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Research Article

Remote sensing for monitoring and assessment of invasive herbaceous plants: the case of *Oenothera drummondii* in coastal ecosystems

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Abstract

Invasive exotic species pose a serious threat to biodiversity, particularly in fragile and degraded habitats. This is the case with *Oenothera drummondii*, which significantly affects certain coastal areas of the Iberian Peninsula. This study area focuses on the Odiel Marshes Natural Area, where populations of this herbaceous plant are drastically affecting native vegetation. The objective is to develop a methodology for the automatic detection of individuals of this species with Unmanned Aerial Vehicles (UAV) equipped with multispectral cameras. The final goal is to optimize monitoring, control, and potential eradication activities.

A photogrammetric flight was carried out over 26.26 ha using a DJI Mavic 3Multiespectral. The model used to distinguish the invasive species from the native vegetation in the area was the C5.0 classification model. A total of 800 individuals were analysed using this model, including samples of the invasive species and three of the most abundant native plant species with a similar appearance. The classification tree results were extrapolated to the entire study area. The results indicate that the use of multispectral bands and vegetation indices allows the C5.0 model to classify the studied species with an error rate of 15.4%. The subsequent application of the classification tree obtained across the entire study area resulted in the detection of *O. drummondii* with an accuracy rate of 83%, demonstrating that this UAV-based technique enables the identification of exotic invasive herbaceous species. This methodology could contribute to management of the species and could be easily applied to other affected areas and species worldwide.

Key words: Alien species, C5.0 classification model, dune, management, multispectral, unmanned aerial vehicles, vegetation indices

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Introduction

The presence of invasive exotic species, driven by climate change, increased goods traffic and globalization, is considered an undeniable effect of global change and one of the main causes of biodiversity loss (Primack 2010; Pyšek et al. 2017; IUCN 2021). This is due both to their high capacity to modify entire ecosystems (Sodhi and Ehrlich 2010) and to the negative impacts associated with their presence and expansion (Richardson et al. 2000).

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In this respect, remote sensing, and particularly the use of Unmanned Aerial Vehicles (UAVs), is an advantageous tool for the monitoring of plant species, as it can provide a large amount of information in a short time using few resources (Wich and Koh 2018; Wich et al. 2021). Accessibility to complex areas and imagery from an aerial perspective provide a new source of information contributing to environmental sciences (Wich and Koh 2018; Wich et al. 2021). Most studies using remote sensing to monitor invasive plant species focus on large, well-distributed formations (trees and/or shrubs), or large areas of homogeneous crops or formations (Peerbhay et al. 2016; Landmann et al. 2020; Holden et al. 2021; Chen and Shi 2023; Da Silva et al. 2023; Pinto et al. 2023). In recent years, the automatic detection of plant species has been carried out using various techniques. Among these, the most common is the use of models such as Random Forest (Chen and Shi 2023; Da Silva et al. 2023; Pinto et al. 2023). However, we are not aware of any studies that attempt to differentiate individuals of herbaceous species in non-homogeneous communities using data mining models, such as the C5.0 model (Kuhn et al. 2023). Studies using such models focus only on large uniform areas (Sun et al. 2017; Rudiyanto et al. 2019; Komaraasih et al. 2020; Nurkholis and Styawati 2021).

In general, coastal zones are more susceptible to the presence of allochthonous flora (López-Tirado et al. 2023) and, as highly vulnerable areas, are much more sensitive to disturbances that affect their dynamics (Muñoz-Vallés and Cambrollé 2014). In the case of the Odiel Marshes Natural Area (Huelva, Spain), we can find several plant species classified as invasive alien species (Dana et al. 2005), such as *Agave americana* L., *Arundo donax* L., and *Carpobrotus* sp. Among these can also be included *Oenothera drummondii* Hook, an herbaceous plant, and a good example of the need for early detection, control and monitoring of the invasion status. The first record of *O. drummondii* in the Odiel Marshes dates from 1996, while in 2014 control studies estimated that it had successfully colonised up to 123 hectares (García-de-Lomas et al. 2015).

Oenothera drummondii is a perennial species with large yellow flowers, native to Mexico and southern USA, and is especially worrying in coastal dune ecosystems (Gallego-Fernández et al. 2019; Díaz-Barradas et al. 2020; Castillo-Infante et al. 2021). The two main characteristics enabling it to establish itself are its high regrowth potential (García-de-Lomas et al. 2015), and its large seed bank of very small seeds (Gallego-Fernández and García-Franco 2021), resistant to seawater (Gallego-Fernández and García-Franco 2021; Gallego-Fernández et al. 2021), the dispersal of which is carried out in the study area mainly by animals (endozoochory).

All this has meant that in less than 30 years the invasion process of this species in the Odiel Marshes has reached stage four, the ultimate stage on the invasion scale (Blackburn et al. 2011), where the population is self-sustaining, and individuals survive, reproduce and disperse at a significant distance from the original point of entry (Kolar and Lodge 2001; García-de-Lomas et al. 2015; Gallego-Fernández et al. 2019), the natural course of expansion of all invasive alien species if they cannot be kept under control or the populations be eradicated (Blackburn et al. 2011).

Although remote sensing for management purposes is on the rise due to its practicality, there is very little information on studies of herbaceous species as small as the species addressed in this study (*Oenothera drummondii*) (Qian et al. 2020; Bakacsy et al. 2023), the average size of which in the study population is 0.3 m in diameter. In this regard, the automatic detection of individuals can provide an advantage in implementing control, monitoring, and eradication measures, as it enables thorough and rigorous population management. This model allows us to generate a decision tree that classifies the sample (different species in our case) according to the values generated for a set of variables associated with the target species.

The main objective of this study is thus the development of a UAV-based methodology that allows us to automatically detect herbaceous species, in our case, an invasive species, using the C5.0 classification model. This model would enable us to assess the extent of the invasion and to provide information that would facilitate and optimise control, monitoring and eradication activities in a heterogeneous and diverse area such as the dunes of the Odiel Marshes Natural Area.

