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The performance of satellite images in mapping aquacultures

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ABSTRACT

Monitoring human pressures is the first step in the management of natural ecosystems, as well as a method to evaluate the effectiveness of the applied conservation measures. In this context, five commercial satellite images (QuickBird bundle, SPOT-5 multispectral, Landsat 7 ETM+, RADARSAT SAR, and ENVISAT ASAR) with various spatial and spectral characteristics have been assessed for their ability to map mussel farms off a coast of northern Greece, where the intensity and uncontrolled expansion of aquacultures is a pressure to a nearby wetland of international importance. The ability to identify the mussel farms on the images from background open water and accurately map these features was tested separately for the two types of mussel farms (pole and long line) present in the study area. The influence of waves on the mussel farms' identification was also investigated. Results indicate that the optimum satellite sensor varied according to mussel farm type, and is not necessarily the one with the highest spatial resolution. Pole farms were identified in all images bearing a spatial resolution superior to 10 m, but were better located and delineated with a high-resolution QuickBird image. Long line farms, on the other hand, were indistinguishable by passive optical sensors, and could only be identified on active microwave images. In addition to this, the findings show that surface waves drastically deteriorate the identification of mussel farms on an ENVISAT image, thus influencing its usefulness for monitoring.

1. Introduction

Marine aquaculture of filter feeder species (bivalves) provides an important source of high quality food and could be considered to be an important management tool to limit pressure on wild fish stocks, which are heavily stressed due to overfishing and pollution in coastal areas [1]. Mussel (*Mytilus galloprovincialis* Lamarck) farming can also influence the amount of phytoplankton in an area, and consequently plays an important role in the state of the ecosystem [2,3].

In the eutrophic Thermaikos Bay (Greece), mussel farming has become an important local economic activity, currently accounting for 88% of the national mussel production [4,5]. A massive expansion that took place in the 1990s was followed by the establishment of a number of illegal farms, as a result of inadequate control. Thus, it has become a major competitor for natural resources in the coastal area. This overexploitation of natural resources constitutes a pressure on the nearby protected estuarine and marine ecosystems [6], by producing large amounts of discarded cells and decaying biomass, reducing the aesthetic value of the coastal zone, acting as water current blockades that may cause toxic or potentially toxic phytoplankton blooms, and disturbing local and migrating wildlife [7,8].

European directives and national legislation have defined the protection scheme for the nearby wetland complex formed by the delta of the rivers Axios, Loudias, and Aliakmonas, where the majority of aquaculture is concentrated. It is characterized as a wetland of international importance according to the Ramsar Convention (site code 59, area 118.1 km^2). In this area, a number of important habitats for rare and endangered species exist, and it is therefore part of a Special Protected Area designated by the implementation of European Directive 79/409/EEC [9] (site code GR1220010, area 295.5 km^2) and a Site of Community Importance following the implementation of European Habitat Directive 92/43/EEC [10] (site code GR1220002, area 336.7 km^2).

Concerns about the potential impacts of mussel farming on the marine environment are continuing to increase along with issues of carrying capacity and sustainability. Monitoring activities are currently being developed on the site, and include baseline monitoring [11] and an operational monitoring project [12], aiming to define the appropriate management interventions. The monitoring activities recommend that number of units, location, area, and density of the aquacultures are measured. Furthermore, marking the accurate

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location of aquacultures is important information to local port authorities, being a potential danger to navigation. Finally, the environmental impact assessment study, which is included in the Spatial Planning of Aquacultures in Thessaloniki Bay [13], has dictated the carrying capacity of aquacultures in Thermaikos Bay. These acts pose the need for operational mapping and monitoring of mussel farming.

