Oil slicks in the Gulf of Guinea - 10 years of Envisat ASAR observations

Zhour Najoui [a], Nellya Amoussou [c], Serge Riazanoff [a,b], Guillaume Aurel [a], Frédéric Frappart[d]

[a]*VisioTerra, 14 rue Albert Einstein Champs-sur-Marne, France, zhour.najoui-nafai@visioterra.fr, serge.riazanoff@visioterra.fr, guillaume.aurel@visioterra.fr.*

[b]*Université Gustave Eiffel – Institut Gaspard Monge -IGM, 5 boulevard Descartes, Champs sur Marne, serge.riazanoff@univ-mlv.fr.*

[c]*Université de Sorbonne Université - Laboratoire d'Océanographie et du Climat : Expérimentations et Approches Numériques (LOCEAN), 4 Place Jussieu, 75005 Paris, lydieamoussou14@gmail.com*

[d]*INRAE, ISPA, UMR 1391 INRAE/Bordeaux Sciences Agro, Villenave d'Ornon, France, frederic.frappart@inrae.fr*

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1. Abstract

Gulf of Guinea is a very active area regarding maritime traffic as well as oil and gas exploitation (platforms). As a result of some actors of both sectors that fail to comply with environmental standards, the region is subject to a large number of oil pollutions. This study aims to detect oil slicks spilled in the Gulf of Guinea and analyse their spatial distribution using Synthetic Aperture Radar (SAR) images. If previous works have already locally mapped oil slicks in this area, this study is the first one to achieve a global statistical analysis based on a very high number of radar images covering 17 Exclusive Economic Zones of the Gulf of Guinea. To carry out the present study, a database of 3,644 SAR images, collected between 2002 and 2012 by the Advanced SAR (ASAR) sensor onboard the European Spatial Agency (ESA) Envisat mission has been used. This database allowed the identification of 18,063 oil slicks. These "Oil slicks" herein detected regroup: "oil spills" - of anthropogenic origin- and "oil seeps" - of natural origin (natural oil reservoir leaks).

2. Introduction

The Deep Water Horizon (DWH) disaster that occurred on April 20, 2010 in the Gulf of Mexico aroused worldwide outrage both for its human and environmental impacts (Leifer et al., 2012). There was great interest of the public, media, politicians and scientists characterized by a meticulous follow-up of the progression of the oil slicks (Caruso et al., 2013; Pinkston and Flemings, 2019). And yet, a disaster similar to that of the DWH would not be surprising along the African coast and in particular in the Gulf of Guinea where recurrent oil spills are observed. These may be caused by deballasting operations (Albakjaji, 2010) and releases due to shipwrecks (Fuhrer, 2012).

If oil constitutes an important economic resource for the countries of the Gulf of Guinea from an economic point of view (Ovadia, 2016), the environmental impact caused by the frequent oil spills provokes serious negative effects on both the environment and the local economy (Jafarzadeh et al., 2021; Okafor-Yarwood, 2018; Yaghmour et al., 2022). The weakness of national monitoring and legislation control is likely to limit the compliance to the major standards followed by large companies. Thus, the provision of observation tools that can enable people of Africa to ensure good monitoring and better management of the Gulf of Guinea is necessary.

Synthetic Aperture Radar (SAR) images have proven to be a useful tool for oil slicks mapping due to the dampening effect that oil has on capillary and small gravity waves, called Bragg waves. The latter are generated on water by local winds and they are responsible for the radar backscattering (Gade et al., 1998; Jackson et al., 2004; Mercier and Girard-Ardhuin, 2006; Shu et al., 2010; Xu et al., 2015). As a consequence, oil slicks appear darker compared nearby undampened water surface where Bragg waves produce brighter radar backscattering. In addition, historical radar images are freely available since 1991 (ERS-1 mission was launched in 1991, ERS-2 in 1995, Envisat in 2002, Sentinel-1a in 2014 and Sentinel-1b in 2016) while near real time radar images are foreseen to be freely available at least until 2030 owing to Sentinel constellation. This availability of data allows extensive studies of past and future pollutions as well as operational detection of oil slicks using satellite radar imagery (Kubat et al., 1998).

In this study, the European Spatial Agency (ESA) mission Envisat has been used. Envisat, the second generation of SAR satellite developed by ESA, was launched on March 1, 2002 and had on board ten widely instruments (Louet and Bruzzi, 1999)). The Advanced Synthetic Aperture Radar (ASAR) used in this study is one of these instruments. Its nominal life (5 years) has been doubled until the loss of the satellite on April 8, 2012 (10 years).

The Gulf of Guinea is now one of the largest oil producing regions of the world, yet very few studies have really analysed its situation regarding oil slicks (both spills and seeps). The studies that have been carried out so far are limited to very specific Exclusive Economic Zones. This is the case with the studies by Jatiault et al. (2017) in the Congo Basin. The present study focuses on the spatial distribution of the oil slicks occurring from 2002 to 2012 by Exclusive Economic Zone (EEZ) throughout the Gulf of Guinea using Envisat ASAR radar images.

3. Presentation of the study area

3.1. Geographic location

The radar images used for this study were acquired over the Gulf of Guinea. This region is located in the Atlantic Ocean in the southwest of Africa. According to the International Hydrographic Organization (Bassou, 2016), it extends from Guinea Bissau to Angola. It covers the EEZs of 16 countries bordering the coast (extending over 7000 km): Guinea Bissau (GNB), Guinea Conakry (GIN), Sierra Leone (SLE), Liberia (LBR), Ivory Coast (CIV), Ghana (GHA), Togo (TGO), Benin (BEN), Nigeria (NGA), Cameroon (CMR), Equatorial Guinea (GNQ), Sao Tome and Principe (STP), Gabon (GAB), Republic of Congo (COG), Democratic Republic of Congo (COD), and Angola (AGO) (fig. 1).

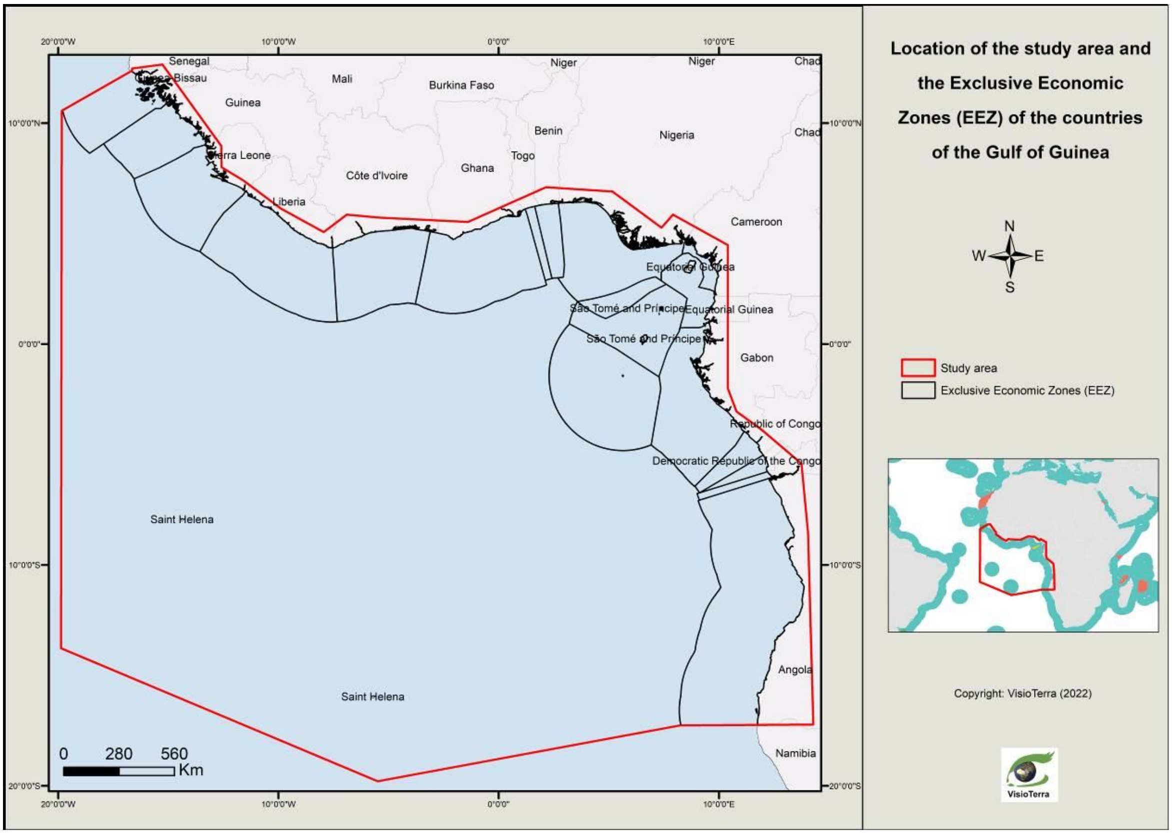

fig. 1 - Location of the study area in the Gulf of Guinea and the Exclusive Economic Zones of the different countries.

