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UPDATE OF THE FRENCH AERIAL ABUNDANCE INDEX FOR 2020 AND FIRST ATTEMPT AT ACCOUNTING FOR THE ENVIRONMENTAL EFFECTS ON BLUEFIN TUNA AVAILABILITY IN THE GULF OF LIONS

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SUMMARY

The French aerial survey over the Gulf of Lions provides an important fisheries independent index for the stock assessment of Eastern Atlantic Bluefin Tuna (EABFT, Thunnus thynnus*). This document presents the 2020 update of this index. Building on recent results highlighting environmentally-driven changes in the availability of young Bluefin tuna in the Gulf of Lions, we propose a modeling approach designed to account for it and we describe how this attempt could be improved in the future. The results suggest that the index obtained from the Bayesian model accounting for wind should be used. The overall results of the survey analysis across all approaches show that 2020 was the year with the highest abundance of bluefin tuna within the Gulf of Lions to date.*

RÉSUMÉ

La prospection aérienne française dans le golfe du Lion fournit un important indice indépendant des pêcheries pour l'évaluation du stock de thon rouge de l'Atlantique Est (EABFT, Thunnus thynnus). *Ce document présente la mise à jour 2020 de cet indice. En nous appuyant sur des résultats récents mettant en évidence des changements d'origine environnementale dans la disponibilité des jeunes thons rouges dans le golfe du Lion, nous proposons une approche de modélisation conçue pour en tenir compte et nous décrivons comment cette tentative pourrait être améliorée à l'avenir. Les résultats suggèrent que l'indice obtenu à partir du modèle bayésien tenant compte du vent devrait être utilisé. Les résultats globaux de l'analyse de la prospection, toutes approches confondues, montrent que 2020 a été l'année où l'abondance de thon rouge dans le golfe du Lion a été la plus élevée à ce jour.*

RESUMEN

La prospección aérea francesa en el golfo de León proporciona un importante índice independiente de la pesquería para la evaluación del stock de atún rojo del Atlántico oriental (EABFT, Thunnus thynnus*). Este documento presenta la actualización de 2020 de este índice. Basándose en resultados recientes que destacan cambios de origen medioambiental en la disponibilidad de atunes rojos jóvenes en el golfo de León, proponemos un enfoque de modelación diseñado para tenerlos en cuenta y describimos cómo podría mejorarse este intento en el futuro. Los resultados sugieren que debería usarse el índice obtenido mediante el modelo Bayesiano que tiene en cuenta el viento. Los resultados globales del análisis de la prospección entre todos los enfoques demuestran que 2020 fue el año con la mayor abundancia de atún rojo en el golfo de León hasta la fecha.*

KEYWORDS

Juvenile Atlantic bluefin tuna, northwest Mediterranean Sea, fisheries independent abundance index, aerial survey, environmental effect, state space models

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1. Introduction

The French aerial survey index has been integrated in the base case VPA of the Eastern Atlantic bluefin tuna (EABFT, *Thunnus thynnus*) stock assessment for the first time in 2017. It goes back to started in 2000 and has been updated yearly since then, with the exception of years 2004-2008. This index is of particular interest for the stock assessment for several reasons. First, it is one of the only two fisheries-independent indexes included. Second, it covers young fishes from the northwest Mediterranean Sea, for which information is scarce, particularly since the enforcement of the recovery plan limiting the catch of fish below 30kg. Therefore, even though the geographical coverage of the juvenile areas is far from being complete as this survey only covers the Gulf of Lions (GoL), this index provides valuable insights into the stock dynamics that cannot be captured by the other available indices which are all relevant for adults. This index is currently integrated within the Management Strategy Evaluation (MSE) process developed within ICCAT.

