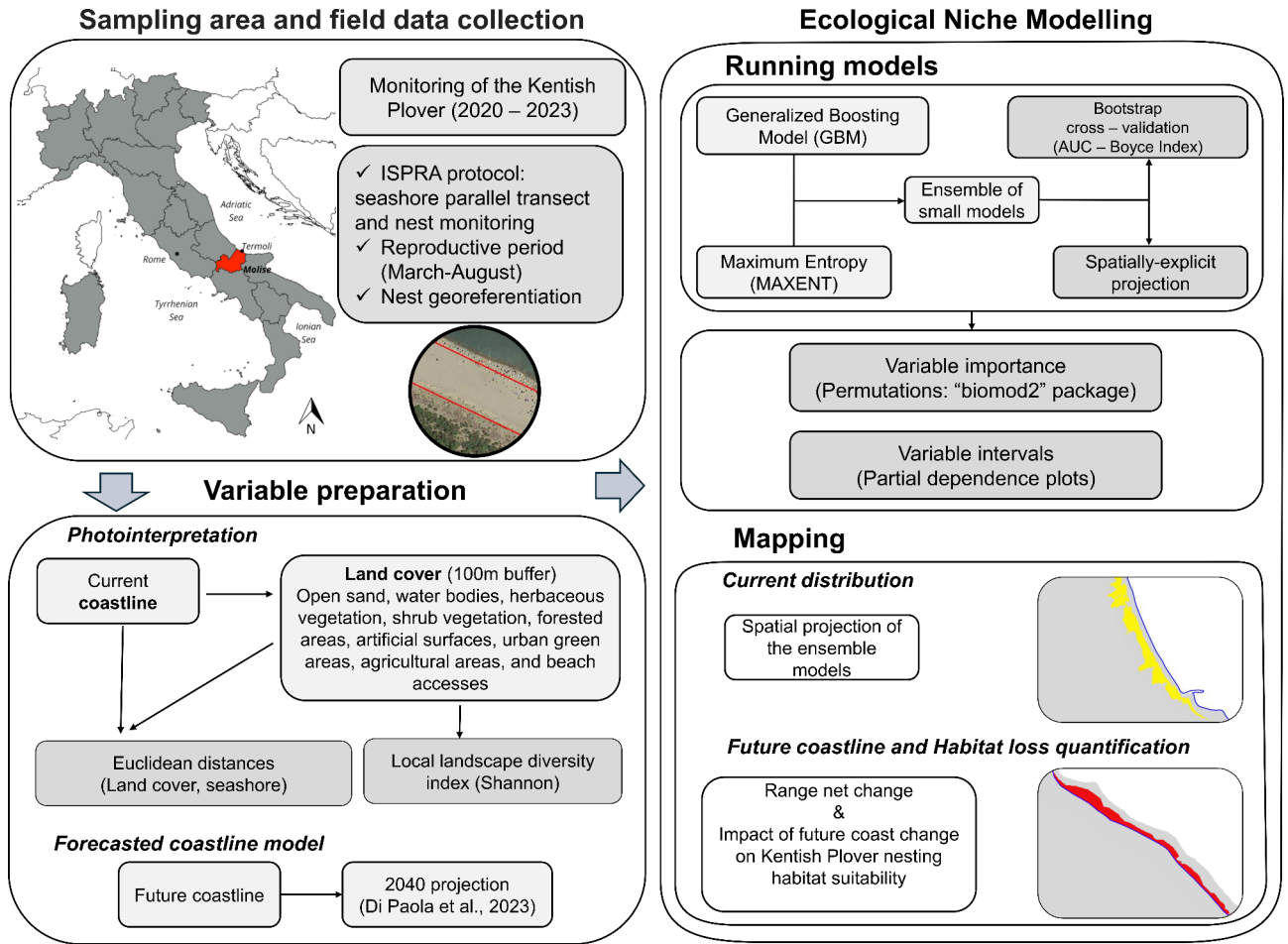


Fig. 1. Flow chart showing the methodological framework used in this research. Maps Data: Google, ©2024 Airbus.



Fig. 2. Adult male (a) and adult female (b) of Kentish Plover; typical Kentish Plover nest with three eggs (c). Pictures by Rosario Balestrieri.

fixed dunes covered by evergreen shrub and small sclerophyllous trees and, in the inner sectors, by wooded dunes covered by coniferous forests^{1,27,28}. These dune ecosystems are currently threatened by coastal erosion and anthropogenic activities, such as beach mechanical cleaning and tourism^{25,29}. Moreover, especially in the first half of the 20th century, the area has been prone to urban expansion, and spread of agriculture and afforestation activities^{25,29}, making the dunes particularly squeezed between progressively eroded coastline and anthropic infrastructures placed in the inland (e.g., highway and railway lines). Nonetheless, the coastal dunes of Molise still host many EU Directive 92/43 Habitat types and, for this reason, this area is largely included in the European Natura 2000 system^{28,29} (Fig. 3). Between the 1950s and the 1990s, these coastal areas underwent considerable

