# Coastal Water Classification Using Remote Sensing Data

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## Abstract

**In this paper, we propose a coastal water quality classification using remote sensing data combined with an optimized fuzzy system. The water classification is based on pollution map derived from surface water map's of four water quality parameters: Turbidity "Turb", Secchi Disk Depth "SDD", Suspended Sediments Concentration "SSC" and Chlorophyll-A "Chl-A" estimated from satellite data. Each water map is processed by an hybridization of fuzzy model and genetic algorithm which is modeled by a set of fuzzy rules extracted from the data through two steps procedure. First, fuzzy rules are generated by unsupervised fuzzy clustering of the input data. In the second step, genetic algorithm is applied to optimize the rules. Our contribution is focused on the use of Pollution Signature Draw (PSD) tool in characterizing water quality of some typical sites. This PSW gives the concentration of each parameter and presents useful information to highlight the pollution degrees of the studied sites. The proposed approach was tested on Algiers bay and has highlighted four pollution levels corresponding to High Pollution (HP), Medium Pollution (MP), Low Pollution (LP) and Clear Water (CW).**

**Keywords:** Water classification, Mapping; Fuzzy system; Genetic algorithm; Pollution Signature.

## 1. Introduction

Unfortunately, the 1200 kms of Algerian coast is considered like as garbage for a different dismissal's types. Worn-waters, urban and industrial rubbishes are all poured at the sea and, so, every year the sea is a source of several diseases. In spite of all the environmental ministry efforts, the statistic results related to the urban and industrial rejects poured in Algiers's coast are alarming [1].

The current environment's ministry methods for establishing water quality are analysis and measurements done in laboratories. While these techniques are very accurate, however they remain insufficient and very expensive for assessing and monitoring water quality on Algerian coast that extends on 1200 km. Actually, remote sensing can overcome this constraint by providing an alternative for water quality monitoring over a range of temporal and spatial scales. Imagery from recent satellites with improved spectral and spatial resolution and the integration of the Geographic Information System (GIS) technologies offer a valuable tool for developing management plans for water pollution and thus allowing quicker and more effective actions to be taken. In this work, we are interested to this type of data to, first, map water quality indices. Then construct Pollution Signature Draw PSD in order to characterize the quality of this water. Finally, we propose a new water quality classification to highlight most polluted sites of Algiers bay.

Remote sensing of water quality monitoring is evaluated by several substances which affect its optical properties. Conventionally, three main components are used to estimate marine water quality in coastal areas. These components are: Suspended Particulate Matters "SPM", chlorophylls "Chl" and dissolved organic matter "DOM" [2]. To these components, we are also interested to water Turbidity (Turb) and its transparency measured by Secchi Disk Depth (SDD).

Various approaches have been developed to estimate coastal water quality parameters from remote sensing data. Due to the simultaneous presence of the three main water components, the relation between water components and remotely subsurface reflectances is complicate and is considered as no-linear. So, the first developed algorithms were empirical and semi-analytical models [3][4]. With the increase of spectral information and the complexity to solve the inverse model, new estimation algorithms inspired from natural phenomena have emerged. Neural networks were successfully used to implement the inverse model and to properly address the non-linearity problem [5]. Besides neural networks, fuzzy systems have proved to be particularly effective in identifying non-linear models too [6]. The most popular approach to fuzzy modeling is based on the identification of fuzzy rules, which describe in linguistic terms the water parameters concentration/ marine subsurface reflectance relationship. Furthermore, an optimization process is usually added to tune these fuzzy rules so that the fuzzy method implements the desired inverse model. Using this approach, a mapping process of coastal water classification is proposed in order to estimate the boundaries of coastal zones according to different water types. To attend this goal, we have followed the next steps:

- **Coastal Water mapping:** water quality maps are estimated using an optimized fuzzy system using the combination of remote sensing data and in-situ measurements. It consists of identifying fuzzy rules [7] which determine the actions that water index must perform if some conditions on multispectral reflectance $R_i$ are satisfied. These rules are extracted from an unsupervised clustering of input-data depending on related membership functions, here we considered a triangular membership functions (see figure 1). After, an accurate definition of the rules coefficients is assigned to genetic algorithm (GA). This latter searches the best chromosomic structure that codifies the different parts of the fuzzy rules to give best optimization results.

