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Methods for evaluating electronic tagging designs for southern bluefin tuna through spatial simulation

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Contents

1 Abstract

While conventional and genetic tagging studies are often based on statistical designs, electronic tagging studies are typically based on ad-hoc or budgetary constraints. Additionally, there are few examples detailing statistical approaches to inform the design of electronic tagging studies. This paper considers how to perform quantitative evaluation of electronic tagging deployments against specific study goals and given hypothesized changes in the extent of movement patterns. Using Markov models of movement, we estimate quarterly transition rates between spatial zones from historical archival tag data for SBT (N=149) spanning 1998 to 2010. As an illustration of the potential for design, these estimates were used to simulate data from four study design scenarios (three of archival tags and 1 design using Pop-up satellite tags). Additionally, we simulated data from a scenario where the movement rate between parts of the GAB doubled relative to historically observed levels. While these initial results would require much further exploration for an actual study design, this paper outlines a framework for a quantitative assessment of optimal electronic tag deployment to deliver robust insights on changes in movement.

2 Introduction

The movement of individual animals is widely recognised as a complex and highly variable process. Establishing the robustness of inferred patterns of movement from statistical descriptions presents significant challenges to researchers. This issue has been noted in the literature and significant effort has been expended on application of new statistical methods to characterise movement. What is less studied is the question of whether a given sample size of tagged individuals is sufficient to characterise movement or to detect changes in movement relative to past patterns.

Electronic tags (e-tags) have provided much information on the movements of southern bluefin tuna (SBT). Deployments of these instruments on SBT has allowed direct observation of the migration cycle of juvenile fish from the Australian surface fishery grounds (Basson et al. 2012; Patterson et al. 2018) as well as migration of sub-adult and adult SBT from the Tasman Sea wintering areas to spawning grounds south of Indonesia (Patterson et al. 2008; Evans et al. 2011).

While a lot has been learnt from SBT e-tagging research since its inception in the late 1990s, the current data set held by Australia is outdated. Large scale deployments of internal e-tags, such as the 'Global Spatial Dynamics of SBT' project (Basson et al. 2012), have not occurred since the early 2000s. Larger fish in the Tasman Sea were tagged slightly later (Patterson et al. 2008; Evans et al. 2011), and deployments occurred in the Australian recreational sector more recently (Tracey et al. 2016), but the majority of the collected data is now at least a decade old. Given changes over the past decade to both the SBT population and their habitat, it is questionable whether these historical data accurately represent contemporary movement patterns.

Over the past decade, the Australian surface fishery has shifted the spatial locus of operations eastward in the GAB in response to an apparent shift in the distribution of the targeted age classes of SBT (typically 2-4 years old). This has led to the Australian industry being interested in further e-tag deployments that would determine the extent of changes to the SBT movement patterns relative to those seen in the early-mid 2000s (Basson et al. 2012; Patterson et al. 2018). Understanding the extent of these changes is also important for researchers and managers because key inputs to the stock assessment and management procedure rely on data collected annually on juveniles in the GAB, i.e., genetic sampling for both the close-kin and gene-tagging projects. Gene-tagging, especially, assumes that sampled fish are mixing with the wider population, as suggested from past tagging studies.

While e-tags provide detailed information on movement (horizontal and vertical), the instruments themselves are expensive (~$1500-4000 USD[1] depending on the tag type) and given typical funding envelopes, it is rare that large numbers of tags can be deployed. Given the expense of tagging and the associated logistics, consideration of the appropriateness of particular tag types and size is required. Few electronic tag deployments have been formally designed—although methods to help guide tagging studies have been developed (e.g., Hartmann & Patterson 2011; Pagendam & Ross 2013; Patterson & Pillans 2018).

In this paper we present a spatial simulation method for evaluating the potential of different e-tag designs to answer specific questions about changes in SBT movement and distribution. In short, our method attempts to determine whether a particular "effect" size (e.g., a change in movement rates/residence) relative to historical baselines would be detectable for a given deployment of a specific type of tag.

We illustrate the method with a simple example investigating changes in movement patterns within the GAB, but the method could be used to investigate other questions (such as those related to the spatial contraction in effort in some areas of the longline fishery, and to changes in the east/west migration of juveniles when they leave the GAB). The method allows us to consider various size deployments of either internally implanted electronic archival tags (hereafter 'archivals') and externally implanted popup satellite tags (PSAT). The advantage of the former is that they collect detailed sensor information over a long period and, being surgically implanted in the viscera of the SBT, do not detach from the fish. The disadvantage of archival tags is that the fish needs to be recaptured and the tag returned—just as is the case for a standard dart tag.

