WP3
Monitoring network improvement for coastal flooding and extreme weather risk management

Activity 3.1
Satellite monitoring for coastal impacts of flooding and extreme weather

D3.1.3 Manual on the developed GBSatAdria SW

PROJECT AND ACTIVITY DETAILS

Project Acronym	AdriaMORE
Project title	Adriatic DSS exploitation for MOnitoring and Risk management of coastal Extreme weather and flooding
Funding Line	Priority Axis 2, Specific Objective 2.2
Program website address	http://www.italy-croatia.eu
Project Partners	LP Abruzzo Region (Italy) P1 Dubrovnik and Neretva Region (Croatia) P2 Meteorological and hydrological service (Croatia) P3 National Research Council (Italy)
Starting date	January 1, 2018
Project length	18 months

Activity	3.1.
Activity Title	Satellite monitoring for coastal impacts of flooding and extreme weather
Work Package	WP3: Monitoring network improvement for coastal flooding and extreme weather risk management
Executive Summary	Activity 3.1, within Work Package 3, is dedicated to satellite observation and statistical analyses of those parameters, such as suspended terrigenous material (TSM) and chlorophyll (Chl) concentration, that may mark desirable/undesirable effects along coasts.
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Data of issues	January 31, 2019
Total Number of pages	21
Distribution list	Italy-Croatia CBC Programme, AdriaMORE partners

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0. INTRODUCTION

Coastal regions are complex environments where geological, biological, and physical processes interact each other. About 50% of the European Union (EU) territory lies on shorelines, 27 member states have coastlines, nearly 50% of its citizens live within 50 km of the coast and 3.5 million EU inhabitants are directly employed in maritime activities. Despite of their importance, several coastal areas have been facing the persistent loss of land due to human interventions and/or natural causes.

Moreover, strong anthropization of coastal (and in-land) environment, over-exploitation of natural resources, and climate change affect the natural amount of phytoplankton along coasts and, therefore, represent a continuous threat to the biodiversity in coastal waters. In particular, a concerning risks for coastal waters is the increase in nutrient inputs of terrestrial/anthropogenic origin that can lead to undesirable modifications of phytoplankton concentration (i.e., eutrophication).

Long-term sustainability of coastal regions mostly depends on the maintenance of the fragile balance between sedimentation supply from rivers and bio-geochemical processes. Coastal plumes are therefore crucial pathways that need to be monitored and analysed. Their pathways and long-term evolution is a key challenge for a thorough understanding of what drives costal geomorphology and eutrophication. Inferring sediment availability and dynamics along shorelines constitutes therefore the primary need for coastal changes while monitoring chlorophyll (Chl) concentration, which is a proxy of phytoplankton biomass, is an efficient tool for recording and understanding the response of the marine ecosystem to human pressures and thus for detecting eutrophication.

1. STATISTICAL TRENDS FROM REMOTE SENSING OBSERVATIONS IN OCEAN COLOUR

Satellite Ocean Colour (OC) data represent an essential observational tool that offers a unique view of the natural environment due to their synopticity and their high temporal and spatial resolution. These characteristics address, indeed, the spatial features of eutrophication phenomena, which cannot be detected from in situ, sparse monitoring stations. Offshore buoys are not often able to represent the complex spatial pattern of Chl concentration trends that are caused by a combination of different environmental factors (such as coastal currents, bathymetry, and river runoffs) and human pressures. At global scale, several works estimated biogechemical trends by using satellite data. Here we performed a satellite-based analysis in the Adriatic Sea.

On the other hand, estimating trends for Total Suspended Matter (TSM) is crucial for quantifying natural and human-made effects on coastal changes by means of remote sensing. Indeed, such an approach will allow us to diagnose sediment mass availability along the coast.

1.1 Detecting Chl and TSM trends in the Adriatic Sea

Here we use Chl and TSM products from the Coastcolour project, launched by ESA to fully exploit the potential of the MERIS instruments, provides us a complete (from 2003-01-04 to 2012-04-07, when the mission ended) series of ocean optics observation of a set of basins, where the presence of case 2, optically complex waters is important. The Coastcolour Product User Guide, available within, completely describes the scope, the reasons, the approach and the products of the project (http://www.coastcolour.org/).

We remove seasonality by using the so-called X-11 decomposition procedure for investigating the temporal variation of OC products. This approach allows variations in the annual cycle by decomposing the original time series into seasonal, irregular and trend-cycle terms [Gregg et al., 2005; Behrenfeld et al., 2006; Barale et al., 2008; Colella et al., 2016].

