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USING ELECTRONIC TAG DATA TO PROVIDE TRANSITION MATRICES FOR MOVEMENT INCLUSIVE POPULATION MODELS

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SUMMARY

We present a telemetry based method for simulating individual based movements, with a demonstration applied to Atlantic Bluefin tuna in support of operational modeling and spatially explicit stock assessments. The simulation model uses parameters derived from movements and positional uncertainty from groups of tagged individuals. We present the method and example output using a subset of the Large Pelagics Research Center (UMass Amherst) database of fish tagged off the Canadian Maritimes. Movement matrices that are constructed from size based simulations may be used directly in operational models already in use. Inclusion of tagging data from recent Eastern Atlantic and Mediterranean tagging efforts would facilitate mixing rate comparisons and provide a more robust estimate of population based movement metrics for stock assessment use.

RÉSUMÉ

Nous présentons une méthode reposant sur la télémétrie servant à simuler les mouvements des spécimens, illustrée en l'appliquant au thon rouge de l'Atlantique en appui à la modélisation opérationnelle et aux évaluations de stocks spatialement explicites. Le modèle de simulation utilise des paramètres calculés sur la base des mouvements et de l'incertitude entourant la position des groupes de spécimens marqués. Nous présentons la méthode et un exemple de résultat utilisant un sous-ensemble de la base de données du centre de recherche sur les grands pélagiques (UMass Amherst) de poissons marqués au large des eaux des provinces maritimes canadiennes. Les matrices de mouvement élaborées à partir des simulations reposant sur la taille peuvent être utilisées directement dans les modèles opérationnels déjà utilisés. L'ajout des données de marquage réalisé dans l'Atlantique Est et en Méditerranée faciliterait les comparaisons des taux de mélange et fournirait une estimation plus solide des métriques des mouvements de la population à des fins d'évaluation des stocks.

RESUMEN

Se presenta un método basado en la telemetría para simular los movimientos de los ejemplares, con una demostración aplicada al atún rojo del Atlántico para apoyar la modelación operativa y las evaluaciones de stock espacialmente explícitas. El modelo de simulación usa parámetros derivados de los movimientos y de la incertidumbre posicional de grupos de ejemplares marcados. Se presenta el método y los resultados del ejemplo usando un subconjunto de la base de datos del Centro de investigación de grandes pelágicos (UMass Amherst) de peces marcados en las pesquerías marítimas de Canadá. Las matrices de movimiento construidas a partir de simulaciones basadas en la talla podrían utilizarse directamente en los modelos operativos que ya se están usando. La inclusión de datos de marcado de los recientes esfuerzos de marcado en el Atlántico este y el Mediterráneo facilitaría las comparaciones de la tasa de mezcla y proporcionaría una estimación más robusta de la medición de los movimientos de la población para su uso en evaluaciones de stock.

KEYWORDS

Simulation, Movement, Stock assessment, Electronic tags, Bluefin tuna

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Introduction

Atlantic bluefin tuna are managed as separate eastern and western stocks (Anon. 2013), but tagging data, genetic, stable isotope and chemical tracer studies suggest that potentially significant mixing exists between these stocks. Failing to account for this mixing could lead to a biased view of stock status and have significant ramifications on the management of the species.

Modeling efforts by managers and researchers have attempted to account for mixing in various ways. Porch (2003) developed the 2-box VPA model, which allows for movement between stocks, and is the current model used by ICCAT to assess the two stocks. The most recent assessment did not, however, include mixing as an input (Anon. 2013). A fully integrated, multi-stock statistical catch at age model (MAST) was developed by Taylor *et al.* (2011) and was built to include conventional and electronic tagging data as well as isotopically assigned natal origin information. The model had convergence issues and difficulty estimating confounded movement parameters, but highlighted areas in which assessment of bluefin tuna (and other species) could be improved.

Management strategy evaluation (MSE) is a priority for Atlantic bluefin tuna management within ICCAT (ICCAT Workshop on Stock Assessment Methods, July, 2014) and a key component towards this is incorporation of an operational model. Kerr *et al.* (2012) developed an operational model, based on the MAST framework, that simulates spawning stock biomass in a spatially explicit fashion under differing assumptions of fishing mortality and other parameters. Movement parameterization was in the form of Markovian state transition matrices where portions of the population moved seasonally between a set of areas (states). Kerr at al.'s (2012) model used movements estimated from MAST, using both bulk transfer and gravity based estimates as alternative operating models for simulation. Each of these estimation methods has drawbacks: Bulk transfer, in which all off-diagonal matrix cells (i.e., transfer coefficients from one area to another) are estimated, made convergence difficult for MAST while the gravity method, in which an 'attraction' coefficient is estimated for each area to derive residence, and movement is derived from relative attraction of other areas in that season, is not realistic.

