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UTILITY ASSESSMENT IN USING OPTICAL AND RADAR DATA TO MONITOR SURFACE WATER DYNAMIC IN WETLAND ECOSYSTEMS, FUENTE DE PIEDRA, SPAIN

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RESUMEN

Los humedales son ecosistemas complejos, dinámicos y sensibles que requieren, para una adecuada conservación, un seguimiento y control tanto de sus cualidades físico-químicas como de las presiones antrópicas que se ejercen sobre los mismos. La idoneidad de las técnicas de teledetección para este fin es una evidencia ya que garantiza una buena disponibilidad, alta frecuencia y gran cobertura de imágenes a bajo coste y armonizadas. En el marco del proyecto SWOS (H2020) se ha generado un conjunto de productos dirigidos al seguimiento y control de los humedales basados en teledetección. Este trabajo presenta la validación de la utilidad de la herramienta disponible para el seguimiento de la dinámica de la lámina de agua (*Surface Water Dynamic* –SWD-). A partir de su aplicación en la Laguna de Fuente de Piedra, se generaron dos conjuntos de datos de frecuencia temporal (TF) utilizando en un caso datos satelitales ópticos (serie Landsat), y en otro de radar de apertura sintética (SAR) (Sentinel-1). El área de la lámina de agua superficial obtenida en ambos casos se correlacionó con datos ambientales *in-situ* como la precipitación, temperatura y el nivel del agua en la laguna. Los resultados obtenidos muestran que el nivel piezométrico es la variable ambiental más correlacionada con los datos de SWD y la que tiene una mayor capacidad predictiva, con una correlación de R=0.932 para Landsat y R=0.936 para SAR. El estudio pone en evidencia la gran utilidad derivada del uso de la teledetección para el seguimiento de la dinámica hidrológica de este humedal y proporciona evidencias de su idoneidad para estimar la superficie de agua y mejorar el monitoreo de la dinámica de la lámina de agua en humedales.

Palabras clave: Landsat, Sentinel 1 SAR, dinámica de aguas, análisis de validación, nivel de inundación.

1. INTRODUCCIÓN

This study describes the approach used in the framework of SWOS Horizon 2020 project for the assessment process of the Surface Water Dynamic (SWD) product in Fuente de Piedra case study, in order to assess its applicability providing accurate open water surface estimations and take a step further in enhancing water dynamics monitoring in wetland ecosystems:

http://portal.swos-service.eu/mapviewer/detail/1.html#/wetland/6/product/3261

The developed SWD methodology assesses the extension of open water areas in wetland ecosystems, which can support and connect with further provisioning services (as the wetland water supply for the habitats, minimum water availability, maximum wetland water extent period etc.). The product considered is the SWD Temporal Frequency (TF), which describes the number of submersion occurrences relative to the number of image acquisitions during the study period in percentage. Two layers were generated for Fuente de Piedra wetland: one using optical satellite data (Landsat time series), covering the period between January 2007 and September 2015, and the other using Synthetic Aperture Radar (SAR) data (Sentinel 1 time series), from November 2014 to March 2017.

2. OBJETIVES

The aim of the assessment process described in this study is to determine the coherence in the SWD layer produced in SWOS project with the actual water levels and meteorological data, providing evidences about the utility of remote sensing in the monitoring of hydrological dynamics in wetland areas.

3. STUDY AREA

Fuente de Piedra is a Mediterranean seasonal saline lake located in the northwest of the province of Malaga, region of Andalucia, in south Spain, covering an area of almost 1,400 hectares. The wetland has shallow, salt water between autumn and spring, and is internationally recognized as home to the largest colony of flamingos on the Iberian Peninsula and the second largest in Europe. It was declared a Ramsar site in 1983 and as nature reserve from 1989, being recognized as Natura 2000 site, Special Protection Area (SPA) and Site of Community Importance (SCI). The lake is close to the wetland areas of Campillos (formed by six small lakes) and the lake of La Ratosa, which together constitute a wetland complex with similar characteristics in terms of its origin and animal and plant communities.

