Improving abundance index for Sol8c9a stock assessment model calibration.

Working document to the Working Group for the Bay of Biscay and the Iberian Waters Ecoregion WGBIE – 6-13 May 2020.

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May 8, 2020

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Abstract

Time series of abundance indices are the main source of information to calibrate stock assessment models. Precise abundance indices are essential for successful conservation and management of fish stocks. Commonly, scientific standardized surveys are used for this aim and to ensure that estimates are unbiased. However, the accuracy of these estimated indices may be low under certain circumstances. In particular the common sole (*Solea solea*) is a species with a biological bathymetric range between 0 and 200 meters in the Iberian Atlantic waters. The annual scientific survey that collects data for demersal species in this area only cover partially this bathymetric range and the resultant abundance indexes are consequently underestimated. In addition, habitat variables, (i.e., bathymetry), can influence these estimates as well as the species spatio-temporal variability. Alternatively, standardized CPUEs (catch per unit effort) derived fishery-dependent data can be used as a proxy of the species abundance. In this study two different spatio-temporal abundances indices were computed and the impacts on the common sole evaluation using as stock assessment model the SPiCT (stochastic surplus production model in continuous time) were analyzed. Both abundance indices were produced using Bayesian hierarchical spatio-temporal models, considering bathymetry as an environmental variable and testing three different spatio-temporal structures (i.e. opportunistic, progressive and persistent) to categorize the spatio-temporal behaviour of the sole. We argue that using explicitly spatio-temporal abundance indexes can improve the assessment of stocks and in particular for the ones that are in a data-limited situation.

Introduction

Fishery independent surveys provide important information for species stock assessment and consequently for fisheries management (Cao et al., 2017). Abundance indices are one of the primary information derived from scientific surveys, and are essential to calibrate species stock assessment models. Therefore the accuracy of the abundance indices is essential for the stocks evaluation and the subsequent management decisions (e.g., total allowable catches).

Commonly scientific surveys are designed with randomized sampling locations and to ensure that estimates, as abundance indices, are unbiased. However, under certain circumstances, surveys may produce imprecise estimates of abundance, particularly for species with preferential habitats that are in strata only partially included in the survey sampling design. Therefore, in these cases, the spatial species variation is not adequately captured.

The common sole (*Solea solea*) is a species with a biological bathymetric range between 0 and 200 meters in the Iberian Atlantic waters. The annual scientific survey that collects data for demersal species in this area only cover partially the sole bathymetric range and the resultant abundance index is probably underestimated.

Recently, spatio-temporal models have been implemented to produce more precise abundance indices than the ones provided by conventional surveys (Cao et al., 2017; Thorson, 2015). Indeed, spatio-temporal models can overcome this problem as they link information on the abundance or presence/absence of a species to the space to predict where (and how much of) a species is likely to be present in unsampled locations elsewhere in a area or period of time (Pennino et al., 2019). Additionally, spatio-temporal models can include as covariates environmental variables, (e.g. bathymetry, temperature, salinity, etc.) and potentially generate more precise estimates of abundance, especially when the underlying species distribution is dependent on habitat features.

Different studies have applied spatio-temporal models to improve abundance indices (Cao et al., 2017; Shelton et al., 2014; Thorson, 2015). For example, Thorson (2015) implemented spatio-temporal models to compare the abundance indices of 28 groundfish species off the U.S. West Coast with conventional surveys indices. Overall, abundance indices showed similar trends but the uncertainty associated with the spatio-temporal indices was widely lower than the one of conventional indices.

Alternatively, fishery-dependent data collected from fishery observers on-board commercial vessels or logbooks can be used to construct standardized indices of relative abundance for stock assessment models (Alonso-Fernández et al., 2019). Several standardization techniques have been used for fishery-dependent data of many species (Campbell, 2015; Maunder and Punt, 2004), including also environmental variables and spatio-temporal effects (Alonso-Fernández et al., 2019; Teo and Block, 2010). Overall these methods have been proved to be a useful tool to address ecological and assessment issues, especially in data limited situations (Alonso-Fernández et al., 2019).

However, few studies showed the impact of using a spatio-temporal index in stock assessment models and the derived performance. Recently, Cao et al. (2017) did this exercise for the northern shrimp (*Pandalus borealis*) in the Gulf of Maine. Results of this study showed that using the spatio-temporal index in the assessment model alters the estimates of recruitment and spawning stock biomass, as well as the determination of the stock status. Also, the inclusion of the spatio-temporal index in the assessment improved the predictive performance of the model reducing the retrospective bias.

Given that the abundance index provides primary information for stock assessment, such studies are essential to better understand the practical improvement of spatio-temporal index standardization.

Within this context, in this study two different spatio-temporal abundance indices were produced using (1) a fishery-independent data-set from 2001-2019 collected trough scientific trawl surveys; and (2) a fishery-dependent data-set collected by observers on-board artisanal fisheries vessels from 2000-2018. Both data-sets were analyzed using a Bayesian hierarchical spatio-temporal models, considering bathymetry as an environmental variable.

Produced indices were included in the common sole SPiCT (stochastic surplus production model in continuous time) stock assessment model and performance were explored.

We argue that using explicitly spatio-temporal abundance indices can improve the assessment of stocks and in particular for the ones that are in a data-limited situation.

Material and Methods

Abundance data

Fishery-independent data

Fishery-independent data were collected during the scientific survey series “SP-NSGFS Q4” by the “Instituto Español de Oceanografía” (IEO) carried out in autumn (September to October) from 2001 to 2019. The ”SP-NSGFS Q4” survey makes use of a stratified sampling design based on depth with three bathymetric strata: 70–120 m, 121–200 m and 201–500 m. Sampling stations consisted of 30 min trawling hauls located randomly within each stratum at the beginning of the design (Figure 1). Approximately 115 hauls divided between the three bathymetric strata were performed every year in this zone, using the baka 44/60 gear and following the protocol of the International Bottom Trawl Survey Working Group (IBTSWG) of ICES (ICES, 2017). Due to the high number of zeros only the first two bathymetric strata (i.e., 70–120 m, 121–200 m) were considered in this study, that correspond with the common sole bathymetric biological range.

Two different variables were analyzed in order to characterize the spatio-temporal behavior of common sole individuals. First, we considered a presence/absence variable to measure the occurrence probability of the species. Secondly, we used the weight by haul (kg) as an indicator of the conditional-to-presence abundance of the species.

Fishery-dependent data

Fishery-dependent data were collected by the Galician government Technical Unit of Artisanal Fisheries (Unidade Técnica de Pesca de Baixura, UTPB, in Galician). Usually an on-board observer is assigned to fishing vessels randomly selected from this sector and covers the full set of multiple gears used in Galician waters and all along the geographical range (Figure 2). In a single trip each vessel usually performs several hauls. At each haul, observers record all basic operational data (i.e., date, geographical position, gear, etc.) and the number and weight of all retained and discarded taxa. The analysed database in this study counts 4350 hauls for which common sole was caught from January 2000 until December 2018.

Before fitting any model, we selected the data for the trammel net which is the most representative gear for the common sole in order to reduce sources of variation. This selection was based on three criteria: i) proportion of hauls with zero catch, ii) total number of individuals sampled and iii) the spatio-temporal coverage. The first and second criterion were used as proxies of gear catchability and thus constant catchability was assumed along the time series (Alonso-Fernández et al., 2019).

Modelling abundance data

Fishery-independent data

The annual scientific survey that collects data for demersal species in the studied area only cover partially the common sole bathymetric range and the resultant abundance index presents a large proportions of zeros observed, i.e., zero inflated data. This data is commonly analysed using two-part models, also known as delta models. Generally, both occurrence and abundance are modelled through independent models. However, the abundance and occurrence processes are often related, thus violating the independence assumption of common delta models. In this study we applied hurdle Bayesian spatio-temporal models that fitted simultaneously the common sole occurrence and conditional-to-presence abundance processes sharing bathymetry effects. These effects were incorporated as described in Paradinas et al. (2017) in order to incorporate information on both the occurrence and the abundance to better fit informed environmental effects.

Bathymetry values were retrieved from the European Marine Observation and Data Network (EMODnet, http://www.emodnet.eu/) with a spatial resolution of 0.02 x 0.02 decimal degrees (20 m).

Models were fitted using the integrated nested Laplace approximation approach (Rue et al., 2009) in the R (R Core Team, 2017) software. For the spatial component the spatial partial differential equations (SPDE) module (Lindgren et al., 2011) of INLA was implemented. With the SPDE, the spatial field (W_s) was modelled as a multivariate normal distribution with zero mean and a Matérn covariance function that depend on its range (r_w) and variance (σ_w).

Additionally, in order to categorize the spatio-temporal behaviour of the common sole, three different spatio-temporal structures were compared (Paradinas et al., 2017) (see Table 1). In particular, opportunistic structures indicate that species change their spatial pattern every year without following any specific pattern. Persistent structures imply that species have a spatial distribution that does not change every year, while the progressive ones indicate that the spatial pattern changes in a correlated way from one year to another. The progressive structure contains an autoregressive ρ_t parameter that controls the degree of autocorrelation between consecutive years. This ρ_t parameter is bounded to $[0, 1]$, where parameter values close to 0 represent more opportunistic behaviors and parameter values close to 1 represent more persistent distributions along time. We also included an extra temporal effect f_t using a second order random walk (RW2) effect to infer any mean intensity changes over time.

