

N° d'ordre : 3708

THESE

En vue de l'obtention du : **DOCTORAT**

Structure de Recherche : Laboratoire de Recherche en Informatique et
Télécommunications.

Discipline : Sciences de l'ingénieur

Spécialité : Informatique et Télécommunications

Présentée et soutenue le 11/11/2022 par :

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***Fusing multimodal satellite information for automatic detecting and studying
coastal upwelling systems***

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Année Universitaire : 2022-2023

Dedication

I want to dedicate this work to my parents

To all my family,

To my friends,

To the science.

Unit of Research

The laboratory of research in computer science and telecommunications(LRIT-URAC 29) at Faculty of sciences of Mohammed V University in Rabat under the direction of the professor **Khalid MINAOUI**.

Acknowledgments

To start, allow me to express my profound gratitude to my thesis advisor, Mr. **Khalid MINAOUI**, Professor of Higher Education (PES) at the faculty of sciences in Mohammed V university Rabat, for allowing me to pursue a Ph.D. on such a fascinating research topic. I am appreciative of his encouragement and assistance during my PhD. He gave me great guidance when I needed it most. His insightful feedback made a significant difference in the work's successful completion.

I would like to express my sincerest gratitude to all the members of the jury who graced me with their presence and valuable feedback by accepting the invitation: the president of the committee Mr. **Moulay Driss RAHMANI**, Professor of Higher Education (PES) at the faculty of sciences in Mohammed V university; the reviewer Mr. **Mohammed OUMSIS**, Professor of Higher Education (PES) at Superior School of Technology (ESTS), Salé; the reviewer Mr. **Ahmed Drissi MALIANI**, Accredited Professor (PH) at faculty of sciences, Rabat; the reviewer Mr. **Aïssa BENAZZOUZ**, Accredited Professor (PH) at Higher Institute of Maritime Studies, Casablanca; And the examiner of my thesis Mr. **Hicham LAANAYA**, Accredited Professor (PH) at faculty of sciences, Rabat;

I want to thank deeply Mr. **Ayoub Tamim**, Professor and Researcher at the Higher Institute of Marine Fisheries in Agadir, for reviewing and verifying the results using his expertise in Moroccan upwelling variability.

Lastly, my family deserves endless gratitude: my father (May God have

mercy on him) for teaching me to appreciate patience and certainty, my mother for teaching me how to be strong with concise purpose, and my sisters and my brothers for their incorporeal support. To my family, I give everything, including this.

This study was financially supported by the "Centre National pour la Recherche Scientifique et Technique" (CNRST) through their Research Excellence Awards Program, as well as by the "Projets Prioritaires de Recherche" under Project PPR2-6, which is financed by the Mohammed V University.

Abstract

Combining multiple images, also known as image fusion, is an effective method for enhancing object detection in image processing. From previous years, fusion methods have been adapted and developed for remote sensing applications. In this work, we use some of the pertinent fusion approaches in order to study the coastal upwelling phenomenon based on combining the features extracted from biological and physical satellite images. In fact, this thesis presents an integrative study by covering the following objectives: (1) Improving the detection of upwelling zones by using the image fusion concept based on applying various methodologies; (2) Evaluating the results of fusion qualitatively by the physical oceanographer as well as proposing an original, new index for validating quantitatively the findings. This index seeks not only to demonstrate the performance of fusion results but also to prove the reliability of any method used to delineate these productive areas; (3) Studying the interannual/seasonal in order to have the ability to diagnostic past change of the upwelling variability, understand the present fluctuations and predict the future state of this oceanographic phenomenon; (5) Defining the degree of correlation between the two most popular upwelling identifiers over the major northern hemisphere upwellings (Central of Canary and Californian systems).

Keywords: Fusion; satellite image; Upwelling; Index of validation; Sea Surface Temperature; Chlorophyll-a Concentration; Correlation.

Résumé

Grâce à la télédétection, plusieurs phénomènes peuvent être contrôlés par différents instruments. Grâce aux satellites, nous pouvons surveiller et étudier les régions côtières d'upwelling en se basant sur les images de la température de surface de la mer (SST) et de la concentration de chlorophylle-a (Chl-a). Cette thèse présente une étude intégrative en couvrant les objectifs suivants: (1) Améliorer la détection des zones d'upwelling en utilisant la fusion de ses caractéristiques biologiques et physiques; (2) Évaluer qualitativement les résultats de la fusion et proposer un indice original qui peut valider quantitativement les résultats; (3) Étudier la variabilité interannuelle/saisonnière afin d'avoir la capacité de diagnostiquer les changements passés de la variabilité de l'upwelling, comprendre les fluctuations actuelles et prévoir l'état futur de ce phénomène océanographique; (4) définir la corrélation entre les deux identificateurs les plus populaires sur la base de l'analyse effectuée sur les principaux systèmes d'upwelling tout au long des côtières du Maroc et de l'Amérique.

Mots clés: Fusion; image satellitaire; Upwelling; Indice de validation; Température de la surface de la mer; Concentration de chlorophyll-a; Corrélation.

Résumé substantiel

Grace à la télédétection, plusieurs phénomènes peuvent être observés par divers équipements. Les zones côtières de remontée d'eau (upwelling) peuvent être aussi surveillées et étudiées à l'aide de données satellitaires basé sur la température de surface de la mer (SST) et la concentration de chlorophylle-a (Chl-a) de l'océan. Cette thèse sert à présenter une étude interdisciplinaire du système d'upwelling côtier afin d'augmenter la qualité de la détection de cette zone en utilisant la fusion des images satellitaires; évaluer qualitativement les résultats obtenus par la fusion et proposer un indice original pour valider quantitativement les résultats; étudier la variabilité interannuelle/saisonnière pour pouvoir diagnostiquer l'évolution passée de l'upwelling, comprendre les fluctuations actuelles, et prédire l'état futur de ce phénomène océanographique; et par la suite, déterminer la relation entre les deux identificateurs les plus courants à l'aide d'une profonde étude faite tout au long des principaux systèmes d'upwelling localisés dans l'hémisphère nord (le centre des systèmes de Canary et Californie). La thèse est divisée en quatre chapitres principaux allant du chapitre 2 au chapitre 6. La plupart d'entre eux ont été publiés ou soumis pour publication dans des revues à comité de lecture. Une description du contenu des chapitres est donnée ci-dessous :

Dans le chapitre 2, je décris le phénomène d'upwelling, son mécanisme et les zones touchées par ce processus océanographique. Je présente également dans la deuxième section de ce chapitre introductif les notions de base de la télédétection ainsi que les images satellites utilisées dans nos contributions.

Dans le chapitre 3, je décris les différentes méthodes couramment utilisées pour extraire les zones d'upwelling à partir d'images de température de surface de la mer (SST) et de chlorophylle-a (Chl-a). J'examine également leurs avantages et leurs limites pour détecter l'upwelling marocain, et je propose une nouvelle approche intuitive et efficace pour améliorer la délimitation de ces zones.

Dans le chapitre 4, on décrit l'importance d'utiliser la fusion d'images dans la segmentation du champ d'upwelling en appliquant les approches populaires en combinant les caractéristiques de SST et Chl-a le long de la côte marocaine. Ensuite, je recommande une méthodologie efficace basée sur quatre étapes principales non seulement pour améliorer les résultats de la délimitation, mais aussi pour corriger le problème de nébulosité montré clairement dans les observations biologiques.

Le chapitre 5 décrit l'évaluation qualitative et quantitative des méthodes définies dans les chapitres précédents. En effet, dans ce chapitre, j'introduis un nouvel indice d'upwelling de validation qui vise à évaluer la performance de toute méthode dédiée à segmenter les régions froides et riches en nutriments à n'importe quel système d'upwelling. Enfin, j'utilise la méthodologie de fusion proposée afin de fournir une vision scientifique sur la variation spatio-temporelle de la dynamique marocaine d'upwelling en analysant plusieurs indices biologiques et physiques au cours de la période 2000-2019.

Au chapitre 6, on applique notre approche de fusion à un autre système d'upwelling (Le système californien) non seulement pour démontrer la performance de la méthodologie proposée et établir une étude interannuelle/saisonnière de ce système, mais aussi pour calculer la corrélation entre les identificateurs les plus populaires du système d'upwelling quelconque à l'aide d'images satellitaires SST et Chl-a.

Mots clés: fusion, Upwelling, image satellitaire, température de la surface de la mer (SST), concentration de chlorophyll-a (Chl-a), variation saisonnière et annuelle, corrélation, segmentation.

Acronyms

Chl-a	Chlorophyll-a
Chl-a_{max}	Maximum value of Chlorophyll-a
CSET	Cross-Shore Ekman Transport
CUI	Coastal Upwelling Index
EBCUS	Eastern Boundary Current upwelling Systems
EBUZ	Eastern Boundary Upwelling Zones
FCM	Fuzzy C-means
MM	Mathematical Morphology
MODIS	Moderate Resolution Imaging Spectroradiometer
NWA	North-West African
PCA	Principal Component Analysis
PCF	Polynomial Curve Fitting
PCHIP	Piecewise Cubic Hermite Interpolating Polynomial
SST	Sea Surface Temperature
<i>SST_{min}</i>	minimum value of Sea Surface Temperature

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Chapter 1

General introduction

Thanks to remote sensing, several oceanographic phenomena can be monitored by different instruments. Through satellites, we can supervise, observe and identify the coastal upwelling regions by using images. In fact, coastal upwelling is a process in which deep, cold water rises toward the surface near the coast. As winds blow away the warm surface water for an adequately long time and in a favorable direction, cold deep and nutrient-rich water rises to replace the warm one. This motion brings up tiny ocean organisms' minerals and other nutrients (such as Phytoplankton which is composed of a photosynthetic pigment called chlorophyll) from the deeper layers of the water. Upwelling causes an increase in phytoplankton growth, which can manifest in various forms. Together, they form the foundation of ocean food chains.

Worldwide, there are mainly four regions affected by this phenomenon that provide more than 50% of the global take of marine fish even if they cover just less than 1% of the global ocean surface. Given the importance of localizing these productive areas, our thesis has the goal to automatically and efficiently identify the cold, nutrient rich coastal upwelling waters using fusion of biological and physical satellite images; to develop a new improved upwelling index for validating the obtained results; as well as to explore its spatio-temporal dynamics. To meet the research's goals, I raised the following questions, which I

attempted to answer in my thesis. The first three questions are about detecting automatically the Moroccan upwelling system, while the last three are about the validation of fusion results quantitatively by describing its spatiotemporal dynamics.

- * Why do the most popular segmentation methods are unable to detect correctly the Moroccan coastal upwelling in SST image?
- * How does fusion of Chl-a and SST images provide efficient extraction of coastal upwelling?
- * What is the pre-processing step should be applied before delineating the desired area?
- * How do validate quantitatively any method used for identifying any upwelling system?
- * How does the fusion grant us to study the spatio-temporal variation of upwelling?
- * To what extent is there a correlation between the biological and the physical properties of coastal upwelling?

The thesis is structured into five main chapters, from chapter 2 to chapter 6. Many of these chapters have been published or submitted for publication in peer-reviewed journals and international conferences. A summary of the chapter's contents is given below:

In chapter 2, I describe the coastal upwelling phenomenon, its mechanism and the zones affected by this oceanographic process. I also present in the second section of this initiative chapter the basic notions of remote sensing as well as the satellite images used in our contributions.

In chapter 3, I review the current methods commonly used to extract upwelling regions from SST and ocean color satellite images. I also discuss their advantages and limitations for detecting the Moroccan upwelling, and then I

propose a new, intuitive, and effective approach for improving the delimitation of upwelling regions.

In chapter 4, I emphasize the significance of using image fusion in the segmentation of upwelling fields by applying popular approaches that combine features of both sea surface temperature (SST) and chlorophyll-a (Chl-a) along the Moroccan coast. Then, I propose an efficient methodology composed of four main steps, which not only improves the delimitation results but also addresses the issue of cloudiness commonly observed in biological data.

The chapter 5 describes the evaluation of the methods defined in the previous chapters qualitatively and quantitatively. Effectively, in this chapter, I introduce a new validation upwelling index that aims to assess the performance of any method dedicated to segment the cold, nutrient-rich regions at any upwelling system. Finally, I make use of the proposed fusion methodology to provide an analysis of the spatiotemporal variation of the Moroccan upwelling dynamics by evaluating various biological and physical indices over the period of 2000-2019.

In chapter 6, we apply our fusion approach over another upwelling system (California one) not only to demonstrate the performance of the proposed methodology and establishing an interannual/seasonal study of this system but also to compute the correlation between the most popular identifiers of upwelling system using both SST and Chl-a satellite images.

Chapter 2

Upwelling and remote sensing

The current chapter focuses on defining upwelling and its types, the underlying physics of coastal upwelling, various upwelling mechanisms and indicators, the ecological impact of coastal upwelling events, the locations of significant upwelling ecosystems, and an overview of the satellite data utilized in this research.

2.1 Upwelling

According to the National Oceanic and Atmospheric Administration, upwelling is defined as "a process in which deep, cold water rises toward the surface"¹. While the American Meteorological Society glossary² defines upwelling as "an ascending motion of subsurface water by which water from deeper layers is brought into the surface layer and is removed from the area of upwelling by divergent horizontal flow". In general, three main forms of oceanic upwelling are distinguished based on wind-driven mechanisms.

¹<https://oceanservice.noaa.gov/facts/upwelling.html>

²<http://amsglossary.allenpress.com/glossary/>

The ice-edge upwelling Frontal structures in salinity and temperature are visible at the ice edge, which are attributed to both melting ice and, at times, wind-driven Ekman-type upwelling. This phenomenon has been observed in various locations, such as the studies by V. Alexander and H. J. Niebauer (Johannessen et al., 1983; Alexander and Niebauer, 1981; Buckley et al., 1979). It is widely believed that ice-edge upwelling is caused by the unequal wind stress exerted on ice and water surfaces when the wind is blowing parallel to the ice edge, with the ice on the right side when looking downwind. This results in stronger wind stress on the ice, leading to cross-ice-edge Ekman transport.

The equatorial upwelling as mention its name, this type of upwelling is apparent close to the Equator. Trade winds at this region blow both south and north, allowing upwelling of deeper, cold water.

The coastal upwelling is occured when winds blowing in a specific direction for a certain period of time push warm water away from the shore, allowing cool water to rise to the surface of the ocean. This process is described in more detail in the next subsection.

2.1.1 Coastal upwelling

Coastal upwelling is the most well-known and widely studied type of upwelling, and it has a significant impact on human activities due to its role in providing important and productive fisheries globally. This oceanographic phenomenon can be defined as "a wind-driven near-shore circulation induced into a stratified rotating ocean" (O'Brien & Hurlburt, 1972). This definition is based on several key concepts:

Wind: is a natural movement of air of any velocity. It is the main engine of coastal upwelling dynamics.

Near-shore circulation: This phenomenon appears at limited zones near the coast of continents.

Stratification: signifies the division of fluid vertically into layers with dif-

ferent properties (density, salinity, temperature...).

Rotation: Earth's rotation produces Coriolis effect that plays a significant role in the dynamics of upwelling.

Description of the upwelling mechanism

The base description of coastal upwelling process is summarized in Figure. 2.1: As winds blow away the warm surface water during adequately long time and in favorable direction, cold water rises to replace the warm one. This hydrometeorological phenomenon is typically the result of both the northeasterly wind effect and the persistence of Ekman transport along the coastline. Noted that without this motion, the surface waters of the open ocean would be very scarce in nutrients.

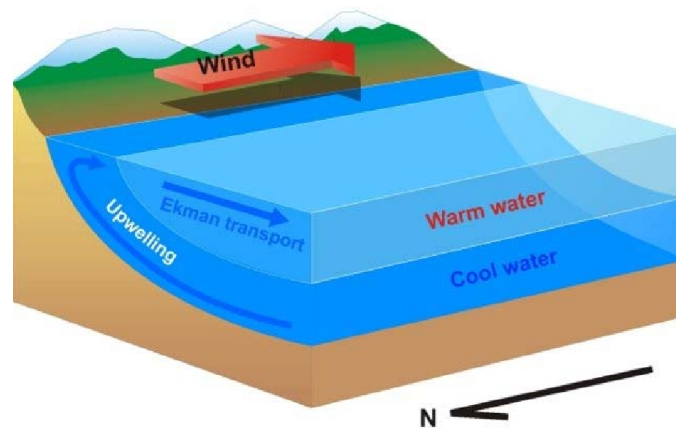


Figure 2.1: Illustration of a northerly wind and a net movement of surface water caused by Ekman transport driving upwelling along a north-south coastline in the northern hemisphere.

To more understand how winds lead to upwelling, let's consider the northern hemisphere case. When winds blow parallel to the coastline from north to south for a prolonged period (wind stress) and in the presence of the Coriolis effect, an offshore Ekman transport is created at the surface, resulting in a net movement of the Ekman layer at a right angle (90 degrees) to the wind. To maintain mass balance, deep water rises to replace the displaced surface water. The upwelled

water is richer in nutrients, saltier, and colder than the surface water normally found in the area (Zhang, Godin, Bellingham, & Ryan, 2012).

Ecological Effects

As a result of the upwelling process, deep and cold water is brought to the ocean surface, which contains nutrients like nitrate, phosphate, and silicate, as well as dissolved gases like oxygen and carbon dioxide. These nutrients and gases are not utilized at depth because of the lack of sunlight. At the surface, they support photosynthesis in small algae called phytoplankton. Upwelling causes an increase in the growth of phytoplankton in various forms, which together form the base of ocean food chains (Figure. 2.2).

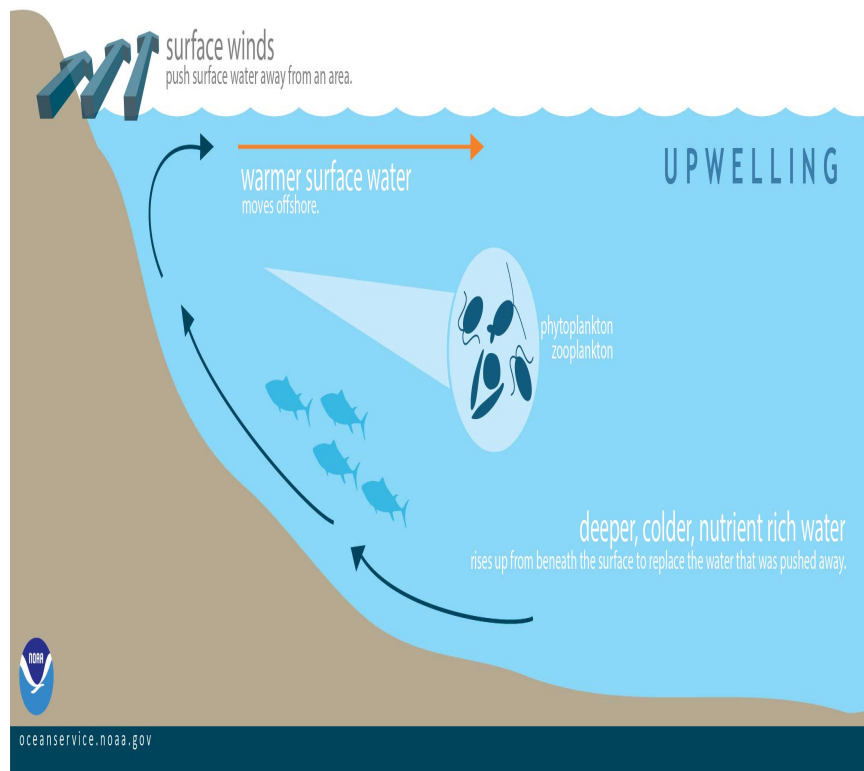


Figure 2.2: Ecological upwelling effect: Upwelling brings up tiny ocean organisms minerals and other nutrients (such as Phytoplankton) from the deeper layers of the water. The Phytoplankton is the first component of the seafood chain.

At the climatic field, upwelled water cools the air of the coastal area. This

change of air temperature promotes the development of sea fog or some low stratus clouds near the coast regions. Fog conditions like these are common in upwelling areas during summer. The warm air above the boundary layer suppresses vertical convection, leading to a more stable air column and weaker precipitation. This is why regions adjacent to coastal upwelling are often deserts, such as the Atacama Desert in Chile, the Namib Desert in southwest Africa, the Baja California Desert in the USA, and the Atlantic coastal desert of Morocco, as reported in the study by Troupin et al. (2011) (Troupin, 2011).

Upwelling features

- **Thermal front:** represents the transition zone between upwelling cold water and warm masses of the offshore waters. An upwelling front is determined when the temperature varies by 1°C or more over a spatial extent of 10km (Tamim, 2015). Each front is characterized by three main elements (Nieto, Demarcq, & McClatchie, 2012): its identity, its state (length, position, direction and intensity) and its behaviour (speed of movement and deformation).
- **Filaments:** are defined as mesoscale cross-shore structures situated along the upwelling front. These tongues of cold upwelled water are narrow, shallow structures originating from the coast. According to their significant biological and chemical roles and effects upon primary production (Troupin, Mason, Beckers, & Sangrà, 2012), many surveys were carried out of studying filament process (Haynes, Barton, & Pilling, 1993; Hagen, Zulicke, & Feistel, 1996; Barton & Arístegui, 2004; Pelegrí et al., 2005).

2.1.2 Upwelling Identification

Conforming to the definition of upwelling given in section 2.1, coastal upwelling areas are characterized by cool inshore water compared to the large ocean. They can easily identified by using Sea Surface Temperature satellite image.

The figures of SST were obtained by plotting all the SST measurements collected by the Moderate Resolution Imaging Spectroradiometer sensor (MODIS, <http://modis.gsfc.nasa.gov/>) on board the Terra satellite (<http://terra.nasa.gov/>).

Colder waters near the eastern boundary coasts are also known by their primary productivity richness. These areas are characterized by higher chlorophyll-a concentration where phytoplankton blooms take place.

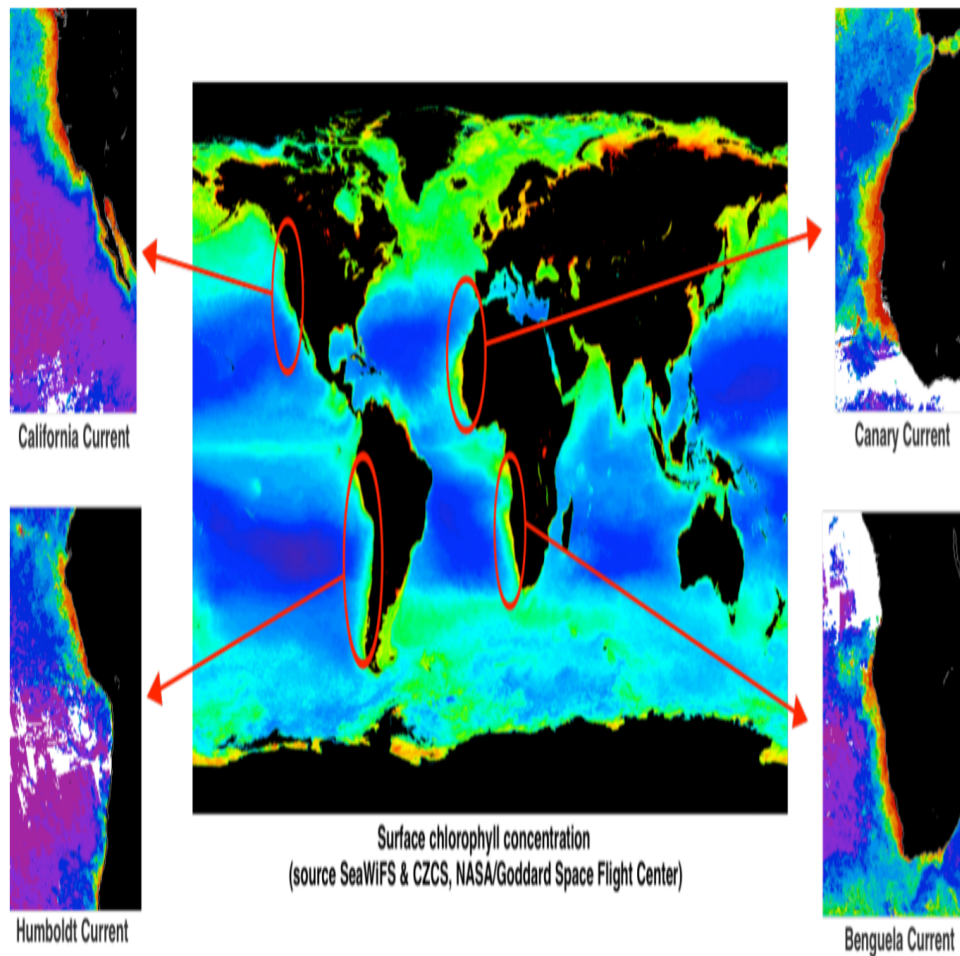


Figure 2.3: Map of Chlorophyll-a concentration, highlighting the main four ecosystems upwelling in the world.

These data are obtained through the different institutions (NASA, SeaWiFS,...). From this glob view map 2.3, we can define four main regions of coastal

upwelling:

- The Canary Current upwelling system, along the Moroccan, Mauritania and Senegal coasts (northwest Africa C_1);
- The Benguela upwelling, located along the coasts of Namibia and South Africa (C_2);
- The California Current upwelling system, located along the west coast of north of America (C_3);
- The Peru-Chile (Humboldt) Current upwelling system, located along the west coast of South America.

And two major equatorial upwelling are also shown on the Fig ,where E_1 is located at the Atlantic ocean and E_2 is appeared in the Pacific one.

It's worth noting that all coastal upwelling regions share a common characteristic: they are located in the eastern part of the main subtropical gyres. As a result, they are referred to as Eastern Boundary Upwelling Systems (EBUS).