The wetland owes its water levels to precipitation runoff and underground water table of the endorheic hydrological basin in which it is located (Rodriguez-Rodriguez et al., 2016). The croplands around the wetland consume large amounts of water resources that affect the quantity and quality of the water underneath (González Báez et al., 2017; Martos-Rosillo et al., 2017). The changes in land uses in the last decades and the expansion of agricultural practices in and around the boundaries are an important pressure on water resources in the area and a major driver of the change in the level of groundwater (Catalán et al., 2002).

The assessment approach is applied in the Fuente de Piedra wetland using the RAMSAR delineation of the wetland plus a buffer area of 500m around it (Figure 1).

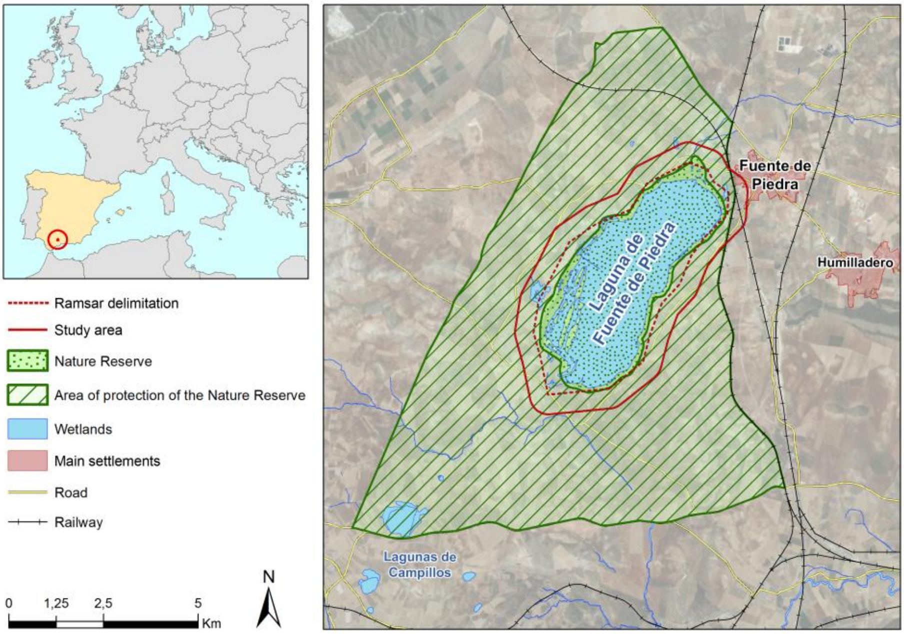

Figure 1. Map of Fuente de Piedra wetland and the study area of the SWD assessment

4. MATERIAL AND METHODS

4.1. SWD Optical data

The SWD indicator derived from Landsat imagery for January 2007 to September 2015 was calculated by using the Modified Normalized Difference Water Index (MNDWI; Hanqiu Xu, 2006). All monthly Landsat 5 and 8 images free of clouds available during this period were selected from the NASA, USGS database in order to have the best temporal coverage of the water extent. Landsat imagery has a spatial and temporal resolucion of 30m and 16 days respectively. MNDWI was calculated by the spectral responds of Green and Short Wave Infra-Red (SWIR) bands of Landsat. The MNDWI identify/discriminate by raster cells the presence or absence of water. The resulting raster values have a range from -1 to +1, where negative values indicate no water content raster cells and positive values indicate water presence. 0 to +1 values were extracted from the resulting layers to produce a binary water mask where value 1 represents water and value 0 no water. To produce the SWD TF product, all these masks are summed and the resulting layer is then normalized from 0 to 1 or 0 to 100 to express the flood periods in percentage (Figure 2). For the assessment approach, the masks were kept separately and the surface water extent of each one was calculated in hectares (the total area that the positive MNDWI cells cover). This surface is understood as open surface water extent area (SWE).