3.2. Geological location

Petroleum is a natural mixture composed mainly of hydrocarbons. It is formed within certain sedimentary rocks by transformation of organic matter (plankton, plants, animals, etc.) which is incorporated into the deposit. It is a slow and gradual process occurring in a sedimentary basin.

Indeed, the transformation of organic matter into oil spans millions of years, and is punctuated by several stages including the formation of an intermediate substance called kerogen. A given layer of sediment sinks and is buried under other layers of sediment. Depending on the filling of the basin, the heat flow and pressure induced by geologic processes, organic matter may change from kerogen to petroleum. Oil being less dense than water, it tends to migrate to the upper layers of the sedimentary strata. These sedimentary strata have a certain geometric configuration defined by the tectonic structure of the basin. During this structuring, different areas may have risen higher (anticlines) or sunk lower (synclines) relatively to the rest of the stratum. When these upper zones are topped by a cover allowing the oil to escape through faults or fractures, they constitute oil deposits exploited nowadays in offshore or onshore areas.

The Gulf of Guinea is located in a passive zone resulting from the opening of the South Atlantic Ocean initiated during the Lower Cretaceous, breaking up south-west Gondwana. The climate during this period was hot, humid and stable, which favours chemical weathering of the mainland. Eroded material brought chemical elements to the Gulf of Guinea; in particular, the Niger Delta transported sediments rich in hydrocarbons. These numerous characteristics make this area a source of natural seepages also called oil seeps (Lawrence et al., 2002)

3.3. Oil exploration in the Gulf of Guinea

The Gulf of Guinea region has entered the global oil landscape comparatively quite recently. In 1982, the signing of the Montego Bay convention extended the maritime territories of riparian countries over their EEZ, 200 nautical miles off their coast, which encouraged offshore exploration (Bassou 2016). The Gulf of Guinea is now one of the largest oil producing regions in the world.

Indeed, since the installation of its first oil platforms (anchored and floating platforms) between 1960 and 1970 (Favennec et al., 2003), the Gulf of Guinea has become one of the favourite destinations of international oil investors (Tull, 2008). The good quality of its oil justifies the attractiveness of foreign countries to the region (Ngodi, 2005). Since the 2000s, it has supplied more than 55 billion barrels, i.e. 5% of world oil production (Mfewou et al., 2018) and 60% of total daily crude oil production in sub-Saharan Africa. Offshore is the default mode of oil extraction in the Gulf of Guinea (Favennec et al., 2003). The depletion of coastal water resources (shallow water; ≤ 200 m) means that the relative share of deep water exploration (Deep water; 450 m - 1800 m), or even in ultra-deep water (1800 m - 3000 m) is increasing. This is the case, for example, off the coast of Gabon.

3.4. Oil pollution and environmental impacts

The Gulf of Guinea is a very active area in oil exploration. The oil spills found there are unparalleled in frequency and their toxicity induces serious repercussions both on the marine environment and on the ecosystem (Bagby et al., 2017; Chalghmi, 2015; Khanna et al., 2018; Langangen et al., 2017; Li et al., 2019; Li and Johnson, 2019; NAE-NRC, 2012; Reuscher et al., 2020).

Several cases of accidents caused by the exploitation of offshore oil are documented. Apart from these cases, several accidents have occurred following the exploitation of offshore oil fields. The frequency of oil spills in the Gulf of Guinea is said to be due, among other things: to oil production operations, inadequate production equipment leading to corrosion of pipelines and tanks, to disasters, sabotage and vandalism (Adelana and Adeosun, 2011).

Environmental consequences include the loss of habitat for corals and seagrass, the destruction of flora (reduction of mangroves and certain species of algae) and that fauna (extinction of sea turtles) (Scheren et al., 2002).

4. Dataset and Method

4.1. Radar data

Several spaceborne SAR systems have been widely used for marine pollution monitoring and mapping (Brekke and Solberg, 2008; Del Frate et al., 2000; Espedal, 1999; Fiscella et al., 2000; Gade et al., 1998; Garcia-Pineda et al., 2008; Kanaa et al., 2003; Li and Johnson, 2019; Liu et al., 1997; Marghany, 2015; Solberg et al., 1999; Suresh et al., 2015). In this study, we used SAR images acquired by Envisat ASAR (Advanced Synthetic Aperture Radar), an ESA mission that lasted from 2002 to 2012. Envisat ASAR operated in C-Band (4.20 – 5.75 GHz) in a variety of modes including WSM (Wide Swath Medium-resolution) that acquired a 400 km by 400 km wide swath image. Its spatial resolution was approximately 150 m by 150 m with a pixel spacing of 75 m by 75 m. It functioned in one of two polarizations types, either HH or VV. ASAR. WSM operated according to the ScanSAR principle, using five predetermined overlapping antenna beams which covered the wide swath. The ScanSAR principle consists in achieving swath widening by the use of an antenna beam which is electronically steerable in elevation (Miranda et al., 2013).

On a radar image, the areas covered by oil appear smooth dark regions with low backscattering. This is due to the damping effect that the oil produces on capillary waves and small waves of gravity. On a free-oil surface, a significant part of the energy will be backscattered towards the radar making it appear lighter (Alpers et al., 2017). The backscatter of the radar signal is also influenced by environmental conditions which are: wind speed and sea state (Fingas and Brown, 2017; Zhang et al., 2014). The ideal wind speed for the detection of oil slicks is in an interval that depends on the authors: - 2 m/s to 10 m/s (MacDonald et al., 2015), - 1.5 m/s to 6.5 m/s (Jatiault et al., 2017), - 2.09 m/s to 8.33 m/s (Najoui, 2017)... Vertical polarization (VV) is the most effective mode for detecting oil spills on the sea surface (Brekke and Solberg, 2008; Jatiault et al., 2017; Najoui et al., 2018a, 2018b).

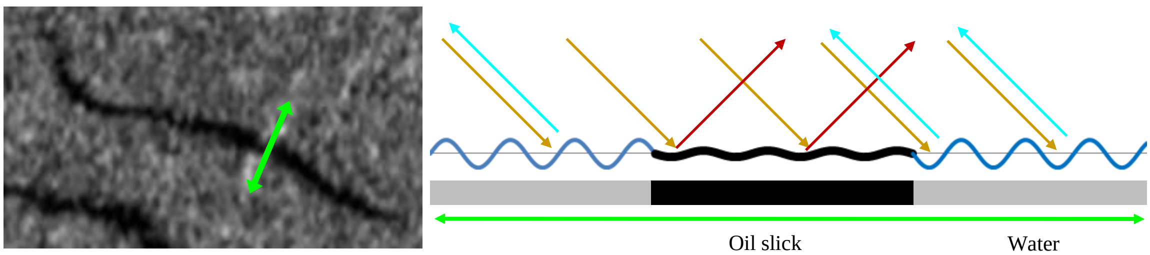

fig. 2 - Backscattering of the radar signal in the presence and absence of oil (Najoui, 2017).

An amount of **3,644** Envisat ASAR WSM images produced and distributed by the European Spatial Agency have been processed over the study area. The fig. 3 illustrates the spatial distribution of the occurrences of Envisat ASAR WSM observations between 2002 and 2012 in the Gulf of Guinea. The number of WSM observations is noticeably higher near the coasts.