For each spatio-temporal model we considered Y_{st} and Z_{st} that denote, respectively, the spatio-temporally distributed occurrence and the conditional-to-presence abundance, where $s = 1, ..., n_t$ is the spatial location and $t = 1, ..., T$ the temporal index, being $i = 1, ..., I$ the bathymetry in location s. Occurrence Y_{st}, was modeled using a Bernoulli distribution with a logit link and conditional-to-presence abundance, Z_{st}, with a gamma distribution with a log link, to capture the overdispersion of the data. Then:

$$\begin{aligned} Y_{st} &\sim \text{Ber}(\pi_{st}) \\ Z_{st} &\sim \text{Gamma}(\mu_{st}, \phi_{st}) \\ \text{logit}(\pi_{st}) &= \alpha^{(Y)} + f_i(d_{ist}) + U_{st}^{(Y)} \\ \log(\mu_{st}) &= \alpha^{(Z)} + \theta_i f_i(d_{ist}) + U_{st}^{(Z)} \end{aligned} \tag{1}$$

where π_{st} represents the probability of occurrence at location s at time t and μ_{st} and ϕ_{st} are the mean and dispersion of the conditional-to-presence abundance. The linear predictors, which contain the effects that link the parameters π_{st} and μ_{st} include: $\alpha^{(Y)}$ and $\alpha^{(Z)}$, that represent the intercepts of each respective variable; $f_i(d_{ist})$ is the bathymetric effect modelled as a RW2 smooth function that allow us to fit any possible non-linear relationship of the bathymetry (Fahrmeir and Lang, 2001) and it is scaled by θ_i to allow for differences in scale across the different linear predictors in shared effects; the final terms $U_{st}^{(Y)}$ and $U_{st}^{(Z)}$ refer to the spatio-temporal structure of the occurrence and conditional-to-presence abundance respectively and may follow any of the three spatio-temporal structures described above.

Fishery-dependent data

Similarly to the precedent abundance data, the fishery-depended data-set was analyzed using Bayesian spatio-temporal models with a gamma distribution and log link. All the spatio-temporal structures were tested and the bathymetry was included as possible predictor and fitted using a RW2 model. In order to capture the intra-annual variability of this abundance index, the month of the fishery haul was also included in the model as fixed effect.

Fishing effort was included as the duration of gear deployment (i.e. soak time). As it is known that gear saturation can exert a significant nonlinear effect on catchability this variable was included as continuous explanatory variable (in minutes, log transformed). The remaining potential source of abundance variability could be due to differences among vessels caused by a skipper effect or unobserved gear characteristics. To remove bias caused by vessel-specific differences in fishing operation, we included a vessel random effect.

The Bayesian approach requires the assignation of prior distributions to every parameter of the model. For both fishery-independent and depended data-sets, vague prior distributions with a zero-mean and a standard deviation of 100 were implemented for all the fixed effects, the variance of the abundance process, and the scaling parameter (θ) of the shared effects. For the geostatistical terms and the ρ parameters of the of the second order random walks penalised complexity priors (PC priors, weak informative priors) (Fuglstad et al., 2018) were assigned. Specifically, we used PC priors that satisfied the following criteria: 1) the probability that the spatial effect range was smaller than 150 km was 0.15, to avoid very small spatial autocorrelation ranges, 2) the probability that the spatial effect variance was greater than 1 was 0.20, to avoid masking the bathymetric effect through the spatial effect, and 3) the probability that ρ was greater than 0.5 in the occurrence model and greater than the observed abundance standard deviation in the abundance model were 0.01. A sensitivity analysis of the choice of priors was performed by verifying that the posterior distributions concentrated well within the support of the priors.

Model selection

In both cases, model selection was performed testing all possible combinations among the possible spatio-temporal structures and variables and using the Watanabe Akaike Information Criterion (WAIC) (Watanabe, 2010) as criteria of the goodness of fit and the Log-Conditional Predictive Ordinates (LCPO) (Roos et al., 2011) as predictive quality measures. For both measures, the smaller the score the better the model.

SPiCT, stochastic surplus production model in continuous time

The SPiCT explicitly models both abundance and fishing dynamics as stochastic processes in a state-space framework. It is formulated as a continuous time model to allow a representation of seasonal fishing patterns and incorporation of sub-annual catch and index data Pedersen and Berg (2017).

The most important input for fitting SPiCT is catch data (by weight). Pedersen and Berg (2017) define the catch as the product of instantaneous fishing mortality and stock biomass. Fishing mortality is not decomposed into the product of effort and catchability. Therefore, it is not necessary to standardise the catch data based on changes in fishing efficiency: all such changes will be encompassed in the instantaneous fishing mortality.

Here we used as catch data the common sole official landings provided by Portugal and Spain in ICES divisions 8.c and 9.a (Figure 3) (2000-2019). For this time-series the observation noise was not constant in time. Indeed, there is some evidence that the common sole catch could be misclassified in the past, which means that common sole official landings might not then have corresponded only to this species but a mix of *Solea solea*, *Solea senegalensis* and *Pegusa lascaris*. Using port sampling length data it was possible to separate the Solea spp. landings and apply the proportions to provide a raised landings for the common sole. However, as in the SPiCT it is possible to add knowledge that certain data points are more uncertain than others, the first 10 years of the catch were considered uncertain relative to the remaining time series and therefore are scaled by a factor 5. In particular using the $stdevfacC$ vector that contains the factor that is multiplied onto the standard deviation of the data points of the corresponding observation vector.

Catch data must be supplemented in the SPiCT model by at least one independent abundance index. An important advantage of SPiCT over other surplus production models is that it allows the use of multiple abundance indices with different time-series in addition to the catch time series. Here we performed three different runs using: 1) only the spatio-temporal abundance index produced with fishery-independent data; 2) only the spatio-temporal abundance index produced with fishery-dependent data; 3) both produced spatio-temporal abundance indices.

The continuous-time SPiCT formulation, time-stepping is achieved through an Euler scheme with a default time increment dt_{Euler} equal to 1/16 (where time is measured in years). As common sole catch data were collected annually, the discrete-time realisation of SPiCT, obtained by setting the time-step dt_{Euler} equal to one, was considered sufficient.

For the ratios between observation and process error for abundance and fishing dynamics, α and β, we specified priors vaguely informative priors as recommended by Pedersen and Berg (2017). Optimisation of the model fit is achieved using log-likelihood functions so that many variables and parameters are log-transformed as standard. Therefore, $\log \alpha$ and $\log \beta$ were assumed to have normal distributions with mean values of log 1 and standard deviations equal to 2.

Production curve shape parameter n was allowed to vary during optimisation and we prescribed a vaguely informative prior normal distribution for $\log n$ with a mean of log 2 (corresponding to the logistic curve) and standard deviation 2. These prior specifications are considered a fair reflection of our prior knowledge of the system. The SPiCT model fit is relatively insensitive to increases in the standard deviation of the lognormal distributions; a standard deviation of 10 did not cause any visible changes in the biomass and fishing mortality trends. No other prior information was available regarding the fishing process or biomass production.

Model and post-processing R code R Core Team (2017) supplied by Pedersen and Berg (2017) was used to fit the model and analyze the results.

Results

Fishery-independent data

According to model selection scores (see Table 2), the occurrence and abundance distributions of the common sole were progressive. Persistent model scores were quite close to the progressive structure, suggesting that distributions were relatively persistent between 2001 and 2019. These results were supported by the strong temporal correlation parameters in the progressive spatio-temporal model (0.98 and 0.96 for the occurrence and abundance processes, respectively).

The predicted bathymetric distribution of occurrence and abundance revealed a clear decrease with depth from 60 m (Figure 4). Bathymetry explained 41% of spatio-temporal variation of the abundance process, which suggests that this habitat variable has an important impact on spatial variation in common sole density.

The overall abundance of the common sole shows a slightly increasing trend (Figure 5). Note that the marginal temporal effect of Figure 5 is in the log scale.

Occurrence and abundance maps (Figures 6 and 7 respectively) highlight two main preferential habitats for the common sole, located over the continental shelf in front of La Coruña and Bilbao cities. It worth to be mentioned that the predictions did not include the extra temporal effect f_t RW2.

Fishery-dependent data

Model selection scores (see Table 3) show that the abundance distribution of the common sole was progressive. The ρ parameter was 0.45, suggesting more opportunistic distributions (i.e., uncorrelated distributions between years).

The predicted bathymetric distribution revealed an increasing abundance trend until 100 m and then a decreasing pattern (Figure 8). Bathymetry explained 31% of spatio-temporal variation of the abundance process.

The overall abundance of the common sole shows a slightly decreasing trend (Figure 9). Note that the marginal temporal effect of Figure 9 is in the log scale.

Abundance maps (Figure 10) highlight not persistent hot-spots but overall two main preferential habitats for the common sole can be identified. They are located one in front of La Coruña city and another in the northern part of the area in front of the Ria do Viveiro. Also in this case, it worth to be mentioned that the predictions did not include the extra temporal effect f_t RW2.

Abundance indices

When the produced spatio-temporal abundance indices are compared with the observed data, in both cases it is possible to see that temporal tendencies are maintained but more smoothed indices are obtained (Figures 11 and 12). However both indices showed significant correlation with observer data, 0.65 with fishery-independent data and 0.70 for fishery-dependent.

SPiCT

For the three runs the assessment converged and all the variance parameters of the model were finite as recommended by Pedersen and Berg (2017). However in the three cases some of the model assumptions based on one-step-ahead residuals (i.e. auto-correlation and normality) were violated (Figures 13, 14 and 15). It worth to be mentioned that slight violations of this assumptions do not necessarily invalidate model results (Mildenberger et al., 2020).

Table 4 shows the model parameter estimates with 95% confidence intervals for all the models. Results are very different among models and the 95% confidence intervals are very wide.

Conclusions

Overall the inclusion of the spatio-temporal indices improved the results of the SPiCT model. Indeed before the standardization of the indices (i.e. using observed data) the SPiCT model did not converge at all. However results are very preliminary and they need to be improved. Future steps will be:

1) improving the standardization of the fishery-independent and dependent data. For the fishery-dependet data standardization could be improved adding seasonal trends and more effort information.

2) include in the predictions and consequent abundance indices the extra temporal effect f_t RW2.

