Seagrasses on the move: Tracing the multi-decadal species distribution trends in lagoon meadows using Landsat imagery

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ABSTRACT

Seagrass meadows play a vital role for lagoon ecosystems and their biota, sustaining multiple ecosystem services. Their distribution and functioning are closely tied to the environmental pressures induced by global changes. Long-term monitoring of seagrass species and communities is, hence, important to depict their response to past and future scenarios. The availability of long term open-access satellite data offers a new remote sensing perspective for monitoring seagrass communities dynamics in shallow waters, especially when combined with machine learning algorithms. In this study, seasonal multispectral images (from 1999 to 2019) were collected from Landsat 5 Thematic Mapper and 8 Operational Land Imager satellites to map the seagrass meadows, at the community and species levels, within the vast Grado and Marano lagoon (Northeast Italy) using a Random Forest (RF) algorithm. RF models were calculated using an extensive field training dataset collected in 2010 ($n = 426$) and reached an overall accuracy of 0.92 and 0.76 for the classification at the community and species levels, respectively. The change detection analysis revealed an increase of 14.16 km^2 ($+$ 39%) of the whole seagrass community cover over the period, at a rate of 1.59 km^{2}year^{-1}. Despite the coarse spatial resolution (30 m) of the Landsat's images, the classification of seagrasses at species level achieved a good overall accuracy (0.76), evidencing *Nanozostera noltei* as the species with the highest cover increase ($+13.87$ km^2 over the time period). The observed expansion is likely caused by an increase of the sea water influence that is radically modifying Adriatic brackish water bodies, emphasizing the connection between the ongoing environmental changes and the rapid responses of seagrass meadows.

1. Introduction

Seagrasses are monocotyledonous marine angiosperms found in most of the worldwide coastal environments. They can form dense and extensive meadows and are one of the most productive coastal ecosystems providing several ecosystem services (Duarte and Chiscano, 1999; Nordlund et al., 2016). Seagrasses support biodiversity by sustaining trophic networks, provide oxygen in the water column, stabilize sediments, regulate nutrient cycles, and represent an important sink of blue carbon (Boscutti et al., 2019; Duarte et al., 2005; Hemminga and Duarte, 2000; Larkum et al., 2006). Despite their great natural value, seagrass meadows are among the most threatened ecosystems on Earth,

undergoing a rapid global decline (Waycott et al., 2009). The causes of this decline have been mainly linked to anthropogenic drivers including eutrophication (Burkholder et al., 2007), alterations of coastal habitats (Micheli et al., 2008), climate crisis (Duarte et al., 2018) as well as the expansion of invasive species (Short et al., 2007).

In contrast to the global decline, several European sites experienced a local expansion of seagrass communities (Barillé et al., 2010; Calleja et al., 2017; de los Santos et al., 2019; Reise and Kohlus, 2008; Zoffoli et al., 2021). These contrasting trends vary among seagrass species, time periods, and are often linked to site-specific characteristics (Dunic et al., 2021; Green et al., 2021). This is particularly true for coastal lagoons (Garrido et al., 2013), where strong environmental gradients promote a

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highly heterogeneous environment (Basset et al., 2013), causing the formation of complex ecological niches (Pérez-Ruzafa et al., 2011). As a result, lagoon meadows are often composed of multi-specific communities (Boscutti et al., 2015), whereas most of the seagrass meadows within the sea domain are monospecific (Short et al., 2007). The interspecific interactions occurring in multi-species meadows (e.g. species competition, see Boardman and Ruesink, 2022) can interplay with abiotic stressors, creating significant niche shifts (Christia et al., 2018).

Tracing single species distribution and extension over time might, hence, greatly improve our understanding of coastal ecosystem processes and functioning in response to environmental changes (Garrido et al., 2013; Menu et al., 2021; Pérez-Ruzafa et al., 2011). This task requires novel effective approaches to monitor seagrass meadow dynamics (Veettil et al., 2020). Satellite remote sensing has been proven to be a relevant tool for long-term monitoring of ecosystem dynamics (Murray et al., 2018). Compared to traditional field-based methods, remote sensing is highly effective due to characteristics such as low cost, high accuracy, temporal repeatability, and large spatial coverage (Pham et al., 2019b). The use of multispectral satellite platforms (e.g. Landsat series) provides free access to a vast historical archive, providing unprecedented retrospective time series collections. More recently, machine learning algorithms have increasingly replaced simple classification algorithms in the remote sensing analyses (Effrosynidis et al., 2018; Pham et al., 2019a, 2019b). They rely on non-parametric approaches, increasing the effectiveness in handling noisy data, and the ability to extract multiple features (Maxwell et al., 2018). These characteristics led to a remarkable improve in classification accuracy, when considering mixed habitats (Pafumi et al., 2023; Pham et al., 2019a; Veettil et al., 2020) and/or using satellite images with coarse spatial resolution (Ha et al., 2020). However, the application of machine learning in coastal waters is still in its infancy (Ha et al., 2020). Successful mapping of seagrass species distribution and dynamics were already performed by using high spatial resolution data, at the expense of a limited time span. For example, Traganos and Reinartz (2018b) and Ariasari et al. (2019) achieved classification overall accuracies of 94% and 83% respectively, using Planet's RapidEye and PlanetScope satellites. Furthermore, Roelfsema et al. (2014) mapped seagrass species combining high spatial resolution sensors (Maxar's WorldView-2, X IKONOS, and X Quickbird-2) and object-based classification approach, highlighting significant seasonal variations of seagrass species distribution. Indeed, other studies based on an intra-annual time scale have suggested that ignoring seasonality could lead to doubtful classifications (Fauzan et al., 2021; Menu et al., 2021). This is particularly relevant for species occupying brackish waters, which are characterized by a high annual species turnover (Zoffoli et al., 2020), resulting in changes in growth period duration, biomass peaks and seed germination (Buia and Marzocchi, 1995; Buia and Mazzella, 1991; Sfriso and Ghetti, 1998). All these population aspects are expected to significantly affect the pixel spectral reflectance (Fyfe, 2003). Therefore, integrating seasonal images into the mapping processes might provide important information to distinguish seagrass species. The diachronic mapping of seagrass species distribution still remains poorly addressed (Calleja et al., 2017; Lønborg et al., 2022; Veettil et al., 2020). New insights are needed to overcome the spatial and spectral limitations offered by historical platforms, such as the Landsat missions (Chen et al., 2016). In this study, we focused our attention on the importance to account for phenological differences between species in the application of machine learning algorithms trained on a large ground-truth dataset. This would allow for more effective extraction of reflectance features, enabling the acquisition of temporal information on the distribution of lagoon seagrass species.

