Results of a Spatial Stock Assessment Model for Alaskan Sablefish

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A research-oriented spatial stock assessment model for Alaskan sablefish was developed to explore estimates of regional biomass and recruitment, while evaluating age-specific movement patterns across federal waters (Cheng *et al.*, 2025). To inform the parameterization of the spatial model, a conceptual model of existing hypotheses regarding sablefish spatial dynamics was developed (Fig. 1). Based on data availability and necessary trade-offs with model complexity, the spatial model was configured with 5 regions, which included: the Bering Sea, Aleutian Islands, Western Gulf of Alaska, Central Gulf of Alaska, and the Eastern Gulf of Alaska (combining West Yakutat and Southeast Outside into a single combined region). Additionally, estimated movement dynamics were specified to be constant over time, but age-specific for 3 age groups: young individuals (ages 2 - 6), intermediate individuals (ages 7 - 15), and old individuals (ages 16 - 31+). The model estimated all parameters by region (except fishery and survey selectivity which were shared across regions by fleet) using the same data (at the regional scale) as the operational single region (Alaska wide) assessment. Additionally, tagging data (releases from the annual NOAA longline survey and recaptures primarily from stakeholder returned tags; Fig. 2-3) was also integrated to help estimate movement and mortality processes (reporting rate was directly estimated at a value of ~27%).

The spatial model suggested that large recruitment events of age-2 individuals often occurred in the Bering Sea, Aleutian Islands, and Central Gulf of Alaska, while the Western and Eastern Gulf of Alaska had comparatively lower levels of recruitment (Fig. 4; first row panel). Conversely, the Central and Eastern Gulf of Alaska maintained the highest spawning biomass (Fig. 4; second row panel). Despite strong age-2 recruitment in the Bering Sea and Aleutian Islands, spawning biomass remained low in these regions. The disconnect between regions of high SSB and those with high recruitment are likely due to unmodeled pre-recruit spatial dynamics (i.e., occurring before sablefish are observed in either fishery or survey compositional data around age-2), potentially caused by larval dispersal and subsequent age-1 movement away from spawning regions, towards juvenile habitat. Movement estimates support historical hypotheses of counter-clockwise age-based movement for Alaskan sablefish (Fig. 1 and 5), wherein younger fish tend to reside in more western regions then move eastward as they mature.

The developed spatial model is meant as a research tool to better understand the regional dynamics and cross-management zone interactions of sablefish in Alaska. Based on initial comparisons with the single region assessment, the existing spatial catch apportionment approach (i.e., a 5-year rolling average of regional survey biomass proportions) appears adequate for mitigating adverse biological effects at the management zone level. Updated model runs are planned on a semi-annual basis to provide further insights into spatial dynamics and regional depletion levels. However, the spatial model will be further explored for use as the basis of management advice in future years, especially given ongoing changes to the NOAA sablefish longline survey experimental design which may necessitate innovative assessment approaches. The spatial model has been partially updated with new data and is presented in the main document as a sensitivity run (*25.15_Spatial*). The full version of the published article (Cheng et al., 2025) is available at the end of this document.

References

Cheng, M. L. H., Marsh, C. A., Goethel, D. R., Hulson, P. F., Echave, K., Williams, B. C., Berger, A. M., *et al.* 2025. Panmictic Panacea? Demonstrating Good Practices for Developing Spatial Stock Assessments Through Application to Alaska Sablefish (*Anoplopoma fimbria*). Fish and Fisheries: faf.70002. https://doi.org/10.1111/faf.70002

Figures

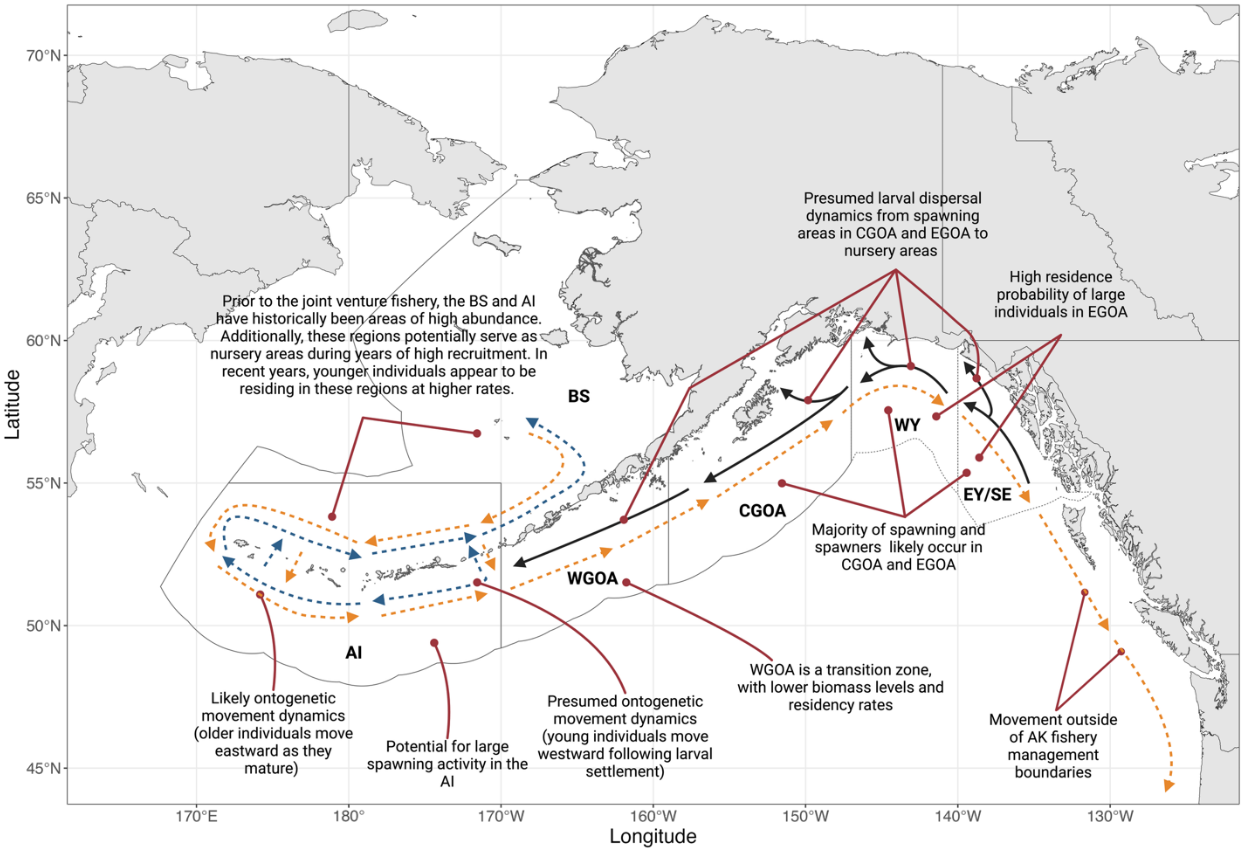

Figure 1. Conceptual model of spatial sablefish dynamics. Black solid arrows represent hypotheses on larval dispersal, blue dashed arrows are hypotheses regarding the movement dynamics of younger individuals, and orange dashed arrows are hypotheses on general movement dynamics of individuals as they mature.

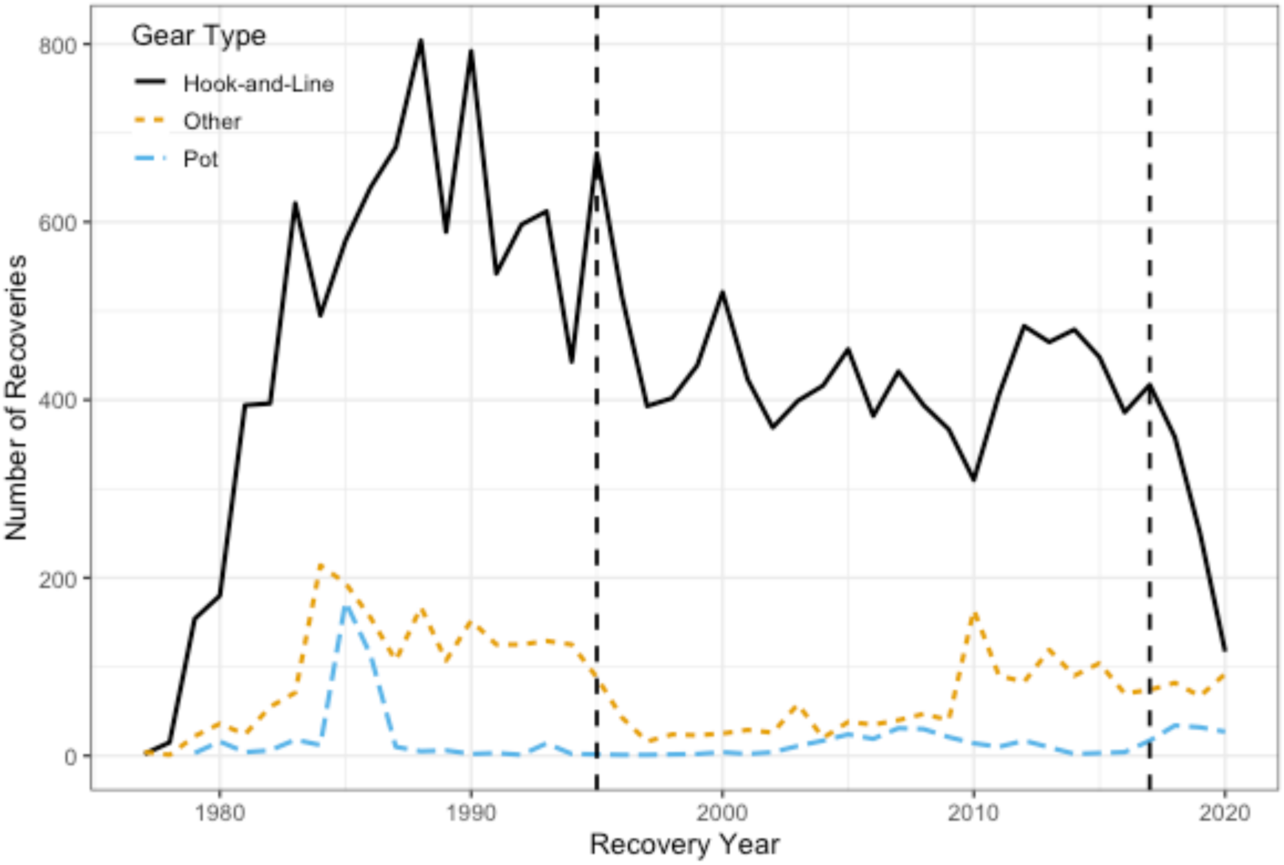

Figure 2. Time-series of recoveries across years and gear types. The number of tag recoveries by are denoted (vertical dashed lines) with fishery management regulatory changes (i.e., an individual fishing quota system started in 1995 and pot gear was legalized in the Gulf of Alaska in 2017).

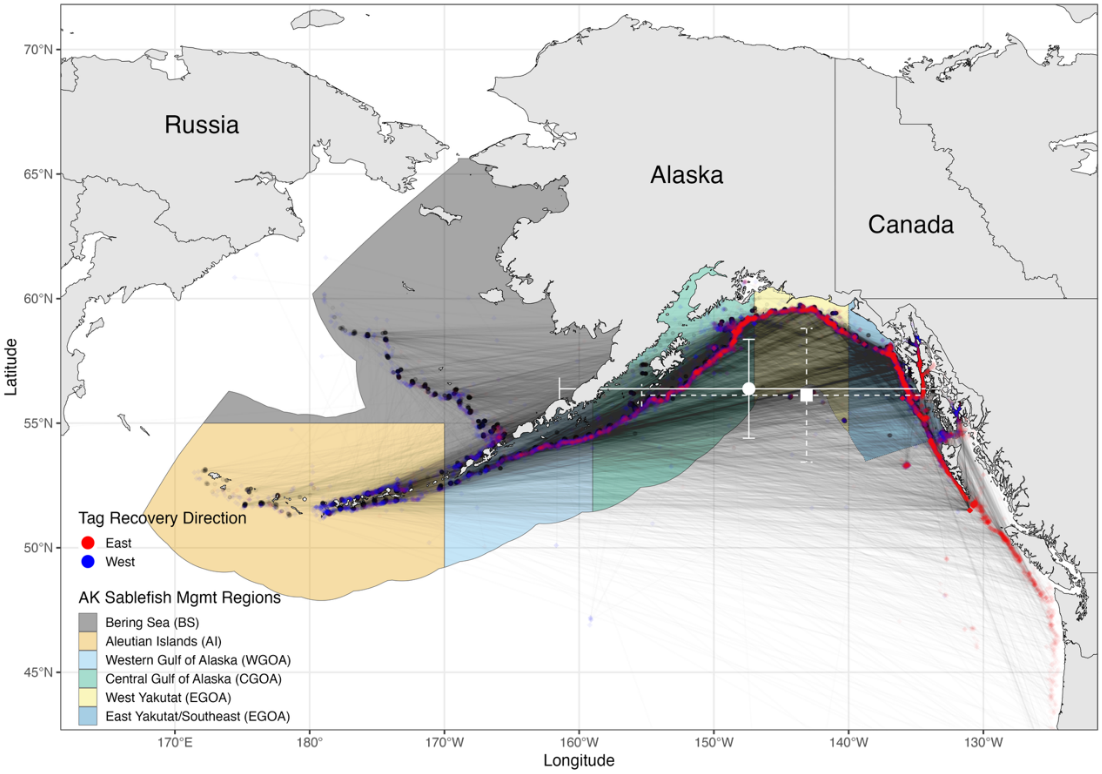

Figure 3. Locations of tag release (black points; *n*=395,146) and recovery events (colored points; *n*=34,833) from 1972 to 2020. Red points indicate general eastward movements (i.e., release longitude > recovery longitude), while blue points indicate general westward movements (i.e., release longitude < recovery longitude). Black lines connect tag release events to its corresponding recovery location. The white point represents the mean release location of individuals and white solid lines are the standard deviation of release locations. The white square denotes the mean recapture location of individuals, with white dotted lines representing the standard deviation of recapture locations. Colored polygons represent Alaska sablefish fishery management boundaries in the US Exclusive Economic Zone.

