Seasonal and inter-annual variability in abundance of the main tropical tunas in the EEZ of Côte d'Ivoire (2000-2019)

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Abstract

The seasonal and inter-annual variability in abundance of the main "local tropical tuna resources" in the EEZ of Côte d'Ivoire was analysed with catch and effort data from French and Spanish purse seiners over the period 2000-2019. A seasonal spatio-temporal model developed by Thorson et al. (2020a) was used to estimate abundance indices for the main tropical tunas by commercial category (<10kg and >=10kg, which correspond roughly to maturity stage: immature and mature respectively), and fishing mode (free school sets and FAD sets). Furthermore, we decomposed the abundance time series into intrinsic mode functions using the CEEMDAN algorithm. The decomposition procedure made it possible to filter out the noise in the signal and extract the seasonal and inter-annual components of the abundance indices. A generalized additive model (GAM) was applied to the abundance indices to reveal the influences of environmental factors on species abundance and spatio-temporal distribution. Biological interpretations of the seasonal and inter-annual variability in tropical tuna abundance were made and the possible effects of environmental variables on this abundance discussed. Our results suggest that there are two main fishing seasons in the EEZ of Côte d'Ivoire. It was also found that mature yellowfin tunas are abundant between the first and second quarter of the year while the best season for skipjack occurs between the third and fourth quarter. In addition, we observed a considerable change over time in the seasonal and inter-annual variability of tropical tunas in this area.

Keywords: abundance indices, seasonal and inter-annual variation, spatio-temporal vector autoregressive model (VAST), tropical tuna.

Highlights

- Assessment of the tuna resources in the Exclusive Economic Zone (EEZ) of Côte d'Ivoire by estimating abundance indices with a seasonal spatio-temporal model.
- Evidence of two marked seasons of abundance in the study area: mature yellowfin from February to June and skipjack from August to December.
- Differences in behaviour (month of peak abundance, sensitivity to environmental variables) of tuna caught on Fish Aggregating Devices (FAD) vs tuna caught on Free-Swimming Schools (FSC).
- Similarity between the dynamics of some abundance indices and some environmental variables.

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1. Introduction

Fishing is of paramount importance in Côte d'Ivoire, as it is one of the main sources of animal protein for the country's poorest households due to its relatively affordable price compared to meat. Socio-economically, the tuna industry plays an important role in employment in Côte d'Ivoire (landing activities, canneries) and exports there. A trade and utilization chain for the tuna bycatch, called "faux poissons", retained on-board by purse seiners and landed in Abidjan (Côte d'Ivoire) has been developed since the early 1990s. Romagny et al. (2000) showed that this sector was of great socioeconomic importance for its actors from landing to consumption. A recent study has shown that in addition to the great social and economic importance of this sector for the local population, it contributes substantially towards food security for the Ivorian people (Monin et al., 2017). Côte d'Ivoire furthermore benefits from the incomes generated by fisheries agreements concluded with long-distance foreign vessels.

Given the essential role of fisheries, and mainly tuna fisheries, coastal countries have established fisheries departments to better manage the exploitation of tuna resources in their EEZ. Due to their highly migratory nature, the management of tuna stocks is carried out at a large regional scale by Regional Fisheries Management Organizations (RFMOs). Despite the need to assess the status of tuna resources at the stock level, little information is produced to know the state of the local resources, thus the coastal countries cannot optimize the management of their EEZ. In Côte d'Ivoire, there are two main types of tuna fisheries: industrial and artisanal. Industrial fisheries are dominated by EU purse seiners, with Spain and France predominant (Failler et al., 2014). Fisheries data for the EU industrial fleet are very well collected and monitored, and remain the best sources of information on the sector. The tuna resources of Côte d'Ivoire are mainly exploited by this fleet within the framework of a fishing agreement between Côte d'Ivoire and the European Union (Failler et al., 2014). The production of artisanal tuna fishery remains significant, but the data collected on this segment remain insufficient for a complete analysis of the sector. To date, local abundance of tuna in the EEZ of Côte d'Ivoire has not been specifically assessed (Cofrepeche, Poseidon, 2012; Failler et al., 2014). However, the downward trend in the reference tonnage of the EU/CIV fisheries agreements (supplementary material S1: Table 1:S1) and the global and local effects of climate change highlight the urgent need for Côte d'Ivoire to study seasonal and inter-annual variation in the tuna resources temporarily found in its EEZ.

Given the lack of direct estimates from scientific surveys, commercial catch per unit of effort (CPUE) is used to derive relative abundance of tuna resources which play an important role in stock assessment and management (Ricker, 1940; Maunder and Langley, 2004; Maunder and Punt, 2004). Nominal CPUEs derived from commercial fisheries are greatly influenced by spatial, temporal, and environmental factors, among others, and need to be standardized (Fonteneau et al., 1999; Maunder and Punt, 2004). Several methods have been applied to standardize CPUE including GLMs and GAMs (Campbell, 2004; Katara et al., 2018); machine learning and data mining techniques (Albeare, 2009; Yang et al., 2015), and spatio-temporal models (Maunder et al., 2020; Thorson et al., 2020b). We use the recent version of the VAST spatio-temporal model developed by Thorson et al. (2020a). This model includes annual, seasonal and spatial variations in density and allows us to capture two important key issues: (i) the standardization of data that are spatially unbalanced over several seasons and (ii) the identification of inter-annual changes in the seasonal chronology of population. The three most important tropical tuna species - skipjack tuna (*Katsuwonus pelamis*, SKJ), yellowfin tuna (*Thunnus albacares*, YFT), and bigeye tuna (*Thunnus obesus*, BET) - were divided into eight class categories taking into account the species, the maturity stage (immature and mature), and the two main fishing modes in the purse seine fishery (free school sets and floating object sets: hereafter referred to as FSC and FOB, respectively [note that FOB can be natural logs but in the large majority of cases are drifting fish aggregating devices known as dFADs]. The categorization of species by school type is legitimate in the sense that the fishing techniques differ. Fishing on dFADs can be analogous to harvesting and collecting, and fishing on free schools to searching and hunting. dFADs increase the catchability of tuna, as compared to sets on free schools by helping fishers locate fish (reducing search time) and allowing a high percentage of successful sets (Moreno et al., 2007). Free schools are dominated by large yellowfin whereas dFADs schools are mainly composed of skipjack and juveniles of the two others species. This distinction will enable evaluation of this aspect in the study area. Several studies have highlighted the major effects of climatic cycles on the distribution and availability of tuna resources in a local area (Maury et al., 2001; Lehodey et al., 2006; Ménard et al., 2007; Marsac, 2017). The variability of climatic conditions can be a non-negligible indicator of the variability in tuna abundance and spatial distribution and consequently justify the analysis of the relationship between environmental variables and tuna abundance indices. The following environmental variables have been selected for this study: sea surface temperature (SST), dissolved oxygen at a depth of 100 meters (DO2_100), chlorophyll concentration (CHL), sea surface salinity (SSS), mixed layer thickness (MLD), sea surface height (SSH) and SST-based coastal upwelling index (CUI_sst). Indeed, some studies showed that upwelling indices are important in explaining the fluctuations of tuna and tuna-like species abundance (Cury and Roy, 1987; Roudaut, 1999).

To analyse the seasonal and inter-annual variation in the European purse seiners CPUEs in the Ivorian EEZ, we first estimated the abundance indices using a Thorson et al. (2020a) seasonal spatio-temporal model. Thereafter, we used a method adapted to analyse non-linear and non-stationary signals (i.e., the CEEMDAN algorithm), with the aim to decompose the CPUE series into a finite and exhaustive number of components, called intrinsic mode functions (IMFs). Finally, we explored the relationships between the estimated abundance indices and the environmental variables using GAMs.