The present work combines a multi-decade (from 1999 to 2019) series of seasonal multispectral satellite images collected from Landsat 5 Thematic Mapper (TM) and 8 Operational Land Imager (OLI) satellites (of the National Aeronautics and Space Administration and the U.S. Geological Survey program) and Random Forest (RF) algorithm to (i) obtain a classification' model of presence and absence of seagrass

meadows in the vast Grado and Marano lagoon (North East Italy), (ii) obtain a classification model of each seagrass species sampled in the study area and (iii) project the seagrass meadows and species cover shifts from 1999 to 2019. To achieve these goals, we first tested whether RF model calculated using all seasonal images allow obtaining higher classification accuracy, both at the community and at the species levels, than RF models calculated with one single seasonal image. Then, the RF models with the highest overall accuracy were used to classify all the images and to calculate the cover of the seagrass community and of each species over the years. This analysis allowed tracing the expansion or regression trends of seagrass meadows, providing detailed insights into of past and ongoing changes.

2. Materials and methods

2.1. Study area and species

The study area covers the Grado and Marano lagoon (45°40′40″ N 13°03′50″ E to 45°46′30″ N 13°27′20″ E), Northern Adriatic Sea (Fig. 1). It is the second major transitional water body of the Italian coastlines with a surface of approximately 160 km^2. It is separated from the sea by six sandbars with a different stage of evolution to islands, interspersed with inlets, covering a coastal length of approximately 35 km. The average distance between sandbars and inner coastline is approximately 5 km. It is characterized by semidiurnal tides with an average range of 65 cm (Gatto and Marocco, 1993). The average salinity of the lagoon is 28.5 psu (eastern basin) and 22.2 psu (western basin). It is included in the European coordinated ecological network of protected areas Natura 2000 (IT3320037) as both a Special Area of Conservation (SAC) and Special Protection Area (SPA) encompassing a complex mosaic of protected habitats.

Three seagrass species are widespread across the lagoon (Falace et al., 2009): *Zostera marina* L., which is a temperate-boreal species; *Nanozostera noltei* (Hornem.) Toml. & Posl (= *Zostera noltii* Hornem.), occurring in European and North African waters; and *Cymodocea nodosa* (Ucria) Ascherson which shows a small range, covering Mediterranean and North African waters (Larkum et al., 2006). *C. nodosa* lives on sandy and muddy substrates, both in open waters and in brackish lagoons (Cancemi et al., 2002). It is recognized as a species with high ecological plasticity, being adapted to wide ranges of salinity, concentration of nutrients and sediments (Garrido et al., 2013). *Z. marina* is a sublittoral species that occurs on soft mud and on firm and coarse sand where the extension of meadows changes continually as a function of the influence of currents, wave action, sediment transport and seed dispersal (Frederiksen et al., 2004). *N. noltei* is widely distributed in shallow, sheltered and muddy subtidal habitats. It can acclimate to different environmental conditions including fluctuations in physical and chemical parameters (Loques et al., 1990). The distribution of the above species within the study area is determined by the presence of strong ecological gradients, such as salinity, water depth, pH and soil characteristics (Boscutti et al., 2015).

2.2. Training data and validation distribution data

The workflow adopted for data acquisition, preparation and to set RF models are summarized in Fig. 2. The field data were collected during the summer season in 2010 (see Boscutti et al., 2015 for details about the field sampling procedure). The presence or absence and the cover percentage of the three seagrass species were recorded for each sampling point, by means of inspection and sampling of the seabed. To reduce the effects introduced by non-vegetated and mixed pixels, the points not falling within the region of interest (ROI) (i.e. main channels and tidal islands of the lagoon), and the points considered mixed (i.e. those in which the co-occurrence of multiple species was recorded), were removed. The removed mixed points represented 16.7% of the original data. Considering the different combinations of the three species' co-
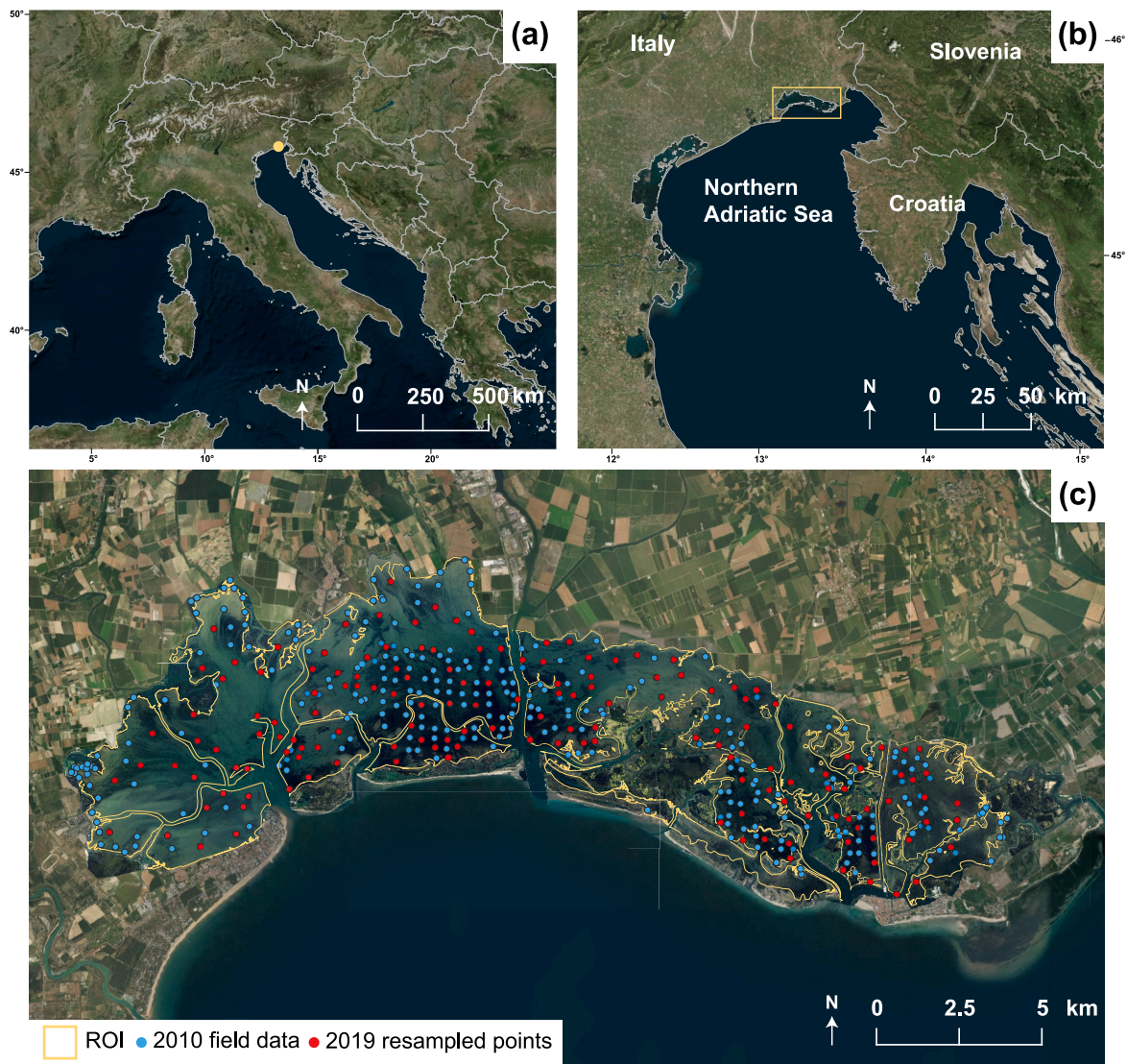
Fig. 1. (a) Location of the study area in Italy, (b) lagoon of Grado and Marano (Northern Adriatic Sea). (c) Distribution of field datapoints collected in 2010 (blue dots) and resampled in 2019 (red dots). The region of interest (ROI) for the habitat mapping (i.e., the mask which delineates only lagoon tidal flats) is contoured with gray line. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

