INVESTIGATION OF SECONDARY INDICATORS OF EXCEPTIONAL CIRCUMSTANCES FOR ATLANTIC BLUEFIN TUNA INCLUDING STOCK OF ORIGIN AND ELECTRONIC TAGGING DATA

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SUMMARY

Newly provided genetics stock of origin and electronic tagging data are compared with those predicted by the reference grid of operating models. Genetics stock of origin data imprecisely fitted by the operating models and generate a wide range of possible predicted data for which all new observations fall within 95% confidence intervals. Tagging data, on the other hand, provide inference of movements not estimated by the operating models. It is however not clear whether these movement discrepancies are important, particularly in light of previous sensitivity analyses that showed very limited impacts of movement on management procedure performance.

RÉSUMÉ

Des données génétiques sur le stock d'origine et de marquage électronique, récemment fournies, ont été comparées à celles prédites par la grille de référence des modèles opérationnels. Les données génétiques sur le stock d'origine ont été ajustées de façon imprécise par les modèles opérationnels et génèrent un vaste ensemble de données prédites possibles pour lesquelles toutes les nouvelles observations se situent dans les intervalles de confiance de 95%. Les données de marquage, par ailleurs, permettent de déduire des déplacements qui ne sont pas estimés par les modèles opérationnels. Il n'est toutefois pas clair si ces divergences dans les déplacements sont importantes, compte tenu notamment du fait que les analyses de sensibilité précédentes montraient des impacts très limités du déplacement sur la performance de la procédure de gestion.

RESUMEN

Los nuevos datos genéticos sobre los stocks de origen y los datos de marcado electrónico se comparan con los previstos por la matriz de referencia de los modelos operativos. Los datos genéticos sobre los stocks de origen se ajustaron de forma imprecisa por los modelos operativos y generan una amplia gama de posibles datos previstos para los que todas las nuevas observaciones se sitúan dentro de intervalos de confianza del 95 %. Los datos de marcado, por su parte, permiten inferir movimientos no estimados por los modelos operativos. Sin embargo, no está claro si estas discrepancias de movimiento son importantes, sobre todo a la luz de análisis de sensibilidad anteriores que mostraron impactos muy limitados del movimiento en el desempeño del procedimiento de ordenación.

KEYWORDS

Management strategy evaluation, bluefin tuna, operating model, management procedure.

1. Introduction

In 2022, Atlantic bluefin tuna operating models were conditioned on a range of data including catches, indices, length compositions, electronic tagging, genetics and otolith microchemistry. Electronic tagging data were only available to 2018 (**Table 1**) and genetics stock of origin data were only available to 2016 in sufficient frequencies to be used in conditioning. In this paper the new data are checked for consistency with operating model predictions and estimated dynamics. New observations of genetics stock-of-origin data (2017 - 2020) are compared to posterior predicted data from the reference set of operating models. Similarly, new observations of electronic tag tracks up to 2022 (**Table 2**) are compared to the movement estimated by the reference set operating models.

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2. Methods

2.1 Genetics Stock of Origin Data

In their raw form, genetics stock of origin (SOO) data are provided as individual 'assignment' scores per fish. These individual assignments can be difficult to interpret because, for example, fish from the Mediterranean that are thought to be eastern fish often have individual assignment scores less than 100% eastern. Similarly, fish from the Gulf of Mexico that are thought to be western fish have individual assignment scores that are greater than 0% eastern. To solve this problem, Carruthers and Butterworth (2019) characterized distributions of individual assignments in the Mediterranean (eastern) and Gulf of Mexico. They then used a mixture-modelling approach to calculate the fraction of eastern fish that would best explain the distribution in individual assignments scores in mixed areas. These derived SOO data could then be compared with model predictions of stock mixing (logit fraction of Eastern fish caught) via a Gaussian likelihood function in operating model conditioning. The only limitation of this approach was that at least 5 individual observations were necessary to do the mixture model calculation of the derived SOO.