PSATs solve the reporting issue by transmitting summarized data via global satellite networks after they detach from the fish and float to the surface. However, the downside is that typically PSATs remain attached for shorter periods of time. Additionally, since they transmit data via satellite, bandwidth limitations and battery power available for transmission means that summarized records must be transmitted. This means that the estimation of the movement path of the tagged fish is more uncertain relative to archivals. However, statistical approaches to estimation of movement paths (Basson et al. 2016, Pedersen et al. 2010; Braun et al. 2018) and the ability to assimilate data from satellite and ocean models into the movement estimation process means that this difference is less of a problem than it has been previously. Finally, PSATs are more expensive per unit (typically ~$4000 USD, compared to approximately ~$1500 USD for an archival tag).

[1] While costs for tags indicated in this paper are approximately correct based on purchases for previous deployments, these should nonetheless be taken as indicative guides. Final cost per unit may differ at the point of initiation of a potential project.

To use e-tags to address a particular question means evaluating the trade-offs between the various factors involved: the price differential between tag types, the probability of recapture and the expected duration of the data record. Added to these aspects is the complexity of the spatial dynamics of fish and whether any potential changes from historical patterns are large enough to be distinguished from natural variability. Fortunately, many of the tag-specific factors (e.g., expected life of a tag, probability of recapture in the case of archivals) can be estimated from previous deployments. But an optimal approach cannot be determined by simply considering each of these factors in isolation.

To address this, we used simulations of SBT movement combined with simulations of tag recapture (for archivals) or tag detachment (for PSATs). In what follows, the term "recapture" is used for archivals to refer to the process of a tag being recaptured in fishery operations and reported/returned, and for PSATs to refer to the process of a PSAT detaching itself and reporting summarized data, which is assumed to be almost 100% reliable. A key difference with PSATs compared to archivals, is therefore that the probability of “recapture” does not typically differ spatially or temporally.

3 Methods

Our proposed approach relies on previous data from juvenile SBT collected by CSIRO and collaborators to estimate movement rates between defined spatial units encompassing the observed juvenile distribution. This provides a historical baseline of movement rates which can then be artificially altered to generate synthetic data which may then be compared against the historical levels. We now provide description of the steps involved and associated statistical details.

3.1 Design study framework

The design approach proceeds as follows:

1. Define spatial regions based on prior knowledge/data of distribution, operation of fisheries, management units or other relevant factors.
2. Use previously collected e-tag data to examine movement patterns of SBT throughout an annual cycle and construct Markov transition matrices which capture the major features of this movement. Using a Bayesian estimation framework (see 3.3.1), we also characterise the posterior distribution of transition matrix entries.
3. Specify a tagging study design scenario based on type of tag, number of tags deployed, and distribution of deployments in space and time.
4. Simulate daily movements for each tag using the specified transition matrices. These may be the historical matrices estimated in step 1 or some modification thereof according to some hypothetical change in movement patterns.
5. Simulate the recapture process relevant to different types of tags.
6. Estimate updated transition matrices based on the simulated movement data for the recaptured tags.

7. Repeat steps 3-5 numerous times and calculate relevant summary statistics from the resulting transition matrices.

Steps 1-6 can then be repeated using transition matrices that have been altered to represent a change in movement dynamics. For example, we might adjust the transitions so that exit rates from state *i* to *j* are, say, twice the rate estimated from historical data. The summary statistics derived using these altered transition matrices can be compared with the original summary statistics to see whether the change could be detected under the study design scenario being assessed.

3.2 Spatial configuration

The first step in the process is to define spatial units (or "states"). In this case, our choices reflected the major residence zones of juvenile SBT as described in Basson et al (2012) and Patterson et al (2018). Accordingly, the spatial domain was divided into m regions as per Figure 1. These were based on qualitative examination of the SBT migration paths and consideration of potential changes to the movement patterns of juvenile SBT within and to/from the Great Australian Bight. In the movement model we used, only daily movements between adjacent states were allowed. Transitions to non-adjacent states were therefore set to zero.