Methods

Study area

The study area is located in the Odiel Marshes Natural Area, in the province of Huelva (southwest of the Iberian Peninsula, Spain), as shown in Fig. 1. It is a protected marshland system situated between the estuaries of the rivers Tinto and Odiel, and is listed as a Wetland-Ramsar, Natura 2000 Network site and Biosphere Reserve (Andalusia Regional Government 2023). This protected site is subject to a wide set of threats including mining drainage (Davila et al. 2019), urban expansion and alien invasions (Gallego-Fernández et al. 2019) among others. The area has an oceanic Mediterranean climate, with average annual temperatures ranging between 17 and 19 °C, and a rainy season from October to April, with an average annual rainfall of 500–700 mm (average from 1952 to 2019) (Andalusia Regional Government 2022; State Meteorology Agency 2024). The study area is specifically located on a recently created beach running alongside the Juan Carlos I breakwater (Fig. 1). This breakwater was constructed in 1981, since when sediment deposits have formed what is now known locally as the Breakwater Beach. There is an initial band of vegetation in the area comprising species such as *Salsola kali* L., *Cakile maritima* Scop. and *Eryngium maritimum* L. in the strandline. Further inshore, among the embryonic shifting dunes, we find species such as *Ammophila arenaria* (L.) Link, *Otanthus maritimus* (L.) Hoffmanns. & Link, and *Retama monosperma* (L.) Boiss., while among the semi-fixed dunes there are species such as *Artemisia crithmifolia* L. and *Lotus creticus* L. (Cabezudo-Artero et al. 2020).

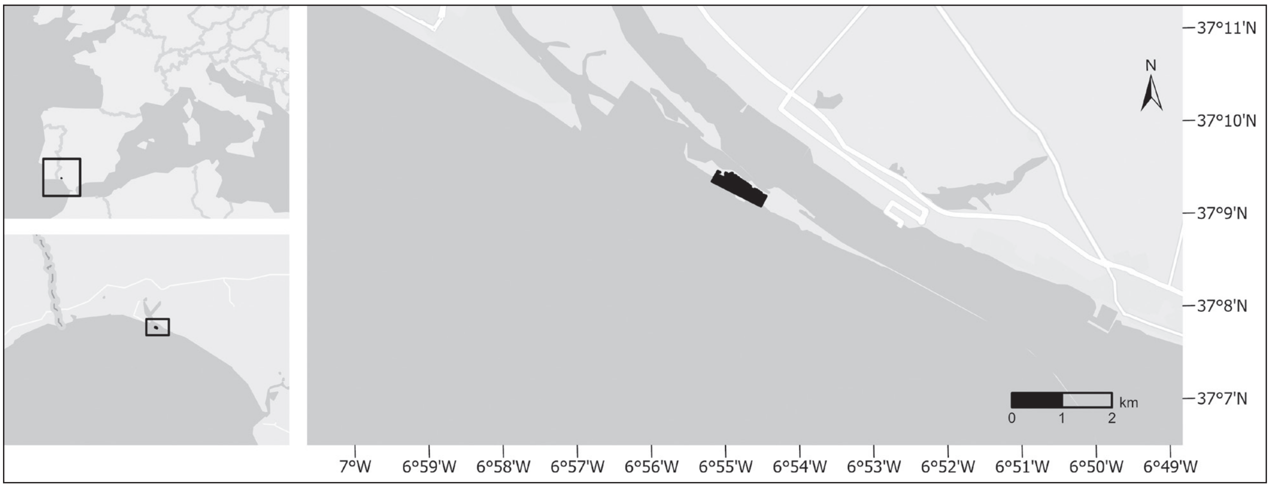

Figure 1. Location of the study area, covering 26.26 ha.

