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SKIPJACK TAGGING DATA PRELIMINARY ANALYSIS, REVIEW AND RECOMMENDATIONS FOR FURTHER DEVELOPMENT AND APPLICATION

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Submitted by

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Skipjack tagging data preliminary analysis, review and recommendations for further development and application

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1 Executive summary

WCPO skipjack tuna (SKJ) assessments currently fit tagging data within an integrated model, which requires assuming that tagged fish are well mixed across broad regions, which is an assumption that is hard to meet and to which the assessment is sensitive. Following promising work in the Eastern Pacific Ocean (EPO), the WCPFC requested this proof-of-concept study (as part of WCPFC Project 123) on estimating movement by analysing WCPO SKJ tagging data externally to the assessment, using the fine-scale movement model `admove`. By modelling the redistribution of tagged fish in continuous space or on a fine grid, the approach relaxes the region-level mixing assumption. The full framework can provide movement, mortality, and biomass estimates for an assessment. This study applies only the movement component, as a first step.

The preliminary analysis of almost 20 thousand Pacific Tuna Tagging Programme tags (10,495 after cleaning and omitting tags recaptured within 14 days) shows that fine-scale movement estimation for WCPO SKJ is generally feasible: a habitat preference for warmer water was estimated, though more complex models were unstable, mainly because of the narrow thermal and spatial range of the recaptures and the absence of effort data. Effort and catch data were not available at the time of this study, so the mortality and biomass modules could not yet be applied for this first phase of work. Reliable movement, mortality, and biomass estimates will require a broader tagging database (wider coverage and length information) and, critically, fine-scale spatial effort and catch data.

We therefore recommend a three-phase programme: (1) robust movement estimation jointly with effort-dependent mortality, including evaluation of recapture-probability assumptions; (2) estimation of a relative biomass index based on the Baranov catch equation, spatially-explicit catch and effort data, and movement rates; and (3) estimation of absolute biomass using the Petersen-type model, based on estimated movement rates and

spatially-explicit catch data. Phase 2 would likely deliver a continuous relative biomass index time series (e.g. 2000-2025), whereas Phase 3 would likely provide only a few estimates for well-sampled periods, though potentially reaching further back in time than the effort-based index. Under the outlined timeline, mortality and biomass indices could be available for the next SKJ assessment in 2028.

2 Background

Stock assessments of skipjack tuna (*Katsuwonus pelamis*, SKJ) by the Pacific Community (SPC) for the Western and Central Pacific Fisheries Commission (WCPFC) rely on tag-recapture data to inform movement, population size and fishing mortality (Teears et al., 2025). For tuna assessments, tagging data are typically fit within integrated age-structured assessment models such as Multifan-CL or Stock Synthesis, which require assuming that tagged fish are well mixed within the untagged population, so that recaptures are representative of the movement and fishing mortality of the wider stock within the assessment regions. This mixing assumption is difficult to meet, as it only holds after a substantial time at liberty or with homogeneously distributed fishing effort, and the way it is handled can have a substantial impact on the assessment. For example, the assumed mixing period after which tagged fish are treated as fully mixed (one or two quarters) *"had the most influence on management quantities"* in the 2019 assessment (Jordan et al., 2022). Assigning a specific mixing period to each release event using a simulation model (Scutt Phillips et al., 2022) led to better-justified choices, but did not remove the sensitivity of the assessment to the mixing assumption (Teears et al., 2025). For these reasons, recent work in the Eastern Pacific Ocean (EPO) has explored analysing tag-recapture data externally to the assessment model, estimating movement, abundance, and mortality directly from the tagging data using fine-scale spatiotemporal models (Mildenberger et al., 2022, 2023, 2024). These externally-derived estimates were then supplied to the integrated assessment as relative and absolute biomass indices (Bi et al., 2024).

The WCPFC has provided funds to SPC to develop a next-generation tuna assessment package (Project 123; Magnusson et al. (2025)). Following the promising EPO work, the WCPFC requested the proof-of-concept external analysis of tagging data for SKJ in the Western and Central Pacific Ocean (WCPO) presented here, with the aim of determining the feasibility and usefulness of the approach for complementing, and potentially simplifying, the development of next-generation tuna assessment models. The approach explores summarising the tagging information externally to the assessment, with the intention that the assessment could build on this summary; the lessons learned are, however, equally relevant for, and could inform the development of, a future joint movement-assessment model.

3 Objective

The quantities most useful for an assessment that could be derived from tagging data are likely environmentally informed movement of the population, absolute or relative biomass indices and fishing and natural mortality rates. Rather than integrating the tagging data into an existing assessment model, this proof-of-concept study explores the analysis of the tagging data in its own right, externally to any population model, adding complexity only as required. It builds on the movement model `admove`, which extends the tagging model previously developed for SKJ in the EPO.

To this end, the report first summarises the methodology of the external tagging framework and its modules for estimating movement, mortality, and biomass. It then presents a preliminary application of the movement module to a subset of the available WCPO tagging data, before discussing the challenges and next steps associated with applying each module to the WCPO SKJ tagging data.

Tagging analyses are typically highly sensitive to assumptions on the reporting rate, mixing rate, and recapture probability. This report discusses to what extent `admove` and biomass models make these assumptions and their effects on derived quantities.

4 Methodology

Estimating assessment-relevant quantities from tagging data requires a framework that accommodates fine-scale positioning data and the underlying fine-scale spatial processes. We present it as a sequence of modules of increasing complexity, each building on the previous: movement, then mortality (by adding spatially-explicit effort), then biomass (from the Baranov catch equation or a spatiotemporal Petersen-type approach), and finally a possible unified framework. The full methodology is documented in the EPO SKJ reports (Mildenberger et al., 2022, 2023, 2024, 2025); here we summarise each module, using the EPO analysis as a worked example, only to the depth needed to judge its applicability to the WCPO.

4.1 Estimating movement

Movement is described by an advection-diffusion process (Thorson et al., 2021): diffusion (undirected movement), taxis (directed movement up the gradient of a habitat preference function), and passive advection from rate fields such as ocean currents. The habitat preference function is a sum of smooth functions of environmental fields (e.g. sea surface temperature, mixed layer depth), with knots and coefficients estimated from the data. Two estimation engines are available: the Continuous Time Markov Chain (CTMC) and the Kalman Filter (KF) (Mildenberger et al., 2022, 2023). Conventional and archival tags can be combined, and recapture-location uncertainty of conventional tags modelled as additional observation variance. The estimated fine-scale rates can be aggregated to box-transfer probabilities for any assessment regions and time steps, decoupling the movement grid from the assessment's spatial structure.

In the EPO, SST was the most robust covariate (preferred window around $25-26°C$), and recapture probability was found to depend strongly on fishing effort: ignoring this biases the estimated movement, so even movement estimation requires effort assumptions, though EPO movement was more sensitive to the spatial presence/absence of effort than to its magnitude (Mildenberger et al., 2025). Properly accounting for this effort dependence requires incorporating fishing mortality into the likelihood, i.e. estimating the mortality module jointly (Section 4.2); movement and mortality are therefore estimated together. To run without an effort correction, however, the module needs only release and recapture locations and environmental fields, both of which were available for the WCPO (Section 5).

4.2 Estimating mortality

Adding spatially-resolved effort both accounts for non-uniform recapture probability and allows us to estimate fishing and natural mortality. Fishing mortality is related to effort (e.g. $F = \lambda E$) and natural mortality assumed constant, so each tag's likelihood follows from the survival and capture probabilities along its path (a Baranov-type formulation); it can be made length-based via a growth model (e.g. Maunder et al., 2018), giving length-specific F and M. As natural mortality is usually fixed in assessments and a major structural uncertainty, an independent length-based estimate is directly useful as input or prior. Like any tagging model, results depend strongly on tag-shedding and reporting-rate assumptions (assuming no tag loss inflates M and deflates F). In the EPO these rates were fixed externally, giving a natural mortality of about 2.75 per year and fleet-specific fishing mortality broadly consistent with values from previous studies (Mildenberger et al., 2023). For the WCPO this module requires spatially-resolved effort and reporting/shedding information (Peatman et al., 2025).

4.3 Estimating biomass

Given movement and mortality, the expected catch per cell and time follows the Baranov equation; modelling the observed catch (e.g. negative binomial) recovers the cell-level population size. Rather than treating cells independently, a spatio-temporal model is placed on the (log) cell-level population sizes, with a covariance structure representing the spatial neighbourhood between cells and the temporal correlation between quarters. This accounts for the correlated nature of abundance and, importantly, yields estimates for cells and times with few or no recoveries; the biomass index at each time step is then obtained by summing the estimated population sizes across all cells in the domain. The relative trend is robust to the effort–F assumption even where the absolute scale is not; in the EPO this produced a quarterly relative biomass index spanning 2000-2023 (Mildenberger et al., 2024) used in the benchmark assessment (Bi et al., 2024). A similar index could be produced for WCPO SKJ over the area, period and temporal resolution for which spatially-explicit effort and catch data are available. Because this approach builds the index from fishing mortality and catch per cell rather than from recaptures directly, its temporal and spatial extent and resolution (e.g. quarterly / $1°$ by $1°$ grid cells) are bounded by the coverage of the effort and catch data, and its extent can therefore not predate the effort data.