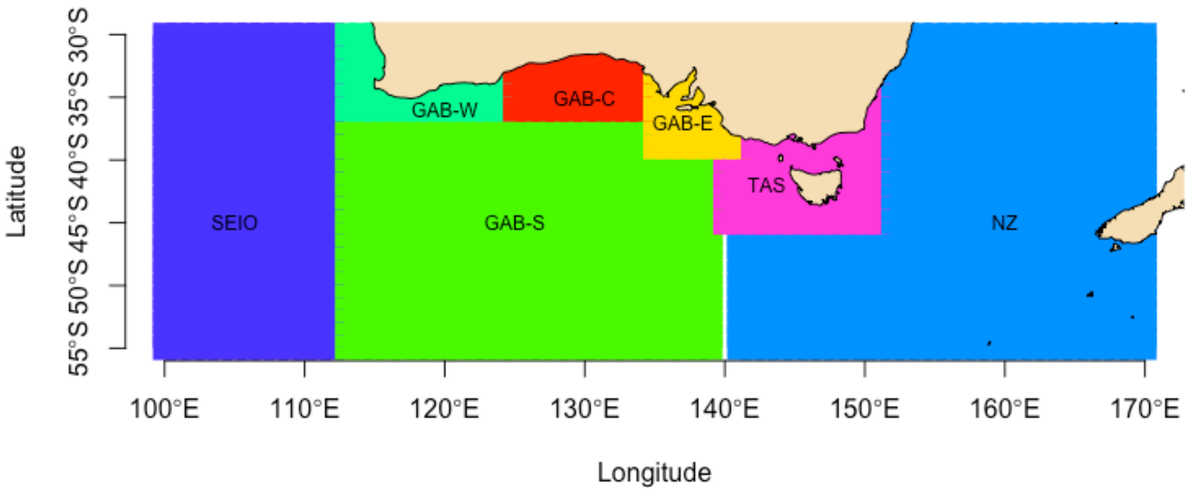


Figure 1. Map of the boundaries of the 7 spatial states used in the model. Twice daily position data from Patterson et al., 2018 was assigned to one of these based on daily location. Note that the western- and eastern- most states extend beyond the bound of the figure to encompass the full range of observed movements (see figures in Patterson et al 2018).

3.3 Markov model background

A discrete Markov chain (MC) describes transitions through time between a discrete set of m states, $S_t = s_1, \dots, s_m$. Here these states are spatial zones shown in Figure 1. The probability of movement from state i to j is assumed to only depend on the current state, i.e., $\Pr(S_t = i | s_0, s_1, \dots, s_{i-1} = j) = \Pr(S_t = i | S_{t-1} = j)$

The transition matrix $\mathbf{A}$ provides the probability of moving between states

$$\mathbf{A} = \begin{pmatrix} a_{11} & a_{22} & \dots & a_{1m} \\ a_{21} & a_{22} & \dots & a_{2m} \\ \vdots & & \ddots & \vdots \\ a_{m1} & a_{m2} & \dots & a_{mm} \end{pmatrix}$$

The first row in $\mathbf{A}$ gives the probability of moving from state 1 to all other states, the second gives the probability of moving from state 2 to other states, and so on. The sum of all entries in a row is equal to one, i.e. $\sum_{j=1}^{m} a_{ij} = 1$. Markov chains are termed irreducible if all states are reachable from all others in $n \geq 1$ transitions. If the chain returns to a particular state at regular intervals, it is said to be periodic; otherwise, it is aperiodic. Aperiodic, irreducible Markov chains are guaranteed to tend to a stationary distribution $\boldsymbol{\lambda}$ such that:

$$\boldsymbol{\lambda}\mathbf{A} = \boldsymbol{\lambda}$$

We now consider the specifics of the model used here.

3.3.1 Time-specific transition matrices

We assume here that within a given portion of the year, the transition matrices are stationary. In this case we can break the year into reasonable time periods q_τ (e.g., quarters or months) and within these we count the number of transitions from state $S_t = i \rightarrow S_{t+1} = j$ which we express as $N_{i \rightarrow j}$. Then, the maximum likelihood estimator of a stationary MC is:

$$\Pr(S_{t+1} = j | S_t = i, t \in q_\tau) = \frac{N_{i \rightarrow j}}{\sum_{k=1}^{m} N_{i \rightarrow k}} \qquad (1)$$

This provides a transition matrix $\mathbf{A}_q = \{a_{ij}\}$ for each time $t \in q_\tau$. From this collection of transition matrices, we can draw simulated transitions through the m states:

$$S_t^* \sim \text{multinomial}\left(A_q | S_{t-1}^*\right) \qquad (2)$$

3.3.2 Incorporating model uncertainty into design

We adopt a Bayesian approach to estimate a posterior density function on observed and unobserved quantities and use this uncertainty in derived components of the design. We assume the prior density for the ith row of the transition matrix is given by $\mathbf{A}_i \sim \text{Dirichlet}(\alpha_{i1}, \dots, \alpha_{in})$. The data distribution is Multinomial as per equation 2. Based on conjugacy of the Dirichlet prior (Agresti & Hitchcock, 2005; Chen et al., 2009), the posterior distribution is given by

$$\mathbf{A}_i | S_i \sim \text{Dirichlet}(N_{i1} + \alpha_{i1}, \dots, N_{im} + \alpha_{im})$$

This means that sampling from the posterior is straightforward, conditional on a choice of α_{in}. In this case our choice was to set all $\alpha_{ij} = 1$, which corresponds to a uniform prior (Chen et al, 2009).

3.4 Modelling the recapture process

Based on SBT data collected to date (e.g., Basson et al 2012; Patterson et al, 2018), we can assume that the tag life is quite long for archival tags--longer in most cases than the time to recapture for an experiment of 4 years or less. For PSATs, the tag life (i.e., time until detachment) is modelled in the recapture process based on when the tag self-reports. Note that we did not include a specific component for modelling tag failure for archival or PSAT tags. This assumption could be modified if necessary.