- **Coastal water characterization:** in this part, we focused our interest on the use of PSD tool to water quality characterization which is evaluated by analyzing several types of PSDs related to typical sites in order to select the most representative's ones.
- **Coastal water classification:** the main PSDs of typical sites are selected and introduced in maximum likelihood classifier in order to generate a pollution map related to Algiers bay. For this site, four pollution levels corresponding to "High pollution", "Medium Pollution", "Few Pollution" and "Clear Water" are considered.

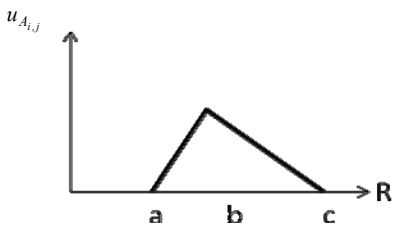


**Fig. 1.** Triangular membership functions.

Our paper is structured as follows; in section 2 we present the procced data used to carry out our approach. The estimation principle of coastal water index maps is described in section 3 where an hybridization of fuzzy model and genetic algorithm is used. Coastal water characterization is outlined in section 4. After, coastal water classification map is presented in section 5. Finally, in section 6, conclusions on the developed process are presented in order to show the contribution of remote sensing data to monitor the coastal water pollution.

## 2. Processed data

To carry out our approach, we have used one image corresponding to ETM+ of Landsat7 satellite covering Algiers bay. We have also used a set of in-situ measurements of SPM, Chl, Turb and SDD collected in Algiers bay. 300 samples of punctual measurements were provided by Institut National des Sciences de la Mer et de l'Aménagement du littoral (ISMAL) covering the studied area. The green points of figure 2 show their geographical locations on ETM+ image. According to the available data $y_i = (SPM, Chl, Turb, SDD)$, we have built a set of data $(R_i, y_i)$ relevant to subsurface reflectances $R_i$ and in situ concentrations $y_i$. Finally, we randomly split the data into two subsets, the training-set composed of the 2/3 of initial data is used to define the fuzzy model whereas the test-set to evaluate its performances.

**Fig. 2.** Composed color of ETM+ image (Red: TM1, Green: TM2, Blue: TM3) acquired on Algiers bay.

## 3. Coastal Water mapping

Coastal water mapping is based on fuzzy rules expressing a set of conditions which assign each pixel to a water type under the form of Takagi-Sugeno-Kang (TSK) rules. The premises of these rules depend on the fuzzy sets $A_{i,j}$ defined on the reflectance domain and the consequences present the local linear $y_i$ model form, like shown by equation 1 [8].

$$\begin{aligned} \text{Rule}_i : &\text{If } (R_1 \text{ is } A_{i,1}) \& \ldots \& (R_M \text{ is } A_{i,M}) \\ &\text{Then } y_i = p_{i,0} + p_{i,1} R_1 + \ldots + p_{i,M} R_M \end{aligned} \quad (1)$$

Thus, to each cluster $C_i$, we assigned a fuzzy set $A_{i,j}$ and the output $y_i$ of in-situ concentration variation is assumed to be locally linear and expressed as following relation: $y_i = p_{0,i} + p_{i,1} R_1 + p_{i,2} R_2 + \ldots + p_{i,M} R_M$, where $R_M$ are the $M$ subsurface reflectances and $(p_{i,0}, p_{i,1}, p_{i,2}, \ldots, p_{i,M})$ are real numbers. More details about the used algorithms partitions are given in [9].

After applying fuzzy partition to our training database, to each cluster $C_i$ we define a fuzzy set $A_i$ and associate a triangular membership function characterized by its parameters (a,b,c), where $b$ corresponds to the abscissa of triangle vertex and $a$ and $c$ are deduced as the intersection of the abscissas axis with the lines on the left and the right sides of $b$; Figure (3.a) shows an example of memberships functions corresponding to each spectral reflectance for SPM index. Recall that these coefficients must be estimated as accurate as possible in order to have an accurate coastal water maps. Then, we applied them to genetic algorithm.