Traditional methods of surveying have been used to map the coastal zone, using land surveying equipment or Global Positioning Systems (GPS) [14,15]. However, land surveying equipment could only cover a short range from the shoreline. Also, the irregular pattern of mussel farms, the physical restrictions (weather conditions, navigation dangers such as loose lines and unmapped shoals) and the increased cost of field survey prevent the implementation of ship-borne GPS measurements in operational monitoring. Satellite remote sensing can provide cost-effective spatially distributed data for coastal zone monitoring [16,17]. The most notable advantages of using satellite imagery are the detailed coverage of large areas at low cost, the uniform coverage of accessible and inaccessible areas, the ability to collect data repeatedly and non-intrusively, and the multispectral nature of the observations.

Remote sensing has been used in coastal zone planning and management as the means of assessment of the level of human pressures, the conservation status of the natural environment, and the effectiveness of the applied conservation measures, by providing reliable information to support decision makers, facilitate reporting, and generally increase stakeholders' understanding. More specifically, remotely sensed data have been used for mapping inter-tidal mussel beds [18], aquatic and coastal habitats [19–22], and coastal zone land cover [23]. It has also been utilized in the assessment of human environmental impacts on aquatic environments [24], coastal zone management [15,25] and design of marine protection areas [26]. In these studies, a variety of space-borne sensors have been used, including passive optical (SPOT, Landsat MSS and TM, SeaWiFS) and active microwave (ERS-1/2, JERS-1, and RADARSAT SAR), each providing several advantages. Problems while using remotely sensed data for mapping features near the coastal zone include difficulty to locate ground control points [27], and appearance of surface waves [28,29].

The aim of this paper is to assess five satellite sensor images with different spatial and spectral characteristics for mapping mussel farms. Specific objectives include (i) assessment of mussel farms' identification ability on the images, (ii) assessment of mussel farms' mapping accuracy, and (iii) investigation of waves' influence on the identification ability.

2. Description of study area

Thermaikos Bay is located in northern Greece, at N 40°53′ E 22°73′. The majority of the mussel growing activity is concentrated around the delta of rivers Axios, Loudias and Aliakmonas, which defines the study area, and covers a total area of almost 30 km^2 (Fig. 1).

The three rivers' basins cover a total area of 32,000 km^2, and drain an intensively cultivated area of 1900 km^2. As a result, a large amount of nutrients is discharged into Thermaikos Bay, which had resulted in a series of algae blooms in 1980s, which had a severe impact on the environment and local fisheries [8,30]. Mussel farms were introduced in the 1960s in the bay as a small-scale activity. Permission for organized extensive mussel farming was granted in 1992, to alleviate the nutrient load and to support local communities. It was soon recognized as an important economic activity in the area, and expanded massively in the late1990s. Relevant authorities report a total annual production of 10,000 tons [31], but other studies put this figure at more than 30,000 tons [5].

Two types of mussel farms have been introduced in the area: pole and long line (Fig. 2). Pole farms are rectangular grids of wooden poles or metallic pipes wedged on muddy seabeds. The construction can be easily identified, as it reaches 1–2 m above sea level. Mussels bunches are hung directly on the horizontal poles and dropping to half a meter above the seabed. Their typical surface is 15 × 100 m, and they are installed in relatively shallow waters (3–6 m depth), usually 150 m apart to allow sufficient nutrition. This is the oldest system, introduced in 1955, and the most productive, reaching an average annual yield of 150–400 tons/ha. Long line farms are rectangular grids of plastic buoys (4 m^3 each) at 8–10 m apart, which are connected with lines and are anchored on the seabed using cement weights. They are difficult to discern on the

