TEMPORAL VARIABILITY IN MERIS WATER CONSTITUENTS MODELLED BY STL DECOMPOSITION IN SW IBERIAN PENINSULA: SAGRES

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ABSTRACT

The MERIS time series for chlorophyll *a* (Chl*a*, from MERIS standard Algal Pigment Index 1 algorithm), total suspended matter (TSM) and yellow substances (YS) are investigated in this work. The study focuses on the temporal variability of the MERIS water constituents off Sagres, in Southwest Iberian Peninsula using stl.fit(), which has been used to decompose the MERIS time series into seasonal (S_t), trend (T_t), and irregular (I_t) components. This approach has the advantages of Seasonal-Trend decomposition procedure based on Loess (STL): it can identify seasonal components changing over time, it is responsive to nonlinear trends, and it is robust in the presence of outliers. Stl.fit() is an automatic procedure that selects the best model based on the lowest error measure by varying the values of the smoothing parameters (s.window and t.window). One of the main outcomes of the decomposition of the time series is that MERIS water products have a strong seasonal component, with increasing dominance from inshore to offshore.

1. INTRODUCTION

Satellite ocean colour remote sensing provides a valuable source of information on the status of marine ecosystems. From 2002 till 2012 the MEdium Resolution Imaging Spectrometer (MERIS) ocean colour sensor onboard the ENVISAT satellite of the European Space Agency measured radiances emerging from the sea to quantify optically significant constituents [1]: chlorophyll a (Chl*a*, obtained through MERIS standard Algal Pigment Index 1 algorithm), total suspended matter (TSM) and yellow substances (YS). This data provides information on phytoplankton biomass and transparency through Chl*a* and TSM, respectively, at large temporal and spatial scales, allowing an understanding of the ecological dynamics [2]. The concentrations of Chla and TSM also contribute to assessments for the "good ecological status" of the European Union (EU) Water Framework Directive 2000/60/EC, and for the "good environmental status" of the EU Marine Strategy Framework Directive, 2008/56/EC.

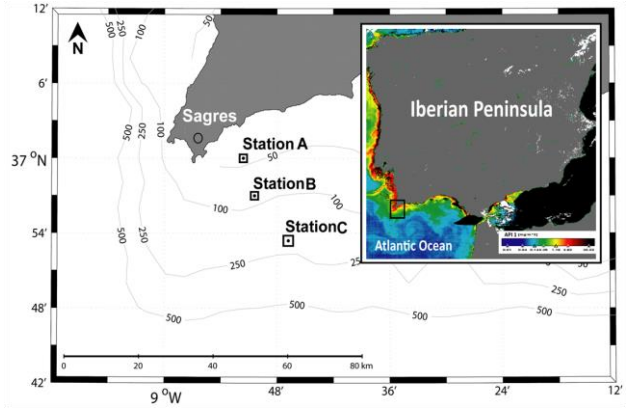

Figure 1. Sagres study site with sampling Stations A, B and C, source: [3].

The present study evaluates the temporal variability of the MERIS water constituents off Sagres, in southwest Iberian Peninsula (Fig. 1). This is one of the MERIS validation study sites, where *in situ* water samples and radiometric measurements were taken from 2008 till 2012, to assess the uncertainties related with the MERIS ocean colour products [4, 5].

To study the time series for Chl*a*, TSM, and YS, a Seasonal-Trend decomposition procedure based on Loess (STL) [6] was applied to decompose the seasonal (S_t), trend (T_t), and irregular (I_t) components using non-parametric regression. The STL decomposition was chosen over other decomposition methods, because it has several advantages, including changing the seasonal component over time and specifying a decomposition that is robust to outliers.

Although STL is already available within the R software, stl()[7], there are significant drawbacks for researchers using this approach; e.g., they often use the default smoothing parameters, instead of specifying them. To overcome these drawbacks, the authors have developed an algorithm, stl.fit(), that selects the best STL model by varying the seasonal and trend smoothing parameters [8]. The choice of the best model is performed by minimizing an error measure. In this case study, the error measure chosen was the Root Mean Square Error (RMSE), although others measures can be chosen, such as the Mean Absolute Percentage Error.