For our application, the chromosome codifies the membership function $(a, b, c)$ of the fuzzy sets coefficients as shown in figure 4. We defined the fitness value as the inverse of the Mean Square Error MSE. Also, we apply the arithmetic crossover and the uniform mutation operators to generate a new population [10]. Chromosomes to be mated are chosen by using the well-known roulette wheel selection method, which associates to each chromosome a probability proportional to its fitness value. We fixed the probability of crossover and mutation to 0.9 and 0.1, respectively. When the average of the fitness values of all the individuals in the population is greater than 99% of the fitness value of the best individual or a prefixed number of iterations has been executed, the GA is considered to have converged [9].

Furthermore, wanting to examine how the optimization influences to adjust the fuzzy rules, we present in Figure (3.b) variation plots of the optimised membership coefficients (a, b, c) around their initial values resulting from the fuzzy estimation for SPM index. Globally, it can be seen that in $R_1$, $R_2$ and $R_3$ channels, the membership functions present a little changes and the points are around the bisectors. Since the SPM concentrations affect mainly the visible spectrum [11], the fuzzy modellisation offers a good interpretation of their variations and deduces accurately model coefficients. Morever, the points are more scattered around the bisectors and more adjustments are recorded for $R_4$, $R_5$ and $R_7$ optimisation.

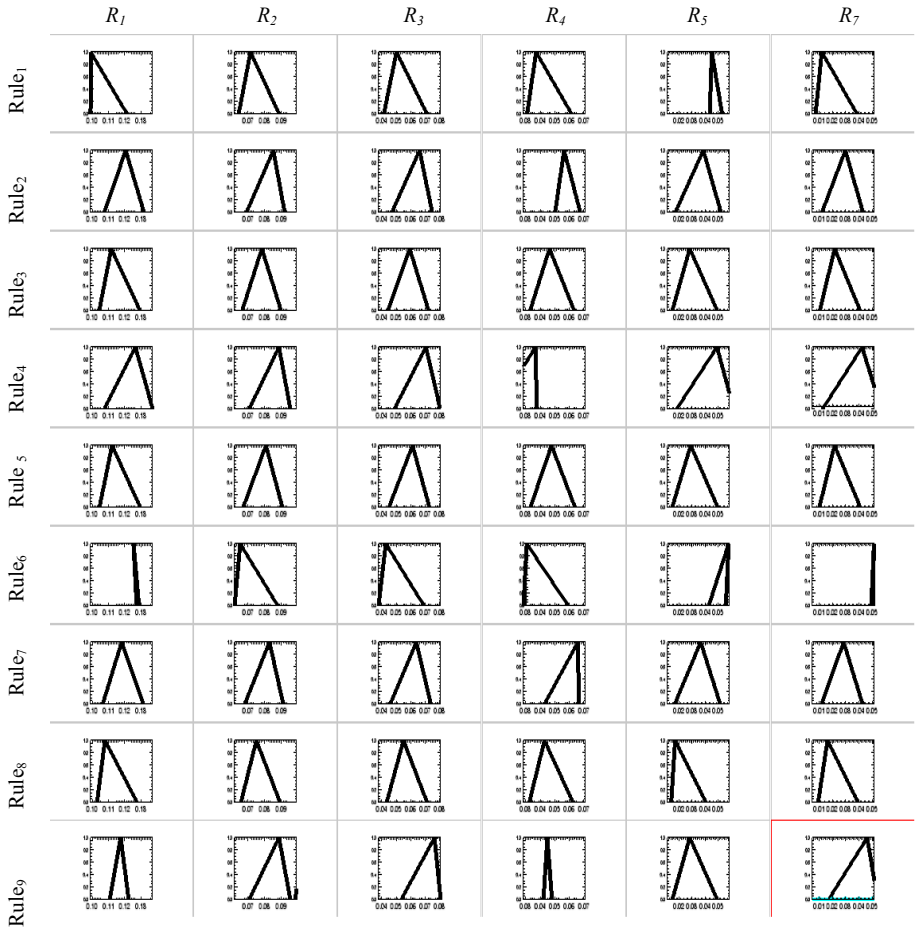


Fig. (3.a). Basic Rules of the fuzzy system used to estimate SPM parameter before GA.