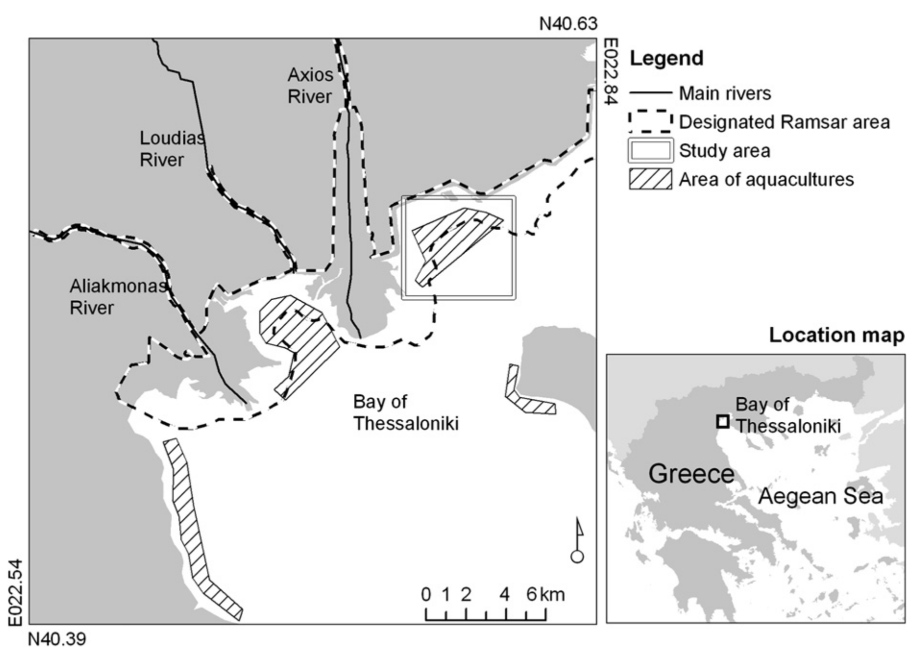

Fig. 1. Location of study area and area of aquacultures.

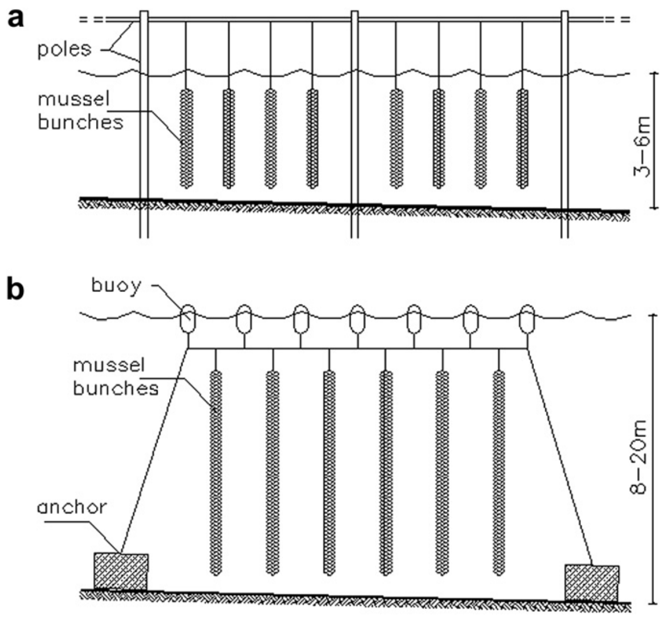

Fig. 2. Illustration of pole (a) and long line (b) mussel farms that occur in the study area.

water, as a fraction of the buoy is emergent (about 0.5 m). Mussel bunches are hung from the horizontal connecting ropes and drop to half a meter above the seabed. Their typical surface is 100 × 150 m, and they are installed in deeper waters (8–20 m depth), usually 250 m apart. It was introduced in 1995, and its average annual yield is 100 tons/ha. The number of pole and long line farms in the area is estimated to 300 and 160, respectively [31].

Due to the fact that they were introduced recently, long line farms are located in deeper waters. They are a rather extensive culture and do not cause serious problems in terms of management and compatibility with the environment. On the other hand, pole farms are concentrated in more closed and limited areas. They are an intensive culture, and the lack of any management plan and control of their density have caused serious problems (malnutrition and suffocation of the mussels), which led to loss of production. Inversely, during years of high production, social problems have risen due to lower commercial prices [7].