A few shortcomings of the index have already been identified. For instance, the index could be based on a standard measure (e.g. schools surface) rather than on the number of schools whose size structure can change over time. Ongoing work using video cameras will allow for analysing and correcting this potential bias, but still require time and manpower-consuming analysis of the videos (e.g. Rouyer *et al.* 2019). Changes in the environment were also identified as potential candidates affecting the presence of bluefin tuna in the Gulf of Lions (Rouyer *et al.* 2020) and recent work confirmed this hypothesis (Rouyer *et al.* 2021). Using fishery data and the aerial survey data, Rouyer etal. (2021) showed that Bluefin tuna availability is driven by northern wind events during the post-spawning period in July. The stronger these events, the higher the availability of fish in the Gulf of Lions. The yearly fluctuations in the aerial survey data appeared to be associated with these events. Such a process has therefore a direct impact on the index as years with stronger northern winds in July will increase the proportion of the bluefin tuna population susceptible to the survey. This study directly answers the Group recommendation on understanding the inter-annual variability of the index and investigating the effect of the environment. As a following step, the document presents a hierarchical Bayesian modeling approach aiming at accounting for environmentally driven changes in bluefin tuna availability in the Gulf of Lions in the index of abundance. The method described is a first attempt that will be improved in the future. The approach developed is similar to the one used in the “distance” R package as it rests on the same set of equations, but adds a modeling layer dealing with the effect of the wind on fish availability.

Indices used for stock assessment and part of the MSE process should be updated yearly to be made available to the SCRS Bluefin species group. The present document therefore provides (i) the 2020 update with the distance package, (ii) the update with the Bayesian approach not accounting for the effect of the environment and (iii) the effect of the Bayesian approach accounting for the effect of the environment.

2. Materials and method

2.1 Database revision and update

For this work, a complete revision of the aerial survey database has been carried out from the raw data. This revision led to minor changes such as the inclusion of 2 flights during which no observations were made (in 2002 and 2015), the deletion of one flight with inconsistencies that questioned the whole data acquired (in 2010), the inclusion of one flight (in 2011) and the correction of detection distances for the year 2016. When the GPS track was available, it was used to compute the effort as the distance flown.

The update of the index was carried out using the same model agreed upon for the 2017 assessment (see Rouyer *et al.* 2017 and Rouyer *et al.* 2020) and using the distance package in R for all computations.

Wind data were obtained from the E.U. Copernicus Marine Service Information website (http://marine.copernicus.eu/) as described in Rouyer *et al.* (2021). Specifically, we used the Global Ocean Wind L4 Reprocessed 6 Hourly Observations dataset at 0.25 x 0.25 degree resolution to extract the northern wind ($m.s^{-1}$).

2.2 Bayesian state space model structure

Correctly representing variation in the abundance of Bluefin tuna within the Gulf of Lions requires to develop a state space modelling approach. Indeed, previous research showed that its availability within the area increases with the strength of Northern wind events during the month of July. Including such a process goes beyond the classical distance sampling framework. The process component we model, albeit simple, describes yearly changes in the stock on one hand as well as the proportion susceptible to the survey depending on the wind intensity in July on the other hand. Meanwhile, the observation process still corresponds to the classical distance sampling protocol linked to the aerial survey.

2.2.1 Process component

For stock assessment purposes, we need an unbiased estimate of the number of schools across years (referred to as NS_y). To reach this goal, the full NSy or a constant portion of it is supposed to be covered by the survey routes, which are consistent over time. Previous research proved this was not the case because of variations in July Northern Winds. Let's call NSA_y the number of schools within the survey area in year y estimated from the survey model (see below). The link between *NSAy* and *NSy* was modeled as:

$$NSA_y \sim Binomial(p.area_y, NS_y)$$

$$logit(p.area_y) = \alpha + \beta * wind.july_y$$

$where\ \alpha$ and β are parameters regulating the effect of wind onto the probability of a school to be attracted by the conditions in the Gulf of Lions through a logit linear relationship. As information is currently lacking (see discussion), for now these parameters were set with strongly informative priors. We assumed that the year with the lowest wind intensity, there was at about .5 probability of a fish school to be within the survey area. For the year with the highest wind intensity in July, we set the probability at about .95. This was done through beta priors (see **Figure 1**) and back transformation (not detailed).