The best data fitting will lead to a model that best describes the stochastic behaviour of the time series; i.e. the one that best captures its dynamics, and so leads to a better inference analysis. The stl.fit() procedure will be made available in the R software, so that it is accessible to a wider community, including other fields of research.

The daily satellite products, extracted from MERIS Level 2 reduced resolution images, were aggregated into monthly means, and the missing observations were estimated by linear interpolation.

Overall, the study characterizes the seasonal and trend patterns of the satellite-derived data, and then relates these patterns to environmental changes and possible causes. These components are useful for a better understanding of the temporal variability of the MERIS constituent products at Sagres.

2. DATA AND METHODS

The extraction of the MERIS time series products are described in [4]. The stl.fit() was applied to 10 years of monthly MERIS time series for API 1, TSM and YS from Sagres between July 2002 and March 2012 at three sampling Stations A, B and C (Fig.1). The stl.fit() procedure was developed and implemented to run under the R software [7] (Fig. 2). After the decomposition of the MERIS time series products, the interquartile range (IQR) was used to assess which component was contributing the most to the observed changes over the time series. An analysis was made of the inter-annual variability in the seasonal component of the MERIS water constituents.

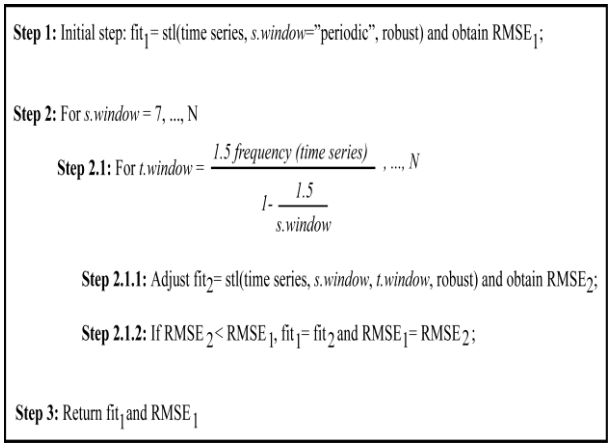

Figure 2. Schematic view of stl.fit(),[8].

3. RESULTS

3.1 Decomposing MERIS time series products using stl.fit()

For all three Stations, the amplitude of the seasonal term of the API 1, TSM and YS (Fig. 3) decreases, and then increases, towards the end of the of the time horizon. This is most evident for the MERIS API 1 product. The trend component for the three water products shows a marked decrease between July 2002 and March 2004 at Station A.

In terms of IQR (Tab. 1), the seasonal component dominates the observed changes over the time series for the MERIS water constituents (Fig. 3).

Table 1. Dominant components (in bold) based on the interquartile range (%) for the MERIS products at Stations A, B and C.

	Station A			**Station B**			**Station C**		
	S_t	**T_t**	**I_t**	**S_t**	**T_t**	**I_t**	**S_t**	**T_t**	**I_t**
API1	75.1	33.9	**76.1**	**75.3**	27.0	19.6	**93.6**	12.7	27.1
TSM	**69.2**	27.5	41.5	**94.9**	26.0	37.4	**62.4**	24.8	52.2
YS	**75.7**	32.9	51.2	**64.9**	28.2	36.6	46.2	18.0	**53.4**