At the time of conditioning, genetics stock of origin data were only available up to 2016, and hence the mixture modelling approach worked from Eastern and Western signatures in the Mediterranean and Gulf of Mexico for data up to 2016. In this analysis, the same signature data to 2016 were used to provide a mixture model estimate of fraction eastern fish, and in this way the new derived SOO data are calculated from the same assumptions as the data used in conditioning.

To compare the new derived SOO data with reference grid operating models requires posterior predicted data for the seasons, areas and years for which there are new data. Posterior predicted data were generated by first characterizing the logit standard deviation σ, among model predicted fraction eastern *G*, and historical derived SOO observations $\hat{G}$, for each operating model *OM*, season *s*, age class *a*, and spatial strata *r*:

$$\sigma_{OM,s,a,r} = \sqrt{\frac{\sum_{y=1}^{n_y}\left(G_{OM,s,a,r,y} - \hat{G}_{y,s,a,r,OM}\right)^2}{n_y - 1}} \quad (1)$$

where *G* is the logit fraction of eastern fish caught:

$$G_{OM,i,s,a,r,y} = ln\left(\frac{f_{OM,s,a,ry}}{1 - fp_{OM,s,a,ry}}\right) \quad (2)$$

and the fraction *f*, is calculated by numbers of eastern and western fish caught *C*:

$$f_{OM,i,s,a,ry} = \frac{C_{OM,s,a,r,y}^{Eastern}}{C_{OM,s,a,r,y}^{Eastern} + C_{OM,s,a,r,y}^{Western}} \quad (3)$$

Posterior predicted data G^{PPD}, for multiple simulations *i*, could then be generated by adding Gaussian observation error ϵ, to operating model estimates of *G*:

$$G_{i,OM,s,a,r,y}^{PPD} = G_{OM,s,a,r,y} + \epsilon_{OM,i,s,a,r,y} \quad (4)$$

where

$$\epsilon_{OM,i,s,a,r,y} \sim N\left(0, \sigma_{OM,s,a,r}\right) \quad (5)$$

2.2 Electronic tagging data

For conditioning operating models, electronic tag tracks were divided up into seasonal transitions from one spatial strata to the same or other spatial strata. For example, 10 eastern tags in the North East Atlantic on age class 3 fish in the second season were redistributed in the third season such that 4 tags remained the North East Atlantic, 1 tag migrated to the West, 2 tags to the South Atlantic and 3 tags to the Mediterranean (fractions of 40%, 10%, 20%

and 30%, respectively). These observed fractions were compared with model predicted movement of eastern fish of age class 3 from the North East area between seasons 2 and 3. A multinomial model was used in conditioning and therefore the variance depends on the number of observed tags in that particular seasonal transition.

The new data (**Table 2**) were included (as before) only if a tag had previously entered a natal area (Mediterranean/Gulf of Mexico) and was of known stock of origin. As before tracks were assigned a seasonal spatial strata based on the spatial strata that the tag spent the most days in.

Model predicted transitions were generated for each simulation *i*, by taking model transition probabilities for a stock *p*, of age class *a*, from a spatial strata *r*, to a spatial strata *k*, and applying a multinomial error structure based on the number of observed tags n_t:

$$T^P_{OM,i,p,a,r,k} = \frac{\hat{T}^P_{OM,i,p,a,r,k}}{\sum_{k=1}^{n_k} \hat{T}^P_{OM,i,p,a,r,k}} \quad (6)$$

Where $\hat{T}$ is a stochastic sample of tag transitions based on the number of observed tags n_t in that transition:

$$\hat{T}^P_{OM,i,p,a,r,k} \sim multinom(\Delta_{OM,i,p,a,r,k}, n_{t,p,a,r}) \quad (7)$$

This approach accounts for the biggest source of variance in these data: the number of tag involved in the transitions. This is not comparable to the calculation of posterior predicted data for the genetics SOO data and the indices of abundance where observation error is based on the fit of the model to the data. In this evaluation of the e-tagging data the predicted distributions are therefore likely to be overly precise.