3) Pedersen and Berg (2017) outline that the SPiCT formulation describes the dynamics of the exploited part of the fish stock. Therefore, abundance index need to be modified to include only the size-classes exploited by fishery.

4) sensitive analysis for the production curve skewness parameter n need to be performed.

Acknowledgments

The authors express their gratitude to all the people that work in the SP-NSGFS Q4 surveys. SP-NSGFS Q4 surveys were co-funded by the EU within the Spanish national program for the collection, management and use of data in the fisheries sector and support for scientific advice regarding the Common Fisheries Policy. This study is indebted with all the on-board observers that carried out the sampling, and with the UTPB that runs the monitoring program of the artisanal fishery sector in Galician waters. This study is a contribution to the project IMPRESS (RTI2018-099868-B-I00) project, ERDF, Ministry of Science, Innovation and Universities - State Research Agency.

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Tables

Model	Notation	Description
Opportunistic	$U_{st} = \boldsymbol{W}_t$	Different and uncorrelated realizations of the spatial field every year.
Persistent	$U_{st} = \boldsymbol{W} + f(t)$	A common realization of the spatial field for all years and an additive temporal trend $f(t)$
Progressive	$U_{st} = \boldsymbol{W}_t + \rho U_{st-1}$	Spatial realizations change over time through a first order autoregressive model. ρ controls the level of correlation between subsequent time events.

Table 1: Summary of fitted spatio-temporal models U_{st}. $\boldsymbol{W}$ represents a geostatistical spatial field, $f(t)$ is a temporal trend function and ρ is an autoregressive correlation parameter bounded to [0,1].

Model	WAIC	LCPO	Time (sec.)
Persistent structure	1732.17	0.52	128.23
Opportunistic structure	1770.42	0.54	121.57
Progressive structure	**1728.22**	**0.61**	**7882.21**

Table 2: Spatio-temporal structures comparison for the conditional-to-presence abundance distribution of common sole model fishery-independent data based on WAIC and LCPO scores. Time scores refer only to the estimation process of the model. The best model is highlighted in bold.

Model	WAIC	LCPO	Time (sec.)
Persistent structure	57602.89	6.62	102.05
Opportunistic structure	57685.80	6.63	107.175
Progressive structure	**57290.89**	**6.50**	**834.471**

Table 3: Spatio-temporal structures comparison for abundance distribution of common sole model fishery-dependent data based on WAIC and LCPO scores. Time scores refer only to the estimation process of the model. The best model is highlighted in bold.

Parameter	estimate	cilow	ciupp	log.est
RUN 1				
$Bmsyd$	266.27011	75.49005	939.19361	5.584511
$Fmsyd$	15.77595	14.83957	16.77142	2.758487
$MSYd$	4200.66483	1246.62167	14154.72351	8.342998
K	4200.6648274	1246.6216654	1.415472e+04	8.3429981
m	532.5402196	150.9800969	1.878387e+03	6.2776584
RUN 2				
$Bmsyd$	3.324751e+05	512.828416	2.155490e+08	12.714320
$Fmsyd$	5.654210e-02	0.011523	2.774462e-01	-2.872769
$MSYd$	1.879885e+04	21.075496	1.676813e+07	9.841551
m	1.879885e+04	21.0754961	1.676813e+07	9.841551
K	6.649501e+05	1025.6568328	4.310981e+08	13.407467
RUN 3				
$Bmsyd$	1945.35	442.82	8546.08	7.57
$Fmsyd$	0.3525605	0.08096485	1.53522	-1.042533
$MSYd$	685.6973461	345.63207027	1360.35076	6.530436
m	7.073595e+02	359.48682933	1.391866e+03	6.5615390
K	3.964599e+03	904.04950017	1.738627e+04	8.2851601

Table 4: Parameter estimates (deterministic) and associated confidence intervals for MSY parameter m, carrying capacity k, biomass at MSY $Bmsyd$, fishing at MSY $Fmsyd$ and $MSYd$.

405 # Figures

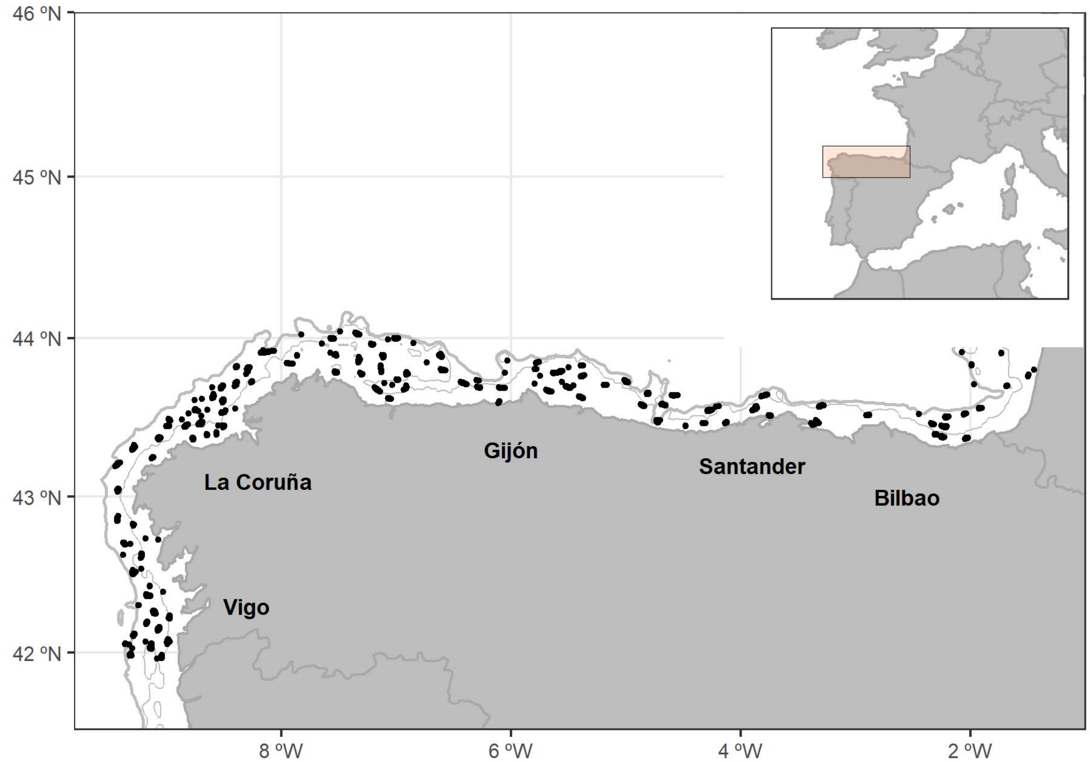

Figure 1: Map of the study area showing the distribution of the annual sampling locations of fishery-independent hauls.

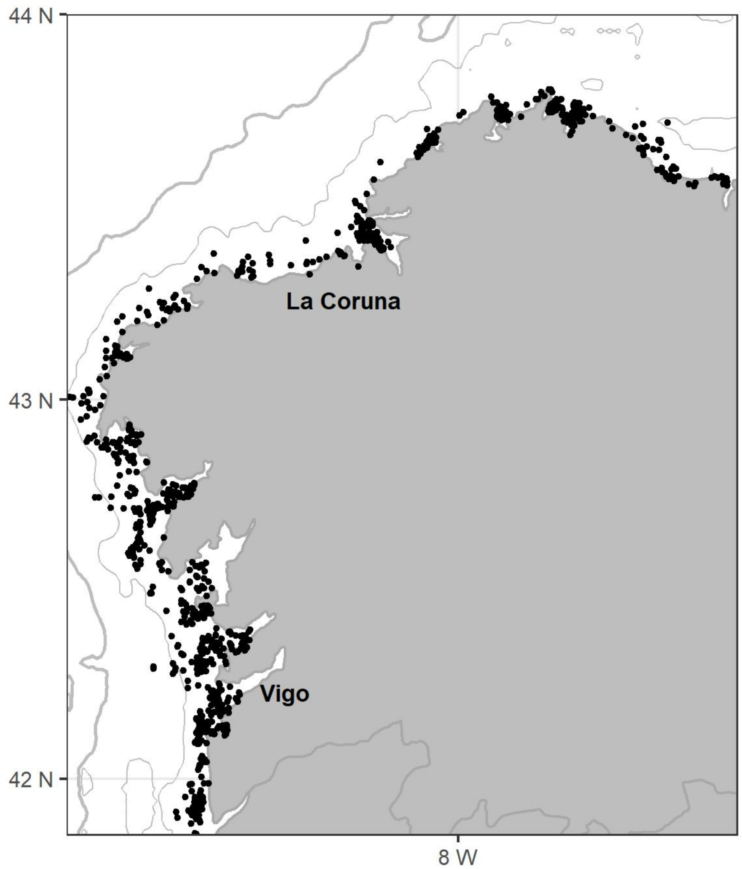

Figure 2: Map of the study area showing the distribution of the fishery-dependent sampling locations.