2. Materials and methods

2.1 Study area

The study area extends between latitudes 1°N and 6°N and longitudes 2°W and 8°W (Fig. 1). This is the smallest area that includes the 1° square that pass through the Ivorian EEZ. The area was selected to facilitate future comparisons with data collected by 1° square degrees and to avoid boundary effects. This area is characterized by a seasonal surface temperature signal due to the presence of two cool seasons, each associated with the coastal upwelling (Morlière, 1970). The main cold season takes place in winter between July and September. Winter cooling is then intensified on the coast by upwelling that brings nutrient-rich water to the surface. A second cooling occurs along the coast in January-February; this second cold season is low-amplitude and short-lived (between one and two months; Cury and Roy, 1987)

2.2 Catch and effort data

Catch and effort data for EU purse seiners operating in the EEZ of Côte d'Ivoire from 2000 to 2019 were compiled and managed by the Tuna Observatory (Ob7) of the French National Research Institute for Sustainable Development (IRD, UMR MARBEC), and the Spanish Institute of Oceanography (IEO) for the French and the Spanish fleets respectively. The raw logbook data produced by the skippers were corrected by the T3 methodology regarding total catch per set (to account for the difference between reported catch at sea and landed catch) and species composition (based on port size sampling), see Pallarés and Hallier (1997) and Duparc et al. (2020), to generate the level 1 logbook database used in this paper. The commercial size category was used as a discriminant factor at the maturity stage of bigeye and yellowfin tuna. Commercial categories 2 and 3 (tuna >=10 kg) are classified as mature and category 1 (tuna <10 kg) is classified as immature (except for skipjack which belongs to this category and was not divided by maturity stage). We know from the literature[5] that 50% size at maturity is reached around 100cm fork length (that is to say around 20kg) for yellowfin and bigeye. However, for the sake of simplicity we used the conventional "size" commercial categories reported in purse seiners logbooks by European skippers (category 1: <10kg; category 2: 10 to 30kg; category 3: >30kg). All sets per boat and per day were combined and assigned to the centroids of these activities. The total number of sets per day per boat has been filtered and days with unrealistic data (over 5 sets per day per boat) deleted. Given that free schools are detected at random at the surface of the sea, the unit of effort associated with this fishing mode was expressed as the searching time (i.e., the time spent on the fishing ground less the duration of all setting operations). In contrast, many dFADs are not encountered randomly, specifically when they are equipped with a GPS buoy and continuously tracked remotely by the purse seiner. In such a case we used the number of dFADs sets as a measurement of the fishing effort. The data were then divided into eight categories according to the species, the maturity stage and the fishing mode. Only catch and effort data from sets conducted out in the study area were selected in this study.

2.3 Environmental data

Six candidate environmental variables were extracted from the EU's Copernicus Marine Environment Monitoring Service (CMEMS) (https://marine.copernicus.eu/) at a monthly mean resolution (Table 1): sea surface temperature (SST), sea surface height (SSH), chlorophyll concentration (CHL), salinity (SSS), mixed-layer thickness (MLD), and dissolved oxygen at a depth of 100 meters (DO2_100). The spatial resolution of the model grid for SSS, SSH, SST, and MLD is 1/12º (0.083º x 0.083º, about 8 km), while the spatial resolution for CHL, DO2_100 is 1/4º (0.25º x 0.25º, about 24 km).

2.4 Coastal upwelling index (CUI_SST)

A seventh environmental variable, the monthly SST-based coastal upwelling index (CUI_SST) was calculated for the Ivorian EEZ. The SST-based coastal upwelling indices are obtained by taking the thermal difference (ΔT) between the coast and the offshore SST at the same latitude. In practice, CUI_SST has been defined as the thermal difference between cold coastal waters and warmer offshore waters at the same latitude (Benazzouz et al., 2014). The general formulation is as follows:

$$\mathrm{CUI}_{\mathrm{SST\ (lat,\ time)}} = \mathrm{SST}_{\mathrm{offshore\ (lat,\ time)}} - \mathrm{SST}_{\mathrm{coastal\ (lat,\ time)}} \qquad (1)$$

The general calculation formula is very simple, but the challenge is to study the best way to define the coastal and offshore zones and to correctly extract the two thermal references to be used for the calculation. The resulting SST-based coastal upwelling index is characterized by a seasonal signal with peaks in the first and third quarter of the year (Fig. 2).

2.5 Methods

2.5.1 The seasonal spatio-temporal model

We applied a vector-autoregressive spatio-temporal delta-generalized linear mixed model to the catch and effort data, using the R package VAST (Thorson, 2019). Recently, VAST has been expanded to account for seasonal and inter-annual variability (Thorson et al., 2020a). This allows an understanding how species distribution and abundance varies within a year by month or season, and also within a month or season across years. It offers reasonable performance even when data are not fully available for one or more combinations of years and

[5] See ICCAT manual, chapter 2 at https://www.iccat.int/en/iccatmanual.html

seasons, which is common in commercial catch data. In order to work at a finer scale temporal resolution (monthly, bi-monthly, quarterly…), the estimates in year-season t are shrunk towards predicting density in adjacent year-seasons (*t-1* and *t+1*), as well as towards estimating density in other seasons in a given year and density in other years for a given season. This specification implies that the model includes a "main effect" for a season and year, as well as an autocorrelated "interaction" of season and year. We present below a brief summary of the principal parameters and philosophy of the model but readers are encouraged to refer to supplementary materials S2 for more technical details.

The VAST model is being implemented using the Poisson-link delta model as recommended by Thorson (2018). The Poisson-link delta model includes the probability p_i that sample i encounters a given species [i.e. $\Pr(B > 0)$], and also the expected measurement r_i given that species is encountered, $\Pr(B \mid B > 0)$:

$$\Pr(B = b_i) = \begin{cases} 1 - p_i & \text{if } B = 0 \\ p_i \times g\{B \mid r_i, \sigma_m^2\} & \text{if } B > 0' \end{cases} \qquad (2)$$

where we specify a lognormal distribution for positive catches. This Poisson-link delta model predicts encounter probability *pi* and positive catch rate r_i by modeling two log-linked linear predictors, $\log(n_i)$ and $\log(w_i)$ for each sample i; n_i and w_i are then transformed to yield p_i and r_i :

$$p_i = 1 - \exp(-a_i \times n_i)\,, r_i = \frac{a_i \times n_i}{p_i} \times w_i\,, \qquad (3)$$

where a_i is the area-swept offset for sample *i*. This model structure is designed so that expected density d_i is the product of encounter probability and positive catch rate and also the product of transformed linear predictors (i.e $d_i = p_i * r_i = n_i * w_i$). These predictors can be interpreted as numbers-density n_i (with units numbers per area) and average weights w_i (with units biomass per number). n_i always enters via the product $a_i * n_i$ such that n_i is expressed as density. We consider effort as a catchability factor in the model. The Poisson-link delta model is useful relative to other delta models because both linear predictors use a log-link function so that all effects are additive in their impact on the predicted log-density. Specifically, we specify that:

$$\log(n_i) = \underbrace{\beta_n^*(t_i)}_{\substack{Year-season\\intercept}} + \underbrace{\omega_n^*(s_i)}_{\substack{Spatial\\main\ effect}} + \underbrace{\xi_{nu}^*(s_i, u_i)}_{\substack{Season\\spatial\ effect}} + \underbrace{\xi_{ny}^*(s_i, y_i)}_{\substack{Year\\spatial\ effect}} + \underbrace{\varepsilon_{nu}^*(s_i, t_i)}_{\substack{Year-season\\spatial\ effect}} + \underbrace{\zeta^*_{\ n}(i)}_{\substack{Catchability\\covariates}} \qquad (4)$$

$$\log(w_i) = \underbrace{\beta_w^*(t_i)}_{\substack{Year-season\\intercept}} + \underbrace{\omega_w^*(s_i)}_{\substack{Spatial\\main\ effect}} + \underbrace{\xi_{wu}^*(s_i, u_i)}_{\substack{Season\\spatial\ effect}} + \underbrace{\xi_{wy}^*(s_i, y_i)}_{\substack{Year\\spatial\ effect}} + \underbrace{\varepsilon_{wu}^*(s_i, t_i)}_{\substack{Year-season\\spatial\ effect}} + \underbrace{\zeta^*_{\ w}(i)}_{\substack{Catchability\\covariates}} \qquad (5)$$

The French purse seiners were targeting mainly free schools while the Spanish purse seiners were targeting drifting FADs. This difference in fishing strategy is less pronounced in the recent years as the use of dFADs-fishing increased in both fleets. There is likely also a vessel size category component in the choice of the fishing strategy. Both covariates (flag and vessel size category [carrying capacity]) have been introduced in the analysis as catchability covariates as suggested by Thorson (2019).