3. Results

3.1 Genetic Stock of Origin

The operating model fit to the genetic stock of origin data is generally poor and hence a high degree of observation error is included in the simulation of posterior predicted data (**Figures 1a** and **1b**). The high variance in the posterior data ensures that all of the new observations (these are the estimates of the mixture model) lie within the 95% interval of the posterior data (**Figure 2**).

3.2 Electronic Tags

Unlike the genetics stock-of-origin, the new tag transition data were unlike model predictions (outside of the 95% interval) in 12 of 52 cases (23%) (**Figure 3**).

4. Discussion

It is not surprising that newly collected genetics stock of origin data are all withing the 95% interval given the very high variance of these simulated data (due to poor operating model fit to these data).

By comparison, the posterior distributions of tag releases are likely to be overly precise – they were generated from the observation error of the data (given the number of tags involved in the transition from a spatial strata and season) and do not include error from the mismatch between observations and model predictions (as is standard for exceptional circumstances protocols and was applied to indices and the genetics stock of origin data). It is worth noting that in previous sensitivity analyses, MP performance was found to be very insensitive to a wide range of alternative movement scenarios.

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References

Carruthers, T. and Butterworth, D.S. 2019. A mixture model interpretation of stock of origin data for Atlantic Bluefin Tuna. Collect. Vol. Sci. Pap. ICCAT, 75(6): 1363-1372 (2019)

Table 1. Details of the electronic tags available at the time of OM conditioning

Group	*n tags*	*From*	*To*	*Areas*
AZTI	20	2005	2011	E_ATL SE_ATL SC_ATL NC_ATL W_ATL NE_ATL
DFO	89	2009	2018	W_ATL NC_ATL NE_ATL CAR GSL SC_ATL SE_ATL GOM E_ATL
DFO-ACADIA	37	2010	2010	GSL W_ATL CAR GOM SC_ATL
DFO-Duke	15	2007	2008	GSL W_ATL CAR GOM SE_ATL W_MED
GBYP	176	2011	2017	SE_ATL W_MED E_ATL E_MED
GBYP-Unimar	40	2007	2015	E_MED W_MED SE_ATL E_ATL NE_ATL
IEO	13	2001	2001	SE_ATL E_ATL NE_ATL W_MED NC_ATL
IFREMER	47	NA	NA	W_MED SE_ATL E_ATL character(0)
LPRC	316	2002	2015	W_ATL GSL SC_ATL NC_ATL CAR GOM E_ATL SE_ATL W_MED
NOAA	31	2010	2013	GOM CAR W_ATL GSL
Stanford	391	1996	2015	W_ATL CAR SC_ATL SE_ATL GOM NC_ATL E_ATL NE_ATL W_MED GSL
UCA	46	2009	2011	W_MED SE_ATL E_ATL NE_ATL
WWF	86	2008	2015	W_MED SE_ATL E_ATL NE_ATL NC_ATL SC_ATL W_ATL E_MED

Table 2. Details of the newly available tags

Group	*n tags*	*From*	*To*	*Areas*
GBYP	136	2017	2022	S_ATL E_ATL N_ATL W_ATL GSL W_MED GOM E_MED
GBYP/WWF	4	2016	2018	W_MED
IFREMER	13	2018	2021	W_MED E_MED S_ATL E_ATL N_ATL
Stanford	42	2002	2018	GOM W_ATL W_MED GSL N_ATL S_ATL E_ATL E_MED
WWF	1	2013	2013	S_ATL W_MED

