Regional Studies in Marine Science 68 (2023) 103265

Contents lists available at ScienceDirect

Regional Studies in Marine Science

journal homepage: www.elsevier.com/locate/rsma

Detection of *Yucca gloriosa* in Mediterranean coastal dunes: A comparative analysis of field-based sampling, human interpretation of UAV imagery and deep learning to develop an effective tool for controlling invasive plants

Luciano Massetti[a,1], Alessio Mo[b,*,2], Elena Cini[b], Marco Paterni[c,3], Silvia Merlino[d,4], Daniela Ciccarelli[b,5]

[a] Institute of Bioeconomy of the National Research Council (IBE-CNR), 50019 Sesto Fiorentino, Italy
[b] Department of Biology, University of Pisa, Via Luca Ghini 13, 56126 Pisa, Italy
[c] Institute of Clinical Physiology of the National Research Council (IFC-CNR), 56124 Pisa, Italy
[d] Institute of Marine Sciences of the National Research Council (ISMAR-CNR), 19032 Lerici, Italy

ARTICLE INFO

Keywords:
Drones
Field sampling
Invasive alien plants (IAPs)
Neural network
Monitoring and management

ABSTRACT

Using UAV imagery is a powerful method for monitoring invasive alien plant species (IAPs), particularly when combined with automatic image analysis conducted by artificial intelligence. To this end, we conducted a pilot study on *Yucca gloriosa*, an invasive species of coastal dunes spread in central Italy. Specifically, we assessed the agreement in quantifying *Y. gloriosa* cover between field-based sampling and human visual screening of UAV images captured at different altitudes. Additionally, we examined the concordance among different operators both before and after a training procedure, comparing a simpler and quicker approach (referred to as the "envelope" method) against a seemingly more precise but time-consuming method (referred to as the "leaf by leaf" method). In our current study, we discovered a good concordance not only between operators and field sampling but also among operators, particularly when using the "envelope" method. Furthermore, we assessed the performance of deep learning in identifying *Y. gloriosa* plants in UAV images compared to visual identification by human operators, achieving an overall accuracy of 96 % for images taken at an altitude of 35 m. Our findings suggest that UAV imagery may serve as a valid alternative to field-based sampling for monitoring IAPs, especially when dealing with plants like *Y. gloriosa*, which have distinctive morphological characteristics that facilitate identification. Consequently, mapping *Y. gloriosa* on Mediterranean coastal dunes can be effectively accomplished using UAV images, even though an automated machine-based approach, thereby expediting and enhancing the reliability of alien species monitoring and management.

1. Introduction

Invasive alien plant species (IAPs) pose significant environmental and economic challenges for Europe (Vilà et al., 2010). The European Commission has enacted regulations on invasive alien species (EC, 2014), urging Member States to implement specific monitoring and surveillance actions to detect both animal and plant invasive species within European countries. Controlling invasive plants often requires expensive and environmentally damaging methods (Weidlich et al., 2020). This, coupled with the growing demand for more sustainable, cost-effective, and environmentally friendly control approaches (de Sá et al., 2018), underscores the importance of biocontrol monitoring. Early detection and mapping of IAPs are among the most effective tools for addressing biological invasions by predicting risks, identifying potential threats, and promoting actions against invaders (McGeoch et al., 2016). Despite historically incomplete and inadequate invasive species

* Corresponding author.
E-mail address: alessio.mo@biologia.unipi.it (A. Mo).
[1] https://orcid.org/0000-0002-0941-5347
[2] https://orcid.org/0000-0003-3129-1747
[3] https://orcid.org/0000-0002-9799-7059
[4] https://orcid.org/0000-0002-4537-2903
[5] https://orcid.org/0000-0001-9715-9779

https://doi.org/10.1016/j.rsma.2023.103265
Received 15 February 2023; Received in revised form 19 October 2023; Accepted 25 October 2023
Available online 26 October 2023

management, new technologies are emerging, and multi-disciplinary approaches are proving effective for detecting, identifying, reporting, and responding to invasive species (Martinez et al., 2020).

Monitoring alien plants relies on survey techniques ranging from traditional field sampling to more recent and advanced methods using unmanned aerial vehicles (UAVs), which are preferred over satellite images due to their high spatial resolution and cost-effectiveness (Müllerová et al., 2017). Free satellite data (e.g., MODIS or Landsat) often have coarser spatial resolution that may not capture specific phenomena. Higher spatial resolution satellite images (e.g., WorldView, Quickbird) from the same platform tend to be costlier than UAV images and can sometimes suffer from co-registration or misalignment issues with other remote sensing or field data.

Visual detection of IAPs involves field-based methods, such as ocular estimates of alien species identification and coverage (using, for instance, the Braun-Blanquet cover scale) within the study area. While this approach can yield accurate data at high spatial resolutions, it is often limited to small spatial extents due to its time-consuming nature and inability to extrapolate information over large areas (Elzinga et al., 1998). In contrast, UAV technology has seen rapid adoption in IAP monitoring, especially in heterogeneous environments like coastal habitats (Klemas, 2015; de Sá et al., 2018; Marzialetti et al., 2021). UAVs capture high-resolution images over contiguous spatial areas, making landscape monitoring less labor-intensive and faster than traditional field sampling surveys, with georeferencing performed by an operator during the flights (Weber et al., 2008; Le Moigne et al., 2011; Müllerová et al., 2017). Additionally, UAVs offer flexibility in data acquisition, allowing for the selection of sensor type (Red-Green-Blue, Multispectral, or Hyperspectral), flight periods and conditions, such as phenological stage, altitude, weather, and image resolution, thus enabling standardized monitoring (Watts et al., 2012; Klemas, 2015; Müllerová et al., 2017).

Orthophotos derived by UAV images can be visually analyzed by operators, typically within a Geographic Information System (GIS) environment. To the best of our knowledge, there are no existing studies in the literature that assess the agreement between traditional field sampling of aliens and the quantification of their cover percentages by operators using UAV images. Most research focused on extrapolating various indices (e.g., cover estimates, canopy volume, plant height) from UAV imagery and evaluating their agreement with field measurements (e.g., plant coverage, number of flowers) for a range of IAPs and ecosystems (Kosmowski et al., 2017; de Sá et al., 2018; Tay et al., 2018; Broussard et al., 2020; Gillan et al., 2020; Karl et al., 2020; Marzialetti et al., 2021; Oldeland et al., 2021; Sladonja et al., 2022). In general, manually detecting the presence of IAPs is a time-consuming procedure, and its accuracy may be influenced by various factors, including the experience and expertise of the operators.

On the other hand, automated analysis techniques, such as deep learning coupled with UAV technology (James and Bradshaw, 2020; Kentsch et al., 2020; Aota et al., 2021; Charles et al., 2021; Lam et al., 2021; Rodriguez et al., 2021), enable the detection of alien plants in digital images (Dash et al., 2019; Sun et al., 2021). Deep learning, a machine learning technique, is utilized to identify and classify information from raw input, such as images, using a multi-layered structure model, such as convolutional neural networks. The model can be trained and tested with supervised examples, providing both input and expected output, allowing it to learn distinguishing features from the data. This technique has proven valuable, especially in plant identification (Zhang et al., 2016).

These automated classification methods are promising because they enhance the capacity for investigating phenomenon over large spatial and temporal scales while reducing the effort required for costly and time-consuming field monitoring. However, ground truth data is still necessary to validate the performance of such systems. It is common practice to build this ground truth data from aerial images interpreted by human operators (James and Bradshaw, 2020; Kentsch et al., 2020; Charles et al., 2021; Lam et al., 2021; Marzialetti et al., 2021; Rodriguez et al., 2021). Nevertheless, even with the availability of high-resolution aerial images, particularly from UAVs, human interpretation can introduce errors due to factors such as phenological stages and the presence of shadows (Lam et al., 2021; Ciccarelli et al., 2023), although few studies have investigated the error introduced by human interpretation (Rodriguez et al., 2021).

In the present study, we focused on coastal sand dune ecosystems, examining the advantages and disadvantages of traditional field-based sampling compared to advanced methods using UAVs for monitoring IAPs. Among European terrestrial environments, coastal dunes are the most invaded habitats (Chytrỳ et al., 2008, 2009) with a flora characterized by 7 % of alien species, two-thirds of which originate from outside Europe and are mostly naturalized and ruderal (Giulio et al., 2020). In Italy, fixed dunes habitats characterized by *Juniperus* sp. pl. are frequently invaded by *Yucca gloriosa* L. (Asparagaceae), an invasive species (Galasso et al., 2018) from the southeastern Atlantic coast of the United States (Rentsch and Leebens-Mack, 2012), introduced to Europe for ornamental purposes. This IAP can establish itself in dune habitats prone to disturbance, displaying a high capacity to cope with drought-stressed conditions, attributed to its ability to switch photosynthesis from C3 to CAM pathways (Heyduk et al., 2016, 2021). In invaded landscapes, *Y. gloriosa* forms dense, monospecific evergreen patches due to its vegetative reproduction, especially through rhizomes, and competes with juniper for space and nutrients (Ciccarelli et al., 2023).