For archival tags, the recapture process can be modelled as follows. Assuming a daily time step, let $p(t)$ be the conditional probability of a tag being recaptured on day *t* given it had not been recaptured up to that point. Let P(t) be the unconditional probability of recapture on day t, then:

P(t) = Pr{NOT recaptured on day 1 to day t-1 } * Pr{ recaptured on day t }

$$= \prod_{k=1}^{t-1} p(k) * p(t)$$

Since a recaptured tag might not be reported, the final probability of a tag being recaptured and reported on day *t* = $p(t) \times \lambda$, where λ is the reporting rate. Note that we are assuming a constant reporting rate across space and time to simplify the notation, but it is straightforward to allow for varying reporting rates.

For PSATs, tags are programmed to detach after a specified length of time (e.g., 12 months after deployment), but they may pop off prior to the scheduled date. Therefore, we model the probability of a tag detaching (and reporting summarised data) using a Weibull distribution, with shape and scale parameters chosen as appropriate for the specific situation (see example below). Other models of tag attachment duration could be employed as appropriate.

3.5 Example: evaluation of a design to detect changes in GAB usage

To illustrate how the simulation method works, we consider an example looking at changes in movement patterns of juveniles in the Great Australian Bight. For the base case scenario, we assume SBT move according to historical patterns, with quarterly transition matrices calculated from historical archival tag data (Q1 = Jan-Mar, Q2 = Apr-Jun, Q3 = Jul-Sep, Q4 = Oct-Dec) (see Results section 4.1 “Historical movement rates”).

We then assume an alternative scenario in which more fish are found in the eastern GAB in quarter 1 than in the central GAB. This is represented by altering the transition matrix for Q1 such that the probability of moving from GAB-C to GAB-E twice as large.

For the study design, we consider the following options:

1. A 3-year study with 50 archival tags deployed in GAB-C at the start of Q1 of year 1.
2. A 3-year study with 100 archival tags deployed in GAB-C at the start of Q1 of year 1.
3. A 3-year study with 200 archival tags deployed in GAB-C at the start of Q1 of year 1.
4. A 1-year study with 30 PSATs deployed in GAB-C at the start of Q1 of year 1.

For archival tags we set the probability of recapture on any given day to be 0.0005 in Q1 and 0.00005 in Q2-Q4; this results in ~15% of the tags being recaptured by the end of the 3-year study, with the majority (~75%) in Q1. Here we assume all recaptured tags are reported. While reporting is expected to be very high for archival tags, it is unlikely to be 100%; however, the 15% recapture rate is close to the historic return rate of tags after 3 years, so we can assume that the recapture probability we have used is low enough to account for any non-reporting. The life of archival tags is assumed to be greater than the length of the study, so that if a tag is recaptured within the 4-year study period, we assume it has recorded valid data for the entire time at liberty–this is reasonable based on historical archival tag data where problems with batteries or tag sensors occurred mostly after 4 years.

To demonstrate how the method may be applied to design of PSAT tagging experiments, we assume that the recapture process (i.e., the time until detachment and successful data download) follows a Weibull distribution with shape and scale parameters of 5 and 260 respectively. These were chosen to give a median time until detachment of 235 days, with an interquartile range of 135-311 days, consistent with historical PSAT deployments scheduled to pop up after 12 months (Patterson et al 2008; Evans et al 2011; Tracey et al 2019).

We stress that the example given here is for illustrative purposes only–several of the assumptions and parameter settings would need to be given greater consideration before drawing any conclusions. For example, we note that there is likely to be differences between the various SBT PSAT studies in terms of tag attachment duration. As previous studies deploying PSAT on SBT were conducted from the period of relatively early deployment of the technology (e.g., Patterson et al 2008) to the point where they are routinely used (Tracey et al, 2019), attachment performance should have improved with technology and experience. A comprehensive design process for PSAT tagging should include a preliminary meta-analysis of attachment duration distributions to estimate recent attachment performance.

4 Results

4.1 Movement rates from historical data

The historical archival tag dataset for juvenile SBT was used to estimate quarterly transition matrices between regions, as defined in Figure 1. In doing so, only the data from years 1998-2010 (149 tags) were used since potential changes in movement dynamics have been noted over the past decade. Our goal was to estimate baseline transition matrices representative of historic movement patterns for comparison with matrices estimated under simulated changes in movement.

The estimated historical transition matrices are given in Table 1. Of note, the inward probabilities for GAB-C (i.e., column 1) are generally higher for all regions in Q1 and Q4. This accords with documented residence of SBT in the GAB over the austral summer. In contrast, the inward probabilities for the SE Indian Ocean (column 6) are highest in Q2 and Q3. Especially notable is the high probability of GAB-S to SEIO transitions over these quarters. Again, this reflects the cyclical migration of these age classes of SBT which has been documented elsewhere (e.g., Basson et al 2012; Patterson et al 2018).