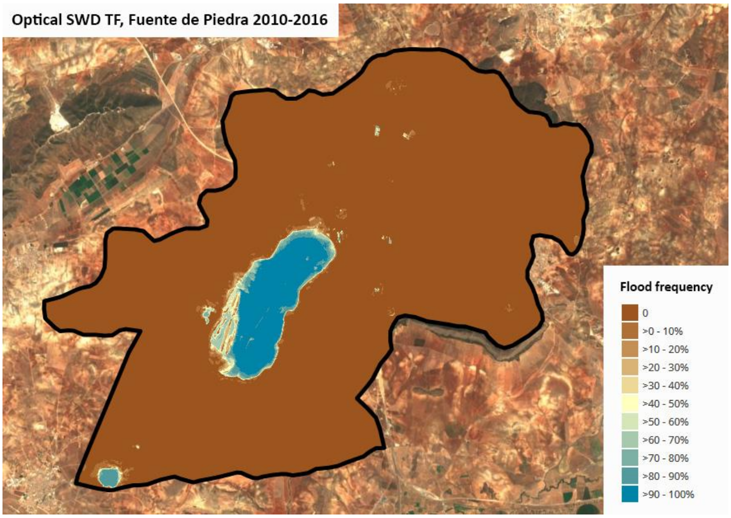

Figure 2. Example of optical SWD TF product of Fuente de Piedra. Years 2010 to 2016.

4.2. SWD SAR data

Mapping water bodies from Synthetic Aperture Radar (SAR) is based on the generalized assumption, that smooth surfaces appear darker in the image than rough surfaces. The radiation touching a point on the Earth’s surface is scattered in different directions and a small portion is returned to the sensor. The rougher the surface, the more radiation is scattered equally in all directions away from the point of impact and more radiation is returned to the sensor. The smoother a surface, on the other hand, the more radiation is scattered specularly away from the sensor and less radiation is thus returned to the sensor. Hence, an image histogram can be thresholded into dark water pixels and brighter land pixels to create a binary water mask. A general overview of water body mapping and wetland remote sensing with SAR in general is given by e.g. (Brisco, 2015; White et al., 2015).The accuracy of this approach, if applied to a single image, strongly depends on the current sea state as waves roughen the water surface, effectively reducing the contrast between water and land. The ability to still differentiate between land and water at higher sea states is dependent on the wavelength/frequency and polarization of the SAR sensor.

Sentinel-1 acquires imagery in C-Band wavelength and mostly in VV polarization. This setup is not the most preferable for the above methodology, for which longer wavelengths and HH polarization would be optimal. Yet, Sentinel-1 has a temporal resolution of 5 days, so the large quantity of images acquired offers the opportunity to not only make use of the image intensity but also its variability over time. The spatial resolution depends on the acquisition mode and the level of processing. For this study, images where acquired from ESA database (Sentinels Data Hub) and the product generated had a resolution of 20 m. No geometrical corrections of the image were made since the area is quite flat and the accuracy of the sensor is considered adequate for the scale of work.

An analysis of differences in the backscatter of the SAR signal allows to distinguish between water and land areas. The SWD derived from Sentinel 1 covers the period from November 2014 to March 2017. The process to produce the SAR based SWD TF was the same used for the optical product (Figure 3). In this case, it should be also noted that data represents open surface water extent area.

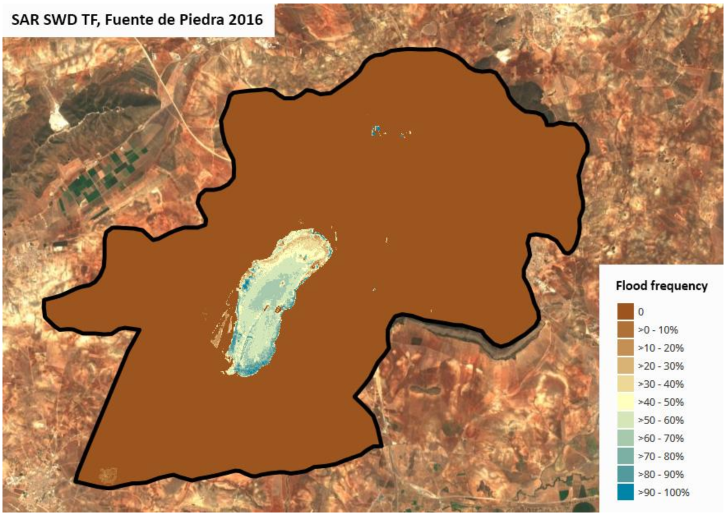

Figure 3. Example of SAR SWD TF product of Fuente de Piedra. Years 2010 to 2016.