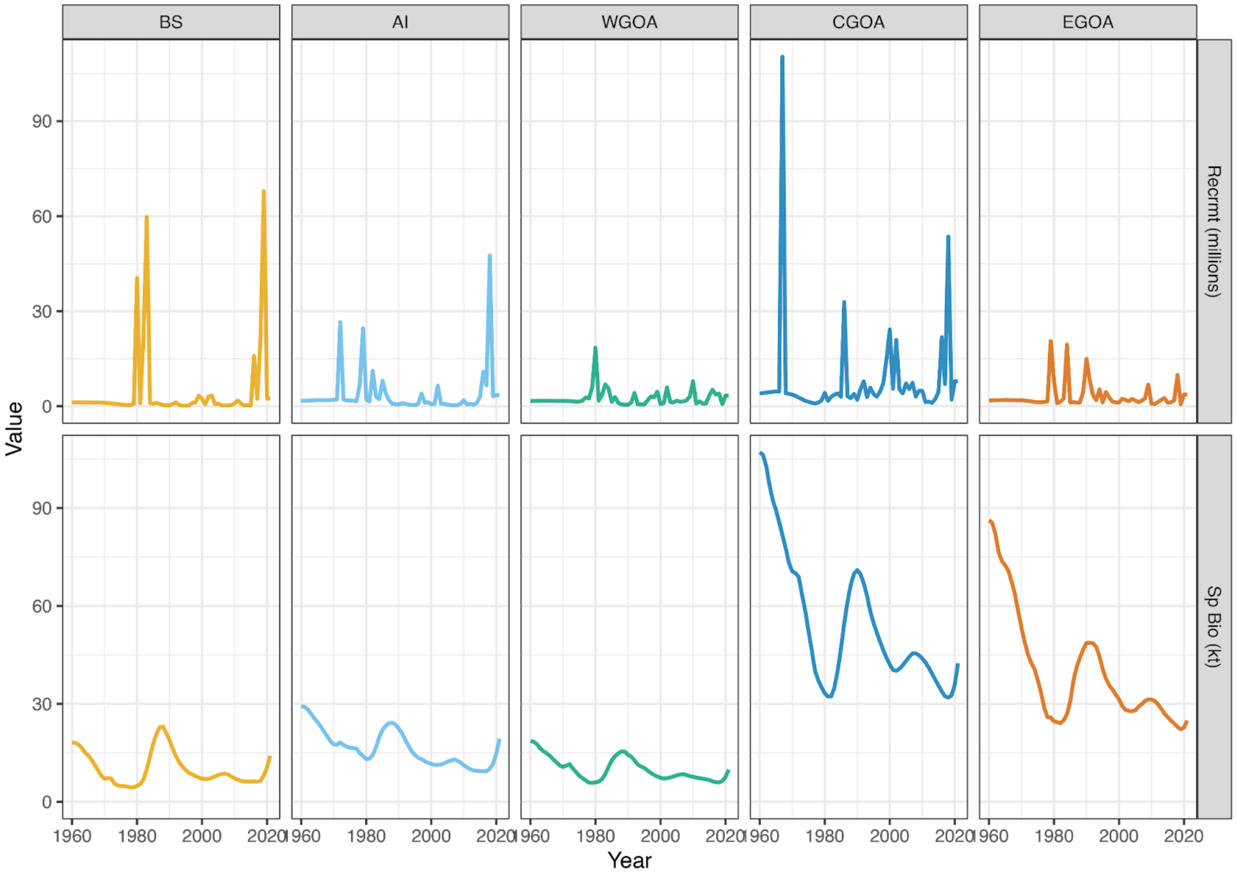

Figure 4. Comparison of time-series estimates from the spatial assessment model by region (panel columns; Bering Sea (BS), Aleutian Islands (AI), Western GOA (WGOA), Central GOA (CGOA), Eastern GOA (EGOA)). Estimates of regional age-2 recruitment (millions) are shown in the first row of panels, while estimates of spawning biomass (kt) are shown in the second row.

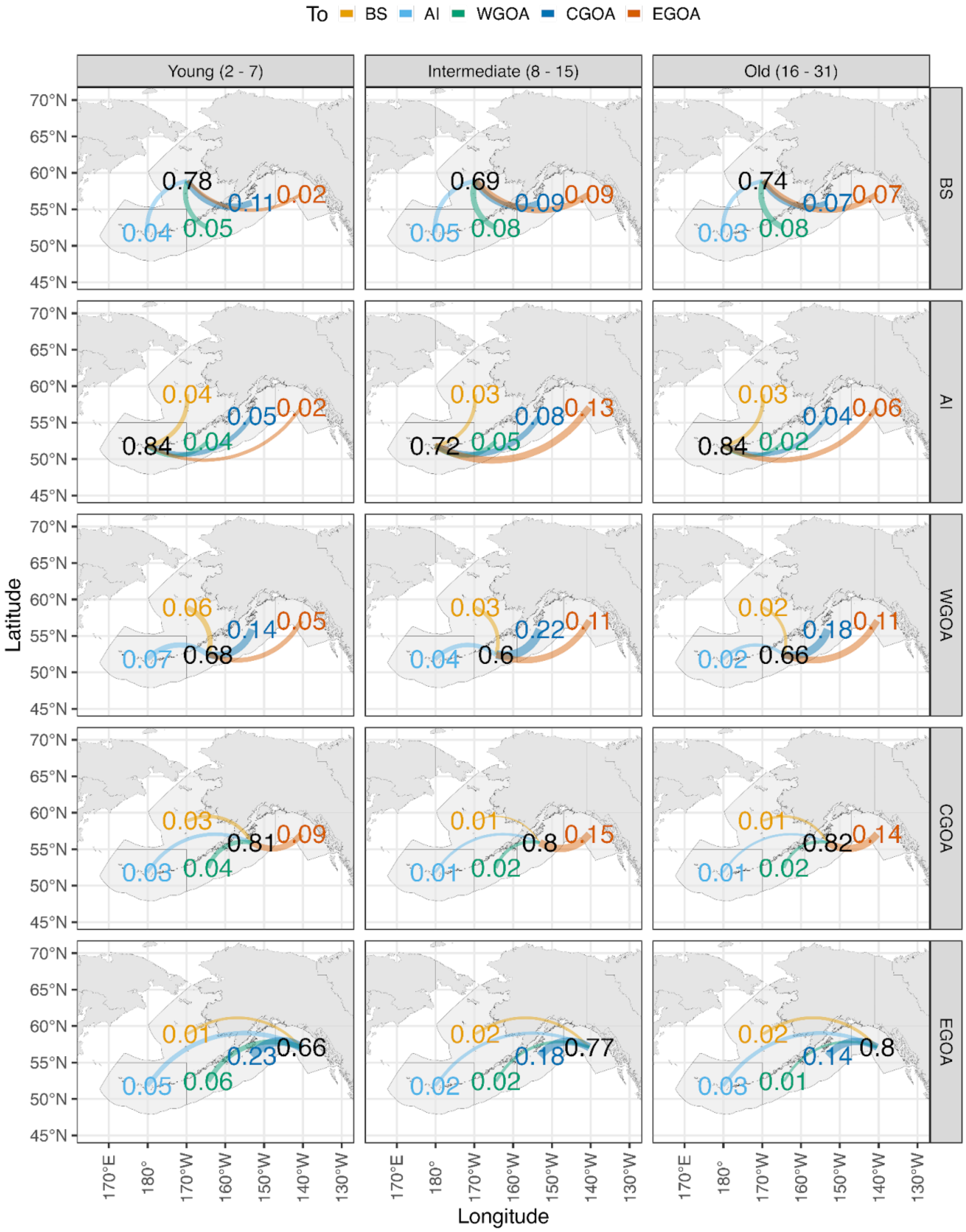

Figure 5. Estimated movement probabilities from the spatial assessment model by region and age groups. Column panels indicate the different age groups (young, intermediate, and old), and row panels represent movement originating from a given spatial region (Bering Sea (BS), Aleutian Islands (AI), Western GOA (WGOA), Central GOA (CGOA), Eastern GOA (EGOA)). Values shown in black are residence probabilities (i.e., the probability of remaining within the same region), while colored values represent the probability of moving into a given spatial region. Line thickness is proportional to movement probabilities, with thicker lines corresponding to higher movement probabilities.

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ORIGINAL ARTICLE

Panmictic Panacea? Demonstrating Good Practices for Developing Spatial Stock Assessments Through Application to Alaska Sablefish (*Anoplopoma fimbria*)

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ABSTRACT

Marine species and associated fisheries demonstrate complex spatial dynamics driven by biological, ecosystem and socioeconomic factors and integrating these spatial dynamics into stock assessment models can improve fishery management advice. While preliminary good practices for developing spatial stock assessment models have been proposed, comprehensive demonstrations applying these practices remain limited. Drawing on these good practices, we provide an end-to-end demonstration of developing a spatial stock assessment using Alaska sablefish (*Anoplopoma fimbria*). Our demonstration emphasises the utility of high-resolution data analysis and conceptual models for informing key model structure decisions, the joint development of spatial and spatially-aggregated models to enhance understanding of population dynamics, and the need for further guidance on integrating tagging data and diagnostic tools in spatial assessments. Spatial models highlighted regional differences in sablefish biomass, recruitment and age structure, but total population estimates generally aligned with outputs from spatially aggregated models. Moreover, the spatial model identified ontogenetic movement patterns for this highly mobile species. Overall, the spatially aggregated model for Alaska sablefish is likely adequate for management advice, but periodic spatial model updates could offer insights into spatial dynamics and regional depletion levels. Thus, we recommend concomitant use of both models: spatially aggregated models for informing population-wide status, and spatial models for informing spatial fishery dynamics and local depletion. The sablefish application represents one of the first implementations of a spatial stock assessment using recently proposed good practices, serving as a valuable guide for future practitioners by underscoring critical decision points and analyses to address them when developing spatial stock assessments.

1 | Introduction

In recent decades, spatial delineation of the world's oceans has rapidly progressed as part of marine spatial planning initiatives to address the competing needs of various sectors involved in the blue economy (Bax et al. 2022). Concurrently, improved understanding of spatial dynamics in governing the productivity and sustainable harvest of living marine resources has facilitated increased implementation of spatial fisheries management strategies (Liu et al. 2016). Thus, provision of scientifically informed management and ocean policy requires development and utilisation of spatial modelling frameworks that align with

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the scale of decision-making. Across the array of disciplines that constitute fisheries science, spatial models have proliferated to address emerging needs (e.g., Ovando et al. 2024). Although the full array of modelling frameworks helps guide spatial fisheries management decisions, advances in spatial stock assessment models can provide the most direct benefits to management advice, given their common use for estimating population status and sustainable catch quotas (Hilborn 2012).

Stock assessment models are simplified mathematical representations of fish population dynamics that are often utilised to determine population status and provide sustainable harvest recommendations (Quinn and Deriso 1999). Traditionally, assessment models have ignored spatial processes, assuming a panmictic unit population with homogeneous dynamics (i.e., spatially-aggregated models; Goethel and Cadrin 2021). In general, spatially-aggregated models can provide adequate management advice when spatial processes are present (Punt et al. 2017), but this is contingent on defining model boundaries that accurately reflect the primary biological and population structure (Berger et al. 2021). Delineating management units to align with biological populations can be difficult because historic management unit delineations often do not correspond with biological populations (Kerr et al. 2014). Moreover, spatially-aggregated assessment models also often need to allocate aggregated catch advice to management units due to conservation or socioeconomic factors (Bosley et al. 2019). By contrast, spatial stock assessments are able to directly integrate complex spatiotemporal dynamics, elucidate drivers of productivity and provide advice at scales relevant to decision-makers (Berger et al. 2017). Therefore, development of spatial assessment models may be necessary to avoid violating the assumption of a unit population, while mitigating associated biases in parameter estimates, population trajectories and harvest advice when spatial dynamics are present (Punt 2019a; Goethel et al. 2021; Bosley et al. 2022).

To date, the use of spatial assessments for operational management advice remains uncommon (Punt 2019b). Examples include a number of broadly distributed tuna species (e.g., Indian Ocean yellowfin tuna, *Thunnus albacares*; Urtizberea et al. 2019). However, spatial assessments are seldom used to manage demersal species, and often rely on simplified spatial processes when implemented (see Punt 2019b for examples). The adoption of spatial assessment models for use in management decision-making is often impeded by institutional inertia to changes in existing assessment and management paradigms, given challenges in identifying spatial biological reference points (Kapur et al. 2021), the need for data at spatially appropriate scales, along with perceived increases in model complexity (Berger et al. 2017). Although use of spatial assessments for provision of management advice is uncommon, their performance has been relatively well-studied in simulation contexts (Punt 2019a, 2019b; Goethel and Cadrin 2021). Oftentimes, spatial assessment models are capable of accounting for complex spatial structure, while providing management quantities at the resolution needed to maintain inter- and intra-population integrity (McGilliard et al. 2015). Yet, when poorly specified (e.g., movement dynamics are inflexible), spatial models may perform worse than spatially implicit (i.e., areas-as-fleets) or spatially-aggregated models, exhibiting large biases in population biomass (Bosley et al. 2022). For instance, Goethel et al. (2024) demonstrated that no single assumption of spatial structure performed best when confronted with simulated data that realistically emulated the real-world (e.g., sparse length compositions and no survey indices), providing further evidence that the utility of a spatial assessment is context-dependent. Critically, their results underscore the need to develop assessment models that encompass multiple spatial structure assumptions to improve ecological and management insights.

Although momentum for the wider application of spatial assessment models is growing (Goethel and Cadrin 2021), good practices in developing spatial assessment models (Punt 2019a; Goethel, Berger, et al. 2023) remain preliminary. Thus, increased documentation of the development process for implementing applied spatial stock assessments is crucial to improve knowledge sharing and highlight the benefits and pitfalls of spatial stock assessments (Goethel et al. 2024). Following the guidance and key decision points outlined by (Goethel, Berger, et al. 2023) in Tables 1–4, we present one of the first end-to-end demonstrations of applying good practices for developing a spatial stock assessment, using Alaska sablefish (*Anoplopoma fimbria*) as a case study (but see Fournier et al. 1998 and Cardinale et al. 2023 for examples of applied spatial assessments). Through comparison with key estimates from a spatially-aggregated assessment model, we highlight areas where improved inference and management recommendations may be possible with a spatial model. The framework presented in this study will help identify and disseminate lessons learned to aid future applications.

2 | Methods

We outline the entire model development process, including: identifying a need for a spatial model, performing a data inventory, implementing a conceptual model to help identify key spatial drivers, and describing the structure of an initial spatial assessment model. We then highlight multiple model structures that were implemented based on key uncertainties and describe how comparisons among model configurations were performed to determine a final 'selected' spatial model. We conclude with methods to compare outputs and insights from the selected spatial model to an operational spatially-aggregated assessment. Throughout, we highlight the data and information used at each step of model development, providing a foundation for refining spatial assessment models for other species.

2.1 | Identifying Need for a Spatial Assessment Model

Sablefish are a highly mobile species that demonstrate complex movement dynamics (Heifetz and Fujioka 1991; Hanselman et al. 2015), resulting in a genetically panmictic population throughout their range in the Northeast Pacific Ocean (Alaska to Southern California; Jasonowicz et al. 2017; Timm et al. 2024). Within Alaska, sablefish are assessed and managed as a single panmictic unit that spans three large marine ecosystems and management regions, including the Bering Sea (BS), Aleutian Islands (AI) and the Gulf of Alaska (GOA; Figure 1). Catch advice, as determined by the operational spatially-aggregated assessment, is apportioned across 6 fishery

TABLE 1 | Primary questions (from Goethel, Berger, et al. 2023) used to identify drivers of spatial dynamics for the sablefish case study along with associated answers that helped guide development of the conceptual model and narrow spatial modelling options.