The uncontrolled increase in number and area of the mussel cultures has several impacts on the wetland and marine environments, and has been recognized as a contributing factor to the wetland complex degradation. These include excessive amounts of discarded cells and decaying biomass, accumulation of large quantities of mud as a mussel metabolism product, and disturbance of local and migrating wildlife. The aesthetic value of the coastal zone is also reduced, repelling eco-tourism activities. In addition, the mussel farms can act as water current blockades, which, in cases of low winds and high temperatures, have caused toxic or potentially toxic phytoplankton blooms [7,8].

3. Materials and methods

3.1. Description and preparation of data sets

Extensive fieldwork was carried out in spring and summer 2005 by the Thessaloniki Port Authority and the Prefecture of Thessaloniki, to locate and map existing mussel farms. The survey was conducted using a hand-held GPS receiver (3 m horizontal accuracy) carried on a vessel. The resulting vector map described the location and size of a sample of mussel farms (60 pole and 36 long line in total) and was used as reference data set. Analyses that follow were based on this stratified sample of farms, which accounts for 20% of the estimated total.

A wide variety of satellite images were used in this study. Images from passive optical sensors included a Landsat 7 ETM+ panchromatic (15 m resolution) acquired on August 5, 2002 at 9:45 a.m. (wind speed 0.5 m/s from NW), a SPOT-5 multispectral (10 m resolution) acquired on August 19, 2004 at 9:49 a.m. (wind speed 0.9 m/s from SSW), and a QuickBird bundle (0.6 and 2.4 m resolution in panchromatic and multispectral, respectively) acquired on April 24, 2002 at 9:24 a.m. (wind speed 1.3 m/s from NE). Images from active microwave sensors included a RADARSAT SAR (HH polarization) in fine beam mode (8 m resolution) acquired on August 4, 2004 at 4:29 a.m. (wind speed 0.5 m/s from N), and an ENVISAT ASAR (HH polarization) in image mode (25 m resolution) acquired on February 17, 2005 at 11:36 a.m. (wind speed 5.3 m/s from NW).

The QuickBird image was rectified into Greek Geodetic Reference System ’87 using the satellite’s rational polynomial coefficients and ground control points from 1:5000 photomaps. Afterwards, the remaining four images were geo-registered to the rectified QuickBird image, which acted as base map. The horizontal registration error obtained was less than one pixel for each rectified image.

Several enhancement techniques were tested on the satellite images to enhance the mapped features’ identification, and the optimal technique was selected for each image, according to its nature and individual conditions. Linear radiometric enhancement was applied to the marine area of QuickBird, SPOT and Landsat images to increase contrast of mussel farms from the surrounding sea surface. Furthermore, the QuickBird image was subjected to pan-sharpening. The forward–reverse principal component transform was used to merge information from panchromatic and multispectral images [32,33]. Spatial filtering techniques were applied to the microwave images to remove noise and therefore improve information extraction. A Lee-sigma (5 × 5 moving window) and two variance filters (15 × 15 and 31 × 31 moving window, respectively) were applied on each microwave image. The resulting enhanced images were displayed in a pseudo-color composite (R, G, B = Variance 15 × 15, Lee-sigma 5 × 5, Variance 31 × 31), as it offered a higher amount of detail and facilitated visual interpretation, in comparison to the raw black and white microwave images [34].

Spectral signatures were collected from mussel farms and open water of each image separately, by overlaying the reference data set on the image and sampling the respective areas of the two features, while avoiding the mixed pixels that may occur near the border of the two features. Mapping the outline of the mussel farms was performed using computer-assisted photo-interpretation and manual on-screen digitizing. The simplest of the mapping techniques among those reported in literature (computer-assisted photo-interpretation, image segmentation, and digital classification) was preferred, as a comparison among methods was not in the aims of this work. Although images were acquired in various seasons, implying different atmospheric conditions, atmospheric correction and radiometric calibration were not necessary, as comparisons were based on post-mapping results [35,36]. The optimum enhancement techniques that were selected were sufficient to facilitate independent mapping on individual images.