2.2.2 Observation component

NSA_y is informed through the data collected from the aerial survey, which are then modeled using a conventional distance sampling set of equations. Within this framework, the detection probability of a school is modeled as dependent upon its distance from the vertical axis of the plane while schools are assumed to be randomly distributed. An average distance-dependent detection rate is then computed and used to estimate the total number of schools within the survey area. The corresponding equation is:

$$NSA.seen_{f,y} \sim Binomial(p.detect_f, NSA_y)$$

With $p.detect_f$ the mean detection probability across the distance surveyed by the observer for flight *f*. The detection probability of a school is assumed to be equal to 1 right under the plane and to decrease with distance from the plane according to a half normal distribution:

$$log(p.detect.school_f) = exp(-d_f^2/(2 \times \Sigma_f^2))$$

$$log(\Sigma_f) = \delta + \gamma \times wind_f + \zeta_f$$

$$\zeta_f \sim Normal(0, \sigma_\zeta)$$

Where d_s^2 is the square of the distance of a school to the plane and Σ_f is a flight dependent parameter controlling the detection rate decrease magnitude with the distance. Here, it is specifically modeled as being related to the wind speed during the flight, which should not be confused with the effect of the wind modeled to account for inter-year fluctuations. Indeed, stronger wind increases waves height and creates white caps, which decrease the detection probability. Lastly ζ_f is a random effect accounting for varying teams of scientific inboard observers.

In practice it is not feasible for the observers to record the exact distance of a school to the plane, specifically in recent years when the densities increased substantially. So the observers attribute each school to a distance bin using markers on the wings of the aircraft. $p.detect_f$ thus corresponds to the average detection rate of the bands midpoint. Such an approximation if often made when working on transect type data.

2.2.3 Bayesian computation

The state space model presented above was fitted within a fully hierarchical bayesian framework. All model parameters posterior distributions were derived using Markov Chain Monte Carlo (MCMC) in JAGS (Plummer 2007). We ran three parallel MCMCs and kept 10000 samples for each after an initial burning of 10000 steps. We checked MCMCs convergence both visually and by means of the Brooks–Gelman–Rubin diagnostic (Spiegelhalter *et al.*, 2002). The regression coefficients had uninformative priors in respect to the posteriors obtained.

To better illustrate changes from the state space approach, we also fitted a regular model distance sampling model in the bayesian framework, i.e. without including the inter-annual wind effect. Equations used correspond to the observation component of the state space approach detailed above.

3. Results

3.1 Updated index

As expected from the revision of the database, the updated index showed a trend very similar to that of the update provided last year. On a retrospective point of view, the main difference was the relatively lower value for 2016 compared to other years. Meanwhile the new year of 2020 appeared as the new high of the whole index, significantly above 2016 which was the previous highest value (**Figure 2**). Overall, results also appeared to confirm a general increasing trend as recently highlighted in Rouyer *et al.* (2021). By 2020, the index appeared about 15 times higher than in the 2000s.

3.2 Bayesian models

Bayesian models revealed rather superior to the classical approach used to update the index. The index obtained through the Bayesian distance sampling model not including the wind effect on fish availability displayed slightly higher values to that of the original updated index, but its CV was about three times lower (**Figure 2 and Figure 3**). Including the effect of the wind moderately decreased the inter-annual variability of the index, whose CV was also much lower than that of the regular updated index. However, a substantial inter-annual variability still remained even when accounting for the additional impact of wind (**Figure 2 and Figure 3**).

4. Discussion

2020 was found to be the record year to date. This year was also characterized by relatively strong northern wind events in July. Even if the fishing season was affected in the context of the pandemic, the longliners encountered a lot of fish and completed the quota in due time, a contrasting situation from 2018 that is consistent with the findings in Rouyer *et al.* (2021).