Empirical information from tagging studies has often been cited as being useful towards stock assessment, and the efforts to date have been split among two camps: Those that seek to use electronic tag data for mortality and/or movement estimation (Miller and Andersen 2008, Eveson *et al.* 2012, Whitlock *et al.* 2012) and those designed to scale individual movements to population levels (Sibert *et al.* 1999, 2006, Sibert and Fournier 2001). In particular, Sibert (2006) showed that advection diffusion population simulations, based on the movement of groups of tagged individuals, may be used to compare distribution in different time periods.

We developed a telemetry based simulation method to parameterize movement in a biologically realistic manner, and to alleviate estimating problems encountered using MAST or the potential biases involved in estimating movement from fishery recaptures of conventional tags. We draw upon a large database of movement information from electronically tagged Atlantic bluefin tuna and introduce a framework which may be used to examine mixing between eastern and western Atlantic bluefin tuna stocks, be input directly into operational and spatially explicit assessment models, and be broadly applicable to other electronic tagging studies and spatial strata.

Methods

Large Pelagics Research Center (UMass Amherst) scientists have tagged over 600 Atlantic bluefin tuna since 1997 in the NW Atlantic with single point and archival pop-up satellite tags and implanted archival tags. While these data contain a wealth of ecologically important information, most fish were tagged opportunistically during summer and fall months and, although the data collection mission was usually 10-12 months, tracks typically had durations of 3-6 months (**Figure 1**). This dataset has a gap in the yearly migration cycle, in which much less information is available for spring and early summer months, compared to fall and early winter months. However, the wide size range tagged (70-300 CFL) and total duration of the LPRC tagging campaigns does make size based and interannual comparisons possible. Tracks from these efforts (n = 242) were estimated using state space Kalman filter methods (Sibert *et al.* 2003, Nielsen and Sibert 2007), including sea surface temperature and bathymetry when available (Lam *et al.* 2008, 2010, Galuardi *et al.* 2010). We use a subset of the overall tagging database (n = 49) as an example of the method. We use tracks from tagged fish > 185 CFL (the commercial limit in the U.S.) and where fish that were at liberty at least 180 days (**Figure 2**).

Raw data, processed tracks, temperature, and depth records are stored in a Microsoft Access relational database (Tagbase) built for electronic tagging records (Lam and Tsontos 2011). We used the analyzepsat package for R (Galuardi 2010) and RODBC package (Ripley and Lapsley 2013) packages for the R statistical language (R Core Team 2014) to query Tagbase and build data structures.

The statistical framework of state space Kalman filters, commonly used for light based geolocation of electronically tagged fish, are extensible towards population level inference (Sibert *et al.* 1999, 2006, Nielsen 2004). Our simulation framework utilized a correlated random walk, parameterized as an advection diffusion (u, v, D) process, similar to that used in Sibert et. al (2006).

$$\alpha_i = \alpha_{i-1} + c_i + \eta_i;\ i = 1, \ldots t_k$$

$$c_i = \begin{pmatrix} u \\ v \end{pmatrix}$$

$$\eta_i = N\sim(0, Q_i)$$

$$Q_i = \begin{pmatrix} 2D_t & 0 \\ 0 & 2D_t \end{pmatrix}$$

Daily position was updated according to the previous time step, plus correlation (c_i), and error (η_i). Advection (u, v) and diffusion parameters (D) make up the correlative and error components respectively.

Use of Kalman filter estimated tracks as a starting point offers an advantage in that the tracks already contain position and uncertainty information from both process and observation. Using these, we calculated u, v and D for groups of tracks in the following manner: For u and v, tracks were deconstructed into longitudinal (u) and latitudinal (v) components and produced weighted mean and variance, summarized by month (**Figure 3**). Since the final error of the estimated tracks is a statistical estimate, incorporating the diffusive component of the process equation and observation error, these error estimates (**Figure 4**) represent a close proxy to a daily diffusion. To obtain D, utilization distributions for groups of tags were constructed within each month, and total area calculated (nm^2) within the 95% utilization was calculated. Finally, using the number of individuals and days represented, a weighted mean and variance of D for that month was produced. Since not every fish was at liberty every month, a global mean and variance from the overall dataset was used for months where no fish were at liberty. In our example this was not necessary but investigation using smaller subsets showed this to be a necessity. **Table 1** summarizes parameter values for this example.