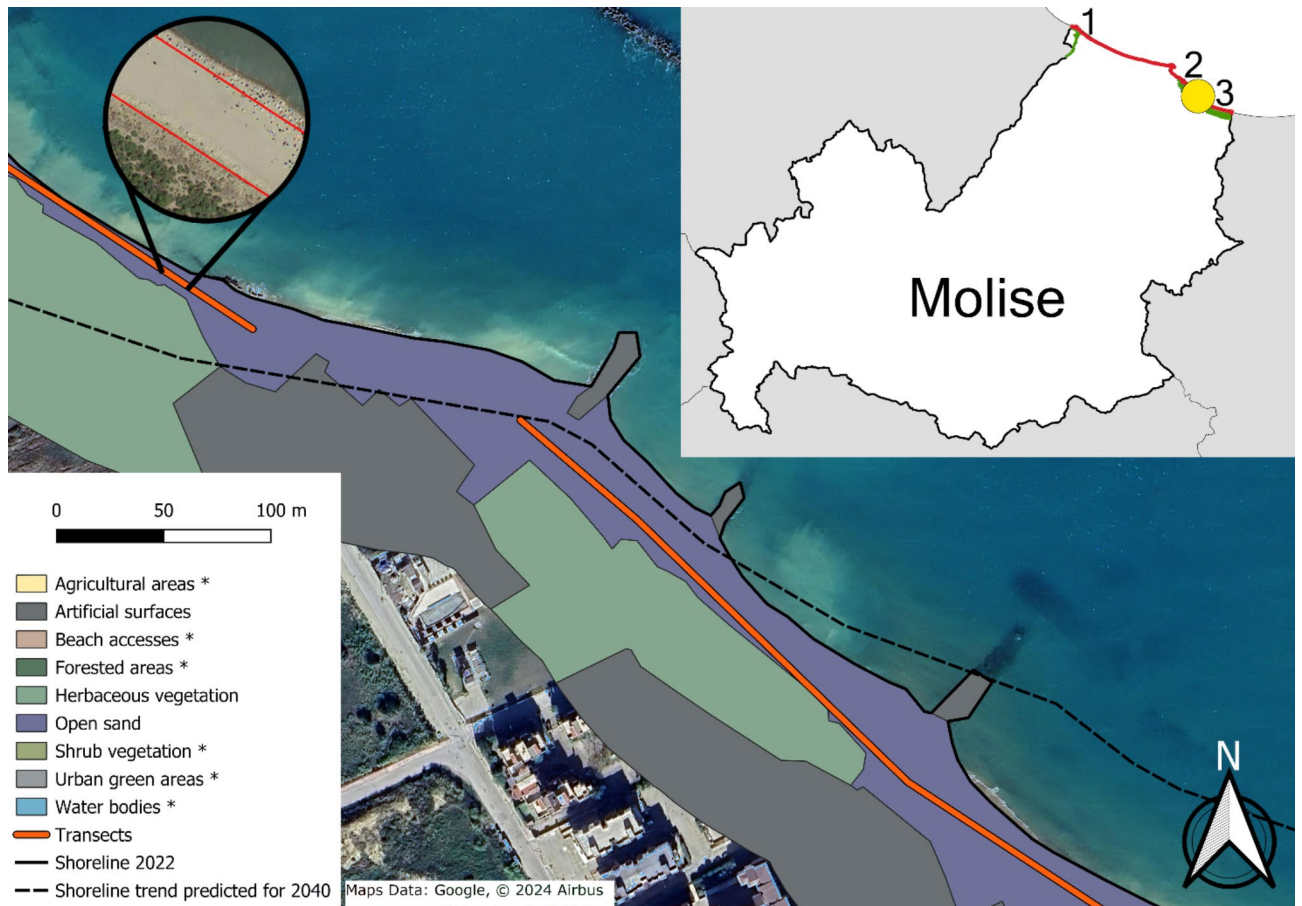


Fig. 3. Zoomed section of the study area over the extent of the projection area. The main map depicts an example of the sampling transects surveyed to detect Kentish Plover's nests, superimposed to the land cover categories used in the modelling phase (labels reported in the legend with an asterisk refer to land cover categories occurring in the study area but not within the extent of the zoomed section). Due to scale limitations, we represented parallel transects as single orange belts (a zoomed detail of the parallel transects is provided in the circular inset). The inset in the upper right corner shows the spatial reference of the study area (i.e., the red line), along with the location of the detail reported in the main map (i.e., the yellow dot). The numbered polygons in green refer to the three Natura 2000 sites inscribed over the study area (i.e., 1: Foce Trigno – Marina di Petacciato [IT7228221]; 2: Foce Biferno – Litorale di Campomarino [IT7222216]; 3: Foce Saccione – Bonifica Ramitelli [IT7222217]). Maps Data: Google, ©2024 Airbus.

transformation³⁰. Yet, following the establishment of protected areas spanning 20 km of coastal dunes two decades ago, the pace of urbanization and agricultural growth has either progressively decreased or come to a complete halt³¹.

Fieldwork and data collection

In Molise region, a monitoring programme has been conducted over the last twenty years on the development of the Kentish Plover breeding population^{23,32,33}. However, these studies are limited to quantifying the number of nests and surviving nestlings, and they do not focus on reproductive ecology or nesting habitat preferences. To calibrate ENMs, we specifically considered data from the monitoring of the Kentish Plover nests carried out from year 2020 to 2023 along the entire coast of Molise region. This monitoring was organized every year by the “National Committee for the Conservation of the Kentish Plover” (represented by its regional reference “Ambiente Basso Molise”) and was based on the monitoring protocol established by the Italian Institute for Environmental Protection and Research (Istituto Superiore per la Protezione e la Ricerca Ambientale, ISPRA¹³, which involves volunteers as well as specialists. To develop this monitoring, 18 beach stretches of 1–2 km were identified, in which two parallel transects were defined, one along the coastline and the other along the strip separating the annual vegetation and the dune (Figs. 1 and 3). Both transects were walked by two operators in parallel by 11 a.m., with the help of binoculars to be able to recognize the individuals of the species from a long distance. During the walk, the surrounding area was observed to identify adult individuals and examine the sand to avoid trampling and because sandy dunes often concentrate footprints of the species, debris, and driftwood around the nests²². In the case of observation of adult individuals, their movements were followed for 15–30 minutes to verify the presence of a nest, as the behaviour of incubating parents is different from the

non-incubating individuals²². Incubating parents show nervous behaviour or alarm calls, while the behaviour of non-incubating individuals is more relaxed^{13,22}. If a nest was found along the transect, the operator observed the surrounding area to verify the absence of adult individuals and geo-referenced the nest. In case of identification of a nest from a distance, one of the operators fixed the point with the binoculars, while the other operator left the transect and approached the nest to take the coordinates. This approach to the nest was only carried out if the adult was far away. If an individual was detected running away or demonstrating nervous behaviour, the operator moved away, and waited for the individual to return. The monitoring was carried out in the reproductive period (March–July) with periodic visits (following the scheme produced by ISPRA), during which each nest was georeferenced and rendered in shapefile format on QGIS version 3.34.0³⁴. We collected a total of 77 Kentish Plover nests, which were subsequently thinned as to factor out any effect of sampling bias, according to Aiello-Lammens et al³⁵. After thinning data considering a maximum distance between nests of 100 m³⁶, we obtained a final calibration dataset of 35 records.

Variable preparation

Using coeval Google images (i.e., year 2022), we digitized the current coastline and visually interpreted a fine scale land cover map (1:800) within a 100 m buffer area generated around the current coastline. This radius was chosen considering that the sandy beach and dune habitat in the study area adds up to an average width of ca. 50 m (10–150 m, as measured from the Google images). Moreover, such radius represents a reasonable measure to exclude feeding ground from breeding sites, since the former usually occurs at a median distance of ca. 160 m from nesting areas³⁷. The land cover categories were those already established for the coastal dune mosaics in the Central Adriatic coast by Malavasi et al³⁰, i.e., open sand, water bodies, herbaceous vegetation, shrub vegetation, forested areas, artificial surfaces (i.e., any impervious surface including piers and breakwaters), urban green areas, agricultural areas, beach accesses, and coastline (Fig. 3). These mapped categories follow a standardized approach developed for the detailed mapping of coastal dunes²⁵. Most of the mapped natural and seminatural categories can be referred to Habitats of European concern as defined by the Habitat Directive (Table 1).

