Rice farming and macrophyte dynamics monitoring through Sentinel-2 MSI as a proxy of disturbance of agricultural practices over an enclosed bay

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Key words: Integrated land and water management, Remote sensing; Agriculture impact

SUMMARY

Coastal regions are highly dynamic and productive ecosystems with high ecological and economical value. Given the co-existence and interaction of different human activities, both in land and on sea, it is a priority an Integrated Coastal Management (ICM) ensuring their sustainability. In this sense, in the biosphere reserve of the Ebro Delta (NW Mediterranean, Spain), natural ecosystems co-exist with human economic activities. Rice farming is the main activity on the area and is likely to have environmental impacts on coastal areas such as bays, where paddies irrigation channels discharge. Therefore, understanding the interaction between rice farming and the coastal ecosystem is essential for developing an ICM. With this aim, we monitored rice paddies, by using remote sensing data, and macrophytes (seagrass meadows and macroalgae mats) in the Delta-Bay system (Alfacs Bay), as disturbance indicator. Using Sentinel-2 MSI imagery, rice growing dynamics and crop phenology were characterized through the Normalized Vegetation Index (NDVI) and Normalized Water Index (NDWI) over a two-year period. Agricultural management practices such as fertilization were obtained from farmers. For aquatic vegetation, after atmospheric correction for ocean colour remote sensing, spectral band combination of Sentinel-2 MSI together with field observations were used in a supervised classification method to assess the spatial coverage of seagrass and macroalgae communities. The combination of NDVI and NDWI proved to be suitable to identify hydroperiod and crop phenology of rice paddies. The supervised classification of the bay's vegetation showed spatiotemporal dynamics related with previous results in scientific literature. Aquatic vegetation presented a different temporal pattern in the northern than in the southern margin of the Alfacs Bay, which can be related to rice crop growing cycle. In the northern margin, where rice irrigation channels flow out (i.e. freshwater, nutrients, etc.), overgrowing macroalgae episodes occurred. However, in the southern margin, without the direct impact of the irrigation network, overgrowing-macroalgae was not reported. These results highlight the need for a global management strategy to ensure the sustainability of both human economic activities and natural systems and prove the suitability of Sentinel-2 as a support tool for future policy decision making.

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1. INTRODUCTION

Coastal regions are highly dynamic and productive ecosystems with high ecological and economical value. They are subjected to considerable anthropogenic pressures such as urban and industrial development, pollution, tourism, aquaculture and agriculture (Ramírez-Pérez *et al*., 2017). Hence, to ensure their conservation, sustainable development and the protection of their resources, it is necessary to implement Integrated Coastal Management (ICM) programs (European Commission, 2002). Agriculture is a good example of a system not only with economic interests but also with ecological benefits and social elements, although these components are not generally considered together (Fulton 1993). For instance, the impacts of agriculture on aquatic ecosystems include both direct and indirect effects. Direct effects include habitat loss due to channelization and wetlands conversion, and indirect effects involve water quality (*e.g.* salinity and temperature) and habitat impacts of sediment, nutrients and other pollutants in agricultural runoff, as well as hydrologic alteration (i.e. volume and timing). Thus leading changes in aquatic habitats, nutrient cycle, oxygen availability, and faunal composition (Blann *et al*., 2009). Understanding these relations and determining the underlying mechanisms is essential information for integrated management planning (Fabbri, 1998). However, because the range of potential interactions and effects with and on the environment, it is necessary to use a proxy for measuring the overall impact. In this sense, within the macrophyte community, seagrass composition, distribution and abundance are often used as a measure of ecosystem health and functioning, although they are often not considered in management decisions (Nordlund *et al*., 2016). Seagrasses are marine flowering plants forming extensive meadows in shallow coastal waters by providing many important ecosystem services such as coastal protection, nursery habitats, carbon sequestration, and sediment trapping and stabilization (Green and Short, 2003; Hemminga and Duarte, 2000). The location of most seagrass ecosystems (i.e. coastal shallow habitats) expose them to both terrestrial and marine based threats and could serve as a sentinel community for agriculture impacts (Knudby and Nordlund, 2011).

The Ebro Delta (Figure 1) is one of the largest (320 km^2) deltas in the north-western Mediterranean Basin. Agriculture is one of the most important economic activities, with ca. 65 % of the delta plain devoted to rice production. Consequently, the hydrology and ecology of shallow coastal habitats (*e.g.* delta bays) are highly influenced by freshwater inputs from the irrigation network (Figure 1), and potentially impacting not only the macrophyte community but also the economic activities carried out in the bays, such as shellfish aquaculture and fisheries. The monitoring of rice crop and macrophyte community (*i.e.* seagrass and macroalgae), may provide useful information on the interaction between systems and support both environmentally and economically responsible decision making by policy-makers. Because of the spatiotemporal variability and coverage of both ecosystems, remote sensing supposes an improvement of conventional monitoring programs by reducing cost, increasing the frequency of data acquisition and covering the whole system (Petus *et al*., 2014; Dekker *et al*., 2006). Multispectral satellites including the visible (VIS) and NIR regions of the spectrum allow monitoring of land and aquatic vegetation (Hossain *et al*., 2015; Van Niel and McVicar, 2004). From this perspective, Sentinel-2 Multispectral imager (S2/MSI) is a suitable tool for monitoring the spatiotemporal dynamics of the whole system. This, thanks to a revisiting period of 5 days (under ideal conditions), 13 spectral bands located within the VIS-NIR and short-wave infrared (SWIR) regions of the spectrum (~ 440 - 2200 nm), and a spatial resolution of 10, 20 or 60 m^2 (depending on the spectral band). The spectral indexes most commonly used for assessing rice crop are the Normalized Difference Vegetation Index (NDVI), based on photosynthetic activity (Huete *et al*., 2002) and the Normalized Difference Water Index (NDWI), which combined with NDVI is used to detect harvest period and hydroperiod (Tornos *et al*., 2015). Remote mapping of macrophytes includes the use of vegetation indexes based on green, red and/or NIR spectral bands, in addition to traditional classification procedures based on fieldwork sampling (Knudby and Nordlund, 2011; Pu *et al*., 2012; Gullström *et al*., 2006). Thus, the main objectives of this study were to analyse rice crop, seagrass and macroalgae spatiotemporal dynamics by using S2/MSI imagery, to assess potential relationship between them, and to discuss the usefulness of S2/MSI imagery for coastal monitoring.