3.2. Assessing mussel farms’ identification on the satellite images

The ability to identify mussel farms on the satellite images, i.e. the strength of the return signal as compared to the background open water, was assessed both visually and statistically. Visual assessment was performed by overlaying the reference data on the mussel farms digitized from each image to check their level of identification from background (open water). The total number of mussel farms that were mapped on each image, using on-screen digitizing, was compared with the number obtained from the reference data set. Statistical comparison was based on the spectral signatures selected from mussel farm pixels and nearby open water pixels, which were extracted from each satellite image. Identification ability was defined as the spectral difference between mussel farm signatures and open water signatures. Among the available methods for assessing spectral difference [37,38], transformed divergence was selected, as it offered several advantages: it has discrete upper and lower bounds which facilitate interpretation, does not have a saturating behavior in high values, and is computationally efficient [39–41]. Transformed divergence ranges from 0 to 2000, with 2000 being the maximum spectral difference, between 1700 and 1900 moderate, and below 1700 low. The highest number of visible farms and the highest value of transformed divergence were the objective functions to select the image with the highest level of mussel farms' identification from background open water.

3.3. Assessing mussel farms' mapping accuracy on the satellite images

The accuracy of mapping mussel farms on the satellite images was assessed using several methods. First, a mussel farm's positioning accuracy was tested by comparing the centroid location mapped on each image with the equivalent location obtained from the reference data set, using root mean square (RMS) error. Second, the area of each mussel farm mapped on each image was compared with the equivalent area obtained from the reference data set. Third, the ability to map the correct shape of mussel farms was tested using a modification of the shape index [42]. While the original index reports deviation of a polygon's shape from the perfect circle [43], this modified shape index identifies deviation from the "normal" shape, which is the rectangular shape of the mussel farms. It can be calculated using formula (1):

$$\mathrm{MSI} = \frac{L}{4\sqrt{A}} \qquad (1)$$

where MSI is the modified shape index, L is the perimeter and A is the area of each tested mussel farm. Values of MSI equal to 1 indicate square shape, lower than 1 indicate circular or convex shape, and higher than 1 indicate rectangular or concave shape. Estimated values of MSI for mapped mussel farms on each image were compared with the values obtained from reference data. The lowest RMS error, and the lowest mean difference of area and MSI were the objective functions to select the image with the highest mapping accuracy. The statistical significance of the differences was tested with paired T-test.

3.4. Assessing the wave influence on the identification of mussel farms

Waves on the sea surface were expected to influence the sea surface reflectance, and thus the level of mussel farms' identification. From the available data set, the ENVISAT image was severely influenced by waves on the western side, while the eastern side was free of waves. In order to investigate the influence of waves in the identification of mussel farms on the image, the study area was divided into two zones: the wave zone and the calm zone. Spectral signatures were collected from mussel farms and open water in both zones, and the spectral difference of mussel farms from open water was estimated using transformed divergence, similar to the identification ability. The objective function to detect the waves' influence was a significant deterioration of the ability to identify mussel farms from the background open water.

4. Results and discussion

4.1. Identification of mussel farms on various satellite images

Overlaying the reference data set on each enhanced image provided the means for visual assessment of the latter, regarding its level of identifying the individual mussel farms. Landsat image provided the least information, as no mussel farms could be clearly identified. SPOT provided adequate information for mapping pole mussel farms (51 of 60), but no long line could be identified. QuickBird has very accurately described pole mussel farms (56 of 60), but no long line farm. Active microwave sensors provided a completely different view. RADARSAT was successful in identifying pole and long line mussel farms (54 of 60 and 28 of 36, respectively). ENVISAT was also successful in identifying pole and long line mussel farms (32 of 36 and 5 of 5, respectively, only in the calm water zone), although the mapping detail was limited due to lower spatial resolution. Despite the efforts to enhance the ENVISAT image, it was severely influenced by sea waves. As a result, information was obscured in the wave-affected areas, therefore reducing the potential number of mussel farms to be mapped to 36 pole and 5 long line. The identified mussel farms (pole and long line), together with a subset of each image, are displayed in Fig. 3. A sample of the study area is only displayed in this figure in order to achieve sufficient scale for display.