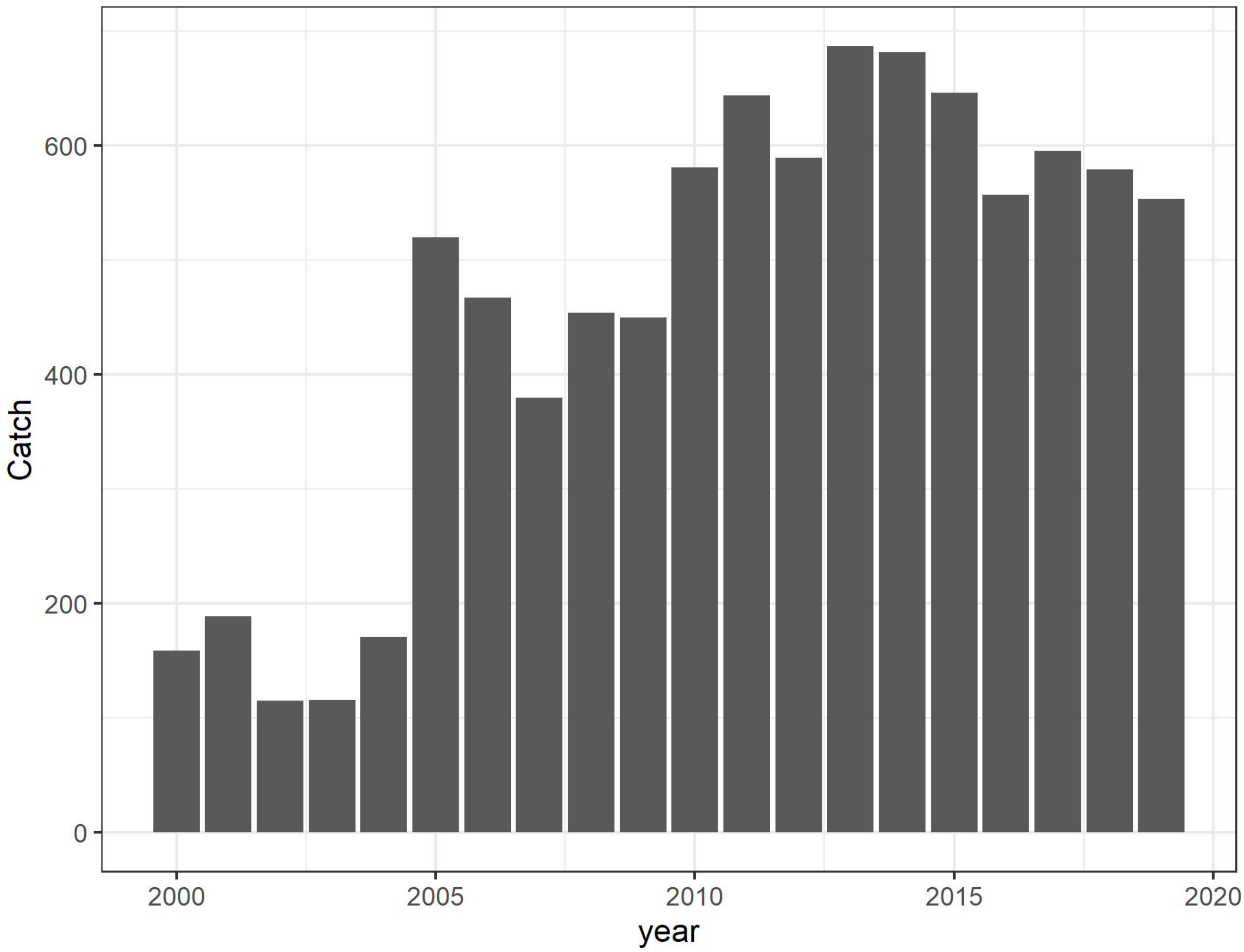

Figure 3: Common sole catch in ICES divisions 8.c and 9.a.

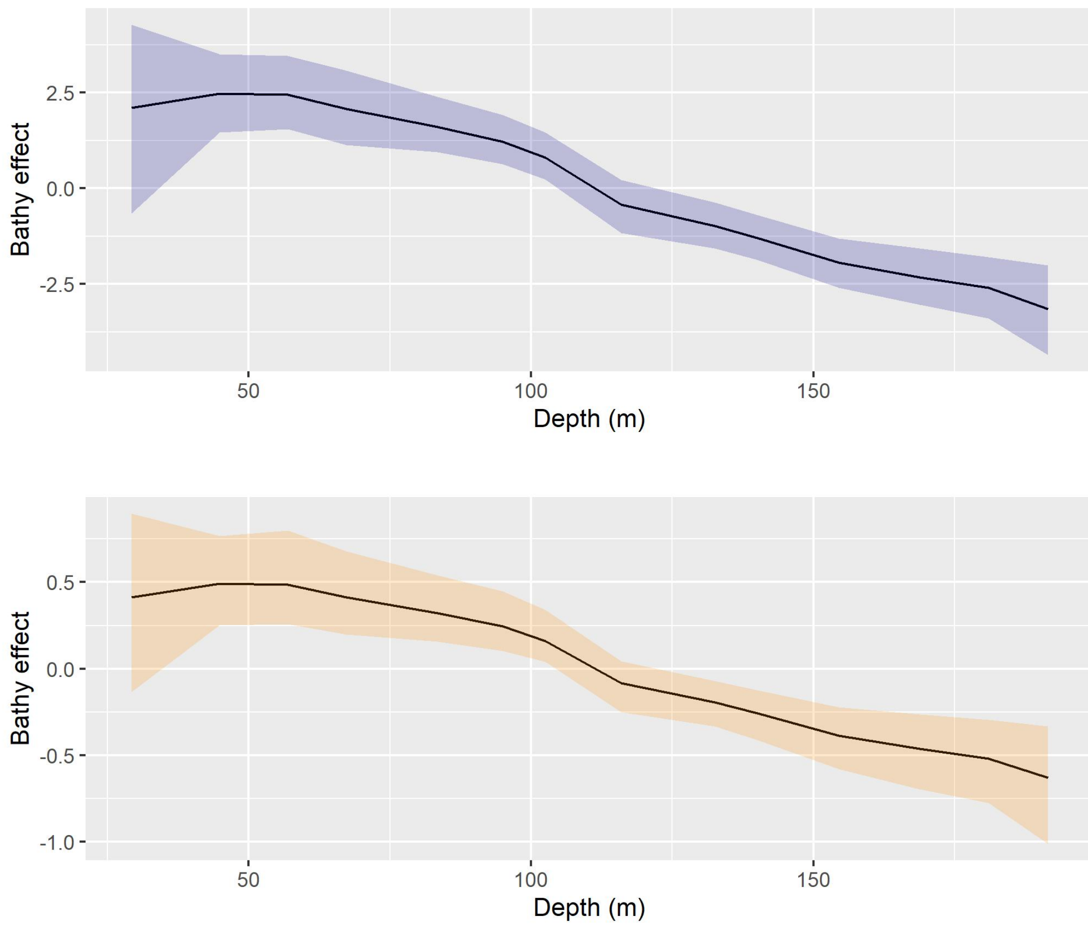

Figure 4: Smooth functions of the predicted occurrence (top) and abundance (bottom) for the bathymetry effect using fishery-independent data-set. The solid line is the smooth function estimate, and shaded regions represent the approximate 95% credibility interval.

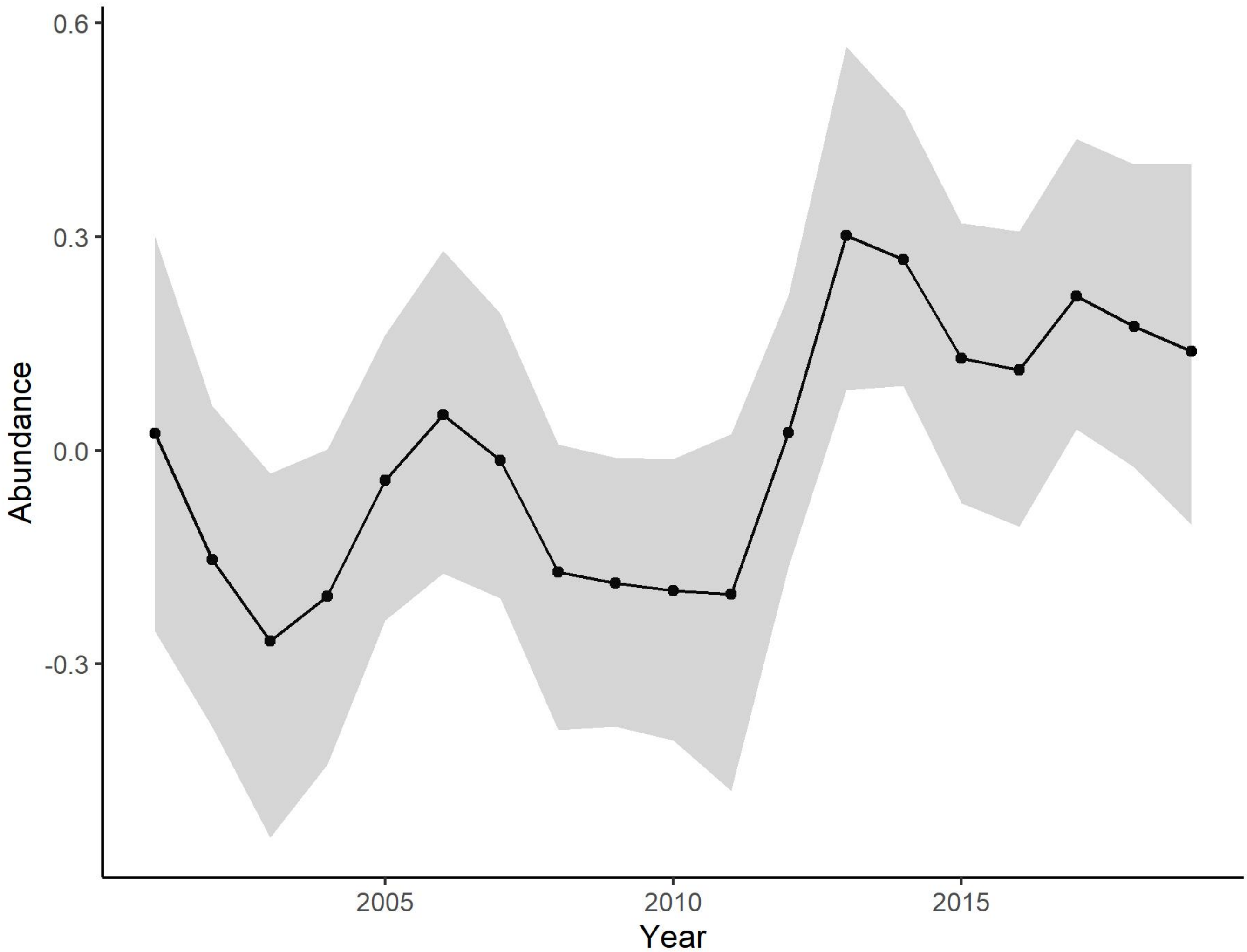

Figure 5: Marginal temporal effects in the linear predictor scale (logarithmic link) of common sole for fishery-independent data. Shaded regions represent the approximate 95% credibility interval.