Question	Answer for sablefish
What are the management needs for a spatial model?	Need to assign catch advice to management units from a single region assessment Must manage multiple fleets with spatially variable harvest patterns Complex ontogenetic movement dynamics cause differential availability of age and size classes to multiple fleets across space and time
What data are available and at what resolution?	Several genetic and tagging studies along with biophysical larval models are available to guide stock identification Biological data, abundance indices and tagging data are reported by fishery management units Regional sample sizes for biological data (e.g., composition or growth data) generally support the increase in spatial model resolution Fishery removals are the limiting dataset, where removals from 1960 to 1976 are reported on a region wide scale, while removals thereafter are reported at the scale of fishery management units
What is the population and spatial structure?	Sablefish are genetically panmictic across their range and exhibit high movement rates, suggesting extensive reproductive mixing (Figure 2; Figure A1) Biophysical models indicate the potential for long dispersal distances, where nursery areas are likely populated by fish from multiple spawning locations Spatial heterogeneity in fishery removals, survey abundance indices and age and length frequencies suggest potential differences in regional productivity and some degree of intra-population structure (Figure 3; Figures A2 and A3) Given high connectivity and coherent ontogenetic movement patterns across the region, yet localised dynamics (e.g., within management units), a single population with spatial heterogeneity is hypothesized High spatial resolution is warranted to capture localised dynamics; five strata matching current management units represents a parsimonious spatial structure to balance regional dynamics, data sample sizes and management needs
Degree and drivers of movement	Larval dispersal is primarily driven by mesoscale eddies and oceanographic currents with large dispersal distances There is high adult movement potential based on tagging data (Figure 2; Figure A3) Time-varying movement is likely that may be linked to population dynamics and environmental conditions (e.g., spawning biomass and recruitment) Apparent ontogenetic movement dynamics are present where young individuals move eastward and old, maturing individuals move westward (Figure 4)
Does biology vary spatially?	Recruitment dynamics are spatially heterogenous and likely localised (Figure 3; Figure A3) Potential exists for spatially varying sablefish growth across the north Pacific, which may translate to spatially varying natural mortality and maturity, but spatial variation in growth in Alaska appears minor (Figure A4)
What are the potential impacts of climate change?	Sablefish are a climate 'winner', where increasing population productivity has been associated with anomalously warm marine conditions (i.e., large marine heatwaves) Increases in population productivity, potentially associated with climate changes, can indirectly impact sablefish dynamics through density-dependent factors (e.g., increased competition for food and habitat) that may cause variation in population processes (e.g., growth and weight) Climate-driven reductions in dissolved oxygen levels have the potential to shift sablefish distributions, where individuals may move to avoid oxygen minimum zones Monitoring of climate impacts (e.g., species redistribution) is generally supported by an annual hook-and-line survey and a comprehensive observer program (Figure A5)
What is the minimally complex model needed to inform management?	Risk of potential localised depletion is masked by the use of a single region model It remains unclear whether existing management approaches that spatially apportion single region catch advice is adequate A five-strata spatial model could better reflect spatial dynamics, aid monitoring of potential regional depletion and directly inform spatial catch advice

management units (i.e., BS, AI and four within the GOA) using a 5-year rolling average of abundance proportions from a longline survey (Goethel, Berger, and Cadrin 2023). Fishery removals are spatially heterogenous and occur primarily through two fleets: the fixed-gear fleet (hook-and-line and longline pot gear) and the trawl fleet (Chen, Goethel, and Cunningham 2024). Although sablefish are panmictic, their complex movement dynamics, current management framework and spatially varied harvest patterns suggest the potential need for spatial modelling approaches. In particular, developing a spatial assessment model could enhance understanding of regional biomass dynamics (e.g., recruitment hotspots), areas at risk of localised depletion and provide further feedback to stakeholders on future spatiotemporal cohort dynamics as large year classes mature and redistribute. Additionally, a spatial assessment could help address stakeholder and management concerns regarding the impact of differential regional harvest by sector on the population and identify the robustness of survey-based catch apportionment strategies.

2.2 | Data Availability and Resolution

Collating data sets and their spatial resolution is critical when considering the types of information available for stock identification, the resolution of a spatial model, and the ability for existing data sources to inform spatial parameter estimates (Cadrin et al. 2023). Alaska sablefish benefit from a long time series of data (e.g., catch, survey abundance indices and tagging), with numerous studies to support stock identification and spatial population structure determinations. For instance, genetic (Jasonowicz et al. 2017; Timm et al. 2024), morphometric (e.g., growth; Kapur et al. 2020) and tagging studies (Heifetz and Fujioka 1991; Maloney and Heifetz 1997; Hanselman et al. 2015), combined with high-resolution biophysical larval individual-based models (IBMs) (Gibson et al. 2019) and a three strata spatial assessment model (non-tag-integrated; Fenske 2022), all provide insight on spatial dynamics.

In general, the dataset with the coarsest spatiotemporal resolution determines the resolution and number of regions that can be feasibly parameterized in a spatial assessment model (Cadrin et al. 2023). For Alaska sablefish, fishery removals were the limiting dataset, which were reported on an Alaska-wide scale from 1960 to 1976 (Fenske 2022) and on the level of fishery management units (BS, AI, western and central GOA, WY, EY/SE) from 1977 onwards. Since the early 1990s, there has been fishery observer data reported with associated geospatial coordinates that include haul or tow level biological (e.g., length, weight and age) and catch data for a subset of fishing trips. An annual fishery-independent longline survey provides biological data and estimates of relative abundance with associated geospatial locations, which has been in operation since 1979. A concurrent sablefish tagging program provides release and recovery location data with an average of 3000 individuals tagged annually. Since 1978, about 400,000 individuals have been tagged, with approximately 34,000 recaptures.

2.3 | Developing a Conceptual Model

Conceptual models of fishery-biological systems provide a holistic synthesis of dynamics that might be integrated into a quantitative modelling framework, while allowing integration of information across knowledge types (e.g., qualitative and quantitative) and encouraging practitioners to acknowledge key uncertainties (Minte-Vera et al. 2024). Our conceptual model focused on formulating hypotheses regarding spatial and temporal dynamics, fleet structure and potential future climate impacts. The conceptual model provided a comprehensive description of sablefish spatial dynamics across Alaska, while helping identify primary processes that may need to be accounted for in the assessment framework, along with key uncertainties requiring the development of alternative model parameterisations. To develop the conceptual model, we collated knowledge based on literature reviews, stakeholder local ecological knowledge and high-resolution data analyses and visualisations using fishery, observer, survey and tagging data. An illustration of the conceptual model is provided in Figure 1, while a summary of the spatial hypotheses integrated (and the information used to inform them) can be found in Tables 1 and 2. Further high-resolution data analyses are provided in Data S1.

2.4 | Population and Spatial Structure

Given that sablefish exhibit genetic panmixia, there is strong support for extensive reproductive mixing (Jasonowicz et al. 2017; Timm et al. 2024). Tagging data (Figure 2; Figure A1) and prior tagging studies (Heifetz and Fujioka 1991; Hanselman et al. 2015) underscore the ability of sablefish to exhibit long-distance and transboundary movements (i.e., ~35% of individuals tagged in Alaska move outside of Alaska management boundaries; Figure 2). Moreover, coherence in sablefish recruitment signals from assessments of Alaska, British Columbia, and West Coast population components indicate a degree of interconnected dynamics likely representing metapopulation structure across their full range (Kapur et al. 2024).

Movement patterns play a significant role in shaping the population and spatial structure of Alaska sablefish. Within Alaska, biophysical IBMs have shown high larval dispersal potential from presumed spawning regions in the eastern GOA, likely influenced by the presence of eddies and various oceanographic currents (Gibson et al. 2019), likely resulting in a common larval pool. Following larval settlement, juvenile sablefish (age-1) typically inhabit nearshore bays of the GOA and exhibit ontogenetic movement patterns from inshore waters to offshore adult continental shelf and shelf-break habitats (Sasaki 1985). Post-settlement movement occurs across their geographic range, with no indication of natal fidelity. Additionally, during periods of extremely high recruitment, the BS shelf may serve as a juvenile nursery area based on the extremely high occurrence of age-1 sablefish (Sasaki 1985; Goethel, Cheng, et al. 2023). It is hypothesised, and generally supported by tagging data, that ontogenetic movement patterns occur in a counterclockwise fashion, with younger individuals in the eastern GOA moving westward as juveniles, and older individuals moving eastward as they mature, remaining in the central and eastern GOA (Heifetz and Fujioka 1991; Maloney and Sigler 2008).

High resolution data analyses were implemented to help identify potential spatial breakpoints in biological or fishery dynamics. For instance, multivariate regression tree models (Lennert-Cody et al. 2010), applied to survey and fishery length frequencies at a high spatial resolution, identified breakpoints by recursively dividing length frequencies based on Kullback–Leibler divergence to quantify spatial

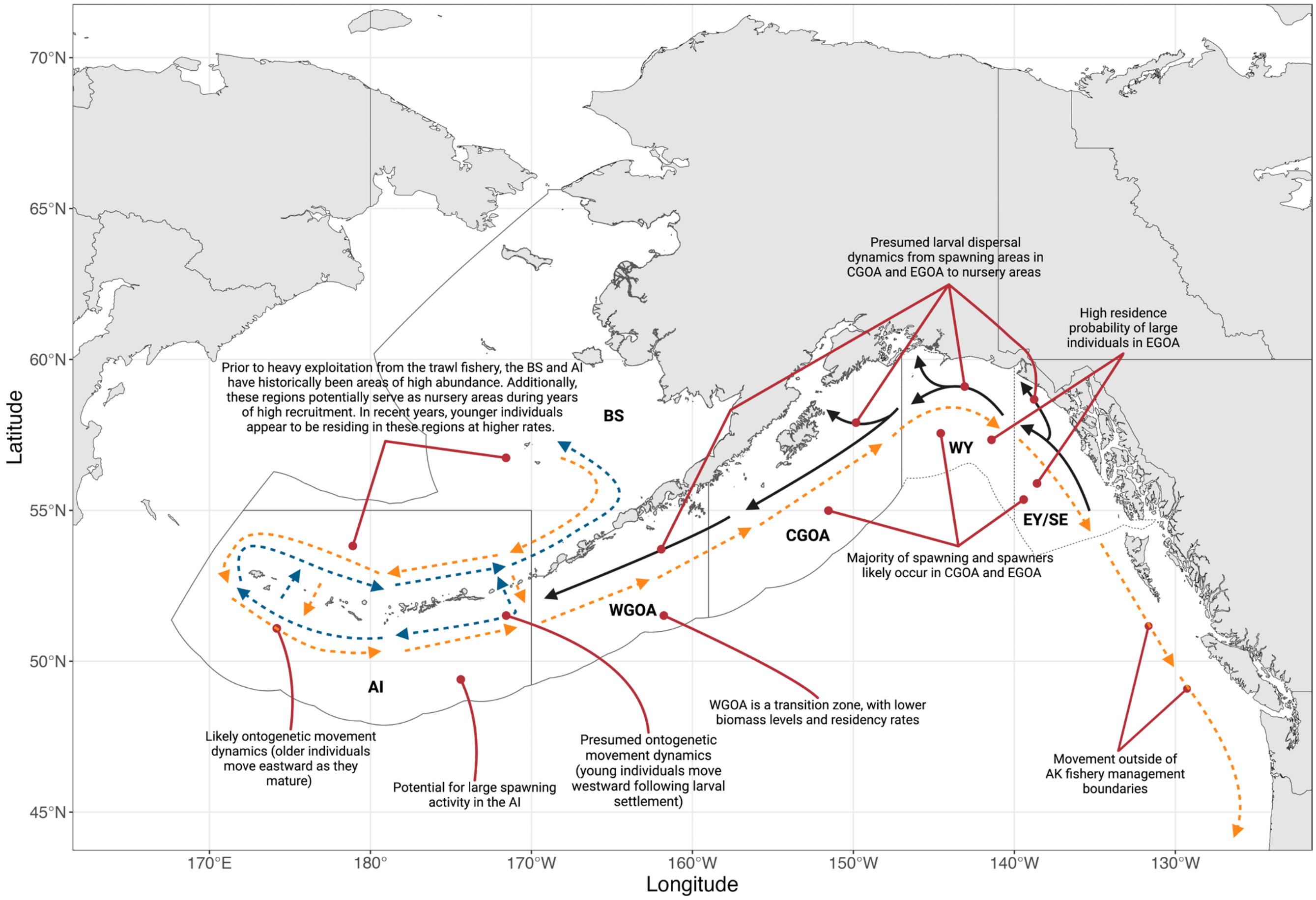

FIGURE 1 | Conceptual model of spatial sablefish dynamics. Black solid arrows represent hypotheses on larval dispersal, blue dashed arrows are hypotheses regarding the movement dynamics of younger individuals and orange dashed arrows are hypotheses on general movement dynamics of individuals as they mature. Abbreviations associated with polygons represent the boundaries utilised for sablefish management (BS, Bering Sea; AI, Aleutian Islands; western Gulf of Alaska, WGOA; central Gulf of Alaska, CGOA; West Yakutat, WY; East Yakutat/Southeast, EY/SE).

heterogeneity. Longitudinal breakpoints derived from survey length frequencies generally aligned with fishery management boundaries, although some breakpoints spanned multiple boundaries (Figure 3A). Specifically, three breakpoints were identified, with the AI split into two separate units, binning the western GOA and BS, and considering much of the central GOA, WY and EY/SE as a single unit. However, breakpoints derived from fishery length frequencies were less consistent in delineating spatial structure, likely because they reflect heterogeneity in fleet structure rather than spatial structure (Figure 3B). Data visualisations by management units were then undertaken for age frequencies aggregated across available years from the survey and fisheries, survey abundance indices and fishery removals to understand potential spatial heterogeneity in population age structure and recruitment dynamics (age-2). Regional differences in age structure (e.g., younger individuals in the west; Figure 3C,D), fishery removals (e.g., highest removals in the east; Figure A2), and survey abundance indices (e.g., differences in relative population scale across regions; Figure A3), all suggested some degree of localised population and fishery dynamics.

Overall, data visualisations suggest fine-scale recruitment and fishery dynamics, along with the likely existence of sub-populations. Metapopulation structure would generally be consistent with broader assumptions of population structure across the entire sablefish distribution (i.e., Northeast Pacific; Kapur et al. 2024). However, high reproductive mixing and lack of genetic structure, long-distance larval dispersal and common ontogenetic movement patterns across potential population sub-units lend stronger support to an assumption of a single population (or an Alaskan sub-population within a coastwide sablefish metapopulation) with spatial heterogeneity (following definitions of Kritzer and Sale 2004). In general, data analyses support the need for multiple strata to effectively model spatial population and fishery dynamics. Although not an exact match with breakpoints identified using the regression tree approach, the current management unit boundaries provide a parsimonious spatial domain that balances fine scale regional dynamics with adequate data sample sizes, while also accounting for additional factors (e.g., fishery operations, biophysical characteristics) and mitigating the need to redefine management units or reassign data (e.g., catch).

2.5 | Movement Patterns

High-resolution data visualisations of age frequencies generally support the counterclockwise ontogenetic movement hypothesis around Alaska: younger individuals are found in

TABLE 2 | Major decision points encountered when developing spatial models (as outlined by Goethel, Berger, et al. 2023) with the type of analyses used to inform each decision, the selected model parametrization chosen and difficulties or uncertainties encountered during the model building process for the Alaska sablefish case study.