The statistical comparison confirms the findings of the visual assessment. Results of spectral distance (transform divergence) between mussel farms and open water using the enhanced channels for the five images are displayed in Table 1. Pole mussel farms were easily recognized emergent constructions, thus, their identification on the image is related to the sensor's spatial resolution. Therefore, spatial resolution lower than 10 m, such as with Landsat, seems to hamper mussel farm mapping.

The inability of the passive optical sensors to identify long line farms could be attributed to the small size and low density of buoys and their color (dark blue). It is unlikely that the limited amount of information for QuickBird is related to the time of acquisition (3 years prior to the fieldwork), as no major changes have occurred [31]. Also, no algal blooms were recorded in the study area on the days of image acquisition [44,45]. On the other hand, the sensitivity of active microwave images to surface roughness is the major factor contributing to the successful identification of long line farms. Although buoys' size is significantly lower than the sensors' spatial resolution, the repeated appearance of buoys increases local surface roughness, thus creating a higher return signal than the surrounding sea surface.

4.2. Mapping accuracy of mussel farms on various satellite images

Results from assessing the mapping accuracy for pole mussel farms using the three methods are displayed in Table 2. Landsat's limited spatial resolution could not provide sufficient detail for any measurement, and was not included in the analyses. Among the other images, QuickBird's location ability was superior, which was expected due to the highest spatial resolution. It is noted that part of the RMS error could be attributed to the accuracy of the reference data set (3 m horizontal accuracy). Area measurements of the mapped pole farm sample in SPOT, RADARSAT and ENVISAT were significantly different from the reference data set, with SPOT being relatively superior. Area measurements performed with QuickBird image closely matched those from the reference data set. Similarly, the mapped pole farm's shape was more accurately mapped on the QuickBird image. A negative sign in MSI difference