A second, spatiotemporal Petersen-type approach instead uses the estimated movement to predict the tagged fish available per cell and estimate absolute abundance based on predicted and observed recaptures and total catch, avoiding direct use of effort data (though effort might still enter via the movement model). As in the relative-index approach, the same spatio-temporal correlation model is applied to the cell-level abundances, borrowing strength across neighbouring cells and quarters to provide estimates where recaptures are sparse or absent before the index is formed. In the EPO it produced a quarterly absolute-biomass time series whose point estimates ranged from about 0.29 to 3.6 million tonnes across quarters, with high but in places acceptable per-quarter uncertainty (CV 0.3-0.6) (Mildenberger et al., 2024). This uncertainty is driven mainly by the number of recaptures, as the Petersen-type variance scales inversely with the recapture count, so cells and quarters with few tagged recaptures are inherently high-CV; over the EPO's large area with many cells without recaptures this was likely the dominant driver (Mildenberger et al., 2024). Uncertainty also grows through time as the at-liberty tagged population is depleted by mortality, emigration and reporting, leaving fewer tags available for recapture; it is further inflated by the propagated uncertainty of the movement estimates that predict the tagged fish available per cell, and by poorly-known nuisance parameters (reporting rate, tag shedding and retention, and tag-induced mortality) that scale the estimate. Because this approach avoids direct use of effort, its temporal extent is set by the tagging record and catch data rather than by spatially-explicit effort information; where historical tagging data can be included, it could therefore extend further back than an effort-based index. Its resolution (e.g. quarterly) is a user choice, but the index becomes increasingly uncertain in periods and areas where few tagged fish remain at liberty or where recaptures are sparse (e.g. very fine spatial and temporal resolution). The index represents the abundance of the population component within the spatial domain over which it is computed; this domain is a user choice, with a practical limit set by where recaptures and catch data are informative. It is therefore often meaningful to restrict the index to a core area with sufficient recaptures: in the EPO, for example, a core area between 20°S and 10°N was defined, corresponding to the region with a considerable number of recaptures (Mildenberger et al., 2024).

Both approaches need reliable movement and fine-scale spatially-explicit catch data. In addition, the Baranov approach additionally needs spatially-explicit effort and an effort–F assumption. Given the WCPO's large area and many cells without recaptures, an absolute index is likely to be uncertain, but could be feasible for a core area in quarters with enough recaptures, however, we suggest a relative abundance index with acceptable uncertainty is feasible.

4.4 A unified framework

The modules are currently applied sequentially, sharing the movement estimates. Integrating them into a single fine-scale spatial state-space model would propagate uncertainty coherently and avoid reusing the same tags across steps, and could estimate biomass without effort data (the movement model always makes implicit effort assumptions: uniform recapture probability, and hence uniform effort, when none is provided), at the cost of greater model complexity and computational demand.

4.5 Assumptions

All modules assume that a tagged fish behaves identically to an untagged fish (same habitat preference, catchability, and mortality). This tagging-effect assumption is made throughout and is *not* relaxed by any module. It should not be confused with the standard mixing assumption of integrated assessments, which requires tagged fish within a broad region to be well mixed; the modules do not rely on region-level mixing. The movement model with the KF engine tracks tag locations in continuous space and therefore makes no spatial-homogeneity (mixing) assumption at all. The remaining modules discretise space onto a fine grid (usually 100-500 km cells, depending on computational demands and data availability) and correspondingly relax the mixing assumption only to the scale of a single grid cell: the CTMC movement engine and the Baranov biomass model assume fish are homogeneously distributed within a cell (a common fishing mortality and catchability), and the Petersen-type model additionally assumes tagged and untagged fish are completely mixed within each cell. The modules further assume tags are retained (no unaccounted shedding) and no tag-induced mortality beyond what is modelled or removed by discarding early recaptures, and that habitat preference and movement are stationary over the analysis period.

5 Preliminary application to WCPO SKJ tags

Based on the mark-recapture tagging data and environmental covariates for the WCPO that were shared during a workshop at DTU in 2025, we explored movement estimation with `admove` (Section 4.1). Spatially- disaggregated catch and effort data were not available for the tuna fisheries in the WCPO for this study (but we understand are available for further work), so the mortality and biomass modules (Sections 4.2 and 4.3) could not be applied in this preliminary application; they are, however, considered in the discussion in the subsequent chapters.

5.1 Data

Almost 20 thousand mark-recapture tags with recapture locations were shared and considered in the preliminary application. These tags came from the Pacific Tuna Tagging Programme (PTTP) and spanned the period 2006-2025. Tags with missing information (2007 tags) or with release or recapture locations on land (11 tags) were removed, as were tags recaptured after December 2022, for which the shared covariate fields were not available (298 tags). We also applied a speed filter, removing tags that implied an average speed of more than 200 km/day based on the direct distance between release and recapture positions (375 tags) . Tagging took place almost continuously over the period, both across years (Table 1) and across months of the year (Table 2).

Table 1: Number of releases per year.

Year	2006	2007	2008	2009	2011	2012	2013	2016	2017	2019	2020	2021	2022
Releases	1732	1190	1252	2130	1683	2734	1196	1	3005	237	1	2	3990

Table 2: Number of releases per month.

Month	1	2	3	4	5	6	7	8	9	10	11	12
Releases	145	1041	2008	1256	1684	1245	340	1181	2891	5618	1744	0

The remaining tags were characterised by short times at liberty and small displacements: the median time at liberty was 19 days (30% recaptured within a week, 60% within a month), and the median displacement between release and recapture location was 66 km, with 25% of tags moving less than 10 km (Fig. 1). Tags recaptured soon after release and close to their release site carry little information about movement: the displacement over a few days is dominated by short-term diffusion and observation error, and provides almost no leverage to resolve how environmental gradients shape directed movement (advection) and spread (diffusion). This limitation is compounded in the WCPO, where the environmental fields explored here vary only weakly across the region, so even longer tracks span comparatively shallow gradients. We therefore explore the sensitivity of the results to excluding these early recaptures at several thresholds (7, 14, and 30 days; see below).

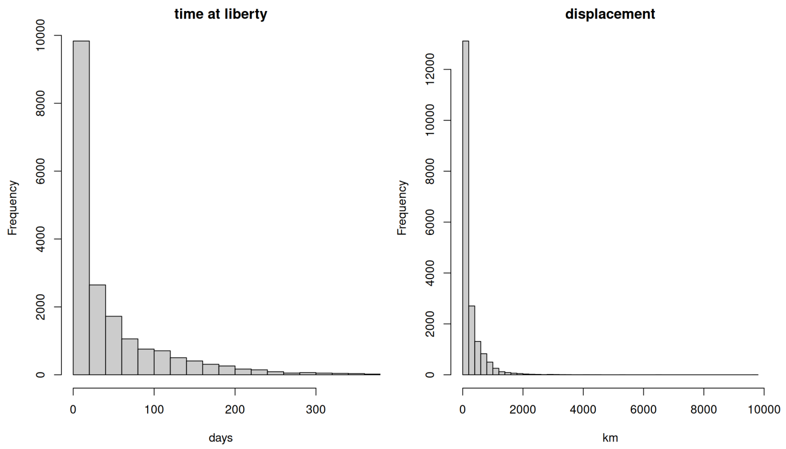

Figure 1: Histogram of time at liberty and displacement.

The tags came from 968 release events, and no archival data were available. Most releases are concentrated between 140° and 165° longitude (93%) and between −10° and 2° latitude (98%) (Fig. 2). The sea surface temperature range experienced by the tags is relatively narrow, between 28°C and 31°C (99%).

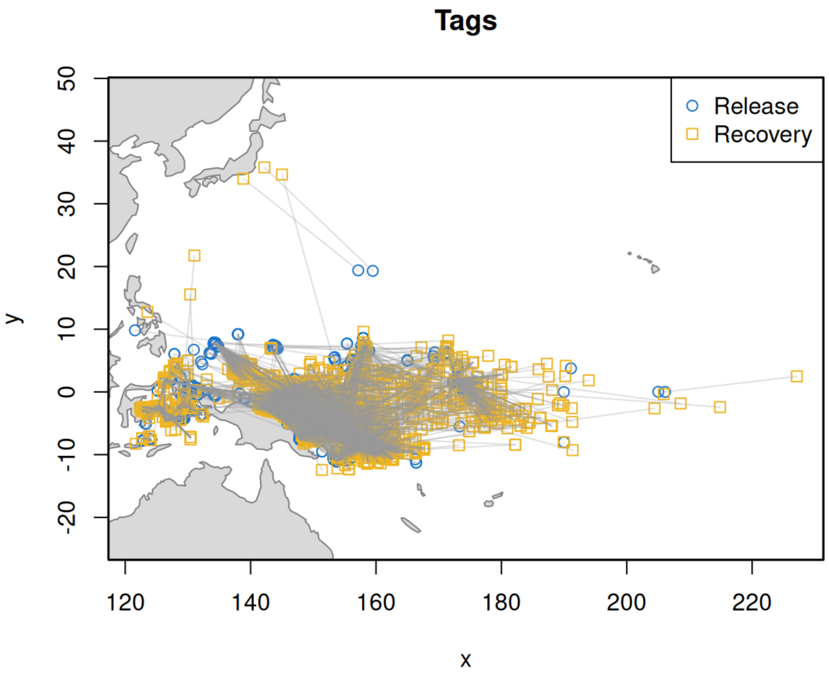

Figure 2: 18778 tags considered for the analysis.