2.1.3 Reasons to study upwelling systems

What makes study of upwelling systems important is their temperature, nutrient content, and chemical composition proprieties that they have compared to the open ocean. In fact, the upwelling regions are cool sea surface temperature due to the upwelled deep water. This colder water has typically much greater concentration of nutrients. When these nutrients get pulled up to the surface and exposed to sunlight, they within it help fuel an ecosystem driven by high primary production. Upwelling systems significantly impact marine ecosystems due to the increased availability of nutrients they bring to the surface.

(Ryther, 1969a) estimated that the upwelling areas provide a mean productivity tends towards $300gC/m^2$ in each year (versus $50gC/m^2$ for the large ocean), while they cover only 0.1% of the total of surface ocean with value of $3.6 \times 10^5 km^2$. Depending on research of (Durand et al., 1998), the main

four EBUS support between 20 – 30% of the global fish catch. More recently, (Jennings, Kaiser, & Reynolds, 2009) reported that approximately 25% of the total global marine fishery come from the eastern boundary upwelling areas that occupy only 5% of the total ocean.

Table 2.1.3 represents the covered surface of the four upwelling systems. The largest marine ecosystem is Humbolt system with $2.5 \times 10^6 Km$ of the total ocean. All of the EBUS except California upwelling system support productivity greater or equal to $300 \text{ gC } m^{-2}yr^{-1}$.

Table 2.1: Characteristics of the four EBUS. Productivity mean is in grams of Carbon for each m^2 in each year ($\text{gC } m^{-2}yr^{-1}$)

Upwelling system	Surface ($\times 10^6$)	Productivity ($\text{gC } m^{-2}yr^{-1}$)
California	2.2	< 150
Humbolt	2.5	150-300
Canary	1.1	> 300
Benguela	1.5	> 300

Given the rich fisheries and the considerable biological resources that the EBUS possess, the fishing sector plays a priority role in socio-economic development of the countries directly affected by the upwelling such as Morocco (Atilah, Orbi, Hilmi, & Mangin, 2005). However, the excessive exploitation of fish resources is causing a worrying decline in the fish stock in these regions, and consequently disturbing the ecological balance of fish populations. In order to best protect biodiversity, the environment and fisheries resources, the dynamics of fish populations must be regulated to knowledge of the physical and biological phenomena of regions (Chassot et al., 2011) . Therefore, studying and monitoring coastal upwelling variability must have a particular interest(Troupin, 2011).

2.2 Remote sensing and image satellite

Remote sensing allows for the observation of various phenomena using various instruments. Satellites provide us with the ability to monitor and analyze the oceans by collecting important data, such as temperature, surface salinity, sea

level, water color, and surface winds, with unparalleled spatial and temporal coverage that cannot be obtained through traditional methods like using boats.

2.2.1 Remote sensing

Remote sensing is the process of obtaining information (physical characteristics) about an object or an area from a distance, typically from aircraft or satellite. The general steps of remote sensing is illustrated in the figure 2.4:

The process begins with radiation emitted by a source of energy or illumination (A) that travels a certain distance and interacts with the atmosphere (B) before reaching the target (C). The energy interacts with the surface of the target, based on the characteristics of radiation and surface properties. This radiation is reflected or diffused towards the sensor (D) which records it and can then transmit the energy by electronic tools to the receiving station (E) where the information is transformed into digital images or photographs. Visual and/or digital interpretation of the obtained image (F) is then necessary to extract the desired information about the target (C).

The final step of the process is the use of the information extracted (G) from the satellite image to better understand the target, discover new aspects about it or solve a particular problem.

In the literature, there are two main types of sensors used in remote sensing: active sensors and passive sensors. For the passive sensors, the source of energy is natural, therefore, this kind of sensors can be used to detect radiation only when the sun shines on the earth. In fact, this energy is either reflected (the visible portion) or absorbed and re-transmitted (thermal infrared) by the target. In contrast to passive remote sensing, an active sensor produces its own artificial energy in order to illuminate the desired area by releasing electromagnetic radiation directed towards this zone, then, the target reflects this radiation which will be captured and measured by the sensor on board the satellite. The major advantage of this kind is the possibility of taking measurements over a span at any time of the day.

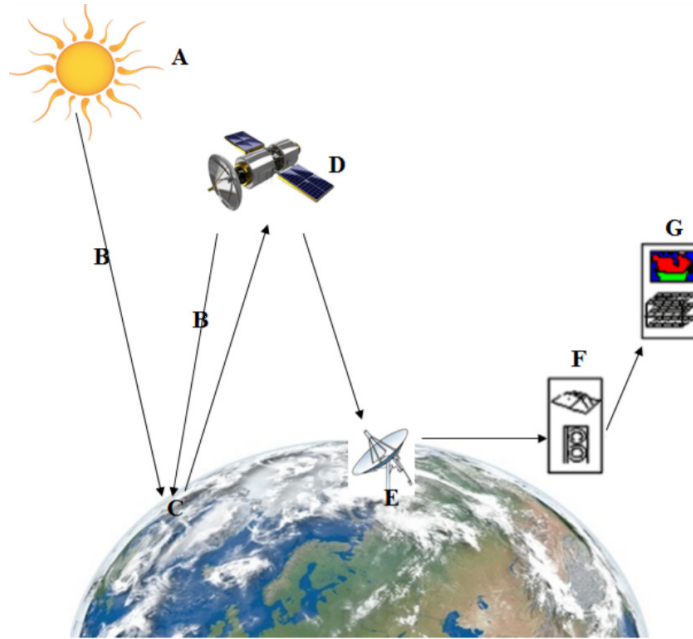


Figure 2.4: Simplified representation of different steps of remote sensing using satellite observation

Even the difference between these two types is smaller but the impact on their functionality is greater(Hill & Zimmerman, 2010).

Type of resolution

In general, the resolution of a digital image is a measurement that indicates the number of pixels (the smallest unit of the image) in an inch (expressed in Dpi or Ppp). In particular, any satellite image is characterized by its own spatial, spectral, radiometric or even temporal resolution.

- **Spatial resolution**

The spatial resolution refers to the smallest distance between two objects by which a given image can be detected by a sensor. When a sensor is able to clarify the detail of an observed area, it is said that has a high spatial resolution. For example, spatial resolution of $1Km$ means that one pixel represents an area $1Km$ by $1Km$ meters on the land surface.

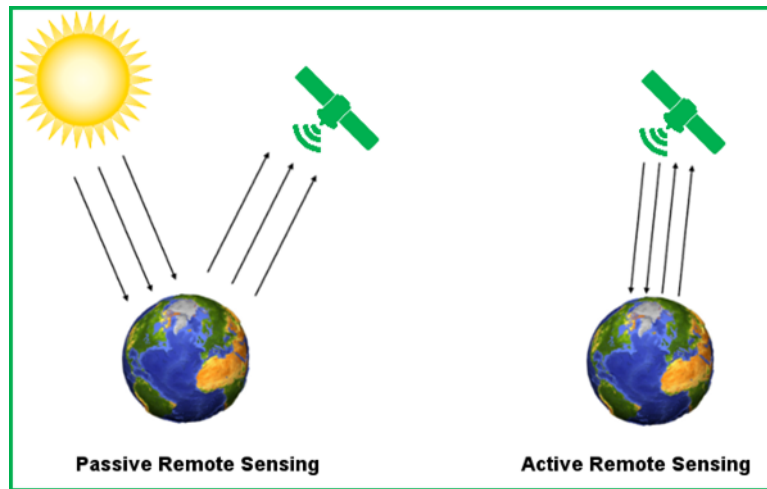


Figure 2.5: The passive and active remote sensing

Figure 2.6 presents an example of polygon land covered by sensor with different resolution values. It mentions that the low spatial resolution value describes clearly the desired zone.

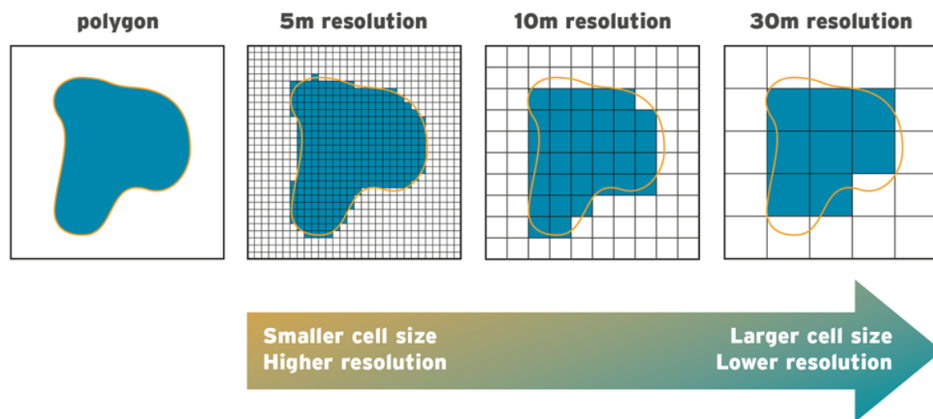


Figure 2.6: An example of high resolution (left) to low resolution (right) covering the same land polygon area

- **Spectral resolution**

Different features and details in an image can often be discriminated by comparing their responses over distinct wavelength ranges (Jensen & Lulla, 1987). Specific classes of features, such as the different rock types require

comparison at much finer wavelength ranges to separate them. Contrariwise, broad classes, such as water and vegetation may be easily distinguishable using broad wavelength ranges (the visible and near infrared). Thus, a sensor with higher spectral resolution is characterized by large number of bands and narrow spectral widths.

- **Radiometric resolution**

It reflects the ability of the sensor to discriminate small variations in electromagnetic energy, so it refers to the number of bits used to record the image. In fact, the electromagnetic energy travels in waves and spans from a broad spectrum from very long waves (radio) to very short waves (gamma rays) (Butcher, 2010). The regions with long wavelengths have low energy and the regions with short wavelengths have high energy (See Figure.5.4b)

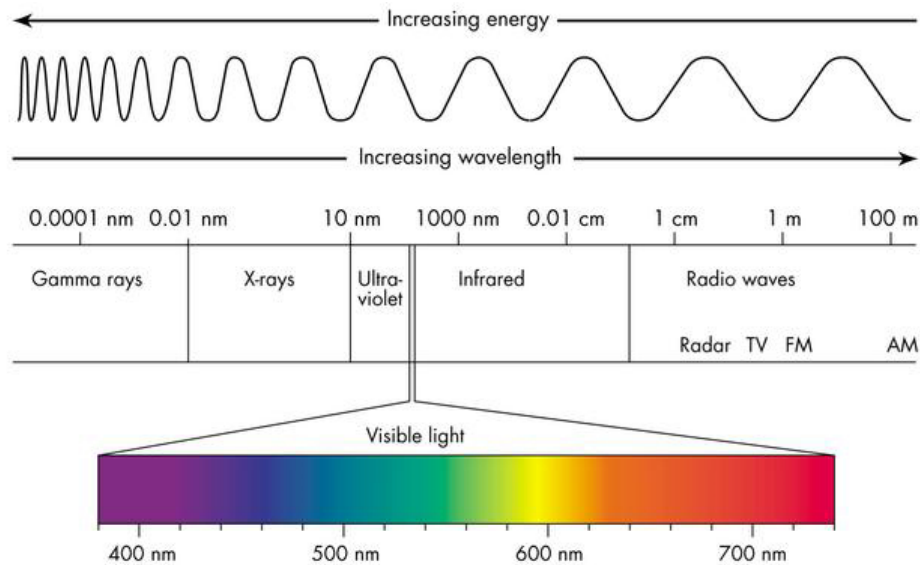


Figure 2.7: The entire range of electromagnetic spectrum showing the different range of light, starting from gamma rays to radio waves.

- **Temporal resolution**

This resolution corresponds to the revisit time of the sensor. It is very important when the interpreters follow the changes which occur on the surface of the earth whether they are natural (for example the color control of the earth, a sea, the supervision of forests) or those produced by humans (such as the development of urban areas or deforestation). In fact, the techniques of having a good temporal resolution are clearly improved by the satellite's ability to point out (to look at the sides, in front, behind time ...).

Typically, we never find a sensor that combines all these types of resolution with good quality, but there are sensors that make a balance between them always taking into consideration the targeted objectives.

2.2.2 Satellite imagery

In this thesis, we use data from the Moderate Resolution Imaging Spectroradiometer (MODIS) provided by the National Aeronautics and Space Administration (NASA). MODIS is a scientific instrument installed on Terra (launched in 2000) and Aqua (launched in 2002) satellites. The orbit of Aqua around the globe is timed to pass from south to north across the equator in the afternoon (EOS PM), while Terra's orbit starts from north to south traversing the equator in the morning. As a result, Terra MODIS and Aqua MODIS cover the entire globe every 1 to 2 days with 36 spectral bands between 0.4 micrometers and 14.4 micrometers, ranging from visible to infrared (See Table 2.2 for more details).

Daily, weekly, monthly and annually images are available at two different spatial resolution values respectively at 4.64 km and 9.26 km (Justice et al., 2002).

The MODIS instrument is useful for monitoring and measuring various earth parameters, which helps to enhance our understanding of global dynamics and processes happening on land, in oceans and in the lower atmosphere (Walker, De Beurs, Wynne, & Gao, 2012; Strugnell, Lucht, & Schaaf, 2001).

Table 2.2: MODIS specifications of 36 spectral bands where bands from 1 to 19 are in μm and bands 20 to 36 are in nm ; Spectral Radiance values are ($W/m^2 \cdot \mu m \cdot sr$); SNR refers to Signal-to-noise ratio ; $NE(\delta)T$ = Noise-equivalent temperature difference

Primary Use	Band	Bandwidth1	Spectral Radiance2	Required SNR3
Land/Cloud/Aerosols Boundaries	1	620 - 670	21.8	128
2	841 - 876	24.7	201	
Land/Cloud/Aerosols Properties	3	459 - 479	35.3	243
4	545 - 565	29.0	228	
5	1230 - 1250	5.4	74	
6	1628 - 1652	7.3	275	
7	2105 - 2155	1.0	110	
Ocean Color/Phytoplankton/Biogeochemistry	8	405 - 420	44.9	880
9	438 - 448	41.9	838	
10	483 - 493	32.1	802	
11	526 - 536	27.9	754	
12	546 - 556	21.0	750	
13	662 - 672	9.5	910	
14	673 - 683	8.7	1087	
15	743 - 753	10.2	586	
16	862 - 877	6.2	516	
Atmospheric Water Vapor	17	890 - 920	10.0	167
18	931 - 941	3.6	57	
19	915 - 965	15.0	250	
Primary Use	Band	Bandwidth1	Spectral Radiance2	Required $NE(\delta)T(K)$ 4
Surface/Cloud Temperature	20	3.660 - 3.840	0.45(300K)	0.05
21	3.929 - 3.989	2.38(335K)	0.20	
22	3.929 - 3.989	0.67(300K)	0.07	
23	4.020 - 4.080	0.79(300K)	0.07	
Atmospheric Temperature	24	4.433 - 4.498	0.17(250K)	0.25
25	4.482 - 4.549	0.59(275K)	0.25	
Cirrus Clouds Water Vapor	26	1.360 - 1.390	6.00	150(SNR)
27	6.535 - 6.895	1.16(240K)	0.25	
28	7.175 - 7.475	2.18(250K)	0.25	
Cloud Properties	29	8.400 - 8.700	9.58(300K)	0.05
Ozone	30	9.580 - 9.880	3.69(250K)	0.25
Surface/Cloud Temperature	31	10.780 - 11.280	9.55(300K)	0.05
32	11.770 - 12.270	8.94(300K)	0.05	
Cloud Top Altitude	33	13.185 - 13.485	4.52(260K)	0.25
34	13.485 - 13.785	3.76(250K)	0.25	
35	13.785 - 14.085	3.11(240K)	0.25	
36	14.085 - 14.385	2.08(220K)	0.35	

Sea Surface Temperature

In the last decades, the calculation of the temperature of water at the ocean surface's every time and every place becomes easily via using the different satellite measurements that are impossible to achieve it with the traditional way like boats and ships. MODIS equipment measures the changes of ocean temperature at each micrometers of the surface layer by calculating how much energy comes off the ocean at different wavelengths. The darkest blue color shows the coldest waters while the warmer offshore waters are presented in darkest red color.

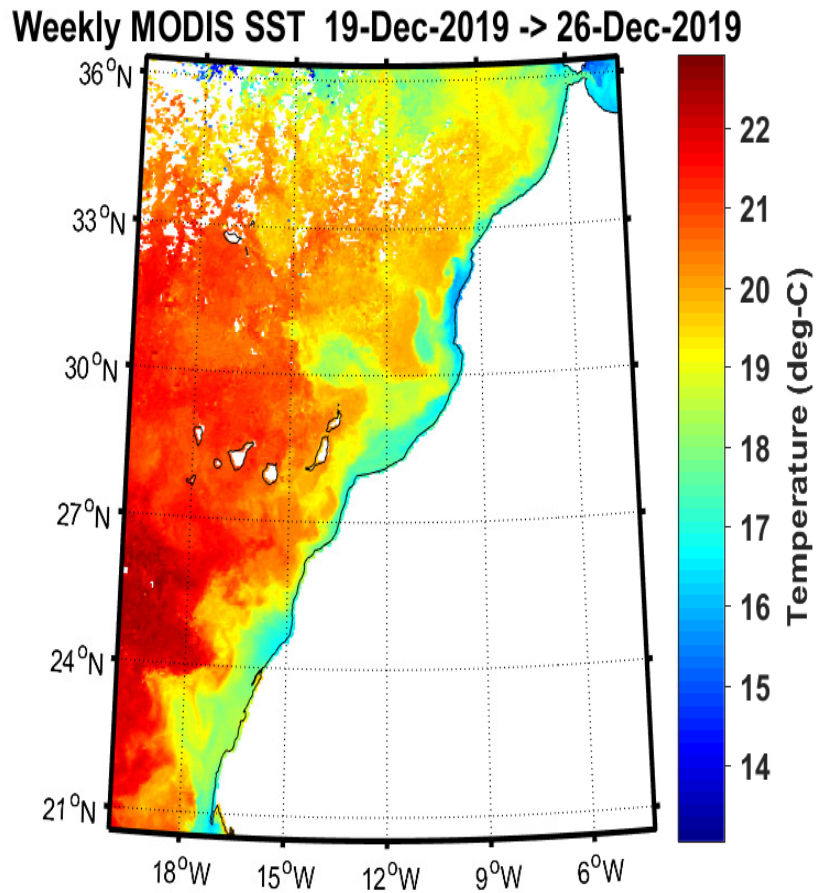


Figure 2.8: Weekly MODIS SST image over the North-West African margin.

Figure 2.8 illustrates an example of MODIS 8-day SST data over the Moroccan coast. Each pixel of the infrared image contains temperature information expressed in Celsius degrees ($^{\circ}\text{C}$). MODIS products are often provided in the NetCDF (Network Common Data Form) format, which allows for easy sharing and access of geoscience data and tools for visualization.

Ocean color image

Oceanic visible satellite image, based on the measurement of chlorophyll-a concentration was also adopted for the identification of coastal upwelling regions (Ambar

& Dias, 2008). The effect of light scattering and absorption in saltwater by molecules, pigments in dissolved organic matter or phytoplankton cells and suspended particles form the basis for remote sensing of the visible spectrum ("ocean colour"). The fluctuations in the visible spectrum caused by the relative concentrations of absorbers and scatterers in the water give the ocean its color. Phytoplankton cells have pigments that absorb a large portion of the visible spectrum of sunlight, with chlorophyll-a being the most prevalent. As phytoplankton converts CO_2 into organic carbon, chlorophyll-a concentrations provide an indicator of primary production in the marine food web, including the rate of growth and carbon fixation of phytoplankton.

Figure 2.9 illustrates an example of MODIS 30-day Chl-a concentration image over the Moroccan Atlantic coast. Each pixel presents Chl-a concentration in ($\log(mg/m^3)$). This image is acquired on the last month of 2019 where a typical upwelling scenario is shown over the studied area.

Wind Speed

Typically, buoys, platforms, and ships monitor ocean winds quite near to the ocean surface. For near-surface ocean wind measurements, the most common reference height is 10 meters above sea level. In situ (on-site) and remote sensing (from afar) devices and techniques are used to detect ocean wind [Wentz et al., 1992]. We're talking about satellite-based measurements here. Two types of microwave instruments used for measuring ocean surface winds are the passive microwave radiometer and the active microwave scatterometer. The ocean surface responds quickly to changes in the wind above it, resulting in a unique pattern of roughness that varies based on the relative speed and direction of the wind in relation to the ocean surface [Risien and Chelton, 2008].

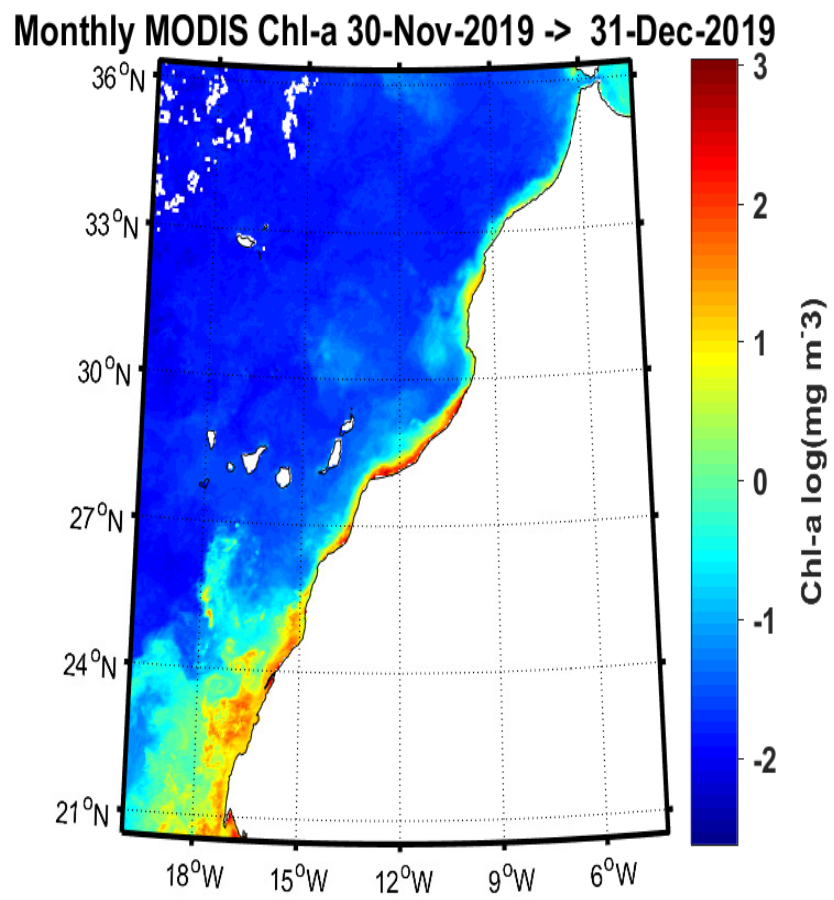


Figure 2.9: Monthly MODIS Chl-a image over the North-West African margin.

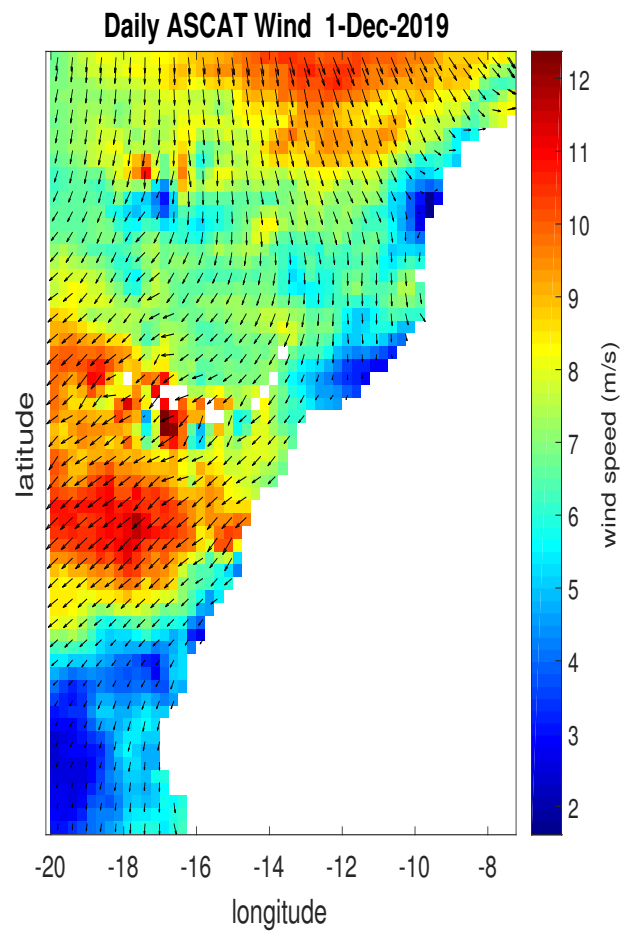


Figure 2.10: Daily ASCAT wind image over the North-West African margin.

Chapter 3

Segmentation of upwelling areas from biological and physical satellite images

In image processing and computer vision, segmentation refers to the division of an image into semantically similar segments (Dey, Zhang, & Zhong, 2010). This process is an essential step for delineating the upwelling areas from SST or Chl-a satellite images. The current chapter is dedicated to examine previously proposed methods for identifying coastal upwelling zones, highlighting their strengths and limitations.

3.1 Image segmentation methods

The popular methods used for image segmentation are: threshold method, edge detection based techniques, region based techniques and clustering based methods. Each type of these methods is different to other depends on the objective of segmentation.

3.1.1 Threshold methods

This approach is the simplest way and yet the powerful technique to identify the desired objects in an image. Based on the intensity, the pixels of image can be divided into foreground and background by comparing the intensity of pixels based on a threshold value and thus resulting a binary image.