This work specifically aimed to test: (i) the agreement between field-based sampling of *Y. gloriosa* and manual screening performed by different operators on UAV images, taken at various altitudes, (ii) inter-operator concordance after a training procedure to minimize the effects related to the experience and expertise of the operators, (iii) the agreement between *Y. gloriosa* identification by visual interpretation of orthophotos and deep learning. The ultimate goal of this research is to reduce the costs associated with manpower in IAPs monitoring by using automated detection systems to facilitate efficient management and control of alien species.

2. Material and methods

2.1. Study site

This research was conducted within the Migliarino-San Rossore-Massaciuccoli Regional Park (MSRM Regional Park), a protected area covering approximately 230 km^2 in northern Tuscany, Italy (Fig. 1). The climate in this region is Mediterranean sub-humid, characterized by an average annual temperature of approximately 15.2 °C and a yearly total rainfall of 879 mm during the period 1991–2020 (http://www.lamma.rete.toscana.it/clima-e-energia/climatologia/clima-pisa last visited on 20–10–2022). The MSRM Park hosts a diverse range of habitats classified as being of Community interest under the Habitats Directive 92/43/EEC (EEC, 1992; Ciccarelli, 2014). Many of these habitats are located along the coastal dunes, which cover 1.7 % of the park's total area, amounting to approximately 3.9 Km^2. One significant threat to these unique and ecologically valuable environments is posed by alien plants (Guarino et al., 2021). In particular, *Y. gloriosa* represents a notable issue within the park as it competes with *Juniperus macrocarpa* in the fixed dunes (Ciccarelli et al., 2023). The field sampling and acquisition of images via UAV were carried out in the "Bufalina Nature Reserve'', a protected area partially included within the Special Area of Conservation (SAC) known as the "Coastal sand dunes of Torre del Lago" (code IT5170001).

2.2. Data collection and image dataset

The procedure employed in this study was structured following four key steps, as schematically illustrated in Fig. 2: (A) fieldwork and UAV

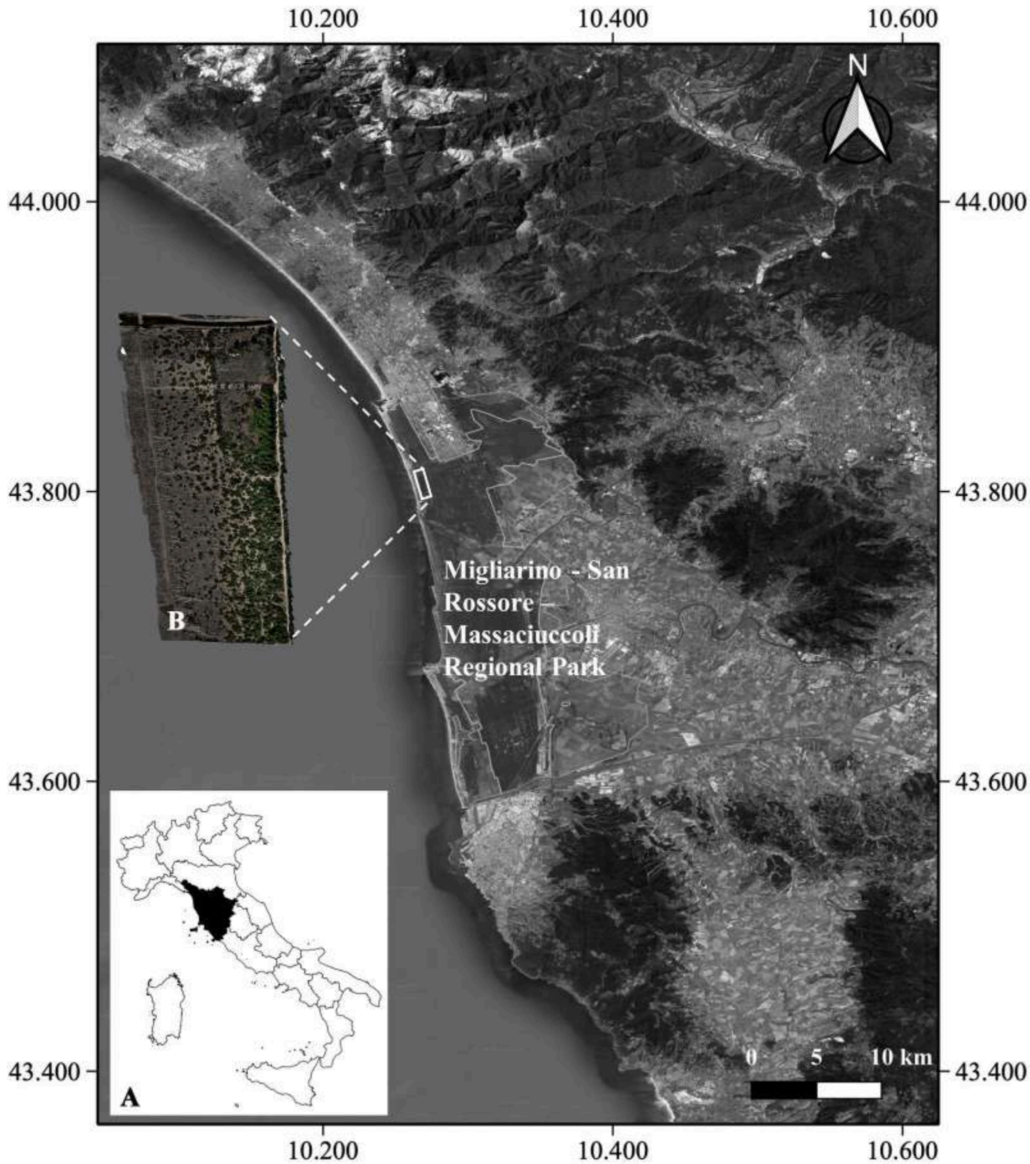


Fig. 1. Overview of the study area and its location. (A) Tuscany region in black. (B) The orthomosaic of the study area, situated within the Migliarino-San Rossore-Massaciuccoli Regional Park.

data acquisition, (B) manual image screening and training framework, (C) identification of *Yucca gloriosa* via a deep learning model, (D) statistical analyses.

We obtained UAV images of the study area using a DJI Phanthom 4 PRO v. 2.0, chosen for its favorable balance between costs-effectiveness and user-friendliness. This drone is equipped with a Red–Green–Blue (RGB) 20 megapixel camera and CMOS 1-inch sensor. To prepare the flight plans for the UAV, we employed the PIX4DCapture application (https://www.pix4d.com/product/pix4dcapture). This software was selected because it requires minimal attention from the pilot in the field, allowing for easy monitoring and control through the user-friendly interface.

The UAV images were captured during two distinct phases: the flowering phase in October and the post-flowering period in May, focusing on *Y. gloriosa*. This approach was adopted to account for any spectral variations associated to the phenological stage of the invasive plant. In October 2020, we selected an area of 90 × 90 m for our study, where we conducted multiple drone flights at various altitudes (15, 20, 25, 30, 35, 40, 45, 50, 60, 70 m above sea level). Our objective was to determine the most optimal altitude for mapping *Y. gloriosa* while minimizing drone usage. The scanning time for these flights varied, taking only 4 min at a height of 70 m, and extending to 16 min at an altitude of 15 m. Consequently, the resolution of the UAV images ranged from 0.4 cm/px at 15 m to 1.8 cm/px at 70 m of altitude. Within this area, we randomly selected 15 plots (1 ×1 m or 2 ×2 m) in which at least one *Y. gloriosa* plant was present. Before conducting the flights, we delimited and marked each plot on the ground affixing numbered control points (GCPs) of 15 × 20 cm (see Fig. 1S of the Supplementary material) to ensure easy recognition by drones (Marzialetti et al., 2021). In the field, two botanical operators visually estimated the cover of *Y. gloriosa* in square meters for each plot. Additionally, we performed the same *Y. gloriosa* cover estimation in these plots using UAV images, which were visually screened by multiple human operators (refer to the subsequent section for a detailed procedure). All images captured at various altitudes by these flights were used to assess both the agreement between field-based *Y. gloriosa* sampling and visual screening conducted by different operators on UAV images, as well as inter-operator concordance both before and after a training procedure. In May 2021, we expanded our study area to 1000 × 300 m and conducted eight flights at an altitude of 35 m above sea level. This altitude had been