The narrow spatial range of the recapture locations is likely driven by the high fishing effort in the area, since high effort implies a high probability of recapture. 99% of the recaptures are located in the warm-water blob northeast of Papua New Guinea (with SST between $28 - 31°C$), which coincides with the area of largest fishing effort (Jordan et al., 2022). No information on the fleet or set type at recapture, nor any biological information on the tagged fish (such as age or length), was used for this proof-of-concept study.

Five covariate fields were available and considered in the analysis: mixed layer depth, sea surface temperature, average temperature over the common depth range for SKJ in the WCPO, and the two (zonal and meridional) components of the ocean currents. These fields were provided on a 1° by 1° grid at monthly resolution.

The data types that would strengthen the analysis are biological (length) information, uncertainty regarding the recapture location and fleet/set information, and fine-scale spatial effort and catch data, and are discussed together with the corresponding next steps in Section 6.

5.2 Preliminary movement results

We fitted the `admove` model (version 0.1.1; https://tokami.github.io/admove/) using the average temperature integrated over the common depth range of SKJ as the covariate field informing the habitat preference, and estimated the habitat preference function as a linear function of that field. Variable diffusion was estimated as a linear function of the same temperature field. While it is generally possible to fit non-linear (smooth) functions, these were not stable across scenarios, likely because of the narrow temperature range experienced by the tags, among other reasons. We used the currents as a physical advection layer acting on all individuals, but estimated the strength with which the currents displace the individuals (assuming the same entrainment in the x and y directions). Two aspects of the current implementation should be noted, as both affect the preliminary results and are taken up in Section 6: the model does not yet implement explicit land boundaries but instead fills missing covariate values near coasts and islands by local interpolation (which affects the habitat gradients, and hence taxis, in the most complex parts of the domain), and the analysis was run in longitude/latitude space even though `admove` is Euclidean, which distorts the estimated diffusion and advection. We removed tags recaptured within 14 days of release, as their movement information is small. Using 30- or 7-day thresholds did not change the results substantially, though it led to small changes in absolute values (Supplementary Section 9.3). The 14-day threshold resulted in 10,495 tags being used in the analysis. Model fitting took approximately 42 min on a laptop (Intel Core i7-8650U, 16 GB RAM, Ubuntu 24.04.4; single core).

Preliminary results imply higher preferences for higher temperatures and higher diffusion for lower temperatures within the range observed (Fig. 3). Entrainment for the currents was estimated at 7.5%.

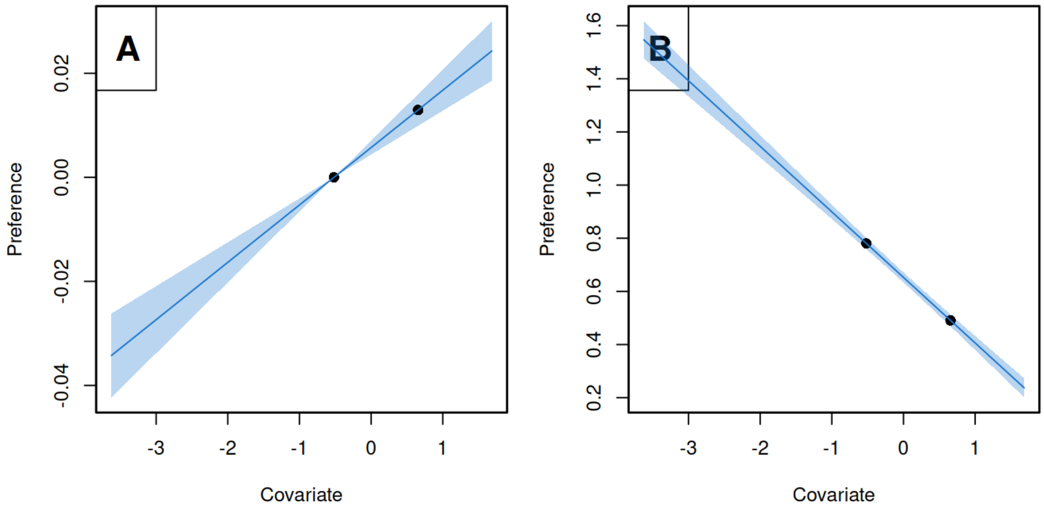

Figure 3: Estimated preference (A) and diffusion (B) as functions of depth-integrated temperature. The two points represent the knot positions, where the value (preference/diffusion) at the first knot is fixed and the second is estimated. Shaded areas represent 95% confidence intervals.

The net effect of the estimated preference function for depth-integrated temperature implies the average taxis presented in Figure 4, alongside the advection and diffusion in space.

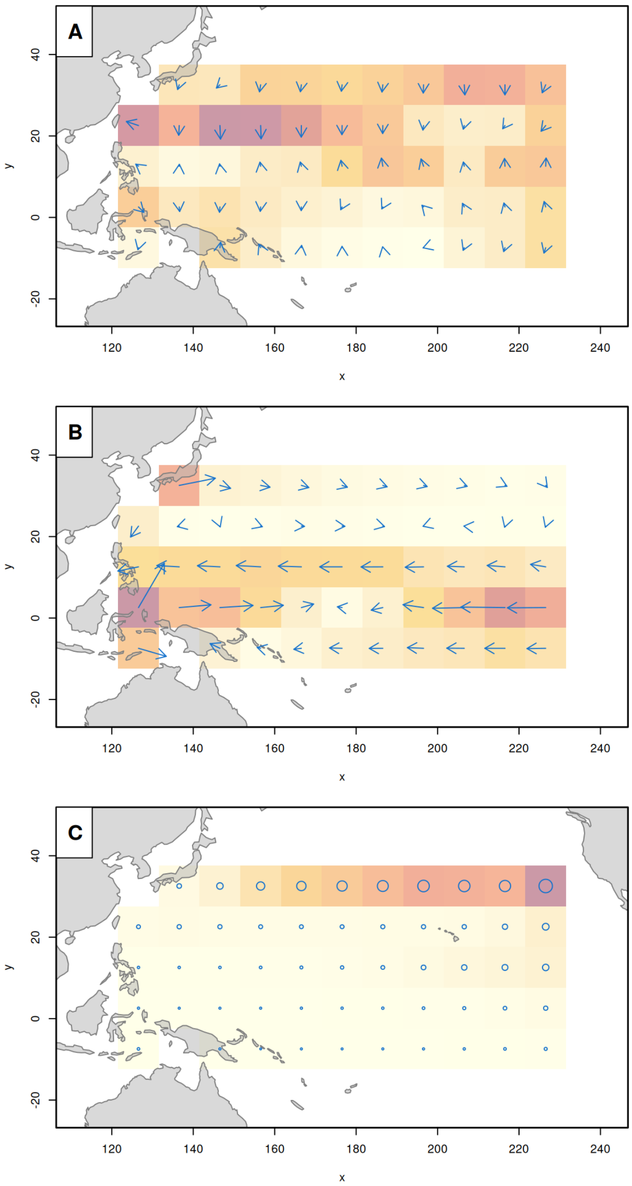

Figure 4: Estimated taxis (A), advection (B), and diffusion (C) for 10° by 10° grid cells. Colours and arrow length or circle size indicate the strength of taxis and diffusion. Arrow direction indicates the net direction of taxis in each grid cell.

The estimated patterns are robust when using sea surface temperature (Supplementary Fig. 11). Using mixed layer depth as covariate shows a higher preference for lower mixed layer depth and results in similar taxis and advection patterns, but different diffusion patterns in space (Supplementary Fig. 12). However, estimating more flexible habitat functions (i.e. more knots), using both temperature and mixed layer depth together or using certain subsets of the database lead to non-convergence or unstable models (Supplementary Sections 9.2 and 9.3). There could be many reasons for these sensitivities to the selected tags. Different habitat preference functions for different subsets could reflect the dominance of different climatic events, such as El Niño and La Niña, and hence different behaviour and movement of SKJ. The sensitivity to more complex habitat preference functions could be due to the narrow temperature range covered by the tags (mainly $28-31°C$), which limits the flexibility that can be estimated over such a range; tags from other tagging programmes covering a wider temperature range could lead to more stable results. A further reason for the observed instabilities could be the failure to account for spatial concentrations of fishing effort, which can produce large numbers of local recaptures. The habitat preference functions might also differ between age or length groups as found in the SEAPODYM analysis (Senina et al., 2025) and the age/length composition of the tagged individuals could differ between periods; this can be evaluated once age/length information for the tags is available. All of this demands more investigation as part of a future project.