The legend conforms to the European standard CORINE land cover expanded to a fourth level of detail for natural and semi-natural areas, which is the most accurate level that can be produced through aerial photos of coastal dune ecosystems (see²⁵ for details). As for possible tidal variation effects on coastline position, they can be considered negligible, since tidal amplitude along the Molise coast adds up to ca. 6–8 cm³⁸. We then computed Euclidean distances from each of these categories using ‘rgrass’ R package³⁹. Additionally, to map habitat diversity, we computed Shannon’s diversity index on the different land cover categories using a moving window of size 25 m using ‘rasterdiv’ R package⁴⁰. This window size was chosen according to the average 50 m width of the sandy beach and dune habitat in the study area, as a smaller size would overly detail the landscape around nests, while a larger radius would cause significant margin effect issues. We rendered all resulting raster images at a spatial resolution of 2 m and assured the absence of multicollinearity ($VIF \leq 5^{41}$). To account for future coastline change, we relied on the 2040 projection presented in Di Paola et al²⁶. This forecasting is based on the Digital Shoreline Analysis System (DSAS) with the Kalman filter methodology. In particular, historical shoreline data from 1869 to 2019 were utilized to create a linear regression model, which projected shoreline positions by combining observed and model-derived data, estimating changes every tenth of a year. Additionally, the study incorporated sea-level rise projections from the IPCC sixth report⁴², specifically the SSP5 8.5 scenario, which anticipates a 0.22 m rise by 2050 due to climate change. This comprehensive approach allows for identifying areas undergoing accretion or at risk of erosion and inundation, taking into account climate change projections. Variables for ENM calibration were prepared for the entire Molise region coast, while predictors for current and future model projections were generated within a projection area corresponding to the southernmost branch of Molise coast (representing ca. 43% of the entire coastline), where 2040 coastline forecasted by Di Paola et al²⁶ is available. While for current projection variables we simply cut the calibration ones within the boundaries of the projection area, for 2040 variables we proceeded as follows: i) set the 2040 coastline by Di Paola et al²⁶ as the new coastal border of the projection area; ii) attributed all the coastal accretion areas (i.e., zones currently underwater but predicted as emerged in 2040) to the open sand land cover category; and iii) re-calculated all the variables considered for current time (i.e., Euclidean distance from each land cover category and coastline, and Shannon diversity index) within this new spatial domain²⁶.

Land cover category	Habitat type according to the habitat directive
Open sand	Beach with Pioneer annual Vegetation. Includes the EU – Habitat: 1210 – Annual vegetation of drift lines.
Water bodies	Inland wetlands and marshes. Non forested areas of low lying land flooded by fresh stagnant or circulating water. Covered by low ligneous, semi-ligneous or herbaceous vegetation. Includes a fine mosaic of inland wetlands EU – Habitats.
Herbaceous vegetation	Herbaceous vegetation growing on fore dune includes the EU – Habitats: 2110 – Embryonic shifting dunes; 2120 – Shifting dunes along the shoreline with <i>Ammophila arenaria</i> ; 2230 – Malcolmietalia dune grasslands.
Shrub vegetation	Shrub vegetation partially includes Woody Dune Vegetation growing on fixed dune conformed by the EU – Habitats: 2250 – *Fixed coastal dunes with <i>Juniperus</i> spp.; 2260 – Cisto-Lavenduletalia dune sclerophyllous scrubs.
Forested areas	Afforestation on coastal dunes mainly with <i>Pinus</i> sp. pl. Referable to the habitat 2270* – Wooded dunes with <i>Pinus pinea</i> and/or <i>Pinus pinaster</i> .

Table 1. Correspondence between natural and seminatural land cover categories and habitat type according to the Habitat Directive.(adapted from³⁰).

Ecological niche models

To calibrate ENMs, we used the so-called “ensemble of small models” approach to avoid model overfitting⁴³, which is a problem when there are few occurrences compared to the number of environmental variables⁴⁴. Accordingly, we calibrated a set of bivariate models, i.e., considering all possible combinations of predictor pairs and then averaging the results of each model. Bivariate models were trained by using two algorithms: Generalized Boosting Model (GBM) and Maximum Entropy (MAXENT), which were listed among the most performing algorithms within an “ensemble of small models” setup⁴⁵. To sample background environments, we generated 10,000 random points in the study area⁴⁶, following the modelling setup proposed as optimal for the “ensemble of small models” framework⁴⁵. To assess the predictive performance of the models, we applied a bootstrap cross-validation approach by randomly dividing the data into 80%, used to calibrate the models, and the remaining part for evaluation purposes⁴⁷. The predictive performance of each model was assessed by measuring the area under the receiver operating characteristic curve (AUC⁴⁸) and the continuous Boyce index (CBI⁴⁹). We dropped poorly calibrated models (i.e., achieving $AUC < 0.7$ ⁴⁶) from the subsequent analyses. Ensemble models were obtained by averaging the projections of individual models, weighted by their respective AUC scores⁵⁰. Ensemble model spatially explicit predictions were generated within the projection area (ca. 176 ha) considering current time and 2040 coastal environment characteristics (as described above)²⁶. Moreover, current and future model projections were converted into presence/absence values selecting three alternative binarization threshold (i.e., ‘equalize sensitivity and specificity’, ‘maximize TSS’ and ‘10th percentile’⁵¹). The impact of future coastal dynamics on Kentish Plover nesting habitat suitability was assessed by calculating the range net change metric on binary maps generated for each model⁵². In particular, the range net change metric was calculated according to the formula $(b - c) / (a + c)$, where a represents the stable habitat area (i.e., predicted suitable in both present and future), b is the gained habitat area (i.e., predicted suitable in future but not present), and c refers to the loss habitat area (i.e., predicted suitable in present but not future)⁵². Lastly, we calculated the relative variable importance from the ensemble models through permutations, as implemented in the “biomod2” package⁵³. We also generated partial dependence plots to explore the shape of the relationship between Kentish Plover nesting habitat suitability and environmental variables. All these analyses were carried out using the ‘ecospat’ R package⁵⁴.

Results

ENMs achieved excellent predictive performances (sensu Swets⁵⁵), with a mean $AUC = 0.923$. (s.d. = 0.04) and a mean $CBI = 0.799$ (s.d. = 0.09). Models showed that the key environmental predictors (i.e., variable importance > 10%) in defining Kentish Plover nesting preferences were Euclidean distances from open sand, artificial surfaces, coastline, herbaceous vegetation, and forested areas (Fig. 4).

Partial dependence plots evidenced that the suitability of the nesting habitat was highest at 0 m from the open sand, drastically decreasing toward higher distances. Suitability also increased a few meters from artificial surfaces and gradually decreased further on (Fig. 4). As for coastline distance, suitability showed a peak between 25 and 40 m. Regarding vegetation, our results indicated that suitability increased at a short distance from herbaceous vegetation and at a greater distance from forested areas (Fig. 4).