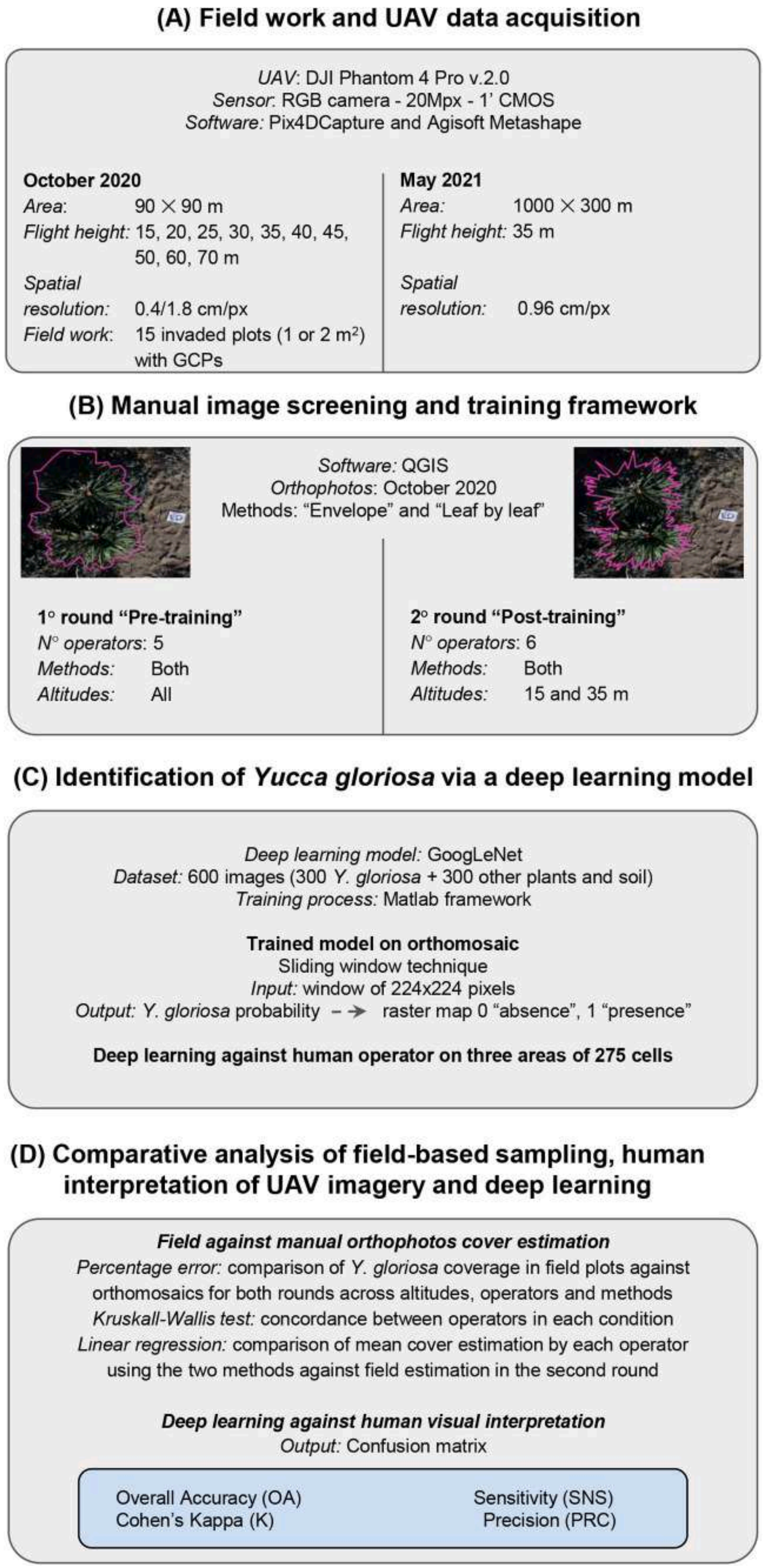


Fig. 2. Workflow diagram summarizing the methodology employed in this study. (A) Fieldwork and UAV data acquisition, (B) Manual image screening and training framework, (C) Identification of *Yucca gloriosa* via a deep learning model, (D) Comparative analysis of field-based sampling, human interpretation of UAV imagery and deep learning.

determined as the most efficient choice in terms of both time and image resolution during our previous assessments. The images captured during this period were used to evaluate the agreement between *Y. gloriosa* identification through human visual interpretation and deep learning.

During both the October 2020 and May 2021 flights, we scheduled them to take place between 11:00 AM and 01:00 PM to minimize the presence of shadows resulting from the inclination of solar radiation at Mediterranean latitudes.

For photogrammetric processing, we utilized Agisoft Metashape software (https://www.agisoft.com/). This software enabled us to generate RGB orthomosaics for each period and altitude by merging individual photos captured during the flights. We ensured an 80 % front and side overlap in these image acquisitions to facilitate accurate photogrammetric processing.

2.3. Manual image screening and training framework

All the orthomosaics were analyzed using the open-source Geographic Information System QGIS 3.4 Madeira using the coordinate system WGS84 (https://www.qgis.org/it/site/). This software enabled us to delineate polygons around individual *Y. gloriosa* plants or small clusters of plants, hereafter referred to as "nuclei", on the orthophotos. Additionally, QGIS automatically calculated the area covered by these polygons in squared meters (Fig. 3). We developed two distinct procedures for delineating the polygons occupied by *Y. gloriosa* plants, named as the "envelope method" and the "leaf by leaf method". In the "envelope method", each operator drew a polygon (outlined by the red line at the bottom of Fig. 3) connecting only the leaf apexes. Conversely, in the "leaf by leaf method" the operator traced a polygon (outlined by the pink line at the bottom of Fig. 3) following the contours of each individual leaf of the plant. The authors of this research employed both the "envelope" and "leaf by leaf" methods to map *Y. gloriosa* in two consecutive rounds. In the first round, all operators manually examined the orthophotos at various altitudes (ranging from 15 to 70 m above sea level) to determine the coverage area occupied by *Y. gloriosa* plants within each plot. Following the first round, we conducted an analysis to assess how the accuracy of manual screening compared to field sampling and the level of inter-operator agreement were influenced by two key factors: a) the selected method of estimating *Y. gloriosa* cover, (i.e., whether the "envelope" or "leaf by leaf" procedure was used); b) the resolution of UAV images. In the second round, all operators underwent a training procedure aimed at standardizing the manual screening of orthomosaics. This training was designed to minimize the potential influence of varying levels of experience and expertise among operators. Following the training, each operator analyzed the same plots in the orthomosaics captured at two altitudes: 15 m (providing the highest orthomosaics resolution) and 35 m (representing an optimal compromise between resolution and the time required to scan the area) employing both the "envelope" and the "leaf by leaf" methods. Like the first round, we conducted an analysis to assess the level of inter-operator agreement. This analysis considered the selected method of visual estimation (i.e., "envelope" or "leaf by leaf") and the altitude at which the orthomosaics were taken.

2.4. Identification of Yucca gloriosa by deep learning

In this study, we developed a deep learning model based on GoogLeNet (Szegedy et al., 2015) to perform the identification of *Y. gloriosa*