2. MATERIALS AND METHODS

2.1 Study area

The climate is Mediterranean with warm dry summers and cool wet winters. Annual mean temperature ranges between 5 and 33 ˚C, and annual precipitation from 500 to 600 mm, being maximum in autumn and minimum in summer. The delta plain contains several valuable ecosystems such as coastal lagoons, sand spits, brackish waters and freshwater springs that provide suitable habitats for a diverse fauna and flora. It is protected as Natural Park (Spain government), Natura 2000 (EU) and Biosphere Reserve (UNESCO), and supports the development of local economy (*e.g.* tourism, agriculture, aquaculture and fisheries). The study area is centered in Alfacs Bay (Figure 1), which receives the freshwater inputs from the southern delta irrigation network. The major economic drivers are agriculture, shellfish farming and fisheries.

Rice is grown from late April to September and left fallow during the rest of the year (Figure 2). In the growing season, water management consists of permanent flooding from sowing time (late April-early May) to two weeks before harvest (September). During the vegetative and early reproductive stages, short periods of drainage can take place as a requirement for the application of herbicides. After harvest, fields are re-inundated for the incorporation of rice straw into the soil. Thereafter fields are either flooded (from October to December) or left to progressively drain, according to the farmers' preferences. From January to March rice fields are left dry for soil labour operations (harrowing and fertilizer application) and re-flooded in Mid-April, at the beginning of the next cultivation period. Standard mineral fertilization is applied with average N doses ranging from 170 to 200 kg N ha^{-1}. Consequently, Alfacs Bay receives the water drained from *ca*. 115 km^2 of cultivated rice fields from April to late December (Martínez-Eixarch *et al*., 2018; Tornos *et al*., 2015).

Alfacs Bay, with an area of 56 km^2, is connected to the sea by a channel of 2.5 km wide and has an average depth of 3.1 m (maximum depth is 7 m). Alfacs Bay ecology and hydrology are mediated by freshwater, nutrient and organic matter inputs from the irrigation network. Irrigation inputs imposes a double layer flow, like typical estuarine circulation pattern. The renewal time is about 15 days when channels are open (Cerralbo *et al*., 2019), and it is characterized by a large annual variation in salinity (ranging between 26 and 37 PSU) and water temperature (8 – 32 ˚C). Macrophyte communities, mainly dominated by *Cymodocea nodosa* (seagrass) and *Caulerpa prolifera* (macroalgae), are distributed in shallow areas (0 – 2 m) along the inner shoreline (Mascaró *et al*., 2014; Pérez and Camp, 1986). Bottom in the northern shore is silty and it is highly influenced by nutrient and organic matter inputs from rice crop discharges. The southern shore is sandy, and it is influenced by marine waters from the open sea (Sanmartí *et al*., 2018) and consequently the zone is oligotrophic, similar to Mediterranean waters.