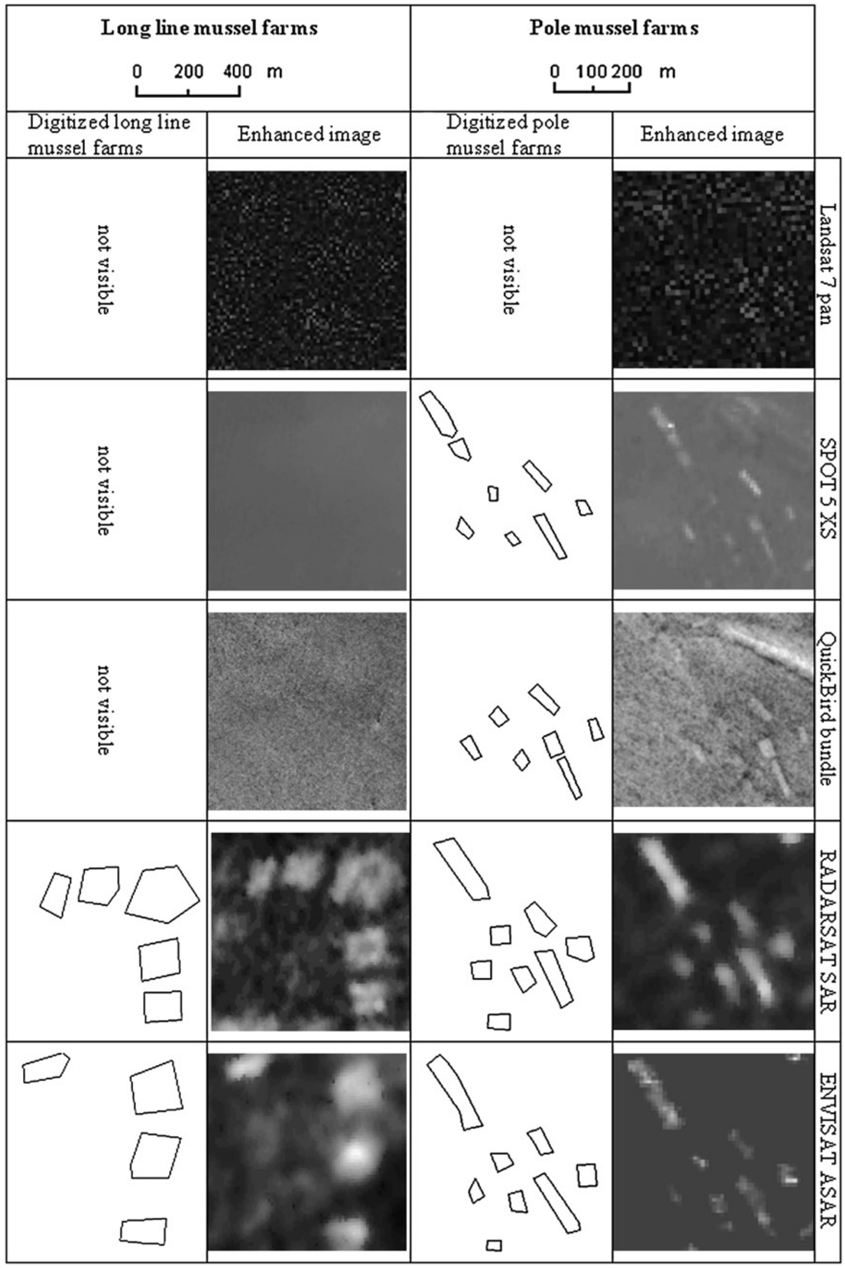

Fig. 3. Visual assessment of images' ability to identify mussel farms (pole and long line) in a subset of the study area. Each case includes a grey scale view of the enhanced satellite image and the resulting digitized mussel farms.

from reference data set indicates that mussel farms were delineated in a circular shape in SPOT, RADARSAT and ENVISAT images.

The results from the mapping accuracy assessment are directly related to the sensor's spatial resolution and positioning accuracy. The significantly higher area estimate for RADARSAT and ENVISAT could be attributed to the adjacency effect, which is the influence of a very bright pixel on the surrounding darker pixels [46,47].

The analyses listed in this section were not performed for long line farms, as they can drift several meters depending on wind direction, therefore inserting a significant error in the positioning assessment.

Table 1
Spectral distance (transformed divergence, no units) between mussel farms and open water

	Landsat	SPOT	QuickBird	RADARSAT	ENVISAT
Pole	107	1989	1993	2000	2000
Long line	0	0	0	1982	2000

4.3. Influence of waves on mussel farms' identification

The spectral difference of mussel farms from open water was estimated for the calm zone and the wave zone in the ENVISAT image. Transformed divergence was 2000 in the calm zone and 258 in the wave zone for pole farms, and 2000 and 114, respectively, for long line farms. This proves that mussel farms' identification deteriorates drastically in the presence of waves. This is attributed

Table 2
Images' accuracy for mapping pole mussel farms

Method	Landsat	SPOT	QuickBird	RADARSAT	ENVISAT
Location (RMSE in m)	–	10.8	7.9	12.1	21.77
Area (mean difference from reference in m^2)	–	485.6*	117.8	2440.6**	2294.9**
MSI (mean difference from reference, no units)	–	−0.031	0.007	−0.131**	−0.118**

*Significant at 95% level.
**Significant at 99% level.

to the interaction of microwave image's signal to surface roughness. A sea surface that is wavy appears as an area of high roughness, therefore providing a high return signal, which is similar to the mussel farms' signal.

The influence of waves on passive optical images was not tested due to lack of appropriate wave-infected data sets.

Mussel farms of this type are typically installed near the coastal zone of bays protected from large open sea waves. The waves discussed in this section refer to small-scale waves caused by wind, which may vary within the bay according to local conditions. Therefore, the wave-affected area in each image depends on the local wind conditions, and may obscure entirely the mapped features.