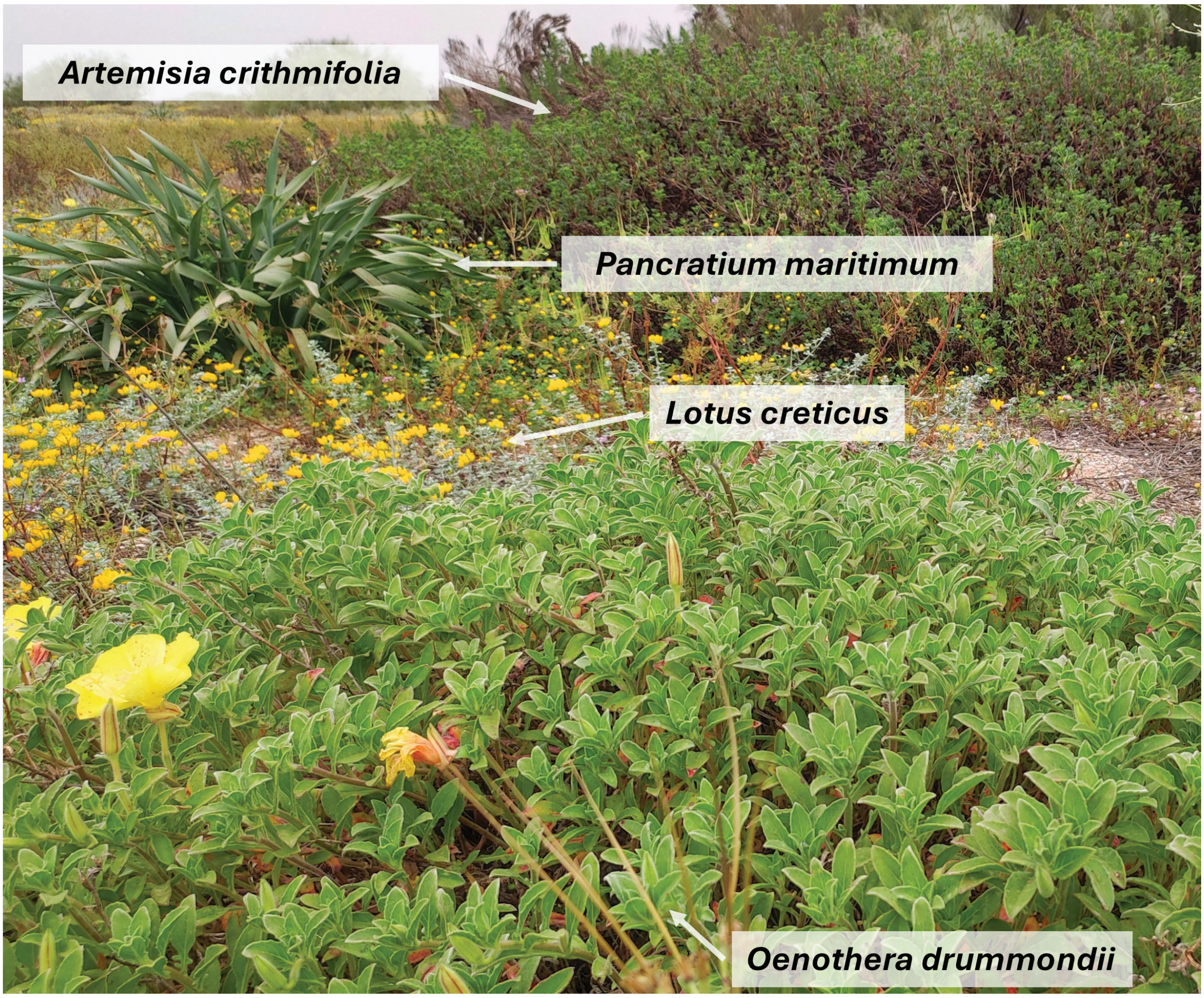

Figure 2. Photograph of the study area. The three selected native species (*Artemisia crithmifolia*, *Lotus creticus* and *Pancratium maritimum*) and the invasive species *(O. drummondii*) are identified. Image taken on March 22, 2024.

For this study, an area identified in previous studies (García-de-Lomas et al. 2015) as the most affected by the invasion of *O. drummondii* was selected. Specifically, 26.26 ha of land were chosen, encompassing the entire dune zone with different plant species (Fig. 2).

Data collection

The study area was flown over by a DJI Mavic 3M (DJI, Shenzhen, China), combining an RGB camera (sensor: CMOS 4/3‘, effective pixels: 20 MP) and a multispectral camera (CMOS 1/2.8’ sensors, effective pixels: 5 MP), with DJI D-RTK 2 positioning and GNSS receiver (DJI, Shenzhen, China). The flight plan was configured as follows: the lateral and longitudinal overlaps were set at 70%; the altitude was 100 m AGL (above ground level); the flight speed was 6 m/s; image capture was by distance interval rate and the sensor angle was 90 degrees. Radiometric correction was carried out by a calibration reflectance panel (MicaSense Inc, Seattle, Washington, USA).

The flight was carried out in March 2024, as this is the month in which the target species (*O. drummondii*) is in a state of high vegetative growth with few flowers (Fig. 2) that could bias the images obtained. These images were then processed with ArcGIS

Drone2map 2023.1.0 software (Esri, Redlands, California, USA) to generate the photogrammetry and so obtain the orthophotos in the Red (R): 650 ± 16 nm, Green (G): 560 ± 16 nm; Red Edge (RE): 730 ± 16 nm and Near InfraRed (NIR): 860 ± 26 nm channels. Five control points were used to ensure a high degree of accuracy in the photogrammetry. These control points were taken using the DJI D-RTK 2 High Precision GNSS Mobile Station. The resulting images have a pixel size of 0.05 m.

Once the orthophotographs had been obtained in the required spectral bands, a series of vegetation indices were calculated using ArcGIS Pro 3.1.0 software (Esri, Redlands, California, USA) to provide complementary information. These vegetation indices were: NDVI (Normalized Difference Vegetation Index), NDRE (Normalized Difference Red Edge Index), GNDVI (Green Normalized Difference Vegetation Index), GCl (Green Chlorophyll Index), and RECl (Red Edge Chlorophyll Index) (Table 1). Then, with the Arcgis Pro select random points tool, a random selection of 200 individuals of the invasive species *O. drummondii* was made, each having a radius greater than 0.2 m and with an intense signal in the infrared false colour composition (NIR-R-G). Likewise, 200 individuals of three common native species of similar size were selected, all again with a radius greater than 0.2 m and with an intense signal in the false colour composition. The selected native species were: *Pancratium maritimum* L., *Artemisia crithmifolia*, and *Lotus creticus* (Fig. 2).

In total, 800 individuals were selected, 200 from each species (Fig. 3A), to constitute the training sample. Other species of larger size and lower abundance, such as *Retama monosperma*, *Arundo donax* L. and *Juniperus phoenicia* subsp. *turbinata* (Guss.) Nyman, easily distinguishable from the target species, were not considered in this study.

Following the selection of the 800 individuals, a 0.4 m diameter buffer was generated from the selected points (Fig. 3A), and the information (the values taken by the different spectral bands and vegetation indices) was extracted from each pixel within these buffers. Each buffer contained an average of 61 pixels (Fig. 3B, C). In total, information was extracted from 48,781 pixels for every band and index.

Analysis and the C5.0 model

In order to reduce the influence of outliers, the median of each buffer was established as the optimal value to perform the subsequent analyses, as this is a measure of central position uninfluenced by extremely biased data. Once the information for the four channels and vegetation indices was obtained for each pixel contained in the buffers, an exploratory analysis of the data was carried out. The data distribution was evaluated using the Kolmogorov-Smirnov normality test for each band across all species. Homoscedasticity between species was evaluated for each

Table 1. Vegetation indices derived from the multispectral bands used in this study.