We simulated 100 tracks, originating along the coast of Nova Scotia in September, for two years each (720 days for simplicity). The fish in our demonstration were tagged primarily in this area and season. A modified version of the ETOPO 1 minute bathymetry (Amante and Eakins 2009) was used to avoid land in the simulations. Depth values at each step either accepted the point as being in water, or rejected it as being on land. Since a primary motivation was to build a framework to benefit Kerr *et al.*'s (2012) operating model, we widened the straits of Gibraltar, Florida and the St. Lawrence channel to allow simulated fish simplified access to all spatial strata (**Figure 5**).

Markovian matrices, have been typically used in movement inclusive population models (Miller and Andersen 2008, Taylor *et al.* 2011, Eveson *et al.* 2012),

$$\begin{pmatrix} \boldsymbol{a_1^1} & \cdots & \boldsymbol{a_1^n} \\ \vdots & \ddots & \vdots \\ \boldsymbol{a_n^1} & \cdots & \boldsymbol{a_n^n} \end{pmatrix}$$

In which fish move from areas (also termed states) at a previous time step ($\boldsymbol{a^1}$) to areas in a subsequent time period ($\boldsymbol{a_1}$). Rows in these matrices must sum to 1, representing proportions of all fish that moved from a previous area. Determination of a single occupied area for the given time step, therefore, is imperative when using the Markovian design. To achieve this we used the first area occupied in each time period as our criteria for area occupancy. Spatial overlays, common in geoprocessing, were used to assign individual locations to areas.

Transitions between time periods were achieved by summing transitions between subsequent time periods for the total simulated population and calculating proportions of the total for each time period. We used a seasonal division as a temporal component where Jan-March was winter, April-June was spring, July-September was summer and October-Dec was fall (i.e., the same seasons defined by MAST and the Kerr *et al.* 2012 operating model). We created shapefiles using Quantum GIS (QGIS Development Team 2009) and did all further manipulation and analysis in R (R Core Team 2014). An R package including all code for these steps is in development.

Results

We demonstrate the methodology of producing movement matrices for operational and assessment frameworks from electronic tagging data. Although analysis of the results from this example is preliminary, visualization of the simulated tracks and matrices highlight several aspects of this process are worth examination.

Seasonal utilization distributions (**Figure 6**) of simulated tracks showed realistic patterns compared to known distribution of adult bluefin tuna in the western Atlantic (Block *et al.* 2005, Walli *et al.* 2009, Galuardi *et al.* 2010). Core distributions (red colors) extended north into the Gulf of St Lawrence (area 2) in the summer season and progressed southward in the fall and winter. Core areas extended into the Gulf of Mexico (area 1) during the winter and spring months and were weak or non-existent in summer and fall months. The overall utilization pattern showed some excursion into the central Atlantic, from Greenland to Brazil. These were weak patterns not present in the observed tracks and are representative of the variability in the movement parameters.

Seasonal transition matrices (**Figure 7**) quantify the movement of the simulated fish between areas. Although the percentages are invariant of the number of individuals they came from (i.e. a transition of 50 out of 100 fish yields the same percentage as 1 out of 2), it is possible to discern when small or large numbers of individuals contributed to the transition. For example, in the fall panel, 100% of simulated fish from area 6 (the North Atlantic) stayed in area 6 from summer to fall. This was likely a single individual or transition and an anomalous pattern. In contrast, in the same panel, 88% of simulated individuals stayed in area 3 from the summer to fall while the remaining 12% were distributed among five other areas. Such precise estimates require many individuals or transitions.

The summer panel shows the presence of simulated fish in the Mediterranean (area 7) but no subsequent transition out of the Mediterranean is present in the fall panel. This situation may arise when, in a multi-year simulation, a transition to a distinct area occurs in the last season simulated. Our simulated fish originated in the northwest Atlantic and acted according to movement parameters from tagged fish originating in the same area. The LPRC dataset contains only a single individual which entered the Mediterranean, and our simulated fish, when taken in aggregate, show a similar pattern.