The Bayesian approach displayed interesting features. The results were consistent with those obtained from the distance package, but the CV was much smaller. The Bayesian approach also allowed to model the distance as a set of bins instead of a continuous function, which is more in line with how the observation is made onboard the aircraft for the survey. Finally, the proposed Bayesian modeling approach allowed us to capture some of the effect of the wind on the availability of bluefin tuna in the Gulf of Lions.

However, extracting the high-frequency fluctuations around the index trend (see Rouyer *et al.* (2021) for method) and comparing them to those of the wind data showed that the effect of the wind after 2013 was only partially accounted for (Fig. 3). This suggests that some improvements should be made to the model. For instance the effect of wind could be non-linear and dependent on the stock abundance. Another aspect is that Rouyer *et al.* (2021) hypothesized that the wind affects yearly fluctuations of the index through varying migrations of bluefin tuna, which are likely to be separated from the longer-term evolution of abundance and therefore could be modeled at a different time-scale. Another likely hypothesis is that before 2009 the Gulf of Lions was subjected to an intense exploitation by purse seiners that stopped afterwards. This intense exploitation affected substantially the local abundance and could well have blurred the environmental effect in these earlier years.

Lastly, tagging data could allow for estimating the fraction of the stock present within the survey area. Building a comprehensive database of tags deployed in the area and covering the survey period may allow us to inform more precisely the process. The probability of tagged fish from the Mediterranean sea to be within survey could be assumed to follow a binomial distribution based on the same probability $p.area_y$ described above:

$$NTA_y \sim Binomial(p.area_y, NT_y)$$

With NT_y the total number of fish tagged in year y and NTA_y the fraction of those present within the survey area.

The Bayesian approach proposed here is an improvement compared to the previous approach. Even if more improvements could be brought to the proposed modeling, the Bayesian index including correction for wind is currently the best one. It should be considered for the reconditioning of the MSE Operating Models.

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Table 1. Prior used and shared across the bayesian models.

Parameter	**Prior**
δ	**Uniform(-5, 5)**
γ	**Uniform(-5, 5)**
σ_ζ	**Uniform(0, 1)**
NSAy or NAy	**Uniform(0, 10000)**

Table 2. Survey characteristics, mean values and associated CV for the Index update, the Bayesian index not including wind correction and the Bayesian index including wind correction.

	Survey characteristics		*Index update*		*Bayesian index (no Wind)*		*Bayesian index (Wind)*	
Year	Effort (km)	Nflights	Density	CV	Density	CV	Density	CV
2000	3787	6	0.0093	0.385	39.414	0.119	43.427	0.129
2001	5186	8	0.0078	0.417	36.539	0.102	52.487	0.137
2002	6602	10	0.0067	0.58	28.417	0.082	30.010	0.093
2003	7365	11	0.0051	0.273	34.465	0.093	46.126	0.126
GAP								
2009	6417	9	0.0177	0.351	100.930	0.048	139.015	0.072
2010	3960	6	0.01367	0.524	87.245	0.045	100.580	0.06
2011	5822	9	0.0255	0.25	112.302	0.053	126.510	0.063
2012	6711	6	0.0171	0.264	98.427	0.045	109.381	0.060
GAP								
2014	5316	8	0.0608	0.273	230.582	0.045	258.851	0.052
2015	4922	8	0.0265	0.242	109.518	0.064	153.756	0.083
2016	6173	10	0.1049	0.2	601.106	0.031	666.431	0.035
2017	6038	10	0.0659	0.243	368.914	0.039	431.051	0.046
2018	7565	11	0.0296	0.172	155.449	0.052	312.806	0.080
2019	7922	11	0.0599	0.139	333.075	0.035	511.451	0.050
2020	5465	9	0.1304	0.153	715.898	0.031	825.754	0.036