Vegetation Index	Formula	Reference
NDVI	$NDVI = \frac{NIR - R}{NIR + R}$	Rouse et al. (1973)
NDRE	$NDRE = \frac{NIR - RE}{NIR + RE}$	Herrmann et al. (2010)
GNDVI	$GNDVI = \frac{NIR - G}{NIR + G}$	Gitelson et al. (1996)
GCl	$GCl = \frac{NIR}{G} - 1$	Gitelson et al. (2003)
RECl	$RECl = \frac{NIR}{RE} - 1$	Gitelson et al. (2003)

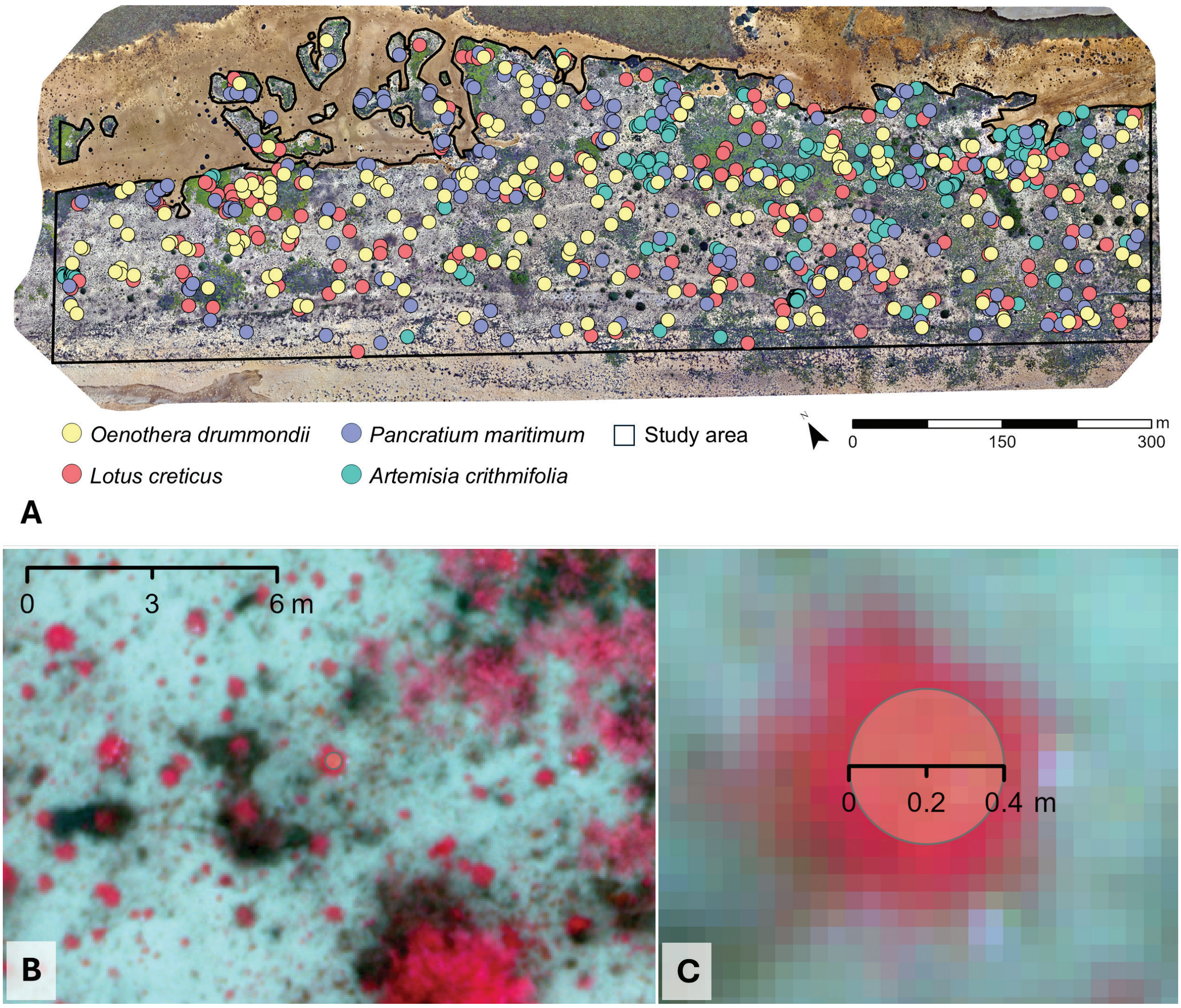

Figure 3. Data collection **A** point selection of the individuals constituting the training sample, with the four selected species **B** A 0.2 m radius buffer generated around an individual of *Oenothera drummondii*. The background image is a false colour composition (NIR-R-G), allowing active biomass to be distinguished as intense reds **C** buffer detail.

band, using Levene's test. Since the assumptions for the application of parametric contrasts were not met, the Kruskal-Wallis non-parametric test was used to analyse significant differences between species for each band or index. Finally, as different distributions were detected among species for the bands and vegetation indices, "*post hoc*" comparisons were performed using the Mann-Whitney U test in pairs, adjusting significance values with the Bonferroni correction. The C5.0 model is a specific decision tree algorithm designed for classification tasks. It operates through the recursive partitioning of the dataset, selecting at each step the variable that provides the highest information gain, thereby minimizing uncertainty (entropy) at each node (Quinlan 1993; Kuhn et al. 2023). This model was carried out with the combination of all bands and vegetation indices and the combination with the lowest error rate was selected. The model was validated using a simple data partition (hold-out), assigning 80% of the data to the training set (train) and 20% to the test set (test). Its performance was evaluated on both sets, confirming that there were no signs of over-fitting. Subsequently, the model was trained using all the available data to generate the final predictions.

The statistical analyses were conducted using the IBM SPSS Statistics software suite (SPSS Inc, Chicago, Illinois, USA), version 29.0.1.0. The Decision Trees and Rule-Based C5.0 model package (Kuhn et al. 2023) was applied in R, version 4.4.0, (Posit Software, PBC, Boston, Massachusetts) to the medians of each buffer for the selected variables and the four species studied. A minimum of 20 cases per node or final group was set as a limit to achieve a more robust and applicable classification tree.