Model projections indicated that current suitable nesting habitat for Kentish Plover occupies 4.4–14.2% of the projection area (ca. 6 ha to 20 ha; depending on the binarization threshold). As for 2040, the suitable nesting habitat will cover between 3.6% and 10.1% of the projection area (ca. 5 ha to 14 ha). Range net change calculation reported values between –16% to –28% (depending on the binarization threshold), indicating the Kentish Plover will lose approximately 22% on average of its current nesting habitat by 2040 (Fig. 5; see also Figures S1 and S2). This figure represents 0.4 – 2.4% of the projection area (ca. 0.6 ha to 3.5 ha). With specific reference to the processes determining coastal dynamics, ca. 18.5% (ca. 32 ha) of the projection area will undergo coastal accretion in 2040, yet only < 1% (< 2 ha) of these new coastal areas will be gained as suitable nesting habitat for the species (Fig. 6). By contrast, approximately 15.5% (ca. 27 ha) of the projection area will be subject to erosion. Following this erosion process, ca. 1.5% (< 3 ha) of the projection area will no longer include suitable nesting habitat for Kentish plover. Moreover, ENM predicted an increase in suitable nesting habitat of ca. 1% (ca. 2 ha) of the projection area, and a decrease of approximately 2% (ca. 3.5 ha), in those parts of the projection area that will not be involved in either accretion or erosion processes (Fig. 6).

Discussion

Data from field monitoring combined with remotely sensed environmental variables proved able to accurately predict Kentish Plover nesting habitat suitability along the Central Adriatic coast, pinpointing to a number of important environmental predictors. Importantly, our results indicated coastal alterations induced by climate change and anthropogenic activities will lead to an average loss of more than 22% in potential nesting habitat for the Kentish Plover in the projection area. The distance from open sand resulted as the most important environmental variable in defining nesting preferences. The area that comprises an extensive mass of open sand spans approximately from the breaker area to the embryonic dunes, coinciding with the upper beach habitat (EU Habitat 1210 Annual vegetation of drift lines). This habitat is generally located in the lower sectors of the dune system, on slightly upwardly concave to flat surfaces and covered by annual vegetation⁵⁶, all properties that characterize these sectors as open areas. Accordingly, our results are coherent with the evidence that the species prefers open areas with low elevation and scarce vegetation^{2,57}. The preference for open sites probably indicates the benefits of places that allow good long-distance visibility for the detection of approaching predators and guarantee the mobility required for ground feeding adults and precocial chicks^{2,16,58}. In addition, Treccani¹⁶ mentioned that cryptic coloration of the Kentish Plover makes it difficult to distinguish it from the substrate where it nests and feeds, thus reducing the possibility of being preyed. This could also explain the high importance

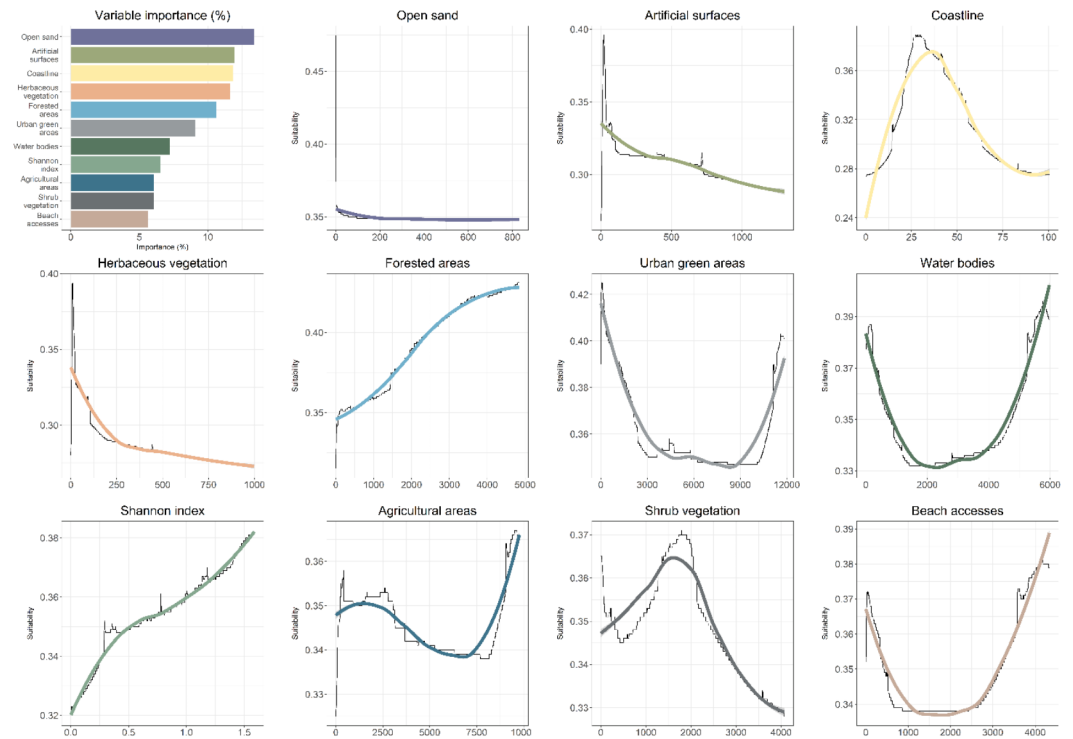


Fig. 4. Barplot in the upper left corner depicts the percentage of relative importance of the environmental variables. All variables are Euclidean distances except Shannon Index. Curves in partial dependence plots report the relation between Kentish Plover nesting habitat and environmental variables. The horizontal axes of all the panels but Shannon index indicate Euclidean distances and are expressed in meters.

of open sand in our study, since the species presents a strong mimesis with this substrate, particularly eggs, as well as juveniles and females.

Our model also highlighted that distance from artificial surfaces have a great importance in defining nesting preferences, with close distances positively affecting Kentish Plover breeding suitability. This result is not in keeping with previous research showing that Kentish Plovers distribution was negatively influenced by built-up areas^{2,15,16}. Noteworthy, the actual adverse effects on biodiversity occurring close to human establishments are highly debated and not univocal^{4,5}. For instance, in the study of Li et al⁵⁹, it was explained how the survival rate of nestlings was slightly higher in unprotected areas close to anthropic zones than in protected areas, probably due to the reduced presence of predators. This phenomenon may explain why the Kentish Plover nesting suitability was higher around man-made areas, since several cases of predation have been reported elsewhere in the region^{23,33,60,61}. Although our model did not provide evidence of the detrimental effects of artificial surfaces, it must be acknowledged that our analysis did not take into account data regarding the hatching success of nests or chick fledging rates. Therefore, our results may not adequately account for human behaviours that have potentially harmful impacts on the species, such as mechanical beach cleaning, which has been frequently cited as the primary cause of nest and chick loss^{23,24,33,60,61}. The fact that the species reported a high nesting suitability near the artificial surfaces supports what Treccani¹⁶ mentioned about the possible coexistence between Kentish Plovers and human activities when appropriate measures are taken. This pattern could be further investigated by e.g., accounting for the intensity of artificial light at night as a metric of human pressure.