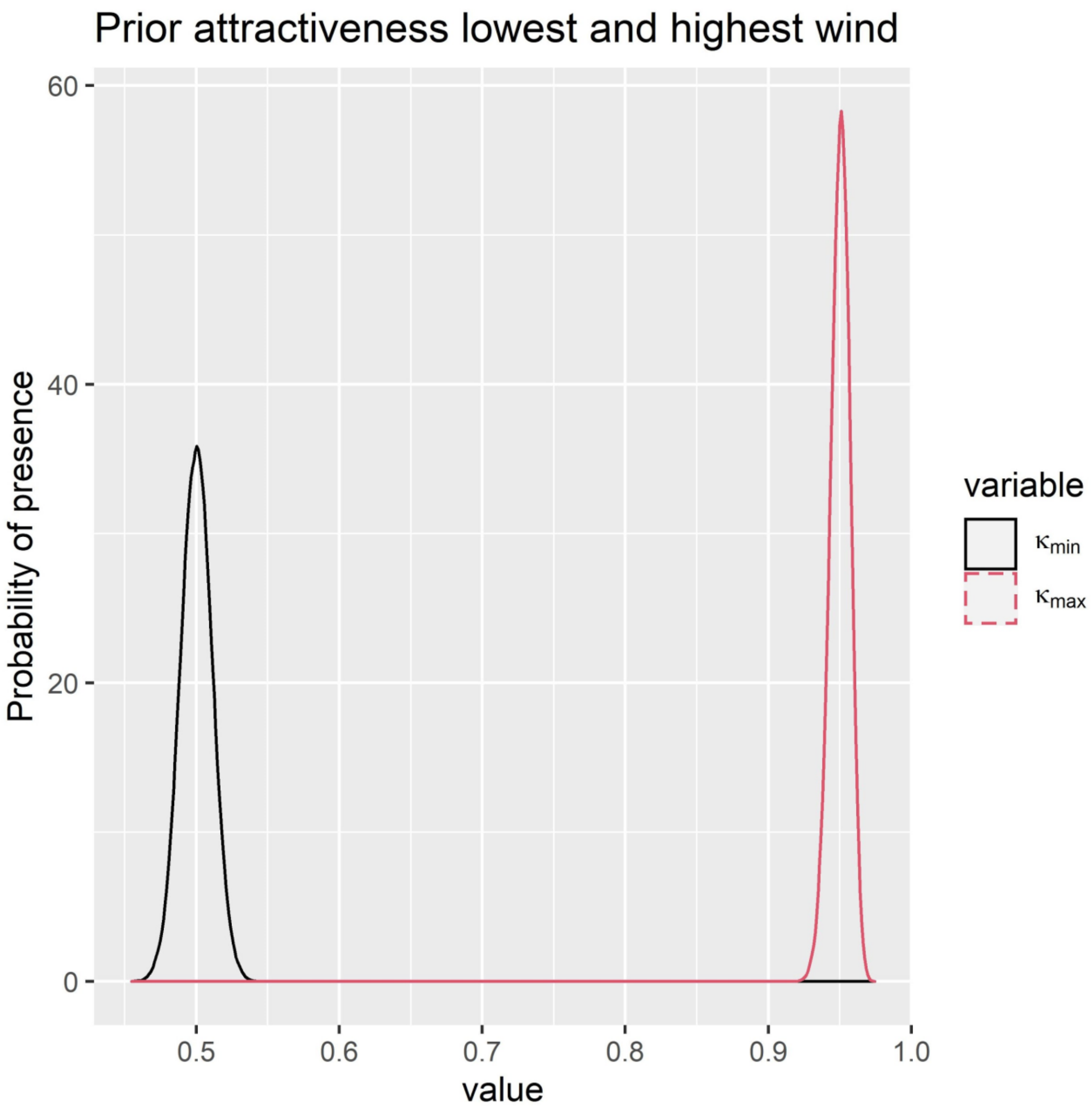

Figure 1. Priors used for the probability of a school to be within the survey area for the lowest and highest wind observed on July.