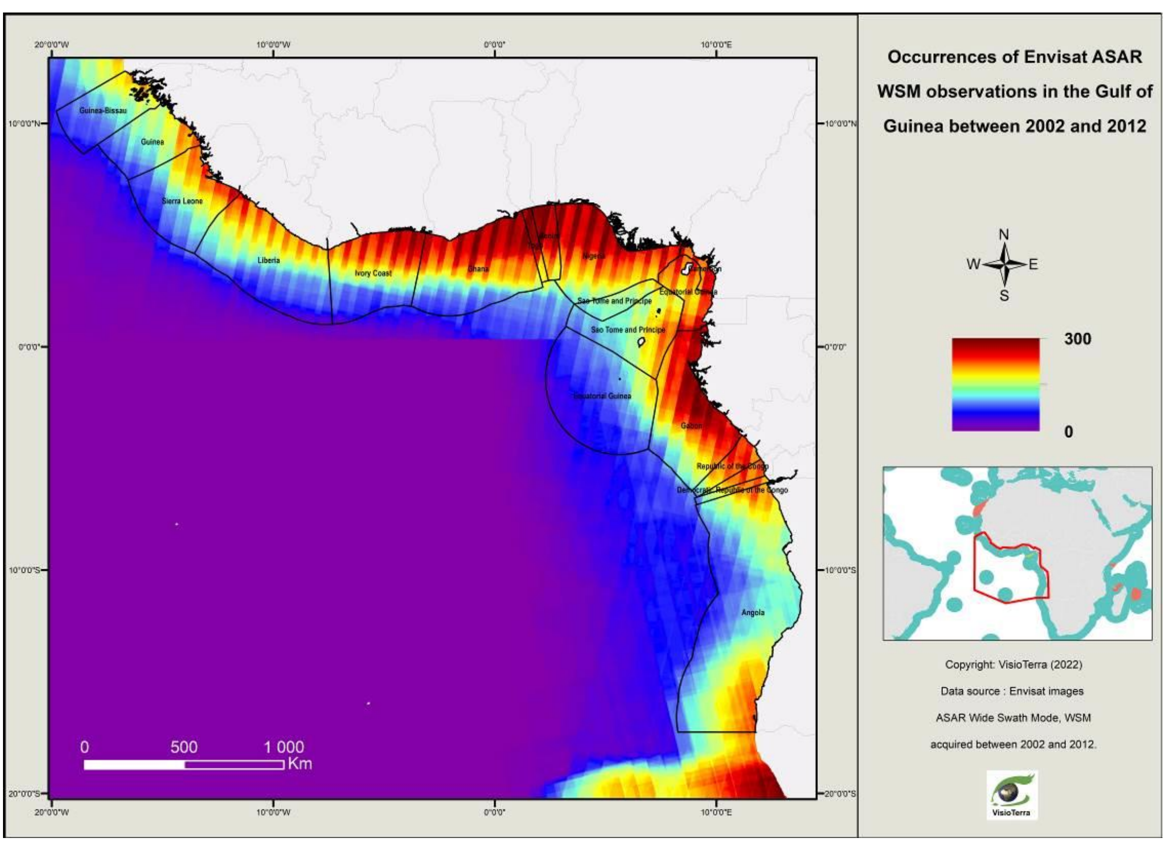

fig. 3 - Occurrences of Envisat ASAR WSM observations between 2002 and 2012.

4.2. Image preprocessing

The database of 3,644 images has been georeferenced in the geographic coordinate reference system over the WGS84 ellipsoid, datum WGS84. A land mask has been applied and the images have been radiometrically corrected. The radiometric correction consists in correcting the brightness variations due to SAR peculiarities. Indeed, the radar backscattering on the offshore area is dominated by non-Lambertian reflections (the surface does not reflect the radiation uniformly in all directions). This non-Lambertian reflection leads to heterogeneity of the brightness in the radar image. The input images have a 16-bits Digital Number (DN) dynamic which requires reduction to 8-bits to be displayable on an usual screen. The applied preprocessing consists in applying a local stretching with an average of 140 and a standard deviation of 60 on a sliding window of 301 pixels in order to optimize the detectability of the oil slicks (fig. 4) (Najoui, 2017; Najoui et al., 2018b).

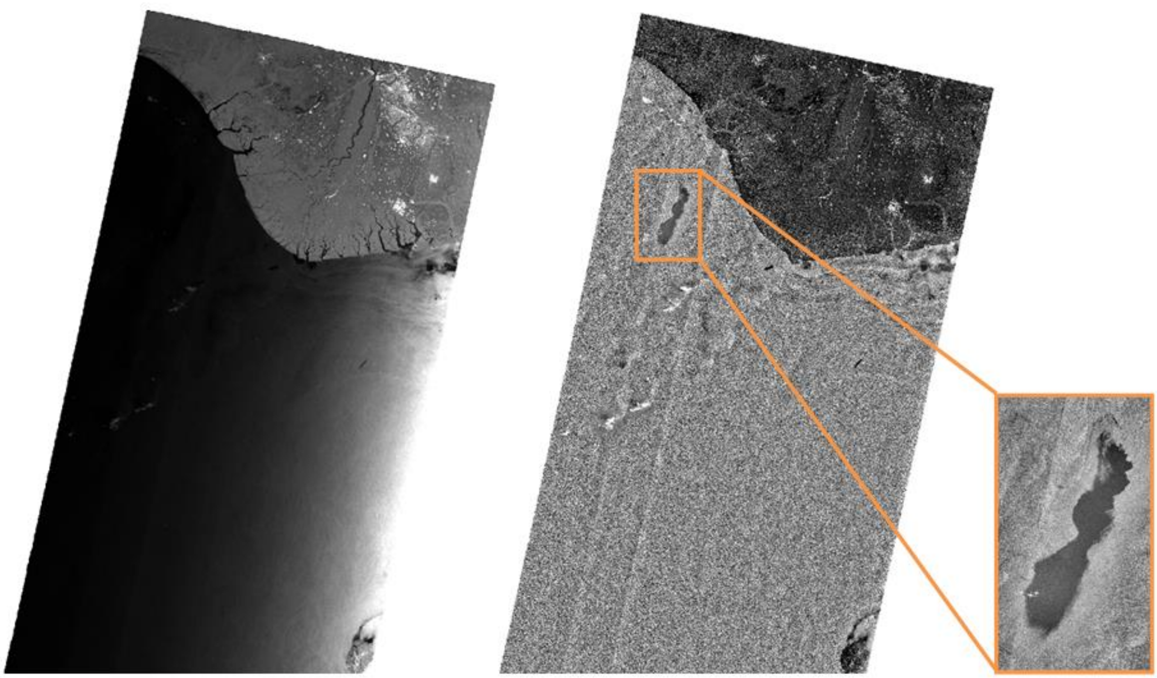

fig. 4 - ASAR WSM images before (left) and after (right) local stretching showing a leak from an oil platform.

4.3. Manual detection

Oil slicks appear as dark patches on radar images because they flatten the surface of the sea. However, in addition to oil slicks, many phenomena also may appear as dark. Non-oil dark patches are termed as look-alikes features that include upwelling, eddies, rainfalls, wind shadows, bathymetry, internal waves, current shear zones, etc. (Brekke and Solberg, 2005; Espedal, 1999; Xu et al., 2015).

Three approaches exist for oil slick detection in SAR images: a manual approach conducted by trained human operators who analyze images to detect oil slicks, the semi-automatic approach where a computer detects all the dark objects in the SAR image using different techniques of segmentation after which an experienced human operator classifies these objects as slicks or look-alikes, and finally the automatic system that uses complex image processing and programming techniques to perform both segmentation and classification.

If we did not found examples of manual detection in the bibliography, the semi-automatic as well as the automatic segmentation and classification are widely illustrated below. Some of the segmentation techniques, or dark spot extraction techniques, that have been used are adaptive thresholding (Solberg et al., 1999), hysteresis thresholding (Kanaa et al., 2003), edge detection using Laplace of Gaussians or Difference of Gaussians (Chang et al., 2008) and wavelets (Liu et al., 1997). Neural network based segmentation techniques were applied by Garcia-Pineda et al. (2008) and Del Frate et al. (2013). Some automatic oil slick detection algorithms are "Classifiers" using a Gaussian density function based on statistical model approach (Solberg et al., 1999), a Mahalanobis classifier (Fiscella et al., 2000), neural networks (Del Frate et al., 2013, 2000; Garcia-Pineda et al., 2008), texture analysis (Marghany, 2001), genetic algorithm (Marghany, 2015), and Automatic Seep Location Estimator (Suresh et al., 2015).

Due to the real unknown accuracy of the semi-automatic and automatic approach, we focus below on a reliable manual detection approach. The manual detection is based on the "Synthetic Aperture Radar marine user's manual" (Jackson et al., 2004). Each of the 3,644 SAR images used in this publication has been manually interpreted independently from the others. Each oil slick has been categorized depending on the interpretation based on morphological and textural criteria (fig. 5). Oil slicks are divided into two major categories: biogenic and mineral. Biogenic oil slicks are organic films made of substances produced by plankton and other marine organisms naturally released into the environment. The mineral oils slicks can be subdivided between natural seeps emitted naturally from the sea bottom and anthropogenic oil spills that originate from ships, refineries, oil terminals, industrial plants, oil platforms and pipelines (Espedal, 1999). For instance, oil spills from platforms or ships induce significant slicks (Johannessen et al., 2000; Leifer et al., 2012; Trivero and Biamino, 2010). If biogenic oil slicks appear as shiny diffracting points on SAR data, oil seeps are characterized by curvilinear shapes due to short-term changes of the strength and orientation of the wind and of the surface currents (Espedal, 1999). Thereafter, a multi-date analysis has been performed. We use all the interpretations at different dates in order to assess the manual interpretation. Indeed, repetitive slicks are more likely due to leaks from static sources: a geological feature for oil seeps, a platform or pipeline for oil spills, for instance. The shape of these oil slicks from static sources is induced by the strength and orientation of the short-term changes of both wind and sea surface current. Usually, this type of slicks from natural oil seeps and oil spill from oil platforms constitutes forms of "astroseeps" or "flower structures". In general, ships that discharge oily effluents do it in route, leaving behind the ship linear-shaped spills or trails. When oil is discharged in a current-free and calm sea, the resulting overall spill geometry will follow the route of the ship. This linearity is used to identify such oil spills. However, when a deballasting ship maneuvers or when a non-uniform surface current is present, then the contour of the spill can deviate significantly from linearity. When oil is discharged from a moving ship, it also spreads laterally, resulting in oil trail which width increases with distance from the ship.