Key model parameters for abundance indices are density predicted, area-weighted density sum, and abundance-weighted mean density. The model estimates the density prediction per year at each fine spatial resolution:

$$
\begin{aligned}
d(s,t) &= n(s,t) \times w(s,t) \\
&= \exp\{\beta_n^*(t) + \omega_n^*(s) + \xi_{nu}^*(s,u) + \xi_{ny}^*(s,y) + \varepsilon_n^*(s,t) + \zeta^*_n\} \\
&\quad \times \exp\{\beta_w^*(t) + \omega_w^*(s) + \xi_{wu}^*(s,u) + \xi_{wy}^*(s,y) + \varepsilon_w^*(s,t) + \zeta^*_w\}
\end{aligned}
\tag{6}
$$

We use density to calculate the total abundance for the entire domain as the area-weighted sum of density $d\,(s,t)$ predicted at a fine spatial resolution:

$$I(t) = \sum_{s=1}^{n_s} a(s)d(s,t) \tag{7}$$

where n_s is the number of fine-scale predictions and a_s is the spatial area associated with each prediction. See the supplementary material S2 for more details on the model, its implementation and results.

2.5.2 Statistical analyses

We decomposed the abundance indices into intrinsic mode functions to extract their seasonal and inter-annual components using the Complete Ensemble Empirical Mode Decomposition with adaptive noise (CEEMDAN) algorithm. The CEEMDAN algorithm belongs to the broad family of Empirical Mode Decomposition (EMD) algorithms (Huang et al., 1998). Torres et al. (2011) introduced this algorithm as a variation of the EEMD algorithm (Wu and Huang, 2009) that allows exact reconstruction of the original signal and better spectral separation of intrinsic mode functions. We used the package "Rlibeemd" (Luukko et al., 2016) to decompose the eight abundance indices using the CEEMDAN algorithm. See the supplementary material S1 for more details on the CEEMDAN algorithm application.

The seasonal and inter-annual components of the abundance indices estimated in this paper are extracted from the CEEMDAN intrinsic mode functions (IMFs). The residual component represents the long-term component (inter-annual component), and the IMFs with annual frequency represent the seasonal (intra-annual) component. Three types of time series in the different IMFs can be observed: (i) some sub-annual (periodic) time series showing at least two local minimum and two local maximum by year (ii) the annual (periodic) time series that had no more than three local peaks (maximum + minimum) and (iii) some supra-annual (periodic) time series. In situations when there was more than one annual frequency component, we considered the average between them to construct the seasonal component. The seasonal component was used for two purposes in this study. First, we calculated the average abundance per season (month or two months in the case of immature yellowfin tuna caught on dFADs) over the entire study period. This allowed us to have the average seasonal factors. Then, we examined the dynamics of seasonality over the entire study period. The packages seasonal (Sax and Eddelbuettel, 2018) and forecast (Hyndman and Khandakar, 2008) were used for plotting the inter-annual variation of the seasonalities of each abundance index.

A Principal Component Analysis (PCA) was used to understand the common variability of the environmental variables used and to characterize environmental conditions of tropical tunas in the EEZ of Côte d'Ivoire.

GAMs (Hastie and Tibshirani, 1987) were used to study the links between the abundance indices by category and the environmental factors because they make it possible to take into account the non-linearity of such relationships (Maury et al., 2001). GAMs allowed the quantification of the percentage of deviance that can be explained by habitat, and to determine the relative contribution of the environmental variables. All statistical analyses were conducted with R 4.2. (R Core Team, 2019). The packages FactoMineR 1.34 (Husson, 2008) and mgcv 1.8–31 (Wood, 2017) were used for PCAs and for GAMs, respectively. The entire data processing and analysis procedure is summarized in Fig.3.

3. Results

Supplementary material S2 presents the estimated abundance indices and the decomposition of each abundance index into intrinsic mode functions using the CEEMDAN algorithm. All these results were analysed to obtain the factors related to the seasonal and inter-annual variation in the abundance of tropical tunas in the area of the EEZ of Côte d'Ivoire.

3.1 Seasonality of abundance indices

Mature yellowfin tuna captured on FSC and skipjack tuna captured on dFADs in the Ivorian EEZ are the categories showing the most obvious seasonality (Fig. 4). The seasonality of the tuna fisheries in the EEZ of Côte d'Ivoire is largely due to these two species. Two main tuna-abundance seasons can be identified. The first, characterized by an abundance of mature yellowfin tuna, takes place between March and July, and the second, characterized by an abundance of skipjack tuna, takes place between August and December (Fig. 4; Table 2). Some shrinkage of the seasonality factor is evident for SKJ on FSC, with amplitude ranging from 23 at the start of the study period to almost 5 over the last years (Fig. 5). The seasonality of the other abundance indices is almost constant throughout the study period (Fig. 5; Fig. 6).

3.2 Inter-annual variations of abundance indices

For sets on dFADs, there is a general downward trend in abundance indices for the majority of the categories (Fig. 7). The abundance indices for mature bigeye tuna show a downward trend from 2000 to 2009 and an upward trend since 2009.

For sets on FSC, there is an overall downward trend in the abundance indices for immature yellowfin tuna and skipjack tuna from 2000 to 2016/2017 and an upward trend from 2016/2017 onwards (Fig. 7). Mature yellowfin tuna increase over the study period. Mature bigeye tuna tend to increase from 2000 to 2006, then decrease to a local minimum in 2014 and increase from 2015 to 2019. Mature yellowfin tuna is the predominant category in the FSC species composition.

3.3 Environmental variability in the study area (PCA results)

The criterion of Kaiser (1960) enables the selection of the first three axes that represent 82.9% of the total variability contained in the environmental variables. PCA showed correspondence between chlorophyll concentration (CHL), coastal upwelling index (CUI_sst) and sea surface salinity (SSS), which were strongly correlated to the positive semi axis of the first principal component, and opposed to sea surface temperature (SST) and sea surface height (SSH) (Table 3; Fig. 8). The first principal component (Dim 1), explained 53.6% of the global variability of the data, highlights the great difference in environmental conditions between the primary cold season characterized by the upwelling phenomena and the primary warm season. From the projection of the months over the first two axes, it can be seen that July, August, and September are on the positive semi axis of the first principal component (Dim1), and April and May are on the negative semi axis of that first component (Supplementary material S1: Fig. 9:S1).

The second component of this PCA explained 16.2% of the global variability of the data. It was strongly correlated to the mixed-layer thickness (MLD) on the positive semi-axes (Table 3). This second component (Dim 2) was interpreted as a mixed layer depth gradient. From the projection of the months over the first two axes, it can be seen that June is on the positive semi axis of the second principal component (Dim2) (Supplementary material S1: Fig. 9:S1).

The third component of this PCA explained 12.3% of the global variability of the data (Fig. 8). It was strongly correlated to the dissolved oxygen at a depth of 100 meters (DO2_100) on the positive semi-axis (Table 3). This third component (Dim 3) was interpreted as a dissolved oxygen gradient which is a sub-surface variable.

3.4 Results of GAM models

All environmental variables were significant in terms of explaining the variability of skipjack abundance indices. There are however some differences between the abundance on FSC that is better explained by dissolved oxygen at a depth of 100 meters (DO2_100), salinity, sea surface temperature (SST), chlorophyll concentration (CHL) and mixed-layer thickness (MLD), while abundance indices on dFADs are better explained by dissolved oxygen at 100 meter depth (DO2_100) (Table 4).

Abundance index for adult yellowfin tunas on dFADs is explained by sea surface height (SSH), sea surface temperature (SST), chlorophyll concentration (CHL) and coastal upwelling index (CUI_sst) while abundance on FSC is linked to sea surface temperature (SST) only, with a higher proportion of the deviance explained for dFADs (Table 4).

Only the dissolved oxygen at a depth of 100 meters (DO2_100) better explains abundance indices for juvenile yellowfin tunas (on dFADs and on FSC). It must be stressed that the deviance explained by environmental factors on the abundance on dFADs is higher than those FSC (Table 4).

For mature bigeye tunas, abundance indices on dFADs are better explained by sea surface temperature (SST) and chlorophyll concentration (CHL) while for FSC sea surface temperature (SST) and mixed-layer thickness (MLD) are the two environmental factors that most impact on the abundance.