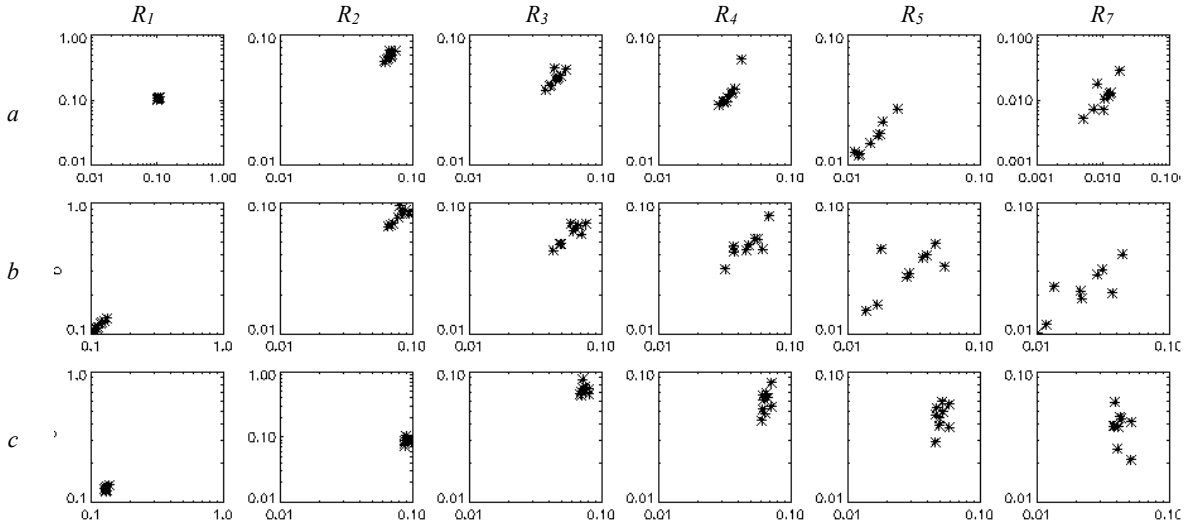


Fig. (3.b) Optimized coefficient a (respectively b, c) versus fuzzy coefficient a (respectively b, c) for each image channel (R1,…, R7).

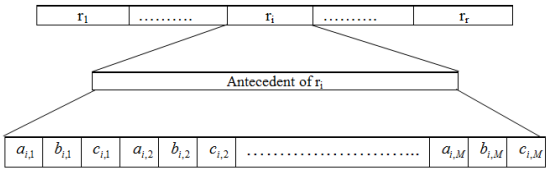


Fig.4. Chromosome codification

The described process was applied to Algiers bay Landsat7 ETM+ image acquired on 03 june 2001 to generate water maps related to each water Index. Table 1 presents an example of statistics results of SPM estimation before and after optimization. We estimated the SPM concentrations and evaluated the performances of the fuzzy model by calculating the mean square error MSE and the correlation coefficient $\rho$. We noticed that fuzzy estimation gives satisfactory results. Furthermore, the optimization process improves these results, the correlation coefficient is increased from 91% to 98%.

**Table 1.** Statistic comparison of SPM estimation process.

| | Fuzzy model | | Genetic optimization | |
|---|---|---|---|---|
| | *MSE* | $\rho$ | *MSE* | $\rho$ |
| Training data | 0,0081039 | 0,9142 | 0.0015308 | 0.9842 |
| Test data | 0,0084515 | 0,9093 | 0.0021842 | 0.9762 |

After optimization, the fuzzy coefficients were applied to full ETM image. The resulting maps represent the spatial variability of water constituents (SPM, Chl, Turb and SDD) in coastal and marine surfaces. To examine this variability, we present in figure 5 the maps in pseudo-colours.