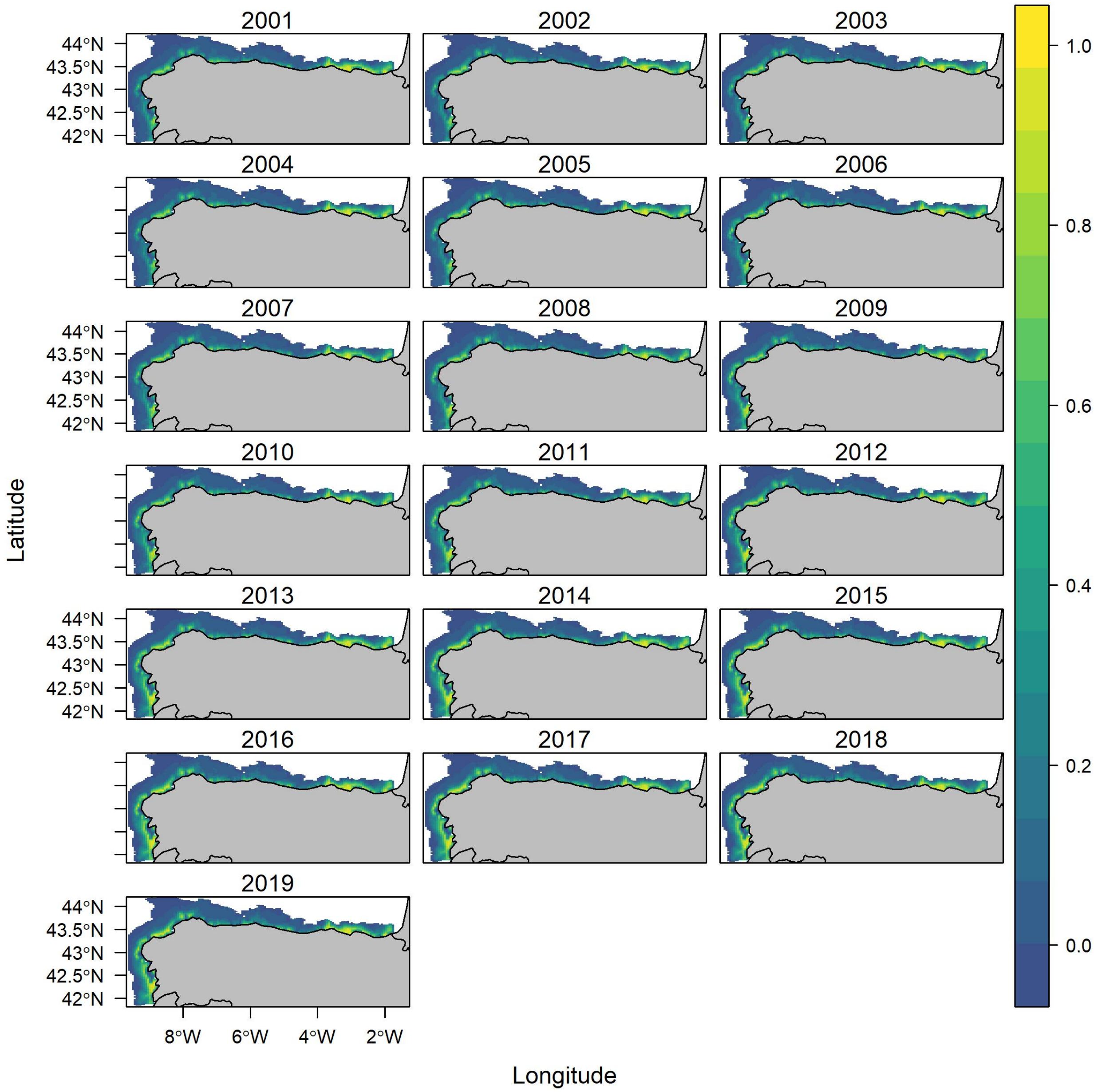

Figure 6: Prediction maps (2001-2019) of the common sole occurrence estimated by the hurdle Bayesian spatio-temporal model for fishery-independent data.

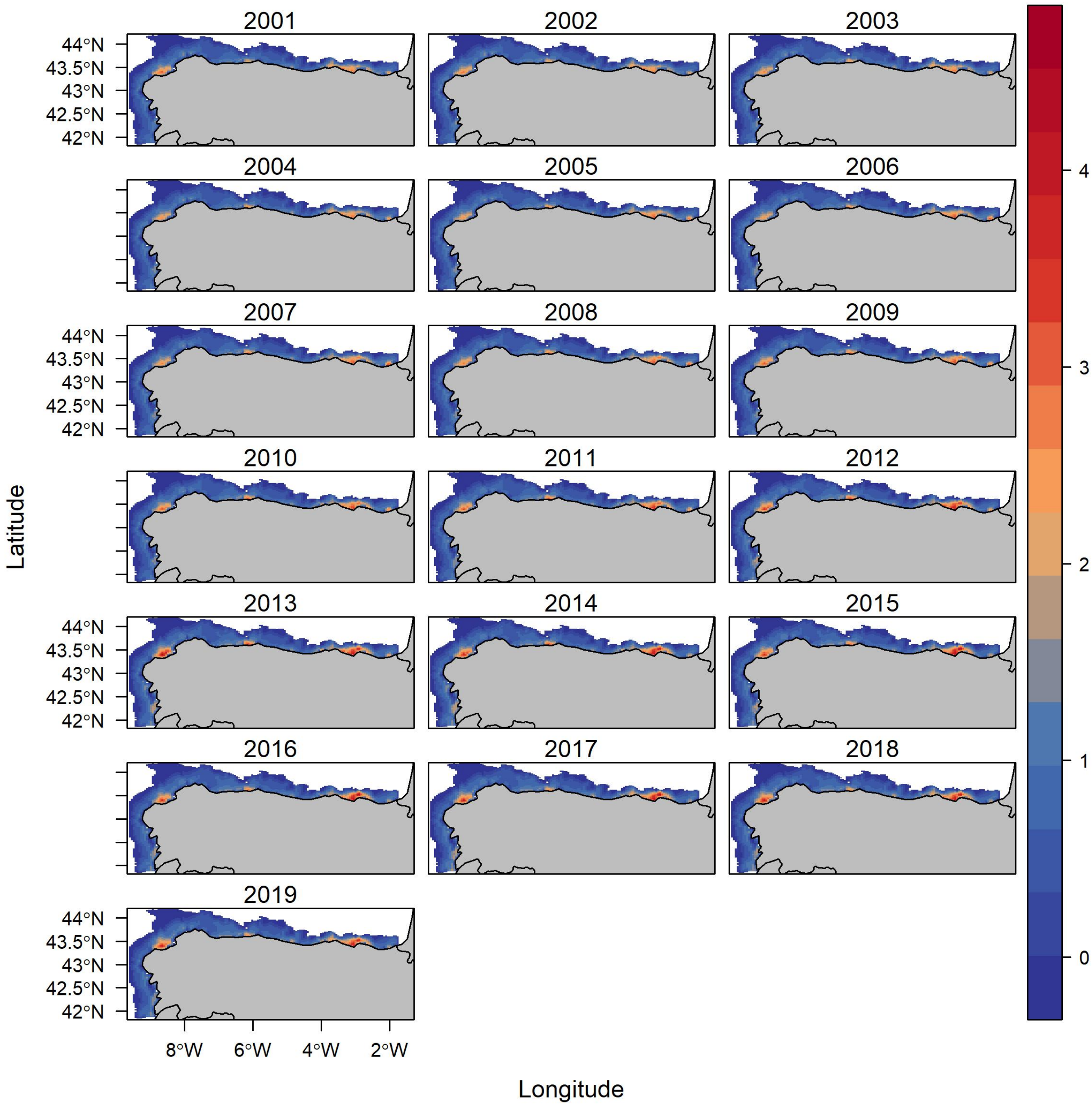

Figure 7: Prediction maps (2001-2019) of the common sole abundance estimated by the hurdle Bayesian spatio-temporal model for fishery-independent data.