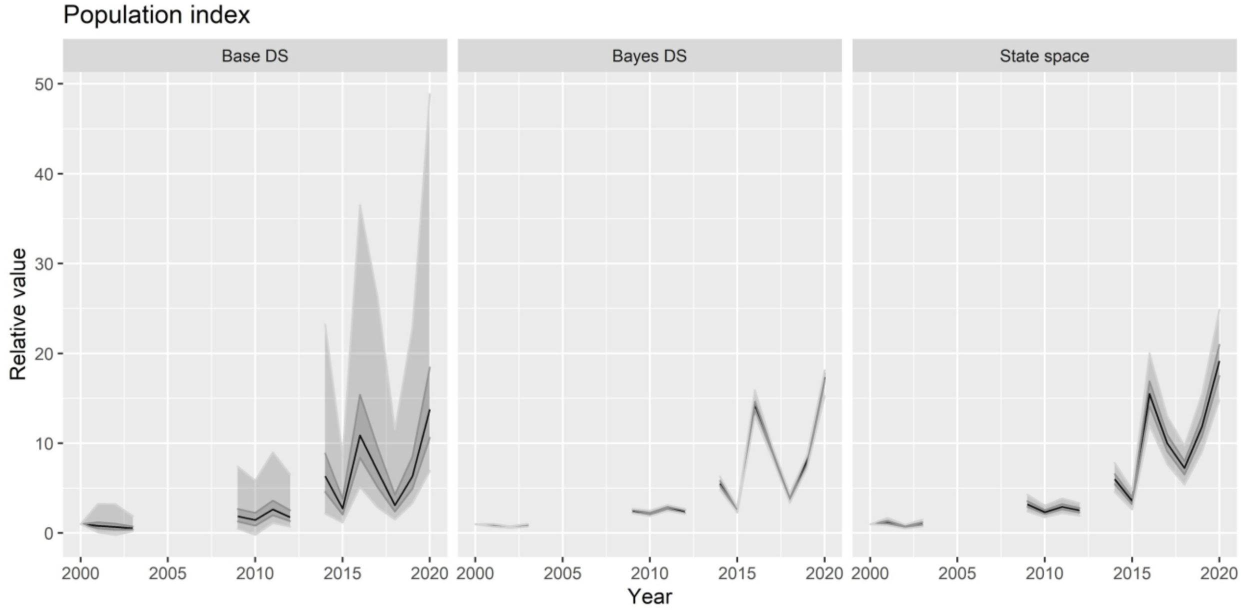

Figure 2. Indices obtained from the French aerial survey using the R distance package (left), the Bayesian approach not including the effect of the wind (center) and the Bayesian approach including the effect of the wind (right).