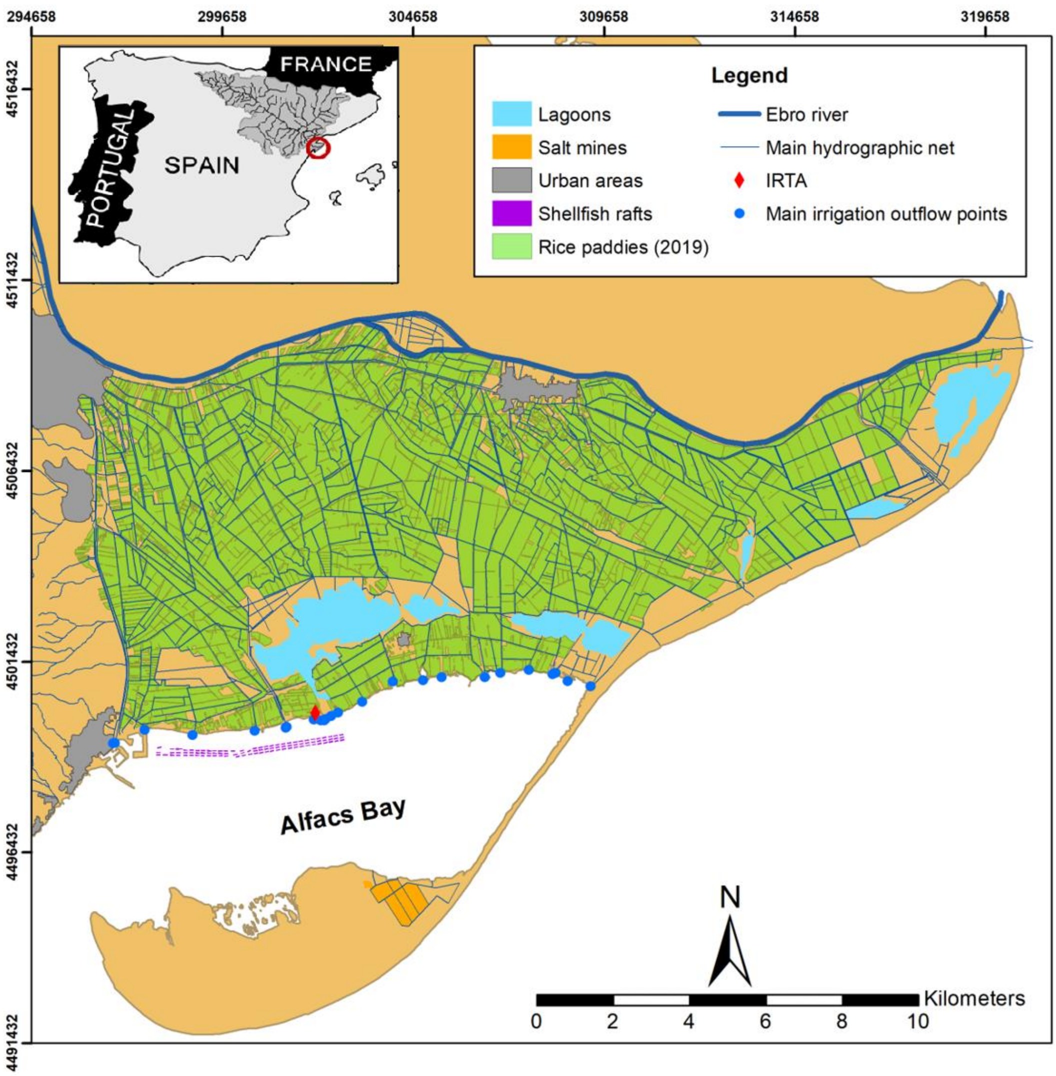

Figure 1. Southern Ebro delta plain and Alfacs bay (NW Mediterranean, Spain)

2.2 Sentinel-2 Data

Different data sets were used for analysing rice crop variation and macrophyte communities (Figure 3). A set of 621 Sentinel-2 (A and B) L2A images (i.e. cloud cover < 30 %) were used as input in Google Earth Engine for monitoring rice paddies. Google Earth Engine (GEE) is a cloud-based platform, which can be used to execute large-scale and long-term geospatial analysis (Gorelick *et al*., 2017). GEE allows direct access to different levels of S2/MSI images, the possibility of filtering satellite imagery (e.g. region of interest, date, cloud cover), and cloud computing band maths generating spectral indexes maps. The level 2A (L2A) official products available on the Copernicus Open Access Hub provide atmospherically corrected images applying Sen2cor processor (Müller-Wilm, 2016). In addition, a set of 56 Sentinel-2 (A and B) L1C images (i.e. not cloud covered) were downloaded from Copernicus Open Access Hub (https://scihub.copernicus.eu/) and atmospherically corrected with POLYMER v4.12 The polynomial based algorithm applied to MERIS (POLYMER), applicable to S2/MSI, is an atmospheric correction algorithm specifically designed for processing of oceanic waters with and without the presence of sun-glint (Steinmetz *et al*., 2011) outputting water surface reflectance images, resampled to 20 m^2. Note that for rice paddies monitoring, images from different orbits were used, while for macrophytes classification only orbit 51 images were selected (differences in number of images; Figure 3).

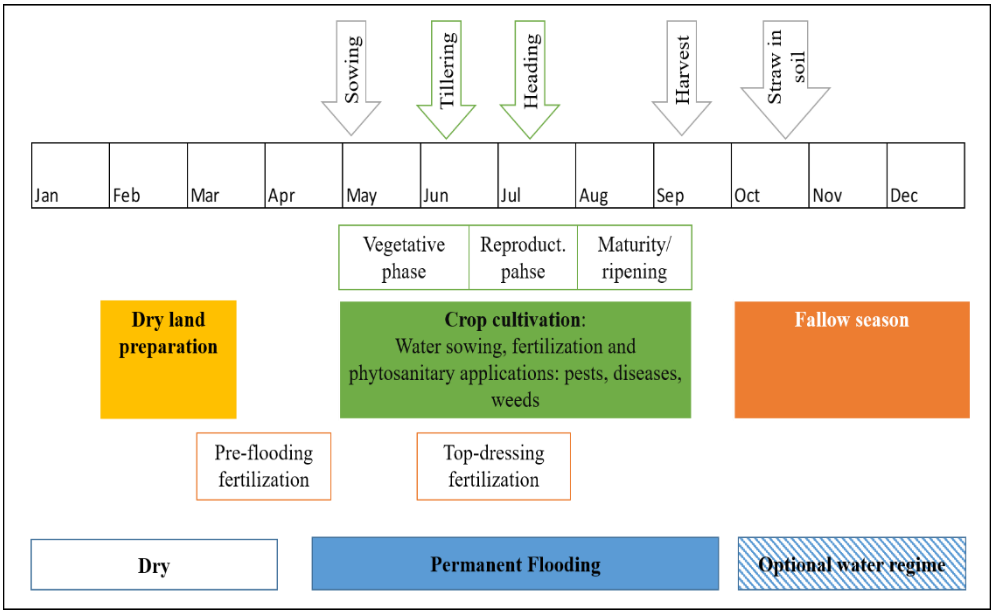

Figure 2. Summary of the rice farming calendar in the Ebro Delta.

2.3 Reference Data

Two sources of ground truth data were used in this study. Rice farming practices and water management including rice sowing, fertilization, and harvesting, were obtained from farmers. Macrophyte field data were gathered from two field campaigns (23.05.19 and 27.12.19) carried out within a time-window of 3- and 0-days respect to the satellite pass This data consisted in a set of 52 points (locations within Alfacs Bay), located with Global Navigation Satellite System (GNSS) receiver, where seabed typology was characterized within polygons accounting for five different categories (turbid, seagrass at high and low densities, algae and 'deep' water). It is important to note that there was not differentiation between epiphyted and ephiphyte-free macrophyte meadows.