Decision point	Analyses used	Selected parametrization	Difficulties encountered
Population structure	Literature review, conceptual model, multivariate regression tree for length frequencies (Figure 3), visualisations of age frequencies (Figure 3), fishery removals (Figure A2), survey abundance indices (Figure A3) and tagging data to infer degree of reproductive mixing (Figure 2; Figure A1)	Single population with spatial heterogeneity	Differentiating between metapopulation and spatial heterogeneity structure is difficult, particularly when density-dependence in recruitment is not/cannot be integrated into the model. Additional challenges were encountered given that only a portion of the distribution was assessed (i.e., there is likely metapopulation structure when considering the full distribution across the Northeast Pacific)
Temporal structure	Expert judgement of sablefish seasonal dynamics (or lack thereof) and analysis of available data time series	Annual timestep from 1960to 2021	Historical catch data (1960–1976) was the limiting dataset, which was reported on a region-wide scale
		Historical regional catch was imputed using average regional catch proportions from 1977 to 2021	The full catch time series was considered in this study to provide information on initial conditions
			No strong seasonal dynamics warranted a sub-annual time step
Spatial resolution	Data inventory, conceptual model, literature review, multivariate regression tree for length frequencies (Figure 3), visualisations of age frequencies (Figure 3), fishery removals (Figure A2) and survey abundance indices (Figure A3)	Spatially stratified with five areas	Multivariate regression tree models identified longitudinal breakpoints in the middle of management boundaries, which were not practical to implement due to data reporting limitations. A 5-region model balanced complexity with management needs
Fleet structure	Literature review, visualisations of sample sizes (Figure A5), and expert judgement based on the existing operational assessment	Two fishery fleets: fixed-gear and trawl gear	Sample size limitations when transitioning to finer spatial resolutions impeded implementing more complex selectivity parametrizations, especially given sex-specific selectivity dynamics
		Time blocked logistic selectivity for fixed-gear fleet	
		Time invariant gamma selectivity for trawl fleet	
Recruitment dynamics	Literature review, conceptual model, visualisations of age frequencies (Figure 3), fishery removals (Figure A2) and survey abundance indices (Figure A3)	Mean recruitment with localised recruitment dynamics	High uncertainty in recruitment estimates during historical periods prior to the availability of compositional data

(Continues)

TABLE 2 | (Continued)

Decision point	Analyses used	Selected parametrization	Difficulties encountered
Regional catchability	Visualisations of fishery removals and survey abundance indices (Figure A2)	Estimated initial abundance-at-age in all spatial regions	Difficult to determine whether spatially varying survey catchability is necessary given similarities in model diagnostics to spatially-invariant catchability models
	Compared parameterizations of spatially invariant and spatially varying survey catchability (Data S3)	Regional abundance was scaled using survey relative abundance indices via a spatially invariant catchability	
Dispersal	Literature review, conceptual model and visualisations of tagging data to infer degree of reproductive mixing (Figure 2; Figure A1)	Full reproductive mixing across Alaska	None, genetic studies highlight lack of structure, tagging indicates high movement potential and larval IBMs indicate large dispersal distances, which all support high reproductive mixing
Movement	Literature reviews, conceptual model, visualisations of tagging data (Figure 2; Figure A1), and center of gravity for sablefish cohorts across time (Figure 4)	Markovian movement with three age blocks: ages 2–7, ages 8–16 and ages 16–31	Conflicting evidence of ontogenetic movement dynamics in literature reviews
	Compared parameterizations of time-varying, age-varying and time-and age-varying movement patterns (Data S3)		Some movement estimates demonstrated relatively high uncertainty
			Parameterizations of time varying movement failed to converge, preventing a comprehensive evaluation of movement hypotheses
			Tagged fish were assumed to have known ages to facilitate estimation of age-varying movement
Demographic variation	Literature reviews and visualisations of regional weight-at-age patterns (Figure A4)	Spatially invariant growth, natural mortality and maturity	The degree of spatial demographic variation that warrants parameterizing spatially varying rates remains unclear

(Continues)

TABLE 2 | (Continued)

Decision point	Analyses used	Selected parametrization	Difficulties encountered
Tagging dynamics	Visualisations of tag recoveries by gear type across time (Figure 5A), frequency of years-at-liberty of recaptured individuals (Figure 5B), and distributions of the number of releases by release year and year-at-liberty (Figure 5C)	Reporting rates estimated in time blocks to coincide with regulatory changes	Adequate parameterization of tag nuisance parameters (reporting rate, tag mixing) was difficult to ascertain
		Tagged cohorts tracked for 15 years	Assessing the representativeness of tagged fish dynamics is difficult to verify
		Tag-mixing period of 1 year was used	Although a rich conventional tagging data set was available, trade-offs in value added (information content) versus noise introduced from nuisance parameters was difficult

western regions (Figure 3C,D, as indicated by the reduced proportion of younger fish in age compositions comparing western and eastern regions) and cohorts move eastward as they age (Figure 4). However, some tagging studies indicate that connectivity patterns are less consistent than indicated by the relatively simple ontogenetic movement hypothesis described by Heifetz and Fujioka (1991). For example, previous tagging analysis demonstrated movement probabilities that were bidirectional across ages, with potential for time-varying dynamics (Hanselman et al. 2015). Given conflicting signals on movement dynamics from data visualisations and previous studies, configurations of the spatial sablefish assessment model should explore both ontogenetic and time-varying movement dynamics.

2.6 | Biological and Demographic Processes

In a previous three strata spatial assessment model for Alaska sablefish, localised age-2 recruitment dynamics were estimated, with western regions (i.e., BS, AI and western GOA) being more productive than eastern regions (central and eastern GOA; Fenske 2022). These conclusions are consistent with observed regional differences in age-structure (Figure 3C,D) and increases in abundance of age-2 individuals in western regions following periods of high recruitment (Figure A3). Note that age-2 recruitment reflects different processes than age-0 recruitment. In particular, although spawning may occur as a panmictic process, spatial heterogeneity in age-2 recruitment can arise due to early life history processes that redistribute individuals (e.g., movement, larval drift) before they are first observed by fisheries or surveys. A defining characteristic of sablefish biology is strong differences in growth by sex, with females reaching larger sizes (Sasaki 1985; Morita et al. 2012). Additionally, a transboundary study suggested that growth rates increase with latitude, where distinct growth regions exist near the northern end of the Southern California Bight and the bifurcation of the North Pacific Current (Kapur et al. 2020). As predicted by life-history theory, these growth differences may also result in spatial variation in natural mortality and maturity, although visual inspection of spatial variation in sablefish growth (i.e., weight-at-age) in Alaska revealed only minor differences across space (Figure A4). Therefore, the spatial assessment model should account for localised recruitment and sex-specific dynamics, with spatially invariant demography (consistent with the assumption of a single population with spatial heterogeneity).

2.7 | Fishery Dynamics

Strong spatiotemporal trends in catch across fleets exist (Figure A2) and each fleet generally targets or encounters different length or age classes (i.e., trawl fleet primarily encounters small fish given the depths fished and exhibits dome-shaped selectivity patterns; Goethel, Cheng, et al. 2023). Furthermore, complex fishery management regulations exist for sablefish, which have varied over time and across management units, including a transition to an individual fishing quota system in 1995 and allowance of pot gear fishing in the GOA in 2017 (Goethel, Cheng, et al. 2023). The model needs to account for differential removals of age classes through time, among fleets and across

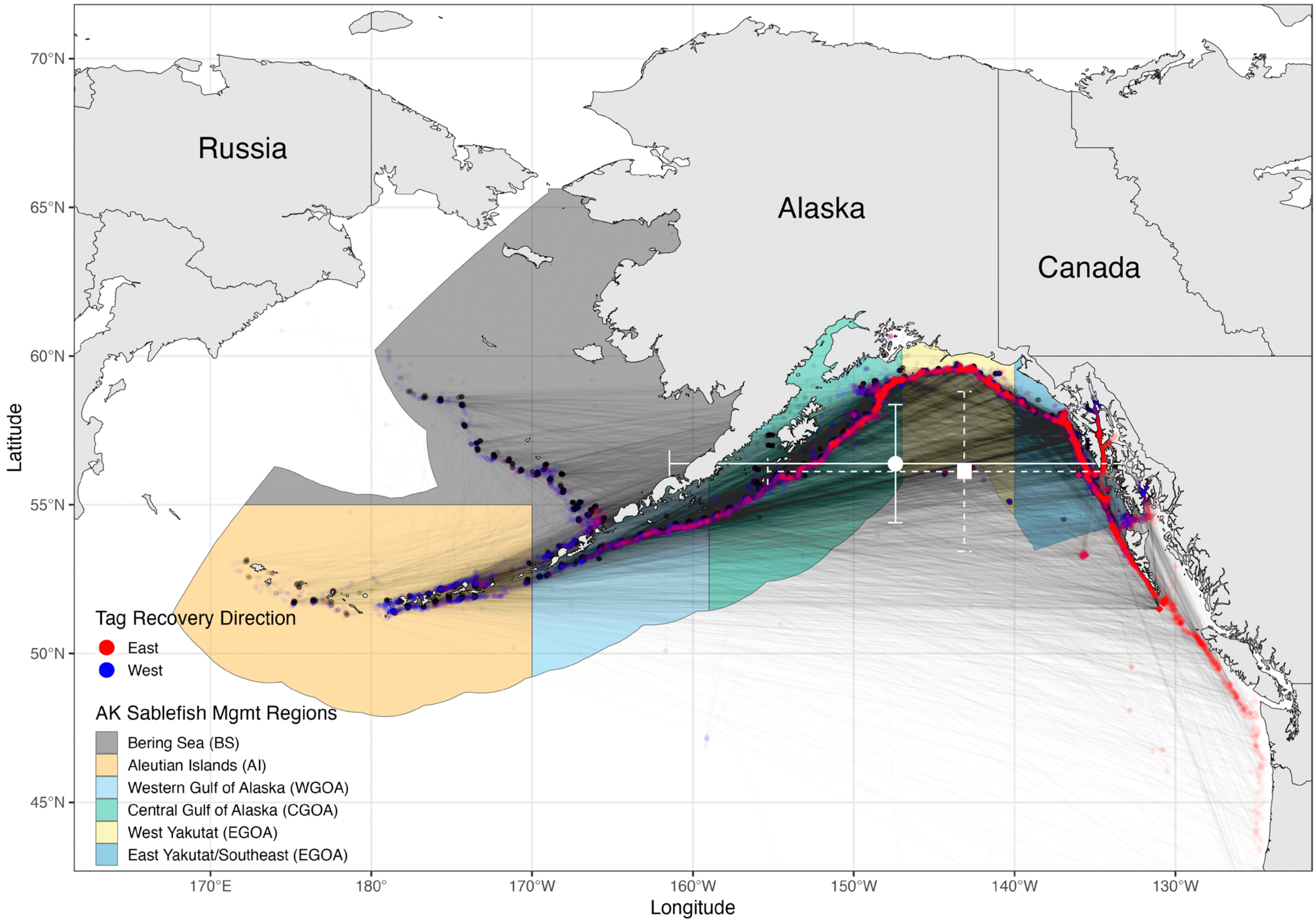

FIGURE 2 | Locations of tag releases (black points; $n = 395{,}146$) and tag recovery events (coloured points; $n = 34{,}833$) from 1972 to 2020. Red points indicate general eastward movements (i.e., release longitude > recovery longitude), while blue points indicate general westward movements (i.e., release longitude < recovery longitude). Black lines connect tag release events to its corresponding recovery location. White point represents the mean release location of individuals and white solid lines are the standard deviation of release locations. The white square denotes the mean recapture location of individuals, with white dotted lines representing the standard deviation of recapture locations. Coloured polygons represent Alaska sablefish fishery management boundaries in the US Exclusive Economic Zone.

space, while considering sex-specific selectivity patterns, all of which will help address spatiotemporal management changes and differential availability of age classes across spatial strata and gear types.

2.8 | Tagging Dynamics

Sablefish have consistently been tagged throughout the entire Alaska region, with recapture locations generally reflecting a combination of the distribution of the resource (i.e., connectivity dynamics) and the fishery (Figure 2). The majority of tag recoveries were from the hook-and-line fishery (Figure 5A) and some changes in tag recovery patterns were observed in 1995 and 2017, coinciding with management changes. Moreover, studies have also suggested that tag reporting rates in the Alaska sablefish fishery likely vary over time and across regions (Heifetz and Maloney 2001). Empirical cumulative distributions of years-at-liberty for recaptured individuals indicated that 82.1% of individuals were recaptured within 10 years-at-liberty, while 91.4% of individuals were recaptured within 15 years-at-liberty (Figure 5B). Additionally, distinct distributions were observed for individuals recaptured within the first year of release, potentially suggesting unique mixing dynamics compared to individuals with longer times-at-liberty (Figure 5C). Because survey releases occur mid-year, newly tagged fish have a limited movement window, likely resulting in these distinct distributions (Figure 5C). Considering the extensive mark-recapture data available for sablefish, the spatial model should integrate tagging data with carefully considered assumptions: accounting for spatially and temporally varying tag reporting rates to mitigate potential biases (Vincent et al. 2020), modelling tags for periods < 15 years to reduce computational demands, and assuming a 1-year tag mixing period.

2.9 | Climate Change Impacts

Sablefish are often considered a climate 'winner', given that unprecedented recruitment has coincided with anomalous marine heatwaves. However, sablefish distributions also appear to be shifting, with younger individuals increasingly being observed in offshore habitats typically occupied by older individuals. Increased productivity as well as overlap between life stages

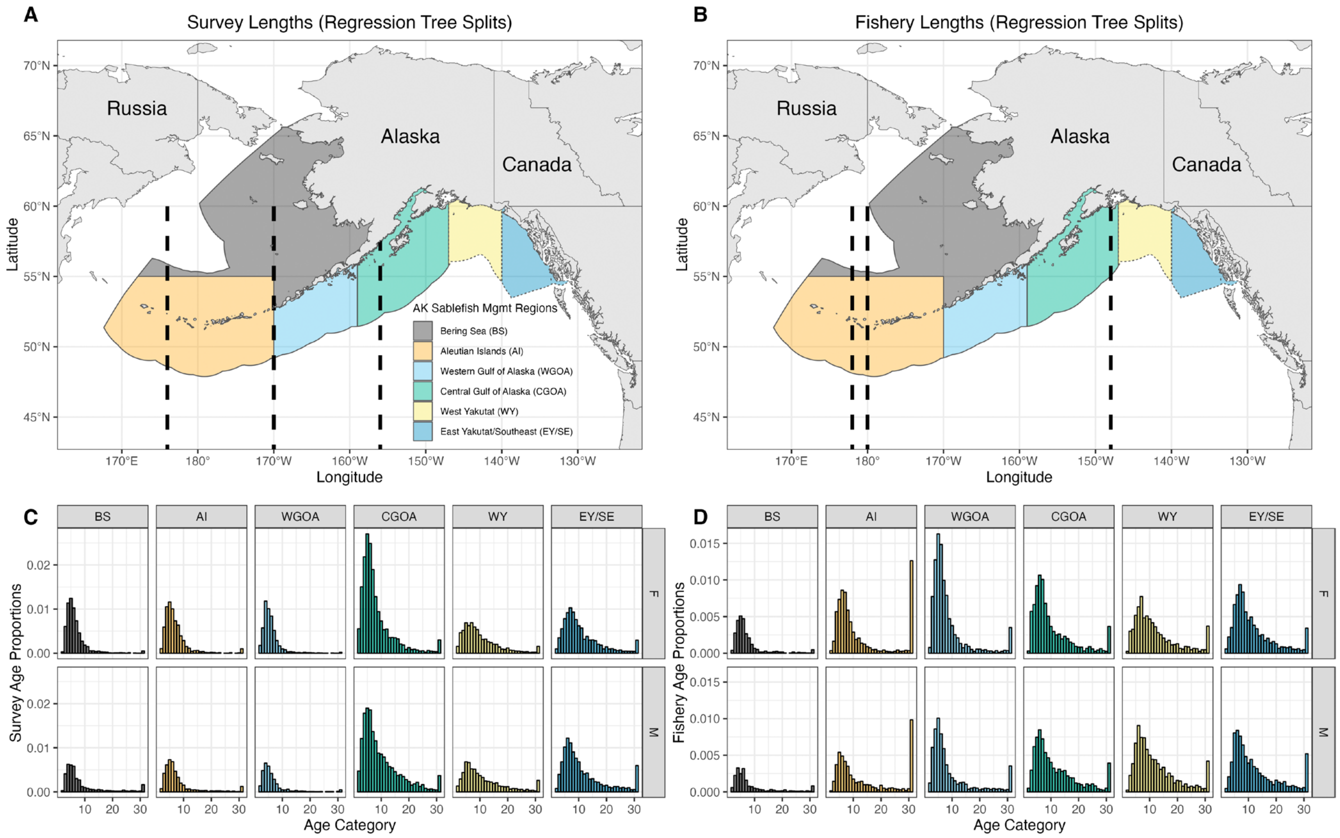

FIGURE 3 | Results from a multivariate regression tree model for survey (A) and fishery length (B) compositions, which helped identify spatial breakpoints in length frequencies. Dashed vertical lines represent regression tree splits, which are defined by recursively dividing length frequencies across space into homogenous subgroups based on Kullback–Leibler divergence. Temporally-aggregated survey (C) and fishery (D) age frequencies are also illustrated, with proportions summing to 1 across regions and sexes. Columns represent fishery management units, while rows indicate sexes ('F' denotes females and 'M' denotes males).