To perform and validate our analysis, the manual detection output has been integrated within a GIS along with several auxiliary data (geological data, marine traffic, oil platforms, oil and gas fields, wind fields, bathymetry, etc.). This work led to the constitution of a dataset with 18,063 interpreted oil slicks.

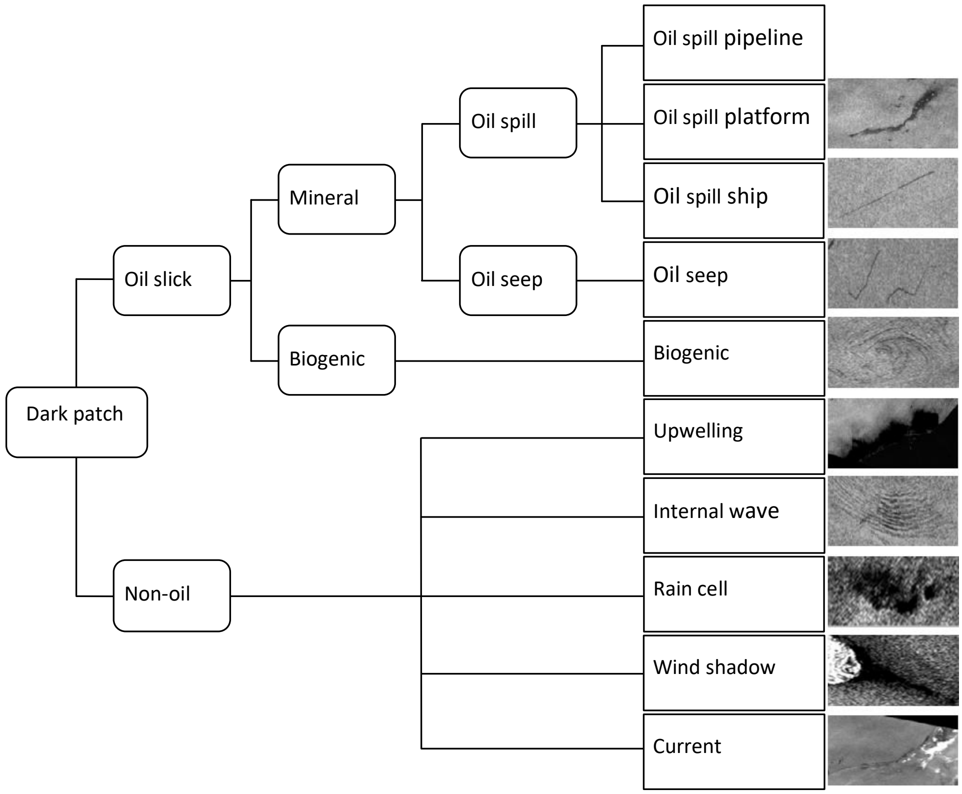

fig. 5 - Main offshore dark patches seen in SAR images.

4.4. Mean area covered in oil

The photo-interpretation described in the previous section results in the delimitation of closed polygons corresponding to the slicks. These polygons are "embedded" in a raster image to perform the statistical study. Because each location within the area of interest has not been imaged an equal number of times by the Envisat satellite, an observation occurrence map has been produced (fig. 3). In fact, each location has not been equally observed because of the partial overlap of neighbouring swaths and the use of both ascending and descending orbits. Hence, it was necessary to locally normalize the oil slicks number distribution by dividing the number of oil slick occurrences by the number of observations made by Envisat ASAR over the study area. This gives relative frequency of the presence of oil per pixel.

The **probability of presence of oil X per pixel ($P_X(l,p)$)** is equal to the number of occurrences of oil X in a pixel ($S_X(l,p)$) divided by the number of observations (O(l,p)) of the same pixel (eq.1).

$$P_X(l,p) = \frac{S_X(l,p)}{O(l,p)} \qquad \text{(eq. 1)}$$

Where :

- $S_X(l,p)$ — is the number of occurrences of the presence of oil X detected on a pixel by photo-interpretation,
- X — is the type of oil. It can be natural leaks (oil seepages), pollution by boats (oil spill ships) and pollution by platforms (oil spill platforms),
- (l,p) — are the coordinates (l, p) of the current pixel representing the rows and columns of the image,

- O(l,p) are the number of observations as they appear in the footprints of the processed images Envisat ASAR WSM,
- $P_X(l,p)$ is the normalized occurrence also called probability of oil presence at pixel (l, p).

For each class X of oil slick among (s) “seepage”, (s) “spill from ship”, and (p) “spill from platform”, the generic definition given in (eq.1) becomes the ones given in (eq.2).

$$P_e(l,p)=\frac{S_e(l,p)}{O(l,p)}\ ,\ P_s(l,p)=\frac{S_s(l,p)}{O(l,p)}\ ,\ P_p(l,p)=\frac{S_p(l,p)}{O(l,p)} \qquad \text{(eq. 2)}$$

Where :

- $S_e(l,p)$, $S_s(l,p)$ et $S_p(l,p)$ are the number of occurrences of oil presence detected on a pixel by photo-interpretation of natural leaks (oil seepages), pollution of boats (oil spill ships) and pollution of platforms (oil spill platforms) respectively,
- (l,p) are the coordinates (l, p) of the current pixel representing the rows and columns of the image,
- O(l,p) are the number of observation as they appear in the footprints of the processed images Envisat ASAR WSM,

The total probability of presence of oil X per pixel ($P_t(l,p)$) is equal to:

$$P_t(l,p)=\frac{S_e(l,p)}{O(l,p)}+\frac{S_s(l,p)}{O(l,p)}+\frac{S_p(l,p)}{O(l,p)} \qquad \text{(eq. 3)}$$

Thus, we denote by $\hat{A}_X$ the mean area covered in oil of origin X in the Gulf of Guinea between 2002 and 2012. This mean area is given by (eq.4).

$$A_X=\sum_{GG}^{l}\sum_{GG}^{p}(P_X(l,p)\times A(l,p))\approx\sum_{GG}^{l}\sum_{GG}^{p}(P_X(l,p))\times\overline{A} \qquad \text{(eq. 4)}$$

Where:

- A(l,p) is the area of the pixel (l,p),
- $\bar{A}$ is the mean area of a pixel. The variation of the area of the pixel (75 m x 75 m) is less than 2.5 % over the Gulf of Guinea.

For a given year Y, the mean area covered in oil of origin X ($\hat{A}_{X,Y}$) is given by (eq.5).

$$A_{X,Y}=\sum_{GG}^{l}\sum_{GG}^{p}(P_{X,Y}(l,p))\times\overline{A} \qquad \text{(eq. 5)}$$

Where:

- $P_{X,Y}(l,p)$ is the probability of presence of oil of origin X for a given year Y for a given pixel (l,p).

For a given year Y and for a given EEZ, the mean area covered in oil of origin X ($\hat{A}_{X,Y,EEZ}$) is given by (eq.6).

$$A_{X,Y,EEZ} = \sum_{EEZ}^{l} \sum_{EEZ}^{p} (P_{X,Y}(l,p)) \times \overline{A} \qquad \text{(eq. 6)}$$

4.5. Mean fraction covered by oil for a given EEZ

For each country's EEZ over a given period of time, we estimated the mean fraction covered in oil of origin X and for a given year Y ($P_{X,Y,EEZ}$) by dividing the mean area covered in oil of origin X for a given year Y for a given EEZ ($\hat{A}_{X,Y,EEZ}$) by the area of the country's EEZ A_{EEZ} (eq.7). When presenting the results, the term EEZ was replaced by the country's ISO code.

$$P_{X,Y,EEZ} = \frac{A_{X,Y,EEZ}}{A_{EEZ}} \qquad \text{(eq. 7)}$$

5. Results and discussion

5.1. Spatial distribution of oil slicks in the Gulf of Guinea

The spatial and temporal analysis on the Gulf of Guinea allowed the photo-interpretation of 18,063 oil slicks. The database of the 18,063 identified objects includes two classes of mineral oil. On the one hand, anthropogenic pollution that come from oil spill platforms and recurring deballasting of oil spill ships. On the other hand, natural oil seepage resurgences which are hints of the presence of hydrocarbon reservoirs in the sub-surface of the Gulf of Guinea. The fig. 6 represents the “hyperlook” of an oil spill platform encountered near the Nigerian coasts.