Considering that the threshold value can be fixed and constant or dynamically changed depending on the image properties', the threshold methods can be categorized into the following three techniques:

- **Simple thresholding** seeks to replace all the pixels greater than a defined threshold T with white color and the rest will be presented with black one. Generally, this binary approach is based on the following equation:

$$J(i, j) = \begin{cases} 1 & \text{if } I(i, j) > T \\ 0 & \text{Otherwise} \end{cases} \quad (3.1)$$

Any pixel for which $I(i, j) > T$ is called an object pixel, while the background in the resulting image J is viewed as black color.

- **Otsu's binarization:** The thresholding process is largely dependent on the selection of an appropriate threshold value. One common method for selecting this value is the Otsu's method(Otsu, 1979), which finds the optimum threshold that separates the classes by minimizing the weighted sum of the within-class variances.

This algorithm determined the threshold value, T , by analyzing the gray-level histogram of an image, and then calculating the within-class variance as the weighted sum of the variances of each cluster:

$$\sigma_{Within}^2 = n_B(t) \times \sigma_B^2(t) + n_F(t) \times \sigma_F^2(t) \quad (3.2)$$

Where $n_B(t)$ and $n_F(t)$ indicate respectively the probabilities of the class of the background and the foreground one separated by t , while σ_B^2 and

σ_F^2 are variances of these two classes. Otsu shows that minimizing the intra-class variance is the same as maximizing inter-class variance:

$$\sigma_{Between}^2 = n_B(t) \times n_F(t) [\mu_B - \mu_F]^2 \quad (3.3)$$

In eq. 3.3, $\mu_B(t) = \sum_{i=0}^{t-1} i \frac{P(i)}{n_B(t)}$ represents the first-order cumulative moment of the background region, which has the intensity less than t . While $\mu_F(t) = \sum_{i=t}^{L-1} i \frac{P(i)}{n_F(t)}$ is the class mean in range of intensity $[t, L-1]$ where L is the length of gray-level histogram.

The optimal threshold value is then defined as the one that maximizes the between-class variance :

$$T = ArgMax(\sigma_{Between}^2(t)) \quad (3.4)$$

Generally, the Otsu's method does not work well if the processed image is very noised and also when the image contains objects (or regions) with different discrete intensities. Even if this method has some limitations (Lee & Park, 1990), it gives satisfactory and promising results in the case of bimodal histogram. As a result, it is widely used and remains one of the most commonly cited thresholding methods.

- **Adaptive Thresholding** looks to calculate the threshold value for each specific portion of image that can be defined by a fixed or moved window. Hence, different thresholds were computed for different portions of the same image. The threshold value can be determined using the mean of the values in a neighboring area or by using a weighted sum of the values in the neighboring area with weights defined by a Gaussian window, which is a function used to specify regions. This algorithm gives better results than the global thresholding methods when the processed image contains varying illumination (Chan, Lam, & Zhu, 1998).

3.1.2 Region based methods

Region based algorithms operate iteratively with the goal to partitioning the image into regions considering that each region R_i is a set of neighboring pixels having common property of homogeneity (color, gray level, texture, shape or other characteristic) and splitting groups of pixels that are dissimilar in properties (Nikolaou & Papamarkos, 2009).

- **Region growing** is the procedure of pixel aggregation that is based on the agglomeration of neighboring pixels to the region by satisfying some predefined criteria (Adams & Bischof, 1994). This current algorithm consists of two major arguments. Firstly, the determination of starting points (seeds). In fact, the choice of the seeded points is the most delicate step of the algorithm. The second argument is assigned by the measure of similarity which may be the difference between a pixel's intensity value and the region's mean. As region growing is very attractive and used for semantic image segmentation (Fan, Zeng, Body, & Hacid, 2005), it is recommended to not starting the algorithm with seeds located in a non-homogeneous area because the similarity measure will produce large variations and the growth will stop very early.
- **Mathematical morphology (MM)** is a branch of image processing which allows for the analysis and processing of geometrical structures. MM is introduced by Matheron and Serra (Matheron, 1975; Serra, 1982; ?, ?). It is called morphology since it aims at analysing the shape and form of objects, and it is mathematical in the sense that the analysis is based on set theory, and lattice algebra (Serra & Soille, 2012).

3.1.3 Edge based techniques

Segmentation of image can be also obtained through the detection of edges, which normally defined as the immense intensity variation between two objects (Pal & Pal, 1993). Practically, all the contours of an image are the results of the

discontinuities of the reluctance function coming from the texture, the shadow or from the discontinuities of the depth that indicate the edge of an object. There are several models of edge (Gonzalez, Woods, et al., 2002) (step, ramp, roof, etc) that are classified according to their intensity profiles.

Edge detection is based on the study of the derivatives of the intensity function of the image, specifically the local extrema of the gradient (first derivative) and the points where the intensity function crosses zero. Laplacian (second derivative) taking into account the risk of the presence of noise on the image to be segmented.

- **Gradient edge detection**

The image $I(x, y)$ is a function of two dimension 2D. Its gradient is written in the following form:

$$G = (G_x, G_y) = \left(\frac{\partial(x, y)}{\partial x}, \frac{\partial(x, y)}{\partial y} \right) \quad (3.5)$$

Where

$$G_x = f(x + 1, y) - f(x - 1, y) \quad (3.6)$$

$$G_y = f(x, y + 1) - f(x, y - 1) \quad (3.7)$$

The gradient is characterized by two principal measures:

- Its magnitude M , measures the force of the contour:

$$M = \sqrt{G_x^2 + G_y^2} \quad (3.8)$$

- Direction θ is often perpendicular to the edge direction, it is computed as:

$$\theta = \arctan\left(\frac{G_y}{G_x}\right) \quad (3.9)$$

- **Canny edge detector**

Canny edge detector is a widely-used convolution gradient-based algorithm, invented in 1986 by John Canny (Canny, 1986), that aims to produce an optimal edge detector that meets three specific criteria:

1. **Good detection:** means that the error rate will be low in the signaling of contours;
2. **Good localization:** indicates that the distance between the detected contours and the real contours of the image should be smaller;
3. **Response clarity:** refers to the uniqueness of response by edge and the absence of false positives.

The optimal detector is a multi-stage process that involves four main steps: i) noise reduction by smoothing the image using a Gaussian filter, ii) edge direction calculation using the arctangent of the gradient in the x and y directions of the processed image $I(x, y)$, iii) non-maxima suppression to eliminate false edge detection responses, and iv) hysteresis by adding weak edges to stronger edges to finalize the detection result.

3.1.4 Clustering based methods

Unlike classification algorithms, clustering based methods not need pre-defined set of features, classes, or groups for segmenting the image into homogeneous clusters. Two widely used algorithms in the clustering based approaches: K-means and Fuzzy C-means.

- **K-means** is a simple unsupervised learning method that addresses clustering problems. The process involves dividing an image into a predetermined number of clusters, with each cluster represented by a centroid. The algorithm begins by randomly initializing the centroids, and then assigns each pixel in the image to the cluster whose centroid it is closest to. Once all the pixels have been assigned to clusters, the centroids are recalculated based on the new assignments, and the process repeats until the centroids no longer move.

At the end of the process, the image is segmented into "K" clusters, and the pixels within each cluster are similar to one another.

- **Fuzzy C-means method (FCM)** is an unsupervised technique based on fuzzy logic, firstly proposed by (Bezdek, Ehrlich, & Full, 1984), commonly used in pattern recognition. It allows for each data point to belong to multiple clusters simultaneously. FCM algorithm can be represented by finding the minimum solution of the following equation:

$$J(X; U, v) = \sum_{i=1}^C \sum_{k=1}^N (\mu_{ik})^m \|x_k - v_i\|^2 \quad (3.10)$$

Where $X = [x_1, x_2, x_3, \dots, x_N]$ is a vector of the analyzed image intensity at the k^{th} pixel. The parameters C and v are respectively, the number of clusters and clusters centroids. While $U = [\mu_{ij}]$ represents the fuzzy partition matrix and $\|x_k - v_i\|$ is the Euclidean norm.

The criterion m is a weighting exponent which controls the fuzziness of the membership of each point. It is varied in the range $[1 \infty]$.

Problem of nonlinear optimization in the above equation 3.10 can be solved by using jointly the below membership functions and cluster centroids:

$$\mu_{ik} = \frac{1}{\sum_{j=1}^C \left(\frac{\|x_k - v_i\|}{\|x_k - v_j\|} \right)^{\frac{2}{m-1}}}, 1 \leq i \leq C, 1 \leq k \leq N \quad (3.11)$$

$$v_i = \frac{\sum_{j=1}^N (\mu_{ij})^m x_j}{\sum_{j=1}^N (\mu_{ij})^m} \quad (3.12)$$

The use of this method is very promising in the coastal upwelling detection task especially when the region of interest is characterized by a cold and homogeneous zone compared to warm and heterogeneous offshore waters (El Aouni, 2019; Tamim, 2015).

3.2 Identification of upwelling regions based on satellite derived SST and Chlorophyll-a images

Given the importance of localizing the coastal upwelling zones (Ryther, 1969b), various studies have been identified these cold areas by using different segmentation methods. Application of edge detection methods looks to delimit objectively the true upwelling fronts from thermal infrared image and ignore the false edges (Cayula & Cornillon, 1995; Sholva, Sitohang, & Wikantika, 2013; Evans, Woodruff, & Trainer, 2005). An improved frontal detection algorithm based on the method developed by (Cayula & Cornillon, 1992) has been addressed in (Nieto et al., 2012) for detecting mesoscale frontal structures in the Canary upwelling system. For instance, (Oram, McWilliams, & Stolzenbach, 2008) proposed a gradient-based edge detector for overcoming the cloudiness problem presented in the remote sensed image and then detecting automatically the significant edges of upwelling features off the Southern California Bight.

As mentioned previously (first section of this chapter), fuzzy clustering is one of the most popular clustering-based methods used for identifying the cold waters from SST observation. Oceanography, fuzzy clustering seeks to resolve the problem of upwelling detection by separating heterogeneous and non-overlapping temperature groups. In fact, several approaches based on fuzzy C-Means method were proposed in order to extract homogeneous cold regions localized near the coastal ocean of Portugal (Sousa, Nascimento, Casimiro, & Boutov, 2008; Nascimento & Franco, 2009b, 2009a; Nascimento, Franco, Sousa, Dias, & Neves, 2012).

The primary focus of this research is on the extraction of the physical and biological features of coastal upwelling systems in the northeastern Atlantic, namely off the coast of Morocco.

3.3 Studied area

This work focuses on the central of the canary current covering Morocco (extended from 21°N to 36°N and 4°W to 19°W). Figure 3.1 shows two climatological (SST and Chl-a) images of the studied region. The data used in this study is MODIS-T weekly SST and Chl-a images, available online at <http://oceancolor.gsfc.nasa.gov/> with a spatial resolution of 4.64×4.64 Km, inducing size images of 378×378 pixels. A total of 908 thermal level 3 infrared observations and 908 Chl-a eight-day images are used, covering the time period from February 2000 to December 2019.

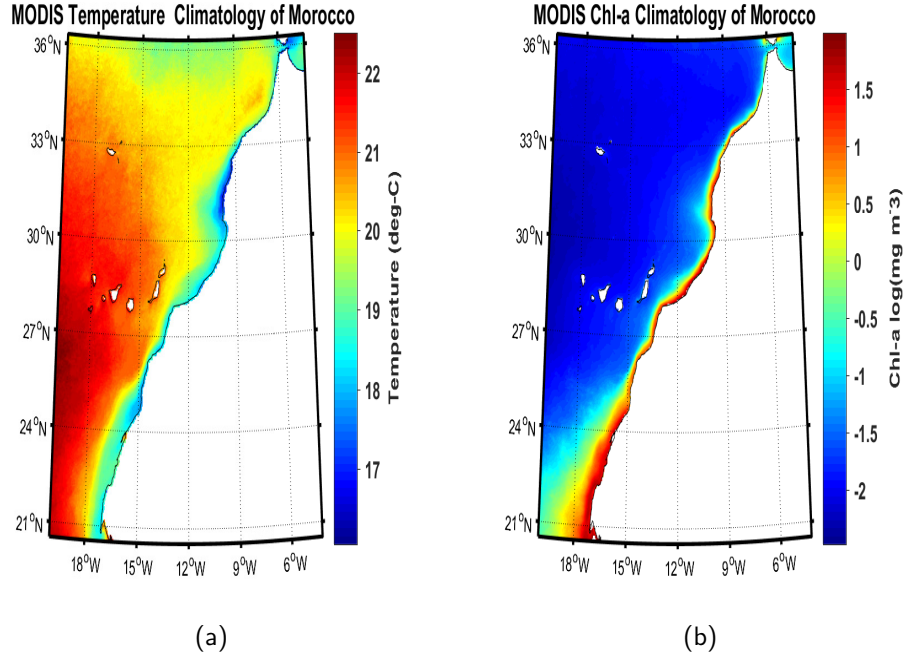


Figure 3.1: Climatological annual means of Moroccan upwelling system of (a) 908 SST images and of (b) 908 Chl-a images for the period 2000 to 2019.

For the rest of thesis, we exploit mostly the example displayed in Figure.3.3 for both 8-SST and 8-Chl-a images obtained at the same date (From 26 February to 5 March 2014). The two images show typical upwelling conditions with a great definition of the main coastal upwelling front in Chl-a image. Contrariwise, the thermal upwelling front is only well defined in the south of 28°N as

shown in the SST one (Fig. 3.1a). In fact, the Chlorophyll-a concentration of upwelling water is distributed longitudinally and meridionally very similar along the Moroccan coastline, in the same manner the offshore water in the open ocean has almost the same concentration of chlorophyll-a. The distribution of sea surface temperature along the coast is non-linear; the northern part may have the same temperature distribution as the inshore of the southern part.

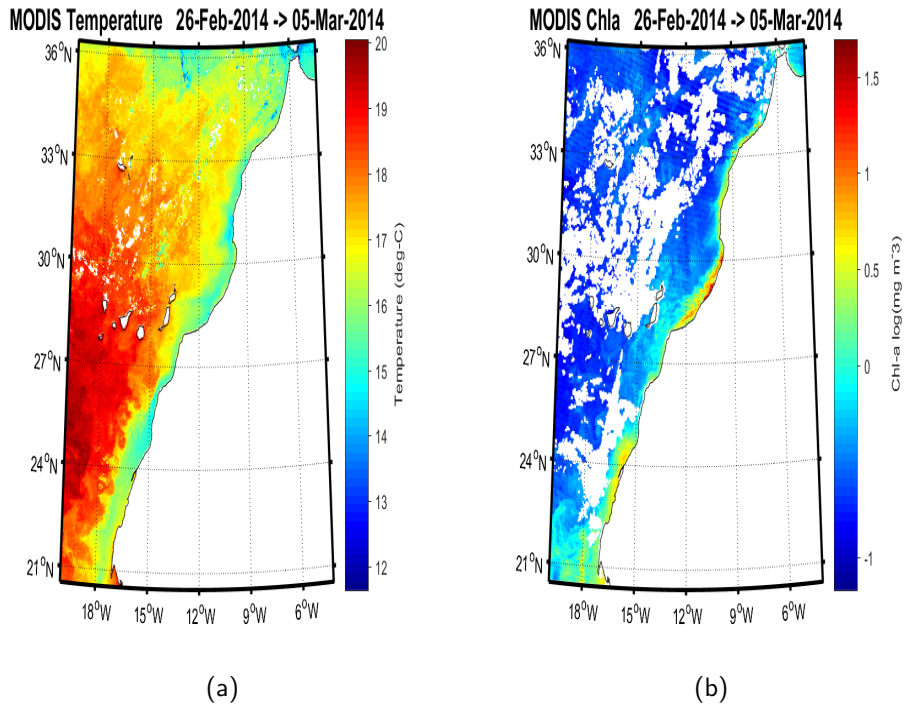


Figure 3.2: MODIS 8-day of (a) SST ($^{\circ}$) and (b) Chl-a [$\log(\text{mg}/\text{m}^3)$] images obtained on the winter of 2014, showing a typical upwelling scenario from physical and biological observations; similar oceanic structures appear in both the images

3.4 Extraction of Moroccan coastal upwelling

Several research studies have been conducted to automatically detect the north-west African upwelling, using satellite observation of sea surface temperature (SST) images (Tamim et al., 2013; Tamim, Minaoui, Daoudi, Atillah, et al., 2014; Tamim, Minaoui, Daoudi, Atillah, & Aboutajdine, 2014, 2015; Tamim,

Yahia, et al., 2015) or ocean color image (El Aouni et al., 2015; El Abidi & Minaoui, 2017). A coarse segmentation is performed for labeling and extracting southern of Moroccan upwelling from SST image using both Otsu's method with an optimal number of clusters determined by different validity indices and region growing (Tamim, Minaoui, Daoudi, Yahia, et al., 2014). Other studies over the same area have been delimited the cool water by using fuzzy C-means (Tamim, Minaoui, Daoudi, Atillah, Yahia, & Aboutajdine, 2014; Tamim et al., 2019; El Aouni, Minaoui, Tamim, Daoudi, & Yahia, 2018). In addition, an improved method was applied along the Moroccan Atlantic coast for separating the colder, nutrient-rich water from the warmer offshore waters (El Aouni et al., 2019). This method was implemented on physical and biological images in order to get efficient results compared to the previous ones. Recently, the authors (El Aouni, Daoudi, Minaoui, & Yahia, 2020) proposed a framework which can be used as a pre-processing stage before delineating the upwelling regions from the SST images.

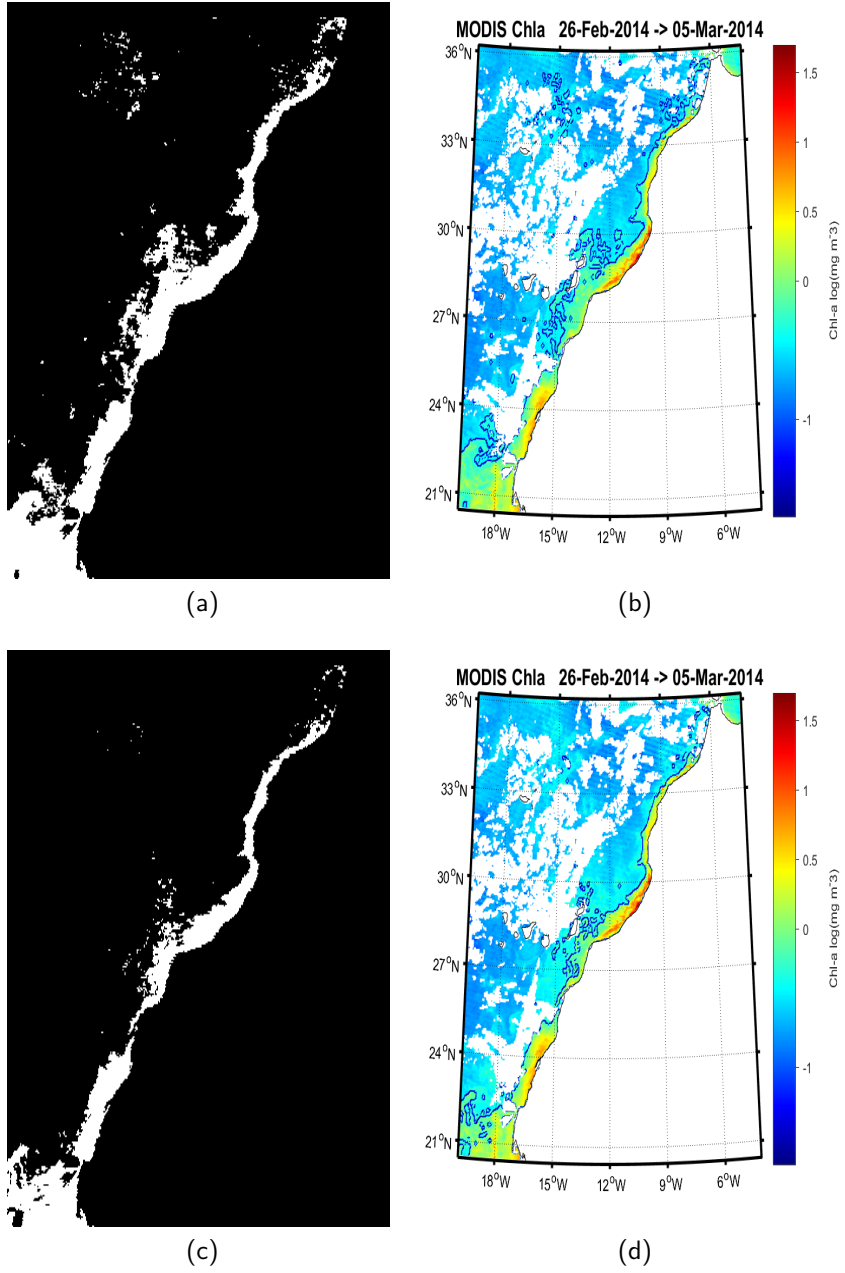


Figure 3.3: Results of segmentation: (a) binary Otsu's method, (b) its edge overlapped on the original chlorophyll-a image; (c) binary FCM method, (d) its edge superimposed on original image highlighting the chlorophyll-a concentration area

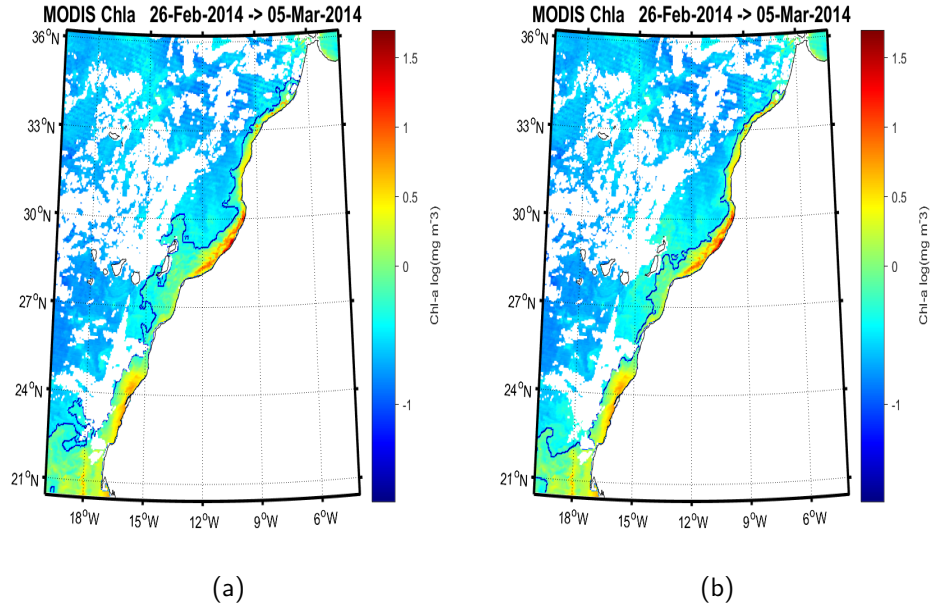


Figure 3.4: Results of Chl-a segmentation after using region growing: (a) Otsu versus (b) FCM methods.