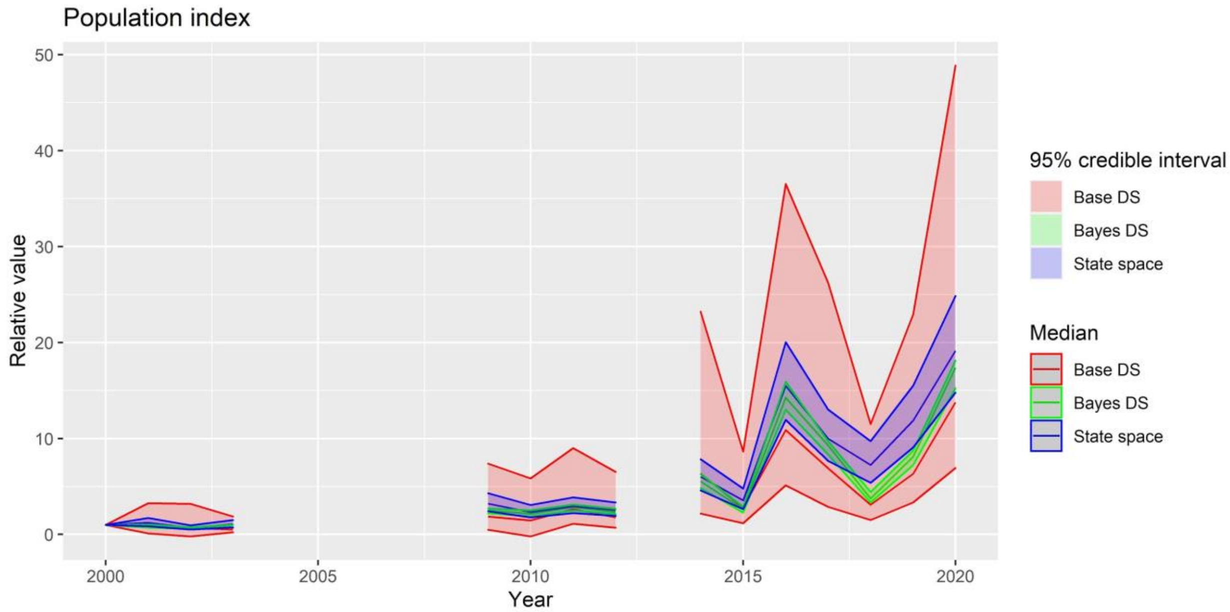

Figure 3. Indices obtained from the French aerial survey using the R distance package (red), the Bayesian approach not including the effect of the wind (green) and the Bayesian approach including the effect of the wind (blue).

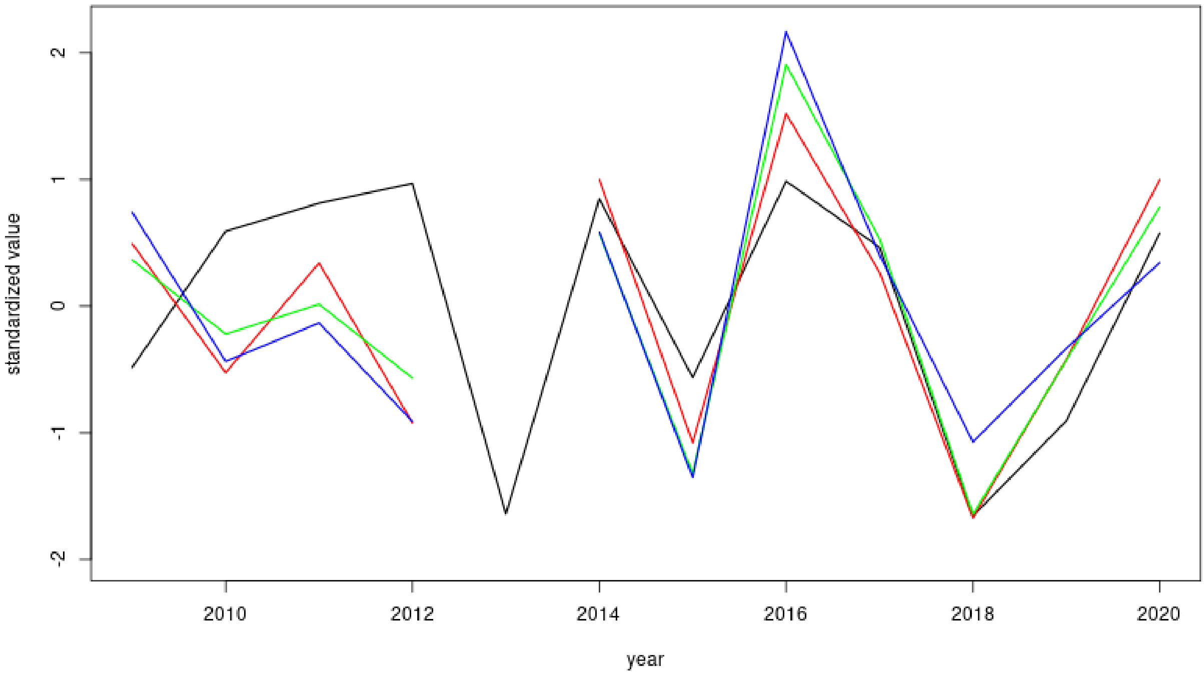

Figure 4. Detrended indices obtained from the French aerial survey using the R distance package (red), the Bayesian approach not including the effect of the wind (green) and the Bayesian approach including the effect of the wind (blue), and time series of the wind in July (black).