Discussion

We demonstrate a straightforward, individual based simulation method for producing fishery-independent movement matrices from electronic tagging data which are applicable for spatially explicit operational and assessment methodologies. The derivation of movement parameters from state-space estimated fish tracks is a practical application that makes use of the observed movements of fish in the wild, and makes no prior assumption on where fish may or may not occupy at particular times of year or life stage. There are several points regarding the method in general, and to the Atlantic bluefin tuna example in particular, which should be noted.

The approach described here is applicable to any spatial structure. We used the 7-box spatial structure from Kerr *et al.* (2012), but the method may be easily applied to any structure desirable. We conducted a preliminary analysis using a 10x10 minute grid in the same manner, but visualizations are more difficult (126x126 matrices). However, numeric input, and results for a model subject to this type of spatial framework (i.e. SS3) are easily obtained.

Large datasets are useful, but small, fully representative datasets may be more revealing. For example, we found that a few, yearlong tracks yielded more information than large numbers of shorter duration tracks. The tracks used for simulation should represent the majority of movement patterns for the strata examined, and, ideally, should cover all months. It is conceivable that the temporal division for parameter derivation could be simplified, for example, to a seasonal representation, but it is likely that simulated fish would not exhibit the true range of movement patterns and movement matrices would be oversimplified (oversmoothed).

The simulation example could be more realistic with the addition of a temperature constraint or likelihood surface. In general, Atlantic bluefin tuna have the widest temperature range of any tuna, but they generally do not spend much time in temperatures above 28^{o}C or below 5^{o}C (Mather *et al.* 1995). A quick comparison of our full dataset (242 tracks) to sea surface temperature climatology showed less than 5% of positions were above 28^{o}C or below 5^{o}C. Implementation of a simple constraint similar to the bathymetric constraint is underway and should yield better informed movement matrices in the future.

Our example using a western Atlantic bluefin tuna dataset demonstrates the method for movement matrix derivation and is a good first step towards better assessments through use of electronic tag data, but several data and operational issues should be addressed to optimize the approach. A primary challenge going forward is that the PSAT tags currently deployed on tunas have been slow to integrate new technology, are expensive and often fail to return the data expected (Musyl *et al.* 2011, Lam *et al.* 2014, Lutcavage *et al.* 2015).

Age considerations were touched upon in our example by using only large individuals. Movement matrices in the MAST and Kerr *et al.* (2012) models were age specific. Appropriate divisions of the LPRC tagging dataset are necessary to optimize estimation of age specific movement matrices. We used a single starting point (coastal Nova Scotian shelf), primarily for convenience, because most of the LPRC's tag deployments began close to this location. Simulations with variable starting points, both by individual and by time released, should be carried out. Likewise, we simulated 100 fish for 2 years but either of these factors may be increased or isolated for performance metrics. Considering the spatial variability inherent in our advection diffusion framework, varying the length of groups of simulations may be more informative than simulating large numbers of individuals. For example, a simulation framework could provide movement parameters that change as the fish ages.

An additional utility of using simulated data is that variance estimates of the transitions may be calculated. This could be accomplished by multiple runs of the same number of individuals released at different locations but moving according to common parameters. These results could be useful towards input as priors in an assessment model and thereby allow some tradeoff between movement and other aspects of the model dynamics (e.g. stock composition). Adjusting the spatial structure can also allow ecologically based examination, for example, testing the effects of biogeochemical regions (Longhurst 1995) on Atlantic bluefin tuna population dynamics.

The most important improvement which can readily be made is the inclusion of electronic tagging information from the Eastern Atlantic. Recently, researchers have successfully tagged dozens of fish with increasing success. These include juvenile fish in the Bay of Biscay (Arregui *et al.* in prep), adult fish released from traps off the Moroccan (Quilez-Badia *et al.* 2013b) and Spanish coasts (Aranda *et al.* 2013), the Gulf of Lyons (Fromentin and Lopuszanski 2013), Balearic Islands and Adriatic Sea (Quilez-Badia *et al.* 2013a). These efforts cover much of the known range of bluefin tuna in the Eastern Atlantic and Mediterranean, and show some interesting developments in terms of movements to historically important fishing grounds (e.g. North Sea) as well as trans-Atlantic migrations at multiple life stages. Constructing movement matrices with this information will create the most robust movement estimation tool to date and allow many more avenues to be explored including mixing rates and potential for movement parameter switching based on encounter rate, season, area etc. Lastly, we note that since our movement matrices are a derived product from estimated tracks of electronically tagged fish, they do not supersede empirical information towards directed ecological studies.