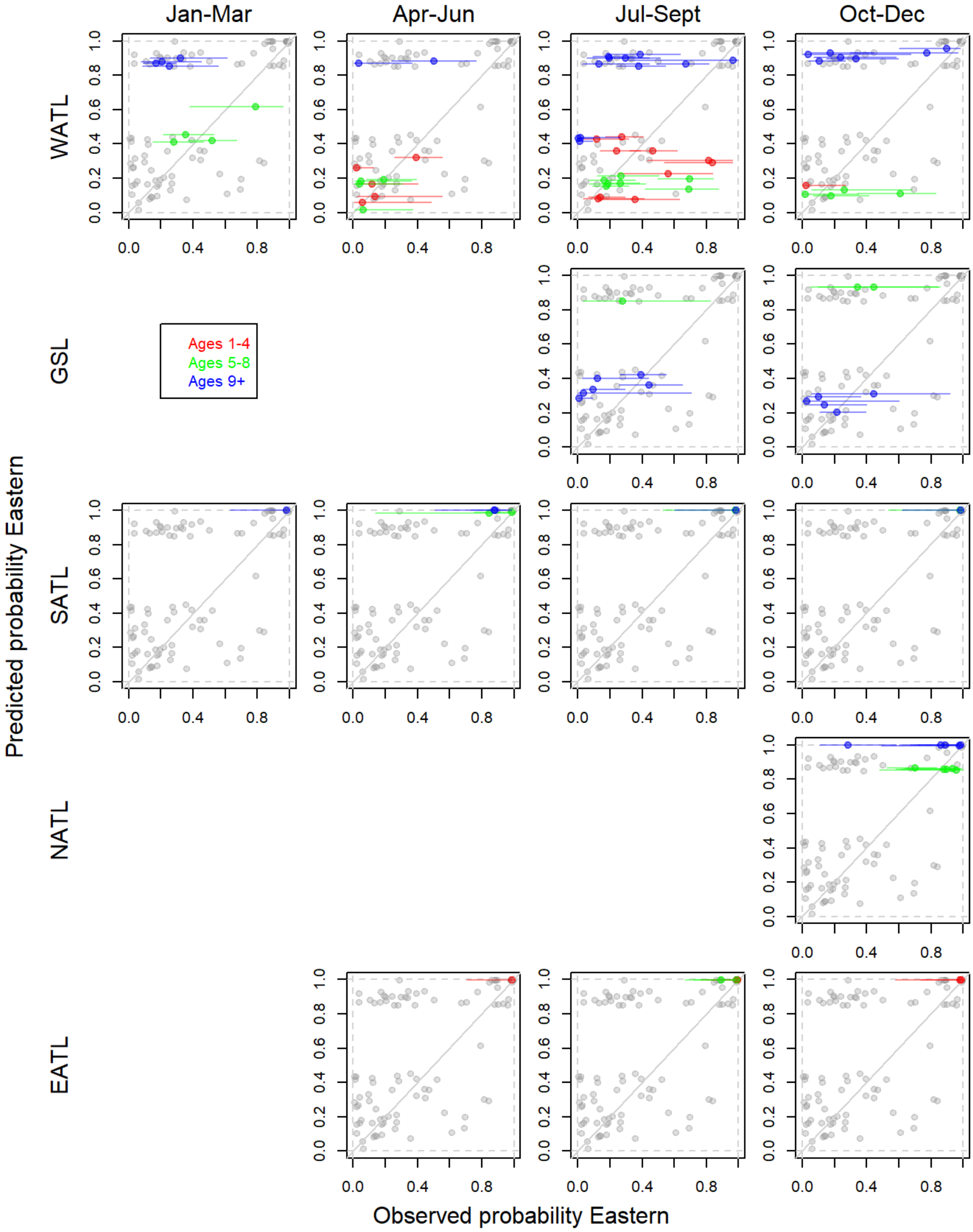

Figure 1a. The fit of the reference case operating model (OM_1) to the genetics stock of origin data. Horizontal bars represent the precision of the observations and are the 90% confidence interval.