4.2 Simulation results

As a check that the simulation methods are working as intended, we calculated the proportion of daily locations in each region by quarter using the historical archival tag data set (from 1998-2010) (i.e., the data set used to calculate the transition matrices in Table 1). We then simulated movement tracks for 100 tagged fish over a 3-year period using the transition matrices from Table 1 and compared the distribution of simulated locations by region and quarter with those from the historical data. The distributions match reasonably well (Figure 2 a,b), which indicates the simulation code is able to capture the distribution of fish over these years.

Next, we simulated movements of 100 tagged fish over a 3-year period using the alternative transition matrices (i.e., those with a higher probability of fish moving from GAB-C to GAB-E in Q1) and compared the distribution of simulated locations by region and quarter with the distribution obtained using the historical transition matrices. As we would expect to see, the proportion of locations in GAB-E relative to GAB-C in Q1 is greater using the alternative transition matrices (Figure 2 b,c).

Table 1: Historical expected (i.e. mean) monthly transition probabilities. These matrices should be read as rows being the "origin" state and columns being the "destination" state. Daily matrix entries were calculated via equation (1) and then transformed to give a monthly 30 day expected transition rate (this produces probabilities of moving between non-adjacent spatial zones – see Figure 1). To improve visual interpretation, all transition probabilities equal to zero have been denoted as "-".

(A) Q1	GAB-C	GAB-E	GAB-S	GAB-W	NZ	SEIO	TAS
GAB-C	0.73	0.12	0.09	0.05	-	-	0.01
GAB-E	0.45	0.31	0.15	0.04	-	-	0.03
GAB-S	0.35	0.16	0.30	0.12	0.01	0.02	0.04
GAB-W	0.32	0.06	0.15	0.45	-	0.01	0.01
NZ	0.02	0.01	0.05	0.01	0.86	-	0.06
SEIO	0.04	0.02	0.11	0.03	-	0.79	0.01
TAS	0.15	0.12	0.25	0.05	0.12	0.01	0.31
(B) Q2	**GAB-C**	**GAB-E**	**GAB-S**	**GAB-W**	**NZ**	**SEIO**	**TAS**
GAB-C	0.57	0.18	0.12	0.09	-	0.02	0.01
GAB-E	0.29	0.38	0.19	0.04	0.01	0.04	0.05
GAB-S	0.13	0.11	0.43	0.06	0.02	0.20	0.05
GAB-W	0.33	0.08	0.19	0.34	-	0.05	0.01
NZ	-	0.01	0.01	-	0.84	-	0.13
SEIO	-	-	0.02	-	-	0.97	-
TAS	0.04	0.09	0.10	0.01	0.19	0.02	0.56
(C) Q3	**GAB-C**	**GAB-E**	**GAB-S**	**GAB-W**	**NZ**	**SEIO**	**TAS**
GAB-C	0.46	0.07	0.18	0.19	-	0.09	-
GAB-E	0.30	0.13	0.26	0.13	0.02	0.13	0.02
GAB-S	0.11	0.05	0.31	0.17	0.01	0.34	0.01
GAB-W	0.06	0.02	0.20	0.45	-	0.27	-
NZ	-	-	0.03	0.01	0.80	0.01	0.14
SEIO	-	-	0.01	0.02	-	0.97	-
TAS	0.02	0.01	0.09	0.02	0.52	0.04	0.30
(D) Q4	**GAB-C**	**GAB-E**	**GAB-S**	**GAB-W**	**NZ**	**SEIO**	**TAS**
GAB-C	0.84	0.05	0.06	0.04	-	0.01	-
GAB-E	0.57	0.22	0.11	0.05	0.01	0.01	0.02
GAB-S	0.35	0.06	0.27	0.19	0.01	0.09	0.02
GAB-W	0.43	0.04	0.18	0.25	-	0.09	0.01
NZ	0.01	0.02	0.01	-	0.76	-	0.20
SEIO	0.03	0.01	0.05	0.04	-	0.87	-
TAS	0.08	0.07	0.07	0.02	0.33	0.01	0.42