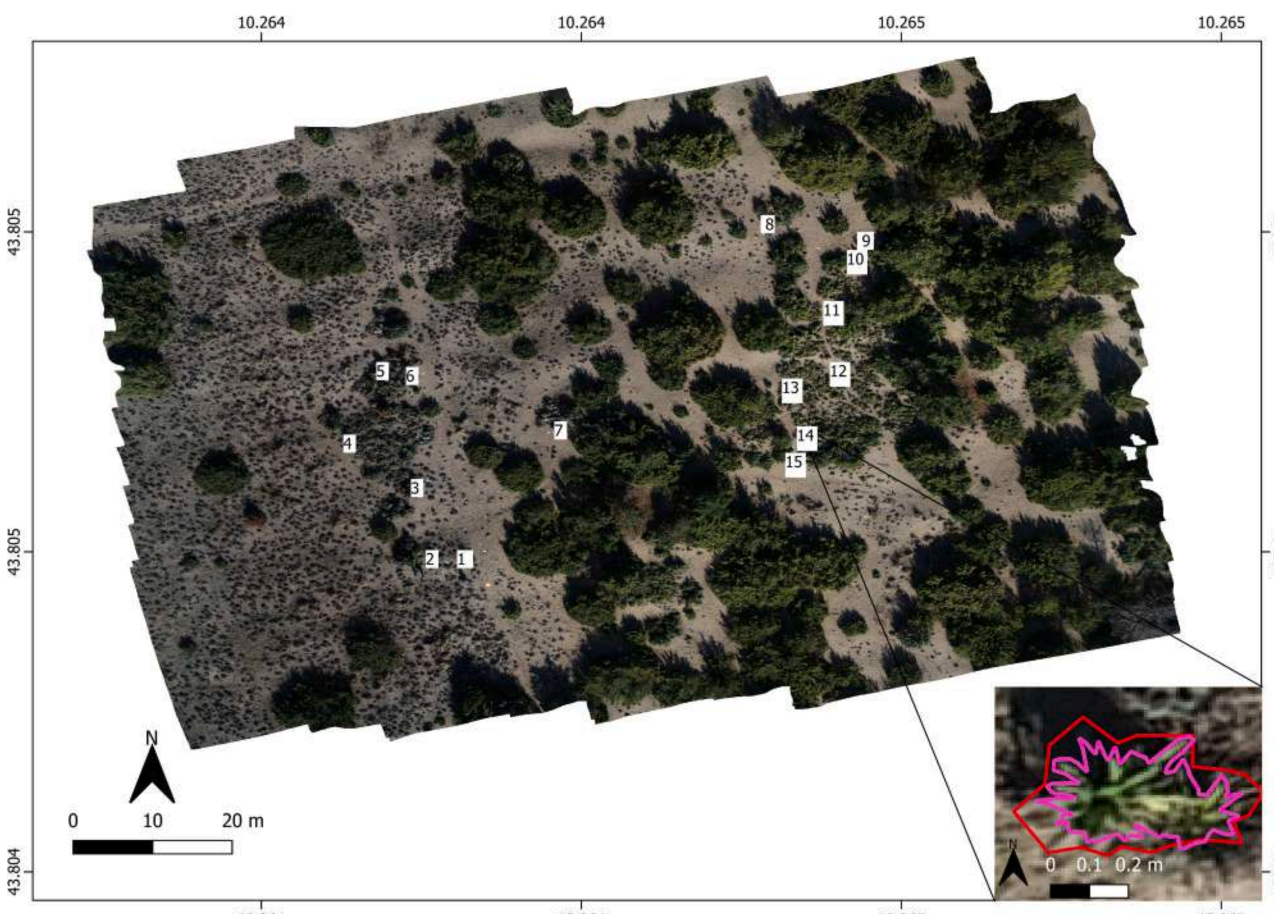


Fig. 3. Orthomosaic of the study area captured by the drone at 15 m of altitude. In the bottom right, a zoomed view of one of 15 plots displays the delimitation of *Yucca gloriosa* coverage, marked with polygons using the "envelope method" (red line) and "leaf by leaf method" (pink line).

within the orthophotos. GoogLeNet is a convolutional neural network, characterized by 22 layers of depth, and it is widely employed for image classification (Mehdipour Ghazi et al., 2017; Mostafa et al., 2022). Our model consists of a total of 57 convolutional layers, 14 pooling layers, one fully connected layer, and it takes color image patches sized 224×224 pixels as input. For training and validation our system, we utilized a dataset consisting of 600 images (224×224 pixels) extracted from UAV acquisitions conducted during diverse monitoring activities. The dataset comprised 300 images of *Y. gloriosa*, and 300 images of other plant species and soil. For our experiments, we partitioned the dataset, allocating 90 % of its contents for training purposes, while the remaining 10 % served as an independent test set (Table 1).

The training process for the identification of *Y. gloriosa* was conducted using the Matlab framework. Our model exhibited convergence at an accuracy level of approximately 94.10 % following the 756th iteration. Subsequently, the trained deep learning model was applied to an orthomosaic generated from drone scans. Specifically, we employed the sliding window technique across the entire image to detect regions containing *Y. gloriosa*. The window dimensions were set to 224×224 pixels, serving as input for the trained model. For each window position, the model provided a probability estimate of the presence or absence of *Y. gloriosa* (refer to Supplementary Fig. 2S for detailed information). This probability information was utilized to generate a raster map denoting the presence of *Y. gloriosa* across the entire scanned area. A value of “1” indicated presence (probability > 0.7), while a value of “0” denoted absence (probability < 0.7) of *Y. gloriosa*. To evaluate the accuracy of this classification method compared to human operator-based classification, we conducted assessments on three randomly selected areas (as illustrated in Fig. 4).

2.5. Statistical analyses

We compared the estimated cover of *Y. gloriosa* on the orthophotos for each plot with the cover obtained in the field, serving as the ground truth. To quantify the accuracy of our estimations, we calculated the Percentage Error (PE), defined as the ratio between the estimated cover on the orthomosaic and the estimated cover in the field. Additionally, we computed the average PE for all 15 plots, categorizing them by altitude and operator. Subsequently, we assessed the differences in percentage error obtained by the operators at various altitudes and between the “envelope” and the “leaf by leaf” methods. We conducted these comparisons using the Kruskall-Wallis non-parametric test, with significance levels set at $p < 0.05$ * and $p < 0.01$ * * for both for the first and the second rounds of testing.

We conducted a linear regression analysis to evaluate the relationship between the estimated *Y. gloriosa* cover obtained by the operator using the two methods (during the second round at a height of 35 m) and the cover measured directly in the field for each individual plot.

The map indicating the presence of *Y. gloriosa*, generated by the trained model, underwent evaluation against visual interpretation by a human operator. Within the study area, three randomly selected regions (cells), each covering an area of 1100 m^2, were chosen. To facilitate this assessment, each cell was subdivided into 275 subcells, using a 2×2 m grid. Three skilled operators were tasked with visually determining the presence or absence of *Y. gloriosa* in each subcell. They assigned values of “0” for absence and “1” for presence. Subsequently, a two-column table was created, with each row indicating the corresponding code assigned to the subcell by both the deep learning model and the operator. The deep learning-based classification was compared to the human operator’s visual classification, with the latter considered the reference standard. A confusion matrix was then calculated to quantify the performance of the deep learning model. The performance of the deep learning model was assessed using several metrics defined as follows (adapted from Campbell, 1996):

- Overall Accuracy (OA) = (TP+TN)/(TP+TN+FP+FN)
- Cohen’s Kappa (K) = (Po-Pe)/(1-Pe)

where Po is the observed agreement and Pe is the expected agreement. It’s typically used to measure the agreement between the deep learning model’s predictions and the ground truth.

- Sensitivity (SNS) = TP/(TP + FN)
  also known as true positive rate or recall and quantifies the proportion of actual positive cases correctly identified by the model.
- Precision (PRC) = TP/(TP + FP)

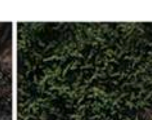
represents the proportion of positive predictions made by the model that are actually true positives.

Where:

- TP (True Positives): The number of cases correctly identified as positive by the deep learning model.
- TN (True Negatives): The number of cases correctly identified as negative by the deep learning model.
- FP (False Positives): The number of cases incorrectly identified as positive by the deep learning model.
- FN (False Negatives): The number of cases incorrectly identified as negative by the deep learning model.
- N (Total Number of Testing Data): The total number of data points in the testing dataset.

All the statistical analyses were conducted using the R software (R Development Core Team, 2016).

Table 1
The training dataset for the deep learning procedure consisted of distinct image classes, each accompanied by a description, a specific number of images, and representative examples for illustration.

Classes	Description	Number of images	Examples
Yucca gloriosa plants	An evergreen shrub, reaching a height of 2.5 m, characterized by long, narrow leaves that are straight and exceptionally rigid. The inflorescence consists of a lengthy panicle of bell-shaped white flowers	300	  
Other	Sandy soil, other coastal dune plants (like *Calamagrostis arenaria*, *Juniperus macrocarpa*, etc.), everything within the environment except for *Y. gloriosa*	300	  