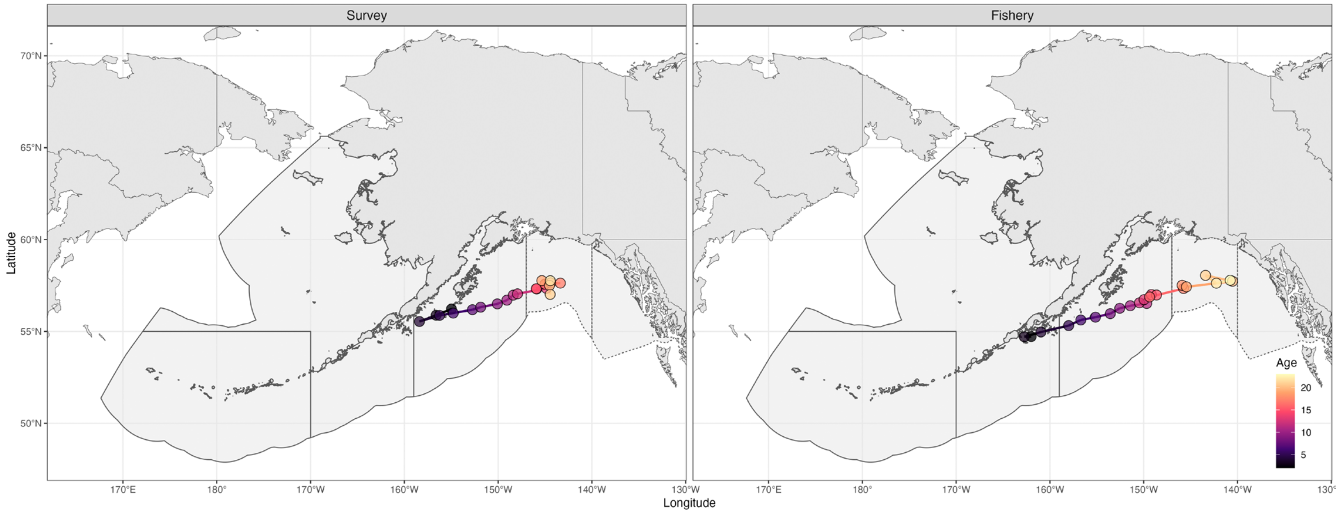

FIGURE 4 | Center of gravity (defined as mean longitude and mean latitude) for observed sablefish ages aggregated across time (colours). Observed data from the domestic longline survey (left panel) and fixed-gear fishery (right panel) are utilised. Point colours vary by age (youngest; black, oldest; yellow). Alaska sablefish fishery management boundaries are depicted as grey polygons.

could manifest in poorer growth conditions due to density-dependent effects (Chen, Goethel, and Hulson, et al. 2024). Furthermore, Essington et al. (2022) observed changes in sablefish distributions in California, which they attributed to climate-driven reductions in dissolved oxygen levels. Environmental changes could influence sablefish depth preferences, where individuals may avoid oxygen minimum zones and shelf areas vulnerable to oxygen depletion. Given these findings, configurations of the spatial assessment model may need to consider flexibility to model time-varying productivity, movement and

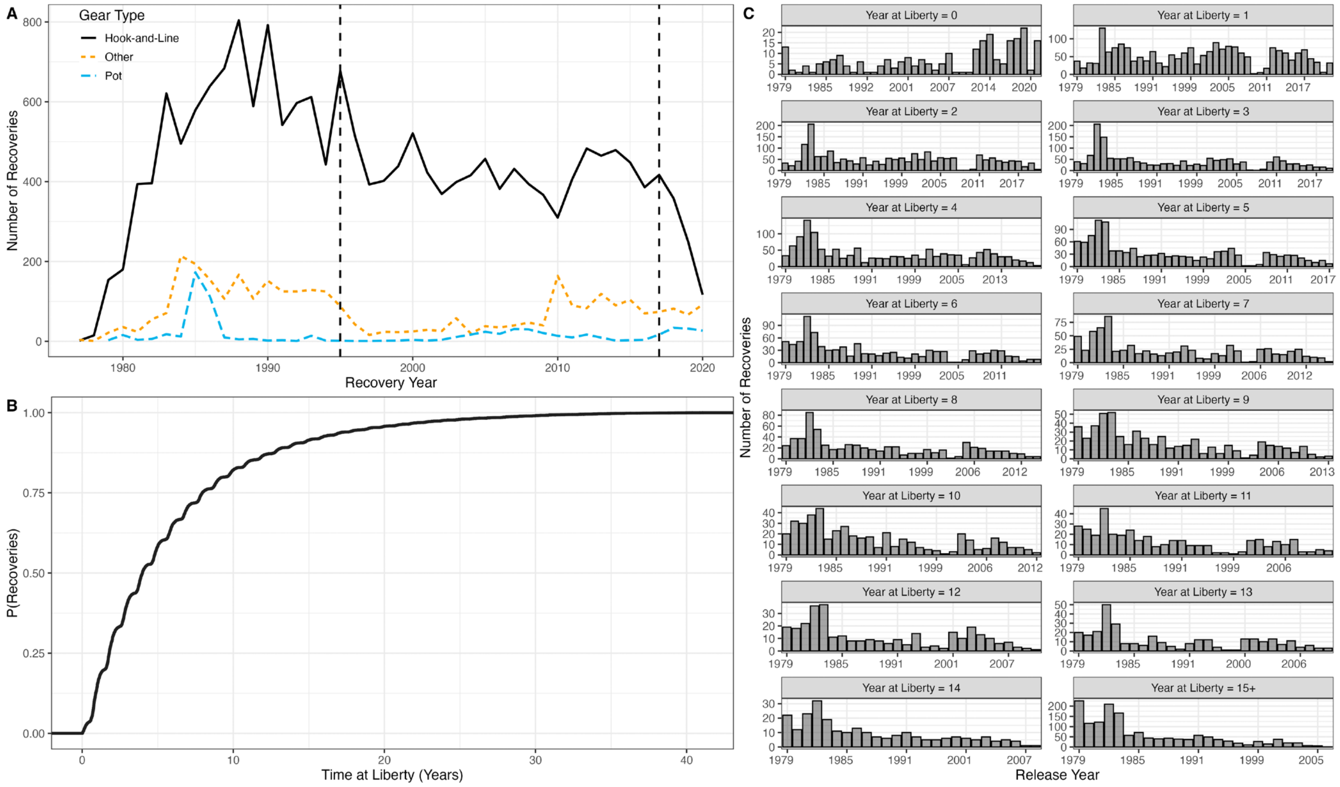

FIGURE 5 | Tag recoveries across recovery and release years, gears, and time at liberty. The number of tag recoveries by each gear type (A) are demarcated (vertical dashed lines) with fishery management regulatory changes (i.e., an individual fishing quota system started in 1995 and pot gear was legalised in the Gulf of Alaska in 2017). The empirical cumulative distribution of the number of recoveries across time at liberty (B) provides an indication of the expected lifespan of a tagged fish. The distribution (C) of the number of recoveries across release years for a given category of year at liberty provides potential information on appropriate tag-mixing periods. Distributions that are distinct likely indicate differences in tag-mixing dynamics (i.e., individuals are not well-mixed).

TABLE 3 | Data sources and observation likelihoods utilised for explorations of spatial model configurations.

Data source	Temporal resolution	Observation likelihoods
Fixed gear removals	1960–2021	Lognormal
Trawl removals	1960–2021	Lognormal
Fixed gear ages	1999–2021	Multinomial
Fixed gear lengths	1991–1998	Multinomial
Trawl lengths	1991–2021	Multinomial
Survey ages	1981–2021 (infrequent sampling from 1981 to 1993, annual sampling from 1996 to 2021)	Multinomial
Survey indices	1979–2021	Lognormal
Tag recoveries	1979–2020	Poisson, negative binomial and multinomial

demographics (e.g., growth) to address potential future impacts of climate change.

2.10 | Generalised Sablefish Spatial Assessment Model

Based on the conceptual model and drawing upon the spatially-aggregated operational sablefish assessment model (Goethel, Cheng, et al. 2023), a flexible spatial assessment model was developed in Template Model Builder (TMB; Kristensen et al. 2016). An integrated population model framework was utilised (Maunder and Punt 2013), where various data types were combined into a single analysis to estimate population dynamics using a joint statistical likelihood. The spatial assessment model was developed to accommodate a variety of key decision points and structural uncertainties identified in the development of the conceptual model (e.g., number of spatial strata, recruitment

TABLE 4 | Summary of spatial model configurations explored in this study and their associated convergence status.

Spatial model	Primary parameterization	Components compared	Convergence status
Base	See formulation of 'Initial Spatial Model' (Methods)	Movement	Yes
Age2Move	Same as *Base*, but movement is estimated in two age blocks (ages 2–16 and ages 17–31)	Movement	Yes
Age3Move	Same as 'Base', but movement is estimated in three age blocks (ages 2–7, ages 8–15 and ages 16–31)	Movement	Yes
Time2Move	Same as *Base*, but movement is estimated in two time blocks (1960–1990 and 1991–2021)	Movement	No
Time3Move	Same as *Base*, but movement is estimated in three time blocks (1960–1995, 1996–2010 and 2011–2021)	Movement	No
Time4Move	Same as *Base*, but movement is estimated in four time blocks (1960–1990, 1991–2000, 2001–2010 and 2011–2021)	Movement	No
Age2Time2Move	Combines movement parameterizations from *Age2Move* and *Time2Move*	Movement	No
Age2Time3Move	Combines movement parameterizations from *Age2Move* and *Time3Move*	Movement	No
Age2Time4Move	Combines movement parameterizations from *Age2Move* and *Time4Move*	Movement	No
Age3Time2Move	Combines movement parameterizations from *Age3Move* and *Time2Move*	Movement	No
Age3Time3Move	Combines movement parameterizations from *Age3Move* and *Time3Move*	Movement	No
Age3Time4Move	Combines movement parameterizations from *Age3Move* and *Time4Move*	Movement	No
NegBin	Same as *Age3Move*, but tag likelihood is assumed to be negative binomial	Tag likelihood	Yes
Mltnml	Same as *Age3Move*, but tag likelihood is assumed to be multinomial	Tag likelihood	Yes
Decadal	Same as *NegBin*, but tag reporting rates are estimated in decadal periods (1978–1989, 1990–1999, 2000–2009 and 2010–2021)	Tag reporting	Yes
FishBlock	Same as *NegBin*, but tag reporting rates are estimated to reflect changes in fishery regulatory events (1978–1995, 1995–2016 and 2017–2021)	Tag reporting	Yes
Space	Same as *NegBin*, but tag reporting rates are estimated spatially across 5 regions	Tag reporting	Yes
SptQ	Same as *FishBlock*, but survey catchability is estimated spatially across 5 regions	Spatial catchability	Yes

Note: The configuration denoted in bold represents the selected spatial model considered in this study.

dynamics, connectivity assumptions and observation likelihoods; Figure 1; Tables 1 and 2).

Similar to the operational stock assessment, all model configurations modelled the sablefish population assuming an annual timestep (here, from 1960 to 2021), and were sex- and age-structured. Population dynamics utilised an exponential mortality model with removals determined by Baranov's catch equation. Each timestep initially began with recruitment and tag releases (when applicable), followed by mortality and ageing processes, movement of individuals via Markovian dynamics, and tag shedding. In addition, observation processes were configured to accommodate a variety of data types, including catch data (time-series), abundance indices (time-series), age and length frequencies of fishery and survey catches and tagging data (counts; see Table 3 for details on data sources). Equations describing population dynamics and observation processes are provided in Data S2 and associated code can be found at https://github.com/chengmatt/SpatialSabieModel.

2.11 | Initial Spatial Model

The initial spatial model (hereafter, model *Base*) aimed to capture key spatial dynamics, while balancing data availability, model parsimony and previous research on spatial stock assessment models (see Table 2 for key decision points and final parametrizations for primary structural components). A single population with spatial heterogeneity was assumed. The population was spatially stratified across five strata, generally aligning with current fishery management boundaries used for Alaska sablefish. However, the WY and EY/SE units were combined into a single region encompassing the entirety of the eastern GOA due to data sample size limitations and similarities in age frequencies as well as relative abundance trends (Figure 3C,D; Figure A3). Movement dynamics were configured with an age- and time-invariant discrete Markov model. Although the conceptual model suggested that movement should vary by age and year, a simplified framework was utilised to initially evaluate the identifiability of movement parameters. It also served as a baseline against which to compare the plausibility of subsequent, more complex spatial model parametrizations. Recruitment dynamics were allowed to vary spatially, with strata-specific mean recruitment and associated deviations to capture localised recruitment patterns. Conversely, weight, length, maturity-at-age and natural mortality (age- and sex-invariant) were modelled as spatially invariant due to the absence of discernable differences in growth patterns (Figure A4) and because of the assumption of a single population (e.g., high reproductive mixing and lack of genetic structure). These demographic parameters were also considered to be temporally invariant given data limitations and considerations of trade-offs in model parsimony and complexity.