The coastline is an area of the beach that offers a high availability of food resources for Kentish Plover, as the species takes advantage of tidal flow and wave motion that expose potential prey above the shoreline¹⁶. This can explain the high importance of the distance from the coastline in our study, as shorebird distributions are known to be strongly influenced by the availability and abundance of specific food resources². However, our results showed that the nesting habitat suitability increases with a distance from the coastline between 25 and 40 m, which might be due to the flooding risk for tides or storms, as other studies have evidenced that is one of the main causes of nest failure^{4,18,62,63}. Coastal erosion has been identified as one of the main causes of the loss of seashore breeding birds^{64,65}. This could be another reason that contributes to the nesting preferences of the Kentish Plover in the Molise region. As a matter of fact, much of the Molise coastline presents a high susceptibility to erosion due to the topographically low-lying dune systems⁶⁶. A range between 25 m and 45 m would allow the species to be close enough to the coastline for feeding, avoiding at the same time the risk of flooding by storms or coastal erosion.

Prior research has indicated that the Kentish Plover exhibits a preference for nesting in places with sparse vegetation, particularly consisting of herbaceous or low-growing plants^{2,5,15,57}. In keeping with this, we found that the distance from nests to herbaceous vegetation and forested areas is of great relevance in defining the

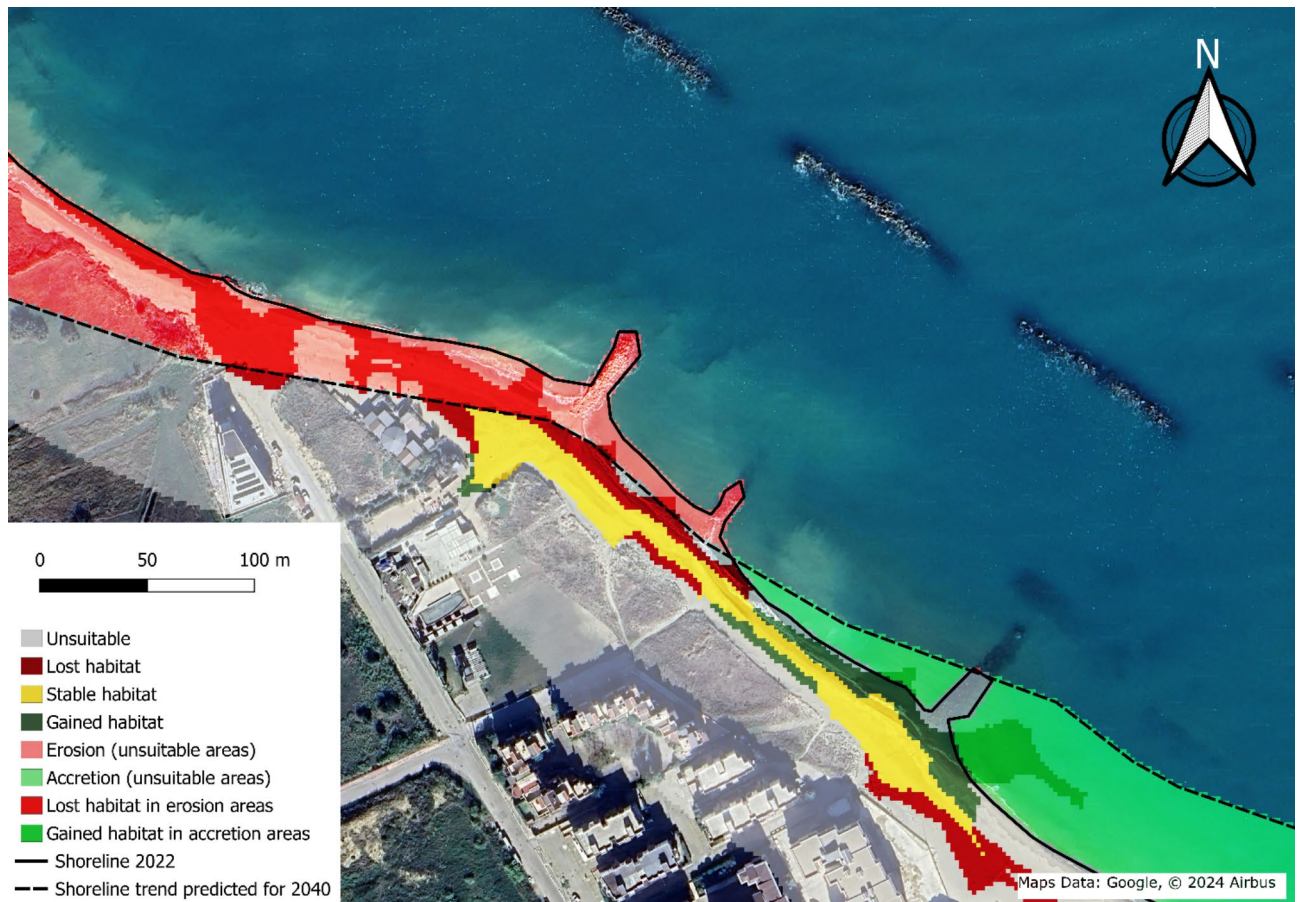


Fig. 5. Model projection (EPSG:32633) showing the predicted range modifications under 2040 based on the coastline shift along a stretch of Molise coast. The presented binary map was created considering the ‘maximize TSS’ binarization threshold. Maps Data: Google, ©2024 Airbus.

nesting preferences of the species. Specifically, we found that nesting habitat suitability increases within a few metres from herbaceous vegetation and decreases markedly from forested areas. This may be explained by the importance of annual vegetation for nesting, as it is used in some cases for nest construction, offers a higher probability of finding trophic resources, and it is essential to provide protection for nests¹⁵. The selection of sparsely vegetated areas by the Kentish Plover, as an anti-predator behaviour, has been reported in several studies^{2,57,67}, as these types of sites allow them to detect approaching predators and provide a flight path to escape from them⁵⁸.

The projection of nesting habitat along the 2040 coastline evidenced an average loss of > 22% of the current breeding habitat as predicted by our model, likely attributable to climate change and anthropogenic factors^{65,68}. This loss is based on the coastline modification generated by coastal erosion and flooding²⁶, which are the main hazards affecting coastal areas, especially low-lying ones⁶⁶. Besides harshening the potential impact of these threats, climate change also plays a significant role in increasing coastal vulnerability, which can be influenced by multiple factors, especially topography and sediment dynamics^{26,66}. Accordingly, our finding can be explained by the fact that the Molise coastline presents a high susceptibility to erosion mainly due to the low-lying dune systems, which are fragmented and damaged by wave action and anthropic activities³³. Moreover, not only eroded areas affected Kentish Plover nesting habitat suitability. In fact, even though the accretion margins of the projection area resulted larger than the erosion ones, we evidenced an overall detrimental effect on the species nesting habitat, which is thus attributable to the whole coastal and landscape dynamics, instead of deriving from single processes. Human expansion and activities along the coast also contribute to coastal vulnerability, altering natural coastal processes, disrupting ecosystems, and increasing exposure to hazards²⁶. Consistent with this, Malavasi et al³⁰ observed that the composition and structure of the typical Molise coastal dune landscape have been drastically modified by human impacts. Particularly, the most relevant drivers are introduction of alien species, trampling, and mechanical beach cleaning, where the latter is known to usually produce biomass or sand removal⁶⁹. Moreover, Molise coast is also threatened by the strengthening of the so-called coastal ‘squeezing’ process, which occurs between the erosion front of the shoreline and the fixed human infrastructures (e.g., highway and railway lines) on the land^{30,56}. Therefore, the infrastructure systems from the land would certainly not allow dune retreat even in scenarios of shoreline change, which makes our results even more alarming. From this perspective, many conservation measures should be implemented to protect coastal landscapes and