occurrence, not enough points representing each mixed class were available for an accurate classification (Roelfsema et al., 2014). Furthermore, the removal of mixed points can lead to a more precise characterization of the species' spectral signatures by reducing the so-called "salt and pepper" effect caused by internal variability within a classification class, which appears as noise in the classification results (Zhang, 2015). The final dataset used in the RF models (see section 2.4) had 426 points (Fig. 1).

Using high spatial resolution digital orthophotos available for 2003 (0.15 m spatial resolution) and 2007 (0.5 m spatial resolution), two new validation point datasets were obtained.

These datasets were used to further validate the classification performance of the models over the considered time period. For both years, a total of 155 points were randomly distributed within the lagoon. Through photointerpretation analysis, an ID corresponding to the presence/absence of seagrass meadows was assigned to each point. In addition, another validation dataset of 155 field training points was available for the year 2019 representing a subsample of the data collected in 2010 (unpublished data), were species occurrence was also recorded (Fig. 1).

2.3. Satellite data and image preprocessing

We used multispectral images from Landsat 5 TM and Landsat 8 OLI. The Landsat mission provides the longest freely available time series, already successfully used in the study of seagrass ecosystem (Chen et al., 2016; Lebrasse et al., 2022). The images were downloaded from the Google Earth Engine platform (Gorelick et al., 2017) as a surface reflectance product. All available images were downloaded for an annual interval from 1999 to 2019. To minimize the effect of the water column in the classification, only the images acquired in days with tide height < 1 m were kept. The tide data were obtained from the historical archive of the tide station of Grado (www.isprambiente.it). After that, each image was masked by removing the pixels classified as clouds or cloud shadow in the Quality Assessment band and those non included in the ROI (i.e. main channels, salt marshes, islands and fishing valleys). The use of the ROI mask reduced the occurrence of possible background noise and elements of confusion for the subsequent classification phases (Zoffoli et al., 2020). Starting from all the available images, 3 seasonal images per year were selected. The temporal definition of the seasons was made by integrating information obtained from previous studies on the phenology of the study species in the coastal lagoons system of the
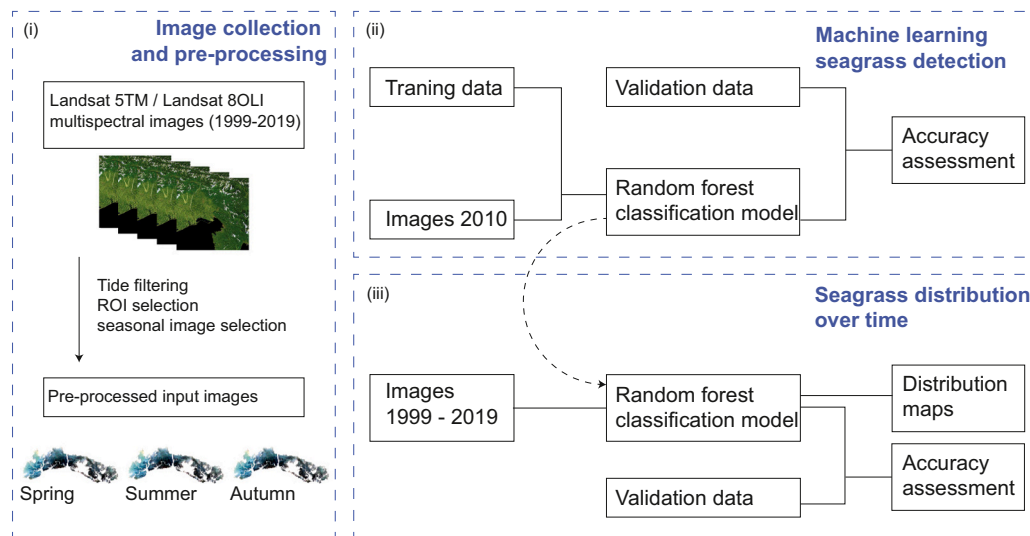
Fig. 2. Workflow of the methodology adopted in this work. Here are represented (i) the image pre-processing phase to obtain the input variables for the RF classification models; (ii) the construction of the model based on the 2010 field survey and multispectral data and (iii) the multi-decade classification phase, its validation, and the change detection step.

northern Adriatic (Buia and Marzocchi, 1995; Guidetti et al., 2001; Sfriso and Ghetti, 1998). The identified seasonal intervals were: (i) March 15th – June 15th (spring season); (ii) June 16th – September 1st (summer season); (iii) September 1st – December 31st (autumn season). Due to the limited temporal resolution of Landsat (i.e., 16 days) together with the presence of images with high cloud cover, no images were available for 2002, 2008, 2015. A total of 51 images covering 17 years were obtained. A radiometric normalization was carried out on each image using the IR-MAD (Canty, 2014) algorithm through the plugin ArrNorm for QGIS software (QGIS Development Team, 2023). The Landsat 5TM image collected on July 3, 2010 was used as a reference due to its quality and proximity of field sampling period. Differences in the Landsat sensors used were mitigated by the use of surface reflectance products whose correction algorithms are consistently optimized to make the end products of the different sensors comparable (Koehler et al., 2022; Vogelmann et al., 2016). It is also considered that factors such as intra- and inter-annual differences in phenology are likely to have a greater impact on spectral signals than differences related to sensor characteristics over time (Vogelmann et al., 2016).