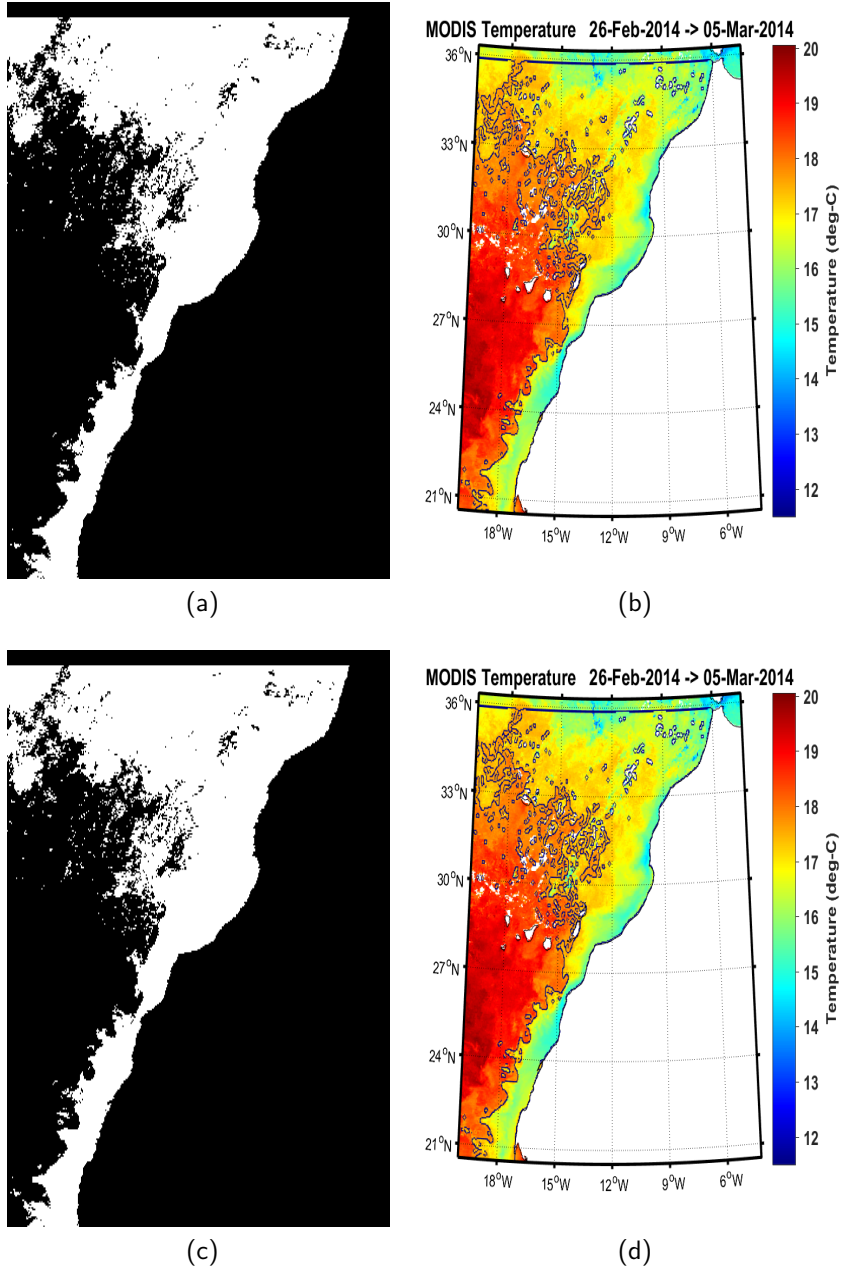


Figure 3.5: Results of segmentation: (a) binary Otsu's method, (b) its edge overlapped on the SST image; (c) binary FCM method, (d) its edge superimposed on original image highlighting the coldest water area

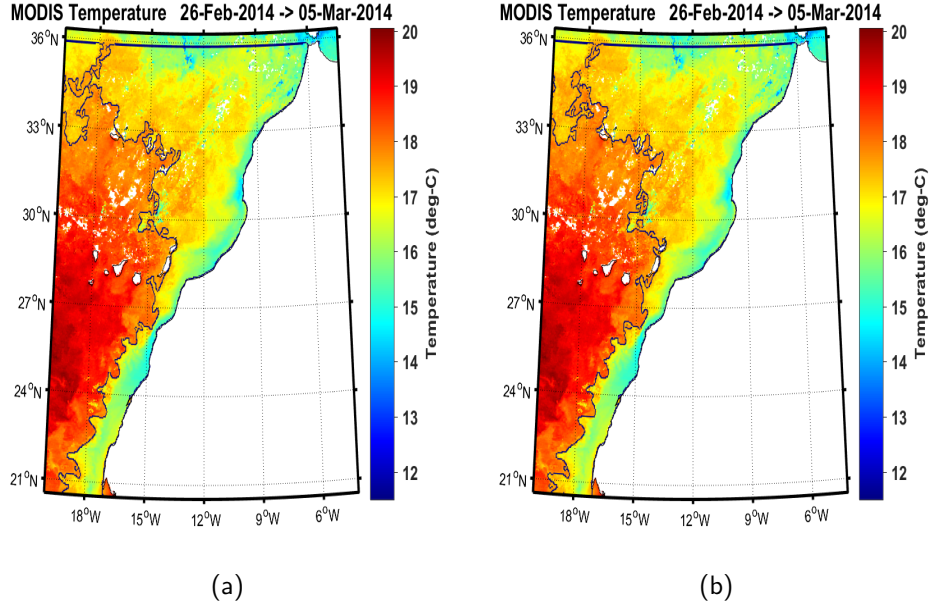


Figure 3.6: Delineating upwelling areas from original SST image using (a) Otsu's method and (b) Fuzzy C-Means. This figure shows that both of hard/fuzzy clustering methods cannot successfully extracting the northern of Moroccan upwelling system

3.5 Discussion and conclusion

In this section, two known methods of segmentation were applied on the original Chl-a and SST images. Their results showed the difference between using hard and fuzzy clustering for detecting upwelling area. For the studied example presented in Fig. 3.3, on the Chl-a side, it was observed that the binary image produced by FCM (see Fig. 3.3c) has the exact shapes of the investigated area compared to the result of Otsu's method (see Fig. 3.3a) where the width of the extracted upwelling water is larger than it should be. This contrast is more apparent when we use region growing after the step of segmentation (See Fig. 3.4). For the other side, the findings of those methods were almost the same principally in the south of Morocco (from 21°N to 27°N).

Both Otsu and FCM techniques over SST image were able to separate correctly the cool coastal water and the warm offshore ocean in the southern re-

gion. However, they are failed to detect the desired area in the central and in the northern of Morocco (up to $27^{\circ}N$) [See Fig. 3.5 and Fig. 3.6]. In order to address this limitation and to improve the segmentation accuracy, new concept will be required in the next chapters.

Chapter 4

Upwelling delimitation based on fusion of biological and thermal observations

Image fusion has getting an increasing attention in the research community with the goal of investigating its benefits to a wide spectrum of applications (remote sensing, computer vision, medical imaging...). In the current chapter, I will present the definition of fusion concept in image processing field followed by the description of its four levels and then I will expose the popular fusion methods. Finally, the fusion results for upwelling identification will be analyzed and compared.

4.1 Image fusion

4.1.1 Definition

One way to enhance object detection in image processing is through image fusion. This technique combines two or more images to produce a fused image that is more informative and of higher quality than the original input images.

4.1.2 Levels of image fusion

The procedure of image fusion can be performed at four levels(Aguilar, 2006):

Pixel level: is the low level of fusion, it is designed to combine raw pixels from different sources into single resolution image. The result of fusion should be more informative, synthetic and suitable for human and/or machine perception than the inputs.

Feature level: In this level, the combination takes place after the extraction of features (edges, colors, corners, lines, textures parameters...) of the images desired to be fused. A feature fusion level representation has certain advantages most important than the level one.

Score level: is the highest level of image fusion, it involves combining the scores obtained from classifiers. These scores include the relevant and rich information when compared to the original images.

Decision level: is the process of merging information at a higher level of abstraction and interpretation. This level involves combining the results from multiple algorithms to produce a final fused decision. In this process, the input sources are processed and classified individually, and their results are then fused together using techniques and methods specific to this stage.

4.2 Benefits

The main purpose of image fusion is not only to reduce the amount of data but also to product images that are more appreciated for machine treatment and visual human perception. In fact, the image fusion seeks to improve the knowledge about the entire globe with the goal to describe it as best as possible as it is. This concept also allows the estimation of a parameter obtained by the combination of values from different sources as well as data association is especially important for target tracking. Furthermore, image fusion is used more and more for recognition applications (detection, identification), and this is among the major objectives of our thesis.

4.3 Fusion methods

4.3.1 Alpha blending

Alpha blending is a method for combining a foreground image with a background image to produce a new blended image (referred as alpha blending) as described by (Porter & Duff, 1984). It enables the control of transparency of the foreground image from completely transparent to completely opaque. If the foreground image is completely transparent, the blended image will be the background image. Conversely, if the transparency is completely opaque, the blended image will be the foreground image. In-between these extremes the degree of transparency can be set and the blended image will be computed as a weighted average of the background and foreground images. This is done by applying an equation that performs the blending:

$$I_F = \alpha \times I_1 + (1 - \alpha) \times I_2 \quad (4.1)$$

In this context, I_1 is the background image, I_2 is the foreground image, and I_F is the blended image. The blending factor, α , determines the degree of transparency between the background and foreground images. The value of this indicator can vary between:

- $\alpha = 0$, if fully transparent;
- $\alpha = 1$, if fully opaque;
- $0 < \alpha < 1$, Otherwise.

4.3.2 Principal Component Analysis

Principal Component Analysis (PCA) is a widely used method for reducing the number of features in a dataset and extracting the most important ones. It is commonly used in object recognition and classification problems (Patel & Patel, 2015). PCA is a mathematical tool that transforms correlated variables into

a smaller number of uncorrelated variables called principal components. The fusion of two images, I_1 and I_2 , is done by calculating a weighted average of the images. The eigenvectors related to the largest eigenvalues of the covariance matrices are used to obtain weights for each image. The first principal component, PC_1 , is associated with the image that has the maximum variance, and the second principal component, PC_2 , is forced to be perpendicular to the first. To create a fused image that is more informative and suitable for human perception, PCA uses the following equation to exploit the unique features of both images:

$$I_F = I_1 \times PC_1 + I_2 \times PC_2 \quad (4.2)$$

4.3.3 Fusion by vote

The easiest way to combine two or more images is through voting, which is based on the combination of indicator functions from the classified input images. This method is particularly useful for fusion decision level. It involves combining the decisions made by classifiers on the classes of the test base.

Let $S_j(x) = i$ denotes the fact that the source S_j decides d_i , i.e. for example assigns the class C_i to the observation x . We assume here that the decisions d_i are exclusive. Each source is associated with the indicator function:

$$M_i^j = \begin{cases} 1 & \text{if } S_j(x) = i \\ 0 & \text{Otherwise} \end{cases} \quad (4.3)$$

Thus, the combination of sources is written by:

$$M_k^E = \sum_{j=1}^N M_k^j(x), \text{ for each } k. \quad (4.4)$$

The combination operator used in this method is both associative and commutative. The majority vote rule selects the decision made by the majority of sources (i.e., the max of M_k^E). However, this simple rule doesn't always have

solutions in all decisions $d_1, \dots, d_n$. For example, if the number of sources is even and half of them decide d_{i1} and the other half decide d_{i2} , or if each source S_j assigns a different class to x . To address this issue, an improved version of the majority vote rule, called the "majority vote" has been introduced, written by:

$$E(x) = \begin{cases} k & \text{if } M_k^E > \frac{N}{2} \\ n+1 & \text{Otherwise} \end{cases} \quad (4.5)$$

From this equation, several results have been shown proving that the voting fusion method provides better performance than all the sources taken separately. This theoretically shows the interest of information fusion.

The voting method is used when information is presented in the form of hypotheses, making it well-suited for merging decisions in classification applications, such as recognition, detection, and identification (Martin, 2005).

4.4 Upwelling extraction based on fusion of SST and Chl-a images

4.4.1 Under-segmentation problem

While results of segmentation methods displayed in Figure.3.6 provide an accurate segmentation of Moroccan upwelling in the southern part (below 28°N), they however fail to give good identification in the northern zone. This failure is due to the under-segmentation issue. The uneven heating of the earth's surface causes non-linear variations in temperature, making it difficult for clustering algorithms to accurately segment regions. For example, offshore waters in the northern part may have similar temperatures to inshore waters in the southern part, creating a non-linearity that cannot be handled by traditional clustering methods. This is highlighted in Figure 4.1 by the black circles that show the same/closer temperature between the northern offshore(from 28°N to 36°N) and southern upwelling regions. In order to address this issue, we propose using a

fusion concept that incorporates multiple methods and not just relying solely on SST data.

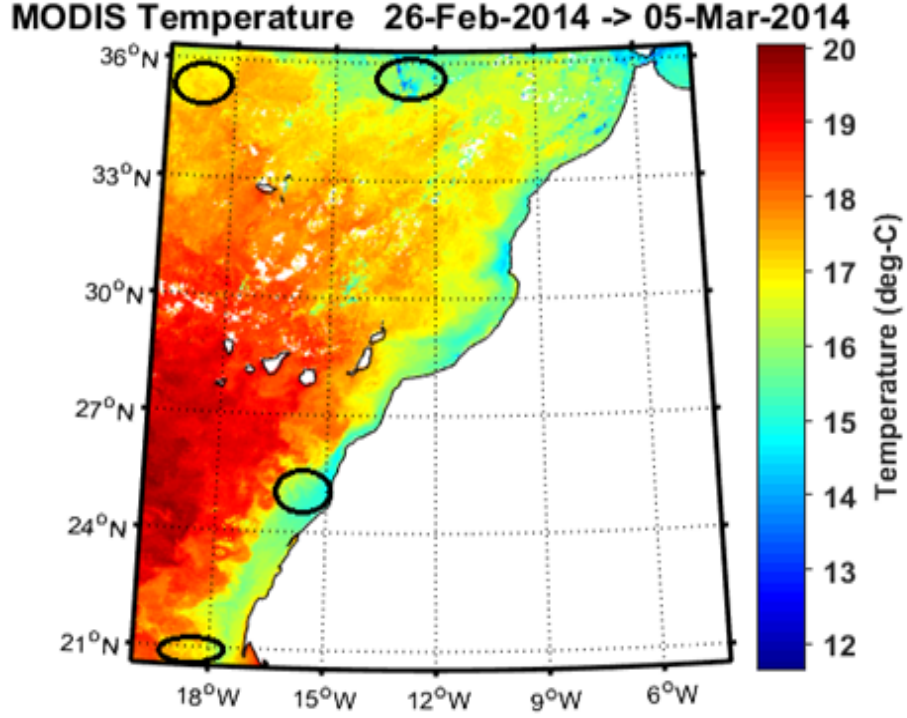


Figure 4.1: A weekly SST image obtained on the year 2014; Black circles highlight the under-segmentation problem shown in the north Atlantic of Morocco where this part has similar temperatures to the inshore of the southern area

4.4.2 Results of fusion methods

In this part, we present two perceptive and efficient fusion methods using hard clustering algorithm (Otsu's method described in Section 3.1.1) for the segmentation step and respectively alpha blending (El Abidi, Minaoui, Tamim, & Laanaya, 2018b) and PCA (El Abidi, Minaoui, Tamim, & Laanaya, 2018a) for the fusion phase. These methods are capable of extracting upwelling areas using simultaneously Chl-a and SST images. Starting by calculating threshold value based on Otsu's method, binary Chl-a image result presents the high chlorophyll-a concentration in white color indicating well extraction of the up-

welling area. Oppositely, we notice the false detection in the segmented SST image generated by under-segmentation as shown in north of Moroccan coastal. The step of fusion is used here to solve this problem by applying one of the following methods:

- The alpha blending technique is adapted by choosing binary Chl-a image as a foreground, while binary SST image is used as a background and the degree of transparency gets 0.5. It must be noted that the value attributed to $\alpha = 0.5$ is selected in order to give the same probability value to each biological and physical image. The combination of these binary inputs produce one blended image more informative and suitable for detecting efficiently the northern part.
- Another image fusion technique that is applied is called Principal Component Analysis (PCA). The PCA fusion is achieved by calculating the weighted average of the segmented Chl-a and binary SST images.

The eigenvectors corresponding to the largest eigenvalues of the covariance matrices of each source are used to determine the weights for each input image. The direction of the maximum variance is used to compute the first principal component, PC_1 , which is related to the segmented chlorophyll-a image. The second principal component, PC_2 , which is associated with the result of Otsu's method applied to the SST image, should be perpendicular to the first.

An alternative fusion method is also recommended for extracting efficiency the upwelling zones. Primarily, we apply fuzzy clustering algorithm to each source image by implementing FCM technique. The main challenge of using any unsupervised method is the definition of number of clusters a priori. For Moroccan upwelling detection, the determination of the optimal number of clusters is based on (El Aouni et al., 2015) for chlorophyll image and on (Tamim et al., 2013) for SST observation. Consequently, for our process, the chosen number is $C = 2$ in favor of obtaining a representative image containing just two

classes: Upwelling and non-Upwelling zones. Secondly, an AND logic is investigated in order to fuse the results of FCM applied over Chl-a and SST images. This logical operator returns the true value when both pixels of the segmented operands are having the information about upwelling existence and gives false otherwise (non upwelling area). These input operands are forced to be taken in the same time and having similar pixels size (Elabidi, Minaoui, Tamim, & Laanaya, 2018).

The outputs of these three fusion methods are illustrated in Figure 4.2 where the counters of upwelling extracted areas are overlapped in the original chlorophyll-a [See left column of Figure. 4.2] and SST [See right column] sources. The results demonstrate that image fusion concept is a great way to overcome the issue presented in northern of Moroccan Atlantic coast over SST image. Furthermore, it is able to detect efficacy and in real time the desired areas.

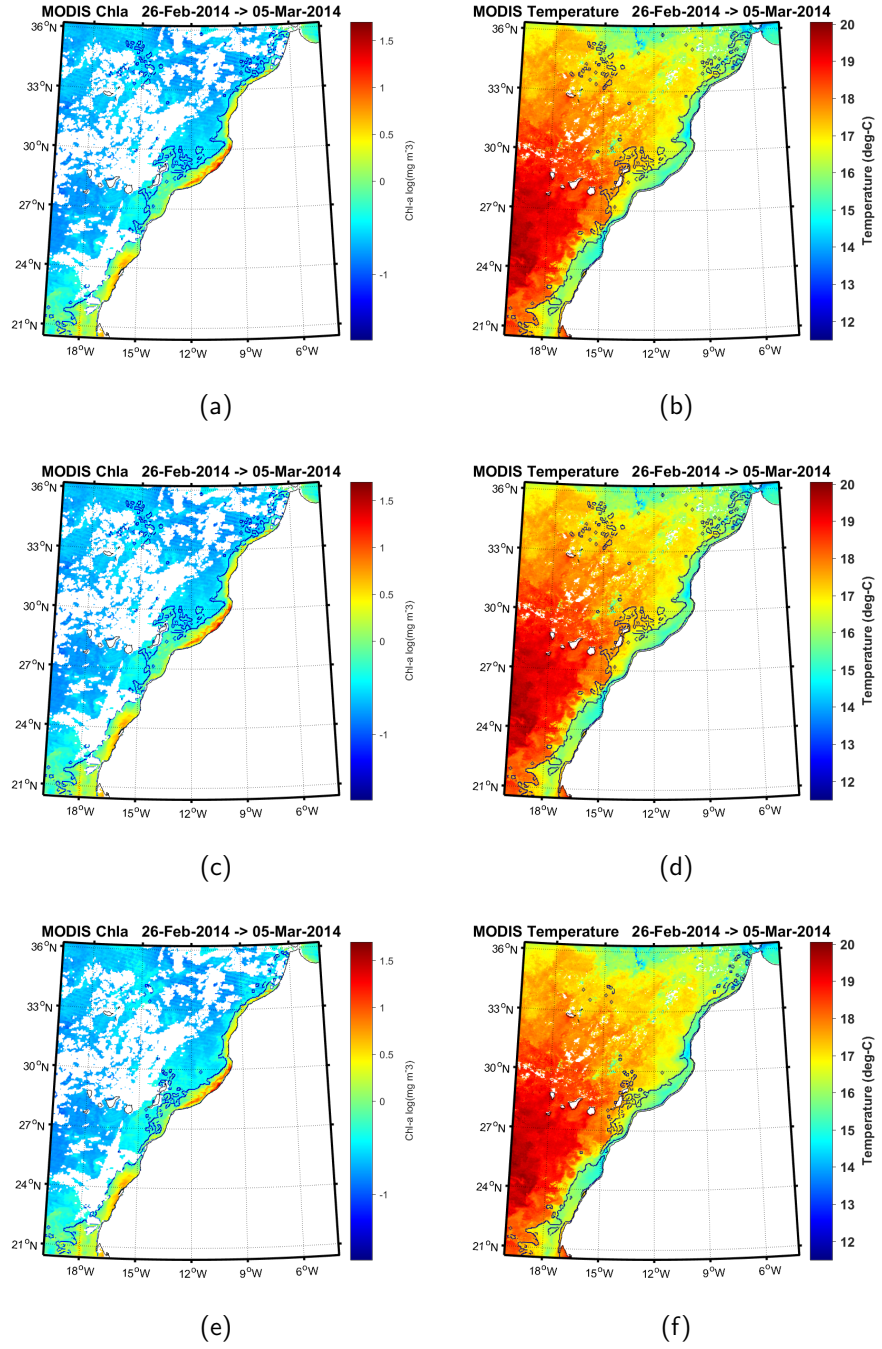


Figure 4.2: Results of fusion methods: (a)-(b) PCA; (c)-(d) Alpha blending; (e)-(f) Logical AND operator overlapped on original Chl-a [left column] and SST image [right column]

4.4.3 Proposed methodology at feature level

Our main goal is addressed to introduce a new and a complete methodology (El Abidi, Minaoui, El Aouni, Tamim, & Laanaya, 2020) that aims to improve the detection of coastal upwelling based on fusion of two pertinent parameters: SST and Chl-a concentration as well as filling the cloud pixels preliminary in order to enhance the result of fusion. In this regard, our proposed approach consists of the four following steps.

Pre-processing step

To improve the quality of upwelling extraction, a pre-processing stage is required to address the problem of cloudiness prior to the fusion process. Depending on the database used (from January 2007 to December 2014), the Chl-a images are more affected by cloudiness than thermal observations. This is due to the different wavelengths and algorithms used to acquire the data. Moroccan Atlantic waters can be partially or completely covered by clouds, as shown in Figure.3.2b and Figure.4.4a. To solve the problem of cloud pixels, we used a polynomial curve fitting method (Thompson & Balch, 1988) which fills the cloud pixels without modifying the unclouded ones. Its mathematical expression is represented in the following equation:

$$\mathcal{P}_n(X) = p_0 + p_1 \times X^1 + p_2 \times X^2 + \dots + p_{n-1} \times X^{n-1} + p_n \times X^n \quad (4.6)$$

The coefficients of $\mathcal{P}_n$ are arranged in ascending powers, where the value of polynomial degree is n . In our case, the value of degree is 5 ($n = 5$) because it gives the best fit (in a least-squares sense) for the original chlorophyll-a images and also because it does not change the pixel intensity variation.

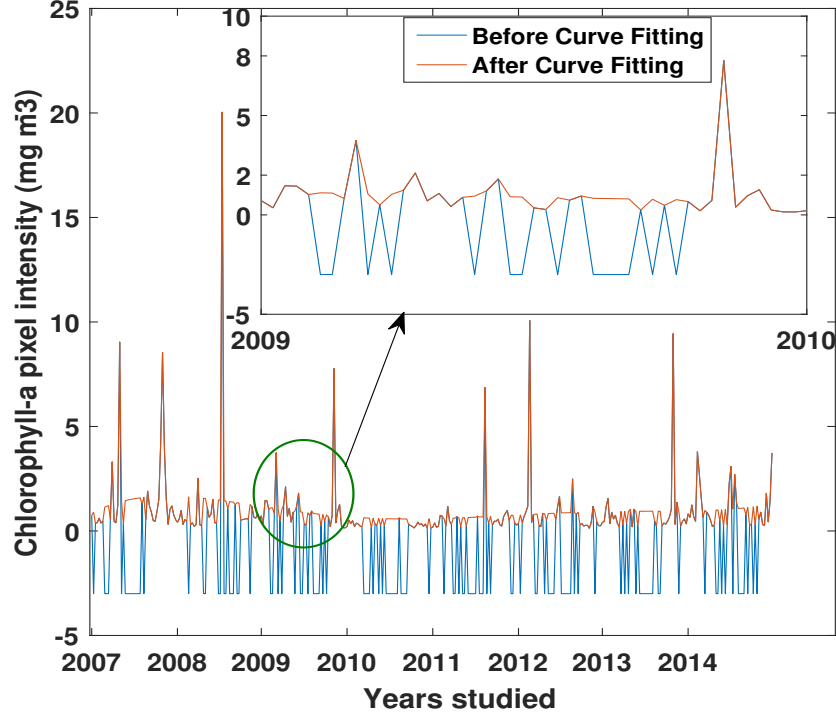


Figure 4.3: Comparison of chlorophyll pixel intensity changes before and after curve fitting in the entire 8-year database, with negative intensity indicating cloud pixel values.

The above curve (Figure. 4.3) shows the intensity variation of an example pixel with coordinates $P(175, 215)$ located in a high chlorophyll-a concentration region. As shown, the negative noisy values caused by clouds are accurately corrected by the polynomial curve fitting method applied to each Chl-a image in the database.

We validated the outputs of the polynomial curve fitting (PCF) method using the universal image quality index "Mean Squared Error (MSE)". To calculate the MSE metric, we used the SST image as a reference. We normalized all the original data for both SST and Chlorophyll-a images and ignored the outlier pixels produced by PCF (their percentage relative to the corrected pixels does not exceed $1.55 \times 10^{-4}\%$). Then, we computed the error between them and

obtained the following values:

- For the clouded pixels, the mean of MSE in all the processed images is 0.21 (MSE=0.21);
- For the unclouded pixels, MSE=0.

The obtained values of MSE indicate that the method used to address the cloudiness problem is effective as it correctly rectifies more than 78% of the noisy pixels in all the chlorophyll-a data used without affecting the unclouded pixels.

Fig4.4b shows the result of PCF on the noisiest image of the data (Fig4.4a). The pre-processed step seeks to create an empiric data model in which we can predict the value of the clouded pixels using the polynomial regression. The mathematical expression of the model computed is defined as below:

$$\mathcal{P}_5(X) = 175.03 - 175.16 \times X^1 - 172.18 \times X^2 + 234.47 \times X^3 - 66.09 \times X^4 + 8.55 \times X^5 \quad (4.7)$$

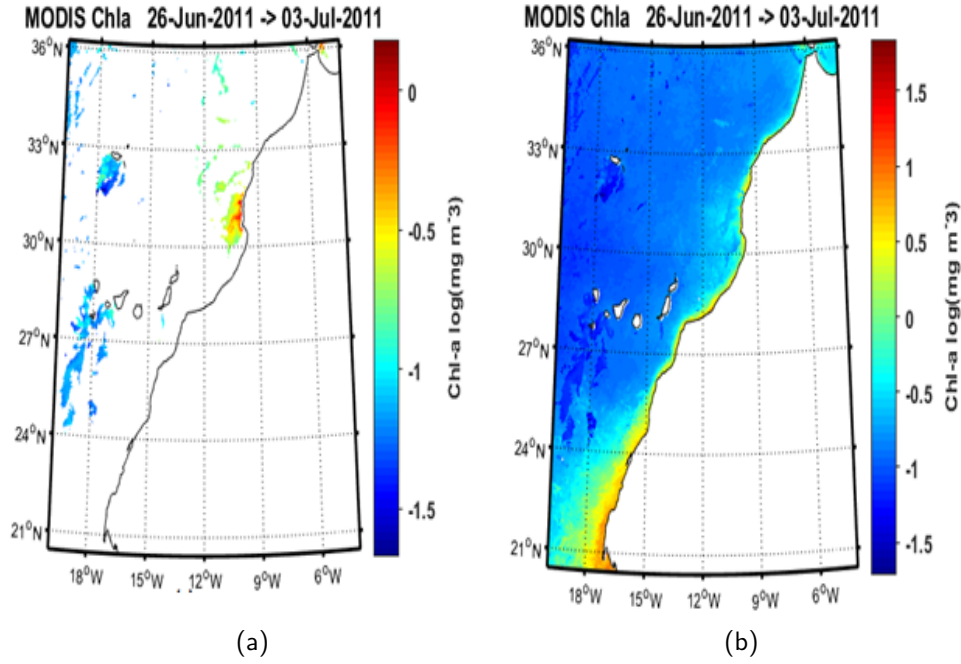


Figure 4.4: The most clouded chlorophyll-a image for the period 2007 to 2014: (a) original and (b) the output of polynomial curve fitting.