In comparison, SKJ in the EPO showed a similar increasing preference for higher water temperatures, however with a peak at around 25°C and a decreasing preference for SST above this. Skipjack are physiologically intolerant of low ambient oxygen (Brill, 1994), and the warmest surface waters in the EPO overlie a shallow oxygen minimum zone that compresses the oxygenated habitat available to them (Mildenberger et al., 2023); the declining upper-temperature preference is therefore more plausibly an oxygen than a thermal limit. In the EPO it was also possible to estimate a more complex (3-knot smooth) habitat preference function for SST, likely because the available tagging data spanned a larger covariate space with temperatures between $20-30°C$ (Mildenberger et al., 2022, 2023). The EPO analysis showed a similar preference for lower mixed layer depth (Supplementary Fig. 12; Mildenberger et al. (2022)). While the final EPO model included a temperature preference function with similar characteristics, it also included a preference function for the kinetic energy of the water, which showed a higher preference for higher kinetic energy (Mildenberger et al., 2024). Here, we used the currents as passive advection fields rather than as a combined field for taxis.

6 Challenges and next steps

The preliminary application revealed the main challenges for a more comprehensive WCPO SKJ tag analysis. We discuss these challenges and the steps needed to address them below and summarise the resulting work programme in Figure 5.

The most important limitation is the data. The recaptures used here are concentrated in a narrow region and span only a narrow range of the environmental covariates, which was likely a main reason for the instability of more flexible habitat preference functions. This narrow range reflects the concentration of fishing effort, and the strong interannual (ENSO) variability of the region further suggests that habitat preference is not stationary over the 20-year period (Senina et al., 2025). Acquiring tags from other programmes, for example the Japanese programme, which covers areas the PTTP does not (Aoki et al., 2025), would broaden the covariate coverage and support more robust and, where warranted, time-varying preferences. Also tags from the EPO could be incorporated into the same model (Senina et al., 2025) or used for cross-validation. Biological information, in particular length at release, is needed (and available) to separate ontogenetic differences in preference and movement and to enable the length-based mortality module. Sufficient time must also be budgeted for data cleaning: the current tags included unrealistic swimming speeds (>200 km/day), recaptures on land, and missing values.

Because recaptures concentrate where effort is high, movement and recapture probability are confounded: the model cannot readily tell whether fish remain in an area because conditions elsewhere are unfavourable or simply because effort there is disproportionately high. Fine-scale spatial effort data are therefore crucial, both to obtain unbiased movement estimates and to enable the mortality module (Section 4.2), and spatial catch data are additionally needed for the biomass module (Section 4.3). Effort is difficult to quantify reliably for purse seiners using FADs, but any measure, such as the number of sets by set type, would allow the sensitivity to effort assumptions to be explored. Mortality and biomass also depend strongly on reporting and tag-shedding rates and on tagger effects such as rapid post-release mortality (Peatman et al., 2025); these are likely more uncertain across the WCPO's many fleets and flag states than in the EPO.

Several implementation challenges are specific to the WCPO. The database is large and the stock area wide (the Pacific Ocean west of 150°), so the Continuous time Markov Chain (CTMC) engine could not be fitted within a 200 Gb memory limit and the KF was used instead; the engine choice interacts with the geometry, and both warrant further work. The complex island geography requires explicit boundary conditions, currently approximated by imputing covariate fields near land, which affects the habitat gradients where the geography is most complex, and the analysis was run in longitude/latitude space even though `admove` is Euclidean, distorting the estimated diffusion and advection. Implementing explicit boundary conditions and working in a projected coordinate system (e.g. azimuthal-equidistant in kilometres) are therefore priorities. Further useful developments are handling recapture-location and -time uncertainty as in the EPO, cross-validation against archival tags (none were available for the WCPO), parallelising the code, formal residual diagnostics (Mildenberger et al., 2025) and cross-validation (Senina et al., 2025), improved documentation, and covariate-free estimation of habitat preference. Some of the custom code developed for movement and mortality estimation for EPO SKJ tags still needs to be generalised and incorporated into `admove`. Similarly, the biomass models need to be packaged into standalone software using RTMB.

Concretely, we propose three phases (Figure 5): Phase 1 assembles a broader, cleaned tagging database (length information, fine-scale effort and catch data) and estimate movement together with effort-dependent mortality as accounting for the spatially-varying recapture probability in the movement model requires incorporating fishing mortality into the likelihood, the movement and mortality modules must be fitted jointly (Sections 4.1

and 4.2), accounting for tagger effects (Peatman et al., 2025). Building on this foundation, Phase 2 estimates a relative (Baranov) biomass index and Phase 3 an absolute (Petersen-type) biomass index (Section 4.3). Importantly, the movement model in Phase 1 is not tied to `admove`: Phases 2 and 3 require movement estimates (i.e. transition probabilities) as input rather than modelling movement internally, so these estimates could equally be supplied by other movement models, such as SEAPODYM (Senina et al., 2025) or even a null constant-diffusion model. Once the Phase 2 and 3 applications are in place, substituting the movement source carries minimal additional development cost, so comparing alternative movement models and their effect on the resulting biomass indices would be a valuable sensitivity analysis.

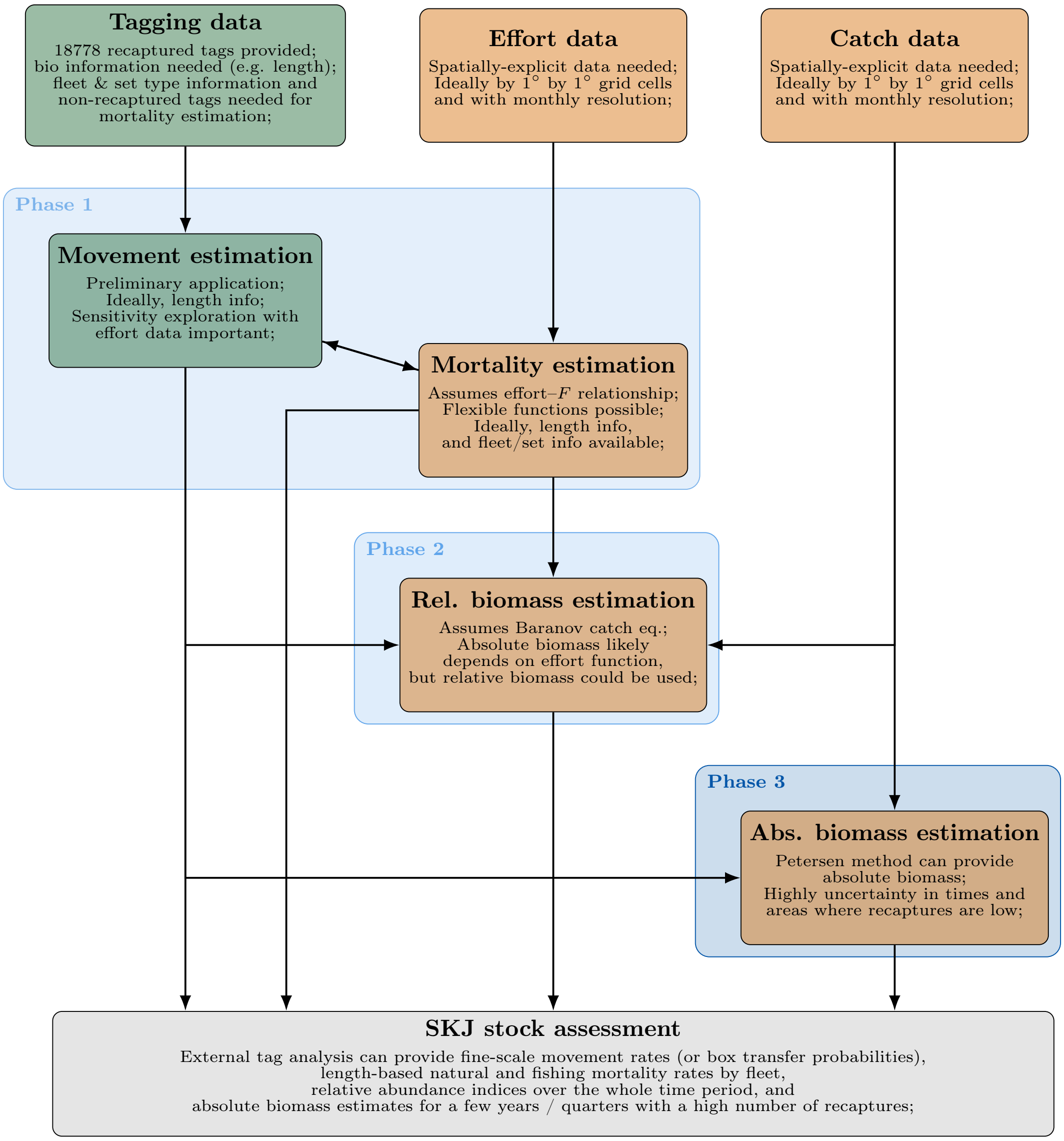

Figure 5: Flow diagram of the framework to analyse tagging data external and derive quantities relevant for the SKJ WCPO stock assessment. Green boxes indicate partly available data and preliminary explored analyses, while orange boxes indicate required data sets and non-trialed components of the preliminary analysis of this report. The two-headed arrow indicates the possibility to account for spatially-varying recapture probability by incorporating the mortality module. External analysis of WCPO SKJ tagging data is suggested to be tackled in 3 phases (blue boxes).