Fishery dynamics were parametrized to include two fleets: the fixed-gear fleet and the trawl fleet. Average region-specific removal proportions by fleet (1977–2021) were used to regionally apportion historical, Alaska-wide removals (1960–1976). Selectivity was sex-specific and modelled independently for both fishery fleets. Spatially invariant selectivity was assumed because availability was explicitly modelled through movement and the number of model partitions impeded direct estimation (i.e., for all combinations of regions, fleets and time blocks). Selectivity for the fixed-gear fleet was modelled as a logistic function with a pre- and post-2017 time-block, reflecting a rapid shift towards pot gear usage in recent years (Chen, Goethel, and Cunningham 2024). Conversely, the trawl fleet's selectivity followed a time-invariant, dome-shaped gamma function to account for the lack of older fish caught in this fleet. Additionally, the model also incorporated two survey fleets: the Japanese (1979–1994) and United States longline surveys (1990–2021). Selectivity for both surveys were also assumed to remain spatially invariant and were represented as a logistic function. Survey catchability was initially considered to be spatially- and temporally-invariant.

Although tagging data can be integrated using Petersen-type models (i.e., using tagging data to derive abundance indices), this approach was not used because survey indices for Alaska sablefish already provide robust abundance trends. Thus, tagging data was integrated through a Brownie tag attrition sub-model, consistent with approaches used in assessments of toothfish (a species comparable to sablefish; Hillary and Day 2021). Tag-induced mortality and annual tag-shedding were specified with estimates derived from previous sablefish tagging analyses (i.e., Beamish and McFarlane 1988). Most recaptured individuals only had length data, requiring length frequencies to be converted to ages. An age-length key based on survey composition data was applied to tagging length frequencies from each release year to determine release age, with the recapture age then determined based on time at liberty. Tracking of tagged cohorts was limited to 15 years at liberty, with a 1-year tag-mixing period assumed. Tag reporting rates were specified to be time-invariant, and a Poisson likelihood was initially utilised to fit tagging data to facilitate model convergence (i.e., without estimating additional parameters).

2.12 | Spatial Model Alternatives

Several model alternatives were developed to evaluate key uncertainties in spatial dynamics that were identified throughout the development of the conceptual model (Table 4). These included: alternative movement parameterisations, tag data likelihoods, tag reporting rate specifications and regional catchability assumptions. The *Base* model was iteratively refined by gradually introducing additional complexity based on comparisons among alternative models. Decisions regarding whether to add complexity were determined using a suite of model diagnostics and expert judgement from the conceptual model. The best supported model was defined as one that demonstrated reasonable model diagnostics (see section on 2.13) and produced biologically plausible dynamics that aligned with the qualitative conceptual model and conformed to expectations. While the conceptual model is partially informed by the same data as the estimation model, leading to the potential for circular logic, we view this as part of a structured, iterative framework. Data are used to inform both the conceptual model and estimation framework, and the conceptual model, in turn, provides context for interpreting and validating results from the estimation model. Importantly, the estimation framework enables the evaluation of key uncertainties not fully captured in the conceptual model (e.g., spatially-varying catchability), allowing for a more comprehensive exploration of uncertainty beyond what the conceptual model provides. A forward stepwise model selection approach was employed to sequentially evaluate and compare multiple parameterisations. Each set of scenarios built sequentially on the previous set by choosing the best supported model within each exploration. That model then served as the starting basis for the next set of scenarios. Therefore, the order of scenarios was chosen strategically to ensure key modelling decisions were not overly influenced by the order of the model comparisons.

Considering uncertainty in sablefish movement dynamics and the importance of flexible movement parameterisations in spatial models (Goethel et al. 2021), a large number of movement parameterisations were explored. Variations on the model *Base* included estimating movement in pre-specified blocks based on age (2 or 3 blocks), time (2, 3 or 4 blocks) and a full factorial configuration combining both age and time (i.e., 2 age blocks paired with 2-, 3- or 4-time blocks, and similarly for 3 age blocks; see Table 4 for model notation). When age-based movement dynamics were specified in blocks, tagging data were fit by grouping recaptured observations into their respective age blocks to reduce computational demand. Because tagging data are often overdispersed and the relative weighting of tagging data has the potential to be influential in the estimation process, three models incorporating different observational likelihoods for tagging data were compared: the Poisson (best supported model from movement comparisons), the Negative Binomial (*NegBin*) and the Multinomial (*Mltnml*) likelihoods. Several alternative tag reporting parameterisations were explored due to the potential for spatial and temporal variation in tag reporting rates (Heifetz and Maloney 2001 and Figure 5A). These alternatives included: a time-invariant tag reporting model (best supported model from tagging likelihood comparisons), a model accounting for decadal changes in reporting (*Decadal*), a model reflecting changes associated with fishery regulatory events (*FishBlock*), and a model incorporating spatially varying reporting rates (*Space*). Finally, the potential advantages of incorporating spatially varying survey catchability (i.e., improved regional abundance scaling) were evaluated by comparing the performance of a model assuming spatially invariant catchability (best supported model from tag reporting comparisons) to one allowing for spatial variation (*SptQ*).

2.13 | Comparisons Among Spatial Model Alternatives

Models that failed to demonstrate convergence were omitted from each comparison and were defined as models that: (1) estimated parameters at or near boundaries, (2) estimated large parameter standard errors (>100), (3) demonstrated a non-positive definite Hessian matrix and (4) produced maximum absolute parameter gradients >0.001. For models that converged, we assessed the negative log-likelihood components and visually inspected model fits to each data source (tagging, abundance indices, catch, age- and length- frequencies). For brevity, we only present comparisons of negative log-likelihood components in the main text. Visualisations of model fits to data sources can be found in Data S3. Moreover, across model alternatives, we compared estimates for spawning biomass, recruitment, mean female age and movement. The associated uncertainties (i.e., coefficient of variation, CV) of the aforementioned estimates were also examined to determine model performance. The best supported model in each comparison was selected based on a combination of the model diagnostics above and evaluated against subject matter expertise (e.g., plausibility of recruitment, movement and fishery dynamics compared to the conceptual model). The model chosen at the last stage of comparisons was considered the selected spatial model.

2.14 | Comparison of the Selected Spatial Model With a Spatially-Aggregated Model

The selected spatial model was compared to a spatially-aggregated model that generally mimicked the operational assessment model (Goethel, Cheng, et al. 2023). The spatially-aggregated model fit the same data as spatial models, but data were aggregated to a single region. Moreover, tagging data were not integrated in the single region model to maintain consistency with the operational assessment model, and to avoid the need for estimating nuisance parameters (e.g., tag reporting). Our comparative analysis aimed to determine if the spatial model:

1. provided new ecological insights on spatial population dynamics,
2. demonstrated improved model fits to observed data,
3. provided parameter estimates and population outputs that were similar in scale and trend,
4. produced similar regional biomass trends to those used in the current survey-based catch apportionment approach.

A variety of visualisations were utilised to illustrate ecological insights from the spatial model, including estimated movement matrices along with region-specific time-series estimates (e.g., spawning biomass). Regionally aggregated time-series estimates from the spatial model were also compared to population-wide estimates from the spatially-aggregated model to identify commonalities in estimated scale and trend. Potential improvements in performance between the spatial model and the spatially-aggregated model were determined by comparing one step ahead residual patterns (Trijoulet et al. 2023) and model fits to abundance indices and compositional data (age/length) at the spatially-aggregated scale. Finally, linear regression and qualitative comparisons were used to evaluate the consistency of regional biomass proportions estimated from the spatial model with a rolling 5-year average of observed biomass proportions from the United States longline survey. The comparisons serve as an implicit measure of the robustness of the currently utilised survey-based catch apportionment strategy, in which a 5-year rolling average of region-specific longline survey biomass proportions is multiplied by the total acceptable biological catch (ABC) to determine regional management area quotas.

3 | Results

3.1 | *Base* Model

The *Base* model was able to achieve model convergence and demonstrated reasonable fits to index data (Figures C1–C3) and biologically plausible (based on conceptual model expectations; Figure 1; Table 1) estimates of spawning biomass, depletion, recruitment and movement (Figures C4–C7). For instance, spawning biomass from model *Base* was highest in the central and eastern GOA (Figure C4) but was most depleted (Figure C5), and large recruitment events often originated from the BS, AI and central GOA (Figure C6). Similarly, movement rates were estimated at relatively high levels (Figure C7) and the western GOA was a region that exhibited low residency rates, consistent with previous studies. Moreover, model *Base* suggested that older individuals tended to reside in the central and eastern GOA regions, as reflected by an older mean female age (Figure C8).

3.2 | Comparisons of Spatial Model Alternatives

3.2.1 | Movement

None of the models that estimated time-varying movement converged, but models estimating age-varying movement with age blocks did converge and were retained for subsequent comparisons (Table 4). Compared to model *Base*, age-varying movement models (models *Age2Move* and *Age3Move*) demonstrated slightly improved fits to abundance indices, age-and length-compositions and tag recovery data (Figures C1A–C3A; Table 5). Age-varying movement models also exhibited reduced uncertainty in regional spawning biomass and recruitment, most notably towards the beginning of the time series (Figures C9A and C10A). Additionally, age-specific movement patterns from both *Age2Move* and *Age3Move* generally aligned with hypotheses from the conceptual model (Figure 1): younger individuals were more likely to reside in western regions (BS and AI) with the probability of remaining in these areas decreasing with age. Older fish were more likely to be found in eastern regions (central and eastern GOA) (Figure C7). However, model *Age2Move* demonstrated considerably higher uncertainty in movement estimates compared to other models, likely due to confounding with recruitment estimates and combining many age classes into a single block. Considering the improved fits and decreased uncertainty from model *Age3Move* (Table 5), the better alignment in movement patterns to the expectations from the conceptual model, and the importance of flexible movement parameterizations in spatial models, this model was selected and retained for subsequent comparisons. Similarity in recruitment trends between *Base* and *Age3Move* (Figure C6) suggests that improved fits likely reflect a better characterisation of population dynamics, rather than artificial adjustments of recruitment estimates stemming from increased model flexibility.

3.2.2 | Tagging Likelihood

Model *Mltnml* failed to achieve convergence and was omitted from further comparisons. Evaluating the remaining alternatives (*Age3Move*—using a Poisson likelihood, and *NegBin*—using a Negative Binomial likelihood), model fits for abundance indices and age-and length frequencies were similar (Figures C1B and C2B; Table 5). Differences in model estimates and associated uncertainty were also minimal (Figure C4B–C11B). Because tagging data tends to be over dispersed due to clustering of tagged individuals (Kolody and Hoyle 2015), the *NegBin* model, which can better account for overdispersion, was utilised for subsequent comparisons.

3.2.3 | Tag Reporting Rate

Tag reporting rate specifications revealed differences in model fits (Figures C1 and C2; Table 5), estimates and uncertainty (Figures C4C–C11C). Notably, model *FishBlock* (incorporating tag reporting rate blocks coinciding with regulatory changes) exhibited minor improvements in model fits to survey abundance indices in the western, central and eastern GOA compared to models *NegBin*, *Decadal* and *Space*. The largest differences were primarily observed in fits to tag recovery data (Figure C3) where model *FishBlock* demonstrated the best fits to tagging data (Figure C3; Table 5). As outlined in the conceptual model (Tables 1 and 2), time-varying tag reporting rates are expected given changes in regulatory frameworks in the Alaska sablefish fishery, thus, model *FishBlock* was utilised for the final set of comparisons.

3.2.4 | Regional Catchability

Model fits and likelihood values from model *SptQ* often exhibited slightly improved fits (Figures C1–C3; Table 5). However, relatively large differences in estimates and uncertainties of spawning biomass, recruitment and movement were detected. Model *SptQ* estimated consistently lower levels of spawning biomass and recruitment in the AI and central GOA, and higher levels in the eastern GOA, compared to *FishBlock* (Figures C4 and C6). Additionally, uncertainty in spawning biomass and recruitment was generally higher for model *SptQ* (Figures C9 and C10). Despite these differences, regional depletion estimates remained fairly consistent between models (Figure C5). Differences in movement estimates were also observed, where model *SptQ* estimated lower residency rates in the AI and higher residence in the eastern GOA across all age blocks. Overall, these results did not agree with the conceptual model, where it was hypothesized that the central GOA was likely the largest region by biomass. Discrepancies may have stemmed from: (1) spatially varying catchability preventing regional biomass from scaling with differences in regional survey abundance indices, unlike in a spatially invariant case where scaling would be anchored to regional differences in these indices, and (2) an over-reliance on catch data to inform regional scale, given that removals are highest in the eastern GOA and lowest in the AI. Although *SptQ* showed slight improvements in model fits compared to *FishBlock*, catch data alone are unlikely to provide sufficient information to accurately scale regional biomass. As such, model *FishBlock* was the selected spatial model utilised for comparisons with the spatially aggregated model.

3.3 | Selected Spatial Model Results

The selected spatial model incorporated age-dependent movement rates, utilised a negative binomial likelihood to fit tagging data, and estimated tag reporting rates coinciding with fishery changes. The model indicated that young sablefish tend to occupy western regions (BS and AI), as reflected in a younger mean age and high residency in these areas, compared to estimates in the eastern GOA (Figures 6 and 7A). Movement patterns indicate potential ontogenetic dynamics, with younger individuals generally concentrated in the west and older individuals shifting eastward as they mature. Regional recruitment estimates were largely consistent across the domain, with large recruitment events occurring fairly synchronously across regions. However, the magnitude of these events was notably higher in the BS, AI and central GOA regions (Figure 7A). Interestingly, relatively large recruitment events appeared in the central GOA around the 2000s, which were not observed to the same extent in other regions. Despite the tendency for large recruitment events to occur in western regions (BS and AI), spawning biomass in the

TABLE 5 | Model fits (joint negative log likelihood) to different data sources across spatial model configurations that achieved convergence in this study.

Spatial model	Fixed gear ages	Fixed gear lengths	Trawl lengths	Survey ages	Survey indices	Tag recoveries	Joint negative log likelihood
*Base**	4555	1525	1895	5171	2603	11,933*	26,266*
*Age2Move**	4573	**1522**	**1894**	5171	2592	29,012*	43,350*
Age3Move	4564	1532	1894	5131	2546	28,733	42,992
NegBin	4545	1535	1895	5105	2527	15,150	29,349
Decadal	4537	1538	1897	5095	2515	15,061	29,234
FishBlock	4539	1539	1899	5081	2509	14,979	29,138
Space	4545	1535	1895	5107	2528	15,107	29,310
SptQ	**4504**	1540	1899	**5054**	**2496**	**14,969**	**29,048**

Note: The bolded spatial model represents the selected spatial model considered in this study, while bolded values represent the minimum for a joint negative log likelihood for a given data source. Tag recoveries for model *Base* were fit as aggregated over time and ages. Tag recoveries for model *Age2Move* were fit as aggregated over two age blocks. Therefore, these models are not directly comparable with configurations that estimate three age blocks and are denoted with an asterisk.

BS and AI was estimated at relatively low values. Spawning biomass in the central GOA was estimated to be the highest, suggesting it may serve as the center of distribution for Alaska sablefish. Overall, trends in spawning biomass and depletion were cyclic with large increases often observed several years following large recruitment events (Figure 7A), which is consistent with the delayed maturity of sablefish. Elevated harvest rates from the fixed-gear fishery were detected in the eastern and western GOA (Figure 7A). Conversely, the trawl fishery exhibited the highest harvest rates in the BS, with consistently low rates across other regions (Figure 7A).