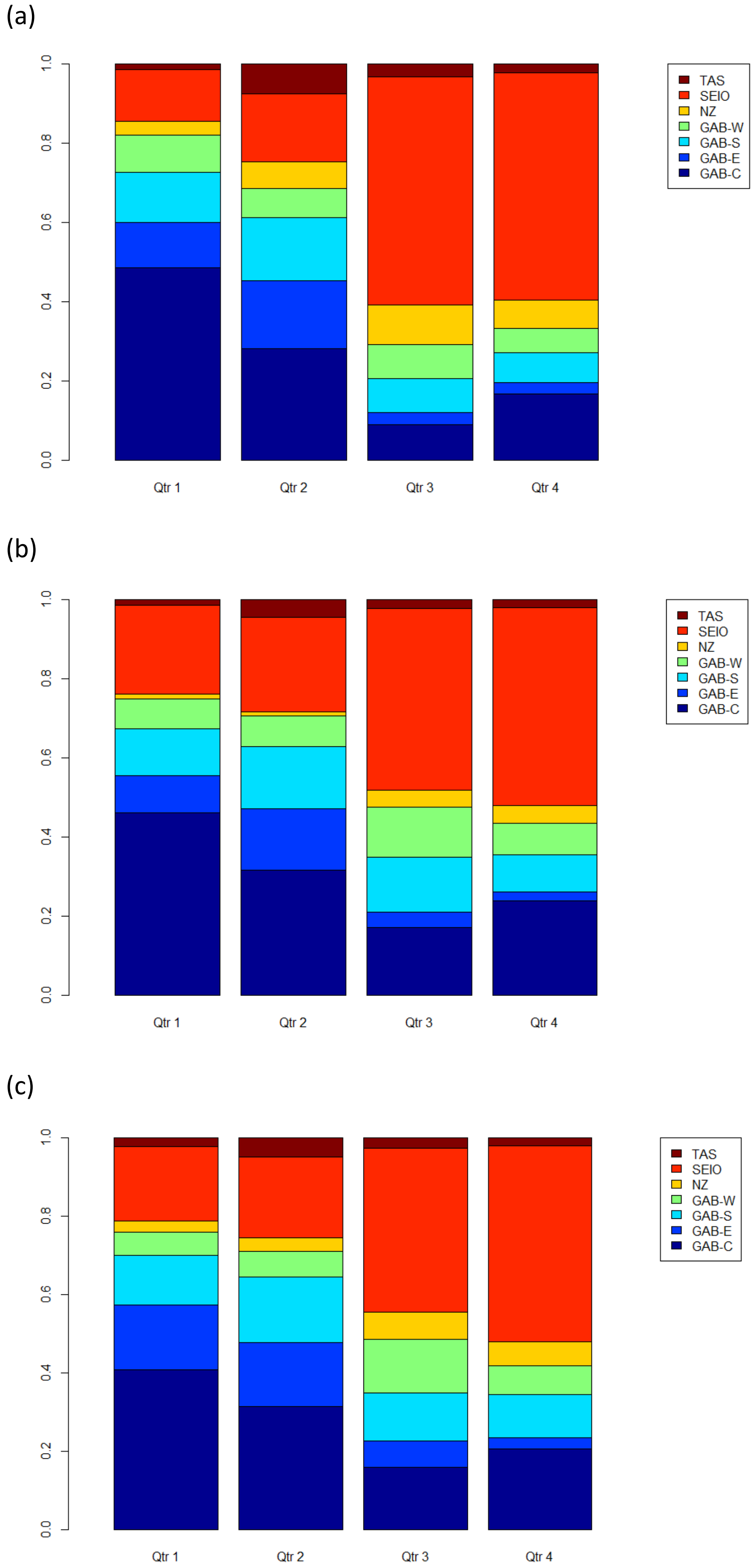
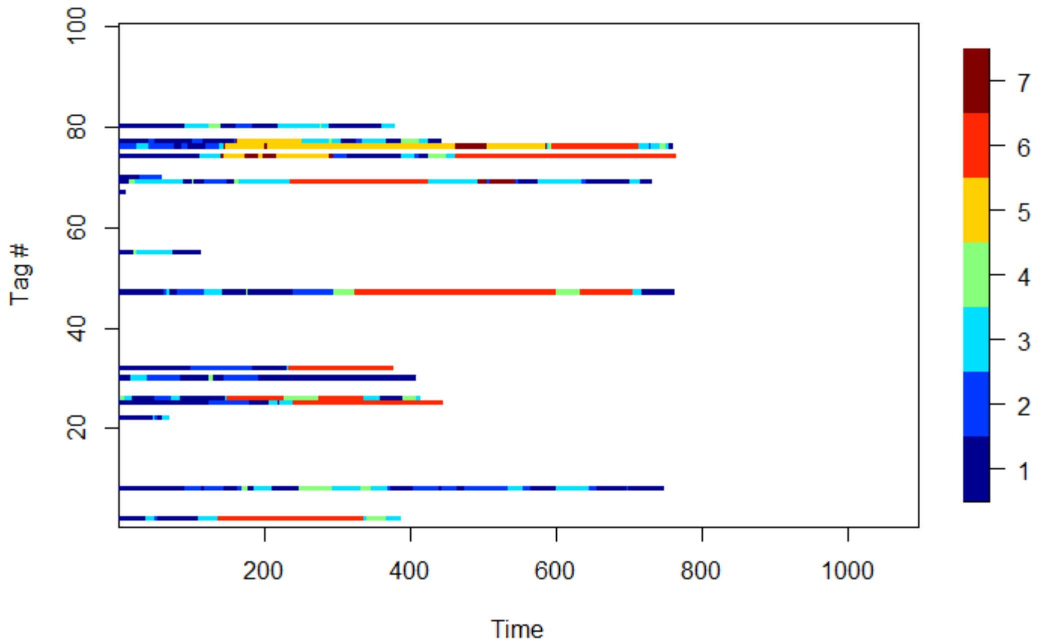
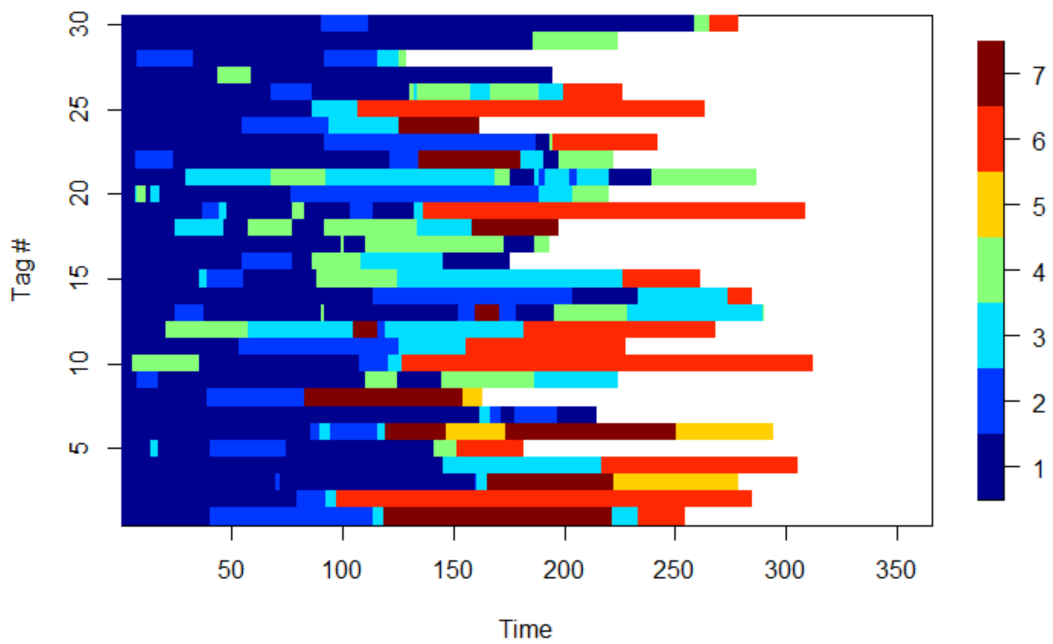