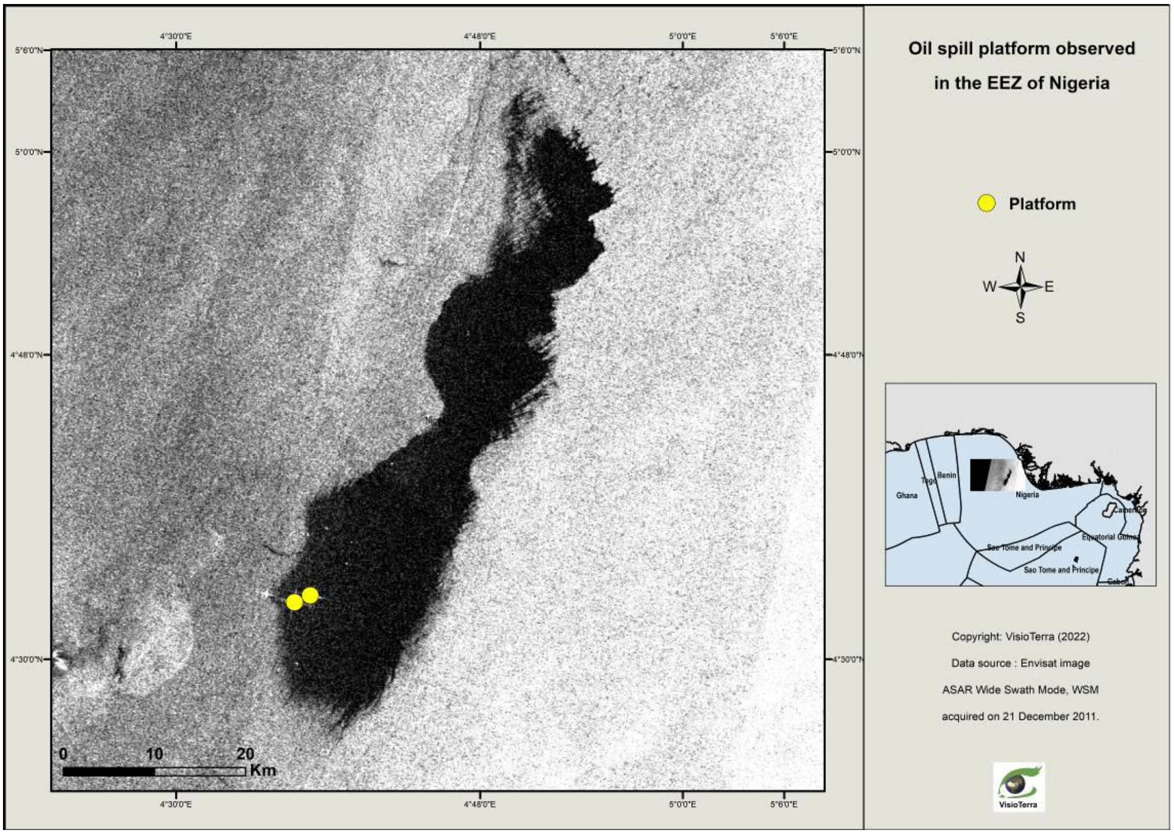

fig. 6 - Oil spill platform observed in the EEZ of Nigeria. The platforms are represented by the yellow dots http://visioterra.org/VtWeb/hyperlook/504c7208cc184c12b42ed036bc9912f3.

The fig. 7 illustrates the spatial distribution of the 18,063 oil slicks that have been detected and then mapped in the Gulf of Guinea over the period 2002-2012. The fig. 8, fig. 9, and fig. 10 respectively show the density maps of oil seepages, spill form ships and spill from platforms.

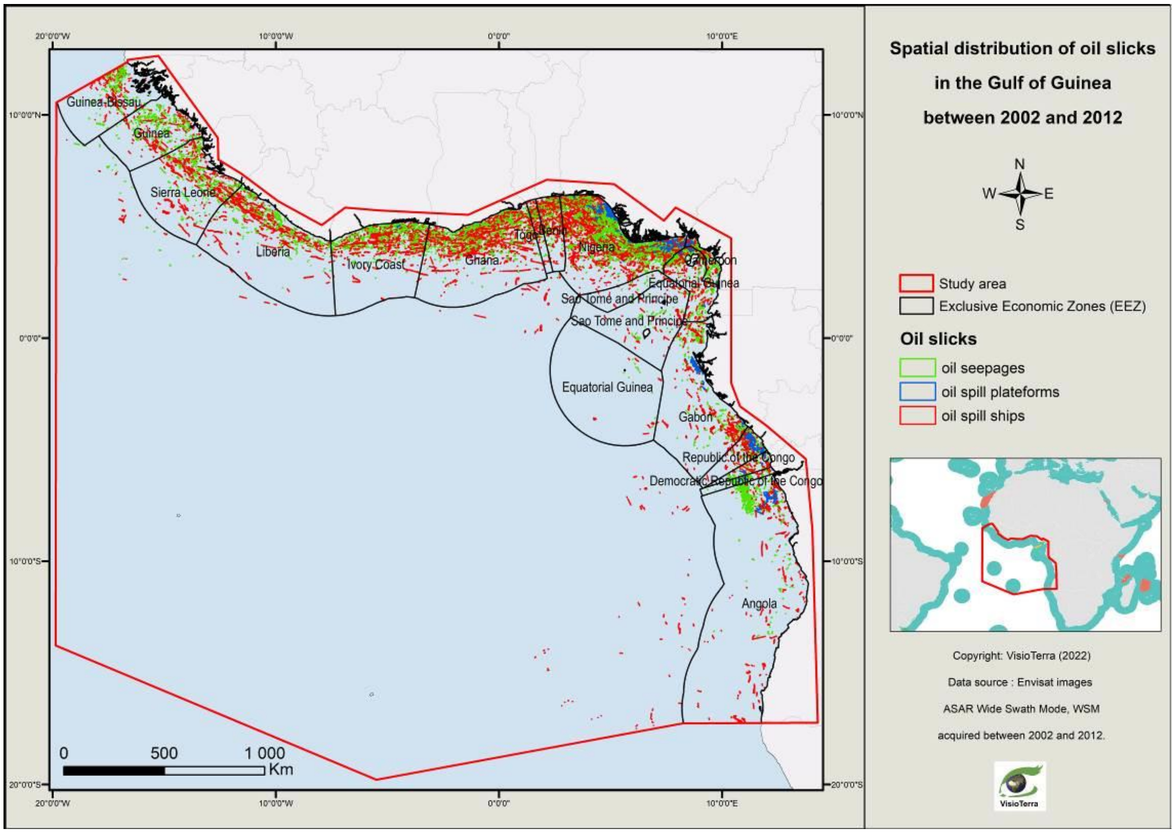

fig. 7 - Spatial distribution of oil slicks in the Gulf of Guinea between 2002 and 2012.

The fig. 8 shows that oil seepages are distributed over all the EEZs in the Gulf of Guinea. This large amount of oil seepages from the Gulf of Guinea could be partly explained by its geology resulting from the opening of the South Atlantic domain initiated in the Lower Cretaceous and by the significant sediment supply from the Niger Delta.

The proximity of the main maritime routes to the coasts contributes to the concentration of discharges in these places. This phenomenon is especially noticed along the coasts of Nigeria which is one of the main shipping routes and occupies a place in maritime piracy (see fig. 9). Thus, there are significant spills of ships there, despite the international convention for the prevention of pollution from ships (MARPOL 73/78), which came into force in 1983. Illegal dumping operations include deballasting and cleaning of ship engines.

Offshore oil platforms have been found all along the coasts of the EEZs of the top oil producing countries (Nigeria, Angola, Republic of Congo, Ghana...) in the Gulf of Guinea (see fig. 10). The oil spills coming from platforms that have been observed in our study are very well correlated with offshore installations.

