MAPPING AQUATIC VEGETATION THROUGH REMOTE SENSING DATA: A COMPARISON OF VEGETATION INDICES PERFORMANCES

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ABSTRACT

Studying and mapping aquatic vegetation through remote sensing is a powerful and effective way to monitor vegetation status, growth and bio-physical parameters, because of the advantages synoptic view have on traditional in situ survey. In this field, Vegetation Indices (VIs) are one of the most used and useful tools. This work aims at running a brief comparison of different VIs in mapping aquatic vegetation over 3 distinct study areas and wetlands ecosystems in Italy, by employing multi-spectral and multi-sensor dataset ranging from aerial to satellite data, with varying spatial (1-30 m) and spectral resolution (0.01-0.15 µm), in order to evaluate the best performing ones. Along with well known indices such as NDVI, SAVI and EVI, two newly derived indices targeted particularly at monitoring aquatic vegetation features are tested: NDAVI and WAVI. From VIs results over the diverse, multitemporal and multisensor dataset, performances in terms of both aquatic vegetation mapping capabilities and vegetation features separability were assessed. Best performances were shown in most of the cases by the newly introduced indices (WAVI, in particular), thus demonstrating the usefulness of a specific index for mapping aquatic vegetation, and the integrated use of them with other VIs can be envisaged in order to effectively exploit and discover a wider range of aquatic vegetation features from multispectral remote sensing data.

INTRODUCTION

Aquatic vegetation, including helophytes and macrophytes, is a crucial component of transitional environments and coastal ecosystems, from a naturalistic and economic point of view. Although those ecosystems are usually studied at local scale and through the use of in situ data and analysis, this target is well suited to be subject of remote sensing analysis, because of the advantages synoptic view have on local surveying approaches. In particular, studying and mapping aquatic vegetation through remote sensing (especially in its optical reflectance properties) is a powerful and effective way to monitor vegetation status, growth and bio-physical parameters, that can effectively complement environmental studies performed in situ. In this field, good monitoring capabilities are ensured by the use of simple and straightforward approaches based on Vegetation Indices (VIs) derived from optical multispectral data, also in the context of re-generating historical data series. The analysis of vegetation communities response to external perturbation has been performed effectively in scientific literature, using remote sensing data, studying both anthropogenic and natural dynamics (1,2). Aquatic vegetation mapping and health status monitoring have been tested through derivation of ad hoc indices and multispectral response properties (3,4). Among the biophysical proxies used in the field, Leaf Area Index (LAI) measures have been used for monitoring terrestrial and aquatic vegetation health status, and LAI correlation with optical response derived VIs has been studied and demonstrated in literature (5), also from the point of view of revealing phenomena such as the die-back syndrome of common reed aquatic vegetation (6). This work aims at running a brief comparison of different VIs in mapping aquatic vegetation over 3 distinct study areas and wetlands ecosystems in Italy, by employing multi-spectral and multi-sensor dataset ranging from aerial to satellite data, with varying spatial (1-30 meter) and spectral resolution (0.01-0.15 µm), in order to evaluate the best performing ones. The main objectives of this work are therefore to evaluate the performance of different Vegetation Indices in mapping aquatic vegetation and assessing the capabilities of the aforementioned two newly introduced indices.

STUDY AREA AND DATASET

Study areas cover the Southern portion of Lake Garda (Northern Italy), the Lakes of Mantua (Northern Italy), and the Venice Lagoon (North-eastern Italy). Lake Garda is one of numerous subalpine lakes and is the largest freshwater basin in Italy. It is characterized by great max depths (360 m) and large volumes (49 km^3). In particular our study is focalized on the Sirmione Peninsula, located at the southern of the lake, this extends for about 4 km into the lake and its shores are characterized by moderate slopes populated by different species of aquatic vegetation (e.g. Phragmites australis in coastal areas, Vallisneria spiralis on the bottom) (7). The lakes of Mantua (Upper, Middle and Lower) are three small (~6 km^2) and shallow basins (average depth ~3.5 m) surrounding the city of Mantua. The lakes are fed by the Mincio River (emissary of Lake Garda). The three lakes are characterized by eutrophic levels, in the coastal area grows P. australis, inside the lake are emergent macrophytes such as Trapa natans and Nelumbo nucifera (3). Venice Lagoon is the largest lagoon in Italy, covering an area of ~550 km^2, with an average depth of only ~1 m. It is characterized by a semidiurnal tidal regime with a range of about ±0.7 m. The lagoon consists of a number of interrelated habitats: islands, salt marshes and tidal flats are connected by channels. These varying habitats host a number of vegetation species (e.g. Salicornia veneta, Spartina maritima in the saltmarsh and P. australis in coastal areas) (8).