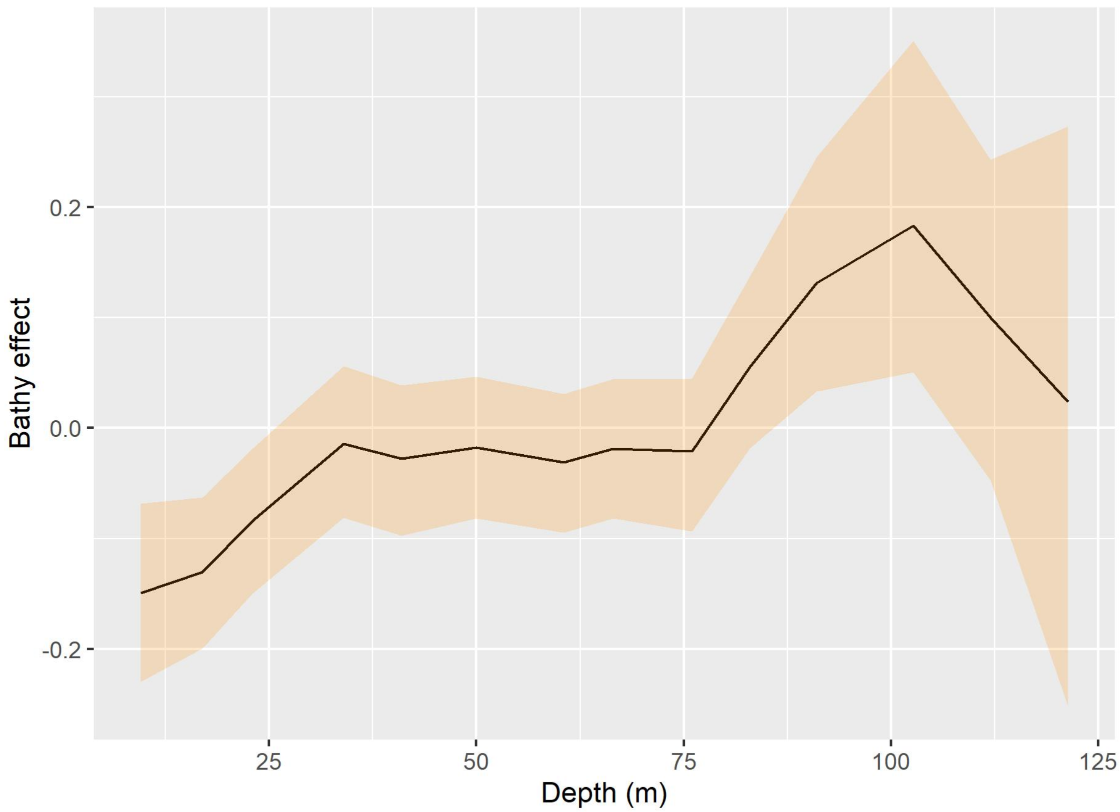

Figure 8: Smooth functions of the predicted abundance for the bathymetry effect using fishery-dependent data-set. The solid line is the smooth function estimate, and shaded regions represent the approximate 95% credibility interval.

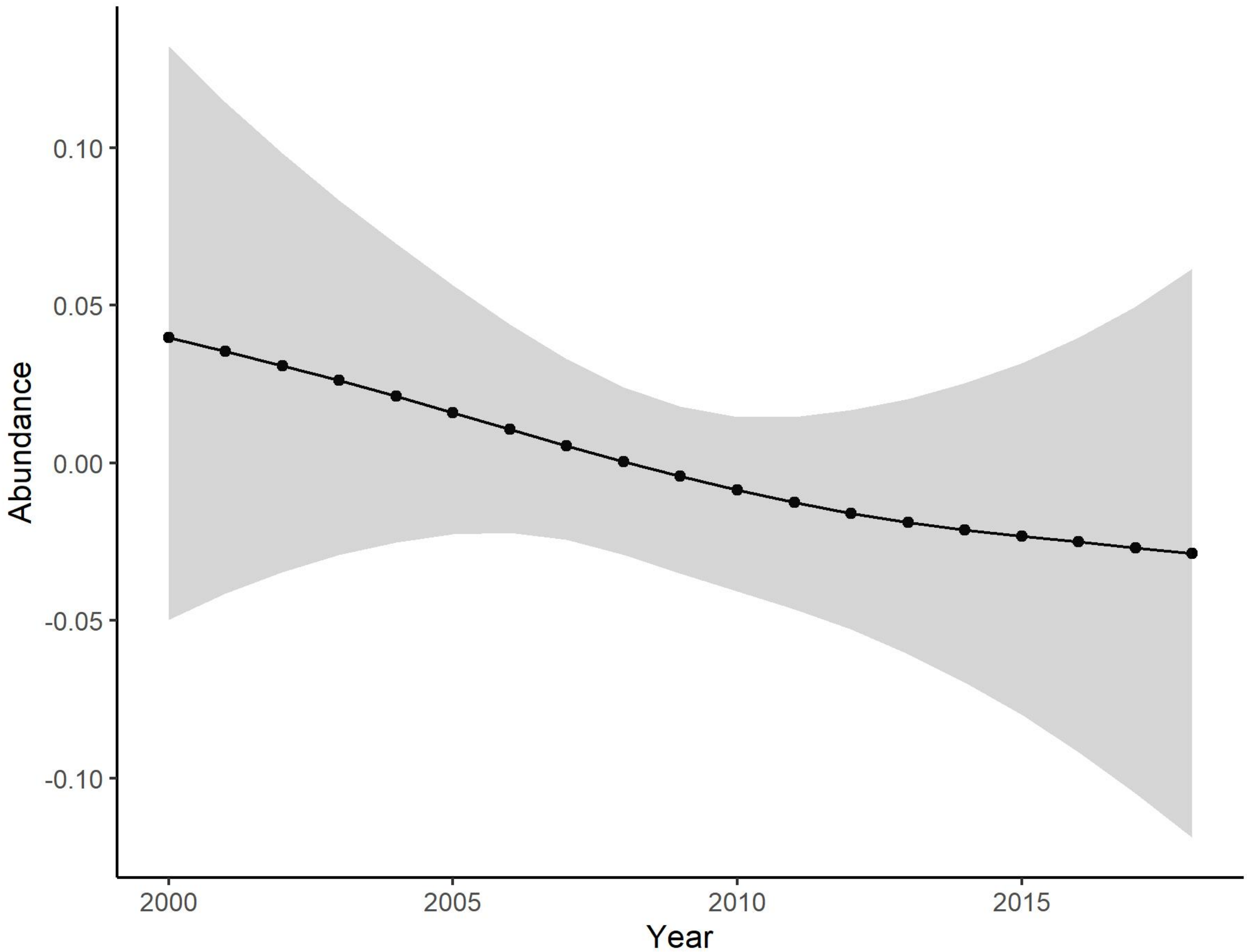

Figure 9: Marginal temporal effects in the linear predictor scale (logarithmic link) of common sole for fishery-dependent data. Shaded regions represent the approximate 95% credibility interval.

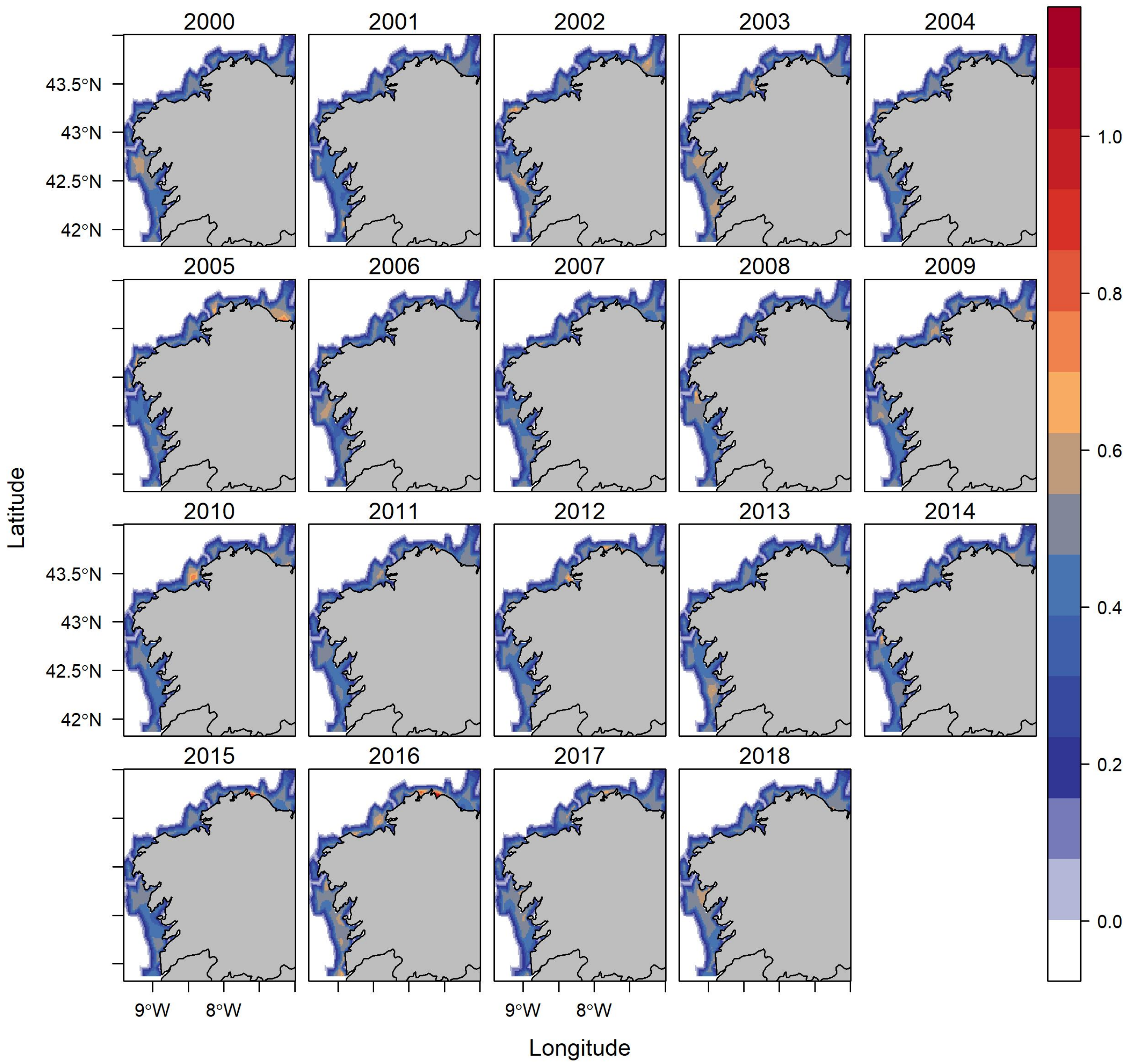

Figure 10: Prediction maps (2000-2018) of the common sole abundance estimated by the Bayesian spatio-temporal model for fishery-dependent data.