3.4 | Comparison of the Spatial and Spatially-Aggregated Models

Overall, considering the differences in complexity, spatial and spatially-aggregated model estimates of population-wide quantities were quite similar across the timeseries (e.g., median relative difference in depletion was ~5%), but spawning biomass estimates (median relative difference ~17%) were slightly higher with lower harvest rates in the spatially-aggregated model (Figure 7B). The spatial model demonstrated some improvements in model fits to survey abundance indices, with slight reductions in both the magnitude and pattern of residuals (Figure C12). However, both models demonstrated relatively poor fits to age and length frequencies, with similar systematic residual patterns observed across ages, sizes and time (Figures C13–C20). For example, both models consistently exhibited systematic patterns of positive residuals for fits to fixed-gear and survey age frequencies (Figures C13–C16), which may reflect limitations in selectivity assumptions, either in the form of inflexible time variation (blocks) or the functional forms used. Regional biomass proportions estimated from the spatial model and the rolling 5-year average of observed survey biomass proportions exhibited some similar trends and moderate correlations across regions (average $R^2 = 0.45$; Figure 8). Observed survey biomass proportions and regional biomass proportions estimated from the spatial model demonstrated similar scaling in the BS, AI and western GOA, but were lower in the central GOA and higher in the eastern GOA (Figure 8A). Although similar scaling was observed in the western GOA, trends appeared uncorrelated ($R^2 < 0.01$) (Figure 8B).

4 | Discussion

4.1 | Insight on Sablefish Spatial Dynamics and Management

Generally, our results supported historical hypotheses regarding sablefish dynamics in Alaska, including the existence of a single spawning population, the presence of complex counter-clockwise ontogenetic movement dynamics, and the influence of environmental drivers on recruitment year class strength (Sasaki 1985; Heifetz and Fujioka 1991). In the selected spatial model, there was a lack of association between regions with high recruitment and regions with large spawning biomass, suggesting that year class strength is not strongly correlated to adult spawning biomass and that ecosystem factors likely promote larval dispersal away from spawning areas. Given synchrony in recruitment patterns across multiple regions during periods of extremely high recruitment, domain-wide environmental factors acting on a common larval pool (single spawning population) are potentially the drivers of year class success (Figure 7). The spatial distribution of recruitment from our spatial model also suggests that the BS, AI and central GOA regions serve as recruitment hotspots, generally supporting previous findings from Fenske (2022) based on a 3-region spatial assessment model. Ontogenetic connectivity dynamics likely interact with spatial recruitment patterns, given that smaller, immature fish tend to be found in the western region before demonstrating a generally eastward migration as they mature (with increased residency rates at older ages in eastern regions of the GOA). The estimated movement patterns differ from conclusions based on a tagging analysis conducted by Hanselman et al. (2015) where bi-directional movement was common across ages with no apparent ontogenetic dynamics. Differences in movement estimates likely stem from the integrated nature of the current framework, which incorporated compositional data, survey indices and tagging data, likely providing additional information on connectivity dynamics (e.g., Figure 4).

The spatial model also provided estimates of regional biomass and depletion, which are critical for understanding whether regional catch apportionment strategies are performing adequately and maintaining sustainable sub-populations. For instance, the spatial model estimated the highest spawning biomass in the central and eastern GOA, but these regions also experience some of the highest harvest rates and depletion levels. However, depletion within each region appears to be at sustainable levels (near or above 40% of virgin spawning biomass), suggesting that current apportionment strategies are adequate, likely aided by high movement rates that help mitigate fishery impacts on any single region (Bosley et al. 2019). Comparisons of regional biomass proportions from the spatial model against observed survey biomass proportions used for catch apportionment showed moderate correlations across most regions, but were uncorrelated in the western GOA. Stronger correlations were likely not detected due to selectivity effects inherent in observed survey biomass proportions, which were not incorporated in the calculation of regional biomass proportions from the spatial model. Moreover, the lack of correlation in the western GOA likely reflects high movement rates out of the area, complicating the detection of biomass trends. Overall, the operational spatially aggregated model provides similar results compared to the spatial model (Figure 7). Moreover, associated survey-based catch apportionment appears to provide adequate management advice (Figure 8), though regions like the western GOA may benefit from additional monitoring efforts. In particular, periodically implementing spatial models in tandem with routine updates of spatially aggregated models would be beneficial for understanding spatiotemporal changes in recruitment, movement, harvest patterns, or risk of localised depletion. Moreover, continued implementation of the spatial assessment could facilitate the development of refined harvest control rules based on spatially explicit biological reference points (e.g., Kapur et al. 2021), including exploration of empirical approaches (e.g., Reuchlin-Hugenholtz et al. 2016), and would provide additional insight into the robustness of existing regulatory frameworks.

4.2 | Model Limitations and Next Steps

While the conceptual model highlighted the importance of incorporating ontogenetic movement patterns, tagging data, which were highly influential on the estimates of age-based movement, only included lengths and necessitated the use of an external age-length key to derive ages. Given the potential for increased ageing bias introduced from indirect ageing methods (as opposed to otolith-based age determination), future evaluation is warranted on how best to utilise tagging data, with emphasis on the development of robust methods for converting recaptured lengths to ages, as well as the relative merits of using abundance indices derived from tagging data. Similarly, time-varying movement proved to be inestimable, despite being a key driver in the conceptual model. Given the potential for long times-at-liberty for sablefish (> 40 years) and the coarse resolution of conventional tagging data (i.e., single release and recapture points), these data are likely limited in their ability to resolve annual movement patterns. For instance, a tag recovered at its release location after 40 years does not imply the fish remained stationary. Rather, unobserved intervening movement most likely occurred during this period. Thus, the coarse resolution of conventional tagging data integrated into this model likely inhibited the estimation of time-varying movement. Nonetheless, allowing for continuous time-varying selectivity could have helped implicitly account for time-varying differences in movement and better address residual patterns in age-and length-frequencies (Lee et al. 2017), but the added complexity was not feasible within the spatial model due to the number of model partitions limiting data sample sizes. Moreover, sex-specific movement may be present for sablefish (Morita et al. 2012), but model explorations were not feasible due to a lack of sex information in the tagging data. Future iterations could consider using fishery-derived sex ratios to partition recaptures and attempt to estimate sex-specific movement patterns.

The specification of spatial boundaries also required several simplifying assumptions compared to observed sablefish spatial dynamics. Multivariate regression tree models using the compositional data identified spatial breakpoints spanning multiple management areas, which were not practical to implement given reporting restrictions tied to management areas. However, future improvements to the regression tree approach are warranted to better account for non-linear two-dimensional (i.e., latitude and longitude) breakpoints, while also potentially integrating multiple data sources simultaneously to better understand the delineation of fishery fleets versus population units. The existing management boundaries further complicated spatial delineations because sablefish exhibit extensive transboundary movements (i.e., between state, federal and international boundaries; Hanselman et al. 2015; Kapur et al. 2024). Consequently, 'demographic leakage' occurs across boundaries, potentially biasing stock assessment results and management advice, especially if substantial unidirectional movement occurs from high to low (or low to high) productivity areas (Berger et al. 2021). As a primarily self-sustaining and the most productive component of the Pacific coast sablefish metapopulation, capturing the intra-Alaska dynamics is likely more important for understanding population drivers than interactions with other components of the metapopulation (Kapur et al. 2024). Similarly, the spatial model provides a higher resolution and more realistic portrayal of population and fishery dynamics compared to the spatially aggregated model, which has similar boundary limitations. Nonetheless, model performance could be improved by implicitly accounting for potential movement to and from other components of the larger sablefish metapopulation, possibly through incorporation of numbers-at-age process errors.

4.3 | Recommendations and Next Steps to Advance Operational Spatial Assessments

Following the 'good practices' outlined by Goethel, Berger, et al. (2023) facilitated the development of a spatial stock assessment model for Alaska sablefish (Table 6). In particular, our process underscored the value of high-resolution data analyses and conceptual models in guiding key decision points (Table 2). Conducting a data inventory and associated visualisations (e.g., spatial distribution of cohorts and regression trees; Figures 2–5)

TABLE 6 | Recommended good practices from Goethel, Berger, and Cadrin (2023) for developing spatial stock assessments and how this advice was utilised during the current study, the benefits of the advice and difficulties encountered in implementing it.

Good practice advice	Implementation approach
Engage stakeholders	Outreach and discussions with stakeholders and managers were imperative for identifying the need for a spatial model, primary drivers of spatial dynamics and structural hypotheses. Continued improvements and refinements are expected as further feedback is provided by stakeholders. A primary impediment to adequately integrating local knowledge in modelling initiatives is identifying how to align scales of perception with data and model resolution, while also translating qualitative insight into quantifiable inputs
Develop flexible and reproducible data workflows	The spatial assessment model was developed in a generalizable manner that could accommodate any number of ages, sexes and spatial strata. The model was also able to accommodate various movement parameterizations (age and time varying), recruitment assumptions (local and global density dependence) and spatial survey and fishery characteristics (catchability and selectivity). Moreover, code for data inputs was developed to facilitate easy exploration of spatial resolution, if needed. Although generalizability is time consuming at the outset, it facilitates comparisons and exploring new features or parametrizations that may not be identified a priori (e.g., various movement parametrizations). Given the inevitable turnover in project team members (as occurred here), reproducibility via collaborative coding platforms (e.g., GitHub) supports continued traction
Identify need for spatial model and perform literature review	Various literature reviews of primary and secondary sources, as well as high resolution data analyses (Figures 2–5; Data S1) were used to identify the need for a spatial model. Identifying the need for a spatial model facilitated the development of the conceptual model, which was integral in guiding the modelling process and reducing model permutations explored
Develop conceptual model of spatial dynamics	A conceptual model of sablefish spatial dynamics was developed by using information derived from literature reviews, coupled with high resolution data analyses (Figures 2–5; Data S1). Generally, the conceptual model was developed using guiding questions from Table 1. The conceptual model was extremely helpful in reducing model permutations, and served as a framework against which to compare spatial assessment results
Narrow model options	Modelling options were narrowed by using a stepwise approach to model building. Initially, a 'base' spatial model was constructed to incorporate dynamics deemed important based on the conceptual model, that were supported by the literature review (i.e., local recruitment, metapopulation dynamics, high movement rates), and likely estimable given the available data. Following the configuration of a 'base' spatial model, we identified key uncertainties in spatial dynamics, which were then iteratively evaluated (i.e., movement, tagging likelihoods, tag reporting rates and spatial catchability)
Use diagnostics to identify final suite of models	Several model diagnostics and expert judgement based on the conceptual model was utilised to identify the final suite of models (Data S3). Use of traditional model diagnostics was challenging as they often indicated similar performance across models. By contrast, the conceptual model proved most useful in identifying the final suite of models
Implement simulations	Though not presented here, a number of simple exploratory simulations and self-tests were performed, which was helpful to determine potential coding errors and robust model structures. Research on developing spatial management strategy evaluations for Alaska sablefish is ongoing
Identify spatial reference points	Given the need for a management strategy evaluation to identify appropriate reference points, and challenges in defining equilibrium concepts for spatial reference points, these were not explicitly identified in this study. Instead, regional depletion (Figure 7) and regional survey exploitable biomass as estimated by the selected spatial model (Figure 8) was utilised as a proxy for spatial reference points. Comparisons of survey exploitable biomass between spatial and spatially-aggregated models were of utility in understanding the robustness of existing catch apportionment strategies and the current management approach
Iterate	The current form of this manuscript builds on initial efforts of Fenkse's (2022), which identified the need for a higher resolution spatial model, along with integration of tagging data. Results from this model iteration will be disseminated to stakeholders via an annual newsletter (the 'Black Cod Almanac'). Future iterations of this model will include using the spatial model as a 'conditioned model' for management strategy evaluations, incorporating state-space components and further refinements based on stakeholder feedback

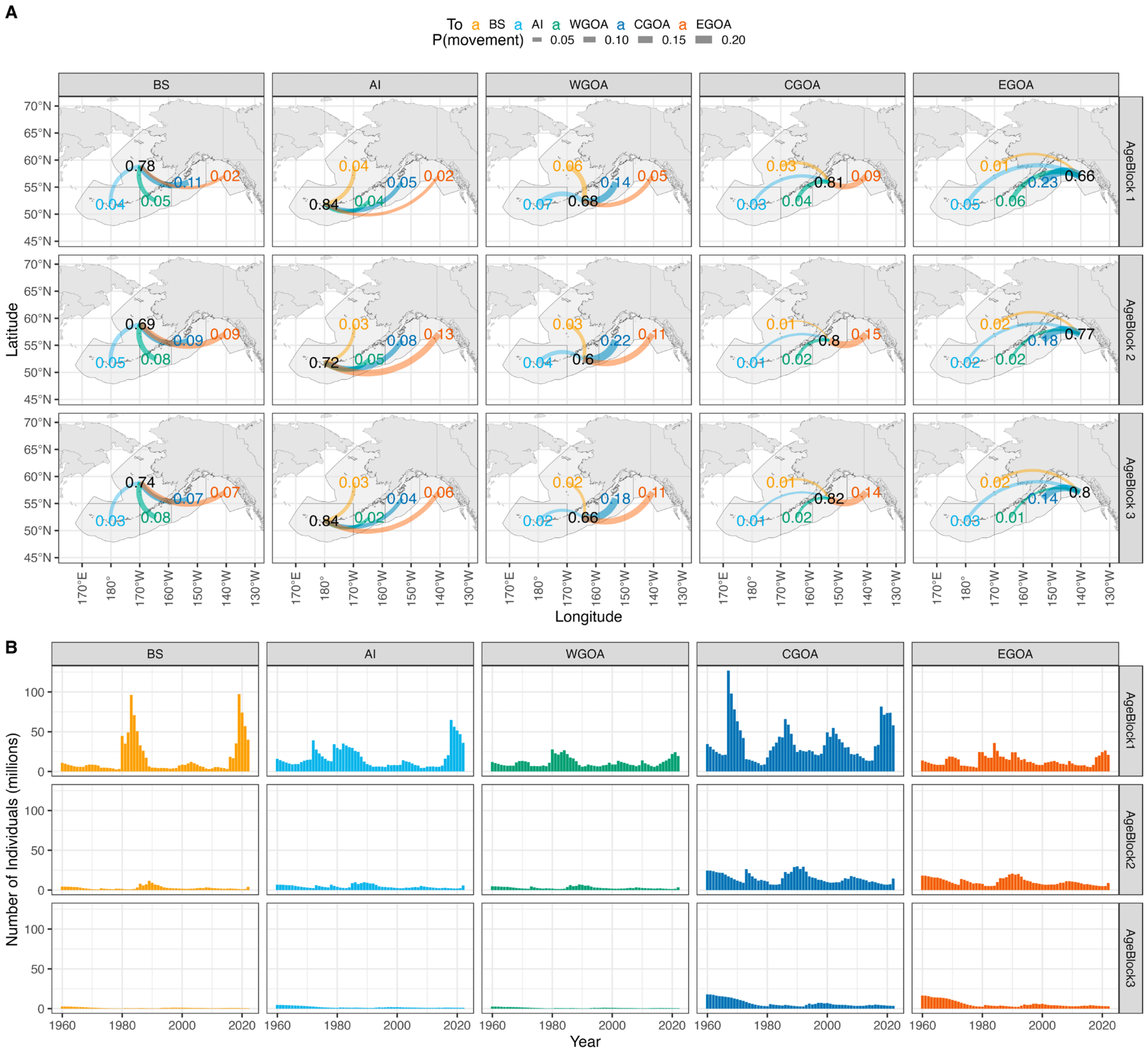

FIGURE 6 | Estimated bulk-transfer movement coefficients (time-invariant) from the selected spatial assessment model (A), where columns represent movement originating from a given spatial unit and rows represent movement for a pre-defined age-block (age-block 1, 2 and 3 corresponds to ages 2–7, 8–15 and 16–31, respectively). Values shown in black represent the probability of residence, while coloured values represent the probability of moving into a given spatial unit. Line thickness is proportional to movement probabilities, with thicker lines corresponding to higher movement probabilities. The strata utilised in the spatial assessment model are illustrated by the grey polygons. The abundance of individuals in a given age-block (B) are shown to illustrate the number of individuals within an age-block potentially moving across regions. Abbreviations in column panels represent the spatial units modelled in the selected spatial model (Bering Sea [BS], Aleutian Islands [AI], Western GOA [WGOA], Central GOA [CGOA], Eastern GOA [EGOA]).

were essential first steps for identifying data limitations, population structure, spatial boundaries, fleet dynamics and movement patterns, which then helped reduced the number of spatial model permutations explored. Importantly, the development of a conceptual model (Figure 1) was integral in guiding the overall modelling process and served as a framework to qualitatively evaluate the plausibility of assessment results. Given that the use of a conceptual model to validate model results can lead to circular logic, we recommend that practitioners also explore alternative models based on more extreme assumptions to evaluate model sensitivity and delineate the bounds of plausible outcomes.