Phase 1 is the foundation and must be delivered first: joint movement and effort-dependent mortality estimation underpins both biomass phases, and the mortality module is expected to have a large influence on the estimated movement patterns. Phases 2 and 3 can then be worked on independently of each other and/or simultaneously. While Phase 2 depends on the effort information and assumptions and likely cannot deliver absolute biomass indices, Phase 3 might be able to deliver absolute biomass estimates, but likely only for a few time steps and for a specified core area and carries a larger risk, as the Petersen method is highly uncertain in regions and times with few recaptures and the unified framework (Section 4.4) is not yet implemented. A potential timeline for each phase is shown in Figure 6.

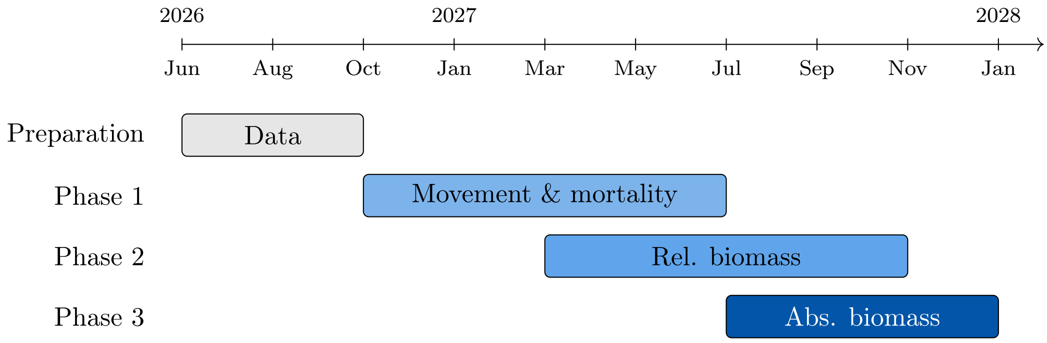

Figure 6: Time line by project phase.

According to this timeline, mortality and biomass indices could be available for the next SKJ assessment in 2028.

7 Conclusion

The framework outlined here can produce movement rates, mortality rates, and biomass indices from the analysis of tagging data and fine-scale spatial catch and effort data externally to any assessment model and is already used operationally for the assessment of SKJ in the EPO (Bi et al., 2024). The framework is continuously improved as part of projects and for various data sets and case studies, such as the development of an RTMB-based R package for the movement model as part of FISHMAP [1] and the incorporation of acoustic tags as part of the Great Lakes project [2].

The preliminary analysis suggests that movement, mortality, and biomass can be estimated for WCPO SKJ, but also revealed considerable challenges. Provided that additional data (further tagging programmes and spatially-resolved effort) become available,

[1] https://orbit.dtu.dk/en/projects/fish-distribution-and-its-role-in-fisheries-management-advice-and/

[2] https://www.glfc.org/project-catalog-project.php?id=155

and working with local tagging experts, we expect a successful analysis. Its advantages over using tags within a larger-region stock assessment are:

- Most importantly, the external approach relaxes (but does not eliminate) the mixing assumption by modelling the redistribution of tagged fish explicitly rather than assuming it, replacing region-level mixing with the weaker requirement that tagged fish are representative of untagged fish at grid-cell scale. In particular, it removes the need to pre-specify a mixing period per release event, one of the most influential assumptions in the WCPO SKJ assessment (Jordan et al., 2022). The relaxation is most complete for movement and only partial for the mortality and biomass modules.
- The approach makes fuller use of the information in each tag, using the actual displacement and time-at-liberty of every tag rather than the coarse region-to-region transitions per time step used by integrated assessments.
- Because movement is estimated in continuous space or on its own fine grid, it is decoupled from the spatial structure of any particular assessment: the movement rates can be aggregated to box-transfer probabilities for any set of assessment regions and time steps, and re-aggregated without re-fitting if that structure changes.
- Movement is linked mechanistically to the environment (habitat preference and ocean currents), so it can be predicted for areas and times without tags and under changing conditions, rather than being a static empirical transfer matrix. This is particularly relevant for a region with strong interannual (ENSO) variability and under a changing climate.
- The approach provides additional ecological information about the fine-scale movement of tuna and its drivers; information on potentially ontogenetic and seasonally-varying movement patterns may itself be useful for the management of SKJ.
- Further investment in the external analysis of SKJ tagging data is not only beneficial for developing quantities for the next-generation stock assessment model, but might also inform a potential fully-integrated assessment model later.

We hope that the results of this report are useful for the development of the next-generation tuna assessment model, either by informing an external analysis of tagging data that supplies box-transfer rates, mortality rates, and/or biomass indices to the assessment model, or as a module for a future fully-integrated assessment model with a fine spatiotemporal scale.

8 Acknowledgments

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Generative AI tools (Anthropic's Claude; opus-4-8; accessed 2026) were used to assist with drafting and editing text in this document. All analytical choices, model specifications, diagnostic interpretations, and conclusions are those of the authors, who reviewed and verified all AI-assisted output. The methodology, model implementation, and the scientific conclusions are the responsibility of the authors.

References

Aoki, Y., Matsubara, N., Tsuda, Y., Nishimoto, M., & Kiyofuji, H. (2025). Japanese data update: Tagging, Size and Biological information.

Bi, R., Maunder, M. N., Xu, H., Minte-Vera, C., Valero, J., & Aires-da-Silva, A. (2024). *Stock assessment of skipjack tuna in the eastern pacific ocean: 2024 benchmark assessment* (IATTC Document No. SAC-15-04). Inter-American Tropical Tuna Commission (IATTC).

Brill, R. W. (1994). A review of temperature and oxygen tolerance studies of tunas pertinent to fisheries oceanography, movement models and stock assessments. *Fisheries Oceanography*, *3*(3), 204–216.

Jordan, C. C., Teears, T., Hampton, J., Davies, N., Phillips, J. S., McKechnie, S., Peatman, T., Macdonald, J., Day, J., Magnusson, A., Scott, R., Scott, F., Pilling, G., & Hamer, P. (2022). Stock assessment of skipjack tuna in the western and central Pacific Ocean: 2022.

Magnusson, A., Davies, N., Pilling, G., & Hamer, P. (2025). Scoping the Next Generation of Tuna Stock Assessment Software: Progress Report (Project 123).

Maunder, M. N., Deriso, R. B., Schaefer, K. M., Fuller, D. W., Aires-da-Silva, A. M., Minte-Vera, C. V., & Campana, S. E. (2018). The growth cessation model: A growth model for species showing a near cessation in growth with application to bigeye tuna (Thunnus obesus). *Marine Biology*, *165*(4), 76.

Mildenberger, T. K., Nielsen, A., & Maunder, M. N. (2022). *Spatiotemporal tagging model for skipjack tuna in the EPO* (IATTC Document No. SAC-13-08). Inter-American Tropical Tuna Commission (IATTC).

Mildenberger, T. K., Nielsen, A., & Maunder, M. N. (2023). *Length-structured spatiotemporal tagging model for skipjack tuna in the EPO* (IATTC Document No. SAC-14-INF-E). Inter-American Tropical Tuna Commission (IATTC). La Jolla, California.

Mildenberger, T. K., Nielsen, A., & Maunder, M. N. (2024). *A spatiotemporal petersen-type model for skipjack tuna in the EPO* (IATTC Document No. SAC-15-INF-G). Inter-American Tropical Tuna Commission (IATTC). La Jolla, California.

Mildenberger, T. K., Nielsen, A., & Maunder, M. N. (2025). *Ongoing development of the spatiotemporal tagging model* (IATTC Document No. SAC-16-INF-D). Inter-American Tropical Tuna Commission (IATTC). La Jolla, California.

Peatman, T., Phillips, J. S., Potts, J., & Nicol, S. (2025). Analysis Of Tagging Data For The 2025 Skipjack Assessment: Corrections To Tag Releases For Tagging Conditions.

Scutt Phillips, J., Lehodey, J., Hampton, J., Hamer, P., Senina, I., & Nicol, S. (2022). Quantifying Rates of Mixing in Tagged, WCPO Skipjack Tuna.

Senina, I., Bonnin, L., Lengaigne, M., Kiyofuji, H., Buenafe, K., Fuller, D., Hampton, J., & Nicol, S. (2025). Reference Model of Skipjack Tuna in the Pacific Ocean Using SEAPODYM Integrating Catch, Length, Tagging, and Early Life History Data.

Teears, T., Davies, N., Hamer, P., Magnusson, A., Peatman, T., Phillips, J. S., Pilling, G., Scott, R., Vidal, T., & Hampton, J. (2025). Stock assessment of skipjack tuna in the western and central Pacific Ocean: 2025.

Thorson, J. T., Barbeaux, S. J., Goethel, D. R., Kearney, K. A., Laman, E. A., Nielsen, J. K., Siskey, M. R., Siwicke, K., & Thompson, G. G. (2021). Estimating fine-scale movement rates and habitat preferences using multiple data sources. *Fish and Fisheries*, *22*(6), 1359–1376.