The analysis performed in this work is coming from remotely sensed only data, derived under a huge variety of technical acquisition characteristics. In fact, the dataset is composed of satellite and aerial images, multitemporal (acquired between June 2004 and May 2012, in different phenological seasons), multispectral to hyperspectral (4 to 242 spectral bands), with spatial resolution ranging from 2 to 100 meter. This, together with the three different study areas already introduced and hosting different aquatic vegetation communities, is meant to ensure a good degree of heterogeneity in the dataset, so that the analysis of VIs performances could cover various real life vegetation conditions. Table 1 lists the main characteristics of this remotely sensed dataset.

Table 1: Remote sensing dataset, over the three different study areas (left column)

	Sensor	Acquisition date	Spatial res [m]	Spectral bands [N°]	Spectral range [µm]	Notes
Lake Garda	AISA	*30 april 2010*	2	100	0.40-0.90	
	MIVIS	*15 july 2010*	2	92	0.44-2.44	*Radiometric normalization reference*
	GeoEye	*26 august 2010*	2	4	0.45-0.90	
	Worldview2	*19 october 2010*	2	8	0.45-0.90	
Lakes of Mantua	TM 5	*21 august 2011*	30	6	0.45-2.25	
	CHRIS	*28 august 2011*	20	18	0.41-1.01	
	APEX	*21 september 2011*	5	98	0.42-0.91	*Radiometric normalization reference*
Venice Lagoon	Hyperion	*18 june 2005*	30	242	0.35-2.55	
	HICO	*25 june 2011*	100	87	0.40-0.90	
	TM 5	*27 june 2011*	30	6	0.45-2.25	*Radiometric normalization reference*
	TM 5	*01 cotober 2011*	30	6	0.45-2.25	
	HICO	*12 may 2012*	100	87	0.40-0.90	

METHODS

For deriving consistent information from such a diverse dataset, the methodological approach adopted must be preceded by a rigorous pre-processing phase, consisting of atmospheric effect correction using MODTRAN radiative transfer code implemented in ATCOR 3-4 software (9), spectral resampling and radiometric normalization (10) of each of the images in the dataset. particular attention is given to spectral resampleing phase, for which the reference spectral bands considered were the most common broadband visible and near infrared (VNIR) sensors (such as Landsat TM, Quickbird, and other sensors). The results are therefore broadband composites with 4 spectral bands shaped on the first 4 bands in Landsat TM spectral ranges (BLUE: 0.45-0.52 µm, GREEN: 0.52-0.60 µm, RED: 0.63-0.69 µm, NIR: 0.76-0.90 µm).

Table 2: Aquatic Vegetation Indices introduced in the study (L=0.5 value has been adopted).

Index	Formula
NDAVI (Normalized Difference Aquatic Vegetation Index)	$\frac{\rho_{\mathrm{NIR}} - \rho_{\mathrm{BLUE}}}{\rho_{\mathrm{NIR}} + \rho_{BLUE}}$
WAVI (Water Adjusted Vegetation Index)	$(1+L)\frac{\rho_{\mathrm{NIR}} - \rho_{\mathrm{BLUE}}}{\rho_{\mathrm{NIR}} + \rho_{BLUE} + L}$