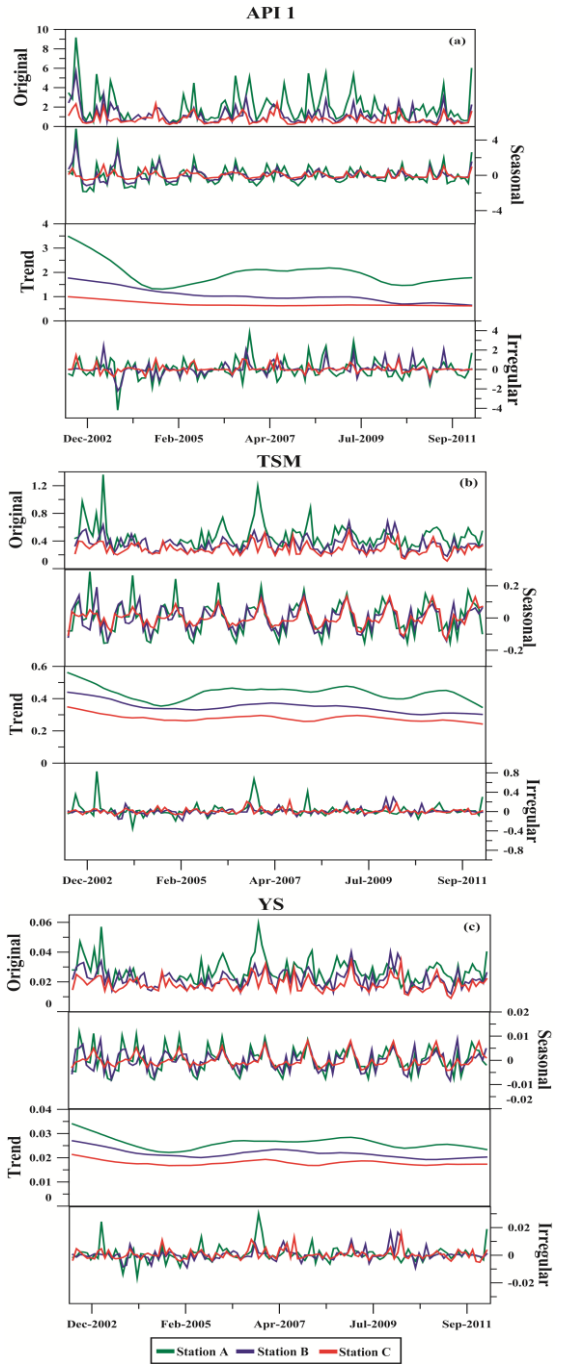

Figure 3. Decomposition plots of MERIS API 1(a), TSM (b) and YS (c) at the three stations using the stl.fit().

3.2 Analysis of the inter-annual variability

The seasonal plot has been used to observe the inter-annual variation of the seasonal component (R function season() in the forecast package [9]). The year-to-year variation of the seasonal component can be seen more clearly over time, and thus any marked changes in the seasonal pattern can be easily identified [10].

The seasonal plots show the months with the highest variability at each station decreasing from Station A to Station C for the three water constituents (Fig. 4).

The seasonal variability can be summarised as follows:
-API 1 at Stations A and B shows high variability in the months of June, December and then between the spring months of March and April, but less pronounced in Station B;
-TSM and YS at Station A exhibits similar high variability between July to October for TSM and between June to October for YS;
-TSM and YS products at Station B present notable variations between the months, except for January and November;
-Station C shows only small changes over the years for the three products (Fig.4).

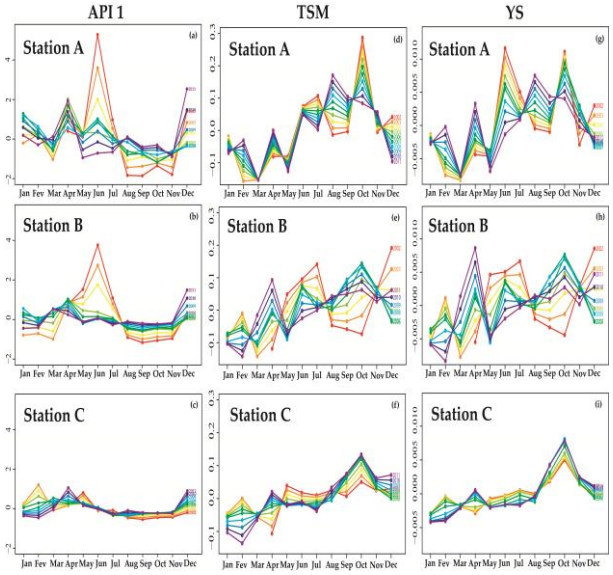

Figure 4. Seasonal variability of the API 1, TSM and YS at Stations A, B and C.

4. DISCUSSION AND CONCLUSIONS

Stl.fit() is a good option for modelling remote sensing time series, particularly, those addressing inter-annual variations.

The decomposition of MERIS water products with stl.ft() shows a seasonal component, with increasing dominance from inshore to offshore.

The inter-annual variability for the seasonal component of the MERIS AP1, TSM and YS at the Sagres stations shows the months with the highest variability at each station (see section 3.2). These results provide important information about periods when management action might be needed, for example, for aquaculture activities, or when *in situ* sampling should be made.

Future studies should also take into account the physical and climatic variables that are related to and influenced by the water constituents off Sagres.

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