For all maps, it is obvious notice that the high parameters values are located near the coast and this phenomenon is more important for the Algiers bay. For example, the concentration of the SPM parameter is closed to 1300mg/l near the coast. In fact, the data partition revealed nine clusters ($C_i$) which correspond to 9 nine rules (equation 1). This means that this site has a high risk of pollution and presents a complex system requiring a high number of rules to interpret this wide variability. This information motivates us to exploit the results maps and propose a new tool to characterize the water quality, to localize the sources of pollution and identify the most polluted sites of Algiers bay.

## 4. Coastal water characterization

The pollution signature draw exploits the obtained maps of figure 5 and provides a tool to evaluate the water quality at any point of the bay. This signature gathers in the same graph the marine indices in the following order: SPM, Chl, Turb and SDD and presents the normalized concentration of each index.

Figure 6(a) shows an example of PSD taken at different distances of wadi Elharrach. In the same graph, we reported a PSD taken at the large of the bay and considered as a reference PSD (purple color). Compared to this latter, we note high concentrations of SPM, Chl, Turb recorded just at the embouchure of the wadi. The discharges poured at the wadi are transported at several meters, and even kilometres from their source as it is illustrated by the PSDs taken at 300m, 900m, 1500m and 3000m from the wadi.

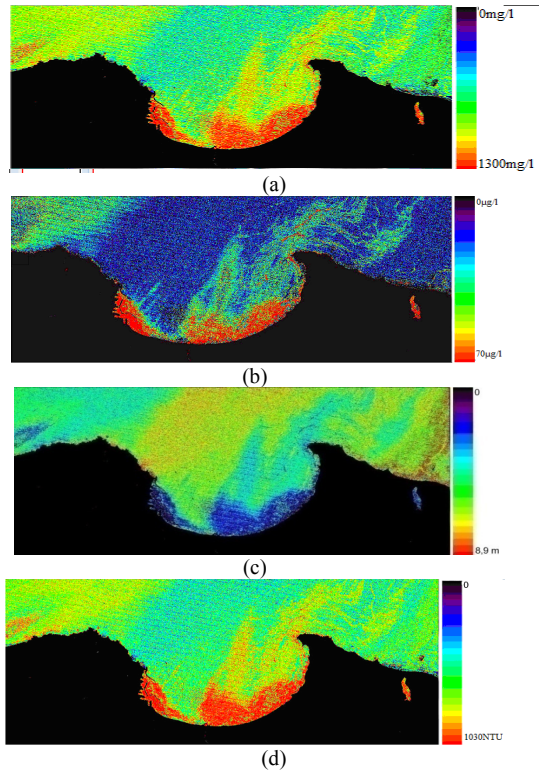


**Fig. 5.** Coastal water indices maps for Algiers bay. (a). SPM map, (b). Chl map, (c). SDD map and (d). Turb map.

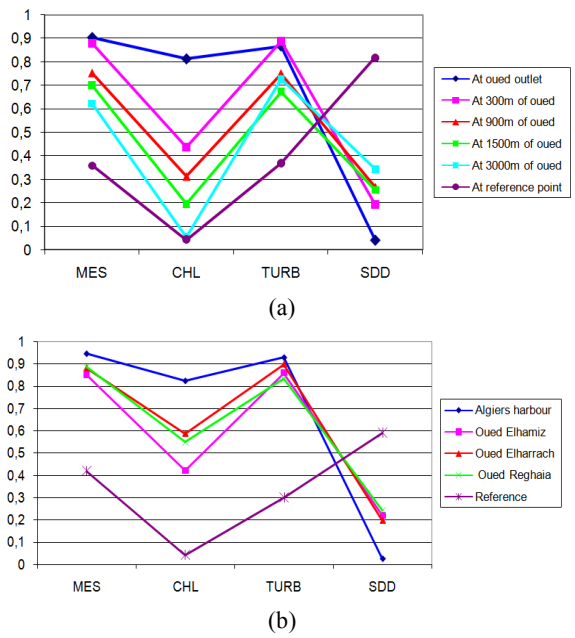


**Fig. 6.** Example of pollution signature. (a). PSDs taken at different distance from wadi Elharrach, (b). PSDs taken at different sites.