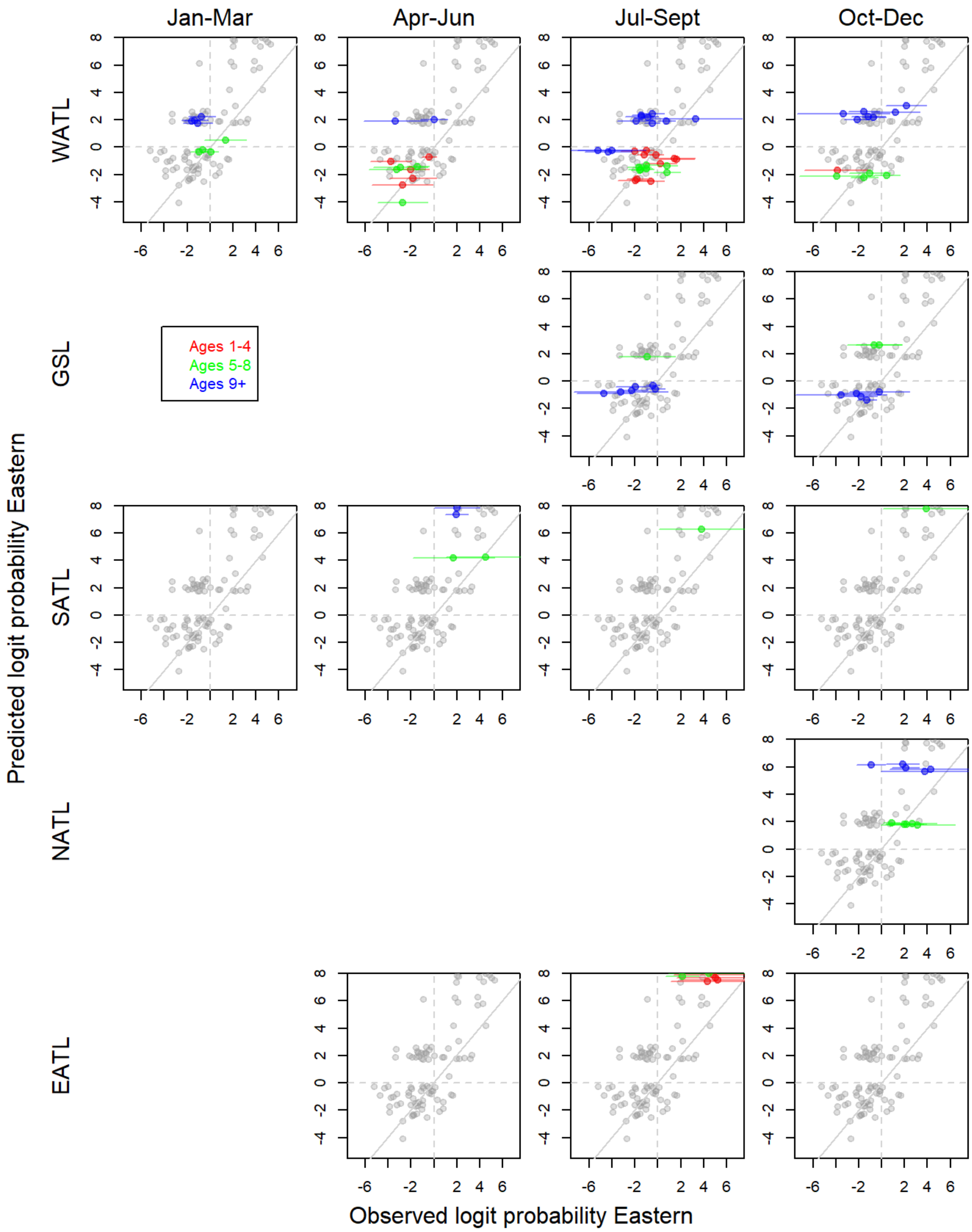

Figure 1b. The fit of the reference case operating model (OM_1) to the genetics stock of origin data phrase as a logit probability (**Figure 1a** is the same data plotted as the probability). Horizontal bars represent the precision of the observations and are the 90% confidence interval.