2.4. Statistical analysis

2.4.1. Random forest classification

Random Forest is a machine learning method combining decision trees and bootstrapping. Developed by Breiman (2001), RF has been found to be insensitive to overtraining, small or noisy datasets. Every decision tree in the implemented RF algorithm is trained with a bootstrapped sample of the training data and, at every split node, a subset of randomly selected features is utilized. Then for each pixel, the final classification is obtained by a majority vote. RF has proven to be an effective tool for mapping coastal and seagrass habitats (Fauzan et al., 2021; Traganos and Reinartz, 2018b; Wicaksono et al., 2019). Two sets of RF models were performed using the multispectral images retrieved in 2010. In the first set, the response variable was the presence/absence of the total seagrass meadows (hereafter identified as seagrass meadows), where areas with <20% seagrass cover were considered absence (Valle et al., 2015; Zoffoli et al., 2020). In the second set, the response variable was the training dataset divided in 4 classes according to the species present, namely (1) *Z. marina*, (2) *N. noltei*, (3) *C. nodosa*, (4) absence (hereafter indicated as species meadows). The species presence was considered if its cover was >20% (Buia et al., 2004). For each dataset, 4

different RF models were generated starting from (i) the images for each season (n images = 1, n bands = 6, n predictors = 6) and (ii) from all the seasonal images (n images = 3, n bands = 6, n predictors = 18). This allowed us to understand which combination of input variables generated the best classification performance. The predictors used as input variables for all the performed models were each 30 m spatial resolution band of each image used (Table S1). The available 2010 field data ($n = 426$) were split into 70% for the training dataset ($n = 303$) and 30% for the validation dataset ($n = 123$). The training dataset was further split into 80% training and 20% testing for RF performance evaluation. The optimization of the hyper-parameters was done by choosing 1000 trees to run the model for presence/absence classification, and 500 trees to run all RF for species discrimination as they featured the best results out of a plethora of runs with different number of trees (Probst et al., 2019). For the best split selection measurement, the Gini Index was used (Breiman, 2001). The number of variables used for each node (*mtry*) were automatically selected by using repeated cross validations performed with 10 folds and 10 repetitions for the seagrass meadow models, while 5 folds and 5 repetitions were used for species meadow models. The available validation dataset was used to create a confusion matrix for image classifications. Based on the confusion matrix, metrics as overall (O.A.), producer (P.A.) and user (U.A.) accuracy for each classified class were calculated (Congalton, 1991). O.A. represents the proportion of correctly classified validation samples (found along the diagonal in the error matrix) to the total number of validation samples, irrespective of class. P.A. quantifies the proportion of accurately classified validation samples within a specific class against the total number of validation samples belonging to that class. U.A. calculates the ratio of correctly identified validation samples within a particular class to the total number of validation samples claiming to be in that class. Finally, the two best RF models (i.e. highest O.A.) for presence/absence mapping and for single species mapping were selected and applied for the time-series analysis from 1999 to 2019. RF models were performed using the *caret* (Kuhn et al., 2023) package of the R software (v. 4.3.1, R Core Team, 2023). The multi-year classification was also validated with the independent datasets expressed as seagrass presence/absence (years 2003 and 2007) and both seagrass and species presence/absence (year 2019).

2.4.2. Change detection and trend analysis

The total area of the seagrass meadows and of each species was

calculated for each year using the images classified as explained above. The presence of positive or negative monotonic trends of seagrass distribution over the twenty-year period was investigated using the modified Mann–Kendall nonparametric trend test for temporally auto-correlated data, using the Hamed and Ramachandra Rao (1998) variance correction approach (Kendall, 1948; Mann, 1945) with the *trend* R package (Pohlert, 2023). The Mann-Kendall test is typically used to detect trends in time series. The null hypothesis determines whether a time series does not have a monotonic trend, while the alternative hypothesis confirms a significant monotonic trend (*p*-value <0.05). This analysis has two main outputs, the z-score and Mann-Kendall tau (τ). The Mann-Kendall tau (τ) option estimates the correlation coefficient and ranges from -1 to $+1$, where 1 means a continuously increasing trend, -1 continuously decreasing trend, and 0 no trend. The z-score with a mean of 0 and a variance of 1 follows the standard normal distribution. Its positive values show uptrends in a time series and the negative values show downtrends. For significant tests, the Sen's slope (Sen, 1968) was calculated. This test is used to calculate the magnitude of trends in the long-term temporal data. Moreover, we used the single species maps obtained through the best RF to obtain the spectral reflectance values of each spectral bands for each species. Due to the violation of linear assumptions, the differences between species of each spectral bands were tested using the non-parametric Kruskal-Wallis test (Gibbons, 1974) through *stats* R package (R Core Team, 2023). Pairwise differences were then calculated using the Dunn's post hoc test, *dunn.test* package (Dinno, 2017; Dunn, 1961; R Core Team, 2023).

3. Results

3.1. The role of seasonality for an accurate image classification

The RF models using all the seasonal images exhibited the best performance (O.A. of 0.92 for seagrass meadows and 0.76 for species meadows) when compared to RF models separately performed with images of a single season (i.e., model spring, summer, autumn) (Table 1). Among the single season RF models, the best performance was obtained by using the spring images, with an O.A. similar to the overall images model both for seagrass and species meadow classification (Table 1). The RF models calculated with the autumn image achieved the lowest classification accuracy for seagrass meadows (O.A. = 0.84) and intermediate performances for species meadow classification (O.A. = 0.69). The RF models performed with the summer image showed intermediate performances for seagrass meadow mapping (O.A. = 0.88) and the lowest performance for species meadow classification (O.A. = 0.61).

According to the mean decrease Gini index, for both seasonal image models the blue band of the summer image was the most important for the split between trees in the RF model and therefore explains most of the variance in seagrass cover, followed by the green bands of the summer and spring images (Fig. S1).

3.2. Seagrass and species meadows RF classification and validation

The best seagrass meadow model was trained with all seasonal images of 2010 (O.A. = 0.92) and showed a U.A. of 0.91 for both the presence and absence pixels. The model predicted seagrass presence (P. A. = 0.94) with greater accuracy than absence (P.A. = 0.88). The O.A. calculated on the independent validation dataset resulted high, with values of 0.90 for 2003, 0.91 for 2007, and 0.86 for 2019. Both U.A. and P.A. of the presence and absence classes remained high (> 0.75) over the different years of validated classification (see Table 2 and Table S3).

The best model for species meadows classification trained with all seasonal images of 2010 obtained an O.A. of 0.76. The class that presented the greatest reliability (i.e., the relative frequency of true occurrence in the field of each class) was *Z. marina* (U.A. 1.00). However, *Z. marina* was the species predicted with lowest accuracy by the model (P.A. = 0.45). The absence class was the class predicted with highest accuracy (P.A. = 0.94) and presented the highest reliability in the classification output (U.A. = 0.88) (Table 2). The class *N. noltei* was predicted with a low accuracy (P.A. = 0.50) (Table 2) related to a confusion with the class *C. nodosa* (Table S3). However, *N. noltei* exhibited an acceptable U.A. (0.70). *C. nodosa* showed the lowest U.A. (0.59) but it was second class better predicted by the model (P.A. =

Table 2

Classification performances calculated on the confusion matrices (expressed as overall, user, producer accuracy) of seagrass meadows and species meadows mapping. 2010 (*) is the reference year for model, 2003 and 2007 are validated with photointerpretation data while 2019 with field data.