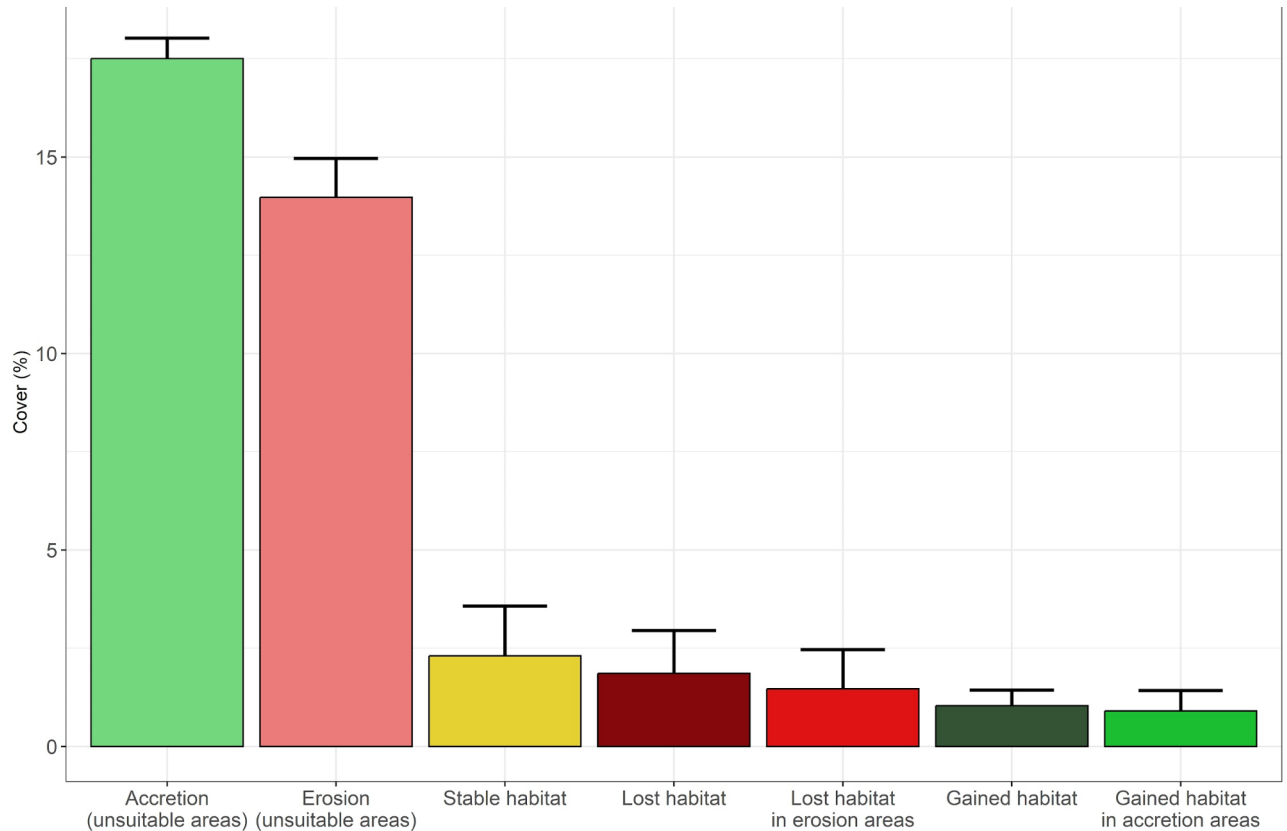


Fig. 6. Mean percentage of the projection area covered by each type of landscape and Kentish Plover nesting habitat modification generated by overlaying current and future ENM projections according to the coastline changes predicted for 2040. Bar height refers to the mean percentage cover values calculated from the three binary maps (i.e., ‘equalize sensitivity and specificity’, ‘maximize TSS’ and ‘10th percentile’), while error whiskers indicate standard deviation values.

eventually the potential nesting habitat of the Kentish Plover, such as e.g., substituting the mechanical beach cleaning procedure with manual collection, or avoiding trampling. In particular, the sustainable management of annual vegetation of drift lines (EU Habitat 1210) may play a key role in the conservation of the Kentish Plover. Indeed, these habitats could act as “umbrella habitat”, as their protection triggers a sort of “chain protection” from the individual habitat to the entire landscape³¹. These habitats should be preserved not only for their intrinsic floristic value, but also as providers of optimal habitat for the Kentish Plover. Conservation efforts for these habitats could benefit from using the Kentish Plover as a flagship species, which could drive public interest and awareness towards these often neglected vegetation communities.

Near–future developed scenarios regarding coastal vulnerability highlight that, without specific interventions, large sectors of the Molise coast will most probably undergo significant erosion and local permanent inundation²⁶. This situation is not only affecting our target species but is one of the main factors jeopardizing the distribution and reproduction of many shorebirds^{70,71}. Ivajnsiĉ et al⁶⁵. suggested that inundation due to sea level rise will result in the loss of habitats that are essential breeding sites for bird species, which will subsequently decrease their breeding success. The awareness that erosion and inundation phenomena could significantly increase in the mid–long term due to sea level rise, should push public administrations and stakeholders towards a strategic approach of integrated coastal zone management^{1,66}. Otherwise, not only a great part of the Kentish Plover habitat will be lost, but also the biodiversity and all the ecological services associated with coastal ecosystems.

Variables for 2040 ENM projection were prepared relying on the assumption that all the land cover categories but coastline and open sand will remain stable within the 16 years period between current time and 2040. This assumption might seem to somewhat undermine the overall plausibility of the outcomes presented in this study. Indeed, the specific context where we set the study, given its peculiar long–term landscape dynamics, allows us to consider this assumption as realistic. In fact, Molise coastline experienced most of its strongest transformations between 1950s and 1990s³⁰. The progressive institution of urban planning constraints (due to the proximity of a highway and a railway) that characterized the second half of this period, along with the establishment of protected areas encompassing more than 20 km of coastal dunes ca. 20 years ago, determined urbanization and agricultural expansion to significantly slow down or cease entirely³¹. In keeping with that, we recently reported how the percentage cover of new vegetated areas that colonized open sand in the 1986–2022 period adds up to less than 1.5% of the study area (i.e., an increase of ca. 0.04% per year; *pers. comm.*). Translating this trend in the future (i.e., from 2024 to 2040), we would obtain an overall average increase in new vegetated areas on open