9 Supplementary Material

9.1 Minimum time after release

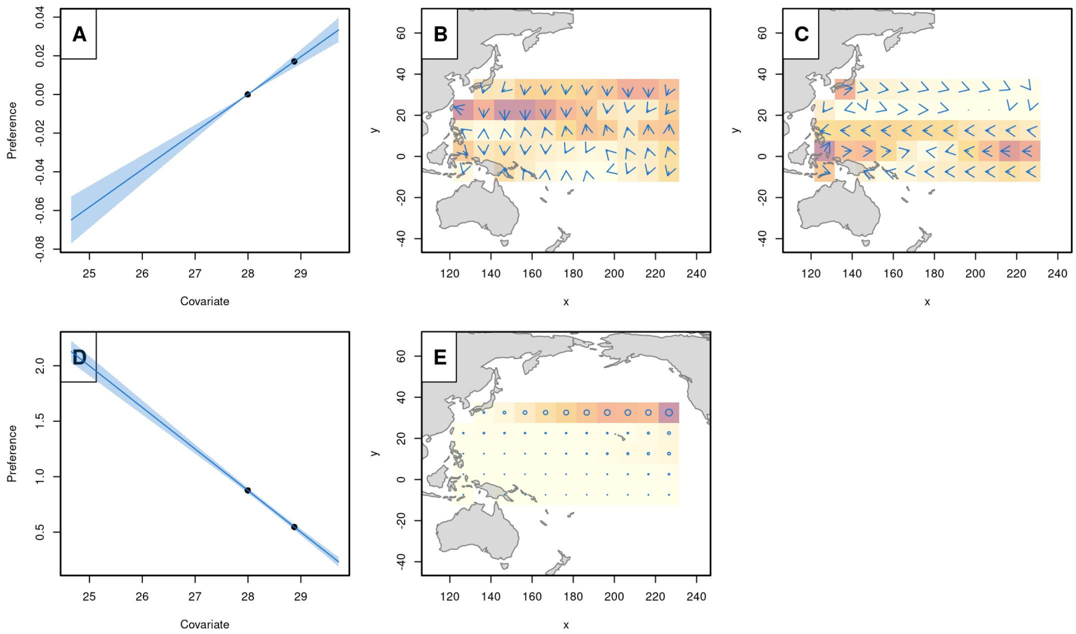

Figure 7: Estimated habitat preference as a function of depth-integrated temperature (A), resulting taxis in space (B), estimated advection through currents (C), estimated diffusion as a function of depth-integrated temperature (D), and resulting diffusion in space (E) for scenario removing tags recovered before **30 days** after release (baseline scenario: 14 days).

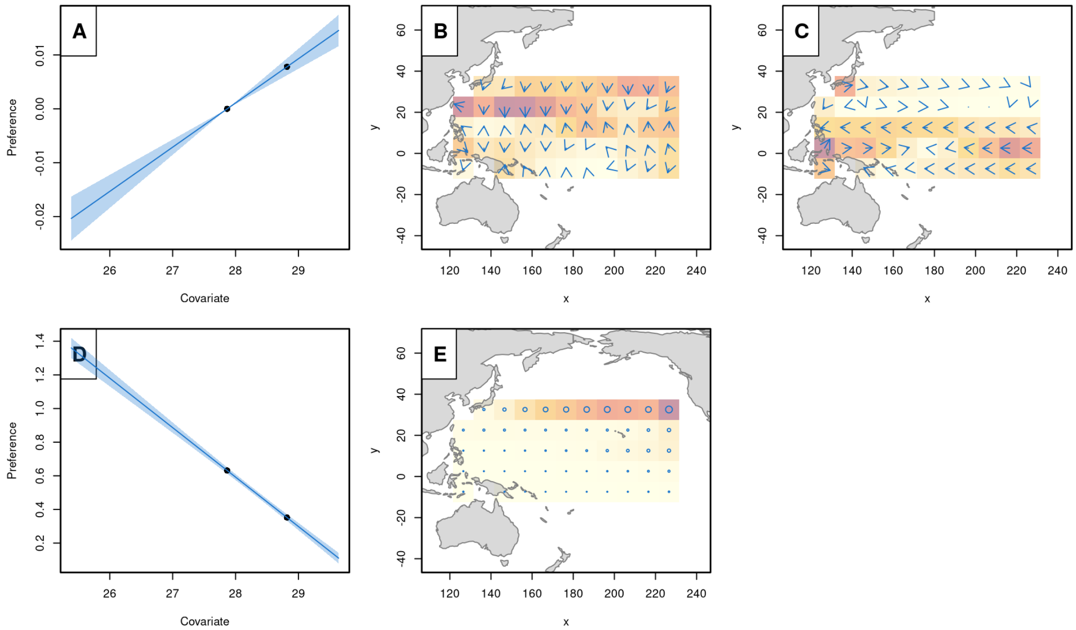

Figure 8: Estimated habitat preference as a function of depth-integrated temperature (A), resulting taxis in space (B), estimated advection through currents (C), estimated diffusion as a function of depth-integrated temperature (D), and resulting diffusion in space (E) for scenario removing tags recovered before **7 days** after release (baseline scenario: 14 days).

9.2 Covariate settings

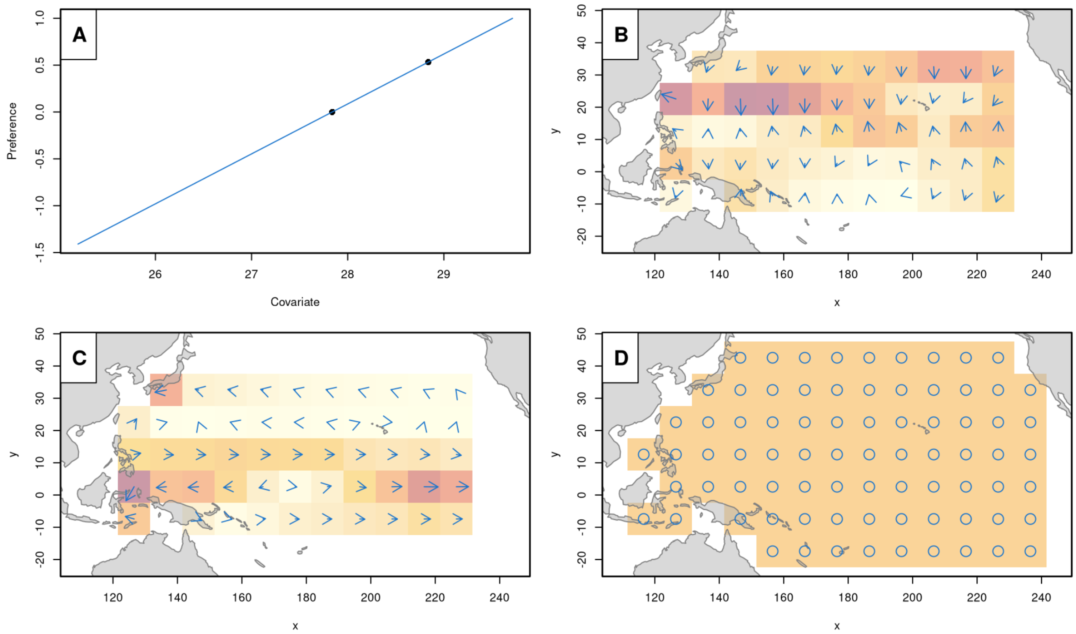

Figure 9: Estimated habitat preference as a function of depth-integrated temperature (A), resulting taxis in space (B), estimated advection through currents (C), and estimated constant diffusion in space (D) for scenario assuming **constant diffusion** (baseline scenario: diffusion as a linear function of depth-integrated temperature). Note that this model did not converge.

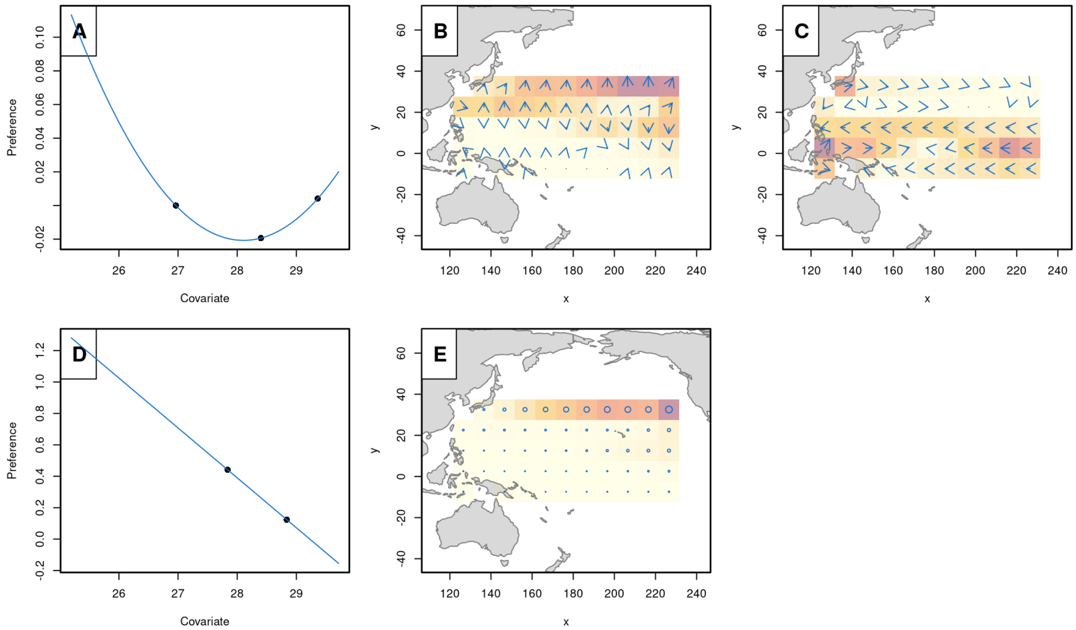

Figure 10: Estimated habitat preference as a function of depth-integrated temperature (A), resulting taxis in space (B), estimated advection through currents (C), estimated diffusion as a function of depth-integrated temperature (D), and resulting diffusion in space (E) for scenario assuming a **more flexible habitat preference function** (smooth function with 3 knots; baseline scenario: linear function of depth-integrated temperature). Note that this model did not converge.