Model verification across the entire study area

Once the decision tree was obtained, it was necessary to verify its effectiveness by applying it to the entire study area. For this purpose, the most representative nodes for each species were selected, and the most descriptive values for the target species, *O. drummondii*, were entered into Arcgis Pro. This approach ensured that all pixels meeting these rules were classified as *O. drummondii*. The goal was to map the decision tree information and translate it into an image format. Prior to this step, the soil was removed (soil being defined as all pixels with an NDVI value below 0.25 and easily excluded due to the sandy substrate of the study area). Once the theoretical distribution map of *O. drummondii* had been extracted from the C5.0 model, we proceeded to check the actual accuracy rate. For this purpose, 400 specimens of what the C5.0 model classified as *O. drummondii* and 400 specimens of what it considered 'other species' were selected at random, and the results obtained from the C5.0 model were checked manually for authenticity ('other species' being defined as all other pixels not considered as *O. drummondii* but with an NDVI value greater than 0.25, which comprised mainly *Pancratium maritimum*, *Artemisia crithmifolia* and *Lotus creticus*, but also included other minority species grouped together and not considered in the study as the aim was to separate *Oenothera drummondii* from other herbaceous species). The sample size required to perform the verification across the entire terrain was 385 points, which was determined using the standard formula for proportion estimation in large populations, with the confidence level set at 95%, the margin of error at 5%, and the scenario of maximum variability represented by an expected proportion of 50%. On the basis of this calculation, we finally selected 400 points for each category. It should also be noted that partially detected *O. drummondii* individuals were not considered as false negatives in this validation.

Results

Fig. 4 shows the data from the four selected species (n = 200) in terms of the four spectral bands and five vegetation indices analysed. The exploratory analysis of the data allowed us to identify significant differences in all but two of the variables among the four species studied (see Suppl. material 1: tables S1, S2). It can be seen that *Artemisia crithmifolia* differs markedly from the other species in all the bands, in the G and infrared bands (RE and NIR). In the case of the RE band, we find almost complete overlap between the values for *Lotus creticus* and *Pancratium maritimum*, but significant differences in G and NIR, these bands thus being more effective in discriminating between these species. It is interesting to note that *Lotus* shows more signal in G and R, and less in NIR and RE, than *O. drummondii*, meaning that a proper combination of bands could form the basis of a promising system to differentiate the different species.

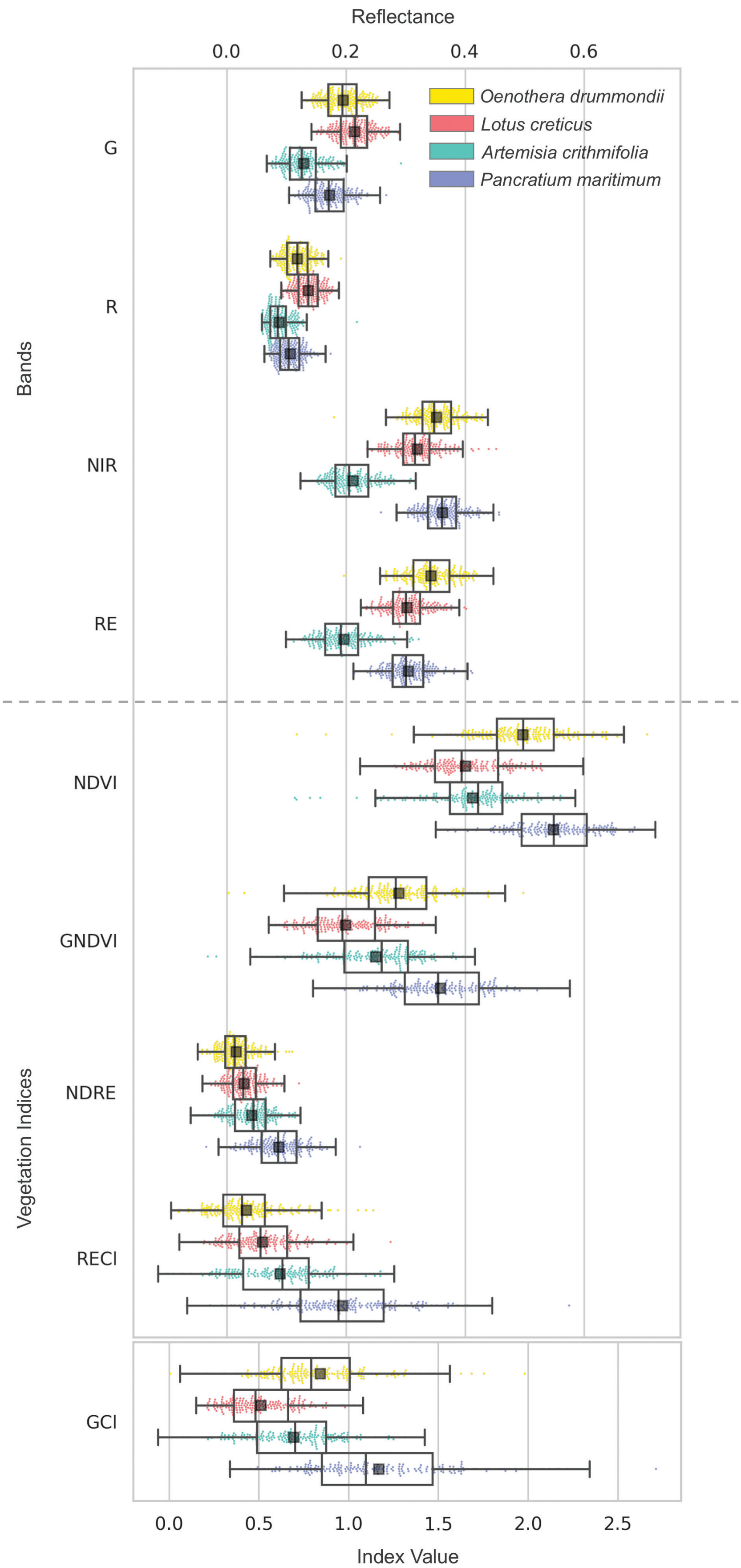

Figure 4. Boxplot of the results obtained. Medians of each buffer and the distribution of data (n = 200 for each species) for all spectral bands and vegetation indices according to each species is shown in the chart. Black square: mean.