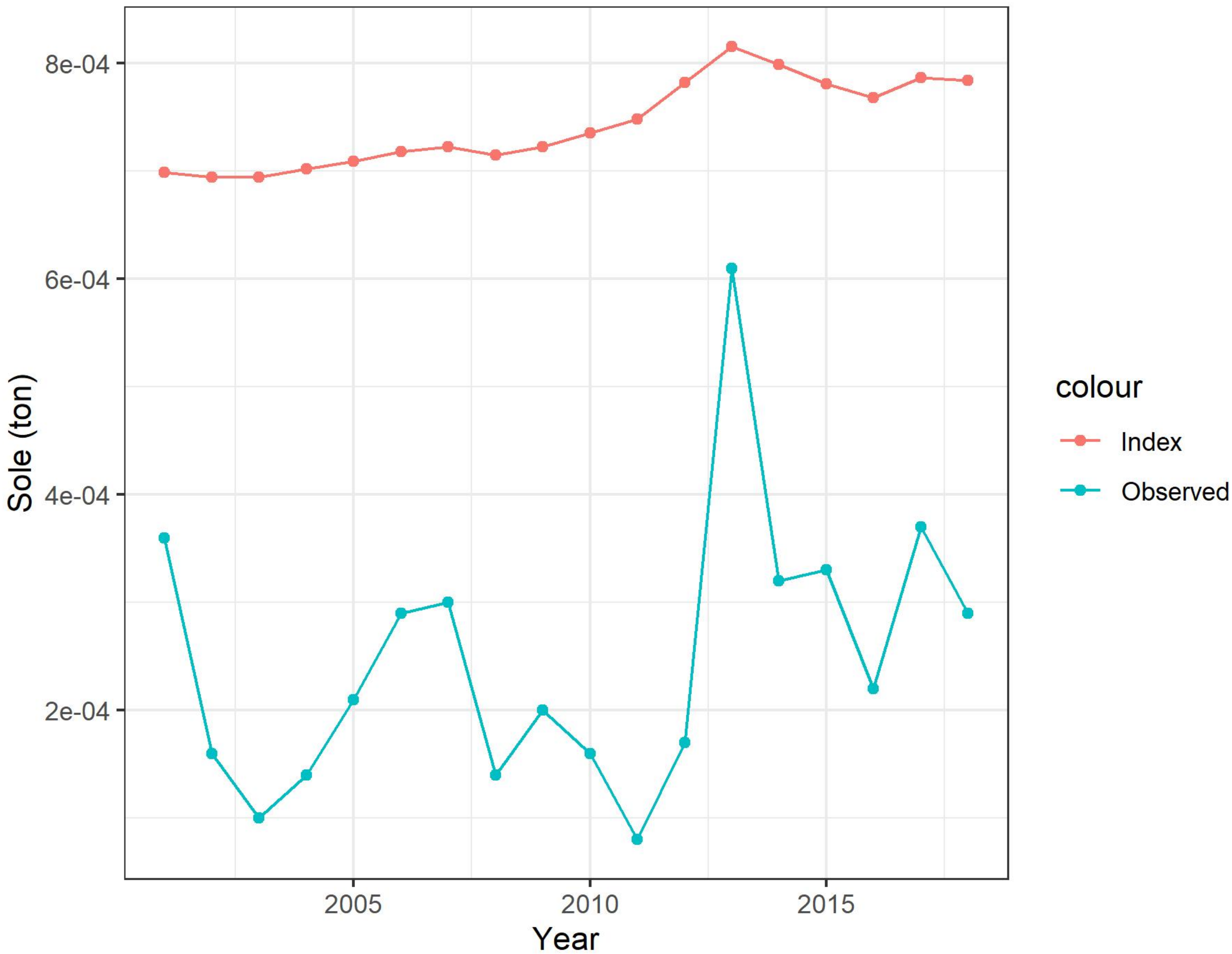

Figure 11: Spatio-temporal abundance index obtained for fishery-independent data (2001-2019) versus the survey abundance index standardized for the three bathymetric strata (i.e. 70–120 m, 121–200 m and 201–500 m).

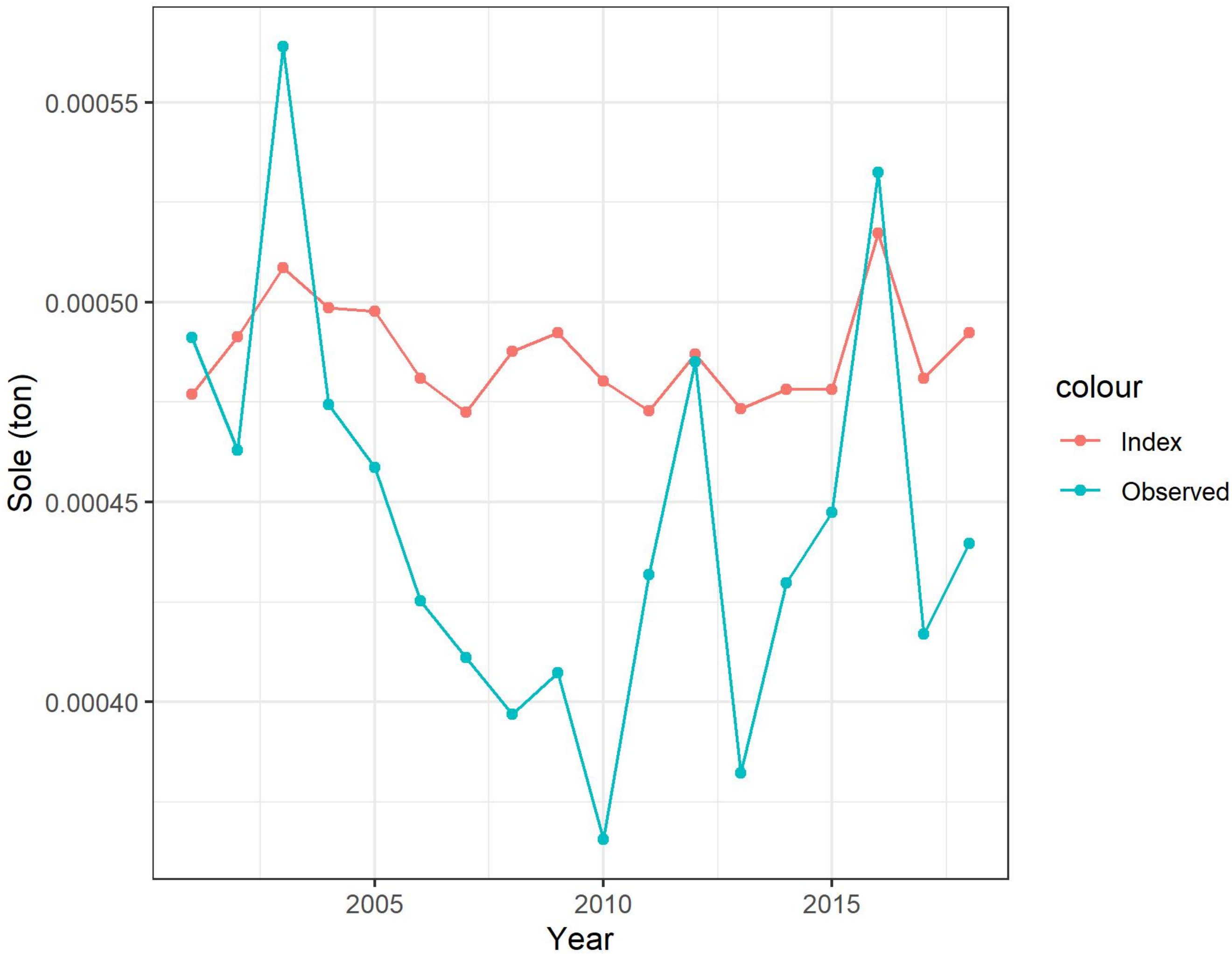

Figure 12: Spatio-temporal abundance index obtained for fishery-dependent data (2000-2018) versus observed fishery-dependent data.