Seagrass meadows					
Year		2003	2007	2010*	2019
Overall accuracy		0.90	0.91	0.92	0.86
User accuracy	Absence	0.83	0.88	0.91	0.88
	Presence	0.98	0.93	0.91	0.84
Producer accuracy	Absence	0.98	0.90	0.88	0.76
	Presence	0.82	0.92	0.94	0.92

Species meadows					
Year		2003	2007	2010*	2019
Overall accuracy		–	–	0.76	0.60
User accuracy	*Z. marina*	–	–	1.00	0.83
	N. noltei	–	–	0.70	0.56
	C. nodosa	–	–	0.59	0.52
	Absence	–	–	0.88	0.78
Producer accuracy	*Z. marina*	–	–	0.45	0.26
	N. noltei	–	–	0.50	0.38
	C. nodosa	–	–	0.78	0.57
	Absence	–	–	0.94	0.78

Table 1

Performance comparison (expressed as overall accuracy, O.A.) of the different RF models generated for the classification of presence/absence of seagrasses (seagrass meadows) and species classification (4 classes, species meadows) for 2010. The images date column reports the acquisition date of the image from Landsat 5TM on the study area. Input variables indicates the number of multispectral bands (6 each image) used by the model to generate the classification. Mtry represents the number of variables to randomly sample as candidates at each split.

Output map	Model ID	Image date	Input variables	Number of classes	Mtry	O.A.
seagrass meadows						
	RF seasonal images	all dates	18	2	2	**0.92**
	RF spring	01/06/2010	6	2	2	0.90
	RF summer	03/07/2010	6	2	2	0.88
	RF autumn	21/09/2010	6	2	2	0.84
species meadows						
	RF seasonal images	all dates	18	4	10	**0.76**
	RF spring	01/06/2010	6	4	2	0.70
	RF summer	03/07/2010	6	4	2	0.61
	RF autumn	21/09/2010	6	4	4	0.69

0.78) followed by the absence class (P.A. = 0.88), the *N. noltei* class (P.A. = 0.79) and *C. nodosa* (P.A. = 0.59). The O.A. obtained using the independent validation dataset for 2019 was 0.60 (Table 2, Table S3).

The pixels classified in the three species by the species meadows model (year 2010) were significantly spectrally separated (Kruskall-Wallis test *p*-value <0.001, df = 2) (Fig. 3, Table S4) considering the reflectance values of the Landsat 5TM bands in 2010. In the green band, however, no significant difference was found between the pixels classified as *N. noltei* and *C. nodosa* (Dunn test *p*-value >0.05), while *Z. marina* was spectrally separated from the two other species (p-value <0.05).

3.3. Projecting seagrass and species meadow distribution changes over time

The spatiotemporal distribution of seagrass and species meadows in the study area over the period from 1999 to 2019 is presented in Fig. 4. In 2010 (i.e., the reference year for the best model), seagrass meadows occupied 35% of the total tidal flat surface, extending 39.22 km^2. Among the three seagrass species, *C. nodosa* covered 72% of the total surface area, being homogeneously distributed throughout the lagoon. Nineteen percent of the total seagrass meadows were occupied by *N. noltei,* mainly distributed in the shallow waters along the inner coastline, behind the sandbars. *Z. marina* represented 9% of the total seagrass cover, mainly occurring in continuous formations near the main lagoon inlets. The year with the lowest recorded cover was 2004, with a total seagrass meadow cover of 21.34 km^2 equal to 19.02% of the lagoon tidal flats. The maximum seagrass meadows cover was estimated in 2014 (56.69 km^2 corresponding to 50.61% of the lagoon tidal flats). The interannual classification showed significant movements of the meadows, resulting in an inward expansion. In the western part of the lagoon, the meadows that expanded in 1999–2007 have started to recede in the last decades (Fig. 4). This resulted in a complete regression of the meadows in the western basin of the lagoon over the 20 years analyzed (Fig. S2).

The seagrass meadow distribution showed a statistically significant increase from 1999 to 2019, with a growth rate of 1.59 km^2 year^{-1}. The single-species distribution estimated in the same period depicted wide fluctuations. Specifically, a statistically significant positive trend was found for *N. noltei*, which showed an increase rate of 0.97 km^2 year^{-1} (p-value = 0.009), whereas the trend calculated for *C. nodosa* and *Z. marina* was not significant (p-value >0.05) (Fig. 5, Table S2).

4. Discussion

This study demonstrated the high efficiency of using Landsat satellite imagery together with RF machine learning algorithm for the detection in change over time of seagrass distribution in lagoon systems. We showed that using multiple seasonal images per year improves classification accuracy, especially when classifying species distribution occurring in dynamics transitional water bodies. Seagrass trend detection allowed to identify a pulse expansion of the overall seagrass meadow in the study area, mainly due to the fluctuations and expansion of *N. noltei*.

4.1. Including seasonality in the classification process

Including seasonal images as input variables for machine learning classification models was found as the most effective approach to maximize the classification accuracy in many environments, such as forests (Praticò et al., 2021; Zhu and Liu, 2014), grasslands (Esch et al., 2014) and Mediterranean rural areas (Senf et al., 2015). Previous studies analyzing the intra-annual variations in seagrass meadows distribution suggested that these communities display large fluctuations in biomass and species cover over seasons (Fauzan et al., 2021; Menu et al., 2021; Roelfsema et al., 2013; Zoffoli et al., 2020). Therefore, the inclusion of the seasonality might greatly improve the accuracy of seagrass in classification models. This translates into a probable reduction of the classification noise due to other environmental factors (e.g., algae blooms, water turbidity) (Acquavita et al., 2015; Christia et al., 2018; Lønborg
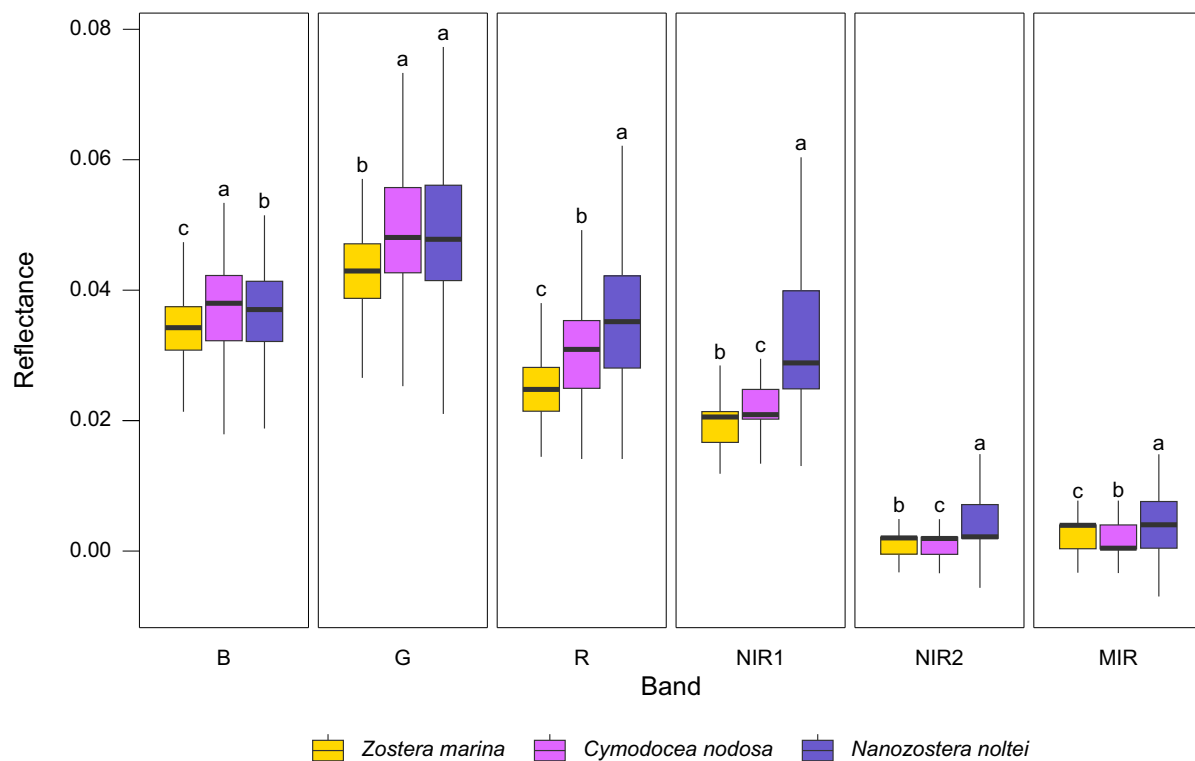