4. Discussion

The need for coastal countries to evaluate their local resources is gaining importance. Andriamahefazafy (2020) highlighted that the inability for coastal countries to evaluate their tuna resources was frustrating for their governments. This highlights their willingness and need to gain an idea of the variability of the abundance of tuna transiting their EEZs as a complement to the regional assessments carried out by tuna RFMOs. We assess the “local tuna stocks” in the EEZ of Côte d'Ivoire by estimating abundance indices. The abundance indices obtained by using VAST served as inputs to other methods to characterize their seasonal and inter-annual variability. In this study, for the sake of simplicity, we used the term “local tuna stock” somewhat inappropriately, because tuna are migratory so the stock concept is more complex than a spatial boundary. We agree with Amon Kothias and Bard (1993) when they define the tuna resources of Côte d'Ivoire as a component of the tropical Atlantic tuna stocks. The estimated abundance indices are therefore interpreted as the tuna outflow remaining in the study area at a given time. In addition, the study area is imperfectly assigned to the Ivorian EEZ, but the selected area extends beyond the Ivorian EEZ and considers boundary effects. One of the major limitations of this study is the selection of the fishery. Several fleets and gear types exploit the tuna resources of the Ivorian EEZ, but our study was limited to the French and Spanish purse seiners. This choice enhances consistency due to the relatively better quality and availability of the data, but interpretations may be affected by gear selectivity. It is important to consider these factors in the conclusions of this research, but as far as we know, this study is the first to estimate a local abundance of tunas with such levels of disaggregation (maturity level and school type) in the Gulf of Guinea region.

Another major limitation of this study is the use of commercial catch and effort information to estimate abundance indices. The relationship between standardized CPUEs and real abundance can be subject to hyperdepletion or hyperstability, depending on the fishing gear (Hilborn and Walters, 1992; Walters, 2003). Tropical purse seine tuna fisheries rely on many factors such as the concentration of schools in clusters (Fonteneau et al., 2017, 2008; Orensanz et al., 1998), and on the continuous introduction of technological developments (e.g., FADs equipped with echosounders) that contribute to the increase in vessels' fishing power (Fonteneau et al., 1999; Torres-Irineo et al., 2014). However, due to the difficulties in obtaining information on new fishing technology introduced on board each vessel, the conventional standardization methods do not really capture the impact of these factors. We know that the estimated abundance indices in this paper are not immune to the biases from which the approximation of abundance by standardized CPUE suffers. However, we have chosen to disaggregate the data by school type and maturity stage to avoid some biases.

With regards to the effects of the environmental conditions on tuna resources, studies have shown that in comparison with other tuna species, skipjack tuna vertical movements are limited and restricted to surface waters because they have a limited tolerance to low levels of dissolved oxygen and very low temperatures (Graham and Dickson, 2004). The fact that the dissolved oxygen at a depth of 100 meters, MLD and SST better explain the variability in skipjack catch rate is due in part to this species-specific characteristic. Our results showed that the peak season of skipjack tuna in Côte d'Ivoire (August – December) coincides with the presence of upwelling, rich in nutrients, during the third quarter of the year. Skipjack tuna are most concentrated inside the EEZ of Côte d'Ivoire during the months with low SST and high CHL (i.e. from August to December with a peak in September) (supplementary material S1: Fig. 2:S1 and Fig. 9:S1). Bard et al. (1988) suggested that the equatorial migration of skipjack tuna is particularly driven by foraging and thus driven by particularly productive zones. The delay of 1-2 months from the peak of the upwelling to the peak of skipjack abundance provides further evidence confirming these general aspects already analysed in the Gulf of Guinea. Indeed, Mendelssohn and Roy (1986) found that higher concentrations of skipjack occur when there was an upwelling one month prior to fishing, followed by a relative warming of the waters two weeks prior to fishing. Our results reinforce this observation while highlighting the differences observed between dFADs and FSC fishing. Mature yellowfin tuna are most concentrated inside the EEZ of Côte d'Ivoire during the months with high SST and high SSH (i.e., from March to July with a peak in April - May) (supplementary material: Fig. 2: S1 and Fig. 9:S1). Several studies have shown that there is significant yellowfin spawning activity in the Gulf of Guinea from December through April (ICCAT, 2019). The seasonality of adult yellowfin tuna in this study is consistent with previous findings in this sub-area of the Gulf of Guinea. The peak in abundance is due to a mixture of genetic migrations related to reproduction which takes place in the first quarter of the year in the study area (Albaret, 1977) and trophic migrations related to the enrichment of the study area in food generated by the presence of coastal upwelling which takes place from January to February (Binet, 1976). In conclusion, the seasonality of tuna abundance in the EEZ of Côte d'Ivoire is consistent with the patterns of tropical tuna characteristics observed at regional scales and a function of local environmental conditions (Mendelssohn and Roy, 1986).

The recent stock assessments of Atlantic tropical tunas have revealed that (1) yellowfin tuna is not overfished and not subject to overfishing, (2) bigeye tuna has been overfished since 1994 and overfishing has been undergoing since 1997, and (3) skipjack tuna are not likely overfished and not subject to overfishing (ICCAT, 2019). When stocks are overfished, one can expect a reduction in biomass, the impact of which is greater at the periphery of the spatial distribution of the stock (e.g., in the EEZ of Côte d'Ivoire) than in the core area, as postulated by the McCall's basin hypothesis (MacCall, 1990). For bigeye, the tropical tuna species most impacted by exploitation, our results suggest a declining trend during the first decade and an increasing trend from 2009 onwards on dFADs and 2014 on FSC components.

The overall trend of bigeye caught on FSC varies slightly from 2000 to 2017 followed by a sudden increase in the last two years (Fig. 3 S1). It is very unlikely to see such an abrupt change in the abundance of a long-lived species such as bigeye. The resulting overall trend could be due to a change in catchability compared to previous years. We reserve the right to interpret it as a change in the abundance of this species. However, since bigeye is rare in this area, a peak in moderate catches could generate such observations. The situation is somewhat different for catches on dFADs. More specific analyses could help better understand the phenomenon observed in the abundance indices of mature bigeye tuna in this study area. The situation is different for yellowfin and skipjack as both species show a general downward trend, with the exception of yellowfin captured on FSC. As we have seen, CHL and SST are responsible for seasonality in abundance indices of skipjack and mature yellowfin. The global trend of these variables over the study period could have affected the overall dynamics of the abundance of both species. Indeed, there is an overall upward trend in SST, and a downward trend in the coastal upwelling index and chlorophyll concentration over the years (Fig. 9). Future analyses more specific to this topic will explain the similarity between trends in these variables and those of some abundance indices estimated in this paper.

Several studies have examined the difference between the behaviour of tropical tuna captured on dFADs or on FSC, and differences in several biological parameters and migrating patterns have been reported (Hallier and Gaertner, 2008). Ménard et al. (2000) suggested that the dFADs fishery may have wide-ranging effects on the migration of tuna in general and on the productivity of skipjack in particular. Coming back to the results of the univariate analysis of the relationship of tuna abundance with environmental variables (Table 5, Table 5), the importance of the dissolved oxygen at 100 meter depth (DO2_100) on the abundance of skipjack can be seen by the percentage of the variance explained: 35.7% on FSC against only 23.3% on dFADs.

In addition, CHL explains 9.58% of the catches on FSC but very little (0.14%) on dFADs. Consequently, as skipjack caught on dFADs are comparable in size with individuals caught on FSC, this suggests that dFADs decrease the dependence of skipjack on several environmental factors that is to say modify its habitat. Moreover, the peak abundance of skipjack catches on dFADs take place one to two months before the peak abundance of catches on free school in a period which could be less favourable in terms of habitat. Some differences in deviance explained (by environmental variables) were also observed between catches on dFADs and catches on FSC for the other categories studied.

Our results suggest that, at the same level of maturity for the same species, the effect of environmental variables on abundance indices differ between dFADs and FSC. These differing effects of environmental variables on tuna abundance have been observed in several studies (Druon et al., 2017; Zainuddin et al., 2019) without reaching a definitive conclusion on how large is the effect of dFAD use on tuna populations.

5. Conclusion

This study highlighted the details of local resources of regionally managed highly migratory species like tropical tunas. General trend and seasonality of such local resources has been assessed and analysed. In an international context where competitiveness is at stake, such analyses with complementary characteristics are essential to better take advantage of the share of global resources over which a country has some rights. This study constitutes one of the proofs of the possibility for some coastal countries to evaluate the variations in abundance of tunas in the waters under their jurisdiction in addition to the broad-scale patterns which are analysed within RFMOs. It revealed changes in abundance indices over the study period (Fig. 7); reductions in amplitude of the seasonality for some combination of species-size categories (Fig. 5) and differences in peak abundance and sensitivity to environmental variability between dFADs and free school fishing (Tables 4 and 5). For skipjack, our results indicate that dFAD-associated schools are less dependent on the variation of several environmental factors than free schools. Our results suggest a strong relationship between the dynamics of some environmental variables and the abundance indices for skipjack and adult yellowfin tunas. This study made it possible to isolate the particularities of the local resource and thus to lay the first bases for possible analyses of the influence of global phenomena (overfishing, climate change, etc.) on the local resource at the EEZ level, thus providing the basis for future management measures.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Credit authorship contribution statement

S. AKIA: Conceptualization, Methodology, Software, Validation, Visualization, Investigation, Writing - original draft.

M. Amande: Conceptualization, Supervision, Writing - review & editing, Supervision.

D. Gaertner: Conceptualization, Resources, Validation, Writing - review & editing, Supervision, Funding acquisition, Project administration.