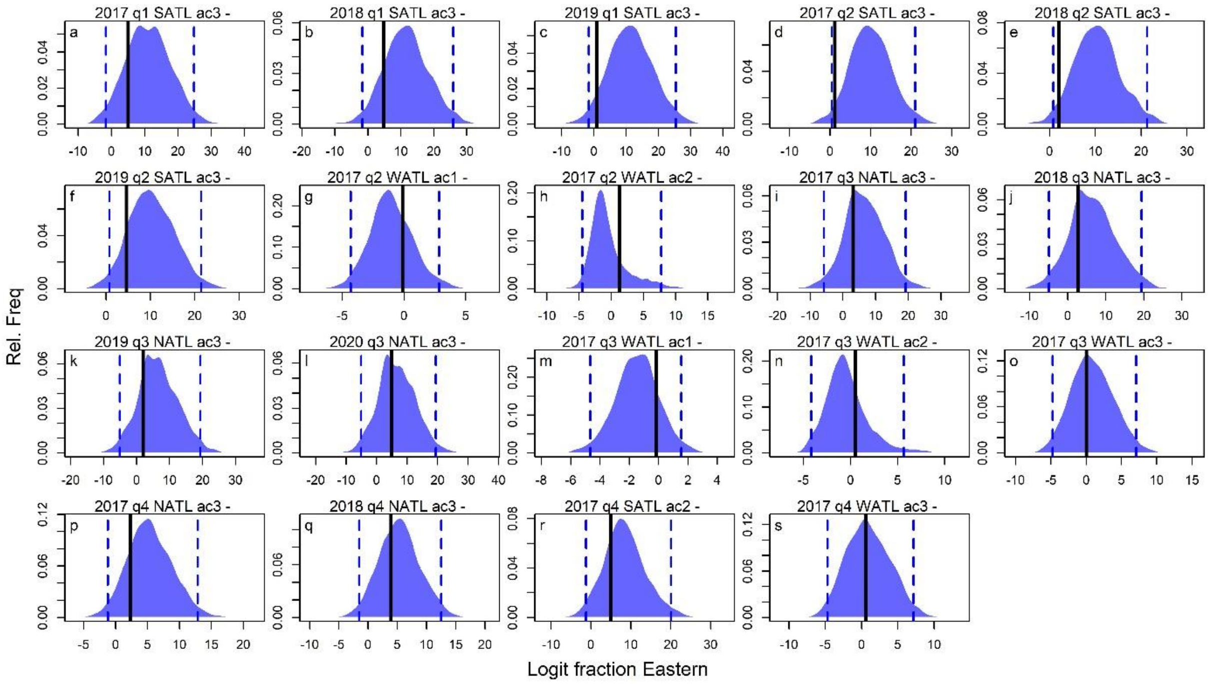

Figure 2. Mixture model estimates (observations, solid vertical line) and posterior predicted distributions of stock of origin (G^{PPD}) from the reference set of operating models (blue distributions). The vertical dashed blue lines represent the 95% interval of posterior predicted data. Observations that are within the 95% interval are coloured black, those outside are coloured red. Observations and posterior predicted data are reported for specific years, quarters, spatial strata and age classes. For example, panel a provides observations and posterior predicted data for the first quarter (q1: January – March) of 2017 for the South Atlantic spatial strata (SATL) age class 3 (ac3). Age classes 1, 2 and 3 consist of ages 1-4, 5-8, 9+, respectively.