We present a method to use telemetry information to inform population dynamic analyses which is flexible and extensible, and may be used in any fishery where electronic tags are deployed. Using a simulation based framework to generate *a priori* movement matrices augments the information from fish with relatively short tracks, reduces bias from opportunistic deployments and should ease parameter estimation load in subsequent operational and assessment modeling frameworks . We will continue to develop and refine these methods towards an open source R package.

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Table 1. Parameter values for tagged bluefin >185cm & >180 days at liberty. Units for *u*, *v* and *D* are nm/day nm^2/day, respectively.

Month	*u*	*v*	*D*	*sd.u*	*sd.v*	*sd.D*
Jan	1.50	-2.49	3555.93	13.25	8.39	3602.31
Feb	-0.48	-1.14	4122.80	17.64	8.06	4442.45
Mar	-2.20	-0.17	6710.12	16.08	10.89	9136.68
Apr	2.03	5.32	6130.54	16.36	7.42	6838.56
May	6.25	1.80	5053.55	22.83	9.91	6520.53
Jun	8.93	6.16	8242.53	31.33	16.99	6779.22
Jul	-4.00	6.84	4526.04	19.84	13.78	5130.74
Aug	0.82	-1.34	1711.50	2.83	4.59	1687.10
Sep	0.90	0.93	3501.14	4.17	4.65	7265.62
Oct	-1.97	-4.51	3813.70	7.67	7.83	7274.15
Nov	-5.86	-8.22	3432.89	8.82	7.77	3605.00
Dec	-2.99	-3.78	3490.49	9.59	7.61	4443.35

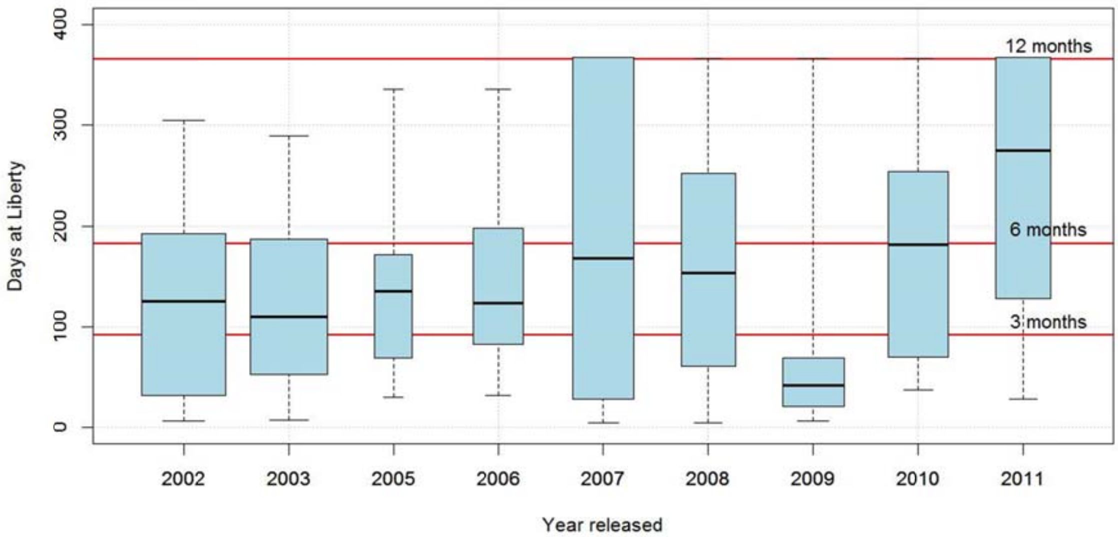

Figure 1. Days at liberty for 242 bluefin tagged with electronic tags. Width is proportional to number of tags within year.