From pre-processed data, VIs images were derived for comparison purposes. A set of five different VIs were subject of comparison for each of the scene of the multi-sensor dataset covering the 3 study areas. Three of the VIs are well known in literature: NDVI (Normalized Difference Vegetation Index) (11), SAVI (Soil Adjusted Vegetation Index) (12), and EVI (Enhanced Vegetation Index) (13); the other two indices, instead are being introduced and tested here: the first and basic one has been called Normalized Difference Aquatic Vegetation Index (NDAVI), and the second one is called Water Adjusted Vegetation Index (WAVI). NDAVI follows the common and broadly tested normalized differencing approach (14,15) and comes as an adaptation of the common NDVI specifically targeted at wetland vegetation, where the vegetation background is usually composed of water rather than soil (Table 2). WAVI is a derivation of NDAVI the same way as SAVI is a derivation of NDVI, through the introduction of a correction factor L to adjust to the influence of vegetation background, which in case of aquatic plants is composed by water.

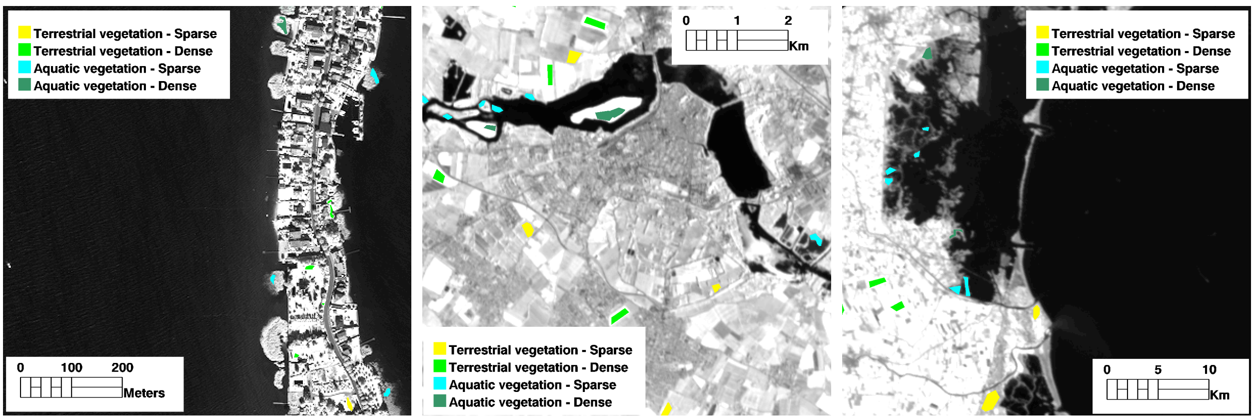

Figure 1: Details of the study areas and highlighted regions of interest used for deriving Vegetation Indices statistics: Lake Garda (on the left), Lakes of Mantua (centre), Venice Lagoon (on the right)

Vegetation Indices statistics aimed at VIs performances evaluation were derived over 4 different vegetation cover classes, with a combination of two vegetation type and two vegetation density: Terrestrial vegetation sparse, Terrestrial vegetation dense, Aquatic vegetation sparse and Aquatic vegetation dense. The discrimination between terrestrial and aquatic vegetation is made simply on the vegetation background characteristics: terrestrial vegetation background is composed by soil, while aquatic vegetation background is composed by water. Discrimination between sparse and dense vegetation is made on the basis of relative predominance of vegetation canopy or vegetation background in a mixed pixel assumption. For each of this four vegetation cover classes, a collection of Regions of Interest (ROIs) have been made for each of the scenes in the remote sensing dataset. In particular, the collection of those ROIs has been guided by in situ surveys and ecosystem direct knowledge for the study areas of southern Lake Garda and the Lakes of Mantua, while for Venice Lagoon the reference used was a thematic map of saltmarshes and reedbeds (8). Figure 1 shows some details of the study areas with superimposed ROIs derived for the 4 vegetation cover classes of interest.

From the ROIs drawn over the multisensor-multitemporal remote sensing dataset, a set of VIs descriptive statistics has been derived for each of the four vegetation cover classes mentioned above. This resulted, for each scene in the dataset, in a database of statistics for every one of the five VIs tested (NDVI, SAVI, EVI, NDAVI and WAVI): average value of VIs (MEAN), dispersion of VIs values around the mean (STD), minimum (MIN) and maximum (MAX) values of VIs. The statistics derived this way, were exploited to test the separability of aquatic vegetation and terrestrial vegetation for each of the VIs utilized, in order to evaluate the index which shows the best performance in terms of distinction of aquatic from terrestrial vegetation features.