For the noisiest Chl-a image, we found that $MSE = 0.18$. This finding value indicates that the first step of our methodology rectifies properly more than 80% of all the clouded pixels of the most noised image.

Segmentation step

After rectifying and filling the clouded pixels, we apply FCM method on SST and on each corrected Chl-a images for separating upwelling areas than the offshore ocean waters. Oceanography, the FCM over sea surface temperature image provides result more appreciated than the Chl-a one, but in the Moroccan coastal it is not the case because of the under-segmentation problem shown in Figure.3.6. Indeed it is true that Chl-a can include pollution, harmful algal blooms and so one, however, on the other side SST observation did not escape this issue, they might also contain some wrong acquisition, for example the dust travelling offshore the western Sahara has been reported to affect SST data in

that region. Back to why Chl-a gives more satisfying results compared to SST, the main reason here is the nature of the data, they present different properties: physical and biological. Chlorophyll-a concentration of upwelling water is meridionally very similar along the coastline, in the same manner the offshore water in the open ocean has almost the same concentration of chlorophyll-a. By that, these two classes are linearly separable, that's what the FCM have shown.

Fusion step

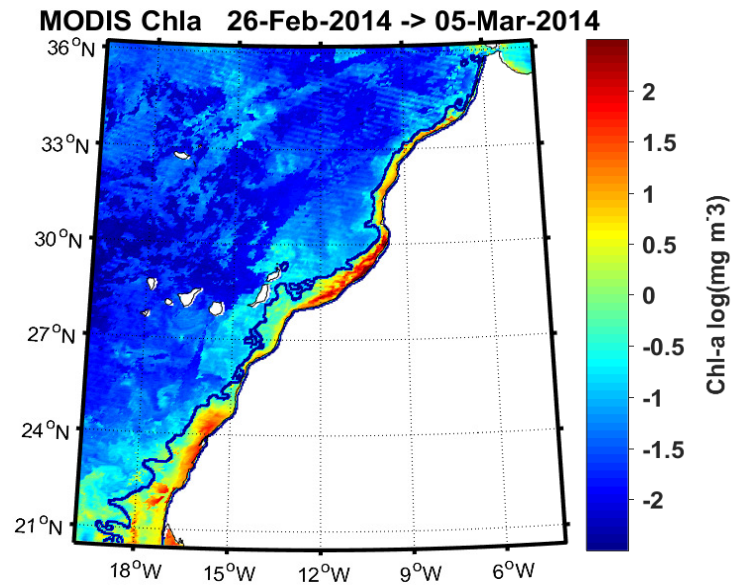
As pointed previously, to correct the issue presented in SST image, we combine the outputs of Fuzzy C-Means by using a simple AND logic. This operator is applied in pixel-by-pixel way, it returns True if both operands (Chl-a and SST labelled images) had the information of upwelling existence and gives False otherwise (lack of cold, nutrient-rich waters). The fundamental reason of choosing such simple operator for fusion is go back to the nature of the studied upwelling system. The Moroccan coastal upwelling is characterized by the high variability of the latitudinal distribution of temperatures which generate the under-segmentation problem when FCM method is applied on SST observation. Furthermore, we operate the AND operator not only to improve the results but also to provide them in real time. Giving both faster and appreciated results is an important aim for oceanographers to identify the coastal upwelling waters.

Post-processing step

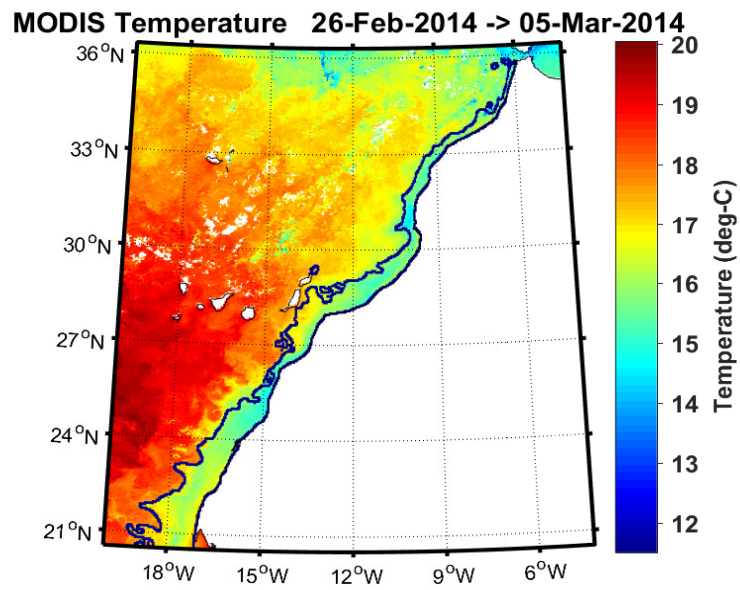
Once the zone covered by the upwelling waters is determined, the next step is to eliminate the tiny and noisy structures that do not belong to the upwelling region. A mathematical morphology technique is implemented to remove these residual pixels using an opening operation. This operation begins by eroding all connected components that are fewer than 10 pixels without eliminating the unconnected pixels that are located near the coastline. Based on our study of the entire database, we found that the suitable value for eliminating the residual pixels without removing the unconnected pixels located near the coast

is 10 pixels.

The result of all the steps is illustrated in Figure. 4.5 where the upwelling boundary is marked with a bolder line on the rectified Chl-a image (Figure. 4.5a) and on an example of the SST observation (Figure. 4.5b). The result shows that the proposed fusion approach is very accurate and effective for upwelling delimitation as it rectifies and predicts cloud values and overcomes the under-segmentation problem caused by clustering algorithms.



(a)



(b)

Figure 4.5: The outcome of the fusion process shown by superimposing the Canny-colored filter on the corrected Chl-a image (a) and the original SST image (b) respectively.

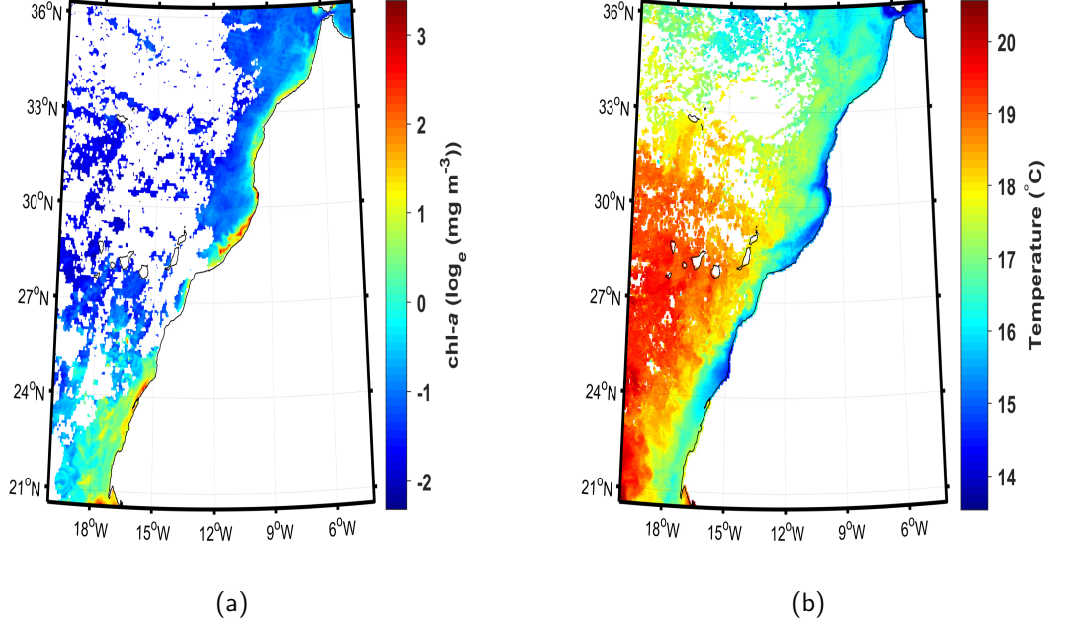


Figure 4.6: (a) Eight-day SST image ($^{\circ}\text{C}$) and (b) chl-a concentration ($\log_e (\text{mg m}^{-3})$) image captured on the second week of March 2016, presenting a typical upwelling scenario from physical and biological observations with cloudiness issue; similar oceanic structures appear in both the images.

4.4.4 Proposed methodology at decision level

In this section, we present a robust methodology (El Abidi & Minaoui, 2022) that combines and improves upon the fusion techniques previously described in the literature for identifying, detecting, and extracting the upwelling zone along the Atlantic coast of Morocco. The methodology is based on the following two main steps, applied to the example shown in Figure 4.6.

Filling clouded pixels

Our initial effort aims to accurately fill the pixels that are cloud-covered. The data we used led us to the conclusion that cloudiness near coastal waters can be seen in varying degrees in both SST and chl-a remotely sensed images. We use the Piecewise Cubic Hermite Interpolating Polynomial (PCHIP) approach to solve this problem. Piecewise polynomial structures are built using PCHIP.

The piecewise cubic polynomial $P(x)$ is used for interpolation while upholding the following characteristics:

- The polynomial $P(x)$ is a cubic Hermite interpolating polynomial for the given data points with defined derivatives (slopes) at the interpolation points on each subinterval $x_k \leq x \leq x_{k+1}$;
- The first derivative of $\frac{dP}{dx}$ is continuous and $P(x)$ interpolates y , i.e., $P(x_j) = y_j$;
- The shape of the data is preserved by the cubic interpolant $P(x)$. The slopes at x_j are selected so that monotonicity and the shape of the data are respected by $P(x)$. As a result, at sites where the data contain local extreme values and on intervals where the data are monotonic, $P(x)$ is also monotonic.

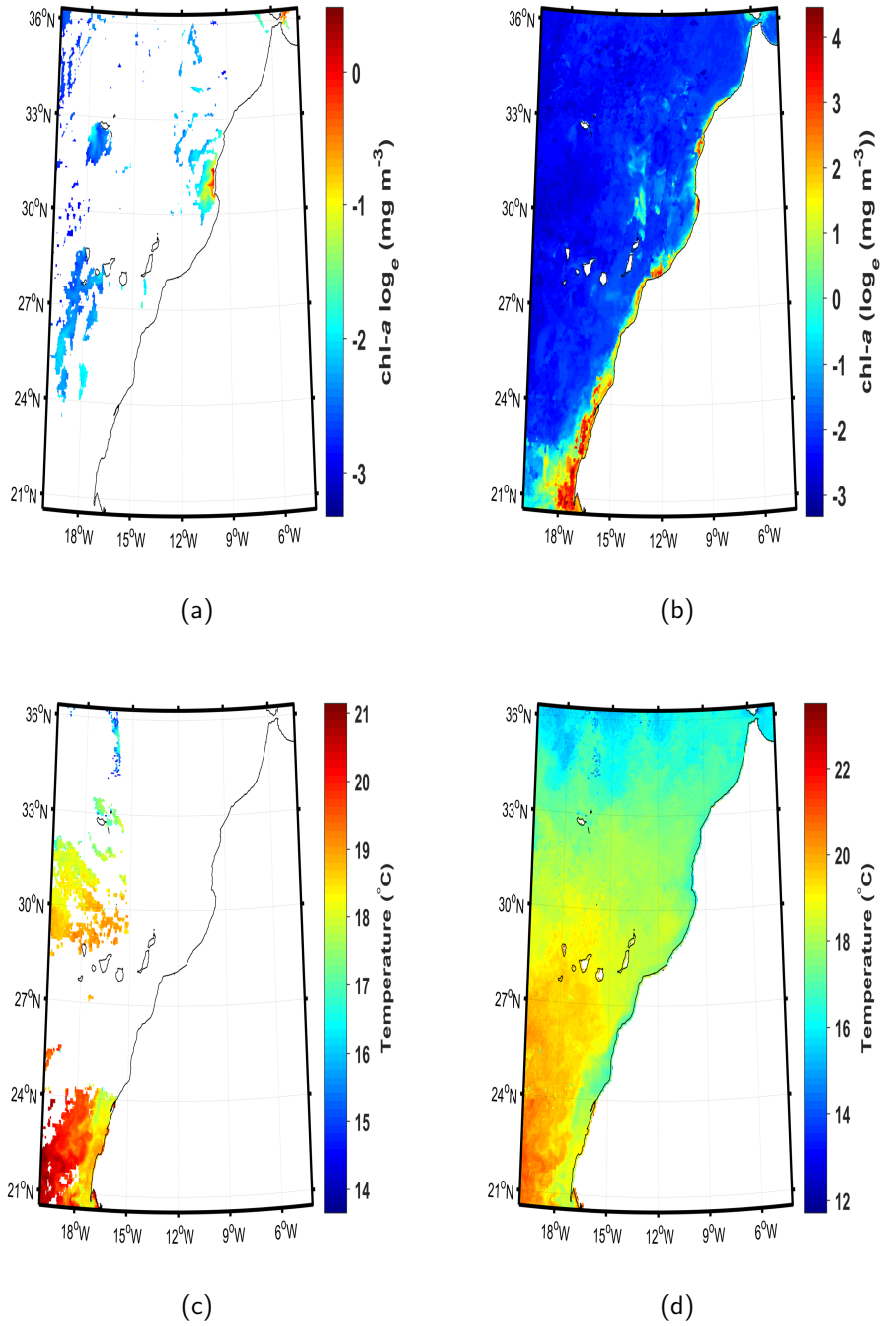


Figure 4.7: The most noisy images in the database, showing chlorophyll-a from June 25th to July 3rd, 2011 (a) and SST from April 7th to 14th, 2002 (c), and their corresponding corrected images (b) and (d).

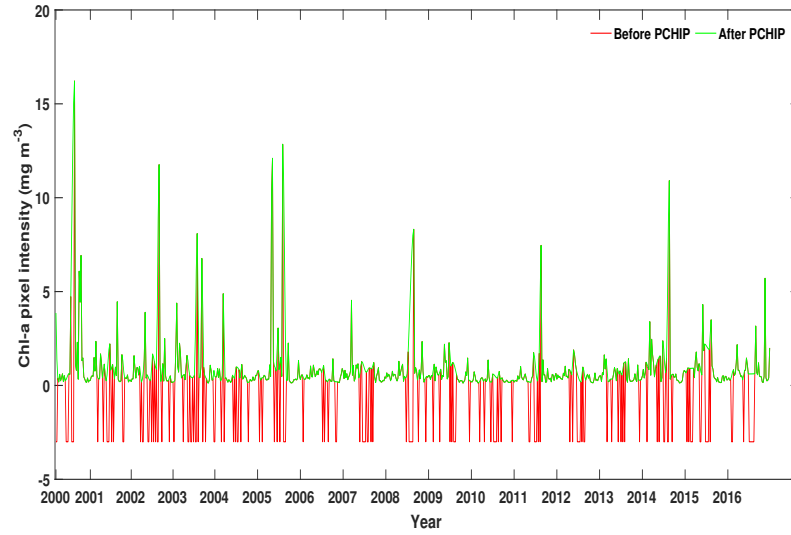
As seen in figure 4.7, the method used to address the cloudiness issue may

preserve the values of original pixels while also accurately predicting the pixels affected by clouds for the most clouded chl-a /SST images.

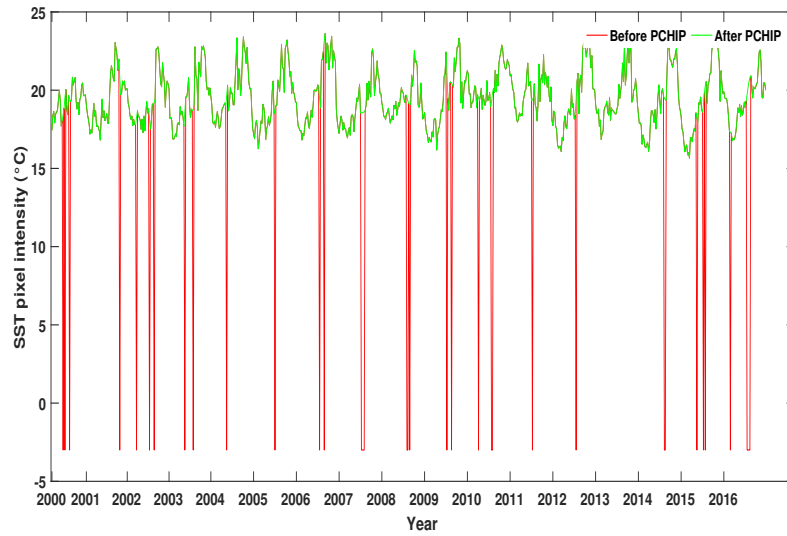
The curves shown in figure 4.8 depict the intensity change of a single pixel at coordinates (153, 215) that are situated in an area of high chlorophyll-a concentration and low SST values. To stand out, we display the cloud pixels with negative values; the red curve shows the pixel's variation throughout the course of seventeen years, while the green curve shows its variation after PCHIP was implemented. We apply the Mean Squared Error (MSE) universal image quality indicator to assess the results of PCHIP, and we discovered that MSE is $MSE = 0.2$ on average across all the data. The acquired value of this index makes it evident that the suggested strategy for resolving the cloudiness issue is appropriate because it accurately corrects more than 79% percent of the noisy pixels in all of the employed Chl-a/SST data without altering the clear ones. Here, the preprocessing step is used to improve the quality of the fusion results as well as to fill in any missing values.

Fusing using major voting

After applying the PCHIP interpolation method to all the datasets, three fusion methodologies, independently created by (El Abidi et al., 2018b; Elabidi et al., 2018; El Abidi et al., 2018a) are used to extract the Moroccan upwelling region in three different ways. This results in three fusion outputs, as seen in the top row of Figure 4.9. Each binary image is the result of a specific fusion technique, and the extracted upwelling area is indicated by the white color.



(a)



(b)

Figure 4.8: Comparison of the intensity changes of (a) Chl-a and (b) SST at the pixel located at coordinates (153, 215) over the period 2000-2016, before and after applying PCHIP.

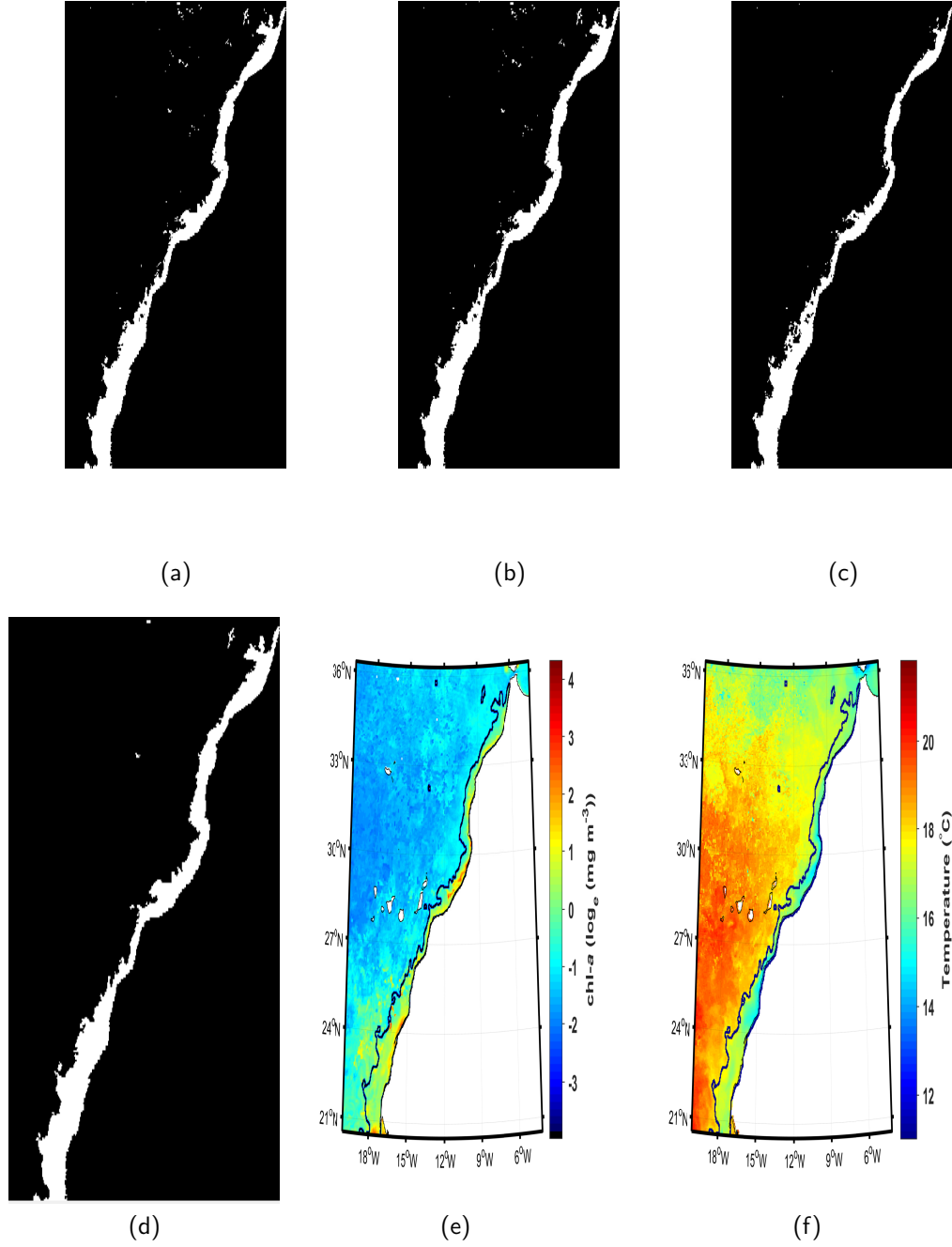


Figure 4.9: The results of three fusion methods are shown in the top row: (a) Principal Component Analysis, (b) Alpha Blending, and (c) AND logic operator. The output of fusion based on majority voting is displayed in (d) as a binary image. The Canny-colored filter is superimposed on the corrected Chl-a (e) and SST (f) images.

We employ a simple, clear, and effective majority voting method based on the combination of results obtained from Principal Component Analysis (PCA), Alpha blending, and AND logic classifiers to improve these results and more accurately define the cool, nutrient-rich waters. To do this, even if a region appeared in at least two input classifiers, we still presume that it is a coastal upwelling region. Let $S_j(x) = i$ represent the fact that the source S_j selects d_i , i.e., gives the observation x the class C_i . Here, we'll make the assumption that the choices are mutually exclusive (three decisions). Every source has a connection to the indicator function:

$$M_i^j = \begin{cases} 1 & \text{if } S_j(x) = i \\ 0 & \text{Otherwise} \end{cases} \quad (4.8)$$

Thus, the combination of sources is defined as:

$$M_k^E = \sum_{j=1}^N M_k^j(x), \text{ for each } k. \quad (4.9)$$

The majority vote rule entails selecting the course of action selected by the greatest number of sources (maximum M_k^E). Several findings from the equation 4.9 demonstrate that the voting fusion method performs better than citing each source individually. This demonstrates, potentially, the appeal of information fusion at the decision level.

For instance, each pixel of the binarized images (figure-4.9(a), (b), and (c)) is consulted to create the final fused image. If the majority of the three algorithms agree that the associated pixel is a 1 (for upwelling class) in their respective subsequent binarized image, then each pixel in the resulting image is set to 1. If not, the pixel in the output image is set to 0 (for the situation of no upwelling; see figure 4.9(d), (e), and (f)). We employed an opening operation to get rid of the remaining pixels that showed up in the offshore by removing all the connected parts that have fewer than ten pixels without removing the unconnected ones from the inshore waters.

4.5 conclusion

This chapter focused on reviewing existing fusion methods for the automatic identification of upwelling regions. The proposed methodology was shown to be particularly well-suited for this task, as it not only improves detection but also addresses the problem of cloudiness and under-segmentation. Overall, the reviewed fusion methods produced very promising results for this complex system, but further validation is needed to confirm their findings both qualitatively and quantitatively.

Chapter 5

Validation of fusion results: Qualitatively and Quantitatively

I address in the current chapter the qualitative evaluation made by the physical oceanographer over all the fusion methods proposed previously, after that, I present the quantitative validation using our new, simple and intuitive upwelling index. Then, we define a group of SST, Chl-a and Wind indices to quantify in detail the interannual and seasonal variability of the Moroccan upwelling system.

5.1 Qualitative evaluation

We validate subjectively the different methods developed for upwelling identification by an experienced user (physical oceanographer). Indeed, he evaluates visually the obtained results, as it has been done in several other studies related to the upwelling detection (Sousa et al., 2008).

An oceanographer visually evaluates the identification and boundaries of upwelling fronts in Chl-a and SST images independently, to ensure that the results

accurately depict the original images without omitting important oceanographic information. Specifically, the evaluation assesses whether the proposed method can correctly identify areas of upwelling. This evaluation is based on expert knowledge of the seasonal variation of upwelling in the Moroccan Atlantic.

The scale used for the oceanographic validation is based on four grades: "Poor", "Acceptable", "Good" and "Excellent". Poor is assigned in these cases:

- When the oceanographer finds that the validated method labels some regions as upwelling, while there is no upwelling in the images;
- When the method does not find upwelling, however the oceanographer can find it scientifically;
- When the main upwelling front extracted by the method is far from what the oceanographer sees.

An example of this grade is displayed in Figure. 5.1. Even if the cool water area is well determined in north, the upwelling water is not identified in south at all while it appears clearly in Chl-a image with high chlorophyll-a concentration.