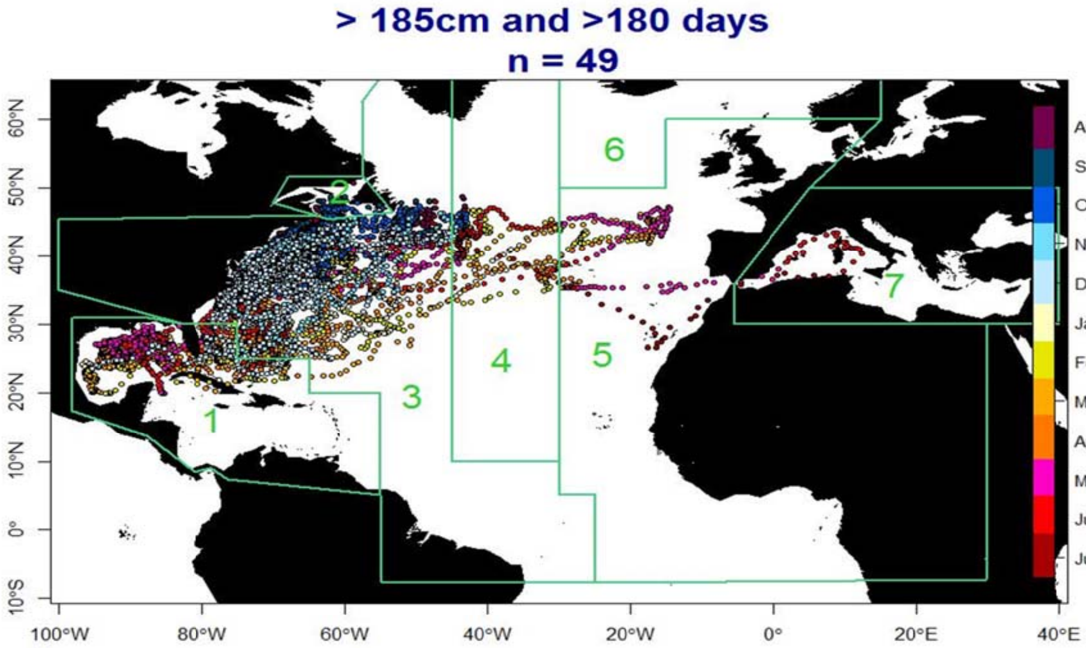

Figure 2. Subset of tagged Atlantic bluefin tuna used in the simulation example (n=49). Green lines and numbers represent the 7-box structure used in the Kerr *et al.* (2012) operational model.

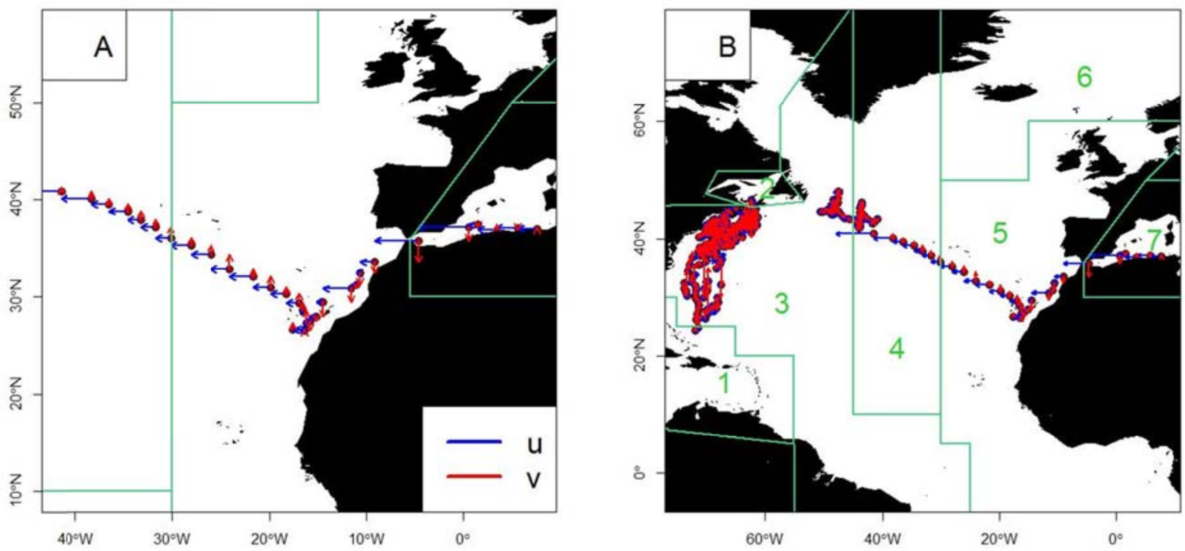

Figure 3. Advection deconstruction example for one fish (A), and many fish (B, n=20) for one month. Green lines and numbers represent the 7-box structure.