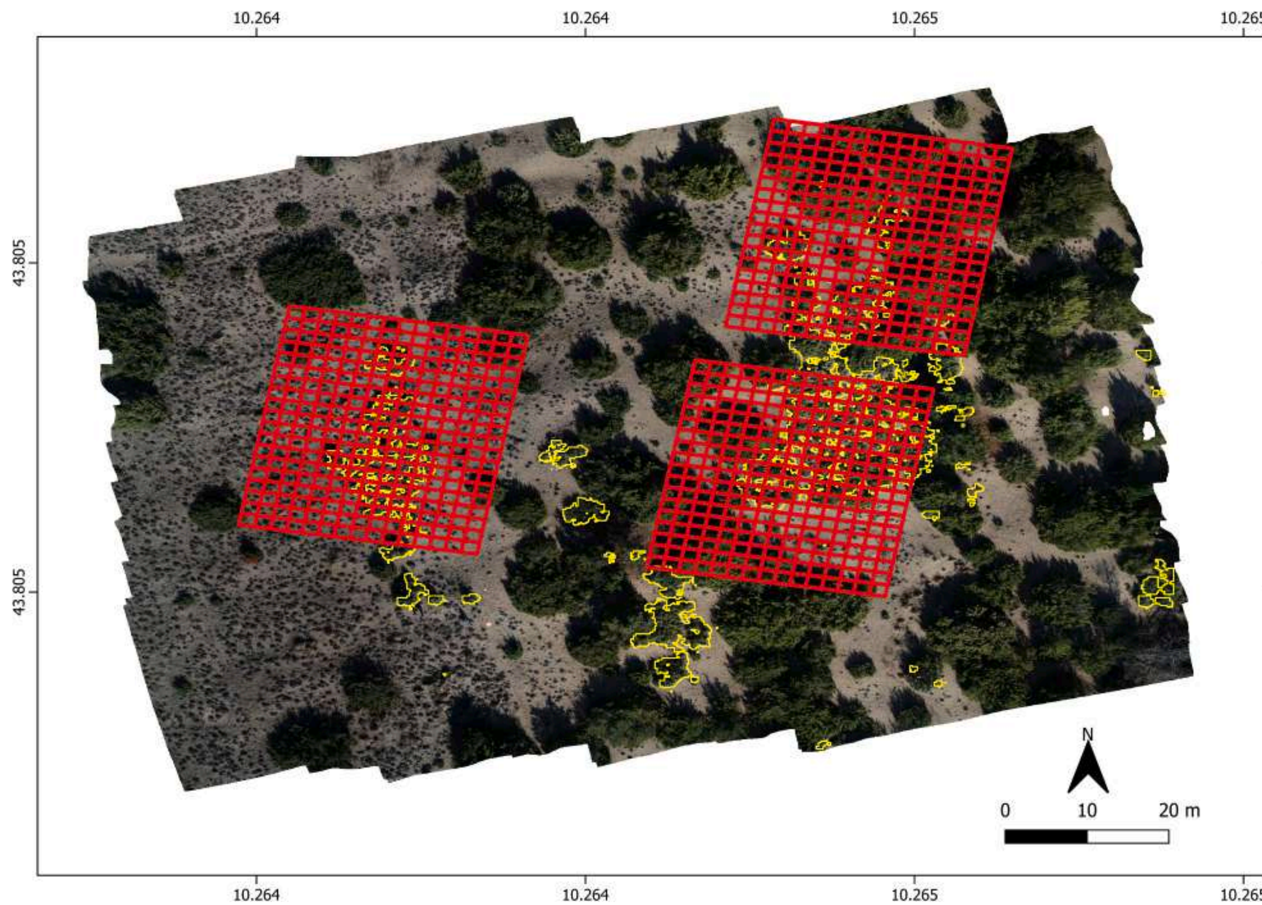


Fig. 4. *Yucca gloriosa* presence (yellow) in the study area, alongside three gridded cells (red) selected for comparing presence/absence as determined by deep learning and human interpretation.

3. Results and discussion

3.1. First round of assessments

During the first round of assessments, the average coverage of *Y. gloriosa*, when categorized by altitude and operator, consistently exhibited overestimation, with average PE between 11.7 % and 25.4% for the "envelope" method (Fig. 5 and Table 1S of the Supplementary material). Conversely, the "leaf by leaf" method yielded an average underestimation, with PE values ranging from 0.1% to −12.9 % (Fig. 5 and Table 2S of the Supplementary material). The Kruskal-Wallis test indicated that PE was significantly influenced only by the method used ($p < 0.01$). However, in the case of the "envelope" method, agreement in cover estimates among operators was observed solely for intermediate altitudes (ranging from 20 m to 50 m), whereas such concordance was not observed for both higher and lower altitudes (Table 1S of the Supplementary material). Concordance among operators was never achieved at any altitude when employing the "leaf by leaf" method. Consequently, these findings suggest that the "envelope" method, when applied at intermediate altitudes (between 20 m and 50 m), appears more suitable for quantifying *Y. gloriosa*, as significant discrepancies in cover estimates among operators were not observed. In general, flying at lower altitudes allows for the capture of more detailed and easily interpretable images. However, this also entails an increase in the number of images and flight operations required to cover a larger area. Therefore, when selecting the optimal flight altitude, it is advisable to strike a balance between image resolution and the total scanning time required for the area. Indeed, flight altitudes vary considerably across studies, ranging from 10 m to 160 m (de Sá et al., 2018; Tay et al., 2018; Kentsch et al., 2020; Charles et al., 2021; Lam et al., 2021; Marzialetti et al., 2021; Oldeland et al., 2021; Rodriguez et al., 2021). Furthermore, it is important to note that European regulations governing UAVs, specifically 2019/945 and 2019/947 (EC, 2019a,b), have established a flight height limit of 120 m for non-regulated areas. In regulated ones, such as those near military installations or airports, drone flights are prohibited. It is crucial to emphasize that there is not a universally optimal altitude suitable for all type of studies. The choice of altitude depends on a combination of technical factors, including UAV flight

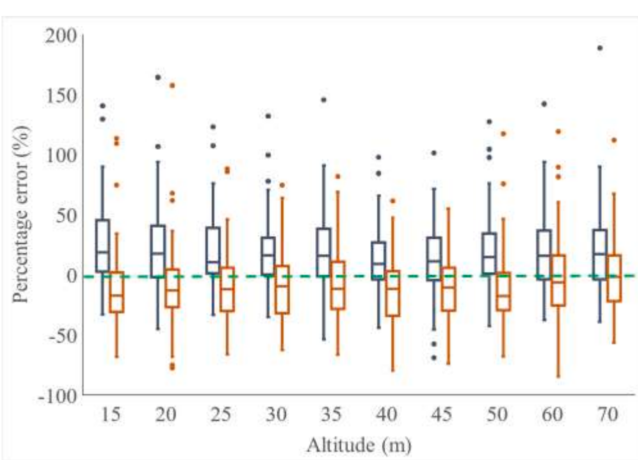


Fig. 5. Boxplots showing percentage errors for five operators at different altitudes during the first round of assessments, using the "envelope" method (blue) and the "leaf by leaf" method (orange). The green dashed line represents the standard method used as ground truth (0 % error).

autonomy and digital camera resolution, plant morphological characteristics such as size and phenology, and environmental factors such as weather conditions and the presence of shading, as well as contrast with the background. In this context, the versatility of drones proves invaluable in multiple aspects, encompassing flight planning, sensor selection, and timing of data acquisition concerning the phenological stage. These considerations collectively contribute to the attainment of optimal data for our specific application (Müllerová et al., 2017; Yao et al., 2019). Consequently, the identification of the ideal altitude for investigating a particular phenomenon becomes a pivotal step in this process. Remarkably, such altitude optimization remains relatively uncommon within the research domain (Lam et al., 2021).

In the present study, given *Y. gloriosa*'s distinctiveness in UAV imagery due to its size, shape, and pronounced contrast against the background, we selected an intermediate flight altitude. This choice was made to expedite scanning while maintaining the accuracy and interpretability of the results. Taking into consideration the performance observed in the first round of assessments with both methods, we determined the optimal flight altitude for *Y. gloriosa* monitoring to be 35 m. This altitude represents a well-balanced compromise between spatial resolution and flight duration, efficiently covering an area of approximately 30 ha (see also Ciccarelli et al., 2023).

3.2. Second round of assessments

After completing a training procedure, all operators conducted a secondary assessment of the areas inhabited by *Y. gloriosa* plants within the 15 selected plots. In line with the outcomes from the first round of assessments, we applied both the "envelope" and the "leaf by leaf" methods to the orthomosaic generated from images captured at an altitude of 35 m. This altitude represented a favorable balance between image resolution and the time needed for drone flights. Additionally, we evaluated the operators' performance using an alternative orthomosaic derived from images acquired at an altitude of 15 m, which provided the highest resolution image but involved a more time-consuming process. Concordance among the operators was achieved at all altitudes for the "envelope" method. Notably, the average PE at 35 m improved compared to the first round, with values of 10.2 % and 20.3 %, respectively (Fig. 6 and Table 3S of the Supplementary material). In the case of the "leaf by leaf" method, operators reached concordance only at an altitude of 35 m (Fig. 6 and Table 4S of the Supplementary material). However, it is worth noting that the average PE at 35 m, while slightly higher than in the first round (−11.7 % vs −7.4 %), showed improved concordance this time (refer to Table 3S and 4 S of the Supplementary material for detailed information).