Separability performances were tested separately for sparse vegetation cover (comparing Aquatic vegetation sparse with Terrestrial vegetation sparse) and dense vegetation cover (comparing Aquatic vegetation dense with Terrestrial vegetation dense), by using a Normalized Overlapping metric:

$$\%\ Overlap = 1 - \Phi\left(\frac{|\mu_1 - \mu_2|}{\sigma_1 + \sigma_2}\right) \qquad (1)$$

where Φ is the cumulative density function of a normal distribution $N(0, 1)$.

Under the hypothesis of normal distribution, this formula shows the cumulative probability value for which two variables pdfs are overlapping, and is therefore showing how much the pdf of one variable is overlapping the pdf of the other variable. The lower is the percentage of overlapping between the two variables distribution, the higher is the separability.

Table 3: VIs comparison in terms of best separability between aquatic and terrestrial vegetation cover: best performing VIs over sparse (columns 5-6) and dense vegetation (columns 7-8), and separability enhancement in terms of Normalized Overlapping difference gained by using NDAVI (columns 9 and 11, sparse and dense vegetation), and WAVI (columns 10 and 12, sparse and dense vegetation). Grey background cells highlight new indices (NDAVI and WAVI) best performances compared to indices already in use (separability gain greater than +5%).

Remote Sensing data source	Spat. res. [m]	Julian day	Site	Best Separability - Sparse veg.		Best Separability - Dense veg.		VIs separability - Sparse veg. (% Overlap Δ)		VIs separability – Dense veg. (% Overlap Δ)	
				1st	*2nd*	*1st*	*2nd*	*NDAVI vs. NDVI*	*WAVI vs. SAVI/EVI*	*NDAVI vs. NDVI*	*WAVI vs. SAVI/EVI*
AISA_30apr2010	2	120	*Garda*	**WAVI(0.5)**	SAVI(0.5)	EVI	SAVI(0.5)	+0,0%	+0,0%	-3,5%	-1,7%
MIVIS_15jul2010	2	196	*Garda*	**WAVI(0.5)**	***NDAVI***	***NDAVI***	**WAVI(0.5)**	**+25,2%**	**+25,2%**	**+9,1%**	**+5,7%**
GeoEye 26aug2010	2	238	*Garda*	**WAVI(0.5)**	***NDAVI***	**WAVI(0.5)**	***NDAVI***	**+15,5%**	**+11,6%**	+2,8%	+2,4%
Worldview2_19oct2010	2	292	*Garda*	**WAVI(0.5)**	***NDAVI***	***NDAVI***	**WAVI(0.5)**	**+15,4%**	**+15,1%**	+2,8%	+1,6%
TM5_21aug2011	30	233	*Mantua*	**WAVI(0.5)**	*NDVI*	***NDAVI***	**WAVI(0.5)**	*-25,7%*	**+17,5%**	**+22,7%**	**+6,5%**
CHRIS_28aug2011	20	240	*Mantua*	**WAVI(0.5)**	*NDVI*	***NDAVI***	**WAVI(0.5)**	*-16,4%*	**+18,6%**	**+40,6%**	**+12,8%**
APEX_21sep2011	5	264	*Mantua*	**WAVI(0.5)**	SAVI(0.5)	***NDAVI***	**WAVI(0.5)**	**+5,9%**	+2,9%	**+36,8%**	**+14,0%**
Hyperion_18jun2005	30	169	*Venice*	**WAVI(0.5)**	SAVI(0.5)	EVI	SAVI(0.5)	-1,1%	+1,0%	*-10,7%*	+0,0%
HICO_25jun2011	100	176	*Venice*	**WAVI(0.5)**	SAVI(0.5)	EVI	SAVI(0.5)	-0,3%	**+6,3%**	-4,5%	-0,3%
TM5_27jun2011	30	178	*Venice*	**WAVI(0.5)**	SAVI(0.5)	SAVI(0.5)	**WAVI(0.5)**	+2,0%	+3,1%	+0,2%	+0,2%
TM5_01oct2011	30	274	*Venice*	**WAVI(0.5)**	SAVI(0.5)	*NDVI*	SAVI(0.5)	+2,3%	+3,3%	-2,4%	-1,5%
HICO_12may2012	100	133	*Venice*	**WAVI(0.5)**	EVI	SAVI(0.5)	EVI	*-12,8%*	+2,4%	-0,1%	+0,0%