P. Pascual: Data Curation, Writing - review & editing.

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Tables and figures

Tables

Table 1 :

Summary of the candidate environmental variables included in this study

Variable acronym	Variable name	Unit
SST	Sea surface temperature	°C
SSH	Sea surface height	meter
CHL	Chlorophyll concentration	mg. m-3
DO2_100	Dissolved oxygen concentration at 100 meters of depth	mmol.m-3
SSS	Salinity	PSU
MLD	Mixed layer thickness	meter
CUI_sst	Coastal upwelling index	°C

Table 2 :

Summary of the seasonal variability of abundance indices in the EEZ of Côte d'Ivoire (2000-2019).

Period	Seasonal factor (Peak-lowest)	Peak month	Peak abundance season	Low abundance season	Change in seasonality over the study period
Mat_BET_FdADs	21.03	August	June-October	Novemb-May	Slight shrinkage
Mat_BET_FSC	7.73	June	April-October	Novemb-March	Almost constant
SKJ_FAD	492.3	October	August-Decem	January-July	Almost constant
SKJ_FSC	11.97	December/ April	October-Decem/ March-May	May-September	Shrinkage
Imm_YFT_ dFADs	42.9	October	July-December	January-June	Almost constant
Imm_YFT_FSC	8.95	November	August-Septem	January-July	Almost constant
Mat_YFT_dFADs	90.2	August	June-September	November-April	Almost constant
Mat_YFT_FSC	177.13	April	March-July	October-January	Almost constant

Table 3:

Correlation between variables and dimensions (Dim1), square cosine (cos), contribution (contrib) and eigenvalue (inertia) of the first three principal components from the PCA analysis for the environmental variables selected in the study.

Variable	Dim.1	contrib	Cos2	Dim.2	contrib	Cos2	Dim.3	contrib	Cos2
SST	-0.90	21.62	0.811	-0.059	0.309	0.004	-0.095	1.044	0.009
SSS	0.654	11.40	0.428	0.431	16.34	0.186	0.386	17.36	0.149
MLD	0.195	1.015	0.038	0.907	72.40	0.823	-0.223	5.815	0.05
CHL	0.914	22.27	0.835	-0.171	2.56	0.029	0.093	1.018	0.009
CUI_sst	0.820	17.95	0.673	-0.280	6.918	0.079	0.073	0.623	0.005
DO2_100	-0.516	7.093	0.266	0.08	0.561	0.006	0.797	74	0.635
SSH	-0.836	18.646	0.7	0.102	0.909	0.01	0.034	0.135	0.001
% Inertia		53.58			16.24			12.62	

Table 4 :

Generalized additive models (univariate) of the eight categories of tuna as functions of seven environmental variables. Deviance explained (in percentage) of log (abundance indices) by each variable are shown. The symbol * means that the coefficient is significant at 5% (p-value <0.05)

Variable	SKJ_FAD	SKJ_FS	YFT_Mat FAD	YFT_Mat FSC	YFT_Imm FAD	YFT_Imm FSC	BET_Mat FAD	BET_Mat FSC
SST	1.60	12.8*	25.5*	25.7*	1.87	2.14*	37.7*	18.1*
DO2_100	25.1*	32.7*	7.72*	3.94e-05	30.6*	19.8*	17.7*	3.13*
SSH	1.28	5.29*	31.9*	1.85*	3.23*	4.99*	20*	10*
CHL	0.32	12*	24.6*	1.46	0.84	4.05*	31.8*	8.6*
SSS	0.81	13.2*	8.91*	4.46*	0.01	3.87*	17*	11.3*
MLD	2.92*	11*	4.61*	4.26*	0.65	0.72	4.32*	18.1*
CUI_sst	0.14	9.58*	15*	2.24*	7.29e-06	0.63	16*	7.22*

Table 5:

Summary of the relationships between environnemental variables and abundance indices. Only factors with explained deviance higher than 10% have been selected and ranked by decreasing order of explained deviance (e.g. Mature BET on FSC, SST > MLD > SSS > SSH).

Species	**Fishing on dFADs**	**Fishing on FSC**
SKJ	DO2_100	D02_100 ; SSS ; SST ; CHL ; MLD
Mature YFT	SSH ; SST ; CHL and CUI_sst	SST
Immature YFT	DO2_100	DO2_100
Mature BET	SST ; CHL ; SSH ; DO2_100 ; SSS ; CUI_sst	SST ; MLD ; SSS and SSH

Figures

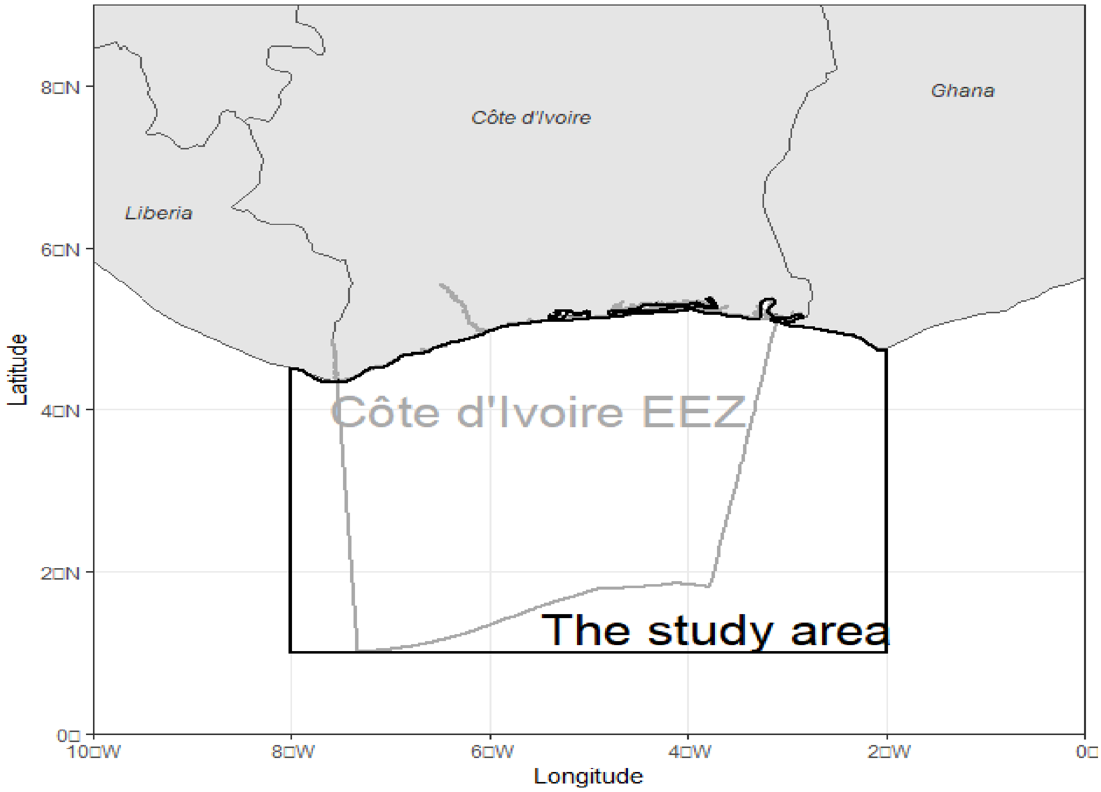

Fig. 1. The EEZ of Côte d'Ivoire and the study area. The area of interest is the square area defined in this figure.