2.4 Rice paddies monitoring

Four spectral indexes were computed, the Normalized Difference Vegetation Index (NDVI; eq.1) and three different Normalized Difference Water Indexes (NDWI1, NDWI2 and NDWI3; eq.2-4) were computed. Monthly averaged spectral indexes were calculated with GEE (Figure 3). Resulting products were 96 images (2 years × 12 months × 4 spectral indexes) at 20 m^2 spatial resolution.
NDVI is a good indicator of vegetation growth and has been widely used to assess phenological information (Wang *et al*., 2012) such as the heading date, and it is also related with culture hydroperiod (Tornos *et al*., 2015). NDWI is sensitive to leaf water content and soil moisture, describing surfaces of water and vegetation with water content or land of scarce humidity areas. Thus, NDWI may help to define harvest date and to assess changes in flooding stages (Tornos *et al*., 2015). NDWI maximizes the vegetation reflectance and minimizes the reflectance of water. The common form of NDWI (here, NDWI3) uses NIR bands as longest, but in this study SWIR bands were used too to exaggerate the response of the spectral index in flood-based agriculture. Modified NDWI using SWIR bands (here, NDWI1 and NDWI2) are known as Land Surface Water Index (Xiao *et al*., 2005). The summarized workflow is presented in figure 4.

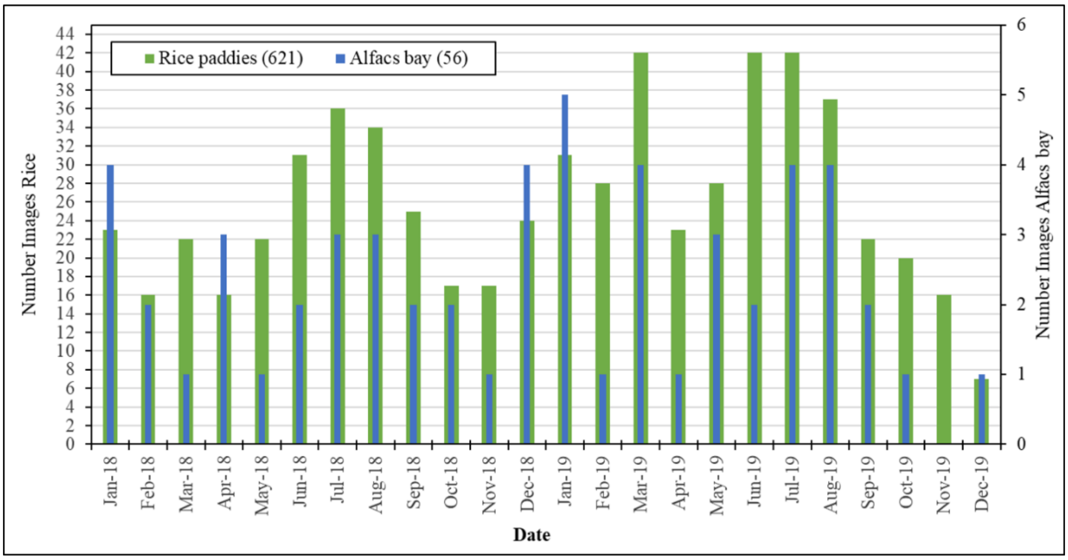

Figure 3. Temporal distribution of S2/MSI images used in this study for rice paddies (green) and macrophytes (blue) timeseries development.

2.5 Macrophytes monitoring

After atmospheric correction conducted with POLYMER, images of water reflectance at 20 m^2 spatial resolution were processed in R 3.6 and QGIS 3.4. The processing followed five main steps. (i) the building of a merged composite of bands B3 (560 nm), B4 (665 nm) and B7 (783 nm); (ii) the computation of green NDVI (GNDVI; eq. 5); (iii) the supervised classification using ground truth data for Support Vector Machine technique (SVM); (iv) timeseries of seabed type; and (v) monthly averaged seabed-class coverage per bay shore (northern and southern).
The GNDVI is related with leaf area index (Yang and Yang, 2009) and due to the use of the NIR band (eq. 5) it is very sensible to bottom reflectance. Thus, GNDVI has been used to differentiate shallow waters with higher probability to harbour macrophytes than deep waters.

$$NDVI = \frac{(R842 - R665)}{(R842 + R665)} \quad \text{eq.1}$$

$$NDWI1 = \frac{(R842 - R1600)}{(R842 + R1600)} \quad \text{eq.2}$$

$$NDWI2 = \frac{(R842 - R2200)}{(R842 + R2200)} \quad \text{eq.3}$$

$$NDWI3 = \frac{(R560 - R842)}{(R560 + R842)} \quad \text{eq.4}$$

$$GNDVI = \frac{(R842 - R560)}{(R842 + R560)} \quad \text{eq.5}$$

Bands B3, B4 and B7 include wavelengths from the green to the NIR edges, which are sensible to seagrass coverage and biomass. These were merged in a single composite as main input for seabed-type classification. Support Vector Machine (SVM) were used as classification method of the seabed-cover. SVM is implemented with Orfeo Tool Box (Grizonnet *et al.*, 2017) in QGIS. SVM is based on a supervised machine learning algorithm that uses a linear model for data classification. The algorithm creates a hyperplane which separates data into classes. The data used as input for the SVM consisted in the polygons for which seabed-type was defined (truth data) and the related pre-processed and merged-composites of S2/MSI images (23/05/19 and 27/12/19). The ratio of training and validation polygons was set to 50 %, and kernel type model was selected because of the non-linearity of the data. Finally, we obtained an image of classified seabed accounting for the 5 classes defined (*i.e.* Seagrass high and low density, algae, water and turbid environments) per date. The summarized workflow is presented in Figure 4.