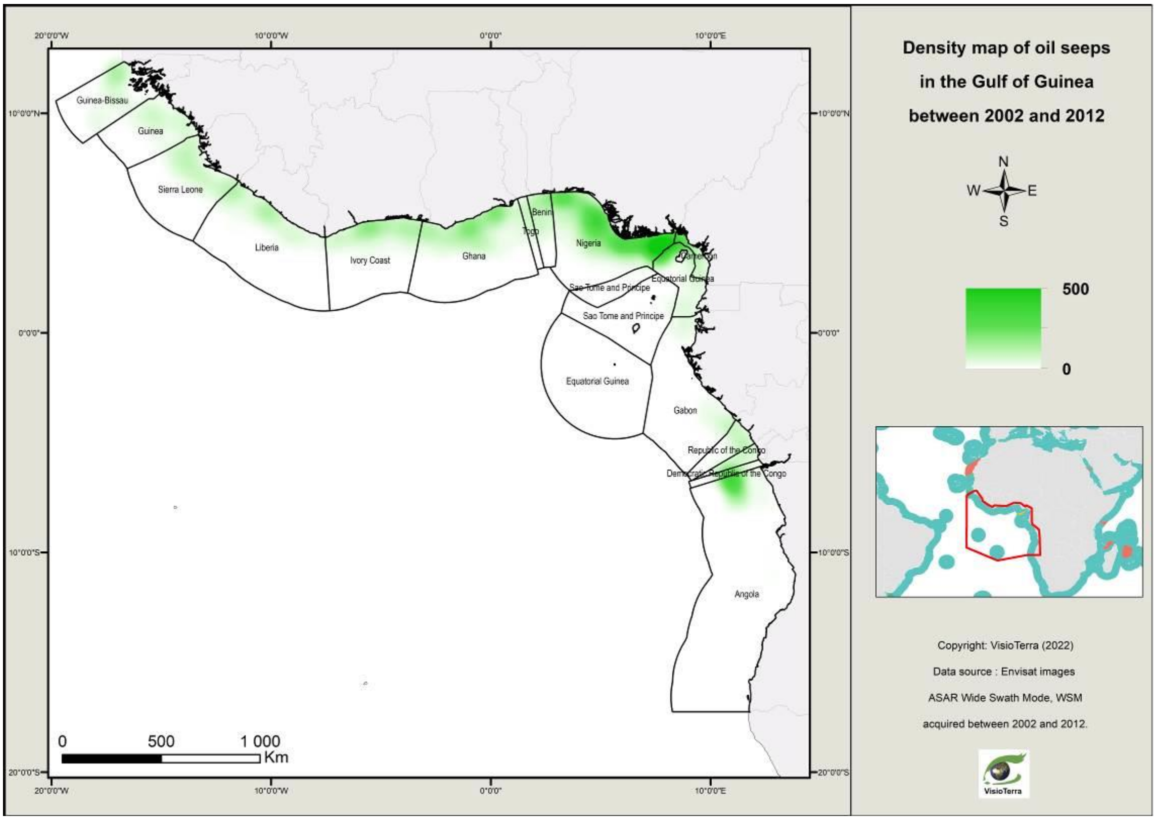

fig. 8 - Density map of oil seeps in the Gulf of Guinea between 2002 and 2012.

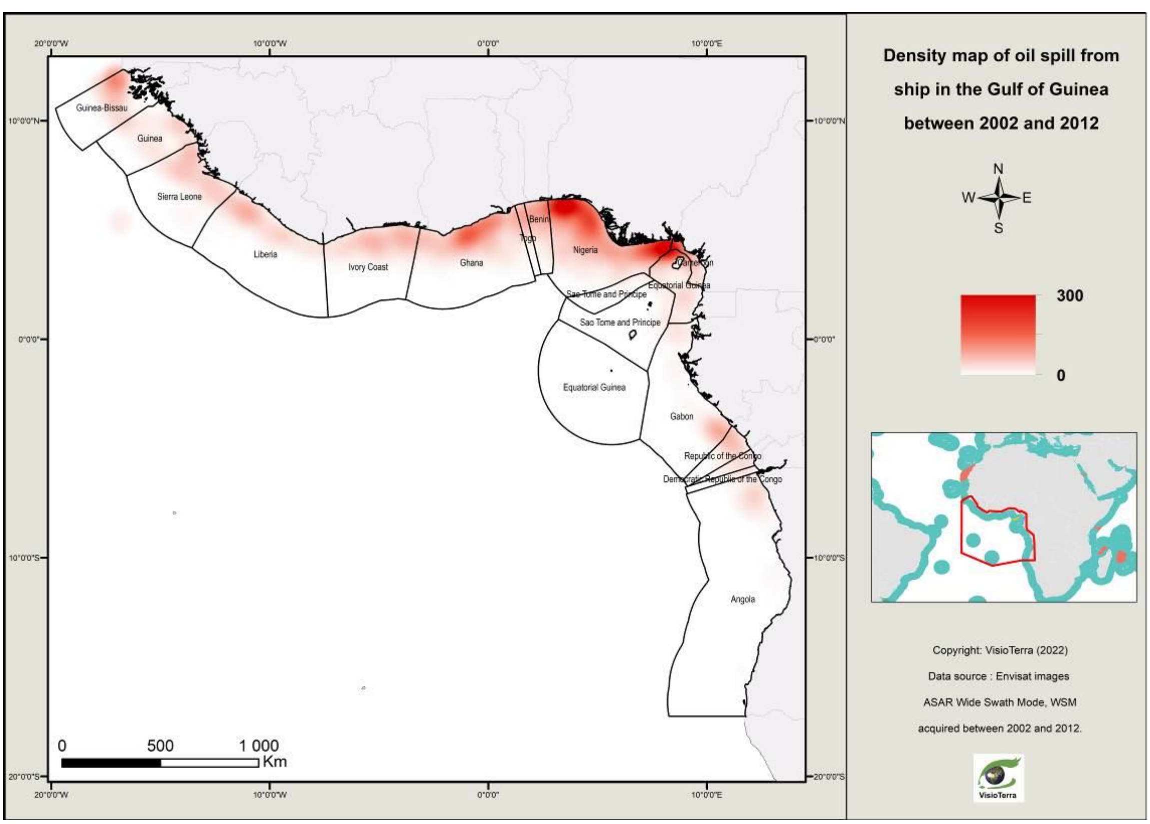

fig. 9 - Density map of oil spill from ship in the Gulf of Guinea between 2002 and 2012.

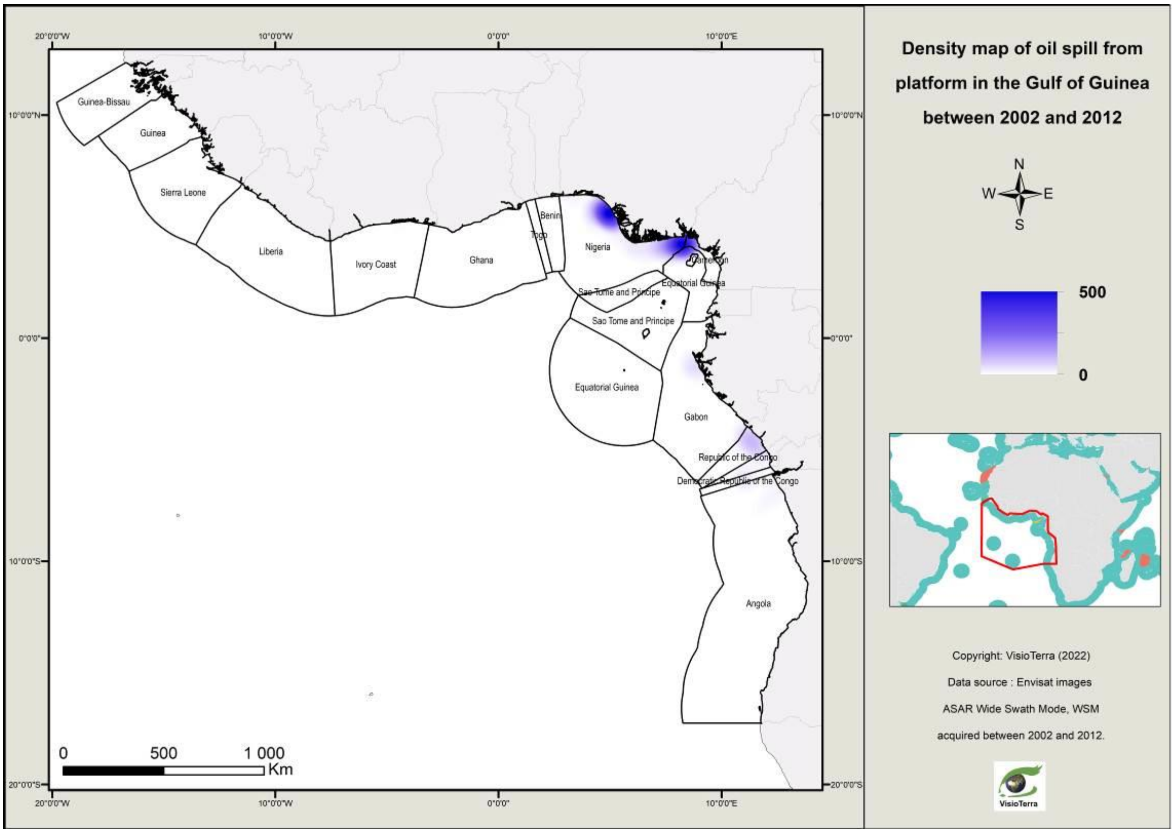

fig. 10 - Density map of oil spill from platform in the Gulf of Guinea between 2002 and 2012.