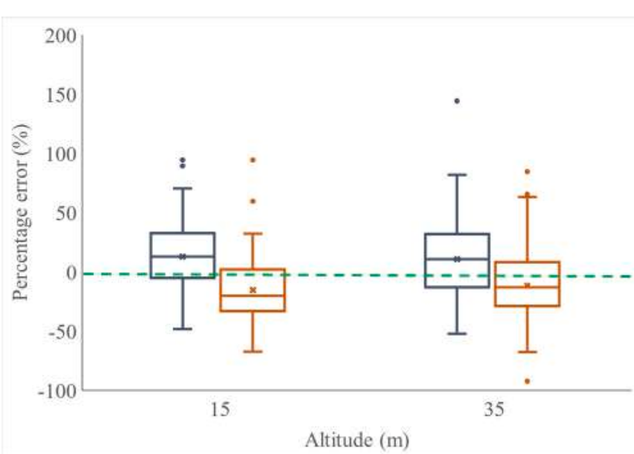


Fig. 6. Boxplots showing percentage errors for six operators at 15 m and 35 m of altitude during the second round of assessments, using the "envelope" method (blue) and the "leaf by leaf" method (orange). The green dashed line represents the standard method used as ground truth (0 % error).

Given our best results in terms of operator concordance at an altitude of 35 m, we exclusively applied linear model analysis to images captured at this altitude. This was done with the goal of comparing the estimated *Y. gloriosa* cover by the operator with the cover measured directly in the field. Similar to the findings in the first round, the "envelope" method consistently overestimated the average coverage of *Y. gloriosa*, whereas the "leaf by leaf" method consistently underestimated. Specifically, operators' cover estimations from images captured at an altitude of 35 m displayed a strong positive correlation with field estimates, both for the "envelope" ($R^2 = 0.94$, $N = 15$) and the "leaf by leaf" ($R^2 = 0.93$, $N = 15$) methods (as illustrated in Fig. 7A and B). This correlation aligns with results observed in other studies (e.g., Tay et al., 2018). Notably, when employing the "envelope" method, we observed that the level of cover overestimation increased with the dimensions of the plants (Fig. 7A). However, this may not pose a significant concern in our case, given that the average dimension of *Y. gloriosa* was approximately 0.5 m (Ciccarelli et al., 2023), which falls before the point on the graph where the error escalates with plant dimension. Conversely, using the "leaf by leaf" method, we noted an inverse correlation between the level of cover underestimation and the dimension of *Y. gloriosa* plants (Fig. 7B). Nevertheless, the levels of PE appear to be similar in both methods. Consequently, we recommend the use of the "envelope" method due to its ease of implementation and efficiency, especially when dealing with plants exhibiting complex three-dimensional structures, such as *Y. gloriosa*. Furthermore, employing the "envelope" method helps reduce the subjective human element in the interpretation process, as evidenced by a higher level of concordance among operators (Kruskal--Wallis p-value for "envelope" = 0.865, as opposed to p-value for "leaf by leaf" = 0.202). Lastly, all these results provide strong evidence for the decision to use drones at an altitude of 35 m for image acquisition in the study area.

3.3. Deep Learning against Human visual interpretation

Out of the 825 cells classified through human identification, six cells were excluded from the analysis due to the operator uncertainty regarding the presence or absence of *Y. gloriosa*. All the accuracy metrics derived from the confusion matrix (Table 2) showcased the effectiveness of the deep learning classification method, boasting notably high values, all exceeding 0.91 (Table 3). Comparatively, other studies that have evaluated the accuracy of automatic classification methods, such as random forest (de Sá et al., 2018; Marzialetti et al., 2021) and deep learning (James and Bradshaw, 2020; Kentsch et al., 2020; Charles et al., 2021; Lam et al., 2021; Aota et al., 2021), have also reported scores surpassing the 0.90 threshold. However, it is essential to acknowledge the complexity of making direct comparisons among studies in the field of plant mapping, given the wide variability in the type of information employed for classification and the diverse objectives pursued. The manual or automated identification of *Y. gloriosa* from UAV images proves to be a highly effective approach, primarily owing to the distinctive morphological characteristics of the species, especially regarding its leaves, which render it easily recognizable.

3.4. Methodological and management considerations

The current study has brought to light both the advantages and limitations of various methodologies for monitoring *Y. gloriosa* in Mediterranean coastal dunes. The most demanding and time-intensive approach remains the visual detection of IAPs in the field. However, this method, when executed at high spatial resolutions, can yield exceptionally accurate results (Elzinga et al., 1998). Traditionally, field-based monitoring was deemed indispensable, particularly in the context of forests where the invasive species often occurs beneath the canopy. Nevertheless, modern advancements in technology, particularly the utilization of UAVs, now afford researchers the ability to investigate

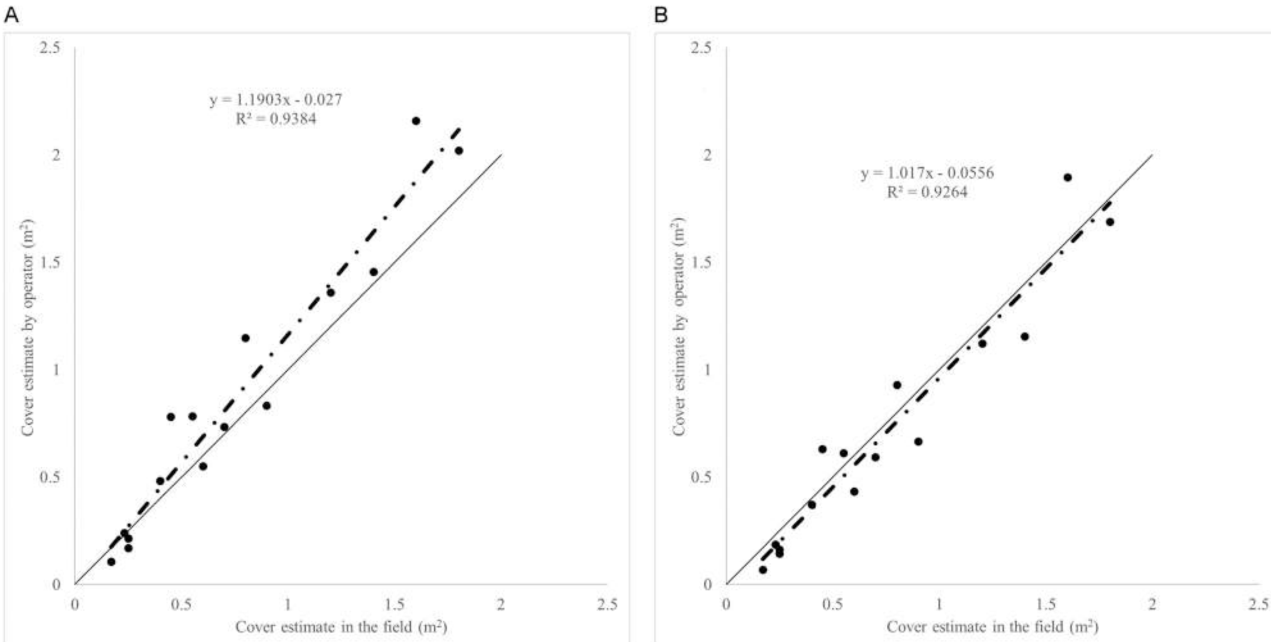


Fig. 7. Comparison of mean cover estimates made by operator for each plot at 35 m of altitude during the second round of assessments, using the "envelope" method (A) and the "leaf by leaf" method (B), against field-based estimates. Dashed lines represent linear regression equations, and the solid line represents the 1:1 values.

Table 2
A 2 × 2 confusion matrix was utilized to tabulate true positives (TP), false negatives (FN), false positives (FP), and true negatives (TN) in relation to the presence (1) or absence (0) of *Y. gloriosa* as predicted by deep learning model against the actual presence/absence (1, 0) evaluated by human identification.

		Predicted presence (Deep learning model)	
		1	0
Actual presence	1	242 (TP)	11 (FN)
(human identification)	0	19 (FP)	547 (TN)

Table 3
The accuracy assessment values of the deep learning method were computed based on the confusion matrix presented in Table 2. All these metrics yield values between 0 and 1, indicative of a perfectly performing classification method.