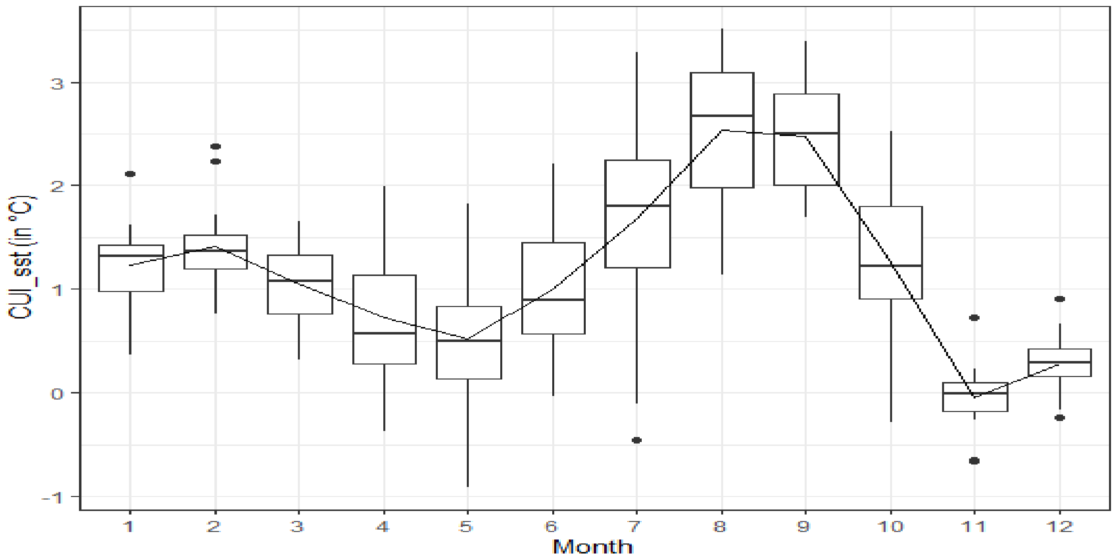

Fig. 2. Seasonal variations in the SST-based coastal upwelling index in the Ivorian EEZ

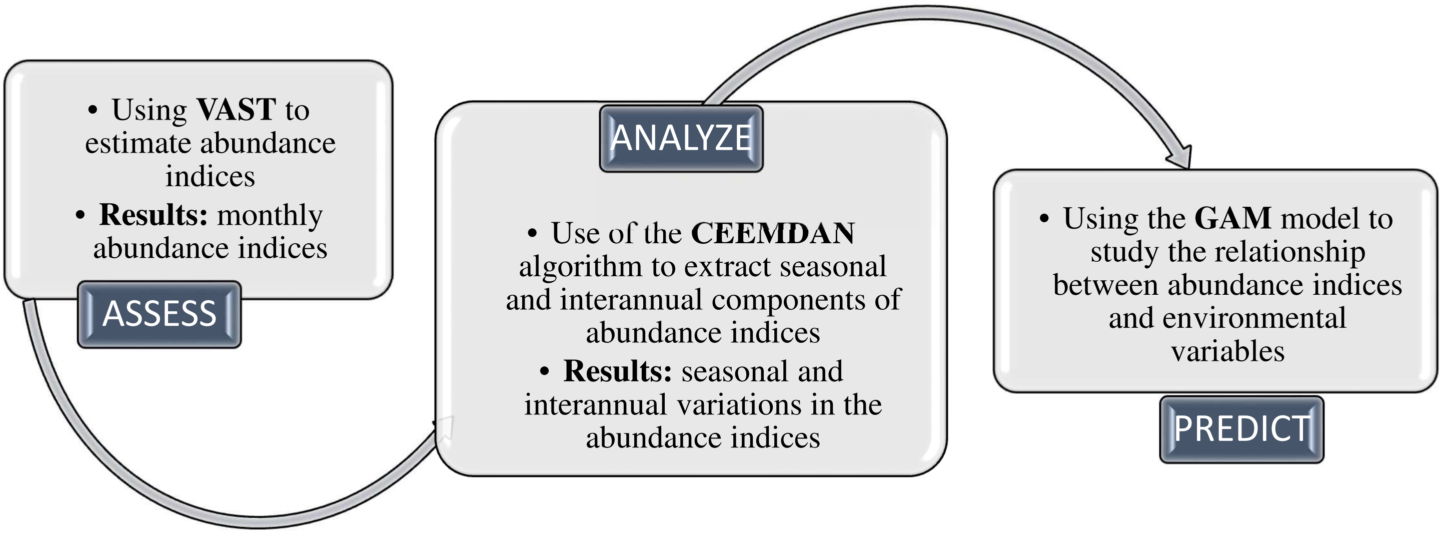

Fig. 1. Schematic representation of the methodology used in this study

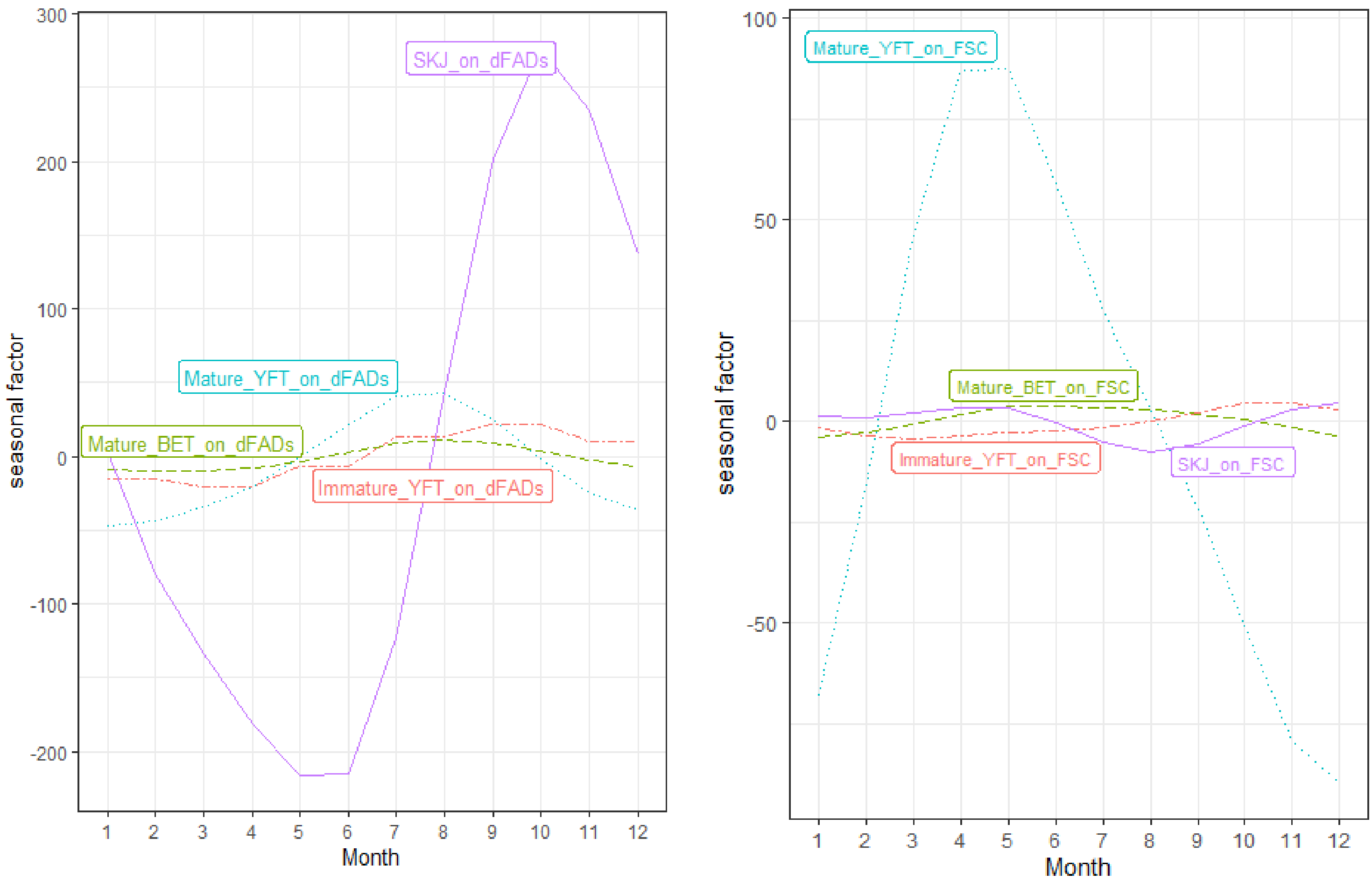

Fig. 4. Average monthly changes in abundance indices for eight categories of tropical tuna analyzed for the 2000-2019 period.