These constations are coherent with histogram analysis of two ROIs extracted from wadi ElHarrach and reference area presented in figure 7. İt can be seen that wadi ElHarrach water

index has highest concentration and has more dence histogram than those extracted at reference area.

Furthermore, the comparison between the PSDs of different sites provides an appreciation of water quality by its degree of pollution and hence, allows the detection of the risky sites. Figure 6(b) shows the average PSDs taken at risky sites (Algiers harbour, Wadi Elharrach, wadi Elhamiz and wadi Reghaia). We also reported in the same graph a reference PSD taken at the large of the bay. It can be seen that Algiers harbour has the highest signature.

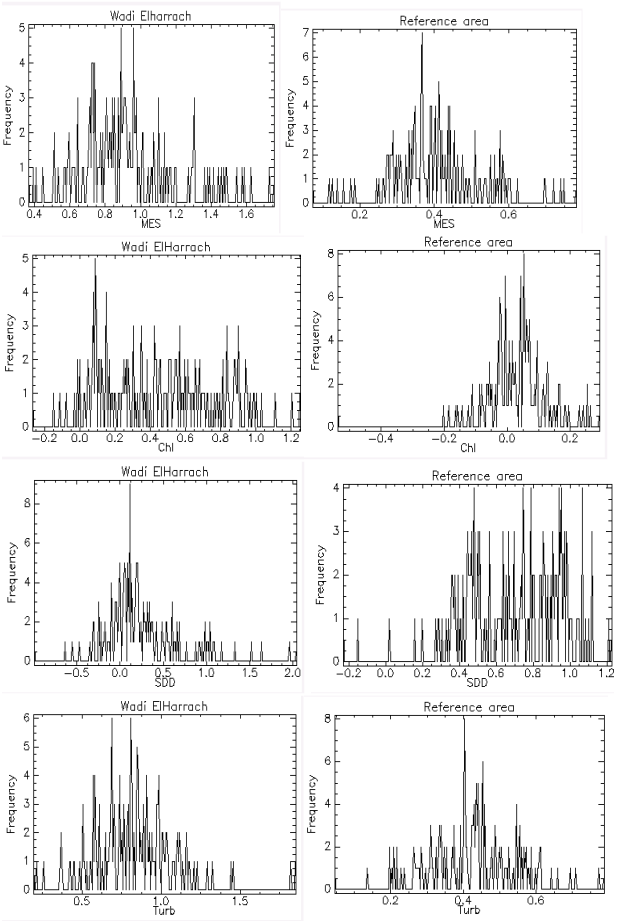


**Fig.7.** Histogram analysis of ROIs extracted at diffrent sites for differnt water index.

## 5. Coastal water classification

Water classification based on the nature of waters components was proposed by Morel and Prieur [12]. Waters of the Case-I are those for which phytoplankton has a role in determining the water optical properties. Whereas the Case-II are determined or strongly influenced by the particulate and dissolved organic matter including the main water constituents as SPM, Chl and DOM. This classification is widely used until nowadays. In this context and from forementioned findings, we typify Algiers Bay coastal waters on the basis of the PSD characterization.

The analysis of some PSD related to risky sites (figure 6(b)) allows the evaluation of the pollution degree of these sites. Indeed, the PSDs of wadi Elharrach and Wadi Reghaia are similar. These sites are characterized by the same type of discharges (industrial discharges and wastewater). Also, wadi Elhamiz has a low PSD value compared to those of wadi Elharrach and wadi Reghaia, but it remains significant when compared to the reference PSD. Thus, Algiers harbour is assigned to case-I (Strong Pollution), Wadi Elharrach and Wadi Reghaia are affected to the case-II (Average Pollution) while Wadi Elhamiz is considered as case-III (Slight Pollution).

From risky sites relevant to different cases of water quality (Strong pollution, Average Pollution and Slight Pollution), we have selected some ROIs (region Of Interest) and extract their corresponding value in SPM, Chl, SDD and Turb images. Also, we selected an ROI in clear water and urban area to construct a training data of five classes. Using Maximum Likelihood [13], the classification result is shown in figure 8. The pollution map highlights the most affected sites which present a high pollution risk. To evaluate our results and with a lake of ground realty, we compare our map to PAC (Plan d'Action Cotier) reports established on Algiers bay [1]. The obtained map highlights the risky sites which are cited in PAC reports.