2.6 Coupling of rice paddies development and seabed-cover

In order to simplify the analysis of the results, monthly data of rice paddies stages and macrophyte coverage were used. For rice paddies, the similarity of the curves described by each index at each pixel was checked with a *k*-means based clustering. Finally, spectral indexes were averaged per pixel within each category and month. Regarding seagrass dynamics, the area of the 5 different classes (in percentage) was computed for each date and then monthly averaged. Three months (March 2018, November 2018 and April 2018) were not included in the analyses because the high water turbidity and the uncertainty associated (Figure 7). Finally, spatiotemporal trends of spectral indexes of rice paddies and seabed-type and -coverage were coupled. The summarized workflow of both land and water monitoring is presented in figure 4.

3. RESULTS

3.1 Water management and crop phenology

All the considered spectral indexes (*i.e.* NDVI and NDWs) did not show significant differences among the five categories identified in the cluster analysis (Figure 5). Land surface water indexes (NDWI1 and NDWI2) were more variable, especially in autumn and winter (October-January), but differences were not so large. Both NDWI1 and NDWI2 showed a similar pattern, but NDWI3 presented a different pattern completely opposite to NDVI. Thus, according to NDVI and NDWI1 temporal patterns, different key farming stages were identified regarding hydroperiod (farming practices) and crop phenology (rice growth). Consequently, flooding, drying, heading and harvest dates could be properly identified (Figure 6) by following the scheme in Table 1. Despite similar trends in NDVI and NDWI1 along the years 2018 and 2019, some differences were observed between years. For instance, in 2018 changes in both NDVI and NDWI1 occurred faster (sharper shapes) than in 2019, thus, in 2018, the first flooding and harvesting were finished in one month compared to the two months observed in 2019. In addition, when comparing both annual cycles, a delay of one month in heading date (July 2018 vs August 2019) was observed.

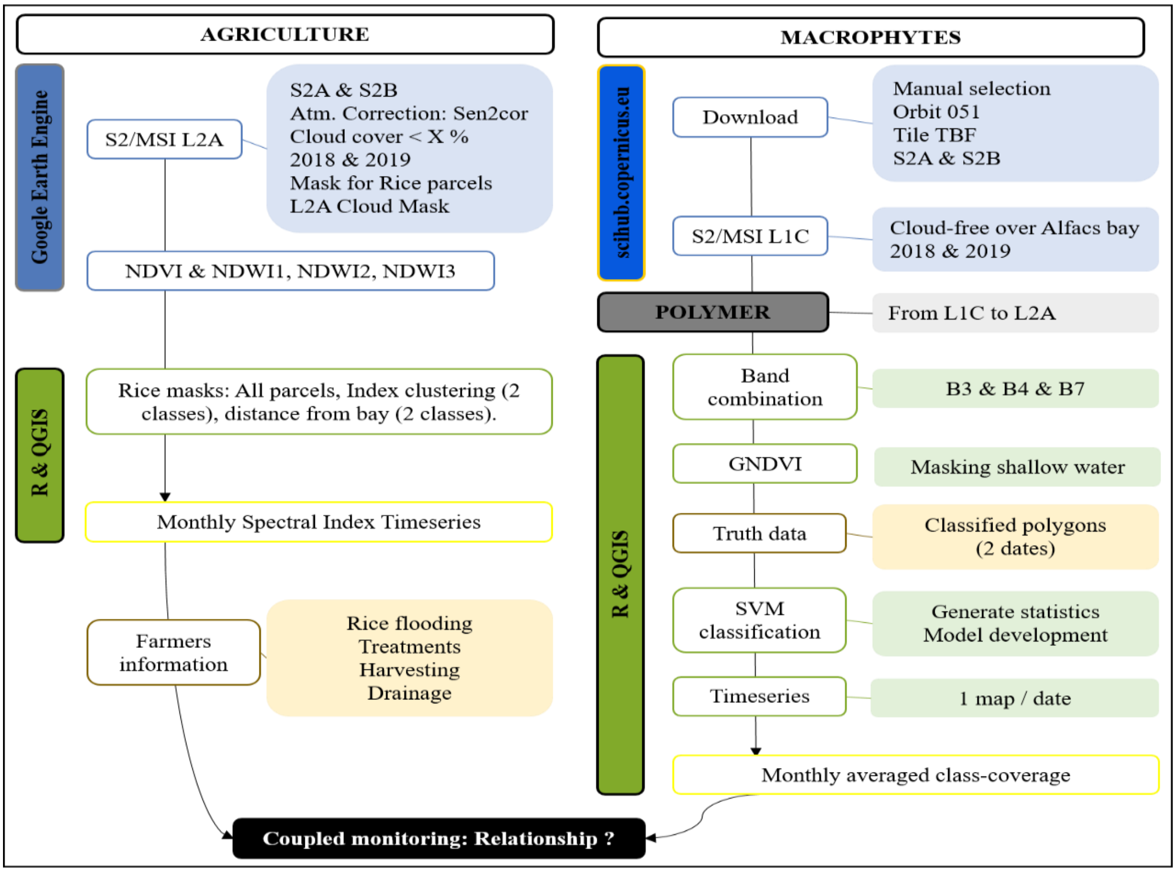

Figure 4. Workflow chart to assess induced-agricultural disturbance over macrophyte communities in Alfacs Bay.