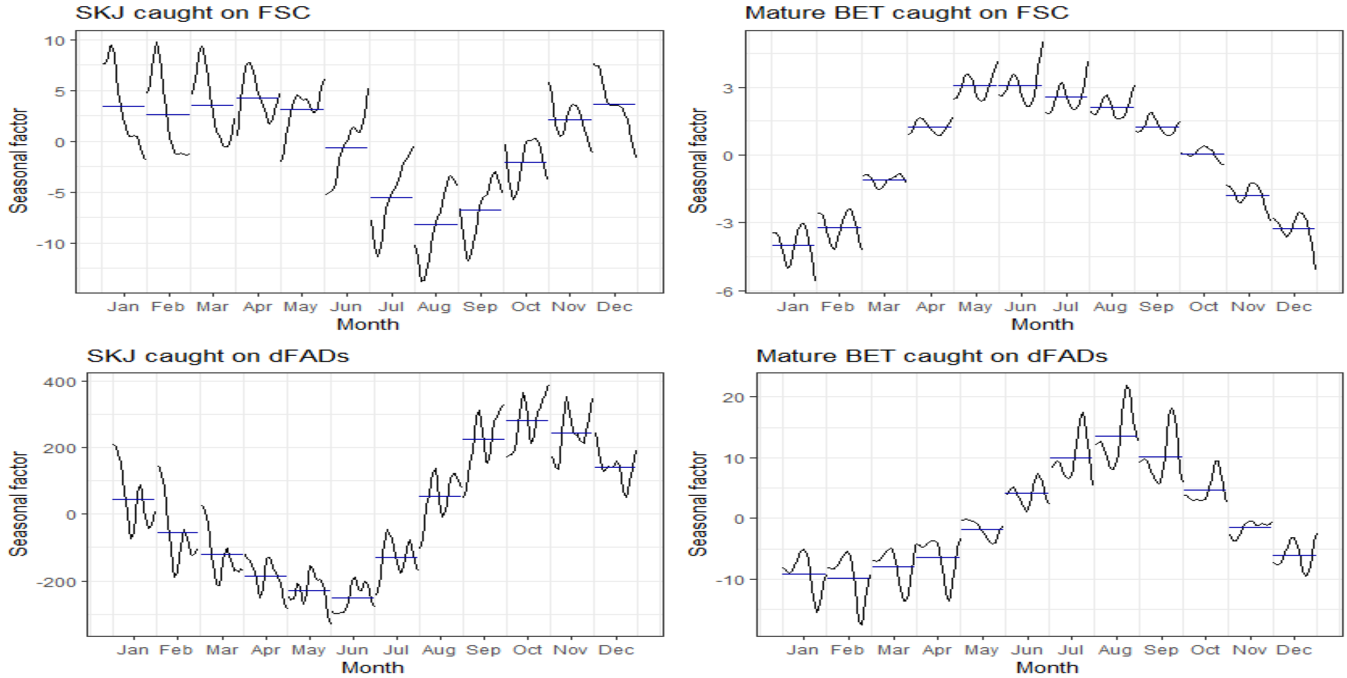

Fig. 5. Interannual variations in monthly abundance indices of skipjack and mature bigeye tuna. The curves observed for each month correspond to the interannual variability of abundance over that month and the horizontal dashes correspond to the monthly average (in trend) over the study period.

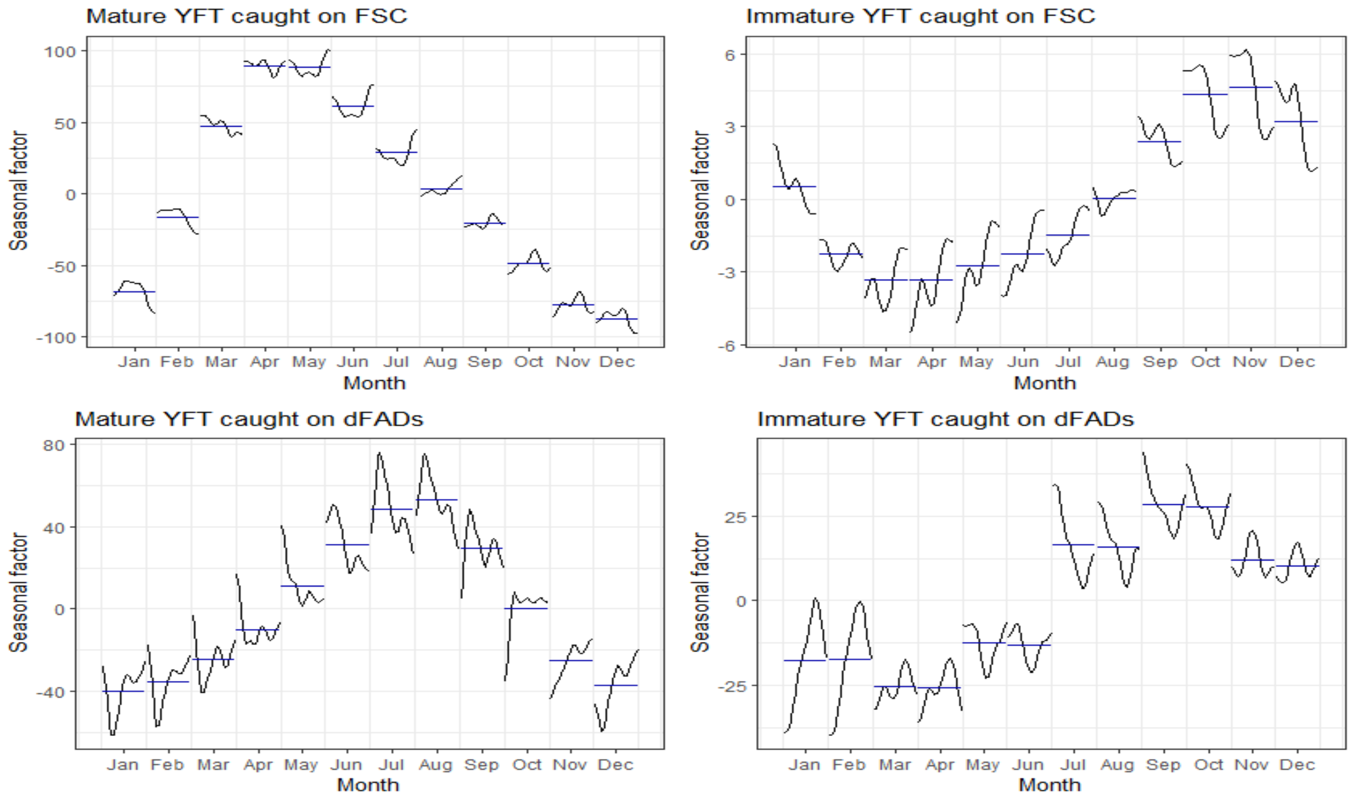

Fig. 6. Interannual variations in monthly abundance indices of yellowfin tuna. The curves observed for each month correspond to the interannual variability of abundance over that month and the horizontal dashes correspond to the monthly average (in trend) over the study period.