4.4. Analysis of costs and images' availability

As already discussed [15,17], the cost of employing satellite remote sensing in coastal resources' surveys is lower as compared to field surveying approaches. Remote sensing is even more cost-effective when the optimum source of satellite imagery is chosen, carefully considering the size of the study area and accuracy requirements [48].

In this study, the costs were kept on the low side because field survey, which can reach as much as 80% of a coastal mapping project's total cost [17], provided auxiliary data to validate the accuracy of the remote sensing work. Regarding the processing costs, all options examined could be handled using standard image processing software (ranging from 10,000€ for an ERDAS Imagine Professional license to 850€ for an Idrisi Andes license), the same trained personnel and similar image processing effort. The individual costs of purchasing the images and their spatial coverage are listed in Table 3. Although Landsat appears to be the most cost-effective, the comparison should be limited to RADARSAT and ENVISAT (0.8 and 0.19€/km^2 of study area, respectively), which were the images displaying both mussel farm types in the study area. The high mapping accuracy offered by the QuickBird satellite comes at the considerably higher cost of 16.54€/km^2 of study area.

All images were acquired from commercial satellite sensors, therefore their availability was only limited by the satellite's revisit period (Table 3) and unexpected system malfunctions. Thus, it should be noted that all tested satellite sensors are able to provide images with the frequency required in an operational monitoring project [11,12]. Recently launched satellites may offer additional instruments for monitoring aquacultures with characteristics similar to the images already tested in this work: ALOS (Advanced Land Observation Satellite) can acquire every 2 days optical and radar images at spatial resolutions as high as 2.5 and 10 m, respectively; TerraSAR can acquire radar images every 2–4 days at 1, 3 or 16 m spatial resolution.

Table 3
Purchase costs (prices of 2008), spatial and temporal coverage of images

	Landsat	SPOT	QuickBird	RADARSAT	ENVISAT
Image cost (€)	1500	2700	4500	2000	600
Image dimensions (km)	172.8 × 183	60 × 60	16.5 × 16.5	50 × 50	56 × 56
Relative cost (€/km^2)	0.05	0.75	16.54	0.80	0.19
Revisit period (days)	16	1–2	1–3	2–5	3–7

5. Conclusions

Five commercial satellite sensor images of various spatial and spectral characteristics have been assessed for mapping mussel farms off a coast of northern Greece, where the intensity and uncontrolled expansion of aquacultures is a pressure to a nearby wetland of international importance. The level of identification of mussel farms from surrounding open water and accuracy of mapping them on each image were tested separately for the two types of mussel farms present in the study area. The influence of waves on the mussel farms' identification was also investigated.

The best satellite for mapping mussel farms in the study area varied for the two types of farms. Pole farms were identified in all images that bore a spatial resolution superior to 10 m, but better located and delineated with a high-resolution QuickBird image. Long line farms, on the other hand, were indistinguishable by passive optical sensors, and could only be identified on active microwave images. Therefore, the finest resolution is not necessarily the best for mussel farm mapping. However, it is important for accurate location and delineation.

The identification of mussel farms declined drastically in the presence of waves. This was attributed to the higher sea surface roughness, which resulted in an increased return signal in microwave images, rendering the farms indistinguishable from wavy sea. Therefore, the presence of waves is a parameter that significantly decreases the image's monitoring ability, and so far has not been included in any image ordering form.

Considering these results, it is suggested that commercial satellite sensors can provide the means for operational mapping of aquaculture activities. Size, density, and proximity of aquaculture activities can be included as pressure indicators in an estuarine or coastal wetland monitoring project, which can be estimated using satellite remote sensing. Therefore, the pressure and state analysis using monitoring indicators can provide valuable information in coastal zone management plans. Furthermore, their effectiveness can be evaluated by detecting the changes before and after the adoption of measures. Future work could extend mussel farm monitoring with a remotely sensed phytoplankton monitoring and warning system, to assist environmental and aquaculture management.

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