Figure 2. Distribution of fish locations amongst areas by quarter based on (a) movement tracks from historical archival tag data (a), and based on simulated movement tracks for 100 fish over 3 years using (b) historical transition matrices and (c) alternative transition matrices, which have a higher probability of fish moving from GAB-C to GAB-E in quarter 1.

Examples of synthetic movement data obtained using the historical transition matrices for one simulation using study design 2 (100 archival tags) and design 4 (30 PSATs) are given in Figure 2. For design 2, archival tags that were not recaptured within the 3-year study period have no data, and thus appear as white lines. For design 4, fewer PSATs were deployed but every tag has data covering the time until detachment.



(a)



(b)

Figure 2. Examples of simulated movement histories of recaptured tags using the historical transition matrices and (a) study design 2 (100 archival tags), and (b) study design 4 (30 PSATS). The colours correspond to spatial states (see legend in Figure 2). White space indicates no data.

4.3 Design evaluation results

Using transition matrices calculated from each of the 100 simulated movement data sets, we can assess whether the increase (doubling) in the transition probability from GAB-C to GAB-E in Q1 can be detected with the different study designs. To do so, we compared the estimates obtained using the historical transition matrices with those obtained using the altered transition matrices. While consideration should be given as to what degree of detected difference would constitute success of a givenn design, for this demonstation, the increased transition probability from GAB-C to GAB-E are deemed undetected in instances where the 95% credible intervals for the estimates overlap.

While there was clear differences between the distributions on the transition rate (which could be noted from informal inspection), the results suggest that designs 1 and 2, with 50 and 100 archival tags respectively, are insufficient for detecting the change (Figure 3 a,b), whereas designs 3 and 4 (with 200 archivals and 30 PSATs respectively) are likely able to detect the change – although the result is marginal and a larger number of simulations would be required to confirm this.