4.3. Data and statistical assessment process

The assessment of the studied was done using as in-situ data the environmental variables temperature, precipitation and water level in the wetland. These data were obtained from the Instituto Geologico y Miniero de España (IGME, 2000) and the Nature Reserve authorities of Fuente de Piedra wetland for the hydrological period January 2007-December 2017. Monthly average temperature and precipitation were calculated from two different meteorological stations located within the wetland basin (Cero del Palo, Herriza-Fuente de Piedra). The piezometry data are monthly and daily level measurements obtained from a limnigraph located in a well in almost the centric part of the lagoon.

Assessment for the optical SWD product was made by observing the statistical correlation between the monthly SWE (paragraph 3.1) and the monthly measurements of the selected environmental variables (precipitation, temperature, water level). The risen hypotheses were: 1) Is there statistical correlation between temporal changes in SWE and temporal changes in piezometry level, precipitation and temperature? 2) Which is the most correlated variable with the SWE? 3) What is the confidence level of this assessment?

Statistical analyses of correlation and linear multi regression were conducted. We applied the Spearman correlation analyses (variables were not normally distributed); respectively how the SWE varies with the water level, precipitation and temperature variability. Linear multi regression analysis is a cause-effect relationship and it is used to fit a relationship between two variables such that one can be predicted from the other, respectively cause-effect relationship of SWE variable and environmental condition variables is tested (3).

The assessment process for SAR SWD data (see paragraph 3.2) was done in comparison with the main environmental variable identified, being the water level. In this case, monthly and daily measurements where used. The purpose was to compare both products and to give answer to the hypothesis: Is the SWD indicator derived by SAR increasing accuracy once compared to Landsat SWD indicator?

Spearman correlation analyses (variables were not normally distribution) and linear multi regression analysis were applied for two temporal distribution variables: a) Mean SWE SAR (in ha/month) and mean water level (in cm/month) and b) Daily SWE SAR (in ha/day) and daily water level (in cm/day).

5. RESULTS

5.1. Optical SWD assessment

Statistical correlations results show a significant positive correlation (0.932) between SWE and water level. Temporal trends in SWE and water level move in the same direction, having a slight rise from 2007 to 2015, once precipitation trendlines seems to slightly decrease from January 2007 to September 2015 (Figure 4). However, hydro-graphical results show clear correlation between the water level, SWE and the precipitation during extremely wet years where the high precipitations can be remarkable in water level and SWE but slightly displaced in time (usually in one-month displacement). For example, high precipitation during December 2009 (230mm) and 2010 (140mm) maintain the water level in maximum fee/quotas (150-170cm) and the SWE in maximum extent (1200-1400ha) (blue circles, Figure 4).