Accuracy assessment metrics	Values
Overall Accuracy (OA)	0.96
Cohen's Kappa (K)	0.91
Sensitivity (SNS)	0.96
Precision (PRC)	0.93

both the horizontal and the vertical structures of plant communities with unprecedented precision (Sun et al., 2021). Furthermore, *Y. gloriosa* is readily distinguishable in UAV imagery due to its size, distinctive shape, and pronounced against the sandy dune background, as detailed in our recent study (Ciccarelli et al., 2023). However, a key inquiry arises: How much does the quantification of *Y. gloriosa* coverage by an operator on UAV images deviate from that determined in the field? Additionally, are there any discernible distinctions between multiple operators, each possessing varying levels of expertise and experience in this task? Our research endeavors have elucidated that the "envelope" method, characterized by its ease and efficiency relative to the "leaf by leaf" method, serves as a robust compromise for quantifying *Y. gloriosa* plants on UAV imagery, irrespective of the operator involved. It is our perspective, however, that the "envelope" method may exhibit limitations when dealing with larger plants (with a coverage exceeding approximately 0.5 m^2 for *Y. gloriosa*). To the best of our knowledge, the reliability and variability associated with human interpretation of orthophotos for the assessment of plant species coverage have not been previously studied. Only a limited number of studies have ventured into the assessments of humans' ability to discern the presence or absence of a species through visual interpretation of aerial photographs (Rodriguez et al., 2021).

Finally, our study demonstrates the effectiveness of using UAV imagery for automated *Y. gloriosa* identification in invasive species monitoring due to its high accuracy. Future research will delve into the potential of deep learning algorithms for *Y. gloriosa* identification, aiming to assess their objectivity, efficiency, and cost-effectiveness in comparison to traditional photointerpretation methods. However, it is important to consider that the question of whether automated classification methods coupled with UAV technology can entirely replace traditional field-based sampling in IAP monitoring does not yield a universal and definitive answer. The feasibility of such a transition largely hinges on several factors, including the morphological characteristics of the IAP, its ease of identification in imagery, the specific vegetational context in which the IAP resides (as structural features differ between herbaceous plant communities and forests), the scale of the study area (given that field-based sampling is inherently more time-consuming than UAV imagery analysis), and the technical capabilities of the drone employed (including flight autonomy and digital camera resolution). Additionally, addressing the need for multiple flights, particularly in cases involving the monitoring of extensive territories, is a limitation that can be addressed through the utilization of fixed-wing flight systems, renowned for their extended flight autonomy. Nevertheless, from a conservation and management perspective, UAV technology represents a promising tool for reducing the manpower costs typically associated with IAP monitoring efforts.

4. Conclusions

To the best of our knowledge, this is the first study that examines the agreement between visual analysis of UAV images conducted by human operators and field sampling for quantifying *Y. gloriosa* cover. Secondly, it investigates the concordance among different operators both before and after training. Thirdly, it compares the efficiency of a streamlined and time-efficient approach, referred to as the "envelope" method, against a seemingly more precise yet time-intensive method, termed the "leaf by leaf" method. Lastly, it evaluates the capacity and reliability of deep learning for identifying *Y. gloriosa* plants in UAV images in comparison to human visual identification.

Our key findings are as follows: a) there exists a strong agreement not only between operators and field-based sampling but also among operators when employing the "envelope" method, which notably expedites the process; b) UAV imagery might represent a credible alternative to traditional field sampling, particularly for plants like *Y. gloriosa* with distinctive morphological traits that facilitate their identification; c) the application of deep learning for *Y. gloriosa* mapping yields results comparable to visual UAV image analysis by human operators.

In summary, our study underscores the potential utility of drones, coupled with deep learning techniques, as effective tools for reducing the human costs associated with monitoring IAPs, thereby enhancing the management and control of *Y. gloriosa* in coastal dune environments.

One future development of this line of research may involve comparing the quantification of *Y. gloriosa* coverage and the accuracy of methods between deep learning and field-based sampling. Additionally, exploring the effectiveness of automatic or semi-automatic classification methods, including pixel-based or object-based approaches, could further enhance our understanding in this field.

CRediT authorship contribution statement

Luciano Massetti: Supervision, Methodology, Investigation, Formal analysis, Writing – original draft. **Alessio Mo**: Formal analysis, Investigation, Writing – original draft, Writing – Review & Editing. **Elena Cini**: Formal analysis, Investigation, Writing – original draft, Writing – Review & Editing. **Marco Paterni**: Data curation, Software, Formal analysis, Validation, Writing – original draft. **Silvia Merlino**: Methodology, Investigation, Formal analysis, Writing – original draft. **Daniela Ciccarelli**: Supervision, Conceptualization, Methodology, Formal analysis, Investigation, Writing – original draft, Writing – Review & Editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data Availability

Data will be made available on request.

Acknowledgements

The authors express their gratitude to the Migliarino - San Rossore - Massaciuccoli Regional Park for granting permission to access the protected area and collect research data.

Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.rsma.2023.103265.

References

Aota, T., Ashizawa, K., Mori, H., Toda, M., Chiba, S., 2021. Detection of *Anolis carolinensis* using drone images and a deep neural network: an effective tool for controlling invasive species. Biol. Invasions 23, 1321–1327. https://doi.org/10.1007/s10530-020-02434-y.

Broussard III, W.P., Visser, J., Brooks, R.P., 2020. Quantifying Vegetation and Landscape Metrics with Hyperspatial Unmanned Aircraft System Imagery in a Coastal Oligohaline Marsh. ESCO. https://doi.org/10.1007/s12237-020-00828-8.

Campbell, J.B., 1996. Introduction to Remote Sensing. Guilford, New York.

Charles, C.P., Kim, P.H.C., de Almeida, A.G., Do Nascimentok, E.V., Da Rocha, L.G.S., Vivaldini, K.C.T., 2021. Detection of invasive vegetation through UAV and Deep Learning. In: 2021 Latin American Robotics Symposium (LARS), 2021 Brazilian Symposium on Robotics (SBR), and 2021 Workshop on Robotics in Education (WRE), pp. 114–119. https://doi.org/10.1109/LARS/SBR/WRE54079.2021.9605371.

Chytrỳ, M., Maskell, L.C., Pino, J., et al., 2008. Habitat invasions by alien plants: a quantitative comparison among Mediterranean, subcontinental and oceanic regions of Europe. J. Appl. Ecol. 45, 448–458. https://doi.org/10.1111/j.1365-2664.2007.01398.x.

Chytrỳ, M., Pyšek, P., Wild, J., Pino, J., Maskell, L.C., Vilà, M., 2009. European map of alien plant invasions based on the quantitative assessment across habitats. Divers. Distr. 15, 98–107. https://doi.org/10.1111/j.1472-4642.2008.00515.x.

Ciccarelli, D., 2014. Mediterranean coastal sand dune vegetation: influence of natural and anthropogenic factors. Environ. Manag. 54, 194–204. https://doi.org/10.1007/s00267-014-0290-2.

Ciccarelli, D., Cini, E., Mo, A., Paterni, M., Massetti, L., Rangel-Buitrago, N., Merlino, S., 2023. The assessment and management of plant invasions with Unmanned Aerial Vehicles. The *Yucca gloriosa* case, Italy. Reg. Stud. Mar. Sci. 57, 102759 https://doi.org/10.1016/j.rsma.2022.102759.

Dash, J., Shakyawar, S.K., Sharma, M., Kaushik, S., 2019. Big data in healthcare: management, analysis and future prospects. J. Big. Data. 6, 54 https://doi.org/10.1186/s40537-019-0217-0.

EC, 2019a. Commission Delegated Regulation (EU) 2019/945 of 12 March 2019 on unmanned aircraft systems and on third-country operators of unmanned aircraft systems. Off. J. L 152 (1), 11/06/2019.

EC, 2019b. Commission Implementing Regulation (EU) 2019/947 of 24 May 2019 on the rules and procedures for the operation of unmanned aircraft (Text with EEA relevance). Off. J. L 152 (45), 11/06/2019.

EC, Directorate-General for Environment, Sundseth, K., 2014. Invasive alien species: a European Union response. Publications Office. ⟨https://data.europa.eu/doi/10.2779/69473⟩.

EEC, 1992. Council directive 92/43/EEC of 21 May 1992 on the conservation of natural habitats and of wild fauna and flora. Off. J. L 206, 7–50. , 22/07/1992 and Its Amending acts.

Elzinga, C.L., Salzer, D.W., Willoughby, J.W., 1998. Measuring and monitoring plant populations. BLM Tech. Ref. 1730–1731.

Galasso, G., Conti, F., Peruzzi, L., et al., 2018. An updated checklist of the vascular flora alien to Italy. Plant Biosys 152, 556–592. https://doi.org/10.1080/11263504.2018.1441197.

Gillan, J.K., Karl, J.W., Leeuwen, W.J.D., 2020. Integrating drone imagery with existing rangeland monitoring programs. Environ. Monit. Assess. 192, 269 https://doi.org/10.1007/s10661-020-8216-3.

Giulio, S., Acosta, A.T.R., Carboni, M., et al., 2020. Alien flora across European coastal dunes. Appl. Veg. Sci. 23, 317–327. https://doi.org/10.1111/avsc.12490.