Fig. 3. Box plot of the reflectance values of the three species identified in the 2010 classification on the Blue (B), green (G), red (R), near-infrared 1 (NIR1), near-infrared 2 (NIR2) and mid-infrared (MIR) of Landsat 5TM sensor. Compact letters indicate significant differences between species in each band, separately analyzed (Dunn test *p* value <0.05). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)
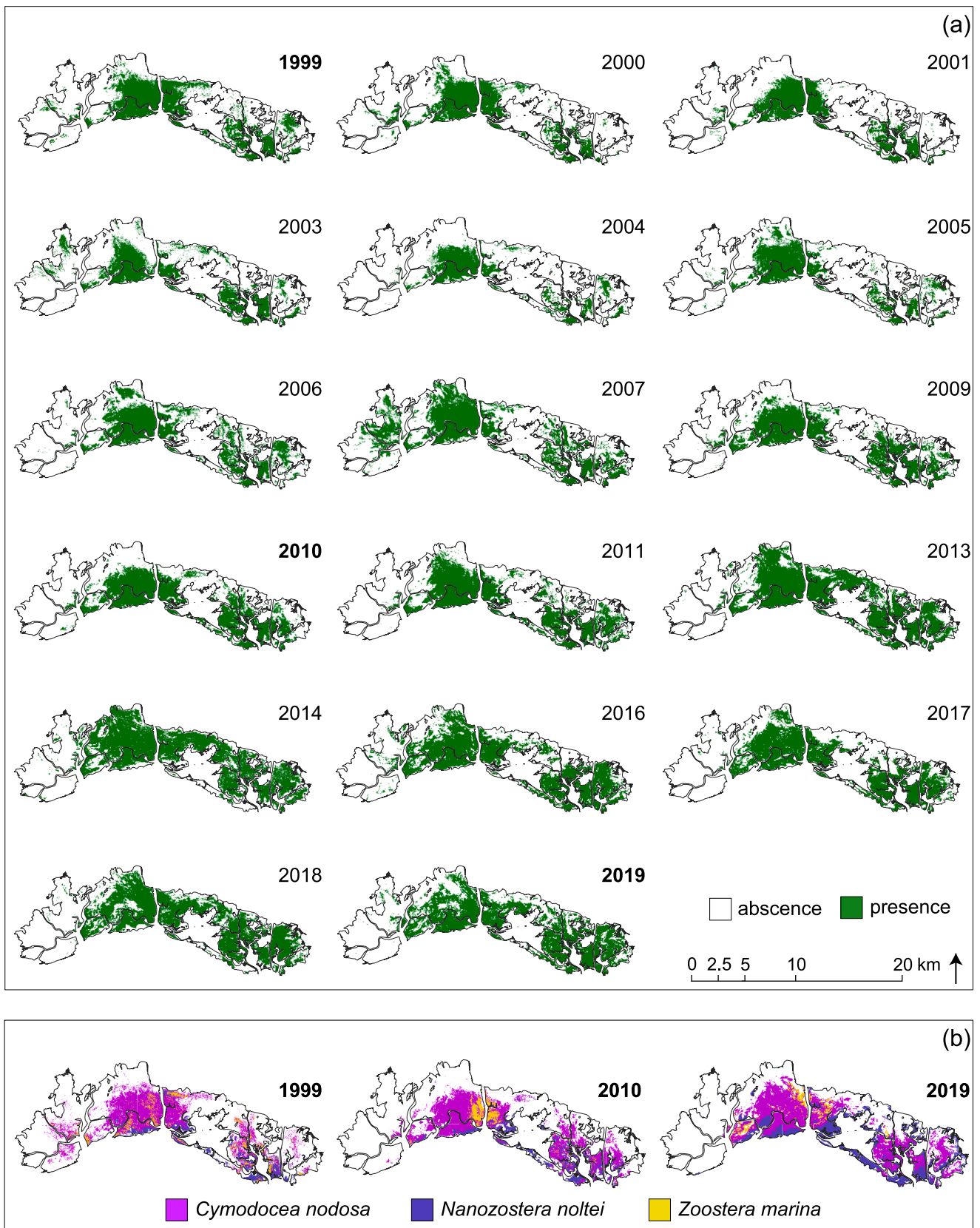
Fig. 4. Time series of seagrass meadow mapping from 1999 to 2019 (a). Species meadow classification maps for the first year under analysis (i.e. 1999), the reference year of the model (i.e. 2010) and the last validated year (i.e. 2019, O.A. 60%), respectively (b), are also shown.
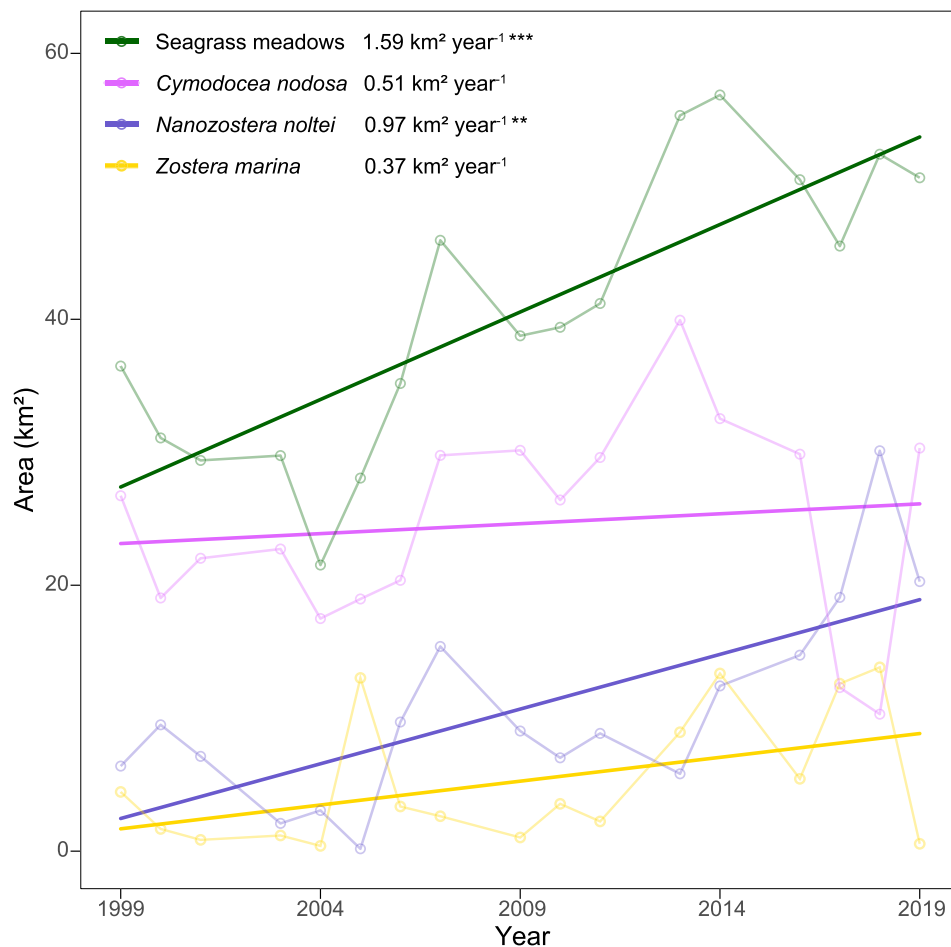
Fig. 5. Trends of seagrass and species meadow cover (km^2) between 1999 and 2019. The plot displays data points representing the estimated area for the years under analysis obtained from the RF classifier. The plot includes a line showing the significative estimated Sen's slope whose value reported in the legend. The stars denote the significance level of the test for each specie (*p-value $\leq$0.05; ** p-value $\leq$0.01; ***p-value $\leq$0.001).