For their part, NDVI and GNDVI show a similar pattern (Fig. 4), although less overlap can be observed between *Artemisia crithmifolia* and *Lotus creticus* in GNDVI than in NDVI. With respect to NDRE, there is less dispersion of values, as the results for all species are concentrated within a narrow data range in comparison with the other vegetation indices. Regarding the GCl index, this shows a pattern very similar to that of GNDVI, while the RECl index follows a similar pattern to that of NDRE, although less narrow.

Fig. 5 shows the decision tree obtained from the C5.0 classification model. The variables finally selected for this study were the GNDVI and the NDRE in combination with the NIR band, on the grounds of a lower error rate in the C5.0 model. A total of 84 combinations of three variables were tested (Suppl. material 1: table S3). The corresponding error rates and confusion matrix are shown in Table 2. The evaluation metrics for each species, derived from the confusion matrix of the C5.0 model, were also calculated (Suppl. material 1: table S4). These results indicate that *Artemisia crithmifolia* is the most successfully classified species (186 hits out of 200 samples, 93% certainty). *Lotus creticus* and *Pancratium maritimum* show very similar classification success rates (172 and 171 respectively: 86 and 85.5% certainty), while for *O. drummondii* the classification rate is moderate (148 out of 200: 74% certainty). In terms of errors, most misclassifications of *O. drummondii* wrongly identified it as *Lotus creticus* (14.5%), followed by *Pancratium maritimum* (10.5%), with an overall error rate for the model of 15.4%. Regarding the frequency of use of the variables by the model, NIR was used in all cases, while NDRE was the least frequently used at 78.5%.

After obtaining from the decision tree the variables defining individual occurrences of *O. drummondii*, the model was applied to the complete study area. The pixels meeting these criteria are mapped in Fig. 6. This image shows the selection of certain individuals that the model considers as *O. drummondii*, while the remainder of the plants remain unselected along with the soil (excluded by the rule of NDVI < 0.25).

Verification of the results of the C5.0 model in distinguishing *Oenothera drummondii* from the other herbaceous species across the whole study area (Table 3) indicates that the actual accuracy rate in classifying this species is similar to that obtained by the theoretical model. Of the 400 random points classified by the model as *O. drummondii*, 302 corresponded to this species, while 98 corresponded to the following plant species: 77 to *Lotus creticus*, 11 to *Retama monosperma*, and 8 to *Pancratium maritimum*. Two of the points could not be identified. Meanwhile, of the 400 points classified as "other plant species" (i.e., all other pixels not considered as *O. drummondii*, but with an NDVI value greater than 0.25), 362 were correctly classified, while 38 of them corresponded to *O. drummondii*. The verification of the model across the whole study area thus gives us an error rate of 17% (83% accuracy, Table 3).

Table 2. Confusion matrix from The Decision Trees and Rule-Based C5.0 model. Evaluation on training data (800 cases). The parameters obtained from the decision tree are size (12) and errors (15.4%). The frequency of use of the three variables used by the classifier to generate the decision tree: NIR (100%), GNDVI (81.50%), NDRE (78.5%). Key: Ac (*Artemisia crithmifolia*), Lc (*Lotus creticus*), Od (*Oenothera drummondii*) and Pm (*Pancratium maritimum*).