Guarino, R., Chytrý, M., Attorre, F., Landucci, F., Marcenò, C., 2021. Alien plant invasions in Mediterranean habitats: an assessment for Sicily. Biol. Invasions. 23, 3091–3107. https://doi.org/10.1007/s10530-021-02561-0.

Heyduk, K., Burrell, N., Lalani, F., Leebens-Mack, J., 2016. Gas exchange and leaf anatomy of a C3-CAM hybrid, *Yucca gloriosa* (Asparagaceae). J. Exp. Bot. 67, 1369–1379. https://doi.org/10.1093/jxb/erv536.

Heyduk, K., Ray, J.N., Leebens-Mack, J., 2021. Leaf anatomy is not correlated to CAM function in a C3+CAM hybrid species, *Yucca gloriosa*. Ann. Bot. 127, 437–449. https://doi.org/10.1093/aob/mcaa036.

James, K., Bradshaw, K., 2020. Detecting plant species in the field with deep learning and drone technology. Methods Ecol. Evol. 11, 1509–1519. https://doi.org/10.1111/2041-210X.13473.

Karl, J.W., Yelich, J.V., Ellison, M.J., Lauritzen, D., 2020. Estimates of willow (*Salix* spp.) canopy volume using unmanned aerial systems. Range Ecol. Manag. 73, 531–537. https://doi.org/10.1016/j.rama.2020.03.001.

Kentsch, S., Lopez Caceres, M.L., Serrano, D., Roure, F., Diez, Y., 2020. Computer vision and deep learning techniques for the analysis of drone-acquired forest images, a transfer learning study. Remote Sens. 12 (8), 1287. https://doi.org/10.3390/rs12081287.

Klemas, V., 2015. Coastal and environmental remote sensing from unmanned aerial vehicles: an overview. J. Coast. Res. 315 (5), 1260–1267. https://doi.org/10.2112/JCOASTRES-D-15-00005.1.

Kosmowski, F., Stevenson, J., Campbell, J., Ambel, A., Tsegay, A.H., 2017. On the ground or in the air? A methodological experiment on crop residue cover measurement in Ethiopia. Environ. Manag. 60, 705–716. https://doi.org/10.1007/s00267-017-0898-0.

Lam, O.H.Y., Dogotari, M., Prüm, M., Vithlani, H.N., Roers, C., Melville, B., Zimmer, F., Becker, R., 2021. An open source workflow for weed mapping in native grassland using unmanned aerial vehicle: using *Rumex obtusifolius* as a case study. Eur. J. Remote Sens. 54, 71–88.

Le Moigne, J., Netanyahu, N.S., Eastman, R.D., 2011. Image Registration for Remote Sensing. Cambridge University Press, Cambridge, UK.

Martinez, B., Reaser, J.K., Dehgan, A., Zamft, B., Baisch, D., McCormick, C., Giordano, A. J., Aicher, R., Selbe, S., 2020. Technology innovation: advancing capacities for the early detection of and rapid response to invasive species. Biol. Invasions 22, 75–100. https://doi.org/10.1007/s10530-019-02146-y.

Marzialetti, F., Frate, L., De Simone, W., Frattaroli, A.R., Acosta, A.T.R., Carranza, M.L., 2021. Unmanned Aerial Vehicle (UAV)-Based mapping of *Acacia saligna* invasion in the Mediterranean coast. Remote Sens. 13, 3361. https://doi.org/10.3390/rs13173361.

McGeoch, M.A., Genovesi, P., Bellingham, P.J., Costello, M.J., McGrannachan, C., Sheppard, A., 2016. Prioritizing species, pathways, and sites to achieve conservation targets for biological invasions. Biol. Invasions 18, 299–314. https://doi.org/10.1007/s10530-015-1013-1.

Mehdipour Ghazi, M., Yanikoglu, B., Aptoula, E., 2017. Plant identification using deep neural networks via optimization of transfer learning parameters. Neurocomputing 235, 228–235. https://doi.org/10.1016/j.neucom.2017.01.018.

Mostafa, A.M., Kumar, S.A., Meraj, T., Rauf, H.T., Alnuaim, A.A., Alkhayyal, M.A., 2022. Guava disease detection using deep convolutional neural networks: a case study of guava plants. Appl. Sci. 12, 239. https://doi.org/10.3390/app12010239.

Müllerová, J., Brůna, J., Bartaloš, T., Dvořák, P., Vítková, M., Pyšek, P., 2017. Timing is important: unmanned aircraft vs. satellite imagery in plant invasion monitoring. Front. Plant. Sci. 8, 887 https://doi.org/10.3389/fpls.2017.00887.

Oldeland, J., Revermann, R., Luther-Mosebach, J., Buttschardt, T., Lehmann, J.R.K., 2021. New tools for old problems – comparing drone- and field-based assessments of a problematic plant species. Environ. Monit. Assess. 193, 90 https://doi.org/10.1007/s10661-021-08852-2.

R Development Core Team, 2016. R: a language and environment for statistical computing. ⟨https://www.r-project.org/⟩.

Rentsch, J.D., Leebens-Mack, J., 2012. Homoploid hybrid origin of *Yucca gloriosa*: intersectional hybrid speciation in *Yucca* (Agavoideae, Asparagaceae). Ecol. Evol. 2, 2213–2222. https://doi.org/10.1002/ece3.328.

Rodriguez III, R., Perroy, R.L., Leary, J., Jenkins, D., Panoff, M., Mandel, T., Perez, P., 2021. Comparing interpretation of high-resolution aerial imagery by humans and artificial intelligence to detect an invasive tree species. Remote Sens. 13, 3503. https://doi.org/10.3390/rs13173503.

de Sá, N.C., Castro, P., Carvalho, S., Marchante, E., López-Núñez, F.A., Marchante, H., 2018. Mapping the flowering of an invasive plant using unmanned aerial vehicles: Is there potential for biocontrol monitoring? Fron. Plant. Sci. 9, 293 https://doi.org/10.3389/fpls.2018.00293.

Sladonja, B., Damijanić, D., Krapac, M., Uzelac, M., Linić, I., Poljuha, D., 2022. Development of drone-based methodology for inventory and monitoring invasive plants along river banks in Croatia. Manag. Biol. Invasions. 13 (4), 679–689. https://doi.org/10.3391/mbi.2022.13.4.06.

Sun, Z., Wang, X., Wang, Z., Yang, L., Xie, Y., Huang, Y., 2021. UAVs as remote sensing platforms in plant ecology: review of applications and challenges. Plant. Ecol. 14, 1003–1023. https://doi.org/10.1093/jpe/rtab089.

Szegedy, C., Liu, W., Jia, Y., Sermanet, P., Reed, S., Anguelov, D., et al., 2015. Going deeper with convolutions. In: 2015 IEEE conference on computer vision and pattern recognition (CVPR), pp. 1–9. https://biblioproxy.cnr.it:2481/10.1109/CVPR.2015.7298594.

Tay, J.Y.L., Erfmeier, A., Kalwij, J.M., 2018. Reaching new heights: can drones replace current methods to study plant population dynamics? Plant. Ecol. 219, 1139–1150. https://doi.org/10.1007/s11258-018-0865-8.

Vilà, M., Basnou, C., Pyšek, P., et al., 2010. How well do we understand the impacts of alien species on ecosystem services? A pan-European cross-taxa assessment. Front. Ecol. Environ. 8, 135–144. https://doi.org/10.1890/080083.

Watts, A.C., Ambrosia, V.G., Hinkley, E.A., 2012. Unmanned aircraft systems in remote sensing and scientific research: classification and considerations of use. Remote Sens. 4, 1671–1692. https://doi.org/10.3390/rs4061671.

Weber, K.T., Théau, J., Serr, K., 2008. Effect of coregistration error on patchy target detection using high-resolution imagery. Remote Sens. Environ. 112, 845–850. https://doi.org/10.1016/j.rse.2007.06.016.

Weidlich, E.W.A., Flórido, F.G., Sorrini, T.B., Brancalion, P.H.S., 2020. Controlling invasive plant species in ecological restoration: a global review. J. Appl. Ecol. 57, 1806–1817. https://doi.org/10.1111/1365-2664.13656.

Yao, H., Qin, R., Chen, X., 2019. Unmanned aerial vehicle for remote sensing applications—a review. Remote Sens. 11, 1443. https://doi.org/10.3390/rs11121443.

Zhang, L., Zhang, L., Du, B., 2016. Deep learning for remote sensing data: a technical tutorial on the state of the art. IEEE Geosci. Remote Sens. Mag. 4, 22–40. https://doi.org/10.1109/MGRS.2016.2540798.