5.2. Mean area covered in oil ($\hat{A}_{X,Y,EEZ}$)

5.2.1. Mean area covered in oil in the Gulf of Guinea ($\hat{A}_{X,Y}$)

The fig. 11 shows the mean area covered in oil in the Gulf of Guinea by year. One can notice that:

- the mean area covered in oil slicks from natural origin (oil seeps) remains more or less stable during the period 2002-2012,
- the mean area covered with oil slicks from oil spill platforms seems to have increased significantly during 2008 and then returned to normal in 2009 until the end of the study period,
- the mean area covered in oil slicks from ships seems to have increased after 2004 with a peak between 2007 and 2008, then have fallen in 2009 and remained stable until the end of the study period.

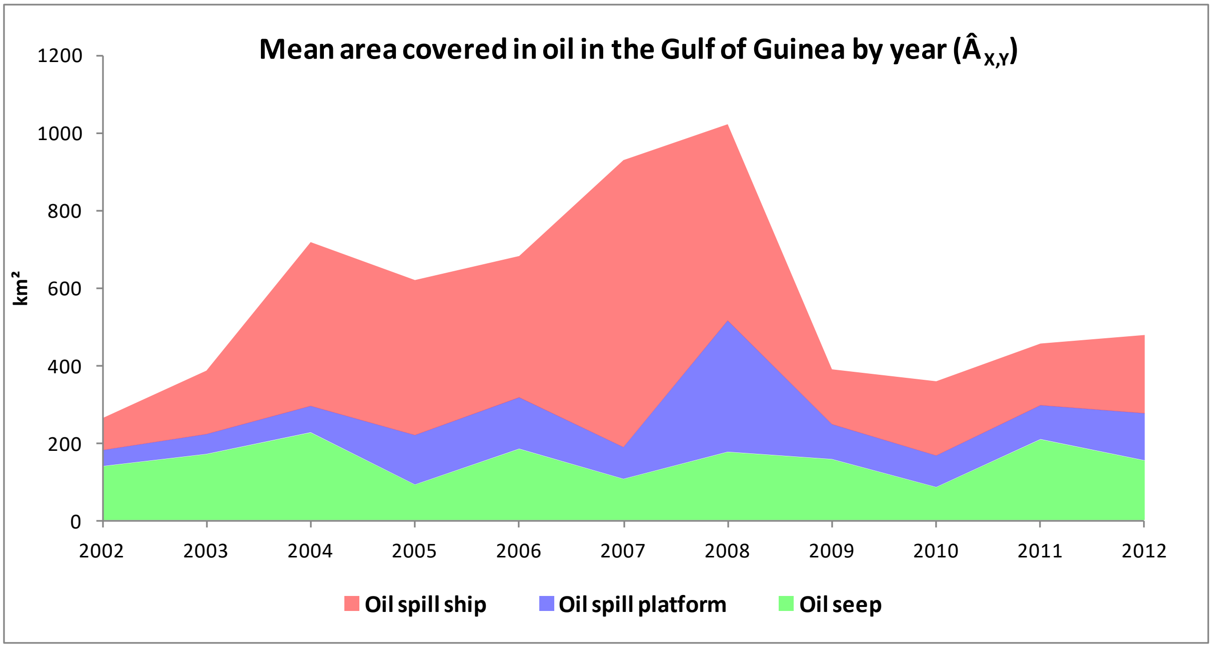

fig. 11 - Mean area covered in oil in the Gulf of Guinea by year ($\hat{A}_{X,Y}$).

5.2.2. Mean area covered in oil by EEZ of country ($\hat{A}_{X,Y,EEZ}$)

The fig. 12 shows the mean area covered in oil by EEZ of countries between 2002 and 2012. The fig. 13 shows the mean area covered in oil by EEZ of countries by year. One may note that the most polluted EEZ are Nigeria followed by Angola, Republic of Congo and Cameroon.

The analysis by EEZ shows that the decrease in oil spills observed between 2008 and 2009 (fig. 11) is governed by the major oil producing countries: Angola, Nigeria and Republic of Congo (fig. 13).

The fall in the mean area covered in oil from platforms and ships may be explained by the economic crisis of 2008. In fact, 2008 world crisis had led to the falling oil prices inducing deficit in the budget of oil companies and governments. For instance, Angola oil production decreased in 2009 following the post-2008 slowdown in global economic activity and the subsequent glut of oil on the global market (Mikidadu, 2018).

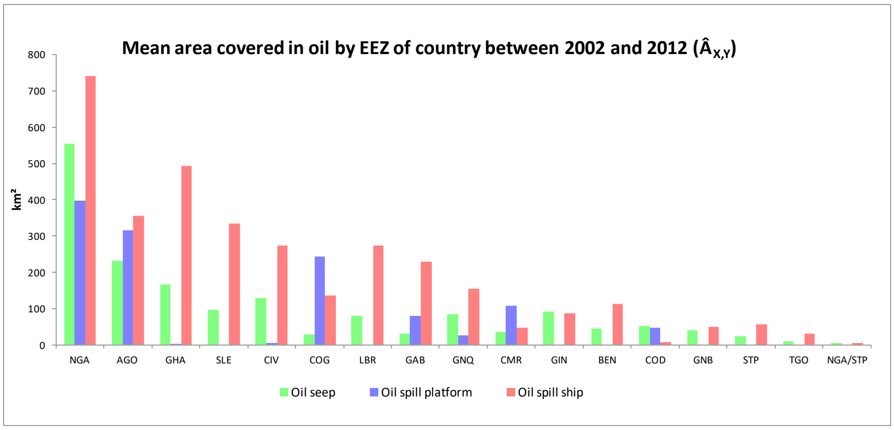

fig. 12 - Mean area covered in oil by EEZ of country ($\hat{A}_{X,Y}$) between 2002 and 2012.