sand of ca. 0.64%. Although we acknowledge our approach may have overlooked some minor transformations that could insist on current land cover categories up to 2040, by and large it seems rather reasonable to consider all the land cover categories but coastline and open sand as predominantly stable within the 2024–2040 time period. Arguably, the 100 m large coastal belt we used to delimit our study area may have introduced a flaw by relying on Euclidean distances to describe the spatial pattern of land cover. Specifically, our approach could have overlooked the contribution of certain land cover categories adjacent to the study area, while favouring more distant landscape elements located within it, thus overemphasising the along-beach dimension rather than the cross-beach one. That said, the Kentish Plover is well known to nest almost exclusively within coastal sandy belts, typically moving further inland only for foraging activities, and mainly when lagoons or salt pans are nearby³⁷. Moreover, several stretches of the Molise coastline are bordered inland by highways and railways, which act as barriers and no-habitat areas. In light of that, any potential effect of land cover categories beyond the 100 m threshold can be considered almost negligible. That said, the width of the buffer considered to identify the extent of the modelling area should be set according to the specific characteristics of the dunes under investigation. In areas where dunes are large, it could be possible to consider wider buffers, while for narrow, squeezed dunes (as those analysed here), small buffers should be preferable.

The modelling approach used in our study showed that the Kentish Plover on the beaches of the Molise region prefers to nest on open sand, 25 to 45 m from the coastline, and at a short distance from herbaceous vegetation. Furthermore, we found that man-made areas do not seem to exert a negative impact on nesting habitat suitability due to the reduced distance where they build their nests. Finally, and most importantly, our results predicted a > 22% average loss of Kentish Plover potential nesting habitat as a consequence of anthropogenic and climate change-induced coastal alterations. Conservation management plans should consider the nesting preferences of the species under study to define more precisely new protected areas or buffer areas. Also, new guidelines for coexistence with humans should be redacted, as the intense tourism activities are still increasing. In addition, the negative trend predicted by our model reinforces the need for action to mitigate the threats of climate change, as not only part of the Kentish Plover's nesting habitat will be lost, but also the ecosystem services associated with coastal landscapes, which are essential for safety and human well-being.

Data availability

The datasets used and/or analysed during the current study available from the corresponding author on reasonable request.

Received: 30 May 2024; Accepted: 27 September 2024

Published online: 07 October 2024

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Acknowledgements

We thank Dr Rosario Balestrieri for his suggestions in the early preparation of the manuscript and during the revision phase. We are grateful to Luigi Lucchese from “Ambiente Basso Molise” for his support during the fieldwork. We also thank the Editor and two anonymous referees for their helpful and constructive suggestions.

Author contributions

P.V.P. and M.D.F. conceived the idea. P.V.P. collected the data. P.V.P., M.F., M.I. and M.D.F. analysed the data. M.F. and M.L.C. prepared the figures. All authors contributed to and approved the final draft of the manuscript.

Funding

This study was supported by “CitAlien” and “Lily” departmental projects funded by the Department of Biosciences and Territory, University of Molise. Moreover, the research was funded by Project DM 1062-10/08/2021, RTD-A (Action IV.6: Green. Code: 39-G-13537-2) and PON-AIM (Programma Operativo Nazionale ricerca e innovazione 2014–2020; ID AIM1897595-2).

Declarations

Competing interests

The authors declare no competing interests.

Additional information

Supplementary Information The online version contains supplementary material available at <https://doi.org/10.1038/s41598-024-74726-5>.

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CONCLUSIONS

This doctoral research enhances and updates current knowledge of several RS technologies for addressing key ecological challenges to coastal ecosystems. It provides a comprehensive assessment of different instruments and methodologies for mapping IAP in coastal environments. Additionally, it presents two case studies that employ different RS techniques to address diverse environmental challenges, including IAP invasions and the impacts of climate change on coastal landscapes.

The systematic literature review revealed the geographical concentration of IAP studies in China and the United States (**Chapter 1**; Villalobos Perna et al., 2023), emphasizing the need to expand research efforts beyond these countries and applying RS methodologies to a wider range of IAP, which would enhance global strategies for biodiversity conservation and ecosystem management. Additionally, the shift from RS-based detection to predictive modeling since 2015 (**Chapter 1**; Villalobos Perna et al., 2023) reflects an increasing emphasis on predictive approaches, which are essential for management and conservation planning. The findings also revealed that the use of RS platforms and analytical methods has evolved over time, shifting from aircraft to UAVs and from frequentist inference to machine learning. (**Chapter 1**; Villalobos Perna et al., 2023), which suggests a clearer trend in technological and computational advancements that enhance the accuracy and efficiency of invasion mapping and detection.

The case study on *Carpobrotus* sp. pl. invasions in Central Italy demonstrates the effectiveness of integrating RGB and multispectral UAV data, reinforcing the role of high-resolution RS data in improving classification accuracy. (**Chapter 2.1**; Innangi et al., 2023). This suggests that an integrated approach enhances classification and detection accuracy, as models have access to more information improving their ability to distinguish features. Moreover, the most reliable results were obtained when mapping the entire plant or its green structures, whereas flower-based mapping resulted in lower accuracy (**Chapter 2.1**; Innangi et al., 2023). This highlights the need to refine segmentation techniques for species with small structures like *Carpobrotus* sp. pl. flowers and allows us to identify key considerations for developing a monitoring protocol. Therefore, future monitoring strategies could optimize the spatial resolution of images and carefully define the algorithm's parameters based on dataset conditions. Furthermore, the study also revealed that a training dataset comprising 20% of the total study area proved sufficient for robust model development (**Chapter 2.1**; Innangi et al., 2023), which indicates that reliable mapping can be achieved with relatively limited training data, although we recommended 30% training data threshold as a suitable balance between manual effort and model effectiveness, especially in studies involving herbaceous plants. Despite

certain biological constraints, UAV remains a valuable tool for IAP detection, offering a scalable and cost-effective solution for IAP management and biodiversity conservation.

The modeling approach for assessing current and future Kentish Plover nesting habitat suitability, revealed that this species in the Molise region exhibits a preference for nesting on open sandy areas, typically 25 to 45 meters from the shoreline and in proximity to herbaceous vegetation (**Chapter 2.2**; Villalobos Perna et al., 2024). The species' preferences suggest that these areas not only offer a high availability of food resources, but also provide protection from predators, flooding risk and erosion (MacDonald, 2010; Norte & Ramos, 2004; Pietrelli & Biondi, 2016; Puglisi, 2015; Treccani, 2021). Given the species' dependence on specific environmental conditions, it is important to consider the preservation and management of these areas to maintain the long-term viability of Kentish Plover populations. Moreover, anthropogenic structures did not appear to negatively influence habitat suitability, as the species tended to nest at relatively short distances from these areas (**Chapter 2.2**; Villalobos Perna et al., 2024). This finding indicates a degree of adaptability to human-modified environments, either to take advantage of the reduced presence of predators (Li et al., 2023) or for reasons yet unknown. This could have important implications for conservation strategies, highlighting the need to balance habitat preservation with sustainable coastal development. Finally, our most critical finding indicates that, due to anthropogenic pressures and climate change-driven coastal modifications, potential nesting habitat for the Kentish Plover is projected to decline by more than 22% on average (**Chapter 2.2**; Villalobos Perna et al., 2024). These findings emphasize the need for immediate mitigation efforts to prevent habitat loss and secure the coastal bird population's future.