Ac	Lc	Od	Pm	
186	7	6	1	Ac
4	172	9	15	Lc
2	29	148	21	Od
1	12	16	171	Pm

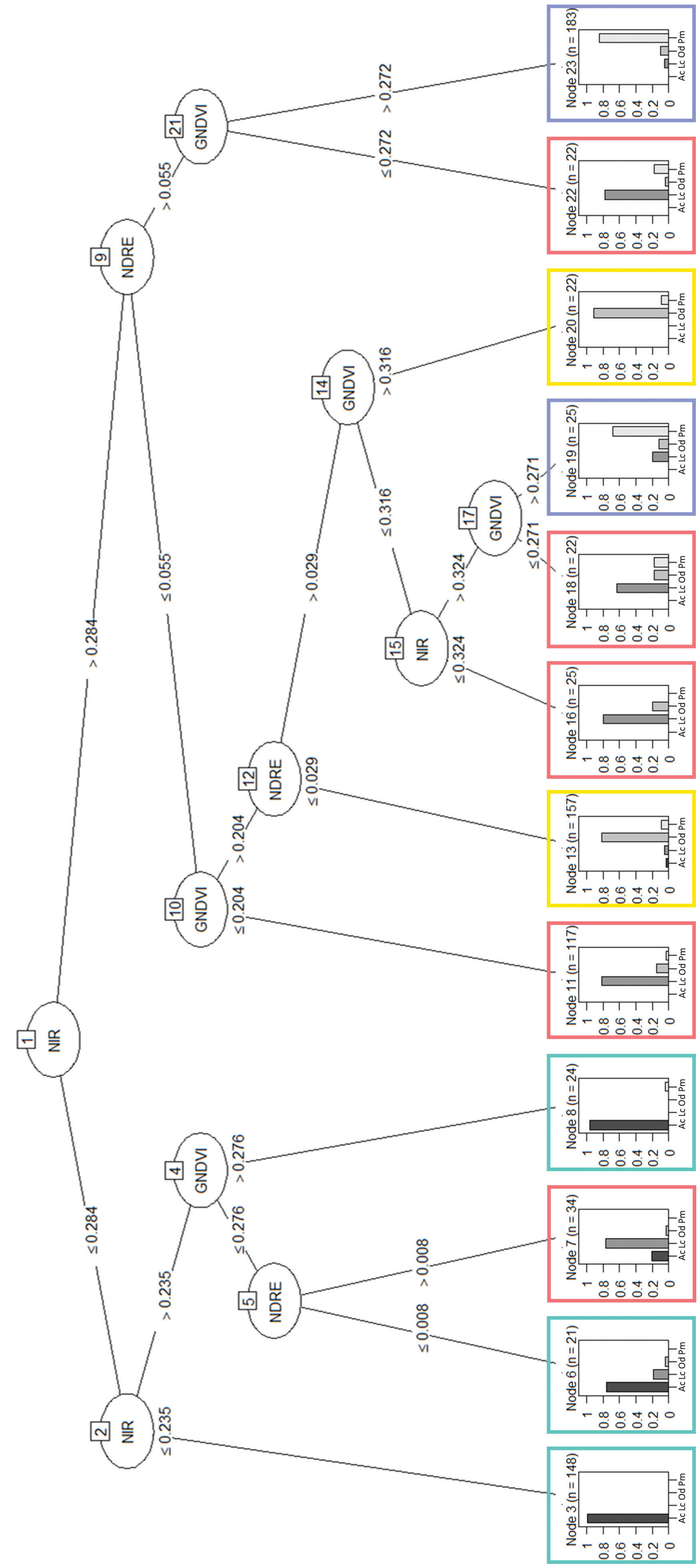

Figure 5. Decision tree obtained by The Decision Trees and Rule-Based C5.0 model. The model was obtained for the four species studied, with respect to the variables NIR, GNIVI and NDRE. The final nodes have been limited to a minimum number of 20 samples per node. Key: Ac (*Artemisia crithmifolia*) in green, Lc (*Lotus creticus*) in red, Od (*Oenothera drummondii*) in yellow and Pm (*Pancratium maritimum*) in blue.

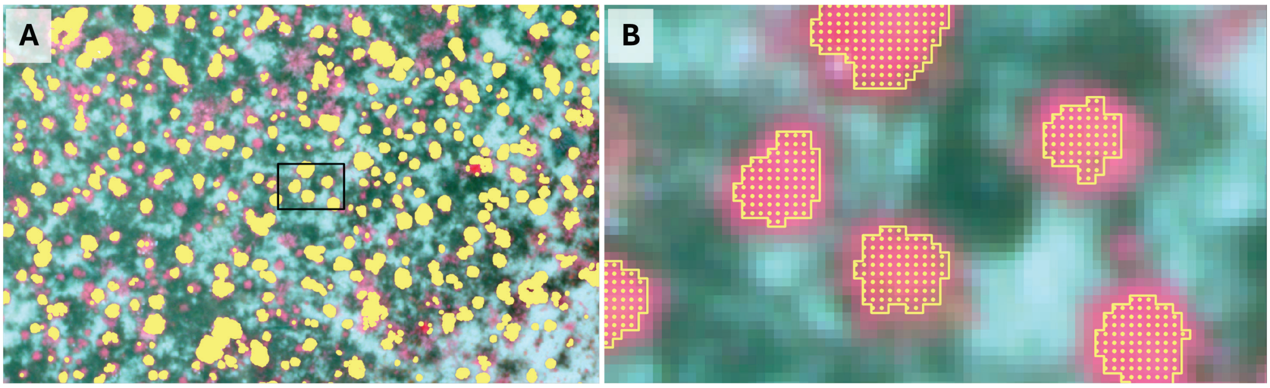

Figure 6. Result of mapping the pixels defined as individuals of *O. drummondii* **A** global view of the selection **B** detail of an area affected by *O. drummondii* and the selection of the pixels corresponding to the species.

Table 3. Confusion matrix obtained from the manual validation of the mapping. This matrix is based on a random sample of 400 points mapped as *O. drummondii*, and 400 points classified as "other plant species" (everything not classified as *O. drummondii*).

	O. drummondii	**Other plants**		
O. drummondii	302	98	*Lotus creticus*	77
			Retama monosperma	11
			Pancratium maritimum	8
			Unidentified	2
Other plants	38	362		

Discussion

The availability of new technologies is revolutionizing the world of scientific research. The incorporation of certain devices, such as UAVs, represents a revolution unimaginable just a few decades ago. These techniques are facilitating environmental analysis and management in many biological conservation challenges (Dash et al. 2019). In this study, we have addressed a critical issue: invasive alien species which are strongly promoted by global change phenomena (Genovesi and Shine 2004). This problem is significantly more intense in sensitive areas, such as the fragile coastal ecosystems chosen for this study (Muñoz-Vallés and Cambrollé 2014; Sühs et al. 2024). Our research has demonstrated that the challenge of identifying an alien invasive herbaceous species using multispectral UAV images can be successfully overcome. It demonstrates a feasible UAV-based methodology for monitoring and evaluating a biological invasion at stage four, which would optimize efforts directed towards the control and/or eradication of the invasive species. In this study a novel classification approach to monitoring biological invasions is proposed that could be easily applied to other regions and species worldwide. However, this application would require prior knowledge of the local flora and vegetation, as well as subsequent analysis to validate the results obtained. Moreover, some technical challenges need to be addressed by managers to apply this methodology in their daily work. Although this is a highly scientific study with complex technical results, its application would be feasible for environmental managers, particularly in protected natural areas like ours, by including the methodology in the management routine. The use of practical technologies such as UAVs even allows for real-time monitoring of particular events such as blooming or ripening, two critical phenological stages in the biological invasion process (Godoy et al. 2009; Yan et al. 2016; Colautti et al. 2017). However, trying to differentiate herbaceous species is a great challenge, as their phenology depends on a wide range of environmental variables.

There are studies where the use of satellite images has been employed for the automatic detection of certain invasive species, typically tree species (Landmann et al. 2020; Holden et al. 2021; Sühs et al. 2024), shrub species (Robinson et al. 2016), and herbaceous species, but always with broad coverage (Thomas et al. 2018). The use of UAVs to automatically locate different species (whether invasive or not) is also a methodology currently gaining traction, as it allows for greater accuracy, particularly when dealing with herbaceous species or small, localized areas (Qian et al. 2020; Da Silva et al. 2023; Pinto et al. 2023). The usual trend in such studies is to combine UAV-captured images with machine learning techniques, specifically convolutional neural networks (Qian et al. 2020; Da Silva et al. 2023). However, to our knowledge, this is the first documented use of image categorization by the C5.0 classification model for this purpose.