However, we realised that the specification of tagging dynamics was underemphasised in the Goethel, Berger, et al. (2023) good practices guide. Tagging data can be extremely informative on spatial processes, but require several key considerations, including estimates of: (1) tag-related mortality and shedding rates, (2) time-at-liberty cutoffs, (3) tag-mixing periods and (4) tag reporting rates (Kolody and Hoyle 2015). Moreover, appropriate observational likelihoods and data weights must be determined to account for overdispersion. In the future, good practices for spatial assessment models should better integrate and emphasise the parameterisation of tagging dynamics, with particular focus

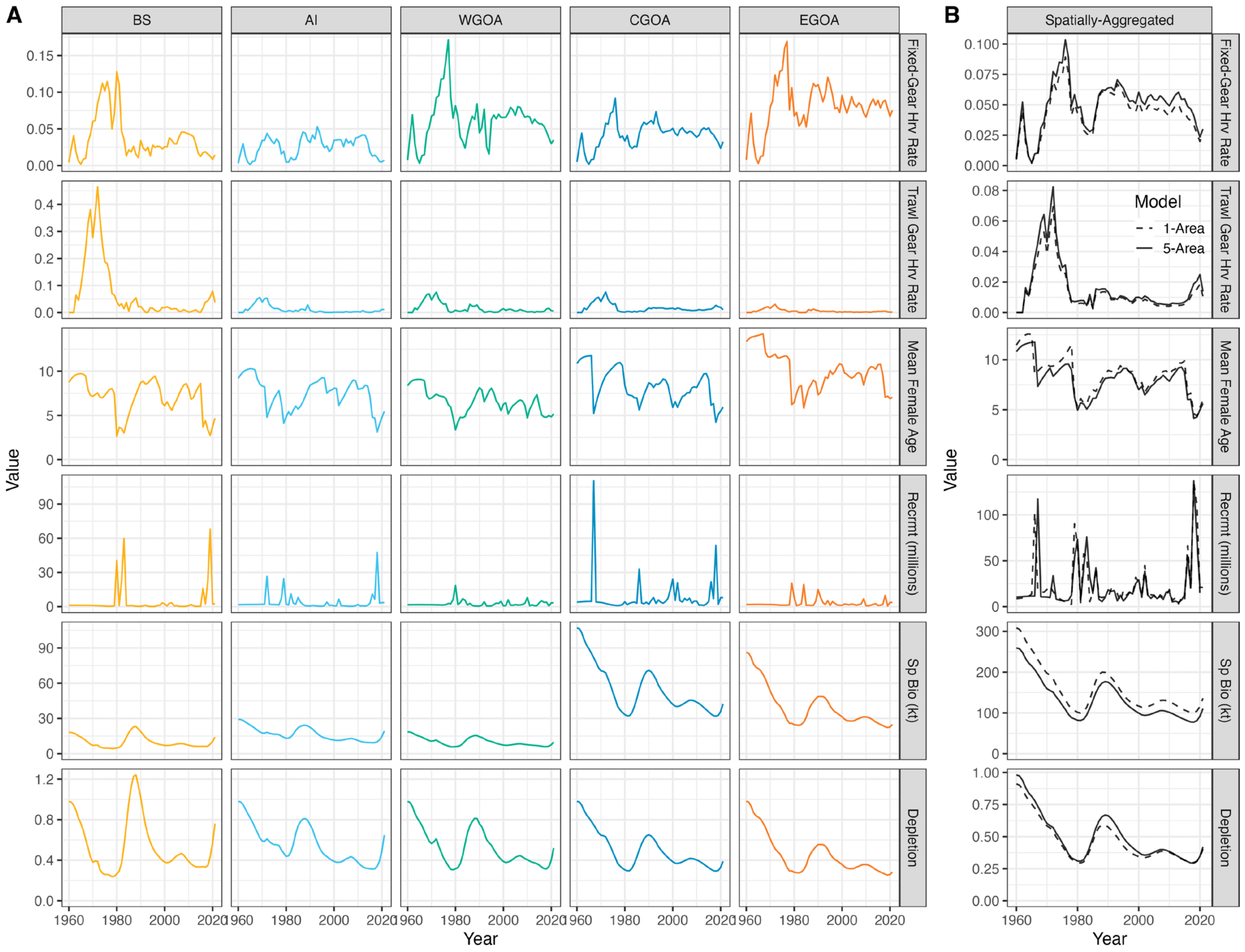

FIGURE 7 | Comparison of time-series estimates from the selected spatial (solid lines) and spatially-aggregated (dashed lines) assessment models by region (A; panel columns; Bering Sea (BS), Aleutian Islands (AI), Western GOA (WGOA), Central GOA (CGOA), Eastern GOA (EGOA)) and for the entire population (B). Estimates for important population quantities (panel rows) are shown for fixed-gear and trawl gear harvest rates (catch divided by exploitable biomass), mean population female age, age-2 recruitment (millions), spawning biomass (kt) and depletion.

on addressing overdispersion in tagging data. Developing methods that better integrate tag data with high-resolution path dependences (e.g., electronic tagging data) into spatial assessment models should also be emphasised, as they can better capture fine-scale movement processes and habitat-driven dynamics (Thorson et al. 2021). Further comparisons of alternative configurations of spatial processes in assessment models are also needed to understand their relative advantages. For instance, the current operational Ross Sea Antarctic Toothfish (*Dissostichus mawsoni*) assessment approximates spatial dynamics implicitly through an areas-as-fleets approach (Grüss et al. 2024). By contrast, other assessments, including this study, have used spatially explicit models with box-transfer movement to represent spatial processes more directly. More recent work in the Ross Sea region has also introduced finer-scale spatial assessments, with movement processes represented using habitat preference functions (Mormede et al. 2017, 2020). Comparing the strengths and limitations of these modelling approaches, particularly in relation to data resolution and the capacity to capture spatial dynamics, will support the continued development of spatial stock assessments.

Additionally, we found that guidance on model selection and diagnostics from Goethel, Berger, et al. (2023) was limited. Evaluating model diagnostics proved particularly challenging due to the dimensions represented in spatial models and the similar estimates produced by spatial model alternatives. Given that comprehensive good practice guides for diagnostics and model selection for spatially-aggregated stock assessment models have only recently been developed (Carvalho et al. 2021; Kapur et al. 2025), it is not surprising that similar guidance is not yet available for spatial models. Additionally, methods for data-weighting in stock assessment models is relatively well established in spatially-aggregated models (Thorson et al. 2023), but few good practice recommendations exist for spatial models, likely attributed to the dearth of studies on data-weighting methods in spatial assessments. Data-weighting can be particularly pertinent in spatial assessments given the diversity of data sources that can inform spatial processes (e.g., conventional and satellite tags; Thorson et al. 2021), and the potential reduction in data (and increases in uncertainty) due to additional spatial partitions. Incorporating random effects into spatial models may help address data-weighting challenges by

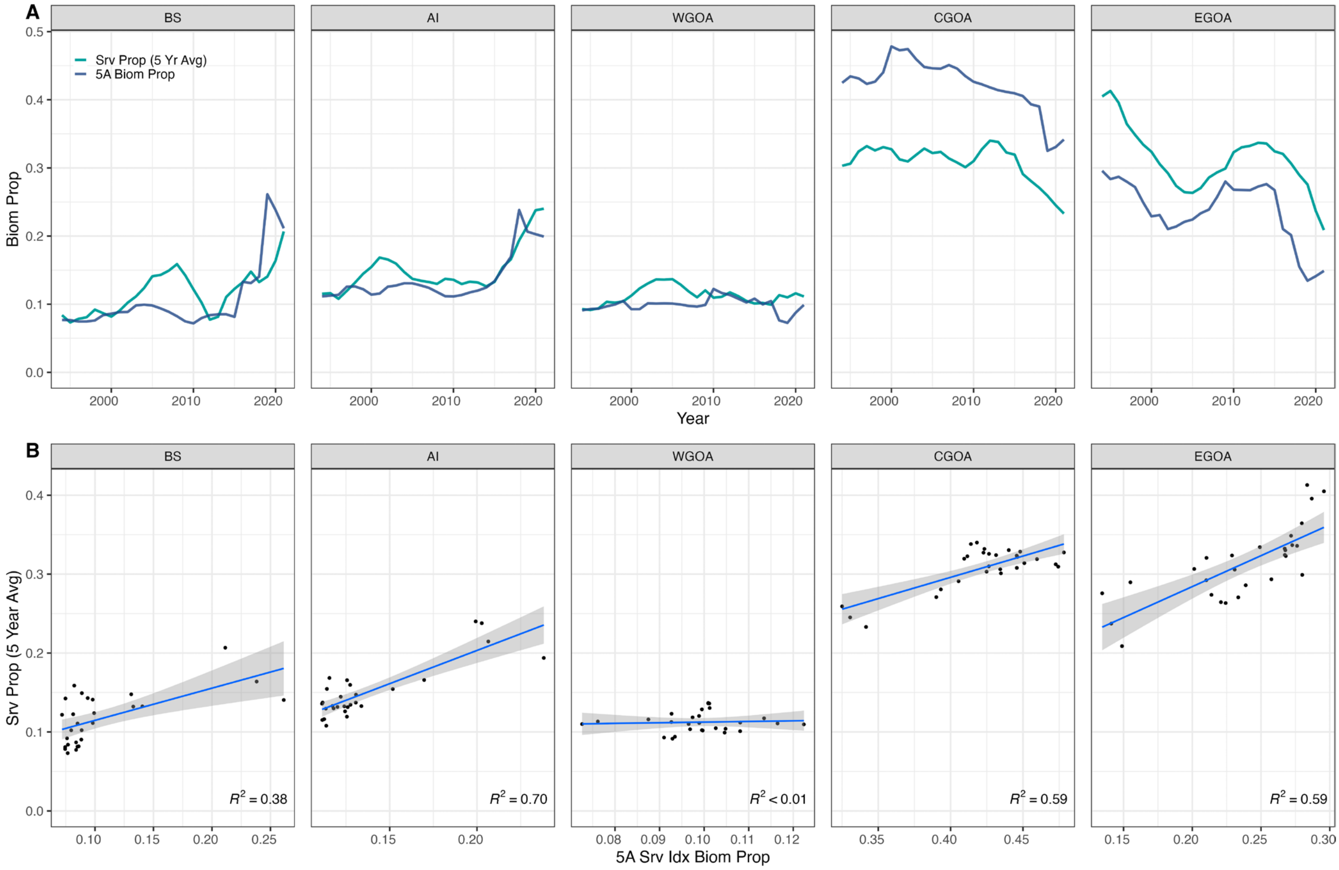

FIGURE 8 | Comparison of regional (panel columns; Bering Sea [BS], Aleutian Islands [AI], Western GOA [WGOA], Central GOA [CGOA], Eastern GOA [EGOA]) biomass proportions (A) between the selected spatial assessment model ('5A Biom Prop', blue) and a rolling 5-year average of observed biomass proportions from the United States longline survey ('Srv Prop [5 Yr Avg]', green). Correlations between regional biomass proportions from the spatial assessment model and survey biomass proportions (B) illustrate how well the current survey-based catch apportionment strategy aligns with regional trends estimated by the spatial model.

decomposing process errors into time-varying parameters and implicitly accounting for model misspecification (Thorson et al. 2023). Moreover, the use of random effects can also aid model parsimony by reducing the number of effective parameters estimated. Overall, enhanced model diagnostic tools, improved recommendations on data weighting and further incorporation of random effects into spatial assessment models are imperative for advancing these models and enabling their use in management decision-making.

Furthermore, many structural impediments (e.g., institutional inertia) remain that often prevent spatial assessment models from being used operationally (Berger et al. 2017). Although we argue that spatial models should be more widely considered as the basis of management advice, they can also inform management decisions more broadly. For example, spatial assessment models can be used in tandem with spatially aggregated models to provide insight on localised depletion and regional recruitment, which is the long-term plan for the sablefish spatial model. Thus, existing perceptions of population-wide dynamics and harvest recommendations from operational spatially aggregated models can be compared to higher resolution dynamics from spatial assessments (i.e., as done in this study) to identify whether perceptions align, and if management appears robust. Moreover, spatial models can aid in conditioning spatial operating models within management strategy evaluation tools, which can be used to refine spatially aggregated assessment parameterisations to implicitly account for underlying spatial dynamics (e.g., through process error in numbers-at-age) or to identify the robustness of existing management procedures when confronted with realistic spatial dynamics.

5 | Conclusions

Parameterizing a spatial stock assessment model is a complex and time-intensive process, requiring the availability of data at appropriate spatial scales and numerous decision points throughout the model development process. Successful integration of spatial models into management frameworks will depend on continued training, investment in analyst capacity and sustained support for data collection programmes (Goethel, Berger, and Cadrin 2023). Moreover, a better understanding is needed of when spatial models are feasible within the constraints of available resources and what represents a maximally robust, minimally complex management procedure when complex spatial dynamics are present. The approach implemented in this study provides a valuable guide demonstrating the challenges and potential solutions for developing spatial assessment models. Ultimately, we expect increased utilisation of spatial assessment models within management contexts in the coming years, given that they provide enhanced understanding of how spatial processes affect population dynamics, their role in facilitating the development of robust and spatially appropriate harvest strategies, and their utility for informing spatial dynamics within ecosystem-based fisheries management initiatives.

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Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

All code used in this study can be found at https://github.com/chengmatt/SpatialSabieModel.

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Supporting Information

Additional supporting information can be found online in the Supporting Information section.