This doctoral research effectively meets its objectives by incorporating RS technologies to improve biodiversity monitoring in coastal ecosystems. The systematic literature review addresses the first specific objective by evaluating the use of RS for mapping IAP in coastal ecosystems. The findings of this work emphasize the need to expand research efforts to other regions and species, improving global conservation strategies. The first insight also provided the necessary knowledge about RS technologies to address our second objective, enabling their application in different case studies aimed at mitigating IAP spread and climate change impacts in the coastal ecosystems of Central and Southern Italy.

The second objective was achieved through two case studies that used RS technologies to analyze ecological challenges in coastal environments of Italy. The study on *Carpobrotus* sp. pl. invasions in Central Italy shows how UAV-based multispectral and RGB data can improve mapping accuracy and contribute to monitoring protocols (Innangi et al., 2023). This case illustrates the use of RS tools for identifying and mapping IAP, in line with the goal of employing advanced technologies such as

machine learning for IAP management. Meanwhile, the assessment of Kentish Plover nesting habitat suitability integrates RS and fieldwork to model biodiversity. The findings reveal the species' strong dependence on specific environmental conditions and its unexpected tolerance to anthropogenic structures, suggesting a possible coexistence with human presence and reinforcing the importance of balancing habitat preservation with sustainable coastal development (Villalobos Perna et al., 2024). The projected 22% decline in nesting habitat driven by anthropogenic pressures and climate change highlights the urgent need for mitigation measures.

The findings of this research have important implications for both theoretical and applied science. The proven effectiveness of UAV combined with machine learning in mapping IAP indicates a scalable methodology to diverse ecosystems. Additionally, integrating remote sensing with modeling is a useful method for predicting how biodiversity might respond to environmental changes, providing information for management strategies. Despite these advancements, certain methodological limitations must be acknowledged. Factors such as the resolution of RS data, the complexity of modeling approaches, and the generalization of findings across different regions may affect the applicability of the results. Future research should focus on refining RS techniques, expanding datasets, and incorporating additional ecological variables to improve predictive accuracy.

Moving forward, insights from this research present several opportunities for future studies. Further research of high-resolution RS data combined with advanced machine learning techniques could enhance the detection and management of IAP. Additionally, long-term monitoring programs that integrate RS and field surveys would provide a better understanding of habitat dynamics, especially in response to climate change and human activities. The findings from this doctoral research may assist policymakers in implementing management and conservation planning actions, enhancing habitat restoration efforts, and supporting the development of sustainable land-use strategies that preserve ecological integrity and ecosystem health alongside human activities.

In summary, this research integrates RS applications with ecological studies, demonstrating their value in both IAP management and biodiversity modeling. By mapping IAP and modeling the habitat of shorebird species, this thesis contributes to a more comprehensive, technology-driven approach to coastal conservation. These findings emphasize the role of RS in sustainable environmental management and highlight its potential as a fundamental tool for addressing current and future ecological challenges.

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- **Villalobos Perna, P.**, Di Febbraro, M., Carranza, M. L., Marzialetti, F., & Innangi, M. (2023). Remote Sensing and Invasive Plants in Coastal Ecosystems: What We Know So Far and Future Prospects. *Land*, 12(2). <https://doi.org/10.3390/land12020341>
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ACKNOWLEDGMENTS

First, I would like to extend my sincere gratitude to my thesis tutor, Professor Mirko Di Febbraro and my co-tutor, Dr. Michele Innangi, for their patient guidance, understanding and exceptional availability throughout these years. Their expertise, suggestions and support have been essential in the development and conclusion of this work. To Professor Maria Laura Carranza, for providing a huge support during the adversities and challenges that a PhD program presents abroad, thank you for guiding me with patience, comprehension and passion in each step.

To my thesis committee Dr. Mattia Iannella and Prof. Marco Malavasi who have contributed with their knowledge and suggestions, I thank you for your time and dedication.

To Luigi Lucchesse, president of "Ambiente Basso Molise" association, who with great generosity included me in the group of volunteers who carry out the monitoring of the Kentish Plover. Thank you for providing me with extensive knowledge, data, and information that helped me to develop my doctoral research.

Thanks to Professor Angela Stanisci and Dr. Maria Carla de Francesco for sharing their valuable knowledge about the study area and one of the species analyzed in my PhD research. Their encouragement and invitations to training events greatly enriched my doctoral work.

Pursuing a PhD in a foreign country has been a transformative experience, full of both academic and personal learning. However, living away from home comes with challenges, and in this regard, I want to thank all the people who gave me their support in difficult times. First, I would like to thank my roommates Chiara and Gaia, who gave me great company, strength and support during the challenging early days abroad. Their kindness and encouragement made all the difference and helped me feel at home. To my colleagues and friends at EnvixLab, and at other Unimol laboratories, I deeply thank you for your company, generosity and help in times of need. Thank you for sharing this process with me and making it more bearable. In particular, I am deeply grateful to Martina, Micaela and Lucia for their friendship and unwavering support when I needed it most. Their generosity in opening their homes, welcoming me into their families, and making me feel less alone in this journey meant more than words can express. Sharing this chapter of my life with all the wonderful people I have mentioned— and my apologies if I forget anyone— has been a truly invaluable and comforting experience that I will never forget.

To my family and all my friends in Argentina, who sent me their unconditional love and support during the most difficult moments of this journey. They not only gave me the wings to fly far from home and pursue my dream, but they also gave me the strength and confidence to keep going when

that dream became difficult. Despite the distance and the challenges of different time zones, they were always present in my life. Thank you for your effort to stay connected, for trying to understand every moment, and for always offering your support. Knowing I could count on you, no matter how far away I was, brought me strength and comfort throughout this experience.

Finally, I would like to express my gratitude to the University of Molise for giving me the opportunity to continue my studies. I am deeply thankful for the chance to learn in an international environment, which not only broadened my scientific perspective but also allowed me to immerse myself in different cultures and viewpoints. Thank you for equipping me with the knowledge and tools necessary to advance my academic career with a more global outlook.

I thank all the people who, directly or indirectly, have contributed to the culmination of this thesis.

To all of you, thank you.



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Azione IV.4 “Dottorati e contratti di ricerca su tematiche dell’innovazione”
e Azione IV.5 “Dottorati su tematiche Green”

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SUGGESTED CITATION:

Villalobos Perna P. (2025). Eyes in the Sky: Remote Sensing Approaches to Coastal Biodiversity Monitoring and Ecosystem Health. Doctoral thesis in Ecology and Territory (DOT197W57F-3). University of Molise, pp (70).

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