Excellent grade is attributed when the oceanographer is satisfied with the segmentation. In fact, the oceanographer agrees that the main upwelling front which we extracted is exactly what he sees while analyzing the images. A very time consuming process, analyzing visually each image's properties physical structures related to the upwelling takes several minutes, and that is why only 92 images at maximum (two successive years 2013 and 2014) have been validated this way.

Figure. 5.2 represents a compound bar graph computed from the oceanographer interpretation about the results of the three proposed fusion methods. Regarding this assessment, we show that the results of Alpha blending technique and the method based on AND logic seem to have closer values notably for "Good" rank where they achieve 39%. The grade "Poor" is attributed to only 8% of the dataset for PCA method, while it is attained more than 12% and less than 15% for the other methods. Overall the 46 Chl-a and 46 SST images

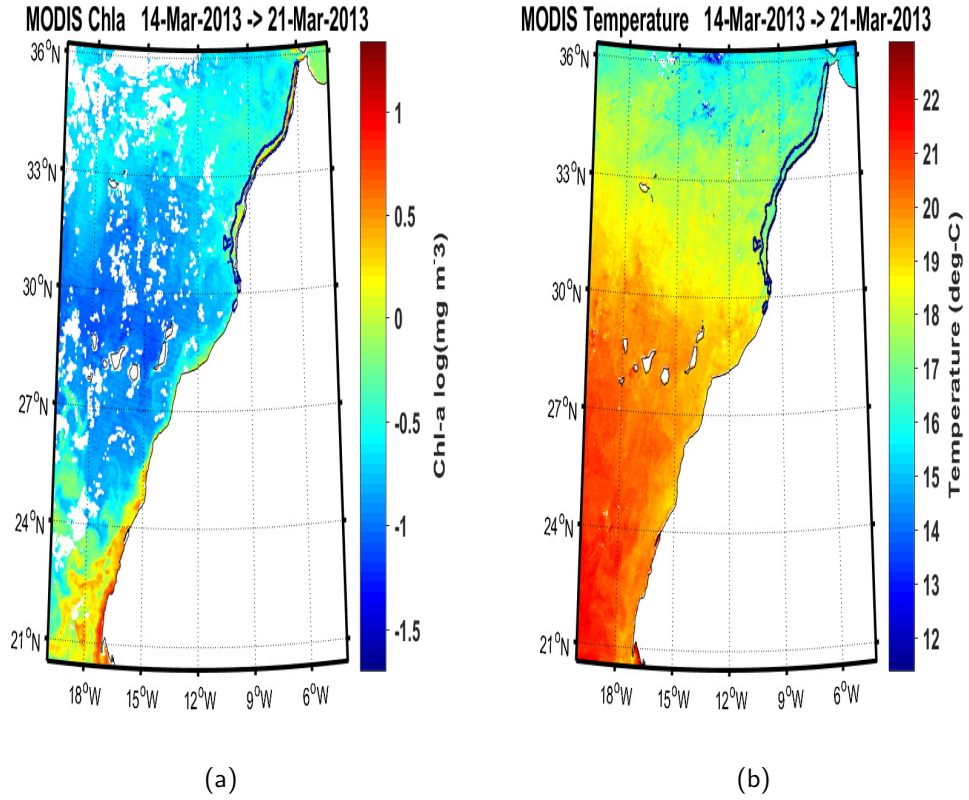


Figure 5.1: An example of the "Poor" grade according to oceanographer validation overlaid on the original (a) chlorophyll-a and (b) SST images.

used in this validation, the result of fusion of 67% is considered as "Good" or "Excellent", showing the performance of the AND logic approach for delineating the Moroccan upwelling.

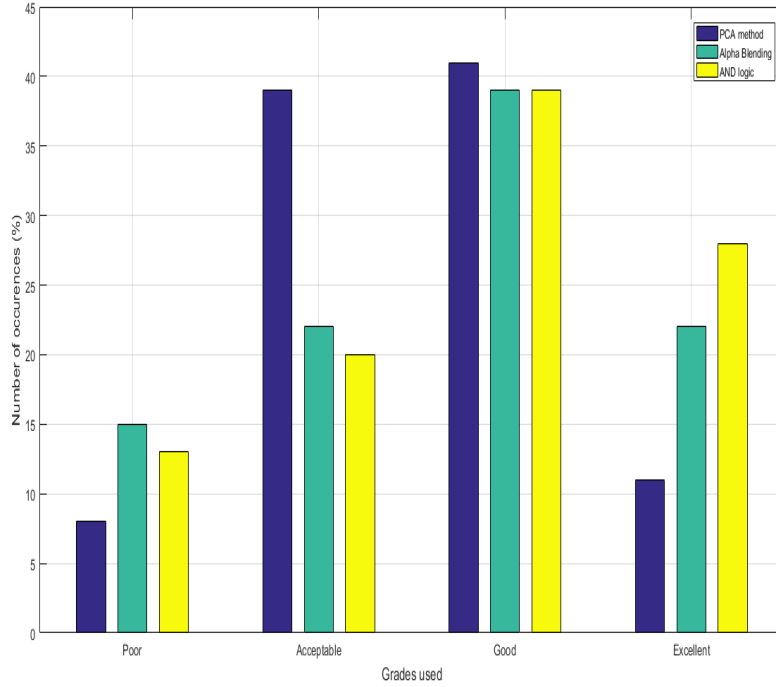


Figure 5.2: A qualitative evaluation of 46 Chl-a and 46 SST images using PCA, Alpha Blending, and AND logic fusion methods was performed by an oceanographer.

A thorough qualitative analysis was also conducted to compare the proposed methodology with the results obtained using FCM on Chl-a and SST. The same grading system previously described was used to evaluate if the results accurately identified the upwelling area without any over-detection or under-detection of structures.

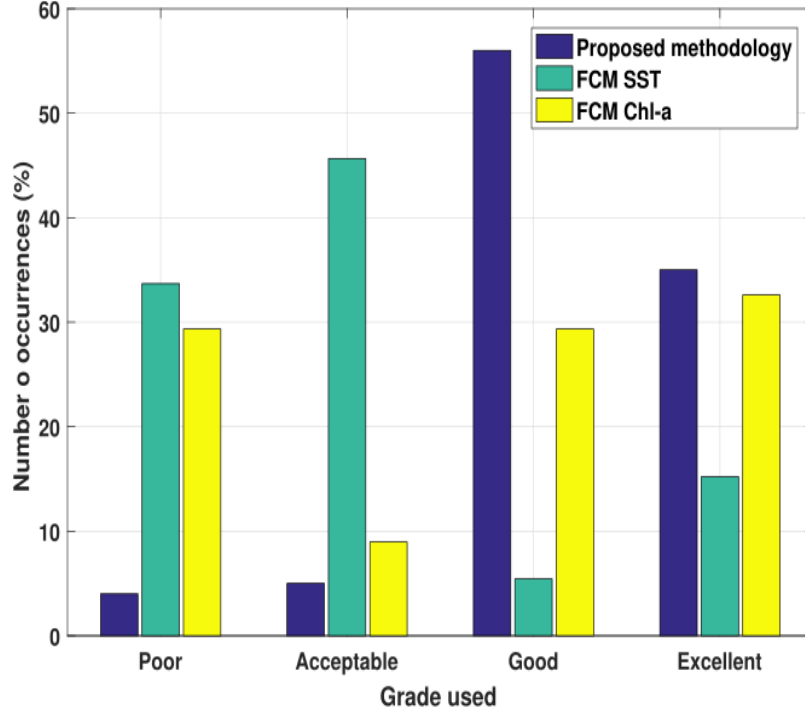


Figure 5.3: Oceanographer’s Qualitative Analysis of Proposed Fusion Method on 92 Chl-a and 92 SST Images from 2013 and 2014

The assessment in Figure. 5.3 shows that the proposed methodology had a 4% "Poor" grade, while the results of FCM over SST and Chl-a had 33% and 29% "Poor" grades respectively. The proposed methodology had a total of 91% "Good" and "Excellent" grades, while FCM on Chl-a had 62% and FCM SST had 21%.

Upon evaluating the three methods using a representative dataset, it was determined that FCM applied to SST observations yielded the poorest results in detecting upwelling waters due to inadequate segmentation. When comparing the proposed methodology with FCM applied to Chl-a, both methods received similar "Excellent" grades, however, the proposed method was found to be more effective in accurately identifying the region of interest in the validated dataset.

5.2 Quantitative validation

The qualitative validation process is still open to subjectivity and requires the expertise of a domain expert for evaluating the results in each analysis. Considering the lack of “ground truth” data in the case of this work: no buoy data would be relevant to detect fronts because of discrepancy of Lagrangian buoy data. So far, the most complete set of Lagrangian buoys available come from the NASA Global Drifter Program which, on top of discrepancy and inaccuracy for detecting fronts (it can be used for example for validation of ocean dynamics), would be extremely challenging for a use in coastal zone context. It is a widely acknowledged fact that validation of ocean data is typically carried out by either having it evaluated by professional oceanographers or by calculating an index of upwelling, as was done in this thesis.

5.2.1 Configuration of radials

When winds blow parallel to the coast in the Northern hemisphere case (like Moroccan Atlantic coast, where winds blow north to south), the Ekman transport occurs a net movement at a 90° angle clockwise from the wind direction (Ekman, 1905). Coastal upwelling is largely dependent on the width of the continental shelf as noted in (Atillah et al., 2005). In order to better encompass the width of the Moroccan shelf, radials were drawn perpendicular to the general direction of the Moroccan coast. To accomplish this, we first established a virtual line P parallel to the coast, and then divided the latitudes of each image into radials R_n that were perpendicular to the coast as shown in Figure.5.4. Each radial should cross the upwelling extracted area (purple color) and the offshore waters (pink line). Actually, the number of radials used for covering the whole of Moroccan territory varies from 1573 for a full resolution image ($0.01^\circ : 1km$) to 320 for a low-resolution spatially sub-sampled image ($0.05^\circ : 5km$).

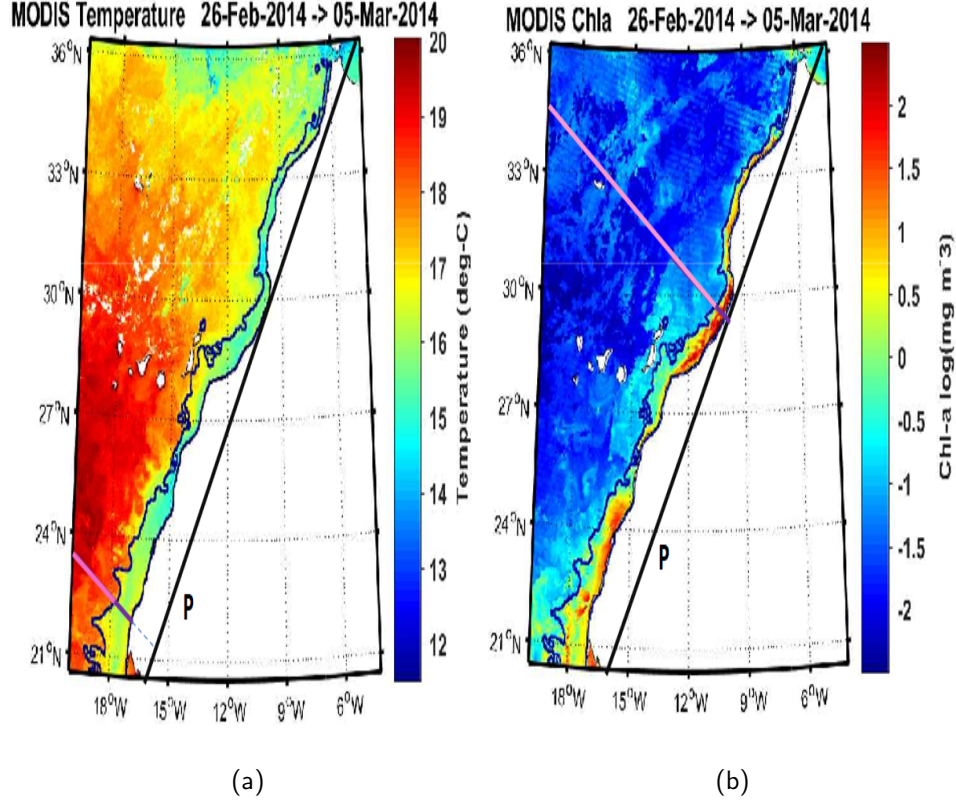


Figure 5.4: Example of radials configured on the result of our proposed fusion methodology over (a) rectified chlorophyll-a and (b) SST images; Each radial should be perpendicular to the coastline (Black line P) and corresponds to a specific latitude: On SST, the radial drawn in south refers to 22°N while on Chl-a it is marked in 29°N (central region).

We objectively evaluate the performance of our proposed methodology by analyzing the results based on the radial representation. Specifically, we assess whether the main upwelling is accurately identified by computing a simple gradient along the extracted upwelling front (the difference between the adjacent pixels in the offshore and upwelling regions). Pixels in the upwelling zone are colder and have higher chlorophyll-a concentrations compared to those in the offshore water. Therefore, the front is correctly identified if the gradient is negative in the Chl-a image and positive in the SST observation for each radial. A "NaN" value is assigned when there is no identifiable upwelling limit on the specified latitude due to lack of upwelling conditions or cloud cover.

Figure.5.5 illustrates the results of the validation indicator of FCM applied to Chl-a and SST images [left range of Figure.5.5a-5.5c] and of our proposed fusion approach (right column). As can be seen from these plots, our method effectively corrects for cloud pixels across all Moroccan latitudes during the period from January 2007 to December 2014, and notably improves detection and resolves the issue of under-segmentation, as shown in Figure.5.5d.

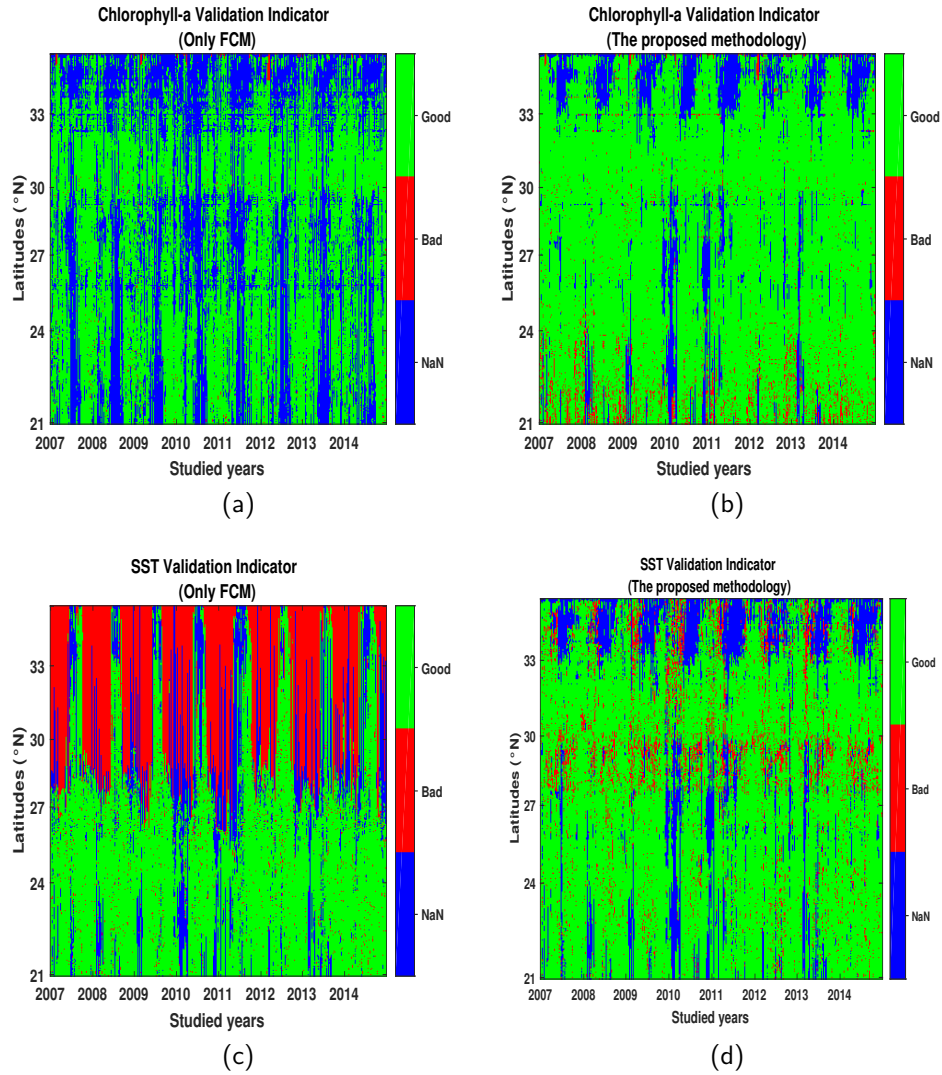


Figure 5.5: Comparison of Validation Indicator for Chl-a and SST Data using FCM and Our Methodology over the Study Period using Time Series Analysis of eight years.

5.2.2 New validation index

The plots in Figure.5.5 allow for the calculation of a new upwelling validation index (V_{Up}). We define our original V_{Up} as follows:

$$V_{Up} = \frac{Number_{NP}}{L_I \times Number_I} \quad (5.1)$$

Where, $Number_{NP}$ is the number of well-classified latitude steps from each type of Chl-a and SST image, determined as the sum of good values across all the studied years. L_I in eq.5.1 represents the number of latitude steps along the Moroccan Atlantic coast area, while $Number_I$ is the total number of processed images (366). The results of V_{Up} are presented in Table 5.1, highlighting the significant difference in values obtained without and with the proposed methodology tested on each data type.

Table 5.1: Validation of Upwelling Index (V_{Up}) on Chl-a and SST Data, with and without the Proposed Methodology

	FCM only	The proposed methodology
V_{Up} on Chl-a	0.625	0.826
V_{Up} on SST	0.542	0.759

The results of this index indicate that our approach effectively improves the identification of the main Moroccan upwelling fronts with a percentage increase of over 20% for Chl-a when compared to the V_{Up} obtained using FCM alone, and more than 21% for the SST database over 8 years. Additionally, the proposed method effectively addresses the issue of under-segmentation observed in the binary SST images in the northern region. In summary, the findings of the quantitative validation clearly demonstrate the superiority of the proposed fusion methodology. This validation supports the qualitative interpretation made by the oceanographer and confirms that the fusion method performs better than using an SST image or a chlorophyll-a image individually.

5.3 Upwelling dynamics from biological and physical satellite images

Analyzing and describing the spatiotemporal variability of upwelling is of critical importance for researchers and oceanographers. Indeed, the interannual/seasonal study gives us the ability to diagnostic past change of the upwelling variability, understand the present fluctuations and predict the future state of this phenomenon in the global term. To do that many of studies proposed different indices using remote sensing data of SST observation, Chl-a image and wind measurements.

5.3.1 Satellite-derived upwelling indices

The changes and dynamics in coastal upwelling are typically studied by calculating various indices, with the goal of understanding the productivity of marine ecosystems and describing the impact of this oceanographic phenomenon on fluctuations in fishery resources. Certainly, upwelling waters affect directly the spatial and temporal evolution of these resources through changing the dynamics of their marine environment.

SST based upwelling index

Several studies, such as (Wooster, Bakun, & McLain, 1976; Nykjær & Van Camp, 1994), have defined SST-based upwelling indices as a simple thermal difference between coastal water and offshore SST taken at the same latitude, in order to quantify the presence and estimate the intensity of upwelling. This thermal index is typically computed from satellite data (Mittelstaedt, 1991; Lathuilière, Echevin, & Lévy, 2008; Marcello, Hernandez-Guerra, Eugenio, & Fonte, 2011; Santos, Gómez-Gesteira, DeCastro, & Álvarez, 2011) or derived from in-situ measurements (Speth, Detlefsen, & Sierts, 1978; Speth & Köhne, 1983; Mittelstaedt, 1983; Van Camp, Nykjaer, Mittelstaedt, & Schlittenhardt, 1991) using

the following formula:

$$CUI = SST_{max} - SST_{min} \quad (5.2)$$

An additional normalised upwelling intensity index, based on SST differences, was proposed by (DEMARCO & FAURE, 2000).

$$CUI = \frac{SST_{max} - SST_{min}}{SST_{max} - SST_{up}} \quad (5.3)$$

While this index is applicable off West Africa, it is difficult to apply in the Moroccan system and to conduct a seasonal study as it is challenging to calculate the original temperature of the upwelled water before it reaches the sea surface (SST_{up}). A more accurate and robust revised methodology to monitor the north West Africa ecosystem is the one described in (Benazzouz et al., 2014). The strength of this method lies in its extensive statistical study spanning from September 1981 to December 2011 (approximately 30 years).

The index proposed here is based on the work of (El Aouni et al., 2019), where the minimal temperature is calculated from the extracted upwelling region and the maximal SST value is reached over offshore waters at each latitude. In our study, we adopt a similar approach but do not utilize their segmentation methods, instead, we use our fusion methodology to extract the minimal temperature from the upwelling region.

Given r is a radial perpendicular to the coastline, T_{max} and T_{min} are respectively the maximum offshore and the most colder inshore temperature, thus, the upwelling index U_T for each latitude r is defined as below:

$$U_T^r = T_{max}^r - T_{min}^r \quad (5.4)$$

Chl-a based upwelling index

The Chl-a upwelling index U_C is considered as the integration of the chlorophyll-a concentration along a given latitude r from the coastline to the extracted

upwelling limit (Demarcq, Barlow, & Hutchings, 2007). It is identical to the mean of Chl-a concentration values multiplying to the upwelling extent over the same radial r .

$$U_C^r = \int_{Coast}^{Limit} Chl - a(r) dr \quad (5.5)$$

Upwelling extension

Latitudinal extension of cooling upwelling waters U_E is defined as the width of the extracted upwelling area, for each latitude, in order to compute later the spatiotemporal variability of upwelling extent for each studied system.

Cross-Shore Ekman Transport index

The Cross-Shore Ekman Transport (U_{CSET}) is an upwelling index that utilizes satellite imagery of wind stress. It is calculated using daily wind measurements at 10m from QuikSCAT and ASCAT satellites with a resolution of 1/4 degree. It estimates the volume of upwelled flow in units of $m^3 s^{-1} m^{-1}$ by assuming the following equation:

$$U_{CSET} = \frac{\tau_y}{\rho \times f} \quad (5.6)$$

Where τ_y is the meridional component of wind stress (expressed in Pascal units) imparted on the ocean by the wind speed, ρ is the surface water density while f is the Coriolis parameter in Newton units.

5.3.2 Interannual variability

In this subsection, we analyse the interannual upwelling activity off the north-western Africa. Three type of datasets were used for the analysis: SST, Chl-a and wind speed satellite images. Approximately 908 weekly SST and 908 weekly Chl-a images covering the period February 2000 to December 2019 and 7236 daily wind speed provided by both QuikSCAT and ASCAT satellites. In order to show/confirm the powerful of our SST index, we compare it with the Ekman index U_{CSET} . Figure 5.6 illustrates the space-time Hôvmoller diagrams of these

indices. U_T is strongly correlated with the interannual Ekman index (Fig.5.6b) at large scale where proportional intensities can be divided in three sub-regions. It is noticeable also that the overall patterns of upwelling extension (see Fig. 5.7a) and Chl-a index (Fig. 5.7b) are very similar and their distribution further may be discussed in three zones.

- Northern region spans from $33^\circ N$ to $35^\circ N$, it is characterized by a limited upwelling extension (not exceeding 48 Km), a low chlorophyll-a concentration ($50mg/m^3Km$), and a low intensity of cold waters near the coast (inexistent/depressed) over the entire 20-year time series. This is consistent with the weakness of U_{CSET} on this sub-region because the direction of winds is not parallel to the coastline.
- Central region covers the zone between $26^\circ N$ to $33^\circ N$ where the extension and the Chl-a index are generally more significant and mainly caused by the giant filament located in the vicinity of Cape Ghir ($31^\circ N$). The giant filament which has the property of transferring bio-optical properties offshore due to the activity of cyclonic eddies supposed to enrich the environment thanks to the Ekman pumping. In fact, the U_E presentation shows high extent of upwelling from spring to autumn with the value $\geq 120Km$ at $31^\circ N$. A meaningful interannual variability is observed at this latitude indicating higher phytoplankton biomass during some years (2001, 2004 and 2012) and lower in others (2006 and 2018). For the U_T , the upwelling is intense throughout all the years along the central region except in the winter season. Indeed, the highest intensity values are marked around the locations where notable upwelling filaments are developed respectively at $27^\circ N$, $28.5^\circ N$, $29^\circ N$ and at $31^\circ N$ (Nieto et al., 2012). In order to interpret the seasonal variability of upwelling intensity, the concentration goes toward the Ekman index. At global scale, U_T and U_{CSET} have similar patterns demonstrating a global positive liaison. In fact, the main pattern of upwelling-favorable winds in the central zone largely occurred around

$27^{\circ}N$ and around $31^{\circ}N$ during April-November for most years.

- Southern Moroccan region between $21^{\circ}N$ to $26^{\circ}N$ is known by a very low upwelling variability indicating a strong and permanent upwelling activity with maximum values mainly located around $26^{\circ}N$ along year. The pattern of both extension and Chl-a indices are correlated with the range values $> 350mgm^{-3}$ km for U_{CSET} and $> 140km$ for U_E index. A maximum intensity is also observed from spring to autumn whereas the values in south varying between $4^{\circ}C$ and $8^{\circ}C$ conforming the intense force of trade winds near the coast (Fig.5.6b). It must be noted that the year 2010 knows decrease of all the upwelling indices and that is because of the extreme negative values of North Atlantic Oscillation (El Aouni et al., 2019).