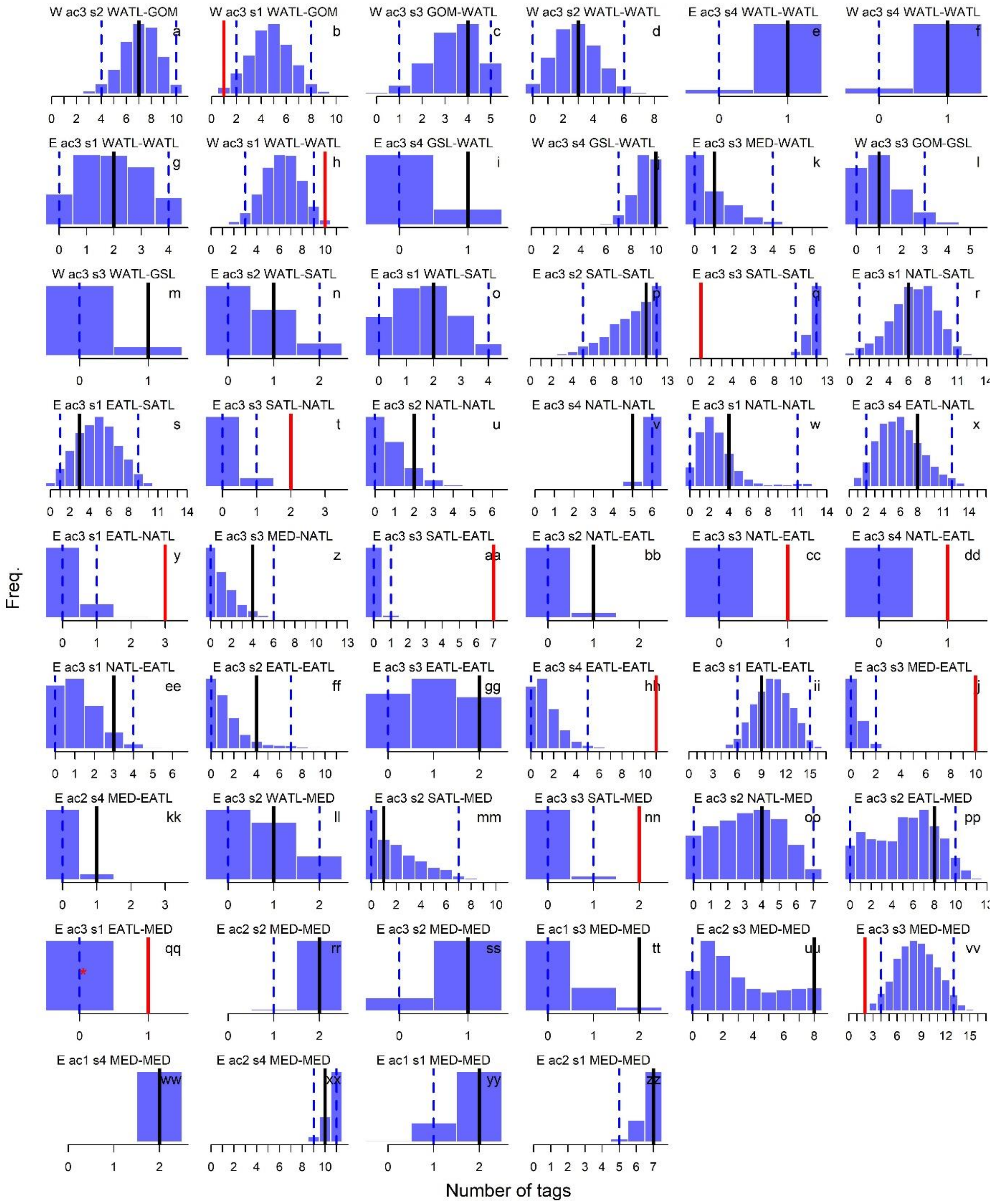

Figure 3. Observations of new electronic tag transitions (**Table 2**) (solid vertical line) and model predicted transitions (T^P) from the reference set of operating models (blue histograms). The vertical dashed blue lines represent the 95% interval of posterior predicted data. Observations that are within the 95% interval are coloured black, those outside are coloured red. Tag transitions are reported by known stock of origin, age class, season and the transition from an spatial strata into a spatial strata in that season. For example panel a shows the model predicted distribution of tags for the Western stock (W) of age class three (ac3) moving in season 2 (s2) between the West Atlantic and the Gulf of Mexico (WATL-GOM). In one instance (panel qq), OMs were conditioned assuming zero movement because to that date no conventional or electronic tag had been observed for this particular transition (red asterisk). Note that these predicted data are not comparable to the calculation of posterior predicted data for other data types where observation error is based on the fit of the model to the data. In this case, precision of the predicted data is based on the sample size of the observed data (the number of observed tags).