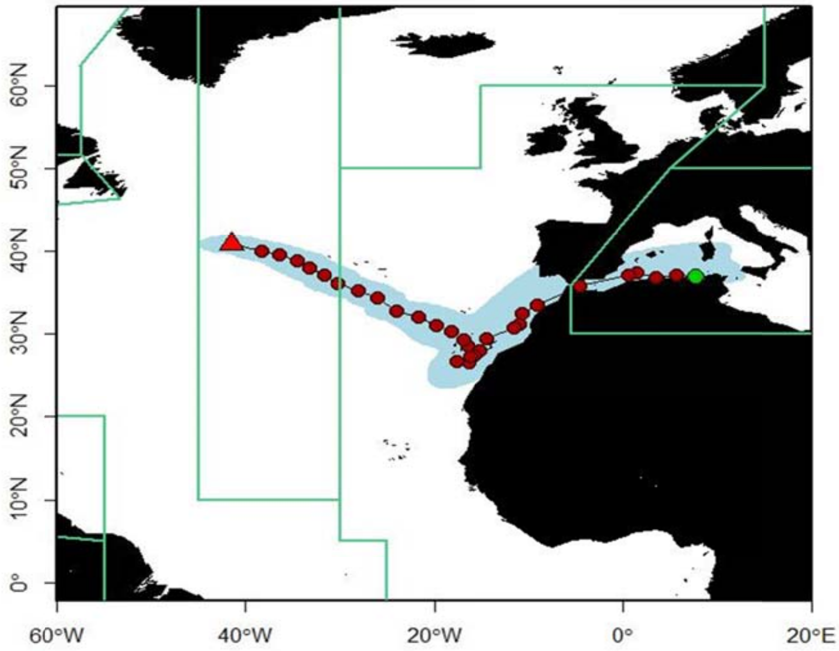

Figure 4. Utilization area (light blue) calculated from error estimates for one fish for one month, used for *D* determination. Green lines represent the 7-box. The green dot and red triangle represent start and end point, respectively, for this fish in this month.

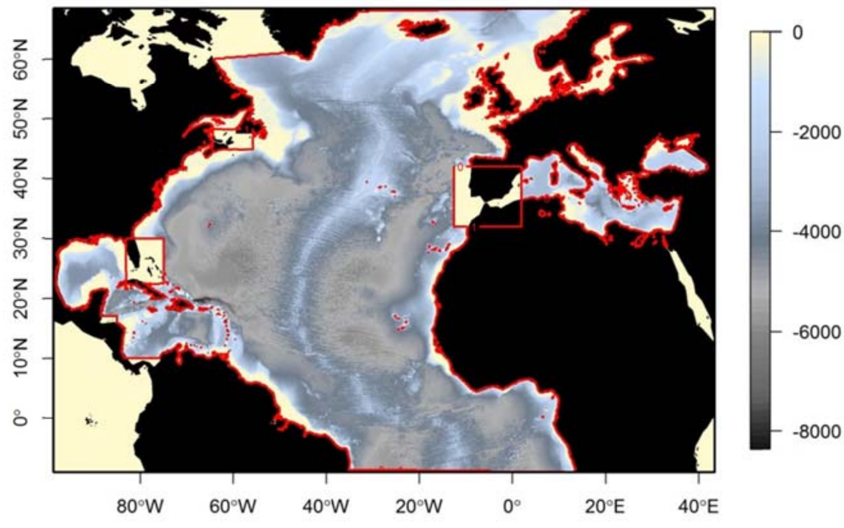

Figure 5. Modified Etopo1 bathymetry. Straits of Florida, Gibraltar and the Gulf of St. Lawrence have been widened (depth=0) while areas outside the 7-box operational framework have been flagged as land values (>0 depth). Depth range is in meters and red lines show the modified depth contours and boundaries.