et al., 2022), often ephemeral over time (Karez et al., 2004). In our study, the inclusion of seasonal images greatly improved seagrass species classification (6% increase in performance, Table 1). Probably, this is because it allows accounting for phenology, partially overcoming the limits of Landsat spectral resolution (Sun et al., 2023). Indeed, several studies reported that the study species have distinct phenology in the Mediterranean area (Kraemer and Mazzella, 1999; Marbà et al., 1996), with species-specific periods of seed germination (Buia and Mazzella, 1991), and vegetative turnover, introducing variation in the spectral signature of individual species over the seasons (Fyfe, 2003). Our results showed that, among the single image RF models, the best performances were achieved with the spring image (Table 1). The phenological patterns of the three species considered have been well characterized in the northern Adriatic coastal systems, highlighting that the most important differentiation between species occurs in the initial phase of the growth period (i.e., from March to June) (Sfriso and Ghetti, 1998), consistently to our results. Despite that, the species meadows classification has shown a reduction in performance over years (Table 2). This may be linked to a possible inherent model bias related to the seasonality approach. On an intra-annual timescale, the variations in the specific spectral signature could be also affected by several aquatic environment factors such as depth, turbidity, and the presence of leaf epiphytes (Bannari et al., 2022; Fyfe, 2003; Veettil et al., 2020). These factors are part of the strong environmental dynamics characterizing lagoon ecosystems, which can exhibit significant year-to-year changes (Christia et al., 2018). For future improving the seagrass species detection this would require (i) the use of fixed image dates (or narrower seasonal

intervals) between years by making the years as uniform as possible or (ii) by developing of a methodological approach that allows the annual characterization of seasonal intervals.

4.2. Random Forest as a tool for seagrasses monitoring: Potential and caveats

Our results confirmed that machine learning is a promising approach to detect the seagrass changes over time, adding important information in the understanding of ecological and marine science issues (Bessinger et al., 2022; Widya et al., 2023). The accuracies obtained for the presence/absence classification model are comparable to previous studies (Ha et al., 2023; Traganos and Reinartz, 2018b), exceeding the performance obtained in other works concerning the mapping of these habitats (Luo, 2018; Wabnitz et al., 2008). In addition, in this study it has been possible to assess the accuracy on change detection analysis, overcoming a major limitation reported for studies using a multi-year time span (Ball et al., 2014; Hossain et al., 2015). Most of the previous studies classified seagrass communities at the community level, and only few attempted of classification at the species level, primarily due to the lack of ground-level data on single species (Ha et al., 2021; Sebastian et al., 2023). In addition, previous studies that have classified individual species were successful due to the use of platforms with high spatial resolution, but available over a short time-period (see for instance Traganos and Reinartz, 2018a, 2018b; Ariasari et al., 2019). Even if poorly addressed, mapping individual species is fundamental since the diversity of seagrasses controls productivity, trophic transfers and

habitat suitability for the whole coastal biodiversity (Dekker et al., 2005; Larkum et al., 2006). To our knowledge, we here present a first attempt for the distinction of individual species using Landsat seasonal images and machine learning approach in a lagoon environment.

As hypothesized, significant differences between species were observed for most of the spectral bands (Fig. 5), and this probably explain the ability of RF in species classification, partially overcoming objective limitations due to the use of medium spatial resolution data. In the green band, no significant differences between *N. noltei* and *C. nodosa* species were observed. This outcome is further highlighted in the confusion matrix metrics of *N. noltei* class (Table 2, Table S3) which were mainly affected by confusion with *C. nodosa* class. In general, *C. nodosa* proved to be the most challenging class for classification. This is likely attributed to its broader ecological and phenotypic plasticity (Mascaró et al., 2009), as suggested in another study conducted in the same study area (Boscutti et al., 2015). Boscutti et al. (2015) reported that the populations of *C. nodosa* growing in brackish exhibit a wide phenotypic plasticity in relation to environmental variations, increasing its morphological and phenological resemblance to other species (e.g., *N. noltei*, Kraemer and Mazzella, 1999; Marbà et al., 1996). The same species has also posed classification challenges in other machine learning-based classification studies (Ivajnšič et al., 2022), suggesting that further investigation is needed to model its space-time dynamics (Traganos and Reinartz, 2018a, 2018b). The confusion induced by *C. nodosa* likely occurred primarily in the reflectance values of the green band, which is particularly important in coastal lagoons as it provides greater light penetration in waters with higher concentrations of suspended and dissolved materials (Kirk, 1994). To solve such limitations, a combination of multi-type and multi-source data has already been suggested as a promising tool (Veettil et al., 2020). Further efforts could also be directed towards promising upscaling approaches to extend the capabilities of analyses conducted at small spatial scales (e.g., unoccupied aerial vehicles, underwater photography, and videography) to larger spatial scales (Veettil et al., 2020; Vuerich et al., 2024; Zoffoli et al., 2021).