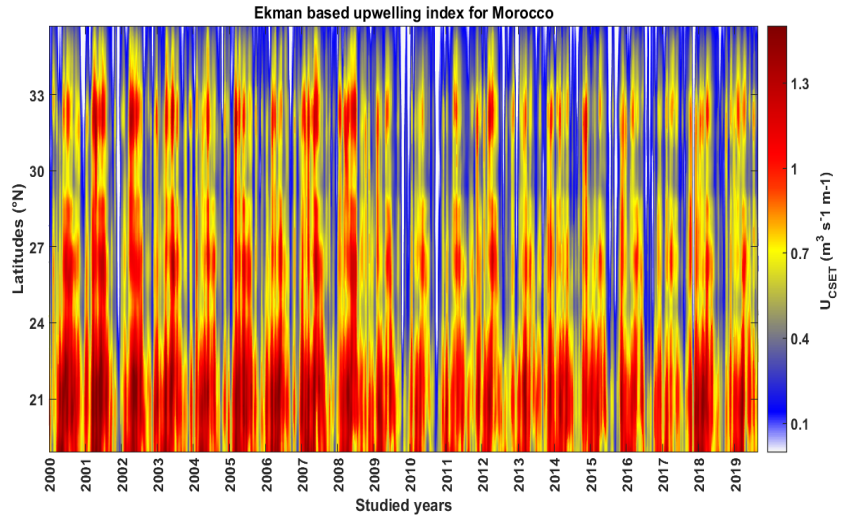
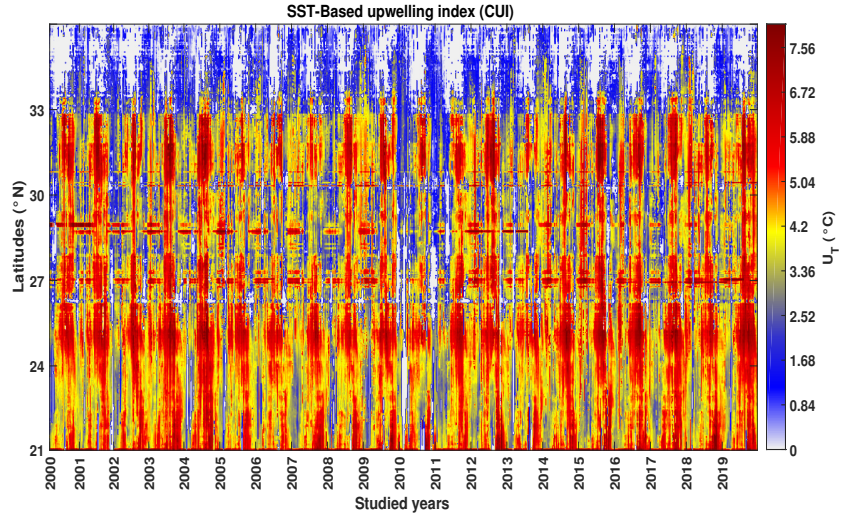


Figure 5.6: Space-time Analysis of (a) SST Upwelling Index and (b) U_{CSET} Index over the North-Western African Coast from 2000 to 2019 using Hovmöller Diagrams.

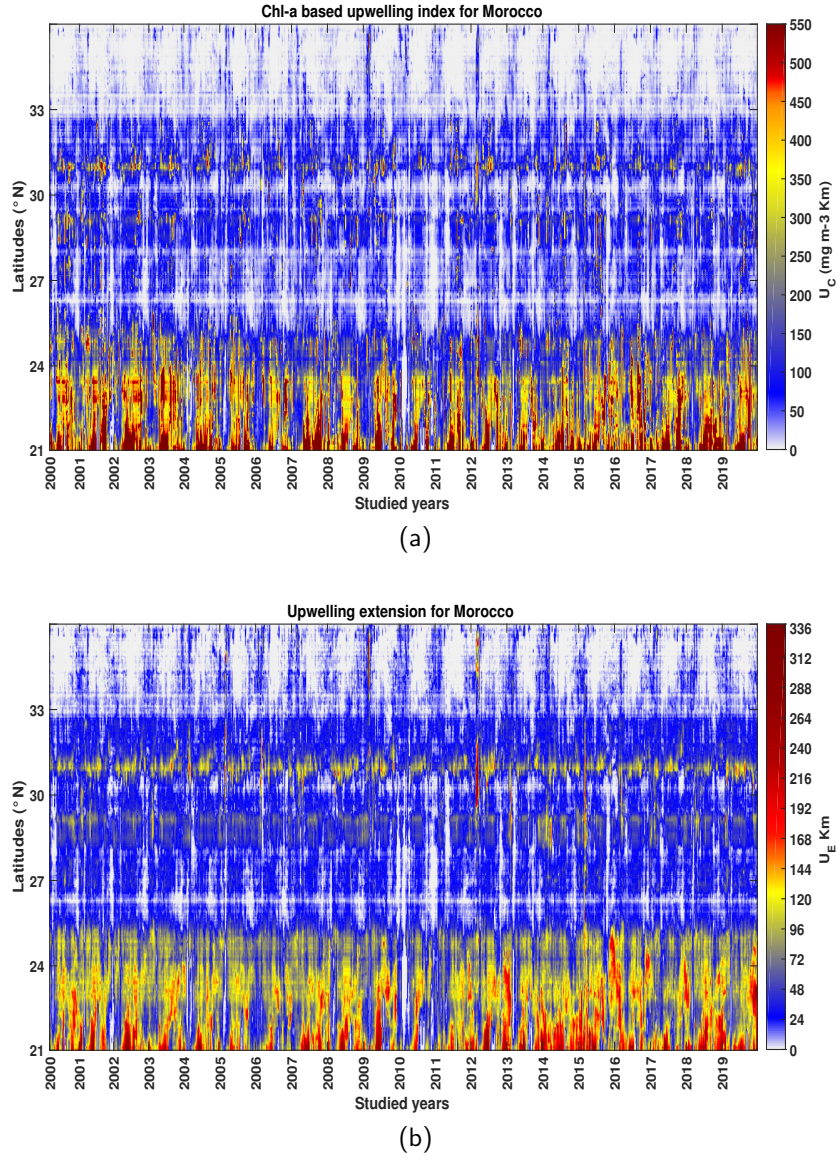


Figure 5.7: 20-Year Space-time Analysis of (a) Chl-a Upwelling Index U_C and (b) Moroccan Upwelling Extent U_E using Hovmoller Diagram.

5.3.3 Seasonal variability

The discussion will focus on the seasonal variability of SST index. The latter has there been calculated as mean monthly values averaged over all the 20 years (from 2000 to 2019). The resulting seasonal cycle of the thermal upwelling index is shown in Fig. 5.8 where the main patterns of variability can be synthesized

into the three characteristic regions:

- The northern region where the upwelling is weak and sometimes even inexistent between April and November.
- The central region where the upwelling is stronger in summer and autumn, with the highest values. While in the others seasons, the variability of upwelling here is mediocre (U_T varies between $3^\circ C$ and $4^\circ C$). In this sub-region, famous upwelling filaments are located in $27^\circ N$ and $29^\circ C$ (Makaoui et al., 2011).
- The southern region defines by permanent upwelling through the year with a clear/intense from spring to autumn.

At a global scale, the patterns of U_T and U_{CSET} are similar, indicating the effectiveness of using the radial thermal difference to assess upwelling intensity when inshore and offshore temperatures are accurately predicted.

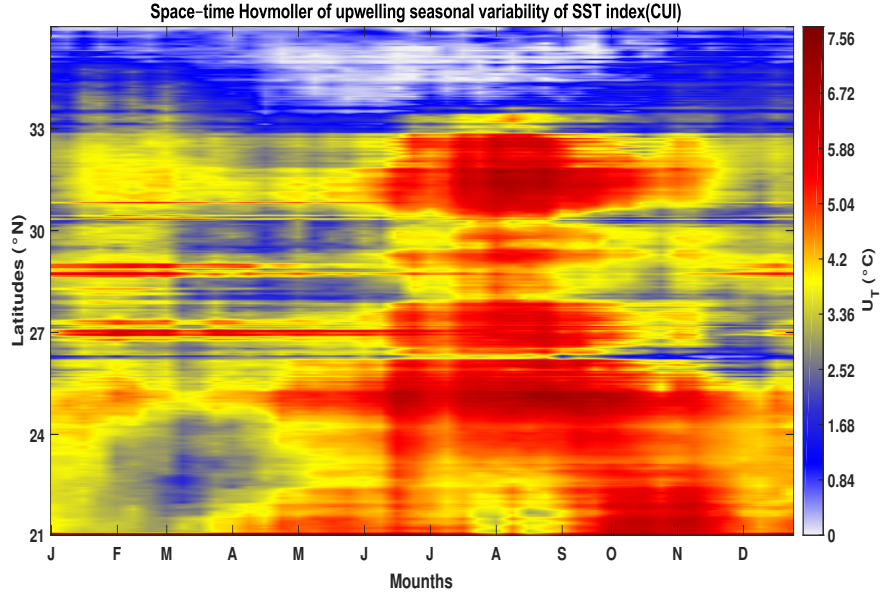


Figure 5.8: Space-time Hôvmoller diagram of upwelling seasonal variability of our thermal index U_T

5.4 conclusion

By utilizing both SST and Chl-a satellite images, we have investigated the seasonal and interannual variability of upwelling activity using our previously developed fusion methodology, which has been shown to have high accuracy in detecting upwelling. Four upwelling indices were used in our analysis, which were computed at every latitude and each time step of the interannual variability: the thermal-based upwelling index (U_T), the Chl-a index (U_C), the extent index (U_E), and the cross-shore Ekman transport (U_{CSET}). Our results indicate that the patterns of upwelling spatial extension estimated using SST and Chl-a are highly similar. This suggests the importance of connections between neighboring coastal regions and between the coastal and offshore waters. We see that utilizing both sensors effectively improves the accuracy and resilience of the forecast of the evolution of the coastal upwelling. Furthermore, during the years 2000 to 2019, we investigated the upwelling processes in relation to their spatiotemporal expansions and intensity. Correspondingly, we were able to identify locations with varying upwelling qualities in terms of upwelling extent and intensity.

Chapter 6

Correlation between biological and physical upwelling parameters

In this chapter, we study the Californian upwelling as another example of eastern boundary upwelling systems. Firstly, we define this system by describing its characteristics. After that, we will extract the upwelling zones using the proposed fusion approach presented previously and then we will compare the Moroccan upwelling with the Californian system in spatio-temporal scales in order to expose the large difference between the major northern hemisphere upwelling systems as well as defining the correlation between the most indicators of upwelling: SST and Chl-a parameters.

6.1 Description of Californian system

The waters along the West coast of North America are characterized by cold, nutrient-rich waters compared to the offshore ones. These areas are situated in east of north Pacific gyre where winds blow north to south. Given the in-

fluence of coastal upwelling on the growth of fish resources and also its impact on environment, various researchers study the Californian upwelling. In the current thesis, we investigate the region that spans from $33^{\circ}N$ to $48^{\circ}N$ and from $116^{\circ}W$ to $130^{\circ}W$ where upwelling is more remarkable. Figure 6.1 shows two climatological annual means of the Californian system of both weekly SST and Chlorophyll-a concentration images provided by NASA's oceancolor website (cited in the subsection 3.3) covering the 2000-2019 archive period. This zone near the coast of united states is expressed by cool and very nutrient enriched water which varies in width from 100 – 400 km (Kämpf & Chapman, 2016).

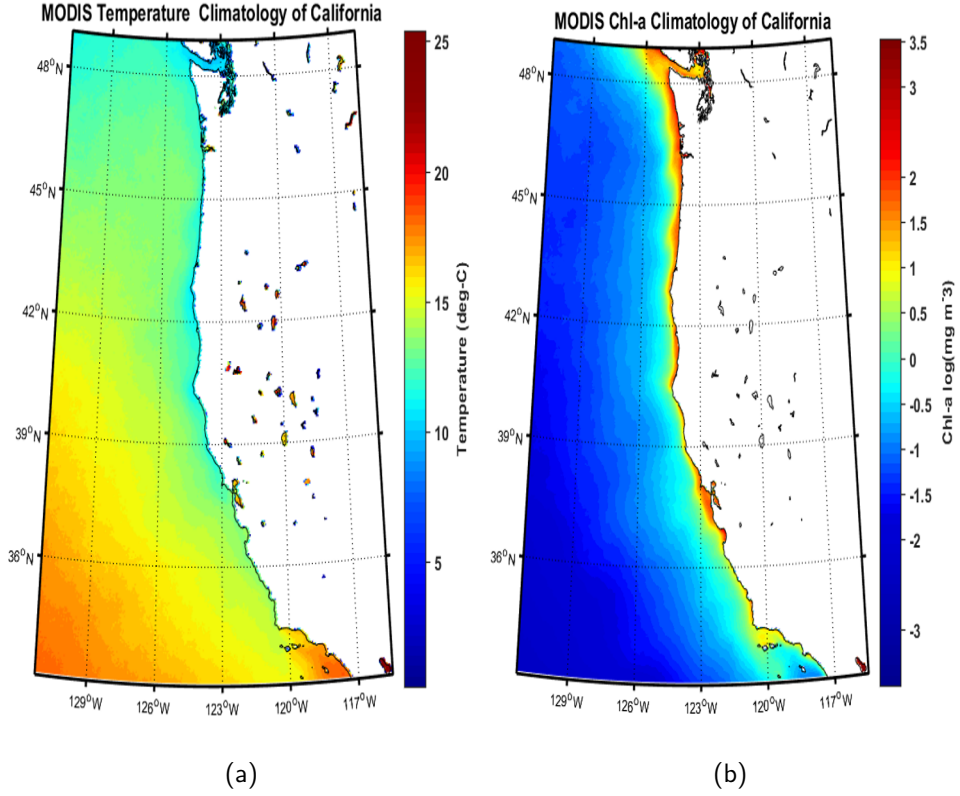


Figure 6.1: Climatological annual means of Californian upwelling system of (a) 908 SST images and of (b) 908 Chl-a images for the period 2000 to 2019.

6.2 Characteristics

Summertime wind-driven upwelling, strong biological production, and a vigorous equatorward upwelling jet define the California Current System. The upwelling jet is normally near to shore to the north of Cape Blanco (43°N), but during the summer it splits from the coast at the cape, reaching further offshore downstream of the separation point. As a result of jet separation, a larger region is impacted by cold, nutrient-rich upwelled waters, which has a significant impact on biological productivity, mesoscale activity, and air-sea interactions. Flow-topography interactions are thought to play a dominant role in jet separation (Checkley Jr & Barth, 2009; Castelao & Luo, 2018).

The weekly images in Figure 6.1 display typical upwelling conditions with well-defined upwelling main front in term of sharpness all over the studied area on both 8-day SST and Chl-a observations. Both images are acquired at the same period.

6.3 Results of fusion

In order to investigate the interannual variation of upwelling dynamics, the same indices (defined in section 5.3) were generated throughout the northern American system (California upwelling). Latitudinal differences, as illustrated in Fig. 6.2, can be divided into three subregions.

- Between 48°N and 45°N: High Chl-a index U_C defining large phytoplankton biomass in this location ($> 900 \text{ mgm}^3 \text{ Km}$) [see Fig. 6.2d], with evident seasonality comparable to the extent index U_E attending its high values throughout the year [see Fig. 6.2c]. The upwelling is strong and consistent throughout the year, but especially so in the summer, autumn, and winter;
- In the central area (from 45°N to 37°N): The upwelling U_E and U_C indices have substantially comparable features. The presence of upwelling

is shown by significant interannual and seasonal variations at $40^{\circ}N$ and $38^{\circ}N$. In the current region, the thermal index U_T has a pattern that is distinct from the other indices but almost identical to that of U_{CSET} [see Fig. reff3f]. where upwelling occurs all year, with a peak in the spring and summer [see Fig.6.2a];

- Upwelling is evident in spring and summer ($CUI > 5^{\circ}C$) and nonexistent in winter in the southern region between $33^{\circ}N$ and $37^{\circ}N$. Furthermore, the difference between SST_{Max} and SST_{Min} is nearly substantial but not excessive ($260km$). To summarize, the strength of upwelling U_T throughout the central and southern California coasts varies dramatically in response to the Ekman transport U_{CSET} divergence [see Fig. 6.2b].

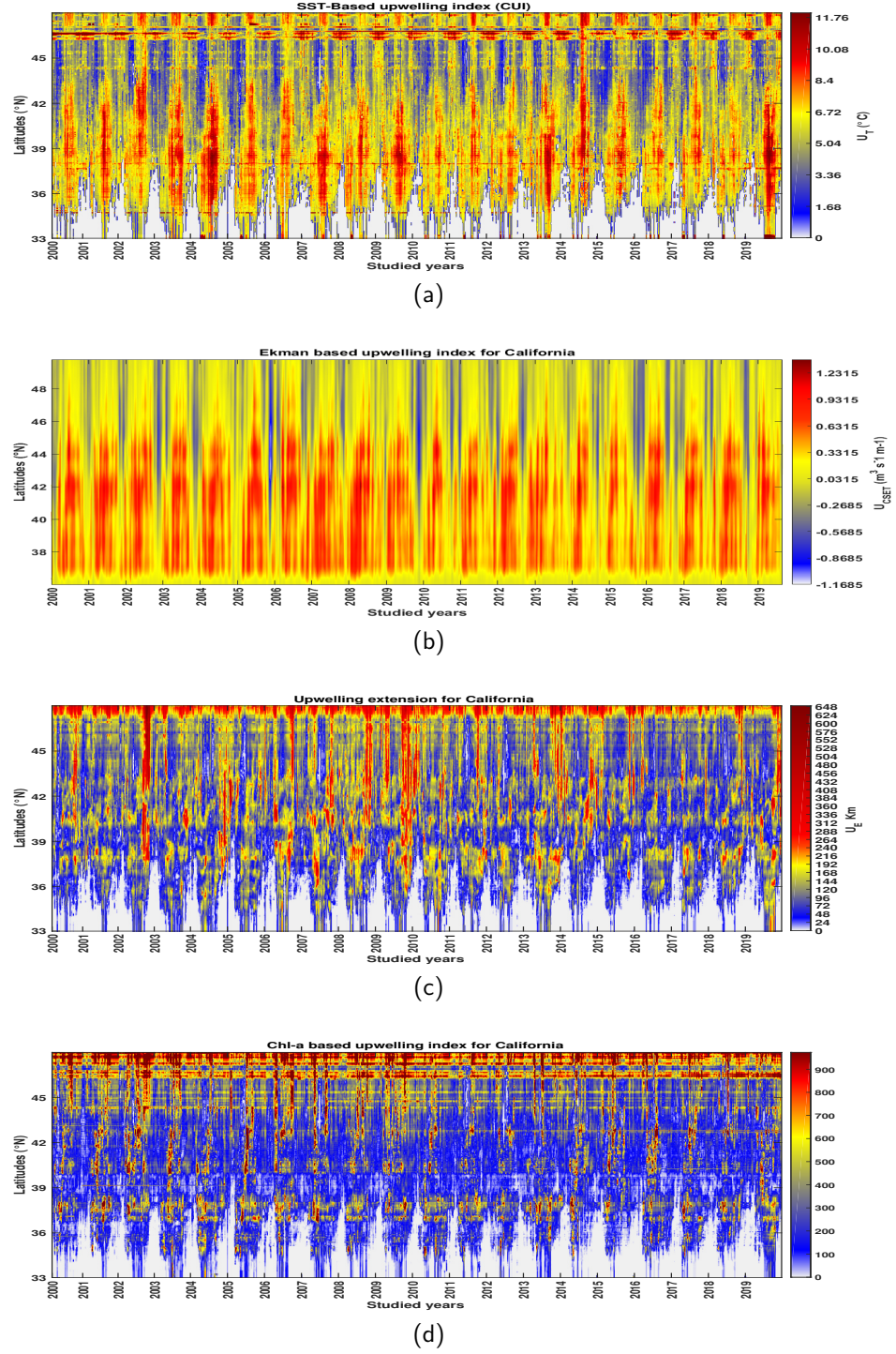


Figure 6.2: Space-time Hôvmoller plots of (a): SST index; (b): Ekman index; (c): upwelling extent; (d): Chl-a index off the north west American coast during the 2000-2019 archive period.

6.4 Comparison of Moroccan and California upwelling systems

When we look at the primary patterns of variability in both ecosystems, we can see that there are large along-shore differences in the strengthening of coastal upwelling, which is mirrored in the distribution of the previously identified indicators. Active upwelling appears to be confined and limited to a small coastal band throughout the whole area, however the area influenced by coastal upwelling might be much larger. Indeed, the study can be divided into three regions: the upper region (up to $33^{\circ}N$ for Morocco and up to $45^{\circ}N$ for California), where the northern American upwelling is constant and strong throughout the year; and the lower region (up to $33^{\circ}N$ for Morocco and up to $45^{\circ}N$ for California). Upwelling is impotent at the north of the Moroccan coast (U_T $3^{\circ}C$) due to the weakness of northeasterly winds (El Aouni et al., 2019), which are the major driver of upwelling activity [see Fig. 6.2c and 6.2b]. During the spring, summer, and fall, the upwelling around the Californian coastline is vigorous and extremely powerful, with the maximum values occurring in August and September.

The Moroccan upwelling (spans from $27^{\circ}N$ to $33^{\circ}N$), on the other hand, is only strong in the summer and fall at the areas where dominant filaments' upwelling is processed (around $27^{\circ}N$, $28.5^{\circ}N$, $29^{\circ}N$, and $31^{\circ}N$). The upwelling is persistent in the southern section of the northwestern African system, but it has low values in the spring (range of [$1^{\circ}C$ - $4^{\circ}C$]). Upwelling is relatively low all year in the north (between $33^{\circ}N$ and $35^{\circ}N$), although reasonable levels are reported from spring. Around May, the strongest upwelling occurs, with two spatial maxima: one near $38.5^{\circ}N$ and another south of $36^{\circ}N$. The upwelling process begins to deteriorate fast in July and continues to deteriorate until October. The upwelling activity about $34^{\circ}N$ is beneficial all year, but upwelling activities to the north change over the winter. The research zone is divided into two sections, on both sides of the $40^{\circ}N$, by the seasonal features of the upwelling:

northern and central California.

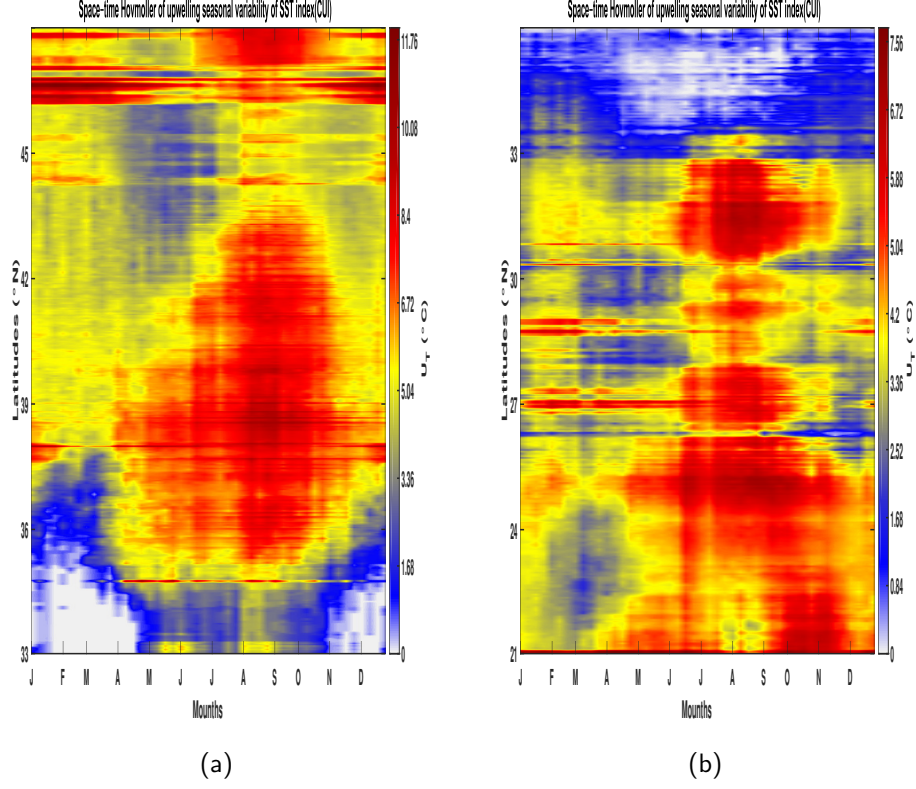


Figure 6.3: Space-time Hôvmoller diagram of upwelling seasonal variability using our thermal index U_T off the north western African coast (a) and off American margin (b) for the period 2000 - 2019.

6.5 Correlation between biological and physical upwelling parameters

In this last section, I will present the relationship between the most popular identifiers of upwelling system. The study starts by exploiting the fusion results of both of the studied systems in order to assess the linear association between the two continuous variables: SST and Chlorophyll-a concentration. I will present the correlation between these two parameters in different scales: spatial and temporal variations.

6.6 Correlation concept

The strength of a linear association between two variables is measured by correlation coefficients. A correlation between variables means that as one variable's value changes, the other tends to change in the same way. We may use the value of one variable to forecast the value of the other variable if we understand that relationship. Generally, the correlation coefficient (R) reflects how closely the values for these two variables are related. A positive correlation is shown by a value greater than zero, whereas a negative correlation is indicated by a number less than zero. In our work, we study the relationship between the minimum SST recorded in the extracted coastal band where the influence of upwelling is supposed to be significant and the maximum value of Chlorophyll-a concentration reached at the same latitude(radial). To do that, we normalize both SST and Chl-a images before computing the correlation strength by using the following equation:

$$R = correlation(normalized(SST_{Min}, log(Chl - a_{Max}))) \quad (6.1)$$

We calculate the correlation degree R to show that the lowest temperature values collected along the cool waters are seasonally connected with the logarithmic of the highest Chl-a concentration values. Table 6.1 shows the findings of this coefficient, highlighting the wide similarity between the values of SST_{Min} and $Chl - a_{Max}$.

Table 6.1: Results of correlation coefficient R Value over the two upwelling systems in a given season.