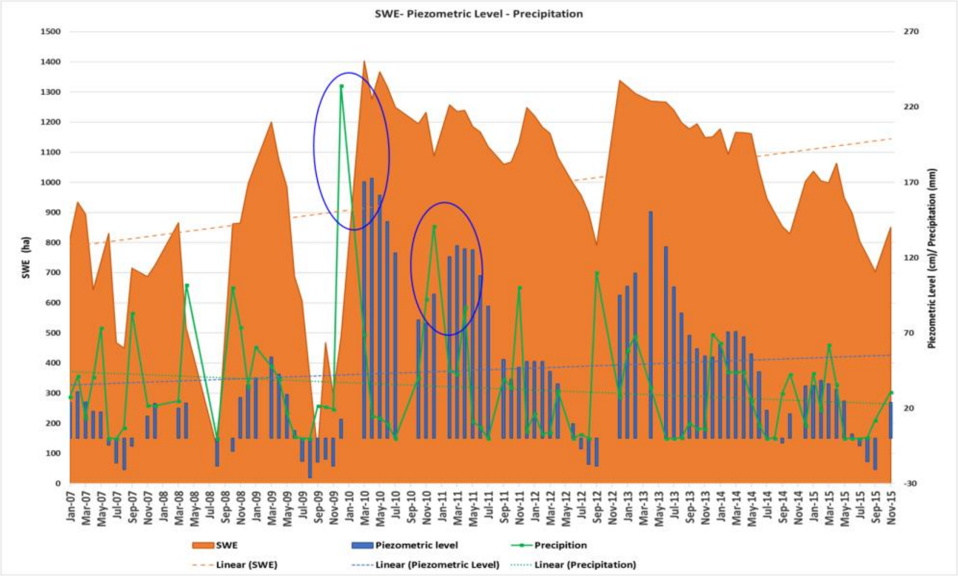

Figure 4. Trend lines between SWE, water level and precipitation variability for the period January 2007-September 2015. Blue circles indicate the highly precipitation months and the notable displaced in the next months.

However mean SWE (for all compared period January 2007-September 2015) is around 970 ha, with a quite high standard deviation (max water extent area = 1404 ha, min water extent area = 105 ha). In minimum 0 or negative water level the SWE detect a minimum water extent about 105ha. It was found a threshold of approximately 30 cm over which the half of the total wetland area is covered by the water.

Further, SWE variable show no significant correlation with precipitation variable and significant negative correlation with temperature variable (Table 1). No significant correlation with precipitation variable might be explained by other hydro-geological effects in the endorheic basin that were not considered in this assessment analysis. Thus, we can expect that not all occurred precipitations are reflected in the wetland SWE. Besides, in the last years it has been observed an important increase in the groundwater pumping mainly by agriculture exploitation, which have decrease the water level in the basin and reflected in the SWE level.

As about the negative correlation with temperature variable, it is of clear understanding that once temperature rise the SWE decries and vice versa. However, to have a better understanding in SWE and temperature correlations it would be necessary to take in account other variables as evaporation, evapotranspiration etc. which are beyond the objectives of the assessment methodology described in this report.

		Mean Temperature (°C)	Mean Precipitation (mm)	Water level (m)
SWE (ha)	Correlation Coefficient	-,296**	,118	**,932****
	Sig. (2-tailed)	,006	,279	,000
	N	86	86	86
Mean Precipition (mm)	Correlation Coefficient	-,597**	1,000	,215*
	Sig. (2-tailed)	,000	-	,047
	N	86	86	86
Piezometriv Level (m)	Correlation Coefficient	-,351**	,215*	1
	Sig. (2-tailed)	,001	,047	-
	N	86	86	86
Mean Temperature (°C)	Correlation Coefficient	1,000	-,597**	-,351**
	Sig. (2-tailed)	-	,000	,001
	N	86	86	86

Table 1. Correlation results

Results from the multi regression model shows a R^2 = 0.644 and water level as the first important predictor for the SWE, while both temperature and precipitation predictor variables were excluded (Table 2). This means that SWE is the best variable in predicting the water extent.

Model	R	R Square	R Adjusted Square	Std. Error of Estimate	Durbin-Watson
1.00	,803a	,644	,640	170,890.00	,683

a. Predictors: (Constant), Water level (cm)

Table 2. Multi regression analysis results

High predictive capacity by water level ground data allows to generate precise simulation models that can help in monitoring water level fluctuations, flood regime and water availability. However, the total predictive level of regression model raises uncertainties. This might come regarded to SWE indicator limitations: 1) the SWE has its´ limitation in detecting water content below vegetation cover, or soils highly saturated in water content; 2) the SWE extraction date does not overlap with the in-situ water level measured date; 3) comparted monthly mean water level, precipitation and temperature with SWE of precise day of same month might create disparity.