RESULTS

Results analysis takes into account the different performances in terms of separation of aquatic vegetation from terrestrial vegetation according to separability measures calculated as Normalized Overlapping (% Overlap, see eq. 1). Table 3 shows vegetation indices performances for sparse vegetation and dense vegetation separability (according to the dual scheme Aquatic vegetation/Terrestrial vegetation). For sparse and dense vegetation the table lists the best performing index and the second best performing index, ranking the performances in term of Normalized Overlapping (eq. 1) calculated from VIs features (Table 3 columns 5-8). The separability performance assessment is then done calculating separability enhancement reached with newly derived VIs (positive values=better separability for new index than literature ones, negative values=worst separability for new index than literature ones), separately for both sparse and dense vegetation, by comparing performances of: (a) simple indices (NDVI Vs. NDAVI, Table 3 columns 9 and 11), and (b) background adjusted indices (WAVI Vs. SAVI/EVI, Table 3 columns 10 and 12)

DISCUSSION AND CONCLUSIONS

From VIs results over the dataset, performances in terms of both aquatic vegetation mapping capabilities and vegetation features separability were assessed, also with the use of ancillary field information and thematic maps reference data. Best performances were shown by different indices depending on the study area and dataset utilized and a syntetic overview coming from Table 3 shows some interesting trends in aquatic and terrestrial vegetation separability evaluated over different VIs, which can be summarized as:

- NDAVI has comparable performance to NDVI over sparse vegetation cover (average difference in Normalized Overlapping of +0.83% over the whole dataset);
- NDAVI outperforms NDVI over dense vegetation cover (average difference in Normalized Overlapping of +7,82% over the whole dataset), with the exception of Hyperion data over Venice Lagoon, for which the influence of radiometric normalization using 2011 reference may have been some small distorting effect due to land cover partial changes and the effects of different tide level;
- WAVI generally outperforms every other index over sparse vegetation cover (average difference in Normalized Overlapping of +8,90% over the whole dataset);
- WAVI outperforms the other background adjusted VIs (SAVI and EVI) over dense vegetation cover (average difference in Normalized Overlapping of +3,29% over the whole dataset), with only minor difference in performance when WAVI is not one of the two best performing index (such as over Venice Lagoon data, showing overlapping differences from -0,1% to -1,7% only).

As for the different seasonality in dataset tested, we can notice that the only scene acquired during spring season (AISA data over Lake Garda) does not see relevant differences in performances for the five VIs, while end of peak season scenes (Worldview2 over Lake Garda and Landsat TM from October 2011 over Venice Lagoon) still can show different performances for different VIs. Moreover, it must be pointed out the quite anomalous behaviour over dense vegetation occurring in Lakes of Mantua study area, with high separability performances for both NDVI and WAVI compared to other indices. This is probably an effect of the peculiar characteristics of aquatic vegetation in this area mainly composed by emergent aquatic plants such as Nelumbo nucifera, Nymphaea alba and Trapa natans, with thick leaves and dense mesophyll and upper surfaces coated with wax that maybe can influence their spectral response.

In conclusion, the work described in this article has shown that newly derived indices such as NDAVI and especially WAVI can enhance distinction of aquatic vegetation from terrestrial vegetation features, in particular in sparse vegetation conditions over a diverse (multisensor, multitemporal, multispectral) and distributed dataset , and those ad hoc derived indices can be therefore used in conjunction with other VIs for monitoring and mapping aquatic vegetation and transitional ecosystems from remote, in integration with in situ data and laboratory ones, to better understand vegetation dynamics in wetland environments

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