Upwelling systems Seasons	Moroccan	Californian
Winter	0.80	0.86
Spring	0.91	0.88
Summer	0.95	0.67
Autumn	0.93	0.79

During all seasons, there is a considerable relationship between these two

factors in the Moroccan upwelling environment. Summer, for example, has a linear association coefficient of 0.95 ($R = 0.95$ with $Pvalue = 10^{-207} \lll 0.05$). Furthermore, a strong correlation exists in the northern American system, with values surpassing 0.67 for each season, with the greatest value is shown in spring ($R = 0.88$, $Pvalue = 1.73 \times 10^{-167} \lll 0.05$).

Table 6.2: The results of R with range of lag [-20 to 20] for different zones of the Moroccan and the Californian upwelling systems

Moroccan upwelling system																					
Lags	-20	-18	-16	-14	-12	-10	-8	-6	-4	-2	0	2	4	6	8	10	12	14	16	18	20
North	-0.88	-0.88	-0.81	-0.68	-0.46	-0.19	0.074	0.37	0.60	0.75	0.89	0.87	0.82	0.70	0.49	0.21	-0.15	-0.51	-0.72	-0.88	-0.96
Central	-0.60	-0.45	-0.06	0.13	0.26	0.41	0.55	0.72	0.79	0.75	0.72	0.65	0.47	0.24	-0.01	-0.30	-0.53	-0.77	-0.82	-0.80	-0.71
South	-0.65	-0.40	-0.30	-0.09	0.021	0.07	0.23	0.48	0.59	0.77	0.78	0.65	0.55	0.36	0.24	0.074	-0.032	-0.21	-0.14	-0.24	-0.44
Californian upwelling system																					
Lags	-20	-18	-16	-14	-12	-10	-8	-6	-4	-2	0	2	4	6	8	10	12	14	16	18	20
North	-0.84	-0.72	-0.56	-0.37	-0.18	0.10	0.38	0.63	0.79	0.87	0.92	0.86	0.75	0.52	0.30	0.06	-0.21	-0.41	-0.50	-0.69	-0.79
Central	-0.65	-0.38	-0.18	0.14	0.40	0.62	0.76	0.87	0.88	0.78	0.72	0.51	0.31	0.01	-0.22	-0.43	-0.61	-0.75	-0.85	-0.88	-0.90
South	-0.54	-0.26	-0.049	0.12	0.31	0.52	0.68	0.79	0.85	0.85	0.79	0.58	0.30	-0.03	-0.37	-0.68	-0.85	-0.87	-0.81	-0.77	-0.75

6.7 Spatial/Temporal correlation between SST_{Min} and $Chl - a_{Max}$

The most evident surface structure, clearly recognized from SST image, is SST_{Min} , the minimal local SST measured from the extracted upwelling region. The quality of the SST field, particularly its spatial resolution, has a big impact on the accuracy of the SST_{Min} estimation. All weekly situations are used to compute the spatial occurrence of the location of the upwelled waters, determined by the location of all SST_{Min} for each coastal position and for each week of the year, in order to refine and secure the spatial determination of the SST_{Min} (a value that could be heavily influenced by data quality). The resulting positions over the two studied ecosystems are reported in terms of occurrence probability in figure 6.4a and 6.4c. It must be noted that almost all the values of SST_{Min} are identified even they are covered by clouds thanks to the proposed methodology unlike (Benazzouz et al., 2014) that excluded 25%

cases because of the invalid values. In the same way, we determine the map of $Chl - a_{Max}$ probabilities by defining the position of the maximum value of Chlorophyll-a concentration computed at each radial for each 8-day over the Moroccan and the Californian upwelling systems [see figure 6.4b and 6.4d].

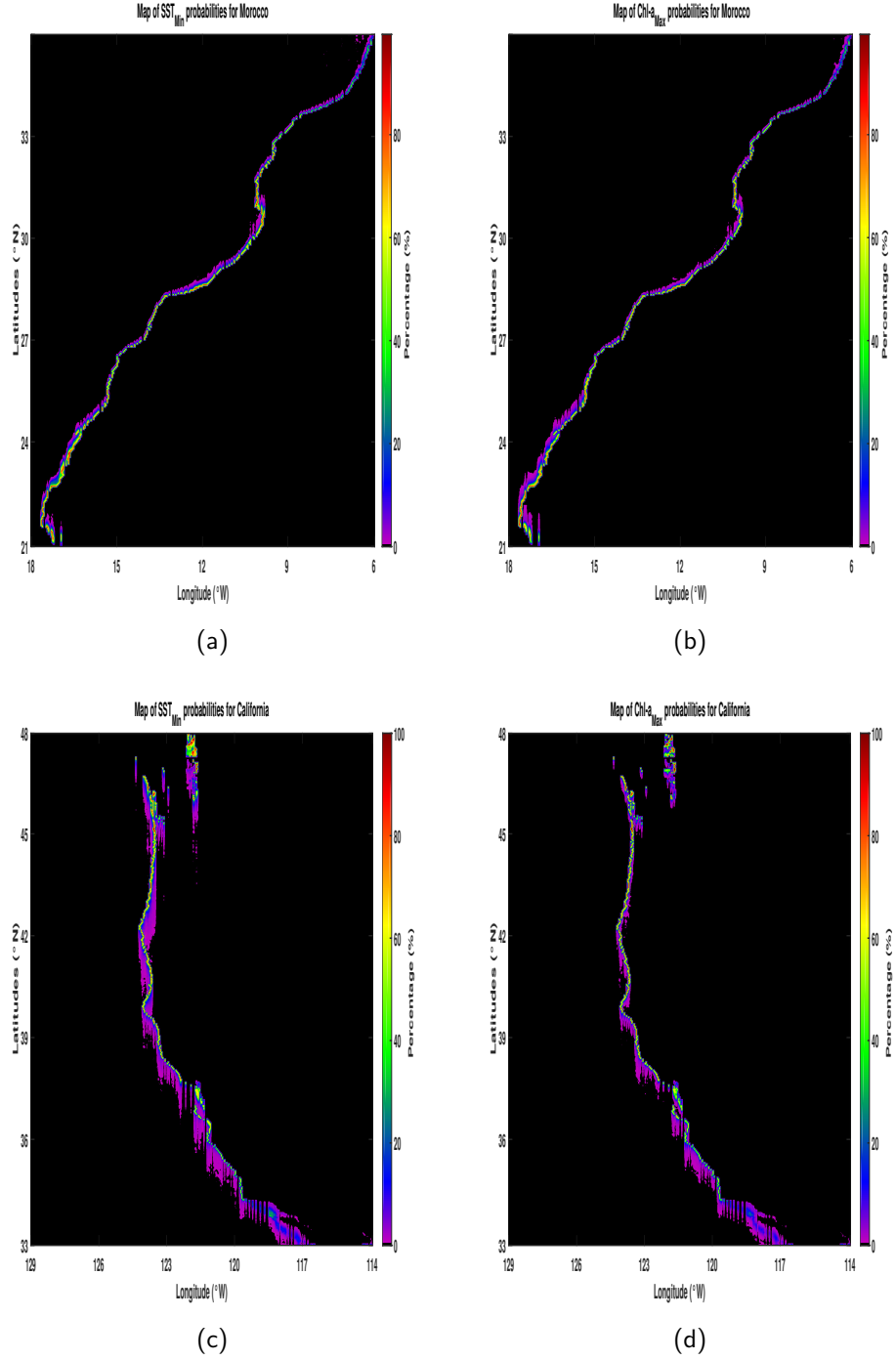


Figure 6.4: Spatial average probability of occurrence of the (a) SST_{Min} and (b) $Chl - a_{Max}$ over the Moroccan Atlantic coast; (c) and (d) respectively for Californian upwelling system.

The results maps of both SST_{Min} and $Chl - a_{Max}$ positions have similar shape indicating a strong spatial correlation between these parameters along the coastline of the two considered zones. Furthermore, the findings agree greatly with the results of previously defined indices. In fact, they show that the occurrences of SST_{Min} and $Chl - a_{Max}$ along the Moroccan coast are mostly remarkable in the central and southern regions, however, the northern region is characterized by a weak significant of upwelling (only less than 50% of data used are represented the location of the upwelled waters which determined by the positions of these two parameters). On the other ecosystem, the north region is influenced by the upwelling where the SST_{Min} and $Chl - a_{Max}$ probabilities can be reached 100%. While, the extent location of the two proxies is more larger with moderate probability values indicating a upwelling variability.

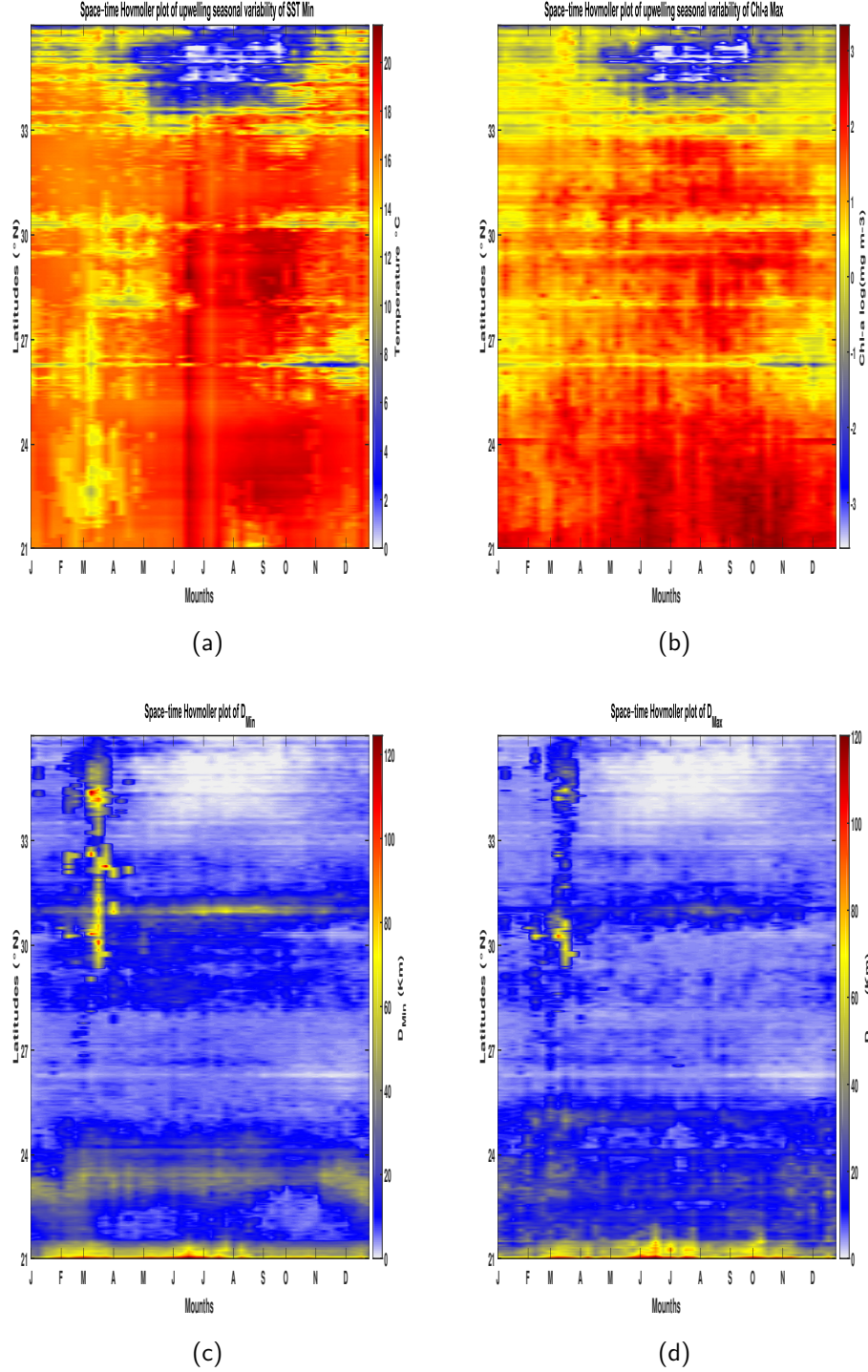
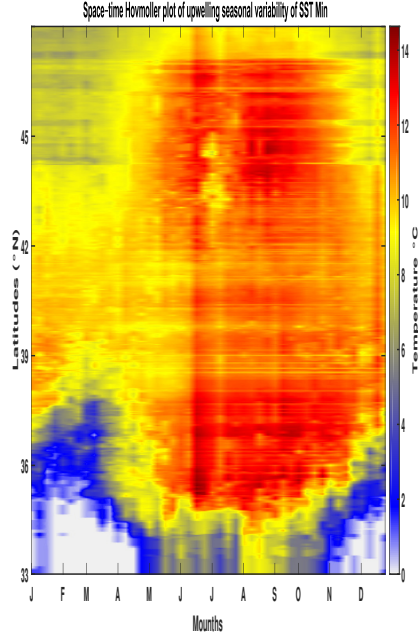
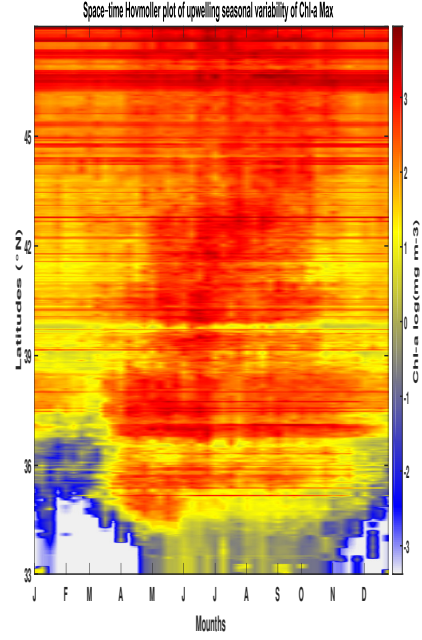


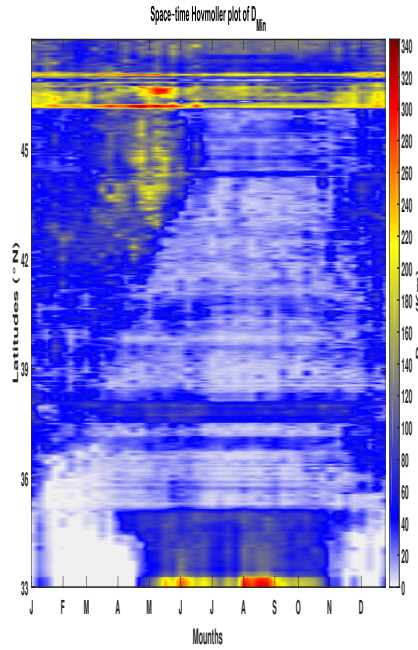
Figure 6.5: Space-time Hovmöller plots of seasonal variability of (a) SST_{Min} and (c) The distance between the coastline and its position; The same manner is applied for (b) $Chl - a_{Max}$ and (d) Its distance along the Moroccan coast.



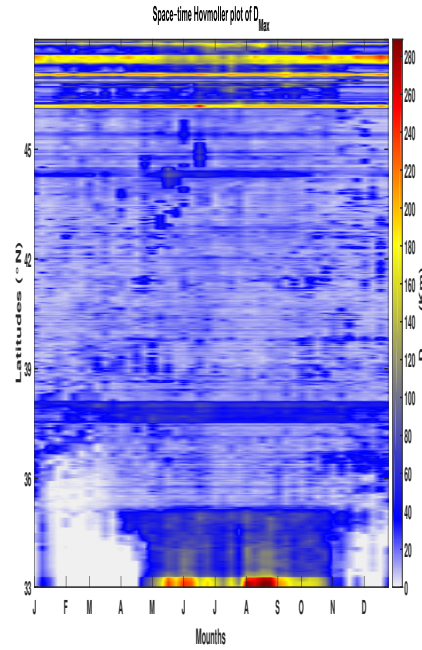
(a)



(b)



(c)



(d)

Figure 6.6: Space-time Hovmöller plots of seasonal variability of (a) SST_{Min} and (c) The distance between the coastline and its position; The same manner is applied for (b) $Chl - a_{Max}$ and (d) Its distance along the Californian coast.

6.8 Discussion and conclusion

This chapter adds to our understanding of the spatiotemporal variability of upwelling processes across two large EBUS along the Moroccan and Californian coastlines, respectively. It gave an outline of the relationship between the most important two upwelling indicators on a seasonal/space scale. From 2000 to 2019, the interannual and seasonal variability of this oceanic phenomenon dynamics is described and evaluated using several upwelling indicators. In both ecosystems, upwelling is known to be a substantially seasonal activity, driven by equatorward winds in early spring. The correlations between the indicators are a common feature of both systems, with the month with the largest correlation always corresponding to the upwelling season, which is mostly spring, summer, and late fall.

Chapter 7

Conclusion

Some of the world's most productive ecosystems are located in the Eastern Boundary Upwelling Zones (EBUZ), particularly the Canary and the Californian Current Upwelling Systems, which are the major world Upwelling regions situated in the northern hemisphere. The goal of this thesis was to build an interdisciplinary study of the coastal upwelling system that would cover a wide range of topics, including the problem of upwelling detection by using a novel concept defined as the fusion of biological and physical upwelling features, validating qualitatively and quantitatively fusion results, monitoring the spatiotemporal variation of its dynamics, and finally, investigating its fluctuations to demonstrate the correlation between the two pertinent parameters of upwelling. The key findings of this analysis will be summarized in the current chapter by responding to the research questions mentioned in the introduction.

Why do the most popular segmentation methods are unable to detect correctly the Moroccan coastal upwelling in SST image? I addressed this issue in chapter 2. Earlier approaches for extracting the Moroccan upwelling zones were discussed. These methods typically begin by applying a hard/fuzzy clustering algorithm to SST satellite image with a defined number of clusters $c = 2$ to distinguish upwelling cold waters from warmer offshore ones, then identifying the cluster with the smallest centroid as upwelling waters.

Based on the fact that all pixels in the upwelling zone must have connectivity with the coastline, a region-growing algorithm is then used to remove noisy structures in the offshore water. Oceanographically, the Earth's surface receives uneven heating which causes a non-linearity in the meridional temperature. For example, the offshore water in the northern part may have a similar temperature to the inshore in the southern part, creating a large non-linearity that cannot be handled by a clustering algorithm. In fact, when the northern offshore temperatures are much lower and/or very close to the southern upwelling temperatures, linear clustering methods like Fuzzy C-Means may mistakenly consider the northern offshore as a coastal upwelling region. Therefore, to correctly identify upwelling areas in this complex system, it is important to use a fusion of Chlorophyll-a and sea surface temperature features in addition to SST data.

How does fusion of Chl-a and SST images provide efficient extraction of coastal upwelling?

What is the pre-processing step should be applied before delineating the desired area? In chapter 3, I mentioned the answer of these two questions. In fact, the first consists on showing how it is important to integrate the image fusion concept in order to detect efficiently the coastal upwelling as well as overcoming the problem of under-segmentation appeared in the northern of SST image. To do that, I proposed three distinct fusion approaches applied separately over the outputs of an unsupervised algorithm. Each of these approaches are based on combining Chl-a and SST features by using: Alpha Blending technique where the classified SST is considered as the background and the foreground is reserved for binary Chl-a image; Principal Component Analysis was also implemented in order to reduce the dimensionality and to preserve only the relevant information between the results of both biological and physical segmented images; AND logic operator was further applied for having one fused image more informative. The second answer was focused on proposing a pre-processing method aimed to correct the cloudiness issue shown mostly in Chl-a

image before applying clustring, fusion methods. The add value of this step is very remarkable in terms of upwelling segmentation performance.

How do validate quantitatively any method used for identifying any upwelling system? I addressed this question in chapter 4 where I presented two types of validation: qualitative and quantitative. The qualitative validation is subjective and requires domain expertise, so we had a physical oceanographer evaluate the results visually to ensure they accurately represent the original images and do not lose any important oceanographic information. However, this method is time-consuming, as it involves analyzing each image's properties and physical structures related to upwelling, taking several minutes per image. To address this issue, we proposed a new, simple and intuitive index for validating any method used to extract coastal upwelling waters. We know that these inshore waters are characterized by locally low temperatures and high concentrations of chlorophyll-a, so the proposed index is determined as the difference between the adjacent pixel limit in the offshore and the other in the upwelling region. This results in a corrected detection that reflects a positive (negative) value of gradient over SST (Chl-a) at each latitude of the delineated image.

How does the fusion grant us to study the spatio-temporal variation of upwelling? I gave the detail of this study off the North-west African coast in the last section of chapter 4 and off the North-west American margin in the primary sections of chapter 5. I used the proposed fusion methodology described in chapter 3 to improve the calculation of the classical coastal upwelling indices. This choice was made primarily to establish a system that guarantees the consistency of daily outputs for improved monitoring. The outputs of both observations was combined into a single output using our fusion approach, which ensured the spatial continuity of the phenomenon and, as a result, improved monitoring. One simple example is the presence of cloud pixels in different locations in the SST and chlorophyll-a images. Additionally, the physics of upwelling, which is characterized by both cold and nutrient-rich

water, also contributes to this issue. By using both SST and chlorophyll-a, we were able to avoid data deficiencies such as dust affecting temperature pixels in the Western Sahara and harmful pigments that can be detected in chlorophyll-a images.

To what extent is there a correlation between the biological and the physical properties of coastal upwelling? I discussed the relationship between these two properties in the last section of chapter 5. Specifically, I posited that the minimum (maximum) SST (Chl-a) value recorded in a cross-shore transect between the coastline and the detected front is considered as an indication of the location of the upwelled waters. Based on this, in both the Moroccan and Californian ecosystems studied, we found a strong positive correlation between SST and Chl-a characteristics using remotely sensed data at spatial and temporal scales during the time period 2000-2019.

List of publications

Journal articles

- Zineb El Abidi, Khalid Minaoui, Anass El Aouni, Ayoub Tamim, Hicham Laanaya: An Efficient Detection of Moroccan Coastal Upwelling Based on Fusion of Chlorophyll-a and Sea Surface Temperature Images With a New Validation Index. *IEEE Geoscience and Remote Sensing Letters*. 18(8): 1322-1326 (2021).
- Zineb El Abidi and Khalid Minaoui, "An improved fusion method for detecting upwelling off the coast of northwest Africa from chlorophyll-a and sea surface temperature satellite images". *Remote Sensing Letters*, 13(11), 1110-1120, (2022).
- Zineb El Abidi, Khalid Minaoui, Aïssa Benazzouz, Khalid Daoudi: "The characteristics and dynamics of the Canary and California eastern boundary coastal upwelling systems based on fusion upwelling extraction method" (Prepared).
- Zineb El Abidi et al, "A comparative study of image fusion methods used for detecting the North-West African Upwelling during the period 2003-2016", undergoing preparation.

International Peer-Reviewed Conferences

- Zineb El Abidi, Khalid Minaoui: "A simple tool for automatic extraction of the Moroccan coastal upwelling from sea surface chlorophyll images," 2017 Intelligent Systems and Computer Vision (ISCV), 2017, pp. 1-4, doi: 10.1109/ISACV.2017.8054928.
- Zineb El Abidi, Khalid Minaoui, Ayoub Tamim, Hicham Laanaya: Detection of Moroccan coastal upwelling using the alpha blending fusion technique of sea surface chlorophyll images and sea surface temperature images. ATSIP 2018: 1-5
- Zineb El Abidi, Khalid Minaoui, Ayoub Tamim, Hicham Laanaya: A Simple Fusion Approach of Chlorophyll Images and Sea Surface Temperature Images for Improving the Detection of Moroccan Coastal Upwelling. IEEE International Geoscience and Remote Sensing Symposium (IGARSS) 2018: 7208-7211 , pp. 7208-7211, doi: 10.1109/IGARSS.2018.8518889.
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Résumé

Grâce à la télédétection, plusieurs phénomènes peuvent être contrôlés par différents instruments. Grâce aux satellites, nous pouvons surveiller et étudier les régions côtières d'upwelling en utilisant des images de température de surface de la mer (SST) et de concentration de chlorophylle-a (Chl-a). Cette thèse présente une étude intégrative en couvrant les domaines suivants : (1) Améliorer la détection des zones d'upwelling en utilisant la fusion de ses caractéristiques biologiques et physiques ; (2) Évaluer qualitativement les résultats de la fusion et proposer un indice original pour valider quantitativement les résultats ; (3) Étudier la variabilité interannuelle/saisonnière afin d'avoir la capacité de diagnostiquer les changements passés de la variabilité de remontée, comprendre les fluctuations actuelles et prévoir l'état futur de ce phénomène océanographique au niveau mondial; (5) définir la corrélation entre les deux identificateurs les plus populaires sur la base de l'analyse effectuée sur les principaux systèmes d'upwelling du courant dans l'hémisphère nord (Centrale des systèmes canarien et californien).

Mots-clefs : image satellitaire ; upwelling ; fusion ; température de surface de la mer ; concentration de chlorophyll-a ; indice de validation.

Abstract

Thanks to remote sensing, several phenomena can be monitored by different instruments. Through satellites, we can supervise and study the coastal upwelling regions by using Sea Surface Temperature (SST) and Chlorophyll-a concentration (Chl-a) images. This thesis presents an integrative study by covering the following fields: (1) Improving the detection of upwelling zones using the fusion of its biological and physical characteristics; (2) Evaluating the results of fusion qualitatively as well as proposing an original index for validating quantitatively the findings; (3) Studying the interannual/seasonal in order to have the ability to diagnostic past change of the upwelling variability, understand the present fluctuations and predict the future state of this oceanographic phenomenon in the global term; (5) Defining the correlation between the two most popular identifiers based on the analysis made on the major northern hemisphere current upwelling systems (Central of Canary and Californian systems).

Key Words: satellite image; upwelling; fusion; Sea Surface Temperature; Chlorophyll-a concentration; validation index.