5.2. SAR SWD assessment

Spearman correlation analysis shows high correlation factor of 0.936 between mean SWE SAR and mean piezometry level (a). However, multi regression analysis shows that the strength of the predictive model is quite higher (R^2 = 0,849; Table 3) while compared to

Landsat ($R^2 = 0.644$; Table 2), which means that accuracy of predicting SWE by SAR is much higher than predicting from Landsat.

Model	**R**	**R Square**	**R Adjusted Square**	**Std. Error of Estimate**
1.00	,920[a]	,847	,841	14,037,534.00

a. Predictors: (Constant), Mean Water level (cm)

Table 3. Multi regression analysis results.

The second assessment process using the daily variables (b) shows not significant differences in correlation factor, unlike the correlation between daily SWE_SAR and water level seems to be slightly lower (0.858) compared to Landsat SWE (0. 932), explained by the fact that additional hydrological behaviours as the surface evaporation and evapotranspiration processes, especially during the summer, are translated into underground flows and thus in the water level.

However, Figure 5 shows clearly how the daily trends in water level are reflected in the SWE. Approaching in the dry summer period, it is observed a short transit period where the water level remains in positive values while the SWE is almost very low or 0 (red circle Figure 5).

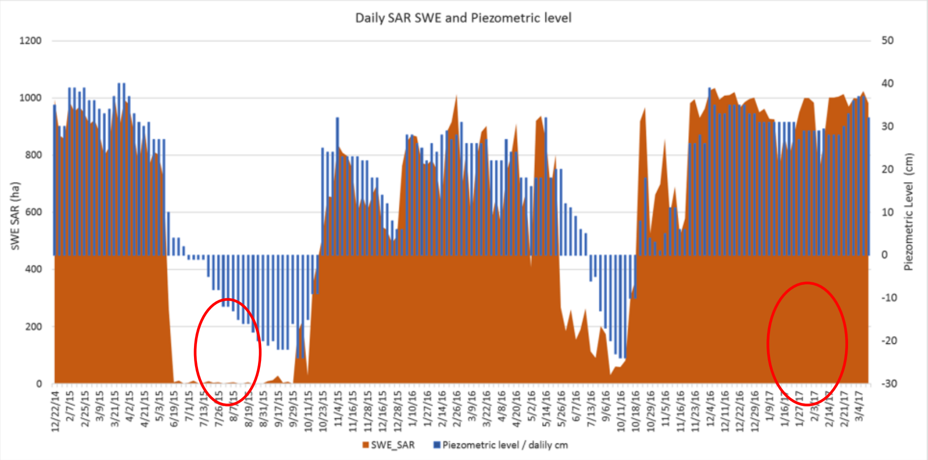

Figure 5. Graphic between daily SWE-SAR variability (in ha) and daily water level variability (in cm) for the period December 2014- March 2017.

6. CONCLUSIONS AND RECOMMENDATIONS

Overall result indicates the high capacity of both SWD products to identify very low water presence in the land surface and give accurate estimations of the water quantity we have available for corresponding water level and its variation.

SAR SWD indicator seams to give high predictive capacity comparing the use of Landsat SWD indicator. However, it would be proper to have a longer assessment period to minimize the level of uncertainty, since Sentinel 1 data are only available from 2014.

Once compare to SAR SWD indicators, the optical SWD indicator seems to overestimate the SWE detected. This probably comes from the low temporal resolution of Landsat imagery (14 days), where SWE were calculated as a mean of maximum three images per month. In case of SAR, the SWE were calculated as a mean of maximum eight images per month, which increase the detection on monthly SWE variation (temporal resolution of Sentinel 1 is 5 days, and without cloud limitations).

As conclusion, we could affirm that SWD indicator (by both sensor Landsat, SAR) is a proper indicator that can help in monitoring water dynamics, identifying areas with high water accumulation in high runoff periods or areas that remain water during extreme drought periods. Those, information supports stakeholders in planning purposes in terms of mitigation, areas of immediate action, areas of strict conservations, etc.

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