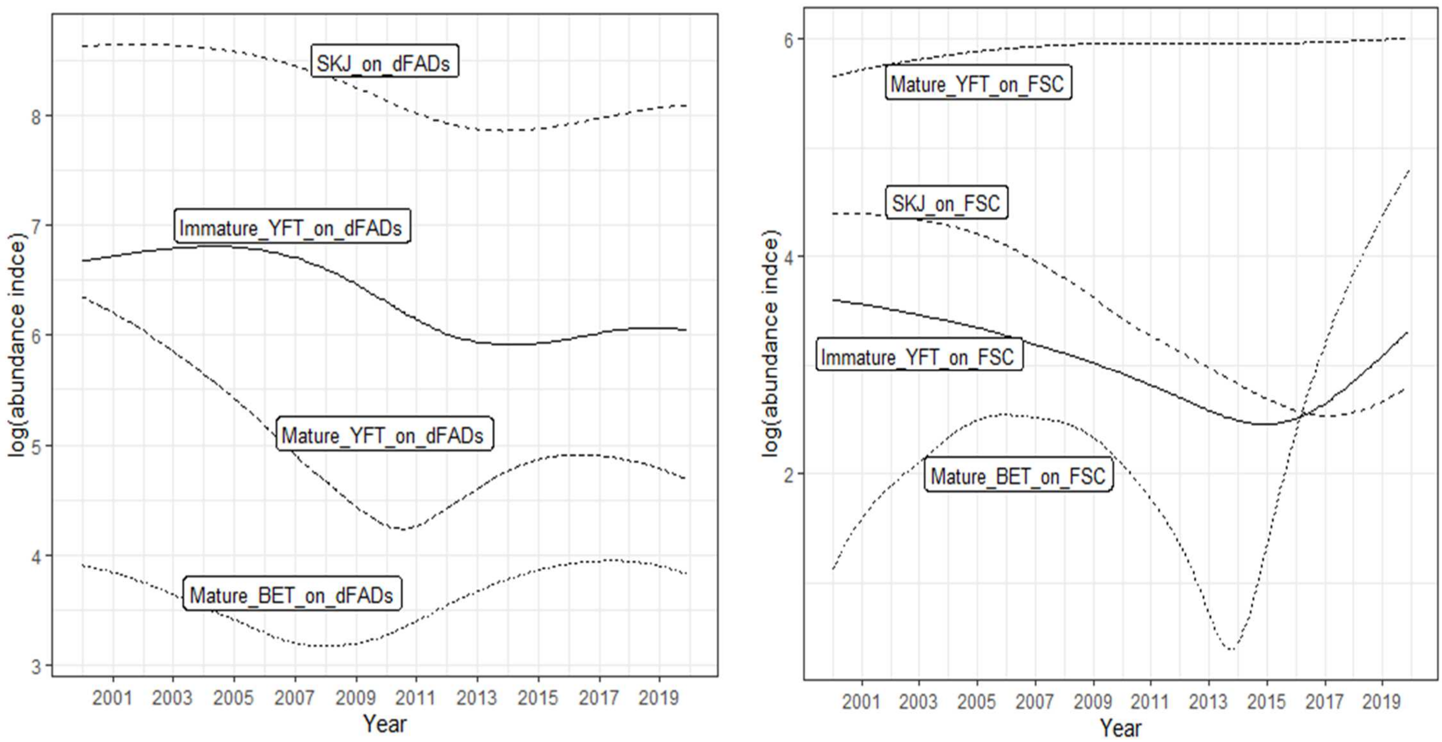

Fig. 7. Interannual variations of abundance indices by fishing mode over the period 2000-2019.

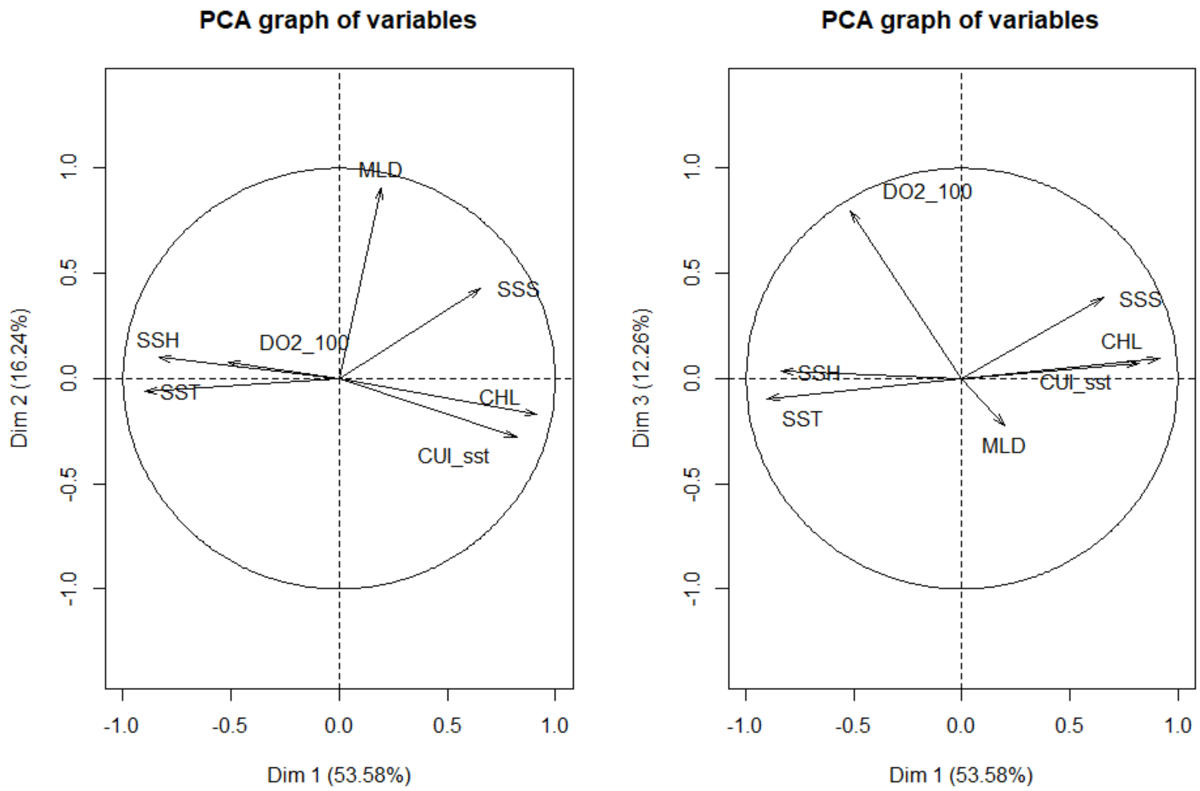

Fig. 8. First (Dim 1), second (Dim 2) and third (Dim 3) axes of the principal component analysis of the sea surface temperature (SST), sea surface height (SSH), sea surface salinity (SSS), chlorophyll concentration (CHL), dissolved oxygen at a depth of 100 meters (DO2_100), mixed-layer thickness (MLD) and coastal upwelling index (CUI_sst) in the EEZ of Côte d'Ivoire.

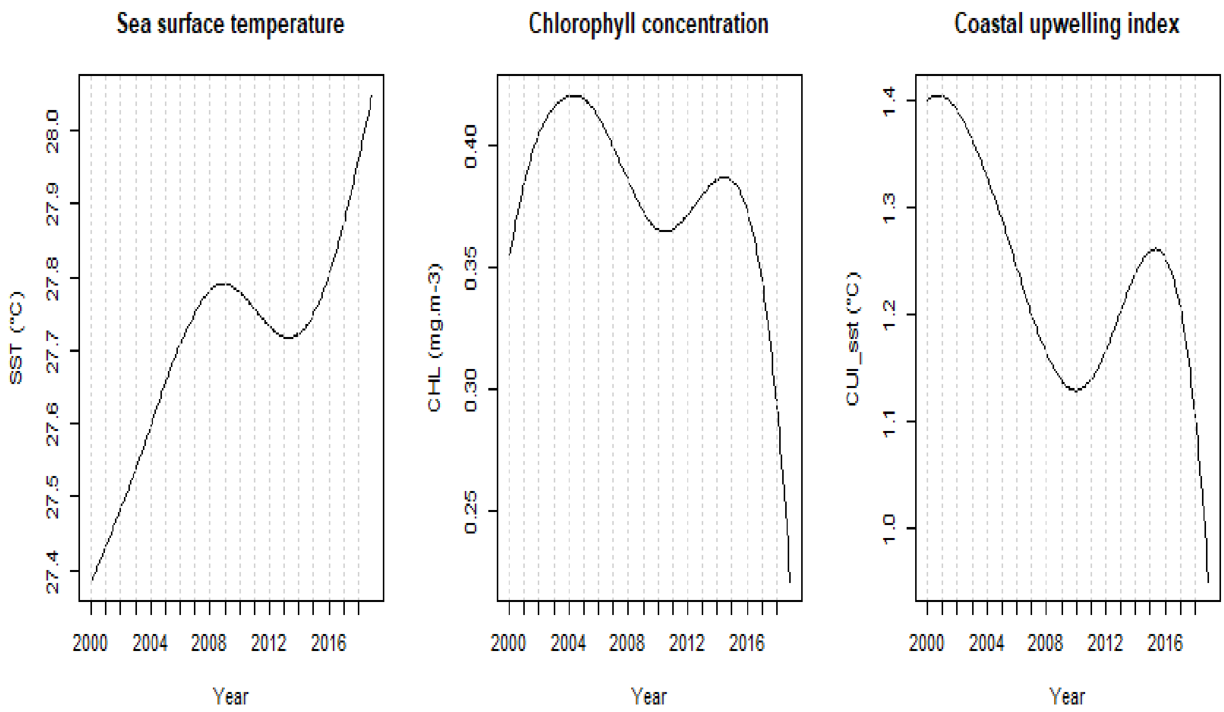

Fig. 9. Interannual variations (global trend) of three environmental variables over the period 2000-2018. The decomposition has been done using the CEEMDAN's algorithm.

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