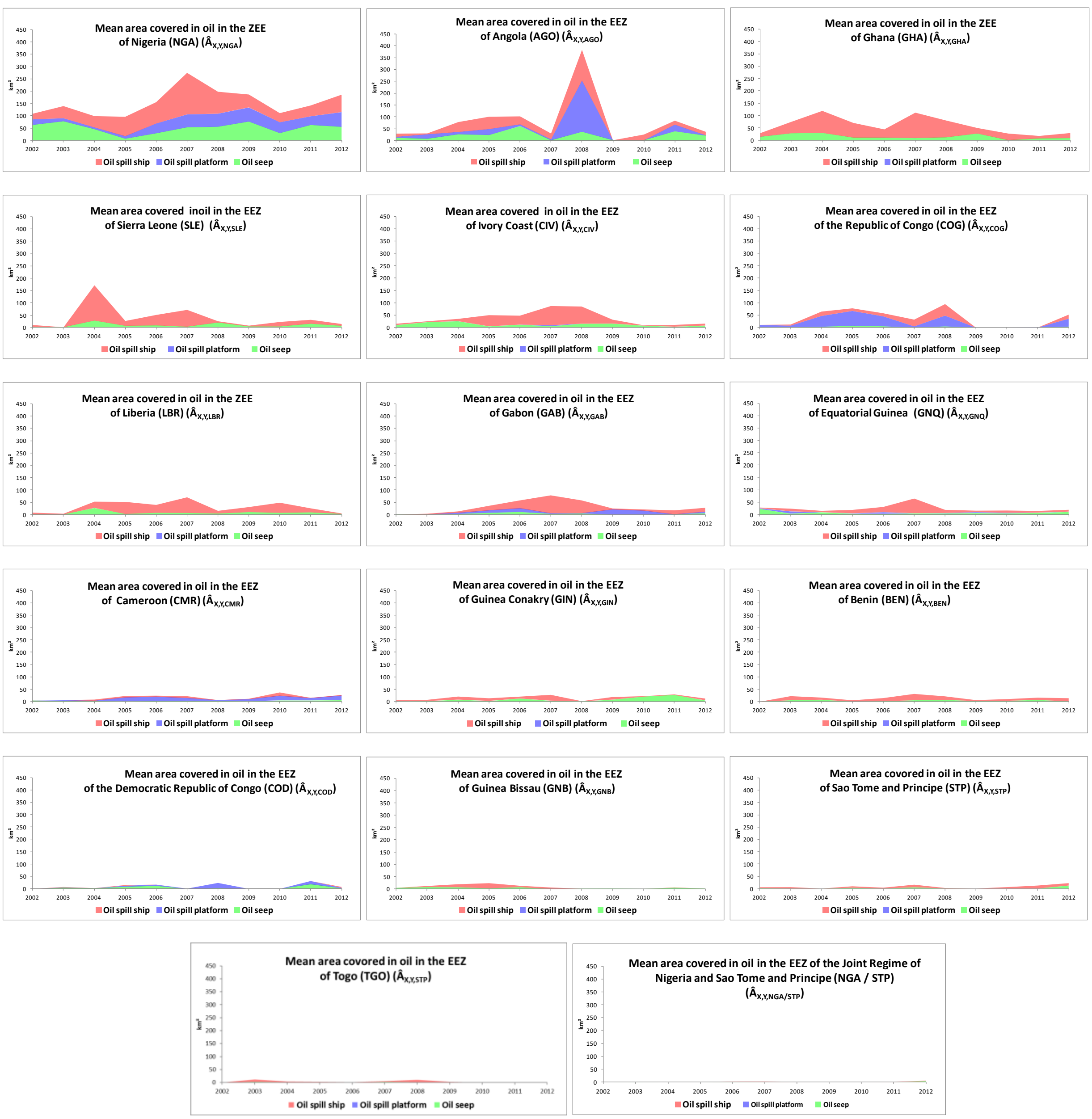

fig. 13 Mean area covered in oil by EEZ of countries per year ($\hat{A}_{X,Y,EEZ}$).

5.3. Mean fraction covered by oil by EEZ ($P_{X,Y,EEZ}$)

The fig. 14 shows the mean fraction covered by oil by EEZ of countries between 2002 and 2012. The fig. 15 shows the mean fraction covered by oil by EEZ of countries by year.

The country mean fraction covered by oil which divides the mean area covered in oil by the country EEZ area (eq.7) gives an idea of the mean probability to be covered by oil by EEZ. Thus, the biggest the mean fraction, the more the area is able to be covered by. One may see that the probability that an oil spill occur is high for the Republic of Congo, Cameroon and Nigeria while the probability that an oil seep occur is high for the Democratic Republic of the Cong, Nigeria and Cameroon.

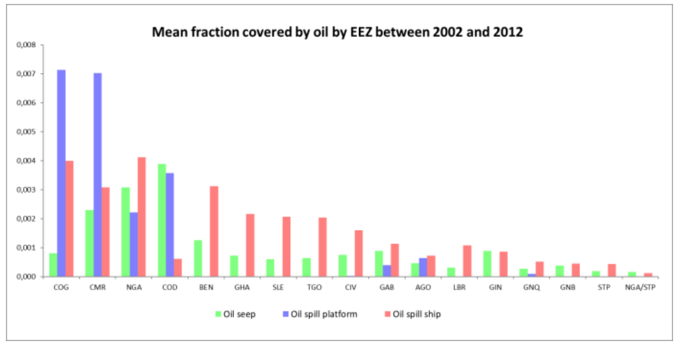

fig. 14 - Mean fraction covered by spilled oil by EEZ between 2002 and 2012.

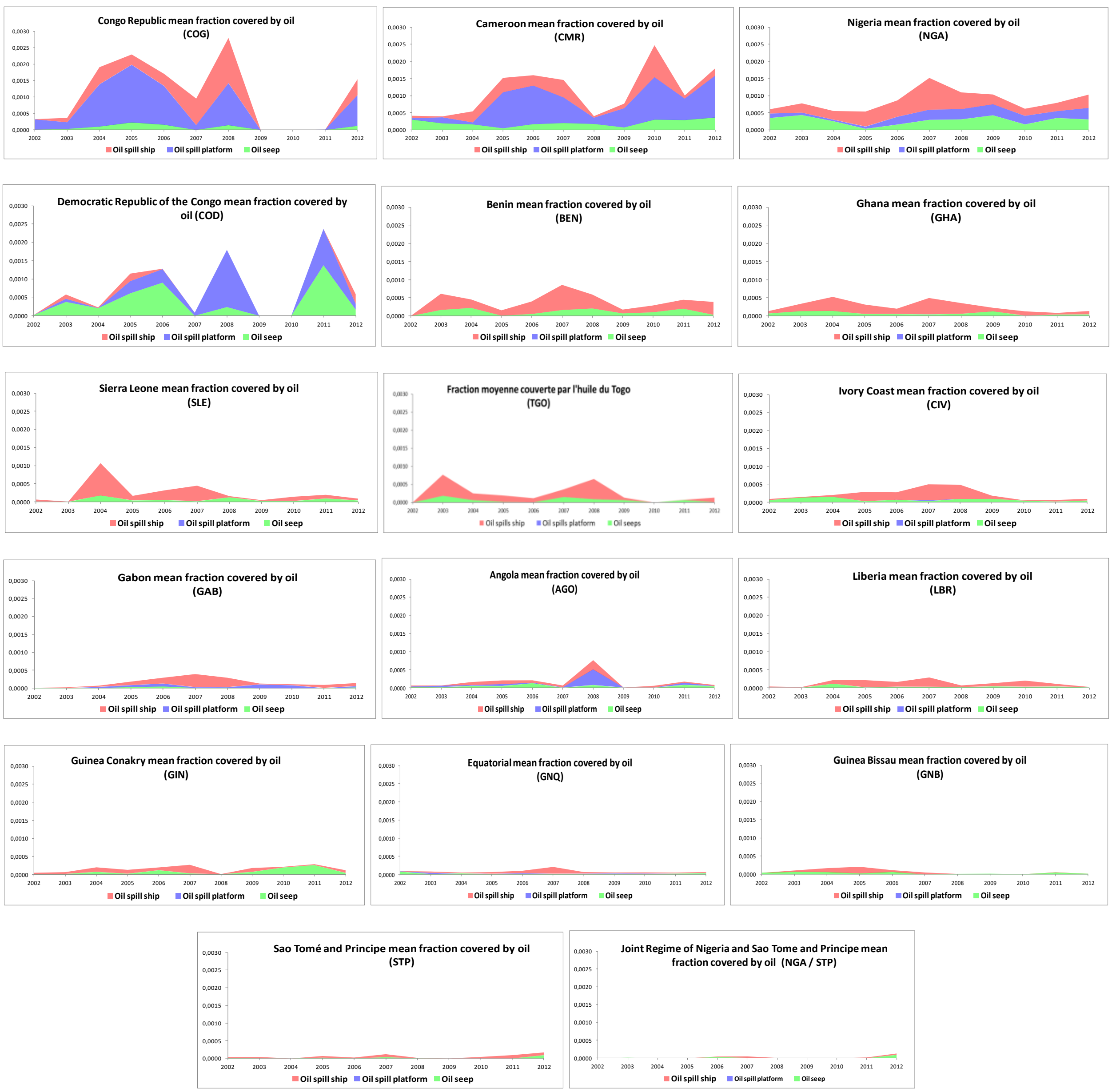

fig. 15 - Mean fraction covered by oil by EEZ by year.

6. Conclusion and perspectives

An unprecedented database of oil spills has been generated over the EEZ of the Gulf of Guinea using the 11 years of acquisitions of SAR images at C-band by ASAR in wide-swat mode (150 m of spatial resolution) contained in the archive of the Envisat mission. This database has been achieved using a manual approach. The present study shows that all of the countries EEZ are sites of natural oil seepages due to the extensive geological context of the Gulf of Guinea. It shows also that oil spills from ships are well correlated to the shipping routes along the coasts of the 17 EEZ of the Gulf of Guinea while oil spills coming from oil platforms are concentrated along the coasts of oil-producing countries like Nigeria, Republic of Congo, Angola, and Ghana. The temporal analysis during 10 years (2002-2012) shows a decrease in the mean area covered by oil between 2008 and 2009. This decreasing is likely to be due to the post-2008 global economic slowdown.

Oil seepages and oil spills monitoring will benefit from Sentinel-1 mission, launched in 2014, owing to its higher spatial resolution (10 m), its temporal sampling (5 days), and its longer period of acquisitions (beyond 2032). This dataset will offer more reliable and timely information for emergency and mitigation policies.

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