Appendix

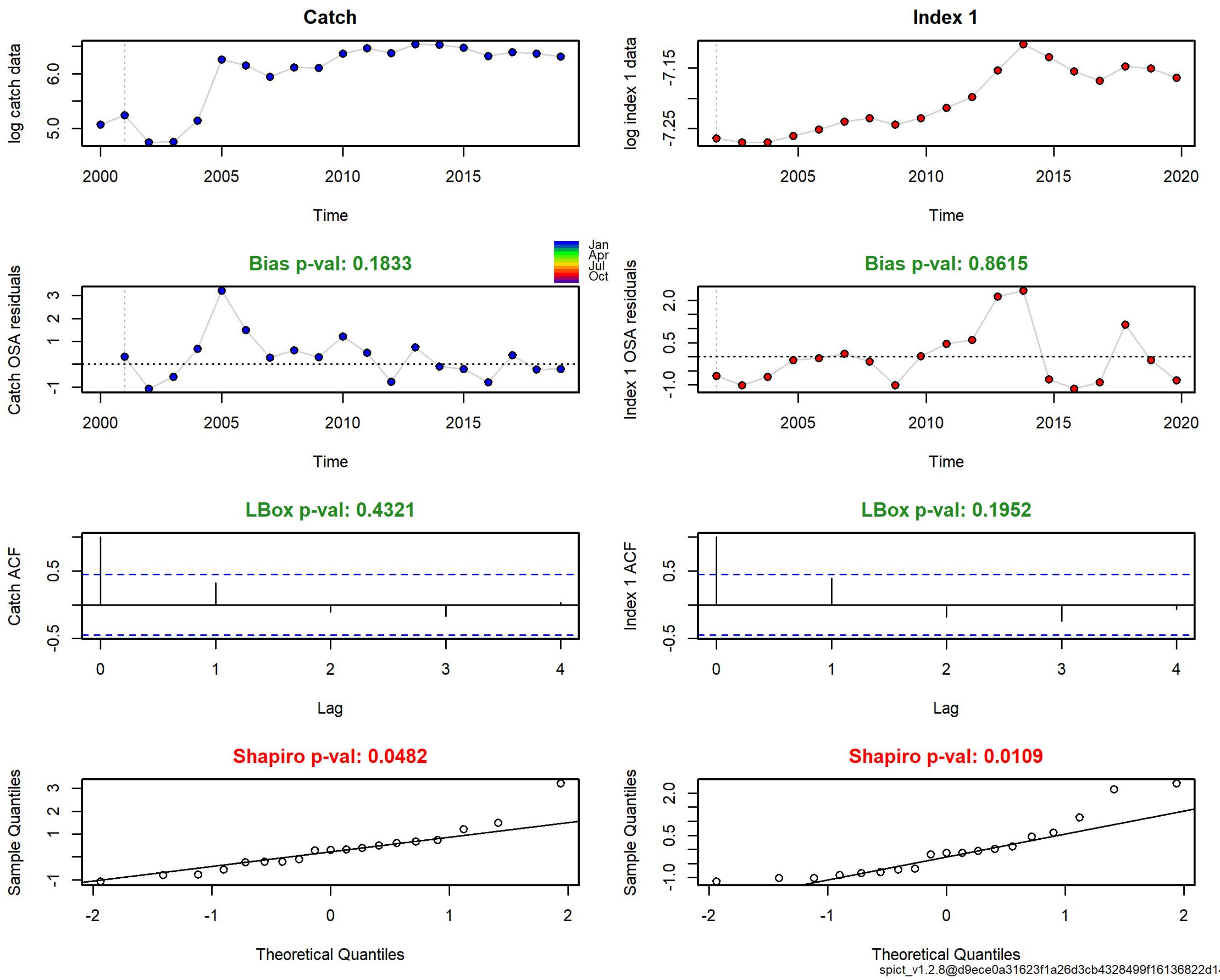

Figure 13: Standard OSA residuals for the run 1 surplus production model obtained using catch data and the spatio-temporal index of fishery-independent data.

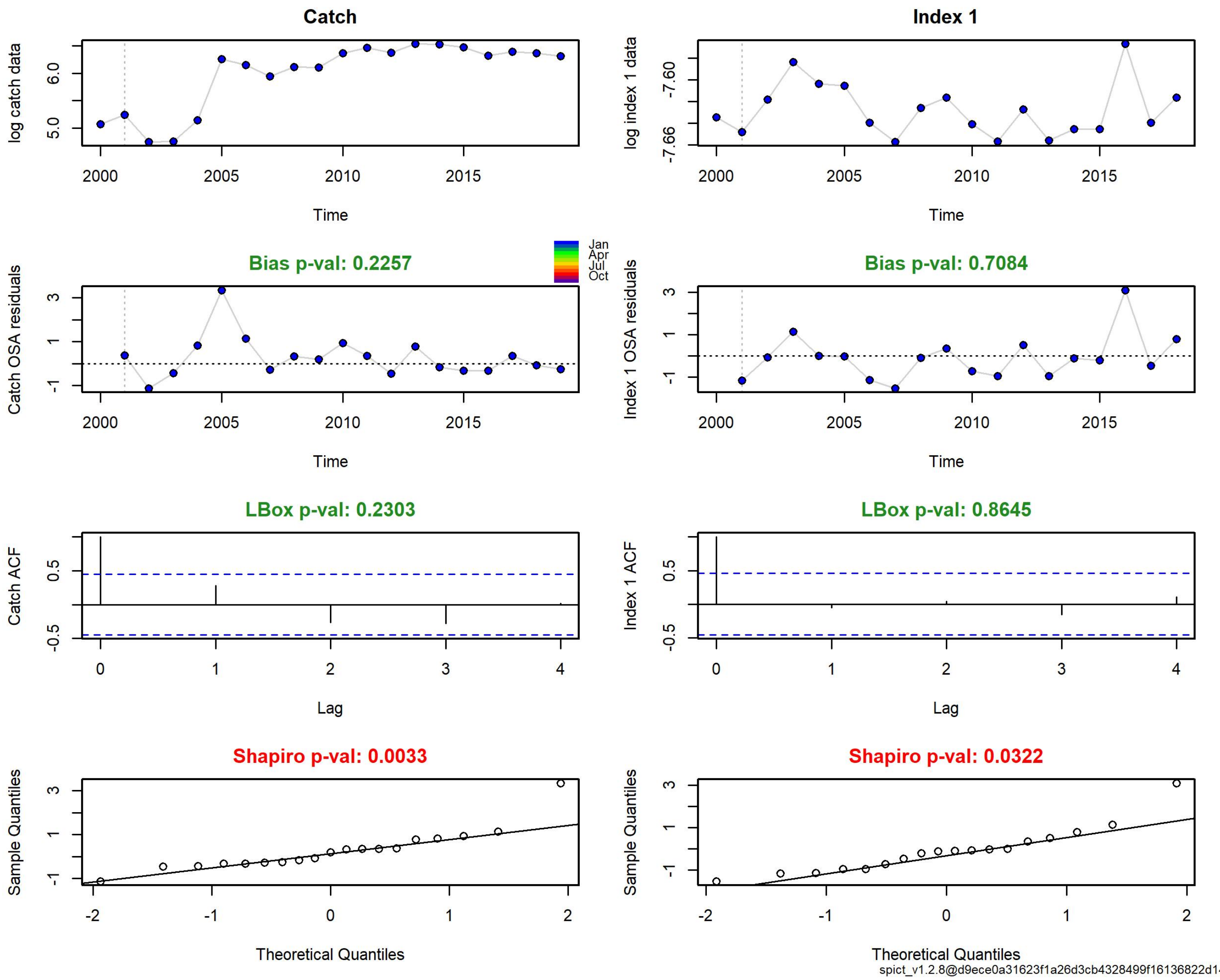

Figure 14: Standard OSA residuals for the run 2 surplus production model obtained using catch data and the spatio-temporal index of fishery-dependent data.

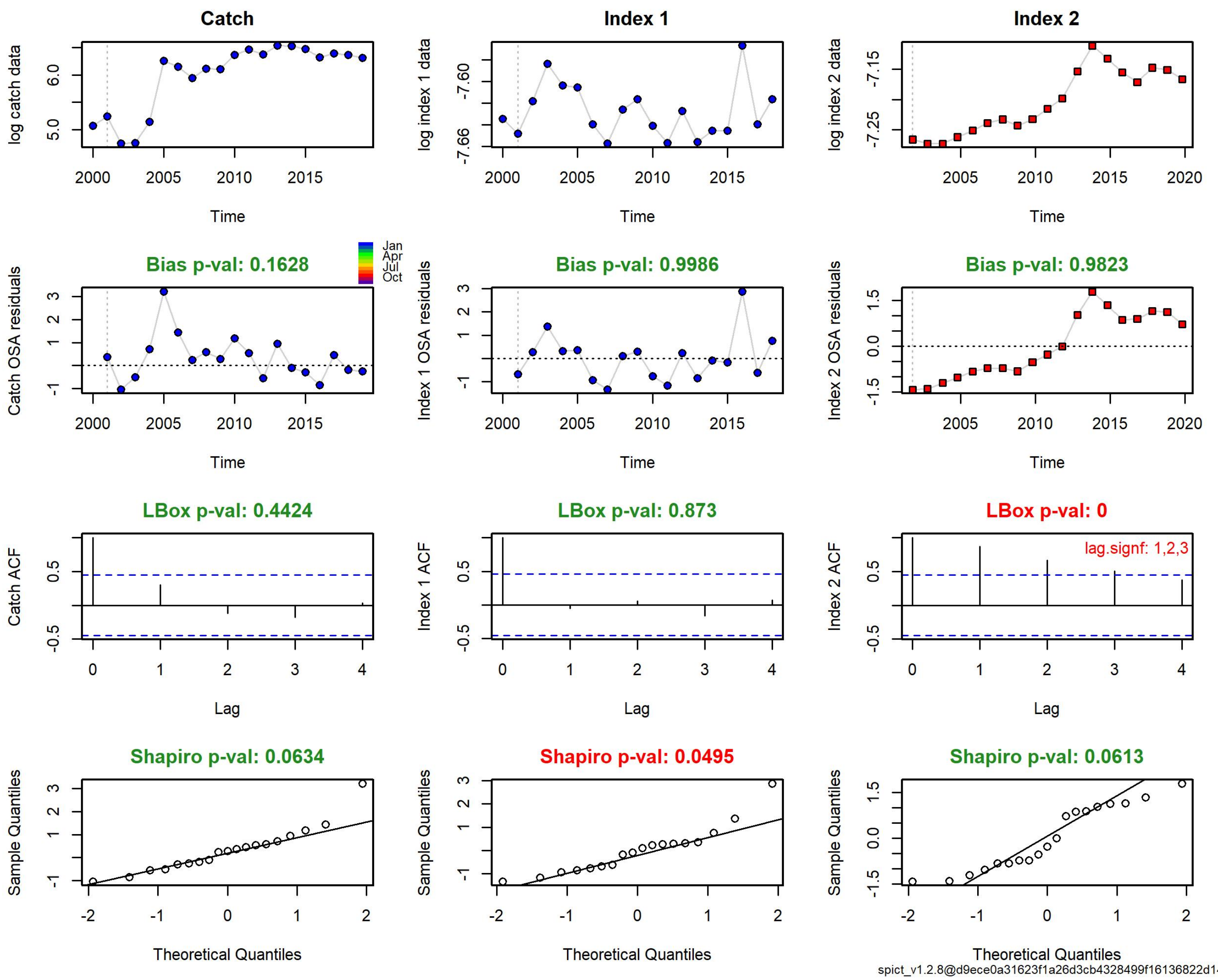

Figure 15: Standard OSA residuals for the run 2 surplus production model obtained using catch data and both spatio-temporal indices.