3.2 Classification of seabed cover

Overall, macrophyte cover showed a seasonal pattern in both northern and southern shores, increasing their surface area during warm months (August-October) and decreasing during cold periods (December-February). Macrophyte coverage ranged between *ca*. 30 and 80 % of the shallow area along the sampling period (years 2018 and 2019), with higher coverage in 2019.

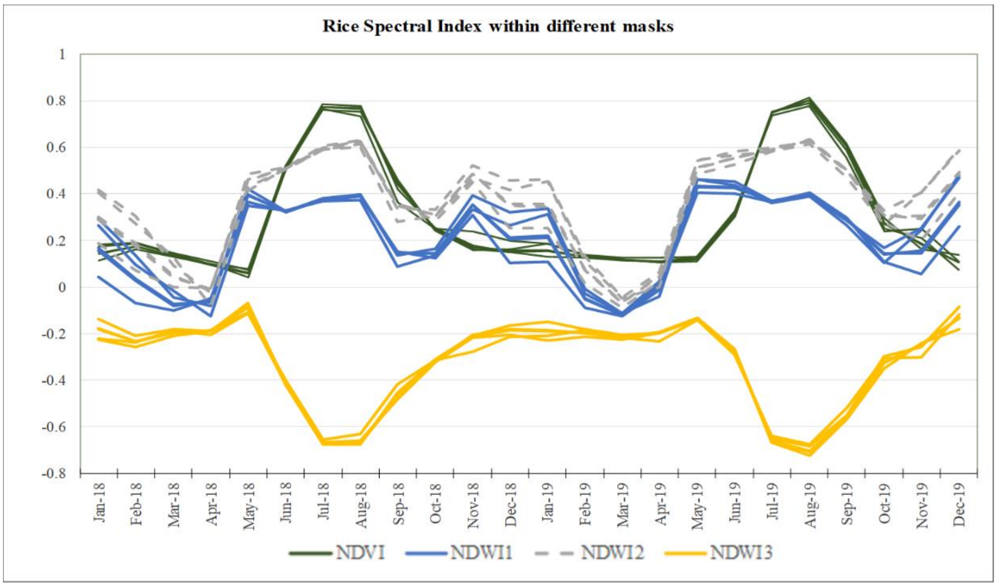

Figure 5. Spectral Index averaged within 5 different categories.

Macrophyte cover also showed significant differences between shores (Figure 7). The northern shore was dominated by green macroalgae, with higher coverage in summer (from June to August), and minimum in winter (December and January), and the peak in seagrass coverage occurred in September-October, following the maximum in macroalgae. However, seagrass cover was higher and dominated the southern shore of Alfacs Bay. The most abundant class was 'low density', and seagrass maximum coverage was observed in September and minimum between April and May. In the southern shore, green macroalgae coverage showed a maximum in February and a minimum in October and December in 2018 and 2019, respectively.

Table 1. Agricultural practices, crop stage and hydroperiod detected by using NDVI and NDWI1 of rice paddies in southern Ebro Delta along single year.

	NDVI	**NDWI1**
Absolute Maximum	Heading date	1st Flooding
Absolute Minimum	1st Flooding	Dry fields
Relative minimum I	-	End of Flooding - Harvest

Water depth (*i.e.* distance to shoreline) was also an important factor affecting macrophyte seasonal dynamics. In winter, seagrass was more abundant in deeper waters (*i.e.* distant from shoreline) with algae in the surface. In early spring, the increase in water turbidity led to the almost disappearance of macrophytes (both algae and seagrass), with seagrasses recovering in mid-late spring, the recovery being faster in shallow waters for ‘low density’ meadows and in deep waters for ‘high density’ seagrass. In summer, algae overgrown in the northern shore, with seagrass abundance limited to the margins of algal mats (Figure 8). In the southern shore, seagrass spread all over the bottom, with lower densities present in shallower areas and higher densities in deeper areas distant from the coast. Finally, in autumn, both seagrass and algae coverage decreased. Interestingly, seabed-coverage showed large variability in 2018 than in 2019. Algae density varied more in the northern shore, while seagrass presented more variations in the southern shore (Figure 7).

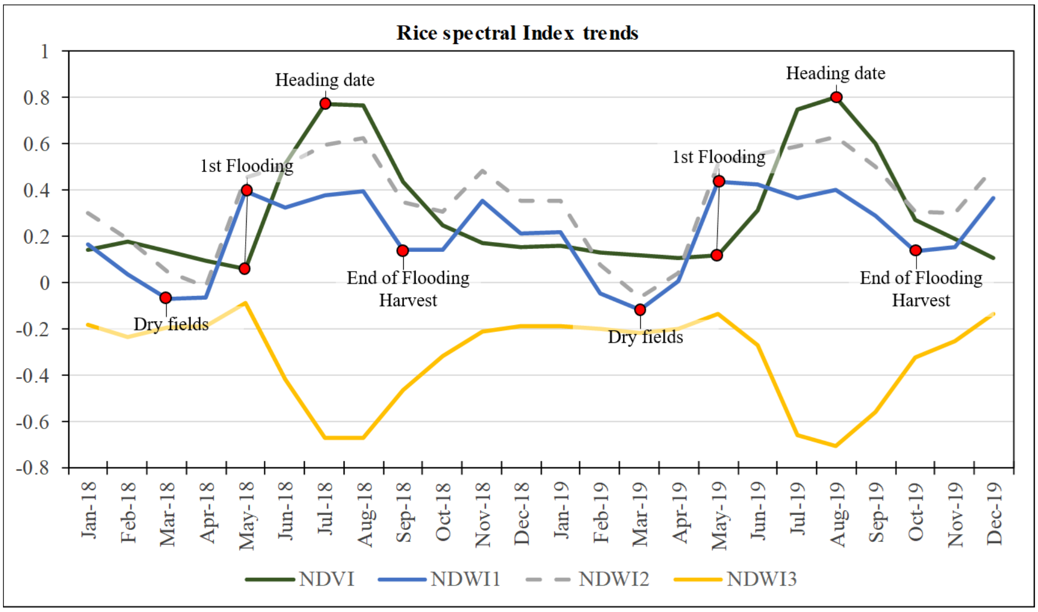

Figure 6. Rice spectral index monthly averaged within whole study area (left axis). Farming practices derived from scheme in Table 1.