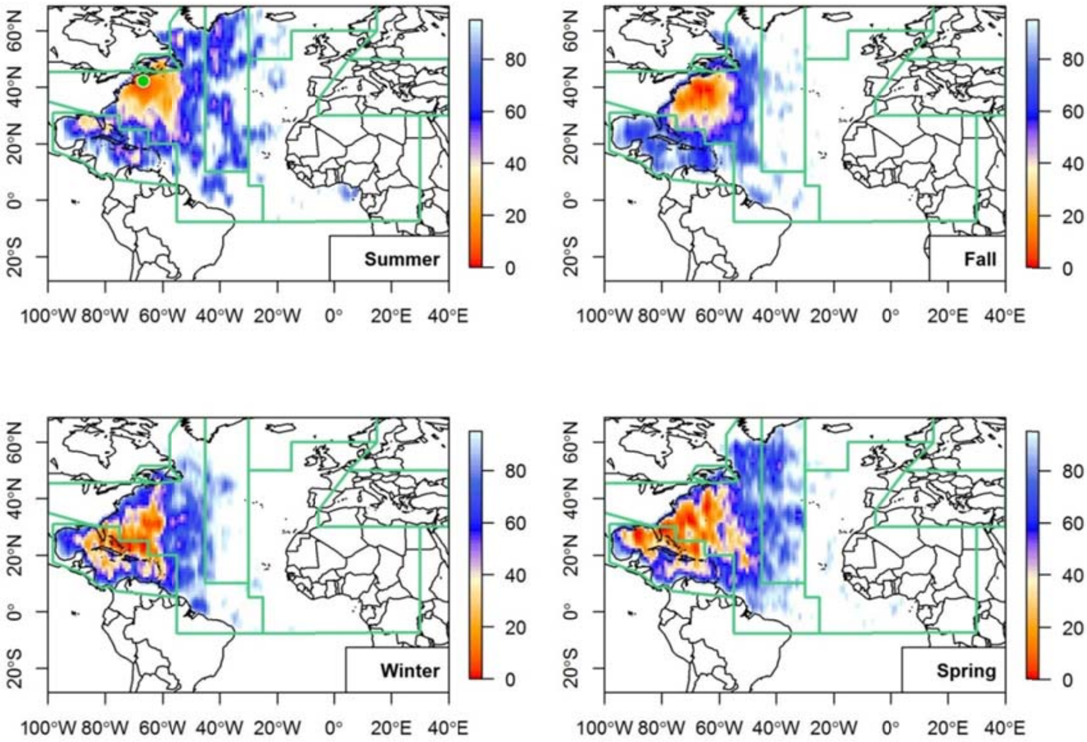

Figure 6 Seasonal utilization distribution (using a fixed estimate of error) of 100 simulated bluefin tuna, released off Nova Scotia (green dot, upper left panel), at liberty for 2 years. Colored bars represent percentage utilization and green lines represent the 7-box structure.

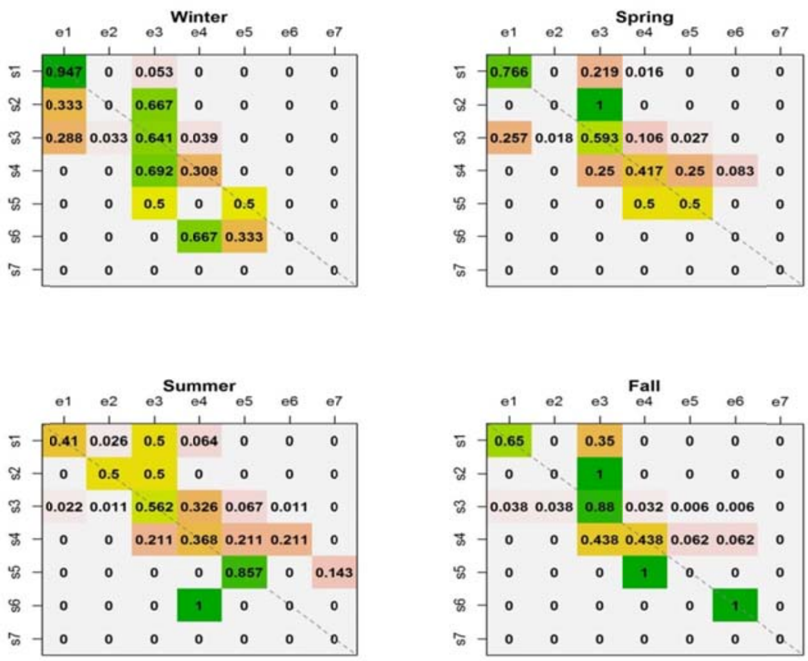

Figure 7. Seasonal transition matrices for simulated bluefin tuna. Row numbers represent occupied areas in the previous season and columns represent the current season. In this notation, s=start area, e=end area and number is the area as defined by the 7-box structure. Colors are conditioned on percentages to aid visualization.