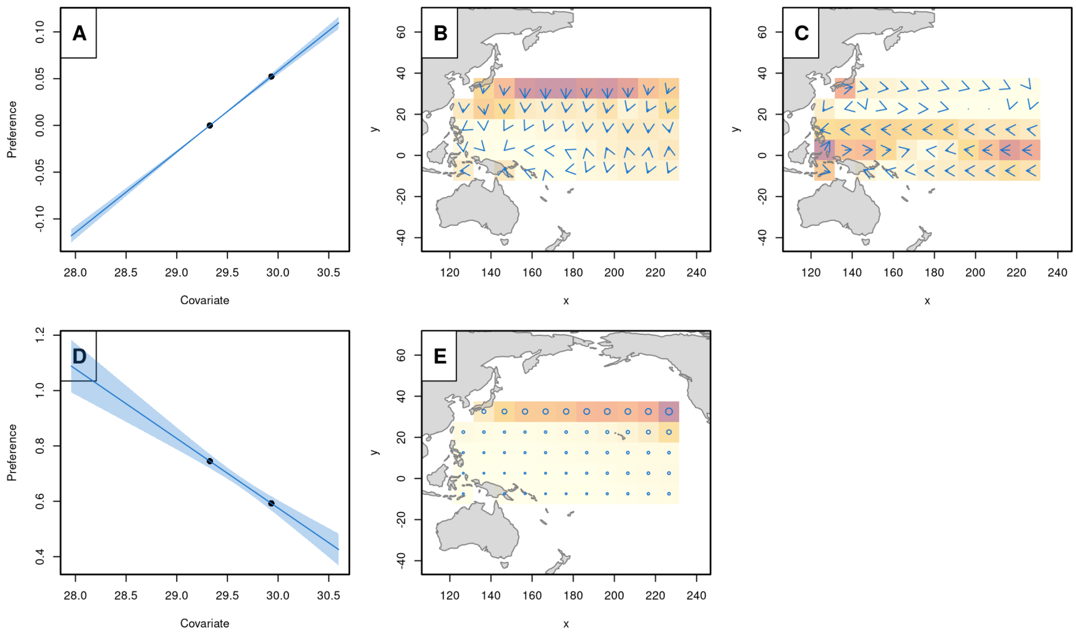

Figure 11: Estimated habitat preference as a function of depth-integrated temperature (A), resulting taxis in space (B), estimated advection through currents (C), estimated diffusion as a function of depth-integrated temperature (D), and resulting diffusion in space (E) for the scenario using **sea surface temperature** as covariate field for taxis and diffusion (default: depth-integrated temperature).

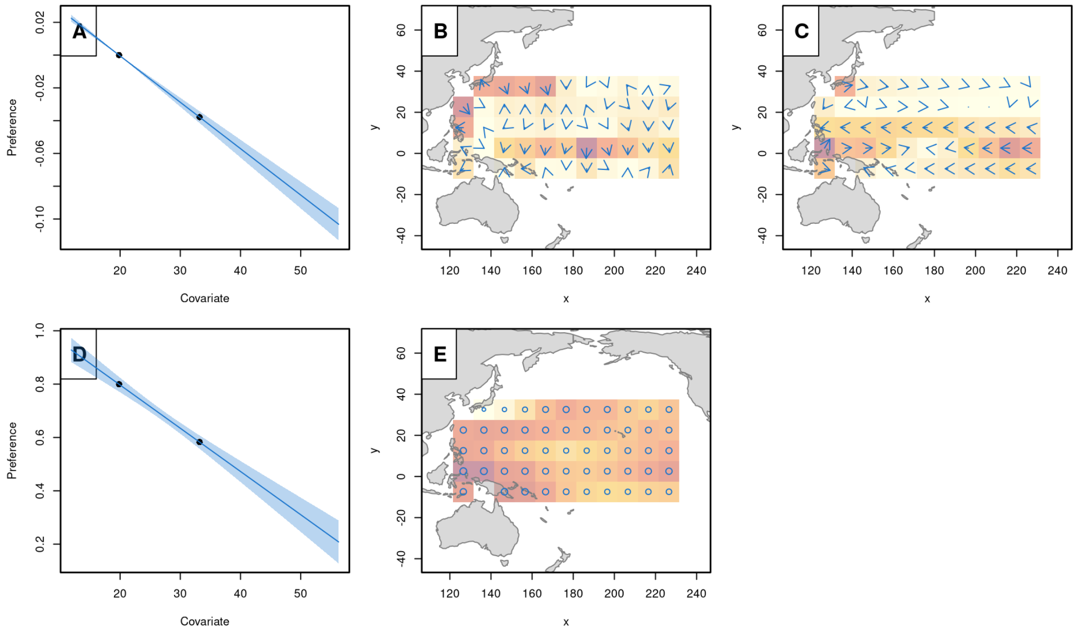

Figure 12: Estimated habitat preference as a function of depth-integrated temperature (A), resulting taxis in space (B), estimated advection through currents (C), estimated diffusion as a function of depth-integrated temperature (D), and resulting diffusion in space (E) for the scenario using **mixed layer depth** as covariate field for taxis and diffusion (default: depth-integrated temperature).

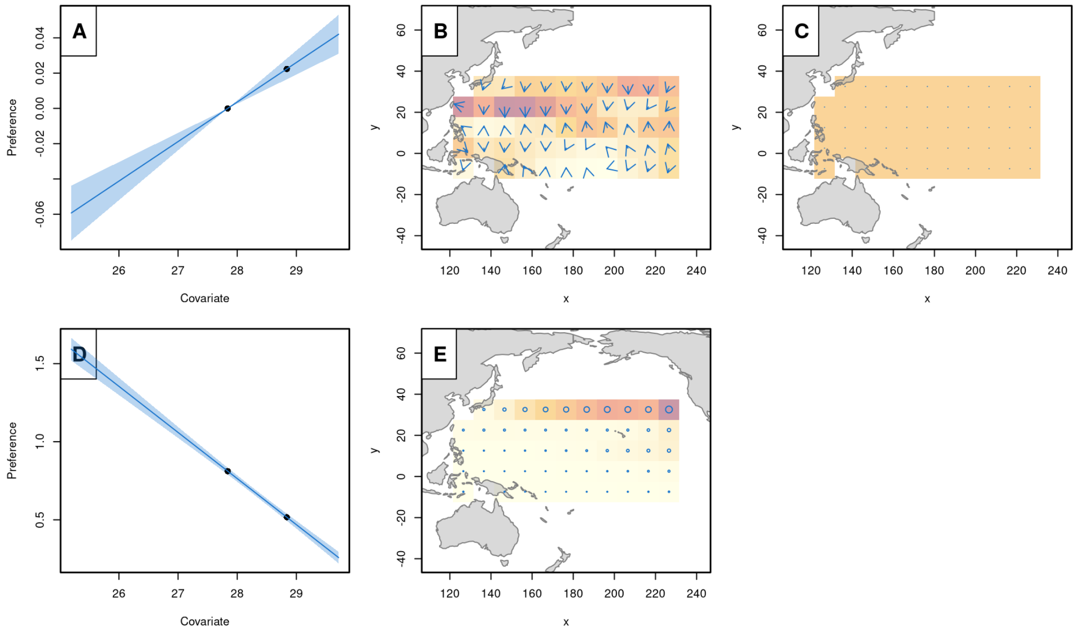

Figure 13: Estimated habitat preference as a function of depth-integrated temperature (A), resulting taxis in space (B), estimated advection through currents (C), estimated diffusion as a function of depth-integrated temperature (D), and resulting diffusion in space (E) for the scenario using **no advection** (default: currents define advection).