4. SUBTITLE

Our results support the feasibility to characterize different aspects related to agricultural practices, crop phenology and hydroperiod characteristics by monitoring the NDVI and NDWI, and thus can be useful in rice farming monitoring. These results are in agreement with those reported by (Tornos et al., 2015), the only previous similar study in the area. The multi-temporal S2/MSI dataset covering southern Ebro delta for 2018-2019 includes more than 600 images based on the availability of clear-sky conditions and low-glint contamination risk. S2/MSI produces more accurate estimates due to its enhanced channel configuration, and its increased combined spatial (20 m^2) and temporal (5 days) resolution than other multispectral satellites, such as Landsat or MERIS. Thus allowing precise determination of both inter and intraannual crop dynamics. Among the tested spectral indices (i.e. NDVI, NDWI1, NDWI2 and

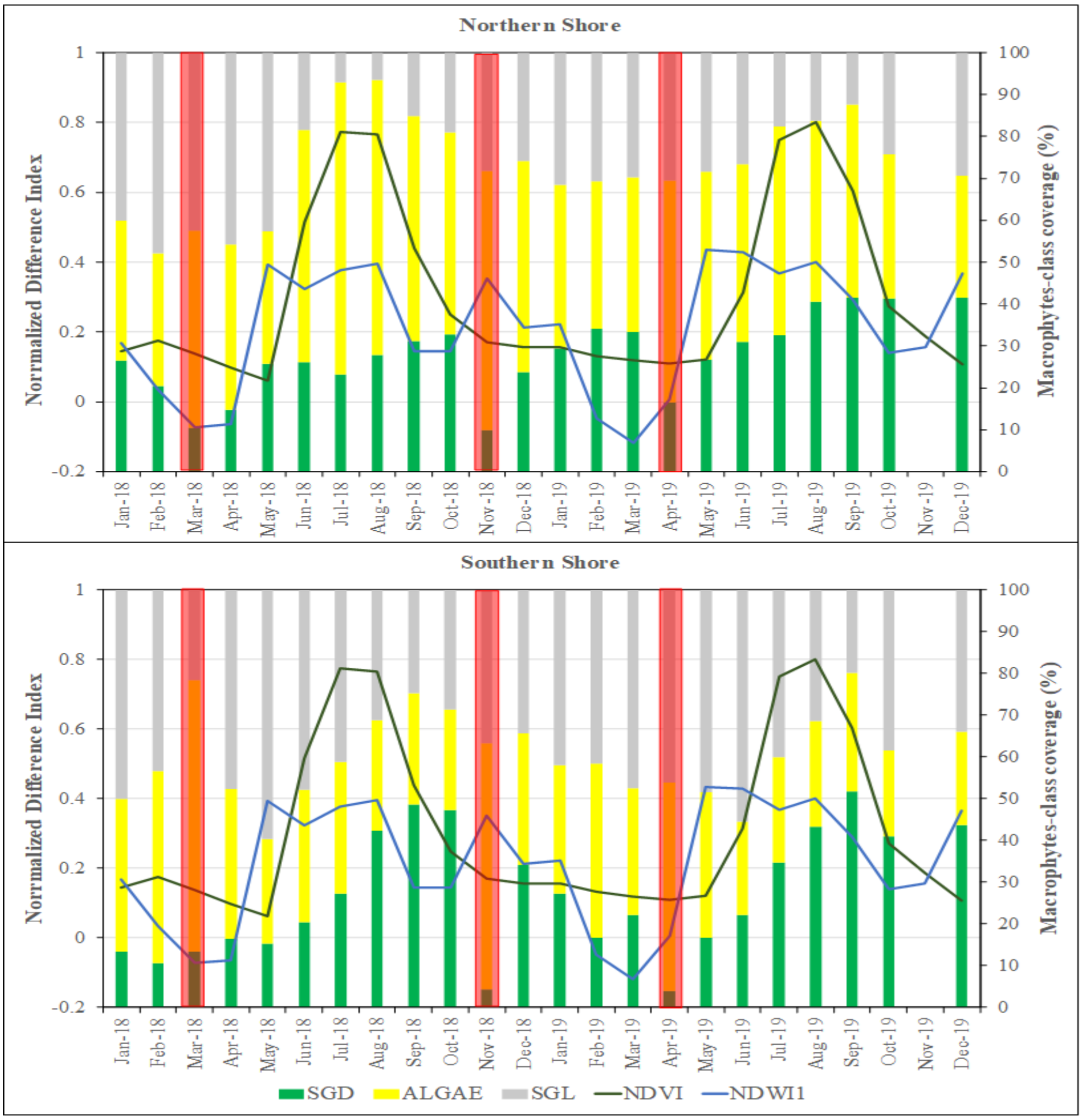

Figure 7. Rice spectral indexes (NDVI and NDWI1) and averaged per cent macrophyte-class. SGD: Seagrass dense, SGL: Seagrass low density and Algae) along the study period. In red, months not considered in the analysis.