4.3. Long-term change

In the study area, the seagrass meadow cover increased 1.59 km^2 per year in the two decades considered. This expansion is contrasting with the observed global decline of marine seagrasses (Dunic et al., 2021; Orth et al., 2006; Waycott et al., 2009; Xu et al., 2021). However, this trend is consistent with other European marine seagrass meadows, that showed similar rates of change in the past decades (de los Santos et al., 2019; Sousa et al., 2019; Zoffoli et al., 2021). In these sites, the increase of seagrass extension has been related to the improvement in water quality, reduction in anthropogenic impacts along the coasts, and habitat conservation efforts (de los Santos et al., 2019). This might suggest that also in the Grado and Marano lagoon the national and regional conservation strategies significantly improved the habitat suitability for seagrass species. On the other hand, it is plausible that an increase of sea influence in the lagoon, due to a reduction of freshwater incoming and the ongoing sea level rise, has led to a shift in the physicochemical characteristics of the water, making the environmental conditions more favorable for marine seagrasses (Boscutti et al., 2015; Fontolan et al., 2012). The increase of sea influence in coastal lagoons has been proven to produce radical modification of the ecosystem's characteristics and functioning (Antonioli et al., 2017; Rova et al., 2023).

Despite the overall increase trend, some areas of the lagoon showed local regression and extinction dynamics (Fig. S 2) revealing the complexity of the system response to environmental changes. This was observed in the western part of the lagoon (i.e. Marano basin) where the seagrass patches occurring in 1999 were lost. Here, the sediment budgets and the lack of channel dredging altered the influence of the sea in this part of the lagoon, favoring a fresh/sea water stratification (Bosa

et al., 2021; Fontolan et al., 2012; Petti et al., 2018), changing the suitability of seabed for seagrasses. On the other hand, the local increase in the extent of the *N. noltei* species (+ 13.87 km^2 between 1999 and 2019) could be linked to the increasing water salinity and more generally to the increase of sea water influence, as previously indicated in other studies (Boscutti et al., 2015; Sousa et al., 2017). Although *Z. marina* and *C. nodosa* did not show significant trends over the decades, their distributions showed important fluctuations with remarkable minimum and maximum extensions. Substantial temporal fluctuations of seagrass species have been already observed both in terms of extension/density and time span (few days, seasonal, or annual) (Calleja et al., 2017; Lønborg et al., 2022; Philippart and Dijkema, 1995; Reise and Kohlus, 2008; Valle et al., 2013; Zoffoli et al., 2021). Looking at the general picture, many of the areas modified over the years have been abandoned and recolonized creating remarkable fluctuation in distribution and cover similarly to what observed in other terrestrial ecosystems (e.g., the carousel model, van der Maarel and Sykes, 1993). This temporal variation might be, hence, the result of a series of successions of communities that have shifted their habitats in response to cyclic/contingent micro and macro environmental changes occurred over time (Boardman and Ruesink, 2022). A striking example of this process could be observed in the sudden regression period recorded for seagrass cover after the summer of 2003 in the whole study area. This seems to coincide with trend reported in other studies that investigated a massive die-off event in various seagrass meadows in Europe due to the extreme summer heatwave in 2003 (Ehlers et al., 2008; Reusch et al., 2005; Zipperle et al., 2009). This suggests a possible analogous impact within the Marano and Grado Lagoon with a rapid recovery in the following years, which requires further investigation.

Besides the long-term perspective, the classification at the species level has provided valuable insights into the spatial structure of seagrass meadows, including the identification of large persistent patches (i.e., core areas). These meadows likely coincide with areas characterized by greater bathymetric uniformity and stability (Dolch et al., 2013), where wave motion and turbidity are attenuated (Ferrarin et al., 2010; Inglis, 1999). These areas may serve as propagule sources during periods of regression, potentially improving the resilience of the communities (Dolch et al., 2013). In conclusion, although the absolute increase in seagrass area may appear as a promising trend, it conceals signals of rapid changes within the lagoon. The expansion of seagrasses in a semiclosed environment may indicate a future dramatic habitat modification (Silva et al., 2020), as the lowering and simplification of lagoon bottoms caused by marine transgression will lead to the rapid narrowing of suitable areas for these species.

5. Conclusion

The results of this study highlighted the potential of conducting a multi-decadal analysis of seagrass meadows in the shallow waters of lagoon environments using multispectral satellite images from the Landsat series. The implementation of the RF machine learning algorithm within a framework that encompasses an extensive ground truth dataset, as well as the inclusion of seasonal imagery, has proven successful in mapping the entire habitat and extending the analysis over the long term. This study also demonstrated the potential of using multispectral imagery at limited spatial resolutions to discriminate individual seagrass species, despite the inherent challenges posed by the substantial environmental fluctuations experienced in lagoon ecosystems and the difficulty in characterizing the spectral signature of seagrasses. The primary limitations were evident in distinguishing *C. nodosa* and future improvements in discriminative capabilities of supervised classification algorithms may result from the inclusion of multisource data, such as environmental data that characterize the ecology of these species or other remote sensing sources.

Finally, the preliminary change detection conducted using the classified maps obtained in this study has shed light on several ecosystem

dynamics, both at the species-specific and community levels. This will require more targeted future studies to understand the driving forces shaping the habitats, using historical time series of physicochemical data recorded in the lagoon. Focusing future efforts on understanding the most effective methodologies for mapping seagrass meadows with satellite imagery holds the potential to characterize their extensive community dynamics and disentangle the interconnections they have with the responses of lagoon ecosystems to current global changes.

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Author contributions

PC, FB, FP, LO, MV conceived the ideas and designed methodology; FB, VC, PC collected data; PC, LO analyzed the data; PC, FP, FB led the writing of the manuscript. All authors contributed critically to the drafts and gave final approval for publication.

CRediT authorship contribution statement

Paolo Cingano: Writing – review & editing, Writing – original draft, Visualization, Methodology, Formal analysis, Data curation, Conceptualization. **Marco Vuerich:** Visualization, Methodology, Data curation, Conceptualization. **Lorenzo Orzan:** Methodology, Formal analysis, Data curation. **Giacomo Trotta:** Writing – review & editing, Methodology, Data curation. **Valentino Casolo:** Writing – review & editing, Data curation. **Edoardo Asquini:** Writing – review & editing, Visualization. **Giovanni Bacaro:** Writing – review & editing, Supervision. **Francesco Boscutti:** Writing – review & editing, Supervision, Project administration, Methodology, Conceptualization.

Declaration of competing interest

The authors have no conflict of interest to declare.

Data availability

In the event this manuscript is accepted, relevant data will be made available in the public Mendeley Data repository.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ecoinf.2024.102685.

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