1.2 Methods

For trend estimation we coupled the Mann-Kendall test and the Sens's method, which are here applied to a de-seasonalized monthly time series as obtained from the X-11 technique. The dataset covers the time period spanning from 2003-01-04 to 2012-04-07, with a daily temporal resolution and a spatial resolution of 300 m. Because the seasonal component can mask small movements in the trend signal, we remove the seasonal signal from Coastcolour chlorophyll dataset before determining the Chl and TSM trend. We use is the X-11 seasonal adjustment methodology (Shiskin, 1978; Dagum, 1980), which is similar to that described in the framework of the X-12-ARIMA seasonal adjustment program of the U.S. Census Bureau (Findley et al., 1998), and that it was already used by Pezzulli et al., (2005) to remove the seasonal signal from Sea Surface Temperature data. This seasonal adjustment method assumes that the time series Y_t can be decomposed into three components: the seasonal signal S_t, the trend component T_t, and an irregular component I_t:

$$Y_t = T_t + S_t + I_t \tag{1}$$

The de-seasonalized time series is then obtained through an iterative process. We first estimate the T_t^1 component by using a 13-term moving average. From this component we derive the de-trended time series

$$SI_t{}^1 = Y_t - T_t^1. \tag{2}$$

Hence, a weighted five-terms moving average is applied to SI_t^1 to derive a preliminary estimate of the smoothed seasonal factor S_t^0, which is then averaged with a 13-term running window, i.e., $M_{2x12}(S_t^0)$. The resultant signal is then normalized as

$$S_t^1 = S_t^0 - M_{2x12}(S_t^0). \tag{3}$$

Finally, S_t^1 is used to derive the initial seasonal adjustment (SA_t^1):

$$SA_t^1 = Y_t - S_t^1 \tag{4}$$

An improved estimate of the trend component T_t^2 is also computed by applying a Henderson trend filter with asymmetric weights to SA_t^1. Therefore, the original time series is de-trended again as

$$SI_t{}^2 = Y_t - T_t^2. \tag{5}$$

Hence, a 7-term seasonal moving average is applied to $SI_t{}^2$ to obtain S_t^2, which is averaged with a 13-term running window i.e., $M_{2x12}(S_t^2)$. The final estimate of the seasonal factors is then obtained as:

$$S_t = S_t^2 - M_{2x12}(S_t^2). \quad (6)$$

The resultant de-seasonalized time series is

$$SA_t = Y_t - S_t \quad (7)$$

To estimate the magnitude of the trend ($mg \cdot m^{-3} \cdot yr^{-1}$) and its significance the Mann Kendall test and the Sens's method (Mann, 1945, Kendall., 1975, Sen 1968) was applied to SA_t.

The rank-based non-parametrical Mann-Kendall (MK) test is the most widely used test (Yue et al., 2002, Aziz et al., 2006, Bulut, 2008) to detect if there is an upward or downward trend of the variable of interest over time.

The MK test is based on the test statistic, S, and it variance, Var(S), defined as:

$$S = \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} sgn(x_j - x_i) \quad (8)$$

$$sgn(x_j - x_i) = \begin{cases} 1 \ \text{if} \left(x_j - x_i\right) > 0 \\ 0 \ \text{if} \left(x_j - x_i\right) = 0 \\ -1 \ \text{if} \left(x_j - x_i\right) < 0 \end{cases} \quad (9)$$

$$Var(S) = \frac{1}{18}\left[n(n-1)(2n+5) - \sum_{p=1}^{q} t_p(t_p - 1)(2t_p + 5)\right], \quad (10)$$

where x is data point at times i and j (j > i), and n is number of data, q is the number of tied groups (a tied group is a set of sample data having the same value), and t_p is the number of data points in the p-th group.

The statistical significance of the test is computed by using the Z value defined as:

$$Z = \begin{cases} \frac{S-1}{\sqrt{Var(S)}} & \text{if } S > 0 \\ 0 & \text{if } S = 0 \\ \frac{S+1}{\sqrt{Var(S)}} & \text{if } S < 0 \end{cases} \quad (11)$$

If |Z| is greater than $Z_{1-\alpha/2}$, where α represents the chosen significance level, then the trend is significant. The magnitude of slope, β, can be determined using the Sen's method as follow:

$$\beta = Median\left[Q_k = \frac{x_j - x_i}{j-i}\right] \quad (12)$$

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