NDWI3), the combination of NDVI and NDWI1 provided the most useful values, with each index showing different possibilities along the crop cycle. According to both indexes, the Ebro Delta was homogeneous in term of rice farming practices and crop development along the study period. However, 2019 showed a delayed crop calendar of ca. ~1 month when compared to 2018, these differences between years could be due to climatic conditions as temperature (2018 warmer than 2019) or rain. For instance, at the start of the growing season, in May, rainfall was 10.4 and 31.3 mm in 2018 and 2019, respectively. Consequently, in order to improve our results, further work should include climatic data. Furthermore, we used monthly averages of spectral indexes, which probably do not fit crop practices, thus further improvement should

allow including more detailed crop practices and management information (e.g. start of flooding, fertilizers application, harvest) by reducing temporal averages of spectral indexes.
In relation to seabed classification, the proposed methodology (i.e. S2/MSI merged composites and SVM-based classification) is effective in classifying macrophyte groups (algae and seagrass), as well as in identifying bare, sparse and dense vegetation zones. Overall, our results were coherent with the literature. For instance, (Sanmartí et al., 2018), found that following the overgrowth of opportunistic macroalgae, seagrasses are displaced to deeper-water areas, thus explaining the replacement dynamic observed between seagrass and algae in the northern shore of Alfacs Bay. However, some aspects need to be improved in order to improve the vegetation classification. For instance, given the similar spectral response, the class turbidity may be including turbid-waters environments, sandy bottoms, and sparse macrophyte areas. In addition, epiphytes (organism growing on the surface of plants) and water depth may increase uncertainty of seabed classification by modifying the spectral reflectance response of seagrass and algae (Hwang et al., 2019). Improve truth data classification (i.e. get more field data and increase the number of classes) would be helpful.

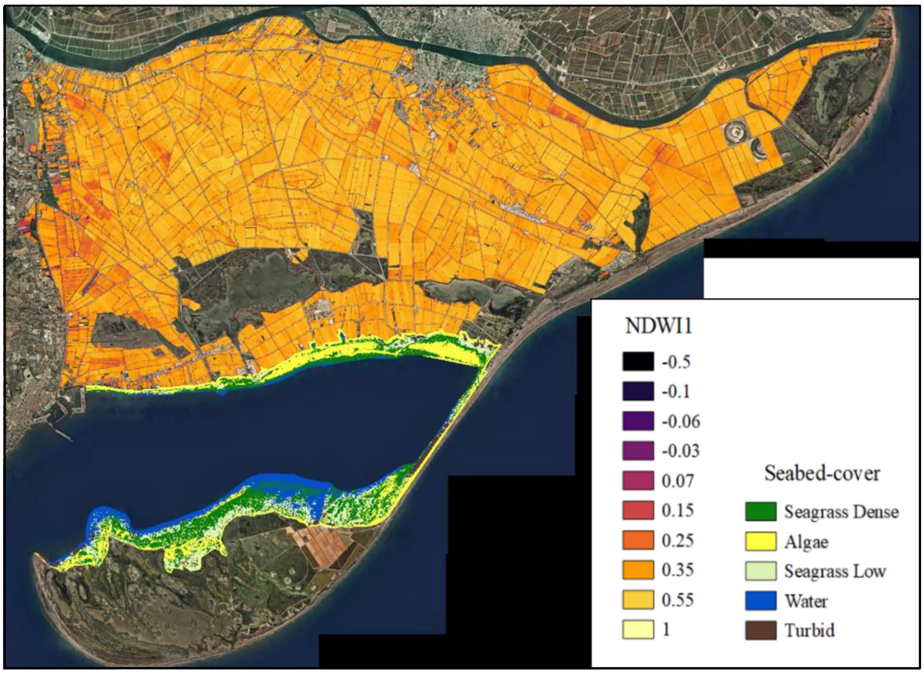

Figure 8. Example of summer scenario (2018). Homogeneous NDWI1 in rice paddies (August average) and macroalgae-seagrass coupled dynamics in Alfacs bay (19/08/18).

The results found also support the link between rice paddies and macrophyte development. Our results are similar to those reported by Pérez *et al.* (2001). They found strong spatial differences in nutrient availability in Alfacs Bay, being higher in the northern shore close to irrigation inputs from rice fields, and the increase in nutrient availability allowed the increase in abundance of green macroalgae during summer (Figure 8), pushing seagrass meadows to deeper areas. Irrigation inputs increase nutrient load and water turbidity thus reducing light penetration.

Under these conditions macroalgae are more competitive than seagrass, overgrowing them and carpets of epiphytes may develop on their leaves (Hemminga and Duarte, 2000). However, in the southern shore of Alfacs Bay nutrient availability is lower, similar to Mediterranean waters, thus seagrasses are more competitive than algae. Consequently, macrophyte composition (algae or seagrass) can be used as sentinel species to assess the effect of rice farming in enclosed aquatic environments. However, in order to better assess the relationship between rice farming and macrophyte abundance and composition in the long term some improvements are necessary. For instance, measuring irrigation flow rate and nutrient concertation, and water plume.

In conclusion, this study presents the first results on coupled monitoring of macrophytes and rice farming in the Ebro Delta by using remote sensing. S2/MSI were used to assess the relationship between changes in macrophyte community and rice farming. Although further improvements are required to better assess their relationship, our results show the potential use of S2/MSI imagery for integrated costal monitoring.

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BIOGRAPHICAL NOTES

The team dedicated to this work brings together specialists from different disciplines (including Vegetal production, remote sensing and image processing, positioning and data analysis) in the study area (Ebro Delta, NE Iberian Peninsula). The authors have published several studies related with rice farming, land and water ecosystem dynamics and modelling in the Ebro Delta.

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