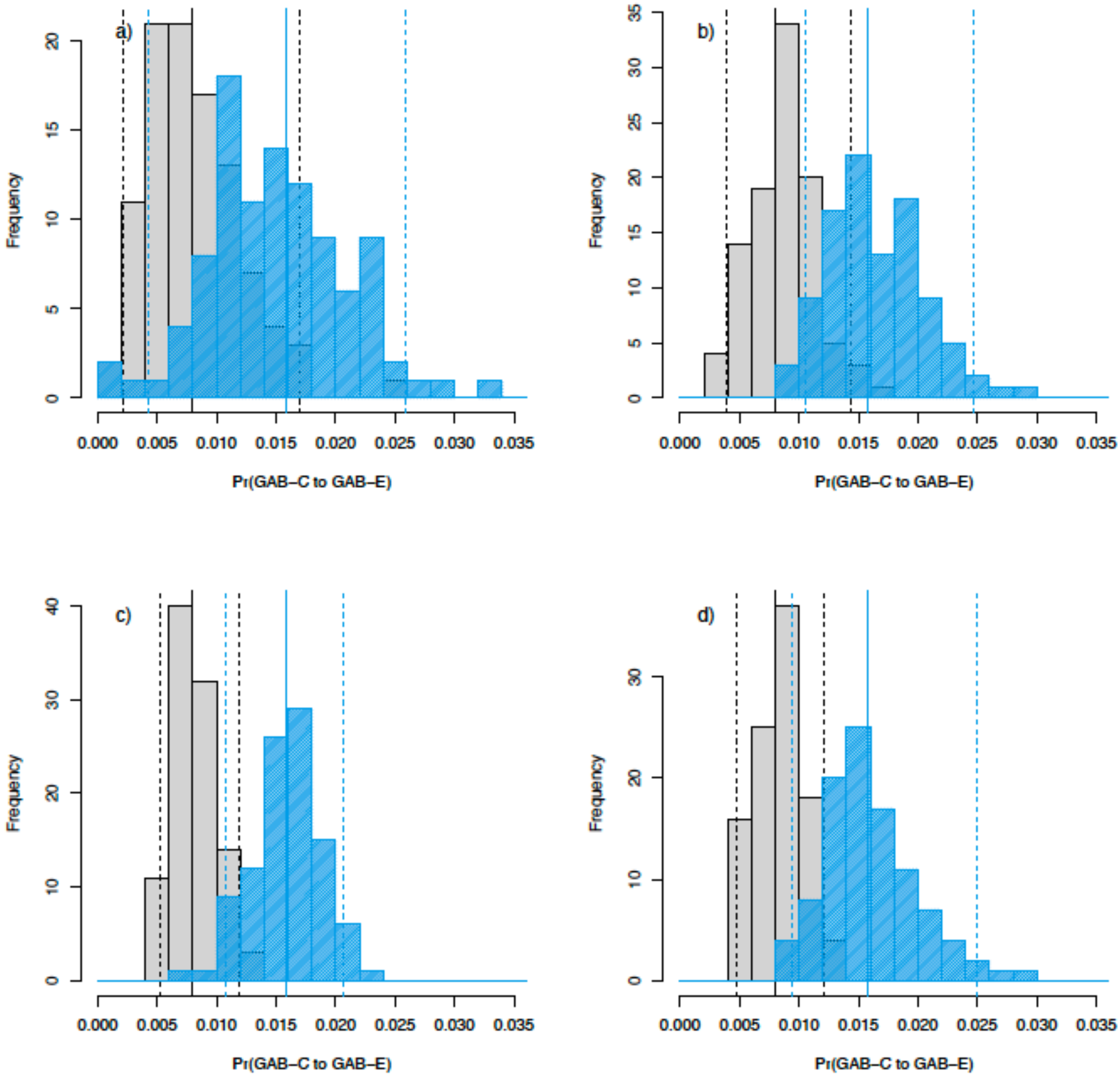


Figure 3. Histogram of transition probability estimates for GAB-C to GAB-E in quarter 1, obtained from 100 draws from the historical transition matrices (grey bars) and alternative transition matrices (blue bars) for study designs 1-4 (a-d). The solid lines show the true values, and the dashed lines show the 95% confidence intervals of the estimates (i.e., 0.025 and 0.975 percentiles).

5 Discussion

We have presented a spatial simulation method for evaluating the ability of different e-tag designs to detect changes in movement patterns. The method we demonstrate was able to recreate movements between spatial zones of the documented juvenile SBT distribution. Our method is reliant on large amounts of historical data to capture patterns of historical movement and having done so generate plausible alternative synthetic data. The approach should guide evaluation of the chances of success of a project at a given level of investment in tags, conditional on the magnitude of the “effect” (i.e. the scale of changes to movement rates).

The example presented is intended as an illustration of how we characterized movement rates from historical SBT archival data, how the method works, and the type of design question that can be examined. For dedicated design of a tagging program, several of the assumptions and parameter settings would need to be carefully considered prior to performing an operation design exercise. For example, further information should inform the model recapture process and more consideration needs to be given to the modelled level of variability in simulated movement tracks). Additionally, this initial study has only performed a small number of simulations and much more intensive simulation would be required for an operational design. Nevertheless, the method indicated an ability to evaluate potential benefits of archival tagging designs which may be investigated further. We invite input from CCSBT members on questions/different movement scenarios for us to consider.

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