## 6. Conclusion

In this study, we proposed a fuzzy-genetic mapping approach for coastal water classification using the combination of remote sensing data and in situ measurements. The first part was focused on coastal water mapping. Multispectral reflectance variations were interpreted by the fuzzy rules and deduce membership's functions which assign each pixel to its relevant pollution degree. These membership's functions were after optimized with genetic algorithm in order to tune the resulting water index mapping. In the second part, the resulting maps were used to construct pollution signature tool to characterize coastal water quality and propose a pollution map which is useful to localize risky sites. These findings were coherent with the ground truth of the studied site. Moreover, and using multitemporal remote sensing images, a PSD analysis can give an important information for coastal water quality monitoring in order to determine seasonal and yearly changes. These objectives are under consideration for future works.

## References


[1]. L. Mohamed, Analyse de durabilité dans le cadre du PAC : Zone côtière algéroise (Algérie). Rapport du 4ème atelier, Alger, pp. 16–17 mai 2004. Available from: www.planbleu.org/publications/pac_alger_atelier4.pdf

[2]. S. Sathyendranath, Remote Sensing of Ocean Colour in Coastal, and Other Optically-Complex Waters, IOCCG Report Number 3, Edited by (Bedford Institute of Oceanography, Canada), 2000.

[3]. J. M. Froidefond andD. Doxaran, Télédétection optique appliquée à l'étude des eaux côtières. Télédétection, 4 (2), pp 579–597, 2004.

[4]. J. Acker, S. Ouillon, R. Gould & R. Arnone, Measuring Marine Suspended Sediment Concentrations from Space: History and Potential, 8th International Conference on Remote Sensing for Marine and Coastal Environments, Halifax, Canada, May 17-19, 2005.

[5]. Y. Zhang, J. Pulliainen, S. Koponen, M. Hallikainen, Application of an empirical neural network to surface water quality estimation in the Gulf of Finland using combined optical data and microwave data, Remote Sensing of Environment 81 pp 327– 336, 2002.

[6]. M. Cococcioni, G. Corsini, B. Lazzerini & F. Marcelloni, Approaching the Ocean Color Problem Using Fuzzy Rules, IEEE Transactions On Systems, Man, And Cybernetics—Part B: Cybernetics, VOL. 34, N° 3, 2004.

[7]. T. Takagi, & M. Sugeno, Fuzzy identification of systems and its application to modeling and control, IEEE Transactions on Systems, Man and Cybernetics, 15, pp. 116-132,1985.

[8]. B. Lounis, S. Rabia, A. Ramoul & A. Belhadj Aissa, An adaptive method using genetic fuzzy system to estimate Suspended Particulates Matters SPM from Landsat and MODIS data. Fourth International Conference on Image and Signal Processing ICISP 2010. Trois-R ivières, Québec, Canada:, ISBN:364213680-X 9783642136801, 2010.

[9]. B. Lounis, A. Belhadj-Aissa. An Optimized Fuzzy System for Coastal Water Quality Mapping Using Remote Sensing Data. In: Gervasi O. et al. (eds) Computational Science and Its Applications – ICCSA 2017. Lecture Notes in Computer Science, vol 10407. Springer, Cham, 2017.

[10]. K. F. Man, K. Tang, S. Kwong, S. Halang, Genetic for control and signal processing, Springer, 1997.

[11]. F. Lahet, Caractérisation optique d'eaux côtières méditerranéennes: mesure, modélisation et inversion de réflectances. Application aux observations satellitales. Thèse de doctorat, Université de Toulon et du Var, 1999.

[12]. A. Morel, & L. Prieur, Analysis of variations in ocean color. Limnology and Oceanography, 22 (4), pp. 709-722, 1977.

[13]. J.P. Cquerez & S. Philipp, Analyse d'images : filtrage et segmentation , Edition Masson, 1997.