The use of data mining to automatically detect individuals of *O. drummondii*, has been demonstrated to be a robust methodology in a species with a large seed bank and high regrowth capacity. These factors mean that the population is made up of a large number of individuals of different sizes (from seedlings of a few centimetres to individuals of several metres in diameter). This circumstance complicates their management and makes their manual removal and control extremely difficult. The ability to automatically identify individuals would allow for better control of the situation by enabling real-time monitoring of the population's evolution. It is in this respect that the C5.0 model, allowing the classification of the given sample using a decision tree, is advantageous. The use of this model has been combined with the use of multispectral technology associated with UAVs. In our scenario, UAV flights have advantages over other types of information obtained, for example, from satellites (Royimani et al. 2019; Landmann et al. 2020; Holden et al. 2021), as herbaceous species in non-homogeneous populations require a higher resolution in order to extract sufficient information from the varying individuals that constitute them. In addition, the use of multispectral technology allows us to use phenological differences between species for a better accuracy rate in differentiating the invasive species from native species in the area (Ojija et al. 2024).

According to previous studies, the reflectance in the visible spectrum (red and green, in this case) is generally due to pigments present in the leaf, while the reflectance in the infrared spectrum (NIR and RE, in this case) depends on its surface and internal structure (Sinclair et al. 1973, Sims and Gamon 2002). In this context, each species shows a distinct spectral fingerprint that enables their identification (Faizan et al. 2024). In the green and red bands, *Lotus creticus* shows the highest reflectance values, followed by *O. drummondii* and *Pancratium maritimum*. In contrast, in the RE and NIR bands, the pattern is very different. In the RE band, *O. drummondii* has the highest reflectance, followed by *Lotus creticus* and *Pancratium maritimum*, with very similar values. These differences are explained by the anatomical variations of these species, even including a monocotyledonous species (*P. maritimum*). This is the case with the various vegetation indices, which show highest values for monocotyledonous plants (*P. maritimum* in this study) that are less ligneous. The species with the next highest values is *O. drummondii*, which blooms almost all year round. However, in the months from December to March it shows a period of intensive vegetative growth with a smaller number of flowers

(Valdes et al. 1987), which is registered by the vegetation indices analysed in this study. It is interesting to note that *Lotus creticus*, a herb, shows the lowest values in these vegetation indices. This is mainly because this species begins to flower in March. The high density of yellow flowers reduces the reflectance in the infrared spectrum and induces lower values in the various vegetation indices. These results indicate that blooming is a critical issue in our proposed methodology. The phenology of the different species should be taken into account before any analysis. Far from being a problem, this discovery could help us to develop a phenological study of the area in question, which we are already carrying out in further investigations. A monthly fly-over would offer a complete study of the different phenologies of the species that would contribute to decision making in eradication activities.

Regarding the results of the C5.0 classification model based on the variables NIR, GNDVI and NDRE, the species with the lowest error rate is *Artemisia crithmifolia*. This may be because this species is the only one with a shrub structure, whose phenology is not so dependent on environmental conditions. Regarding the main objective of this study (the differentiation of *O. drummondii* from the other three native species), the results indicate that most of the misidentifications are with *Lotus creticus* and *Pancratium maritimum*. In contrast to the case above, these three species are herbaceous and although their phenologies are not identical, their vegetative growth periods partially overlap. However, the error rate of the model is only 15.4%, which suggests that this model can distinguish these species with a high degree of reliability.

The application of the model to the complete study area shows that the accuracy rate for *O. drummondii* is 83%, very similar to that obtained from the C5.0 model (84.6%). This application also shows that the highest number of misidentifications occur with *Lotus creticus*, as predicted by the theoretical model. In the case of *R. monosperma*, complementary UAVs-LiDAR data could improve future models. The results indicate that the data mining technique recognises herbaceous differences and distinguishes the invasive *O. drummondii* from other species native to the area with a success rate of 83%. In contrast to other techniques, based on convolutional and recurrent neural networks (Qian et al. 2020; Schiefer et al. 2020; Guo et al. 2022), the C5.0 model used in this study works with the information extracted from individual pixels and the results it returns are used to locate individual pixels again. This enables the location of specimens of different shapes and sizes, as all pixels meeting the rule stipulated by the decision tree model will be mapped.

Conclusion

In conclusion, this study has demonstrated the ability of a modern technique in the form of UAVs to identify herbaceous invasive plant species. Although the methodology requires some prior training and a deep knowledge of the flora in the study area, the strategy could be easily implemented in the routine management of protected sites. The species has shown a distinct pattern in the selected bands and vegetation indices in the study month (March). The C5.0 model was shown to be capable of differentiating the species with high degree of accuracy. The application of the classification tree to the whole study area with the objective of distinguishing the target species was demonstrated to be a robust technique for managing the invasion. Future research is ongoing, and is focused on improving the accuracy with complementary technology such as UAVs-LiDAR.

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Additional information

Conflict of interest

The authors have declared that no competing interests exist.

Ethical statement

No ethical statement was reported.

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Author contributions

Conceptualization: CPC, PJH. Data curation: PJH, CPC, NM, RFV. Formal analysis: MOM. Funding acquisition: PJH. Investigation: CPC, PJH, NM, MOM. Methodology: NM, PJH, MOM, CPC. Project administration: PJH. Resources: CPC, PJH. Software: CPC, MOM, NM. Supervision: PJH, CPC. Validation: CPC, NM. Visualization: NM. Writing - original draft: NM, PJH. Writing - review and editing: CPC, RFV, MOM.

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Data availability

All of the data that support the findings of this study are available in the main text or Supplementary Information.

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Supplementary material 1

Supplementary information

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