9.3 Data subsets

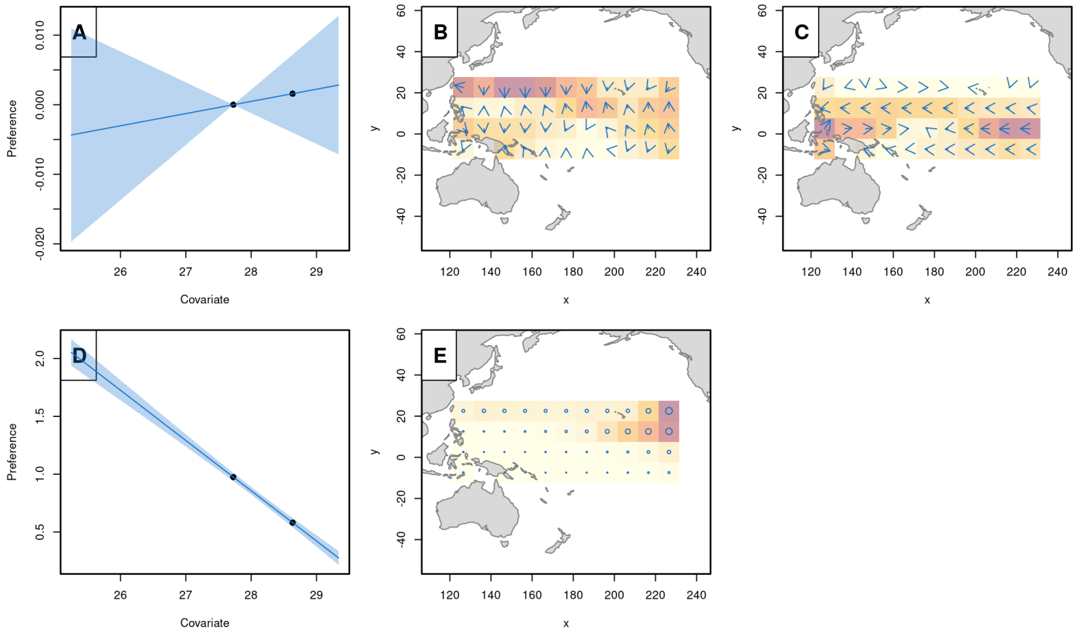

Figure 14: Estimated habitat preference as a function of depth-integrated temperature (A), resulting taxis in space (B), estimated advection through currents (C), estimated diffusion as a function of depth-integrated temperature (D), and resulting diffusion in space (E) for the scenario using **only tags before August 2010** (default: all tags in 2006-2022).

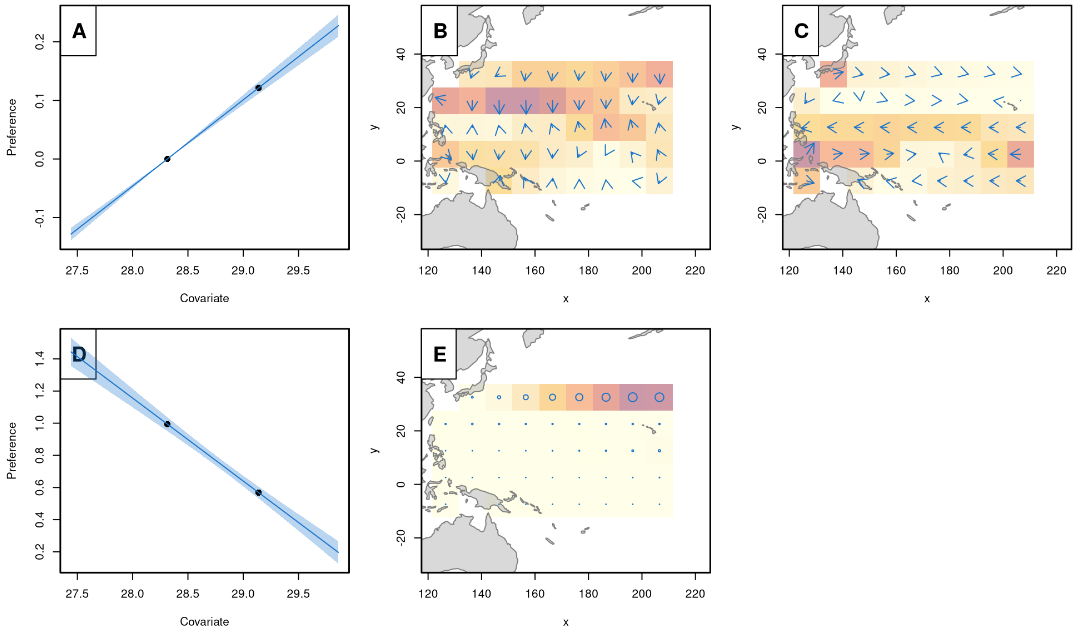

Figure 15: Estimated habitat preference as a function of depth-integrated temperature (A), resulting taxis in space (B), estimated advection through currents (C), estimated diffusion as a function of depth-integrated temperature (D), and resulting diffusion in space (E) for the scenario using **only tags between August 2010 and January 2016** (default: all tags in 2006-2022).

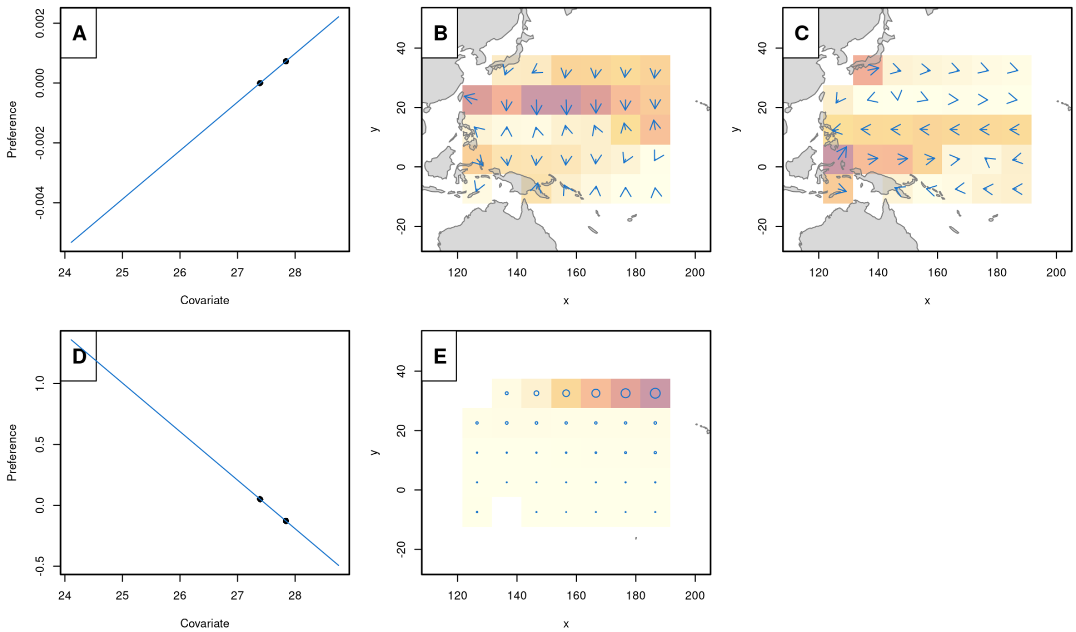

Figure 16: Estimated habitat preference as a function of depth-integrated temperature (A), resulting taxis in space (B), estimated advection through currents (C), estimated diffusion as a function of depth-integrated temperature (D), and resulting diffusion in space (E) for the scenario using **only tags between January 2016 and November 2021** (default: all tags in 2006-2022). Note that this model did not converge.

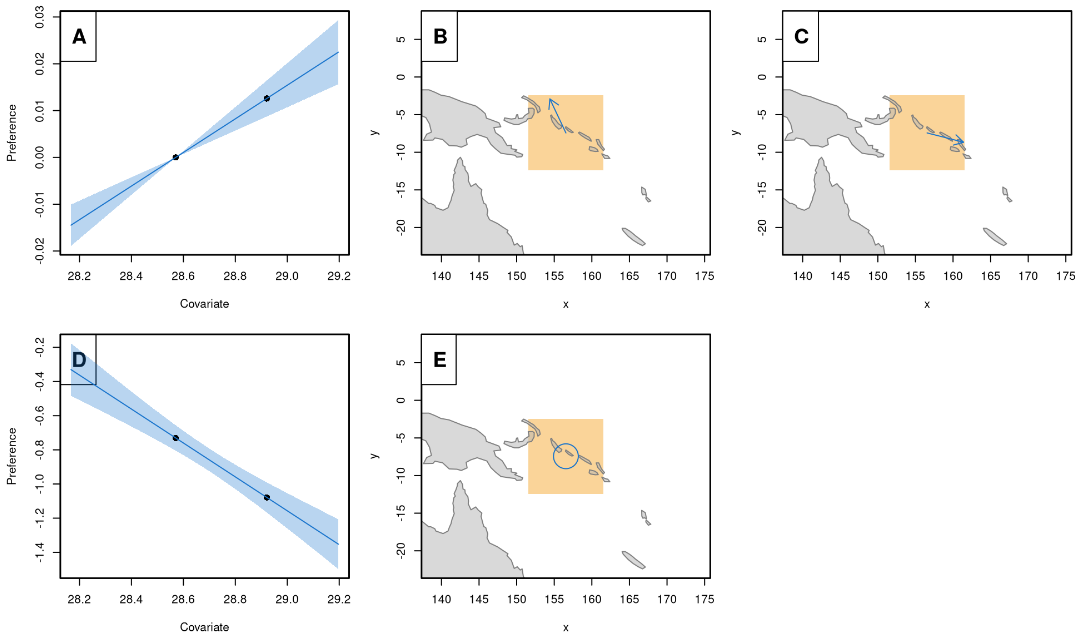

Figure 17: Estimated habitat preference as a function of depth-integrated temperature (A), resulting taxis in space (B), estimated advection through currents (C), estimated diffusion as a function of depth-integrated temperature (D), and resulting diffusion in space (E) for the scenario using **only tags after November 2021** (default: all tags in 2006-2022).